Adjusting to Natural Disasters

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Abstract

People can answer the risks presented by natural disasters in a number of ways; they can move out of harms way, they can self protect, or they can insure. This paper uses the largest U.S. natural disaster on record, Hurricane Andrew, to evaluate how people and housing markets respond to a large disaster. Our analysis combines a unique *ex post* database on the storm's damage along with information from the 1990 and 2000 Censuses as well as information on housing sales in Dade County, Florida where the storm hit. The results suggest that the economic capacity of households to adjust explains most of the differences in demographic groups' patterns of adjustment to the hurricane damage. Low income households respond primarily by moving into low-rent housing in areas that experienced heavy damage. Middle income households move away to avoid risk, and the wealthy, for whom insurance and self-protection is most affordable, remain. This pattern of adjustment is roughly mean neutral, so an analysis based on summary measures would miss these important adjustments. Our analysis of the housing sales record indicates that the new risk information provided by the event reduced the rate of appreciation in prices by about fifty percent for the zones with the highest FEMA flood risk ratings. This finding is corroborated at the qualitative level by the Census data.

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I. Introduction

Natural disasters force adjustment. The Indian Ocean tsunami, severe storms in the western U.S. and hurricanes in Florida made 2004 a year for renewing our collective awareness of this fact. This paper uses Hurricane Andrew, the largest U.S. natural disaster on record, to investigate two questions.[1] We first consider how people adjust. People can answer the risks presented by natural disasters in a number of ways: they can move out of harms way; they can self-protect, building structures less vulnerable to damage; or they can insure. This paper provides a snapshot of the socio-economic forces that reshaped Dade County, Florida after Andrew made landfall and destroyed a large portion of the private housing and commenrcial facilities. The second part of the analysis looks at the net effect of these adjustments on the value of homes in areas that were perceived to be subject to increased risk after this natural disaster. Both aspects of the analysis bear directly on our ability to design policies that facilitate people's ability to return to their everyday activities after disasters.

We take advantage of a unique *ex post* evaluation of Andrew's damage conducted by the National Oceanic and Atmospheric Administration (NOAA) and published in the

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[1] Robert Hartwig, Senior Vice President and Chief Economist of the Insurance Information Institute, used this characterization in describing the impact of hurricanes on economic activity in hurricane prone counties. He observed that:

> "Hurricane Andrew, until September 11, 2001, was the global insurance industry's event of record. For nearly a decade it was the disaster against which all other disasters worldwide were compared….Andrew struck Florida in August 1992 with 140 mile-per-hour winds and produced insured losses of $15.5 billion – about $20 billion in current (2001) dollars. …Although Andrew has now been eclipsed as the largest insurance event in world history (by September 11)…It remains the largest natural disaster on record in terms of insured losses, not only in the United States but world-wide…" (Hartwig [2002] pp.1-2, parenthetical phrase added).

Miami Herald on December 20, 1992 (referred to later as the NOAA/Miami Herald data). This summary includes information on 420 subdivisions or condominium developments in the area affected by Andrew. To evaluate how people adjusted after the storm, we use the 1990 and 2000 Censuses to compare the demographic and economic attributes of the populations in Dade County at the block group level before and after the storm. When matched with the NOAA/Miami Herald data on the damages and the FEMA flood maps that identify areas subject to differentiated risks of coastal flooding, these records produce a picture of the spatial adjustments that took place.

Our findings confirm some prior beliefs about this hurricane and overturn others. In contrast to the popular views of the storm's impact, white, middle-income households were more likely to experience significant damage than poor minority households. Financial capacity, as reflected by home ownership and education, are key factors in who adjusted to the damage. In the eight years after Andrew the population in areas with 50 percent or more of the homes damaged so seriously as to be rated uninhabitable grew faster than areas with less damage. White and black homeowners and white renters moved away from damaged areas. Hispanic households, both owners and renters, moved into the areas with hurricane damage. Lower income households tended to move into damaged areas while middle income moved out. In general, the storm's damage did not affect higher income households. In 2000, households with annual incomes over 150,000 were the only group likely to be attracted to areas with a comparable "type" of household – i.e. to areas where the same income level households lived in 1990.

More broadly, the analysis also highlights the potential importance of household heterogeneity on the meaurement of spatially-delineated environmental impacts; the changes to the income distribution that we find are roughly mean neutral, so a comparable study based on summary measures would miss much of the story.[2]

The second half of the analysis – the evaluation the economic consequences of these adjustments – makes use of two different strategies. The first evaluates the changes in the distributions of rents and homeowners' beliefs about their homes' values between the 1990 and 2000 Censuses in response to average damage and the fraction of a block group in a FEMA risk zone. The second matches the damage information to a repeat sales hedonic property value data set for residential properties in Dade County. Both analyses confirm that these types of adjustments have implications for markets. The repeat sales findings indicate that, after controlling for damage, the information conveyed by Andrew caused the prices of homes in high risk areas to appreciate more slowly than their counterparts throughout Dade County. Our estimates imply a fifty to sixty percent reduction in the average increase in home prices for homes located in areas perceived to be higher risk as a result of the storm. The change in the Census median measures over the decade also suggests slower appreciation. However, the estimate is smaller.

Section two describes the unique configuration of spatially delineated data required to undertake the analysis. The third section develops the hypotheses motivating our expectation for differences in households' adjustments. Our results are developed in Section four in two parts. First we describe the changing features of neighborhoods based on the 1990 and 2000 Censuses for the county. After that we summarize the highlights of the repeat sales analysis of residential home sales in Dade

[2]Recently, quasi-experiments (such as the one performed here) have raised questions about the the viability of earlier hedonic studies on the value of air quality improvements and superfund clean up (see Chay and Greenstone [forthcoming] and Greenstone and Gallagher [2004]). The current paper bears on this discussion as well. To the extent that changes in these other environmental amenities result in large distributional changes like those found here, quasi-experiments based on summary data may be biased.

County. This model uses the spatial location and timing of the most recent and the immediately preceding sales of homes in areas with varying flood risks to identify the market responses to Andrew's damage and any risk information homebuyers associate with the hurricane. At the micro level, adjustment in home prices for locations with higher fractions of damaged properties likely reflects the *net* impact of repairs and market perceptions of the construction quality of homes. Our comparison of the results from a repeat sales analysis using actual transactions with the same logic applied to changes in the median home values from the 1990 and 2000 Censuses finds that both strategies would conclude that Andrew caused homebuyers to revise their assessment of the risks from buying homes in FEMA's Special Flood Hazard Zones.

II. Data

In December 1992 the Miami Herald published a special report analyzing the factors responsible for areas with significant damage that were far from the storm's strongest winds. As part of the report, the newspaper included the full documentation for the NOAA damage assessment by subdivision. Using the map included with the Miami Herald's feature article it was possible to align the roadways in the Miami Herald map with an Arcview map of the primary roads within the county. A set of 306 grids was defined to match the subdivision records to our two other databases. The first task linked the grids to Census block groups. Each block group was assigned the average (area weighted if a subdivision crossed Census boundaries) damage measure for the subdivision falling within its boundary. The second used the latitude and longitude of each home in the repeat sales data to identify its grid and assign an average damage estimate.

These damage estimates serve two roles. For our analysis of the composition of the block groups they are proxies for the extent to which neighborhoods offer opportunities for nearly complete replacement of residential structures. When one hundred percent of the homes in a neighborhood are judged to be uninhabitable, then we expect that there is the opportunity to transform completely the composition of the area. The impact of smaller amounts of damage on changes in the composition of a block group depends on the relative importance of quality filtering versus the externalities effects attributed to different demographic and economic groups.

