

FLOOD RISK, HOMEOWNER'S FLOOD RISK PERCEPTION AND INSURANCE

by

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(Under the Direction of Susana Ferreira)

ABSTRACT

This dissertation analyzes the perception of flood risk as captured in property prices and in the decision of buying flood insurance. First, we examine whether property price differentials reflecting flood risk increase following a large flood event, and whether this change is temporary or permanent. We use single family residential property sales in Dougherty County, Georgia, between 1985 and 2004 in a difference-in-differences spatial hedonic model framework. After the 1994 “flood of the century,” prices of properties in the 100-year floodplain fell significantly. This effect was, however, short-lived. In spatial hedonic models that explicitly incorporate both linear and non-linear temporal flood-zone effects, we show that the flood risk discount disappeared between four to nine years after the flood depending upon the specification.

Second, in addition to knowing whether a property lies in the floodplain, we use a unique dataset with the actual inundation maps for the city of Albany, GA, to estimate the changes in implicit flood risk premium following the 1994 flood in Georgia. We find that the discount for properties in the inundated area is substantially larger than in comparable properties in the floodplain areas that did not get inundated. This suggests that, in addition to capturing an information effect, the larger discount in inundated properties reflects potential uninsurable flood damages, and supports

a hypothesis that homeowners respond better to what they have visualized (“seeing is believing”).

Third, we determine the market penetration rate for flood insurance in Georgia. Additionally, we estimate a fixed effects model pooling the data from 1978 to 2010 across 153 counties in Georgia to identify the determinants that influence the decision to buy flood insurance at the county level. The empirical analysis supports the hypothesis that income and price significantly influence the decision to buy the flood insurance. Our findings also suggest that recent flood events and the proportion of the county in the floodplain have a significant positive impact on the decision to buy flood insurance. Education level, race and age also have a significant impact on the decision to buy flood insurance.

INDEX WORDS: Flood Risk, Insurance, Spatial Hedonic Models, Fixed Effects Model

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A Dissertation Submitted to the Graduate Faculty of the University of Georgia in Partial
Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2013

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DEDICATION

Dedicated to my parents Mr. Vishwa Mangal Atreya and Mrs. Sabala Atreya.

ACKNOWLEDGEMENTS

I would like to thank my major advisor Dr. Susana Ferreira for her guidance and her invaluable assistance during the development of my dissertation.

I also deeply appreciate my committee members Dr. Jeffrey H. Dorfman, Dr. Elizabeth Kramer and Dr. Warren P. Kriesel, who provided valuable suggestions and insights into the dissertation.

Special thanks to Dr. Susana Ferreira (USGS 104B/Georgia Water Resource Institute project number 2011GA275B), Dr. Warren Kriesel, and the Department of Ag. & Applied Economics for financial support.

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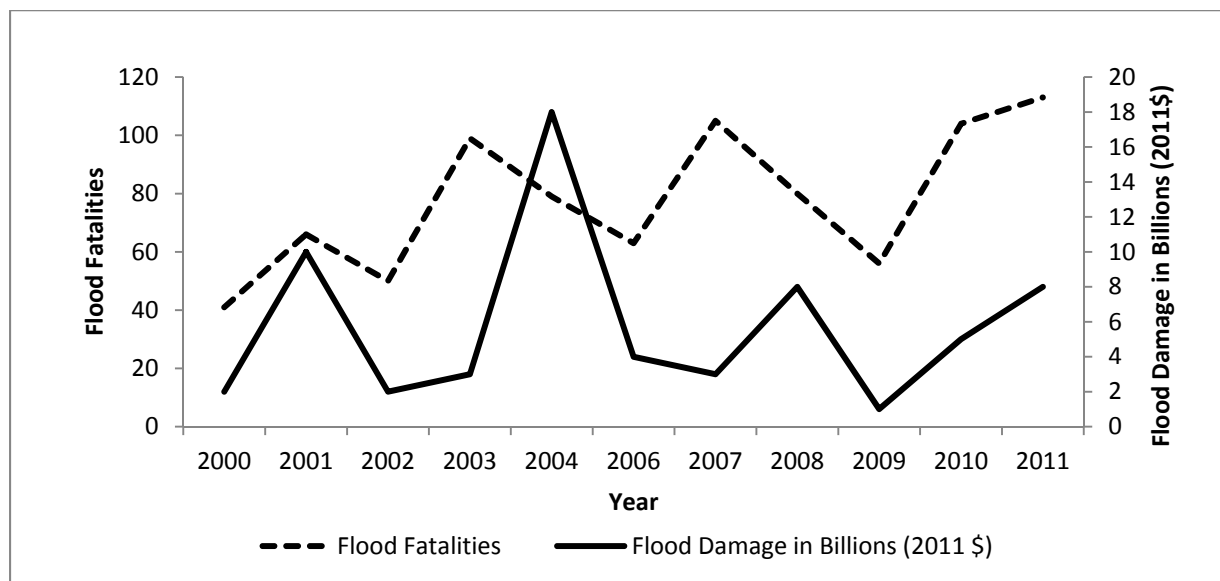
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CHAPTER 1

INTRODUCTION

1.1 Background

Floods account for more losses than any other natural disaster in the United States in terms of property damages, human fatalities, and disaster relief costs (Mitchell and Thomas 2001; King, 2011). Figure 1.1 shows flood damages and flood fatalities in the United States between the years 2000 and 2011. During that period, on average, floods caused damages of \$9.6 billion and 75 deaths per year.¹



Source: Author's calculations from National Oceanic and Atmospheric Administration (NOAA) Hydrologic Information System-Flood Loss Data. Damages and Fatalities from Hurricane Katrina and Rita in 2005 are excluded.

Figure 1.1: Flood Damage and Fatalities in United States (2000-2011)

¹ Even excluding Hurricane Katrina in 2005 (the costliest natural disaster ever in the United States), floods caused on average damages of \$5.4 billion and 71 deaths per year. Hurricane Katrina impacted 90,000 square miles of US coastline, killed more than 1800 people, and created damages to the property and infrastructure in excess of \$100 billion (Cutter et. al, 2006).

Although flood damage fluctuates greatly from year to year, estimates indicate that there is an increasing trend over the past century, despite federal encouragement and local efforts to mitigate flood hazards and regulate development in flood-prone areas (Pielke, et al., 2002). In response to increasing flood events and the damages borne by those events, the National Flood Insurance Program (NFIP), a Federal Emergency Management Agency (FEMA) managed program was established by the National Flood Insurance Act of 1968 to allow homeowners, renters and business owners to purchase insurance against flood losses in participating communities that choose to adopt minimum floodplain management policies. To determine a household's risk, and therefore premiums, Flood Insurance Rate Maps (FIRMs) are produced by NFIP that map 100-year and 500-year floodplains in participating communities. The 100-year floodplain, which is also referred to as a "Special Flood Hazard Area (SFHA)" is an area with a 1% chance of flooding in any given year and a 26% chance of flooding at least once during a 30-year mortgage period. On the other hand, 500-year floodplain, also referred to as "moderate risk area" is the area with 0.2% chance of flooding in any given year and a 6% chance of flooding at least once during a 30-year mortgage period. Few property owners purchased flood insurance in the early years of the NFIP, and in 1973 and 1994; Congress passed laws requiring structures in 100-year floodplain with loans from federally insured or regulated lenders to have flood insurance.

Factors cited by the U.S. Congress Office of Technology Assessment for increased vulnerability to flood damages in the U.S. are new development of areas insufficiently mapped for flood risk, policies such as subsidies that encourage development in floodplains and, most importantly, the growing population in and near floodplains.

Currently, 22 percent of all NFIP policies-in-force are subsidized policies. Subsidized policies are not priced actuarially, meaning they are not priced using hydrologic models that include catastrophic loss year scenarios. FEMA (2002) estimates that subsidized policies charge a premium of only 35 to 40% of what an actuarially fair rate would be. Thus, the subsidized policies prevent the NFIP program from developing a catastrophe reserve (Bin, Bishop and Kousky, 2011). A large portion of the subsidized structures (pre-FIRMs) were built before the FIRMs for a community were available and were offered at discounted rates to encourage communities to join the program. The idea was to have homeowners cover at least some of the costs of flood losses (on the supposition that full rates would be so high that individuals would not insure and thus require more disaster aid), and to prevent the abandonment of otherwise economically viable structures through high premiums (Hayes and Neal 2009).

Increasing population in and near floodplains is of particular interest to our study. Buildings or other structures placed in the floodplain are prone to flood damage; however, both people and capital have been moving into floodplains, driving up the costs when a flood occurs (Montz and Grintfest 1986, Hipple, Drazkowski, and Thorsell 2005). In the United States, as of year 2000, there were over six million buildings located in 100-year floodplains (Burby, 2001). However, over half of U.S. flood losses occur outside the 100-year floodplain, either in the 500-hundred year floodplain (described as having moderate risk) or outside both mapped floodplains (Smith, 2000; Frech, 2005). Between 1990 and 2000, the only years for which comprehensive data is available for population change within the flood-impacted areas, an analysis of US Census data shows that a 17% increase in population took place within the delineated 500-year floodplain (Hipple et. al. 2005).

In the first chapter of the dissertation I analyze homebuyers' understanding of flood risks by examining whether property prices reflect the location in the flood plain in Dougherty County, Georgia. In 1994, Dougherty County suffered the greatest damage due to a major flood (the "flood of the century") caused by tropical storm Alberto. The flood submerged most of South Albany, inundating 4,200 residences with \$99.4 million in damages to residential, commercial and other structures (Formwalt, 1996). We use the 1994 flood event as an information shock and test whether it had an impact on the flood risk discount (i.e. on the perceived flood risk), and whether this impact was persistent over time or it faded in the absence of additional flooding events.

Under the mandatory purchase requirement, homebuyers should be informed if their property is located in the 100-year floodplain well before they purchase it. However, it has been noted that this is not always the case. For example, Chivers and Flores (2002) showed that many homebuyers in Colorado did not know about the flood risk or the cost of flood insurance until the closing or later. In such cases, the flood risk is not conveyed by the location of the property in the floodplain, since the homebuyers are unaware of this information. In some instances the homeowners learn about flood risk the hard way, i.e. after an actual inundation occurs. In addition, due to availability heuristic (Tversky and Kahneman, 1982), a bias in probability judgment, according to which people use the ease of which examples of hazard can be brought to mind as a means of estimating the probability of a hazard, it can be assumed that people respond better to what they have experienced directly, i.e., they respond better to an actual inundation.

In the third chapter of the dissertation I compare the flood risk discount for properties in the actually inundated area to properties in the floodplain but outside the inundated area. Previous studies have used FEMA designated flood hazard maps as a proxy for flood risk

(Shilling et al., 1985; MacDonald et al., 1987; Speyrer and Ragas, 1991; Harrison et al., 2001; Beatley et al., 2002), and specific flood events as an information shock on perceived flood risk (Bin and Polasky, 2004; Carbone et al., 2006; Kousky, 2010). In addition to FEMA hazard maps classifying floodplain areas, we use a map of the area that was not just at risk but inundated by the 1994 flood. By distinguishing between floodplain area and inundated area we can tease out a "pure information effect" associated with being located in the floodplain as captured by the FIRM maps from an "inundation effect" captured by the inundation map. The novelty of this chapter is that we were able to control for the damages caused by the flood by limiting our analysis to a smaller area in Dougherty County for which the damage data were available.

Although properties in the 100-year floodplain are required to buy flood insurance, the effectiveness of this requirement in practice is questionable. Take up rates have been found to be very low in many parts of the country (Tobin and Calfee, 2005). For example, less than 15 percent of the people affected by the 1993 floods in the Midwest had flood insurance, even though they lived on recognized 100-year floodplain. Low take up rates were also found after hurricane Katrina in 2005. Only 40 percent of the residents in Orleans Parish had flood insurance (Hartwig and Wilkinson, 2005). Despite low take up rates and significant flood events where payments exceeded the premium collected, Georgia has never been explored in terms of the demand for flood insurance in Georgia and how well the NFIP is performing in penetrating the market in Georgia. In the third chapter of the dissertation, we determine the flood insurance market penetration rates in counties in Georgia. In addition, we also determine, at the county level, the characteristics of the buyers of flood insurance in Georgia.

1.2 Objectives

This main objective of this dissertation is to determine whether property prices reflect flood risk, and how the perception of flood risk changes in the aftermath of large flood events. We also determine the demand for flood insurance in Georgia. In particular, we answer the following questions:

1. Do homeowners update their flood risk discount following a large flood event? If so, is the change in the perceived risk discount persistent or does it fade over time?
2. Is the shock to the perceived risk discount following a large flood event an “information effect” or an “inundation effect”?
3. What the characteristics of the buyers of flood insurance in Georgia?

Chapters 3, 4 and 5 are structured to answer aforementioned set of questions. A brief discussion of the econometric methods used in those chapters is presented in chapter 2.

CHAPTER 2

ECONOMETRIC METHODS

To address the first two objectives, we use spatial hedonic property models in a difference-difference (DD) framework. The hedonic property model is one of the most widely accepted models for estimating the monetary tradeoffs for quality attributes of private goods and spatially delineated environmental amenities (Palmquist and Smith, 2001). An important econometric issue in hedonic property models concerns the potential spatial dependence of the observations. Neighboring properties are likely to share common unobserved location features, similar structural characteristics due to contemporaneous construction, neighborhood effects and other causes of spatial dependence. Ignoring the problem could result in inefficient or inconsistent parameter estimates (Anselin and Bera, 1998). Thus, in this dissertation we use spatial hedonic property models that account for potential spatial dependence among neighboring properties.

2.1 Spatial Models

It is expected that the spatial dependence- spatial lag and spatial autocorrelation characterizes any spatial data and that a mixture of these effects will be present in housing market cross section data, resulting in a violation of the assumption of the error term being independent and identically distributed (Anselin, 1988; Anselin 2005).² The data used in hedonic property models are spatial in nature because they are based on house sale in a given area and as a result, the OLS estimates of the hedonic property model could be biased and inconsistent (Mueller and

² Spatial lag refers to spatial dependencies across observations of the dependent variable and spatial autocorrelation refers to spatial dependence across error terms.

Loomis, 2008). Much of the literature to handle the spatial dependence was developed following Cliff and Ord (1973, 1981). Spatial dependence in the dependent variable is taken into account by including a right-hand-side variable known as spatial lag. A spatial lag process indicates that values of the dependent variable are related for the reasons beyond sharing similar characteristics (Bell and Bockstael, 2000). Each observation of the spatial-lag variable is a weighted average of the values of the dependent variable observed for the other cross sectional units (Drukker et. al, 2011). On the other hand, the spatial error model handles the spatial dependence through the error term. Maximum likelihood (ML) estimation and generalized two stage least square (G2SLS) estimation are the only two consistent procedures for spatial models that contain a spatially lagged dependent variable as well as a spatially autocorrelated error term (Kelejian and Pucha, 1998). Maximum likelihood estimation requires distributional assumption whereas the G2SLS does not.³ In chapter 3 and 4 we find that the error terms are not normally distributed. Thus, we employ a generalized spatial two stage least squares (GS2SLS) estimator that produces consistent estimates (Arraiz, et al., 2010).

2.1.1 Spatial Lag Dependence Model

Under the assumption that the selling price of a property at a location influences the price of the neighboring properties, spatial dependence of properties is modeled by including a spatially lagged dependent variable into the hedonic property model. This model captures the intuitive idea that the neighboring properties act as an explanatory variable of the property price at a location. As a result spatial lag model takes the form

$$\begin{aligned} \mathbf{y} &= \lambda \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \\ \boldsymbol{\varepsilon} &\sim N(0, \sigma^2) \end{aligned} \quad (2.1.1)$$

³ The Maximum likelihood estimates obtained by using a `spregl` command in STATA are based on the assumption of normality of error term.

where $\mathbf{y}$ is a $n \times 1$ vector of property prices, $\mathbf{W}$ is the pre-specified $n \times n$ matrix of spatial weights which relates the sale price of one property to the sale prices of other properties in the sample, λ is a spatial lag operator, $\mathbf{X}$ is a $n \times k$ matrix of explanatory variables including house structural characteristics, location characteristics and environmental attributes of interest, $\boldsymbol{\beta}$ is a $k \times 1$ vector of parameters to be estimated, and $\boldsymbol{\varepsilon}$ is a $n \times 1$ vector of errors.

2.1.2 Spatial Error Dependence Model

Spatial correlation among regression errors can arise due to erroneously omitting spatially-correlated variable(s) and measurement error or misspecification of the functional form. The location of a house influences its selling price, and nearby houses will be affected by the same location factors. The inclusion of all the location variables is not always fulfilled and thus the effects of all the omitted variables are included in the error term. In such a case, if the omitted variables are spatially correlated so are the error terms. The spatial error model takes the form

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \quad (2.1.2)$$

where

$$\begin{aligned} \boldsymbol{\varepsilon} &= \rho \mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\mu} \\ \boldsymbol{\mu} &\sim N(0, \sigma^2) \end{aligned}$$

ρ is a coefficient in spatially correlated errors, a spatial parameter similar to λ in (2.1.1) and all other notations are as previously defined.

2.1.3 Spatial Weighting Matrix

Spatial weighting matrices parameterize Tobler's first law of geography, "Everything is related to everything else, but near things are more related than distant things". A spatial weights matrix is used to relate an observation at one location to other observations in the system by specifying a neighborhood for each observation. Including a spatial weights matrix in the model corrects for potential problems due to spatial effects, e.g., inefficient parameter estimates. A spatial lag term

Wy weighted by neighbor's proximities to each observation considers a weighted sum of neighboring observations to the dependent variable (**y**). When considering a weighted sum of neighboring errors (**ε**), a proximity-weighted error term **Wε** is created. The spatial weights matrix is based on the prior knowledge about the underlying spatial structure of the variable of interest (**y**) or associated error term (**ε**). If the specification is a good approximation to the reality, it would “correctly” describe the dependence among all neighbors of any given observation.

We use two different types of weights matrices: a contiguity matrix and the inverse distance matrix. The contiguity matrix is based on the shared borders among neighboring properties, whereas the inverse distance matrix is based on the distance between each property. For a contiguity-based matrix, if two polygons are contiguous they are considered neighbors. For a distance-based matrix, a critical value of distance must be specified within which two points are thought to be neighbors. Specifically, a contiguity-based spatial weights matrix (**W**) is typically specified as:

$$w_{ij} = \begin{cases} 1 & \text{if contiguous properties} \\ 0 & \text{otherwise} \end{cases},$$

where w_{ij} is the ij^{th} element of **W**.

A distance-based spatial weights matrix (**M**) is specified as:

$$m_{ij} = \begin{cases} 1/d_{ij} & \text{if } d_{ij} < b \\ 0 & \text{otherwise} \end{cases},$$

where m_{ij} is the ij^{th} element of **M**. The term d_{ij} is the distance between properties i and j calculated based on their latitude and longitude and b is the distance after which the spatial dependence vanishes.⁴ The relationship in the distance-based spatial weights matrix is typically

⁴ A distance of 200 meter is specified in chapter 3 based on the semivariance analysis. Details on the semivariance is discussed in chapter 3

represented as an inverse function of distance. A Distance-based spatial weights matrix is widely used in applications where the data are best represented by points, for example, houses at different locations: the prices/error terms associated with close neighbors are more highly correlated than those of distant neighbors.

2.1.4 A spatial-autoregressive model with spatial-autoregressive disturbances (SARAR)

The combined spatial lag model with the spatial error model is generally referred to as spatial-autoregressive model with spatial-autoregressive disturbances (SARAR) (Anselin and Florax, 1999). The SARAR model takes the form:

$$\mathbf{y} = \lambda \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \quad (2.1.3)$$

where

$$\begin{aligned} \boldsymbol{\varepsilon} &= \rho \mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\mu} \\ \boldsymbol{\mu} &\sim N(0, \sigma^2) \end{aligned}$$

All the notations are as previously defined. The spatial interactions are modeled through spatial lags, and the model allows for spatial interaction in the dependent variables and the error term. Because the model in the above equations is a first-order spatial-autoregressive process with first-order spatial-autoregressive disturbances it is also referred to as a SARAR (1, 1). Setting $\rho=0$ yields a spatial lag model and setting $\lambda=0$ yields a spatial error model. The spatial weighting matrices are taken to be known and non stochastic. In chapter 3 and 4 we use the SARAR model to allow for spatial interactions in the dependent variable as well as spatial considerations through a spatially weighted error structure.

2.2 Difference in Difference (DD) Model

A Difference in Difference (DD) is a quasi experimental method used to measure the difference in average outcome in treatment group before and after treatment minus the difference in average outcome in the control group before and after treatment. To illustrate a DD model, suppose we

wish to evaluate the impact of a flood event or treatment on the property prices. Let there be two groups indexed by treatment status, $T=0, 1$ where 0 indicates properties that do not fall in the floodplain, i.e. the control group, and 1 indicates properties that fall in the floodplain, i.e. the treatment group. Let us also assume that we observe the properties in two time periods, $t=0, 1$ where 0 indicates the time period before the treatment group receives the treatment i.e. pre-treatment, and 1 indicates the time period after the treatment group receives treatment i.e. post-treatment. The properties will therefore, have two observations each, one pre-treatment and one post-treatment. Let p_0^T and p_1^T be the prices of the properties for the treatment group ($T=1$ i.e. the properties in floodplain) before and after the treatment (i.e. before and after the flood), respectively, and let p_0^c and p_1^c be the corresponding prices of the properties for the control group ($T=0$ i.e. the properties outside the floodplain) before and after the treatment. The subscript corresponds to time period and the superscript corresponds to the treatment status (in or out of the floodplain). The price P_i for each individual property is modeled by the following equation

$$p_i = \alpha + \beta T_i + \gamma t_i + \delta(T_i * t_i) + \varepsilon_i$$

Where α is a constant term, β is a treatment group (floodplain properties) specific effect (accounts for difference between treatment and control), γ is time trend common to control and treatment group, δ is a true effect of treatment (i.e. the flood) and ε_i is a random error term. In the above model, the DD estimator is the difference in outcome (prices) in the treatment group (floodplain properties) before and after treatment (flood) *minus* the difference in outcome in the control group (properties outside floodplain) before and after treatment (flood) which is as follows:

$$\hat{\delta}_{DD} = p_1^T - p_0^T - (p_1^c - p_0^c) \quad (2.2.1)$$

Taking the expectation of this estimator we can see that it is unbiased

$$\begin{aligned}
\hat{\delta}_{DD} &= E(p_1^T) - E(p_0^T) - [E(p_1^c) - E(p_0^c)] \\
&= \alpha + \beta + \gamma + \delta - (\alpha + \beta) - (\alpha + \gamma - \alpha) \\
&= \delta
\end{aligned} \tag{2.2.2}$$

Here we are interested in the parameter δ that determine the true effect of the treatment i.e. the true effect of the flood on the floodplain properties. The DD model specification applicable in this dissertation is discussed in the chapters below.

