# Trapped in Place? Segmented Resilience to Hurricanes in the Gulf Coast, 1970-2005

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## Abstract

Hurricanes pose a continuing hazard to populations in coastal regions. This study estimates the impact of hurricane wind damage and storm surge on population change in the U.S Gulf Coast during 1970-2005. Geophysical models are used to simulate the spatial extent and intensity of wind damage and storm surge from all 32 hurricanes that struck the region in this period, and multivariate spatial time-series models are used to estimate the impacts of hurricanes on population change. Population growth is found to be reduced significantly for up to three successive years after counties experience wind damage, particularly at higher levels of damage. There is evidence of negative effects on population even in adjacent counties that were not directly impacted by hurricane winds. Storm surge is associated with reduced population growth in the year after the hurricane. Model extensions show that change in the white and young adult population is more immediately and strongly affected than change for blacks and elderly residents. Negative effects on population are stronger in counties with lower poverty rates. This specific pattern of impacts is interpreted as evidence of a form of *segmented resilience*, in which advantaged population groups are more able to move out of harm's way while socially vulnerable groups are less mobile.

**Trapped in Place? Segmented Resilience to Hurricanes in the Gulf Coast, 1970-2005**

In recent years, the demographic implications of extreme weather events have received increasing attention. The growing research and policy interest is partly due to the high visibility of catastrophic events, such as Hurricane Katrina (2005), and the Asian and Japanese Tsunami (2004, 2011), and the concern about the impacts of climate change and increasing weather variability on local populations especially in coastal regions. In the United States, major hurricanes have caused more damage to local populations and ecosystems than any other natural disasters (Pielke et al 2008; Pielke and Landsea 1998).[1] An understanding of the demographic implications of such events requires bringing together data and theories from the physical sciences and demography (Fussell , Curtiss and Ward 2014). Efforts to understand the impacts of hurricanes from a physical science perspective are rooted in the concept of resilience (Folke 2006; Holling 1973). The mainstream theory holds that ecosystem biodiversity, functional redundancy, and spatial heterogeneity confer a capacity to recover from catastrophic damage (Adger et al 2005). Ecosystems are resilient, referring to their capacity "to absorb recurrent disturbances such as hurricanes or floods so as to retain essential structures, processes, and feedbacks" (2005, p. 1036). Though many social scientists are wary of adopting ecological theory directly or by analogy, what Tierney, Lindell, and Perry (2001) call the 'classic' sociological paradigm of disasters also presumes a return to equilibrium in disaster-hit communities. However, not all population groups and local communities are expected to be equally resilient (Dash, Peacock and Morrow 1997, Peacock and Girard 1997, Smith et al 2006). Rather than asking how "society" as a whole recovers from disaster, these scholars focus on specific population segments, asking who is most exposed to risk (locational vulnerability) and who is best able to deal with it (social vulnerability). If **resilience** is the mainstream hypothesis for ecosystems, **segmented resilience** is a more usual expectation for human communities. We study the phenomenon of segmented resilience by examining the impacts of hurricanes on population change in the United States Gulf Coast in the period 1970-2005.

We begin by reviewing the key concepts of locational and social vulnerability, summarizing the well-developed literature about which population groups are vulnerable, and translating alternative theories into hypotheses about hurricanes' impact on population change. We then describe our research design, which involves estimating damage from all hurricanes on the Gulf Coast in the period 1970-2005 and linking those estimates with information on the resident population of those areas. We introduce an existing meteorological model that we adapted to the Gulf Coast. This allows us to estimate the spatial extent of wind damage from every individual hurricane using publicly available data on storm tracks from the National Oceanic and Atmospheric Administration (NOAA). We also use models developed by NOAA to estimate the spatial extent of storm surge from every hurricane. These estimates are the basis for evaluating the impact of hurricanes through spatial time series models of annual population change in the years 1970-2005.

**Vulnerability and resilience**

Much theorization about resilience is framed in terms of vulnerability, which can be conceptualized along two dimensions. The first dimension is the risk faced by populations by virtue of their residential location (particularly, proximity to the coast), which we refer to as **locational vulnerability**. Early writing about disasters based on the risk-hazard (RH) paradigm conceptualized hazards as accidental, unforeseeable agents (Kates 1985; Burton et al 1978). More recently scholars are paying attention to the fact that many hazards have a known spatial pattern, with the consequence that one can assess people's risk by knowing where they live. Hence Turner et al (2003, p. 8076) argue for a place-based approach to account for the strong variation in vulnerability by location. The second dimension is people's capacity to deal with disaster, which we call **social vulnerability**. The influential pressure-and-release (PAR) model (Blaikie et al 1994) emphasizes that vulnerability depends on the interaction between the existence and location of a natural hazard, on the one hand, and the various factors that influence whether individuals or communities are able to respond effectively, on the other. In this vein Chambers defined vulnerability as having "two sides," an external side of risks and an internal side of means to cope (1989, p. 1; see Cutter's [1996] notion of the "hazards of place," also Hewitt 1997 and Tierney 2007).

Researchers deal with both dimensions of vulnerability. In the environmental justice literature the emphasis is on locational vulnerability, measured as unequal exposure to environmental risk (Bullard 1990; Bullard 1993) and its community health impacts (Pastor, Sadd et al. 2001). Researchers have demonstrated that measures of social capital are correlated with proximity to certain hazardous sites and other indicators of neighborhood well-being (Diez-Roux 1997; Sampson, Morenoff et al 1999; Buka et al 2002; Morenoff 2003). Bolin (2006), drawing on the literature on environmental health, argues that various processes of social marginalization result in inequalities in exposure to hazards and access to opportunities. An exception is noted in a study of coastal South Carolina (Cutter, Mitchell and Scott 2000), where areas most exposed to hazards (located along the coast and waterways) were populated by more advantaged groups that consider proximity to water to be an amenity. The more usual expectation is for routine processes of urban and rural development to create cumulative disadvantages for many residents, constituting a stratification of places (Logan and Molotch 1987) that reinforces other dimensions of social inequality.

The environmental justice literature focuses on anthropogenic hazards that typically are long lasting and on processes that over time bring disadvantaged population groups into greater proximity to those hazards. More relevant to the study of episodic natural events such as hurricanes is the literature on the impact of disasters on human communities. This literature acknowledges that locational vulnerability may be greater for population groups that have fewer resources. As McGranahan, Balk and Anderson (2007, p. 20) point out, "the poorest residents of the cities of low-income countries are often forced (implicitly or explicitly) to settle in flood plains or other hazard-prone locations, as they cannot afford more suitable alternatives." Their locational disadvantage is similar to the problem highlighted by the environmental justice literature.

