Flood Insurance Coverage in the Coastal Zone

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Abstract

We explore behavior and test theory regarding the determinants of flood insurance demand in the coastal zone using micro-data for nine southeastern counties. Overall estimates indicate price inelastic demand, though subsidized policyholders have greater coverage and are more price sensitive. Only 12% of survey respondents in the 100-year flood zone claim flood insurance was required by their lender in 1998. While mortgage-borrowers exhibit no difference in coverage level, they do exhibit less elastic demand. Flood insurance demand is positively correlated with the level of flood risk, and households facing higher erosion hazard demand greater coverage. Community level erosion hazard mitigation projects influence flood insurance holdings, with beach replenishment acting as a complement.

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

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Introduction

Over the past 50 years, coastal areas in the United States have witnessed a growing populace 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 (in 2005 dollars)). Analysis of climate data suggests that we are entering a period of increased storm activity and intensity (Goldenberg et al. 2001; Webster et al. 2005) which could exacerbate coastal risk.

The National Flood Insurance Program (NFIP) offers indemnification from flood hazard (and some erosion hazards) in communities that agree to regulate development in the floodplain. In this paper, we analyze flood insurance coverage choice in the coastal zone, utilizing household micro-data from 6074 parcels in nine southeastern U.S. counties. 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). The data 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 by Kriesel and Landry); 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 demand. Many of our findings are based on analysis of a much larger dataset than that of Kriesel and Landry – observations in their regression model were limited by missing covariates from a household survey.

Consistent with previous research (U.S. GAO 1983; Browne and Hoyt 2000; Kriesel and Landry 2004; Dixon et al. 2006), we find evidence of price inelastic demand for flood insurance. Unlike previous research, we explore price elasticity across subsidized and non-subsidized insurance policies, finding that subsidized policyholders exhibit greater coverage and elastic demand.[1] Despite federal regulations, only 12% of households in the 100-year floodplain claim they were required to hold flood insurance by their lender in 1998. In contrast to Kriesel and Landry (2004), we find that mortgage borrowers hold no greater flood insurance coverage, but they do exhibit less elastic flood insurance demand. While we make no attempt to discern between different models of individual choice under uncertainty, some findings are consistent with expected utility theory: coverage demand is greater in the highest risk (V-zone) areas and lower in the least risk (B/C/X-zones) areas relative to more moderate risk (A-zone) areas.

We provide initial evidence of the relationship between erosion risk and flood insurance demand, finding that coverage is positively correlated with the erosion rate at the nearest shoreline for properties in actively eroding zones. This suggests that erosion

[1] This finding is consistent with Grace, Klein, and Kleindorfer (2004), who find a positive effect of subsidy upon demand for catastrophe and non-catastrophe home insurance in Florida and New York (the latter effect not significant for New York).

risk may induce flood insurance purchase.[2] Surprisingly, flood insurance coverage is also greater along shorelines that are actively accreting, but the effect is very small. Further, we consider the relationship between flood insurance and other forms of erosion risk management. Building upon Kriesel and Landry (2004), we analyze the effects of large-scale erosion control projects on insurance demand, but find a difference between structural fortification (i.e. seawalls) and beach replenishment (i.e. adding sand to the beach). We find evidence that coverage is higher in areas that manage erosion through beach replenishment and lower in areas that are structurally fortified, though the latter effect is not statistically significant. Nonetheless, the findings suggest a difference in the way households view community protection policies vis-à-vis formal insurance. Interpretation suggests that coastal households may perceive shoreline armoring as "self insurance", a form of community protection that decreases the expected loss conditional on a flood or storm (Ehrlich and Becker 1972). Self insurance is a substitute for formal insurance. Beach replenishment, on the other hand, appears to be a complement with flood insurance. Since flood insurance rates do not explicitly reflect beach replenishment, we speculate that these types of projects may change local residents' perceptions of coastal risk.

National Flood Insurance Program

Historically, problems related to adverse selection, the catastrophic nature of flooding, and government's predilection for disaster aid has precluded private insurers from voluntarily offering coverage for flood hazard (Anderson 1974, Kunreuther 1998b).

[2] 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.