2.3 Fixed Effects Model

In the last essay of the dissertation we use regression analysis to explain the determinants of flood insurance adoption at the county level in Georgia. Although we control for a number of variables relevant to explain insurance adoption decisions (e.g. education, age, race, recent flood etc.), to mitigate the risk of omitted variables bias we use a fixed effects (FE) model. The FE model allows us to control for unobserved county characteristics as long as these are constant over time (Wooldridge, 2001). The key insight is that if the unobserved county characteristics do not change over time, then any changes in the dependent variable must be due to influences other than those fixed characteristics (Stock and Watson, 2003).

Another important assumption of the FE model is that those time-invariant characteristics are unique to the county and should not be correlated with other county characteristics. Also the individuals' error term and the constant (which captures county characteristics) should not be correlated with the others. If the error terms are correlated then fixed effects is not suitable. The fixed effects model takes the form:

$$Y_{it} = \alpha_i + \beta_i X_{it} + \varepsilon_{it}, \tag{2.3.1}$$

where α_i ($i=1 \dots n$) is the unknown intercept for each county (n county specific intercepts)

Y_{it} is the dependent variable where i =county and t =time

X_{it} is the one independent variable and β_i is the coefficient for that independent variable.

ε_{it} is the error term

We pooled data across 153 counties in Georgia for the period 1978-2010 and estimated the fixed effects model. The details on the variables used in the model are explained in chapter 5.

CHAPTER 3

FORGETTING THE FLOOD? AN ANALYSIS OF THE FLOOD RISK DISCOUNT OVER TIME

3.1. Introduction

Floods are the most common natural disaster. Between 1985 and 2009, floods represented 40 percent of all natural disasters worldwide and accounted for 13 percent of the deaths and 53 percent of the number of people affected by all natural disasters (EMDAT, 2010).⁵ In the United States, floods kill about 140 people and cause \$6 billion in property damage in the average year (USGS, 2006). Between 1955 and 2009 economic damages from flooding in the United States amounted to over \$260 billion in constant 2009 dollars.

Flood damage has increased in the United States, despite local efforts and federal encouragement to mitigate flood hazards and regulate development in flood-prone areas (Pielke, et al., 2002). IPCC (2001) and SwissRe (2006) have reported a similar trend across the world. The increased damages are believed to have two causes. The first is an increase in the frequency and intensity of extreme weather events associated with climate change. A warmer climate, with its increased weather variability, is expected to increase the risk of both floods and droughts (Wetherald and Manabe, 2002). The second cause, and of particular interest to this paper, is the increased value of property at risk in hazardous areas (Kunreuther and Michel-Kerjan, 2007). Both capital and people have been moving into flood plains and other high-risk areas (Freeman,

⁵ To be considered a disaster and included in the widely used EM-DAT global disaster database, an event needs to fulfill at least one of the following criteria: (i) 10 or more people killed, (ii) 100 or more people reported affected (typically displaced), (iii) a declaration of a state of emergency, or (iv) a call for international assistance (OFDA/CRED 2010).

2003; IPCC, 2007) driving up the costs, economic and otherwise when a flood occurs. In the United States, as of year 2000, there were over six million buildings located in 100-year floodplains, that is, areas with a 1% chance of flooding in any given year (Burby, 2001). This raises important questions about the perceptions of floods: Do homebuyers have accurate information about flood risks? Do they understand this information? Does the flood risk discount increase following a large flood event? If so, is this effect persistent over time?

Several previous studies have addressed the first two questions, and have shown that a house located within a floodplain sells for a lower market value than an equivalent house located outside the floodplain (Shilling et al., 1985; MacDonald et al., 1987; Speyrer and Ragas, 1991; Harrison et al., 2001; Beatley et al., 2002; Bin and Polasky, 2004; Bin and Kruse, 2006; Bin et al., 2008; Kousky, 2010). However, they also find that if property buyers underestimate the cost of flooding, or if they are relatively unaware of flood hazards, there might be little reduction in the value of properties within a floodplain.

Fewer studies have investigated the third question, or how actual flood events alter flood risk discounts (Skantz and Strickland, 1996; Bin and Polasky, 2004; Carbone et al., 2006; Kousky, 2010; Bin and Landry, 2012). These studies find that after a significant flood event, properties within the floodplain experience a drop in market value compared to equivalent houses located outside the floodplain, and they argue that the event acts as a source of updated risk information. However, the results are mixed. For example, Kousky shows that, after the 1993 flood on the Missouri and Mississippi rivers, property prices in the 100-year floodplain did not change significantly but prices of properties in the 500-year floodplain declined by 2%. On the contrary, Bin and Landry find that it is properties within the 100-year flood plain that were discounted, by between 6% and 22%, after a large flood event. To the best of our knowledge,

these two are the only studies that, in addition, have looked at the fourth question, or at the persistence of changes in the flood risk discount induced by a large flood event. The results in both papers suggest that consumer willingness to pay for a decrease in flood risk after the flood event decays with time. However, in Kousky's analysis the results are statistically insignificant and Bin and Landry's temporal analysis is restricted to post-flood property transactions, starting 3 years after the flood event.

We intend to add to this scarce literature by examining whether changes in the flood risk discount induced by a large flood event in 1994 in Dougherty County, Georgia, are temporary or permanent by accounting explicitly for the number of years since the flood has taken place. We use a difference-in-differences (DD) framework as in Bin and Landry, and Kousky. In addition, our hedonic model accounts for spatial dependence among neighboring properties via a combination of spatial lagging of the dependent variable and correcting for autocorrelation in the error term.

Unlike Kousky but like Bin and Landry, we find a significant increase in the discount for properties in the 100-year floodplain immediately after the flood. The price differential between properties in the 100-year floodplain and those outside the floodplain reached levels between 25% and 44%. The discount for 500-year floodplain properties was insignificant in most of the specifications. Our estimates are above the 6-22% increase identified by Bin and Landry (although their estimates are for three years after the flood and only include the effect of flood i.e. they ignore the baseline flood zone effect which is included in our estimates). The large discount is, however, short lived. We find that it decays rapidly, disappearing four to nine years after the flood depending upon the specification.

The existence of a large discount for properties in the 100-year floodplain in the aftermath of the flood is certainly consistent with flood damages mainly affecting those properties. The 1994 “flood of the century” reached a record depth of 43 feet in the Flint River, inundating over 4,000 properties and causing damages to community infrastructure. Unfortunately, one of the limitations of our paper is that, like previous papers, we do not have information on specific damages to residential properties. However, we do not believe that flood damages are solely responsible for the evolution of the flood risk discount. A marked increase in the number of flood insurance policies in force in Dougherty County immediately after the 1994 flood, followed by a gradual drop in insurance adoption in subsequent years, suggests an increase in the loss probability perceived by homeowners after the flood event that fades over time. This suggests that part of the increase in the discount and its subsequent decay could be explained by the existence of the “availability heuristic” (Tversky and Kahneman, 1973) which is defined as a cognitive heuristic in which a decision maker relies upon knowledge that is readily available (e.g. what is recent or dramatic) rather than searching alternative information sources. Under this explanation, the flood would act as a source of new information heightening flood risk perceptions, but this effect would diminish with time as the recall of the event fades over time.

3.2 Study Area

In 1994, the Flint River overran its banks from the effects of Tropical Storm Alberto, causing a major flood in Southwest Georgia. Dougherty County, where 15 people were killed and almost 78,000 people were displaced by the flood, suffered the greatest damage. Divided by the Flint River into two halves, Dougherty County was founded in the early 1800s and today it is the core of a metropolitan area. Illustrated in Figure 3.1, it has a total area of 334.64 square miles, of which 329.60 square miles are land and 5.04 square miles are water (US Census Bureau, 2010).

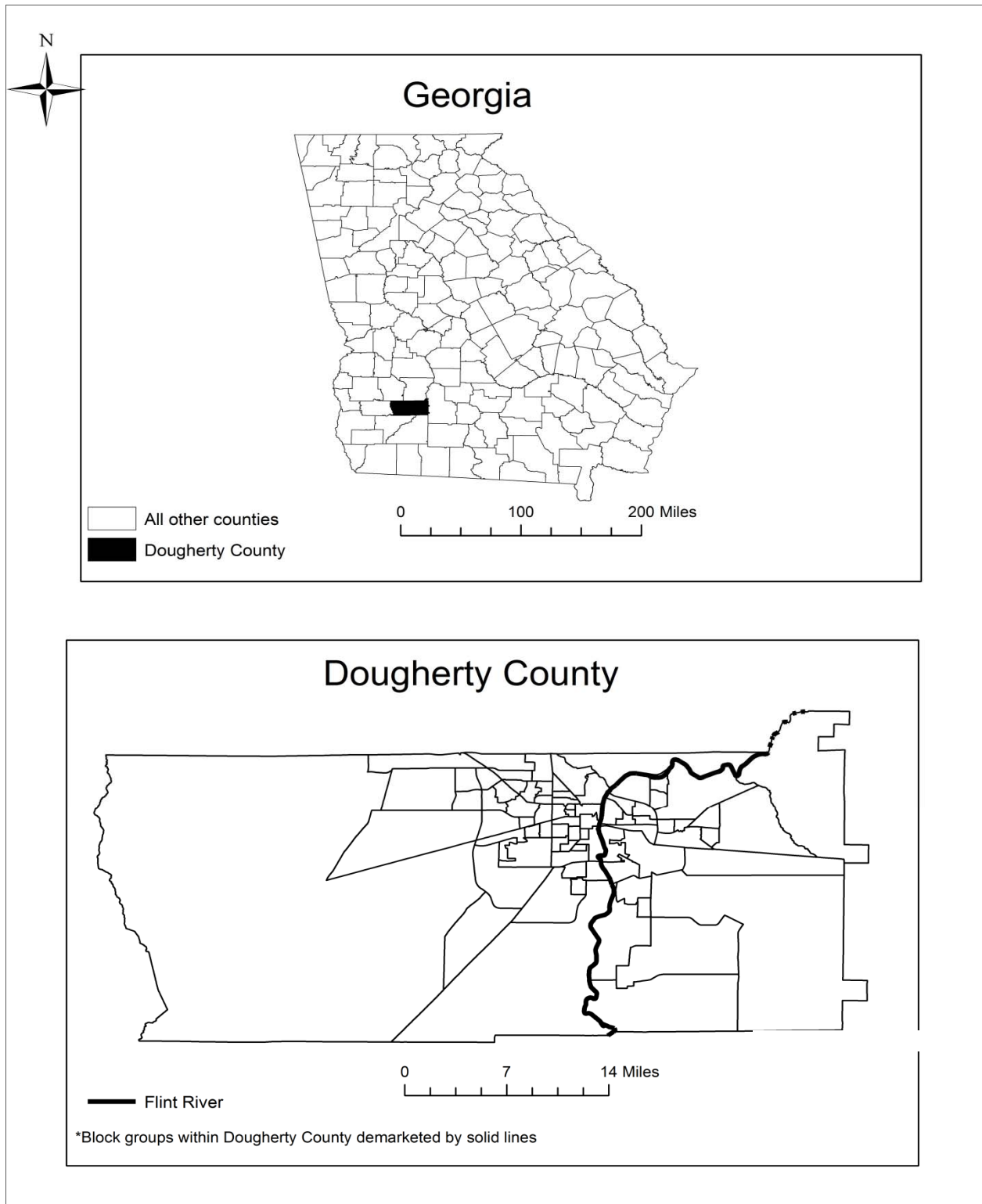


Figure 3.1: Study area -Dougherty County, GA, showing City of Albany and Flint River

The city of Albany was hit worst by the flood. Peak discharges greater than the 100-year flood discharge were recorded at all U.S. Geological Survey (USGS) gauging stations on the Flint River (Stamey, 1996). According to the USGS, the Flint River peaked at a stage about five feet higher than that of a flood in 1925, which was the previous maximum flood ever recorded at Albany. The flood submerged most of South Albany, inundating 4,200 residences with \$99.4 million in damages to residential, commercial and other structures, 62,502 tons of flood debris dumped in landfills, 4,907 workers temporarily unemployed, and \$80 million in home and small business loans issued by the Small Business Administration (Formwalt, 1996).

According to the Federal Emergency Management Agency (FEMA), nearly 20,000 communities across the United States and its territories participate in the National Flood Insurance Program (NFIP). When a community joins the NFIP it agrees to adopt and enforce floodplain management ordinances to reduce future flood damage. In exchange, the NFIP makes federally backed flood insurance available to homeowners, renters, and business owners in these communities. Federal flood insurance was considered to be an economically efficient way to indemnify flood victims and to have individuals internalize some of the risk of property ownership in the floodplains (Dan, 1974). Community participation in the NFIP is voluntary. In order to actuarially rate new construction for flood insurance and create broad-based awareness of the flood hazards, FEMA maps 100-year and 500-year floodplains in participating communities. These hazard zones are mutually exclusive, representing different annual probabilities of flooding; 1% and 0.2% in a given year, respectively. The City of Albany has been a participating community in the NFIP since 1974. All the other parts of Dougherty County joined the NFIP in 1978 (FEMA, 2012a). Most homeowners with mortgages in the 100-year

floodplain are mandated to buy flood insurance, so they should be more aware of the associated flood hazard than homeowners of properties in the 500-year floodplain, who are not required to buy flood insurance. In our analysis we differentiate between the two types of properties. Figure 3.2 is a map of the Flint River, housing units and the associated floodplains for the southwestern part of Dougherty County.

Almost 10.7 percent of the properties sold between the years of 1985 to 2004 fall in the floodplain. Many properties in the designated flood hazard zones had not experienced a flood in decades. At the same time there have been cases of properties outside the 100-year flood zone that have unexpectedly experienced floods. In some cases, individuals in the 100-year flood plain may erroneously think that since they have experienced a flood, there will not be more flooding in 100 years. In these cases the risks and costs associated with living in a flood prone area may not be fully understood by homebuyers.

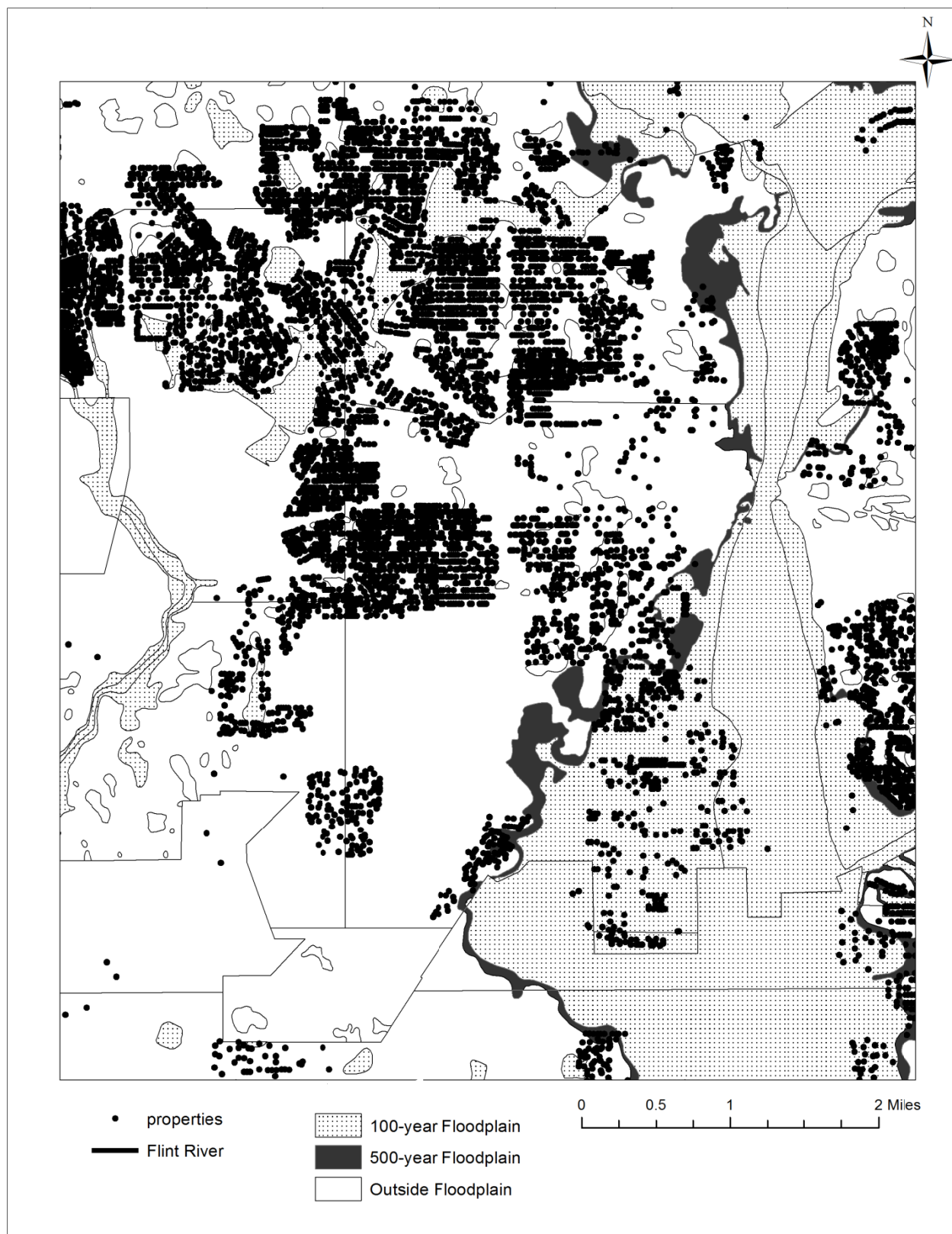


Figure 3.2: Flint River, Housing Units and Associated Floodplains in Dougherty County

3.3 Methods

Hedonic models (Rosen, 1974; Freeman, 2003) have been used extensively to estimate the contribution to the total value of a property of each characteristic possessed by the property. Hedonic property models have also been proven to be an effective tool for estimating the marginal willingness to pay (MWTP) for changes in environmental quality since their early applications in the late 1960s (Halstead, et al., 1997). Like earlier studies we use a hedonic model to determine the shadow value of a non-market environmental attribute: flood risk. In hedonic property models, the price of a property, P , is modeled as a function of structural characteristics, S (e.g. number of rooms, size of the house), neighborhood and location characteristics, L (e.g. distance to rivers, distance to parks, median household income, percent of non-whites in the neighborhood), and an environmental variable of interest, in this case flood risk as captured by location in the floodplain, R .

$$P_{it} = \beta_0 + \beta_1' L_i + \beta_2' S_{it} + \beta_3 R_i + \varepsilon_{it} \quad (3.1)$$

In equation (1) subscripts i and t represent property and time respectively. $\beta_3 = \frac{\partial P_{it}}{\partial R_i}$, the marginal implicit hedonic price for flood risk, should capture the MWTP for a reduction in flood risk for those individuals with no insurance. Under conditions of perfect information and full insurance, it is equal to the sum of the incremental insurance costs and the marginal option value. This marginal option value is associated with the residual risk for non-insurable losses, or the difference between the loss from flooding and the payment from the insurance company. Non-insurable losses include personal items with sentimental value, the risk of injury and death, the hassle of being displaced, damage to community infrastructure, etc. (McDonald et al. 1987).

Regarding the functional form, we performed a Box-Cox transformation of the dependent variable and after comparing the residual sum of squares we concluded that the natural log of price as the dependent variable was the best specification for our model. After testing several transformations of the independent variables, the location variables $\mathbf{L}$ were best fitted in their log form while the other attributes $\mathbf{S}$ were fitted best in their quadratic specification, which is consistent with the functional form used by Bin and Polasky.

To measure flood risk we use two dummy variables, one for the 100-year floodplain and one for the 500-year floodplain. There were around 800 properties in zone D which FEMA defines as “an area of undetermined but possible flood hazard.” These properties were dropped from the analysis, but including them in the 100-year floodplain, or, alternatively in the 500-year floodplain, did not affect the results.⁶ Thus, the hedonic model would be:

$$\ln(P_{it}) = \beta_0 + \beta'_1 \ln \mathbf{L}_i + \beta'_2 \mathbf{S}_{it} + \beta'_3 \mathbf{S}_{it}^2 + \beta_4 100yrFP_i + \beta_5 500yrFP_i + \delta_t + \varepsilon_{it} \quad (3.2)$$

The variable $100yrFP$ (100-year floodplain) in this model is a dummy equal to 1 if the property falls within the 100-year floodplain and 0 otherwise. Similarly, the variable $500yrFP$ (500-year floodplain) is a dummy equal to 1 if the property falls within the 500-year floodplain and 0 otherwise. Year fixed effects (δ_t) were included to capture annual shocks that may affect all of the properties. Throughout, we use heteroskedasticity-consistent standard errors.

In order to determine the effect of the 1994 flood on property prices the DD model traditionally used is:

$$\begin{aligned} \ln(P_{it}) = & \beta_0 + \beta'_1 \ln \mathbf{L}_i + \beta'_2 \mathbf{S}_{it} + \beta'_3 \mathbf{S}_{it}^2 + \beta_4 100yrFP_i + \beta_5 500yrFP_i \\ & + \beta_6 Flood_{it} + \beta_7 100yrFP_i * Flood_{it} + \beta_8 500yrFP_i * Flood_{it} + \delta_t + \varepsilon_{it} \end{aligned} \quad (3.3)$$

⁶ These results are available upon request.

This DD model has been used in previous studies (Bin and Landry; Kousky) to examine the information effects of a natural disaster. In this model, properties that fall within a floodplain are the treatment group and properties outside the floodplain are the control group. The DD design allows us to isolate the effect attributable to the flood from other contemporaneous variables (e.g. macroeconomic changes in the housing market, changes in the local housing market), since the control group experiences some or all of the contemporaneous influences that affect property values in the treatment group but offers lower flood risk. The variable *Flood* is a dummy variable equal to one if the sale happened after the flood (July 1994 in our case). The coefficient on the interaction term between the 100-year floodplain and the flood variable ($100yrFP * Flood$) tells us how the 1994 flood might have affected the prices of properties that are in the 100-year floodplain and that are sold after the 1994 flood. A similar interpretation applies to the 500-year floodplain and the flood dummy interaction.

