Places as Recovery Machines: Vulnerability and Neighborhood Change After Major Hurricanes

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This study advances a conceptual framework for understanding the transformation of places into recovery machines after major hurricanes. This framework contends that in the years following such disasters, pro-growth coalitions take advantage of new sources of material and symbolic capital to promote further demographic growth. It also contends that the spatial nature of this growth varies significantly as a result of social inequalities among residential subpopulations, contributing to uneven transformation of local neighborhoods across affected regions. To test hypotheses derived from this framework, we combine innovative Geographic Information Systems data from "billion dollar" storms of the early 1990s with demographic data from local census tracts. Results support the recovery machine framework and imply that post-disaster resilience may contribute to the creation of larger, more segregated versions of affected regions that await exposure with the next major disaster.

Early sociological research on disasters treated them as "strategic research sites" in which to study social dynamics (Merton 1969). The idea was that the veil of everyday life makes it difficult to see the normal operation of social phenomena, but extreme disruption caused by disasters can help to lift this veil, revealing the inner workings of society. From this perspective, not only can sociologists contribute to understanding what happens when disaster strikes, they can also use these events to extend sociological theories of human behavior and organization generally, beyond the confines of disasters themselves.

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More recently, sociologists and kindred scholars have come to conceptualize natural disasters not simply as opportunistic, if unfortunate, events but as the intersection of environmental hazards and vulnerable people (see Blaikie et al. 1994; Rosa 2006; Tierney 2006). This conceptual shift emphasizes that disasters do not result from hazardous forces external to society (e.g., God or nature) but from the intersection of these forces with social systems that render some populations more vulnerable than others. This attention to social vulnerability implies that natural disasters do not just happen. Rather, they unfold through historical processes that generate social inequalities in the capacity to anticipate, resist and recover from hazards when they occur.

Recognition that natural disasters derive in part from social arrangements with historical underpinnings has broadened interest in their study and increased the range of analytical tools applied to them, including Geographic Information Systems that can illuminate the causal structure and spatial variation in social vulnerabilities to environmental hazards. In a good example of this approach, Cutter and colleagues (2000) overlay social and environmental data to examine a wide array of threats to coastal South Carolina, including disruption from floods, hurricanes, tornadoes and earthquakes. They find that areas of greatest risk for social disruption from such hazards do not correspond to areas of greatest physical risk because the latter tend to be located along the coast and waterways where personal resources are high. This "hazards in context" approach underscores the multifaceted nature of social vulnerability and moves researchers and policymakers beyond the simplistic assumption that the most environmentally hazardous places are always occupied by the most socially vulnerable populations. However, important analytical gaps in this line of research remain.

For example, most research in this vein still focuses on social vulnerabilities in regions *before* disasters strike. Few studies, by contrast, have investigated how these inequalities are reproduced after disasters, and fewer still have examined this question for more than one case. One reason for this shortcoming is empirical. Until recently, data on disasters have remained relatively scarce, often amounting to little more than "congeries of rumors, clippings from old newspaper stories, and guesses." (Wright and Rossi 1981:156) This situation means that in-depth case studies of disasters are difficult, and analyses of multiple disasters to test general propositions are more difficult still.

Another reason for this shortcoming is conceptual. In opening the door to greater sociological understanding of natural disasters, vulnerability science has highlighted the unfolding of local social conditions before a hazard hits, paying less attention to what happens afterward. Recent studies of post-disaster "resilience" are beginning to redress this shortcoming, but they too remain rooted in case study methodology (e.g., Vale and Campanella 2005). Consequently, we know very little about how regions, in general, change during long-term recovery from major disasters and whether this change tends to mitigate or exacerbate pre-existing vulnerabilities.

In the sections that follow we address this shortcoming by first discussing regional growth dynamics under ordinary circumstances, paying particular attention to growth in environmentally hazardous places. We then explain how pro-growth coalitions become infused with material and symbolic capital to rebuild after major hurricanes, and how different residential subpopulations help to effect and are affected by this post-storm recovery process, creating uneven patterns of regional change. To make sense of these dynamics, we advance the idea of places as "recovery machines," which builds from the established concept of places as "growth machines" but moves beyond it to highlight how power and vulnerability emerge after disaster strikes and long-term recovery begins. This recovery machine framework helps us to understand how places rebuild following major hurricanes and yet still fail to address key social vulnerabilities that await exposure on an even larger scale with the next disaster.

To evaluate the empirical utility of our framework, we investigate demographic changes in U.S. regions hit by major hurricanes during the early 1990s. We define major hurricanes as storms that caused more than $1 billion in property damage. For these regions we merge census tract demographic data from the Neighborhood Change Database with biophysical data from HAZUS-MH file, which is a GIS-applicable software that contains meteorological and engineering models used to estimate wind speed damage from past hurricanes. This innovative combination of census data and HAZUS wind speed estimates allows us to model spatial variations in hurricane damage and recovery within affected regions. With this information, we can test and refine propositions about how regions and constituent neighborhoods change five to ten years after a major hurricane strikes.

Before the Storm: Growth Machines & Vulnerability

For centuries humans have settled in environmentally hazardous areas because, as it happens, these places are highly conducive to habitation and production (Jones 1980). River valleys, for example, offer fertile soils and easy passage for canals, railroads and highways, despite being vulnerable to flooding. Sea coasts and wetlands provide aquaculture, petroleum and inexpensive transport, in addition to being susceptible to hurricanes, tsunamis and erosion. Edges of tectonic plates create ideal harbors that serve commercial interests, as well as being prone to earthquakes and volcanic eruptions. For these reasons, humans the world over continue to amass in hazardous areas, particularly along the coasts. Today eight of the ten largest cities in the world are on or near the ocean, as is half the world's population (United Nations 2004).

In the United States patterns are no different. Since 1970, the number of U.S. residents living in coastal counties has grown from 110 million to more than 150 million, accounting for more than half of the national population. As these numbers have grown, population densities have increased to an average of 172,000 persons per square mile, more than thrice the average found in non-coastal counties (*Statistical Abstracts 2005*, Table 23). On the Atlantic and Gulf coasts, where hurricanes are most common, 86 million people now crowd onto 262,000 square miles of land, where capital investments continue to grow exponentially. During the last decade alone, insured property values along these coasts doubled, now totaling more than $7 trillion – the annual gross national products of Germany and Japan combined (Steinberg 2006:202; AIR World Corporation 2005). These developments mean that even if the number and strength of coastal hazards do not increase in coming years, as some predict they will (McGranahan, Balk and Anderson 2007), their social and economic impacts will still rise as a result of social forces that continue to concentrate people and wealth along the nation's shores.

In considering these social forces, it would be easy to presume that they simply reflect an aggregation of commercial interests and individual tastes for sun and surf, but this is only part of the story. In order for businesses, individuals and families to actualize these interests and tastes, coastal settlements must grow, and this growth requires broader political and economic forces to promote and legitimate ongoing development. Sociological efforts to understand these dynamics, past and present, span many traditions but among the most prominent is the idea of places as "growth machines." (Molotch 1976; Logan and Molotch 1987; for review see Jonas and Wilson 1999) We review the basic tenets of this idea to illuminate the political economy of place-making before major hurricanes hit and then consider how these dynamics change in the wake of such disasters, as long-term recovery unfolds.

The first tenet of the growth machine thesis is that all settlements, at least in the United States, have a dual nature. On the one hand, they constitute "home," where people develop meaningful social relationships, deep attachments to place, and a fundamental sense of community. On the other hand, they also constitute commodities that are subdivided into lots to be bought and sold, rented and leased for profit in the market. This duality of place creates conflict between groups primarily interested in preserving and improving the local quality of life, or "use values," and groups primarily interested in maximizing profits, or "exchange values." Second, these two sides are unequal. Developers, realtors, bankers, utility companies and other businesses that profit from continued growth tend to be more powerful than individual homeowners, neighborhood associations and civic groups that advocate primarily for use values, and they use this power to "capture" local officials and have them act in the interests of maximizing growth. This pro-growth alliance, in fact, is what the "growth machine" refers to: a coalition of business elites united with local political officials in pursuit of ongoing economic and demographic growth. Third, these pro-development coalitions promote their "growth ethic" by asserting that such growth is good for everyone because it brings new jobs, taxes and stature to the area. In this way, actors who benefit most from continued development present it as a public good to be pursued aggressively and with great civic pride by all. Consider the advertisement by the state of Louisiana in *Business Week* using taxpayer dollars: "Nature made it perfect. We made it profitable." (cited in Logan and Moloth 1987)

From this perspective, the continued concentration of people and property along the nation's coasts is more than a matter of geographic circumstance and individual choice. It is also a product of powerful local actors and institutions working together to generate and extract exchange values through ongoing land-use intensification. Local governments are instrumental in these efforts because they hold legal authority over zoning and land-use decisions and because they are well positioned to leverage capital investments that drive local growth. Municipal governments can, for example, disregard federal flood maps, facilitate drainage and landfill projects, create allowances for new shipping lanes and coastal port facilities, reduce taxes in locally defined enterprise zones, and generally shape where and to what extent infrastructural improvements will occur. In hazard-prone areas, these pro-growth initiatives typically outstrip disaster mitigation efforts and in the process erode wetlands, forests and other natural buffers to environmental hazards such as hurricanes. In this manner, coastal regions are becoming more vulnerable – not just quantitatively in terms of the growing number 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 environmental preparedness and mitigation.