Climate disaster studies also focus on differential social vulnerability – the capacity to respond to new conditions or resilience. There is considerable agreement on who is likely to be more resilient, especially based on age, gender, race, and socioeconomic status (Cutler, Boruff and Shirley 2003). Cochrane (1975) argues that lower income groups consistently bear a disproportionate share of the losses, even if they are not more likely to be placed in the path of disaster. In other words, social vulnerability can be distinct from local vulnerability. Lower income persons receive, in most instances, the smallest proportion of disaster relief; they are the least likely to be insured (for health, life or property); and they live in dwellings which are of the poorest construction and most subject to damage. Elliott and Pais (2006) show that low income blacks were the most likely to lose their jobs in the wake of Hurricane Katrina. Dash, Peacock, and Morrow (1997) in their study of Hurricane Andrew conclude that housing, job, business, and tax revenue losses were proportionately greater in the minority community. They also argue that poorer communities tend to lack an organizational capacity to manage recovery efforts or to command attention in the process of recovery. Bolin and Stanford (1998) find no evidence in the Northridge earthquake in Los Angeles that lower income households were over-represented in the victim pool; in this case, general exposure cut across race, ethnicity and class. But while relief efforts were focused on middle-class homeowners, 80% of the damage in that earthquake was sustained by multifamily and low-rent rental housing (Wu and Lindell 2004).

Resilience also has both a locational and social aspect. It is usually conceptualized as the ability to withstand a disaster, to remain in place, or return and rebuild homes and livelihoods. Being uprooted, in contrast, is seen as a failure of resilience. The locational aspect is apparent in the frequent assumption that “a severe enough shock will lead to displacement and migration” (Black et al 2013, p. S35). As examples they cite results at both the community and household level. Gray and Mueller (2012) refer to this as the “conventional narrative” that predicts large-scale and permanent population displacement due to extreme climate events that disproportionately affect vulnerable population groups. Mexican municipalities which experienced higher frequency of droughts, floods, and hurricanes between 1990 and 2000 had higher emigration rates than neighboring communities (Saldana and Sandberg 2009). Households with exposure to heavy rains associated with Hurricane Mitch in Nicaragua were more likely to have migrated from their original homes (Carvajal and Pereira 2010). Migration caused by climate disasters creates “environmental refugees” (Myers 2002, Wilbanks et al 2007).

The sense that outmigration represents a lack of resilience stems from the observation that on average, all segments of the population are immobile, preferring not to migrate due to environmental changes. This is what some scholars refer to as the “immobility paradox” (Findley 2011; Fischer and Malmberg 2001). If so, one would not expect hurricanes to cause population shifts except in extreme cases and for people who have no other options. A contrasting view is that people who remain in the face of risk may simply be trapped in place. In this view, it is normal for people to wish to mitigate locational vulnerability, but migration requires resources, and socially disadvantaged population groups may find themselves unable to leave risky environments. “Trapped populations are vulnerable to stress but without the ability or resources to move” (Black et al 2013, p. S36, see also Wisener et al 2004, Findley 2011). On this point Black et al (2013) cite Herren’s (1991) study of the response to droughts by herders in Kenya in the 1980s. In Kenya the poorest herders were the worst affected because they had no option other than to remain in place, while the middle income were able to move away temporarily and later return to rebuild their herds. Hunter (2005) makes a similar point, citing Chan’s (1995) finding that rich and poor families are unequally affected by crop failure and flooding in Malaysia due to differential mobility.

Following this same line of thought, Gray and Mueller (2012) note that migration in normal conditions is selective of people with above-average access to human, social and financial capital, which conflicts with the expectation that disadvantaged persons are most likely to be displaced by climate events. Their own research in Bangladesh in 1994-2010 showed that rural communities that experienced crop failure had greater local and long distance outmigration at the community level (that is, many people moved away), but households who personally experienced crop failure were less likely to move. In the case of Hurricane Katrina, Elliott and Pais (2006) show that low income blacks were the least likely to be able to evacuate from New Orleans prior to the hurricane. Post-hurricane, they find that homeowners were more likely than renters to plan to return, but among homeowners the people with lower incomes were more likely than affluent households to return because of their more limited choices – "their mortgage obligations coupled with lower household incomes afford them less opportunity to pursue options elsewhere" (2006, p. 315).

There is also evidence of selective outmigration in response to hurricane risk on the Gulf Coast. In an analysis of population shifts during 1950-2005 (*citation withheld for journal review*), we traced the trends in exposure to hurricane wind damage for different population groups: whites and blacks, young adults (age 20-34) and older persons (age 65+), and persons above and below the official poverty line. In 1950, higher shares of non-poor, young adults and whites lived in higher risk counties. The more advantaged population groups had higher exposure to hurricanes. This pattern is reminiscent of the finding by Cutter, Mitchell and Scott (2000) for South Carolina, where more advantaged groups were described as living at higher risk because of the greater amenity of living near water. But there was a crossover as time passed. By 2010 non-poor residents and young adults were less likely to live in higher risk counties. Through 2000 there was also a racial shift as blacks became more exposed to risk than whites, but this was reversed as a result of massive displacement of black population after Hurricane Katrina. Why did the initial 1950 pattern change? A hypothesis that we can pursue in the present study is that the change occurred as a result of differential response to actual hurricanes: in other words, hurricanes cause selective outmigration or shifts in the composition of new residents. This discussion points to a process of **segmented resilience** where different populations have different opportunities, costs and benefits related to staying in place or migrating in the face of adverse environmental events.

**Hypotheses**

In this section, we translate these general theories and past research findings into working hypotheses about the impacts of hurricanes on population change. What might we expect to find on the Gulf Coast and how can we interpret the findings in terms of vulnerability and resilience? Some longitudinal studies have found no net impact of natural disasters on subsequent population change (Wright et al 1979, Frisema et al 1977), which is consistent with the **resilience hypothesis** in the ecological literature or with the immobility paradox mentioned above. Indeed one point of view is that the insurance settlements and federal or state aid due to a disaster provide new opportunities for future development (see Albala-Bertrand 1993). We could call this a **stimulus hypothesis**. A third perspective is the **segmented resilience** hypothesis developed above, where different groups are affected in distinct ways.

From the experience of Hurricane Andrew (Smith et al 2006) segmented resilience seems to be reflected in more rapid return (the wealthy returned more quickly to their prior locations) and also in the ability to move to safer locations (middle income households moved away from more precarious sites and were replaced by lower income households). It is also possible for impacts to differ for different population groups and in different locations in relation to hurricane-damaged areas. A study of three major hurricanes (Hurricanes Bob, Andrew, and Opal in New England and the Gulf Coast) demonstrates this variability (Pais and Elliott 2008). In the "recovery core" of neighborhoods with the most severe damage, elite groups (which they define as whites, homeowners, and wealthy residents) reinforced their presence through insurance settlements and social capital, while non-elite groups were displaced, with a net decline in population (that is, segmented resilience manifested in differential 'staying in place'). In an "inner ring" around this zone, with less damage, this study found substantial population growth as people displaced from the core still sought to maintain proximity to their prior social and economic networks (that is, support for the stimulus hypothesis). Finally an "outer ring" not hit by the hurricane at all displayed no shift from prior growth patterns.

