Forgetting the Flood?: An Analysis of the Flood Risk Discount over Time

Ajita Atreya, Susana Ferreira, Warren Kriesel

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ABSTRACT. *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 nonlinear temporal flood-zone effects, we show that the flood risk discount disappeared between four and nine years after the flood, depending upon the specification.* (JEL Q51, Q54)

I. INTRODUCTION

Floods are the most common natural disaster. Between 1985 and 2009, floods represented 40% of all natural disasters worldwide and accounted for 13% of the deaths and 53% of the number of people affected by all natural disasters (CRED 2010).[1] 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, Downton, and Miller 2002). IPCC (2001) and Swiss Re (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 2003; IPCC 2007), driving up the costs—economic and otherwise—when a flood occurs. In the United States, as of the 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, Benjamin, and Sirmans 1985; MacDonald, Murdoch, and White 1987; Speyrer and Ragas 1991; Harrison, Smersh, and Schwartz 2001; Beatley, Brower, and Schwab 2002; Bin and

[1] 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: (1) 10 or more people killed, (2) 100 or more people reported affected (typically displaced), (3) a declaration of a state of emergency, or (4) a call for international assistance (CRED 2010).

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The authors are, respectively, postdoctoral research fellow, Wharton Risk Management and Decision Processes Center, University of Pennsylvania, Philadelphia; associate professor; and associate professor, Department of Agricultural and Applied Economics, University of Georgia, Athens.

Polasky 2004; Bin and Kruse 2006; Bin, Kruse, and Landry 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: how actual flood events alter flood risk discounts (Skantz and Strickland 1996; Bin and Polasky 2004; Carbone, Hallstrom, and Smith 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: 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 postflood property transactions, starting three 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, were 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 described by 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 of between 25% and 44%. The discount for 500-year floodplain properties was insignificant in most of the specifications. Our estimates are above the 6% to 22% increase identified by Bin and Landry (although their estimates are for three years after the flood and include only the effect of the flood, that is, they ignore the baseline flood zone effect that 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, as in previous papers, we do not have information on damages specific 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.

II. STUDY AREA

In 1994, the Flint River overran its banks from the effects of Tropical Storm Alberto, causing a major flood in southwestern 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 1, it has a total area of 334.64 square miles, of which 329.60 square miles is land and 5.04 square miles is water (U.S. Census Bureau 2010). 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 (Anderson 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 2012). 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 2 is a map of the Flint River, housing units, and the associated floodplains for the southwestern part of Dougherty County. Almost 10.7% 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 for 100 years. In these cases the risks and costs associated with living in a flood-prone area may not be fully understood by homebuyers.

III. 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, Bouvier, and Hansen 1997). Like earlier studies we use a hedonic model to determine the shadow value of a nonmarket environmental