An important econometric issue in hedonic models concerns the potential spatial dependence of the observations. Neighboring properties are likely to share common unobserved location features, similar structural characteristics due to contemporaneous construction, neighborhood effects and other causes of spatial dependence. Ignoring the problem could result in inefficient or inconsistent parameter estimates (Anselin and Bera, 1998). Testing for the presence of spatial dependence can proceed via maximum likelihood estimation of alternative models and applying appropriate Lagrange multiplier tests. Another approach tests the significance of Moran's I spatial autocorrelation coefficient estimated from the OLS residuals. However, both approaches require the specification of a spatial weights matrix.

As noted by Donovan et al. (2007), the specification of the matrix can be arbitrary and it can influence the outcome of the tests. To minimize the guess work, our analysis follows their

lead and employs a semivariance analysis of the properties. This is a geostatistical technique that was first employed in mining exploration but has since been used in varied fields including environmental health and hydrology (Cressie, 1992). Following Cressie, the semivariance for pairs of parcels is given by:

$$\hat{\gamma}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} (z(x_i + h) - z(x_i))^2, \quad (3.4)$$

where the z values are the parcels' characteristic of interest, x_i refers to the parcels, h is a given distance interval between pairs of parcels (we used 20 meters) and $n(h)$ is the number of parcel pairs within the interval. Spatial dependence is indicated by increasing semivariance as the distance between pairs is increased, i.e. as properties lose their grouping into neighborhoods they become less alike. If the semivariance is plotted over distance, insight into the weights matrix specification can be obtained.

Figure 3.3 displays plots of two semivariances for pairs of properties within 20 meter intervals, going out to 1,000 meters.⁷

⁷ The analysis was conducted within SAS's Proc Variogram.

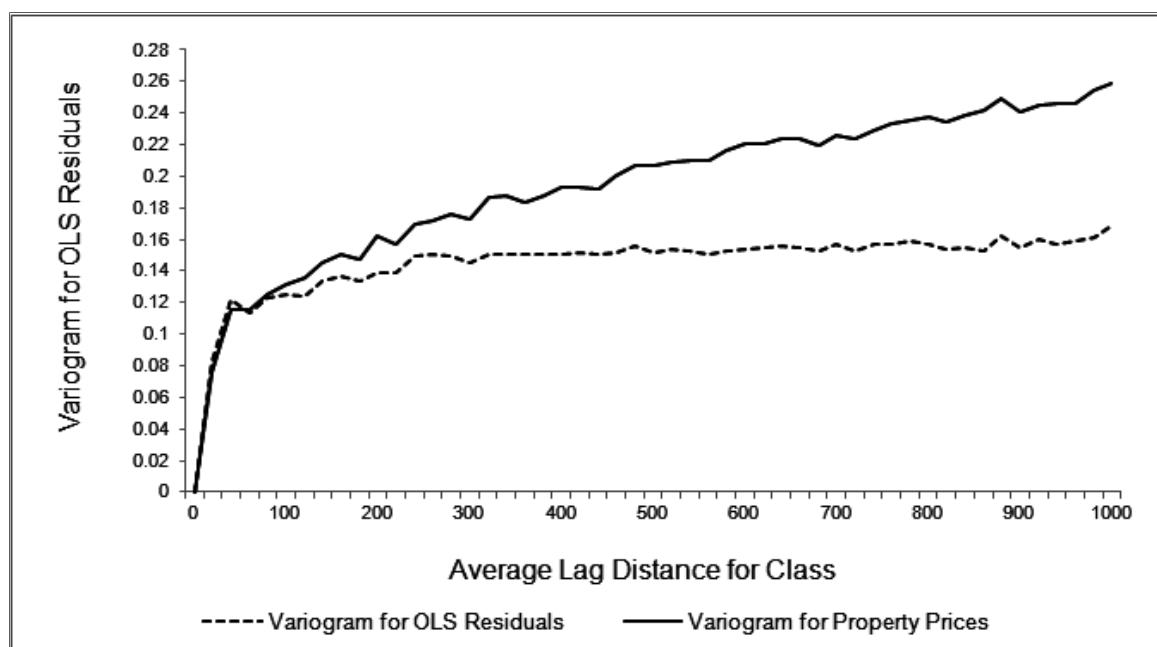


Figure 3.3: Semivariance Graph of Observed (log) Prices and OLS Residuals.

In the lowest plotted line, the regression's residual semivariance increases dramatically in the first intervals up to about 50 meters, then it increases slightly to 200 meters after which it levels off. Within the GIS overlay of Dougherty County, these distances are measured from the parcels' centroids rather than the actual houses. Given the size of the parcels, pairs within 50 meters of each other tend to represent contiguous properties. Pairs within 200 meters of each other are separated by four to six neighboring houses. The second plot of the semivariance of the regression's dependent variable, the logarithm of property price, also increases dramatically from the origin but it continues to increase over the full range of distance intervals. While the prices display the classic symptoms of spatial dependence, the residuals only display a neighbor effect. This comparison of the two plots suggests that the regression model is accounting for the majority of spatial dependence with its set of spatial and neighborhood-level variables.

Concerning the spatial weights matrix, W , this analysis suggests that two different specifications may be appropriate. In our estimation, we use two common parameterizations for

W: a contiguity matrix, where adjacent properties get a weight of one and zero otherwise, and an inverse distance matrix, whose ij element $w_{ij} = \frac{1}{d_{ij}}$, where d_{ij} is the distance between parcels i and j for distances less than 200 meters, and $w_{ij} = 0$ otherwise.⁸ The second specification would be the most appropriate if the additional increase in semivariance between 50 and 200 meters, from 0.13 to 0.15, is large enough to indicate spatial dependence when the first specification does not.

We incorporate the spatial weights matrix, W, into a spatially lagged and autoregressive disturbance model which is frequently referred to as a SARAR model (Anselin and Florax, 1995). The model allows for spatial interactions in the dependent variable, the exogenous variables, and the disturbances. Spatial interactions in the dependent variable are modeled through a spatial lag structure that assumes an indirect effect based on proximity; the weighted average of other housing prices affects the price of each house. The error term incorporates spatial considerations through a spatially weighted error structure which assumes at least one omitted variable that varies spatially leading to measurement error. The general form of our SARAR model is as follows:

$$\begin{aligned} \ln(P_{it}) = & \beta_0 + \lambda \sum_j w_{ij} \ln(P_{jt}) + \beta'_1 \ln \mathbf{L}_i + \beta'_2 \mathbf{S}_{it} + \beta'_3 \mathbf{S}_{it}^2 + \beta_4 100yrFP_i + \beta_5 500yrFP_i \\ & + \beta_6 Flood_{it} + \beta_7 100yrFP_i * Flood_{it} + \beta_8 500yrFP_i * Flood_{it} \\ & + \beta_9 f(years) + \beta_{10} f(years) * 100yrFP_i + \beta_{11} f(years) * 500FP_i + \delta_t + \varepsilon_{it} \end{aligned} \quad (3.5)$$

where $\varepsilon_{it} = \rho \sum_j m_{ij} \varepsilon_{jt} + u_{it}$, and the disturbances u_{it} are assumed to be independent and identically distributed.

⁸ We use a min-max normalized inverse distance matrix since normalizing a matrix by a scalar preserves symmetry and the basic model specification (Drukker et. al, 2011).

In the above model, we expanded the traditional DD model to incorporate a potential decay effect of the risk premium by incorporating an interaction term between the floodplain variables and $f(\text{years})$, where the variable “years” is the number of years after the 1994 flood. We estimated (5) with different functional forms for $f(\text{years})$ including a linear time trend, $f(\text{years}) = \text{years}$, and the non-linear natural logarithm, $f(\text{years}) = \ln(\text{years})$; ratio, $f(\text{years}) = (\text{years} - 1)/\text{years}$; and square root $f(\text{years}) = \sqrt{\text{years}}$. In addition, we introduce λ and ρ ; a spatial lag parameter and a spatial autocorrelation coefficient, respectively. W and M are $n \times n$ spatial weights matrices that are taken to be known and non-stochastic. As in Fingleton (2008), Fingleton and Le Gallo (2008), Kissling and Carl (2008), and Kelejian and Prucha (2010) we assume $W=M$.⁹

The existence of spatial autocorrelation increases the possibility that the errors will not be distributed normally. In fact, the skewness and kurtosis coefficients of the residuals from the OLS regressions were -0.88 and 6.65, respectively indicating that the error term violates normality in our case.¹⁰ Maximum likelihood estimation procedures, such as those used by Bin and Landry, depend on the assumption of normality of the regression error term, while the generalized method of moments approach does not. Thus, we employ a generalized spatial two stage least squares (GS2SLS) estimator that produces consistent estimates (Arraiz, et al., 2010).¹¹

The GS2SLS estimator produces consistent estimates also when the disturbances are

⁹ According to Anselin and Bera, the SARAR model requires that either $W \neq M$ or the existence of one or more explanatory variables. The latter is true for our model.

¹⁰ The Jarque-Bera test for normality of the residuals ($JB=3430 > \chi^2_{\text{critical}}(5.99)$) also indicated that the residuals are not normally distributed.

¹¹ We use the *spreg gs2sls* command in *STATA 12.1* that implements Arraiz et al. (2010) and Drukker, Egger, and Prucha (2009) estimators and allows for both spatial lag and spatial error corrections. The SARAR estimators are produced in four steps: 1) Consistent estimates of β and λ are obtained by instrumental-variables estimation. Following Kelejian and Prucha (1998) the valid instruments are the linearly independent columns of the exogenous variables X , WX , and W^2X , which is used as default by the program. 2) ρ and the variance σ^2 are estimated by GMM using a sample constructed from functions of the residuals. The moment conditions explicitly allow for heteroskedastic innovations. 3) The estimates of ρ and σ^2 are used to perform a spatial Cochrane-Orcutt transformation of the data and obtain more efficient estimates of β and λ . 4) The efficient estimates of β and λ are used to obtain an efficient GMM estimator of ρ .

heteroskedastic, as is our case,¹² while the ML estimator could produce inconsistent estimates in the presence of heteroskedasticity (Arraiz, et al., 2010).

3.4 Data

Our dataset combines individual property sales data for residential homes in Dougherty County from the Dougherty County's Tax Assessor's office for years 1985 to 2004, with a parcel-level GIS database.

In order to use the spatial weight matrices to control for the lag and error dependence in our model, we limit our sample to the most recent sale, i.e. there are no repeated sales.¹³ The property records contain information on housing characteristics (number of bedrooms, number of bathrooms, total square footage, total acres, size of the house, etc.), vector **S** in equations (1)-(5), as well as sale date and sale price. All the property sale prices were adjusted to 2004 constant dollars using the housing price index for the Albany metropolitan area from the Office of Federal Housing Enterprise Oversight (OFHEO).¹⁴

Regarding the proximity and neighborhood variables **L**, GIS was utilized to measure the distance from each property to important features that could influence property values such as nearby major highways, railroads, and amenities such as parks and rivers. The neighborhood characteristics (median household income and percent of non-white residents) were determined at the block group level using 2000 census data.¹⁵ To measure flood risk, we used a GIS layer of

¹² The Breush-Pagan/Cook Weisberg test for heteroskedasticity (646.99) rejected the null hypothesis of constant variance.

¹³ To create an inverse distance matrix the observations must have unique coordinates. For a contiguity matrix the only requirement is that the shape file of the dataset be a polygon.

¹⁴ We use the OFHEO index over other housing price indices such as the Case-Shiller index. While the OFHEO index is available for 363 Metropolitan Statistical Areas (MSAs) including Albany, GA, which is the focus of our study, the Case-Shiller index covers only 20 major MSAs which include Atlanta, but not our study area. Visual inspection of the OFHEO indices for Atlanta and Albany suggests that these are very different real estate markets subject to different demand conditions. The growth rate of Census population figures for the Atlanta MSA was 3.1% per year between 1985 and 2010, but only 0.56% for the Albany MSA.

¹⁵ Block Groups generally contain between 600 and 3,000 people, with a typical size of 1,500 people.

FEMA Q3 flood data to identify parcels in 100-year and 500-year floodplains as represented on flood insurance rate maps (FIRMs) published in 1996.¹⁶

Studies have shown that there are price premiums associated with elevated properties (McKenzie and Levendis, 2010). To see if that is true for Dougherty County, elevation of each property was determined using the GIS file of contour lines, by overlaying the properties on to 1:100,000-scale elevation layers for Dougherty County which is produced by USGS. There could be some houses that were elevated more, especially after the community's admission into the NFIP, to meet the minimum elevation requirements set by the program.¹⁷ In order to capture the additional elevation effect we control for the properties that were built after 1978, i.e. after the NFIP began. We included NFIP as a dummy equal to 1 if the property was built after 1978 (0 otherwise).

After dropping properties for which data were missing, or whose sale price was less than \$4,000 or more than \$500,000, or that were not single family residential properties, 8,042 property transactions were included in the dataset.¹⁸ Table 1 presents their descriptive statistics.

¹⁶ As part of a countywide flood map modernization program, the state of Georgia in cooperation with FEMA published a new floodplain map for Dougherty County in 2009. In our analysis, we choose the 1996 map as the large flood event in our study occurred in 1994 and all of our sales transaction occurred before 2009. In addition, the 1996 map is the first digitized map that incorporates all Dougherty County. Older, non-digitized maps are either for the City of Albany or for the rest of Dougherty County and not for the same year.

¹⁷ Communities participating in the NFIP must fully comply with its building code that requires the lowest floor of any new residential building to be elevated above the base flood elevation.

¹⁸ Properties sold for less than \$4,000 were probably family transfers and not real sales. Since the maximum NFIP coverage is \$250,000, flood insurance is less important for very expensive houses

Table 3.1: Variables and Descriptive Statistics

Variables	Description	Mean	Std. Dev.	Min	Max
Price	Sale price of property adjusted to 2004 constant dollars	83,998	62,720	4,366	426,390
Flood Variables					
100yr FP	1 if 100-year flood zone, 0 otherwise	0.085	0.27	0	1
500yr FP	1 if 500-year flood zone, 0 otherwise	0.022	0.14	0	1
Years	Number of years after 1994 flood	3.96	3.59	0	10
Location Attributes in Meters					
Elevation	Elevation of property	206	17	153	309
River	Distance to nearest river	810	663	3	5,699
Lake	Distance to nearest lake	529	364	0	2,440
Railroad	Distance to nearest railroad	1,896	1,812	17	11,153
Highway	Distance to nearest highway	44	46	0.006	699
Utilities	Distance to nearest utility lines	2,904	1,827	9	13,179
Park	Distance to nearest park	3,468	2,679	57	18,511
School	Distance to nearest school	1,804	2,040	25	15,136
Flint	Distance to Flint River	4,782	3,420	63	21,388
Structural Attributes					
Age	Age of the Property	29	18	1	108
Acres	Total acreage of the property	0.98	5	0.01	266
Bedrooms	Number of bedrooms	3	0.56	1	12
Fullbths	Number of full baths	2	0.69	0	7
Halfbths	Number of half baths	0.17	0.38	0	2
Htdsqft	Heated square feet	1,666	750	352	18,783
Fireplace	Number of fireplaces	0.48	0.57	0	6
Dummy variables					
AC	1 if central AC present, 0 otherwise	0.88	0.32	0	1
Garage	1 if garage present, 0 otherwise	0.17	0.38	0	1
Brick	1 if brick exterior, 0 otherwise	0.01	0.13	0	1
Flood	1 if sold after July 1994, 0 otherwise	0.71	0.44	0	1
NFIP	1 if the property was built after the National Flood Insurance Program, 0 otherwise	0.26	0.44	0	1
Neighborhood Variables (2000 Census By Block Group)					
Income	Median household income	39,102	18,890	6,907	80,000
PcNW	Percent of non-white residents	0.53	0.30	0	1

The average house was 29 years old with the oldest home built in 1885 and the newest built in 2004. The mean property value in 2004 constant dollars was about \$83,998. The mean distance to the Flint River was about 4.8 kilometers. The average of median household incomes in the census block groups was about \$39,102. 71 percent of the properties were sold after the 1994 flood. 26 percent of the houses were built after the NFIP, and the mean elevation was 206 meters. Of all sales between 1985 and 2004, 8.5 percent of the properties were in the 100-year floodplain and 2.2 percent of the properties were in the 500-year floodplain.

Economic theory does not provide definite guidance on the correct data range to be used in hedonic models, except that the contribution of the various characteristics to the value of the house should have been relatively stable over that time period (Palmquist, 2005). Our sample period (1985-2004) covers 10 years before and after the 1994 flood. This time period should be long enough to capture the time trend in the flood risk discount following the 1994 flood, while excluding more recent, post-recession observations. In order to check the stability of the housing attributes during this time period, we performed a series of paired t-tests on the characteristics of the average property before and after the 1994 flood and we failed to reject the null of equal means for the two time periods for most of the attributes.¹⁹ Notably, the proportion of houses in the floodplain, and most of the structural variables, including important attributes such as lot size (acres) and the heated squared footage, are not significantly different across the two sub-samples. Griliches (1971) offers an alternative guide to aggregation over time in hedonic regressions, based on the comparison of the standard errors in the constrained and unconstrained regressions. Aggregation is rejected if the standard error increases by more than ten percent. We compared

¹⁹ In addition, we performed an aggregate paired t-test on pre- and post-flood data whose p-value is equal to 0.30, so again we fail to reject the null of equal means. We also performed a Wilcoxon-Mann-Whitney test for the continuous variables and a chi-square test for the binary variables to examine whether the characteristics of parcels sold differ pre- and post-flood and found that the results matched with the paired t-tests. Results for these tests are available upon request.

the standard error of the regression using the 1985-2004 sample with that of regressions using subsets of the data that utilize shorter time periods (1989-1999, 1985-1994, 1994-2004) and found that the increase in standard error was not larger than 1% in any case, and thus decided on the 1985-2004 sample to capture the decay in the flood risk discount over the longer time period.

3.5 Results

3.5.1 Estimates of the SARAR Model using a Contiguity Matrix

Table 3.2 shows the coefficient estimates of equation (3.5), the SARAR model, using a contiguity matrix as the spatial weights matrix. The columns differ in terms of the functional form of the time-decay effect, $f(\text{years})$.

The significant spatial autocorrelation parameter (ρ) and spatial autoregressive coefficient (λ), towards the bottom of Table 3.2, suggest that for all the specifications there is, in fact, spatial dependence among the properties in our dataset in the expected direction: a positive adjacency effect. We expect a positive λ since, for example, a higher sale price of neighboring properties should result in a higher average sale price, *ceteris paribus*. Conforming to intuition, λ is significant at a 1 percent level and robustly estimated at 0.002 across the specifications, indicating that if the weighted average of neighboring houses' sale price increases by 1 percent, the sale price of an individual house increases by approximately 0.002 percent. Regarding the interpretation of the regression coefficients, in the spatial lag model, marginal effects are calculated by multiplying the estimates times a spatial multiplier, $1/(1-\lambda)$ (Kim, Phipps, and Anselin, 2003). A larger λ means a larger spatial dependence and thus, a larger spatial multiplier.

The coefficient for NFIP is positive and significant, implying that homes constructed under the more stringent building codes, and for which, *ceteris paribus*, expected flood damages should be lower, are worth more. The neighborhood variables, median household income and

percent of non-white residents by block group, have an expected significant positive and negative sign respectively. All coefficients for the structural housing characteristics have the expected sign and most of them are statistically significant.

Table 3.2: SARAR Model Results for Dougherty County using a Contiguity Matrix

VARIABLES	Type of Decay ($f(\text{years})$)			
	years	$\ln(\text{years})$	$(\text{year}-1)/\text{year}$	$\text{sqrt}(\text{years})$
100yr FP	-0.0979* (0.0526)	-0.0977* (0.0526)	-0.0969* (0.0526)	-0.0975* (0.0526)
500yr FP	0.0687 (0.0857)	0.0693 (0.0857)	0.0709 (0.0857)	0.0699 (0.0857)
Flood	0.108** (0.0492)	0.112** (0.0491)	0.117** (0.0490)	0.126** (0.0489)
100yr FP*Flood	-0.287*** (0.0803)	-0.339*** (0.0843)	-0.406*** (0.0923)	-0.477*** (0.102)
500yr FP*Flood	-0.257* (0.147)	-0.236 (0.145)	-0.198 (0.145)	-0.285 (0.178)
$f(\text{years})$	0.00703 (0.0310)	0.107 (0.296)	1.116 (2.817)	0.0629 (0.192)
100yr FP* $f(\text{years})$	0.0470*** (0.00991)	0.211*** (0.0406)	0.559*** (0.104)	0.205*** (0.0376)
500yr FP* $f(\text{years})$	0.0208 (0.0193)	0.0608 (0.0698)	0.0720 (0.158)	0.0635 (0.0666)
NFIP	0.222*** (0.0267)	0.222*** (0.0267)	0.222*** (0.0267)	0.222*** (0.0267)
Elevation	0.00117** (0.000558)	0.00117** (0.000557)	0.00118** (0.000557)	0.00117** (0.000557)
Ln (River)	-0.0353*** (0.00983)	-0.0351*** (0.00983)	-0.0348*** (0.00983)	-0.0352*** (0.00983)
Ln (Flint)	0.0525*** (0.0141)	0.0521*** (0.0141)	0.0518*** (0.0141)	0.0526*** (0.0141)
Ln (lakepond)	-0.0290*** (0.0100)	-0.0291*** (0.0100)	-0.0291*** (0.0100)	-0.0289*** (0.0100)
Ln (Railroad)	-0.00393 (0.00867)	-0.00375 (0.00866)	-0.00370 (0.00866)	-0.00374 (0.00866)
Ln (Highway)	-0.0114* (0.00614)	-0.0114* (0.00613)	-0.0114* (0.00613)	-0.0115* (0.00613)
Ln (Utilities)	-0.0298** (0.0147)	-0.0298** (0.0147)	-0.0301** (0.0147)	-0.0298** (0.0147)
Ln (Park)	-0.0416*** (0.0101)	-0.0416*** (0.0101)	-0.0416*** (0.0101)	-0.0414*** (0.0101)
Ln (school)	-0.0258*** (0.01000)	-0.0258*** (0.00998)	-0.0258*** (0.00997)	-0.0259*** (0.00998)
Acres	0.0121*** (0.00379)	0.0121*** (0.00378)	0.0122*** (0.00378)	0.0121*** (0.00379)

Acresq	-3.46e-05*** (1.34e-05)	-3.46e-05*** (1.34e-05)	-3.50e-05*** (1.34e-05)	-3.45e-05*** (1.34e-05)
Age	0.0327*** (0.00222)	0.0326*** (0.00222)	0.0327*** (0.00222)	0.0327*** (0.00222)
Agesq	-0.000417*** (2.85e-05)	-0.000416*** (2.85e-05)	-0.000417*** (2.85e-05)	-0.000417*** (2.85e-05)
Bedrooms	0.0715 (0.111)	0.0717 (0.110)	0.0717 (0.110)	0.0716 (0.110)
Bedsq	-0.00360 (0.0175)	-0.00357 (0.0175)	-0.00352 (0.0175)	-0.00359 (0.0175)
Fullbths	0.431*** (0.0593)	0.430*** (0.0593)	0.431*** (0.0593)	0.430*** (0.0592)
Fullbathsq	-0.0765*** (0.0156)	-0.0765*** (0.0156)	-0.0766*** (0.0156)	-0.0764*** (0.0156)
Halfbths	0.367*** (0.104)	0.364*** (0.105)	0.362*** (0.105)	0.365*** (0.104)
Halfbathsq	-0.309*** (0.0997)	-0.307*** (0.0999)	-0.304*** (0.100)	-0.308*** (0.0997)
Htdsqft	0.000296*** (3.18e-05)	0.000296*** (3.18e-05)	0.000296*** (3.18e-05)	0.000296*** (3.18e-05)
Htsqftsq	-1.62e-08*** (4.60e-09)	-1.62e-08*** (4.60e-09)	-1.62e-08*** (4.61e-09)	-1.61e-08*** (4.59e-09)
Fireplace	0.0608*** (0.0144)	0.0605*** (0.0144)	0.0603*** (0.0144)	0.0606*** (0.0144)
Garage	0.123*** (0.0207)	0.123*** (0.0207)	0.123*** (0.0207)	0.123*** (0.0207)
AC	0.181*** (0.0263)	0.181*** (0.0263)	0.181*** (0.0263)	0.181*** (0.0263)
Brick Exterior	0.0644 (0.0452)	0.0631 (0.0454)	0.0606 (0.0456)	0.0630 (0.0453)
Ln(Income)	0.208*** (0.0557)	0.207*** (0.0560)	0.206*** (0.0559)	0.207*** (0.0559)
Non-Whites (%)	-0.00344*** (0.000557)	-0.00344*** (0.000559)	-0.00346*** (0.000560)	-0.00345*** (0.000558)
Lambda	0.00206*** (0.000735)	0.00206*** (0.000734)	0.00205*** (0.000734)	0.00206*** (0.000734)
Rho	0.112*** (0.0111)	0.112*** (0.0111)	0.113*** (0.0112)	0.113*** (0.0111)
Year fixed Effects	Yes	Yes	Yes	Yes
Observations	8,042	8,042	8,042	8,042

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The quadratic specification seems to capture diminishing marginal effects for acres, age, full baths, half baths and heated squared footage. The results indicate that proximity to rivers (except for the Flint River), lakes and ponds, highways, utility lines, parks, and schools increases

the property prices significantly. There was a small price premium associated with elevated properties; when evaluated for an average priced home the premium per meter equals almost \$98 across all the decay functions.

