Ecological Economics 68 (2009) 2627–2636

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

Analysis

# Modeling national flood insurance policy holding at the county scale in Florida, 1999–2005 ☆

Sammy Zahran [a,*], Stephan Weiler [b,1], Samuel D. Brody [c,2], Michael K. Lindell [d,3], Wesley E. Highfield [c,4]

[a] *Department of Sociology, Colorado State University, B235 Clark Building, Fort Collins, CO, 80523-1784, United States*
[b] *Department of Economics, Colorado State University, Fort Collins, CO, 80523-1771, United States*
[c] *Environmental Planning and Sustainability Research Unit, Department of Landscape Architecture & Urban Planning, Texas A&M University, College Station, TX 77843-3137, United States*
[d] *Department of Landscape Architecture and Urban Planning, Texas A&M University, College Station, TX 77843-3137, United States*

ARTICLE INFO

*Article history:*
Received 4 November 2008
Received in revised form 6 April 2009
Accepted 20 April 2009
Available online 18 May 2009

*Keywords:*
National Flood Insurance Program
Florida
Flood mitigation
Community rating system
Flood risk
Moral hazard

*JEL classification:*
H76
Q58
R52

ABSTRACT

We analyze household flood insurance purchases in Florida from 1999 to 2005, and the extent to which household insurance purchases correspond with flood mitigation activities by local governments involved in the Federal Emergency Management Agency's (FEMA) Community Rating System (CRS). Regression results indicate that household flood insurance purchases correlate strongly with local government mitigation activities, adjusting for hazard experience, hazard proximity, and community demography. Policy implications of this observed relationship are discussed, assuming four temporal order and floodplain development scenarios, with particular attention to the congruence of outcomes relative to policy objectives.



## 1. Introduction

Although flood insurance statistics are well-monitored, little is known on why household flood insurance purchasing behavior varies spatially and temporally. This research problem is particularly relevant because FEMA has historically encountered problems encouraging communities and their residents to participate in the National Flood Insurance Program's (NFIP) Community Rating System (CRS). Our study addresses this issue by investigating household flood insurance purchases in Florida from 1999 to 2005, and the extent to which household insurance purchases correspond with flood mitigation activities by local governments involved in FEMA's CRS program. Specifically, we analyze annual counts of flood insurance policy holders for every local jurisdiction in Florida participating in the CRS. Using multivariate statistical models, we isolate the effect local government mitigation activities on flood insurance taking, adjusting for *hazard experience*, *hazard proximity*, and *demographic variables*. Results from our study provide useful information on conditions that explain local variation in the decision to buy flood insurance. Such knowledge can be used by flood managers to increase policy holding in vulnerable areas, perhaps improve the effectiveness of the CRS program, and avoid the significant potential for unintended consequences that are directly antithetical to the goals of the program itself.

The following section details our theoretical intuition on the relationship between CRS-incentivized mitigation activities and flood insurance purchasing behavior, as well as highlights existing literature on household adjustments to environmental hazards, particularly flood insurance purchases. Next, we describe our sample selection, variable measurement, and data analysis procedures. Results are reported in two phases. First, we examine policy holding over the study period using descriptive statistics and GIS-derived maps. Second, we analyze a series of Prais-Winsten regression panel models that longitudinally predict variation in policy counts. Then, we interpret our findings and discuss

☆ This article is based on research supported in part by the U.S. National Science Foundation Grant No. CMS 0346673 and SES 0527699. The findings and opinions reported are those of the authors and are not necessarily endorsed by the funding organizations or those who provided assistance with various aspects of the study.
* Corresponding author. Tel.: +1 970 491 1877(Office); fax: +1 970 491 2191.
*E-mail addresses:* szahran@colostate.edu (S. Zahran), Stephan.Weiler@colostate.edu (S. Weiler), sbrody@archmail.tamu.edu (S.D. Brody), mlindell@archone.tamu.edu (M.K. Lindell), highfield@tamu.edu (W.E. Highfield).
[1] Tel.: +1 970 491 5538.
[2] Tel.: +1 979 458 4623.
[3] Tel.: +1 979 862 3969.
[4] Tel.: +1 979 845 7813.

0921-8009/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.ecolecon.2009.04.021

their policy implications with special attention to the symmetry of outcomes relative to CRS program goals. Finally, we outline an agenda for future research on examining the effectiveness of flood loss reduction programs in the U.S. and better understanding how planners can minimize the rising costs of floods nationwide.

### 1.1. Community rating system and insurance purchasing

A plausible explanation for household flood insurance purchases is the extent to which local governments are involved in flood mitigation efforts. In response to escalating costs associated with repairing damage caused by floods, households are increasingly opting for government-subsidized insurance under the NFIP. Established in 1968 as a federal initiative to reduce the financial burden imposed on flood victims, the NFIP has become the primary mitigation vehicle for communities to fiscally shield themselves against the adverse impacts of chronic flooding in the United States.[5] One important feature of the NFIP is the Community Rating System (CRS), which was created to reward localities for flood mitigation activities that exceed the NFIP's minimum floodplain management standards. Communities that implement programs to improve their flood preparedness rating are rewarded with insurance premium discounts.

The CRS rewards 18 flood mitigation activities organized into four categories of flood management. Series 300, or public information activities, involve local government actions that inform local populations about flood hazards, insurance, and protection measures. Series 400 activities (maps and regulation) involve regulatory enactment and enforcement actions that exceed the NFIP minimum standards. Series 500 activities (damage reduction) involve damage reduction measures like acquiring, relocating, or retrofitting existing buildings and maintaining drainage and retention basins. Series 600 activities (flood preparedness) coordinate local managerial efforts to minimize the effects of a flood on people, property, and building contents. Up to 4500 points are awarded for flood mitigation activities, with points earned by a locality corresponding to financial benefits in the form of flood insurance premium discounts.

The number of points a locality can earn varies by individual mitigation activity. For example, activity *420 Open Space Preservation* awards up to 900 points for restriction of development in flood prone areas. One specific activity involves the protection or restoration of natural areas with beneficial flood functions such as wetlands (Brody et al., 2007; Costanza et al., 2008). The CRS points earned by a locality (ranging from 0 to 4500) correspond to a class rating that ranges from 10 to 1 (where 10 is the lowest class, and 1 is the highest class representing exemplary performance). For example, a community with 1005 CRS points earned is classified as an 8, while a community with 2800 CRS points earned gets a classification of 5. Table 1 summarizes the scoring logic of the CRS program. Across the country, the vast majority (89%) of CRS participating localities fall in the class range of 10 to 7. The same distribution obtains in Florida (see Table 1).

An important incentive for improving a community's CRS class rating is a discount in flood insurance premiums for local residents. Premium rate discounts range from 0 to 45%. For example, a locality with 1600 CRS points is rated as a Class 7, with residents in this locality entitled to a 15% premium reduction in federal flood insurance. The premium discount is designed to create an incentive for local governments to engage in flood mitigation activities. Specifically, as local governments increase their flood protection efforts, premium discounts increase—which creates an incentive for local residents to support community-wide flood hazard reduction activities. Our study empirically examines whether local government mitigation efforts (as reflected in CRS points earned) do, in fact, increase flood hazard insurance purchases by property owners. In the next section, we discuss other variables that may account for spatial variation in household flood insurance purchasing.