As we will show below, the pattern of change in the Gulf Coast fits well with the segmented resilience hypothesis, where whites, young adults, and people in non-poor counties responded to hurricane damage by moving away in each of the three years following a hurricane. In contrast African Americans, older people, and people in poorer counties experienced little net population change.

**Data and Methods**

We study the impact of individual hurricanes on annual population changes for the years 1970-2005. We include 476 Gulf Coast counties in the states of Alabama, Florida (Panhandle only), Georgia, Louisiana, Mississippi and Texas. In this 36 year period some areas never experienced hurricanes while others were hit multiple times at varying intervals and intensities. The key independent variables are our original county-level hurricane damage estimates. The key outcome variable is annual population change, drawing on total population and race- and age-specific population estimates for counties. . Although we think migration is the main component of these population changes, it is also possible that there is some impact through fertility and mortality. Researchers often complement census data with surveys or other case-specific data sources that can identify who moved and distinguish between in-migration and out-migration (e.g., Fussell, Hunter and Gray 2014). Population estimates only show net change. The main advantage of relying on census data is that it allows us to conduct a large scale comparative, across-time and -space analysis of effects of extreme weather events.

Counties are large, diverse, and complex enough to be treated as meaningful ecological units – residential settlements or market areas. Although an argument could be made for studying impacts at a more local scale, such as census tracts, counties are the smallest unit for which annual data are available. There is also a substantive reason to study counties rather than neighborhoods. We use findings from New Orleans to explain this point. Blacks were disproportionately displaced by Hurricane Katrina (Logan 2008) in large part because they were historically segregated within New Orleans into low-lying areas known to be vulnerable to flooding (Colten 2005). There was also a racial disparity in return migration (whites returned more quickly than blacks), but this was explained by the fact that blacks' neighborhoods had suffered greater damage (Fussell, Sastry, and VanLandingham 2010). The greater population heterogeneity of counties, because of their larger size, makes it less likely in a county-level study to confuse effects of racial makeup (or age and class composition) with effects of locational vulnerability that we would be unable to measure directly.

### *1. Measuring population change*

Population estimates made by the Census Bureau are a reliable source for annual population data. The Population Estimates Branch updates population information from the most recent census with information found in the annual administrative records of Federal agencies (tax records, Medicare records and some vital statistics) and state agencies (school enrollments, vital statistics, and information about group quarters like college dorms or prisons). These are combined to produce current population estimates and the components of population change. The Bureau estimates net migration but cannot distinguish in-migration from out-migration. We use annual estimates of the total population, the white and black populations, and the young adult and elderly populations.

We define young adults as ages 20-34 and the elderly as 65 and above. Beginning in the 1970s three racial groups were included in Census estimates: White, Black and Other. Unfortunately there was no separate annual tabulation for non-Hispanics vs. Hispanics by race until 2000. In order to maintain roughly similar categories over time, we focus on total population, white population, and black population without respect to Hispanic origin. This means that Hispanics are included in the annual population data for both whites and blacks (but mainly for whites).

There was a continuing increase in Gulf Coast population – total population was 80% higher in 2005 than in 1970. The region attracted substantial net in-migration beginning in the 1950s, reversing a trend of out-migration in previous decades (Heaton and Fuguitt 1980). A large reduction in black out-migration combined with a moderate black return in the 1970s to produce growth in the black population (Robinson 1990; Adelman et al 2000). There has also been a region-wide increase in Hispanic and Asian immigrants, reaching beyond the traditional Texas and Florida centers of Mexican and Cuban settlement (Schmid 2003). We adjust for temporal shifts that affect the whole region by including dummy variables for each year in our multivariate models.

There was also much variation across counties. The average county grew at 1.2% annually, and the top 5% of counties grew at a rate of above 5% while the bottom 5% of counties lost population at a rate of 1.75% or greater. The average growth rate also varied over time, with a trough reaching well below 0.5% in the 1980s. To deal with systematic variations across counties, we estimate time series regression models for the 1970-2005 period for annual percentage change in population using county fixed effects.[2] As a result, all variation in the dependent variable is within counties.

We also introduce data on the county's poverty rate, which is available only from the decennial census. We introduce it as an interaction term in models of impacts. The question that we investigate is whether impacts on population change (total, white, black, young adult, and elderly) vary between poorer and richer counties. We use the 1990 poverty rate to indicate the approximate poverty level in the whole period. If annual poverty data were available it would be preferable to study effects of hurricanes on change in the poor and non-poor populations. However, treating it as a contextual variable in this way yields useful findings about how hurricane effects vary according to the class composition of county residents.

***2. Estimating hurricane wind damage and storm surge***

Detailed records of what areas were damaged by hurricanes and to what extent only exist for recent hurricane events. Therefore in the first phase of this research our task was to reconstruct estimates of the land area that was affected by every hurricane, the gradient from higher to lower intensity of wind, the implied level of damage on the ground, and the extent of storm surge (for more technical details, see *citation* w*ithheld for journal review*). The available data maintained by NOAA are the hurricane track records that can be represented as a series of line segments representing the hurricane's path as it made landfall and continued inwards on land. These data also record wind speeds at regular intervals. Storm surge models also require information on land elevation and tide levels at the time that the hurricane reached the coast. Elevation data are drawn from a Digital Elevation Model (DEM) provided in the National Elevation Dataset (http://ned.usgs.gov). Tide data are based on the water high at the nearest tidal station to the hurricane track as recorded in the 18 hours prior to landfall, as recommended by NOAA.

An existing meteorological model (HURRECON, see Boose et al. 2004) was used to reconstruct the impacts of hurricanes and patterns of actual wind damage from historical records collated by time and place for all 32 hurricane-strength storms in the study area between 1970-2005. As described by Boose and his collaborators (2004), wind damage is measured on a modification of the original Fujita scale intended for hurricanes (Fujita 1971). There is now an "enhanced Fujita scale" that is recommended for studies of tornados but not for hurricanes (Womble et al 2009): we therefore depend on the original Fujita scale as modified by Boose et al. (2004).