Inserting this perspective into disaster studies moves us beyond the simple recognition that some groups are more vulnerable to environmental hazards than others to illuminate how this vulnerability is generated by ongoing and unequal struggles over local development. In turn, it also raises the question of how these struggles change after a major disaster hits, as competing interests respond to opportunities created by the damage, displacement and rebuilding that ensues, that is, as the local growth machine transforms into a recovery machine.

After the Storm: Recovery Machines & Vulnerability

Past experience indicates that when a major hurricane hits and initial emergency response and restoration recede, places enter into a long term recovery that can last up to 10 years depending on the scale and scope of the disaster (Burton, Kates and White 1978:176). During this recovery, funds available for (re)development increase substantially via private insurance claims and government disaster aid. For example, one year after Hurricane Katrina struck the Gulf Coast in 2005, the federal government had already committed $111 billion in aid to the affected region, and private insurers had distributed more than $16 billion to nearly a million homeowners (Insurance Information Institute 2006). This level and type of capital injection flows through local institutions and the hands of better-off residents to fuel the rise of a recovery machine that skews the balance of power even further in favor of developers, residential elites and their allies, who exercise disproportionate control over these post-disaster systems of capital.

One reason for this heightened imbalance during the recovery phase is that our contemporary system of disaster relief is designed to respond financially when disasters destroy *property*, not when they destroy homes and communities (Steinberg 2006). Another reason is that, symbolically, this hyper-infusion of public and private funds after disaster typically brings with it a political mandate to (re)build bigger and better than ever as public testament to the resilience of the local spirit. Within this political climate, growth, not just recovery, becomes a moral prescription that is promoted as being not only good for the local economy but for the collective psyche, a way to put the disaster "behind us." These twin forces for growth – material and symbolic – dwarf pre-hurricane sources of opposition to pro-growth development and blur differentiation between use and exchange values to the further advantage of pro-growth coalitions. This shift does not deny that disasters can also open the door to new sources of political opposition and debate, as the social order becomes disrupted. However, the same disruption that allows for these new sources of public input also tends to undercut their organizational capacities, relegating them to the margins of local recovery efforts.

Prior studies on the long-term effects of natural disasters lend empirical support to this view of post-disaster recovery (Cochrane 1975; Dacy and Kunreuther 1969; Douty 1977; Friesema et al. 1979; Geipel 1991; Haas et al. 1977; Wright et al. 1979). Cumulatively, they indicate that regions hit hard by environmental hazards tend to rebound within a few years to achieve a "functional recovery" defined as "the replacement of the population and of the functioning equivalent of their needs in homes, jobs, capital stock and urban activities." (Haas 1977:3)

Our contention, however, is that the recovery machine rarely stops at functional recovery and, instead, uses its newfound resources and power to expand aggressively following major disasters, increasing local populations, housing units and newcomers during a time when such growth might be reasonably scrutinized as socially and environmentally imprudent. We also contend that these developments further polarize local residential populations. So while it is true, for example, that the rich generally have more power and resources than the poor, this inequality increases following major hurricanes for several reasons.

First, disasters destroy housing supply while simultaneously increasing demand for reconstruction labor in the affected region. Without rent controls and similar housing initiatives, these developments decrease vacancy rates and increase housing costs, which tend to squeeze more vulnerable groups, particularly renters, from their neighborhoods. After Hurricane Katrina hit, the average rent in New Orleans increased 70 percent, from $800 to $1,350 per month, during the first year of recovery (Meitrodt 2006). At the other end of the spectrum, middle-class homeowners who can afford full 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 but actually upgrade it. These residents typically re-roof with stronger materials, install fancier kitchens, improve existing electrical systems, and install new amenities that further increase the value, and cost, of local housing 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 called it the Matthew Effect in action: "Benefits accrue to those who possess wealth and social and cultural capital, while larger proportional losses are borne by the poor and marginalized."

Scholarly research tends to affirm these observations. Studies have shown, for example, that poorer residents often live in structurally weaker dwellings that are left uninhabitable when disasters strike (Cochrane 1975) and that these same residents often lack the financial resources necessary to recover "in place." (Bolin and Stanford 1998; Hewitt 1997) Research also shows that poorer residents have more difficulty accessing (Dash et al. 1997) and navigating (Rovai 1994; Forthergill 2004) bureaucratic systems of disaster assistance. Meanwhile more affluent residents are well-positioned to absorb available housing following displacement, thereby exacerbating post-disaster housing shortages for less-affluent residents (Quarantelli 1994; see also Elliott and Pais 2006). Consequently, researchers commonly discover that after a major disaster, "Low income families find themselves moving frequently from one place to another (or even leaving the city forever), or in housing they can't afford." (Hass et al.1977:xxviii) Exacerbating these processes is the fact that municipal budgets become highly strained after major disasters, limiting public funds (and political will) for affordable housing in favor of infrastructural improvement and economic development.

In addition to amplifying inequalities among pre-existing subpopulations, the recovery machine also attracts a sizeable newcomer population to work in the "reconstruction" sector of building trades and allied industries such as demolition, hauling and sanitation. Consistent with building booms in non-disaster areas (e.g., Waldinger and Lichter 2003), this demand now attracts sizeable Latino-immigrant work forces that have become popularly dubbed "hurricane chasers" for their rapid response capabilities. At least two factors contribute to this type of labor influx. First, for a variety of reasons, Latino immigrants are more willing than native-born workers to live and work in unpleasant, even illegal, conditions to earn good wages that typically come from recovery and reconstruction work. Second, employers operating in this sector often prefer such workers over native-born, particularly black, counterparts. Estimates from New Orleans indicate that nearly half of the reconstruction jobs generated by Hurricane Katrina were filled by new Latinos to the area (Fletcher, Pham, Stover and Vinck 2006). In the same study, employers told interviewers they preferred immigrant Latinos to local workers because, "Latinos have a reputation for industriousness and a willingness to tolerate the difficult and uncomfortable working conditions involved in debris removal and demolition work." (Fletcher et al. 2006:11) As functional recovery is achieved and new growth begins, many of these "reconstruction" jobs disappear but not before local preference for and experience with immigrant labor becomes (further) institutionalized within local housing and labor markets, changing local ethnic systems of stratification and the allocation of resources that flow through them.

Spatial Dimensions of Transformation after Major Hurricanes

To understand the spatial logic of recovery machines, we conceptualize regions hit by major hurricanes as consisting of three zones of impact: the recovery core, the inner ring and the outer ring. The *recovery core* consists of coastal neighborhoods where the greatest physical damage from the hurricane takes place. It is where storm surge and category two or higher winds destroy roofs, siding, doors and windows as well as toss debris about, causing severe damage, if not complete structural failure. Within this zone, we expect residential elites (e.g., homeowners, whites and the wealthy) to use their private insurance settlements and social capital to recover in place, recoup their losses and rebuild while residential non-elites (e.g., renters, blacks and the elderly) get squeezed from the area as a result of inadequate resources, rising rents and regressive disaster relief policies. The culmination is a form of "elite entrenchment," wherein more powerful residential groups dig in, upgrade and use their political and social resources to keep new growth out, as others are forced from the area.

Surrounding this core zone is the *inner ring* of recovery. This zone resides just outside the recovery core where the hurricane's impact is consistent with category one force winds, as well as further inland where major structural damage associated with category two or higher winds is dispersed and the overall extent of physical damage is lower than in the core zone of the disaster. Within this inner ring we expect pro-growth development to be much more substantial and ethnically diverse than in the recovery core for several reasons. First, less concentrated property damage means lower pressures and opportunities for elite entrenchment, as well as clearer signals for safe investment and development opportunities. Second, many residential non-elites (e.g., minorities, renters and elderly) who become displaced from the core zone of recovery may wish to remain near their former neighborhoods in order to maintain spatial habits and social networks useful in coping with the disaster and ensuing displacement. Finally, new immigrant laborers drawn to the region are likely to find neighborhoods in this inner ring attractive because of their proximity to reconstruction jobs in the recovery core and because of the relative affordability of housing in this zone, particularly inland. We suspect that these dynamics will produce substantial population growth and ethnic diversification in the inner ring, where evidence of the recovery machine will be most evident in aggregate terms.

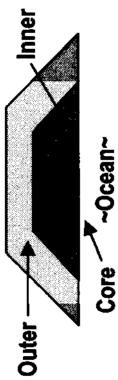
The third zone of recovery, the *outer ring*, is where winds fail to reach hurricane status, and where we expect aggregate growth in people, housing and newcomers commensurate with what would have occurred had no major hurricane hit the region. In essence, neighborhoods in this zone serve as our "control" group. We expect growth in this zone to be positive but not as great as in the inner ring of recovery. We also expect this growth to have a different demographic character than in the other two zones. Specifically, neighborhoods in the outer ring will show less evidence of elite entrenchment, non-elite displacement and immigrant influx. Instead, they will exhibit moderate aggregate growth driven largely by native-born newcomers, similar to patterns and processes evident before the hurricane.

In Table 1 we summarize the recovery machine framework and associated spatial hypotheses for each set of key regional actors. Below, we discuss the data used to test these hypotheses empirically.