**Table 1**
Credit points earned, classification awarded, premium reductions, and distribution of Florida localities in the community rating system (as of 2005).

| Credit points | Class | Premium reduction | | Florida localities | |
|---|---|---|---|---|---|
| | | Special flood hazard area (SFHA) | Non-SFHA | Number of Florida localities | Percentage of Florida localities |
| 4500+ | 1 | 45% | 10% | 0 | 0 |
| 4000–4499 | 2 | 40% | 10% | 0 | 0 |
| 3500–3999 | 3 | 35% | 10% | 0 | 0 |
| 3000–3499 | 4 | 30% | 10% | 0 | 0 |
| 2500–2999 | 5 | 25% | 10% | 6 | 2.9 |
| 2000–2499 | 6 | 20% | 10% | 13 | 6.2 |
| 1500–1999 | 7 | 15% | 5% | 60 | 28.6 |
| 1000–1499 | 8 | 10% | 5% | 97 | 46.2 |
| 500–999 | 9 | 5% | 5% | 34 | 16.2 |
| 0–499 | 10 | 0% | 0% | 0 | 0 |

### 1.2. Alternative explanations

In addition to local government interventions, researchers have identified a number of variables to explain why hazard insurance purchase is far from universal among households at risk from environmental hazards (Jackson and Mukerjee, 1974; Sullivan et al., 1977; Palm et al., 1990; Garcia, 1989; Davis, 1989; Lindell and Prater, 2000; Blanchard-Boehm et al., 2001; Gares, 2002). Important variables include: *hazard experience, hazard proximity, and demographic characteristics.*

Research findings are consistent with respect to *flood hazard experience* and insurance purchase.[6] Specifically, Baumann and Sims (1978), Laska (1990) and Lindell and Hwang (2008) all find significant correlations between flood experience and flood insurance purchasing. Blanchard-Boehm et al. (2001) also report increased insurance purchases after a flood, with the percentage of households with flood insurance increasing from 52% at the time of the flood to 62% at the time of their survey 6 months later. Similarly, Browne and Hoyt (2000) find that flood insurance purchases are highly correlated with the level of flood losses the previous year. With respect to *hazard proximity* and insurance purchasing, Montz (1982) and Lindell and Hwang (2008) report that hazard proximity is significantly correlated with flood hazard insurance purchase. Similar results were reported by Gares (2002), who found that a majority (52%) of those in the 100 year floodplain had flood insurance, whereas only a small minority (5%) of those outside the floodplain had insurance. The positive association between flood hazard proximity and flood insurance purchases is partially explained by a NFIP mandate requiring all homes and commercial buildings in the 100 year floodplain to purchase federal flood insurance.

[5] Although the NFIP has been criticized for its effect on subsidizing and thus encouraging floodplain development, the overall equitability of the program, and the high financial costs of repetitive losses, and the allowance of floodplain and wetland alteration in order to raise the floor elevations of structures in the 100 year floodplain (Birkland et al., 2003; Godschalk et al., 1999), it continues to act as an important technique for financing disaster recovery. As of February, 2008, there were over 5.5 million policies in force insurance over $1.1 trillion in property (FEMA: http://www.fema.gov/business/nfip/statistics/stats.shtm). Since January of 1978, the Federal Emergency Management Agency (FEMA) has paid out over $33.5 billion to cover approximately 1.6 million individual losses (http://bsa.nfipstat.com/reports/1040.htm).

[6] Empirical results on the relationship between hazard experience and household insurance purchasing vary by hazard type. Flood experience increases insurance purchase and earthquake experience has a negligible effect on household adjustment. Palm and Hodgson's (1992) follow-up study on the impact of the Loma Prieta earthquake report negligible effects of past experience on insurance purchase. Many of those in the impacted counties of Santa Clara and Contra Costa were affected by property damage (53% and 11%, respectively), personally knew someone injured (14% and 11%), or knew someone whose home was damaged in the event (65% and 32%). Countywide rates of insurance purchase increased marginally in the impacted counties (11% and 7%), and minimally in the non-impact counties of Los Angeles and San Bernardino (6% and 1%, respectively). These data led Palm and Hodgson (1992) to conclude that behavior and risk perceptions changed only slightly in the most significantly impacted counties and remained stable for the remainder of the sample. Later, Palm (1995) report that earthquake experience was unrelated to earthquake insurance purchase.

In addition to *hazard experience* and *proximity*, research shows that household *demographic characteristics* may influence flood mitigation activities and household flood insurance taking (May, 1992; Mileti, 1999). Community-wide levels of wealth and education may shape flood mitigation efforts. Wealthy communities have more expensive property at risk from flooding and therefore have a greater stake in ensuring protective measures are taken. Also, wealthier jurisdictions will most likely have the financial resources to implement costly strategies, such as structural relocation or drainage improvements. These and other characteristics such as the human capital or the percentage of educated persons residing in a locality, may determine the way local flood managers calculate expected costs and benefits of an intervention, as well as shape the willingness and capacity of households to find relevant information and purchase insurance (Lindell and Perry, 2000; Lindell and Whitney, 2000; Lindell and Prater, 2002).

Overall, the literature on household hazard insurance purchases, together with information about the design of the CRS program, provides direction on local contextual variables that may explain the number of NFIP policies in force within each county. In the next section, we detail variables used to model spatial and temporal variation in the degree to which households purchase flood insurance in Florida.

## 2. Methods

### 2.1. Study area

We selected Florida as our study area for two reasons. First, of the 960 municipalities participating in the CRS program nationwide, 207 are in Florida—about 22% of all municipalities involved. In Florida, 44 of 67 counties independently participate in the program, with another 8 counties having at least one incorporated municipality participating in the CRS. At 78% participation, no other state has this level of municipal involvement. Second, Florida counties suffer disproportionately from floods. Over the study period examined, 19 Florida counties appeared in the top quintile nationally on cumulative property loss (in year 2000 adjusted dollars) from floods, and 24 counties are in the top quintile in terms of the number of floods experienced. According to data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS)[7], Florida counties suffered 1370 floods, and $789.6 million in property losses from 1999–2004. Flood losses in Florida are caused by both recurrent small flood events and large, widespread storms of short duration.[8] It is the combination of high community participation in the CRS program and high flood risk that make Florida an excellent location for testing the spatial correlates of NFIP purchasing behavior.

### 2.2. Dependent variable

Our dependent variable, *National Flood Insurance policies*, is measured as the total number of FEMA National Flood Insurance Program policies in a county divided by the number of households multiplied by 100 (see Table 2 for summary of all variable operations). Skewness (1.28) and kurtosis (3.53) values show evidence of non-normality (see Table 3 for summary statistics) so we log transform the dependent variable to normalize its distribution for the regression analyses.

[7] The SHELDUS database consists of a county-level inventory of 18 natural hazard types, including hurricanes, floods, wildfires, and drought. Hazard event records include a start and end date, estimated property damage and crop loss, as well as the number of human injuries and deaths. SHELDUS data are derived from public sources like National Climatic Data Center monthly publications and NGDC's Tsunami Event Database. The data are limited to disaster events that cause more than $50,000 in crop loss or property damage.

[8] For example, during a two day period in early October of 2000 Broward, Collier, Miami-Dade, and Monroe Counties collectively received over a foot of rain, causing over $450 million dollars of flood damage, prompting over 51,000 individuals to request financial assistance from the Federal Emergency Management Agency (Brody et al., 2009).

**Table 2**
Variable operations, data sources, and expected direction.

| Variable name | Variable operation | Sign | Data source |
|---|---|---|---|
| *Intervention variable* | | | |
| CRS points | CRS points earned for activities that mitigate flood outcomes, including mapping and regulation, damage reduction, flood preparedness, and public information, divided by 500 | + | FEMA community rating system 1999–2005 |
| *Demographic variables* | | | |
| Median home value (10,000) | Value is an estimation of how much a property (house and lot) would sell for in market. Includes only specified owner-occupied housing units. Median value calculations are rounded to the nearest hundred dollars. Values for 1990 and 2000 Censuses are used to estimate intervening years. Dollars expressed in $10,000 increments | + | US Census Bureau, 1990, 2000 |
| Percent college educated | Number of persons age 25 and over with a bachelor's, master's, professional, or doctorate degree divided by the total population 25+ years of age multiplied by 100. Values for the 1990 and 2000 Censuses are used to estimate intervening years | + | US Census Bureau, 1990, 2000 |
| *Hazard proximity variables* | | | |
| Floodplain percentage | Total land area of a county in the floodplain divided by the total land area (in square kilometers) and multiplied 100 | + | FEMA Digital Q3 flood data |
| Stream density | Total length of streams in a county area divided by the total land area (in square kilometers) and multiplied 100 | + | National hydrography dataset |
| Coastal county | Measured dichotomously. County receive a score of 1 if it is a NOAA Designated Coastal County (at least 15% area in coastal watershed); and a score of 0 if it is not | + | National Oceanic and Atmospheric Administration |
| *Hazard experience variables* | | | |
| Flood frequency | Ten year rolling average of the total annual number of flood disasters recorded in a county | + | Spatial hazard events and losses database, 1990–2005 |
| Flood property damage (100,000) | Ten year rolling average of the total annual flood caused property damage recorded in a county (in year 2000 inflation adjusted dollars). Dollars expressed in $100,000 increments | + | Spatial hazard events and losses database, 1990–2005 |
| *Dependent variable* | | | |
| NFIP policies (natural log) | The Natural log of the total number of FEMA National Flood Insurance Program policies divided by the number of households multiplied by 100 | | FEMA community rating system 1999–2005 |

