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Abstract

We explore behavior and test theory regarding the determinants of flood insurance coverage in the coastal zone using household-level data for nine southeastern counties. We use Tobit regression models to assess the importance and magnitude of insurance cost, risk factors, community characteristics, and household attributes on flood insurance purchase for residential building structures. Overall estimates indicate price inelastic demand, though subsidized policyholders are more sensitive to price and hold greater flood insurance coverage (controlling for value of asset at risk). We find support for rational choice in the coastal zone, with flood insurance coverage positively correlated in the level of flood risk. We find evidence that coastal erosion risk effects flood insurance demand, and that community level erosion hazard mitigation projects influence flood insurance holdings, with shoreline armoring appearing to act as a substitute and beach replenishment appearing to act as a complement.

Key words: Insurance coverage, flood, hazard, coastal, erosion, Tobit model

JEL codes: D81, H11, Q54

Flood Insurance Coverage in the Coastal Zone

Introduction

Over the past 50 years, coastal areas in the United States have witnessed a growing populace, an evolving social environment, and increased economic activity. On the East and Gulf coasts, the burgeoning population faces considerable risk from coastal storms (hurricanes and nor'easters) that periodically cause extensive flooding, wind, and erosion damage. Increasing coastal populations, development in hazard-prone areas, rising construction costs and increased value at risk have contributed to rising monetary losses due to these natural hazards (Kunreuther 1998a; Wharton 2008). Nordhaus (2006) estimates the value of capital stock in low-lying coastal areas vulnerable to natural hazards at $1.2 trillion (about 3% of GDP (2005 dollars)), and recent predictions suggest that we are entering a period of increased storm activity (Goldenberg et al. 2001; Webster et al. 2005) which could exacerbate coastal risk.

Historically, the catastrophic nature of flood risk and government's predilection for disaster aid has precluded private insurers from voluntarily offering coverage (Anderson 1974, Kunreuther 1998b). Since the late 1960s, the U.S. federal government has played an expanded role in providing protection from flood and other coastal hazards. The National Flood Insurance Act of 1968 made federal flood insurance available,[1] through the National Flood Insurance Program (NFIP), to communities that agreed to manage development in floodplains, with subsequent legislation (Flood Disaster Protection Act of 1973, National Flood Insurance Reform Act of 1994) designed to

[1] The NFIP is actually a cooperative venture of federal, state, and local governments and private insurers. The federal government sets flood insurance premiums, stipulates building standards, designates flood hazard areas, and authorizes hazard mitigation projects. State and local governments can augment building standards, enforce building codes, and administer some hazard mitigation projects. Private insurance companies sell and service flood insurance policies (Burby 2001).

augment incentives for insurance purchase and hazard mitigation projects (Pasterick 1998). The National Flood Insurance Reform Act of 1994 charged the Federal Emergency Management Agency (FEMA) with evaluating the effects of coastal erosion on coastal communities and the NFIP (Heinz Center 2000). In light of increasing coastal populations and predictions of increasing coastal storm intensity, there is heightened concern about natural hazard exposure in coastal areas and the viability of NFIP. Understanding household demand for coverage is a key element in assessing the viability of the market for flood insurance and the role of market insurance vis-à-vis and in conjunction with other forms of indemnification from coastal hazards.

Due to the large number and diversity of affected communities, delineation of flood risk under the Flood Disaster Protection Act of 1973 proved a laborious task, leading to the development of the NFIP in phases. The "Emergency Phase" of the program offered insurance at subsidized rates to households in communities that agreed to adopt floodplain management ordinances. Subsidized insurance rates applied only until detailed Flood Insurance Rate Maps (FIRMs) could be produced, after which new construction would pay "actuarial" rates determined by location in the flood zone, structural characteristics (e.g., elevation), and the existence of community hazard mitigation projects (in the "Regular Phase" of the program).[2] Construction after the publication of FIRMs was required to meet new building standards designed to make structures more flood resistant. As of 1997, 35% of properties in the flood zone

[2] There exists skepticism over whether the actuarial NFIP rate schedules accurately reflect expected loss; prior to the 2005 hurricane season (a record loss year), the NFIP exhibited a cumulative deficit of $3 billion after 37 years of operation (Wharton 2008).

nationwide were eligible for explicitly subsidized insurance, paying approximately 37% of the actuarial premium (Burby 2001).[3]

Since its inception, the NFIP has suffered from low levels of participation among homeowners. The Flood Disaster Protection Act of 1973 required communities be enrolled in NFIP in order to qualify for certain types of federal disaster assistance and required flood insurance purchase for federally-backed (FHA) mortgage loans in high-risk areas (Pasterick 1998). Mandatory purchase requirements were strengthened under the National Flood Insurance Reform Act of 1994, and programs were expanded to encourage local hazard mitigation projects. Nonetheless, evidence suggests that mandatory purchase requirements are not aggressively enforced after the initial year of a mortgage contract (Kunreuther 1996; Palm 1998; Tobin and Calfee 2005), so that after a loan is secured participation becomes *de facto* voluntary.[4] In 1997, market penetration for the NFIP across the U.S. was estimated at 26% of eligible parcels (PricewaterhouseCoopers 1999). Explanations for low market penetration have included ignorance of and lack of experience with flood hazard, subjective misperceptions of the likelihood of flooding and magnitude of loss, lack of awareness of the availability of flood insurance or belief that the price is too high, and "charity hazard" — a reliance on assistance from others (e.g. government) in the event of disaster (Kunreuther 1984, Lewis and Nickerson 1989, Kunreuther 1996, Browne and Hoyt 2000).

In this paper, we focus on flood insurance coverage choice in the coastal zone, utilizing household micro-data from 6074 parcels in nine southeastern U.S. counties.

[3] The Congressional Budget Office estimates that the extent of subsidy has dropped to 25% of policies as of 2005 (Marron 2006).

[4] Recent anecdotal evidence suggests that enforcement of mandatory purchase provisions has improved. For the period over which we have data, however, mandatory purchase provisions were apparently not aggressively enforced.

These data were collected by the H.J. Heinz III Center for Science, Economics, and Environment, under the direction of FEMA, pursuant to addressing questions regarding the impact of shoreline erosion on coastal communities and the NFIP (Heinz 2000), and were utilized by Kriesel and Landry (2004) to examine participation in the NFIP. We expand upon their analysis in a number of ways: i) our empirical model considers not only participation, but also the level of coverage elected; ii) we improve upon the insurance premium covariate by employing NFIP rate schedules to determine marginal price measures that reflect specific property risk attributes (rather than average imputed prices as employed in Kriesel and Landry (2004)); and iii) we explore a greater array of specifications and covariates in our analysis in order to test economic and behavioral determinants of flood insurance coverage.

Consistent with previous research, we find evidence of price inelastic demand for flood insurance. Price elasticity varies across subsidized and non-subsidized insurance policies, with subsidized policyholders exhibiting greater overall coverage (controlling for the value of asset at risk) and elastic demand. Our findings provide support for rational choice theory in general, with coverage demand greater in the highest risk (V-zone) areas and lower in the least risk (B/C/X-zone) areas relative to more moderate risk (A-zone) areas (controlling for insurance price and value at risk).

Coverage is increasing in the erosion rate at the nearest shoreline and higher for those households that claim to possess knowledge of the erosion rate at the nearest shoe, suggesting that erosion risk may induce flood insurance purchase.[5] Further, we find evidence that coverage is higher in areas that manage erosion through beach

[5] The Flood Disaster Protection Act of 1973 clarified terms under which coastal erosion losses would be considered indemnified under flood insurance provisions. Erosion losses must be associated with flooding conditions in order to be covered.

replenishment and lower in areas that are structurally fortified, suggesting a difference between the way households view community protection policies vis-à-vis formal insurance (complementary in the case of beach replenishment and as a substitute in the case of shoreline armoring). Results of the extended models suggest that flood insurance is a normal good, and demand is increasing in the level of education.