Hurricanes exhibit some common structures in their wind fields: (1) in the northern hemisphere, wind rotates around the hurricane center in a counter clock-wise direction as the hurricane eye moves along the track; and (2) wind velocity increases from the eye outward until reaching its maximum at the hurricane eye wall and then decaying exponentially (Neumann 1987; Boose, Foster and Fluet 1994; Vickery, Skerlj, and Twisdale 2000). HURRECON models the shape and extent of the hurricane's surface wind field (sustained wind speed, peak gust speed, and wind direction) based on meteorological data (location of the eye and intensity at every six hours along the track) and surface type (land or water). It requires setting two parameters that describe how the wind velocity and direction change with the radial distance away from the hurricane eye to the eyewall and beyond. These are the Radius of Maximum Wind (RMW, or the size of the hurricane eyewall), and a wind profile exponent *b*.

The first step in estimating wind damage was to estimate RMW and *b*. For this purpose we collected newspaper damage reports from 20 hurricanes in three states with varying intensity from H1 to H5 on the Saffir/Simpson scale. We then selected values of RMW and b to maximize the fit between model estimates and reported damage. Local newspapers across Texas, Louisiana, and Mississippi were reviewed for the week of each hurricane that passed near their area of coverage and reports of damage were collected and coded for damage level on the modified Fujita scale (Boose et al. 2004; Fujita 1971). For example, it was reported in the *Daily Corinthian* (Corinth, MS) on 8/19/69 that "the destructive force of Camille was felt this far inland as this tree in City Park was the victim of high winds and heavy rain which moved to this end of the state." The damage was coded on the Fujita scale as F0 at this location; an F0 hurricane is characterized on the Fujita scale as 'minor damage' to crops and trees (e.g. leaves blown off), minor damage to buildings (e.g. antennae or chimneys blown off), and to trains and boats. On the other hand, an F1 scale of damage is described as 'trees blown down' or 'buildings unroofed' and boats sunk or destroyed. Newspaper reports were used to calibrate the wind damage measures on the Fujita scale to actual reported damage *(citation withheld for journal review).* We obtained a total of 1276 damage reports (including some reports coded as 'no damage').

Newspaper reports suffer from multiple sources of unreliability and we do not rely on them directly for our estimates. However we believe that the pattern of reports for a whole county offers a reasonable basis to select appropriate HURRECON model parameters. Damage reports from nine hurricanes were used to select the parameters that provided the best fit between reported and estimated damage. Reports from the remaining eleven hurricanes were used to verify the selected parameters (for example, the average correlation of estimated and observed damage for the verification hurricanes is 0.59). The model was then applied uniformly to all 32 hurricanes in the period 1970-2005.

Figure 1 illustrates this modeling exercise in the case of Hurricane Camille in 1969. Panel (a) shows the locations and levels (on the Fujita scale) of damage from newspaper reports. Panel (b) shows the result of interpolating these damage reports to a smooth spatial gradient and then summarizing damage to the county level (using the highest damage within the county to represent the county value). Panel (c) shows the best fitting model, and panel (d) shows the result of converting estimated damage to the county level. The result from panel (d) is used as the wind damage for the county in the following analyses.

Figure 1 about here

We compute the hurricane storm surge by using the Sea, Lake and Overland Surges from Hurricanes (SLOSH) model, which is the model used by the National Hurricane Center to predict hurricane storm surge for emergency management (Jelesnianski, Chen, and Shaffer 1992). The National Hurricane Center has published surge maps for several more recent hurricanes, but not for the majority of storms in this analysis. Fortunately the methodology for applying this model is well developed. SLOSH is a two-dimensional, finite element implementation of the equations of fluid motion in basins (these are modeling areas along the coast that have been defined by NOAA – see http://www.nhc.noaa.gov/surge/faq.php). For each hurricane, we selected the basin that would contain the modeled surge, and in some cases we combined more than one basin. For every basin NOAA has developed algorithms to link the pattern of storm surge to the intensity of winds, central pressure, forward speed, size, and angle of approach of a particular hurricane. These algorithms take into account the width and slope of the continental shelf and local features such as concavity of coastlines, bays, rivers, etc.

The variable inputs to SLOSH are the storm track in a sequence of six-hourly positions, plus the radius of maximum wind (RMW) and central pressure. Unlike our treatment of wind fields after landfall, where we wished to adjust RMW to improve fit to reported wind damage, we adopt a standard estimator of RMW for the surge analysis based on the latitude and intensity of the hurricane center as reported by NOAA (Neumann 1987).

A final consideration is the relation of water level to ground level, which depends on land elevation (DEM). We use the elevation data provided by the National Elevation Dataset (NED, http://ned.usgs.gov/) and correct for the astronomical tide based on the time of landfall. Given these inputs, the SLOSH model provides at every location in the basin the changing surge heights over the hurricane's life course, and the maximum surge height. We use the maximum surge height, plus height of tide, as the modeled storm surge. We then interpolate a raster storm surge surface by using a nearest neighbor interpolation (for details see *citation withheld*).

### *3. Spatial Temporal Models*

Our multivariate analysis of hurricane impacts covers the 32 hurricanes that occurred during 1970-2005, the period in which we have consistent annual population estimates by race/ethnicity and age. We treat hurricanes as exogenous shocks, i.e., randomly assigned across space and time. They are relatively rare events. Of the 476 counties within the study region, 395 experienced no wind damage in any year. Using county-years as the unit of analysis (n = 17,136) there was direct hurricane damage in the county itself in 5.4% of cases. A larger number of counties were adjacent to a county that experienced damage. For example, 555 county-years were far-misses as defined below, where there was F0 damage in second-order neighbor counties but not in adjacent counties, while 310 county-years directly experienced F1+ damage.

We use county fixed-effects to control for any time-invariant county characteristics that could be associated with population change or hurricane damage, such as nearness to the coast. In addition we include dummy variables to represent individual years. This removes any region-wide fluctuations in population, including both long-term trends and short-term cyclical disturbances that affected the entire region. An extended version of each model includes interactions between the damage categories and county poverty rate in 1990. Because poverty is a constant for each county, we do not include a direct effect of poverty.

The impact of hurricanes on population and migration is an inherently spatial phenomenon. There are two main reasons why a phenomenon occurring at one point in space would impact another point. The first is measurement imprecision – since many of the boundaries of the units used in regional analysis (such as counties) are arbitrarily defined, the chosen unit may not perfectly capture the scale at which the phenomena under study occurs (Fussell, Hunter and Gray 2014). The second reason is substantive – there may be effects of spatial interaction, such as diffusion, spill-over, interdependence, or other spatial externalities. Many of the hypotheses and theories in the literature on the demographic implications of environmental events have spatial implications. For instance, migration and displacement processes move people across regions, e.g. neighboring non-hit areas may gain displaced population from regions that experience direct damage. In addition, disaster effects may not be neatly contained within county borders and damage in one county may spill over into neighboring counties through the movement of population, sharing of resources (or the loss of shared resources), and the continuous-surface nature of hurricane damage. We experimented with several ways to incorporate spatial effects, and we present here the simplest version: hurricane damage in an adjacent county or a county in a second-order neighbor (i.e., adjacent to an adjacent county) is captured through a series of dummy variables that measure wind damage in the given county and in its neighbors. We use five categories, in increasing order of damage severity, the first of which is treated as the reference category:

0. <u>No damage</u> in focal county, no damage in neighboring counties in a given year. This is the reference category in the multivariate models. This category would apply to all counties in the years where no hurricanes occurred.

