The Demand for Homeowners Insurance with Bundled Catastrophe Coverage*

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Abstract

This paper analyzes the demand for homeowners insurance in markets subject to catastrophe losses and where consumers have choices in configuring their coverage for catastrophe and non-catastrophe perils. We estimate the demand for homeowner insurance in Florida and New York using two-stage least squares regression with advisory indicated loss costs as our proxy for the quantity of real insurance services demanded. We decompose the demand for insurance into the demand for coverage of catastrophe perils (i.e., hurricanes or windstorms) and the demand for non-catastrophe coverage and estimate these demand functions separately. Our results are relatively consistent in New York and Florida, including evidence that catastrophe demand is more price elastic than non-catastrophe demand. We also find evidence that consumers value options that expand coverage, buy more insurance when it is subsidized through regulatory price constraints, and consider state guaranty fund provisions when purchasing insurance.

Introduction

The risk of natural disasters in the U.S. has significantly increased in recent years, affecting private insurance markets and creating troublesome problems for disaster-prone areas. The threat of mega-catastrophes resulting from intense hurricanes or earthquakes striking major population centers has dramatically altered the insurance environment. Estimates of probable maximum losses (PMLs) to insurers from a mega-catastrophe striking the U.S. range up to $100 billion depending on the location and intensity of the event (Grace, et. al., 2001). While insurers' capital has increased and they have employed other measures to increase their security against catastrophe losses, a severe disaster could still have a significant financial impact on the industry (Cummins, Doherty, and Lo, 1999; ISO, 1996a).

Increased catastrophe risk poses difficult challenges for insurers, reinsurers, property owners and public officials (Kleindorfer and Kunreuther, 1999). The fundamental dilemma concerns insurers' ability to finance low-probability, high-consequence (LPHC) events, which generates a host of interrelated issues with respect to how the risk of such events are managed, financed and priced at various levels (Russell and Jaffe, 1997). Insurers have sought to raise their prices and decrease their exposure to catastrophe losses, while looking for efficient ways to diversify their exposure through reinsurance and securitization.

However, states have resisted insurers' efforts to raise prices and manage their exposures in an attempt to preserve the availability and affordability of insurance coverage (Klein, 1998). Regulatory restrictions have been complemented by state government insurance mechanisms with significant flaws (Marlett and Eastman, 1998). Government policies have imposed substantial cross-subsides from low-risk to high-risk areas as well as cross subsidies from non-catastrophe lines of insurance to the catastrophe lines. These policies distort incentives and undermine the ability of market forces to make necessary adjustments and operate effectively in managing catastrophe risk (Grace, Klein and Kleindorfer, 1999).

As concerns about natural disasters increased, researchers have begun to explore the special problems disasters pose as well as their implications for insurance markets. Understandably, research on catastrophe risk has focused on the topics of industry capacity, reinsurance, securitization, and mitigation. Yet, much less is known about the microeconomics of catastrophe insurance markets at the primary level (i.e., transactions between primary insurers and individual consumers).

This paper constitutes the first significant attempt to examine the nature of the demand for insurance against natural disasters at a detailed, microeconomic level. Our examination has been made possible with the unprecedented assembly of an extensive, detailed database on residential insurance transactions affected by catastrophe risk. These data are supplemented by information on insurer financial and organizational characteristics and the demographics of residential households at a Zip code level.

We explore several significant aspects of residential insurance markets threatened by natural disasters. We concentrate on the key determinants of the demand for residential/catastrophe insurance and their effects on the quantity, quality and price of insurance purchased. Among the phenomena we seek to illuminate are the sensitivity of demand to prices, income, policy features, and the bundling/unbundling of perils and coverages. Further, we examine insurer and consumer decisions in different market and regulatory environments – Florida and New York – over a four-year period 1995-1998.

Our analysis of the demand for home insurance under catastrophe risk yields a number of interesting results. First, for both New York and Florida, the demand for catastrophe coverage is more price elastic than for non-catastrophe coverage. Secondly, we find that the income elasticities of demand are generally inelastic and, for the case of New York, insurance is an inferior good. We also find that rate compression by regulators increases the demand for insurance in both the New York and Florida markets. Regulation has had a bigger impact in the Florida market where rate compression has been more severe. We also find that consumers tend to value some coverage additions more than others. We also find evidence consumers consider guaranty fund provisions when purchasing insurance. For Florida, we find high quality solvency prospects (as measured by A.M. Best ratings) are more important for consumers who may have claims above Florida guaranty fund coverage limits than for those consumers who would not have claims above the coverage limit.

The paper proceeds as follows: the next section describes the data and the definitional issues of price and quantity; the third section contains a description of the methodology and the results; and the final section summarizes the results of our analysis.

THE DEMAND FOR HOMEOWNERS INSURANCE

To obtain estimates of the demand for homeowners insurance products, significant amounts of micro-level data are required. With the assistance of the Insurance Services Office (ISO), we obtained essentially transaction-level information from a group of primary insurers writing business in Florida and New York that report detailed premium and exposure data to ISO. We use the data for the four-year period 1995-1998 for the analyses that are reported here.[1]

The database contains full homeowners premium and exposure data for 60 companies, comprising some 20 groups, taken as a snapshot in the first quarter of each of the four years, 1995-1998. Each exposure record contains slightly aggregated information on similar groups of policies in every Zip code in which reporting companies did business. The information contains relevant data regarding the characteristics of the policies actually purchased by homeowners for each such company, including premiums, structural information on the nature of the insured property, and coverages purchased. Additionally, we have compiled financial and organizational data on the insurers in our sample, as well as household economic and demographic data (from the 1990 Census) by Zip code.

Defining Price and Output

"Price" for insurance products, as for other products and services, is defined on the basis of value-added per unit (in this case, per dollar) of output. At the policy level, this value-added measure of price can be captured by subtracting the discounted value of expected losses covered by the policy from the policy's premium.[2] Denoting by $L(F, Z)$ the expected losses for a policy h with features F and by $P(F, X, Z)$, its premium, we obtain the following definition of price $p(F, X, Z)$ for a homeowners policy $h = (F, X, Z)$ characterized by the parameters (F, X) and indexed

[1] The sample of insurers was drawn from the top 50 insurer groups in New York and Florida in terms of market share. It should be noted that our database contains only a subset of insurers that report statistical data to ISO. A cross-section of companies is represented in terms of size, organizational forms, and distribution systems. We control for possible sample bias in our estimations.

by consumer and loss characteristics *Z*:

$$p(F,X,Z) = \frac{P(F,X,Z) - PV((L(F,Z))}{PV(L(F,Z))} = \frac{(1+r)P(F,X,Z) - L(F,Z)}{L(F,Z)} \quad (1)$$

where *PV(L(F, Z)) = L(F, Z)/(1+r)* is the present value of expected losses on the policy for the policy period and "*r*" is the insurer's return on equity for the period. *L(F,Z)* is the indicated loss costs per unit of coverage for the policy features (*F*) and structure (*Z*) in question. The ISO data provides information on the premium charged for each policy (or group of identical policies), "*r*" is the average ratio of investment income to earned premiums for insurers, and *L(F, Z)* represents the advisory Indicated Loss Costs (ILC), as computed using ISO filed loss cost manuals and rules, for the policy characteristics *(F, Z)*.[3]

We employ the indicated loss costs as a measure of real insurance services output. Using ISO loss cost filing information on catastrophe loss costs and non-catastrophe loss costs, we calculated an expected indicated loss cost for each contract in our database.[4] ISO employed Risk Management Services (RMS) and its CAT model to develop the catastrophe portion of the indicated loss costs. The ISO-estimated non-catastrophe indicated loss costs that are based on standard actuarial analysis of historical data and cost trends. The ISO database and procedures allowed us to compute an expected annual loss for each possible combination of location, policy

[2] Note that we do not consider the effects of taxes in this model. See Myers and Cohn (1987) and Cummins (1990) for a more detailed discussion of "price" in the insurance context. See also Cummins, Weiss and Zi (1999) for a related empirical study of price and profitability using frontier efficiency methods. As noted in the latter paper, the definition of price in (3) properly accounts for the insurer's expenses and the opportunity costs of the owner's capital invested in the insurance business.

[3] We discuss the ISO procedures briefly in Grace et. al., (1999) and in Grace et. al., (2000). These advisory Indicated Loss Costs are our best estimates of the expected annual costs resulting from policy features, structural characteristics and location of a property. The non-catastrophe portion of Indicated Loss Costs is based on actuarial experience and the catastrophe portion is based on catastrophe modeling results. As discussed below, the expected loss costs implied in individual insurers' prices can vary from the ISO Indicated Loss Costs, which represent overall industry projected costs. Also, Indicated Loss Costs are not necessarily the same loss costs approved by regulators.

[4] ISO advisory loss costs filings and associated information present indicated, filed and implemented (i.e., approved) loss costs for a "base" policy and a number of rating factors and rules which effectively enable one to calculate a loss cost for a particular policy, reflecting a set of standard coverage and risk characteristics.

form, and additional contract terms. For example, ISO loss cost information can be used to determine the annual catastrophe and non-catastrophe costs that would be expected to be claimed under a given homeowners policy form that covers a brick house in Zip code 30029 with certain specified coverage provisions, endorsements, and exclusions, such as ordinance/law coverage.

