Spatial Variation in Flood Risk Perception: A Spatial Econometric Approach

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Abstract

We use hedonic property models to estimate the spatial variation in flood risk perception in the city of Albany, GA. In addition to knowing whether a property lies in the floodplain, we have a unique dataset with actual inundation maps from tropical storm Alberto that hit Albany in 1994. In the absence of information on the structural damages caused by a flood, having information on the actual inundated area can be useful to tease out the information effect of a flood shock from potential reconstruction or other costs. 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. Our results suggest 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 of capturing an information effect, the larger discount in inundated properties captures potential reconstruction costs, and supports a hypothesis that homeowners respond better to what they have visualized ("seeing is believing").

Key words: Flood Risk, Inundation, Spatial Econometrics, Hedonic Valuation

I. Introduction

A key element in hazard and disaster management is the understanding of how stakeholders 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), and in the flow of information about the probability of the flood hazard; and also 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). The actual amount of flood damage caused by a specific flood event is higher in areas more exposed to the hazard and, 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 Albany as a source of flood risk information to homeowners in Albany and examines the spatial variation in perceived flood risk. In particular, we compare the flood risk discount for properties in the actually inundated area vis-a-vis properties in the flood plain but not in the inundated area.

Previous studies have used FEMA designated flood hazard maps as a proxy for flood risk zones (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 a dummy to capture the informational effect on perceived flood risk (Bin and Polasky, 2004; Carbone et al., 2006; Kousky, 2010). In addition to FEMA hazard maps, we use a map of the area that was inundated by the 1994 flood in Albany to tease out the information effect from other potential effects of flooding (most notably cleaning and reconstruction costs) on property prices. 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 event, the discount in properties in the inundated area will be large for 2 reasons: First, because homeowners are more likely to have experienced physical damages after the flood, and second because people respond better to what they have experienced directly (“seeing is believing”). More generally, this paper analyzes whether there is spatial variation in the flood risk perception, i.e. whether the flood risk discount is limited to the area directly affected by the flood or whether it extends beyond and how far beyond the heavily affected area.

Our study area is in the City of Albany near the Flint River where the majority of the flood damage occurred. We used a hedonic property model in a difference-in-difference (DD) framework to determine the risk perception in the actually inundated study area and also to determine changes in implicit prices of properties in the floodplain and over various distance-to-inundation bands. We find a significant discount of 47% in properties in the inundated area. We also find that the proximity to the inundated area decreased the property prices significantly. These results were robust to incorporating spatial lag and spatial error term corrections in the econometric models.

II. Study Area

Albany was founded in the early 1800s along the Flint River in Southwest Georgia. The city of Albany has a total area of 55.9 square miles, of which 55.5 square miles is land and 0.3 square miles is water (US Census Bureau, 2010). In 1994, a severe flood caused by tropical storm Alberto hit Albany, and destroyed parts of downtown and south Albany, causing 15 deaths and displacing almost 22,000 people. Peak discharges greater than the 100-year flood discharge were recorded at all US Geological Survey (USGS) Flint River gauging stations (Stamey, 1996). According to USGS, 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.

According to FEMA, nearly 20,000 communities across the US and its territories participate in the National Flood Insurance Program (NFIP) enacted in 1968, by adopting and enforcing 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. 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 flood plains in participating communities. Albany, Georgia is one of the participating communities in NFIP since 1974. 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.

With a major goal of reducing vulnerability of people and areas most at risk from natural hazards, 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. 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 shows the study area and the inundated area when the water surface altitude is 192.5 feet at Flint River, which corresponds to the 1994 flood caused by tropical storm Alberto. In addition to the FEMA hazard maps, we use this map of the area that was actually inundated by the 1994 flood in Albany to capture flood risk.

III. 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 an environmental variable of interest, in this case location with respect to the inundated area (*IND*). We use a quasi-experimental approach known as a Difference-In-Difference (DD) method to measure the effect of a large flood event on flood prone property prices. The DD method allows us to isolate the effect attributable to the flood event from the effect of other contemporaneous variables that might have influenced the property prices.