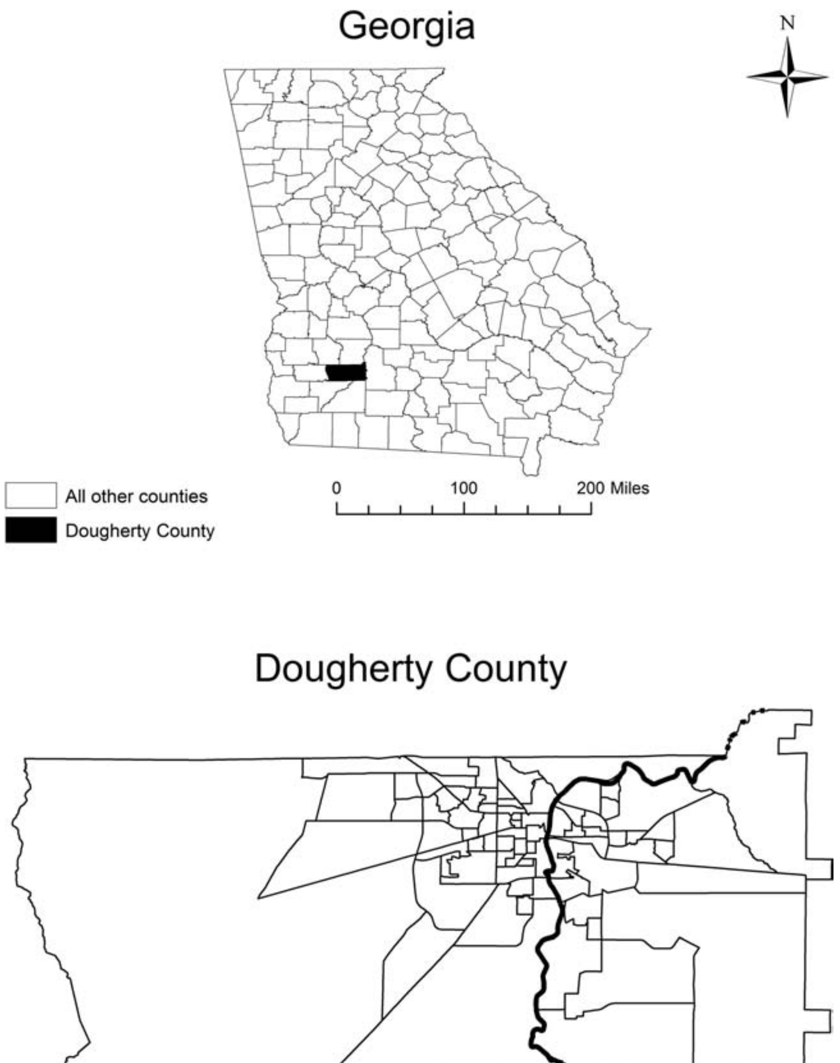

FIGURE 1
Study Area: Dougherty County, Showing City of Albany and Flint River (Block Groups Demarcated by Solid Lines)

attribute: flood risk. In hedonic property models, the price of a property, P, is modeled 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 rivers, distance to parks, median household income, percent of nonwhites in the neighborhood); and an environmental variable of interest, in this case flood risk as captured by location in the floodplain, R:

$$P_{it} = \beta_0 + \boldsymbol{\beta}_1'\mathbf{L}_i + \boldsymbol{\beta}_2'\mathbf{S}_{it} + \beta_3 R_i + \varepsilon_{it}. \quad [1]$$