Since the late 1960s, the U.S. federal government has played an expanded role in providing protection from floods and other coastal hazards. The National Flood Insurance Act of 1968 made federal flood insurance available,[3] through the 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 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 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 the community enters the "Regular Phase" of the program. New construction in the regular

[3] 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 certifies hazard mitigation projects. State and local governments can augment building standards, enforce building codes, and administer hazard mitigation projects. Private insurance companies sell and service flood insurance policies under the Write-Your-Own (WYO) program (Burby 2001).

phase is required to meet more stringent building standards designed to make structures more flood resistant and receives "actuarial" insurance rates determined by flood zone, structural characteristics, and the existence of community hazard mitigation projects.[4] As of 1997, 35% of properties in the flood zone nationwide were eligible for explicitly subsidized insurance, paying approximately 37% of the actuarial premium (Burby 2001).[5]

Since its inception, the NFIP has suffered from low levels of participation among residential 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 mortgages in the 100-year floodplain (Special Flood Hazard Area or 'SFHA') made by federally-regulated lenders (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.[6] 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

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[4] 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).

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

[6] 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.

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).

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:

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

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 $0 < \lambda < 1$).[7] Introducing an exogenous constant deductible to the loss state increases optimal coverage. Flood insurance coverage on structure is capped at \$250,000, which restricts the range of C, though this limit is not binding for the majority of properties (Michel-Kerjan and Kousky 2008) Under common assumptions, demand for insurance coverage is decreasing in price and increasing in risk

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

factors (π and L). For actuarially unfair insurance ($p > \pi$), the relationship between demand and wealth (A) depends upon the nature of risk aversion (see, for instance, Schlesinger (1981) and Cummins and Mahul (2004)).

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 subjective misperception of risk, optimism bias (i.e. "it can't happen to me"), desire to reduce anxiety about risk, wanting to legitimize a decision in the eyes of others, a tendency to behave as do one's peers, and an inclination 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). 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) or through defining utility over changes in wealth (Kahneman and Tversky 1979). Though not explicitly considered in model (1), the likelihood and expected magnitude of disaster assistance may affect the demand for flood insurance. An expectation of unconditional assistance in the event of a disaster would serve as a substitute to formal flood insurance.

There exists little empirical work on demand for flood insurance coverage. Baumann and Sims (1978) find evidence that past experience with disasters motivates insurance adoption, as do social class and personality. 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). Browne 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 mortgages by federally-regulated lenders 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 SFHA and higher for communities with a larger number of parcels in SFHA. The authors attribute the latter finding to more aggressive marketing of and more familiarity with flood insurance on the part of insurance agents in such communities. Dixon et al. (2006) find that 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 federal rules, their results suggest that mortgage requirements result in a much higher likelihood of participation in NFIP. 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 exploring a greater array of specifications and covariates in our analysis in order to test economic and behavioral determinants of flood insurance coverage. Our baseline specifications allow for an analysis of the entire dataset, rather than relying upon survey returns as in Kriesel and Landry. 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

Our 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[8] 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 randomly 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 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, 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, and flood zone. Parcel and structure characteristics from the county tax assessor database were

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

appended to the data.[9] 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, 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 dollars), with a minimum of zero and a maximum of $250,000.[10] 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 premiums were calculated using descriptive information on the property, the level of elected coverage, and detailed NFIP rate tables from 2004 (adjusted back to 1998 levels).[11] 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 base flood elevation (BFE – estimated height of the 100-year flood), Community Ratings

[9] Details of the data collection effort are available in Heinz Center (2000).
[10] 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.
[11] 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.

System (CRS) score, the level of coverage, and chosen deductible.[12] We discuss each of these factors in turn.

Most of the properties in our data (50%) are located in the V- zone, 100-year flood zone with additional risk due to high-velocity waves associated with storm surge. Forty-one percent are located in the 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[13] 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 pay lower rates. Almost 70% of structures in our dataset are elevated on piles, and 18% have obstructions below the property. Average elevation above BFE was 3.3 feet, with a high of 97 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

[12] 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 induce price differences on the extensive margin.

[13] 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.

mitigation projects, baseline flood risk); a lower CRS score decreases flood insurance premiums. It is worth noting that beach replenishment is not a flood hazard mitigation strategy recognized by the CRS, and while CRS does offer credits for levee maintenance, it apparently does not offer similar credits for construction of sea walls or other forms of armoring along ocean coastlines. 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.[14] 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 (Browne and Hoyt 2000; Kriesel and Landry 2004) has employed an estimate of the average insurance price.

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 = 1668 for policy holders) on deductible level[15] and no information on replacement value.[16] To make full use of the available data, we consider two measures of marginal premium — a high and a low estimate — in order to assess the responsiveness of

[14] Basic coverage rates on building contents 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.
[15] Of these data, 50% claim structure deductible of \$500 and 80% claim deductible of \$1000 or less.
[16] Building assessed values are often outdated and procedures for reassessment vary across counties, while housing sales prices reflect both structure and land values.

