PLACES AS RECOVERY MACHINES: VULNERABILITY AND NEIGHBORHOOD CHANGE AFTER MAJOR HURRICANES*

Jeremy Pais
Department of Sociology and
Center for Social and Demographic Analysis
State University of New York at Albany
Albany, NY 12222
jp578587@albany.edu

James R. Elliott
Department of Sociology
University of Oregon
Eugene OR, 97403
elliott@uoregon.edu

Abstract

In this study we contribute to sociological understanding of environmental hazards by advancing a conceptual framework for understanding the transformation of places into recovery machines after major hurricanes and by introducing a method for testing and refining general propositions about how this transformation reshapes local neighborhood demographics over the long term, paying particular attention to patterns and processes of power and vulnerability. Findings from the 1990s reveal that affected regions grew substantially after major hurricanes and that this growth was highly uneven, with elite entrenchment characterizing the core zone of recovery and rapid, ethno-racially diverse growth dominating the surrounding, inner ring of recovery. These dynamics suggest that disaster recovery reproduces on larger scales the types of social vulnerabilities exposed at time of impact.

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Early sociological research treated natural disasters as "strategic research sites" in which to study social relations thrown into high relief by catastrophic events (e.g., Merton 1969, xi). More recently, researchers have come to conceptualize natural disasters as the impacts of environmental hazards on vulnerable people (see Blaikie et al. 1994; Rosa 2006; Tierney 2006). This conceptual shift emphasizes that disasters do not stem from forces external to society (e.g., God or nature) but rather from social systems that render some populations more vulnerable than others to prospective hazards. This endogenous view of vulnerability implies that natural disasters do not simply happen but rather unfold through historical processes that generate local inequalities in risks and resources long before the hazard itself occurs.

Recognition that natural disasters are fundamentally social phenomena with historical underpinnings has broadened interest in their study and increased the range of analytical tools applied to them, including Geographic Information Systems (GIS) that can illuminate the causal structure and spatial variation in local vulnerabilities to environmental hazards. In a good example of this approach, Cutter and colleagues (2000) overlay demographic and biophysical data to examine a wide array of environmental threats to coastal South Carolina, including floods, hurricanes, tornadoes and earthquakes. They find that the greatest risks of social disruption do not correspond to the areas of greatest environmental risk because the riskiest areas tend to be located along the coast and waterways where, in happens, property values and personal resources are high.

This "hazards in context" approach underscores the multifaceted nature of vulnerability and moves researchers and policymakers beyond the simplistic assumption that the most socially vulnerable populations always occupy the most environmentally risky places. However, important analytical gaps in this line of research remain. For example, most research in this vein still focuses on social inequalities in a region before disaster strikes. Few studies, by contrast, have investigated how these inequalities are reproduced in the long-term recovery process, and fewer still have examined this question for more than one case. One reason for this analytical gap 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 & Rossi 1981:156). This situation means that in-depth case studies of disasters are difficult and analyses of multiple disasters to test general propositions about their effects is more difficult still.

Another reason for the gap 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 & Campanella 2005). Consequently, we know very little about how neighborhoods, in general, change during long-term recovery from major hurricanes.

This study addresses these gaps by investigating demographic changes in U.S. neighborhoods hit by major hurricanes during the early 1990s, defined as storms that caused over a billion dollars in property damage. In these regions we merge localized storm data from a national meteorological database with demographic data for local census tracts to test and refine propositions about how neighborhoods change five to ten years after a major hurricane. As theoretical guidance we develop the idea of places as "recovery machines." This idea builds from the established concept of places as "growth machines" but moves beyond it to highlight how new patterns and processes of power and vulnerability emerge after disaster strikes and long-term transformation begins.

Before the Storm: Growth Machines & Vulnerability

Human settlements have long favored hazard-prone areas because, as it turns out, they are highly conducive to habitation and production (Jones 1980). River valleys, for example, offer fertile soils and easy passage for canals, railroads and highways, in addition to being flood-prone. Sea coasts and wetlands provide fish, 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, in addition to suffering earthquakes and volcanic eruptions. Because of these benefits, humans the world-over continue to amass in hazardous regions, particularly along the coasts. In fact eight of today's ten largest cities in the world hug a coast, as does half the global population (United Nations 2004).

In the United States these patterns are no different. Since 1970, the number of U.S. residents living in coastal counties has grown from 110 million to over 150 million, accounting for over half of the nation's population on only a quarter of its land mass. As this concentration has grown, coastal 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, and capital investments continue to grow exponentially. During the last decade alone, insured property values along the Atlantic and Gulf coasts doubled and now total over $7 trillion—the 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 hurricanes do not increase in coming years, their social and economic impacts will as 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 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 organize, promote and legitimate ongoing development. Sociological efforts to theorize these efforts, past and present, span many traditions but recently have emphasized the idea of cities as "growth machines" (Molotch 1976; Logan & Molotch 1987; for review see Jonas & Wilson 1999). We review the basic tenets of this perspective here to illuminate the political economy of places prior to major hurricanes and then consider how places transform into "recovery machines" once hurricanes strike and long-term recovery begins.

The first tenet of the growth machine thesis is that all towns and cities 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, towns and cities also constitute commodities that are subdivided into lots to be bought and sold, built and renovated, rented and leased for profit in the market. This duality 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 other 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 exchange values. This is what the term "growth machine" refers to: a coalition of business elites united with local political officials in pursuit of local economic and demographic growth. Third, these pro-development coalitions promote their "growth ethic" by asserting that growth is good for everyone because it brings new jobs, taxes and stature to the area. In this way, actors who benefit most, economically and politically, 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 & Moloth 1987).

