The Second Disaster: Demographic Transformation of Disadvantaged Neighborhoods following Major Hurricanes*

[Preliminary Draft]

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* Preliminary draft submitted for presentation at the 2008 annual meeting of the Population Association of America in New Orleans. Please do not cite without authors permission.

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Abstract
In the United States, recovery from major disasters depends greatly on private resources and federal initiatives aimed at restoring business and property rather than local communities. As a consequence of these policies, disadvantaged neighborhoods remain vulnerable not just to environmental hazards but to recovery processes that unfold in their wake—the so-called "second disaster." To date, however, prior research has provided no systematic analysis of neighborhood vulnerability and associated demographic change following major coastal disasters. We provide such an analysis by integrating biophysical and demographic data to study the transformation of socially unequal neighborhoods after major hurricanes during the early 1990s. Results from spatially lagged regression analyses provide new information about the average extent, direction, and spatial patterning of such change and how it varies by local levels of social disadvantage. [*More detailed results forthcoming.*]

Introduction

Within disaster studies, scholars have advanced the concept of vulnerability to emphasize the point that while hazards such as earthquakes, floods and hurricanes are natural, disasters are not. Instead, they represent the "actualization of social vulnerability" (Lewis, 1999). This conceptualization emphasizes that disasters do not simply 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 perspective recognizes that natural disasters don't just happen. Rather, they unfold through historical processes that generate social inequalities in local capacity to anticipate, resist and recover from hazards when they occur.

This understanding that natural disasters derive from social arrangements as well as from environmental forces has broadened interest in their study and increased the range of analytical tools applied to them. One key tool has been Geographic Information Systems (GIS) software that can map the spatial structure of social vulnerability within given environments (e.g., Cutter et al.). Even with these advances, however, important questions remain. One of these questions is how neighborhoods change in the wake of disaster, and how this change varies for socially advantaged and disadvantaged areas. One reason we don't know much about this basic issue 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 neighborhood vulnerability and change are more difficult still.

Another reason for the shortcoming is conceptual. In opening the door to greater sociological understanding of natural disasters, vulnerability science has come to emphasize the historical construction of social vulnerabilities *before* hazards strike, paying less attention to what happens thereafter. Recent studies of post-disaster "resilience" have begun to redress this shortcoming, but they too remain deeply rooted in case study methodology (e.g., Vale & Campanella 2005) and largely ignore the question of how different types of neighborhoods change in the wake of disaster, as recovery proceeds.

In present study we fill this gap by analyzing neighborhood change in U.S. areas struck by major hurricanes during the early 1990s. By major hurricanes, we mean storms that caused at least a billion dollars in property damage, i.e., "Big Ones." For each of these regions, we merge census data from the Neighborhood Change Database (NCDB) with storm data from the HAZUS-MH database, which provides localized estimates of windspeed damage for past hurricanes. This innovative combination of census data and hazard data allows us to model differences in local neighborhood recovery and how they vary by pre-existing levels of social disadvantage.

Neighborhood Disadvantage & Disaster Recovery

Prior research on natural disasters stresses the point that how areas experience and recover from environmental hazards depends greatly on their position within overlapping systems of stratification at global, national, and local levels (for a review, see Bankoff, Frerks & Hilhorst 2007). This position, in turn, is both reflected and constituted within local neighborhood settings, where racial, ethnic, and class relations intersect to maintain pockets of social advantage and disadvantage. Our central proposition is that these social forces influence how neighborhoods recover from, as well as face, natural disasters and that this subject deserves greater empirical attention for several reasons.

First, government disaster policy isn't designed to provide special assistance to disadvantaged neighborhoods after disaster. Instead, it has evolved as a hodge-podge of programs aimed more at restoring property and business than actual communities, often through channels shaped by economic and political interest rather than by need (see Perrow 2007; Steinberg 2006). For example, Garrett and Sobel (2002) studied the allocation of disaster funds by the Federal Emergency Management Agency since its establishment in 1978. They found that, among other things, funding favored states that were critical to national elections and/or had representatives on FEMA oversight committees. Their evidence was so strong, in fact, that the researchers conclude that, "Our models predict that nearly half of all disaster relief is motivated politically rather than by need" (cited in Perrow 2002: 46). As a result, FEMA has done very little to reduce, or even address, concentrations of social disadvantage that feed coastal disasters. Instead, Perrow (2002: 44) explains, "Short-term interests seize on disasters as opportunities to be exploited."

Another reason to care about the fate of disadvantaged neighborhoods in harm's way is that their milieu changes radically during disaster recovery. For starters, structural damage tends to create housing scarcities that increase local rents, exacerbating pre-existing problems with affordable housing. In analyses of New Orleans after Hurricane Katrina, researchers found that average rents increased seventy percent during the first year of recovery (Meitrodt 2006). These problems are compounded by commitments to "free market" recovery, which tend to favor construction and reconstruction of larger, more valuable housing over the repair and development of low-cost alternatives, including public housing options. These housing challenges, in turn, are amplified by the erosion of local social service networks that become more complex and over-burdened in the wake of major disasters. Part of this erosion stems from the poorly coordinated entry of new state, federal and philanthropic organizations into the local service arena, and part of it stems from the devolution of welfare services to local authorities during the 1990s, which makes it difficult for local governments to respond adequately to sudden, catastrophic increases in client needs and populations. The result is an uncoordinated tangle of social services through which disadvantaged individuals and communities often slip.