Models

In the simplest DD model, to determine the changes in property prices in the actually inundated area after the 1994 flood, the control group is composed of properties that are outside the inundated area and the following specification is used:

$$\begin{aligned}\ln(P_{it}) = \beta_0 + \boldsymbol{\beta}_1^{'} \ln \mathbf{L_i} + \boldsymbol{\beta}_2^{'}\mathbf{S}_{it} + \boldsymbol{\beta}_3^{'}\mathbf{S}_{it}^2 + \beta_4 IND_i + \beta_5 Flood_i + \beta_6 IND_i * Flood_i \\ \beta_7 years + \beta_8 years * IND_i + \delta_t + \varepsilon_{it}\end{aligned} \tag{1}$$

The variable *IND* (inundation) is a dummy equal to 1 if the property was inundated by 1994 flood and 0 otherwise. The variable *Flood* is a dummy variable equal to one if the sale happened after the flood (July 1994). The interaction term between the inundation variable (*IND*) and *Flood* tells us how the 1994 flood might have affected the prices of properties that are in the inundated area 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 *years* and the inundation variable. The variable "*years*" is a time trend that represents the number of years after the 1994 flood. The interaction term estimates how the risk premium changed over time after the flood. Previous papers (Bin and Landry, Atreya et al. 2011) find this temporal decay effect to be important. Year fixed effects (δ_t) were included to capture yearly shocks that affect all the properties. Subscripts *i* and *t* represent property and time respectively.

Unfortunately, we do not have information on the structural damages (if any) suffered by the properties in the inundated area. However, we can assume that the depth of the flood water acts as a proxy to the degree of structural damages to the properties in the inundated area. Depth of the flood water in the inundated study area at a gauge height of 43 feet and an altitude of 192.5 feet corresponding to the 1994 flooding was extracted using a raster map developed by USGS.[1] We determined the effect of flood depth on property prices using the specification below:

$$\begin{aligned}\ln(P_{it}) = {} & \beta_0 + \boldsymbol{\beta}_{\mathbf{1}}' \ln \mathbf{L}_i + \boldsymbol{\beta}_{\mathbf{2}}' \mathbf{S}_{it} + \boldsymbol{\beta}_{\mathbf{3}}' \mathbf{S}_{it}^2 + \beta_4 Depth_i + \beta_5 Flood_i + \beta_6 Depth_i * Flood_i \\ & \beta_7 years + \beta_8 years * Depth_i + \delta_t + \varepsilon_{it}\end{aligned} \qquad (2)$$

The variable "*Depth*" is the depth of the flood water in feet. 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. Again, the control groups are properties outside the inundated area.

Previous studies have found that a significant flood event acts as a source of updated risk information (Skantz and Strickland, 1996; Bin and Polasky, 2004; Carbone et al., 2006; Kousky, 2010; Bin and Landry, 2011; Atreya et al., 2011). Following this literature, to determine the information effect of the 1994 flood event on property prices we used the FEMA designated floodplain maps and estimated the following specification:

$$\begin{aligned}\ln(P_{it}) = {} & \beta_0 + \boldsymbol{\beta}_{\mathbf{1}}' \ln \mathbf{L}_i + \boldsymbol{\beta}_{\mathbf{2}}' \mathbf{S}_{it} + \boldsymbol{\beta}_{\mathbf{3}}' \mathbf{S}_{it}^2 + \beta_4 FP_i + \beta_5 Flood_i + \beta_6 FP_i * Flood_i \\ & \beta_7 years + \beta_8 years * FP_i + \delta_t + \varepsilon_{it}\end{aligned} \qquad (3)$$

where the variable *FP* is a dummy equal to 1 if the property falls in the 100-year floodplain and zero otherwise, and the control group are properties outside the floodplain.

Although imperfectly, given that we have no information on the actual structural damage suffered by the specific properties, we try to tease out a potential information effect of the flood shock from potential reconstruction and other inundation-related costs (inundation effect). We do

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[1] The depth value was generated by subtracting the land surface elevation from the model elevation.

that by using an interaction term between the floodplain dummy variable and the inundation dummy variable in a specification as follows:

$$\begin{aligned}\ln(P_{it}) &= \beta_0 + \boldsymbol{\beta}_{\mathbf{1}}^{'} \ln \mathbf{L}_i + \boldsymbol{\beta}_{\mathbf{2}}^{'}\mathbf{S}_{it} + \boldsymbol{\beta}_{\mathbf{3}}^{'}\mathbf{S}_{it}^2 + \beta_4 IND_i + \beta_5 FP_i \\ &+ \beta_6 Flood_i + \beta_7 IND_i * Flood_i + \beta_8 FP_i * Flood_i + \beta_9 IND_i * FP_i + \beta_{10} FP_i * IND_i * Flood_i \\ &+ \beta_{11} years + \beta_{12} years * FP_i + \beta_{13} years * IND_i + \delta_t + \varepsilon_{it}\end{aligned} \tag{4}$$

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*). Model 5 explores the effect of the 1994 flood in these mutually exclusive groups using *NIN_OFP* as the control group.