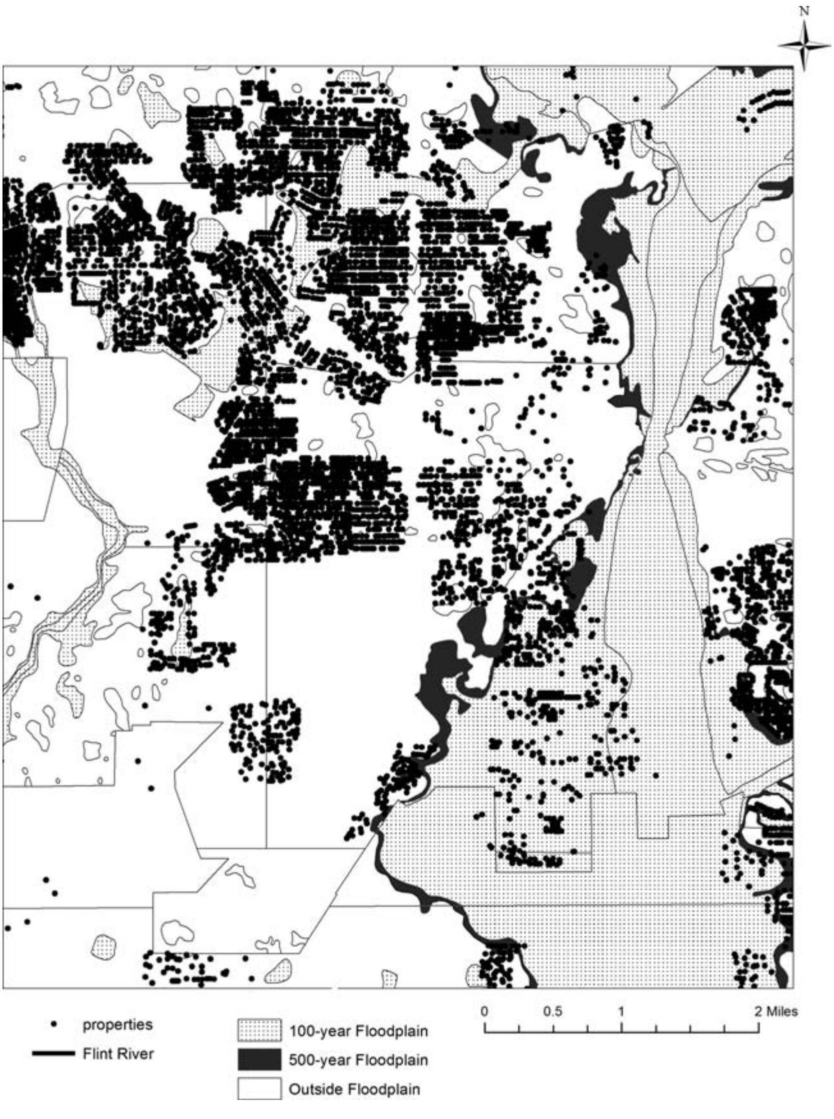

FIGURE 2
Flint River, Housing Units, and Associated Floodplains in Dougherty County

In equation [1] subscripts i and t represent property and time, respectively. $\beta_3 = \partial P_{it}/\partial R_i$, 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 noninsurable losses, or the difference between the loss from flooding and the payment from the insurance company. Noninsurable losses include personal items with sentimental value, the risk of injury and death, the hassle of being displaced, damage to community infrastructure, and so forth (McDonald, Murdoch, and White 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 **L** were best fitted in their log form, while the other attributes **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.[2] Thus, the hedonic model would be

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

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

$$\begin{aligned} \ln(P_{it}) = \beta_0 &+ \boldsymbol{\beta}_1' \ln \mathbf{L}_i + \boldsymbol{\beta}_2' \mathbf{S}_{it} + \boldsymbol{\beta}_3' \mathbf{S}_{it}^2 \\ &+ \beta_4 100yrFP_i + \beta_5 500yrFP_i \\ &+ \beta_6 Flood_{it} + \beta_7 100yrFP_i{*}Flood_{it} \\ &+ \beta_8 500yrFP_i{*}Flood_{it} + \delta_t + \varepsilon_{it}. \quad [3] \end{aligned}$$

[2] These results are available upon request.

This DD model has been used in previous studies (Bin and Landry, and 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 1 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 variables (*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 ordinary least squares (OLS) residuals. However, both approaches require the specification of a spatial weights matrix.

As noted by Donovan, Champ, and Butry (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

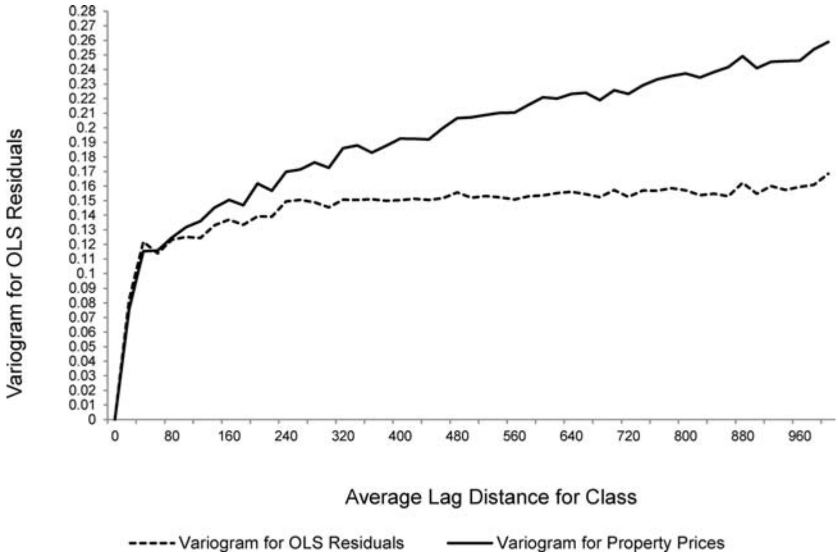

FIGURE 3
Semivariance Graph of Observed (log) Prices and Ordinary Least Squares (OLS) Residuals

been used in varied fields including environmental health and hydrology (Cressie 1993). Following Cressie, the semivariance for pairs of parcels is given by

$$\hat{\gamma}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} (z(x_i + h) - z(x_i))^2, \qquad [4]$$