Flood Insurance Coverage: Theory and Empirics

Optimal insurance coverage has been analyzed within an expected utility (EU) maximization framework by Smith (1968) and Mossin (1968). We briefly sketch a simple version of the model in the context of flood insurance. Let utility $U(\bullet)$ be defined over individual wealth, $Y = A + L$, with A representing endowed wealth and L the value of property exposed to risk. Assume risk aversion: $U'(Y) > 0$ and $U''(Y) < 0$. The probability of loss L is π. The individual may purchase insurance coverage C, providing indemnity under the loss scenario, with $0 \leq C \leq L$. The insurance premium is proportional to C, given by pC. The individual purchase decision problem is:

$$\max_{C} = E[U(Y)] = \pi U(A + (1-p)C) + (1-\pi)U(A + L - pC), \qquad (1)$$

where C is the object of optimization. It is widely recognized that maximization of (1) implies full coverage ($C = L$) if insurance is actuarially fair ($p = \pi$) and less than full coverage is if the premium includes a loading factor ($p = (1+\lambda)\pi$ for $0 < \lambda < 1$).[6] Introducing an exogenous constant deductible to the loss state increases optimal coverage, while a piecewise linear pricing schedule will not alter the nature of the solution as long as unit price on initial coverage (p_1) is less than the unit price of

[6] Inclusion of a loading factor in the premium to cover administrative costs is standard practice in private insurance markets. Differential loading factors across policies may also reflect an attempt to alleviate adverse selection.

subsequent coverage (p_2); this is the premium structure for the NFIP, with p_1 applying to initial structure coverage ($0 - $50,000), and p_2 applying to additional coverage ($50,000 - $250,000 [the upper limit on structure coverage]).[7]

Camerer and Kunreuther (1989) observe that public perceptions of risk often differ from expert objective assessments. Optimal insurance coverage changes in predictable ways if one allows for subjective loss probabilities across individuals that differ from objective assessments of insurers; downward bias in subjective risk assessment reduces optimal coverage, *ceteris paribus*, as the insurance will appear too expensive. A number of plausible decision making heuristics give rise to what are considered behavioral anomalies in the context of EU and lead to systematic errors in optimization; behavioral anomalies include optimism bias (i.e. "it can't happen to me"), desire to reduce anxiety about risk, concerns about the appearance of prudence when others learn about one's decisions, wanting to behave as others (i.e. influence of social norms), and a tendency to ignore low probability events (Camerer and Kunreuther 1989; McClelland, Schulze, and Coursey 1993; Kunreuther 1996; Palm 1998; Krantz and Kunreuther 2007). Lack of information on probabilities and magnitudes of loss may invalidate the EU framework in (1), while saliency of accurate risk information may vary over time and by context (Kunreuther, Sanderson, and Vetschera 1985; Krantz and Kunreuther 2007). On the other hand, if full insurance is legally required with strictly enforced provisions, insurance coverage may not be an object of discretionary choice. Variations in optimal coverage choice can also be explored through the introduction of different forms of utility in (1) (e.g. Braun and Muermann 2004; Lee 2007). Though not

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[7] As long as $p_1 < p_2$, the kinked budget constraint still produces a convex set of consumption possibilities over which the consumer chooses. Optimization will produce a unique solution, though the first-order conditions may not hold with equality at the kink-point.

explicitly considered in model (1), the likelihood and expected magnitude of disaster assistance may affect the demand for flood insurance.

There exists little empirical work on flood insurance coverage. Baumann and Sims (1978) find evidence that past experience with disasters motivates insurance adoption, as do social class and personality.[8] Survey research suggests that lower income and non-white households, women, and elderly all tend to exhibit greater fear of disasters, though it is unclear whether this fear translates into insurance purchase or other types of mitigation and protective behavior (Palm 1998). Brown and Hoyt (2000) use state level panel data to estimate a flood insurance demand model. They find a negative price effect (inelastic in a market penetration model and approximately unitary in a coverage level model) and positive income effect on flood insurance demand. Consistent with previous findings, their results suggest that demand is increasing in flood damages of the prior year. Contrary to expectations, they find that insurance demand is decreasing in the number of federally-backed (FHA) mortgages and increasing in the amount of federal disaster assistance.

National data gathered by Dixon et al. (2006) support the finding that market penetration rates are not sensitive to price, and further suggest that penetration is significantly higher in special flood hazard areas (SFHA — also known as A-zone)[9] and higher for communities with a larger number of parcels in the SFHA. The authors attribute the latter finding to more aggressive marketing of and more familiarity with flood insurance on the part of insurers in such communities. Dixon et al. (2006) find that

[8] Baumann and Sims find that the internal-external locus of control is significantly related to insurance adoption, with those who feel that they are in control of their destinies are more likely to hold insurance than those he feel their lives to be directed by external forces.
[9] The SFHA is the flood zone that exhibits a 1 percent chance of flooding each year.

the probability of purchasing insurance is substantially higher in communities subject to coastal flooding than in communities that are not—63 percent versus 35 percent. They speculate that demand for flood insurance may be lower in communities not subject to coastal flooding because there is less appreciation for flood risk or because the type of coverage offered by flood insurance policies is less attractive in inland areas.

Michel-Kerjan and Kousky (2008) examine county-level panel data and individual-level policy data to explore characteristics of the flood insurance market in Florida (which represents approximately 40% of policies in force and total dollars of coverage). They find that the overwhelming majority of policyholders elect the lowest level of deductible ($500), and that coverage levels have increased in reaction to the floods of 2004, while deductibles have decreased. For most policyholders, the $250,000 limit on structure coverage is not binding, as their replacement value is less than this limit. Further, they find that Florida's average flood insurance premium is the lowest in the nation, and surprisingly, the average Florida premium level has decreased in the most recent year of their data.

Kriesel and Landry (2004) use household level data from the coastal zone to examine participation in NFIP. They find price inelastic demand for flood insurance and a positive income effect. Consistent with NFIP requirements their results suggest that mortgaged properties are much more likely to be covered by flood insurance. Further they find that insurance participation is higher in coastal areas that are fortified with artificial erosion protection (shoreline armoring and/or beach replenishment), lower for properties located further back from the shoreline, and lower for geographical areas that have a higher hurricane return period (lower hurricane risk).

We expand upon the analysis of Kriesel and Landry by considering both participation and coverage level in our empirical model, employing different measures of flood insurance premiums, and explore a greater array of specifications and covariates in our analysis in order to test economic and behavioral determinants of flood insurance coverage. Our approach is more similar to the analysis of Guiso and Jappelli (1998), which examines casualty insurance in Italy and how coverage is influenced by uninsurable household wealth risk and other factors.

Flood Insurance Coverage Data

We make use of flood insurance coverage data studied by Kriesel and Landry (2004), but append a complement of information in order to conduct additional analysis. These data were gathered by the H.J. Heinz III Center for Science, Economics, and the Environment, under the direction of FEMA, to address issues of flood insurance and coastal erosion. The sampling frame is residential parcels in the near-shore zone[10] of nine coastal counties in Delaware, North Carolina, South Carolina, Georgia, Florida, and Texas. A stratified random sample of the near-shore zone was selected across the nine counties using a T-shaped sampling frame within each county in order to ensure adequate coverage on the oceanfront; weights are used to adjust all reported statistics for representation of the near-shore zone.