When the damage measure is used with our repeat sales model that is based on individual home sales, the interpretation of the variable is somewhat different. In this case, two effects are being represented simultaneously. The first is as a control for the likelihood of damage to that structure as a result of the hurricane and with it the prospects that the house may have been altered as part of the repair. The damage measure serves as a proxy variable because our micro level housing data only include information on the home attributes as of the most recent sale. As a result, it is not possible to control for alterations due to the repairs of any storm damage. This effect could be especially important for sales that bracket the storm. The second influence stems from the overall pattern of Andrew's damage. It was not perceived to be consistently associated with wind damage.[5] An important motivation for the special report published in the Miami Herald was explaining the heterogeneity in storm impacts by subdivision. Thus, at the micro level, these measures may also be reflecting changes in perceived structural integrity of the homes within a subdivision as a result of the reports of storm damage.[6] Our estimates of the effects of the storm on price changes describe the net effect of these two influences.

Between the 1990 and 2000 Censuses, the definition of block groups for the county changed, expanding from 1048 in 1990 to 1222 in 2000. This change reflects the increase in population in the county and the need to re-align Census summaries to match the new population distribution. The expansion in the number of block groups is a response to population growth. Thus, how it is treated could be important to the way any of the demographic changes are measured. To avoid mixing the potential for endogeneity in the neighborhood definition with the event being studied (i.e. Andrew's damage) we focus on the 1990 definition of block groups.

Our analysis considers two different samples. First, we construct area weighted averages of Census statistics from the 2000 block groups so that each record can be matched to its 1990 counterpart. As a cross check to these results, we repeat the analysis

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[5] We obtained the original Wakimoto and Black [1994] maps describing the wind patterns for Andrew with the assistance of Roger Wakimoto. A cross tabular analysis of the Miami Herald damage survey data with an approximate wind based delineator of the damage suggests higher wind areas were more likely to experience damage. Nonetheless, the Miami Herald story "Less Winds, Lots of Damage," December 20, 1992, documents a large number of exceptions.

[6] We do not have access at the micro level to the repair history of properties, building permits, or other information that would allow distinguishing individual properties that were damaged. Thus these average measures are assumed to serve as a proxy for damage. At the same time they also signal that a subdivision may be of lower construction quality. The Miami Herald feature clearly documents problems in the county's building inspections, noting that "Unsupervised and understaffed, with civil service rules that give them job protection, Dade's building inspectors were no match for the development of the 1980s." Lisa Getter, "Inspections: A Breakdown in the System," Miami Herald, December 20, 1992.

using the sample of block groups that did not change between the two Censues. Table 1 reports an overall summary of the demographic and economic patterns in 1990 and 2000 using the full sample of area weighted estimates based on the 1990 block groups. The average proportion of each demographic and economic category across block groups is reported for three samples. The last two columns labeled “overall” provide these average proportions for all the block groups between 1990 and 2000. The first two sets of columns decompose this set into block groups experiencing 50% or greater of their homes as uninhabitable based on the NOAA-Miami Herald survey. The number of block groups in this category is 27. The second group includes those with less than 50% uninhabitable. The number of observations in this category ranges from 968 to 997 depending on the variable selected.

This decomposition suggests the hurricane’s damage was *not* disproportionately experienced by minority or poor households. In 1990 block groups with 50% or over damage were largely white (both owner and rental households) in the income range from 25,000 to 60,000. When we consider the proportions in 2000, white households moved out (both owners and renters). Hispanic households moved in. The changes in the relative number of Hispanic households in damaged areas partially reflects the overall growth in their share in the county. However this is not the full story. If we consider the white, African American, and hispanic households who report they migrated into the county in the last five years from elsewhere, then we would find white households are the largest share of these new residents -- 46.4 percent of the toal for these three groups. Hispanic households account for next largest share at 41.5 percent.

Middle income households moved out and the lower (15,000-25,000) and high income groups moved in. Of course, these summaries are simple averages and do not take account of initial conditions in each area. In addition, they would change somewhat if we modify the threshold used to isolate the high damage block groups. This separation at 50% leads to a relatively small sample of block groups that underlies the means used to characterize who is adjusting to extensive damage. In section four we use regression models to evaluate how the difference in damage at block groups affect changes in their composition.

The second component of our analysis uses a repeat sales database for residential properties in the county. Our housing data include records for all sales of residential properties in Dade County, Florida from 1983 to 2000. They were purchased from a commercial vendor (First American Real Estate Solutions) and provide the characteristics of the properties at the time of the most recent sale, the date of each sale (year, month, and day), the sales price, the latitude and longitude coordinates, and a variety of variables describing the homes. Our focus is on a subset of the sales – properties that sold at least twice – and we consider the two most recent sales. These sales data were cleaned to remove several types of transactions, including: properties that sold for less than $100; properties that were bought and sold within a period of several months and had a price difference exceeding $500,000; and properties where the first sale was for land only and the second sale included land and a structure. We limited the sample to properties built after 1982 because of changes in federal legislation grandfathering subsidized insurance for older properties and other state level insurance changes that may have special implications for homes built before this date.

Each record in our sample was merged with the Federal Emergency Management Agency's G3 flood map for the county. Information about the Special Flood Hazard Area (SFHA) is in the public domain. The Coastal Barrier Act of 1982 required lenders to notify homebuyers about a property's flood risk due to location in an SFHA. The geo-coded sales were also merged with a spatially delineated map of the path of Hurricane Andrew as well as the grid cells for the NOAA-Miami Herald data.

Three areas with differing flood hazard risks can be distinguished from the FEMA maps for Dade County – AE, AH, and X500 designations. AE corresponds to the highest risk category. Homes built after 1974 in these locations have the highest rates for flood insurance.[7] The rates in AE zones range from \$0.16 to \$0.39 per \$100 of coverage depending on base floor elevation (BFE). The AH areas are somewhat lower risk, generally corresponding to higher elevations of about – one to three BFE. X500 are usually described as areas with negligible risk.

The primary sources of damage in a hurricane are often wind and storm surge. These impacts need not correspond to the areas designated by the SFHA as most hazardous. In the case of Andrew, damage was also not readily predicted by sustained wind and gusts. Andrew's wind speeds were estimated to be above 133 miles per hour (mph) with gusts over 175 mph in some areas. Yet some subdivisions experiencing substantially lower winds were completely destroyed. This inconsistent pattern of damage was responsible for the Miami Herald investigation and special series of articles. Their conclusion was that damage in areas not experiencing strong winds or storm surges was due to poor housing construction and lax standards.

[7] The Federal flood insurance program provides for subsidized rates for homes built before 1974.

From our perspective this record is an advantage for a quasi-experiment – the structural properties of individual neighborhoods could not be known in advance. They are revealed by damage caused by Andrew. Initial location decisions would not be able to take account of the expected structural integrity of the homes. Before the storm, the FEMA hazard areas were the only signals available to homebuyers. After the storm we hypothesize that these same FEMA areas and the reported damage are interpreted differently. Our data allows consideration of both the pattern of damage and the FEMA risk classes. By using grids to assign the Miami-Herald damage measure we assure that any stigma to undamaged homes in housing subdivisions that experience substantial damage as well as specific effects on damaged homes are taken into account in measuring the effects of risk information.

We hypothesize that this construction effect will be known as a result of the Miami Herald report. Thus, the only other basis for using the storm to separately delineate areas with risk is based on the FEMA hazard categories. Our analysis of repeat sales focuses on the SFHA risk designations because they align with insurance rates and are the most consistent risk information available to homebuyers in making *ex ante* location choices.