$$\begin{aligned}\ln(P_{it}) &= \beta_0 + \boldsymbol{\beta}_{\mathbf{1}}^{'} \ln \mathbf{L}_i + \boldsymbol{\beta}_{\mathbf{2}}^{'}\mathbf{S}_{it} + \boldsymbol{\beta}_{\mathbf{3}}^{'}\mathbf{S}_{it}^2 + \beta_4 IN\_FP_i + \beta_5 IN\_OFP_i + \beta_6 NIN\_FP_i \\ &+ \beta_7 Flood_i + \beta_8 IN\_FP_i * Flood_i + \beta_9 IN\_OFP_i * Flood_i + \beta_{10} NIN\_FP_i * Flood_i \\ &+ \beta_{11} years + \beta_{12} years * IN\_FP_i + \beta_{13} years * IN\_OFP_i + \beta_{14} years * NIN\_FP_i \\ &+ \delta_t + \varepsilon_{it}\end{aligned} \tag{5}$$

Finally, we investigate how far beyond the inundated area the flood risk discount persists. For that purpose, we determined the distance of each property to the nearest inundated point and estimated the following model:

$$\begin{aligned}\ln(P_{it}) &= \beta_0 + \boldsymbol{\beta}_{\mathbf{1}}^{'} \ln \mathbf{L}_i + \boldsymbol{\beta}_{\mathbf{2}}^{'}\mathbf{S}_{it} + \boldsymbol{\beta}_{\mathbf{3}}^{'}\mathbf{S}_{it}^2 + \beta_4 IND_i + \beta_5 Flood_i + \beta_6 IND_i * Flood_i \\ &\beta_7 years + \beta_8 years * IND + \beta_9 Near\_IND + \delta_t + \varepsilon_{it}\end{aligned} \tag{6}$$

where *Near_IND* is a continuous variable capturing the distance of a property to the nearest inundated point.

In addition, we also grouped properties into three mutually exclusive distance bands based on different buffer zones around the inundated area: a quarter of a mile (*QtrMile*), between a quarter and half of a mile (*Halfmile*) and between half and a three-fourth of a mile away (*Th_FrMile*) (Figure 2) leading to the following specification:

$$\begin{aligned}\ln(P_{it}) = \beta_0 + \boldsymbol{\beta}_1^{'} \ln \mathbf{L}_i + \boldsymbol{\beta}_2^{'}\mathbf{S}_{it} + \boldsymbol{\beta}_3^{'}\mathbf{S}_{it}^2 + \beta_4 IND_i + \beta_5 Flood + \beta_6 IND_i * Flood \\ \beta_7 years + \beta_8 years * IND_i + \beta_9 Qtrmile + \beta_{10} Halfmile + \beta_{11} Th\_FrMile + \delta_t + \varepsilon_{it}\end{aligned} \tag{7}$$

<u>*Spatial Econometric Issues*</u>

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 leading to inefficient or inconsistent estimates we use 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 (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. The general form of our SARAR model for equation (1) is as follows:

$$\begin{aligned}\ln(P_{it}) = \beta_0 + \lambda W_i \ln(P_{it}) + \boldsymbol{\beta}_1^{'} \ln \mathbf{L}_i + \boldsymbol{\beta}_2^{'}\mathbf{S}_{it} + \boldsymbol{\beta}_3^{'}\mathbf{S}_{it}^2 + \beta_4 IND_i + \beta_5 Flood_i + \beta_6 IND_i * Flood_i \\ \beta_7 years + \beta_8 years * IND_i + \delta_t + \varepsilon_{it}\end{aligned} \tag{8}$$

Where, $\varepsilon_{it} = \rho M_i \varepsilon_{it} + u_{it}$ and λ and ρ are the spatial autocorrelation parameter and spatial autoregressive coefficients, respectively. W and M are n x n spatial weighting 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.[2] Concerning the spatial weights matrix, W, two different specifications can be appropriate, 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.[3] The existence of spatial autocorrelation increases the possibility that the errors will not be distributed normally.[4] Thus, we employed a generalized two-stage least squares estimator that produces consistent estimates (Arraiz, et al., 2010). The disturbances u_{it} are assumed to be independent and identically distributed (IID). All the models (1-7) were estimated using both, standard OLS and SARAR specifications.

IV. Data

We used three 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 ; and USGS and FEMA for simulated flood inundation and floodplain maps of Flint River at Albany. Each property is a single-family residence sold between 1985 and 2010.

Individual property sales data contain information on housing characteristics such as number of bedrooms, number of bathrooms, heated square feet, presence of garage etc. in

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[2] 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.

[3] 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. However, for robustness we used both contiguity and IDW matrices in the reduced sample of 1690 observations. The results were robust to using either W matrix.