A third reason to care about how disadvantaged neighborhoods change after disaster is that this change influences the range and character of vulnerability to future hazards. If policies allow disadvantaged areas to deteriorate further during recovery from major disasters, then regional vulnerability is likely to increase; likewise, if disadvantaged residents are increasingly concentrated within expanding pockets of such disadvantage and vulnerability. The implication is that to develop safer coastal regions and better policies for achieving this goal, we must improve our understanding of how disadvantaged neighborhoods recover from disaster. At present, we simply don't know about this type of recovery. In fact, prior research may be read to predict any one of three types of change:

Hypothesizing Neighborhood Change after Disaster

Possibility 1: Functional Recovery to the Status Quo

One line of research on the demographic effects of natural disasters suggests 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; See also Cochrane 1975; Dacy & Kunreuther 1969; Douty 1977; Friesema et al. 1979; Geipel 1991; Haas et al. 1977; Wright et al. 1979). For example, in one of the more rigorous studies, 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. Based on their analyses of affected and unaffected neighborhoods, they concluded that no significant demographic 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.

Although none of these studies explicitly examines how such changes vary by neighborhood disadvantage, they can be read to imply that all areas tend to recover more or less to their status quo. This would mean relatively little aggregate demographic change in disadvantaged neighborhoods following disaster.

> H1: Disaster recovery restores neighborhoods to pre-existing conditions (as measured by relative disadvantage, blight, residential stability, homownership rates, and reliance on public assistance).

Possibility 2: Neighborhood Polarization & Increasing Disadvantage

Another possibility is that neighborhoods in the affected region become increasingly unequal. One reason to expect such polarization is that as low-income neighborhoods struggle to recover, more affluent neighborhoods often receive financial windfalls from government assistance and personal insurance claims that not only allow residents to restore their housing but upgrade it. These residents often 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."

At the other end of regional spectrum, prior studies have found 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 and exacerbate housing shortages among less-affluent residents (Quarantelli 1994; see also Elliott & Pais 2006). 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 increase, further concentrating and segregating socially disadvantaged populations into blighted areas, characterized by declining homeownership, heavy residential turnover, and increased reliance on public assistance. This trajectory would imply that current recovery practices and policies exacerbate local vulnerabilities rather than alleviating them.

> H2: Disadvantaged neighborhoods will become more disadvantaged after disaster (as uneven recovery and declines in safe, affordable housing throughout the affected region concentrate displaced, vulnerable residents in pre-existing areas of disadvantage, which deteriorate during recovery).

> [Corollary: Advantaged neighborhoods become more advantaged, as those who can afford to stay do. Result: a socioeconomic polarization of neighborhoods within the region as a whole during disaster recovery.]

Possibility 3: Neighborhood Displacement & Decreasing Disadvantage
A third possibility for recovery dynamics is that formerly disadvantaged neighborhoods become less disadvantaged because recovery dynamics (e.g., rising rents and weakened social services) displace, rather than concentrate, social disadvantage. For example, researchers commonly report 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.

> H3: Disadvantaged neighborhoods will become less disadvantaged after disaster (as recovery processes displace vulnerable residents who lack the capacity "to recover in place").

Note: Both Hypotheses #2 and #3 emphasize the vulnerability of residents in disadvantaged neighborhoods, but they predict different recovery outcomes stemming from this vulnerability. One predicts further concentration and spatial consolidation of disadvantage during recovery; the other predicts displacement. We suspect that these trajectories may differ on the coast than inland, and in areas of greater, rather than less, wind damage.

Data

To test our hypotheses about neighborhood disadvantage and disaster recovery, we must specify which hurricanes qualify for analysis, how affected regions and constituent subregions will be identified, and what our primary units and variables of analysis will be. To start, we selected hurricanes that caused over a billion dollars worth of damage during the early 1990s because of their sheer impact and because of their likelihood of happening again 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 recovery processes 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 affected regions 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, and select all tracts that experienced at least tropical-storm force winds (51-74 miles per hour).[3] 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]

Estimating Neighborhood Disadvantage and 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.

Consistent with other studies of neighborhood disadvantage (e.g., Hannon 2005; McNulty 2001), we operationalize this concept at the tract level using a standardized index of four highly correlated variables: the poverty rate; median household income (reverse coded); percentage of families that are female-headed with children under 18; and the percent of male joblessness among those ages 18-64. All of these variables are standardized separately for each region and year of observation using Z-scores and then summed to a single index. Cronbach's alpha for this index is .89 in 1990 and .90 in 2000, indicating a high degree of statistical reliability in the measurement of a single unidimentional latent construct.