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 $5.97. 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%) of 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 zone.[17] 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

[17] 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.

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 exhibit *geotime* less than 10 years. 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.[18] Sixty percent of the imputed value is taken to represent the value of housing structure (net of land value). The average property sales price is $187,177 (1997 dollars), and the average imputed housing asset value is $143,683. The average ratio of flood insurance coverage to 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.

We turn next to survey data gathered from the mail questionnaire. We find evidence of response bias in these data, as 82% of respondents are identified as NFIP participants. This is considerably greater than the overall sample average of 52%. As

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

such, analysis of the raw data could lead to erroneous inference on price responsiveness and other effects. We reweight observations in this dataset to correct for the over-representation of NFIP participants (in addition to the T-shaped sampling frame, discussed above). Nonetheless, there could be other unobservable sources of response bias, and thus the descriptive statistics and regression results associated with these data should be interpreted and applied with caution.

Table 3 presents the weighted descriptive statistics for the survey data. 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. This suggests that for almost one-third of households, availability of flood insurance played some role in the decision to purchase a beach house. There is some evidence of a problem with retention of flood insurance, as 11% indicate that they have allowed their policy to lapse at some time in the past. Ten percent indicate that they have submitted an insurance claim for flood damages in the past.

A number of survey items inquired about awareness of and community response to erosion hazard. Only 28% of respondents claimed to be aware of the erosion rate at the nearest shore at the time of purchase. This is not surprising, as there are no disclosure provisions in relation to erosion hazard. 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. These policy options are sometimes used in conjunction, and 10% of respondents claimed both policies were being pursued at the nearest shore.[19]

A relatively low proportion of homeowners (39%) hold a mortgage on their beach house. Focusing on homes in the 100-year floodplain, the proportion of mortgages drops to 34%, and surprising only 12% of those with mortgages claim that they were required to purchase flood insurance by their mortgage lender. The majority of respondents (35%) utilize their property as a vacation home, allowing it to remain vacant when they are not using it. We conjecture that this pattern of usage could be a proxy for wealth, as these owners choose to forego rental income on their beach house. Thirty percent of respondents use the property as part-time rental and part-time vacation home. Almost a quarter utilize their property as their primary residence, and 10% offer their beach house 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.

[19] Unfortunately, presence of shoreline protection projects was not verified by onsite inspection. Nonetheless, it is likely perception of shoreline protection that influences flood insurance decisions, so our data are appropriate in this regard.

Econometric Models of Flood Insurance Coverage Demand

We employ multiple regression analysis to explore determinants of flood insurance coverage choice for residential building structures in the near-shore coastal zone. Following EU theory of insurance choice under uncertainty (Smith 1969, Mossin 1969), insurance price, the probability and size of loss, and endowed wealth are primary demand parameters. We use NFIP rate tables and detailed property characteristics to determine each household's marginal price of flood insurance (the amount charged for additional $100 coverage). Risk factors include presence in a flood zone and elevation above BFE; we hypothesize that households in higher risk zones and with lower elevation will demand greater coverage, but the higher cost of insurance in these zones makes the effect uncertain. Likewise, the correlation between price and risk factors complicate the estimation of pure price elasticity. Income, only available in the survey data, serves as imperfect proxy for wealth. In addition, we record whether the beach home is a vacation home and conjecture that this could also proxy for wealth.[20] 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

[20] At the suggestion of an anonymous reviewer, we explored using the University of Michigan's *Panel Study of Income Dynamics* dataset to estimate a wealth imputation equation. Having obtained data for the six states of interest in 1999, we are able to estimate OLS models for household wealth. The models exhibit R^2 of less than 10%, with 1999 household wealth (including and excluding real estate equity) as dependent variables and income, employment status, retirement status, education attainment, location, age of the primary owner, existence of a mortgage on the property, the number of children in the household, and state fixed effects as independent variables. Results indicate that employment status, retirement status, education level, and mortgage status, are statistically significant predictors of household wealth. When we estimate Tobit regression models that includes generated wealth (with bootstrapped standard errors (Efron and Tibshirani 1986; Shao and Sitter 1996)), we are not able to make any inference on wealth effects because the parameter estimates are not statistically significant. As such, we have chosen not to include these results, but results are available from the authors upon request.

depending upon their own assessment of the protection offered. Other covariates in the model include household demographic factors.