Data

To evaluate our framework and its spatial manifestations requires that we select a set of hurricanes for analysis, develop a means to circumscribe affected regions and constituent zones of impact, and specify a primary unit of analysis and key sets of variables for examination. We selected hurricanes that caused more than $1 billion in property damage during the early 1990s for a couple reasons. First, their scale assures us that the disaster exerted a real impact on the observed region; it was not

Table 1: Summary of the Recovery Machine Framework and Associated Hypotheses of Neighborhood Change Following a Major Hurricane



Key Regional Actors	Emblematic Groups & Subpopulations	General Propositions	Spatial Hypotheses
Recovery Machine Proper	The usual growth machine actors (developers, allies and local officials) fueled by capital infusion (government disaster funds and private insurance claims), as well as political mandate to (re)build.	Will promote economic and demographic growth in the affected region as a whole during the recovery phase.	This growth in (a) total population, (b) housing units, and (c) newcomers will be lowest in the recovery core and greatest in the inner ring, as displaced residents and newcomers settle into these neighborhoods for new job and housing opportunities.
Residential Elites	Homeowners, higher-income residents and whites.	Will use personal and social resources to rebuild, upgrade and suppress growth in their own neighborhoods, particularly in areas hit hardest by the disaster, where simultaneous displacement of residential non-elites will contribute to patterns of elite entrenchment.	Elite entrenchment will increase (a) median incomes, (b) housing values, and (c) shares of whites most in the recovery core (i.e., in coastal neighborhoods hit hardest by hurricane winds and storm surge).

simply incidental to other events occurring at or around the same time but actually destroyed and/or damaged substantial portions of the built environment. Second, by restricting our analyses to the early 1990s we can examine recent recovery dynamics but still allow sufficient time for long-term effects to unfold by the 2000 U.S. Census – the most recent, reliable source of general data on regional change.

Using the National Oceanic and Atmospheric Administration's list of "Billion Dollar U.S. Weather Disasters" (in constant 2002 dollars), we identify three such hurricanes and four regions for analysis: Hurricane Bob, which hit New England in 1991, causing an estimated $2.1 billion in damage; Hurricane Andrew, which first hit southern Florida and later southwestern Louisiana in 1992, causing an estimated $35.6 billion in damage; and Hurricane Opal, which hit the Florida Panhandle in 1995, causing an estimated $2.1 billion in damage.

Residential Non-Elites	Blacks, renters and the elderly	Will experience relative displacement and exclusion from the most heavily damaged neighborhoods and (re)settle in nearby neighborhoods.	These processes will *decrease* shares of (a) African Americans, (b) renters, and (c) the elderly in the recovery core zone and will *increase* their shares in the inner ring of recovery.
Latino/Immigrant Newcomers	Latinos, immigrants and multi-worker households (3+ workers)	Will migrate to the affected region in response to new job opportunities, as initial rebuilding efforts turn to long-term recovery opportunities.	This immigrant-labor influx will increase the presence of (a) Latinos, (b) immigrants, and (c) crowded residences most in the inner ring of recovery, where proximity to new jobs will couple with more affordable housing to attract long-term settlement.

Delineating Affected Regions and Zones of Impact

Delineating the exact regions affected by these big storms is complicated by a number of factors. Foremost, hurricanes are not well-contained hazards, so determining where exactly they strike can be difficult but essential in analyses such as ours, which require standardization of techniques across multiple disasters, as well as delineation of different zones of impact. Our research into these challenges indicates that the best approach is to use the Hazards-U.S. database. The HAZUS database is a federally sponsored program developed under contract with the National Institute of Building Sciences, which has developed a wind modeling technology to estimate hurricane intensities across affected regions in addition to economic, infrastructural and building losses, all to the geographic level of census tracts. This technology was designed to help emergency managers prepare for and mitigate against hurricanes, floods and earthquakes.

In the present study, we apply the HAZUS database retrospectively and limit its use to the historical wind-modeling component for several reasons. First, the HAZUS wind modeling technology comes from an established field of research, has been extensively validated, and requires fewer assumptions about the built environment than more experimental components of the database aimed at loss estimation.[1] Second, our focus on past storms prevents us from using the economic and building-loss estimation tools because historical data on these items are unavailable within HAZUS, given the database's emphasis on forecasting and mitigation against future disasters.

Using these historically estimated wind speeds from HAZUS, we delineate affected regions as all census tracts that experienced at least tropical-storm force winds (more than 50 miles per hour) for our hurricane of interest.[2] We then categorize each census tract in these affected regions by its maximum wind speed during the hurricane, according to the Saffir-Simpson Scale. The Saffir-Simpson Scale is a tool used by meteorologists and officials to communicate hurricane threat associated with a given storm (Saffir 1977; Simpson & Riehl 1981). The scale is based on maximum sustained wind speeds and ranges from tropical-storm force winds (51-74 miles per hour) to hurricane intensities ranging from Category 1 to Category 5.[3] In our sample, census tracts that did not experience at least tropical storm-force winds are considered outside the affected region and are excluded from analysis. The result is a sample of 2,847 census tracts across our four study regions. Maps of these regions with the HAZUS-generated storm tracks and associated wind speeds appear in Figure 1.

In addition to using estimated wind speeds to delineate affected regions as a whole, we use these tools and coastal location (yes/no) to identify distinct zones of impact within the affected region. We designate coastal tracts that experienced Category 2+ winds (and typical storm surges of 6 feet or more) as the "recovery core," where the greatest damage occurred. We designate the surrounding "inner ring of recovery" as inland tracts that experienced similar wind speeds (i.e., Category 2+) but no storm surge by virtue of their inland location, and nearby census tracts (coastal and inland) that experienced only Category 1 winds. Finally, we identify census tracts (coastal and inland) that experienced only tropical-storm force winds as constituting the "outer ring of recovery," where damage was present but relatively minor. We use these three zonal designations – core, inner ring and outer ring – for interpretive purposes. In statistical analyses, we estimate the effects of each factor – wind speed and coastal location – separately and interactively to provide readers with the fullest information

Figure 1. Storm Tracks and Affected Regions for Billion Dollar Hurricanes of the Early 1990s

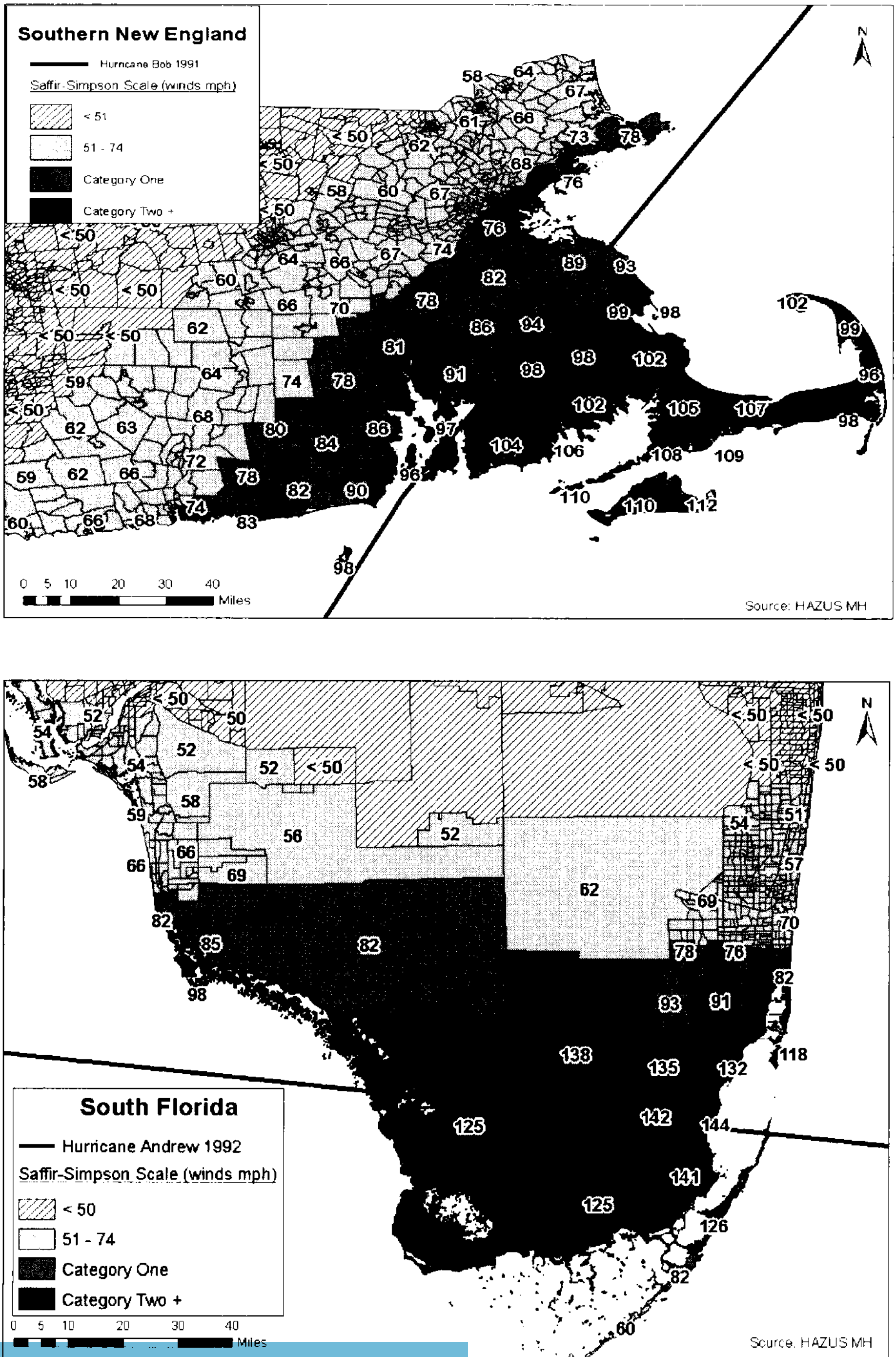
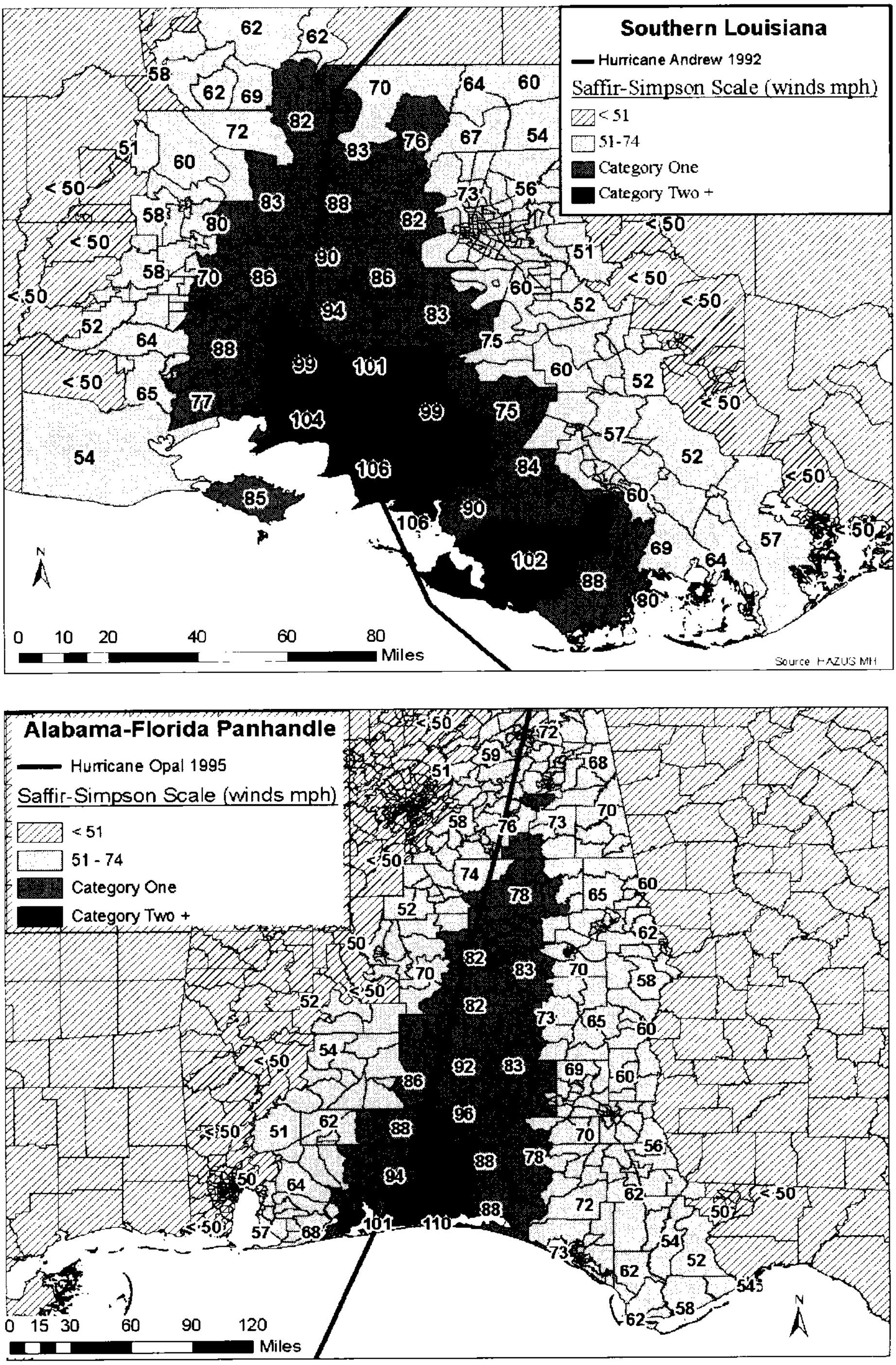