The coefficients of the floodplain variable (*100yrFP*) indicate that there was a weakly significant pre-flood discount of about 9% associated with properties in the 100-year floodplain,²⁰ equivalent to \$7,560 when evaluated at the average house price. Previous studies also find that location within the floodplain reduces property values by between 4 to 12%. The flood risk discount is often larger than the capitalized value of flood insurance premiums, indicating the presence of an incremental option value for non-insurable losses. This is the case for our estimates, which are larger than the present value of the insurance premium under discount rates of 3, 5 and 7 percent for an average home. The present value of the flood insurance premium at a 3% discount rate for an average house is equal to \$7,505 (Table 3.3).

²⁰ Note that in a semilogarithmic equation such as (5), the marginal effect of the dummy *100yrFP* in, say, the first column is given by $(\exp(-0.979)-1)*(1/(1-0.00206))=-0.09$ (Halvorsen and Palmquist, 1980). We thank a reviewer for pointing this out. Note that we also take into account the spatial multiplier $1/(1-\lambda)$ when determining the marginal effect.

Table 3.3: Present Value of Flood Insurance Premiums at Various Discount Rates

Value of Houses	Annual Flood Insurance Premium	Present Value of Insurance Premiums Under Discount Rates of		
		3%	5%	7%
\$75,000	\$203	\$ 6,742	\$4,055	\$2,896
\$83,998	\$226	\$ 7,505	\$ 4,514	\$ 3,224
\$200,000	\$540	\$ 17,999	\$ 10,800	\$7,714

Note: The flood insurance premium for an average valued single-family house in the 100-year floodplain, without a basement and with estimated base flood elevation of 3 feet or more, is equal to \$226. This is calculated using 0.27 as the annual post firm construction rate per \$100 of coverage as designated in the NFIP flood insurance manual.

500-year floodplain properties were not discounted significantly before the 1994 flood. This suggests that before the 1994 flood, homebuyers in the 500-year floodplain in Dougherty County (for which the purchase of insurance is not mandatory) were probably unaware of the flood risk and, therefore, the flood risk was not capitalized into property prices.

In a DD framework, assuming that properties outside the floodplain represent a valid control group, the causal effect of the 1994 major flood event on flood prone property values is reflected in the coefficients of the interaction terms between the flood and floodplain dummies. The results in the first column of Table 3.2 indicate that immediately after the 1994 flood, with the linear time decay function, there is a 32% discount for the 100-year floodplain properties. This includes a 9% baseline flood zone estimate, calculated from the coefficient for the *100yrFP*, plus 23% calculated from the *100yrFP*Flood* coefficient.²¹ This discount is equivalent to \$26,880 evaluated for an average priced home in Dougherty County. With the non-linear decay functions the initial increase in risk discount immediately following the flood is even higher with the price differential between 35%-44%. This is consistent with the results of Bin and Landry, i.e. the discounts with non-linear time decay functions are higher than with the linear time trend.

²¹ The discount is calculated following Halvorsen and Palmquist as $(\exp(-0.0979-0.287)-1)*(1/(1-0.00206))=0.320$.

The discount for 500-year floodplain properties was almost 23% with a linear decay function, although weakly significant and not robust across different decay specifications.

The large price drop for the 100-year flood zone properties induced by the flood, however, is not persistent over time. The flood risk decay effect is prominent and statistically significant as indicated by positive and significant $100yrFP*f(years)$ interaction terms across all specifications in Table 3.2. Figure 3.4 depicts the decay of the flood risk discount over time after the 1994 flood. As noted above, these calculations account for the 9% baseline flood zone effect as well as the $100yrFP*f(years)$ term and the spatial multiplier. In the model with a linear decay effect a 100-year floodplain property is discounted by \$24,100 the first year after the flood, by \$21,200 the second year after the flood, and so on.²² For all the decay functions, the pure time effect, $f(years)$, is insignificant, with the flood risk discount vanishing seven to nine years after the flood, point at which it becomes positive.

²² The discount for the first year after the flood is given by $(\exp(-0.0979-0.287+0.0470*1)-1)*(1/(1-0.00206))*83,998=-\$24,135$.

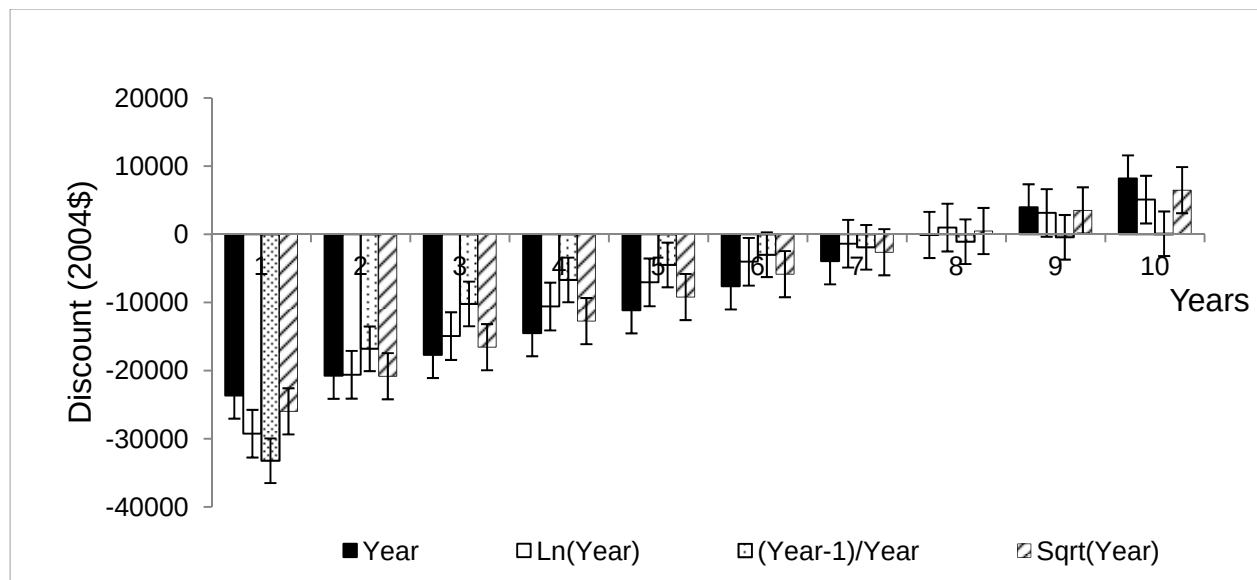


Figure 3.4: Flood Risk Discounts in Dougherty County after the 1994 flood: SARAR Estimates using a Contiguity Matrix, with their Confidence Intervals.

Finally, although our estimates are larger than those in Bin and Landry, it should be noted that, in addition of including the baseline flood zone effect, they are calculated immediately after the flood, while Bin and Landry's temporal analysis starts three years after the flood event.

3.5.2 Estimates of the SARAR Model using an Inverse Distance Matrix

The estimates from the SARAR model using an inverse distance weights matrix are presented in Table 3.4.

Table 3.4: SARAR Model Results for Dougherty County using an Inverse Distance Matrix

VARIABLES	Type of Decay $f(\text{years})$			
	years	$\ln(\text{years})$	$(\text{year}-1)/\text{year}$	$\text{sqrt}(\text{years})$
100yr FP	-0.0261 (0.0549)	-0.0276 (0.0548)	-0.0271 (0.0548)	-0.0272 (0.0548)
500yr FP	0.0756 (0.0894)	0.0757 (0.0895)	0.0776 (0.0896)	0.0763 (0.0894)
Flood	0.116** (0.0484)	0.119** (0.0483)	0.124*** (0.0481)	0.132*** (0.0481)
100yr FP*Flood	-0.292*** (0.0798)	-0.347*** (0.0839)	-0.423*** (0.0916)	-0.470*** (0.101)
500yr FP*Flood	-0.289** (0.145)	-0.268* (0.144)	-0.230 (0.144)	-0.335* (0.177)
$f(\text{years})$	0.0133 (0.0305)	0.157 (0.291)	1.428 (2.758)	0.0967 (0.189)
100yr FP* $f(\text{years})$	0.0425*** (0.00988)	0.197*** (0.0406)	0.541*** (0.103)	0.189*** (0.0375)
500yr FP* $f(\text{years})$	0.0295 (0.0190)	0.0926 (0.0690)	0.138 (0.155)	0.0933 (0.0662)
Lambda	0.0293*** (0.00794)	0.0291*** (0.00792)	0.0287*** (0.00794)	0.0290*** (0.00792)
Rho	1.511*** (0.0899)	1.509*** (0.0897)	1.514*** (0.0899)	1.511*** (0.0899)
Year Fixed Effects	Yes	Yes	Yes	Yes
Structural Attributes	Yes	Yes	Yes	Yes
Location Attributes	Yes	Yes	Yes	Yes
Observations	8,042	8,042	8,042	8,042

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

As in Table 3.2, the columns differ according to how the time-decay effect, $f(\text{years})$, is specified. Table 3.4 only presents the coefficients of interest, but the model includes the same structural and location attributes as in Table 3.2 (full results are available upon request). Using the inverse distance matrix we find that λ is significant and an order of magnitude larger than it was in Table 3.2, which means the inverse distance matrix is accounting for much more spatial dependence than the contiguity matrix. Dependence in the error term is also confirmed by a significant ρ parameter. Although this increase in the spatial multiplier can be offset by changes

in the magnitude of the model beta coefficients, we find that in contrast with results from the contiguity matrix specifications, in Table 3.2, properties in the 100-year floodplain were not discounted before the 1994 flood. Results of the effect of the flood and decay effect are, however, robust. For example, according to the linear temporal decay specification, the price discounts for properties in the 100-year flood plain increased by 26% immediately after the 1994 flood (Figure 3.5). Consistent with the previous models we find a higher discount with the non-linear time decay function $f(years)$, up to a 39% in the case of $\sqrt{years}$. The decay of the negative effect of the flood on property prices was faster than in previous models, however. The flood risk discount for 100-year floodplain properties vanishes and becomes positive four to six years after the flood depending upon the functional form used for the decay function (Figure 3.5).

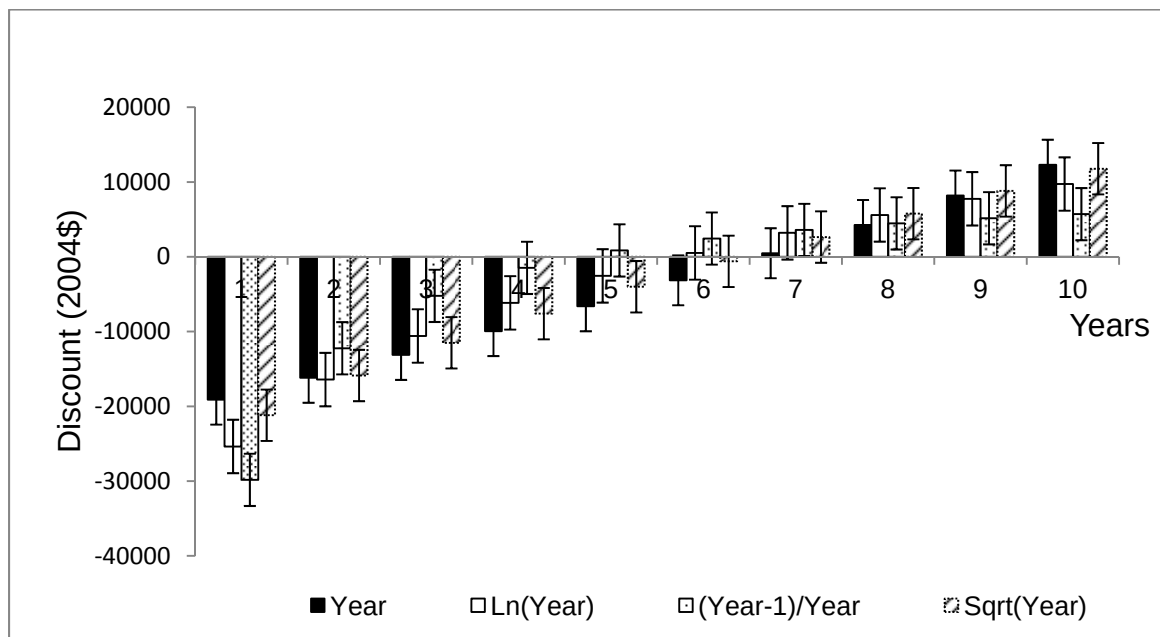


Figure 3.5: Flood Risk Discount in Dougherty County after the 1994 Flood: SARAR Estimates using an Inverse Distance Matrix, with their Confidence Intervals.

3.5.3 Estimates with Year Dummies-Floodplain Interactions

As a robustness check, we estimated all the models using an alternative temporal decay specification with interaction terms between the floodplain and year dummies. This specification allows us to determine the decay in the flood risk discount over the years after the 1994 flood without imposing a particular functional form in the time decay function. The results are presented in Table 3.5.

Table 3.5: Robustness Test: Models with Year Dummies-Floodplain Interaction

VARIABLES	Contiguity Matrix	Inverse Distance Matrix
	lnprice	lnprice
100yr FP	-0.0936** (0.0454)	-0.0202 (0.0483)
500yr FP	0.0723 (0.0812)	0.0871 (0.0818)
Flood	0.139*** (0.0531)	0.144*** (0.0520)
100yr FP*Flood	-0.660*** (0.131)	-0.652*** (0.128)
500yr FP*Flood	-0.171 (0.267)	-0.189 (0.261)
100yrFP*Dum95	0.340** (0.146)	0.271* (0.143)
100yrFP*Dum96	0.592*** (0.150)	0.639*** (0.147)
100yrFP*Dum97	0.630*** (0.157)	0.608*** (0.154)
100yrFP*Dum98	0.564*** (0.155)	0.536*** (0.152)
100yrFP*Dum99	0.594*** (0.159)	0.584*** (0.156)
100yrFP*Dum00	0.852*** (0.152)	0.771*** (0.149)
100yrFP*Dum01	0.804*** (0.161)	0.736*** (0.157)
100yrFP*Dum02	0.838*** (0.150)	0.782*** (0.147)
100yrFP*Dum03	0.659*** (0.147)	0.591*** (0.143)
100yrFP*Dum04	0.730*** (0.148)	0.706*** (0.145)
500yrFP*Dum95	0.0280 (0.306)	0.0371 (0.298)
500yrFP*Dum96	0.190 (0.298)	0.163 (0.290)
500yrFP*Dum97	-0.607* (0.321)	-0.561* (0.311)
500yrFP*Dum98	-0.289 (0.308)	-0.259 (0.300)
500yrFP*Dum99	0.0101 (0.324)	-0.00618 (0.316)
500yrFP*Dum00	0.148 (0.298)	0.182 (0.290)
500yrFP*Dum01	0.360 (0.302)	0.402 (0.296)

500yrFP*Dum02	-0.0391 (0.287)	0.00281 (0.283)
500yrFP*Dum03	0.368 (0.318)	0.392 (0.309)
500yrFP*Dum04	-0.0232 (0.305)	0.0634 (0.298)
Lambda	0.00200*** (0.000739)	0.0287*** (0.00795)
Rho	0.113*** (0.00774)	1.559*** (0.0751)
Structural Attributes	Yes	Yes
Location Attributes	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	8,042	8,042

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We find that, using SARAR estimation, there is a significant pre-flood discount of 9% when using a contiguity matrix, and it is insignificant when using an inverse distance matrix. This result is consistent with the results presented in Tables 3.2 and 3.4. Immediately after the 1994 flood there was an additional large significant discount for 100-year floodplain properties given by the statistically significant $100yrFP*Flood$ variable. As in previous models we also find a significant decay effect of the risk discount which is given by a positive and statistically significant floodplain and year dummy variables. In both specifications, we find that the flood risk discount becomes positive five years after the 1994 flood. The temporal evolution of the flood risk discount from these models, depicted in Figure 3.6, is roughly consistent with that depicted in Figure 3.5 for the spatial model fitted using an inverse distance matrix.

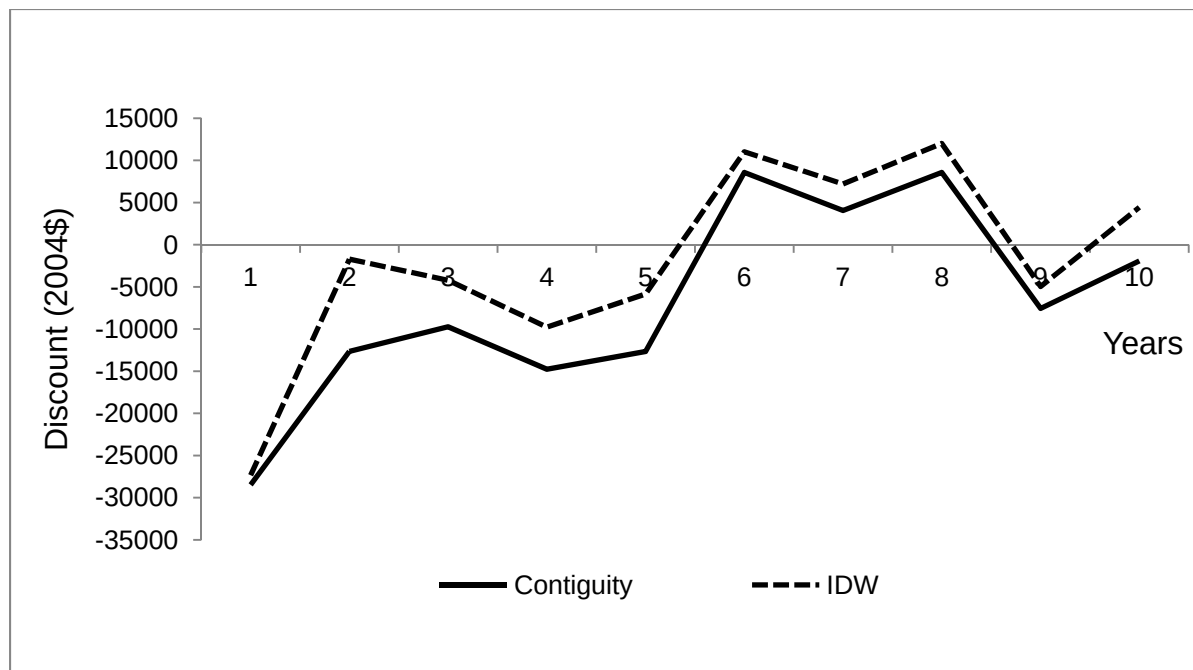


Figure 3.6: Flood Risk Discount in Dougherty County after the 1994 flood: Estimates using the Year Dummies and Floodplain Interaction, for two Spatial Weights Matrices.

3.6 Discussion

This study offers evidence of the effect of a large 1994 flood event on the price of flood-prone properties in Dougherty County, Georgia, while also exploring the degree to which the effect of the flood on property price differentials recedes over time. We account for the spatial dependence of the observations using two versions of a spatially lagged and autoregressive disturbance model. Before the flood, we find some evidence that residents in Dougherty County seemed to be aware of the flood risk in 100-year floodplain properties as suggested by significant price discount estimates in the SARAR model fitted with a contiguity spatial weights matrix. The estimated discount for floodplain properties is larger than the present value of the insurance premium under discount rates of 3, 5 and 7 percent indicating that property buyers may be considering uninsurable losses in their decisions. The discount for properties in the 100-year floodplain increased after the 1994 flood to values varying between 25% and 44% depending

upon how the time effect was specified. However, this effect is transitory. In both spatial regression models the risk discount for 100-year floodplain properties decays rapidly. It vanishes and then becomes positive four to nine years after the flood. The decaying risk premium is consistent with the results of Bin and Landry. They found that the price discount for flood zone location in Pitt County, NC vanished five to six years after Hurricane Floyd.