Indicated loss costs for a particular policy are an estimate of the expected claims costs (including claims adjustment expenses) of insurance coverage under the terms of that policy for a particular house. Thus, indicated loss costs are a proxy for the amount of insurance embodied in a specific policy. One could also employ the Coverage A limit as a proxy for the insurance embodied in a policy. However, while the Coverage A limit reflects the replacement cost of the home, it does not necessarily reflect the risk of loss to the home.[5] It is essentially the maximum possible insured loss rather than the expected loss.[6] Thus, indicated loss costs are employed as the output measure.

We estimate three demand equations. The first is for the catastrophe coverage and the second is for the non-catastrophe coverage. The third is for both coverages combined, which we label "total coverage." These demand equations are all of the following general form:

$$L(F,Z)_{i=C,NC,TOT} = \beta_{1i}F + \beta_{2i}Z + \beta_{3i}X + \beta_{4i}P + e_i \tag{2}$$

where $L(F,Z)_i$ reflects the quantity demanded of real insurance services measured by the Indicated Loss Costs for catastrophe, non-catastrophe, or total coverage, F represents a vector of policy form terms, Z represents a vector of neighborhood characteristics, X represents a vector of company characteristics, and P represents price.

The basic contract features of the policies are summarized in Table 1. The HO3 policy is the

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5 Insurers typically require homeowners to insure at least 70-80 percent of the insured value of their home (e.g., its market value or replacement cost) and are reluctant to sell coverage significantly exceeding market value or replacement cost. Most insurers use a model or formula to estimate the market value or replacement cost of a home.

6 Actually, the maximum expected loss encompasses the limits of all non-liability coverages minus deductibles, but other coverage limits are typically stated as percentages of the Coverage A limit. The standard HO3 policy contains standard percentage limits for these other coverage, but insureds may select alternative limits.

Table 1
Comparison of Homeowners Contracts Basic Terms

	Policy Form				
Contract Terms …	HO1 (sold in few states like NY)	HO2	HO3 Typical	HO5 Most Comprehensive	HO8
Insurance Covers …	Named Perils Only	Named Perils Only	Everything Except Exclusions (all perils)	Everything Except Exclusions (all perils)	Named Perils Only
Home	x	x	x	x	x
Other Attached Property and Structures	x	x	x	x	x
Personal Property	Not Covered	Not Covered	x	x	x
Loss of Use	x	x	x	x	x
Personal Liability to Others	x	x	x	x	x
Medical Payments to Others	x	x	x	x	x
Replacement cost Coverage or Repair	Repair	Repair	Repair but Endorsement Available (contents)	Replace	Repair (contents and Home)
Ordinance or Law Coverage	Endorsement Available	Endorsement Available	Endorsement Available	x	Endorsement Available?
Off Premises Theft Coverage	Endorsement Available	Endorsement Available	Endorsement Available	x	Endorsement Available?

Source: Authors' analysis of Standard ISO Contracts for Florida and New York

typical contract sold. It has coverages for the home and attached structures, detached structures, personal property, loss of use, personal liability, and medical payments to others. There are also options (not shown in Table 1) to cover personal property at a greater value than the standard limits, or to cover liability at a greater level than the standard limit ($100,000), e.g., 10 percent of the home's insured value. The standard HO5 policy offers broader coverage than an HO3 policy. The standard HO3 policy provides named-perils coverage for personal property; the standard HO5 policy provides open-perils coverage on personal property. It is possible to purchase an HO15 endorsement on an HO3 policy to replicate the coverage provided by an HO5 policy – we treat the HO3/HO15 combination as an HO5 policy. The third most relevant policy form HO8 covers a more limited set of named perils than HO3 policies. HO1 policies (sold in only a few states including New York) are similar to the HO8 policy, but do not cover personal property. The HO2 policy is more akin to the HO3 policy but does not cover personal property.

For appropriate policy forms, consumers can choose to purchase actual cash value or replacement cost coverage on personal property. Ordinance or law coverage is typically chosen

Table 2

Mean Prices and Premium Level for Various Policy Forms in New York and Florida

Florida	HO2	HO3	HO5	HO8
No of Contracts	4,381	977,850	71,659	210
Percent of Contracts	0.42%	92.77%	6.80%	0.02%
Premium	$ 443.81	$ 704.17	$ 1,038.85	$ 490.53
Price	1.452	1.2682	1.0255	1.777

New York	HO1	HO2	HO3	HO5
No of Contracts	8,847	473,487	1,675,717	172,897
Percent of Contracts	0.38%	20.31%	71.89%	7.42%
Premium	.	$ 492.84	$ 639.59	$ 869.01
Price	.	2.047	1.634	1.308

as an endorsement on HO3 policies while it is a standard coverage in HO5 policies.[7] Finally, there is a wind device protection credit that consumers in Florida can obtain if they have installed specified mitigation features, such as storm shutters or roof straps.[8]

Table 2 shows some descriptive statistics on the various contracts in our data set for Florida and New York during the period 1995-1998. We see that HO3 contracts make up the majority of contracts written in both states. Overall, HO3 contracts account for approximately 92 percent of all contracts written in Florida by our sample companies. The other policy forms account for the remainder of the transactions sampled. In New York, the same pattern is evident where HO3 is the most common contract. HO3 polices account for 71.9 percent followed by HO2 polices which account for 20.3 percent.

In both Florida and New York, the average **premium** (total premiums divided by insured

[7] Ordinance or Law Coverage will upgrade a rebuilt house after a covered loss to the current building code. Without the coverage, the house will be "repaired" or rebuilt according to code only as long as doing so does not exceed the Coverage A limit on the policy.

[8] HO-8 policies cover a more limited set of perils than other policy forms and theft coverage is restricted to property on the premises with a limit of $1,000. Also, as HO8 policies are often written on old homes, the insurer agrees to repair or replace a damaged home with materials of like kind and quality but not necessarily original materials or special workmanship such as plaster walls or intricate wooden moldings.

house years) by policy form increases with the scope of coverage. This makes intuitive sense. Further, the average **price** varies by policy form.[9] The average price decreases as the scope of coverage increases. This is what one would expect as there are certain fixed expenses in servicing a given policy that would not increase as the underlying loss cost increases.

DEMAND ESTIMATION FOR HOMEOWNERS INSURANCE POLICIES

In this section we estimate the demand for homeowners insurance in Florida using two-stage least squares regression fixed-effects model for New York and Florida. We estimate the demand at the level of the Zip code rather than the individual. We have individual contract data, but the market in which the consumer makes purchases is larger than the "home." This means that some homeowners may shop for insurance and that the demographic characteristics of a consumer's neighborhood (in addition to the consumer's home characteristics) may influence the type of insurance he purchases. Because we have the Zip code location of the insured house and we have access to Zip code level information from the Census, we assume, for now, that a consumer shops in a market defined by the Zip code.[10]

A second problem is that the demand for homeowners insurance is derived from the demand for housing. We account for the demand for housing by including the value of the insurance contract's coverage A limit, which reflects the value of the individual's house as an endogenous variable. Factors expected to influence housing demand include such Zip code characteristics as median income and Census reported household characteristics, and these factors are used as instrumental variables in our two-stage least squares estimation below.

The ISO data is generally available for nearly 900,000 house-years in Florida, 220,000 house-years for each of the four years studied. However, we have a smaller set of usable data. In

[9] We actually use PRICE1 = 1 + PRICE = [(1+r)(Premiums – Indicated Loss Costs)]/[Indicated Loss Costs] as our price variable; adding 1 to PRICE simply assures that our price measure in equation (3) is always positive.

[10] We recognize that some Zip codes are quite large geographically and many are diverse demographically, but this is the smallest level of aggregation that will permit analysis of our data.

Florida, we have approximately usable 663,500 house years over the four-year period that are aggregated to approximately 43,000 unique observations by firm and Zip Code. Some data are excluded due to incompatible records, the generation of new Zip codes over the reporting period (making their integration with collateral Census data difficult), and missing information on some records. For New York, there are 2,335,000 house years. When these data are aggregated to the firm and Zip code level, approximately 70,000 unique observations are obtained.

Table 3 provides the descriptive statistics for Florida (Panel A) and for New York (Panel B) based on the data used in our econometric analysis. Note that average premiums and loss costs are higher in Florida than in New York. Also, as in Table 2, the measure of price (Price+1) is greater in New York than in Florida. In addition to the effect of fixed expenses (in relation to increasing loss costs), greater rate suppression and compression in Florida could contribute to its lower average price mark-up.

Table 3 Panel A.