Figure 1 *continued*



possible. Wind speeds are top-coded at Category 2+ because sustained speeds of 96 miles per hour and higher are more than sufficient to create serious structural damage.

Estimating Neighborhood Change

Next, we must specify our primary unit of analysis and key sets of variables for examination. Because we are interested in aggregate spatial changes associated with the recovery machine and because the HAZUS database allows us to work at the level of individual census tracts, we use these tracts as our primary unit of analysis, using data from the 1990 census (pre-storm) and 2000 census (post-storm) to examine neighborhood change associated with the recovery machine. A census tract is a spatial unit commonly used to approximate a neighborhood and contains roughly 4,000 persons, on average. To examine these data, we use Geoltyics' Neighborhood Change Database, which normalizes tract boundaries across decennial censuses. This normalization means that although tract boundaries can change over time, our analyses of tract-level changes in affected regions and subregions are for fixed spatial units over time using 2000 boundaries.

Using this approach, we examine three indicators of change for each set of regional actors. For the recovery machine proper, we examine changes in total population, housing units and newcomers, with the latter defined as migrants from outside the county who arrived in 1995-2000, that is, after the respective hurricane hit. For residential elites, we examine changes in median household incomes, median home values (both in constant 1999 dollars),[4] and the percentage of whites in the tract, all of which are common indicators of socio-demographic change in prior research on post-disaster recovery (see Friesema et al. 1977; Wright et al. 1979). For residential non-elites, we assess changes in the percentage of non-Hispanic blacks, the percentage of renter-occupied housing, and the percentage of elderly (65 years of age and older) in affected tracts, each of which has been used to identify and assess social vulnerability to environmental hazards in prior research (see Cutter et al. 2000; Tierney 2006). For immigrant influx and crowding, we assess changes in the percentage of foreign-born residents, the percentage of Hispanics, and the percentage of households with three or more workers in the tract. Descriptive statistics for these tract-level variables are summarized in Table 2.

Results

The first part of the recovery machine framework hypothesizes that regions hit by major hurricanes do not simply rebound to pre-disaster population and housing levels but exceed them as pro-growth coalitions gain capital and political momentum during the recovery phase. To test this hypothesis, we pooled our census tract data from 1990 and 2000 to solve a series of simple equations of the following general form:

$$\text{Tract Characteristic}_{it} = \alpha + \beta(\text{year}_t\text{: 2000}) + u_i + e_{it},$$

where i is an index for the observed census tract, t is an index for time (0 = 1990; 1 = 2000), and β is our coefficient of interest, representing the average change across the observed time period (1990-2000). The error structure ($u_i + e_{it}$) assumes that each census tract varies in its intercept but not its error term, effectively controlling for fixed "case effects" over time. Rather than display the full set of regression results, Table 3 reports the mean of each tract-level variable in 1990 (pre-storm), followed by the

Table 2: Descriptive Statistics for Census Tracts in Hurricane Regions under Analysis

Tract-Level Variables (N = 2,847 tracts)	Range	Mean	S.D.
Recovery Machine			
1990 Total population	112 – 11843	4422.82	1768.07
2000 Total population	19 – 18547	4902.94	2160.79
1990 Total housing units	0 – 9658	1874.01	887.91
2000 Total housing units	0 – 16023	2082.39	1089.04
1990 Total newcomers (# out of county migrants)	0 – 7496	845.67	667.62
2000 Total newcomers (# out of county migrants)	5 – 9445	919.97	765.64
Residential Elites			
1990 Median household income (in 1999 $)	3750 – 200001	44687	21062
2000 Median household income	3571 – 200001	43056	19554
1990 Median home value (natural log of 1999 $)	8.91 – 13.12	11.52	.64
2000 Median home value (natural log)	8.27 – 13.12	11.49	.59
1990 % Non-Hispanic white	0 – 1	.75	.29
2000 % Non-Hispanic white	0 – 1	.68	.30
Residential Non-Elites			
1990 % Non-Hispanic black	0 – 1	.14	.23
2000 % Non-Hispanic black	0 – .99	.16	.24
1990 % Housing units, renter occupied	0 – 1	.44	.22
2000 % Housing units, renter occupied	0 – 1	.42	.23
1990 % over 65 years old	0 – .81	.14	.08
2000 % over 65 years old	0 – .85	.14	.08
Immigrant Labor Influx & Crowding			
1990 % Foreign-born	0 – .87	.12	.16
2000 % Foreign-bom	0 – .84	.15	.18

estimated percentage change by 2000 (β/α) for all tracts, collectively and in each region separately.