1. Far Miss: No damage in focal county, F0+ damage in second order neighbors (but not in adjacent counties).

2. Near Miss: No damage in focal county, but immediate or first-order neighbors experienced an F0+ hurricane in the same year.

3. F0 damage in focal county: This damage category reflects counties that experienced F0 damage from hurricanes in a particular year.

4. F1+ damage in focal county: This damage category represents counties that experienced at least one F1+ hurricane in a particular year.

Exploratory analyses showed that the most consistent results are based on F0 or F1 (or higher) levels of damage. As noted above, at F0 trees are damaged, there is minor damage to buildings and roofs, and utility wires are downed. At F1 trees are blown down or uprooted, buildings lose their roofs, chimneys are downed, masonry walls are blown down, and moving autos are pushed off the road. We initially considered models where F2-F4 damage was included as a separate category, but these did not improve model fit.

The measure of storm surge is based on a simple dichotomy, whether or not there was any flooding, and is a count of the number of times the county experienced flooding in a given year (a relatively rare occurrence). This measure is entered with a one year lag. We also experimented with a more stringent measure of storm surge – the fraction of county land area flooded at least one foot. This measure identified very rare events and was more likely to occur in areas with high wind damage making the wind damage and storm surge variables redundant. We found no significant effects for storm surge as lagged more than one time period, or as interacted with poverty status and we do not present those model variations here.

The effect of adverse environmental events on population change and migration is likely to have important temporal features. Migration is a temporal process, often conceptualized as long-term, short-term, permanent, etc. (Fussell, Curtiss and Ward 2014). The effects of environmental events can likewise be fairly instantaneous, delayed, lingering, marked by reversals or cumulation. Some population groups might evacuate immediately only to return within a short time. Other groups or neighborhoods might not evacuate immediately but instead face population loss over time as cities or regions fail to bounce back. To account for these temporal effects, we incorporate multiple time lags by modeling population change between time *t* and *t+1* as a function of wind damage in the previous year (*t*), the year before (*t-1*), and the year before that (*t-2*):

$$\textit{Population change}_{i,t} = f\,(\textit{Damage}_{i,t-1}, \textit{Damage}_{i,t-2}, \textit{Damage}_{i,t-3}, \textit{Year dummies and interactions})$$

where *i* refers to counties, *t* refers to time periods, and *Damage* includes wind damage in all three years and storm surge in the first year.

**Impacts of Hurricanes on Population Change**

The multivariate analyses of hurricane impacts are summarized in Tables 1-3. As stated above, these are fixed-effects models, which have the advantage that all time-invariant characteristics of counties are controlled. Region-wide fluctuations over time are also controlled through a series of dummy variables for the year (not shown in the tables). There are no other predictors that need to be controlled in order to estimate the independent effect of hurricane damage, which we interpret here as a random exogenous shock. Table 1 reports models for total population change, Table 2 for black and white population change, and Table 3 for young adults and older adults. We present two models for each population group; Model 1 includes direct effects of wind damage at three time lags and storm surge in the prior year. Model 2 adds interactions of wind damage with poverty.

Table 1 reports models for annual population change (measured as a percentage change from the prior year). Model 1 shows significant and negative direct effects of wind damage for all three time lags and also a negative effect of flooding on population growth. The strongest effects, as could be expected, are for F1+ wind damage. The consistently negative effects counter both the stimulus hypothesis and the resilience hypothesis (or immobility paradox assumption). These effects are additive, so from the direct effects alone over a three year period F1+ hurricane damage and storm surge would reduce population growth by about 1% compared to its expected trajectory (=-.123-.189-.464-.290). The negative effects of a ‘near miss’ show that there are significant spatial effects in the first two years. A positive coefficient would have indicated growth, presumably due to displacement of population from neighboring counties. Instead the negative effects suggest spill-over of hurricane impacts from neighboring counties.

Table 1 about here

The inclusion of interaction effects does not change the explained variance but it adds considerably to our understanding of where population effects can be found. Let us focus on the interactions of poverty with F1+ damage. These coefficients are positive and significant at all three time lags. This means that in counties with very low poverty the negative effects of hurricanes on population change predominate. However in counties with high poverty, the negative direct effect is counterbalanced by the positive interaction term of poverty with hurricane wind damage. To illustrate this pattern we choose two poverty cut-offs – counties at the 10$^{th}$ percentile in poverty (13% poor) in 1990, and counties at the 90$^{th}$ percentile (36% poor). An F1+ hurricane in the previous year is associated with a 0.55% total population decline in a low poverty county (=-1.04+[13*0.038]) compared to a 0.33 population *increase* in a high poverty county (=-1.04+[36*0.038]). All these calculations are in comparison to the case if there were no hurricane wind damage in a focal county or its first or second order neighbors. Again these effects are additive, so we can calculate the three-year net effects of F1+ wind damage and flooding. There would be population loss of about 2.3% in a low-poverty county vs. a nearly 0.5% gain in a high-poverty county.

We now repeat this analysis separately for white and black population change. To estimate the model for black population we omitted counties with fewer than 200 black residents in the previous year, because we found that the values of percentage change when calculated against a very small population base fluctuated erratically. Table 2 reports that the adjusted $R^2$ for the white model is much higher (.48) than for the black model (.22). On average, the population impacts of hurricane wind damage on black population change are weaker than for white population change. Based on the Model 1 coefficients, a combination of F1+ damage and flooding would have a cumulative impact over three years of reducing black population growth by about 0.6%. White population would decline about 1.1%, almost twice as much.  Nevertheless wind damage has significant negative effects for both black and white populations, although flooding has a significant effect only for white population.

Table 2 about here

Model 2 shows some significant interactions with poverty for both blacks and whites.  In the first year these appear larger for black population but the effects are more consistent over different time lags for whites (especially for F1+ damage).  Both blacks and whites appear to be more likely to remain in place after hurricanes in poorer counties but to leave more affluent counties.   Calculating cumulative effects of F1+ damage and flooding over three years for black population, the impact for black population would be loss of 2.5% in low poverty counties but gain of 2.3% in high poverty counties.  For white population the swing across poverty levels is smaller: population loss of 2.3% in low poverty counties but a minimal gain of 0.4% in high poverty counties.  These results suggest that blacks are as likely as whites to leave impacted low poverty areas.