From this perspective, the ongoing concentration of people and property along the nation's coasts is more than a matter of geographic circumstance and personal 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 become 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 hurricane preparedness and mitigation.

This perspective moves us beyond the simple recognition that some groups are more vulnerable than others to environmental risks to emphasize 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 disaster hits and competing interests respond to opportunities created by the damage, displacement and rebuilding that ensues, that is, as the growth machine transforms into a recovery machine.

After the Storm: Recovery Machines & Vulnerability

After major hurricanes hit and initial emergency and reconstruction efforts recede, places enter into a long term recovery phase that can last one to ten years depending on the scale and scope of the disaster (Burton, Kates & White 1978:176). During this phase, funds available for (re)development increase substantially via private insurance claims and government disaster aid. One year after Hurricane Katrina hit the Gulf Coast in 2005, for example, the federal government had already committed $111 billion in aid to the affected region and private insurers had paid over $16 billion to nearly one million homeowners (Insurance Information Institute 2006). We contend that these monies fuel the recovery machine and skew the balance of power even further in favor of developers and their allies, who exercise disproportionate control over these systems of capital.

One reason for this heightened power imbalance is that these systems of disaster relief are designed to respond financially when natural disasters destroy *property*, not when they destroy homes and communities (Steinberg 2006). Another reason is that, symbolically, this hyper-infusion of public and private dollars that flow into disaster regions brings with it a political imperative to rebuild bigger and better than ever as a public sign of resilience and triumph of the local spirit. In this climate, growth, not just recovery, becomes a moral prescription that is promoted as being good not only 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—erode pre-hurricane sources of opposition to value-free development and blur differentiation between use and exchange values to further advantage pro-growth coalitions.

Prior studies on long-term effects of natural disasters lend empirical support to this view (Cochrane 1975; Dacy & 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 and 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). We contend 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 reasonably be scrutinized.

We also contend that these developments further polarize local residential populations, so that 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 region. Without rent controls and similar housing initiatives, the result is declining vacancy rates and rising housing costs that drive more vulnerable groups from their neighborhoods. In New Orleans, for example, a survey of more than 1,400 apartments a year after Hurricane Katrina revealed that the average rent had increased 70 percent, from $800 per month to $1,350 (Meitrodt 2006).

At the other end of the spectrum, 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 allow them to restore their housing but 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 in Charleston, South Carolina, a local newspaper editor dubbed this dynamic the Jacuzzi effect–"A lot of people had Jacuzzis after Hugo who didn't have them before" (see Mullener 2005). Tierney (2006:210) calls 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."

More systematic research affirms these assessments. For example, studies show that poorer residents are more likely to live in shabby dwellings left uninhabitable by disasters (Cochrane 1975) and that they often lack the financial resources necessary to recover "in place" (Bolin & 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 for disaster aid. Meanwhile higher-income victims can quickly absorb surplus housing, exacerbating housing shortages among less-affluent residents (Quarantelli 1994; see also Elliott & 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 developments is the fact that municipal budgets are highly strained after major disasters, limiting public funds for affordable housing in favor of infrastructural recovery.

Within this recovery environment, inequalities can further increase if residential elites seize opportunities to upgrade not just their homes but a bundle of neighborhood factors. Such "community improvement" is typically accomplished in one of two ways: either by making poor and otherwise marginal residents less poor and less marginalized; or by replacing such residents with not-so-poor and not-so-marginalized residents. After major disasters, elite residents become politically freer and better financed to pursue the latter strategy through acts of social closure and exclusion, resulting in elite entrenchment in neighborhoods along social as well as economic lines. In the wake of Hurricane Katrina, for example, evidence indicates that landlords, as well as employers, along the Gulf Coast shunned black applicants (Haubert 2006). The nearly all-white parish of St. Bernard even passed an ordinance restricting post-storm rentals to family members, excluding blacks, Latinos and Asians in effect, if not intent.

Finally, in addition to empowering local growth machines and residential elites, the recovery machine creates rapid, substantial demand for labor in the "reconstruction" sector, comprised of construction and allied industries such as demolition, hauling and sanitation. Consistent with research elsewhere in non-disaster areas (e.g., Waldinger and Lichter 2003), studies conducted in major hurricane zones now consistently show a strong influx of immigrant Latino workers to fill these jobs along with strong employer preference for such workers over native-born, particularly black, counterparts. Estimates from New Orleans indicate that nearly half the reconstruction jobs generated by Hurricane Katrina were filled by new Latinos to the area (Fletcher, Pham, Stover & 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 new "reconstruction" jobs will disappear but not before preference for and experience with immigrant labor becomes (further) institutionalized within local housing and labor markets.

Recovery Machines & Neighborhood Change

As outlined above, our concept of the recovery machine includes four sets of actors: the *recovery machine proper*, consisting of pro-growth actors and their allies; *residential elites*, consisting of subpopulations with greater social power and resources; *residential non-elites*, consisting of subpopulations with less social power and resources; and *immigrant influx*, consisting of new Latino/immigrant laborers, often crowding together residentially to make ends meet. We contend that these actors come together to form a dynamic and contentious recovery machine that generates new growth in disaster regions and that this new growth is spatially uneven in ways reflecting the unequal resources and power of these respective actors.

In neighborhoods along the coast that experience the greatest damage—storm surge plus high winds—we expect to find strong patterns of elite entrenchment, wherein more powerful social groups (e.g., homeowners, whites and the wealthy) use insurance claims, institutional skills, and social closure to dig in and "upgrade" their neighborhoods as well as their houses. This "community improvement" within the *recovery core* can involve flexing political muscle and asserting social position to keep new growth out, as well as squeezing renters, lower-income residents, and minorities elsewhere, if not overtly then by failing to oppose broader structural change (e.g., rising rents and regressive disaster allocations) that achieve the same end.