Consistent with our hypothesis, results show significant growth in population and housing during the observed period. Specifically, the average census tract grew in population and housing by more than 11 percent, representing 500 additional persons and 200 additional residential units in each "neighborhood" unit. Proportionally, this growth was greatest in southern Florida following Hurricane Andrew and in the Panhandle following Hurricane Opal, where populations grew by roughly 19 percent and 14 percent, respectively. Although some of this growth may have occurred prior to the observed hurricane, it appears clear that even "billion dollar" storms do not halt or reverse local development. Moreover, this growth is consistently observable in each of the four affected regions, as well as in the full sample, strengthening support

1990 % Hispanic	0 – .96	.09	.19
2000 % Hispanic	0 – .95	.12	.21
1990 % Households w/ 3 or more workers	0 – .40	.14	.06
2000 % Households w/ 3 or more workers	0 – .38	.11	.05
Indicators of Spatial Variation			
Inland tract	0 – 1	.76	.43
Coastal tract	0 – 1	.24	.43
Category 0 winds (51-74 miles per hour)	0 – 1	.43	.50
Category 1 winds (75-95 miles per hour)	0 – 1	.40	.49
Category 2+ winds (96 miles per hour or greater)	0 – 1	.15	.36
Control Variables			
No change in tract boundary (yes/no)	0 – 1	.54	.50
Tract boundary merged, corrected (yes/no)	0 – 1	.02	.14
Tract boundary split, corrected (yes/no)	0 – 1	.44	.50
1990 Population density (persons per square mile of land)	.30 – 86600	5060.76	7399.07
1990 Vacancy rate below 5% (yes/no)	0 – 1	.27	.45
Hurricane region 1: Bob 1991, Southern New England	0 – 1	.49	.50
Hurricane region 2: Andrew 1992, South Florida	0 – 1	.22	.41
Hurricane region 3: Andrew 1992, Louisiana	0 – 1	.09	.29
Hurricane region 4: Opal 1995, AL/FL Panhandle	0 – 1	.20	.40

Table 3: Estimated Average Change in Census Tract Characteristics, by Total Sample and for Specific Hurricane-Affected Regions

	All Regions		Hurricane Affected Regions: Bob 1991		Andrew 1992 (FL)		Andrew 1992 (LA)		Opal 1995	
	Mean 1990	Aver.% Change 1990-2000	Mean 1990	Aver.% Change 1990-2000	Mean 1990	Aver.% Change 1990-2000	Mean 1990	Aver.% Change 1990-2000	Mean 1990	Aver.% Change 1990-2000
Recovery Machine										
Total population	4,285	11.2*	4,334	6.0*	5,183	18.9*	4,148	9.2*	3,686	14.0*
Total housing units	1,815	11.5*	1,802	6.3*	2,336	13.3*	1,677	11.1*	1,556	21.8*
Total newcomers	791	9.4*	804	7.0*	1,027	5.0	549	27.9*	704	15.5*
Residential Elites										
Median household income	42,268	3.9*	49,878	3.6*	41,473	1.3	30,542	10.5*	30,307	5.8*
Median home values	123,902	-3.1	170,958	-9.6*	119,471	6.0	56,685	17.4*	49,788	17.1*
% Non-Hispanic white	75.2	-8.8*	85.7	-6.7*	50.2	23.7*	64.0	-7.2*	72.6	-4.8*
Residential Non-Elites										
% Non-Hispanic black	15.0	16.1*	6.4	20.6*	17.5	25.4*	33.1	11.5	25.4	8.8
% Rental units	44.8	-3.6*	47.6	-4.6*	48.0	-5.6*	42.9	-3.7	36.8	.3
% Over 65 years old	14.3	-0.6	13.9	-0.7	18.5	-5.3	10.8	8.3*	13.6	3.8
Latino/Immigrant Newcomers										
% Foreign-born	10.8	27.4*	10.8	25.7*	31.7	20.4*	1.8	34.3*	1.2	54.5*
% Hispanic	7.5	39.0*	4.8	53.9*	31.1	21.8*	1.4	8.8	.8	96.1*
% Households w/3+ workers	14.0	-18.5*	16.9	-22.9*	12.9	-8.6*	9.2	.2	10.5	-22.2*
N (# census tracts)	2,847		1,395		627		268		557	

Notes: Tract Characteristic it = $\alpha + \beta(\text{year}_{it}\text{: 1990/2000}) + u_i + e_{it}$; estimated for the pooled sample of 1990 and 2000 values, with β/α representing average % change. Estimated by taking the total population ages 5 and above and subtracting the number of residents that lived in same county five years prior. This is growth directly attributable to in-migration from outside the respective county. $^*p < .05$

for the proposition that local recovery machines promote rather than discourage growth in the wake of major disasters.

To investigate this growth further we can compare the migration of newcomers into the area before and after the storm. The census question regarding "residence five years ago" allows for such comparison for 1985-90 (pre-storm) and 1995-00 (post-storm) and provides two additional insights. First, supplemental analyses of this variable (not shown) affirm that coastal regions are very fluid demographically. By the time of each census, roughly half of all residents in our observed tracts reported living at another address five years earlier. Second, this residential churning is driven not just by local residents moving within counties. Although this type of move is common throughout the United States, results in Table 3 show that after a major hurricane, the number of newcomers migrating into affected tracts from other counties increased by an average of 9 percent over pre-storm levels, from 790 in-migrants during 1985-90 to 865 during 1995-00.

Moreover, the greatest increase in such newcomers occurred where in-migration rates had been lowest before the hurricane. In our analyses, these regions included southwest Louisiana after Hurricane Andrew and the Florida Panhandle after Hurricane Opal, where in-migration increased 28 and 16 percent respectively. Steinberg's (2006) study of southern Florida documents one reason for this accelerated in-migration. Local boosters do everything in their power to encourage optimism and to downplay media coverage after a disaster: "The less said the better," according to one *Miami Herald* editorial. "People forget rather quickly. It is wiser to let them do so." (cited in Steinberg 2006:63)

These findings are significant not only for their documentation of unchecked growth following major hurricanes but also for what they tell us about empirical assessments of this growth. Prior research by Wright and colleagues (1979) examined tract-level changes during the 1960s for all areas experiencing a hurricane, tornado or flood during that decade. Their analyses, which were unable to normalize tract boundaries over time or make fine-grained distinctions between affected and unaffected neighborhoods, lead to the conclusion that no significant changes occurred in the average tract after a natural disaster. In fact, they write that (1979:198), "Census tracts contain a lot of people, property, and capital… 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." Friesema and colleagues (1977) reached similar conclusions in their time-series analysis of city-level indicators of social and economic characteristics before and after natural disasters. By contrast, our analyses normalize tract boundaries over time, use more precise delineations of affected regions, and do so for the nation's costliest disasters, where one might reasonably expect growth to be most constricted as a result of extensive property damage, displacement and rising insurance rates. We find precisely the opposite pattern: substantial growth in population, housing and in-migration is the norm.

In addition to this aggregate growth, Table 3 also indicates substantial increases in minority and foreign-born populations following major hurricanes. On average, black shares of local populations increased 16 percent in our sample, and foreign-born and Hispanic shares increased 27 and 39 percent, respectively. These patterns imply that regions do not simply grow after major hurricanes but also become more ethno-racially diverse, raising questions about residential accommodation and uneven development during the recovery period.

Spatial Variation in Neighborhood Change after Major Hurricanes

The second part of our recovery machine framework hypothesizes that the growth documented above will unfold unevenly across affected regions. Specifically, evidence of elite entrenchment will characterize the hardest hit zone, aggregate growth and relative increases in socially vulnerable populations will characterize the surrounding inner ring, and more moderate patterns of growth and change will characterize the outer ring. To test these spatial hypotheses, we estimate a series of time-lagged, linear regression equations with and without spatially weighted error terms. The general model, estimated separately for each tract characteristic of interest (e.g., population change), takes the following general form:

$$\text{Tract characteristic}_{i,2000} = \alpha + \beta_1(\text{Tract characteristic}_{i,1990}) + \beta_{2,3}[\text{Saffir-Simpson wind speed category}] + \beta_4(\text{Coastal/inland location}) + \beta_{5\text{-}11}[\text{Controls}] + \lambda W\mu + e$$

where i is an index for the observed census tract and $\lambda W\mu$ is a first order, row standardized spatial weight of lagged error terms used to correct for spatial dependence among observed census tracts (see Anselin and Bera 1998). Model diagnostics for this spatial dependence are included at the bottom of tables 4-7. Lower estimates of the Akaike Information Criterion for the spatial error model compared with the Ordinary Least Squares model consistently demonstrate that the spatial error model is statistically preferable to the non-spatial error model for all tract characteristics. Moreover, attenuation of the global Moran's I residuals between the two models reveals that unaccounted spatial relationships influencing the dependent variable have been properly controlled with the spatial error model. Inclusion of the time-lagged dependent variable (Tract characteristic$_{i,1990}$) as an explanatory variable renders coefficients for all non-lagged variables in the model, such as wind speed and coastal/inland location, robust estimates of change in the observed tract characteristic during the 1990-2000 period.

In addition to these spatial indicators of interest, we also include several statistical controls commonly used in analyses of post-disaster demographic change (see Friesema et al. 1977; Wright et al. 1979). Population density (persons per square mile in 1990) controls for differential growth dynamics in rural, suburban and urban tracts; low vacancy rates control for pre-existing, tight housing demand (below 5 percent in 1990: yes/no); and regional dummy variables control for regionally specific growth trajectories. We also include dummy indicators for the type of tract-boundary change that occurred between 1990 and 2000 (merged: yes/no; split: yes/no; no change [reference]). We include these last controls because although the NCDB normalizes tract boundaries between censuses, 44 percent of tracts in our analysis split between 1990 and 2000. By including indicators of the type of boundary change that occurred, we can reduce the chance of compiling errors and introduce redundancy that improves statistical estimation. If we were examining spatial units that differed drastically in size, such as cities, we would also weight our model by the average of the square root of the respective spatial populations in 1990 and 2000 (see Maddala 1977:268). However, because census tracts are designed and measured to minimize such extreme variation, this weighting is unnecessary.

To test for interactive, as well as additive, effects of coastal/inland location and wind speed, we estimate a second model for each tract-level characteristic that includes interaction terms for these two spatial indicators. We report results from our additive model in Model A and results from our interaction model in Model B for each dependent variable. Results highlighted in gray in tables 4-7 are coefficients of central interest and discussed below.

We turn first to spatial variation in population, housing and newcomer growth in Table 4. Our hypothesis was that such growth would be lower in the hardest-hit tracts, where elite entrenchment is likely, but greater in surrounding tracts where new and displaced residents are likely to concentrate during the recovery phase. Results in Table 4 support this hypothesis. Appropriate calculations from Model A (the best fit model) show that, net of other factors, population growth was greatest in inland tracts experiencing only moderate, Category 1, winds (0 + 158 = 158), followed by coastal counterparts (-80 + 158 = 78). In other words, the greatest population growth tended to occur in tracts comprising what we call the inner ring of recovery. By contrast the least growth, as hypothesized, occurred in coastal tracts experiencing the highest winds (Category 2+) and associated storm surge, an area we call the core zone of recovery (-80 + -7 = -87).