In addition to changes in this index over time, we examine change in four additional indicators of neighborhood vulnerability: residential stability, homeownership, vacant structures, and density of public assistance. Descriptive statistics for these tract-level variables are provided in Table 1. In addition to these 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; regional dummy variables control for regionally specific growth trajectories; and a dummy variable indicating whether a tract was more than 70 percent non-white controls for the effects of extreme racial segregation.

In addition to these controls, we 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 indicators 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.

[Table 1 about here]

Because coastal tracts tend to vary qualitatively from inland tracts both in terms of their hurricane damage (storm surge, in addition to wind damage) and in terms of their pre-storm affluence, they exhibit different distributions of pre-existing neighborhood disadvantage as well as potential trajectories of change. To account for this difference and to refine our spatial understanding of neighborhood change, we fit our statistical models separately for coastal and inland tracts and include an indicator of maximum windspeed as a indicator of localized storm damage. Our general expectation is that demographic change, regardless of type, will tend to be greater in areas hit harder by the hurricane, all else equal (i.e., those on the coast and those experiencing higher windspeeds).

In estimating these models of change, spatial autocorrelation is a potential concern because similar neighborhoods tend to cluster spatially, yielding correlated observations that can yield inaccurate slope estimates and standard errors (Anselin, 1988). To account for this spatial autocorrelation, we construct and include a spatially lagged indicator of neighborhood disadvantage in 1990. This variable as a control and source of additional information the spatial patterning of neighborhood change following major disasters.

Results

[*Preliminary – To be updated and refined prior to annual meeting*.]

Do disadvantaged neighborhoods become more disadvantaged during recovery?

To answer this question, we first estimated the following equation:

$$\text{Disadvantage Index}_{i,2000} = \partial + \beta_1(\text{Disadvantage Index}_{i,1990}) + \beta_2(\text{Hurricane Windspeed}) + \beta_n[\text{Control Variables}] + e,$$

where control variables include our spatial lag variable for Disadvantage Index$_{i,1990}$ as well as the other variables described above.

In short, *preliminary* results reported in Table 2 indicate that changes in neighborhood disadvantage vary greatly by associated windspeeds and coastal location. Figure 2 illustrates these divergent trajectories clearly and shows that, all else equal, neighborhood disadvantage tends to decline with wind damage in coastal tracts, whereas inland, neighborhood disadvantage tends to increase with wind damage. In other words, Hypothesis 2 and 3 each look to be correct but in different settings. Along the coast, increased wind-damage appears to displace more vulnerable residents; whereas inland, it appears to attract and/or concentrate more vulnerable residents.

[Table 2 & Figure 2 about here]

Do disadvantaged neighborhoods become more vulnerable in other ways during recovery?
To answer this question, we estimated lagged models of the following general form:

$$\text{Tract Characteristic}_{i,2000} = \partial + \beta_1(\text{Tract characteristic}_{i,1990}) + \beta_2(\text{Disadvantage Index}_{i,1990}) + \beta_2(\text{Hurricane Windspeed}) + \beta_n[\text{Control Variables}] + e.$$

Tract characteristics of interest are residential stability, homeownership rates, rates of public assistance, and rates of vacant housing (a proxy for physical blight).

Preliminary results are reported in Tables 3-6. In short, they indicate that, net of other factors, neighborhood disadvantage is positively and significantly associated with declines in residential stability (community cohesion) and homeownership (direct control), as well as increases in vacant units (blight) and welfare receipt (dependence). These patterns tend to be stronger and more consistent in inland tracts than coastal tracts, especially those surrounded by similarly disadvantaged neighborhoods (as indicated by findings for our spatial lag variable and supplementary analyses (not shown) that indicate strong spatial dependence in trajectories of post-disaster recovery and change).

[Tables 3-6 about here]

Additional analyses and results forthcoming.

Conclusion

[*Preliminary – to be updated and refined prior to annual meeting*.]

Results indicate that under current policy arrangements, disadvantaged neighborhoods tend to become even more disadvantaged and socially vulnerable as they recover from major coastal disasters, deepening pre-existing inequalities and complicating planning and recovery efforts for future hazards. Efforts at policy reform must acknowledge these dynamics and seek their reversal if we are to construct truly resilience communities.