The final step is to estimate these models separately for the young adult and older populations. Table 3 shows some stark differences in Model 1.  For the young adult population there are negative effects, but there are significant coefficients only in the third year for older persons.  In addition the size of effects is greater for young persons in the third year for both F0 and F1+ damage and for flooding.  A general implication is that the elderly are much less likely than young adults to migrate away from higher risk locations, and it takes them longer to do so.  This finding is consistent with the notion that older people are more rooted in place and have more difficulty arranging a move.  The differences are large: the cumulative impact over three years of F1+ damage plus flooding is a predicted 1.7% decline in young adult population, but only a 0.5% decline for older persons.

Table 3 about here

There are also differences between younger and older adults in Model 2 that includes interaction terms between poverty and hurricane damage.  In this model the negative direct effects of wind damage for young adults are much larger than in Model 1, and there are significant interactions with poverty with a one-year and three-year lag.  The estimates for older population change show a larger negative direct effect of F1+ damage in year three than did Model 1, but no interaction effects in years two and three. Again a calculation of cumulative effects is revealing. For young adults in a county with F1+damage and flooding the prediction is a loss of 3.4% in a low poverty county but a slight gain of 0.3% in a high poverty county. For older persons the loss in a low poverty county is predicted to be only 0.7%, or a loss of 0.2% in a high poverty county. These results suggest 1) not only are older persons less responsive to hurricane damage, but 2) their response is not so much affected by the poverty status of their local environment as is true for young adults.

**Conclusion**

An important contribution of this research is a more precise measurement of hurricane damage in a spatial and temporal context. This study draws on a data set on wind damage and storm surge that allows researchers to reconstruct the spatial extent of wind damage from hurricanes that occurred decades ago, at a time when few contemporaneous reports were systematically collected. Detailed mapping of damage is important because hurricanes, like many other environmental hazards, have a strong spatial pattern. If one knows that an extremely intense storm like Hurricane Camille (1969) hit the Mississippi coast, that does not mean that all of Mississippi, or only Mississippi, was hard hit. F4 wind speeds were only found prior to landfall, according to our model, and F3 only in counties adjacent to the coast. It is necessary to estimate at what point the wind field dropped to lower and lower intensities as the storm moved beyond the coast. The damage mapping accomplished here made possible all of our analyses, and it will be available for other future studies and other research designs.

The substantive question addressed here is how hurricanes affected population change during 1970-2005 in the U.S. Gulf Coast. We have interpreted the results in terms of individual-level migration choices in response to disasters. There are indications that some groups tend to move away from high risk zones while others are less likely to do so. We caution that our analyses do not directly tap migration choices. Our data allow us to study aggregate changes. But if there is an overall population loss, or a loss in a particular population category following a hurricane, we cannot tell if it was due to migration out of the place, reduced movement into it, or some combination of the twoWe can draw logical inferences about why one group may react differently than another (e.g., we presume that whites have more resources than blacks, which is certainly true in terms of income, education, wealth, and other measurable factors). Yet we have no information about individuals' perceptions or calculations. In order to study individual-level components of disaster-influenced migration, a superior research design would follow individuals over time, identify when they are exposed to hurricane risk, track their subsequent movement, and interview them about how they made decisions to stay or move. However, such research would miss the long-term and aggregate impacts of hurricanes on population change and cannot fully exploit the spatial and temporal variations in storm damage in the way that is done here.

With this caveat, the present study makes several contributions to our knowledge about vulnerability and resilience of communities in the face of hurricanes. First with respect to risk, we add to the observation by (*citation omitted*) that in the early postwar years – starting in 1950 – the groups most exposed to hurricane risk were those with social advantages: the young, white, and more affluent. But over time a different lineup emerged, as these categories of residents steadily shifted their location to safer areas while until very recently the less advantaged (older, black, poor) moved increasingly into harm's way. Our findings on the impacts of individual hurricanes are consistent with the interpretation that the change resulted from the accumulation over time of local responses to hurricane damage. On average hurricanes resulted in disproportionate population losses for whites and young adults, while blacks and older persons were less responsive to these events.

Second, our findings about hurricane impacts contradict some reasonable hypotheses found in the disaster literature. The resilience hypothesis of a quick return to normalcy is undermined by our finding that there are negative effects extending as long as three years after a hurricane event, and that these negative effects are experienced even by counties that are not directly affected by wind damage. It is possible that over a longer time period there is a return to the previous equilibrium, but this study offers no evidence for that conjecture. Areas repeatedly hit by hurricanes could be expected to continue a downward trajectory. The stimulus hypothesis is also undermined, at least in the short run, as it predicted that capital flows from insurance and federal/state assistance actually promote economic activity, which might lead to a population influx.

Third, there is consistent support for a segmented resilience hypothesis, which posits that different population groups are affected differently by disaster risk.  But the segmentation is in the opposite direction of what most researchers have anticipated – “resilience” (if that is the right term for it) is manifested not in a quick return to one’s original location, but in a faster exit to a safer place.  In this vein we find evidence that the white population is more immediately depressed by a hurricane than is black population, and young adults more than seniors.  We also find that more affluent counties are the ones where the negative effects of a hurricane are stronger, while populations in poorer counties (white or black, young or old) are less affected.  And with respect to spatial effects, we find some evidence that far and near misses (that is, the experience of hurricanes in nearby areas) have negative effects, and not the positive ones that one might expect if there was population displacement from those nearby places.

These findings raise new questions for future research.  Do the population changes caused by hurricanes result from higher out-migration or reduced in-migration?  Why are older persons and African Americans relatively immobile?  Would they prefer to move but find it hard to do so, or do they perceive risks differently than young adults and whites?  Are the potential benefits of leaving smaller for them because of their different position in the labor or housing market or reliance on local social networks?  Due to the limits of census data, we measured poverty as a contextual variable – a characteristic of a county.  How might our results appear differently if we could have measured population shifts separately for affluent and poor households?  And more generally, would one reach different conclusions when treating resilience as an attribute of persons and households (people who leave or stay) versus resilient places and communities?   In this study the findings by race and age (at the individual level) fit neatly with the effects of county-level poverty – disadvantages at both levels were consistent with thinking of mobility as form of resilience.  More complete findings could be drawn from multi-level research with parallel measures for both individuals and communities.