Florida Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
Insured Risk Characteristics				
% Of Homes With Frame Construction	0.305	0.337	0.000	1.000
% Of Homes With Brick Construction	0.690	0.338	0.000	1.000
Protection Code (1 Is Highest)	4.927	1.731	1.000	10.000
Contract Terms				
Total Indicated Loss Costs	$ 884.51	1102.030	$ 121.93	$ 26,567.09
Catastrophe Related Modeled Indicated Loss Costs	$ 509.73	859.337	$ -	$ 21,962.30
Non-Catastrophe Indicated Loss Costs	$ 374.78	290.342	$ 87.63	$ 5,548.80
Log Of (Price +1)	0.148	0.485	-3.515	1.591
Price + 1	1.292	0.575	0.030	4.911
% Of Ho3 Policies In Zip Code	0.889	0.261	0.000	1.000
% Of Ho5 Polices In Zip Code	0.117	0.266	0.000	1.000
% Of Ho8 Policies In Zip Code	0.000	0.016	0.000	1.000
% Of Policies With Wind Exclusion (Fl Only)	0.016	0.106	0.000	1.000
% Of Policies With Replacement Cost Coverage	0.910	0.199	0.000	1.000
% Of Policies With Ord Or Law Coverage	0.525	0.463	0.000	1.000
Coverage A Limit	$ 140,527	91715.950	$ 12,000	$ 1,009,091
Wind Deductible	$ 741.54	1449.74	$ 100.00	$ 9,994.70
Fire Deductible	$ 379.80	158.976	$ 100.00	$ 1,200.00
% Of Total Indicated Lost Costs That Are Due To Cat Costs	0.424	0.228	0.000	0.911
% With Wind Protection Device Credit (Fl)	0.062	0.206	0.000	1.000
Neighborhood Characteristics				
% Of Implemented Loss Costs To Indicated Loss Costs	0.690	0.065	0.478	0.920
Median Year Of Construction In Zip	1974.320	8.008	1943.000	1988.000
% Of Homes In Zip Code With A Mortgage	0.871	0.082	0.000	1.000
Leverage Ratio Of Median Mortgage Costs To Median Income	0.026	0.006	0.000	0.083
Leverage Ratio Of Median Mortgage Costs To Median Home Value	0.009	0.001	0.000	0.024
Log Of Average Age Of Pop In Zip Code	3.642	0.165	3.065	4.275
% Of Households In Urban Areas	0.999	0.000	0.999	0.999
% Of Persons In Zip Aged 65 Or Over	0.178	0.112	0.000	0.824
Median Income	$ 29,629.40	$ 9,650.77	$ 7,890.00	$ 78,668.00
Firm Characteristics				
Direct Writer	0.157	0.364	0.000	1.000
Stock Company	0.893	0.309	0.000	1.000
Auto Premiums Written By Company	$ 29,032,243	47,672,173.11	$ 2	$ 181,509,056
Life Premiums Written By Sister Company	$ 30,078,038	56,541,229.77	$ 0	$ 182,655,744
Total Assets Of Company Selling Policy	$3,125,676,695	4,307,150,626.00	$ 34,816,452	$ 21,168,613,920
Am Best Rating Of A+ Or Higher	0.575	0.494	0.000	1.000
Am Best Rating Of A	0.250	0.433	0.000	1.000
Am Best Rating Of A-	0.156	0.363	0.000	1.000
Am Best Rating Of B+	0.011	0.106	0.000	1.000
Am Best Rating Of Nr2	0.007	0.085	0.000	1.000
Time Indicators				
1995 Indicator				
1996 Indicator	0.251	0.434	0.000	1.000
1997 Indicator	0.257	0.437	0.000	1.000
1998 Indicator	0.266	0.442	0.000	1.000

N = 40,971

ESTIMATION OF QUANTITY DEMAND

Table 4 shows the results of our 2SLS estimation of the demand for contracts for homeowners insurance in Florida. We estimate the model using company fixed effects using the indicated loss costs (in the logged form) as our proxy of the quantity of insurance demanded and PRICE1 in the logged form as our proxy for price. In the model shown in Table 4, we estimate several endogenous variables. While PRICE1 is estimated endogenously variable, we also account for several other endogenous variables including house value, deductibles, and the choice to invest in wind protection devices.

Table 3 Panel B

New York Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
Insured Risk Characteristics				
% Of Homes With Frame Construction	0.887	0.229	0.000	1.000
% Of Homes With Brick Construction	0.112	0.228	0.000	1.000
Protection Code (1 Is Highest)	6.437	2.370	1.000	10.000
Contract Terms				
Total Indicated Loss Costs	$ 448.43	262.123	$ 102.82	$ 4,309.08
Catastrophe Related Modeled Indicated Loss Costs	$ 41.33	102.178	$ 0.14	$ 1,909.33
Non-Catastrophe Indicated Loss Costs	$ 407.10	227.753	$ 89.53	$ 4,242.24
"Price + 1"	1.725	0.549	0.137	4.974
% Of Ho1 Policies In Zip Code (Ny Only)	0.004	0.032	0.000	0.833
% Of Ho2 Policies In Zip Code (Ny Only)	0.178	0.271	0.000	1.000
% Of Ho3 Policies In Zip Code	0.736	0.316	0.000	1.000
% Of Ho5 Polices In Zip Code	0.082	0.213	0.000	1.000
% Of Ho8 Policies In Zip Code	0.000	0.004	0.000	1.000
% Of Policies With Replacement Cost Coverage	0.672	0.335	0.000	1.000
% Of Policies With Ord Or Law Coverage	0.352	0.444	0.000	1.000
Coverage A Limit	183.562	104.966	5.000	1009.090
Wind Deductible	5.738	0.517	4.605	9.209
Fire Deductible	342.208	162.506	50.000	1200.000
% Of Total Indicated Lost Costs That Are Due To Cat Costs	0.008	0.704	-1.000	1.000
Off Premises Theft Coverage	0.028	0.120	0.000	1.000
Neighborhood Characteristics				
% Of Implemented Loss Costs To Indicated Loss Costs	0.919	0.109	0.000	1.107
Median Year Of Construction In Zip	1955.720	10.615	1939.000	1988.000
% Of Homes In Zip Code With A Mortgage	0.796	0.114	0.000	1.000
Leverage Ratio Of Median Mortgage Costs To Median Income	0.025	0.008	0.000	0.140
Leverage Ratio Of Median Mortgage Costs To Median Home V	0.007	0.002	0.000	0.037
% Of Households In Urban Areas	0.552	0.497	0.000	1.000
% Of Persons In Zip Aged 65 Or Over	0.135	0.050	0.000	0.677
Median Income	$ 40,004.39	16663.760	$ 4,999.00	$ 150,001.00
Firm Characteristics				
Direct Writer	0.134	0.341	0.000	1.000
Stock Company	0.902	0.297	0.000	1.000
Auto Premiums Written By Company	$ 44,084,866	40809184	$ 526	$ 152,694,176
Life Premiums Written By Sister Company	$ 193,270,586	289152435	$ 3,436	$ 904,290,112
Total Assets Of Company Selling Policy	$ 3,120,947,934	3750565022	$ 19,213,992	$ 20,535,422,976
Am Best Rating Of A+ Or Higher	0.466	0.499	0.000	1.000
Am Best Rating Of A	0.392	0.488	0.000	1.000
Am Best Rating Of A-	0.142	0.349	0.000	1.000
Time Indicators				
1995 Indicator	0.216	0.412	0.000	1.000
1996 Indicator	0.260	0.439	0.000	1.000
1997 Indicator	0.253	0.435	0.000	1.000
1998 Indicator	0.271	0.445	0.000	1.000

N = 66,426

As noted above, the indicated loss costs in the PRICE equation were computed separately for each contract in our database. Since we wish to estimate the demand for catastrophe coverage as well as the demand for non-catastrophe coverage, we computed separately the catastrophe and non-catastrophe portions of indicated loss costs for each policy in the sample.[11] Thus, we can think of the homeowners' policy as a joint (or bundled) product where the coverage for the catastrophe peril and the coverage for non-catastrophe perils are typically not always combined in the same contract. Further, consumers can vary or tradeoff the amounts of their catastrophe coverage and non-catastrophe coverage in their choice of coverage provisions. By estimating the two demands separately, we are acknowledging that different factors may affect the demands for insurance for these two sets of perils.

As mentioned above we estimate three models. The first is for the total demand. The other two "demand" equations estimated are for cat and non-cat coverages. However, the latter two equations estimations are not really estimates of demand for cat and non-cat coverage separately. One cannot purchase these products separately as they are bundled together. Further, we only have price information on the total demand and we use this price measure (PRICE1) in both the cat and non-cat demands. The estimates of cat and non-cat demand are indicative of the relationships between the variables and our measure of quantity demanded, but they are not proper demand functions. However, they can give us indications of the relationships between the explanatory variables and our measure of quantity demanded.

Before discussing the regression results in general, there are two sets of coefficients to highlight. The first is the price elasticity of demand. The coefficient on the log of PRICE1 (Column 1) for the total demand equation is –1.079. This is somewhat elastic. However, if we decompose the price sensitivity of demand for catastrophe coverage, shown in Column 4, we see

[11] The decomposition of the non-catastrophe and catastrophe portions of indicated loss costs has become a standard feature of advisory loss cost filings and insurer pricing. The term "cat loading" is sometimes used to characterize the catastrophe component of the expected loss cost. Because catastrophes occur infrequently, modeling techniques must be used to calculate catastrophe loadings, as analysis of historical data is insufficient for this purpose. The cat expected loss costs used in this study were computed from the Risk Management Solutions (RMS) catastrophe model in support of ISO loss cost estimations. While proprietary, interested readers can find more on the RMS model at http://www.rms.com/Catastrophe/Models/ and RMS (1995).

that it is even more elastic with an estimated coefficient of –1.915.[12] In contrast, the price elasticity for non-catastrophe coverage (Column 9) is approximately -0.40, which is inelastic. We see this same pattern in Table 5 for the New York results. However, in general, the demand for total insurance and its components is less price elastic in New York than in Florida.