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 m), 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, in other words, 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 displays plots of two semivariances for pairs of properties within 20 m intervals, going out to 1,000 m.[3] In the lowest plotted line, the regression's residual semivariance increases dramatically in the first intervals up to about 50 m, then it increases slightly to 200 m, after which it levels off. Within the GIS overlay of Doughtery County, these distances are measured from the parcels' centroids rather than the actual houses. Given the size of the parcels, pairs within 50 m of each other tend to represent contiguous properties. Pairs within 200 m 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 display only 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

[3] The analysis was conducted within SAS's Proc Variogram.

ij element $w_{ij} = 1/d_{ij}$, where d_{ij} is the distance between parcels i and j for distances less than 200 m, and $w_{ij} = 0$ otherwise.[4] The second specification would be the most appropriate if the additional increase in semivariance between 50 and 200 m, 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 that 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 that assumes at least one omitted variable that varies spatially leading to measurement error. The general form of our SARAR model is as follows:

$$\begin{aligned}\ln(P_{it}) = {} & \beta_0 + \lambda\sum_j w_{ij}\ln(P_{jt}) + \boldsymbol{\beta}_1'\ln\mathbf{L}_i + \boldsymbol{\beta}_2'\mathbf{S}_{it} \\ & + \boldsymbol{\beta}_3'\mathbf{S}_{it}^2 + \beta_4 100yrFP_i + \beta_5 500yrFP_i \\ & + \beta_6 Flood_{it} + \beta_7 100yrFP_i{*}Flood_{it} \\ & + \beta_8 500yrFP_i{*}Flood_{it} + \beta_9 f(Years) \\ & + \beta_{10} f(Years){*}100yrFP_i \\ & + \beta_{11} f(Years){*}500FP_i + \delta_t + \varepsilon_{it}, \qquad [5]\end{aligned}$$

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.

In the above model, we expanded the traditional DD model to incorporate a potential decay effect of the risk premium by including an interaction term between the floodplain variables and $f(Years)$, where the variable *Years* is the number of years after the 1994 flood. We estimated [5] with different functional forms for $f(Years)$ including a linear time trend, $f(Years) = Years$, and the nonlinear natural logarithm, $f(Years) = \ln(Years)$; ratio, $f(Years) = (Years - 1)/Years$; and square root, $f(Years) = Sqrt(Years)$. 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 nonstochastic. Like Fingleton (2008), Fingleton and Le Gallo (2008), Kissling and Carl (2008), and Kelejian and Prucha (2010), we assume $\mathbf{W} = \mathbf{M}$.[5]

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.[6] Maximum likelihood (ML) 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 (GMM) approach does not. Thus, we employ a generalized spatial two-stage least squares (GS2SLS) estimator that produces consistent estimates (Arraiz et al. 2010).[7] The GS2SLS estimator produces consistent estimates also when the disturbances are heteroskedastic, as is our case,[8] while the ML es-

[4] 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).

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

[6] The Jarque-Bera test for normality of the residuals ($JB = 3{,}430 > \chi^2_{\text{critical}}$ (5.99)) also indicated that the residuals are not normally distributed.

[7] We use the *spreg gs2sls* command in *STATA 12.1* that implements Arraiz et al.'s (2010) and Drukker, Egger, and Prucha's (2009) estimators and allows for both spatial lag and spatial error corrections. The SARAR estimators are produced in four steps: (1) Consistent estimates of $\boldsymbol{\beta}$ 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 $\mathbf{W}^2\mathbf{X}$, which is used as the 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 $\boldsymbol{\beta}$ and λ. (4) The efficient estimates of $\boldsymbol{\beta}$ and λ are used to obtain an efficient GMM estimator of ρ.

[8] The Breush-Pagan/Cook Weisberg test for heteroskedaticity (646.99) rejected the null hypothesis of constant variance.

timator could produce inconsistent estimates in the presence of heteroskedasticity (Arraiz et al. 2010).