**Table 3**
Descriptive statistics on dependent and independent variables.

| Variables | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 |
|---|---|---|---|---|---|---|---|
| *Dependent variable* | | | | | | | |
| NFIP (percent) | 18.41 | 18.19 | 17.39 | 16.99 | 17.00 | 17.41 | 18.52 |
| | (20.22) | (20.03) | (19.45) | (19.29) | (19.22) | (19.33) | (20.03) |
| *Intervention variable* | | | | | | | |
| CRS points | 1.60 | 1.91 | 2.02 | 2.14 | 2.16 | 2.26 | 2.44 |
| | (.75) | (.81) | (.88) | (.95) | (.95) | (.97) | (1.01) |
| *Demographic variables* | | | | | | | |
| College educated | 18.34 | 18.54 | 18.55 | 18.85 | 19.16 | 19.71 | 20.05 |
| | (8.17) | (8.29) | (8.44) | (8.52) | (8.68) | (8.77) | (8.93) |
| Median home value | 9.94 | 10.20 | 10.43 | 10.68 | 10.99 | 11.39 | 11.70 |
| | (3.05) | (3.17) | (3.24) | (3.37) | (3.49) | (3.60) | (3.72) |
| *Hazard proximity variables* | | | | | | | |
| Floodplain | 27.40 | 28.21 | 28.37 | 28.15 | 28.15 | 28.31 | 28.31 |
| | (11.23) | (12.46) | (12.24) | (12.22) | (12.22) | (12.29) | (12.29) |
| Stream density | .008 | .008 | .008 | .008 | .008 | .008 | .008 |
| | (.005) | (.005) | (.005) | (.005) | (.005) | (.005) | (.005) |
| Coastal county | .938 | .939 | .941 | .942 | .942 | .941 | .941 |
| | (.245) | (.242) | (.238) | (.235) | (.235) | (.238) | (.238) |
| *Hazard experience variables* | | | | | | | |
| Flood frequency | 1.06 | 1.15 | 1.21 | 1.19 | 1.14 | 1.01 | .977 |
| | (.879) | (.957) | (.986) | (.967) | (.997) | (.994) | (.962) |
| Flood property damage | 20.58 | 29.67 | 29.59 | 29.66 | 20.97 | 21.02 | 21.08 |
| | (19.37) | (60.09) | (59.04) | (58.50) | (59.49) | (60.02) | (59.24) |
| *N* | 48 | 49 | 51 | 52 | 52 | 51 | 51 |

Standard deviations are in parentheses.

### 2.3. Independent variables

As noted earlier, four types of variables are used to predict NFIP policy purchases: *local government interventions*, *demographic characteristics*, *hazard proximity*, and *hazard experience*. First, our *local government intervention* variable, *CRS points*, is estimated as the total population-weighted points earned by a county divided by 500. Our population-weighting procedure requires some explanation. Most counties in Florida earn their own CRS points. In some cases, independent municipalities within a county earn separate points for flood mitigation efforts. In such cases, we population-adjust and summarize the mitigation activities of municipalities within that county. Fig. 1 illustrates the logic of measurement, showing Lee County and its municipalities of Bonita Springs, Cape Coral, Sanibel, and Fort Meyers Beach and City. Lee County is located on the southwest coast of Florida, approximately 200 km south of the Tampa Bay area. As of 2000, each municipality earned different CRS point totals. First, we subtract population totals of the municipalities from the total county population to derive the balance of residents in Lee County. Second, the population of each municipality is divided by the total county population to derive a weight. Third, we multiply this municipal weight by the observed CRS point total for each municipality. Fourth, we summarize population weighted CRS points to derive our county estimate. This procedure is performed for all participating counties, and the communities within those counties, for the period 1999–2005. We divide CRS points earned by 500 because insurance premium discounts move in five percent increments corresponding to 500 point intervals.

Two demographic variables are measured: *median home value* and *percent college educated*. *Median home value* estimates a property's (house and lot) sale price in the open market. This figure includes only specified owner-occupied housing units. Median value calculations are rounded to the nearest hundred dollars, and divided by $10,000. *Percent college educated* is measured as the total number of persons age 25 and over with a bachelor's, master's, professional, or doctorate degree divided by the total population 25+ years of age multiplied by 100. Median home value and education figures from the 1990 and 2000 Population and Housing Censuses are used to forecast beyond the year 2000, assuming linear change.

Three *hazard proximity* or hydrology variables are tested: *floodplain percentage, stream density, and coastal proximity*. *Floodplain percentage* is measured as the total land area of a county (in square kilometers) located in the 100-year floodplain (delineated areas that have a one percent chance of flooding in any 1 year), divided by the total land area multiplied by 100. Floodplain estimates are from the most recent FEMA Digital Q3 flood data. Our *stream density* variable is calculated in a GIS using the National Hydrography Dataset (NHD), and measured as the total length of all streams in a county jurisdiction divided by the total land area multiplied by 100. Both floodplain percentage and stream density are time invariant variables. *Coastal county* is measured dichotomously, with county receiving a score of 1 if it is a NOAA Designated Coastal County (at least 15% area in coastal watershed), and a score of 0 if it is not. Theoretically, coastal localities with a high fraction of land area in the 100-year floodplain ought to have a greater number of policies in force given that all households and commercial entities in the floodplain are legally required to purchase NFIP policies.

Finally, two *hazard experience* or flood risk variables are estimated: *flood frequency* and *flood property damage*. Both variables are measured at the county scale (the finest spatial resolution available). *Flood frequency* is measured as a ten-year rolling average of the annual number of flood events recorded in a county. To estimate the intensity of flood events, we calculate a ten-year rolling average of the annual property damage incurred from flood events. Property damage figures are in year 2000 US dollars. Data on flood frequency and property damage are from SHELDUS.