III. Non-Market and Market Responses

A. Background

When a large share of the private and public capital supporting daily activities is significantly damaged, decisions must be made about how to respond. The larger the impact of a disaster, the greater, in principle, is the opportunity to observe social and economic adjustment. Most of the available economic models of household adjustment to exogenous changes in community attributes are intended to describe responses to relatively small changes in features of a home or a neighborhood. In the empirical tests of these models the attributes of interest are assumed to be conveyed to homeowners through their locational choices. Households are assumed to be heterogeneous with different preferences for location specific amenities. As a rule, they assume there is one or more endogenous (to the adjustment process) attributes of neighborhoods that can reinforce or retard responses to an exogenous change in the location specific attribute. For example, in the externality/filtering models (Coulson and Bond [1990]) average neighborhood income is hypothesized to be a factor that influences household preferences for a neighborhood. It also changes as people alter their choices for neighborhoods. As a result, changes in mean income can enhance or reduce the effects of an exogenous change in a neighborhood attribute. The overall outcome on composition of an area depends on the size and direction of the effect of neighborhood mean income on the marginal willingness to pay for the attribute that changes. A comparable set of influences can be found in the sorting models that would have consistent predictions for large changes in neighborhood attributes and indeterminant implications for small (see Banzhaf and Walsh [2004]).[8]

[8] The externality/filtering and sorting models rely on common formal structure. The first identifies two types of households who must select among locations with continuous variation in an exogenous attribute. Sorting models assume a finite set of communities and continuous variation in household taste. Banzhaf and Walsh illustrate their analysis with two communities varying in an exogenous attribute and describe sorting among communities. In both structures an equilibrium is defined. With filtering it is the law of one price whereas with sorting it is boundary indifference. Comparative statics with each relation given constraints linking household heterogeneity to endogenous outcomes yields the results implying how heterogeneity affects the impact of a change in the exogenous attribute. Both models require some version of the single cross condition and a large change to derive unambiguous hypotheses about outcomes. This requirement for a large change is a key advantage for analysis of outcomes after natural disasters.

This research has two implications for our analysis. First, it implies that the larger the damage in a neighborhood, the greater the prospects for a change in measures of its demographic and economic composition. Such changes offer the opportunity, given individuals have the resources to pay for adjustment, to observe whether the exogenous change offsets any endogenous retarding (or enhancing) effects of the changes in the existing composition of a neighborhood. Second, they suggest we are more likely to uncover effects of damage by comparing changes in the distributions of the household types with the 1990 and 2000 Censuses rather than changes in measures of the central tendencies for these distributions.

B. Models

Our strategy for keeping track of who adjusts uses a simple regression format. We estimates how $\left(y_{j(t+10)} - y_{jt}\right)$ varies with the average proportion of homes that are judged uninhabitable. y_{jt} is the proportion of households (or individuals depending on the measure being summarized) in category *j* for *t* = 1990. For example this could be the proportion in a racial group or it could be the proportion born in Florida. This simple specification is estimated using a variety of additional control variables, including the baseline (i.e. 1990) proportion of households (or individuals) in each group, the location of block groups in relation to FEMA flood zones, and the potential effects of a neighborhood bordering Homestead Air Force Base. This facility was closed after the hurricane due to extensive damage. Our basic model is given in equation (1) with d_j designating the Miami Herald damage measure and z_{jk} a set of variables that correspond to the different controls investigated as part of evaluating the robustness of our conclusions.

$$\left(y_{j(t+10)} - y_{jt}\right) = \alpha_0 + \alpha_1 d_j + \sum_k \tau_k z_{jk} + \varepsilon_j \qquad (1)$$

ε_j is a random error assumed to be classically well behaved

α_0, α_1, and τ_k are parameters to be estimated

For some of the economic variables, such as the distributions of incomes, rents, and housing values, the cell definitions used in reporting each distribution changed between the two Censuses. These changes in the 2000 expand the resolution in the middle categories and change the upper censoring point. We redefined the 2000 categories for rents, housing values, and income so they matched the 1990 categories.

For property values and rents these models generalize the logic proposed by Chay and Greenstone [forthcoming] to use quasi-random experiments to avoid bias in estimating the incremental value of changes in site specific amenities. That is, in a hedonic model the process assuring that the estimated differences in the equilibrium prices with amenities will reflect incremental willingness to pay relies on sorting behavior on the part of those buying the homes. People select the best locations they can afford. Nonetheless, there may be unobserved differences in the households selecting locations with low amenity levels in comparison to those with high levels. Use of an exogenous instrument and a difference-in-difference framework allows the effect of interest and the influence of unobserved heterogeneity to be distinguished.

Applications of this logic for environmental effects have generally relied on county (or Census tract) level mean or median housing values across Censuses. To the extent there is a change in the composition of the housing available as a result of the amenity differences, the “average” may not be distinguishing a marginal value for the change in the amenity. Instead it bundles an induced change in the structural attributes of what constitutes the average housing with the amenity change. Use of changes in the distributions of housing values or rents allows greater control over the “types” of housing through the value and rent brackets. Unfortunately it does not provide a basis for measuring the marginal willingness to pay for amenities. Thus, a final stage in our analysis compares our estimates of changes in the distribution with what would have been concluded if we used the median rents and housing values in 1990 and 2000 with the 1990 block group definition.

Ideally one would have data on individual home sales and the ability to observe how prices changed before and after the hurricane. As we noted in the previous section, we purchased data to meet this ideal -- a transactions-based set of home sales for Dade County. So, it is possible to develop a repeat sales model based on these micro data and compare the two strategies for evaluating the effects of Andrew.

The repeat sales model alters the focus of our attention from the block group, as a proxy for a neighborhood, to the individual property. The sales price (R_{it}, i identifies each property and t the time of sale) is assumed to be a function of each home’s characteristics (x_{ik}) including locational attributes. These locational features distinguish the three FEMA flood hazard areas – AE, AH, and X500. For each area we hypothesize a different subjective belief about the risk of damage due to coastal storms. Equation (2) outlines the model.

$$\ln R_{it} = \sum_k c_k x_{ik} + \sum_{l=1}^{3} F_{li}\left(b_{lt} + \beta p_{lt} + \eta_i + e_{it}\right) + \sum_{l=1}^{3}\left(1 - F_{li}\right)\left(\gamma_{lt} + \beta \phi_{lt} + \eta_i + e_{it}\right) \qquad (2)$$

The first term, $\sum_k c_k x_{ik}$, captures the effect of the housing characteristics. These attributes describe the features of the home and its lot. They would generally include its size, the lot size, age, the number of baths, presence of pool, carport, etc. η_i is an idiosyncratic, time invariant effect due to unobserved heterogeneity. F_{li} is a qualitative variable identifying the location of properties inside the *l*the zone (l =1) versus outside the zone, (l = 0). The sample also includes homes in areas without any of these flood zone designations. We assume households have different subjective probabilities of a hurricane strike causing damage within each of these areas. In our example with l = 1, they might be designated as p_{lt} and ϕ_{lt}, respectively. b_{lt} and γ_{lt} are the time effects for properties inside and outside each flood zone. e_{it} is assumed to be a well-behaved error (i.e. independent and identically distributed).

Andrew's extensive damage to Dade County required households to adjust.[9] Even if a home was not damaged as a result of the hurricane, we hypothesize that owners at the time of the hurricane and potential buyers thereafter would perceive the risks of coastal hazards damaging each location differently. These different perceptions imply the initial sales prices would be based on one set of subjective beliefs in each FEMA zone; after the hurricane they are based on another.

For example, if we assume before Andrew $p_{lt} = p_{l0}$ and $\phi_{lt} = \phi_{l0}$, then after Andrew, households have received the new information and adjust their risk assessments to $p_{lt} = p_{l1}$ and $\phi_{lt} = \phi_{l0}$ for the two areas. Defining $A_t = 1$ if Andrew occurred and

[9] See West and Lenz [1994] for background. David Lenz provided us an unpublished report on the damage after Andrew conducted using American Red Cross estimates of damage by the Metropolitan Dade County Planning Department (Kerr [1993]). This summary suggests a loss of 47,100 housing units in South Dade County. 101,000 individuals, according to these estimates, were dislocated in the four months after Andrew and about 57,000 of these people moved out of the county.