References

[*To be completed*]

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

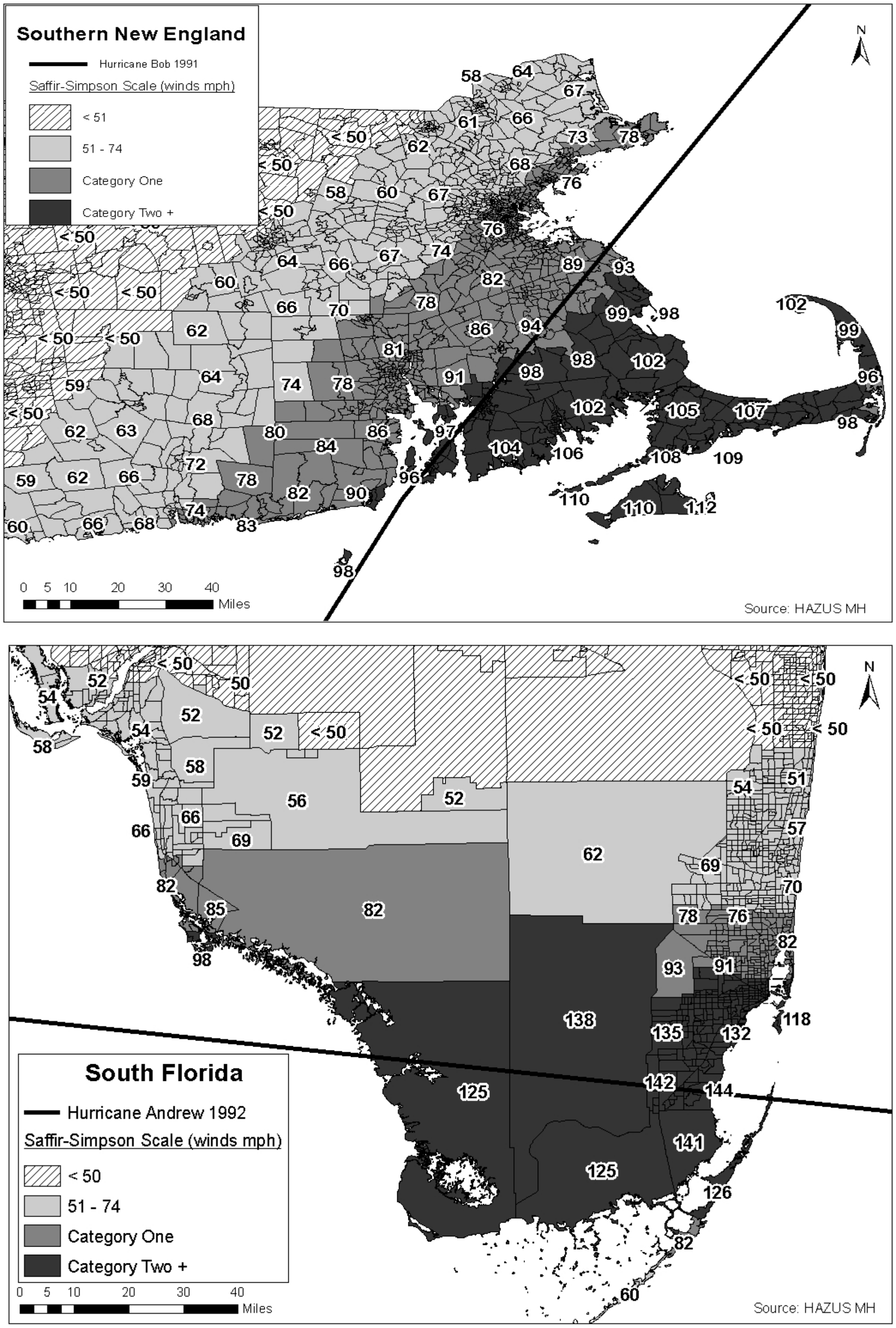
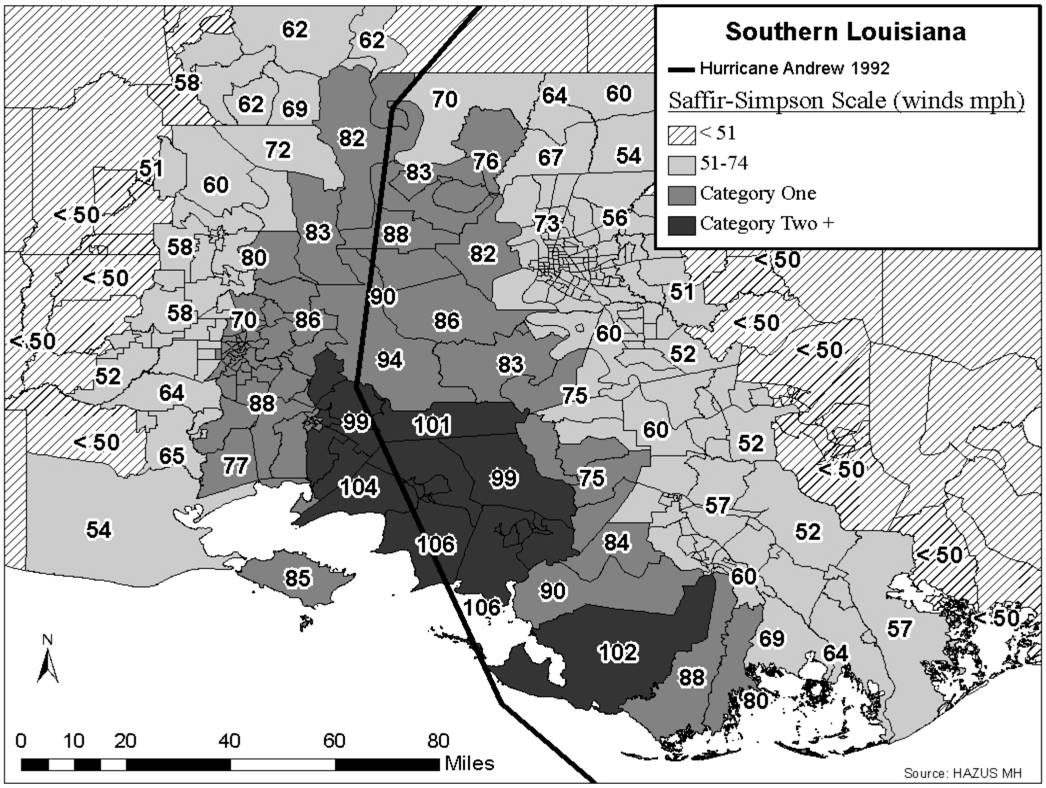