In surrounding neighborhoods, located near but not in this recovery core, growth and development is likely to be much more substantial and ethnically diverse for several reasons.

First, in these areas, particularly inland, severity of damage and levels of financial inflows from private and public sources will be lower, dampening opportunities for elite entrenchment and signaling safer investment opportunities for recovery growth generally. Second, many residential non-elites (e.g., minorities, renters and elderly) displaced from the recovery core may wish to remain near their old neighborhoods to maintain spatial habits and networks that help restore a sense of normalcy following disaster and displacement. Finally, new immigrant laborers drawn to the region are likely to find neighborhoods near, but not in the recovery core, convenient because of their proximity to reconstruction jobs in the recovery core and relative affordability, particularly inland. These dynamics will produce an *inner ring* of recovery that is likely to grow larger and more diverse in years following a major hurricane.

Finally, in the *outer ring* of recovery beyond the core and inner ring and where winds failed to reach hurricane status, we expect aggregate growth in people, housing and newcomers commensurate with what would have occurred if no major hurricane had hit. This growth is likely to be positive but not as great as in the inner ring of recovery, and it is likely to have a different demographic character. We expect neighborhoods in this outer ring will show less evidence of elite entrenchment, non-elite displacement, and immigrant influx. Instead, they will exhibit moderate growth driven largely by the continued relocation of native-born residents to the region.

In Table 1 we summarize these propositions and spatial hypotheses for each set of actors that comprise the recovery machine. This summary does not imply that other factors are unimportant for recovery dynamics or patterns and processes we identify are inevitable. However, we do believe that they are critical for understanding post-hurricane recovery and for broadening our understanding of vulnerability beyond individuals and households to the level of neighborhoods. Below, we discuss the data used to examine these propositions and hypotheses empirically.

[Table 1 about here]

Data

To test our propositions about the recovery machine and its spatial manifestations, we must specify which hurricanes qualify for analysis, how affected regions and constituent subregions can be identified, and what our primary unit and variables of analysis will be. To start, we focus on hurricanes that caused over a billion dollars worth of damage because of their sheer impact and because of their likelihood of reoccurrence in coming years, as people and property continue to concentrate along the coasts. We restrict our focus to hurricanes that made landfall between 1991 and 1995 in order to allow sufficient time for long-term recovery to unfold by the time of the 2000 census—the most recent, reliable source of data on neighborhood-level demographics.

Using the National Oceanic and Atmospheric Administration's (NOAA) list of "Billion Dollar U.S. Weather Disasters" (in constant 2002 dollars), we identify three such hurricanes and four regions for our 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.

Delineating Affected Regions & Subregions

Next, delineating the specific regions of impact after major hurricanes presents unique challenges. Foremost, hurricanes are not well-contained hazards. So determining where exactly they hit can be complicated but essential in an analysis such as ours, which requires standardization across multiple storms and regional contexts for purposes of generalization. Our research into these challenges indicates that the best approach is to use the Hazards U.S. (HAZUS) database. The HAZUS database is a federally sponsored program developed under contract with the National Institute of Building Sciences (NIBS), 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 give emergency managers a tool to 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 wind-modeling component for several reasons. First, the HAZUS wind modeling technology stems 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.[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, given HAZUS's emphasis on forecasting and mitigation.

Using wind speeds from HAZUS, we delineate affected regions as consisting of all census tracts that experienced at least tropical-storm force winds (over 50 miles per hour) for the hurricanes of interest.[2] We then categorize each census tract in the 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 and 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. The result is a sample of 2,847 census tracts across the four study regions. Maps of these regions with the HAZUS-generated storm tracks and associated wind speeds appear in Figure 1.

[Figure 1 about here]

In addition to using estimated wind speeds to delineate affected regions, we also use these tools and coastal location (yes/no) to specify subregions where we expect spatial variation in long-term recoveries. We designate coastal tracts that experienced Category 2+ winds (and typical storm surges of six feet or greater) as constituting the "core zone of recovery," where the greatest damage occurred. We designate the surrounding "inner ring of recovery" as consisting of inland tracts that experienced similar wind speeds (i.e., Category 2+) but no storm surge as a result 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 force winds as constituting the "outer ring of recovery," where damage was present but relatively minimal. We use these subregional 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 possible.

Estimating Neighborhood Change

Once affected regions and subregions are identified, we use census-tract data from the 1990 (pre-storm) and 2000 (post-storm) population censuses to examine neighborhood change. A census tract is a spatial unit meant to proximate a neighborhood and contains roughly 4,000 persons, on average. To examine these data, we use Geoltyics' Neighborhood Change Database (NCDB), which normalizes tract boundaries across decennial censuses. Thus, 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 central indicators of change for each dimension, or set of actors, in our analysis. For the recovery machine proper, we examine changes in total population, housing units and newcomers to the region, with the latter defined as migrants from outside the county who arrived in 1995-2000, that is, after the 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 households with three or more workers in the tract. Descriptive statistics for these tract-level variables are summarized in Table 2.

[Table 2 about here]

Results

We begin with the question of how the average neighborhood, or census tract, changes roughly five to ten years following a devastating hurricane. To answer this question, we pooled our tract-level data from 1990 and 2000 and estimated a simple fixed effects model of the following general form:

$$\text{Tract Characteristic}_i = \partial + \beta(\text{year}_t\text{: 1990/2000}) + u_i + e_{it},$$

where β is our coefficient of interest, and 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 array of regression results, Table 3 reports the mean value of each tract-level variable in 1990 (pre-storm), followed by the estimated percentage change by 2000 (post-storm) for the sample as a whole and for each region separately.