We also employ a selection variable to test for differences between our sample insurers and other insurers in the market. One question that could be raised about our analysis is whether the companies in our database are representative of all insurers selling homeowners insurance in Florida and New York.

In our sample, we have 60 companies in the sample over the four years. In Florida, over the time period we study, this represents about 30 percent of the total homeowners' premiums written in each year. In New York, the ISO Reporting firms write about 35 percent of the market. The firms in our sample may be significantly different than the other firms in the market. We control for this probability by estimating a probit regression that attempts to classify those companies that are in our sample, i.e., they are companies that report data to ISO and not other

[12] Note here that the price elasticity measures for cat and non-cat are not defined in the traditional way. For example, since we only have a price variable for the total price (the price of cat and non-cat coverage bundled together), our elasticity is actually the percentage change in total price over the percentage change in the quantity demanded of cat coverage (or non-catastrophic cover).

statistical agents.[13] This selection model employs firm specific characteristics to determine whether the firm is an "ISO Reporter."[14]

For Florida (Table 4), the selection indicator (λ) is significantly negative for catastrophe coverage, thus implying that the ISO Reporting companies are less likely to provide catastrophe coverage than those that do not report to the ISO. Thus, the mean level of catastrophic insurance demanded is statistically "lower" for reporting companies than non-reporting companies.[15] In Table 5, we see the same result for New York - the selection parameter is negative and significant for the catastrophe demand. For the overall level of demand and for the non-catastrophic coverage we see positive coefficients which are only significant for the Florida overall demand. However, while statistically significant, these selection coefficients do not have any appreciable economic effects on estimated demand.

FLORIDA

Insured Risk Characteristics

First we construct three variables based upon the standard base loss cost for a particular type of home with a given set of coverages in a Zip code. This standard base loss cost is employed to provide an index for the level of risk in the Zip code. We calculate four indicator variables based

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[13] In Florida and New York, regulators require insurers to report statistical data to one of several designated agents. ISO and the National Association of Independent Insurers (NAII) are the two principal agents; other statistical agents account for only a small portion of insurers operating in these markets. An increasing number of insurers have selected ISO as their statistical agent, which has broadened the types of insurers in its database. At the same time, among the ISO reporting firms, several declined to authorize the use of their data for this study. These tended to be insurers with more unique products and portfolios of exposures.

[14] The selection regression we estimate is: *Probit* [(ISO Reporter and Participant) =1, 0 otherwise] = *f*(log of total assets, log of Florida homeowners premiums, Best Capital Adequacy Ratio, business concentration ratio (top four lines), geographical four state concentration ratio, percent of claims paid within two years, percent of claim value paid within two years, Stock Dummy, Direct Writer Dummy, and year dummies). From this regression, we obtain the inverse Mills ratio for each observation as $\lambda = -\phi(X'\beta)/\Phi(X'\beta)$ from the estimates of the probit regression where $\phi(*)$ represents the normal density function and $\Phi(*)$ represents the cumulative normal distribution function (see Green, 2000). This variable can be employed in the demand equation to account for the fact that only some firms report to ISO. In our model, the coefficient on λ in the demand equation represents the effect on the quantity demanded for a firm that reports data to ISO. If the coefficient is positive (negative), then the mean level of demand is higher (lower) relative to firms who do not report to ISO all other things being equal.

on the standard loss costs based on whether the Zip code is above (or below) the median standard loss costs for cat loss costs or non-cat loss costs. Thus, we have HH (above median for both cat and non-cat standard costs), HL and LH (above median for one, but not the other) and LL (below median for both cat and non-cat standard loss costs). In Florida the HH Zip codes are in South Florida and in the Tampa-St. Petersburg-Clearwater area. In contrast the LL area is north and central Florida.

We hypothesize higher risk areas are likely to have demand for coverage all other things being equal. We see this is true for those Zip codes that have both above median costs for both cat and non-cat risks. The HL and LH indicator variables are not significant for the overall demand. However, we see that all three "risk" variables are significantly related to the demand for catastrophic coverage. In contrast, for non-catastrophic coverage all three are significant, but the above median for cat and below median for non-cat (HL) is negatively related to the demand for coverage.

In estimating the effect of the construction type on demand, superior fire resistant homes (SFR) are treated as the "base case" in our specification of dummy variables (i.e., SFR is omitted homes to avoid multicollinearity with indicators for other construction types). *A priori*, one would expect demand to be lower for the SFR category if fire risk was a major component of the demand for insurance. Thus, we would hypothesize consumers with wooden frame homes would have a higher demand for insurance than consumers with SFR homes. This is supported by our results as the percentage of homes with frame construction in a Zip code is positively related to the overall demand for coverage. Further, we see this relationship is strong and significant for non-catastrophe coverage but insignificant for catastrophe coverage. This suggests that SFR homes do not have characteristics that decrease their vulnerability to windstorm damage.

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[15] Several large "direct writers" with significant amounts of exposures in coastal areas report their statistical data to NAII, another statistical reporting agent, the National Association of Independent Insurers.

For brick construction, we see no significant relationship for the overall demand, but we see a positive relationship for both catastrophe and non-catastrophe equations suggesting that, relative to owners of SFR homes, owners of brick homes tend to have a higher demand for both catastrophe and non-catastrophe coverages.

The protection code is the ISO designated rating of the local community's fire and police protection. A higher code means the protection level is lower and implies that risk is higher. Consistent with this, we see in our statistical results that as the protection code increases (public services are of lower quality), the demand for insurance increases.

Contract Terms

In addition to price, there are a number of other variables that reflect various contract choices. The first is policy type. Recall that the HO5 policy offers the broadest coverage (omitted to avoid multicollinearity) and should be the most preferred, all other things equal including price. If HO5 polices are preferred to all other policies, then there should be negative coefficients on the percentages of HO3 and HO8 polices in a Zip code. Our results are partially consistent with this hypothesis as the percentage of HO3 policies in a Zip is negatively related to the demand for coverage. This is true across the various types of coverage, catastrophe, non-catastrophe and combined. However, our estimations yield a positive coefficient for the percentage of HO8 policies in the total demand equation. One possible explanation for this result is that HO8 policies tend to be written in older urban neighborhoods where the risk of non-catastrophe perils such as fire and theft can be very high.

Table 4

Two Stage Least Squares Results

Florida Contract Demand Equations For Total Loss Costs, Catastrophic Loss Costs,a nd Non-Catastrophic Loss Costs