$A_t = 0$ otherwise, p_{lt} and ϕ_{lt} can be defined recognizing this hypothesized discrete change in risks for the two locations by equations (3) and (4), respectively.

$$p_{lt} = A_t p_{l1} + (1 - A_t) p_{l0} \tag{3}$$

$$\phi_{lt} = A_t \phi_{11} + (1 - A_t) \phi_{l0} \tag{4}$$

Substituting (3) and (4) into equation (2) yields equation (5).

$$\begin{aligned} \ln R_{it} = \sum_k c_k x_{ik} + \sum_{l=1}^{3} F_{li} \left(b_{lt} + \beta \left(A_t p_{l1} + (1 - A_t) p_{l0} \right) + \eta_i + e_{it} \right) + \\ \sum_{l=1}^{3} (1 - F_{li}) \left(\gamma_{lt} + \beta \left(A_t \phi_{l1} + (1 - A_t) \phi_{l0} \right) + \eta_i + e_{it} \right) \end{aligned} \tag{5}$$

To evaluate how adjustment is displayed through markets and the importance of these altered expectations we need to be able to distinguish these effects from the heterogeneity in individual properties. We use a difference-in-difference framework to control for this heterogeneity. Our housing sales sample is limited to houses that sold at least twice between 1983 and 2000. We base our analysis on the two most recent sales.

Differencing equation (5) for the same property i for sales in years t and s, we have equation (6).

$$\begin{aligned} \ln\left(R_{it} / R_{is} \right) = \sum_{l=1}^{3} (\gamma_{lt} - \gamma_{ls}) + \sum_{l=1}^{3} F_{li} \left((b_{lt} - b_{ls}) - (\gamma_{lt} - \gamma_{ls}) \right) + \sum_{l=1}^{3} \beta (\phi_{l1} - \phi_{l0})(A_t - A_s) + \\ \sum_{l=1}^{3} \beta \cdot \left((p_{l1} - p_{l0}) - (\phi_{l1} - \phi_{l0}) \right) F_{li} \cdot (A_t - A_s) + (e_{it} - e_{is}) \end{aligned} \tag{6}$$

To derive equation (6) the structural characteristics are assumed to remain constant so that these terms cancel from the estimating equation. The interaction term indicating the sales bracketed Andrew and that a property is in the l^{th} hazard zone for our example measures $\beta[(p_{l1} - p_{l0}) - (\phi_{l1} - \phi_{l0})]$. To estimate this effect we assume that: (a) there are no significant changes in housing attributes between the two time periods (e.g.

the x_k's remain the same); (b) the partial effects of structural attributes on the log of the sale prices are constant (i.e. the c_k's do not change); and (c) the unobserved heterogeneity is not differentially influenced by the event.

The sum of the term identifying sales that bracket Andrew and the one identifying those in each of the flood risk zones estimates how the market evaluated the new risk for these areas (i.e. $\beta(p_{l1} - p_{l0})$; for l = 1, 2, 3). When the Miami-Herald damage measure is introduced into the model and interacted with variables identifying sales bracketing the storm, we can estimate the net effect of hurricane stigma for subdivisions with significant damage as well as modifications to damaged properties as part of their repairs.. It is also possible to include variables reflecting different aspects of the market adjustment, including the time since Andrew (i.e. the time between August 23-24, 1992 and the most recent sale of each home in the sample) and the time between the two sales for each price difference.

Another change to our simple description of the model involves including fixed effects to account for the changes in insurance arising with the 1994 federal flood insurance legislation. These variables are distinguished by zone and the date of the most recent sale in relationship to the implementation data for the changes in the federal flood insurance program (i.e. 1996). Florida's response to the insurance crisis created by Andrew was to create two state run property and casualty underwriting associations. During the period of our sample, popular descriptions of the program suggest that the property insurance was under-priced and did not signal the risks of coastal locations.[10] We hypothesize the changes in the federal program, both increasing rates and enforcing a

[10] Longman [1994].

requirement for insurance, may have been especially important if the two sales bracketed Andrew and the second sale fell after the policy change. We also include an inverse Mills ratio to evaluate the potential for selection effects that arises by limiting the sample to properties with at least two sales.[11]

Finally, our application permits the first comparison of two strategies for using the hedonic logic together with a quasi-random experiment to isolate the effects of locationally delineated attributes. Chay and Greenstone [forthcoming] demonstrated the importance of using exogenous instruments in testing the effects of site specific amenities and disamenities. Their analysis relies on Census measures for property values, medians or means for counties. Our unit is the block group. We have micro and aggregate data for the same external event so it is possible to evaluate the performance of a Census-based comparison.

IV. Results

A. Who Adjusts

Our analysis of the changes in the composition of the Census blocks in Dade County between 1990 and 2000 is divided into three components. First we consider simple models describing whether the proportionate change in a demographic or economic variable describing the population changes with the NOAA/Miami Herald damage measure assigned to each block group. These analyses include such variables as the counts of white, black, and Hispanic homeowners or the households in the 40 to 60,000 dollar income bracket, and so forth. We report models with two samples. With

[11] These estimates are the two-step Heckman [1979] approach using Huber's [1967] robust estimates for the standard errors. The selection model was estimated using fixed effects for each of the sale years for each of the properties. See Appendix A for the estimates.

the full sample of block groups we collapse the 2000 block groups to 1990 definitions. We use two sets of area weights in this process. When the variable being summarized is a count we apply the fraction of the 2000 block group that is from the original 1990 definition. Assuming uniform density of the relevant population in each 2000 block group this process assigns the correct weight to each component.

For continuous measures, such as the median income or the median value for homeowners' reports for their home's sale price, the appropriate weight is the fraction of the 1990 block group that is in the 2000 block group. These weights sum to unity when we collapse the 2000 summary statistics to the 1990 map for block groups.

We also evaluate whether the relationships between the proportionate changes and the NOAA/Miami Herald damage measure depend on the initial (i.e. in 1990) fraction of each group in each 1990 block group. To evaluate the potential effect of the area weights used to reconstruct our sample, we repeat these analyses using samples with only the block groups that did not change between 1990 and 2000. Finally we also consider whether the FEMA flood zones influence the locational choices of different groups.

Table 2 reports the first simple analysis, considering in the top panel whether the fraction of households reporting that they stayed in the same house was influenced by the NOAA/Miami Herald damage measure assigned to each block group. Damage did not affect leaving one's house or county. It does appear to influence the relocation patterns of those households born outside Florida. These groups avoid areas with damage. Native Floridians are then a disproportionately higher share of the population. None of these results is affected by the sample.

Table 3 reports the simple models for demographic variables, income, rents, and housing values. Each entry in the table corresponds to a different model where the dependent variable is the proportionate change between the 1990 and 2000 Censuses and the independent variable is the NOAA/Miami Herald damage measure (d_j in equation (1)) or this measure along with the 1990 proportion of the relevant group in each block group (WI for 'with initial conditions'). We do not report estimates for the parameters associated with this baseline proportion. The table entries indicate its sign and significance as a gauge for the robustness of the estimates for the damage measure.