[Table 3 about here]

Overall, results show strong growth in total population, housing units and newcomers during long-term recovery. Statistically, the average census tract grew in population and housing by over 11 percent, or roughly 500 persons and 200 residential units during the observed period. Although some of this growth may have occurred prior to the respective hurricanes, it is clear that even the nation's largest, costliest storms do not reverse or even halt local development. Moreover, this growth is consistently observable in each of the four affected regions, as well as in the full sample, strengthening support for the proposition that local recovery machines promote rather than discourage growth in the wake of major disasters. 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. In absolute terms, these increases amount to approximately 614,000 and 287,000 *additional* people in each region, respectively, despite major devastation.

One way to gain greater insight into this growth is to compare the migration of newcomers to the area before and after the storm. The census question regarding "residence five years ago" allows such analysis for the 1985-90 (pre-storm) and 1995-00 (post-storm) periods and provides two additional insights. First, supplemental findings (not shown) affirm that coastal regions are extremely fluid demographically. At the end of each five-year period, half of all residents in the affected tracts had lived at a different address five years earlier. Second, this residential churning is not driven solely by local residents moving within respective counties. Although this type of move is common, results in Table 3 indicate that after a major hurricane, the number of migrants moving into affected tracts from other counties actually increased by an average of nine percent over pre-storm levels, from 790 out-of-county in-migrants to 865.

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). Regionally, the greatest upsurge in such newcomers occurred in regions with the lowest inflows before the disaster. In our analyses, these regions included southwest Louisiana after Hurricane Andrew and the Florida Panhandle after Hurricane Opal, where newcomer increases were 28 and 16 percent above pre-storm rates respectively.

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 U.S. metro areas experiencing a hurricane, tornado or flood during the decade. Their analyses, which could not 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 experiencing a natural disaster during the preceding decade. 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 restricted as a result of extensive property damage, displacement and rising insurance rates. We find precisely the opposite pattern: substantial growth is the norm.

In addition to this growth, Table 3 also indicates substantial increases in minority and foreign-born presence following major hurricanes. On average, African-American shares of local populations increased 16 percent, and foreign-born and Hispanic shares increased 27 and 39 percent, respectively. These patterns imply that regions not only grow after major hurricanes but also become more ethno-racially diverse, raising questions about residential accommodation and uneven development characteristic of rapidly growing places. To address these issues, we turn to our spatial analyses.

Spatial Variation in Neighborhood Change after Major Hurricanes

We suspect that the post-disaster growth documented above is not geographically even across affected regions. Instead, we hypothesize that elite entrenchment will characterize the hardest hit areas, that aggregate growth and relative increases in socially vulnerable populations will characterize the surrounding inner ring, and that more moderate patterns of growth and change will characterize the outer ring of recovery. To test these spatial hypotheses (see Table 1), we estimate a series of time-lagged, linear regression equations fit 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:

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

where i is the tract characteristic of interest 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 & Bera 1998). Model diagnostics for this spatial dependence are included at the bottom of Tables 4-7. Lower estimates of the Akaike Information Criterion (AIC) 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, such as wind speed and coastal/inland location, robust estimates of change in the observed tract characteristic during 1990-2000.

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 indicators control for regionally specific growth trajectories. We also include dummy indicators for the type of tract-boundary change that may have occurred between 1990 and 2000 (merged: yes/no; split: yes/no; no change [reference]). We include these 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, since census tracts are designed and measured to minimize such extreme variation, such 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 tract-level variable. Results highlighted in gray 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 is that such growth will be lower in the hardest-hit tracts, where elite entrenchment is likely, but greater in surrounding areas, where new and displaced residents are likely to concentrate during long-term recovery. 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 recovery core (-80+-7= -87).

[Table 4 about here]

To help visualize these and related spatial patterns, Figure 2 graphs estimated rates of change in the recovery core and inner ring, relative to the outer ring, 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 hypothetical measure of change that might have occurred had no major hurricane hit, thus serving as a statistical benchmark against which to compare developments in harder hit areas nearby. This manner of presentation 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 outer ring of recovery, that is, in areas experiencing only tropical-storm force winds. 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 in the hardest hit areas and greatest in the surrounding vicinities. To assess the character of this growth, we turn to our indicators of residential composition.

[Figure 2 about here]

Results in Table 5 reveal that for the three indicators of residential elites—median household income, median housing value and percent white—the interaction model (Model B) offers the best fit. All else equal, these results indicate a strong U-curve in which all three indicators increased most in coastal areas experiencing the least damage, then declined dramatically in nearby coastal and inland areas that experienced moderate damage (Category 1), and then increased again in coastal areas that experienced the greatest damage (Category 2+). 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 more evident, with white relative gains occurring in the core zone of recovery and white relative losses occurring 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 and elite entrenchment in the recovery core, where damage is greatest, coupled with declining household incomes, housing values and white representation in the surrounding inner ring.

[Table 5 about here]

Results for indicators of residential non-elites appear in Table 6 and generally show the inverse pattern, adding further support to our hypotheses. As depicted in Panel (c) of Figure 2, African Americans and renters each experienced absolute representational declines in the recovery core alongside significant growth in the surrounding inner ring, all else equal. However, the failure of this pattern to reach statistical significance at the .05-level for African Americans, coupled with the strong lagged effect of this indicator (.909; $p<.001$), also implies that the relative growth of black populations following major hurricanes (see Table 3) does little to change existing residential segregation patterns in affected regions; it simply brings more of the same.