The finding that there is a significant discount for properties in 100-year floodplain after a major flood event is consistent with the earlier studies. However, we find a comparatively higher discount than previous studies. Part of this difference may be due to the fact that we report the total flood risk discount (i.e. including the pre-flood baseline flood zone effect) immediately after the flood while the study by Bin and Landry analyses the changes starting three years after the flood event.

Together with the large drop in prices of flood-prone properties immediately after the flood, the positive flood effect in the SARAR models four to nine years after the event is consistent with a pattern of flood damages depressing property values initially, and the subsequent reconstruction increasing the post-flood value of affected properties. Tropical Storm Alberto has been called the worst natural disaster ever in the State of Georgia, and Dougherty County suffered more than any other area in terms of monetary damages and lives impacted. More than 9,000 acres of land were flooded in the City of Albany affecting approximately 23% of the residential properties and damaging a number of community facilities and infrastructure. After the flood the City of Albany embarked on an extensive planning process and on award-winning recovery programs. This involved new construction and restoration, as well as expansion and rehabilitation of existing structures. Unfortunately, we do not have detailed information on whether and to what extent properties in our dataset were damaged by the flood,

but there is no evidence that damages to structures were solely responsible for the evolution of the flood risk premium after the 1994 flood.

Additional evidence is presented in Table 2.6 which shows the annual percentage change in the number of flood insurance policies in force in Dougherty County from 1985 to 2004.

Table 3.6: Flood Insurance Policies-in-force in Dougherty County, GA

Year	PIF	% Change
1985	468	3.31
1986	497	6.19
1987	459	-7.64
1988	453	-1.30
1989	465	2.64
1990	592	27.31
1991	560	-5.40
1992	687	22.67
1993	691	0.58
1994	2,840	310.99
1995	3,404	19.85
1996	2,716	-20.21
1997	2,172	-20.02
1998	2,436	12.15
1999	2,229	-8.497
2000	2,180	-2.19
2001	1,973	-9.49
2002	1,908	-3.29
2003	1,897	-0.57
2004	1,877	-1.05

Source: NFIP Legacy Systems Services, 2010

The number of policies in force in 1994 increased by 311%, from 691 to 2,840 after the flood, and in the following year by 20% to a record high 3,404 policies in force. The dramatic increase in the demand for insurance immediately after the 1994 flood suggests an increase in the loss probability perceived by homeowners. This heightened risk perception apparently began its decline in 1996. The demand for flood insurance subsequently fell in the absence of any

additional significant flood events. The decay in risk perceptions is consistent with Tversky's and Kahneman's theory of availability heuristic, a cognitive illusion that is influenced by what is recent or dramatic. As the recollection of a flood experience fades over time, the construction of the availability heuristic based on that event becomes more difficult (Pryce, et al., 2011).

Another potential driver of changes in the price differential between houses inside and outside the 100-year floodplain could be changes in flood insurance premiums. However, insurance rates are exogenous and did not change after the 1994 flood (Susan Bernstein, FEMA, personal communication September 2012). In fact, the national average flood insurance premium per policy between 1994 and 1995 fell by about 3% in real terms (FEMA 2012b). The flood elevation of the first floor of the structure relative to the flood depth on the floodplain determines property-specific flood risk data to guide construction and insurance decisions. Before FEMA began its map modernization programs in 2003, many flood insurance risk maps on which the flood insurance rates are based were 20-25 years old and did not accurately reflect residual risk behind or below flood control structures, giving residents living behind them a false sense of security (King, 2011). Moreover, even if the insurance rates had increased, Kriesel and Landry (2004) show that the purchase of NFIP policies is inelastic with respect to price.

CHAPTER 4

SEEING IS BELIEVING? EVIDENCE FROM PROPERTY PRICES IN INUNDATED AREA

4.1 Introduction

A key element in hazard and disaster management is the understanding of how individuals perceive risk. Risk perception is the subjective assessment of the probability of a specific hazard happening and of the consequences of the negative outcome (Sjöberg, 2000). Individuals in a community may assess the risk of being flooded differently, because there are discrepancies in the probability of the flood hazard (e.g. as homes differ in terms of their location with respect to the floodplain), or in the flow of information about the probability of the flood hazard, for example because individuals are exposed to different scenarios of flooding (e.g. from being actually inundated to merely hearing about a flood event in the media). Intuitively, we would expect the flood risk perception of individuals to be more pronounced in those areas directly hit by a flood.

This paper considers the 1994 "flood of the century" in the city of Albany, Georgia, as a source of flood risk information to homeowners in Albany and determines the changes in implicit flood risk premium following the flood. In particular, we compare the flood risk discount for properties in the actually inundated area to properties in the floodplain but outside the inundated area. In the United States, the Federal Emergency Management Agency (FEMA) uses a system of flood zones to convey information about the severity or type of flooding in those areas. Previous studies have used FEMA designated flood hazard maps as a proxy for flood risk (Shilling et al., 1985; MacDonald et al., 1987; Speyrer and Ragas, 1991; Harrison et al.,

2001; Beatley et al., 2002), and specific flood events as an information shock on perceived flood risk (Bin and Polasky, 2004; Carbone et al., 2006; Kousky, 2010). For example, Kousky finds that property prices in the 100-year floodplain did not change significantly but prices of properties in the 500-year floodplain declined by 2% in St. Louis County, Missouri, following the 1993 flood in the Mississippi and Missouri rivers. Bin and Landry (2012) find that price differentials in Pitt County, North Carolina, increased in the wake of Hurricanes Fran and Floyd. These results suggest the existence of the "availability heuristic" (Tversky and Kahneman, 1973), which is defined as a cognitive heuristic in which a decision maker relies upon knowledge that is readily available (e.g. what is recent or dramatic) rather than searching alternative information sources, when evaluating flood risks. In addition to finding a discount for 100-year floodplain properties after a significant flood event in Dougherty County, Georgia, Atreya et al., 2013 finds that the discount however, is temporary and vanishes four to nine years after the flood. Like any other earlier papers, they were not able to control for the damages caused by the flooding because of the unavailability of damage data for the whole of Dougherty County. However, in this paper, we limit our analysis to a smaller area in Dougherty County for which the damage data were available to be able to control for the damages caused by the 1994 flood. In addition to FEMA hazard maps classifying floodplain areas, we use a map of the area that was not just at risk but inundated by the 1994 flood in Albany to tease out a "pure information effect" associated with being located in the floodplain from an "inundation effect". To the extent of our knowledge, this is the first paper that uses actual inundation maps to determine the effects of flood events on property prices.

We hypothesize that, following a large flood, the discount in properties in the inundated area will be large for two reasons: first, because homeowners in inundated areas are more likely

to have experienced physical damages after the flood, and second, in terms of heightened flood risk perception, because people respond better to what they have experienced directly (“seeing is believing”). While, in principle, under conditions of perfect information and full insurance, flood insurance could cover cleaning and reconstruction costs, an increase in the discount of properties in the inundated area would reflect the incremental insurance costs and the residual risk for non-insurable losses, or the difference between the loss from flooding and the payment from the insurance company. Non-insurable losses include personal items with sentimental value, the risk of injury and death, the hassle of being displaced, damage to community infrastructure, etc.

We use a spatial hedonic property model in a difference-in-difference (DD) framework to determine the impact of the flood event on the estimated flood risk discount and to tease out the “inundation effect” from the “information effect” of a flood. Some studies have shown that flood risk is capitalized into property prices, and the price difference between houses inside and out of floodplain are often consistent with the discounted sum of future flood insurance payments (Harrison, Smersh, and Swartz 2001; Bin and Polasky 2004). Like Bin and Landry (2012) we do not find a significant discount for floodplain properties before the flood, but in the wake of the 1994 flooding event we find a significant, large discount of 20-34% for floodplain properties. Consistent with previous studies (Atreya et. al 2013; Bin and Landry 2012) the flood discount vanishes over time. However, it is not possible to tell whether the estimated discount is the result of a pure information effect or an inundation effect. Many floodplain properties were in fact inundated and we suspect that a big part of the discount arises from the inundation and not from just being located in the floodplain.

To tease out a pure information effect, if any, from an inundation effect we divided our study area into four mutually exclusive groups: inundated and in the floodplain, inundated outside the floodplain, non-inundated and in the floodplain, and non-inundated outside the floodplain. If there is an information effect associated with being located in the floodplain, one might expect to see a discount for non-inundated floodplain properties as well, but our results suggest that this is not the case. We did not find any discount for the floodplain properties when we dropped the inundated properties from the model. The non inundated properties, including those in the floodplain, were not discounted significantly following the flood. Our results suggest that it is an inundation effect rather than a pure information effect that is capitalized into property prices. Despite federal requirement for flood insurance for floodplain properties, the lack of evidence of a pure information effect and of a persistent risk premium suggest limited awareness about flood hazards among buyers of floodplain properties.

4.2 Study Area

The city of Albany was founded in the early 1800s along the Flint River in Southwest Georgia. It comprises a total area of 55.8 square miles (55.5 square miles of land and 0.3 square miles of water, US Census Bureau, 2010). In 1994, a severe flood caused by tropical storm Alberto destroyed parts of downtown and south Albany, causing 15 deaths and displacing almost one-third people. Peak discharges greater than the 100-year flood discharge were recorded at all US Geological Survey (USGS) Flint River gauging stations (Stamey, 1996). At Albany, the Flint River peaked at a stage about 5 ft higher than the 1925 flood, which was the previous maximum flood recorded at that gauging station.

Albany is one of the nearly 20,000 communities across the US and its territories voluntarily participating in the National Flood Insurance Program (NFIP). The NFIP makes

federally backed flood insurance available to homeowners, renters, and business owners in participating communities, that in exchange adopt and enforce floodplain management ordinances to reduce future flood damage. In order to actuarially rate new construction for flood insurance and create broad-based awareness of the flood hazards, FEMA maps 100-year and 500-year flood plains in participating communities.²³ Homes and buildings in high risk flood areas, those with 1% or greater chance of flooding in any given year, and with mortgages from federally regulated or insured lenders are required to have flood insurance.

In addition to FEMA hazard maps, typically used in the literature to model flood risk, we use a map of the area that was actually inundated by the 1994 flood. The USGS along with partners (the National Weather Service (NWS), the U.S. Army Corps of Engineers (USACE), the Federal Emergency Management Agency (FEMA), state agencies, local agencies, and universities), has developed a web-based tool for flood response and mitigation with a major goal of reducing vulnerability of people and areas most at risk from natural hazards. It provides digital geospatial flood-inundation maps that show flood water extent and depth on the land surface. USGS has modeled potential flow characteristics of flooding along a 4.8-mile reach of the Flint River in Albany, Georgia, simulated using recent digital-elevation-model data and the USGS finite-element surface-water modeling system for two-dimensional flow in the horizontal plane. Simulated inundated areas, in 1-foot (ft) increments, were created by USGS for water-surface altitudes at the Flint River at Albany stream gage from 179.5-ft altitude to 192.5-ft altitude. Figure 1 show the study area and the inundated area for a water surface altitude of 192.5 feet at Flint River, which corresponds to the 1994 flood caused by tropical storm Alberto.

²³ 100-year and 500-year floodplain refer to the flooding probability, 1% and 0.2% in a given year, respectively.

4.3 Methods

Following the standard hedonic model (Rosen, 1974; Freeman, 2003), we model the price of a property, P , as a function of structural characteristics, $\mathbf{S}$, (e.g. number of rooms, size of the house), neighborhood and location characteristics, $\mathbf{L}$, (e.g. distance to river, distance to parks), and the location with respect to the inundated area (IND) in addition to the location in floodplain (FP). We use a quasi-experimental Difference-In-Difference (DD) approach to measure the effect of a large flood event on flood prone property prices. A DD model has been used in previous studies (Atreya et. al, Bin and Landry; Kousky) to examine the information effects of a natural disaster. The DD design allows us to isolate the effect attributable to the flood from other contemporaneous variables (e.g. macroeconomic changes in the housing market, changes in local housing markets), since the control group experiences some or all of the contemporaneous influences that affect property values in the treatment group but offers lower flood risk. Following the literature (Bin and Landry, Atreya et al.) the simplest model uses the FEMA designated floodplain maps to measure flood risk in the following specification:

$$\ln(P_{it}) = \beta_0 + \lambda \sum_j w_{ij} \ln(P_{jt}) + \beta_1' \ln \mathbf{L}_i + \beta_2' \mathbf{S}_{it} + \beta_3' \mathbf{S}_{it}^2 + \beta_4 FP_i + \beta_5 Flood_{it} + \beta_6 FP_i * Flood_{it} + \beta_7 f(years) + \beta_8 f(years) * FP_i + \beta_9 Damage_i + \delta_i + \varepsilon_{it} \quad (4.1)$$

In the DD design, FP is a dummy equal to 1 if the property falls in the floodplain and zero otherwise, and the control group are properties outside the floodplain. The variable $Flood$ is a dummy variable equal to one if the sale happened after the flood (July 1994). The interaction term between the Floodplain variable (FP) and $Flood$ tells us how the 1994 flood might have affected the prices of properties that are in the floodplain and that are sold after the 1994 flood.

To examine the persistence of risk premium over time after the 1994 flood we used interaction terms between $f(years)$ and the inundation variable, where “ $years$ ” is the number of

years after the 1994 flood. Previous papers (Bin and Landry, Atreya et al.) find this temporal decay effect to be important. In addition to using the linear time trend ($f(\text{years}) = \text{years}$), we explored an alternative, non-linear functional form, the natural logarithm, $f(\text{years}) = \ln(\text{years})$.

With the variable *Damage* we seek to control for the physical damages of the properties affected by the flood. Unfortunately, we do not have information on flood damages at the structure level (if any) suffered by the properties in the inundated area, so we consider two alternative indicators. First, we considered a second damage variable, the average dollar losses from the 1994 flood at census block level, generated using HAZUS, a software developed by FEMA to estimate flood damages.²⁴ Second, for robustness, assuming that the depth of the flood water acts as a proxy to the degree of structural damages to the properties in the inundated area, we extracted the flood depth in the inundated study area at a gauge height of 43 feet and an altitude of 192.5 feet corresponding to the 1994 flood using a raster map developed by USGS.²⁵ Because inundation depth reflects both flood severity and the ground elevation of a building (Zhai and Fukuzono, 2003), we subtracted the land surface elevation from the model elevation. We hypothesize structural damages to be greater for properties located at higher flood depths, and thus, expect to find a higher price discount for those properties.

We performed a Box-Cox transformation of the dependent variable and after comparing the residual sum of squares we concluded that the natural log of price as the dependent variable was the best specification for our model. After testing several transformations of the independent variables, the location variables *L* were best fitted in their log form while the other attributes *S* were fitted best in their quadratic specification. Year fixed effects (δ_t) were included to capture

²⁴ The HAZUS generated data was provided by Paul P. Hearn, Chief, Research Station, Eastern Geographic Science Centre, U.S. Geological Survey, and Eastern Region.

Retrieved from: <http://wim.usgs.gov/FIMI/FloodInundationMapper.html>

²⁵ The depth value was generated by subtracting the land surface elevation from the model elevation.

yearly shocks that affect all the properties. Subscripts i and t represent property and time respectively.

An important econometric issue in hedonic models concerns the potential spatial dependence of the observations. Neighboring properties are likely to share common unobserved location features, similar structural characteristics due to contemporaneous construction, neighborhood effects and other causes of spatial dependence. Ignoring the problem could result in inefficient or inconsistent parameter estimates (Anselin and Bera, 1998). To account for spatial dependence we use a spatially lagged and autoregressive disturbance model, frequently referred to as a SARAR model (Anselin and Florax, 1995). We incorporate the spatial weights matrix, W and M into the SARAR model. The model allows for spatial interactions in the dependent variable, the exogenous variables, and the disturbances. Spatial interactions in the dependent variable are modeled through a spatial lag structure that assumes an indirect effect based on proximity (i.e. the weighted average of other housing prices affects the price of each house). The error term incorporates spatial considerations through a spatially weighted error structure which assumes at least one omitted variable that varies spatially leading to measurement error.

In equation (4.1) $\varepsilon_{it} = \rho \sum_j m_{ij} \varepsilon_{jt} + u_{it}$, and the disturbances u_{it} are assumed to be independent and identically distributed. w_{ij} and m_{ij} are the elements of W and M , two $n \times n$ spatial weights matrices that are taken to be known and non-stochastic, and λ and ρ are the spatial autocorrelation parameter and spatial autoregressive coefficients, respectively. As in Fingleton (2008), Fingleton and Le Gallo (2008), Kissling and Carl (2008), and Kelejian and

Prucha (2010) we assume $W=M^{26}$. Concerning the spatial weights matrix, W , two frequently used specifications can be appropriate, a contiguity matrix and inverse distance matrix. In our estimation, we used a contiguity matrix, where adjacent properties get a weight of one and zero otherwise.²⁷

In order to explore the inundation effect and, to determine the changes in property prices in the inundated area after the 1994 flood, we used the USGS inundation map of the study area. In the specification below, the control group is composed of properties that are outside the inundated area:

$$\ln(P_{it}) = \beta_0 + \lambda \sum_j w_{ij} \ln(P_{jt}) + \beta_1' \ln L_i + \beta_2' S_{it} + \beta_3' S_{it}^2 + \beta_4 IND_i + \beta_5 Flood_{it} + \beta_6 IND_i * Flood_{it} + \beta_7 f(years) + \beta_8 f(years) * IND_i + \beta_9 Damage_i + \delta_i + \varepsilon_{it} \quad (4.2)$$

where the variable IND (inundation) is a dummy equal to 1 if the property was inundated by 1994 flood and 0 otherwise.

We also divided the properties within the study area into four mutually exclusive groups: inundated and in the floodplain (IN_FP), inundated outside the floodplain (IN_OFP), non-inundated and in the floodplain (NIN_FP) and non-inundated outside the floodplain (NIN_OFP). Table 4.1 shows the number of properties in each group.

²⁶ According to Anselin and Bera, the SARAR model requires that either $W \neq M$ or the existence of one or more explanatory variables. The latter is true for our model.

²⁷ We did not use an Inverse Distance Weights matrix (IDW) because IDW requires the observations to be unique and we would lose half of our observations leading to a substantially smaller sample size.

Table 4.1: Number of Properties in Different Flood Hazard Categories, Albany

Category	Number of Properties
Inundated (IN)	793
Non-Inundated (NIN)	1892
Inside Floodplain (FP)	615
Outside Floodplain (OFP)	2070
Inundated and In Floodplain (IN_FP)	551
Inundated but outside Floodplain (IN_OFP)	242
Non-Inundated and In floodplain (NIN_FP)	64
Non Inundated outside floodplain (NIN_OFP)	1828

Model 4.3 explores the effect of the 1994 flood in these mutually exclusive groups using the properties outside both the floodplain and inundated areas, *NIN_OFP* as the control group.

$$\begin{aligned}
\ln(P_{it}) = & \beta_0 + \lambda \sum_j w_{ij} \ln(P_{jt}) + \beta_1' \ln \mathbf{L}_i + \beta_2' \mathbf{S}_{it} + \beta_3' \mathbf{S}_{it}^2 + \beta_4 IN_FP_i + \beta_5 IN_OFP_i + \beta_6 NIN_FP_i + \\
& + \beta_7 Flood_{it} + \beta_8 IN_FP * Flood_{it} + \beta_9 IN_OFP_i * Flood_{it} + \beta_{10} NIN_FP_i * Flood_{it} + \beta_{11} f(years) + \\
& + \beta_{12} f(years) * IN_FP_i + \beta_{13} f(years) * IN_OFP_i + \beta_{14} f(years) * NIN_FP_i + \beta_{15} Damage_i + \delta_i + \varepsilon_{it}
\end{aligned}
\tag{4.3}$$

Finally, regarding the estimation procedure, Maximum likelihood (ML) estimation and generalized spatial two stage least square (GS2SLS) estimation are the only two consistent procedures for spatial models that contain a spatially lagged dependent variable as well as a spatially autocorrelated error term (Kelejian and Pucha, 1998). Maximum likelihood estimation requires distributional assumption whereas the GS2SLS does not. The Maximum likelihood estimates obtained by using a `speg` command in STATA are based on the assumption of normality of error term. The existence of spatial autocorrelation increases the possibility that the

errors will not be distributed normally.²⁸ Thus, we employ a generalized spatial two stage least squares (GS2SLS) estimator that produces consistent estimates (Arraiz, et al., 2010).²⁹ The GS2SLS estimator produces consistent estimates also when the disturbances are heteroskedastic, as is our case,³⁰ while the ML estimator could produce inconsistent estimates in the presence of heteroskedasticity (Arraiz et al., 2010).

4.4 Data

We used four data sources to construct our dataset: the Dougherty County's Tax Assessor's Office for individual property sales for residential homes in the city of Albany; Georgia's GIS clearinghouse for parcel level Geographic Information System (GIS) data; USGS and FEMA for flood inundation and floodplain maps of Flint River at Albany; and USGS Flood Inundation Mapper to estimate potential losses from the 1994 flood at census block level. Each property is a single-family residence sold between 1985 and 2007.

Individual property sales data contain information on housing characteristics S such as number of bedrooms, number of bathrooms, heated square feet, presence of garage etc. in addition to sale date and sale price P . Property sale prices were adjusted to 2007 constant dollars, using the housing price index for Albany metropolitan area from the Office of federal Housing

²⁸ The Jarque-Bera test for normality of the residuals suggested that the residuals are not normally distributed (Skewness=0.16 and Kurtosis=4.49)

²⁹ We use the *spreg gs2sls* command in *STATA 12.1* that implements Arraiz et al. (2010) and Drukker, Egger, and Prucha (2009) estimators and allows for both spatial lag and spatial error corrections. The SARAR estimators are produced in four steps: 1) Consistent estimates of β and λ are obtained by instrumental-variables estimation. Following Kelejian and Prucha (1998) the valid instruments are the linearly independent columns of the exogenous variables X , WX , and W^2X , which is used as default by the program. 2) ρ and the variance σ^2 are estimated by GMM using a sample constructed from functions of the residuals. The moment conditions explicitly allow for heteroskedastic innovations. 3) The estimates of ρ and σ^2 are used to perform a spatial Cochrane-Orcutt transformation of the data and obtain more efficient estimates of β and λ . 4) The efficient estimates of β and λ are used to obtain an efficient GMM estimator of ρ .