Table 1 displays a breakdown of the 6074 parcels that were selected for the study. Galveston County, Texas and Dare County, North Carolina provide the most observations (18.5% and 17.6% of the sample, respectively), while Lee County, Florida

[10] For the purposes of this study, the near-shore zone is defined as parcels within approximately 1000 feet of the ocean.

and Glynn County, Georgia provide the fewest (7.5% and 5.4% of the sample, respectively). For each parcel, contractors made onsite visits to collect information, such as structure elevation above base flood elevation (BFE), foundation type, presence of basement or other obstruction below the main floor, ocean frontage, etc. Geographic information systems were employed to estimate distance from the shoreline, distance from the central business district, flood zone, and historical erosion rate. Parcel and structure characteristics from the county tax assessor's database were appended to the onsite data.[11] The sample was then merged by address with the Federal Insurance Administration's policies-in-force database in order to provide accurate information on market penetration and coverage levels. Of the 6074 parcels with complete data, 52 percent of property owners were identified as holders of flood insurance. Lastly, the dataset was complemented with information from a survey questionnaire sent to the home address of all parcel owners in the sample during 1998. The response rates, indicated in the last column of table 1, vary significantly across counties, with a high of 53% in Dare County, North Carolina and a low of 19% in Sussex County, Delaware. The overall survey response rate was 34%.

Table 2 reports weighted descriptive statistics on insurance, parcel, and structure characteristics for the entire sample. The average flood insurance coverage for structure in the sample (obtained from both policies-in-force data and mail survey) was $71,600 ($1998), with a minimum of zero and a maximum of $250,000.[12] Average coverage for NFIP participants was $142,431. The next two rows of table 2 indicate measures of marginal flood insurance premium expressed in dollars per $100 coverage. Marginal

[11] Details of the data collection effort are available in Heinz Center (2000).
[12] Almost 50% of the respondents in our dataset hold no flood insurance, while consistent with the findings of Michel-Kerjan and Kousky (2008) only 7.5% elect for the maximum coverage of $250,000.

premiums were calculated using descriptive information on the property and detailed NFIP rate tables from 2004 (adjusted back to 1998 levels).[13] At the parcel level, flood insurance premiums depend upon a number of factors, including: flood zone, year of construction relative to publication of FIRM, presence of basement or obstruction below a property, type of structure, elevation above BFE, Community Ratings System (CRS) score, the level of coverage, and chosen deductible.[14] We discuss each of these factors in turn.

Most of the properties in our data (50%) are located in the V flood zone, 100-year flood zone with additional risk due to high-velocity waves associated with storm surge. Forty-one percent are located in the standard SFHA or A-zone (100-year flood zone), and 9% are located in the B/C/X-zones (500-year flood or lower risk zones). Houses built before the publication of FIRMs in their community and those in the V-zone built between 1975 and 1981[15] are "grandfathered" in the NFIP and pay explicitly subsidized insurance rates. Fifty-seven percent of the parcels in our dataset qualified for subsidized insurance under these guidelines. Subsidized and regular flood insurance premiums vary by flood zone, with structures in the V-zone paying the highest rates and structures in the X-zone paying the lowest rates. Subsidized rates vary according to whether a basement or other obstruction is present and by type of structure (single or multiple-family). Regular rates vary by number of building stories, presence of basement or obstruction, structure type, and elevation above BFE. Post-FIRM structures with greater elevation

[13] Flood insurance rates have been generally increasing over time. Between 1998 and 2004 there were three targeted rate increases that we had to factor into our marginal premium calculations.

[14] Total premium also includes a $30 Federal Policy Fee that applies to high-risk areas, an Increased Cost of Compliance coverage premium, and a Probation Surcharge (if applicable). These additional fees do not affect the marginal premium, but may induce price differences on the extensive margin.

[15] Post-FIRM structures in the V-zone built between 1975 and 1981 are "grandfathered' because building standards did not take account of damage due to wave heights. The level of the subsidy is different for pre-FIRM structures and these "grandfathered" V-zone structures.

pay lower rates. Almost 70% of structures in our dataset are elevated on piles, and 18% have obstructions below the property. Average elevation above base flood elevation (BFE - height of the 100-year flood) was 3.3 feet, with a high of 30 feet and a low of -12.5 feet (that is 12.5 feet *below* BFE).

The National Flood Insurance Reform Act of 1994 established the Community Rating System (CRS) to evaluate and summarize mitigation projects in a community. The CRS score ranges from 1 (many mitigation projects, low flood risk) to 10 (little or no mitigation projects, baseline flood risk); a lower CRS score decreases flood insurance premiums. The average CRS score for our sample was 8.3 with a low of 5 and a high of 10. All premiums are adjusted to reflect the CRS score for the community, with discounts ranging from 0% (for a score of 10) to 25% (for a score of 5).

Premiums also vary by amount of coverage. A basic lower rate applies to the first \$50,000 of coverage on structure, while a higher rate applies to additional coverage up to the \$250,000 limit on structure.[16] Knowing coverage level, we are able to apply the marginal rate in our empirical analysis. The marginal rate should affect decision making via the theoretical model in (1). Previous research (Kriesel and Landry 2004) has employed an estimate of the average insurance rate.

The standard deductible for NFIP structure coverage is \$500. Reduced premiums are awarded for those opting for a higher deductible, up to \$5,000 deductible on single-family structures. Premiums for post-FIRM structures in the V-zone built after 1981 (approximately 14% of our data) depend upon the ratio of coverage level to replacement value ('replacement cost ratio'). Unfortunately, our data contain limited information (N

[16] Basic contents coverage rates apply to the first \$20,000 in insurance, with higher rates applying to additional coverage up to the \$100,000 limit on contents. We do not consider contents coverage in this paper.

= 1668 for policy holders) on deductible level[17] and no information on replacement value.[18] To make full use of the available data, we consider two measures of marginal premium — a high and a low version — in order to assess the responsiveness of coverage demand to premium level. The high premium model assumes all households elect the standard $500 deductible and that post-FIRM structures in the V-zone built after 1981 select a level of coverage that is less than 50% of the structure replacement cost. The data of Michel-Kerjan and Kousky (2008) suggest that 98% of Florida policyholders select a deductible less than the maximum and 80% choose the lowest deductible of $500. Thus, the high premium assumptions probably provide the most accurate results. The average high marginal premium is $1.01 per $100 coverage with a minimum of $0.06 and a maximum of $6.00. The price elasticity from the coverage model that employs the high marginal premium will be a lower bound on the true value. The low premium model assumes all households elect a $1000 deductible and that post-FIRM structures in the V-zone built after 1981 select a level of coverage that is greater than or equal to 75% of the replacement cost. The average low marginal premium is $0.87 per $100 coverage with a minimum of $0.06 and a maximum of $3.90. The price elasticity from the coverage model that employs the low marginal premium will be an upper bound on the true value.

The average historical beach erosion rate is 2.7 feet per year for those properties in an actively eroding zone (71% of the sample). A much smaller proportion (6.5%) or parcels are in accreting zones, with an average accretion rate of 0.2 feet per year. The remaining 22.5% of parcels are classified as being in neither an erosion or accretion

[17] Of these data, 50% claim structure deductible of $500 and 80% claim deductible of $1000 or less.
[18] Building assessed values are often outdated and housing sales prices reflect both structure and land values.

zone.[19] Kriesel, Randall and Lichtkoppler (1993) use a variable transformation, *geotime*, to measure erosive pressure on a parcel. *Geotime* is defined as the ratio of setback (or distance from the shoreline) to historical erosion rate, providing an estimate of the number of years a parcel is expected to remain in the face of constant, deterministic shoreline erosion. Average *geotime* in our sample is 787 years, but approximately 30% of the parcels exhibited *geotime* less than 10 years. The hurricane return period, the mean number of years expected to elapse between landfall of major hurricanes in an area, was calculated at the county level from summary information provided by FEMA. The average is 47 years, with a low of 16 years and a high of 190 years. The average distance from the shore is 318 feet and 42% of properties are oceanfront.