Change in the elderly population, however, offers perhaps the strongest exception to our hypotheses. 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 in the wake of a major disaster.

[Table 6 about here]

Finally, results in Table 7 speak to spatial variation in the influx of Hispanics, immigrants and to residential crowding. As with growth in local black populations, growth in local Hispanic populations shows no strong spatial variation beyond what existed before the storm, as indicated by the lack of statistically significant spatial indicators and the strong, positive coefficients for the lagged dependent variable in Models A and B. However, when we graph the estimated changes in Hispanic populations across the three zones of interest, results in Panel (d) of Figure 2 reveal patterns that, while not statistically significant at the .05-level, are nonetheless consistent with our hypothesis that such influx is greatest in the inner ring of recovery, and lowest in the recovery core. This pattern is even stronger for foreign-born populations. All else equal, results show large, statistically significant increases in the relative size of local foreign-born populations in the inner ring of recovery, with comparative declines the recovery core.

Together, these findings imply that new immigrant and Hispanic growth in post-disaster regions tends to concentrate in tracts with pre-existing coethnic populations located near but not actually in areas of greatest damage, helping to fuel population growth in the region as a whole. 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). The *New York Times* reporter explains that, "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."

[Table 7 about here]

Finally, with respect to crowding, we examine changes in the percentage of housing units with three or more workers. Results indicate that while such crowding generally decreases in affected regions following major hurricanes (see Table 3), this tendency is reversed in the inner ring of recovery, particularly in inland tracts closest to the point of greatest coastal damage. Within these tracts, as hypothesized, increases in households with three or more workers occur alongside increases in the foreign-born population, all else equal.

Conclusion

Humans have and will continue to settle in environmentally dangerous places, particularly along the coast, where hurricanes threaten. To understand social vulnerabilities associated with these settlement patterns, researchers must look beyond the question of how social inequalities condition exposure to environmental hazards to ask how such inequalities influence long-term recovery, as places rebuild and establish the “new normal” following major disasters. In this study, we advanced a conceptual framework for making sociological sense of these dynamics and offered a new methodological approach for examining their empirical consequences for affected regions. This framework focused on the idea of post-disaster places as recovery machines and argues that the same coalitions and inequalities that drive, as well as characterize, growth in hazard-prone places before major disasters become amplified during long-term reconstruction efforts, in concert with emergent processes of elite entrenchment, non-elite displacement and immigrant influx. Our methodological approach combined state-of-the-art atmospheric data with local census data to examine these propositions empirically. Our findings from major storms of the early 1990s lead us to several conclusions.

First, although major hurricanes may not cause local growth in population, housing and newcomers over the long-term, they certainly do not discourage it. Despite suffering billions of dollars in property damage, the regions we investigated all showed significant growth over the long term; hazards be damned. Second, this growth tends to be highly uneven within affected regions. In the core zone of impact, where storm surge, winds and reconstruction funds are greatest, long-term recovery tends to take the form of elite entrenchment, characterized by relative thinning of local populations and housing stocks alongside relative exclusion of growing black, Latino and foreign-born populations. These less powerful groups, by contrast, tend to concentrate within a rapidly expanding inner ring of recovery. As a consequence of these twin developments, recovery machines come to produce bigger, more diverse versions of their pre-disaster selves, threatening to expose similar social vulnerabilities on even greater scale when the next disaster hits.

These findings support our conceptualization of the recovery machine and its spatial manifestations; however, we also found patterns that can further refine this conceptualization. First, consistent with prior vulnerability studies, we began with the hypothesis that senior citizens are economically and politically weak, relative to younger populations, and therefore susceptible to displacement in long-term recovery efforts. Our results refute this hypothesis. In coastal neighborhoods in particular, elderly presence actually increases noticeably during long-term recovery, suggesting that elite entrenchment may reflect an attachment to place that generally increases with age. In other words, the type of gentrification found in core zones of recovery following major hurricanes seems very different from the type of gentrification found in many of today's urban neighborhoods, where the constituents are more likely to be young, highly mobile professionals.

The second refinement involves race and ethnicity. Our results indicate that post-disaster regions generally experience increases in their black and Latino populations as they recover. While these trends reveal some spatial unevenness with regard to storm impact, they also indicate that this growth is more likely to conform to pre-existing patterns of residential settlement, amplifying and solidifying established racial geographies, rather than challenging them.

While we believe these findings are important, they are not without limitation. The first and most obvious limitation is that we examined data from only three hurricanes and four regions. These data allowed us to probe, for the first time, 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 types of 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 and finally, in light of Hurricane Katrina, an upper bound of ten years for disaster recovery may be short. If this is the case, then patterns and processes we document here as part of the recovery machine may (or may not) last far longer than we anticipate, potentially generating even greater social vulnerabilities that await future exposure with the next big storm.

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 a hurricane wind field 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 is 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] Tropical storm winds range from 51 to 73 miles per hour and generally have no associated storm surge along the coast. 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.