IV. DATA

Our dataset combines individual property sales data for residential homes in Dougherty County from the Dougherty County's tax assessor's office for the 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, that is, there are no repeated sales.[9] 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).[10]

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 nonwhite residents) were determined at the block group level using 2000 census data.[11] To measure flood risk, we used a GIS layer of FEMA Q3 flood data to identify parcels in 100-year and 500-year floodplains as represented on flood insurance rate maps published in 1996.[12]

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 onto 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.[13] In order to capture the additional elevation effect, we control for the properties that were built after 1978, that is, 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.[14] Table 1 presents their descriptive statistics. 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 \$83,998. The mean distance to the Flint River was about 4.8 km. The average of median household incomes in the census block groups was

[9] 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.

[10] 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, Georgia, 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.

[11] Block groups generally contain between 600 and 3,000 people, with a typical size of 1,500 people.

[12] 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 of Dougherty County. Older, nondigitized maps are either for the city of Albany or for the rest of Dougherty County and not for the same year.

[13] Communities participating in the NFIP must fully comply with its building code, which requires the lowest floor of any new residential building to be elevated above the base flood elevation.

[14] 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 1
Variables and Descriptive Statistics

Variable	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					
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
100yrFP	1 if in 100-year flood zone, 0 otherwise	0.085	0.27	0	1
500yrFP	1 if in 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 (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
Structure					
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
AC	1 if central air conditioning 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
Neighborhood (2000 Census by block group)					
Income	Median household income	39,102	18,890	6,907	80,000
Nonwhites	Percent of nonwhite residents	0.53	0.30	0	1

$39,102. Seventy-one percent of the properties were sold after the 1994 flood; 26% of the houses were built after the NFIP, and the mean elevation was 206 m. Of all sales between 1985 and 2004, 8.5% of the properties were in the 100-year floodplain and 2.2% 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, postrecession 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.[15] 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 subsamples. Griliches (1971) offers an al-

[15] In addition, we performed an aggregate paired t-test on pre- and postflood data whose p-value is equal to 0.30, so again we fail to reject the null of equal means. We also performed a Wilcoxson-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 postflood and found that the results matched with the paired t-tests. Results for these tests are available upon request.

ternative 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 10%. We compared 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 we decided on the 1985–2004 sample to capture the decay in the flood risk discount over the longer time period.

V. RESULTS

Estimates of the SARAR Model Using a Contiguity Matrix

Table 2 shows the coefficient estimates of equation [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, $f(Years)$.

The significant spatial autocorrelation parameter (ρ) and spatial autoregressive coefficient (λ), toward the bottom of Table 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% level and robustly estimated at 0.002 across the specifications, indicating that if the weighted average of neighboring houses' sale price increases by 1%, the sale price of an individual house increases by approximately 0.002%. 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 nonwhite 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. 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 preflood discount of about 9% associated with properties in the 100-year floodplain,[16] 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% and 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 noninsurable 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% 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). The 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 man-

[16] 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 2
SARAR Model Results for Dougherty County Using a Contiguity Matrix

	Type of Decay (f(*Years*))			
Variable	*Years*	ln(*Years*)	(*Year* − 1)/*Year*	*Sqrt*(*Years*)
100yrFP	−0.0979* (0.0526)	−0.0977* (0.0526)	−0.0969* (0.0526)	−0.0975* (0.0526)
500yrFP	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)
100yrFP × *Flood*	−0.287*** (0.0803)	−0.339*** (0.0843)	−0.406*** (0.0923)	−0.477*** (0.102)
500yrFP × *Flood*	−0.257* (0.147)	−0.236 (0.145)	−0.198 (0.145)	−0.285 (0.178)
f(*Years*)	0.00703 (0.0310)	0.107 (0.296)	1.116 (2.817)	0.0629 (0.192)
100yrFP × f(*Years*)	0.0470*** (0.00991)	0.211*** (0.0406)	0.559*** (0.104)	0.205*** (0.0376)
500yrFP × f(*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(*Lake*)	−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)
Nonwhites (%)	−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

Note: Robust standard errors in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

TABLE 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 ft or more, is equal to $226. This is calculated using 0.27 as the annual postfirm construction rate per $100 of coverage as designated in the National Flood Insurance Program flood insurance manual.