## Footnotes

1. In a recent fifteen year period (1998-2012) there were 149 major disaster declarations due to hurricanes and tropical storms in the United States, mostly on the Gulf Coast and South Atlantic states (http://www.fema.gov/disasters/grid/year?field_disaster_type_term_tid_1=6840&=GO).

2. Models were run in STATA using procedure areg (cluster *county*).

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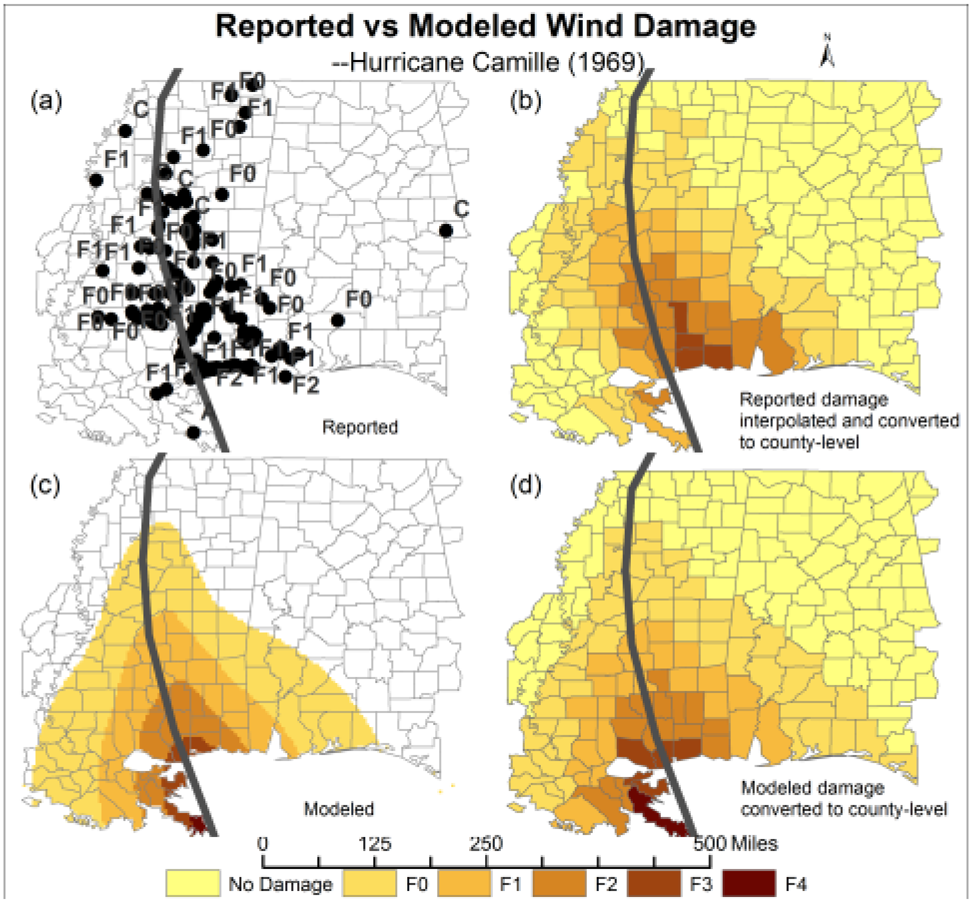


Figure 1. Comparison of reported damage (a) and damage estimated from the best fitting model (c) for Camille (1969), showing interpolation (b) and conversion to the county level (d).

**Table 1. Estimated effects of hurricane damage with time lags (fixed effects for counties; standard errors in parentheses)**

| | Model 1 | Model 2 |
|---|---|---|
| **Previous year (ref = no damage)** | | |
| **Far miss** | -0.123 (0.072) | -0.559 (0.236)* |
| **Near miss** | -0.175 (0.074)* | -0.601 (0.243)* |
| **F0 damage** | -0.105 (0.08) | -0.541 (0.319) |
| **F1 + damage** | -0.123 (0.096) | -1.04 (0.254)*** |
| **Year t-2 (ref = no damage)** | | |
| **Far miss** | -0.002 (0.075) | -0.181 (0.254) |
| **Near miss** | -0.223 (0.107)* | -0.562 (0.338) |
| **F0 damage** | -0.394 (0.123)** | -0.672 (0.377) |
| **F1 + damage** | -0.189 (0.093)* | -0.862 (0.288)** |
| **Year t-3 (ref = no damage)** | | |
| **Far miss** | 0.022 (0.083) | -0.427 (0.249) |
| **Near miss** | -0.081 (0.084) | 0.203 (0.326) |
| **F0 damage** | -0.261 (0.128)* | -0.252 (0.585) |
| **F1 + damage** | -0.464 (0.1)*** | -1.729 (0.295)*** |
| **Flooded (binary, t-1)** | -0.290 (0.089)** | -0.241 (0.091)** |
| **Interactions with poverty** | | |
| **Previous year (ref = no damage)** | | |
| **Far miss** | | 0.017 (0.009)* |
| **Near miss** | | 0.017 (0.009)* |
| **F0 damage** | | 0.017 (0.012) |
| **F1 + damage** | | 0.038 (0.009)*** |
| **Year t-2 (ref = no damage)** | | |
| **Far miss** | | 0.007 (0.01) |
| **Near miss** | | 0.014 (0.011) |
| **F0 damage** | | 0.011 (0.016) |
| **F1 + damage** | | 0.029 (0.012)* |
| **Year t-3 (ref = no damage)** | | |
| **Far miss** | | 0.018 (0.009) |
| **Near miss** | | -0.012 (0.013) |
| **F0 damage** | | 0 (0.021) |
| **F1 + damage** | | 0.054 (0.011)*** |
| **Constant** | 0.734 (0.060)*** | 0.733 (0.059)*** |
| **$R^2$** | 0.45 | 0.45 |
| **N** | 15,708 | 15,708 |