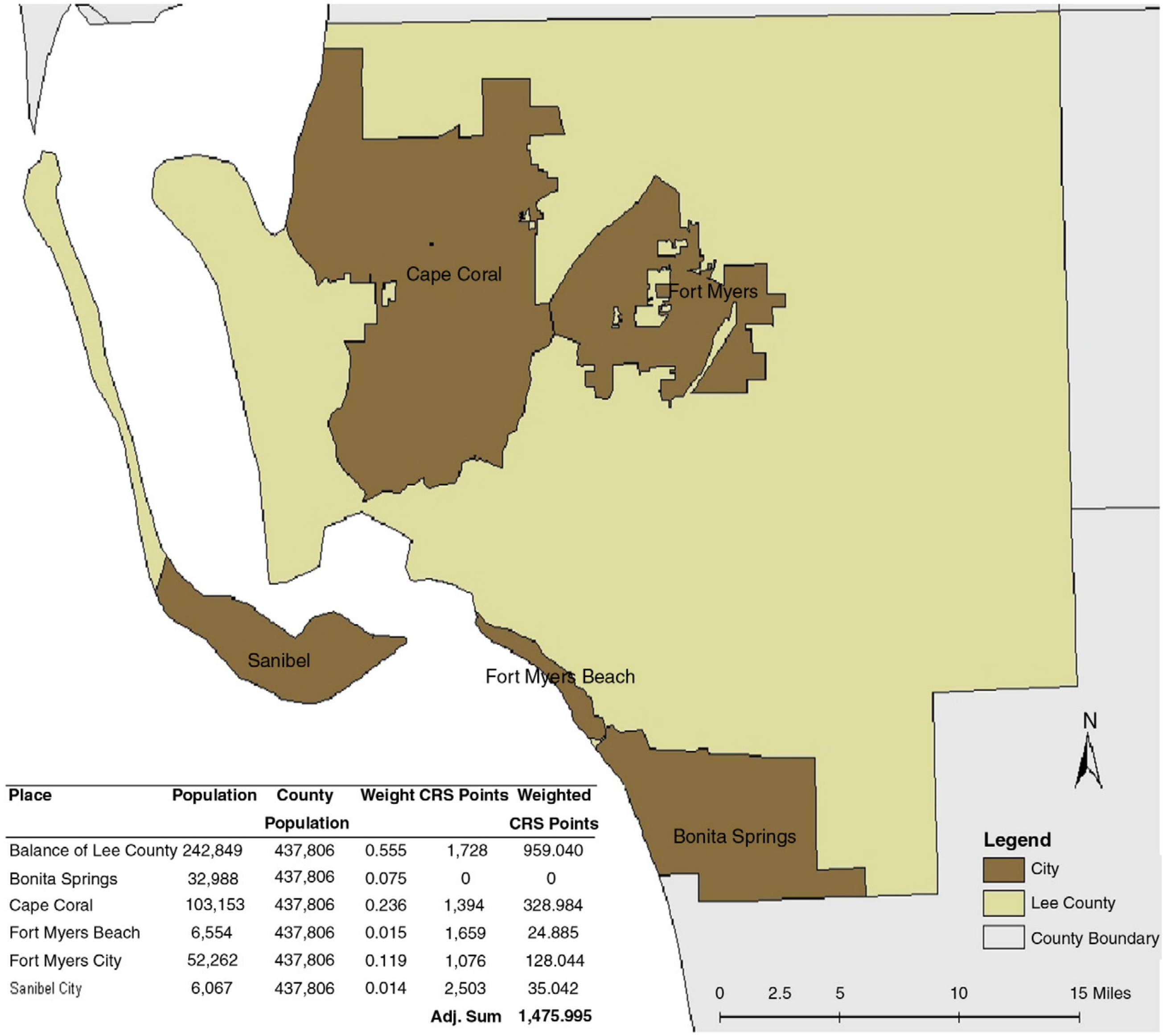
### 2.4. Model selection

Data are indexed by both unit (county) and time (year). To efficiently model our dependent variable, *NFIP policies*, we screen for *serial autocorrelation*, *contemporaneous correlation*, and *heteroskedasticity*. First, to screen for serial autocorrelation we conduct a Wooldridge test (Wooldridge, 2002; Drukker, 2003)—results are positive and significant ($F=19.685$, $p<.001$). Second, we execute a Pesaran's test for cross-sectional dependence (CD test). Contemporaneous correlation is present in our dependent variable across all models specified, (Pesaran = 20.140, $p=.000$, average absolute value of the off-diagonal elements = .509). Third, to screen for heteroskedasticity we perform an auxiliary regression procedure (Glejser, 1969). We estimate an ordinary least-squares (OLS) regression model, and then regress the absolute value of OLS residuals on independent variables. The *F* statistic provides a reasonable test of panel heteroskedasticity against the null hypothesis of homoskedasticity (Worrall and Pratt, 2004). In a reduced model with CRS points earned as an independent variable, we find a statistically significant *F* statistic of 21.01 ($p<.001$).

With data structure assessed, we narrow the pool of statistical approaches. First, pooled OLS is not an option given the presence of serial autocorrelation and cross-sectional dependence. Second, fixed-effects panel regression is not appropriate given our use of time-invariant control variables like floodplain percentage and stream density. Third, random-effects panel regression is inappropriate given both serial autocorrelation and contemporaneous correlation. Two procedures are appropriate when dealing with data structure issues outlined above: Feasible Generalized Least Squares (FGLS) and Ordinary Least Squares with correlated Panel Corrected Standard Errors (PCSE). Research shows that FGLS produces inefficient estimates when $T \leq N$ (Beck and Katz, 1995). In our sample, $T=7$ and $N=52$. Thus, we selected Prais-Winsten Regression with Correlated Panels Corrected Standard Errors (PCSE) to correct for serial autocorrelation, heteroskedasticity, and contemporaneous correlation. This analytic procedure yields conservative and efficient standard errors, significance values, and confidence intervals.

## 3. Results

We begin by ranking the top 15 counties on the number of NFIP policies per 100 households as of the year 2000 (see Table 4). The




| Place | Population | County Population | Weight | CRS Points | Weighted CRS Points |
|---|---|---|---|---|---|
| Balance of Lee County | 242,849 | 437,806 | 0.555 | 1,728 | 959.040 |
| Bonita Springs | 32,988 | 437,806 | 0.075 | 0 | 0 |
| Cape Coral | 103,153 | 437,806 | 0.236 | 1,394 | 328.984 |
| Fort Myers Beach | 6,554 | 437,806 | 0.015 | 1,659 | 24.885 |
| Fort Myers City | 52,262 | 437,806 | 0.119 | 1,076 | 128.044 |
| Sanibel City | 6,067 | 437,806 | 0.014 | 2,503 | 35.042 |
| | | | | Adj. Sum | 1,475.995 |

**Fig. 1.** The logic of population weighted measurement of CRS points for each county.

following seven counties have values of at least 50 NFIP policies per 100 households: Collier, Franklin, Lee, Broward, St. Johns, Santa Rosa and Charlotte. Five of the seven counties in the southeast region of Florida and four of ten counties in the northwest region are among the top 15 NFIP policy holding counties. Independent sample *t*-test results (assuming unequal variances) show that counties in the southeast and northwest regions of the state have significantly higher percentages of land area in the 100-year floodplain (29.99 versus 27.35%, $t = 2.025$, $p = .044$), and significantly higher rolling averages of property damage from flood events ($5.44 million versus $1.19 million, $t = 5.32$, $p < .001$).[9] Counties with large numbers of policy holders also have higher CRS mitigation scores.

Fig. 2 shows the spatial distribution of NFIP policies per 100 households for CRS participating localities, (averaged across 1999–2005). The distribution is divided into equal intervals, with higher counts of NFIP polices per 100 households in darker colors and lower counts in lighter colors. Without exception, higher NFIP purchasing counties are coastally located, wrapping the southern tip of the state (and encircling the Everglades). These coastal counties have at least 15% of land area in a coastal watershed, making them susceptible to repetitive flooding.

Fig. 3 shows the geography of population-weighted CRS points earned by counties. The distribution is divided into 500 point intervals corresponding to the discount structure of the CRS program. Recall, localities earn points for CRS-prescribed flood mitigation activities, with points earned corresponding to insurance premium discounts that flow to local residents (that move in 5% intervals). As with the distribution of NFIP policies, localities with higher mitigation scores are predominately located on the west coast of the state. The top three counties on CRS points earned—Charlotte, Lee, and Manatee—also appear among the top counties on NFIP policy holding. The apparent correspondence between NFIP polices per 100 households and CRS points earned is confirmed by a strong positive Pearson's correlation of $r = .41$.

[9] The point-biserial correlations of regional land area in the floodplain and flood property damage are 0.068 ($p \geq .10$) and 0.375 ($p \leq .001$), respectively. Thus, regional differences in the percentage of land area in the flood plain are trivial but regional differences in property damage are relatively substantial.

**Table 4**
Top 15 counties in Florida by NFIP polices per 100 households as of 2000.

| Rank | County | Region | Households | NFIP polices | Polices per household |
|---|---|---|---|---|---|
| 1 | Collier | Southwest | 102,973 | 75,199 | 73.03 |
| 2 | Franklin | Northwest | 4096 | 2634 | 64.31 |
| 3 | Lee | Southwest | 188,599 | 112,014 | 59.39 |
| 4 | Broward | Southeast | 654,445 | 383,593 | 58.61 |
| 5 | St. Johns | Northeast | 56,640.88 | 32,546 | 57.46 |
| 6 | Santa Rosa | Northwest | 47,441.44 | 25,353 | 53.44 |
| 7 | Charlotte | Southwest | 63,864 | 32,308 | 50.59 |
| 8 | Dade | Southeast | 776,774 | 312,417 | 40.22 |
| 9 | Indian River | Southeast | 49,137 | 18,829 | 38.32 |
| 10 | Pinellas | Tampa Bay | 414,968 | 124,303 | 29.95 |
| 11 | Palm Beach | Southeast | 474,175 | 132,140 | 27.87 |
| 12 | Martin | Southeast | 55,288 | 15,251 | 27.58 |
| 13 | Gulf | Northwest | 4931 | 1225 | 24.84 |
| 14 | Okaloosa | Northwest | 66,269 | 15,544 | 23.46 |
| 15 | Manatee | Tampa Bay | 114,595 | 26,533 | 23.15 |

Table 5 displays the intercorrelations among the dependent (X1 = Number of flood insurance policyholders), and independent variables (X2 = CRS rating through X8 = flood frequency). The correlations of the independent variables with the dependent variable are generally consistent with our hypotheses but suggest that the hazard proximity variables are unlikely to emerge as significant predictors of insurance purchases. Moreover, there are low intercorrelations among the independent variables, suggesting that multicollinearity will not be a problem in the estimation of the regression equations.