Size of potential loss should be related to the value of the asset at risk. 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 (net of land value). 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 and county fixed effects are included.[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]

As the asset value is imputed, we transform the dependent variable of our model to the ratio of coverage to imputed asset value in order to avoid the generated regressor problem (Murphy and Topel 1986). Thus: $y_i = cov / \hat{a}$, where cov is chosen coverage level and $\hat{a}$ is imputed asset value. This specification is a minor alteration of our theoretical framework (1) and does not change the fundamental nature of the decision problem. As a robustness check, we also estimate regression models with raw coverage

[21] The R^2 indicates that the 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.

level as dependent variable and include imputed asset value as an explanatory variable, employing bootstrapping to produce reliable standard errors (Efron and Tibshirani 1986; Shao and Sitter 1996). While interpretation of coefficients changes, results are generally consistent across both specifications.[23]

We employ the Tobit model (Tobin 1958, Wooldridge 2001), which assumes that flood insurance coverage is censored at zero. The dependent variable for a Tobit model is:

$$y_i = \begin{cases} y_i^*; LL < y \\ LL; y_i^* \leq LL \end{cases}, \tag{2}$$

where y_i is the observed response variable, y_i^* is the latent response variable, and LL is the lower limit ($0). Due to the presence of the error term in the hedonic regression, there is no upper bound on y_i. The Tobit model assumes the continuous portion of the error distribution is reasonably approximated by a Gaussian probability density, while the censored value is represented by cumulative Gaussian probability masses. The log-likelihood function for the Tobit model is:

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

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, including county fixed effects, and β and σ parameters to be estimated. Due to differences in sub-sample sizes across counties (see table 1), we cluster standard errors at the county level.

[23] Results for the bootstrapped coverage models are available from authors on request.

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 that rely on survey data). A modified Newton-Raphson algorithm is used to obtain parameter estimates (Amemiya 1973, 1985). Marginal effects are transformations of (3) that provide an estimate of the effect that a unit change in an element of the vector x have upon the response variable. Marginal effects for the Tobit model are calculated as:

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

for each continuous element j of the vector x, where $E(\bullet)$ is the expectations operator. Marginal effects for discrete covariates h are calculated as:

$$\frac{\Delta E(y \mid x)}{\Delta x_h} = E(y \mid x_{-h}, x_h = 1) - E(y \mid x_{-h}, x_h = 0).^{24} \tag{5}$$

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

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

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.

Results

[24] For the Tobit model, $E(y \mid x) = \Phi(\frac{x'\beta}{\sigma})x'\beta + \sigma\phi(\frac{x'\beta}{\sigma})$.

Tables 5 and 6 report parameter estimates for various specifications of the Tobit models (3), employing high and low estimate of marginal insurance premium, respectively. Each table includes 4 models. The first model serves as a baseline and includes marginal flood insurance premium, indicators for the V and B/C/X flood zones (excluded category is A-zone), the hurricane return interval (*return*), and the historical average erosion rate (*er*) or accretion rate (*ar*). An additional risk factor, elevation above BFE, exhibited statistically insignificant parameter estimates in all models and was subsequently dropped from the analysis. Model 2 explores differences in coverage for subsidized policyholders. We note that both models 1 and 2 make use of a much larger dataset than was utilized in the analysis of Kriesel and Landry (2004), because these specifications do not rely on survey data. Due to possible response bias in the survey data, we view the results in models 1 and 2 as more reliable. Models 3 and 4 explore additional covariates that are only available in the survey data, specifically the influence of local hazard mitigation projects and household level variables, respectively. Asterisks indicate covariates that are statistically significant at various levels.

All specifications exhibit a negative flood insurance price coefficient. Estimates of price elasticity of demand are ε_p = -0.620 for the high premium model and ε_p = -0.870 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. Model 2 explores the variability in coverage by subsidy class. Subsidized policyholders exhibit greater demand for flood insurance, with a marginal effect ranging from \$0.289 - \$0.745 per \$1 imputed asset value, depending upon which price specification is used. Subsidized policyholders are also much more price sensitive than non-subsidized policyholders; price elasticity is ε_p = -1.550 for subsidized policyholders compared to ε_p = -0.133 for non-subsidized in the high premium model, or ε_p = -4.478 for subsidized compared to ε_p = -0.502 for the low premium model.