³⁰ The Breush-Pagan/Cook Weisberg test for heteroskedasticity (chi square=48.90, p-value=0.000) rejected the null hypothesis of constant variance.

Enterprise Oversight (OFHEO).³¹ The GIS database was utilized to determine the location attributes of the properties *L* such as proximity to rivers, railroad, major roads, parks etc. The neighborhood characteristics (median household income and percent of non-white residents) were determined at the block group level using 2000 census data.³² The floodplain map published as Q3 data by FEMA was used to determine if the parcel was within or outside the 100-year floodplain.³³ Simulated flood inundation for a water surface altitude of 192.5 feet at Albany's stream gauge corresponding to the 1994 flood was used to determine the inundated area. We confined our study area to the flood inundation study area at Flint River, Albany, prepared by USGS (Figure 3.1), which includes a little over 2,600 single-family residences.

³¹ We use the OFHEO index over other housing price indices such as the Case-Shiller index. While the OFHEO index is available for 363 Metropolitan Statistical Areas (MSAs) including Albany, GA, which is the focus of our study, the Case-Shiller index covers only 20 major MSAs which include Atlanta, but not our study area. Visual inspection of the OFHEO indices for Atlanta and Albany suggests that these are very different real estate markets subject to different demand conditions. The growth rate of Census population figures for the Atlanta MSA was 3.1% per year between 1985 and 2010, but only 0.56% for the Albany MSA.

³² Block Groups generally contain between 600 and 3,000 people, with a typical size of 1,500 people.

³³ We did not consider a separate variable for properties in 500-year floodplain, as there were only 183 properties in this category. In addition, homeowners are not required to buy flood insurance if they are located in 500-year floodplain and therefore might be unaware of the flood hazard associated with being in 500-year floodplain. Results were robust to defining the floodplain variable by merging both the 100- and 500-year floodplain properties. As part of a countywide flood map modernization program, the state of Georgia in cooperation with FEMA published a new floodplain map for Dougherty County in 2009. In our analysis, we choose the 1996 map as the large flood event in our study occurred in 1994 and all of our sales transaction occurred before 2009. In addition, the 1996 map is the first digitized map that incorporates all Dougherty County. Older, non-digitized maps are either for the City of Albany or for the rest of Dougherty County and not for the same year.

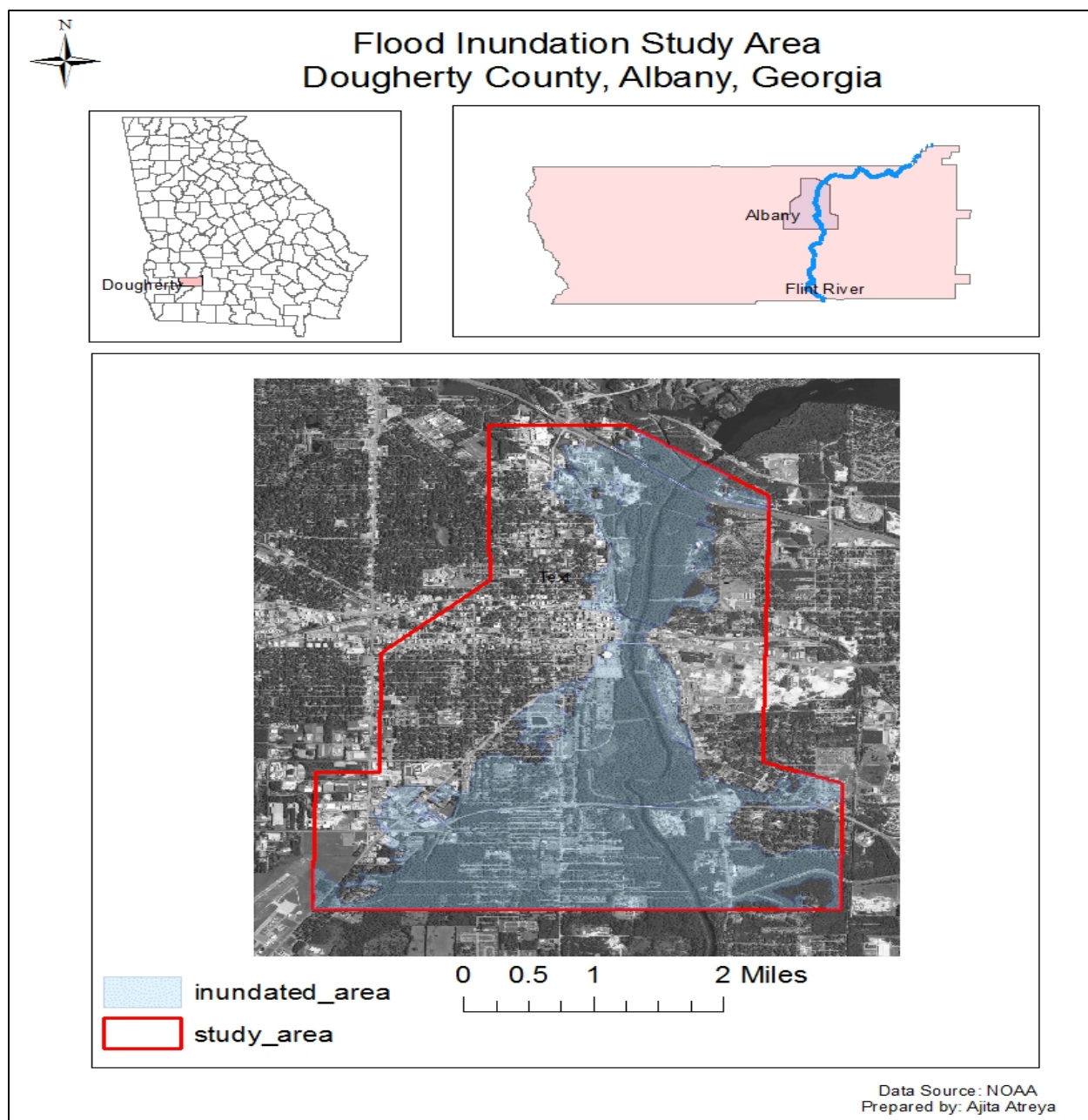


Figure 4.1: Flood Inundation Study Area, Albany, Georgia

Table 4.2 reports the summary statistics for all the variables considered in the analysis. The mean property price was 80,221 in 2007 constant dollars. The oldest property was built in 1883. The average property had 0.26 acres. The maximum elevation was 216 meters and the minimum

elevation 175 meters. Mean distance to the nearest River was 471 meters. Of all the sales between 1985 and 2007, 23% of the properties were in the 100-year floodplain and 29% of the properties in the sample were inundated during the 1994 flood.

Table 4.2: Variables and Descriptive Statistics of “Flood Inundation Study Area”, Albany

Variable	Description	Mean	Std. Dev.	Min	Max
Price	Sale price of Property adjusted to 2007 constant dollars	80,221	153,157	1854	140000
IND	An inundated area during 1994 Flood	29%	45%	0	1
Depth	Flood depth during 1994 Flood (feet)	5.04	2.20	0.09	14.23
Avg_Dam	Average Damage by census block (Thousand\$)	0.37	2.32	0	27.5
Years	Number of years after 1994 Flood	4.88	4.56	0	13
Elevation	Elevation of Property in Meter	191.82	9.32	175	216
River	Distance to Nearest River	671.47	466.20	5.86	2345.59
Lake	Distance to Nearest Lake	727.02	350.74	10.19	1680.89
Railroad	Distance to Nearest Railroad	1044.55	638.91	21.06	2749.45
Roads	Distance to Nearest Road	29.86	22.69	0.02	154.09
Utilities	Distance to Nearest Utility Lines	3461.51	1445.52	734.5	6267.88
Park	Distance to Nearest Park	1771.21	737.00	46.53	3136.76
School	Distance to Nearest School	853.64	434.58	44.47	2036.38
Year built	Year the Property was built	1961.89	22.38	1883	2008
Acres	Total Acreage of the Property	0.26	0.20	0	3.73
Bedrooms	Number of Bedrooms	2.81	0.58	0	8
Fullbths	Number of Full baths	1.31	0.51	1	7
Halfbths	Number of Half Baths	0.10	0.30	0	2
Htdsqft	Heated Square Feet	1195.23	426.54	480	4714
Fireplace	Number of Fireplaces	0.14	0.35	0	1
AC	1 if central AC present, else 0	0.67	0.47	0	1
Garage	1 if garage present, else 0	0.03	0.16	0	1
Brick	1 if Brick exterior, else 0	0.03	0.17	0	1
Flood	1 if sold after July 1994, else 0	0.70	0.46	0	1
FP	1 if 100yr Floodplain, else 0	0.23	0.42	0	1
IN_FP	1 if inundated in FP, else 0	0.21	0.40	0	1
IN_OFP	1 if inundated outside FP, else 0	0.09	0.29	0	1
NIN_FP	1 if non inundated in FP, else 0	0.02	0.15	0	1
NIN_OFP	1 if non inundated outside FP, else 0	0.68	0.47	0	1
Income	Median household income by census block group	20,545	6,110	6,907	42,964
PcBlk	Percent of non-whites by census block group	85%	20%	15.8	100

Economic theory does not provide definite guidance on the correct data range to be used in hedonic models, except that the contribution of the various characteristics to the value of the house should have been relatively stable over that time period (Palmquist, 2005). Our sample period (1985-2007) covers more than 10 years after the 1994 flood. This time period is long enough to capture the time trend in the flood risk discount following the 1994 flood, while excluding more recent, post-recession observations. In order to check the stability of the housing attributes during this time period, we performed a series of paired t-tests on the characteristics of the average property before and after the 1994 flood and we failed to reject the null of equal means for the two time periods for most of the attributes.³⁴ Notably, the proportion of houses in the floodplain, and most of the structural variables, including important attributes such as lot size (acres) and the heated squared footage, are not significantly different across the two sub-samples.

4.5 Results

Table 4.3 reports the SARAR estimates of the DD models presented in Section 3 using a linear time trend ($f(years) = years$) and the average flood damage at the census block level as a proxy for flood damages.

In the first column of Table 4.3, we present the estimates of Model 4.1, which following previous studies simply estimates the effect of the flood on the prices of floodplain properties irrespective of whether the property was inundated or not. We find that properties in the floodplain were sold for 33% less than an equivalent property outside the floodplain immediately following the 1994 flood, which is equivalent to \$26,500 when evaluated at the average price home.³⁵ However, consistent with previous studies that find a temporal decay effect (Atreya et

³⁴ Results for these tests are available upon request.

³⁵ In a semilogarithmic equation such as (1), the marginal effect of the dummy $FP*Flood$ in the first column is given by $(\exp(-0.395)-1)*(1/(1-0.00557)) = -0.33$. (Halvorsen and Palmquist, 1980). Note that, we also take into account the spatial multiplier $1/(1-\lambda)$ when determining the marginal effect.

al., Bin and Landry), we find that the large discount is short lived. Seven years after the flood it is not statistically different from zero.

In the second column, we estimated the effect of the 1994 flood on flood prone properties in the study area as determined by whether they fall in the inundated area or outside the inundated area (Model 4.2). We find that immediately after the flood, properties in the inundated area sold for 39% less than equivalent properties outside the inundated area. Again, we find that the discount for the properties in the inundated area diminished over time vanishing seven years after the flood.

To tease out the effect of being inundated from the informational effect of being in the floodplain, we estimated Model 4.3 wherein we divided the study area into four mutually exclusive groups to see the effect of the 1994 flood in each of these groups. We find that inundated floodplain properties (*IN_FP*) were discounted by 41% immediately after the flood. Similarly, we find a significant discount of 33% for the properties that were inundated but were located outside the floodplain (*IN_OFP*). Interestingly, the non-inundated properties were not discounted significantly even if they were located in the floodplain (*NIN_FP*). This suggests that, it is in fact the inundation effect that is capitalized into property prices. We suspect that the discount seen for the floodplain properties in previous papers that do not control for whether the property was inundated or not is in fact due to the inundation effect rather than the information of being in the flood plain. However, across all the specifications, we find that the price discount is temporary, decaying over time. The parameter estimates of the interaction term between the flood risk variables (*FP*, *IND*, *IN_FP* and *IN_OFP* and the *Years* variable are always positive and statistically significant.

Table 4.3: SARAR Estimates of Difference-In-Difference (DD) Model with Linear Time Trend (Years)

Variables	Model 1	Model 2	Model 3
FP	-0.0664 (0.100)		
FP*Flood	-0.395*** (0.122)		
FP*Years	0.0503*** (0.0126)		
IND		-0.0445 (0.0889)	
IND*Flood		-0.496*** (0.115)	
IND*Years		0.0649*** (0.0115)	
IN_FP			-0.0999 (0.111)
IN_OFP			0.0164 (0.138)
NIN_FP			0.0269 (0.198)
Flood	0.149 (0.196)	0.188 (0.196)	0.183 (0.196)
IN_FP*Flood			-0.526*** (0.129)
IN_OFP*Flood			-0.397** (0.200)
NIN_FP*Flood			0.387 (0.354)
$f(\text{Years})$	-0.000836 (0.00838)	-0.00842 (0.00858)	-0.00555 (0.00868)
IN_FP* $f(\text{Years})$			0.0709*** (0.0134)
IN_OFP* $f(\text{Years})$			0.0458** (0.0179)
NIN_FP* $f(\text{Years})$			-0.0604* (0.0342)
Damage (= census block average damage)	-0.0270*** (0.00870)	-0.0254*** (0.00863)	-0.0236*** (0.00873)
Elevation	0.00358 (0.00317)	0.00412 (0.00318)	0.00333 (0.00328)
Ln(River)	-0.0411 (0.0567)	-0.0204 (0.0529)	-0.0365 (0.0568)
Ln(Lake)	0.0417 (0.0513)	0.0482 (0.0509)	0.0393 (0.0522)
Ln(Railroad)	-0.186*** (0.0300)	-0.186*** (0.0294)	-0.183*** (0.0301)
Ln(Road)	-0.0200 (0.0167)	-0.0201 (0.0167)	-0.0197 (0.0167)

Ln(Utility)	-0.0207 (0.0608)	-0.0348 (0.0584)	-0.0208 (0.0621)
Ln(Park)	-0.237*** (0.0555)	-0.230*** (0.0532)	-0.242*** (0.0560)
Ln(School)	-0.0673* (0.0382)	-0.0692* (0.0382)	-0.0717* (0.0383)
Acres	0.157 (0.189)	0.189 (0.189)	0.172 (0.190)
Acres^2	0.0176 (0.0667)	0.00961 (0.0667)	0.0140 (0.0667)
Age	-0.00175 (0.00282)	-0.00199 (0.00283)	-0.00223 (0.00285)
Age^2	-0.00010*** (3.04e-05)	-9.88e-05*** (3.05e-05)	-9.9e-05*** (3.07e-05)
Bedroom	-0.0226 (0.152)	-0.0356 (0.152)	-0.0317 (0.152)
Bedroom^2	0.00115 (0.0260)	0.00394 (0.0260)	0.00348 (0.0259)
Fullbath	0.0813 (0.128)	0.0925 (0.128)	0.0830 (0.128)
Fullbath^2	-0.0280 (0.0350)	-0.0310 (0.0349)	-0.0299 (0.0349)
Halfbath	-0.383 (0.460)	-0.393 (0.459)	-0.397 (0.459)
Halfbath^2	0.339 (0.446)	0.348 (0.445)	0.350 (0.444)
Heated sqft	0.000361** (0.000173)	0.000344** (0.000173)	0.00035** (0.000172)
Heated Sqft^2	2.17e-08 (4.64e-08)	2.32e-08 (4.63e-08)	2.29e-08 (4.63e-08)
Fireplace	0.0633 (0.0578)	0.0693 (0.0577)	0.0686 (0.0577)
Brick Ext.	0.0286 (0.117)	0.0352 (0.117)	0.0349 (0.117)
AC	0.00520 (0.0455)	0.0104 (0.0454)	0.0106 (0.0454)
Garage	0.0875 (0.112)	0.101 (0.111)	0.0964 (0.111)
Ln(Income)	0.530*** (0.122)	0.537*** (0.121)	0.540*** (0.123)
% of Black	-0.0270 (0.116)	-0.0120 (0.116)	-0.0222 (0.117)
Constant	8.745*** (2.300)	8.378*** (2.310)	8.713*** (2.342)
Lambda	0.00557*** (0.000890)	0.00552*** (0.000894)	0.0056*** (0.000894)
Rho	0.0585*** (0.00501)	0.0591*** (0.00500)	0.0590*** (0.00501)
R-squared	0.185	0.190	0.191
Observations	2,685	2,685	2,685

Robust Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The significant spatial autocorrelation parameter (ρ) and spatial autoregressive coefficient (λ), towards the bottom of Table 4.3 suggest that for all the specifications there is, in fact, spatial dependence among the properties in our dataset in the expected direction: a positive adjacency effect. We expect a positive λ since, for example, a higher sale price of neighboring properties should result in a higher average sale price, *ceteris paribus*. Conforming to intuition, λ is significant at a 1 percent level and robustly estimated at 0.0055-0.0056 across specifications, indicating that if the weighted average of neighboring houses' sale price increases by 1 percent, the sale price of an individual house increases by approximately 0.0055 percent.³⁶ Regarding the interpretation of the regression coefficients, in the spatial lag model, marginal effects are calculated by multiplying the estimates times a spatial multiplier, $1/(1-\lambda)$ (Kim, Phipps, and Anselin, 2003). A larger λ means a larger spatial dependence and thus, a larger spatial multiplier.

Regarding other controls, across all the specifications, the median household income by block group has an expected significant positive sign. Proximity to the railroad, parks and schools increases the property prices significantly as does the heated square footage. We find that a one foot increase in the heated square foot is expected to increase the property price by \$29. Flood damages have an expected negative sign and are significant (at a 1 percent level). As a robustness check, in Table 4.4 we report the SARAR estimates of the DD models for an alternative proxy for flood damages, flood depth. This variable also has a negative sign although it is not statistically significant at the conventional levels. However, the results for the variables of interest are virtually identical: a 34% discount for floodplain properties (*FP*), 40% discount for inundated properties (*IND*), 42% discount for inundated floodplain properties (*IN_FP*) and 33% discount for inundated and outside floodplain properties (*IN_OFP*). As an additional

³⁶ This is a very small impact on the neighboring properties which suggest that the estimated coefficient should be robust to using the traditional OLS model. Confirming to our intuition the OLS results were robust to the SARAR model results.

robustness check, we reestimated the models, this time with a non-linear, logarithmic time trend ($\ln year$) (Table 4.5).

Table 4.4: SARAR Estimates of Difference-In-Difference (DD) Model with Linear Time Trend ($Years$) and alternative definition of damages

Variables	Model 1	Model 2	Model 3
FP	-0.0624 (0.104)		
FP*Flood	-0.417*** (0.122)		
FP*Years	0.0576*** (0.0124)		
IND		0.0426 (0.113)	
IND*Flood		-0.512*** (0.115)	
IND*Years		0.0706*** (0.0114)	
IN_FP			-0.0249 (0.134)
IN_OFP			0.121 (0.154)
NIN_FP			0.0223 (0.198)
Flood	0.0847 (0.195)	0.132 (0.195)	0.133 (0.195)
IN_FP*Flood			-0.547*** (0.129)
IN_OFP*Flood			-0.401** (0.200)
NIN_FP*Flood			0.388 (0.355)
$f(Years)$	0.00413 (0.00826)	-0.00424 (0.00847)	-0.00159 (0.00857)
IN_FP* $f(Years)$			0.0784*** (0.0131)
IN_OFP* $f(Years)$			0.0468*** (0.0179)
NIN_FP* $f(Years)$			-0.0597* (0.0342)
$Damage = \text{flood depth}$	-0.0188 (0.0116)	-0.0275* (0.0165)	-0.0264 (0.0166)
Lambda	0.00541*** (0.000889)	0.00541*** (0.000892)	0.00549*** (0.000891)
Rho	0.0580*** (0.00504)	0.0587*** (0.00504)	0.0585*** (0.00506)
Observations	0.186 2,685	0.191 2,685	0.192 2,685

Notes: Robust Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; all the structural attributes, location attributes, and year fixed effects are included in the model (their estimated coefficients are available upon request).

Table 4.5: SARAR Estimates of Difference-In-Difference (DD) Models for Flood Risk using Logarithmic Time Trend (*lnYears*).

VARIABLES	Model 1	Model 2	Model 3
FP	-0.128 (0.103)		
FP*Flood	-0.230** (0.108)		
FP*Years	0.156*** (0.0508)		
IND		-0.0988 (0.0921)	
IND*Flood		-0.202** (0.101)	
IND*Years		0.140*** (0.0466)	
IN_FP			-0.161 (0.114)
IN_OFP			-0.0220 (0.145)
NIN_FP			-0.0205 (0.204)
Flood	0.131 (0.201)	0.136 (0.199)	0.0298 (0.199)
IN_FP*Flood			-0.240** (0.114)
IN_OFP*Flood			-0.130 (0.174)
NIN_FP*Flood			-0.198 (0.314)
<i>f</i> (Years)	-0.0821*** (0.0239)	-0.0853*** (0.0245)	-0.0878*** (0.0248)
IN_FP* <i>f</i> (years)			0.170*** (0.0536)
IN_OFP* <i>f</i> (years)			0.0710 (0.0766)
NIN_FP* <i>f</i> (years)			0.0930 (0.145)
<i>Damage</i> (= census block average damage)	-0.0312*** (0.00859)	-0.0320*** (0.00856)	-0.0306*** (0.00863)
Lambda	0.00547*** (0.000894)	0.00549*** (0.000895)	0.00551*** (0.000897)
Rho	0.0590*** (0.00509)	0.0589*** (0.00509)	0.0589*** (0.00510)
R-Squared	0.190	0.186	0.191
Observations	2,685	2,685	2,685

Notes: Robust Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; all the structural attributes, location attributes, and year fixed effects are included in the model (their estimated coefficients are available upon request).

As in Table 4.3, we do not find a significant discount for floodplain properties (*FP*) or inundated properties (*IND*) before the 1994 flood. Flood risks are capitalized into property prices only after

the flood as indicated by the interactions of these two variables with the flood dummy. Compared to the linear decay specification, the estimates of Model 4.1 indicate a lower discount of floodplain properties immediately following the flood (but still sizeable at 21%),³⁷ and a slower decay, consistent with a logarithmic specification; the discount is not statistically different from zero nine years after the flood. The same pattern is observed when flood risk is defined in terms of being located in the inundated area (Model 4.2). As before, the non-inundated properties were not discounted significantly after the flood even if they were located in the floodplain (*NIN_FP* is not statistically significant in Model 4.3).