Next, in Table 6, we report Prais-Winsten regression coefficients (with correlated panels corrected standard errors) predicting the natural log of the number of NFIP policies per 100 households from 1999 to 2005. Variables are loaded incrementally, beginning with our local government intervention variable (CRS points) and ending with a fully saturated model of demographic, hazard proximity, and hazard experience control variables. Because coefficients behave consistently across all specifications we concentrate our interpretation on the full model. Table 7 shows marginal effects (or elasticities) and intervals of confidence with model parameters fixed at sample means and the mean of each predictor.

Beginning with our intervention variable, results in Table 6 (Model 4) show that a unit increase in CRS points earned (measured in 500 point increments) increases the natural log of NFIP policies per 100 households by .101% ($p<.001$). If we take the antilog of our coefficient ($e^{101}$), we find that an additional 500 points in the CRS program increases the expected count of NFIP policies per 100 households by a multiplicative factor of 1.106 or 10.6%. In Miami-Dade county, with 45.77 NFIP polices per 100 households (as of 2005), a 500 point increase in CRS points increases the NFIP policy count by about 4.62 households per 100 ($45.77 * 1.101$). In raw numbers, if Miami-Dade flood managers undertake mitigation efforts that earn 500 points, we can expect an increase of roughly 4000 households with NFIP protection (assuming 834,932 households as of 2005). Similarly, Table 7 shows that a one percent

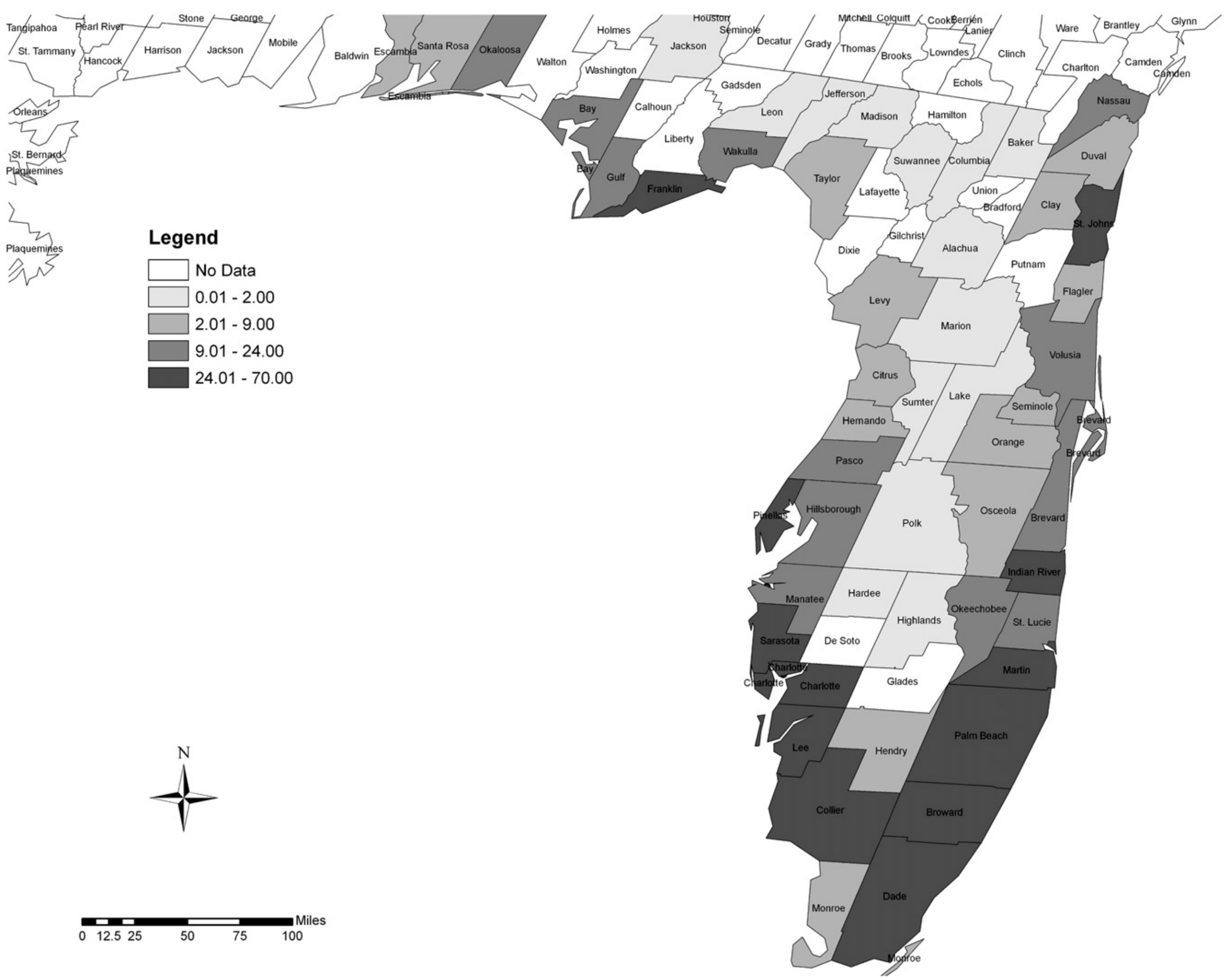



**Fig. 2.** Average annual number of NFIP policies per 100 households for CRS participating localities, 1999–2005.

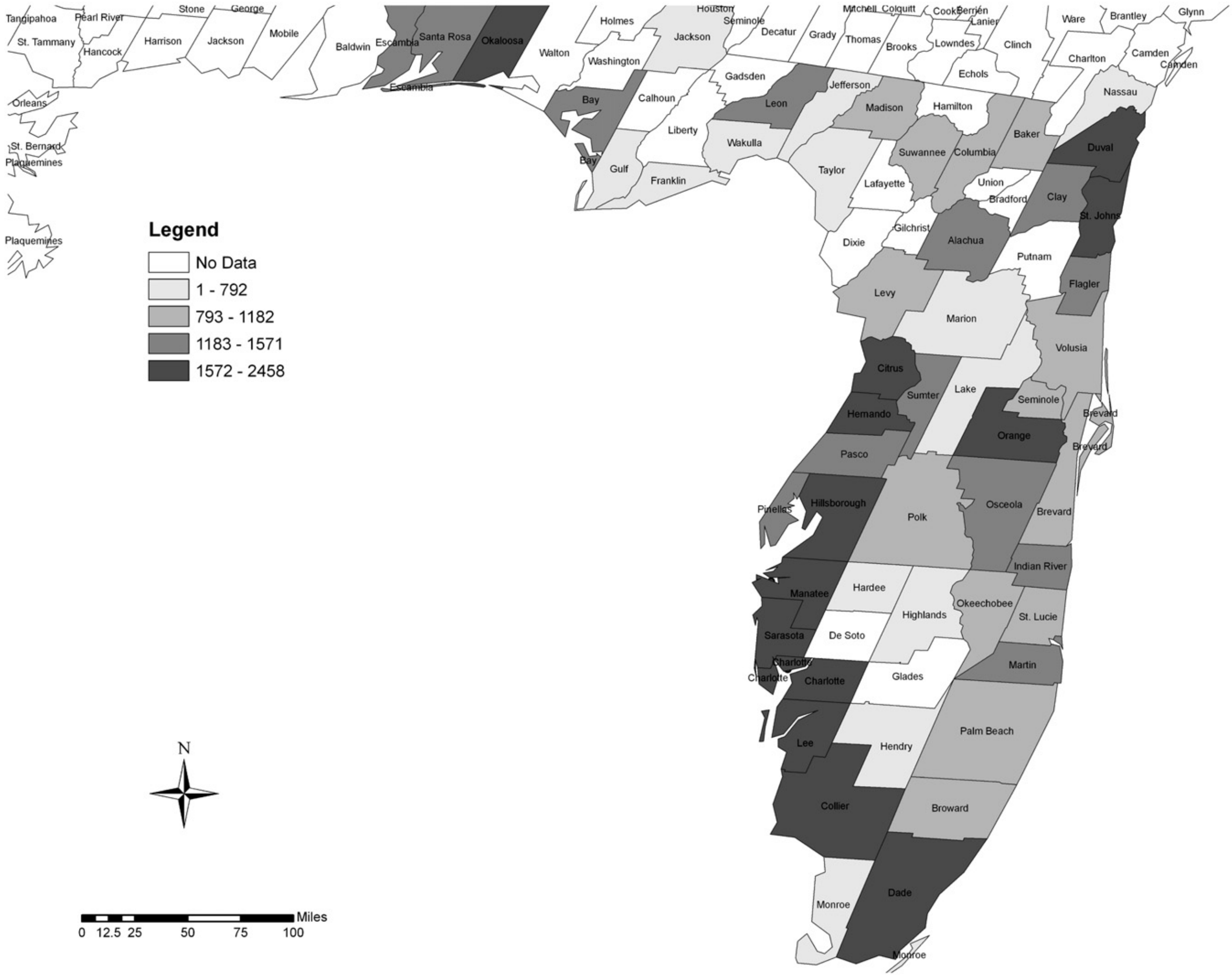



**Fig. 3.** Average CRS points earned for flood mitigation activities in CRS participating localities, 1999–2005.

increase in CRS points earned (from the mean) yields an increase of .129 to .292% (95% confidence intervals) in the number of NFIP policies per 100 households. Fig. 4 traces the elasticity of the CRS-NFIP relationship (along with floodplain percentage and flood count parameters) over selected values. Results from this figure show that the marginal effect of CRS points earned is upward sloping over a range of regressor values.