All models indicate higher insurance coverage in the V-zone and lower insurance coverage in the B/C/X-zones relative to the A-zone. For the high premium models, the marginal effect for V-zone is $0.26 to $0.30 per dollar of asset value, while the marginal effect for presence in B/C/X zones is -$0.05 to -$0.06 per dollar of asset value. For the low premium model, the marginal effect for V-zone is $0.33 to $0.70 per dollar of asset value, while the marginal effect for presence in B/C/X zones is -$0.05 to -$0.20 per dollar of asset value. Results from model 1 suggest that those households facing higher erosion hazard demand greater flood insurance coverage. The elasticity of the rate of shoreline erosion is 0.03 to 0.06 in the high premium models, and 0.06 to 0.11 in the low premium models. Somewhat surprisingly, the rate of shoreline accretion also exhibits a positive elasticity, but the estimated effects are very small — 0.001 to 0.004 in the high premium models and 0.003 to 0.004 in the low premium models. The coefficient for hurricane return interval has the expected negative sign in model 1 for the high premium specification, but an unexpected positive sign in all other models. This likely reflects the poor nature of this proxy for hurricane risk.

Turning to model 3, we find that flood insurance holdings are greater in locations that manage coastal erosion through beach replenishment. The marginal effect is $0.17 to $0.18 per dollar of asset value. Parameter estimates suggest that flood insurance holdings are lower in locations that employ coastal armoring, but the effect is not statistically significant. Results of model 4 explore the effect of mortgage status on demand and price elasticity. Those households that hold a mortgage have more flood insurance coverage, but the effect is not statistically significant. As expected, mortgage holders exhibit much lower price elasticity than those that do not hold a mortgage. For the high price model, ε_p = -0.035 for mortgage holders compared to ε_p = -0.370 for owners of non-mortgaged property. For the low price model ε_p = -0.113 under a mortgage versus ε_p = -0.720 for those without a mortgage.

The income parameter was not statistically significant in either specification, nor was our wealth proxy — a dummy variable identifying properties that are vacation homes. The latter was dropped from the analysis. Flood insurance demand is lower for those with high school as their highest level of educational attainment (relative to those with graduate training) – marginal effect is -\$0.11 to -\$0.12 per dollar of asset value. Retired individuals exhibit lower demand in the high price model (about \$0.06 per dollar of asset value), but this effect is not statistically significant in the low price model.

Discussion

Consistent with previous research, we find overall 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. Moreover, since NFIP premiums reflect property risk characteristics, we are not able to isolate a pure price effect using Tobit regression analysis. 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 -0.620 to -0.870. As existing data suggest that most flood insurance policyholders elect for low deductibles (Michel-Kerjan and Kousky 2008), the former estimate is arguably better.

Owners of houses built before the production of FIRMs or built in the V-zone before building codes were adjusted to take account of storm surge receive explicitly subsidized flood insurance rates; fifty-seven percent of the parcels in our dataset meet these guidelines. Examining demand by subsidy class, we find that explicitly subsidized policyholders exhibit greater demand for coverage (ranging from $0.289 to $0.745 per $1 asset value) than non-subsidized policyholders. Accordingly, we find greater price elasticity of demand for subsidized policyholders ranging from -1.550 to -4.478, compared to 0.133 to -0.502 for non-subsidized policyholders. Again, we deem the former as likely better estimates in both cases. These are the first elasticity estimates, to our knowledge, that distinguish between subsidy classes. Using the subset of survey data, we are also able to analyze demand and price elasticity by mortgage status. Those households that hold a mortgage (somewhat surprisingly, only 39% of survey respondents) exhibit no statistically significant difference in flood insurance demand,[25] but do exhibit a much lower price elasticity (ranging from -0.035 to -0.113) than those that do not hold a mortgage (ε_p ranging from -0.270 to -0.370). Given the potential for response bias in the survey data, these differences must be interpreted with caution. Nonetheless, the ability to examine price elasticity in the absence of explicit controls on

[25] In addition, an interaction term for mortgage status and presence in the SFHA was statistically insignificant.

demand via federal policy makes this result noteworthy. Our estimates suggest that voluntary demand is price inelastic.

The Congressional Budget Office estimates that NFIP "collects about 60 percent of the premiums needed for actuarial balance, leaving a cost to taxpayers estimated at about$1.3 billion per year" (Marron 2006, pg. 1). This shortfall reflects both the explicit subsidy for certain classes of parcels as well as the reputed lack of actuarial rates for other parcels. 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 policyholders.

To the extent that mortgage requirements mandate a specified level of flood insurance coverage, price increases will have little effect on demand. Our data suggest that mortgage contracts are not as common in the coastal zone as in other housing markets. This likely reflects the long tenure of many families in the coastal zone and significant wealth of many recent in-migrants. Further, of those mortgage borrowers located in the SFHA, only 12% claim they were required to purchase flood insurance by their mortgage lender in 1998. Our data also suggest that 11% of respondents have allowed their flood insurance coverage to lapse as some time in the past. These results are consistent with the suggestion that lenders have not been especially 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. The potential lack of enforcement of federal provisions for flood insurance purchase is a problem that requires further analysis. Moreover, since mortgages appear to be somewhat rare in the coastal zone (caveats on potential response bias in our survey data notwithstanding), mortgage requirements will have limited impact on flood insurance coverage.