datory) 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 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* variable, plus 23% calculated from the *100yrFP*Flood* coefficient.[17] This discount is equivalent to $26,880 evaluated for an average-priced home in Dougherty County. With the nonlinear decay functions the initial increase in risk discount immediately following the flood is even higher, with the price differential between 35% and 44%. This is consistent with the results of Bin and Landry, namely, the discounts with nonlinear time decay functions are higher than with the linear time trend. 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 the positive and significant *100yrFP*f*(*Years*) interaction terms across all specifications in Table 2. Figure 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 an average-priced 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.[18] 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, at which point it becomes positive. Finally, although our estimates are larger than those of Bin and Landry, it should be noted that, in addition to 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.

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 4. As in Table 2, the columns differ according to how the time-decay effect, *f*(*Years*), is specified. Table 4 presents only the

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

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

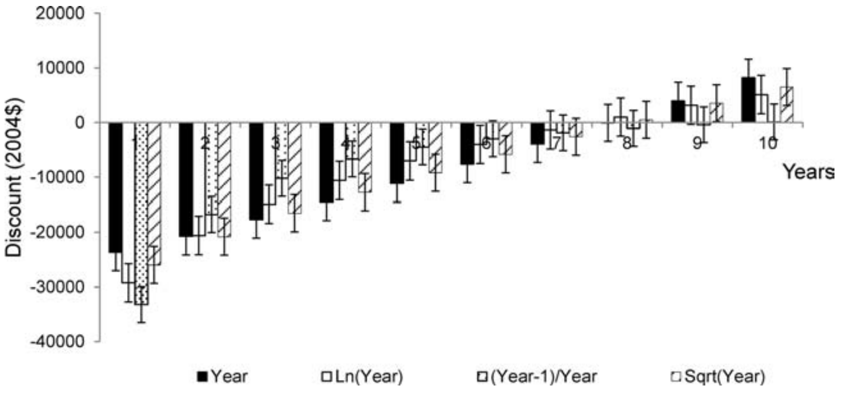

FIGURE 4
Flood Risk Discounts in Dougherty County after the 1994 Flood: SARAR Estimates Using a Contiguity Matrix, with Their 95% Confidence Intervals

TABLE 4
SARAR Model Results for Dougherty County Using an Inverse Distance Matrix

	Type of Decay (f(*Years*))			
Variable	*Years*	ln(*Years*)	(*Year* − 1)/*Year*	*Sqrt*(*Years*)
100yrFP	− 0.0261 (0.0549)	− 0.0276 (0.0548)	− 0.0271 (0.0548)	− 0.0272 (0.0548)
500yrFP	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)
100yrFP × *Flood*	− 0.292*** (0.0798)	− 0.347*** (0.0839)	− 0.423*** (0.0916)	− 0.470*** (0.101)
500yrFP × *Flood*	− 0.289** (0.145)	− 0.268* (0.144)	− 0.230 (0.144)	− 0.335* (0.177)
f(*Years*)	0.0133 (0.0305)	0.157 (0.291)	1.428 (2.758)	0.0967 (0.189)
100yrFP × f(*Years*)	0.0425*** (0.00988)	0.197*** (0.0406)	0.541*** (0.103)	0.189*** (0.0375)
500yrFP × f(*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

Note: Robust standard errors in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

coefficients of interest, but the model includes the same structural and location attributes as in Table 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 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 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 5). Consistent with the previous models we find a higher discount with the nonlinear time decay function f(*Years*), up to 39% in the case of *Sqrt*(*Years*). The decay