*** p < .05, ** p < .01, ***p<.001**

**Table 2. Estimated effects of hurricane damage with time lags**
**(fixed effects for counties; standard errors in parentheses)**

| | Black population change | | White population change | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 1 | Model 2 |
| **Previous year (ref = no damage)** | | | | |
| **Far miss** | -0.104 (0.173) | -0.318 (0.387) | -0.132 (0.074) | -0.566 (0.249)* |
| **Near miss** | -0.324 (0.169) | -1.466 (0.525)** | -0.149 (0.076) | -0.498 (0.267) |
| **F0 damage** | 0.051 (0.17) | -1.078 (0.575) | -0.133 (0.082) | -0.47 (0.306) |
| **F1 + damage** | 0.173 (0.225) | -2.275 (0.891)* | -0.155 (0.095) | -0.993 (0.26)*** |
| **Year t-2 (ref = no damage)** | | | | |
| **Far miss** | 0.054 (0.115) | 0.328 (0.487) | 0.027 (0.076) | -0.222 (0.272) |
| **Near miss** | -0.341 (0.153)* | -1.457 (0.606)* | -0.205 (0.106) | -0.416 (0.347) |
| **F0 damage** | -0.459 (0.17)** | -1.059 (0.545) | -0.377 (0.118)** | -0.646 (0.379) |
| **F1 + damage** | -0.012 (0.205) | -0.968 (0.819) | -0.21 (0.087)* | -0.919 (0.266)** |
| **Year t-3 (ref = no damage)** | | | | |
| **Far miss** | -0.103 (0.112) | -0.287 (0.436) | 0.059 (0.085) | -0.554 (0.261)* |
| **Near miss** | -0.272 (0.126)* | -0.569 (0.573) | -0.096 (0.085) | 0.303 (0.336) |
| **F0 damage** | -0.301 (0.181) | -0.839 (1.114) | -0.277 (0.121)* | -0.273 (0.52) |
| **F1 + damage** | -0.458 (0.15)** | -1.826 (0.622)** | -0.499 (0.102)*** | -1.655 (0.307)*** |
| **Flooded (binary, t-1)** | -0.27 (0.167) | -0.144 (0.181) | -0.273 (0.093)** | -0.232 (0.095)* |
| **Interactions with poverty** | | | | |
| **Previous year (ref = no damage)** | | | | |
| **Far miss** | | 0.009 (0.015) | | 0.017 (0.009) |
| **Near miss** | | 0.047 (0.02)* | | 0.014 (0.01) |
| **F0 damage** | | 0.046 (0.023)* | | 0.013 (0.011) |
| **F1 + damage** | | 0.106 (0.042)* | | 0.035 (0.01)*** |
| **Year t-2 (ref = no damage)** | | | | |
| **Far miss** | | -0.01 (0.019) | | 0.01 (0.011) |
| **Near miss** | | 0.046 (0.022)* | | 0.009 (0.011) |
| **F0 damage** | | 0.025 (0.024) | | 0.011 (0.015) |
| **F1 + damage** | | 0.042 (0.038) | | 0.031 (0.011)** |
| **Year t-3 (ref = no damage)** | | | | |
| **Far miss** | | 0.008 (0.017) | | 0.024 (0.01)* |
| **Near miss** | | 0.013 (0.022) | | -0.016 (0.013) |
| **F0 damage** | | 0.023 (0.045) | | 0 (0.019) |
| **F1 + damage** | | 0.061 (0.029)* | | 0.05 (0.011)*** |
| **Constant** | 1.049 (0.177)*** | 1.039 (0.176)*** | 0.61 (0.062)*** | 0.61 (0.061)*** |
| **$R^2$** | 0.22 | 0.22 | 0.48 | 0.48 |
| **N** | 14,184 | 14,184 | 15,708 | 15,708 |

*** p < .05, ** p < .01, ***p<.001**

**Table 3. Estimated effects of hurricane damage with time lags**
**(fixed effects for counties; standard errors in parentheses)**

| | Young adult change | | Elder population change | |
|---|---|---|---|---|
| | **Model 1** | **Model 2** | **Model 1** | **Model 2** |
| **Previous year (ref = no damage)** | | | | |
| **Far miss** | -0.106 (0.113) | -1.177 (0.349)** | -0.089 (0.066) | -0.174 (0.211) |
| **Near miss** | -0.247 (0.102)* | -0.662 (0.335)* | 0.039 (0.067) | -0.458 (0.24) |
| **F0 damage** | -0.084 (0.115) | -0.535 (0.417) | 0.037 (0.07) | -0.486 (0.233)* |
| **F1 + damage** | -0.332 (0.141)* | -1.56 (0.44)*** | 0.045 (0.103) | -0.374 (0.266) |
| **Year t-2 (ref = no damage)** | | | | |
| **Far miss** | -0.056 (0.102) | -0.319 (0.335) | 0.05 (0.07) | 0.068 (0.239) |
| **Near miss** | -0.39 (0.15)** | -0.653 (0.491) | -0.022 (0.064) | -0.315 (0.212) |
| **F0 damage** | -0.522 (0.173)** | -0.396 (0.474) | -0.036 (0.088) | -0.441 (0.28) |
| **F1 + damage** | -0.392 (0.139)** | -1.123 (0.472)* | -0.008 (0.082) | 0.103 (0.265) |
| **Year t-3 (ref = no damage)** | | | | |
| **Far miss** | 0.093 (0.136) | -0.343 (0.387) | -0.027 (0.062) | -0.325 (0.192) |
| **Near miss** | -0.068 (0.136) | 0.788 (0.484) | -0.04 (0.061) | -0.224 (0.217) |
| **F0 damage** | -0.301 (0.142)* | -0.678 (0.443) | -0.184 (0.086)* | -0.263 (0.365) |
| **F1 + damage** | -0.561 (0.136)*** | -2.387 (0.404)*** | -0.268 (0.085)** | -0.56 (0.242)* |
| **Flooded (binary) (t)** | -0.464 (0.118)*** | -0.403 (0.12)** | -0.226 (0.097)* | -0.185 (0.099) |
| **Interactions with poverty** | | | | |
| **Previous year (ref = no damage)** | | | | |
| **Far miss** | | 0.042 (0.014)** | | 0.004 (0.008) |
| **Near miss** | | 0.016 (0.012) | | 0.02 (0.009)* |
| **F0 damage** | | 0.018 (0.015) | | 0.021 (0.009)* |
| **F1 + damage** | | 0.051 (0.016)** | | 0.017 (0.01) |
| **Year t-2 (ref = no damage)** | | | | |
| **Far miss** | | 0.01 (0.014) | | -0.001 (0.009) |
| **Near miss** | | 0.011 (0.016) | | 0.012 (0.008) |
| **F0 damage** | | -0.006 (0.02) | | 0.017 (0.011) |
| **F1 + damage** | | 0.031 (0.019) | | -0.005 (0.011) |
| **Year t-3 (ref = no damage)** | | | | |
| **Far miss** | | 0.017 (0.014) | | 0.012 (0.007) |
| **Near miss** | | -0.035 (0.018) | | 0.008 (0.008) |
| **F0 damage** | | 0.015 (0.019) | | 0.003 (0.013) |
| **F1 + damage** | | 0.079 (0.015)*** | | 0.012 (0.009) |
| **Constant** | 0.273 (0.11)* | 0.276 (0.11)* | 1.888 (0.07)*** | 1.883 (0.07)*** |
| **$R^2$** | 0.46 | 0.46 | 0.55 | 0.55 |
| **N** | 15,708 | 15,708 | 15,708 | 15,708 |

*** p < .05, ** p < .01, ***p<.001**