Figure 1, Cont. –



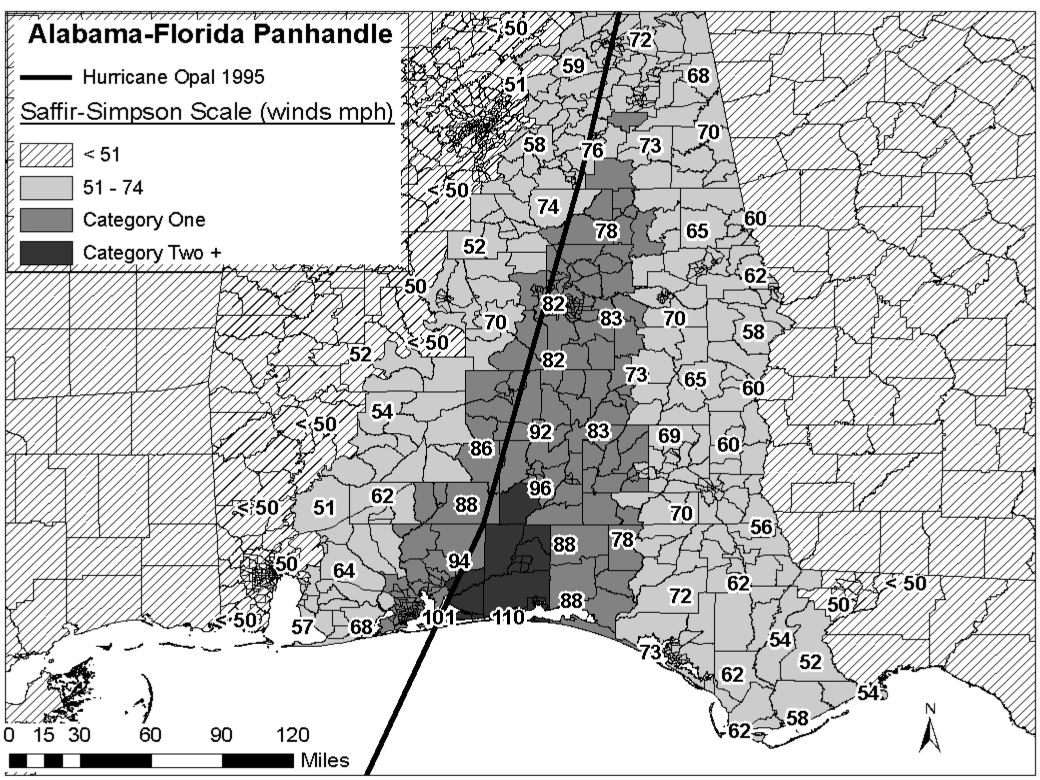
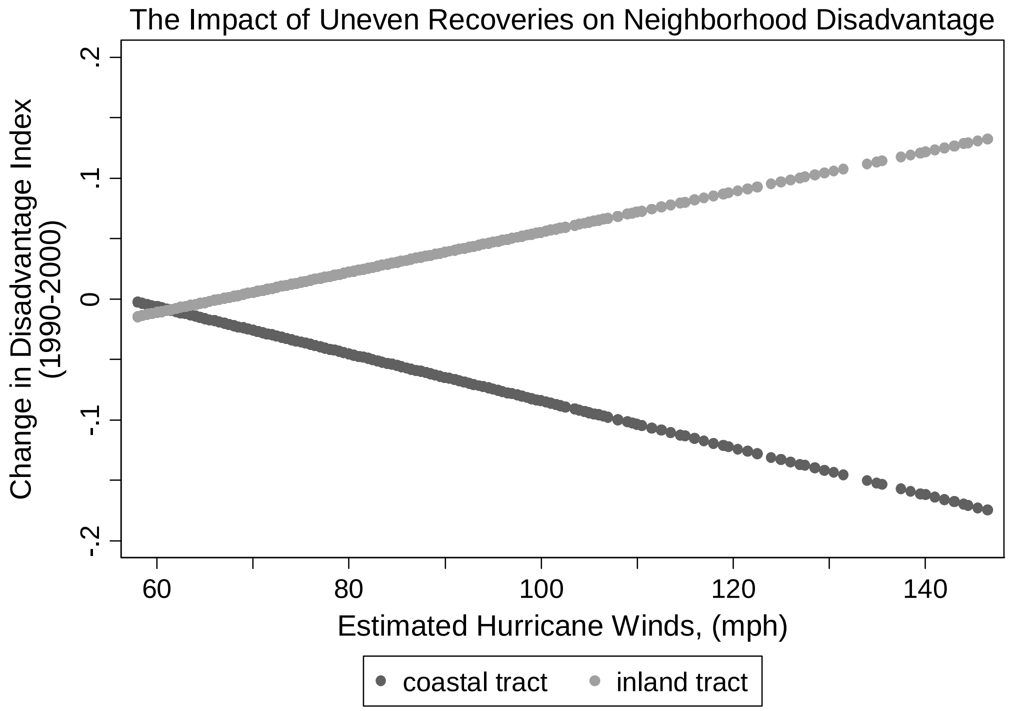