[4] The Jarque-Bera test for normality of the residuals suggested that the residuals are not normally distributed.

addition to sale date and sale price. Property sale prices were adjusted to 2010 constant dollars, using the housing price index for Albany metropolitan area from the Office of federal Housing Enterprise Oversight. The GIS database was utilized to determine the location attributes of the properties such as proximity to river, railroad, major roads, parks etc. The floodplain map published as Q3 data by FEMA was used to determine if the parcel was within the 100-year or outside the floodplain.[5] 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 1), which includes a little over 3000 single family residences.

Table 1 reports the summary statistics for all the variables considered in the analysis. The mean property price was 77,621 in 2010 constant dollars. The oldest property was built in 1883. The average property had 0.25 acres. The maximum elevation was 216 meters and the minimum elevation 175 meters. Mean distance to Flint River was 4,526 feet. Of all the sales between 1985 and 2010, 23% of the properties were in high risk zone (those with a 1% annual chance of getting flooded or a 26% chance of getting flooded at least once during a 30-year mortgage period). 30.6% of the properties in the sample were inundated during the 1994 flood.

V. Results

Table 2 reports the OLS estimates of the DD models presented in Section III. The five columns in Table 2 correspond to the corresponding models in Section III.

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[5] 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.

In the first 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 1). We find that immediately after the flood, properties in the inundated area sell for 48% less than the properties outside the inundated area. However, consistent with previous studies that find a temporal decay effect (Atreya et al 2011, Bin and Landry 2011), we find that the large discount is short lived. We find that it decays rapidly; at the rate of 6.5 percent annually for inundated properties. Overall our 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.

The second column in Table 2 presents the estimates for Model 2, i.e. the specification in which we control for the depth of the flood. We find that one feet increase in the flood depth decreased the property prices by 8.2% which is equivalent to $6,364 when evaluated at an average priced property. The average depth of properties in the *inundated* area is 5.02 feet (Table 1). Thus, for an average flood depth of 5.02 feet the 8.2% per feet discount is equivalent to 41% which is comparable to post flood discounts we find for inundated area across all the specifications.

In the third column of Table 2, we present the estimates of Model 3, which following previous studies simply estimates the effect of the flood on floodplain properties irrespective of whether the property was inundated or not. We find that the properties 100-year floodplain were sold for 40% less than an equivalent property outside the floodplain immediately following the 1994 flood.

To tease out the effect of being inundated from the informational effect of being in the floodplain, we estimated Model 4. We find that the inundated properties were discounted by 41% immediately after the flood and that there was no significant additional discount associated with being in the floodplain. This suggests that, it is in fact the inundation effect that is capitalized into property prices and not accounting for location in the inundation area might overestimate the information effect of being located on the floodplain that previous studies have estimated.

Finally, we divided the study area into four mutually exclusive groups as described in Model 5 to see the effect of the 1994 flood in each of these groups. In column 5, we find that there was a significant discount of 52% and 37% for inundated properties that lie in floodplain or outside of the floodplain, respectively. This supports our previous finding that it is actually the inundation effect that is captured by the model rather than just an information effect.

Across all the specifications, we find that there is a discount of close to or more than 40% for properties that were in the inundated area suggesting that this discount is mainly driven from an inundation rather than an informational effect. We also suspect that the discount seen in column 3 (Model 3) for the floodplain properties is in fact due to the inundation effect rather than 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 (*IND*, *FP*, *IN_FP* etc.) and the *Years* variable are always positive and statistically significant.

Table 3 presents the SARAR estimation results for Models (1)-(5). The results again robustly indicate that the inundated properties are discounted significantly after the 1994 flood. In column 1, we find a significant discount of 47% for inundated property immediately following the flood. In column 2, we find that the depth of the flood has a negative impact on property prices after the 1994 flood as shown by a significant and negative *Depth*Flood* variable (-0.082). In column III, we find that there is a 39% price discount for the floodplain properties immediately after the flood. We suspect the price discount in floodplain properties is due to the inundation effect since we do not see a significant effect of being in the floodplain in column 4 when we estimated Model 4 that tries to tease out the different impacts of the floodplain and inundation variables. In column 4, we find a significant discount for the properties that are inundated irrespective of whether they are in the floodplain or outside the floodplain. Finally, in column 5, as in the OLS model, we find a significant discount for inundated properties both in and outside the floodplain as suggested by a negative and statistically significant estimates for *IN_FP*Flood* and *IN_OFP*Flood*.

In order to further examine the spatial variation in the flood risk discount we estimated equations (6) and (7), the estimates of which are presented in Table 4. We find that the proximity of a property to the inundated area decreased the property prices by 0.02% per meter. In the specification that includes mutually exclusive buffer zones around the inundated area, we also find a monotonically decreasing effect of proximity to the inundated area on property prices. Properties closer to the inundated area (within a quarter mile), sell for a lower price. This discount is estimated at 20% and it is statistically significant in the SARAR specification, while it is slightly smaller and statistically insignificant in the OLS specification.