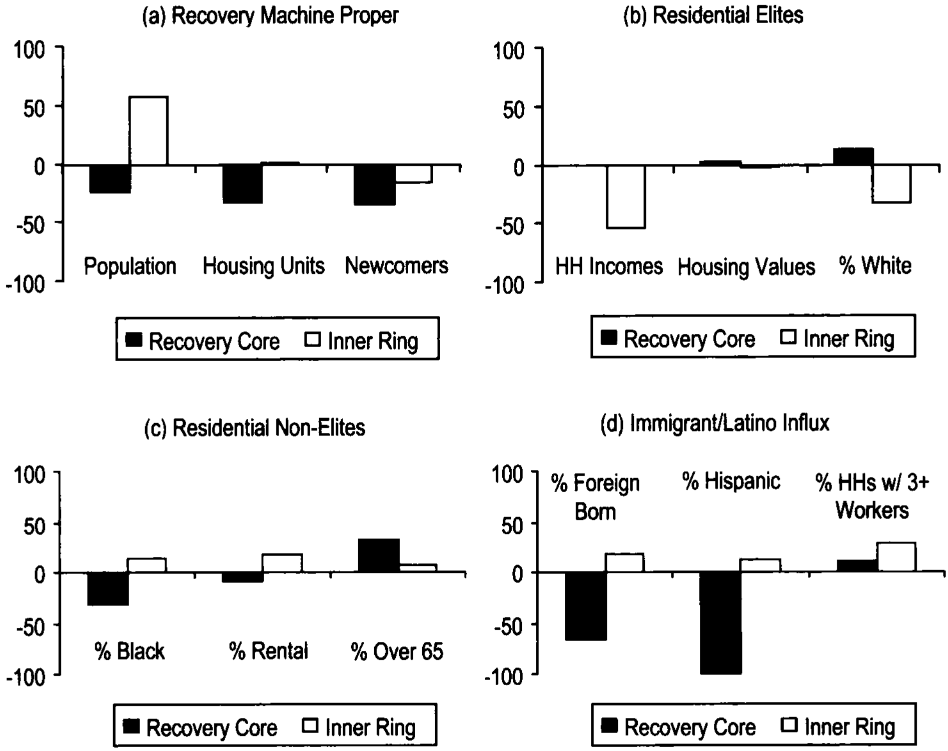
Table 4: Spatial Error Models for Recovery Machine Proper

	2000 Tract Characteristics					
	Total Population		Total Housing Units		Total Newcomers	
	(A)	(B)	(A)	(B)	(A)	(B)
1990 Tract Characteristic	1.048***	1.049***	1.102***	1.102***	.903***	.903***
	(.011)	(.011)	(.011)	(.011)	(.014)	(.014)
Merged boundary	154.912	151.902	-13.585	-13.751	158.602**	158.652**
	(123.207)	(123.150)	(57.015)	(57.013)	(60.192)	(60.191)
Split boundary	150.644***	153.321***	47.920**	49.307**	40.549*	41.038*
	(40.223)	(40.283)	(18.361)	(18.399)	(17.963)	(18.041)
Same boundary (ref.)	—	—	—	—	—	—
1990 Pop. Density	-.024***	-.024***	-.012***	-.012***	.000	.000
	(.004)	(.004)	(.002)	(.002)	(.001)	(.001)
1990 Vacancy rate	-80.201	-78.471	1.790	2.154	-30.767	-30.454
	(43.291)	(43.282)	(19.925)	(19.929)	(19.876)	(19.892)
South NE: Bob 1991	-111.945	-107.565	-150.407***	-148.472***	-58.571*	-58.271*
	(109.817)	(110.072)	(44.087)	(44.096)	(28.175)	(28.202)
South FL: Andrew 1992	546.238***	562.540***	-1.358	-.110	-7.255	-5.860
	(128.465)	(129.335)	(51.639)	(51.922)	(32.474)	(32.792)
LA: Andrew 1992	-129.938	-121.933	-135.795*	-132.020*	22.068	22.873
	(157.642)	(158.102)	(63.002)	(63.056)	(39.601)	(39.683)
FL/AL: Opal 1995 (ref.)	—	—	—	—	—	—
Spatial Indicators						
Coastal tract	-79.955	-49.118	-1.227	40.749	**71.348****	74.627
	(63.237)	(123.283)	(28.086)	(54.243)	(22.684)	(42.016)
Inland tract (ref.)	—	—	—	—	—	—

Category 2+ winds	-6.965	-66.099	-50.804	-51.137	**-114.180***	-120.079***
	(107.508)	(121.047)	(44.292)	(50.583)	(29.651)	(36.263)
Category 1 winds	**157.901***	186.054*	29.024	42.173	21.483	24.313
	(75.509)	(80.275)	(31.699)	(33.849)	(22.124)	(24.154)
Category 0 winds (ref.)	—	—	—	—	—	—
Coastal-Wind Interactions						
Category 2+ X Coast		91.009		-31.146		9.848
		(168.161)		(74.418)		(61.327)
Category 1 X Coast		-115.691		-69.223		-12.058
		(146.826)		(64.792)		(52.633)
Spatial Error (Wμ)	.557***	.558***	.491***	.491***	.169***	.169***
	(.021)	(.021)	(.022)	(.022)	(.028)	(.028)
Constant	206.512*	193.716	131.981**	125.191**	163.556***	162.375***
	(105.431)	(106.716)	(42.774)	(43.233)	(27.894)	(28.457)
R^2	.81	.81	.84	.84	.66	.66
N	2847		2847		2847	
Model Diagnostics						
Spatial Error AIC	47253.10	47254.80	42775.20	42778.0	42858.70	42862.50
OLS AIC	47903.90		43222.30		42896.30	
OLS Moran's I residuals	.354		.237		.077	
Spatial Error Moran's I residuals	-.014		-.010		-.005	

Notes: Unstandardized coefficients for the spatial error models are presented.
(Standard Errors in Parentheses)
$^*p < .05$ $^{**}p < .01$ $^{***}p < .001$

Figure 2. Average Estimated Rates of Change, Relative to the Outer Ring of Recovery



Source: Respective best-fit models in tables 4-7.

Notes: Bars indicate the estimated rate of change relative to the outer ring of recovery, in percentage terms, holding all other variables constant. The Recovery Core consists of coastal tracts that experienced Category 2+ winds (and accompanying storm surge). The Inner Ring consists of inland tracts that experienced Category 2+ winds and all tracts that experienced Category 1 winds. The Outer Ring [our reference category] consists of all tracts that experienced only tropical-storm force winds (51-74 miles per hour), offering a benchmark for comparison.

For example, Panel (a) indicates that population growth was roughly 70 percent greater in the Inner Ring of recovery than in the Outer Ring of recovery, all else equal; whereas growth in the Recovery Core was roughly 35 percent lower than in the Outer Ring of recovery during the same period.

To help visualize these and subsequent spatial patterns, Figure 2 graphs estimated rates of change in the recovery core and the surrounding inner ring, relative to the outer ring of recovery, net of other factors in our spatial error model. (See the footnote in Figure 2 for specifics.) The logic behind these calculations is that the outer ring of recovery provides a benchmark against which to compare developments in harder hit areas nearby. This type of comparison renders support for our hypothesis easier to see. Specifically, Panel (a) of Figure 2 shows that, all else equal, population growth tended to be 30 percent lower in the recovery core but 70 percent higher in the inner ring than in comparable tracts within the surrounding outer ring of recovery. Similarly, results show that housing growth and in-migration from outside the county tended to be lowest in the recovery core, as hypothesized. Although the variation in housing growth is not statistically significant at the .05-level, these patterns are nonetheless consistent with the argument that growth is least likely to occur in the hardest hit tracts and most likely to occur in the surrounding vicinity.

Our hypothesis for residential elites predicts that these groups will dig in and upgrade in the hardest hit areas, as non-elites are squeezed out, producing patterns indicative of elite entrenchment (e.g., more whites with increasing incomes and housing values). To test this argument we examine three indicators – median household income, median housing value and percent white. Results in Table 5 indicate that the interaction model (Model B) offers the best fit for each indicator. All else equal, these results reveal a strong spatial U-curve in which all three indicators increase most in coastal tracts experiencing the least damage, then decline dramatically in nearby coastal and inland tracts that experienced moderate damage (inner ring), and then increase again in coastal areas that experienced the greatest damage (recovery core). This pattern is particularly evident in household incomes. Calculations displayed in Panel (b) of Figure 2 show that while median household incomes rose equally in the recovery core and outer ring, all else equal, they failed to keep pace in the inner ring of recovery where population growth was greatest.

In this graphical depiction, the racial contours of these changes also become easier to see, with white populations growing most in the recovery core, as hypothesized, and decreasing in the surrounding, inner ring of recovery – the same general pattern as for housing values, only much stronger. Overall, these patterns support the notion of limited growth coupled with white-elite entrenchment in the core zone of recovery, where damage and private-insurance payouts are greatest.