4.6 Conclusions

Natural hazards provide exogenous risk information. Previous studies have found that the information provided by large floods is capitalized into property prices. These studies use floodplain maps to measure flood risk. Our study utilizes a flood inundation map in addition to the traditional FEMA floodplain map to determine the effect of the 1994 flood caused by Tropical Storm Alberto in Albany, Georgia. This allows us to explore whether a potential effect of the flood was borne due to a pure information effect or an inundation effect.

The overall pattern of the findings suggests that there was a discount for floodplain properties only after the flooding, particularly in the floodplain properties that were inundated as well. Our results accord with Tversky and Kahneman's "availability heuristic" (1973), which postulates judgments of probability to be reflective of the availability of information. When the impacts of floods are visualized and remembered, subjective risk probabilities are high, but as the effects of flooding fades over time (e.g. due to reconstruction), subjective probabilities decay and eventually vanish. In absence of additional flooding, the price differential between the

³⁷ Given by $(\exp(-0.23)-1)*(1/(1-0.00547))$.

floodplain properties and the non-floodplain properties did indeed decayed and vanished. However, there was no significant discount associated with properties in the floodplain if they were not in the inundated area. These results suggest that most of the discount in property prices in the area affected by a large flood event comes from being in the actually inundated area, and that not accounting for whether properties in the floodplains are also in the inundated area may overestimate the informational effect of large flood events. In addition to an information effect, the discount in inundated properties captures potential uninsurable reconstruction and psychological costs, and supports a hypothesis that homeowners respond better to what they have visualized (“seeing is believing”). Not accounting for the inundation effect could also lead to underestimating value loss of inundated properties.

CHAPTER 5

AN EVALUATION OF THE NATIONAL FLOOD INSURANCE PROGRAM (NFIP) IN GEORGIA

5.1 Introduction

The National Flood Insurance Program (NFIP), a Federal Emergency Management Agency (FEMA) managed program established by the National Flood Insurance Act of 1968, provides flood insurance coverage to communities that choose to adopt minimum floodplain management policies. Flood Insurance Rate Maps (FIRMs) produced by FEMA depict the location of properties with respect to the floodplain throughout participating communities, to determine household's risk and associated premium. Due to low take-up rates, in 1973, Congress mandated flood insurance to properties in 100-year floodplains with a mortgage from a federally backed or regulated lender. The base flood, or 100-year flood, is a flood event having a 1% or greater probability of occurring in any given year. Homeowners can purchase up to \$250,000 of building coverage and up to \$100,000 of content coverage. However, as of June 2011, there were just over 5.5 million policies in force in the US, still indicating low take-up rates.³⁸

The NFIP has been a subject of tremendous interest since 2005 when it was flooded with claims from hurricanes Katrina and Rita, and was eventually drowned in debt. The program was able to support itself through 2005, but after those hurricanes, the NFIP had to borrow heavily from the treasury and its debt currently exceeds \$17 billion. The claims of the recent hurricane

³⁸ In United States as of year 2000, there were over six million buildings located in 100-year floodplain (Burby, 2000). If the NFIP is enforced correctly there should at least be 6 million policies in force even ignoring the fact that a huge percentage of NFIP policies are bought by those who live outside the 100-year floodplain.

Sandy have further increased the debt of NFIP.³⁹ Since the NFIP does not bring in enough premiums to cover all the incurred cost the program is currently the target of reform and increased scrutiny with questions regarding the effectiveness and distributional implications of NFIP policies. There are ongoing debates regarding who benefits and who bears the cost of this program (Bin, Bishop and Kousky, 2011).

The NFIP is highly concentrated geographically, with 40 percent of all policies in force nationwide located in Florida and close to 70 percent of all policies in force in just five states: Florida, Texas, Louisiana, California and New Jersey (Michel-Kerjan and Kousky, 2010). According to FEMA, for the state of Georgia, between 1978 and 2010 there were 97,723 policies in force, the total premium collected was almost 6.4 million dollars and the total coverage amount was more than 23 billion dollars. Probably because the NFIP policies in force were not as highly concentrated in Georgia as in Florida, between 1978 and 2010 there were four years of large floods (1979, 1990, 1994 and 2009)⁴⁰ where the payouts exceeded the premium collected (as opposed to none in Florida), suggesting that Georgia is not well prepared to cover its costs if a huge flood comes its way, which also makes Georgia an interesting case to determine who is buying the flood insurance.

A recent study by Bin, Bishop and Kousky (2011), determined how the NFIP's price and payouts correlate to per-capita county income. They found that the NFIP has spread costs and benefits fairly uniformly across county income levels. However, in Georgia, as of 2009, there were more than 91,000 NFIP policies in force and over a third of these belonged to homeowners

³⁹ According to FEMA (2013), \$2.95 billion in National Flood Insurance Program payments were made to policy holders after hurricane Sandy. More than \$928.5 million in FEMA grants was approved for individuals and households that include nearly \$800.4 million for housing assistance and \$128.1 million for other needs.

⁴⁰ Large amounts of rainfall over southeastern United States including Georgia resulted in floods in April 1979. Widespread flooding occurred in February and March of 1990 throughout large parts of northwestern and west central Georgia as a result of tropical storm Marco. Tropical storm Alberto caused a widespread flooding throughout most parts of Georgia in 1994. In 2009 a large flood affected several counties throughout northern Georgia.

living or working outside high-risk, i.e. outside 100-year floodplains where the purchase of flood insurance is not required. This scenario suggests that the NFIP in Georgia might be reaching out to certain income groups, probably the wealthiest property owners. Previous studies have shown that houses with higher income purchase a greater amount of flood insurance i.e. flood insurance is a “normal good” (Brown and Hoyt, 2000; Kriesel and Landry, 2004; Landry and Jahan-Parvar, 2008).

There are three basic goals of NFIP: to better indemnify individuals for flood losses through insurance; to reduce flood damages through management and regulation; and to reduce federal expenditures for disaster assistance and flood control (FEMA, 2002). Effective loss prevention at the individual, local, state and federal levels must begin well before a flood event. However, the performance of NFIP is, most of the time, evaluated only after significant losses, for example, after hurricanes Katrina and Rita. In order to avoid this for the state of Georgia, it is important to begin by understanding the demand for flood insurance.

One of the first empirical analyses that examined homeowner’s demand for flood insurance was provided by Browne and Hoyt (2000). Their analysis was aggregated at the state level. They found a small negative price effect and positive income effect on flood insurance demand suggesting that the demand for insurance at the state level does not appear to be very price sensitive, and states with higher average income tend to exhibit greater flood insurance demand. Kriesel and Landry (2004) use household level data from the coastal zone to examine participation in NFIP for nine southeastern U.S. counties. They find a positive income effect and price inelastic demand for flood insurance. Michel-Kerjan and Kousky (2010) explore the flood insurance market in Florida using county-level and individual policy-level data. They find that

policyholders choose the lowest level of deductible (\$500), and while the floods of 2004 increased the coverage level, the deductibles have decreased in Florida.

In this paper we examine the demand for flood insurance in Georgia. Although historically Georgia has been hit by many significant flood events, the case of Georgia has never been explored before. The data used in our paper are aggregated at the county level including coastal as well as inland counties. We first estimate county-level market penetration rates, that is, the proportion of households in a county that have purchased flood insurance. As expected, flood insurance market penetration rates are highest in coastal counties where the proportion of land in the floodplain is higher. This result supports the finding by Dixon et al. (2006) that the probability of purchasing insurance is substantially higher in communities subject to coastal flooding than in communities that are not. Second, we estimate an econometric model for the flood insurance purchasing decision in terms of county characteristics. Unlike previous studies, we account for household characteristics such as the education level, race and age. In addition, we control for flood risk with variables measuring the proportion of land in the county in the floodplain and variables referring to previous flood damages and disaster relief.

The results indicate that income and price significantly influence the decision to buy flood insurance. Brown and Hoyt (2000) estimated the price elasticity of demand for flood insurance to be -0.32. Consistent with this study we estimate the price elasticity at -0.24 to -0.26 depending upon the specification. We find the income elasticity to be positive and statistically significant consistent with the previous studies (Brown and Hoyt, 2000; Kriesel and Landry, 2004) in a random effects model. We also find that recent flood events have a significant positive impact on decision to buy flood insurance which is consistent with Kunreuther's (1990) hypothesis that risk perception influence insurance purchasing behavior. However, we find that

disaster relief effort do not influence the decision to purchase the flood insurance. We find that education level and age have a significant impact on the decision to buy flood insurance.

5.2 Literature Review

5.2.1 National Flood Insurance Program

In the United States, providing public relief for private damages caused by disasters dates back to at least 1794, when Congress passed a Bill providing compensation to unidentified victims of disasters (Landis, 1998). Congress passed at least 128 specific legislative acts offering *ad hoc* relief from floods, fires and other disasters between 1803 and 1947 (Moss, 1999).

The National Flood Insurance Act of 1968 created the NFIP, as a voluntary partnership between the federal government and local communities. Since the inception of the NFIP, the program have been responsible for several key functions: developing the flood map, establishing the deductible/limit menu, and setting associated premiums-including establishing rules to determine subsidized premium for certain existing properties (Michel-Kerjan, 2010).

A significant political problem with the NFIP lies in its implementation. Effective flood damage prevention depends a great deal on the ability and willingness of community planners and property owners to adapt to the program. In a survey conducted after a decade of the NFIP establishment it was found that only 12 percent or fewer responding individuals of a community participating in the NFIP were aware of the building codes or land use regulations to mitigate flood damage; and only 1 percent were aware of the insurance mechanism to manage flood risk (Kunreuther et al, 1978).

In addition to problems with the implementation of the NFIP, hurricane Katrina in 2005 demonstrated that the federal flood insurance was insufficient to secure all policy holders and restore the damage. Limitations on federal claims and the unwillingness of private insurers to

pay for storm-related damages left some policyholders unable to rebuild. Despite the limitations on federal flood insurance claims, hurricane Katrina still led to a debt of almost \$17 billion to the U.S. Treasury.

Various proposals regarding the reform of NFIP have been suggested since Katrina brought NFIP to the front of the policy agenda, which include long-term contracts instead of one-year renewable policies (Kunreuther and Kerjan, 2010); using federal funds to compensate existing landowners and targeting properties deemed high-risk or environmentally sensitive to purchase flood insurance (Barnhizer, 2003).

5.2.2 Theory and Empirics: Flood Insurance Coverage

The demand for flood insurance varies across individuals since each individual has a different attitude towards flood risk. The estimation of the decision to buy flood insurance becomes challenging due to unobserved and varying attitudes towards the flood risk. Economically, the decision to purchase flood insurance, given the varying attitudes of the individuals, can be based on a model of expected utility maximization (e.g. Varian, 1994). The expected utility model for an individual with a property valued at W ; probability p that a flood will cause a capital loss of L ; and insurance payment of πq where π is the actuarial estimate of the probability of a loss and q is the amount the insurance will pay if the loss happens, is given by:

$$\text{Max}\{pU(W - L - \pi q + q) + (1 - p)U(W - \pi q)\}, \quad (5.1)$$

where the individual's expected well-being is the probability-weighted sum of monetary well-being under both outcomes. Maximized expected utility is found by differentiating this function with respect to the level of insurance coverage, q , and setting the first order condition equal to zero which gives:

$$\frac{U'(W - L + q^*(1 - \pi))}{U'(W - \pi q^*)} = \frac{1 - p}{p} * \frac{\pi}{1 - \pi}, \quad (5.2)$$

where U' is the marginal utility and q^* is the optimum coverage. This condition states that the property owner will purchase insurance coverage up to the point where her marginal rate of substitution between consumption under the two outcomes is equal to the price ratio.

Under risk aversion the expected utility function is concave, i.e. $U''(W) < 0$, and it follows that if insurance is actuarially fair, that is if $p = \pi$, then the total amount of wealth in each state must be equal (given that the marginal utilities in each state are equal) which leads to $L = q^*$. Therefore a risk averse individual will purchase an amount of insurance coverage that fully protects her against the potential loss under full coverage.

However, NFIP does not ensure full protection, and the partial protection depends on the availability of maximum coverage rather than on the degree of risk aversion. Flood insurance coverage on structures is capped at \$250,000, which restricts the range of q , though this limit is not binding for the majority of properties (Michel-Kerjan and Kousky 2008). Under common assumptions, demand for insurance coverage is decreasing in price and increasing in risk factors (π and L). For actuarially unfair insurance ($p \neq \pi$), the relationship between demand and wealth (W) depends upon the nature of risk aversion (Schlesinger 1981, Cummins and Mahul 2004).

Studies have shown that purchasing insurance can lead to moral hazard. Moral hazard implies a behavioral change by economic agents in response to a policy or program that makes them less careful about their actions than true losses would dictate, effectively changing the likelihood of incurring those losses (Zahran et.al. 2008). Boulware (2009) argues that the NFIP creates a moral hazard, encouraging development by under-pricing insurance in developable areas with increased flood risk. Due to the reduced cost of associated floodplain insurance homeowners are more willing to move into high flood risk areas, increasing the overall social cost through the now larger population residing in high-risk areas. At the start of 2010, there

were 8.6 million people living within the 100-year Coastal Flood Hazard Area (CFHA), comprised by coastal areas with 1% or larger annual chance of getting flooded every year (Crowell et. al, 2010). Browne et al. (2009) find that NFIP participation increased both single family and multifamily development in Florida counties; however they find no evidence that induced development from the program is any more or less more severe in high flood risk areas.

5.3 Methods

One of the goals of the NFIP program is to insure those at risk from flood damages. One of the ways to evaluate how well the program is doing in Georgia is to analyze whether the households in the floodplain are buying the flood insurance since those are the properties that are at the risk of getting flooded. We do that by determining the penetration rate of the NFIP and how it varies across different market segments at the county level.

5.3.1 Market Penetration Rates by County in Georgia

We develop estimates of market penetration rates based on the number of policies in force, and the number of housing units⁴¹ in counties across Georgia. One of the hindrances in determining the market penetration rate is the unavailability of data on the number of properties in the floodplain. However, the use of total housing units in a county gives us tentative idea on the market penetration rate.

5.3.2 Fixed Effects Model

In order to determine the characteristics of counties that buy flood insurance, we pooled data across 153 counties⁴² in Georgia for the period 1978-2010 and estimated the following equation:

⁴¹ A **housing unit** is a house, an apartment, a mobile home, a group of rooms, or a single room that is occupied (or if vacant, is intended for occupancy) as separate living quarters. Separate living quarters are those in which the occupants live and eat separately from any other persons in the building and which have direct access from the outside of the building or through a common hall. Retrieved from U.S. Bureau of the Census, 2010 Census of Population and Housing. Updated every 10 years. <http://factfinder.census.gov>.

⁴² Out of 159 counties in Georgia 153 counties was included in the analysis since there was not a single policies-in-force in 6 counties: Clay, Lincoln, Marion, Schley, Treutlen and Webster.

$$\begin{aligned}
\log(PIF / 1000 pop)_{it} = & \beta_0 + \alpha_i + \beta_1 \log(Price_{it}) + \beta_2 \log(Income) \\
& + \beta_3 \log(Recent_Flood_{it}) + \beta_4 \log(Relief_Exp_{it}) \\
& + \beta_5 (Race)_{it} + \beta_6 (Education)_{it} + \beta_7 (Age)_{it} + \varepsilon_{it}
\end{aligned} \tag{5.3}$$

The dependent variable is the number of flood insurance policies purchased per 1,000 population in a county during a year. We measured the cost per thousand dollars of flood insurance coverage (*Price*) by dividing the dollar value of the premium paid for flood insurance in the county during the year by the dollar value of insurance coverage (in thousands) in the county during the year. The income variable ($\log(Income)$) is the log of per capita income in the county during the year. To control for the effect that a recent flood may have on individuals' demand for flood insurance we use the variable *Recent_Flood* that measures the dollar value of total flood damage per capita in the county during the preceding year. In our previous paper, we find that the discount for properties in floodplains vanishes only after 4 to 9 years after a recent flood event suggesting that a flood that happened few years back could influence the homeowner's decision to buy flood insurance. To capture such effect, we included a six year lag for the *Recent_Flood* variable. To measure the effect of disaster aid on the decision to buy flood insurance, we included per capita flood disaster relief expenditure (*Relief_Exp*) by FEMA. For the same reasons stated for the recent flood variable we also included a six year lag for the *Relief_Exp* variable.

One major objective of our paper is to determine the characteristics of the households that buy flood insurance at a county level. For that reason, we include in our model the variables *Race*, *Education*, and *Age* of the owner occupied household. Race is measured with two variables, one for the percent of black population and one for the percent of white population in a county. The education variable measures the percent of high school graduates and the percent of college graduates in a county. Five different age categories are included in the model: age groups

25 to 34, 35 to 44, 45 to 54, 55 to 64 and 65 & up. All these variables are entered as the percentage of total population in a county.

We also want to determine whether the policies in force (per thousand people) increase with the increase in the proportion of the county land area at risk of flooding as measured by location in the floodplain. Using zonal analysis in Arc GIS we determined the percentage of county within the 100-year floodplain (*Percent FP*).⁴³

The decision to buy flood insurance could also be dependent on whether the county is a coastal or an inland county. Homeowners in coastal counties may be more aware of the flood risk they face than the homeowners in inland counties. To control the effect that a coastal county might have on the decision to buy the flood insurance we included a dummy *coast* which equals to 1 if the county is coastal and 0 otherwise.

Lastly, to control for the fact that community participation is required for homeowners to be able to buy the flood insurance, we included a variable *NoNFIP* in our model which is the number of communities in a county that do not participate in the NFIP.

We estimated the model using county fixed effects. That is, in equation (5.3) α_i denotes a county-specific intercept that controls for unobserved characteristics at the county level that are constant over time. We note, however, that the location in the floodplain variable ("*Percent FP*"), the *coast* dummy and the *NoNFIP* variable does not vary over time and would drop from a fixed-effects model. We estimated equation (5.3) using random-effects when the model included these variables.⁴⁴

⁴³ 100-year floodplain was used since flood insurance is mandatory for the 100 year floodplain properties only.

⁴⁴ The Floodplain maps in Georgia have not been updated in years. Georgia entered into a partnership with FEMA to develop and update flood hazard maps for all 159 counties. This map modernization program started in 2009 for Georgia.

5.4 Data

We collected our data from several sources. With more than 40 years of history behind the NFIP, and results well documented, county-level data on the NFIP policies in force (PIF) from 1978-2010 was provided to the author by FEMA⁴⁵. In addition, FEMA provided the data on flood insurance premium dollars collected, flood insurance coverage, disaster relief expenditure by FEMA, and a GIS file of the floodplain map for all the counties in Georgia. Table 5.1 shows the summary statistics for total policies-in-force, total premium and total coverage for years 1978-2010 in Georgia. The number of NFIP policy holders has increased by almost 51 percent in the last 10 years and the premium intake has steadily increased over time, mainly from more policies in force and rising prices.

Table 5.1: NFIP Policies-In-Force, Premium and Coverage in Georgia from 1978-2010

Year	Policies-In-Force (PIF)	Premium Collected (\$)	Coverage (\$ thousands)	Average Premium (\$)	Average Coverage (\$ thousands)
1978	10,502	861,713	343,034	32,664	82
1979	13,348	1,105,861	472,011	35,362	82
1980	14,570	1,250,727	578,935	39,735	85
1981	14,563	1,921,371	651,969	44,769	131
1982	15,036	2,771,714	711,642	47,329	184
1983	15,596	2,905,571	783,435	50,233	186
1984	16,774	3,391,955	938,647	55,958	202
1985	18,018	3,895,232	1,228,856	68,202	216
1986	19,706	4,651,514	1,498,005	76,018	236
1987	20,396	5,267,443	1,665,969	81,681	258
1988	21,271	5,595,801	1,839,428	86,476	263
1989	23,167	6,467,600	2,388,232	103,088	279
1990	32,844	9,128,278	3,170,013	96,517	277
1991	28,238	8,756,679	2,805,169	99,340	310
1992	29,511	9,744,305	2,963,670	100,426	330
1993	31,816	10,803,381	3,337,091	104,887	339
1994	40,234	13,974,896	4,205,946	104,537	347

⁴⁵ Thanks to Susan Bernstein, Esq., I&PR Mitigation Directorate, NFIP, FEMA, DHS for providing the data to the author via email.

1995	45,271	16,511,970	5,049,496	111,539	364
1996	49,049	19,206,888	5,938,711	121,077	391
1997	53,431	22,613,901	6,932,214	129,741	423
1998	57,335	25,853,306	7,813,618	136,280	450
1999	61,480	27,262,323	8,779,346	142,800	443
2000	64,933	28,446,564	9,768,575	150,441	438
2001	66,539	29,442,985	10,511,775	157,979	442
2002	67,840	30,852,160	11,221,265	165,408	454
2003	70,080	33,396,557	12,041,183	171,821	476
2004	72,699	35,963,182	13,520,381	185,978	494
2005	79,317	39,881,447	15,700,573	197,947	502
2006	87,478	45,786,366	18,320,810	209,433	523
2007	90,206	50,360,780	19,856,870	220,128	558
2008	92,182	54,860,728	20,894,858	226,670	595
2009	97,396	59,427,670	22,533,477	231,359	610
2010	97,723	63,256,224	23,047,444	235,845	647

Data on total flood damage per capita in the previous year was collected from SHELDUS, a county-level hazard dataset derived from National Climatic data centre⁴⁶. All the socio-demographic variables: *Income*, *Race*, *Education*, and *Age* come from the Bureau of Economic Analysis (BEA) and the U.S. Census Bureau. The variable *Income* is a yearly data; however we interpolated decennial data from U.S. Census Bureau on *Race*, *Education* and *Age* to get yearly estimates.⁴⁷

Table 5.2 reports the summary statistics of the variables included in the model. The average number of policies-in-force per thousand population at the county level was 4.95. Per capita income was on an average almost \$26,000. The average cost per thousand dollar of flood insurance coverage was \$4.46 in 2010 constant dollars. The mean flood damage per capita during the preceding year was \$10.99, however, on average only \$0.004 per capita was spent on

⁴⁶ SHELDUS refers to Spatial Hazard Events and Losses Database for United States. Details on how the data is collected can be found at <http://webra.cas.sc.edu/hvri/products/sheldusmetadata.aspx>.