VI. Conclusion

Natural hazards provide exogenous risk information to the households. Previous studies have found that this information is capitalized into property prices. These studies, however, use floodplain maps to measure flood risk. Our study of the 1994 "flood of the century" in Albany suggests 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. Our results thus suggest 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 of an information effect, the discount in inundated properties captures potential reconstruction and psychological costs, and supports a hypothesis that homeowners respond better to what they have visualized (“seeing is believing”). Unfortunately, without data on actual damages on the properties in the inundated area we are not able to estimate the relative magnitude of these effects.

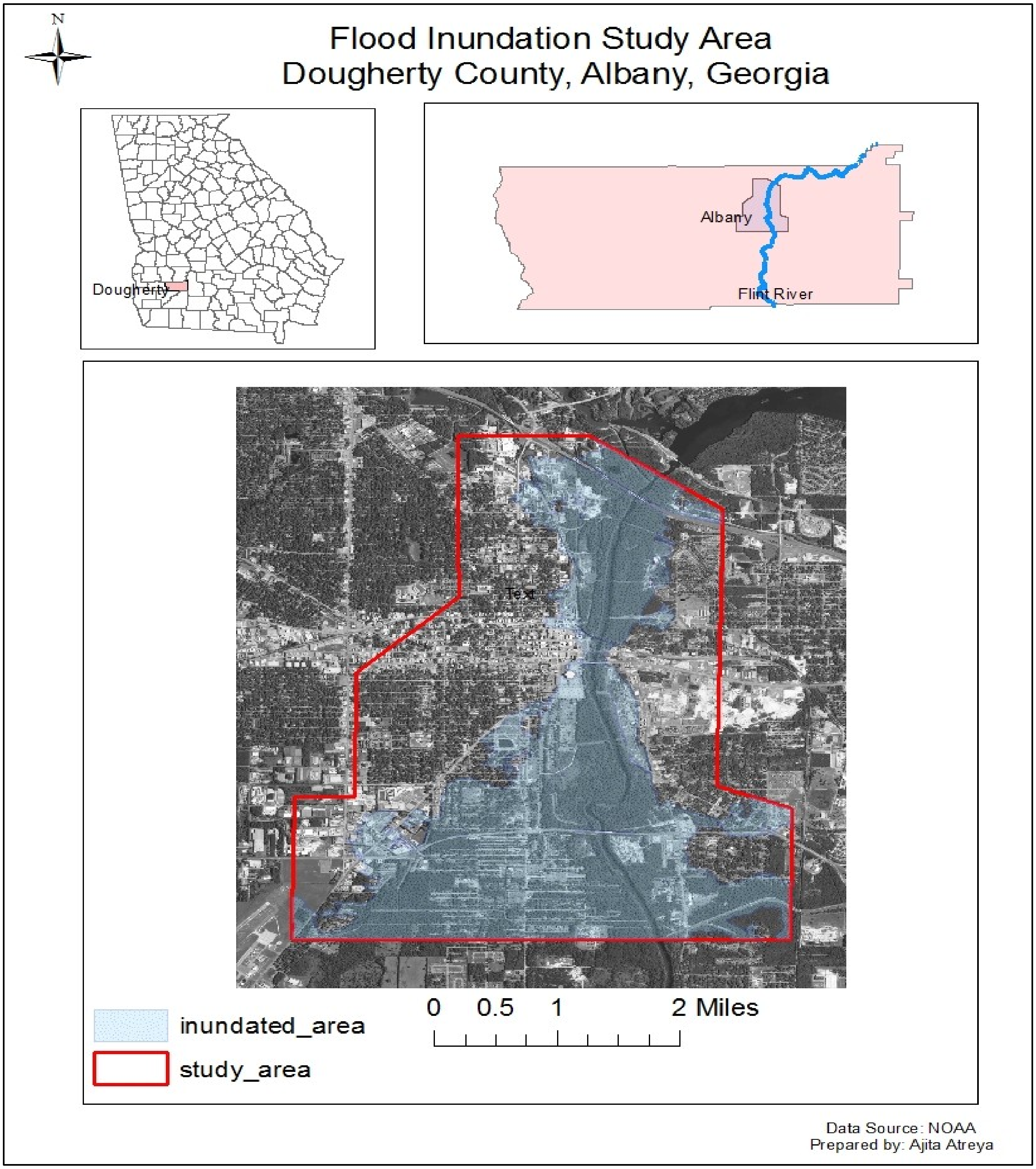
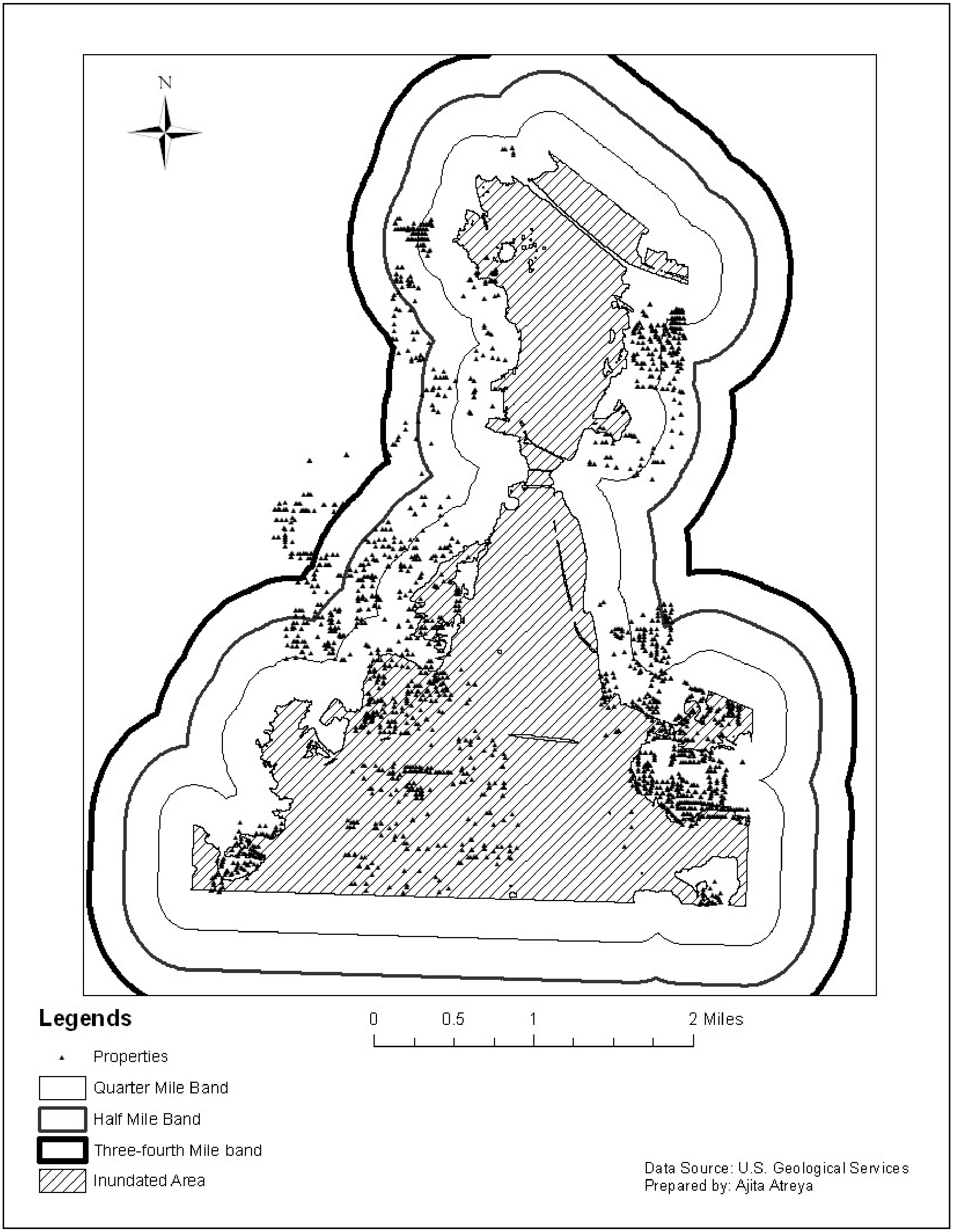