Our hypothesis for non-elite residents – specifically, blacks, renters and the elderly – are the inverse. We expect their relative shares to

Table 5: Spatial Error Models for Residential Elites

	2000 Tract Characteristics					
	Median Household Income		**Median Housing Values**		**% Non-Hispanic White**	
	(A)	(B)	(A)	(B)	(A)	(B)
1990 Tract Characteristic	.945***	.945***	.814***	.811***	.916***	.916***
	(.011)	(.011)	(.015)	(.015)	(.008)	(.008)
Merged boundary	7850.156***	7855.937***	.293***	.293***	.002	.002
	(1103.112)	(1101.998)	(.035)	(.035)	(.010)	(.010)
Split boundary	686.982*	757.553*	.025*	.027*	-.006	-.005
	(330.367)	(331.296)	(.011)	(.011)	(.003)	(.003)
Same boundary (ref.)	—	—	—	—	—	—
1990 Pop. Density	-.090**	-.091**	.000	.000	-1.55e-06***	-1.62e-06***
	(.028)	(.028)	(.000)	(.000)	(.000)	(.000)
1990 Vacancy rate	1303.048***	1326.868***	.030*	.030*	.017***	.017***
	(369.046)	(368.886)	(.012)	(.012)	(.004)	(.004)
South NE: Bob 1991	1342.754*	1410.032*	-.137***	-.131***	-.015	-.013
	(608.911)	(608.412)	(.028)	(.028)	(.008)	(.008)
South FL: Andrew 1992	-399.170	-316.207	-.029	-.026	-.113***	-.115***
	(655.232)	(659.861)	(.027)	(.027)	(.009)	(.009)
LA: Andrew 1992	1535.467*	1656.561*	-.017	-.012	-.013	-.011
	(775.979)	(775.915)	(.031)	(.032)	(.012)	(.012)
FL/AL: Opal 1995 (ref.)	—	—	—	—	—	—
Spatial Indicators						
Coastal tract	1993.480***	**3073.010*** **	.073***	**.129*** **	.019***	**.050*** **
	(424.199)	(784.616)	(.015)	(.027)	(.005)	(.008)

Inland tract (ref.)					—	—
Category 2+	-1032.986	-1292.197	-.017	-.013	.017*	**.026****
	(579.047)	(696.988)	(.022)	(.026)	(.008)	(.009)
Category 1	-1649.043***	**-1213.804****	-.030	-.012	-.014**	-.007
	(426.733)	(463.042)	(.016)	(.017)	(.005)	(.006)
Category 0 (ref.)					—	—
Coastal-Wind Interactions						
Category 2+ X Coast		-256.542		-.051		**-.043*****
		(1145.656)		(.038)		(.012)
Category 1 X Coast		**-2174.923***		**-.094****		**-.043*****
		(985.306)		(.033)		(.010)
Spatial Error (Wμ)	.239***	.238***	.439***	.443***	.582***	.582***
	(.027)	(.027)	(.023)	(.023)	(.020)	(.020)
Constant	3258.010***	3039.358***	2.166***	2.183***	.034***	.030**
	(610.470)	(618.039)	(.158)	(.158)	(.010)	(.010)
R^2	.85	.85	.81	.81	.94	.94
N	2847		2847		2847	
Model Diagnostics						
Spatial Error AIC	59403.60	59401.30	454.54	450.60	-6251.94	-6267.36
OLS AIC	59471.20		696.23		-5575.11	
OLS Moran's I residuals	.097		.175		.351	
Spatial Error Moran's I residuals	-.007		-.025		-.028	

Notes: Unstandardized coefficients for spatial error models are presented.
Median housing values are in natural log form. In 1999 dollars.
(Standard Errors in Parentheses)
$^*p < .05$ $^{**}p < .01$ $^{***}p < .001$

increase markedly in the inner ring, due in part to displacement and exclusion from the recovery core and from similar but less intense processes operating in the outer ring.

In support, results in Table 6 and their graphical depiction in Panel (c) of Figure 2, show significant increases in rental units within the inner ring (alongside declines in relative household incomes and white shares of the population). On the other hand, the elderly population presents a different pattern. Results reveal that tracts with the greatest wind damage (Category 2+) also experienced the greatest relative increases in senior citizens, particularly along the coast. This pattern is also evident in Panel (c) of Figure 2, suggesting that elite entrenchment in the recovery core is fed in part by older populations that remain deeply attached to their homes and neighborhoods, even (or especially) in the wake of a major disaster. The implication is that the type of gentrification found in these areas after major hurricanes is very different from that found in many of today's urban neighborhoods, where the constituents are more likely to be young, highly mobile professionals.

By contrast, results for blacks show no significant spatial variation across affected regions. Instead, the large and highly significant spatial error coefficients (and large OLS Moran's I residuals) indicate that where growing black populations (re)settle in affected regions after a major hurricane is determined largely by where members concentrated *before* the hurricane. This finding means that the relative growth of black populations following major storms (see Table 3) does little to alter pre-existing residential segregation patterns; it simply brings more of the same.

Finally, results in Table 7 speak to spatial variation in the growth of Hispanic-immigrant populations and related patterns of residential crowding after major hurricanes. Our hypothesis for these groups is similar to that for other residential non-elites: specifically, growth will concentrate in the inner ring, but it will derive less from local displacement and more from labor in-migration attracted to the region by reconstruction jobs. Results again yield mixed support for our framework. In support, regression results in Table 7 and the graph in Panel (d) of Figure 2 show relatively large and statistically significant increases in the relative size of local foreign-born populations in the inner ring of recovery, with comparative declines in the recovery core, as predicted. Results also show that although local shares of housing with three or more workers generally decrease in affected regions after major hurricanes (see Table 3), this tendency is reversed in the inner ring of recovery, particularly within inland tracts closest to the core zone of recovery. These patterns imply that, as hypothesized, within the inner ring of recovery, increases in households with three or more workers coincide with increases in foreign-born residents, all else equal, which

Table 6: Spatial Error Models for Residential Non-Elites

	2000 Tract Characteristic %					
	Non-Hispanic Black		Rentals		Over 65	
	(A)	(B)	(A)	(B)	(A)	(B)
1990 Tract Characteristic	.909***	.909***	.963***	.963***	.753***	.753***
	(.008)	(.008)	(.008)	(.008)	(.012)	(.012)
Merged boundary	-.003	-.003	.001	.001	-.012*	-.012
	(.007)	(.007)	(.010)	(.010)	(.006)	(.006)
Split boundary	.000	.000	-.010***	-.011***	.001	.001
	(.002)	(.002)	(.003)	(.003)	(.002)	(.002)
Same boundary (ref.)	—	—	—	—	—	—
1990 Pop. Density	5.55e-07*	5.63e-07*	1.27e-006***	1.27e-006***	-8.95e-07***	-9.04e-07***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
1990 Vacancy rate	-.005	-.005	.005	.005	.002	.002
	(.003)	(.003)	(.003)	(.003)	(.002)	(.002)
South NE: Bob 1991	-.037***	-.037***	-.030***	-.030***	-.001	-.001
	(.010)	(.010)	(.004)	(.004)	(.003)	(.003)
South FL: Andrew 1992	.009	.009	-.030***	-.028***	-.004	-.004
	(.012)	(.012)	(.005)	(.005)	(.004)	(.004)
LA: Andrew 1992	.017	.016	-.022***	-.023***	-.004	-.003
	(.014)	(.014)	(.005)	(.005)	(.004)	(.004)
FL/AL: Opal 1995 (ref.)	—	—			—	—
Spatial Indicators						
Coast tract	-.007	-.010	-.005	**-.014***	.002	.009*
	(.004)	(.008)	(.003)	(.006)	(.002)	(.005)
Inland tract (ref.)	—	—			—	—
Category 2+ winds	-.012	-.012	-.008*	**-.015****	**.011****	.012**

Table 6 *continued*

	2000 Tract Characteristic %					
	Non-Hispanic Black		Rentals		Over 65	
	(A)	(B)	(A)	(B)	(A)	(B)
	(.009)	(.009)	(.004)	(.005)	(.003)	(.004)
Category 1 winds	.004	.004	.004	.003	.000	.002
	(.006)	(.006)	(.003)	(.004)	(.002)	(.003)
Category 0 winds (ref.)	—	—			—	—
Coastal-Wind Interactions						
Category 2+ X Coast		.003		**.021***		-.007
		(.011)		(.009)		(.007)
Category 1 X Coast		.004		.008		-.010
		(.009)		(.008)		(.006)
Spatial Error (Wμ)	.718***	.718***	.007	.006	.282***	.278***
	(.016)	(.016)	(.030)	(.030)	(.026)	(.026)
Constant	.054***	.054***	.017***	.018***	.038***	.037***
	(.009)	(.009)	(.005)	(.005)	(.003)	(.003)
R^2	.95	.95	.89	.90	.68	.68
N	2847		2847		2847	
Spatial Diagnostics						
SpatialError AIC	-8103.31	-8099.50	-6824.05	-6825.03	-9761.26	-9760.14
OLS AIC	-6906.12		-6824.00		-9644.29	
OLS Moran's I residuals	.455		.002		.141	
Spatial Error Moran's I residuals	-.025		.000		-.006	

Notes: Unstandardized coefficients for spatial error models are presented.
(Standard Errors in Parentheses)
$^*p < .05$ $^{**}p < .01$ $^{***}p < .001$

also coincides with relative declines in household incomes, housing values, homeownership and white residence.