⁴⁷ We calibrated an exponential curve to the decennial data (1980, 1990, and 2000) for each county. Using a linear curve to estimate the data, however, did not change the results.

disaster relief by FEMA. On average 14.34 % of the county area falls in the floodplain with minimum of 2.03% (Macon County) and a maximum of 72.24% (Glynn County).

Table 5.2: Variables and Descriptive Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
PIF/1000pop	Policy in force per 1000 population	4.95	19.25	0.01	240.28
Income	Per capita Income (in thousands)	25.5	6.92	12.52	65.38
Price	Cost per 1000 dollar of coverage	4.46	2.39	0.37	30.38
Recent_Flood	Flood damage per capita during prior year	10.99	113.00	0	3986.23
Relief_Exp	Disaster Assistance per capita	0.004	0.083	0	3.366
Black %	Percent of black	25.60	17.17	0	82.99
White %	Percent of white	69.00	16.52	18.9	98.8
High school graduates	Percent of high school graduates	32.81	5.36	16.5	54
College graduates	Percent of college graduates	13.16	7.06	4.24	48.1
Age25to34	percent of age group 25 to 34	15.15	3.80	7	45.24
Age35to44	percent of age group 35 to 44	17.06	3.62	9.9	36.50
Age 45to54	percent of age group 45 to 54	12.81	1.98	0.96	18.6
Age55to64	percent of age group 55 to 64	8.31	2.82	0.37	17.5
Age65&up	percent of age group 65 & up	11.08	3.55	0.44	29.2
Floodplain %	Percent of floodplain	14.34	12.91	2.03	72.24
Coast	Coast=1 if coastal county, 0 otherwise	0.17	0.37	0	1
No NFIP Participation	Number of communities in a county that do not participate in the NFIP	0.62	1.06	0	6

We also compared the statistics of the variables for coastal counties with those in the inland counties. Table 5.3 reports the comparison of the summary statistics between the coastal counties and inland counties. We find that that the average number policies in force per thousand population was 20 in coastal counties and almost 2 in inland counties. Cost per thousand dollar of insurance coverage was a little higher in inland counties compared to coastal counties. Interestingly, the mean flood damage per capita during the preceding year was higher in inland

counties and the dollars per capita spent on disaster relief was higher for coastal counties. The county average demographics differ by only 1-2% between coastal and inland counties.

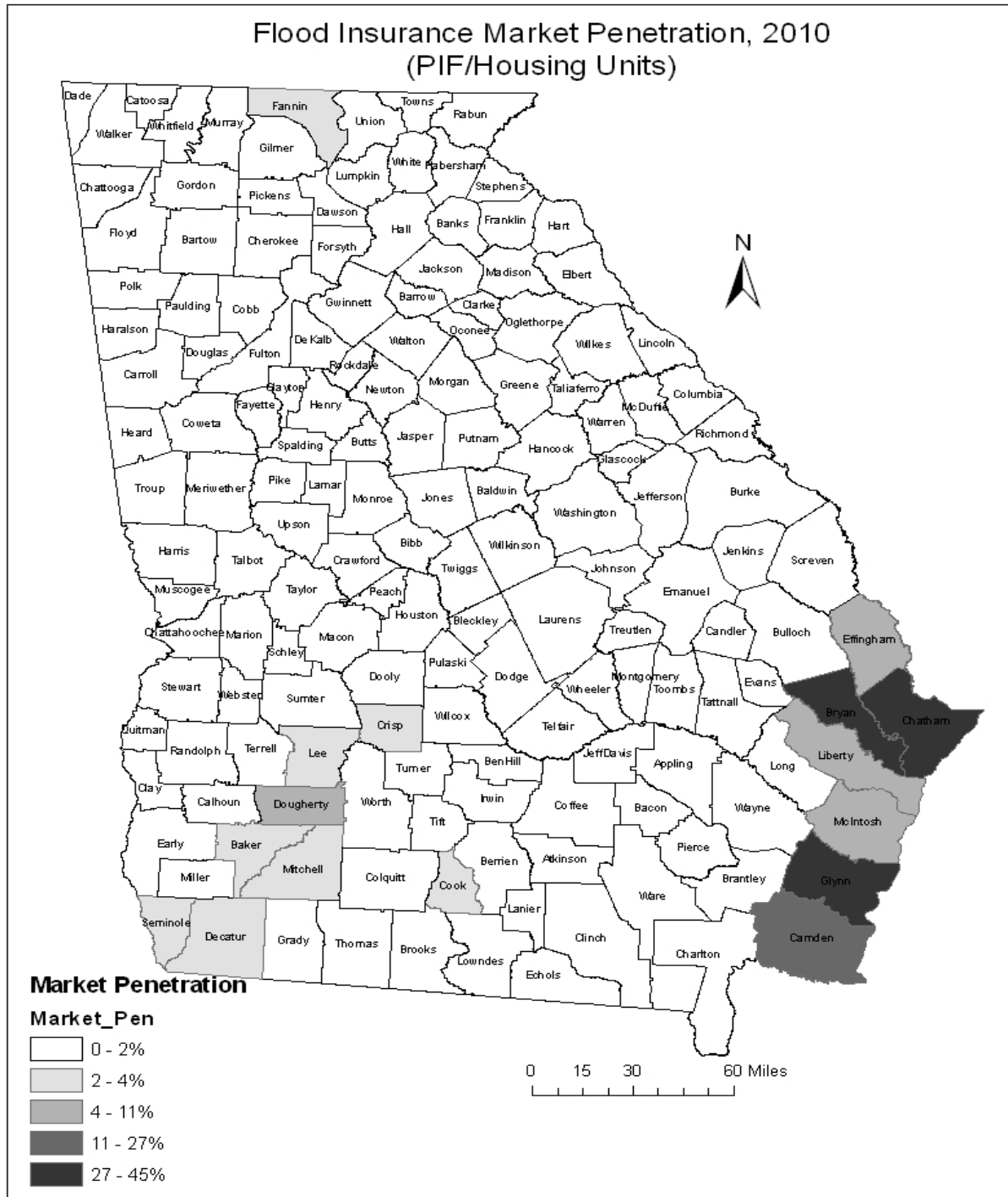
Table 5.3: Variables and Descriptive Statistics: Coastal Counties Vs. Inland Counties

Variables	Coastal Counties		Inland Counties	
	Mean	Std. Dev.	Mean	Std. Dev.
PIF/1000pop	20.53	43.43	1.83	3.05
Income (in thousands)	23.32	5.94	26.40	6.66
Price	4.16	2.14	4.52	2.43
Recent_Flood	6.63	57.56	11.86	121.07
Relief_Exp	0.01	0.14	0.002	0.07
Black %	26.59	11.10	25.40	18.14
White %	69.62	11.91	68.87	17.29
High school graduates	34.88	5.56	32.39	5.22
College graduates	11.45	5.32	13.51	7.32
Age25to34	14.87	2.87	15.20	3.96
Age35to44	17.21	3.53	17.03	3.64
Age 45to54	12.17	2.45	12.94	1.84
Age55to64	7.55	2.67	8.46	2.82
Age65&up	10.04	3.51	11.29	3.52
Floodplain %	31.37	21.21	10.93	6.37
No NFIP Participation	0.49	0.87	0.64	1.09

5.5 Results

5.5.1 Market Penetration Rates

Figure 5.1 shows the market penetration rates in the counties in Georgia for 2010. They are measured as the percentage of households with a policy. We divided the total number of residential policies in force in a county in 2010 by the number of household in a county from the 2010 US Census. This does not take account of the fact that some homeowners are at greater risk than the others, but does give some indication of market penetration. The top five Georgia counties with the highest percentage of market penetration in 2010 were Glynn (44.86%), Bryan (40.28%), Chatham (27.42%), Camden (19.22%), and McIntosh (10.50%).



Source: Author prepared map based on data provided by FEMA.

Figure 5.1: Flood Insurance Market Penetration, Georgia (2010)

Not surprisingly there is a strong correspondence between the market penetration and the proportion of floodplains within a county.⁴⁸ The coastal counties where the percentage of floodplain is larger tend to have the highest penetration rates (Table 4.3), most likely because residents are aware of the risk they face. Our measure of market penetration, however, refers to the total number of properties in a county, and not specifically to those in the floodplain. This could explain why in a few counties like Ware and Clinch the flood insurance market penetration is low, as a result, for example, of the number of properties in the floodplain being relatively low.⁴⁹ Unfortunately, we do not have data available to determine if that is the case.

The other factor that could potentially explain the market penetration rate is a recent flooding event in a county. Atreya et. al (2013) find that after a significant flood event in 1994 the take up rates were high in Dougherty County, Georgia. Since the calculated penetration rates correspond to 2010, the rates are expected to be higher for counties where a recent flooding took place.⁵⁰ We note that, in 2009, there were 3 different flooding events in Glynn County which explains a high market penetration apart from Glynn County being a coastal county. We expected a higher market penetration rates in Northern Georgia and Atlanta Metropolitan area due to historic flooding in 2009, however the market penetration rates are lower in these areas probably due to the fact that the floodplain proportion is lower in inland counties and the flood insurance is not mandatory for the properties that lie outside the 100 year floodplain.

⁴⁸ We find a significant positive correlation (0.70) between the market penetration rate and the percentage of floodplain in the counties.

⁴⁹ The housing density in Ware and Clinch County is 18 and 3 per square mile respectively which explains its low market penetration rate, 1.07% and 1.03% respectively.

⁵⁰ Atreya et. al (2013) find that people forget about the flood risk 4-9 years after a significant flood event., therefore a flood that occurred after 2000 is expected to have an impact on our calculated market penetration rates.

Table 5.4: Percent of Floodplain and Market Penetration Rate (Top 10) in Georgia (2010)

County	Floodplain (%)	County	Market Penetration (%)
Glynn	72.24	Glynn	44.86
Chatham	72.22	Bryan	40.28
Camden	54.68	Chatham	27.42
Bryan	54.14	Camden	19.22
Ware	52.43	McIntosh	10.50
Clinch	49.15	Liberty	7.95
Liberty	49.11	Effingham	5.16
Charlton	47.81	Dougherty	4.90
Long	35.06	Seminole	3.85
Cook	32.90	Lee	3.86

5.5.2 Fixed Effects Model Results

We report the results of the estimation of equation (3) in Table 5.4. The first column shows the estimates from the fixed-effects model. We compare these results with those from the random-effects model in second column. Since the proportion of floodplain in a county did not change over time we included the *Percent FP* variable in column three and estimated as a random effect model.⁵¹ The other variables that were fixed over time are *coast* and *No NFIP* participation. We included those variables in our random effects model in column three.

⁵¹ We also performed a Hausman test that rejected the null that the fixed-effect model is more appropriate against a random-effects model (p-value=0.5).

Table 5.5: Empirical Results (Dependent Variable: Policies in force/1000 population)

Variables	Fixed Effects	Random Effects	Random Effects with additional controls
Log (Income)	0.258 (0.198)	0.367* (0.193)	0.352* (0.191)
Log (Price)	-0.261*** (0.0402)	-0.252*** (0.0405)	-0.241*** (0.0401)
Log (Recent_Flood)	0.0159** (0.00800)	0.0166** (0.00814)	0.0163** (0.00808)
L1. Log (Recent_Flood)	0.0185** (0.00777)	0.0190** (0.00791)	0.0185** (0.00785)
L2. Log (Recent_Flood)	0.0171** (0.00797)	0.0180** (0.00812)	0.0176** (0.00805)
L3. Log (Recent_Flood)	0.00364 (0.00802)	0.00441 (0.00817)	0.00405 (0.00811)
L4. Log (Recent_Flood)	0.00835 (0.00773)	0.00868 (0.00787)	0.00834 (0.00781)
L5. Log (Recent_Flood)	0.00206 (0.00783)	0.00264 (0.00798)	0.00253 (0.00791)
Log (Relief_exp)	0.0703 (0.0713)	0.0724 (0.0727)	0.0732 (0.0721)
L1. Log (Relief_exp)	0.0463 (0.0727)	0.0473 (0.0740)	0.0484 (0.0734)
L2. Log (Relief_exp)	0.0269 (0.0729)	0.0259 (0.0743)	0.0269 (0.0737)
L3. Log (Relief_exp)	0.0133 (0.0739)	0.0112 (0.0752)	0.0121 (0.0746)
L4. Log (Relief_exp)	0.0513 (0.0797)	0.0514 (0.0812)	0.0528 (0.0806)
L5. Log (Relief_exp)	0.0316 (0.0841)	0.0375 (0.0856)	0.0385 (0.0849)
High School Grads %	0.0376*** (0.00428)	0.0397*** (0.00429)	0.0381*** (0.00425)
College Grads %	0.0268*** (0.00657)	0.0323*** (0.00630)	0.0317*** (0.00620)
Black %	0.0161*** (0.00345)	0.0136*** (0.00329)	0.0132*** (0.00324)
White %	0.00438 (0.00437)	0.000792 (0.00389)	0.00125 (0.00381)
Age25to34 %	0.0188* (0.0106)	0.0145 (0.0105)	0.0153 (0.0103)
Age35to44 %	0.0273** (0.0126)	0.0183 (0.0123)	0.0227* (0.0122)
Age45to54%	0.0805*** (0.0183)	0.0733*** (0.0180)	0.0763*** (0.0178)
Age55to64%	0.0356 (0.0244)	0.0128 (0.0238)	0.0262 (0.0235)

Age65&up %	0.0988*** (0.0182)	0.0745*** (0.0166)	0.0815*** (0.0163)
Floodplain %			0.0491*** (0.00886)
Coast Dummy			0.493* (0.292)
No NFIP Participation			-0.375*** (0.0816)
Constant	-7.474*** (2.045)	-8.644*** (1.987)	-9.273*** (1.969)
Observations	2,887	2,887	2,887
R-squared	0.670		
Number of panel groups	138	138	138

The empirical analysis supports the hypothesis that income and price significantly influences the decision to buy flood insurance across the random effects model. The estimated income elasticity is 0.35 to 0.36. In all the models, we find the coefficient for the price of insurance (the cost per thousand dollars of coverage) to be negative and significant (-0.24 to -0.26). The result is consistent with the previous studies (Browne and Hoyt, 2000; Kriesel and Landry, 2004) that the amount of insurance policies in force in a county is not very sensitive to price changes.

Our empirical findings also suggest that flood damage per capita in the previous year has a significant positive impact on the decision to buy flood insurance which is consistent with Kunreuther's (1990) hypothesis that risk perception influences the insurance purchasing behavior. In chapter 1, we find that in Dougherty County, Georgia, the number of policies in force increased dramatically immediately after the "1994 flood of the century" suggesting that recent flood experience in a county leads to more individuals buying the flood insurance. Replacing the per capita damage in the previous year by the number of flood events in each county in the previous year did not change the results. There was still a significant positive impact of a flood experience on the number of policies in force. Confirming our intuition that the floods that happened few years back would have a significant impact on decision to buy flood

insurance, we find that the floods that occurred up to three years back is likely to influence the decision to buy flood insurance. We also find that disaster relief efforts do not influence the decision to purchase flood insurance.

Regarding the characteristics of the households purchasing the flood insurance, we find that education has a significant impact. Across all the specifications, we find that counties with more high school graduates and more college graduates are more likely to buy flood insurance. An increase in the black population in a county would increase the policies in force indicating that these populations are more likely to buy the flood insurance. We divided the age group of owner occupied household in four different ranges. We find that with increasing age the demand for flood insurance is also increasing with an exception of age group 55 to 64. In fixed effects model, we find that, a one percent increase in the age group 25 to 34 in a county is associated with an approximately 0.01 percent increase in the policies-in-force in a county. Similarly, a one percent increase in the age group 35 to 44 in a county is associated with an approximately 0.02 percent increase in the policies-in-force. A 0.08 percent increase in the policies-in-force is associated with a one percent increase in age group 45 to 54 in a county. Finally, a 0.09 percent increase in the policies-in-force is associated with a one percent increase in age group 65 and above in a county.

In column 3 of Table 5.3, we estimated a random-effects model to be able to determine the impact of the proportion of land area within a floodplain in a county on the number of flood insurance policies in force. As expected, we find a positive relationship between the proportion of floodplain in a county and the policies in force in a county implying that vulnerable counties, those exposed to flood risk, are in fact more likely to buy flood insurance. In addition, we controlled for whether the county is a coastal county or an inland county and also controlled for

the number of communities in a county that do not participate in the NFIP. We find that increase in the number of communities that do not participate in the NFIP decreases the number of policies-in-force in a county. We also find that the coastal counties are more likely to buy flood insurance compared to inland counties.

5.6 Conclusions

In response to mounting flood losses and the ever increasing cost of disaster relief to the tax payers, the U.S. congress created the NFIP to mitigate flood losses through community-enforced building and zoning ordinances and to provide access to affordable, federally backed flood insurance protection for homeowners. The NFIP is supposed to be funded with premiums collected from policyholders. It remained solvent till 2005 until hurricane Katrina struck. NFIP was flooded with claims and was eventually drowned to debt after 2005. The program is not structured to build a capital surplus nor is it able to purchase reinsurance to cover catastrophic losses. NFIP's current debt and the current premium structure have raised concerns regarding its long term financial solvency. On the other hand, a significant portion of the flood losses that occur each year remains uninsured (Brown and Hoyt, 2000). Some advocacy groups have argued that the program disproportionately benefits wealthy households, many of them expensive waterfront properties, but with a few exceptions (e.g. Bin, Bishop and Kousky, 2011), there has not been much research done to determine who benefits from the NFIP and who bears the cost within the program.

Given the recent scrutiny of the NFIP program, it is important to determine the flood insurance market penetration rate and to determine who are buying the flood insurance to enforcing the NFIP policies towards building a resilient community. Our analysis of the factors that influence the purchasing decision of flood insurance in Georgia is an effort to understand

who are buying flood insurance and how well the NFIP is doing in terms of penetrating the market in Georgia. Georgia is an interesting case study where flood insurance payments have exceeded premium collected four times between 1978 and 2010, indicating that the state is not well-prepared to cover the cost of the claims if a large scale flood were to take place in the future.

Ideally, we would have performed the analysis using household level data, but unfortunately data at this level of disaggregation is not available. We use county level data that provides more information than the state level data that previous studies have used.

As one would expect the flood insurance market penetration rate is higher in the coastal counties in Georgia. The inland counties in Georgia such as Hancock (0.018%) and Bleckley (0.018%) are among the ones where the penetration rate is very low.⁵² Thus, it is important for NFIP to understand why the market penetration rate is so low in inland counties while an estimated 1.7 million 100 year floods occur in the 100-year floodplains of inland counties (Dixon et al., 2006). Perhaps a future study can determine if the flood insurance in inland counties is less attractive due to lower annual losses or due to residents underestimating the flood risk or few people are living in floodplain.

Our analysis at the county level for the period 1978-2010 in Georgia suggests that, as we would expect, the counties with higher average income are more likely to buy flood insurance. We also find that the higher the price of the flood insurance per 1000 dollars of coverage, the lower will be the number of policies in force. We also find that having experienced a recent flood event has a positive significant effect on the number of policies in force purchased, supporting the hypothesis of “availability heuristic”. Availability heuristic is explained as a bias in probability judgment (Tversky and Kahneman, 1982). According to this heuristic, people use the

⁵² These two counties represent the two lowest market penetration rates in Georgia.

ease of which examples of a hazard can be brought to mind as a means for estimating a probability of a hazard. A recent flood event can be easily brought to mind and therefore helps in increasing the probability of future flood which eventually leads to purchasing flood insurance. We find that racial composition and education have a significant effect on the decision to buy flood insurance at the county level. Everything else equal, increasing the education level results in more adoption flood insurance. We find that an increase in the number of elderly people in a county would increase the number of flood insurance policies in force.

CHAPTER 6

CONCLUSIONS

As discussed in Chapter 1, the main objective of this dissertation is to determine whether property prices in the floodplain reflect flood risk and how the perception of the flood risk changes in the aftermath of large flood events. We determine if homeowners update their flood risk discount following a large flood event and whether the perceived risk discount is persistent or temporary in Dougherty County, Georgia. We account for the spatial dependence of the observations using two versions of a spatially lagged and autoregressive disturbance model. The results suggest that after the 1994 “flood of the century” in Georgia prices of properties in 100-year floodplain fell significantly, however, the effect was transitory. The effect vanished four to nine years after the flood. The outcome of this research is not surprising considering the presence of Tversky and Kahneman’s theory of availability heuristic, a cognitive illusion that is influenced by what is recent or dramatic. Until one remembers a significant flood event the subjective risk probabilities are very high, but as the flooding events fades away from one’s memory subjective risk probabilities diminish and disappear in absence of any additional flooding.

Assuming that people respond better to what they have experienced directly, in addition to using the Federal Emergency Management Agency (FEMA) designated flood hazard maps for the city of Albany, Georgia, we use an actual inundation map to compare the flood risk discount for properties in actually inundated area to properties in floodplain but outside inundated area. The novelty of this analysis is that we were able to control for the damages borne by the 1994 flood in city of Albany, which is often regarded as an omitted variable. The motivation for the

comparison is that, in cases where homebuyers are unaware of the flood risk in the floodplain, probably due to lack of information or the underestimation of the flood risk, they learn about the flood risk the hard way, after an actual inundation occurs and thus, the risk reflected in the property prices could potentially be due to inundation. We find that there was no significant discount associated with properties in the floodplain if they are not inundated. The results suggest that the discount in property prices in the area affected by a large flood comes from being in the actually inundated area, and that not accounting for whether properties in the floodplains are also in the inundated area may overestimate the informational effect of large flood event.

Finally, we determine the National Flood Insurance Program's (NFIP) market penetration rate and the characteristics of buyers of flood insurance in Georgia. The novelty of this research is that we include the county average demographics in our model. For example, we find that a higher number of high school graduates and college graduates in a county lead to a higher expected number of policies in force. The same pattern was true for the age group 25-54 and the age group 65 and above. As expected, the coastal counties in Georgia have a higher flood insurance market penetration rates than the inland counties, probably because the homeowners in coastal counties are aware of the flood risk they face. The market penetration was the highest in the Glynn County (44.86%) which is on the coast. In addition to Glynn County being a coastal county, we suspect the high market penetration in Glynn County is also driven by a series of recent flood events in the county. We note that, in 2009, there were 3 different flooding events in Glynn County. We find that the demand for flood insurance was inelastic; the increase in the price of the flood insurance decreased the number of policies-in-force in counties in Georgia. We also find that increased income led to an increased number flood insurance policies-in-force.

Also, an increase in the flood damage per capita in the previous year led to an increase in the number of policies-in-force which also exemplifies the availability heuristic explained earlier.

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