The tax assessor's database provides information on assessed building and land values, recent sales price, year of construction, year of sale, and other structural variables. Building and land assessed values are unreliable measures of value for our analysis due to differences in assessment and updating across municipalities. Since information on sales price is limited (N = 2844), we employ hedonic price regression to produce imputed current property values.[20] The average property sales price is $187,177 (1997$), and the average predicted asset value is $143,683. The average ratio of flood insurance coverage to estimated asset value is 0.651. Year of construction is used to determine whether the structure was built after the publication of a FIRM in the community. Post-FIRM buildings are required to meet more stringent building standards and pay 'actuarial' flood insurance rates.

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[19] The erosion rates were calculated by state coastal zone managers. In some cases, managers set the erosion rate to zero if structural fortification (i.e. seawalls) were in place.

[20] The hedonic price regression results are presented in table 4. The estimated model is used to impute housing sales price in 1997.

We turn next to survey data gathered from the mail questionnaire. The descriptive statistics are weighted for non-response bias of NFIP non-participants (in addition to the T-shaped sampling frame) and are presented in table 3. Household income is measured by a nominal response to 8 income categories, with the mid-point utilized as an estimate. The average income is over $100,000. Twenty percent of respondents have high school as the highest level of educational attainment; 43% are college graduates, and 36% have at least some graduate school training. Forty-five percent are retired, and 5% work part-time. The average age is 61 years, and the average household has 0.46 children.

Sixty-eight percent of respondents indicated that they would have purchased their coastal home regardless of whether flood insurance was available, and 11% indicate that they have allowed their flood insurance to lapse at some time in the past. Ten percent indicate that they have submitted an insurance claim for flood damages in the past. Thirty-nine percent identify their property as mortgaged, but surprising only 15% claim that they were required to purchase flood insurance by their mortgage lender. Only 28% of respondents claimed to be aware of the erosion rate at the nearest shore. Nineteen percent indicated that shoreline armoring was being used to combat erosion at the shoreline nearest their property, while 35% indicated that beach replenishment was being utilized at the nearest shoreline. The majority of respondents (35%) utilize their property as a vacation home. Thirty percent use the property as part-time rental and part-time vacation home. Almost a quarter utilize the property as their primary residence, and 10% offer the property as a full-time rental.

A subset of respondents (N = 292) provided information regarding why they did not hold flood insurance. The majority (30%) indicated that flood insurance was too expensive. A quarter indicated that they perceived the risk of flooding as very low, while 20% claimed they were not required to purchase flood insurance. Nine percent indicated that flood insurance was unavailable.

Econometric Models of Flood Insurance Coverage

We employ multiple regression analysis to explore determinants of flood insurance coverage choice for residential building structures in the near-shore coastal zone. We consider two models, one of coverage level with imputed asset value included as a covariate (referred to as the 'coverage' model), and the other of the ratio of coverage level to imputed asset value (referred to as the 'ratio' model). Flood insurance coverage is a censored variable because it cannot be below \$0 (and for the coverage model, it cannot exceed the \$250,000 upper limit). We use the Tobit model (Tobin 1958, Wooldridge 2001), which assumes that the continuous portion of the error distribution is reasonably approximated by a Gaussian probability density, while the censored values are represented by cumulative Gaussian probability masses. Due to the use of an imputed regressor in the coverage model, we use bootstrapping to obtain reliable standard errors.

Let y_i be the amount of flood insurance coverage elected, or the ratio of coverage to asset value. The dependent variable for a Tobit model can be censored as follows:

$$y_i = \begin{cases} UL; y_i^* > UL \\ y_i^*; LL \le y_i^* \le UL \\ LL; y_i^* < LL \end{cases}, \tag{2}$$

where y_i is the observed response variable (coverage level or ratio of coverage to asset value), y_i^* is the latent response variable, UL is the upper limit on coverage ($250,000) and LL is the lower limit ($0). The upper limit applies only to the coverage model. The log-likelihood function for the Tobit model is:

$$LF = \sum_{i \in \{y_i = LL\}} \ln \Phi(\frac{LL - x_i'\beta}{\sigma}) + \sum_{i \in \{LL < y_i < UL\}} \ln \frac{1}{\sigma} \phi(\frac{y_i - x_i'\beta}{\sigma}) + \sum_{i \in \{y_i = UL\}} \ln \Phi(-\frac{UL - x_i'\beta}{\sigma}) \tag{3}$$

for the coverage model, and:

$$LF = \sum_{i \in \{y_i = LL\}} \ln \Phi(\frac{LL - x_i'\beta}{\sigma}) + \sum_{i \in \{LL < y_i < UL\}} \ln \frac{1}{\sigma} \phi(\frac{y_i - x_i'\beta}{\sigma}) \tag{3'}$$

for the ratio model, where $\phi(\bullet)$ represents the standard normal probability density function, $\Phi(\bullet)$ represents the standard normal cumulative distribution function, x is a vector of covariates hypothesized to effect demand for flood insurance coverage, and β and σ parameters to be estimated.

Economic theory provides guidance on the specification of covariates for our regression models (Smith 1969, Mossin 1969). The marginal price of flood insurance (i.e. the amount charged for additional $100 coverage) is a primary parameter in the specification of demand, as is household income. Risk factors, such as presence in a flood zone, should affect demand; we hypothesize that households in higher risk zones will demand greater coverage, but the higher cost of insurance in these zones makes the effect uncertain. We also explore erosion hazard factors, such as the erosion/accretion rate and the presence of erosion mitigation projects (shoreline armoring or beach replenishment) in the nearby area. Households may view such projects as substitutes or complements to formal flood insurance depending upon their own assessment of the protection offered. Other covariates in the model include property usage and household demographic factors.

Theory and intuition suggest that the value of the asset at risk should affect insurance demand. Unfortunately, we have limited information on property replacement values. We employ hedonic price regression analysis to produce imputed current property values, and take a proportion of the imputed value as an estimate of the replacement value of the structure at risk. The hedonic price regression parameters for the entire sample are displayed in table 4. The estimation utilizes a semi-log functional form and includes housing sales between 1980 and 1997. Due to missing data, the specification is fairly restrictive, including only square footage and lot size (both in quadratic form), dummy variables for missing information on square footage or lot size, the age of the structure at time of sale, dummy variables for oceanfront and vacant lots at time of sale, and distance to the central business district (CBD). Year fixed effects are included for 1980 - 1996.[21] The estimated model is used to impute housing sales price in 1997, and 60% of the estimated sales price provides a proxy for the structure asset value.[22]

Method of estimation is quasi-maximum likelihood, as weights (ω_i) are applied to each observation of the log-likelihood function to correct for the T-shaped sampling frame (and under-representation of flood insurance non-participants in the case of models 3 and 4). A modified Newton-Raphson algorithm is used to obtain parameter estimates (Amemiya 1973, 1985). Marginal effects are transformations of (3) and (3') that provide

[21] The R^2 indicates that the included covariates explain 51% of the variation in log of housing sales prices, and the F-statistic for the model is statistically significant at the 1% level. All parameters have the expected sign and all are statistically significant at the 5% level for a Type I error, except for missing lot size, and Glynn County and Sussex County dummy variables.