Figure 2



Source: Estimated regression equation reported in Table 2, with all other variables set to pooled sample means.

$$\text{Disadvantage Index}_{i,2000} = \partial + \beta_1(\text{Disadvantage Index}_{i,1990}) + \beta_2(\text{Hurricane Windspeed}) + \beta_n[\text{Control Variables}] + e,$$

Where control variables include the following: a spatial lag variable for Disadvantage Index$_{i,1990}$; an indicator of tract boundary change between 1990 and 2000 (none [reference]; expansion; contraction); storm/region (Bob/New England; Andrew-I/Florida [reference]; Andrew-II/Louisiana; Opal/Florida); population density (persons per square mile); and a indicator of minority concentration (1=over 70 percent minority; 0=otherwise).

Table 1: Descriptive Statistics

Neighborhood Characteristics	Min	Max	Total Mean	Total S.D.	Coastal Mean	Coastal S.D.	Inland Mean	Inland S.D.
Control Variables:								
Tract boundary merged, corrected (yes/no)	.00	1.00	.02	.14	.05	.21	.01	.11
Tract boundary split, corrected (yes/no)	.00	1.00	.44	.50	.44	.50	.44	.50
No change in tract boundary (yes/no)	.00	1.00	.54	.50	.51	.50	.55	.50
Hurricane region 1: Bob 1991, Southern New England	.00	1.00	.49	.50	.60	.49	.45	.50
Hurricane region 2: Andrew 1992, South Florida	.00	1.00	.22	.41	.23	.42	.22	.41
Hurricane region 3: Andrew 1992, Louisiana	.00	1.00	.09	.29	.02	.14	.12	.32
Hurricane region 4: Opal 1995, AL/FL Panhandle	.00	1.00	.20	.40	.15	.36	.21	.41
1990 Population density (1000 persons per square mile of land)	.00	.09	.01	.01	.00	.01	.01	.01
Minority Composition >70% (yes/no)	.00	1.00	.12	.33	.05	.21	.15	.36
Key Variables:								
Disadvantage Index, 2000	-2.49	3.54	.00	.88	-.05	.83	.02	.89
Disadvantage Index, 1990	-2.66	3.83	.00	.86	.01	.78	.00	.88
Spatially Lagged Disadvantage Index, 1990	-1.65	2.66	-.01	.65	.00	.55	-.02	.68
Maximum Sustained Hurricane Winds (mph)	58.00	146.50	79.81	16.44	86.22	16.15	77.78	16.01
Neighborhood Change Variables:								
Proportion on Public Assistance, 2000	.00	.60	.09	.07	.08	.07	.09	.07
Proportion on Public Assistance, 1990	.00	.51	.08	.07	.07	.07	.09	.08
Proportion in the Same House, 1995-2000	.00	.96	.56	.13	.53	.13	.56	.13
Proportion in the Same House, 1985-1990	.00	.86	.54	.14	.52	.14	.55	.14
Proportion Homeowners, 1990	.00	1.00	.56	.22	.51	.22	.60	.22
Proportion Homeowners, 2000	.00	1.00	.58	.23	.48	.21	.58	.21
Proportion Vacant Housing Units, 2000	.00	.99	.09	.10	.14	.15	.07	.07
Proportion Vacant Housing Units, 1990	.00	.77	.10	.10	.16	.16	.09	.07
N			2847		685		2162	

Table 2: Linear Regression Coefficients Predicting Neighborhood Disadvantage in 2000 [1]