White owners and renters appear to avoid damaged areas. It appears that black households with home equity adopt the same adjustments in qualitative terms as the white households. The size of their responses coefficient is smaller and its significance is sensitive to the sample used. Black renters and Hispanic households, both owners and renters, increase in the damaged areas. While some of the Hispanic increase reflects an overall increase in this demographic group, as suggested in the average proportionate growth measures by demographic groups for the county as a whole (in Table 1), there is also a disproportionate growth in the damaged areas. Considering the results for groups based on the various educational levels achieved, the proportions with less than high school along those with graduate degrees are consistently significant and negatively related to the damage measure.[12]

Use of the proportionate changes in the groups in the income cells allows more direct consideration of the heterogeneity arguments associated with the tipping/sorting models used to describe how the composition of a community changes in response to an

[12] In interpreting estimates it might seem implausible to have all negative estimates. However, both the numerator and the denominator in each ratio for each educational category are changing between census years. Moreover we are not including all educational categoreies in the decompostion.

exogenous shock. When we used the median income, the difference in the log of the median income in the two Census is negatively related to damage, but not significant at the ten percent level (p-value is 0.11). The results in table 3 help to explain why.

The proportion of households in the lowest two income categories (less than 15K and 15K to 25K) grows while the middle income group (40K to 60K) declines. Upper income groups do not significantly change in response to the damage areas. This pattern is broadly consistent with the expectations of sorting models. In a Tiebout model households adjust to local public goods (and bads) based on their ability to pay. The middle income group may have the ability to pay for adjustment. Moving to avoid risk is the way they appear to adjust. Lower income groups may be taking advantage of the lower rents in these areas. They do not have the ability to pay for moving out to another lower risk area as an adjustment. The damage and re-construction creates an opportunity when the replacement of residential structures is with lower cost units.

Higher income households have the ability to self protect and to insure. As a result, it seems reasonable to expect a wider array of adjustment possibilities. Moving out of an area may be the last alternative for this group. Thus, there is a reasonable explanation for a lack of any changes with this group. The high coastal risk areas also correspond to areas with high coastal amenities. High income households in these zones may have already self protected.

Rents and housing values adapt to support the changing composition of households in the damaged block groups. The proportion of lower rent units increased in damaged areas and the higher rent decreased. The same effects can be traced in the signs and significance of the owner reported housing values. The proportion in the range 40K to 100K increased with damage while those in the 100K to 250K decreased. There was no change in the proportions in the higher valued categories with respect to damage.

Table 4 considers whether the adjustments are affected by the ability to avoid risky areas. That is, controlling for the average NOAA-Miami damage in a block group we consider whether the fraction in the block group in different FEMA risk categories influenced the proportionate changes in each demographic group and income category. These estimates are based on the full sample of block groups. As noted earlier AE is classified the highest risk category for coastal flooding, AH next highest, and X500 minimal risk. Homestead is a dummy variable to indicate whether the block group bordered the Homestead Air Force Base (=1 and 0 otherwise). This facility was closed after being completely destroyed by the hurricane. We might expect two influences with this variable. The first is associated with initial land uses around the base and the second with the scale of the effects of damage along with the base closing to depress land values and reduce economic activity.

White owners and renters, tend to avoid block groups with the highest risk (AE). Hispanic owners and renters and black renters seem to disproportionately increase in block groups with the highest risk. The results for income groups are not as clear-cut as they are for the demographic categories. Low income groups decrease in the block groups with the largest fraction of their area in the high risk FEMA category and increase in the AH category. Other income groups have largely insignificant coefficients for the area variables. There are a few exceptions with the most intriguing of these estimates associated with the over 150K group increasing with the area of the block group in the high risk category. This seemingly counter-intuitive result likely reflects the higher amenity levels associated with these same locations and the ability of this group to self protect and insure against the risks posed in these areas.

Overall, these results confirm the importance of models that account for heterogeneity in describing the patterns of household adjustment to disasters. As expected, ability to pay appears to be important to understanding why we observe differences in demographic groups' responses to damage caused by natural disasters. Comparing the responses of black homeowners and renters we find the former behaves more comparably with white households. Ethnic attachment to neighborhoods, as hypothesized in social interaction models and as proxied in our analysis by the 1990 proportion of Hispanic households, does not overturn the results suggesting these groups, both owners and renters, are more likely to move into damaged areas. In their case treating home ownership as a proxy for ability to pay would not allow us to reconcile these findings with what was estimated for other groups.

There appears to be an especially interesting story in the changes in the income distributions. Lower income groups increase in damaged areas and the proportion of middle income groups decreases, suggesting there is adjustment to both damage and potentially the perception of increased risk. The lower income groups may be taking advantage of lower rents. Thus, this finding contrasts with Breen's (1997) results suggesting little change in demographics in response decisions to use new areas for facilities with increased environmental risk.[13]

Our analysis suggests higher income groups do not adjust to damage and, if anything, tend to move to coastal locations with higher risks of flooding damage. Had

[13] Breen [1997] and Banzhaf and Walsh [2004] find comparable results for Hispanic populations' responses to other sources of environmental risks.

we used the change in the median income between the two Censuses, our conclusion would have been much different. That is, analysis of the change in the log of the median income leads to the mistaken impression that the hurricane's damage was not an influence on the proportionate change in average income of households in Dade County's block groups. It would have suggested the size of the area in high risk zones was negative and significant influence. Equation (7) provides these estimates (with *t* ratios in parentheses).[14]

$$\ln\left(\tilde{m}_{t+10}\right) - \ln\left(\tilde{m}_t\right) = \underset{(13.14)}{0.298} - \underset{(-1.60)}{0.19} \cdot NOAA\ Damage \\ \underset{(-2.95)}{-0.11}\ AE \underset{(-0.29)}{-0.02}\ AH \underset{(-1.58)}{-0.10}\ X500 \qquad (7)$$

$n = 1022$

$R^2 = 0.01$

The significant negative coefficient for the proportion of the block group in the AE zone would miss the likely amenity effect we found through a more detailed examination of the income distribution changes. Recall the highest income groups *increased* in block groups based on analysis of the proportionate changes in the cells of the income distribution.

Finally the rent and homeowners' stated home values also present a complex set of changes with proportionate growth in the fraction in the lowest categories for areas where Andrew's damage was greatest and declines in the intermediate values for these same areas. These changes add to the challenges faced by the use of summary measures to isolate an exogenous effect. We return to this issue below.

[14] $\tilde{m}_t$ designates median income in t = 1990 and t+10 = 2000; NOAA Damage is the average proportion uninhabitable; AE, AH, and X500 are the proportion of area in each block group in the specific flood zone designation.

B. Market Responses to Damage and Risk information

Table 5 report the results from our repeat sales model based on the transactions database described earlier. Using latitude and longitude it is possible to locate each property into FEMA flood zones as well as the grids for storm damage. The dependent variable is the difference in the log of the sales prices for the two most recent sales of each property as implied by equation (6) earlier. Our zone variables are dummy variables identifying whether or not each home is in each FEMA flood risk area. The variables measuring the time between sales and the time since Andrew, as well as a qualitative variable identifying whether the two sales bracket Andrew, are used to control for the various implications of the timing of the events represented in the model. We also include the average value for the NOAA/Miami Herald damage variable assigned to each home for those cases with sales that bracket Andrew (zero is assigned for those that do not).

Two aspects of our findings are especially important to understanding the role of market adjustment. The hurricane did appear to lead to significant discounting in the rate of appreciation of homes in the FEMA coastal risk zones. The estimated magnitude of the impacts for AE and AH zones is consistent with their relative risks. While the estimated effects of the two zones would not be judged to be significantly different ($F(1,9907) = 2.14$), this is a relatively close call. The p-value for equality of these two effects would imply the effect of AE is greater than AH with a one sided test. Including the damage estimate suggests the stigma associated with using storm damage to judge construction quality may offset any improvements made to damaged homes as part of the post hurricane repairs. Overall, the hurricane had dramatic effects on market expectations. The pace of appreciation of homes in the highest risk areas was reduced by 50 to 60 percent.