[22] Sixty percent is the average value of the ratio of building assessed value to total assessed value in our dataset.

an estimate of the effect that a unit change in an element of the vector x have upon the response variable (insurance coverage in raw or ratio form). Marginal effects for the double-censored Tobit (coverage) model are calculated as:

$$\frac{\partial E(y \mid x)}{\partial x_j} = \Phi(\frac{x'\beta}{\sigma})\beta_j + 2500\phi(\frac{x'\beta - 2500}{\sigma})\frac{\beta_j}{\sigma} \quad (4)$$

for each continuous element j of the vector x, where $E(\bullet)$ is the expectations operator. Marginal effects for the single-censored Tobit (ratio) model are calculated as:

$$\frac{\partial E(y \mid x)}{\partial x_j} = \Phi(\frac{x'\beta}{\sigma})\beta_j \quad (4')$$

Marginal effects for discrete covariates in both models are calculated as:

$$\frac{\Delta E(y \mid x)}{\Delta x_h} = E(y \mid x_{-h}, x_h = 1) - E(y \mid x_{-h}, x_h = 0). \quad (5)$$ [23]

Elasticities transform marginal effects into unit-free, percentage change effects, and are calculated as:

$$\varepsilon_j = \frac{\partial E(y \mid x)}{\partial x_j} \times \frac{\bar{x}_j}{\bar{y}} \quad \text{or} \quad \varepsilon_h = \frac{\Delta E(y \mid x)}{\Delta x_h} \times \frac{1}{\bar{y}} \quad (6)$$

where $\bar{x}$ and $\bar{y}$ are weighted means of the independent and response variables, respectively, and the latter discrete measure effect is a half-elasticity.

We are concerned about the possible introduction of bias in estimation of parameters of coverage models (3) due to the presence of an imputed regressor — housing asset value. Such imputed regressors by construction suffer from sampling error. These errors introduce bias into hypothesis tests based on covariance matrices inferred

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[23] For the double-censored Tobit, $E(y \mid x) = \Phi(\frac{x'\beta}{\sigma})x'\beta + \sigma\phi(\frac{x'\beta}{\sigma}) + 2500\Phi(\frac{x'\beta - 2500}{\sigma})$, while for the single-censored Tobit, $E(y \mid x) = \Phi(\frac{x'\beta}{\sigma})x'\beta + \sigma\phi(\frac{x'\beta}{\sigma})$.

from regressions which include imputed regressors. These biases are persistent and do not disappear in large samples; to obtain reliable and unbiased results, the imputed regressor problem must be addressed. Murphy and Topel (1985) propose a solution to the imputed (or 'generated') regressor problem, but their results focus on linear models and are not easily extended to non-linear models, such as Tobit. We, thus, employ a bootstrapping procedure (Efron and Tibshirani 1986) to estimate the standard errors for the coverage models.[24] With each resampled dataset, we estimate both the first stage imputation (i.e. hedonic price) equation and the second stage Tobit model (Shao and Sitter 1996). We repeat this procedure 2000 times, and calculate standard errors from the distribution of estimated coefficients.

Results

We report bootstrapped coefficients and standard errors for the Tobit coverage (3) model in tables 5 and 6, employing high and low estimate of marginal insurance premium, respectively. Each table includes 4 models, the first of which serves as a baseline and includes marginal premium, indicators for the V and B/C/X flood zones, imputed asset value, the hurricane return interval, and the historical average erosion rate (*er*) or accretion rate (*ar*). Model 2 explores differences in coverage for subsidized policyholders, while models 3 and 4 utilize survey data to explore the influence of local hazard mitigation projects and household level variables, respectively. An asterisk indicates covariates which are *not* statistically significant at the 5% level for a Type I

[24] The ratio model does not utilize a bootstrap because the imputed regressor is in the denominator of the dependent variable.

error. As models 1 and 2 utilize the full dataset, we deem these estimates more reliable for covariates that are included in all models.

All coverage model specifications exhibit a negative flood insurance price coefficient. Our estimates of price elasticity of demand are ε_p = -0.308 for the high premium model and ε_p = -0.745 for the low premium model. Thus, both models indicate inelastic demand, with the high premium providing an arguably better estimate and a lower bound on the responsiveness of flood insurance demand to price. Models 2 explore the variability in coverage by subsidy class. Subsidized policyholders are much more price sensitive than non-subsidized, ε_p = -1.092 compared to ε_p = -0.330, respectively for the high premium model (ε_p = -1.697 compared to ε_p = -0.366 for the low). Surprisingly, these results also indicate that those households that face subsidized rates purchase less flood insurance (marginal effect = -$44,100 (-$52,448) for the high (low) premium model).

All coverage models indicate significantly higher insurance coverage in the V-zone and lower insurance coverage in the B/C/X-zones relative to the A-zone. For example, results from model 1, table 5 suggest that location within the V-zone increases flood insurance coverage by $50,802, all else being equal, while location in the B/C/X-zone decreases flood insurance coverage by $38,248. Of the models that utilize the full dataset, the estimated marginal effect for V-zone ranges from $50,802 to $79,545; the estimated marginal effect for X-zone ranges from -$38,248 to -$53,833. Estimated asset value is statistically insignificant in all specifications, except for the fourth model (which focuses on the sub-sample of survey respondents). Results from these models suggest that a 1% increase in asset value increases flood insurance coverage by between 0.32%

and 0.35%. The effect of hurricane return period is consistently negative in all coverage models except one (in which it is statistically insignificant), suggesting that lower hurricane risk is associated with lower flood insurance coverage. The estimated effect ranges from -\$2700 to -\$3900 for a one-year increase in the return interval.

Results from models 1 suggest that those households facing higher erosion hazard demand greater flood insurance coverage, with a marginal effect of around \$3400 for one foot increase in the erosion rate in each specification, though this effect is insignificant in models 2. The rate of shoreline accretion has no statistically significant effect on flood insurance demand. According to the results in models 3, community hazard mitigation projects do not affect demand for flood insurance coverage. Models 4 explore the effect of household-level factors on the demand for flood insurance. The income elasticity in both models is around $\varepsilon_I = 0.57$, indicating flood insurance is a normal good. Those with a mortgage hold much higher flood insurance coverage, with a marginal effect of \$84,832 (\$78,069) in the high (low) premium model. Lastly, those with high school as their highest level of educational attainment hold less flood insurance that those with graduate level training (marginal effect around -\$70,000).

We turn next to the ratio models in tables 7 and 8, displaying parameter estimates for the ratio of flood insurance coverage to estimated asset value using a single-censored Tobit model (equation 3'). Again we find evidence of inelastic demand, on average, with $\varepsilon_p = -0.579$ as a lower bound on responsiveness and $\varepsilon_p = -0.826$ as an upper bound. In accord with the coverage models, subsidized policyholders exhibit elastic demand ($\varepsilon_p = -1.743$ as a lower bound and $\varepsilon_p = -2.459$ as an upper bound), while non-subsidized policyholders exhibit very low elasticity ($\varepsilon_p = -0.105$ as a lower bound and $\varepsilon_p = -0.249$ as an upper bound). In contrast to the coverage models, subsidized policyholders exhibit greater demand flood insurance when the dependent variable is expressed as a ratio (marginal effect ranging from \$0.333 - \$0.379 per \$1 asset value).

We find presence in the V flood-zone increases flood insurance coverage relative to the A-zone. The marginal effect is \$0.38 (between \$0.44 and \$0.57) per dollar of asset value for the high (low) flood insurance premium models. Presence in lower flood risk zones (B/C/X), on the other hand, diminishes flood insurance coverage by \$0.12 - \$0.19 per dollar of asset value (across both models). Flood insurance coverage is higher in locations with higher erosion, though the effect is somewhat small — \$0.03 - \$0.05 per dollar asset value for each foot increase in the erosion rate. The coefficient for hurricane return interval has an unexpected positive sign in the ratio models, possibly reflecting the poor nature of this proxy for hurricane risk.