**Table 5**
Intercorrelations among variables*.

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1. Policy holders | 1.000 | | | | | | | | |
| 2. CRS rating | .414 | 1.000 | | | | | | | |
| 3. Home value | .384 | .117 | 1.000 | | | | | | |
| 4. Education | .202 | .248 | .364 | 1.000 | | | | | |
| 5. Floodplain | .046 | −.274 | −.084 | −.267 | 1.000 | | | | |
| 6. Stream density | .001 | .054 | −.138 | −.071 | −.210 | 1.000 | | | |
| 7. Coastal county | .291 | .100 | .160 | −.191 | −.016 | .142 | 1.000 | | |
| 8. Flood damage | .268 | .087 | .137 | −.091 | .068 | −.200 | .080 | 1.000 | |
| 9. Flood frequency | .220 | .395 | −.051 | .010 | −.303 | .289 | .050 | −.014 | 1.000 |

*$N=354$, all $r>.12$ are significant at $p<.05$.

On demographic variables, Table 6 shows that a unit increase in median home value (measured in $10,000 units) increases the expected count of NFIP policies by a multiplicative factor of 1.110 ($e^{.096}$). A $10,000 increase in median home value is roughly statistically equivalent to a 500 point increase in CRS points earned in terms of increasing the size of a local insurance pool. According to Table 7, a percent increase in median home values has a 1.04 proportional effect on flood policy purchasing ($p<.001$). Similarly a unit change in percent college educated significantly increases the count of policyholders per 100 households ($b=.031$, $p<.001$). Taken together, demographic variables show that NFIP policy counts move predictably with home-embedded wealth and educational attainment levels of a locality.

Next, we address whether NFIP policy counts correlate with local hazard proximity conditions. As expected, in Table 6 a unit increase in the fraction of local land area in the FEMA-defined floodplain increases the count of policy holders by a multiplicative factor of 1.02, or 2% ($e^{.021}$). According to Fig. 4, the marginal effect of the percentage of land area in the floodplain increases steeply beyond the 50th percentile (representing more than a quarter of land area in the floodplain). In fact, a percent increase in the fraction of land area in the floodplain from a starting point of 45% and upward, increases the percentage of NFIP policy holders per 100 households by at least 1%. Likewise, coastal counties have higher expected counts of NFIP policy holders ($b=1.491$, $p=.036$).

Finally, as hypothesized, prior flood experience significantly drives flood insurance purchases. Both the frequency and intensity of prior

**Table 6**
Prais-Winsten Regression with Correlated Panels Corrected Standard Errors (PCSEs) predicting the natural log of the number of National Flood Insurance Policies per 100 households at the county scale, 1999–2005.

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| *Intervention variable* | | | | |
| CRS points | .1367*** | .131*** | .120*** | .101*** |
| | (.016) | (.024) | (.023) | (.020) |
| *Demographic variables* | | | | |
| Median home value | | .118*** | .092*** | .096*** |
| | | (.012) | (.012) | (.012) |
| College educated | | .010*** | .028*** | .031*** |
| | | (.003) | (.004) | (.003) |
| *Hazard proximity variables* | | | | |
| Floodplain | | | .017*** | .021*** |
| | | | (.003) | (.003) |
| Stream density | | | 7.67 | .168 |
| | | | (5.34) | (5.21) |
| Coastal county | | | 1.509*** | 1.491*** |
| | | | (.150) | |
| *Hazard experience variables* | | | | |
| Flood frequency | | | | .237** |
| | | | | (.043) |
| Flood property damage | | | | .001*** |
| | | | | (.000) |
| Constant | 1.848*** | .414*** | −1.596* | −1.966*** |
| | (.075) | (.129) | (.150) | (.164) |
| Rho | .923 | .887 | .895 | .883 |
| Observations | 354 | 354 | 354 | 354 |
| FIP codes | 52 | 52 | 52 | 52 |
| *R*-squared | .4832 | .5191 | .5678 | .5815 |
| Wald $\chi^2$ | 72.89** | 442.72** | 6341.18*** | 5823.29*** |

Null hypothesis test of coefficient equals zero.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

flooding increase the expected count of insurance holders. The addition of one flood per year increases the number of NFIP policy holders per 100 households by a multiplicative factor of 1.27, or 27% ($e^{.237}$). For the average county in Florida (with 17.69 NFIP policies per 100 households), a multiplicative factor of 1.29 yields an increase of about five NFIP policies per 100 households ($17.69*1.27=22.46$). In raw terms, an increase of five policies per 100 households means 6,404 more NFIP policies for an average Florida county (with 128,077 households). The elasticity of the relationship between flood frequency and NFIP policies shown in Fig. 4 reveals a takeoff point at the 75 percentile (corresponding to 1.3 floods per year). All other variables held equal, results also show that the rolling average of flood-related property damage (in $100,000 units) significantly increases NFIP policy purchases ($b=.001$, $p=.005$).

**Table 7**
Marginal effects* with parameters fixed at means (following Prais-Winsten Regression with Correlated Panels Corrected Standard Errors).

| | dy/ex | Std. Err. | z | Lower 95% | Upper 95% | X |
|---|---|---|---|---|---|---|
| *Intervention variable* | | | | | | |
| CRS points | .211 | .042 | 5.05 | .129 | .292 | 2.082 |
| *Demographic variables* | | | | | | |
| Median home value | 1.04 | .120 | 8.63 | .800 | 1.27 | 10.770 |
| College educated | .590 | .061 | 9.65 | .470 | .710 | 19.038 |
| *Hazard proximity variables* | | | | | | |
| Floodplain | .598 | .076 | 7.86 | .449 | .747 | 28.136 |
| Stream density | .001 | .040 | 003 | −.077 | .080 | .0077 |
| Coastal county | 1.40 | .060 | 23.40 | 1.28 | 1.52 | .941 |
| *Hazard experience variables* | | | | | | |
| Flood frequency | .262 | .048 | 5.46 | .168 | .356 | 1.106 |
| Flood property damage | .021 | .010 | 2.16 | .002 | .040 | 24.662 |

* To find elasticities of $y$ with respect to $x_j$, we take the semi-elasticity $dy/dlog(x_j)$ of our log-linear model. County elasticity reflects a discrete change of dummy variable from 0 to 1.

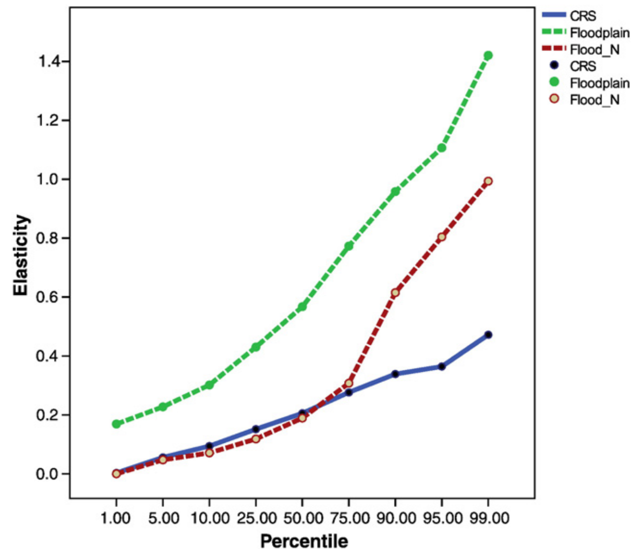



**Fig. 4.** Point elasticities of selected regressors on NFIP Policies per 100 households.

## 4. Discussion and conclusion

The policy insights of the observed relationship between CRS points earned by a locality and the count of NFIP policies per 100 households depends on the temporal order of the relationship, and whether the observed increases in NFIP policies occur in or out of the floodplain. Table 8 summarizes four scenarios with qualitatively different policy implications. On the horizontal axis (columns), we set two causal possibilities. Floodplain status (in or out) is on the vertical axis (rows). Given the widely varying policy implications of these scenarios, we consider them relative to the core goals of the mitigation policy itself, from those most congruent with these goals to those potentially most antithetical to the policy's objectives.