	Coastal tracts (I)	Inland tracts(I)	Coastal tracts (II)	Inland tracts (II)
Disadvantage Index, 1990	.815***	.751***	.929***	.812***
	(.028)	(.016)	(.102)	(.053)
Spatially Lagged Disadvantaged Index, 1990	.211***	.193***	.209***	.194***
	(.041)	(.022)	(.041)	(.022)
Tract boundary merged	-.239**	-.072	-.244**	-.075
	(.074)	(.077)	(.074)	(.077)
Tract boundary split	-.015	.005	-.016	.005
	(.031)	(.018)	(.031)	(.018)
No change in tract boundary (ref.)	--	--	--	--
Bob 1991, Southern New England	.136**	-.089***	.141**	-.087***
	(.045)	(.025)	(.045)	(.025)
Andrew 1992, South Florida	-.193***	-.015	-.186***	-.014
	(.052)	(.030)	(.052)	(.030)
Andrew 1992, Louisiana	.117	-.027	.119	-.026
	(.111)	(.031)	(.111)	(.031)
Opal 1995, AL/FL Panhandle (ref.)	--	--	--	--
1990 Population density	.169	5.825***	-.129	5.824***
	(2.731)	(1.376)	(2.742)	(1.376)
Minority Composition >70% (yes/no)	.114	.054	.130	.056
	(.082)	(.031)	(.083)	(.031)
Maximum Sustained Hurricane Winds (mph)	-.002*	.002**	-.002*	.001*
	(.001)	(.001)	(.001)	(.001)
Interaction Effects				
Hurricane Winds X Disadvantage Index, 1990			-.001	-.001
			(.001)	(.001)
Constant	.089	-.089	.103	-.081
	(.092)	(.046)	(.093)	(.047)
R^2	.79	.80	.79	.81
N	685	2162	685	2162

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

1. Standard Errors are in parentheses

Table 3: Linear Regression Coefficients Predicting Proportion in Same House, 1995-2000[1]

	Coastal tracts (I)	Inland tracts (I)	Coastal tracts (II)	Inland tracts (II)
Proportion in Same House,1985-1990	.643***	.659***	.644***	.658***
	(.027)	(.017)	(.027)	(.017)
Spatially Lagged Same House , 1985-1990	.133**	.120***	.138***	.120***
	(.039)	(.025)	(.039)	(.025)
Disadvantage Index, 1990	-.027***	-.021***	.000	-.026**
	(.004)	(.002)	(.018)	(.009)
Tract boundary merged	-.026*	.009	-.027*	.010
	(.013)	(.014)	(.013)	(.014)
Tract boundary split	.000	.006	.000	.006
	(.005)	(.003)	(.005)	(.003)
No change in tract boundary (ref.)	--	--	--	--
Bob 1991, Southern New England	.004	.006	.004	.005
	(.009)	(.004)	(.009)	(.004)
Andrew 1992, South Florida	-.014	.024***	-.012	.024***
	(.009)	(.006)	(.009)	(.006)
Andrew 1992, Louisiana	-.002	-.013*	-.003	-.013*
	(.021)	(.006)	(.021)	(.006)
Opal 1995, AL/FL Panhandle (ref.)	--	--	--	--
1990 Population density	-1.758***	-1.694***	-1.814***	-1.700***
	(.464)	(.260)	(.465)	(.260)
Minority Composition >70% (yes/no)	.061***	.045***	.064***	.045***
	(.015)	(.006)	(.015)	(.006)
Maximum Sustained Hurricane Winds (mph)	.000**	.000**	.000*	.000**
	(.000)	(.000)	(.000)	(.000)
Interaction Effect Hurricane Winds X Disadvantage Index, 1990			.000	.000
			(.000)	(.000)
Constant	.095***	.101***	.096***	.101***
	(.023)	(.014)	(.023)	(.014)
R^2	.73	.69	.74	.69
N	685	2162	685	2162

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

1. Standard Errors are in parentheses

Table 4: Linear Regression Coefficients Predicting Proportion Homeowners in 2000[1]

	Coastal tracts (I)	Inland tracts (I)	Coastal tracts (II)	Inland tracts (II)
Proportion Homeowners,1990	.905***	.877***	.905***	.877***
	(.018)	(.013)	(.018)	(.013)
Spatially Lagged Homeowners, 1990	-.009	.052**	-.008	.052**
	(.021)	(.017)	(.021)	(.018)
Disadvantage Index, 1990	-.028***	-.022***	-.022	-.019
	(.004)	(.003)	(.016)	(.010)
Tract boundary merged	-.001	.015	-.002	.014
	(.011)	(.015)	(.011)	(.015)
Tract boundary split	.007	.009**	.007	.009**
	(.005)	(.003)	(.005)	(.003)
No change in tract boundary (ref.)	--	--	--	--
Bob 1991, Southern New England	.002	.031***	.002	.031***
	(.007)	(.005)	(.007)	(.005)
Andrew 1992, South Florida	-.013	.036***	-.013	.036***
	(.008)	(.006)	(.008)	(.006)
Andrew 1992, Louisiana	.002	.028***	.002	.028***
	(.017)	(.006)	(.017)	(.006)
Opal 1995, AL/FL Panhandle (ref.)	--	--	--	--
1990 Population density	-.828*	-1.126***	-.842*	-1.128***
	(.420)	(.311)	(.422)	(.311)
Minority Composition >70% (yes/no)	.013	.010	.013	.010
	(.013)	(.006)	(.013)	(.006)
Maximum Sustained Hurricane Winds (mph)	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)
Interaction Effect				
Hurricane Winds X Disadvantage Index, 1990			.000	.000
			(.000)	(.000)
Constant	.087***	.026	.087***	.026
	(.017)	(.014)	(.017)	(.014)
R^2	.93	.89	.93	.89
N	685	2162	685	2162