By contrast, and similar to blacks, regression results for Hispanics in Table 7 also show no significant variation with respect to the storm's path. In fact, these two racial/ethnic indicators are the only demographic factors (out of nine) for which no such association was found. Moreover, as with blacks, large and highly significant spatial error coefficients (and large OLS Moran's I residuals) indicate that the key spatial determinant of where Hispanic population growth occurs after a major hurricane is where resident members resided before the storm. Although the long term implications of this growth are difficult to predict, a recent account of events in New Orleans following Hurricane Katrina put matters succinctly: "First came the storm. Then came the workers. Now comes the baby boom." (Porter 2006) As the *New York Times* reporter explained, "In the latest twist to the demographic transformation of New Orleans since it was swamped by Hurricane Katrina last year, hundreds of babies are being born to Latino immigrant workers, both legal and illegal, who flocked to the city to toil on its reconstruction."

Conclusion

Humans have and will continue to settle in environmentally dangerous places, particularly along the coast, where hurricanes threaten. U.S. society provides a rich example rather than an exception to this ongoing tendency. To understand vulnerabilities associated with such settlement dynamics, we must look beyond the question of how social inequalities condition exposure to environmental hazards to ask also how such inequalities are reproduced in the recovery process, as places rebuild from major coastal disasters. In this study, we advanced a "recovery machine" framework for making sociological sense of these dynamics and offered a new methodological approach for examining their demographic consequences. As laid forth, this framework has two basic components.

The first component argues that the same political coalitions and inequalities that drive local growth in hazard-prone places before major hurricanes gain strength from new material and symbolic resources that flow unequally to regions after such events. The second component of our framework argues that the result is not simply more growth in areas of obvious environmental hazard but also transformation of local neighborhoods through unequal and emergent processes of elite entrenchment, non-elite displacement and immigrant-labor influx. Our empirical analyses offer support and refinement of this framework.

First, in support, our results affirm that regions grow substantially after major hurricanes. In the four regions we studied, this growth brought

Table 7: Spatial Error Models for Immigrant/ Latino Influx

	2000 Tract Characteristics %					
	Foreign Born		Hispanic		Households w/ 3+ Workers	
	(A)	(B)	(A)	(B)	(A)	(B)
1990 Tract Characteristic	.855***	.855***	.966***	.966***	.422***	.421***
	(.012)	(.012)	(.011)	(.011)	(.015)	(.015)
Merged boundary	.002	.002	.005	.005	-.001	-.001
	(.005)	(.005)	(.006)	(.006)	(.005)	(.005)
Split boundary	.005**	.005**	.002	.002	.001	.001
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Same boundary (ref.)	—	—	—	—	—	—
1990 Pop. Density	1.15e-06***	1.17e-06***	5.13e-07**	5.27e-07**	-4.51e-07***	-4.54e-07***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
1990 Vacancy rate	-.006**	-.006**	-.006**	-.006**	.000	.000
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
South NE: Bob 1991	.026***	.026***	.017**	.017**	.023***	.024***
	(.005)	(.005)	(.007)	(.007)	(.003)	(.003)
South FL: Andrew 1992	.095***	.095***	.068***	.069***	.027***	.026***
	(.007)	(.007)	(.008)	(.008)	(.004)	(.004)
LA: Andrew 1992	-.002	-.002	-.008	-.008	.015***	.015***
	(.008)	(.008)	(.010)	(.010)	(.004)	(.004)
FL/AL: Opal 1995 (ref.)	—	—	—	—	—	—
Spatial Indicators						
Coastal tract	-.001	-.007	-.003	-.011	-.009***	-.007
	(.003)	(.006)	(.003)	(.006)	(.002)	(.004)
Inland tract	—	—	—	—	—	—

Category 2+ Winds	-.007	-.007	-.005	-.009	.008*	.010**
	(.005)	(.006)	(.006)	(.007)	(.003)	(.004)
Category 1 Winds	.008*	.007	.003	.002	.007**	.007**
	(.004)	(.004)	(.004)	(.004)	(.002)	(.002)
Category 0 (ref.)	—	—	—	—	—	—
Coastal-Wind Interactions						
Category 2+ X Coast		.009		.010		-.002
		(.007)		(.007)		(.005)
Category 1 X Coast		.004		.015		-.006
		(.008)		(.008)		(.006)
Spatial Error (Wμ)	.607***	.604***	.671***	.671***	.359***	.359***
	(.019)	(.019)	(.017)	(.017)	(.025)	(.025)
Constant	.005	.006	.008	.009	.036***	.036***
	(.005)	(.005)	(.006)	(.006)	(.003)	(.003)
R^2	.94	.94	.96	.96	.49	.49
N	2847		2847		2847	
Model Diagnostics						
Spatial Error AIC	-9780.57	-9778.32	-9460.02	-9459.37	-10720.20	-10717.40
OLS AIC	-9041.78		-8462.37		-10547.00	
OLS Moran's I residuals	.366		.420		.160	
Spatial Error Moran's I residuals	-.029		-.026		-.007	

Notes: Unstandardized coefficients for spatial error models are presented.
(Standard Errors in Parentheses)
*p < .05 **p < .01 ***p < .001

roughly 1.4 million *additional* people and 600,000 *additional* housing units to areas that experienced "billion dollar" storms during the early 1990s. Second, findings affirm that this growth tends to be spatially uneven. Demographically, coastal neighborhoods that experienced the brunt of these major hurricanes tended to become smaller, whiter and older during the recovery phase. By contrast, surrounding neighborhoods in the inner ring of recovery tended to grow dramatically, fueled by expanding black and Latino/immigrant populations and by households with declining incomes relative to the rest of the affected region. Results also help to refine our framework by showing that this growth in black and Latino populations tends to cluster in areas where group members already concentrated before the disaster, thereby expanding and solidifying pre-existing patterns of residential segregation rather than challenging them.

These patterns offer a "good news/bad news" view of post-disaster recovery. On the one hand, the tendency for places to rebound beyond mere functional recovery provides an optimistic view of local capacities for resilience. On the other hand, the social and spatial unevenness of this growth can undercut this resilience, especially if residential segregation, low incomes and lack of homeownership characterize growing minority populations in the region, as our results indicate they do. To the extent that such social inequalities amplify vulnerabilities to environmental hazards, they also imply that such vulnerabilities are not just pre-disaster conditions. They are also part of the post-disaster recovery process. Viewed from this perspective, a more apt metaphor for recovery may not be the "Jacuzzi effect" but the "treadmill of destruction," whereby disaster zones reproduce larger, more socially divided versions of themselves as they rebuild and await the next major disaster.

Of course, as with all research, there are limitations to our analyses. The first and most obvious limitation is that we examined data from only three hurricanes and four regions. These data allowed us to probe the effects of hurricane recovery on various types of neighborhood characteristics. Future research will benefit from analyses that extend beyond these disasters to consider cross-national comparisons and/or analyses of recovery from different environmental hazards, such as earthquakes and floods. The second limitation is that our analyses relied on spatially aggregated census indicators that capture net population changes but not the gross changes that generated them. So, for example, it could be that many blacks, Latinos and renters are in fact driven entirely from the region after disaster but that this selective out-migration is counterbalanced by equally selective in-migration. Third, in light of Hurricane Katrina, an upper bound of 10 years for disaster recovery may be short. If so, the patterns and processes we document here as part of the recovery machine may take far longer to unfold in extreme cases than we anticipate here.

In addition, the potential for intra-actor conflict deserves more attention.[5] For example, after disasters there is ample room for conflict to emerge among local governments, bankers, and insurers as they vie for different combinations of use- and exchange-value maximization. There is also room for conflict among residential non-elites, as displacement and disruption threaten to fan racial and ethnic tensions, especially in the context of immigrant influx. There is also room for conflict among different levels of government actors (local, state and federal), as they direct and fund different pieces of the recovery process according to their own interests and resources. These sources of conflict might muddy our "machine" analogy, but more importantly, they direct our attention to how and under what conditions these different pieces and processes come together to produce the impacts described in the present study. We look forward to more research on these issues in the future.

Notes

1. To estimate hurricane paths and local wind speeds, the HAZUS database uses mathematical simulation models first tested by Russell (1971) and most recently refined by Vickery et al. (2000a, and 200b). The methodology samples statistical distributions of known hurricane parameters using a Monte Carlo technique. Wind estimates are then calculated using known information about the storm that includes central pressure, speed of the system, storm heading, and distance from the eye to hurricane force winds. The methodology has been validated using historical records for all major hurricanes between 1886 and 2001. The results indicate that HAZUS generates an accurate representation of hurricane wind fields and is a valid instrument for estimating structural damage from hurricane winds. Other sources of data were considered, such as aggregate insurance claims and federal recovery funds; however, such data at proper geographic scale for spatial analysis are not available.

2. In the HAZUS database, advanced damage and loss-estimating tools use peak wind gust, not the one-minute wind average estimate (*HUZUS-MH MR1Technical Manual*: 2003(3):49). Validity tests on building damage in HAZUS revealed a stronger relationship with peak wind gusts than with the standard one-minute average estimates. To compensate for this discrepancy we took the average between the estimated peak gust and maximum sustained wind speed for each census tract in the respective hurricane region.

3. Category 1 winds range from 74 to 95 miles per hour and typically cause cosmetic damage to the landscape with no significant damage to buildings. Category 2 winds range from 96 to 110 miles per hour, causing damage to roofs, windows and doors, and jeopardizing poorly secured structures. Category 3 winds range from 111-130 miles per hour and can cause immense

structural damage, with storm surges generally 9 to 12 feet above normal (see www.noaa.org).

4. Values for tracts that reported zero median income (three tracts) and/or housing values (41 tracts) have been imputed. The natural log of median housing value is used because the non-transformed distribution is positively skewed, causing the residuals to be heteroscadastic.

5. We thank one of the anonymous reviewers for this insight.

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