Variables	Endogenous Variable	Hypothesized sign	Total Indicated Lost Costs (1) Coefficient	(2) Std. Error	(3) t-stat	(4) Prob	Catastrophic Indicated Loss Costs (5) Coefficient	(6) Std. Error	(7) t-stat	(8) Prob	Non-Catastrophic Indicated Loss (9) Coefficient	(10) Std. Error	(11) t-stat
Intercept		?	8.767	0.936	9.360	0.000	-6.797	3.229	-2.100	0.036	14.872	0.769	19.340
Selection Variable		?	0.018	0.021	0.880	0.379	-0.628	0.072	-8.720	0.000	0.104	0.017	6.080
Insured Risk Characteristics													
Above Median For Both Cat And Non Cat Costs (Hh)		+	0.308	0.011	28.590	0.000	0.777	0.037	20.910	0.000	0.102	0.009	11.590
Above Median For Cat And Below Median For Non Cat Costs (Hl)		+	0.004	0.008	0.460	0.646	0.605	0.028	21.870	0.000	-0.261	0.007	-39.670
Above Median For Non Cat And Below Median For Cat Costs (Lh)		+	0.002	0.005	0.490	0.624	0.121	0.018	6.880	0.000	0.071	0.004	16.830
% Of Homes With Frame Construction		+	0.225	0.027	8.210	0.000	0.274	0.095	2.900	0.004	0.344	0.023	15.280
% Of Homes With Brick Construction		+/-	0.119	0.028	4.310	0.000	0.417	0.095	4.370	0.000	0.167	0.023	7.340
Protection Code (1 Is Highest)		+/-	0.037	0.001	32.460	0.000	0.028	0.004	7.210	0.000	0.034	0.001	35.830
Contract Terms													
Log Of (Price +1)	x	-	-1.079	0.013	-80.070	0.000	-1.915	0.046	-41.210	0.000	-0.404	0.011	-36.490
% Of Ho3 Policies In Zip Code		-	-0.205	0.010	-21.110	0.000	-0.100	0.033	-2.990	0.003	-0.289	0.008	-36.230
% Of Ho8 Policies In Zip Code		-	0.314	0.101	3.120	0.002	0.069	0.347	0.200	0.841	0.145	0.083	1.750
% Of Policies With Wind Exclusion (Fl Only)		-	0.330	0.026	12.510	0.000	0.292	0.091	3.210	0.001	0.400	0.022	18.430
% Of Policies With Replacement Cost Coverage		+	-0.001	0.008	-0.170	0.865	-0.012	0.029	-0.410	0.682	0.098	0.007	14.110
% Of Policies With Ord Or Law Coverage		+/-	0.101	0.018	5.480	0.000	-0.190	0.063	-3.000	0.003	0.149	0.015	9.900
Log Of Coverage A Limit		+	0.600	0.029	20.780	0.000	-0.763	0.100	-7.660	0.000	0.784	0.024	33.050
Log Of Wind Deductible	x	+/-	-0.015	0.009	-1.670	0.095	0.114	0.031	3.640	0.000	-0.102	0.007	-13.640
Log Of Fire Deductible	x	+/-	0.500	0.044	11.340	0.000	2.670	0.152	17.580	0.000	-0.403	0.036	-11.160
% With Wind Protection Device Credit (Fl)	x	?	0.286	0.073	3.910	0.000	-1.588	0.252	-6.310	0.000	0.540	0.060	9.010
Neighborhood Characteristics													
% Of Implemented Loss Costs To Indicated Loss Costs		-	-0.282	0.022	-12.590	0.000	-0.438	0.077	-5.660	0.000	-0.292	0.018	-15.870
Median Year Of Construction In Zip		-	-0.008	0.000	-30.450	0.000	-0.007	0.001	-7.340	0.000	-0.007	0.000	-34.610
% Of Homes In Zip Code With A Mortgage		+/-	-0.022	0.032	-0.690	0.490	0.540	0.110	4.920	0.000	-0.049	0.026	-1.870
Leverage Ratio Of Median Mortgage Costs To Median Income		?	6.022	0.566	10.640	0.000	13.777	1.952	7.060	0.000	4.881	0.465	10.500
Leverage Ratio Of Median Mortgage Costs To Median Home Value		?	-5.621	1.378	-4.080	0.000	-39.387	4.751	-8.290	0.000	-0.521	1.131	-0.460
Log Of Average Age Of Pop In Zip Code		?	0.025	0.036	0.700	0.484	0.643	0.124	5.170	0.000	-0.129	0.030	-4.360
% Of Households In Urban Areas		+/-	-0.013	0.006	-2.370	0.018	0.092	0.019	4.720	0.000	-0.071	0.005	-15.370
% Of Persons In Zip Aged 65 Or Over		+	-0.366	0.053	-6.890	0.000	-0.739	0.183	-4.030	0.000	-0.118	0.044	-2.700
Log Of Median Income		+/-	0.061	0.019	3.250	0.001	0.315	0.065	4.860	0.000	0.105	0.015	6.780
Firm Characteristics													
Direct Writer		?	-0.961	0.119	-8.110	0.000	-0.581	0.409	-1.420	0.156	-0.828	0.097	-8.510
Stock Company		?	-0.571	0.172	-3.310	0.001	-0.892	0.594	-1.500	0.134	-0.218	0.142	-1.540
Log Of Auto Premiums Written By Company		?	0.017	0.003	6.590	0.000	0.018	0.009	2.040	0.041	0.020	0.002	9.410
Log Of Life Premiums Written By Associated Company		?	0.002	0.005	0.490	0.624	0.121	0.018	6.880	0.000	0.071	0.004	16.830
Log Of Total Assets Of Firm Selling Policy		?	0.332	0.040	8.330	0.000	0.238	0.138	1.730	0.084	0.206	0.033	6.280
Am Best Rating Of A		?	0.057	0.015	3.760	0.000	0.625	0.052	11.970	0.000	-0.149	0.012	-11.980
Am Best Rating Of A-		?	0.039	0.018	2.180	0.029	0.493	0.062	8.010	0.000	-0.083	0.015	-5.660
Am Best Rating Of B+		?	0.670	0.183	3.670	0.000	0.285	0.629	0.450	0.653	0.310	0.150	2.070
Am Best Rating Of Nr2		?	0.912	0.187	4.880	0.000	0.705	0.644	1.100	0.271	0.435	0.153	2.830
Time Indicators													
1996 Indicator		+	0.004	0.014	0.290	0.772	0.199	0.048	4.150	0.000	0.003	0.011	0.250
1997 Indicator		+	0.091	0.029	3.170	0.002	0.355	0.099	3.570	0.000	0.096	0.024	4.050
1998 Indicator		+	0.094	0.032	2.890	0.004	0.452	0.112	4.030	0.000	0.077	0.027	2.880
N	40,971												
R^2			0.937				0.797				0.891		

Table 5

Two Stage Least Squares Results

New York Contract Demand Equations For Total Loss Costs, Catastrophic Loss Costs,a nd Non-Catastrophic Loss Costs

Variables		Hypothesized	Total Indicated Lost Costs (1)	(2)	(3)	(4)	Catastrophic Indicated Loss Costs (5)	(6)	(7)	(8)	Non-Catastrophic Indicated Loss Costs (9)	(10)	(11)	(12)
Endogenous Variable		sign	Coefficient	Std. Error	t-stat	Prob	Coefficient	Std. Error	t-stat	Prob	Coefficient	Std. Error	t-stat	Prob
Intercept		?	0.817	0.336	2.430	0.015	-13.553	0.796	-17.030	0.000	0.823	0.454	1.810	0.070
Selection Variable		?	0.118	0.039	3.010	0.003	-0.308	0.093	-3.330	0.001	0.257	0.053	4.860	0.000
Insured Risk Characteristics														
Above Median For Both Cat And Non Cat Costs (Hh)			0.160	0.008	20.220	0.000	0.751	0.019	40.110	0.000	0.102	0.011	9.520	0.000
Above Median For Cat And Below Median For Non Cat Costs (Hl)			-0.002	0.005	-0.320	0.749	0.648	0.012	53.070	0.000	-0.025	0.007	-3.570	0.000
Above Median For Non Cat And Below Median For Cat Costs (Lh)			0.148	0.008	17.900	0.000	-0.315	0.020	-16.070	0.000	0.109	0.011	9.690	0.000
% Of Homes With Frame Construction		**+**	0.036	0.034	1.060	0.289	0.654	0.080	8.150	0.000	-0.114	0.046	-2.480	0.013
% Of Homes With Brick Construction		**+/-**	-0.020	0.035	-0.560	0.575	-0.360	0.079	-4.540	0.000	-0.044	0.038	-1.170	0.242
Protection Code (1 Is Highest)		**+/-**	0.035	0.001	33.340	0.000	-0.011	0.002	-4.290	0.000	0.039	0.001	27.360	0.000
Contract Terms														
Log Of (Price +1)	**x**	**-**	-0.857	0.047	-18.380	0.000	-2.064	0.110	-18.720	0.000	-0.331	0.063	-5.260	0.000
% Of Ho1 Policies In Zip Code (Ny Only)		**-**	0.003	0.032	0.110	0.912	0.233	0.075	3.120	0.002	-0.055	0.043	-1.300	0.194
% Of Ho2 Policies In Zip Code (Ny Only)		**-**	-0.163	0.020	-8.030	0.000	0.564	0.048	11.710	0.000	-0.320	0.027	-11.630	0.000
% Of Ho3 Policies In Zip Code		**-**	-0.145	0.011	-13.650	0.000	0.261	0.025	10.420	0.000	-0.237	0.014	-16.580	0.000
% Of Policies With Replacement Cost Coverage		**+**	-0.023	0.008	-2.840	0.005	0.049	0.019	2.530	0.011	-0.024	0.011	-2.140	0.032
% Of Policies With Ord Or Law Coverage		**+/-**	0.028	0.005	5.110	0.000	0.038	0.013	2.930	0.003	0.024	0.007	3.240	0.001
Log Of Coverage A Limit	**x**	**+**	0.778	0.032	24.680	0.000	1.231	0.075	16.490	0.000	0.594	0.043	13.940	0.000
Log Of Wind Deductible	**x**	+/-	0.090	0.024	3.760	0.000	0.423	0.057	7.440	0.000	-0.037	0.032	-1.150	0.250
Log Of Fire Deductible	**x**	+/-	0.299	0.068	4.410	0.000	-1.124	0.161	-7.000	0.000	0.780	0.092	8.510	0.000
% Off Premises Coverage Exclusion (Ny)		**+**	0.042	0.015	2.860	0.004	0.345	0.035	9.970	0.000	-0.068	0.020	-3.440	0.001
Neighborhood Characteristics														
% Of Implemented Loss Costs To Indicated Loss Costs		**-**	-0.013	0.010	-1.340	0.180	-0.074	0.023	-3.160	0.002	-0.019	0.013	-1.410	0.159
Median Year Of Construction In Zip		**-**	-0.001	0.000	-6.090	0.000	0.003	0.000	10.570	0.000	-0.001	0.000	-4.100	0.000
% Of Homes In Zip Code With A Mortgage		**+/-**	-0.025	0.014	-1.770	0.077	0.218	0.033	6.550	0.000	-0.043	0.019	-2.260	0.024
Leverage Ratio Of Median Mortgage Costs To Median Income		**?**	-0.319	0.332	-0.960	0.337	0.452	0.784	0.580	0.562	-2.336	0.448	-5.210	0.000
Leverage Ratio Of Median Mortgage Costs To Median Home Value		**?**	-2.180	1.095	-1.990	0.047	-16.632	2.590	-6.420	0.000	6.278	1.479	4.250	0.000
Log Of Average Age Of Pop In Zip Code		**?**	-0.047	0.023	-2.030	0.042	0.151	0.055	2.740	0.006	-0.122	0.031	-3.870	0.000
% Of Households In Urban Areas			0.064	0.006	10.020	0.000	-0.069	0.015	-4.570	0.000	0.094	0.009	10.950	0.000
% Of Persons In Zip Aged 65 Or Over		**+**	0.076	0.048	1.580	0.114	0.953	0.113	8.420	0.000	0.005	0.065	0.080	0.936
Log Of Median Income		**+/-**	-0.029	0.011	-2.630	0.009	0.248	0.026	9.590	0.000	-0.038	0.015	-2.570	0.010
Firm Characteristics														
Direct Writer		?	-0.041	0.032	-1.280	0.201	-0.334	0.075	-4.430	0.000	0.066	0.043	1.540	0.124
Stock Company		?	0.059	0.021	2.760	0.006	0.469	0.050	9.310	0.000	-0.097	0.029	-3.370	0.001
Log Of Auto Premiums Written By Company		?	0.006	0.002	2.850	0.004	0.005	0.005	0.860	0.390	0.006	0.003	2.130	0.033
Log Of Life Premiums Written By Associated Company		?	0.020	0.002	12.140	0.000	0.014	0.004	3.750	0.000	0.021	0.002	9.350	0.000
Log Of Total Assets Of Firm Selling Policy		?	0.041	0.009	4.530	0.000	0.114	0.021	5.390	0.000	0.012	0.012	0.990	0.322
Am Best Rating Of A		?	0.012	0.006	1.940	0.052	-0.048	0.011	-4.140	0.000	-0.016	0.005	-2.980	0.003
Am Best Rating Of A-		?	0.040	0.009	4.570	0.000	0.007	0.018	0.390	0.697	-0.015	0.009	-1.730	0.084
Time Indicators														
1996 Indicator		+	-0.006	0.003	-1.750	0.080	0.020	0.007	2.660	0.008	-0.016	0.004	-3.670	0.000
1997 Indicator		+	0.002	0.005	0.340	0.734	0.120	0.013	9.270	0.000	-0.045	0.007	-6.050	0.000
1998 Indicator		+	0.014	0.010	1.390	0.165	0.278	0.024	11.530	0.000	-0.090	0.014	-6.500	0.000
N	66,426													
R^2			0.819				0.691				0.731			