We find evidence of significantly higher insurance coverage in the V-zone (ranging from \$0.26 to \$0.70 per \$1 asset value) and lower insurance coverage in the B/C/X-zones (ranging from -\$0.05 to -\$0.20 per \$1 asset value) 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. Nonetheless, optimistic subjective risk perceptions do seem to influence flood insurance purchase for some survey respondents. A subset of survey data provided information on perspectives of NFIP non-participants. Sixty-two percent of non-participants in the V- and A-flood zones indicated that the price of insurance was too high or that the risk of flooding was very low.

We employ housing use data to test for wealth effects on flood insurance demand. Our survey data identify those households that use their coastal property as a vacation home. 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 other households. Our vacation-home dummy variable was not statistically significant in our regression models, however. Thus, our findings are not particularly insightful regarding wealth, and this remains a difficult topic to explore empirically. While the sign of the coefficient on the natural log of income was positive, the parameter was not statistically significant.

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 elasticity is 0.03 to 0.11, suggesting a 1 percent increase in the erosion rate raises flood insurance demand by 0.03 to 0.11 percent. Surprisingly location on an accreting shoreline also has a positive effect on flood insurance demand, but the elasticity is very small, ranging from 0.001 to 0.004. Both of these results are relative to locations that are classified as "neither eroding nor accreting". These results suggest that some homeowners view flood insurance as a form of partial protection from erosion hazard. Lastly, consistent with the findings of Kriesel and Landry (2004), we find evidence that community level erosion hazard mitigation projects influence flood insurance holdings. In contrast to the results of Kriesel and Landry, however, we find a possible asymmetry across the types of projects. Beach replenishment appears to be complementary with flood insurance (increasing coverage by around \$0.18 per \$1 asset value), while the estimated effect of shoreline armoring is negative, but statistically insignificant.[26] Interpretation suggests that shoreline armoring may be seen as "self insurance", a form of community hazard mitigation that decreases the expected loss conditional on a flood or storm (Ehrlich and Becker 1972). Since it

[26] At the suggestion of an anonymous reviewer, we explored an additional specification that included an interaction term for *armor* and *replenish*, thus identifying areas where both erosion management policies were pursued in conjunction. The estimated parameter for this term was not statistically significant.

reduces expected loss while not affecting insurance price, self insurance is a substitute for formal insurance. Seawalls buffer the hinterland against erosion and can act as a levee in providing protection from storm surge. If households believe seawalls are effective in this manner, they may feel protected against hurricane flooding and erosion risk, thus purchasing less flood insurance. As such, expansion of shoreline armoring in coastal areas could discourage flood insurance purchase. More exploration of this relationship is warranted, however, as parameter estimates on shoreline armoring are not statistically significant.

Beach replenishment, on the other hand, appears to be complementary to flood insurance purchase. "Self protection" projects that lower the probability of loss, and thus the price of insurance, are complements to formal insurance (Ehrlich and Becker 1972). To our knowledge, however, beach replenishment activities are not explicitly recognized under the Community Ratings System or other flood insurance rate-setting provisions. Like shoreline armoring, beach replenishment also buffers against erosion and can absorb some of the energy associated with storm surge, but our results suggest that households see this form of protection as complementary to flood insurance. Households may see beach replenishment as an inferior form of protection, but may support it in order to maintain recreation potential of the beach. (Structurally fortified coastlines often exhibit poor beach quality.) It is also possible that beach replenishment serves as a reminder of coastal risks, as beach sand has to be replenished at regular intervals to compensate for erosion. Loss of beach may heighten perception of erosion and flood risk.

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. Despite federal regulations, mortgage borrowers do not exhibit higher flood insurance coverage, but do exhibit significantly lower price elasticity. The extent of mortgage borrowing appears to be low in the coastal zone, and even for those households that are borrowers, enforcement of flood insurance requirements appears to be low in 1998.

The accuracy of our price elasticity estimates is compromised by correlation between insurance price and property risk factors; the ability to control for risk factors in our analysis is limited. Thus, since premiums reflect riskiness of the asset, it is difficult to identify the component of demand that is purely driven by price. Future research should focus on attempting to use thresholds in the price schedule that exhibit minimal differences in risk to identify a pure price effect. Such estimates would be very useful for policy analysis of potential price changes for NFIP.