Interestingly, the outcomes from scenarios outside the highly exposed floodplain are those that correspond most closely to policy intentions. Scenario III (in the bottom left hand corner) assumes flood mitigation activities go first and policy purchasing behavior goes second. Scenario III also assumes that the bulk of increased NFIP purchasing behavior occurs outside the floodplain. From the standpoint of NFIP administrators, Scenario III is most desirable; in fact, it constitutes the finest expression of the CRS incentive design. Recall, the CRS program discounts the cost of flood insurance at a level corresponding to the amount of flood mitigation work performed by local hazard managers. If the growth in NFIP policy purchases is outside the floodplain, then the CRS program lowers impacts per

**Table 8**
Policy implications of causal order of CRS mitigation and NFIP policies by floodplain status.

| | CRS mitigation (*X*) followed by NFIP policies (*Y*) | NFIP policies (*X*) followed by CRS mitigation (*Y*) |
|---|---|---|
| In floodplain | Scenario I. moral hazard | Scenario II. Responsive risk mitigation |
| Out floodplain | Scenario III. Insurance pool expansion | Scenario IV. Premium cost reduction |

flood, reduces the cost of owning insurance, and draws lower risk residents into the insurance pool.

In Scenario IV, NFIP insurance purchases are causally prior and purchasing growth occurs outside the floodplain. From an NFIP administrator's perspective, this is the most benign scenario. Increased participation by lower risk residents enhances the solvency of the program. The growth in CRS points after an increase in the number of NFIP policies also implies an economic and political rationality on the part of local flood managers. As the size of the insurance pool outside the floodplain increases, more residents stand to benefit from structural and nonstructural mitigation efforts, given the handsome premium discounts that accompany risk reduction.

Yet despite the relatively desirable outcomes of the non-floodplain contexts of Scenarios III and IV, they are relatively unlikely because of *adverse selection*. That is, behavioral decision theory suggests those outside the floodplain are disproportionately likely to forego insurance purchase whereas those inside the floodplain are disproportionately likely to make these purchases (Kunreuther, 1998) and this is confirmed by empirical research (Gares, 2002). Scenarios I and II are in fact the natural focus of the flood mitigation policies given their greater flood exposure, and are the more likely policy-relevant contexts given that the majority of NFIP policies in force are in the floodplain. We continue to consider outcomes in order of their relative congruence with policy objectives, with floodplain Scenarios II and I respectively yielding outcomes progressively further from core mitigation goals.

In Scenario II (top right hand corner), NFIP policy purchasing is causally prior, with the observed increase in NFIP policies occurring in the floodplain. In this scenario, CRS-rewarded activities work to mitigate negative flood impacts on homeowners and businesses already at risk. Moreover, if a locality accumulates more than 500 points, those at risk enjoy at least a five percent discount in insurance premiums. In Scenario II, the policy significance of the positive association between NFIP policies and CRS points is best characterized as responsive risk mitigation. Local flood managers are reacting to floodplain development activities, deploying a range of structural and nonstructural mitigation activities to attenuate future losses. Development trends themselves are putting more households and businesses at risk, with policy responding to such trends by mitigating ensuing broader risk exposure. Policy does not change the risk calculus of individuals, but simply attempts to reduce the potential losses of settled floodplain residents.

Scenario I, in the top left hand corner, assumes that CRS mitigation activities are causally prior to NFIP policy purchases, and that the observed increase in NFIP policies is primarily in the floodplain. This scenario presents potentially the most serious problem relative to the original intent of mitigation policies, and may undermine the solvency of the CRS program. Insofar as CRS mitigation activities reduce the risk of death or injury (Zahran et al., 2008) and dollar losses per flood event (Brody et al., 2007, 2008), Scenario I produces less impact per flood but more households exposed to the risk of recurrent flooding, as flood mitigation activities themselves perversely draw homeowners and businesses into the floodplain.

In this context, the CRS program actually rewards floodplain in-migration and development through lower insurance premiums. Such unintended consequences of policy create a situation of "moral hazard" that is often traversed in the economics literature (Pauly, 2003). Moral hazard implies a behavioral change by economic agents in response to a policy or program that makes them less careful about their actions than true losses would dictate, effectively changing the likelihood of incurring those losses. The canonical example involves consumers taking fewer precautions about objects that are insured, since they do not face the full cost of losses if those objects are somehow damaged. In these cases, though, society as a whole still faces the entirety of such losses. Accordingly, insured car owners may be less willing than socially optimal to install anti-theft devices or avoid low-security parking areas. Consumers in such cases are behaving fully rationally, simply responding to shifting incentives, yet their actions may be suboptimal from a societal perspective. In the present case, potential homeowners and/or businesses may be more willing to move into high-risk flood areas than is socially optimal, since the NFIP reduces the cost of associated floodplain insurance. This broader exposure to potential flood damage would increase overall potential social cost through the now-larger population residing in high-risk areas, yet nevertheless is consistent with each household's new set of cost-based incentives.

Two perspectives, both drawn from the economics literature, help reinforce this case. For expositional simplicity, we focus here on household decision-making based on income-maximization; a parallel case can be made for businesses' profit-maximizing choices. The floodplain residence situation is analogous to a principal/agent problem, where the government is the principal. The "problem" occurs when agents, who can act on their own, behave in a way that diverges from the goal of the principal, whose success is determined by the actions of the agents under its purview (Grossman and Hart, 1983). The household "agents" make choices about whether to move into floodplains. Their objective is to maximize household income and non-pecuniary benefits of residing in coastal areas like esthetics and access to recreation (Rappaport and Sachs, 2003), adjusted for the cost of flood insurance premiums. Before policy, premiums are higher, reducing the number of willing households. The principal's goal is to minimize total losses from floods. Policy is meant to mitigate those losses, but in fact changes the agents' calculus by reducing the cost of insurance premiums. This change in calculus leads to even more households exposed to potential flood damage, directly contrary to the principal's goal.

The benefit/cost framework complements this principal/agent approach. Households will move into floodplain areas until the benefit to the marginal household choosing such a location exactly offsets the marginal cost, the traditional optimizing first-order condition. With absolutely no insurance, households are strongly discouraged to move due to the sizable downside risks borne by the household alone in the case of flooding. Insurance reduces a household's exposure, thus reducing the marginal cost of a move, adjusted for the insurance premium and the probability-weighted impact of any deductible in the event of a disaster. However, mitigation policy effectively reduces the marginal cost of such a floodplain residence further through reduced insurance costs. Households previously unwilling to move given higher marginal costs relative to their gains from moving are now enticed to the floodplain location as costs decrease. Given the greater number of exposed households, the total cost of flood damage over all households may well have grown in parallel, again contrary to the goals of the federal government enacting the policy.

The situation is similar to the context described by Weiler and Theobald (2004), who explored innovative residential locations in rural areas of the Intermountain West. First-movers to such innovative locations, and infrastructural subsidies to such movers, literally pave the way for considerable in-migration to areas with high wildfire risks. These burgeoning communities greatly increase the potential damage by otherwise "backcountry" wildfires, while also raising associated firefighting costs as resources are disproportionately devoted to saving structures. Those innovative households themselves create new risks for the sparking of wildfires as well. Again, policies that are intended to help support rural residences in fact create entirely new and often unintended costs that society as a whole now bears.