In contrast to the coverage models, flood insurance holdings are greater in locations that manage coastal erosion through beach replenishment and lower in locations that employ coastal armoring when demand is expressed as a ratio. Marginal effects for both models indicate around \$0.28 higher coverage per \$1 asset value in communities that employ beach replenishment and approximately \$0.14 lower coverage per \$1 asset value in communities that utilize shoreline armoring. Results of model 4 lend further support to the suggestion that mortgage status has a large impact on insurance coverage (marginal effect ranging from \$0.36 to \$0.39 per \$1 asset value). The income elasticity is around 0.2 for both specifications. Flood insurance demand is lower for those with high school as highest educational attainment (relative to those with graduate training).

Discussion

Consistent with previous research, we find inelastic demand for flood insurance (U.S. GAO 1983; Browne and Hoyt 2000; Kriesel and Landry 2004; Dixon et al. 2006). We believe that our estimates may be more accurate than previous estimates due to the fact that we employ marginal measures of insurance premium and utilize household-level micro data. Our results, however, are limited to coastal properties in the southeast. Due to the lack of information on deductible and replacement value, we estimate dual models employing a high and low estimate of marginal premium for all specifications. Despite this limitation our price elasticity estimates are rather tight; the overall estimate ranges from -0.308 to -0.745. Estimates that employ the ratio of coverage to estimated asset value also find evidence of inelastic demand, with ε_p ranging from -0.579 to -0.826. In both cases, the former estimate is arguably better due to underlying assumptions.

Our results also provide some insight into the differences in coverage and elasticity across subsidized and non-subsidized flood insurance policies. We find greater price elasticity of demand for subsidized policyholders in both the coverage and ratio specifications, ranging from -1.092 to -1.697 for the coverage models and from -1.743 to -2.459 for the ratio models. In all models, price elasticity of demand for non-subsidized policyholders is very low, ranging from -0.084 to -0.15 for the coverage models and from -0.105 to -0.249 for the ratio models. In terms of raw coverage, subsidized policyholders demand less coverage (ranging from -\$44,100 to -\$52,448) than non-subsidized policyholders. When we examine demand as a ratio of coverage to asset value, however, subsidized policyholder demand greater coverage (ranging from \$0.333 to \$0.379 per \$1 asset value) than non-subsidized policyholders. These results probably reflect the lower market value of subsidized parcels, which should be older and more vulnerable to hazards (since they were constructed before flood mitigation building standards were in force).

The Congressional Budget Office (Marron 2006) estimates that flood insurance premium payments make up about 60% of the actuarial balance, leaving the general taxpayer responsible for an estimated $1.3 billion per year. Our results support the contention that moderate increases in flood insurance premiums will probably not induce wholesale cancellation of policies, but the reduction in demand is likely to be significantly greater for subsidized than non-subsidized policyholders. To the extent that mortgage requirements mandate a specified level of flood insurance coverage, price increases will have little effect on demand but will clearly induce negative welfare effects on coastal households (assuming that the quality of post-disaster payouts and assistance remains constant).[25] Holding of a property mortgage induces the largest positive marginal effects in our models — on the order of $78,000 - $85,000 in the coverage model and ranging from $0.36 - $0.39 per $1 asset value for the ratio model.

The efficacy of the mortgage requirement provision, however, has limits. The raw data suggest that in 1998 only 39% of coastal properties were mortgaged. This likely reflects a high level of wealth for many coastal property owners. The low proportion of mortgages limits the influence of mandatory purchase provisions tied to mortgage status. Moreover only 15% claim that they are required to hold flood insurance despite the federal mandate for FDIC-backed mortgages. The raw data suggest that 11% of respondents have allowed their flood insurance coverage to lapse as some time in the past. This result is consistent with the suggestion that lenders have not been especially

[25] The reduction in public funds for flood-related payouts will induce countervailing welfare increases for the general populace (assuming that the savings in public expenditures are utilized for other programs that people value or rebated to tax payers in tax cuts).

zealous in enforcing insurance purchase requirements as required by law (Kunreuther 1984; Kunreuther 1996; Pasterick 1998), but anecdotal evidence suggests that more recent data may not show a similar tendency.[26] The subset of survey data providing information on why those that have foregone flood insurance have made such a choice indicates that subjective assessments of flooding tend to be lower than objective estimates, as 55% of respondents claim that the price of insurance is too high or that the risk of flooding is very low.

Our results provide some support for rational decision making with regard to flood risk in the coastal zone. We find evidence of significantly higher insurance coverage in the V-zone (ranging from \$50,800 to \$79,500 in the coverage models and from \$0.33 to \$0.44 per \$1 asset vale in the ratio models) and lower insurance coverage in the X-zone (ranging from -\$38,200 to -\$53,800 in the coverage models and from -\$0.12 to -\$0.19 per \$1 asset vale in the ratio models) relative to the A-zone. This pattern of results suggests that, conditional on the price of flood insurance and the value of the asset at risk, homeowners anticipate higher damage and thus purchase greater coverage in the 100-year flood zone with high velocity waves relative to the standard 100-year flood zone, and that anticipation of damage and purchase of insurance coverage is lower in flood zones with less risk. From the coverage models, we find flood insurance demand is increasing in the estimated value of the asset at risk, but the effect is statistically insignificant in most models (save for models 4, for which the estimated marginal effect is between \$100 and \$200 dollars of coverage for a \$1000 increase in asset value). Flood

[26] Also, in auxiliary regressions (results available upon request) we find evidence that new homeowners are no more likely to hold greater flood insurance coverage than other households in the coastal zone — a result counter to what we might expect if homeowners enroll in the flood insurance program at the time of house purchase to satisfy mortgage lender requirements, but subsequently let their coverage lapse.

insurance demand is increasing in hurricane risk, as reflected in the hurricane return interval, for the coverage models. The marginal effect is between $2700 and $3900 for a one year decrease in the hurricane return interval. This covariate, however, has a counter-intuitive positive parameter in the ratio models. Thus, the result is not robust across specifications.

We employ housing use data to test for wealth effects on flood insurance demand. Our data include information on those households that use their coastal property as a vacation home, as their primary residence, or as a rental unit. The rental market for housing in coastal areas is typically very active. Those households that own multiple homes (at least one in the coastal zone) and choose to forego rental income on their coastal property are likely wealthier than those that supply in the rental market or those for whom the coastal property is their primary residence. Neither the vacation home dummy variable nor the primary residence dummy variable, however, proves to have any explanatory power in our regression models. Thus, our findings are not particularly insightful regarding wealth, and this remains a difficult topic to explore empirically. Consistent with previous research (Browne and Hoyt 2000; Kriesel and Landry 2004) we find a positive and statistically significant income elasticity in each model, around ε_I = 0.57 for the coverage model and ε_I = 0.22 for the ratio model.

The FEMA project that these data were collected for sought to explore the effect of coastal erosion on the NFIP. The Flood Disaster Protection Act of 1973 made explicit the terms under which damages due to coastal erosion would be indemnified under flood insurance provisions. In particular, erosion losses must be associated with flooding conditions in order to be covered by flood insurance. It is unclear, however, to what extent erosion risk affects expected loss and flood insurance demand. The data provide some insight regarding the latter. We find that households facing higher erosion hazard demand greater flood insurance coverage. The estimated marginal effects are on the order of roughly \$3300 per one foot increase in the annual historical erosion rate in the coverage model (though the effect is statistically insignificant in model 2), and between \$0.03 and \$0.05 per \$1 asset value for each one foot increase in the erosion rate in the ratio model. These results suggest that some homeowners view flood insurance as a form of partial indemnification from erosion hazard. Moreover, those claiming knowledge of the erosion rate at the nearest shore hold more flood insurance (around \$0.06 per \$1 asset value) in the ratio model, while the effect of this covariate is statistically insignificant in the coverage model. This result could point to an insurance demand effect that erosion information has on coastal property owners, but, on the other hand, may simply reflect correlation across insurance purchase and information attainment that reflects common unobserved heterogeneity at the household level (i.e. risk-aversion).