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

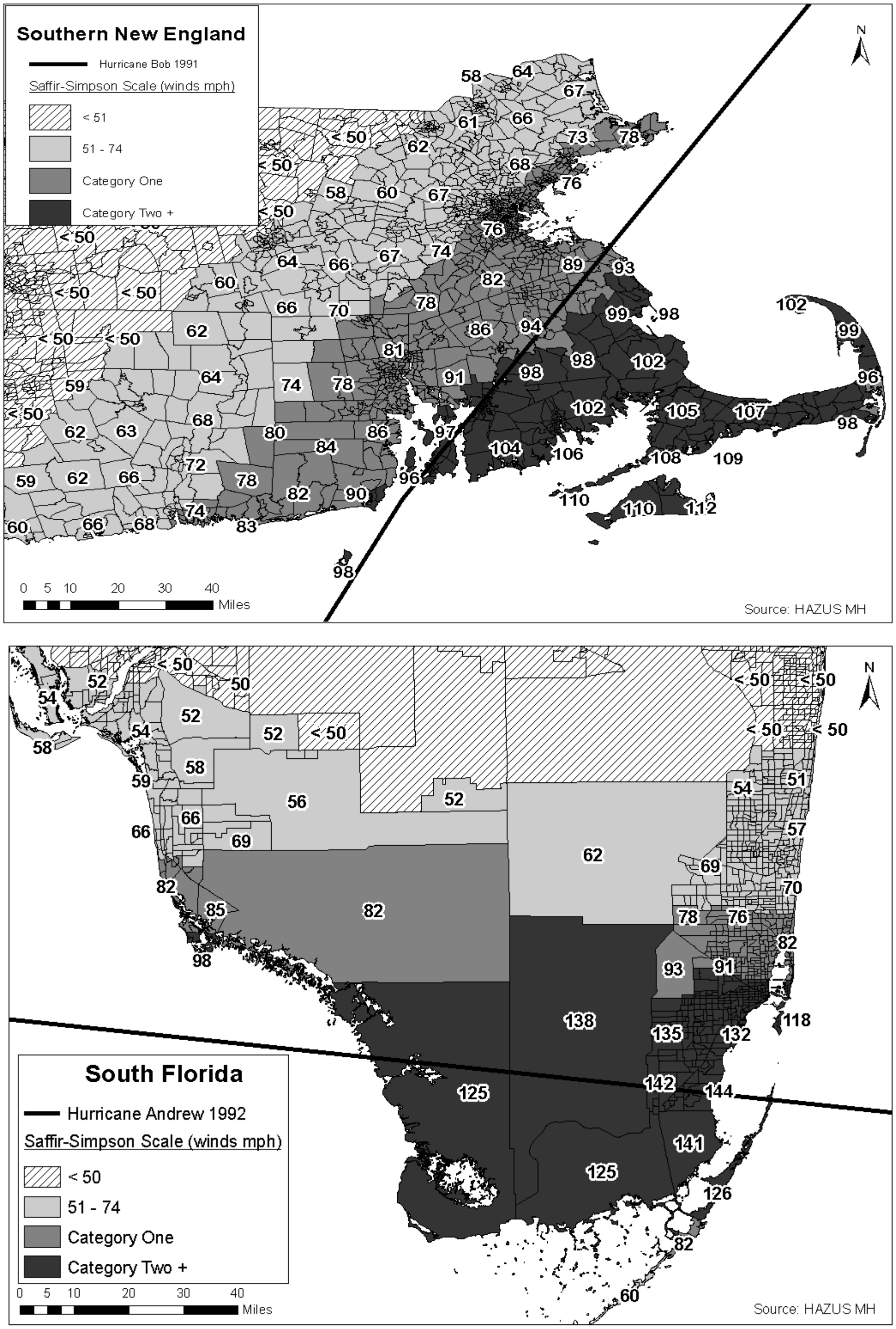
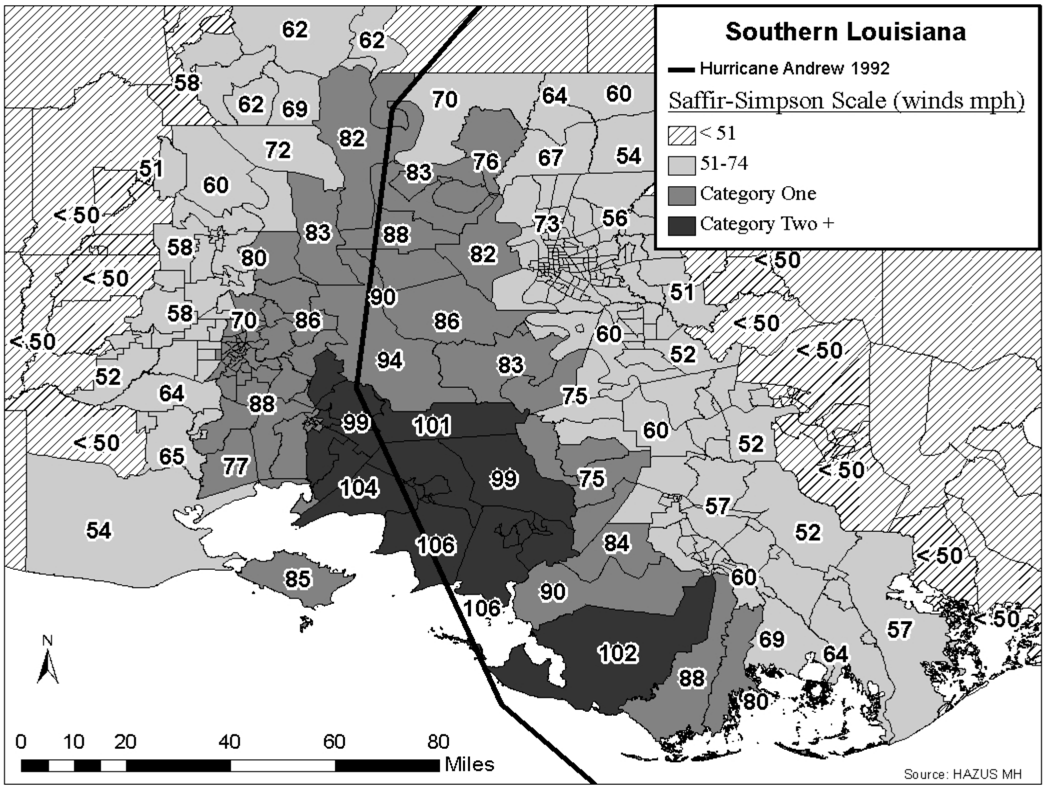