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

1. Standard Errors are in parentheses

Table 5: Linear Regression Coefficients Predicting Proportion on Public Assistance in 2000[1]

	Coastal tracts (I)	Inland tracts (I)	Coastal tracts (II)	Inland tracts (II)
Proportion Public Assistance,1990	.646***	.566***	.637***	.565***
	(.038)	(.021)	(.038)	(.021)
Spatially Lagged Public Assistance, 1990	.147**	.202***	.147**	.200***
	(.045)	(.022)	(.044)	(.022)
Disadvantage Index, 1990	.016***	.013***	-.008	.006
	(.003)	(.002)	(.009)	(.005)
Tract boundary merged	-.008	-.016*	-.007	-.016*
	(.007)	(.007)	(.007)	(.007)
Tract boundary split	-.001	.001	-.001	.001
	(.003)	(.002)	(.003)	(.002)
No change in tract boundary (ref.)	--	--	--	--
Bob 1991, Southern New England	-.010*	.004*	-.011**	.004
	(.004)	(.002)	(.004)	(.002)
Andrew 1992, South Florida	-.003	.026***	-.005	.026***
	(.005)	(.003)	(.005)	(.003)
Andrew 1992, Louisiana	-.018	-.013***	-.018	-.013***
	(.010)	(.003)	(.010)	(.003)
Opal 1995, AL/FL Panhandle (ref.)	--	--	--	--
1990 Population density	.206	-.001	.283	.000
	(.239)	(.122)	(.240)	(.122)
Minority Composition >70% (yes/no)	.020*	.008**	.017*	.007*
	(.008)	(.003)	(.008)	(.003)
Maximum Sustained Hurricane Winds (mph)	.000	.000	.000	.000**
	(.000)	(.000)	(.000)	(.000)
Interaction Effect Hurricane Winds X Disadvantage Index, 1990			.000	.000
			(.000)	(.000)
Constant	.021*	.009*	.019*	.008
	(.008)	(.005)	(.009)	(.005)
R^2	.76	.76	.76	.76
N	685	2162	685	2162

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

1. Standard Errors are in parentheses

Table 6: Linear Regression Coefficients Predicting Proportion Vacant Housing Units in 2000[1]

	Coastal tracts (I)	Inland tracts (I)	Coastal tracts (II)	Inland tracts (II)
Proportion Vacant Housing Units,1990	.788***	.504***	.788***	.504***
	(.023)	(.021)	(.023)	(.020)
Spatially Lagged Vacant Housing Units , 1990	.111***	.125***	.110***	.126***
	(.030)	(.027)	(.030)	(.027)
Disadvantage Index, 1990	-.001	.014***	-.010	-.010
	(.003)	(.001)	(.014)	(.005)
Tract boundary merged	.006	-.003	.007	-.002
	(.011)	(.008)	(.011)	(.008)
Tract boundary split	-.007	-.004*	-.007	-.004*
	(.004)	(.002)	(.004)	(.002)
No change in tract boundary (ref.)	--	--	--	--
Bob 1991, Southern New England	-.017**	-.051***	-.018**	-.052***
	(.006)	(.003)	(.006)	(.003)
Andrew 1992, South Florida	.003	-.040***	.002	-.041***
	(.007)	(.003)	(.007)	(.003)
Andrew 1992, Louisiana	.022	-.036***	.022	-.037***
	(.016)	(.003)	(.016)	(.003)
Opal 1995, AL/FL Panhandle (ref.)	--	--	--	--
1990 Population density	.087	-.819***	.111	-.821***
	(.370)	(.139)	(.373)	(.138)
Minority Composition >70% (yes/no)	-.010	-.009**	-.011	-.010**
	(.012)	(.003)	(.012)	(.003)
Maximum Sustained Hurricane Winds (mph)	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)
Interaction Effect				
Hurricane Winds X Disadvantage Index, 1990			.000	.000***
			(.000)	(.000)
Constant	-.007	.056***	-.008	.053
	(.013)	(.006)	(.013)	(.006)
R^2	.86	.62	.86	.62
N	685	2162	685	2162

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

1. Standard Errors are in parentheses