The market impact of Andrew's damage was considerable. For those areas experiencing complete damage, property values decline by about thirty-four percent. It is important to acknowledge that this result is based on average damage to an area, not specific damage to individual properties. Moreover, the properties used to estimate this effect were no longer damaged at the time they were sold and entered our sample. The reason the contribution of the damage coefficient does not have a large impact on the overall measure of the capitalization of the revised risk information is that the average damage measures for the properties in our sample are small. The properties in the repeat sales sample were in areas where approximately 16 percent were uninhabitable as a result of damage from the storm.

The last aspect of our analysis re-visits the Census block data and uses the median home values (as evaluated by owners) and the median rents to evaluate the extent of the risk information and damage effects of the hurricane. Tables 6 and 7 report our estimates. In table 6 the proportionate changes in median housing value and rent display some consistency with the transactions data.[15] Column (1) evaluates the effect of the Miami Herald damage measure and FEMA risk zones on the change in housing values. There are no apparent effects of the hurricane damage on median housing values. There is some consistency with the risk information effect with the proportion of a block group's area in either the AE or the AH zones reducing the appreciation in median

[15] These models rely on the difference in the log of the median values of homeowners' assessments of what their homes would sell for between the 1990 and 2000 Censuses.

housing values. These effects are not significantly different. Column (2) evaluates the sensitivity of these findings to including measures of the change in the characteristics of owner occupied housing over the same period, and we see there is no difference in the general conclusions one would draw from the analysis.

When we compare these estimates to the results from individual housing sales, it is clear there are challenges in interpreting both the damage and risk zone measures. At the block group level both measure the spatial extent of their respective influence and can, as a result, be interpreted in several ways. For example, the Miami Herald damage measure could be interpreted as a proxy for the extent of loss in the housing stock as well as potential stigma associated with poor construction. The proportionate area measures for the FEMA flood zones may reflect supply of locations and risk of coastal flooding. Without the ability to observe actual housing sales that bracket Andrew, we cannot "control" how these effects are allowed to influence the change in housing values. At best the Census analysis reflects the permanence of each set of effects. In this context damage appears to have no permanent effect on "average" values while risk does.

Columns (3) and (4) parallel the models for homeowner values, with (3) as the simple model and (4) including controls for the changing composition of rental housing. In the case of the proportionate change in median rent, only the area in the highest FEMA risk zone has a significant negative effect on the change in rents between the two Censuses.

Table 7 describes how the effects of damage and areas in risk zones influence changes in the proportion of the homes in each home value interval and in each rent category. These groupings offer another strategy for controlling for all the housing attributes that could have been included in the models in table 6 using means. The distributional approach may well offer a better control because of the likely narrower difference in attributes across the housing units in each cell.

Overall the results using the Census data are mixed – they isolate the increase in the proportions in the low home value and low rent categories with damage, as we discussed in the case of the simple models earlier, though the significance of these effects is somewhat lower. The high risk FEMA zones tend to reduce the number of homes in the middle value group and increase those in the lowest housing value group as well as those in the 400,000 to 500,000 home value group. The change in the composition of the distribution from middle values to the lowest value category seems to dominate the effect at the highest end of the distribution. It is likely what drives the overall negative effect observed for the medians. The effects estimated for NOAA damage are comparable to what we found with the simple models.

Thus, this comparative assessment suggests the task of detecting quasi-experimental effects on market responses using Census aggregates is challenging. The heterogeneous behavior that sorting models seek to depict is *real*. It affects changes in the demographics as well as the ability of summary statistics such as medians to isolate the role of the spatially delineated changes in the amenities. It is usually asserted that these effects are most reliably uncovered with the quasi experimental designs

To the extent our hurricane example is representative, the analysis of changes in medians based on spatial areas would best be interpreted as tests of the effect of an amenity (or disamenity) rather than as estimates of the magnitude of its incremental value. There are simply too many changes in the composition of the distribution of homes (or rental units) that can be taking place. This is especially true for a large scale event. With smaller sources of impact the discrepancies may be smaller, but in these cases the ability to detect them reliably may also be diminished.

V. Implications

This analysis has implications for three areas of ongoing research. The first involves insights into who adjusts to large scale disasters. Most of differences in adjustment across groups differing in educational and racial background are likely to be due to their economic capacity to undertake changes in their residential locations. The pattern no doubt reflects differences in these groups' available income and wealth. Whites, both homeowners and renters, are likely to have access to greater resources to permit their adaptation than Hispanics or black households who don't own their homes.

Several authors' concerns about the confounding effects of household heterogeneity for the composition of communities after exogenous changes in amenities are confirmed with the large scale damage associated with Andrew. Our analysis of the distributions of income, housing values, and rents indicate that the underlying shifts in these distributions can yield ambiguous results for the medians. Nonetheless, the pattern of change in each of these distributions is consistent with the low income groups being least able to adjust to natural disasters. It seems reasonable to conclude that this lack of responsiveness is due largely to economic capacity and not ethnic influences. Indeed, the hypothesis that the social interaction effect associated with attachment to neighborhoods with "like" groups was only supported for the highest income households. All other groups' patterns of adjustment implied movement away from areas with a large fraction of "their group" in 1990.

The second area where our analyses offer some new results concerns the change in market prices for housing. Our repeat sales analysis documents that the hurricane's damage serves, on net, as an *ex post* signal of poor quality housing construction for residential properties. Moreover, the hurricane appears to have caused re-consideration of the risk designations implied by FEMA's flood hazard areas. Market price changes for sales that bracket Andrew are consistent with the risk ordering of the FEMA zones.

A comparison of Census based estimates of the market capitalization of the signals provided by hurricane Andrew's risk information confirms in qualitative terms the lessons derived from the analysis of individual transactions. The contrast between the potential interpretations for the variables we used to control for the damage and risk information associated with the storm highlights the challenges in using summary statistics to implement a quasi-experimental design. Sorting models imply that heterogeneity in preferences and unobservable features of constraints can have large effects on the adjustments households can make in response to large, exogenous shocks. These differences are likely to show up as changes in the distribution of housing values that may not be easily detected with measures of changes in the central tendency.

Our findings of consistent qualitative results between our analyses of the micro level repeat sales outcomes and the changes between the 1990 and 2000 Censuses medians may reflect the long term nature of the change in perceptions of the hazards of coastal locations. The distribution changes suggest that the highest income groups appear to be self protecting and insuring. For the other groups the results suggest that their actions depend on whether they have the economic capacity to adjust their locations.

Finally, it is difficult to draw transferable lessons from one analysis of adjustment to a large scale disaster for other disastrous events, both natural and manmade. It is clear that economic circumstances of households seem to be the most important factor in understanding responses. Perhaps the best lesson is that there is a great deal that can be recovered from *ex post* studies of asset prices. A better mapping of the spatial effects of the disasters to residential and other sales prices together with more explicit treatment of neighborhood features offers a research strategy with considerable potential. It will require more detailed and immediate record keeping after disasters. Our analysis was possible because there was a controversy after Andrew over the performance of Dade County's building inspectors. This public outrage lead to a special study of the features of damaged areas and the records that permit our study. More systematic record-keeping creates opportunities to learn how to improve the public role in *ex post* adjustment.