Figure 1: Flood Inundation Study Area, Albany, Georgia



Data Source: U.S. Geological Services
Prepared by: Ajita Atreya

Figure 2: The Distance Bands based on Different Buffer Zones around the Inundated Area.

Table 1: Variables and Descriptive Statistics of "Flood Inundation Study Area", Albany

Variable	Description	Mean	Std. Dev.	Min	Max
price	Sale price of Property adjusted to 2010 constant dollars	77,621	146298.6	1854	1400000
IN	An inundated area during 1994 Flood	30.6%	46.1%	0	1
Depth	Flood depth during 1994 Flood (feet)	5.02	2.25	0.09	14.23
Years	Number of years after 1994 Flood	5.96	5.33	0	16
Near_IND	Distance to Nearest Inundated Area (m)	245.96	320.93	0	1677.66
Elevation	Elevation of Property in Meter	191.60	9.34	175	216
River	Distance to Nearest River in Feet	2186.48	1525.62	19.24	7695.5
Lake	Distance to Nearest Lake in Feet	2389.39	1141.53	33.42	5514.74
Railroad	Distance to Nearest Railroad in Feet	3469.32	2112.04	69.09	9020.49
Roads	Distance to Nearest Road in Feet	97.93	74.76	0.05	505.53
Utilities	Distance to Nearest Utility Lines in Feet	11407.27	4748.22	2409.79	20563.9
Park	Distance to Nearest Park in Feet	5765.67	2424.77	152.65	10291.2
School	Distance to Nearest School in Feet	2820.652	1422.16	145.9	6681.04
Flint	Distance to Flint River in Feet	4526.79	1996.96	1007	11726.2
Year built	Year the Property was built	1961.715	22.34672	1883	2009
Acres	Total Acreage of the Property	0.25	0.20	0	3.73
Bedrooms	Number of Bedrooms	2.81	0.58	0	8
Fullbths	Number of Full baths	1.30	0.51	0	7
Halfbths	Number of Half Baths	0.10	0.30	0	2
Htdsqft	Heated Square Feet	1195.77	425.04	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	0.16	0	1
Flood	1 if sold after July 1994, else 0	0.73	0.44	0	1
FP	1 if 100yr Floodplain, else 0	23%	42%	0	1
IN_FP	1 if inundated in FP, else 0	21.5%	41%	0	1
IN_OFP	1 if inundated outside FP, else 0	9.1%	21%	0	1
NIN_FP	1 if non inundated in FP, else 0	2.5%	15%	0	1
NIN_OFP	1 if non inundated outside FP, else 0	66.9%	47%	0	1
Th_FrMile	1 if between half and a three fourth of a mile, else 0	5.0%	21%	0	1
HalfMile	1 if between quarter and a half of a mile, else 0	20.0%	40.0%	0	1
QtrMile	1 if within a quarter of a mile of IND area, else 0	0.41%	49%	0	1
Income	Median household income by census block group	20,479	6,055	6,907	42,964
PcBlk	Percent of non-whites by census block group	84%	20%	18%	100%
Year Fixed	Effect (1985-2010)				

Table 2: OLS Estimates of Difference-In-Difference (DD) Models for Flood Risk

	(1)	(2)	(3)	(4)	(5)
VARIABLES	LNPRICE	LNPRICE	LNPRICE	LNPRICE	LNPRICE
IN	-0.158**			-0.107	
	(0.0773)			(0.121)	
Flood	0.366**	0.379**	0.292*	0.367**	0.363**
	(0.163)	(0.161)	(0.160)	(0.164)	(0.163)
IN*Flood	-0.485***			-0.419**	
	(0.114)			(0.182)	
Years	-0.0309***	-0.0284***	-0.0225**	-0.0318***	-0.0309***
	(0.00928)	(0.00910)	(0.00885)	(0.00928)	(0.00921)
IN*Years	0.0658***			0.0544***	
	(0.00944)			(0.0134)	
Depth		-0.0358**			
		(0.0150)			
Depth*Flood		-0.0827***			
		(0.0204)			
Depth*Years		0.0110***			
		(0.00158)			
FP			-0.160*	-0.135	
			(0.0932)	(0.156)	
FP*Flood			-0.406***	0.0831	
			(0.124)	(0.271)	
FP*Year			0.0591***	0.0170	
			(0.0104)	(0.0147)	
FP*IN				0.0418	
				(0.207)	
FP*Flood*IN				-0.175	
				(0.257)	
IN_FP					-0.201*
					(0.103)
IN_OFP					-0.108
					(0.121)
NIN_FP					-0.136
					(0.156)
IN_FP*Flood					-0.521***
					(0.129)
IN_OFP*Flood					-0.375**
					(0.185)
NIN_FP*Flood					0.263
					(0.439)
IN_FP*Years					0.0725***
					(0.0110)
IN_OFP*Years					0.0492***
					(0.0140)
NIN_FP*Years					-0.00254
					(0.0351)
Ln(Income)	0.517***	0.507***	0.531***	0.528***	0.530***
	(0.106)	(0.106)	(0.108)	(0.109)	(0.109)

Ln(PcBlk)	-0.0521	-0.0714	-0.0470	-0.0552	-0.0551
	(0.0963)	(0.0970)	(0.0985)	(0.0987)	(0.0988)
Constant	9.027***	9.463***	8.821***	9.083***	9.078***
	(1.897)	(1.916)	(1.930)	(1.965)	(1.967)
Location attributes	Yes	Yes	Yes	Yes	Yes
Structural attributes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	3,005	3,005	3,005	3,005	3,005
R-squared	0.183	0.184	0.178	0.184	0.184