Figure 1, Cont. –



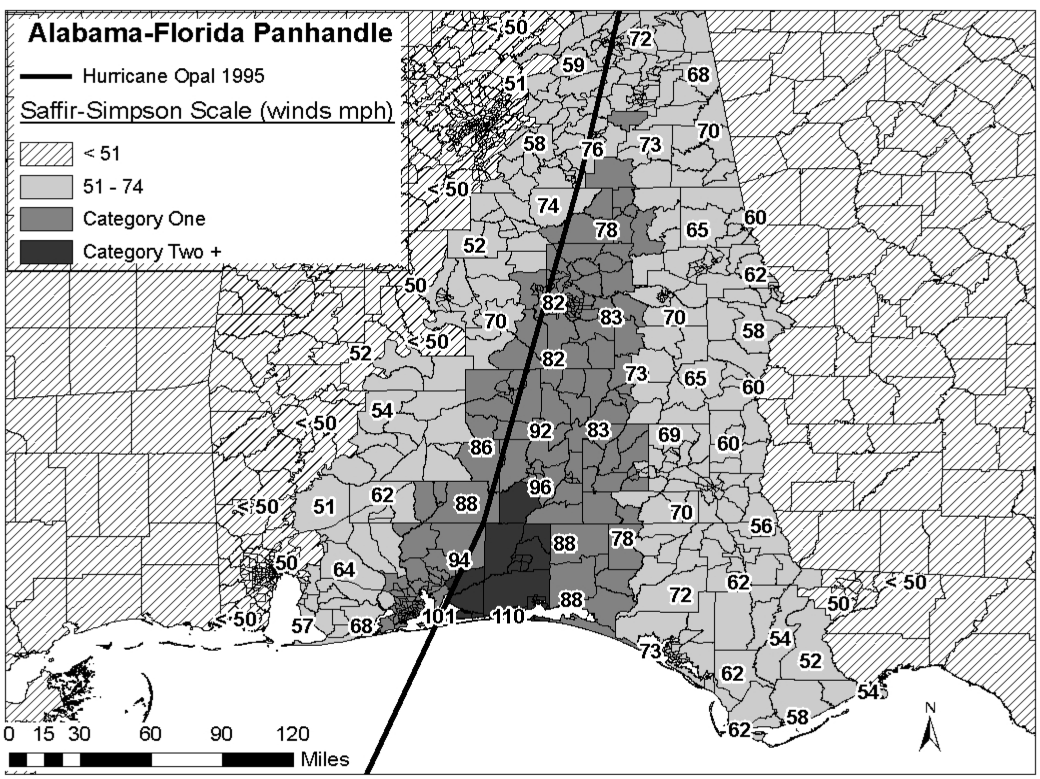
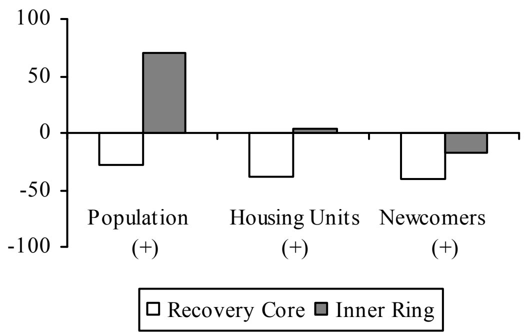
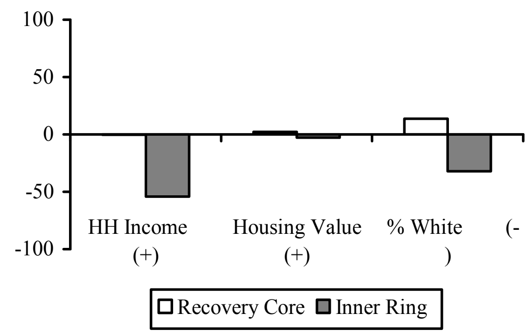


Figure 2: Average Estimated Rate of Change, Relative to the Outer Ring of Recovery (%)[1]

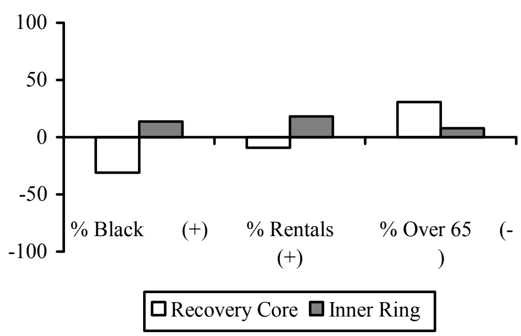
(a) Recovery Machine Proper



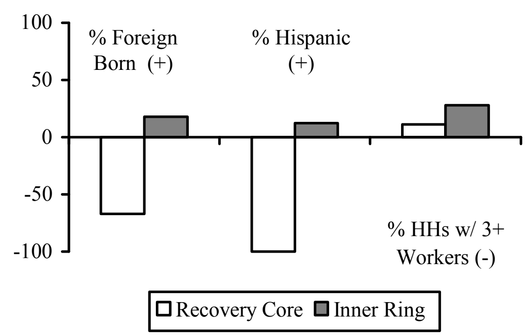
(b) Residential Elites



(c) Residential Non-Elites



(d) Immigrant/Latino Influx



Source: These estimates come from the respective best fit model in Tables 4-7.