Lastly, consistent with the findings of Kriesel and Landry (2004), we find some evidence that community level erosion hazard mitigation projects influence flood insurance holdings, but the effect is not consistently significant across model specifications. Statistical significance is found only in the ratio models. For these models, in contrast to the results of Kriesel and Landry, we find asymmetry across the type of project, with shoreline armoring appearing to act as a substitute for flood insurance (reducing coverage by around \$0.15 per \$1 asset value) and beach replenishment appearing to act as a complement (increasing coverage by around \$0.28 per \$1 asset value). This distinction is important as communities often apply for credit within the context of the Community Ratings System for hazard mitigation projects in order to reduce their flood insurance premiums. The NFIP may be more inclined to recognize and award credit for projects that are seen as complementary to flood insurance holdings.

Conclusions

We use Tobit regression models to explore behavior and test theory regarding the determinants of flood insurance coverage in the coastal zone using micro-level data for nine southeastern U.S. counties. Unlike previous research, we incorporate both the extensive and intensive margin of demand and employ measures of marginal insurance premium to assess price elasticity. Overall estimates indicate price inelastic demand, though subsidized policyholders are more sensitive to price and hold greater flood insurance coverage (controlling for value of asset at risk).

We find support for rational choice in the coastal zone, with flood insurance coverage correlated in the level of flood risk, controlling for insurance price and value of the threatened asset. In one set of models, flood insurance demand is increasing in hurricane risk, as reflected in the hurricane return interval, but this result is not robust across specifications. The other set of models provide counter-intuitive results with regard to hurricane risk, likely reflecting error in this county-level proxy for hurricane risk. We attempt to proxy for household wealth, using dummy variable that reflect how the owner uses the property, but results are statistically insignificant. We find a positive and statistically significant income elasticity that is less than one indicating the flood insurance is a normal good.

We find evidence that erosion risk does affect flood insurance demand, as households facing higher erosion hazard demand greater insurance coverage and those that claim knowledge of the erosion rate at the nearest shore hold more flood insurance. Lastly, we find some evidence that community level erosion hazard mitigation projects influence flood insurance holdings, with shoreline armoring appearing to act as a substitute and beach replenishment appearing to act as a complement for flood insurance in our ratio models. Unfortunately, we are unable to address the importance of "charity hazard", or a reliance on third-party assistance in the event of natural disaster. Finding data that will allow for an assessment of charity hazard vis-à-vis other determinants of flood insurance demand remains an important topic for future research.

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Table 1: Coastal Counties Included in Study

County	Number in Sample	Percentage of Total	Survey Responses (Rate)
Brazoria, Texas	488	0.080	121 (0.248)
Brevard, Florida	547	0.090	134 (0.245)
Brunswick, North Carolina	623	0.103	282 (0.453)
Dare, North Carolina	1069	0.176	564 (0.528)
Galveston, Texas	1124	0.185	423 0.376
Georgetown, South Carolina	493	0.081	193 (0.391)
Glynn, Georgia	326	0.054	68 (0.209)
Lee, Florida	455	0.075	129 (0.283)
Sussex, Delaware	949	0.156	178 (0.188)
TOTAL (AVERAGE)	6074	1.000	0.344

Table 2: Insurance, Parcel, and Structure Descriptive Statistics

Variable	Definition	N	Mean	Std Dev
part*	NFIP participation indicator	6074	0.521	0.569
flcov	NFIP flood insurance coverage ($100)	5834	716.653	987.352
flratio	NFIP flood insurance coverage / asset value	5773	0.651	1.052
prem_hi	Marginal flood insurance premium (high)	6072	1.014	1.167
prem_lo	Marginal flood insurance premium (low)	6072	0.869	1.023
vzone*	V flood zone indicator	6074	0.505	0.570
azone*	A flood zone indicator	6074	0.410	0.561
xzone*	X flood zone indicator	6074	0.085	0.318
postfirm*	Indicator for structure built after FIRM	6074	0.627	0.551
subsidy*	Indicator for subsidized insurance	6074	0.571	0.564
elev	Elevation above base flood elevation (BFE)	5882	3.305	15.751
brkaway*	Indicator for breakaway walls present below structure	6074	0.065	0.280
obstct*	Indicator for obstructions present below structure	6074	0.184	0.442
piles*	Indicator for structure on piles	6074	0.689	0.528
crs	Community Ratings System classification (1998)	6072	8.346	1.475
er	Erosion rate (feet/year)	6069	2.713	3.720
ar	Accretion rate (feet/year)	6074	0.191	2.068
geotime	number of years expected before erosion reduces setback to zero	6074	787.924	8751.90
hur_ret	Hurricane return interval (years)	6074	47.110	61.779
cbra*	CBRA indicator	6074	0.056	0.263
distance	Distance from the shore (feet)	6074	318.416	270.492
ocean*	Oceanfront property indicator	6074	0.421	0.563
hp	Housing sales price (1000s current $)	2844	187.177	669.815
asset_val	Generated asset value (1000s current $)	6010	143.683	220.613
yearbuilt	Year structure built	4632	1973.50	19.007
yearsold	Year parcel sold	3740	1986.74	13.545
age_at_sale	Age of structure when sold	6074	8.207	16.024
sqft	Square footage	3947	2276.67	3142.42
vacant*	indicator for vacant lot when sold	6074	0.540	0.568
dcbdm	Distance from central business district (m)	6074	4342.15	5801.51
* - dummy variable; descriptive statistics are weighted to correct for T-scale sampling scheme.				

Table 3: Household Descriptive Statistics from Mail Questionnaire

Variable	Definition	N	Mean	Stnd Dev
incom	Categorical income variable	1711	101.431	105.838
gradsch*	Graduate school indicator	1798	0.357	0.675
college*	College graduate indicator	1798	0.436	0.699
hschool*	High school graduate indicator	1798	0.206	0.570
parttime*	Part-time employed indicator	1789	0.049	0.305
retired*	Retired indicator	1789	0.456	0.702
age	Age of respondent	1775	61.208	17.323
children	Number of children in the household	1899	0.462	1.738
pur_wo_ins*	Indicates the individual would have purchased the property regardless of whether flood insurance was available.	1715	0.681	0.665
lapse_ins*	Indicates flood insurance coverage has lapsed in the past	1643	0.111	0.451
claim*	Indicates previous flood insurance claim has been submitted and settled	1899	0.102	0.437
mort*	Indicates property is mortgaged	1825	0.390	0.690
requ*	Indicates mortgage lender required flood insurance purchase	1767	0.154	0.498
ero_know*	Indicates respondent has seen information on the erosion rate at the nearest shore	1899	0.281	0.649
armor*	Indicates shoreline armoring employed at the nearest shore	1899	0.192	0.569
nourish*	Indicates beach replenishment employed at the nearest shore	1899	0.349	0.688
primary*	Indicates coastal property is primary residence	1814	0.240	0.600
vacation*	Indicates coastal property is vacation home	1814	0.350	0.671
pt_rent*	Indicates coastal property is part-time rental	1814	0.307	0.648
rental*	Indicates coastal property is full-time rental	1814	0.101	0.424
- Explanations for not holding flood insurance (subset)				
norisk*	Indicates respondent thinks the risk of flooding is very low	292	0.248	1.058
notreq*	Indicates flood insurance not required	292	0.200	0.980
too_exp*	Indicates respondent thinks flood insurance is too expensive	292	0.300	1.123
notavail*	Indicates that flood insurance is perceived as not available	292	0.088	0.696

* - dummy variable; descriptive statistics are weighted to correct for T-scale sampling scheme and over-representation of flood insurance participants.