In Florida, insureds may elect to have coverage for windstorms excluded from their policy (presuming they are not prevented from doing so by a lender's insurance requirements). We would expect that wind exclusion would negatively affect demand. However, our results yield a positive coefficient suggesting a positive effect on demand. This is true for both the catastrophe coverage and non-catastrophe coverage and may be due to the fact that the Zips with a high percentage of excluded polices are in higher risk Zip codes. Arguably, the demand for insurance should be stronger in these areas, all other things equal. Consequently, our wind exclusion variable may be picking up the effect of omitted variables reflecting this higher risk and demand that are visible to insurers and insureds but not researchers.

If consumers value policy options such as replacement cost coverage, then the addition of these options should be associated with higher levels of demand if the benefits of the options outweigh their incremental cost to consumers. We see this is true for ordinance or law coverage, but not for replacement cost coverage on personal property for the overall demand. Ordinance or law coverage is a policy option that will pay the additional costs of repairing a home to the standards of any new ordinances or building codes that have been enacted since the home was built. This is not surprising as Florida has significantly strengthened its building codes since Hurricane Andrew occurred, increasing the value of this additional coverage for homeowners. However, we see that ordinance or law coverage is not valued for the cat coverage, but it is valued for the non-cat coverage.

The regression coefficient on replacement cost coverage is not significant for overall demand, suggesting consumers may not value it as much. However, its coefficient is not significant in the catastrophe demand equation, but it is significantly positive in the non-catastrophe demand equation. This implies that this policy option is valued more for non-catastrophic perils than for -catastrophic perils. Indeed, being able to replace property damaged from fire or loss through theft may be of significant concern to homeowners, whereas repairing structural damage may be the principal concern with respect to the wind peril.[16]

The Coverage A limit (on the dwelling and attached structures) is our proxy for the replacement cost of the home and is treated as an endogenous variable.[17] One would expect that insurance demand would increase as the replacement cost of the home increases, all other things held constant. Our statistical results are generally consistent with this expectation; as the value of the home (Coverage A limit) increases, the quantity of insurance demanded increases. An interesting exception is the demand for catastrophic coverage. In this case we see that individuals with higher valued homes do not value additional increases in coverage perhaps due to the higher cost of coverage of higher valued homes.

The fire and wind deductibles are also endogenously determined. Higher deductibles may increase or decrease the demand for insurance. First, as the deductible increases, the premium should fall reflecting the lower loss costs covered by the policy. But whether the price falls or not depends on the ratio of premium reductions to loss cost reductions (see (3)). In any case, the homeowner may use the premium savings to purchase additional coverages that are considered to be a better "value", such as higher policy limits. Indeed, trading higher deductibles for higher limits is commonly advised by insurance experts.[18] In addition, as the deductible increases, the value of the coverage decreases and the consumer has to bear more risk. Demand for the

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[16] Indeed, in areas with a high catastrophe risk (and high catastrophe loadings in the coast of insurance), insureds may forgo replacement cost coverage on personal property in order to afford and purchase more adequate structural coverage for catastrophe losses.

[17] As mentioned earlier, insurers typically require a homeowner to carry a Coverage A limit equal to at least 70-80 percent of the replacement cost of his home. Limits on the other property coverages are stated as percentages of the Coverage A limit. Further, the problem of inadequate coverage limits has received increasing attention and has probably prompted insureds and insurers to maintain coverage limits closer to the replacement cost of homes.

[18] The expense load and price mark-up on lower deductibles are very high. Insureds likely become increasingly attuned to this as their premium increases, as revealed by a significant increase in the size of the deductibles chosen by policyholders in Florida and New York between 1995 and 1998 (see Grace et. al., 2001). For example, in Florida in 1998, 43.4 percent of sample policies carried a wind deductible in excess of $1,000, compared to only 4 percent in 1995.

resulting lower-valued coverage could also decrease. Thus, the sign of the deductible's coefficient gives us some indication which effect is more important: the premium-reduction effect or the coverage effect.

For the wind deductible, we see that the coefficient on the overall demand is negative. This implies that the coverage effect dominates. Increases in the deductible reduce the demand for insurance all other things held constant. However, if we look at the coefficient in Column 5, we see that it is positive implying consumers would take a higher deductible for catastrophe coverage because the premium-reduction effect dominates. Higher deductibles imply lower premiums and this encourages consumers to purchase more insurance. This is plausible as consumers facing greater catastrophe risk may be more concerned about having adequate coverage to cover large losses than absorbing a larger deductible in the event of a hurricane.[19] For the non-catastrophe coverage, the wind deductible is negative, indicating that the coverage effect dominates. This is also plausible, as non-catastrophe perils tend to involve more frequent and smaller losses.

For the fire deductible, we see a different phenomenon. The coefficient on the fire deductible in the total demand equation is positive implying that the increase in the deductible lowers premium sufficiently to increase demand. For catastrophe coverage, the relationship is negative and significant. While catastrophes are not fire related (at least not in Florida) and the fire deductible's coverage effect dominates for catastrophe coverage. In Column 9, we see that, for non-catastrophe coverage, the coefficient on the fire deductible is negative, suggesting that coverage effect dominates the premium-reduction effect in the demand for non-catastrophe coverage.

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[19] We should note it is likely that insurers have made the pricing of large deductibles very attractive to consumers as this viewed as one of several effective strategies to manage an insurer's catastrophe exposure.

Finally, we treat the decision to employ a windstorm protection device such as storm shutters as endogenous. There is no *a priori* hypothesis regarding the effect of this variable on the demand for insurance. If the presence of protection devices increases demand for insurance, then the protection devices are complements to traditional insurance. In contrast, if there is a negative relationship between the presence of the protection devices and insurance demand, then one might reasonably conclude that the devices were a substitute for traditional insurance. Our coefficient results are positive for overall and non-cat coverage implying that the windstorm device credit is associated with higher insurance demand, all other things held constant. However, we see that negative effect for the cat demand suggesting that the device is a potential substitute for insurance.

Neighborhood Characteristics and Regulation

The first neighborhood characteristic is the ratio of implemented loss costs to indicated loss costs. This also may be viewed as a regulatory variable as regulators tend to vary the severity of price constraints by rating territory. Because regulators seek to keep insurance "affordable", their constraints are more severe or binding in higher-cost areas (see Grace et al., 2001). The implemented loss costs are those costs that the regulator allows to be used in making full rate calculations for homeowners' policies in a given rating territory. As mentioned previously, we think of this ratio as a measurement of rate suppression or rate compression.[20] As the implemented loss costs are reduced by regulation (relative to the expected or indicated loss costs) the consumer gets a lower price for coverage. As the ratio increases, the price reduction diminishes. This ratio is measured at the level of the ISO rating territory and it varies through the

[20] We define "rate suppression" as a binding regulatory ceiling on the overall rate level charged by an insurer. "Rate compression" is defined as a binding regulatory constraint on the rate differential between low and high-risk territories. In practice, regulators tend to both compress and suppress rates by imposing severe constraints on the rates for the highest-risk territories, without a compensating increase in the rates for low-risk territories to produce an adequate overall rate level.

state. Thus one would expect that a higher ratio would reduce the demand for coverage. As regulatory price suppression is reduced, price rises, and as price rises, the quantity demanded falls. In fact, we find this to be the case for all three demand functions.