Table 1: The Composition of Dade County by Damage Class from Andrew: 1990 and 2000 Censuses

	Greater Than 50%		Less Than 50%		Overall Summary	
	1990	2000	1990	2000	1990	2000
<u>I. Demographic Composition</u>						
Owner Occupied						
White	0.663	0.499	0.489	0.417	0.494	0.419
Black	0.122	0.122	0.213	0.221	0.211	0.218
Hispanic	0.149	0.298	0.267	0.309	0.264	0.309
Renters						
White	0.589	0.388	0.410	0.369	0.415	0.370
Black	0.166	0.220	0.256	0.248	0.254	0.246
Hispanic	0.185	0.293	0.290	0.315	0.288	0.315
<u>II. Income Distribution</u>						
Less than 15,000	0.189	0.175	0.317	0.247	0.313	0.245
15,000 – 25,000	0.138	0.167	0.178	0.148	0.177	0.149
25,000 – 40,000	0.229	0.198	0.196	0.177	0.197	0.178
40,000 – 60,000	0.284	0.174	0.151	0.159	0.155	0.159
60,000 – 150,000	0.149	0.256	0.131	0.216	0.132	0.217
over 150,000	0.011	0.031	0.026	0.052	0.026	0.052

Table 2: Types of Adjustments in Response to Andrew's Damage[a]

Model	**Same Block Group**	**Area Weighted 2000 to 1990**
A. STAYING PUT		
Proportion – Same House	-0.04 (-0.88)	0.00 (0.03)
Proportion – Same County	0.04 (1.00)	0.04 (1.37)
B. CHANGES IN COMPOSITION BASED ON BIRTH AREA		
Midwest	-0.03 (-2.54)	-0.04 (-4.75)
Northeast	-0.02 (-1.16)	-0.03 (-1.61)
South	-0.10 (-4.97)	-0.08 (-4.37)
West	-0.01 (-0.79)	-0.00 (-0.30)
Florida	0.06 (1.84)	0.06 (2.36)

[a] The numbers in parentheses are t-ratios for the null hypothesis of no association.

Table 3: Demographic and Economic Adjustments to Andrew's Damage[a]

Model	**Same Block Group**		**Area Weighted 2000 to 1990**	
	S	**WI[b]**	**S**	**WI[b]**
A. DEMOGRAPHIC				
1. Owner Occupied				
Proportion – White	-0.12 (-3.29)	-0.06 N (-1.92) S	-0.14 (-4.56)	-0.07 N (-2.89) S
Proportion – Black	-0.09 (-2.83)	-0.09 N (-2.90) S	-0.03 (-0.98)	-0.03 N (-1.26) S
Proportion – Hispanic	0.17 (8.29)	0.13 N (6.46) S	0.16 (8.39)	0.11 N (6.35) S
2. Renters				
Proportion – White	-0.16 (-3.36)	-0.10 N (-2.58) S	-0.20 (-5.20)	-0.12 N (-3.79) S
Proportion – Black	0.07 (1.71)	0.06 N (1.68) S	0.07 (1.97)	0.06 N (1.79) S
Proportion – Hispanic	0.11 (3.29)	0.05 N (1.85) S	0.14 (5.17)	0.08 N (3.44) S
B. EDUCATION				
Proportion less than H.S.	-0.21 (-2.99)	-0.21 P (-2.98) S	-0.21 (-3.63)	-0.20 P (-3.57) I
Proportion with H.S.	-0.05 (-1.49)	-0.06 N (-1.91) S	-0.04 (-1.73)	-0.03 N (-1.40) S
Proportion with Some College	-0.00 (-0.18)	-0.03 N (-1.30) S	-0.01 (-0.63)	-0.02 N (-1.17) S
Proportion with College	-0.04 (-2.00)	-0.04 P (-1.87) I	-0.03 (-1.72)	-0.03 P (-1.57) S
Proportion with Graduate School	-0.06 (-2.10)	-0.07 N (-2.30) S	-0.05 (-2.44)	-0.06 N (-2.66) S

[a] The numbers in parentheses are t-ratios for the null hypothesis of no association.
[b] This column corresponds to models that include the damage measure for Andrew along with the initial count of the group being modeled in each block group in 1990. The letters refer to the sign and significance of a term included to reflect the count of households in the relevant group in 1990.
N= negative, P = positive, S = significant, I = insignificant.

C. INCOME				
Proportion Income < 15K	0.09 (2.63)	0.09 N (2.54) S	0.11 (3.47)	0.10 N (3.24) S
Proportion 15K < Income < 25K	0.06 (1.85)	0.06 N (1.99) S	0.05 (1.91)	0.05 N (1.90) S
Proportion 25K < Income < 40K	0.02 (0.64)	0.04 N (1.04) S	-0.02 (-0.66)	-0.02 N (-0.57) S
Proportion 40K < Income < 60K	-0.16 (-5.39)	-0.14 N (-4.48) S	-0.17 (-6.79)	-0.16 N (-6.51) S
Proportion 60K < Income < 150K	-0.04 (-1.03)	-0.03 N (-0.81) S	0.03 (1.02)	0.03 N (1.10) S
Proportion Income > 150K	0.03 (1.38)	0.03 P (1.56) S	0.01 (0.52)	0.01 P (0.77) S
D. RENTS				
Proportion Rent < 250	-0.05 (-1.10)	-0.03 N (-0.81) S	-0.06 (-1.61)	-0.04 N (-1.31) S
Proportion 250 < Rent < 500	0.26 (3.29)	0.23 N (3.06) S	0.31 (4.70)	0.26 N (4.18) S
Proportion 500 < Rent < 750	-0.20 (-2.19)	-0.21 N (-2.20) S	-0.22 (-2.76)	-0.23 N (-2.93) S
Proportion 750 < Rent < 1000	-0.02 (-0.23)	-0.02 N (-0.20) I	-0.12 (-1.87)	-0.12 N (-1.88) I
Proportion Rent > 1000	0.01 (0.13)	-0.00 N (-0.03) S	0.09 (1.55)	0.09 P (1.59) I
E. HOUSING VALUES (HV)				
Proportion HV < 40K	-0.04 (-0.63)	0.06 N (1.16) S	-0.03 (-0.59)	0.04 N (0.83) S
Proportion 40K < HV < 100K	0.36 (2.96)	0.47 N (4.30) S	0.19 (2.02)	0.27 N (3.01) S
Proportion 100K < HV < 250K	-0.35 (-3.16)	-0.33 N (-3.13) S	-0.16 (-1.95)	-0.16 N (-1.96) S
Proportion 250K < HV < 400K	0.02 (0.46)	0.02 N (0.47) I	0.00 (0.06)	0.00 N (0.07) I
Proportion 400K < HV < 500K	0.01 (0.75)	0.01 N (0.73) I	0.00 (0.23)	0.00 N (0.22) I
Proportion HV > 500K	-0.00 (-0.07)	-0.00 P (-0.01) S	-0.00 (-0.14)	0.00 P (0.02) S

Table 4: Adjustment and Risk Information[a]

	NOAA / Miami Herald Damage	FEMA Flood Zones			Homestead Air Force Base
		AE	AH	X500	
A. <u>DEMOGRAPHIC</u>					
1. Owner Occupied					
Proportion – White	-0.13 (-4.05)	-0.03 (-3.10)	-0.01 (-0.46)	0.04 (2.10)	-0.12 (-1.34)
Proportion – Black	-0.04 (-1.28)	0.01 (1.51)	-0.01 (-0.60)	-0.03 (-2.00)	0.13 (1.61)
Proportion – Hispanic	0.15 (8.03)	0.02 (3.67)	0.02 (1.99)	0.01 (0.57)	-0.01 (-0.25)
2. Renter					
Proportion – White	-0.20 (-4.95)	-0.04 (-3.08)	0.00 (0.10)	0.01 (0.49)	-0.07 (-0.82)
Proportion – Black	0.07 (1.86)	0.03 (2.39)	0.02 (0.88)	-0.00 (-0.25)	-0.06 (-0.75)
Proportion – Hispanic	0.13 (4.77)	0.02 (1.98)	0.01 (0.49)	0.01 (0.42)	0.10 (1.69)

[a] The numbers in parentheses are t-ratios for the null hypothesis of no association.