While we do not attempt to discern between competing models of individual choice under uncertainty, we find some 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. We find a counter-intuitive sign, however, for hurricane return interval, likely reflecting error in this county-level proxy for hurricane risk. We attempt to proxy for household wealth, using a dummy variable indicating vacation homes, but results are statistically insignificant. In addition, our estimates of income elasticity are not statistically significant.

We find evidence that erosion risk does affect flood insurance demand, as households facing higher erosion hazard demand greater insurance coverage. Surprising, demand is also increasing in the rate of shoreline accretion for areas that are accreting, but the effect is extremely small. Lastly, we find evidence that community level erosion hazard mitigation projects influence flood insurance holdings, with beach replenishment appearing to act as a complement for flood insurance and shoreline armoring possibly acting as a substitute. 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	Min	Max
part*	NFIP participation indicator	6074	0.521	0.569	0	1
flcov	NFIP flood insurance coverage ($100)	5834	716.653	987.352	0	2500
flratio	NFIP flood insurance coverage / asset value	5773	0.651	1.052	0	10.24
prem_hi	Marginal flood insurance premium (high)	6072	1.014	1.167	0.060	5.700
prem_lo	Marginal flood insurance premium (low)	6072	0.869	1.023	0.056	3.897
vzone*	V flood zone indicator	6074	0.505	0.570	0	1
azone*	A flood zone indicator	6074	0.410	0.561	0	1
xzone*	X flood zone indicator	6074	0.085	0.318	0	1
postfirm*	Indicator for structure built after FIRM	6074	0.627	0.551	0	1
subsidy*	Indicator for subsidized insurance	6074	0.571	0.564	0	1
elev	Elevation above base flood elevation (BFE)	5881	3.305	15.751	-12.420	97.260
brkaway*	Indicator for breakaway walls present below structure	6074	0.065	0.280	0	1
obstct*	Indicator for obstructions present below structure	6074	0.184	0.442	0	1
piles*	Indicator for structure on piles	6074	0.689	0.528	0	1
crs	Community Ratings System classification (1998)	6072	8.346	1.475	5	10
er	Erosion rate (feet/year)	6069	2.713	3.720	0	21.467
ar	Accretion rate (feet/year)	6074	0.191	2.068	0	29.850
geotime	number of years expected before erosion reduces setback to zero	6074	787.924	8751.90	0	287,280
return	Hurricane return interval (years)	6074	47.110	61.779	16	190
cbra*	CBRA indicator	6074	0.056	0.263	0	1
distance	Distance from the shore (feet)	6074	318.416	270.492	0	1593.200
ocean*	Oceanfront property indicator	6074	0.421	0.563	0	1
hp	Housing sales price (1000s current $)	2844	187.177	669.815	1.000	10000.00
asset_val	Generated asset value (1000s current $); 60% of imputed price	6010	143.683	220.613	0.002	5146.20
yearbuilt	Year structure built	4632	1973.50	19.007	1892	1998
yearsold	Year parcel sold	3740	1986.74	13.545	1900	1998
age_at_sale	Age of structure when sold	6074	8.207	16.024	0	94
sqft	Square footage	3930	2276.67	3142.42	120	20,000
vacant*	indicator for vacant lot when sold	6074	0.540	0.568	0	1
dcbdm	Distance from central business district (m)	6074	4342.15	5801.51	32.186	29628.02