Older homes tend to be higher risk and one would expect that their owners would have a higher demand for coverage, all other things equal. Our results are consistent with this - as the median year of a home's construction in a Zip code increases (i.e., it is a newer home), the demand for coverage falls. This is true for all three Florida demand models.

The percentage of homes with a mortgage may have either a positive or a negative effect. Mortgage lenders generally require homeowners insurance to complete the mortgage transaction. This implies that the greater the percentage of homes with mortgages, the greater the demand for insurance. However, while borrowers must meet certain insurance coverage requirements, they are not required to purchase the broadest coverage available. Further, consumers may scrimp on their insurance if they have low equity (which could also increase their mortgage payments). This moral hazard phenomenon may result in a negative coefficient on the percentage of homes in a Zip code with a mortgage. Another reason that the percentage of homes with a mortgage may be negatively related to the demand for insurance may involve an owner's tenure in a home. Mortgages are paid off over time, but consumers do not necessarily update their insurance coverage each year. Thus, in Zip codes with a higher percentage of mortgages, it may be that those who have been in their house a long time have a lower demand for coverage, everything else held constant.

We see that in Florida the percentage of mortgages in a Zip code is negatively related to the total demand for insurance. This relationship is positive for catastrophe coverage but negative for non-catastrophe coverage. This suggests that, for non-catastrophe coverage, the moral hazard explanation and/or "tenure effect" dominates the decision to purchase insurance. However, it is interesting to see that as the percentage of mortgages increases in a Zip code, the demand for catastrophe coverage increases. It is not clear why the moral hazard effect and/or the tenure effect should be that different between the demands for catastrophe and non-catastrophe coverages. One possibility is that lenders impose greater insurance requirements for homes subject to greater catastrophe risk.

We further examine the relationship between having a mortgage and the demand for insurance with additional variables. The first such variable is the ratio of median housing costs for homes with mortgages (in the Zip code) to the median income in the Zip.[21] The higher this ratio, the tighter is a homeowner's budget constraint on non-housing expenditures. A positive relationship between this ratio and demand would imply that, while cash poor, the homeowner wishes to avoid default on his mortgage (due to uninsured losses) and thus will purchase more insurance. A negative coefficient would imply that consumers attempt to scrimp on their insurance coverage as they have less money to spend on non-housing items. Our results yield a positive coefficient for the housing cost/income ratio in all three demand functions. This suggests that homeowners' aversion to risk and default dominates over concerns about having to economize on non-housing items. We should also note that high housing costs relative to income may reflect the importance of housing to a consumer and this could also increase the demand for insurance. Further, Florida law protects a person's entire home value from a bankruptcy proceeding. Thus, as long as a person can pay their mortgage, one can not lose a home though bankruptcy. Other states like New York protect a much smaller amount ($10,000).

A second variable is the ratio of mortgage costs to the median home value. This is a measure of a homeowner's leverage, i.e., higher mortgage payments relative to home value imply less equity. As leverage increases, one would expect a reduced incentive to purchase insurance. We

[21] These include things like taxes, mortgage payment, and fees.

find this to be consistent with our Florida results. As the ratio of mortgage costs to home value increases (i.e., leverage increases), the demand for insurance decreases.

A plausible story emerges from these results. Cash-strapped homeowners who place a high value on their housing may be primarily concerned with avoiding uninsured losses and negative credit ratings that would arise from default on their mortgage or other debts. On the other hand, all other things equal, highly leveraged homeowners (rich or poor), may be inclined to take their chances on incurring uninsured losses from a low-probability event that could force them to default on their mortgage.

There is no *a prior* expectation on the sign of the coefficient for the average age of the population in a Zip code. On the one hand, families with young children may tend to be more risk averse and have a higher demand for insurance. On the other hand, young single homeowners may be less risk averse than older homeowners. Other factors associated with age and risk aversion may confound the relationship between age and the demand for insurance we observe. Some elderly homeowners may be very risk averse, while others may be less concerned about the risk of financial losses because of a shorter time horizon or greater assets. In our results, we see that the coefficient for the age variable is not significant for overall demand, and negative for non-catastrophe demand. However, it is positive for catastrophe demand.

Since Florida is a retirement state, it is appropriate to look at the effect that the percentage of retirees may have on the demand for insurance. We proxy retirees in the Zip code by the number of people 65 years old or older. If we look at demand equations, we see a negative relationship between retirees and demand.

The percentage of households in urban areas should be related to insurance demand. This is because urban homes tend to be of lower value or have higher catastrophe risks. If they are lower valued, then more urban households should have a negative effect on the demand for insurance.

If they are higher risk, then the relationship may be positive. Note that the coastal areas in Florida tend to have the highest population concentrations because of their attractiveness to retirees, tourists and others. We see that in Florida, the percentage of urban households is negatively related to overall demand. This is also true for the demand for non-catastrophe coverage, but the urban coefficient is positive for catastrophe coverage. This suggests that the "low value effect" dominates in the demand for non-catastrophe coverage and the urban-catastrophe risk association dominates in the demand for catastrophe coverage.

Finally, we examine income. The expected sign on and the magnitude of the coefficient for income is ambiguous because of two competing hypotheses. First, insurance may be thought of as an inferior good. If the coefficient on income is negative it implies that increases in income reduce the demand for insurance. Arrow (1964) conjectured that individuals have declining absolute risk aversion. This implies that as income increases the demand for insurance should diminish. Mossin (1968), in turn, proved that if a person faced a price of insurance greater than the actuarially fair value, but below the price at which no insurance would be purchased, and the consumer exhibited decreasing absolute risk aversion, then the amount of insurance coverage fell as wealth increased. Mossin did not consider the case where higher incomes might generate more assets at risk and thus the higher income person would have greater losses to insure against. This yields the alternative hypothesis that income could have a positive coefficient in the insurance demand equation.

Further, Briys, Dionne and Eeckhoudt (1989) have pointed out that the income demand elasticity for insurance will be positive if and only if absolute risk aversion does not decrease significantly rapidly enough or if and only if the variation of risk aversion is lower than a minimal bound. Cleeton and Zellner (1993) undertake a similar analysis and operationalize Briys *et al.'s* conclusion slightly differently. They find that the income elasticity of demand for insurance will be positive over all prices if $\varphi_a + \eta > 1$ where φ_a is the elasticity of relative risk aversion to initial income and η is the elasticity of the amount at risk with respect to initial income. This implies that if potential losses change as wealth changes (which makes sense in our case as wealthier people may buy more expensive houses, exposing themselves to higher potential losses), we may see a positive relationship between income and insurance purchased.

Our estimated coefficients on income are positive, but relatively inelastic. This implies one of two things. First, while we control for housing value, we may not be capturing all of the relationships between higher incomes and higher demand for housing. Alternatively, the positive relationship can be due to the decreasing effect on the demand for insurance due to decreasing absolute risk aversion.[22]

Firm Characteristics

In Florida, consumers tend to buy coverage from agency writers and mutual companies. Overall demand shows a negative relationship between direct writers and stock companies. We included auto premiums written by the insured's homeowners company to account for some potential consumer transactions costs savings from dealing with one insurer. We find that the coefficient on the auto premiums written is positive which implies that consumers value this particular combination as it is customary for companies to provide discounts for multiple polices with the company. Further, we see a positive relationship for life premiums written by a sister company. Again, we conjecture that consumers would like the ability to deal with one insurance company. We see some evidence of this for the demand for total coverage and the demand for catastrophe coverage.

[22] We estimated a regression between the log of the median home value and the log of income holding other things constant such as the characteristics of the house, insurance prices, and neighborhood characteristics constant. The elasticity of median house value with respect to income, our measure of η, was estimated to be 1.04. Thus, as long as φ_a was greater than (approx) -.04 we would expect to see a positive elasticity between income and the amount of insurance purchased.

The size of the company is also a proxy for its soundness, reputation and/or its ability to achieve economies of scale. Our conjecture here is that larger companies are financially stronger and are able to take advantage of economies of scale. What we see is that for our sample companies, that company size has a positive effect on all three demands.

Another indication of firm solvency quality is its A.M. Best Rating. In this model, the A+ and higher category is the omitted category. If a high rating is valuable, then each of the other rating coefficients should be negative. If consumers favor lower prices over greater financial strength, then we might see negative coefficients on all of the higher ratings and a positive coefficient on the lower ratings.

In fact, we see in Table 4 that the lower rated companies tend to be associated with higher levels of demand. For overall demand consumers do not value additional solvency safety in determining how much overall insurance and non-catastrophe insurance they purchase. We see this by the fact that as the rating declines the coefficients increase. In contrast, we see that for cat coverages higher rated companies are generally preferred (since they have positive valued coefficients). If we look at the non-cat coverage, we see that higher rated companies have negative coefficients. This implies that consumers value increased safety in case of a catastrophic event, but not for non-catastrophic events. This is likely because a catastrophe is more likely to put pressure on the solvency of the insurer.