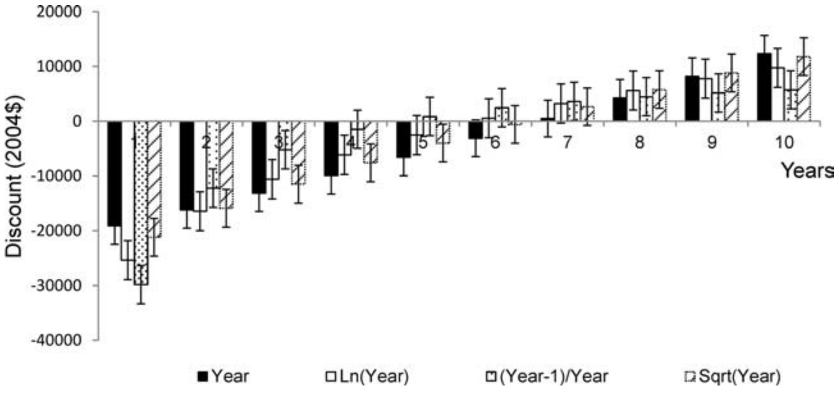

FIGURE 5
Flood Risk Discounts in Dougherty County after the 1994 Flood: SARAR Estimates Using an Inverse Distance Matrix, with Their 95% Confidence Intervals

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 5).

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 5. We find that, using SARAR estimation, there is a significant preflood discount of 9% when using a contiguity matrix, but it is insignificant when using an inverse distance matrix. This result is consistent with the results presented in Tables 2 and 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 positive and statistically significant floodplain and year dummy interactions. 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 6, is roughly consistent with that depicted in Figure 5 for the spatial model fitted using an inverse distance matrix.

VI. 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%, 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

TABLE 5
Robustness Test: Models with Year Dummies–Floodplain Interaction Terms

Variable	Contiguity Matrix ln(*Price*)	Inverse Distance Matrix ln(*Price*)
100yrFP	− 0.0936** (0.0454)	− 0.0202 (0.0483)
500yrFP	0.0723 (0.0812)	0.0871 (0.0818)
Flood	0.139*** (0.0531)	0.144*** (0.0520)
100yrFP × *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

Note: Robust standard errors in parentheses.
* $p<0.1$; ** $p<0.05$; *** $p<0.01$.

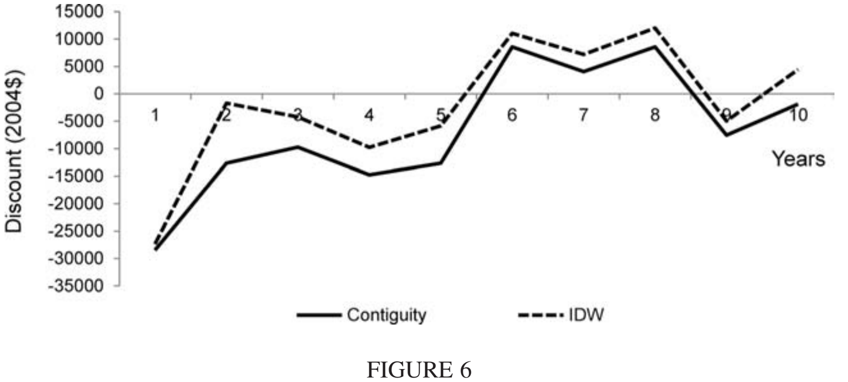

FIGURE 6
Flood Risk Discount in Dougherty County after the 1994 Flood: Estimates Using Year Dummies and Floodplain Interaction Terms, for Two Spatial Weights Matrices

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, North Carolina, vanished five to six years after Hurricane Floyd.

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

TABLE 6
Flood Insurance Policies in Force (PIF) in Dougherty County

Year	PIF	% Change
1985	468	3.31
1986	497	6.20
1987	459	− 7.65
1988	453	− 1.31
1989	465	2.65
1990	592	27.31
1991	560	− 5.41
1992	687	22.68
1993	691	0.58
1994	2,840	311.00
1995	3,404	19.86
1996	2,716	− 20.21
1997	2,172	− 20.03
1998	2,436	12.15
1999	2,229	− 8.50
2000	2,180	− 2.20
2001	1,973	− 9.50
2002	1,908	− 3.29
2003	1,897	− 0.58
2004	1,877	− 1.05

Source: NFIP Legacy System, 2010, "Historical Georgia Policies as of 12/31 Each Year"; Excel file provided by Susan Bernstein, FEMA, May 29, 2012.

Additional evidence is presented in Table 6 that shows the annual percentage change in the number of flood insurance policies in force in Dougherty County from 1985 to 2004. 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, Chen, and Galster 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.[19] In fact, the national average flood insurance premium per policy between 1994 and 1995 fell by about 0.63% in real terms (FEMA 2013). 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 to 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.

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