* - 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	Std Dev	Min	Max
incom	Categorical income variable	1711	101.431	105.838	20	250
gradsch*	Graduate school indicator	1798	0.357	0.675	0	1
college*	College graduate indicator	1798	0.436	0.699	0	1
hschool*	High school graduate indicator	1798	0.206	0.570	0	1
parttime*	Part-time employed indicator	1789	0.049	0.305	0	1
retired*	Retired indicator	1789	0.456	0.702	0	1
age	Age of respondent	1775	61.208	17.323	25	95
children	Number of children in the household	1899	0.462	1.738	0	13
no_ins*	Indicates the individual would have purchased the property regardless of whether flood insurance was available.	1715	0.681	0.665	0	1
lapse_ins*	Indicates flood insurance coverage has lapsed in the past	1643	0.111	0.451	0	1
claim*	Indicates previous flood insurance claim has been submitted and settled	1899	0.102	0.437	0	1
mort*	Indicates property is mortgaged	1825	0.390	0.690	0	1
requ*	Indicates mortgage lender required flood insurance purchase in SFHA	629	0.114	0.378	0	1
ero_know*	Indicates respondent has seen information on the erosion rate at the nearest shore	1899	0.281	0.649	0	1
armor*	Indicates shoreline armoring employed at the nearest shore	1899	0.192	0.569	0	1
replenish*	Indicates beach replenishment employed at the nearest shore	1899	0.349	0.688	0	1
primary*	Indicates coastal property is primary residence	1814	0.240	0.600	0	1
vacation*	Indicates coastal property is vacation home	1814	0.350	0.671	0	1
pt_rent*	Indicates coastal property is part-time rental	1814	0.307	0.648	0	1
rental*	Indicates coastal property is full-time rental	1814	0.101	0.424	0	1
- Explanations for not holding flood insurance (subset)						
norisk*	Indicates respondent thinks the risk of flooding is very low	292	0.248	1.058	0	1
notreq*	Indicates flood insurance not required	292	0.200	0.980	0	1
too_exp*	Indicates respondent thinks flood insurance is too expensive	292	0.300	1.123	0	1
notavail*	Indicates that flood insurance is perceived as not available	292	0.088	0.696	0	1
* - 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 ($p < 0.0001$)	
*** - statistically significant for 1% probability of Type I error; ** - statistically significant for 5% probability of Type I error; excluded county dummy variable is Lee County, FL		

Table 5: 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	-0.773***	0.314	-0.392***	0.029	-0.187***	0.027	-0.188***	0.030
subsidy			1.001***	0.046				
prem×sub			-1.926***	0.063				
vzone	0.604***	0.040	0.826***	0.038	-0.053	0.042	-0.058	0.042
xzone	-0.119*	0.062	-0.251***	0.056	-0.188**	0.074	-0.176**	0.074
return	-0.038***	0.014	0.038**	0.015	0.019*	0.010	0.014	0.010
er	0.031***	0.006	0.029***	0.006				
ar	0.027***	0.010	0.017*	0.009				
armor					-0.055	0.042		
replenish					0.184***	0.037		
mort							0.065	0.043
prem×mort							0.106***	0.039
ln(income)							0.037	0.023
retired							-0.060*	0.035
college							0.010	0.034
hschool							-0.128***	0.049
Constant	1.042***	0.235	-0.405*	0.244	0.304*	0.178	0.024	0.337
sigma	0.663***	0.026	0.524***	0.020	0.392***	0.025	0.378***	0.025
county fixed effects	YES		YES		YES		YES	
weight	T-scale		T-scale		T-scale & non-participant		T-scale & non-participant	
lnL	-8593		-7953		-2629		-2200	
LRT (df) *p*	1242 (14) <0.0001		2522 (16) <0.0001		424 (14) <0.0001		424 (18) <0.0001	
N	5766		5766		1668		1469	

*** - statistically significant for 1% probability of Type I error; ** - statistically significant for 5% probability of Type I error; * - statistically significant for 10% probability of Type I error

Table 6: 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	-1.392***	0.045	-0.716***	0.045	-0.456***	0.040	-0.429***	0.044
subsidy			0.873***	0.045				
prem×sub			-1.697***	0.070				
vzone	0.743***	0.039	0.792***	0.036	0.043	0.041	0.021	0.042
xzone	-0.134**	0.058	-0.227***	0.055	-0.176**	0.072	-0.166**	0.072
return	0.014	0.014	0.050***	0.015	0.027***	0.010	0.020*	0.010
er	0.032***	0.006	0.028***	0.006				
ar	0.025***	0.009	0.016*	0.009				
armor					-0.039	0.041		
replenish					0.180***	0.036		
mort							0.042	0.044
prem×mort							0.167***	0.057
ln(income)							0.026	0.022
retired							0.056	0.035
college							0.021	0.033
hschool							-0.114**	0.049
constant	0.398*	0.229	-0.520**	0.243	0.232	0.177	0.112	0.334
sigma	0.619***	0.023	0.523***	0.020	0.390***	0.025	0.376***	0.025
county fixed effects	YES		YES		YES		YES	
weight	T-scale		T-scale		T-scale & non-participant		T-scale & non-participant	
lnL	-8247		-7925		-2585		-2169	
LRT	1934 (14) <0.0001		2578 (16) <0.0001		512 (14) <0.0001		486 (18) <0.0001	
N	5766		5766		1668		1469	

*** - statistically significant for 1% probability of Type I error; ** - statistically significant for 5% probability of Type I error; * - statistically significant for 10% probability of Type I error