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

Table 3: SARAR Estimates of Difference-In-Difference (DD) Models for Flood Risk

	(1)	(2)	(3)	(4)	(5)
VARIABLES	LNPRICE	LNPRICE	LNPRICE	LNPRICE	LNPRICE
IN	-0.113			-0.0347	
	(0.0871)			(0.138)	
Flood	0.206	0.213	0.139	0.219	0.215
	(0.200)	(0.198)	(0.199)	(0.200)	(0.200)
Flood*IN	-0.474***			-0.477***	
	(0.109)			(0.183)	
Year	-0.0299***	-0.0287***	-0.0206**	-0.0300***	-0.0292***
	(0.00858)	(0.00846)	(0.00839)	(0.00861)	(0.00866)
IN*Year	0.0622***			0.0583***	
	(0.00879)			(0.0128)	
Depth		-0.0269*			
		(0.0158)			
Depth*Flood		-0.0815***			
		(0.0192)			
Depth*Year		0.0108***			
		(0.00147)			
FP			-0.148	0.000641	
			(0.0978)	(0.197)	
FP*FLOOD			-0.392***	-0.0888	
			(0.115)	(0.259)	
FP*Years			0.0504***	0.00534	
			(0.00937)	(0.0136)	
FP*IN				-0.157	
				(0.248)	
FP*Flood*IN				0.0875	
				(0.280)	
IN_FP					-0.192*
					(0.108)
IN_OFP					-0.0355
					(0.138)
NIN_FP					0.000594
					(0.197)
IN_FP*Flood					-0.487***
					(0.121)
IN_OFP*Flood					-0.432**
					(0.191)
NIN_FP*Flood					0.0749
					(0.332)
IN_FP*Years					0.0647***
					(0.00988)
IN_OFP*Years					0.0531***
					(0.0144)
NIN_FP*Years					-0.0128
					(0.0267)
Ln(Income)	0.503***	0.502***	0.511***	0.515***	0.516***

	(0.115)	(0.116)	(0.116)	(0.116)	(0.116)
Ln(PcBlk)	-0.0647	-0.0743	-0.0726	-0.0733	-0.0730
	(0.112)	(0.112)	(0.111)	(0.112)	(0.112)
Lambda	0.00492***	0.00493***	0.00497***	0.00499***	0.00500***
	(0.000811)	(0.000815)	(0.000806)	(0.000809)	(0.000809)
Rho	0.0597***	0.0602***	0.0589***	0.0593***	0.0593***
	(0.00449)	(0.00451)	(0.00449)	(0.00450)	(0.00450)
Constant	9.193***	9.359***	9.450***	9.555***	9.542***
	(2.194)	(2.206)	(2.191)	(2.225)	(2.225)
Location attributes	Yes	Yes	Yes	Yes	Yes
Structural attributes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	3,005	3,005	3,005	3,005	3,005

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

Table 4: Estimation of Spatial Decay in Flood Risk Discount

	(OLS DD Model)		(SARAR DD Model)	
VARIABLES	LNPRICE	LNPRICE	LNPRICE	LNPRICE
IN	-0.118	-0.286**	-0.0705	-0.279**
	(0.0776)	(0.124)	(0.0892)	(0.125)
Flood	0.383**	0.388**	0.221	0.231
	(0.163)	(0.165)	(0.200)	(0.199)
Flood*IN	-0.489***	-0.487***	-0.479***	-0.480***
	(0.114)	(0.113)	(0.109)	(0.109)
Years	-0.0313***	-0.0310***	-0.0303***	-0.0306***
	(0.00926)	(0.00933)	(0.00858)	(0.00857)
IN*Years	0.0668***	0.0664***	0.0630***	0.0629***
	(0.00946)	(0.00946)	(0.00879)	(0.00878)
Qtrmile		-0.162		-0.208**
		(0.101)		(0.103)
Halfmile		-0.000279		-0.0504
		(0.104)		(0.107)
Th_Frmile		0.0675		0.0283
		(0.125)		(0.130)
Near_IND	0.000210**		0.000219**	
	(8.60e-05)		(9.72e-05)	
Lambda			0.00498***	0.00503***
			(0.000806)	(0.000803)
Rho			0.0592***	0.0588***
			(0.00446)	(0.00445)
Constant	9.494***	10.24***	9.538***	10.12***
	(1.911)	(1.946)	(2.189)	(2.199)
Location attributes	Yes	Yes	Yes	Yes
Structural attributes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,005	3,005	3,005	3,005
R-squared	0.185	0.187		

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

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