[1] Bars indicate the average estimated rate of change relative to the outer ring of recovery, in percentage terms, holding all else constant (e.g., [Core Average-Outer Ring Average]/Outer Ring Average). The (+) or (-) indicates whether the overall rate of change in observed tracts was positive or negative during the observed decade (see Table 3). 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 tracts that experienced Category 1 winds. The Outer Ring consists of tracts that experienced only tropical-storm force winds (51-74 miles per hour), offering a hypothetical benchmark for rates of change had no major hurricane hit.

Table 1. Summary of the Recovery Machine and Associated Hypotheses Regarding Neighborhood Change following a Major Hurricane.

Generalized Actors	**Emblematic Groups & Subpopulations**	**General Propositions**	**Spatial Hypotheses** [outer] [outer] [outer] [outer] [outer] [outer] *[inner] [inner] [inner]* [outer] [outer] *[inner]* **[core]** *[inner]* [outer] **~~ ocean ~~**
Recovery Machine Proper	Usual growth machine actors (e.g., developers, allies, and local officials) fueled by capital influx (government disaster funds; private insurance claims) and political imperative to (re)build.	Promote long-term economic and demographic growth in the affected region as a whole.	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.	Take advantage of financial and political windfalls in heavily damaged neighborhoods to facilitate elite entrenchment (i.e., suppress growth and increase representation of their own kind to the exclusion/displacement of renters, poor and minorities).	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, where recovery funds paid to property owners are greatest).
Residential Non-Elites	African Americans, renters, and the elderly	Experience relative displacement and exclusion from existing neighborhoods and resettle in nearby neighborhoods.	This resettlement 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.
Immigrant Influx	Latinos, immigrants, and crowded residents	Settle into the region over the long term to acquire new jobs, as initial rebuilding efforts turn to long-term recovery.	This increase in (a) Latinos, (b) immigrants, and (c) crowded residents will be greatest in the inner ring of recovery.

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

Tract-Level Variables (N=2,847)	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-born	0	-	.84	.15	.18
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	.67	.47
Coastal tract	0	-	1	.17	.38
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 Neighborhood Characteristics, for All and Specific Hurricane-Affected Regions.[1]

			Hurricane Affected Regions							
	All Regions		**Bob 1991**		**Andrew 1992 (FL)**		**Andrew 1992 (LA)**		**Opal 1995**	
	Mean (1990)	Ave.% Change 1990-2000	Mean (1990)	Ave.% Change 1990-2000	Mean (1990)	Ave.% Change 1990-2000	Mean (1990)	Ave.% Change 1990-2000	Mean (1990)	Ave.% Change 1990-2000
Growth Machine Proper										
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[2]	791	9.4*	804	7.0*	1,027	5.0	549	27.9*	704	15.5*
Residential Elites										
Median household income ($1999)	42,268	3.9*	49,878	3.6*	41,473	1.3	30,542	10.5*	30,307	5.8*
Median home values ln($1999)	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	0.3
% over 65 years old	14.3	-0.6	13.9	-0.7	18.5	-5.3	10.8	8.3*	13.6	3.8
Immigrant/Latino Influx										
% 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	0.8	96.1*
% Households w/3+ workers	14.0	-18.5*	16.9	-22.9*	12.9	-8.6*	9.2	0.2	10.5	-22.2*
N (# of census tract-years)	5,694		2,790		1,254		536		1,114	

* $p < .05$

[1] Tract Characteristic$_{it} = \partial + \beta(\text{year}_{it}\text{: 1990/2000}) + u_i + e_{it}$; estimated for the pooled sample of 1990 and 2000 values, with β/∂ representing average % change.

[2] Estimated by taking the total population ages five and above and subtracting the number of residents that lived in same county five years previous. This is growth directly attributable to in-migration from outside the respective county.

Table 4: Spatial Error Models for Recovery Machine Proper (Standard Errors)[1]

	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 ($\lambda W \mu$)	.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	47253.1	47254.8	42775.2	42778	42858.70	42862.50
OLS AIC	47903.9		43222.3		42896.30	
OLS Moran's I residuals	.354		.237		.077	
Spatial Error Moran's I residuals	-.014		-.010		-.005	

* p < .05; ** p < .01; *** p < .001

[1] Unstandardized coefficients for the spatial error models are presented.

Table 5: Spatial Error Models for Residential Elites (Standard Errors) [1]

	2000 Tract Characteristics					
	Median Household Income ($1999)		**Median Housing Values ln($1999)[2]**		**% 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 (λWμ)	.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	59471.2		696.23		-5575.11	
OLS Moran's I residuals	.097		.175		.351	
Spatial Error Moran's I residuals	-.007		-.025		-.028	

* p < .05; ** p < .01; *** p < .001

[1] Unstandardized coefficients for spatial error models are presented.

[2] Median housing values are in natural log form.

Table 6: Spatial Error Models for Residential Non-Elites (Standard Errors)[1]

	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**
	(.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 (λWμ)	.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	

* p < .05; ** p < .01; *** p < .001

[1] Unstandardized coefficients for spatial error models are presented.

Table 7: Spatial Error Models for Immigrant/ Latino Influx (Standard Errors)[1]

	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 ($\lambda W\mu$)	.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	-10720.2	-10717.4
OLS AIC	-9041.78		-8462.37		-10547	
OLS Moran's I residuals	.366		.420		.160	
Spatial Error Moran's I residuals	-.029		-.026		-.007	

* p < .05; ** p < .01; *** p < .001

[1] Unstandardized coefficients for spatial error models are presented.