3. Income					
Proportion Income < 15K	0.10 (3.39)	-0.02 (-1.58)	0.06 (2.88)	0.06 (3.37)	-0.03 (-0.34)
Proportion 15K < Income < 25K	0.05 (1.95)	0.00 (0.32)	-0.03 (-1.69)	-0.03 (-2.19)	-0.01 (-0.16)
Proportion 25K < Income < 40K	-0.02 (-0.58)	0.01 (0.91)	-0.02 (-1.01)	-0.01 (-0.82)	-0.01 (-0.15)
Proportion 40K < Income < 60K	-0.17 (-6.52)	-0.00 (-0.46)	-0.04 (-2.37)	-0.02 (-1.32)	0.04 (0.55)
Proportion 60K < Income < 150K	0.02 (1.71)	-0.00 (-0.26)	0.03 (1.84)	0.00 (0.29)	0.05 (0.60)
Proportion Income > 150K	0.01 (0.64)	0.01 (2.21)	-0.00 (-0.55)	0.00 (0.03)	-0.03 (-0.78)

Table 5: Micro Level Repeat Sales Models for Andrew's Effects on Residential Housing Prices[a]

Independent Variables	(1)
ZONE EFFECTS	
In Zone AE	0.035 (0.56)
In Zone AH	0.040 (0.74)
In Zone X500	0.558 (5.44)
In Zone AE * time between sales	-0.012 (-3.72)
In Zone AH * time between sales	-0.014 (-4.41)
In Zone X500 * time between sales	-0.010 (-4.42)
ANDREW EFFECTS	
Sales Bracket Andrew	-0.555 (-8.50)
Sales Bracket Andrew * time since Andrew	-0.007 (-1.36)
Sales Bracket Andrew * In Zone AE	-0.001 (-0.01)
Sales Bracket Andrew * In Zone AH	-0.129 (-1.60)
Sales Bracket Andrew * In Zone X500	0.635 (3.66)
Sales Bracket Andrew * In Zone AE * time since Andrew	-0.012 (-3.72)
Sales Bracket Andrew * In Zone AH * time since Andrew	-0.014 (-4.41)
Sales Bracket Andrew * In Zone X500 * time since Andrew	-0.010 (-4.42)
Sales Bracket Andrew * In Zone AE * After Federal Flood Insurance	-0.266 (-2.44)
Sales Bracket Andrew * In Zone AH * After Federal Flood Insurance	-0.187 (-2.40)
Sales Bracket Andrew * In Zone X500 * After Federal Flood Insurance	0.242 (1.18)
NOAA / *Miami Herald* Percent Uninhabitable * Sales Bracket Andrew	-0.336 (-7.70)

[a] The numbers in parenthesis below the estimated coefficients are the ratios of these coefficients to robust estimates of their standard errors.

OTHER VARIABLES	
Time between sales	0.010 (12.44)
Time between sales * Located in SFHA	0.010 (3.55)
Inverse Mills Ratio	-1.154 (-33.67)
Intercept	0.657 (12.45)
R^2	0.205
Number of Observations	9,929
Proportional Effect on Appreciation in Housing Prices	
WITHOUT DAMAGE ADJUSTMENT	
In Zone AE	-0.560 (p-value=0.00)
In Zone AH	-0.447 (p-value=0.00)
In Zone X500	-0.297 (p-value=0.43)
WITH DAMAGE ADJUSTMENT	
In Zone AE	-0.614 (p-value=0.00)
In Zone AH	-0.501 (p-value=0.00)
In Zone X500	-0.350 (p-value=0.64)

Table 6: Census Based Estimates of Andrew's Effects on Median Housing Values and Rents, 1900-2000[a]

Independent Variable	Home Owner Values		Rents	
	(1)	**(2)[b]**	**(3)**	**(4)[c]**
NOAA / Miami Herald Damage	-0.014 (-0.12)	-0.014 (-0.12)	0.071 (0.58)	0.058 (0.49)
Proportion in AE Zone	-0.110 (-2.61)	-0.111 (-2.62)	-0.085 (-2.15)	-0.108 (-3.21)
Proportion in AH Zone	-0.175 (-2.22)	-0.178 (-2.26)	0.074 (0.95)	0.020 (0.29)
Proportion in X500 Zone	0.044 (0.64)	0.052 (0.75)	-0.076 (-1.15)	-0.006 (-0.10)
Constant	0.349 (14.43)	0.342 (13.78)	0.237 (10.30)	0.260 (13.07)
Other Controls for Attributes	No	Yes	No	Yes
No. of Observations	945	945	977	803
R^2	0.012	0.017	0.008	0.041

[a] The numbers in parentheses are t-ratios for the null hypothesis of no association.
[b] The controls for the homeowners' equation include the change in the proportion of owner occupied homes with 5 rooms or less, the change in the proportion of one family homes, the change in the proportion of owner occupied mobile homes, the change in the proportion of homes with 2 or more bedrooms, and the change in the proportion of homes with complete kitchens.
[c] The controls for the rental equation include the change in the proportion of rental mobile homes and the change in the proportion of rental units with 2 or more bedrooms.

Table 7: Census Based Estimates of Andrew's Effect on Distribution of Housing Values and Rents[a]

	NOAA / Miami Herald Damage	FEMA Flood Zones		
		Zone AE	Zone AH	Zone X500
Homeowner Values				
Proportion HV < 40K	-0.04 (-0.80)	0.06 (3.78)	0.04 (1.24)	0.02 (0.91)
Proportion 40K < HV < 100K	0.18 (1.89)	-0.01 (-0.40)	0.00 (0.06)	-0.08 (-1.49)
Proportion 100K < HV < 250K	-0.13 (-1.59)	-0.06 (-2.02)	-0.07 (-1.32)	0.07 (1.52)
Proportion 250K < HV < 400K	-0.00 (-0.11)	-0.01 (-0.60)	0.02 (0.99)	-0.01 (-0.90)
Proportion 400K < HV < 500K	0.00 (0.03)	0.01 (2.52)	0.01 (0.72)	-0.00 (-0.54)
Proportion HV > 500K	-0.00 (-0.23)	0.00 (0.82)	0.01 (0.59)	0.00 (0.05)
Rents				
Proportion Rent < 250	-0.05 (-1.54)	0.00 (0.29)	0.02 (0.80)	0.05 (2.71)
Proportion 250 < Rent < 500	0.31 (4.74)	-0.08 (-4.05)	0.02 (0.42)	0.00 (0.11)
Proportion 500 < Rent < 750	-0.21 (-2.60)	0.06 (2.58)	-0.10 (-2.01)	-0.04 (-0.94)
Proportion 750 < Rent < 1000	-0.11 (-1.79)	0.00 (0.19)	-0.01 (-0.18)	0.02 (0.60)
Proportion Rent > 1000	0.06 (1.16)	0.01 (0.66)	0.07 (2.01)	-0.04 (-1.22)

[a] The numbers in parentheses are t-ratios for the null hypothesis of no association.

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Appendix A: Probit Selection Models for Housing Sales

Year Built Fixed Effect	Estimator Parameter
	Dade County
1983	0.101 (0.87)
1984	-0.010 (-0.09)
1985	-0.078 (-0.70)
1986	-0.055 (-0.50)
1987	-0.186 (-1.73)
1988	-0.179 (-1.68)
1989	-0.303 (-2.91)
1990	-0.236 (-2.27)
1991	-0.290 (-2.71)
1992	-0.450 (-4.01)
1993	-0.864 (-8.26)
1994	-0.884 (-8.36)
1995	-0.916 (-8.42)
1996	-0.952 (-8.77)
1997	-1.237 (-10.78)
1998	-1.118 (-9.85)
1999	-- --
Intercept	0.320 (3.36)
Number of Observations	10,534
Pseudo R^2	0.0712