Table 4: Hedonic Price Regression Model

Variable	Coefficient	Standard Error
sqft	2.53E-4	2.26E-5
$sqft^2$	-7.55E-9	1.04E-9
no_sqft	0.1901	0.0854
lotsize	1.58E-5	1.96E-6
$lotsize^2$	-3.29E-11	6.96E-12
no_lotsize	0.0828*	0.1784
age_at_sale	-0.0076	0.0013
vacant	-0.4956	0.0506
ocean	0.4642	0.0375
distance_CBD	-2.354E-5	3.87E-6
glyn_GA	0.2220*	0.1211
suss_DE	0.1536*	0.0822
dare_NC	-0.4872	0.0669
brev_FL	-0.6178	0.0664
geor_SC	-0.3683	0.0959
brun_NC	-0.4929	0.0729
galv_TX	-0.7462	0.0690
braz_TX	-1.2398	0.2004
constant	12.1179	0.0942
year dummy variables	YES	
N	2002	
R^2	0.5163	
F (p-value)	59.97 ($p < 0.0001$)	
* - not statistically significant for 5% probability of Type I error; excluded county dummy variable is Lee County, FL		

Table 5: Tobit Coverage Model Results (High Premium)

	Model 1		Model 2		Model 3		Model 4	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
premium	-176.059	38.144	-258.441	38.910	-469.956	84.486	-409.299	77.810
subsidy			-371.130	86.017				
prem×sub			-514.888	98.237				
vzone	406.039	94.721	657.380	85.390	726.830	164.412	462.990	136.495
xzone	-318.916	152.319	-466.992	146.820	-1057.221	260.755	-1095.051	234.928
asset_val	0.438*	0.312	0.338*	0.251	-0.468*	0.330	1.294	0.503
hur_ret	-32.267	6.823	-21.303	5.864	-38.989	12.918	-5.722*	10.516
er	27.388	10.619	14.951*	10.308				
ar	-19.87*	11.057	-3.537*	13.029				
armor					75.618*	141.400		
nourish					-6.191*	123.251		
ero_know							99.900*	103.359
vacation							136.080*	121.763
primary							192.205*	147.666
mort							839.804	114.619
income							5.203	0.819
retired							-69.369*	112.915
college							-109.195*	109.894
hschool							-573.076	144.686
constant	1493.695	195.232	1604.375	165.792	1223.423	325.188	-438.170*	317.304
sigma	1625	1.014	1499	1.015	1536	1.021	1272	1.020
state fixed effects	YES		YES		YES		YES	
Wald (df) *p*	967.5 (12) <0.0001		1311 (14) <0.0001		715.5 (14) <0.0001		1332 (18) <0.0001	
N	5766		5766		1668		1446	

* - not statistically significant for 5% probability of Type I error; standard errors are approximated by bootstrap.

Table 6: Tobit Coverage Model Results (Low Premium)

	Model 1		Model 2		Model 3		Model 4	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
premium	-486.512	59.022	-411.271	66.355	-1039.705	133.492	-836.280	118.033
subsidy			-406.932	88.550				
prem×sub			-356.041	107.391				
vzone	515.521	80.538	624.860	81.757	864.865	156.955	569.170	141.316
xzone	-338.715	146.481	-452.635	141.850	-1028.172	244.126	-1059.675	219.983
asset_val	0.221*	0.281	0.309*	0.237	-0.503*	0.326	1.177	0.483
hur_ret	-25.935	6.295	-21.131	5.895	-26.497	12.699	1.085*	10.502
er	27.379	10.706	16.302*	10.435				
ar	-16.695*	9.866	-4.270*	13.379				
armor					90.030*	137.338		
nourish					-17.978*	117.667		
ero_know							77.701*	101.872
vacation							126.935*	119.937
primary							177.737*	146.095
mort							789.364	112.759
income							5.073	0.783
retired							-33.622*	111.855
college							-79.006*	104.319
hschool							-548.876	139.403
constant	1485.499	178.857	1616.584	165.689	1279.922	326.989	-335.004*	316.187
sigma	1549	1.015	1495	1.014	1474	1.021	1237	1.020
state fixed effects	YES		YES		YES		YES	
Wald (df) p	1268 (12) <0.0001		1344 (14) <0.0001		871.7 (14) <0.0001		1433 (18) <0.0001	
N	5766		5766		1791		1731	
* - not statistically significant for 5% probability of Type I error; standard errors are approximated by bootstrap.								

Table 7: Tobit Ratio Model Results (High Premium)

	Model 1		Model 2		Model 3		Model 4	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
premium	-0.703	0.027	-0.202	0.031	-0.421	0.033	-0.285	0.030
subsidy			0.734	0.058				
prem×sub			-1.503	0.053				
vzone	0.771	0.053	0.833	0.052	0.160	0.067	0.077*	0.065
xzone	-0.246	0.076	-0.299	0.069	-0.805	0.093	-0.934	0.089
hur_ret	0.025	0.004	0.022	0.004	0.002*	0.005	0.019	0.004
er	0.086	0.006	0.073	0.006				
ar	0.014*	0.009	0.012*	0.009				
armor					-0.290	0.067		
nourish					0.508	0.054		
ero_know							0.103*	0.048
vacation							0.038*	0.057
primary							-0.004*	0.069
mort							0.600	0.051
income							0.002	0.000
retired							-0.100*	0.052
college							-0.079*	0.050
hschool							-0.529	0.068
constant	-0.198*	0.119	0.031*	0.112	0.622	0.130	0.031*	0.147
sigma	1.454	0.018	1.328	0.016	1.276	0.023	1.100	0.020
state fixed effects	YES		YES		YES		YES	
lnL	-9187		-8570		-4271		-3364	
LRT (df) *p*	1052 (11) <0.0001		2286 (13) <0.0001		562 (11) <0.0001		774 (17) <0.0001	
N	5766		5766		1668		1446	

* - not statistically significant for 5% probability of Type I error

Table 8: Tobit Ratio Model Results (Low Premium)

	Model 1		Model 2		Model 3		Model 4	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
premium	-1.199	0.036	-0.472	0.047	-0.840	0.045	-0.602	0.043
subsidy			0.570	0.057				
prem×sub			-1.289	0.062				
vzone	0.896	0.051	0.849	0.050	0.281	0.065	0.165	0.063
xzone	-0.270	0.072	-0.298	0.069	-0.794	0.091	-0.911	0.087
hur_ret	0.032	0.004	0.025	0.004	0.014	0.005	0.025	0.004
er	0.080	0.006	0.074	0.006				
ar	0.014*	0.009	0.012*	0.009				
armor					-0.256	0.065		
nourish					0.495	0.053		
ero_know							0.086*	0.048
vacation							0.030*	0.056
primary							-0.012*	0.068
mort							0.567	0.050
income							0.002	0.000
retired							-0.073*	0.051
college							-0.056*	0.049
hschool							-0.509	0.067
constant	0.040*	0.114	0.085*	0.112	0.567	0.127	0.097*	0.145
sigma	1.382	0.017	1.326	0.016	1.237	0.022	1.078	0.019
state fixed effects	YES		YES		YES		YES	
lnL	-8822		-8556		-4157		-3302	
LRT	1782 (11) <0.0001		2314 (13) <0.0001		790 (11) <0.0001		898 (17) <0.0001	
N	5766		5766		1668		1446	

* - not statistically significant for 5% probability of Type I error; standard errors are approximated by bootstrap.