The four scenarios thus sketch a variety of policy insights to be gleaned from the FEMA NFIP mitigation efforts, from the congruence of Scenario III's outcomes with policy objectives to Scenario I's morally hazardous set of antithetical incentives created by the policy itself. Because policy implications depend fundamentally on which scenario occurs, if possible, future research ought to figure the correct causal sequence and where policy purchases spatially occur. As the discussion above indicates, the timing of a community's flood mitigation efforts is significantly related to the impact of these efforts on the viability of the NFIP. This raises an important question about the causes of the mitigation efforts that are later reflected in the community's CRS ratings. The data presented in Table 5 are consistent with recent work by Lindell and Hwang (2008) indicating that prospective homeowners are attracted to floodplains by amenities—such as housing structure characteristics, neighborhood quality, accessibility, and environmental amenities—and are deterred by hazard proximity *only to the extent that they perceive a significant flood risk*. That is, the effect of hazard proximity on house values and hazard adjustment adoption is mediated by risk perception. However, when hazard proximity actually causes frequent hazard experience (damaging floods), it is likely that property owners—especially highly educated, affluent, White homeowners—will pressure their local governments to engage in the types of hazard mitigation activities that result in higher CRS ratings (see Prater and Lindell, 2000, for a discussion of the politics of hazard mitigation). When hazard proximity has the potential to cause damaging floods, local government must effectively communicate the likelihood and severity of flood risks to local residents (Lindell and Perry, 2004).

Although this explanation accounts for the available data, it needs further elaboration and testing at both the household and community levels. Once the dynamics of floodplain occupancy and insurance purchase are better understood, the CRS point scheme can be modified to reward mitigation activities that minimize floodplain in-migration and increase flood insurance purchases by households outside the floodplain. Future studies should also consider how CRS-incentivized flood mitigation activities may be adapted to account for increased inland flood hazard caused by urban development that increases the speed of rainfall runoff, and thus increases the size of the 100 year floodplain. Such research should also address the increased coastal flood hazard expected to be caused by the substantial sea-level rise forecast by the Intergovernmental Panel on Climate Change (2007).

## References

Baumann, D.D., Sims, J.H., 1978. Flood insurance: some determinants of adoption. Economic Geography 54, 189–196.
Beck, N., Katz, J.N., 1995. What to do (and not to do) with time-series cross-section data. American Political Science Review 89 (3), 634–647.
Birkland, T.A., Burby, R.J., Conrad, D., Cortner, H., Michener, W.K., 2003. River ecology and flood hazard mitigation. Natural Hazards Review 4, 46–54.
Blanchard-Boehm, R.D., Berry, K.A., Showalter, P.S., 2001. Should flood insurance be mandatory? Insights in the wake of the 1997 New Year's Day flood in Reno–Sparks, Nevada. Applied Geography 21, 199–221.
Brody, S.D., Zahran, S., Maghelal, P., Grover, H., Highfield, W.E., 2007. The rising costs of floods: examining the impact of planning and development decisions on property damage in Florida. Journal of the American Planning Association 73 (3), 330–345.
Brody, S.D., Zahran, S., Highfield, Wesley E., Grover, H., Vedlitz, 2008. Identifying the impact of the built environment on flood damage in Texas. Disasters 32 (1), 1–18.
Brody, S.D., Zahran, S., Highfield, W.E., Bernhardt, S.P., Vedlitz, A., 2009. Policy learning for flood mitigation: a longitudinal assessment of the community rating system in Florida. Risk Analysis 29 (6), 912–929.
Browne, M.J., Hoyt, R.E., 2000. The demand for flood insurance: empirical evidence. Journal of Risk and Uncertainty 20 (3), 291–306.
Costanza, R., Pérez-Maqueo, O., Luisa Martinez, M., Sutton, P., Anderson, S.J., Mulder, K., 2008. The value of coastal wetlands for hurricane protection. Ambio 37 (4), 241–248.
Davis, M.S., 1989. Living along the fault line: an update on earthquake awareness and preparedness in Southern California. Urban Resources 5, 8–14.
Drukker, D.M., 2003. Testing for serial correlation in linear panel-data models. The Stata Journal 3 (2), 168–177.
Garcia, E.M., 1989. Earthquake preparedness in California: a survey of Irvine residents. Urban Resources 5, 15–19.
Gares, P., 2002. Adoption of insurance coverage and modes of information transfer: case study of Eastern North Carolina floodplain residents. Natural Hazards Review 3, 126–133.
Glejser, H., 1969. A new test for heteroskedasticity. Journal of the American Statistical Association 64, 316–323.
Godschalk, D.R., Beatley, T., Berke, P., Brower, D.J., E.J., 1999. Natural Hazard Mitigation: Recasting Disaster Policy and Planning. Island Press, Washington, DC.
Grossman, S., Hart, O., 1983. An analysis of the principal-agent problem. Econometrica 51, 7–45.
Intergovernmental Panel on Climate Change, 2007. Climate Change 2007 Synthesis Report. IPCC, Geneva, Switzerland.
Jackson, E.L., Mukerjee, T., 1974. Human adjustment to the earthquake hazard of San Francisco, California. In: White, G.F. (Ed.), Natural Hazards: Local, National and Global. InOxford University Press, New York, pp. 160–166.
Kunreuther, H., 1998. Insurability conditions and the supply of coverage. In: Kunreuther, H., Roth, R.J. (Eds.), Paying the Price: The Status and Role of Insurance against Natural Disasters in the United States. InJoseph Henry Press, Washington DC, pp. 17–50.
Laska, S., 1990. Homeowner adaptation to flooding: an application of the general hazards coping theory. Environment and Behavior 22, 320–357.
Lindell, M.K., Hwang, S.N., 2008. Households' perceived personal risk and responses in a multi-hazard environment. Risk Analysis 28, 539–556.
Lindell, M.K., Perry, R.W., 2000. Household adjustment to earthquake hazard: a review of research. Environment and Behavior 32, 590–630.
Lindell, M.K., Perry, R.W., 2004. Communicating Environmental Risk in Multiethnic Communities. Sage, Thousand Oaks CA.
Lindell, M.K., Prater, C.S., 2000. Household adoption of seismic hazard adjustments: a comparison of residents in two states. International Journal of Mass Emergencies and Disasters 18, 317–338 Available at www.ijmed.org.
Lindell, M.K., Prater, C.S., 2002. Risk area residents' perceptions and adoption of seismic hazard adjustments. Journal of Applied Social Psychology 32, 2377–2392.
Lindell, M.K., Whitney, D.J., 2000. Correlates of seismic hazard adjustment adoption. Risk Analysis 20, 13–25.
May, P.J., 1992. Policy learning and failure. Journal of Public Policy 12, 331–354.
Mileti, D.S., 1999. Disasters by Design: A Reassessment of Natural Hazards in the United States. Joseph Henry Press, Washington DC.
Montz, B.E., 1982. The effect of location on the adoption of hazard mitigation measures. Professional Geographer 34, 416–423.
Palm, R., 1995. Earthquake Insurance: A Longitudinal Study of California Homeowners. Westview Press, Boulder CO.
Palm, R., Hodgson, M., 1992. After a California Earthquake: Attitude and Behavior Change. University of Chicago Press, Chicago.
Palm, R., Hodgson, M., Blanchard, R.D., Lyons, D., 1990. Earthquake Insurance in California. Westview Press, Boulder CO.
Pauly, M., 2003. The economics of moral hazard: comment. In: Laffont, J.J. (Ed.), The Principal Agent Model: An Economic Theory of Incentives. InElgar, Cheltenham.
Prater, C.S., Lindell, M.K., 2000. Politics of hazard mitigation. Natural Hazards Review 1, 73–82.
Rappaport, J., Sachs, J., 2003. The United States as a coastal nation. Journal of Economic Growth 8 (1), 5–46.
Sullivan, R., Mustart, D.A., Galehouse, J.S., 1977. Living in earthquake country. California Geology 30, 3–8.
Weiler, S., Theobald, D., 2004. Pioneers of rural sprawl in the Rocky Mountain West. Review of Regional Studies 33 (3), 264–283.
Wooldridge, J., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press.
Worrall, J.L., Pratt, T.C., 2004. On the consequences of ignoring unobserved heterogeneity when estimating macro-level models of crime. Social Science Research 33, 79–105.
Zahran, S., Brody, S.D., Peacock, W.G., Vedlitz, A., Grover, H., 2008. Social vulnerability and the natural and built environment: a model of flood casualties in Texas, 1997–2001. Disasters 32 (4). doi: 10.1111/j.0361-3666.2008.01054.x.