The company with a NR2 rating appears to be an anomaly. Category NR2 is a not rated category. There was one firm in the date set with an NR2 rating and the reason the firm was not rated was due to fact that the company started operation right after Hurricane Andrew, thus A.M. Best did not have the ability to properly rate the company. This firm is a wholly owned subsidiary of an A++ rated company. Thus, the company is not exactly a high-risk firm. Currently, it holds an A rating from A.M. Best. In light of these facts, if we look at the catastrophe demand, we see that consumers value a strong company, but not necessarily the strongest company.

Thus, consumers may choose price over quality when it comes to non-catastrophe coverage where there is less of a concern that an insurer will become insolvent. We should note that while the existence of guaranty fund coverage is not widely publicized, consumers may still believe that they will receive some protection from an insurer's insolvency, which would lessen the value they place on financial strength. The moral hazard effects of guaranty fund coverage have received considerable attention in the insurance economics literature (see Cummins, 1988 for example) and we explore this further in the last part of our analysis.

NEW YORK

We also estimated demand equations for New York to see how different market and regulatory conditions affect our findings. Coastal areas of New York, such as Long Island, face a moderate degree of catastrophe risk. Regulatory constraints on insurers' rates appear to have been less severe in New York because cost pressures have been more moderate (see Grace et. al., 2001). We would not expect the risk of non-catastrophe perils in urban areas to be eclipsed by catastrophe risk as in Florida. We employ similar demand models in our analysis of the New York market, with some small adjustments to reflect coverage options specific to New York.

Insured Risk Characteristics

For New York in Table 5, we do see some differences compared to the results we obtained for Florida. Relative to superior fire resistant structures, owners of brick homes have a significantly lower demand and owners of wood frame construction have a higher demand for total insurance. We also see that owners of wood frame homes have a higher demand for catastrophe coverage, but owners of brick homes have a lower demand for non-catastrophe coverage. The reason for the negative effect of brick homes (relative to SFR homes) is not immediately obvious – it is possible that owners of SFR homes are more risk averse and purchase more insurance as well as make other investments to lower risk. Further, as in Florida, as the level of public protection services declines, the demand for insurance increases.

We also undertake to examine the effect of being in a higher or lower risk area. As with Florida we examine the indicated loss costs above and below the mean. Thus, we have HH (above median for both cat and not cast standard costs), HL and LH (Above median for one, but not the other) and LL (below median for both cat and not cat standard loss costs). In New York the HH area is Long Island while the LL area is most of the remainder of New York State.

Contract Terms

If we examine the policy choices in New York in Table 5, we see that HO1, HO2 and HO3 policies have negative coefficients implying that they are not valued as highly as HO5 polices. This pattern with respect to policy form is true across the different demand models and consistent with what one would expect.

Replacement cost coverage on personal property and ordinance or law coverage both have positive signs suggesting that consumers do value these additional policy options. However, we do see that that the coefficient on ordinance or law coverage is negative for catastrophe demand implying that, for this coverage, ordinance or law coverage does not add sufficient value for the consumer to offset its higher cost. We should note that the problem of substandard construction and the need to strengthen building codes have not been issues in New York, unlike the case in Florida. As in Florida, we see that the Coverage A limit is positively related to the demand for insurance. This is true for both catastrophe and non-catastrophe coverages.

The coefficients on the wind and fire deductibles differ from the coefficients estimated for Florida. Overall, increases in the fire deductible are related to a lower demand for insurance, while increases in the wind deductible are related to higher levels of demand. Looking at the catastrophe and non-catastrophe results, however, we see the wind deductible is negatively related to the demand for catastrophe coverage. This implies that for catastrophe coverage in New York, the coverage effect dominates the price effect for the wind deductible. The same is true for the fire deductible for catastrophe coverage.

When we examine the relationships of wind and fire deductibles to the demand for non-catastrophe coverage, we see that the coefficient on wind is positive and the coefficient on fire is negative. This contrasts with the results for catastrophe demand in New York and with the corresponding Florida coefficients. This is likely due to the fact that the expected amount of catastrophe wind damage is much lower for New York than for Florida.

Finally, New York also allows homeowners policies to exclude off premises theft coverage. This exclusion should reduce the price of insurance. One would expect a positive effect on demand for this exclusion if consumers preferred the exclusion given the resulting premium discount (or alternatively did not value the coverage enough to pay the higher cost). What we see is that the coefficient on the exclusion variable has a positive sign, implying that consumers opting for the exclusion purchase more insurance, all other things equal. This makes sense as it suggests that consumers who exclude off premises losses can use the premium savings to expand other coverages. This may be especially attractive to owners of homes in high-risk urban areas.

Neighborhood Characteristics and Regulation

Looking at the regulatory subsidy variable - the ratio of the implemented loss costs to the indicated loss costs (our measure of price suppression) - we generally obtained the same results we obtained in Florida. That is, as the ratio increased, prices were allowed to rise closer to their market level and the demand for insurance decreased. Note again that rate suppression and compression in Florida was much more severe than in New York. This could explain why the subsidy effect is smaller in New York. Note for a given ratio, the amount of the subsidy in

Florida would be higher because loss costs and premiums are considerably higher in Florida.

The median year of construction is expected to be negatively related to the demand for insurance. The relationship between the year of construction and total insurance demand is not statistically significant. For catastrophe demand, the relationship is positive and significant, but small in magnitude. This could be caused by greater new home construction in coastal areas.

The percentage of homes with mortgages is positively related to the demand for insurance but the relationship is weak. This variable was only statistically significant in the catastrophe demand equation. As we suggest for Florida, lenders may impose more stringent insurance requirements in areas subject to coastal windstorms.

The pattern for the two measures related to mortgage costs and leverage (the ratio of mortgage costs to income and the ratio of mortgage costs to home value) exhibit a different pattern than in Florida. The measure of the tightness of the budget constraint is not statistically significant in the total demand equation. However, for the catastrophe demand and non-catastrophe demand equations, the coefficients for this variable are significantly negative. This implies that, as their budgets becomes tighter, consumers demand less insurance, all other things held constant. For the second leverage ratio, the estimated coefficient is not statistically significant in the total demand equation, but is significantly positive in the catastrophe and non-catastrophe demand equations, which differs somewhat from our Florida results. It is possible that the high price of land in certain areas of New York counteracts any moral hazard effect associated with higher leverage.[23]

Age appears to affect only the demand for catastrophe coverage. This contrasts with what we found for Florida. Also, the percentage of people over age 65 affects demand differently in

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[23] The greater the value of the land, the greater is the incentive of an owner to avoid foreclosure if his home is destroyed. This is one reason given for why lenders do not require earthquake insurance in areas of California where land prices are high.

New York than in Florida. For the total and catastrophe demand equations this variable is significantly positive, but it is not statistically significant in the non-catastrophe demand equation. It is possible that elderly homeowners in more catastrophe-prone areas in New York have greater reason to secure their homes for themselves and their heirs.

In addition, the percentage of homes in urban areas is positively related to overall demand and the demand for catastrophe coverage, reflecting the increased risk level of urban homes. As in Florida, coastal areas in New York tend to be heavily developed.

Finally, we see that in New York, insurance is an inferior good. As income increases, the demand for total coverage and non-catastrophe coverage decreases. In contrast, income increases the demand for catastrophe coverage.

Firm Characteristics

In New York, the type of distribution system used by an insurer does not appear to affect the demand for insurance. Direct writers may have a greater edge in insurance markets that are growing more rapidly, such as Florida's. The demand for total coverage and non-catastrophe coverage appears to be lower for stock insurers than mutuals. It may be that well-established mutual insurers in New York have retained considerable customer loyalty. Further, the ability to purchase home and other insurance coverages from the same company does not appear to affect demand.

We also see that in New York firm size does seem to be positively related to the demand for both catastrophe coverage and total, but is negatively related to non-catastrophe demand. This makes some sense in that catastrophes are more likely to stress a small insurer than non-catastrophe losses.

In New York, there are only three categories of A.M. Best company ratings in the data set (A+ and higher, A, and A-). The category of A+ and higher is omitted. We see that for the overall demand, there are no significant differences among the rating categories, but if we look at the catastrophe demand equation we see that the two lower categories are preferred to the A+ category. The opposite is true for the non-catastrophe equation. In this case, A+ and higher is the preferred rating. This contrasts with the Florida results and may be due to the fact that we do not have a sufficient dispersion of quality among firms in New York to produce reliable estimates of the effects of quality. Another explanation is that consumers are less willing to pay a higher price for catastrophe coverage from a higher-rated insurer but are more willing to do so for non-catastrophe coverage. This may make some sense if consumers view an insurer's ability to handle non-catastrophe losses as a more significant issue than its ability to handle catastrophe losses, which are less frequent and less severe in New York than in Florida.

GUARANTY FUNDS

To conclude our analysis, we examine the effects of guaranty fund coverage of insolvent insurers' claims on the demand for insurance. All states have insurance guaranty funds that pay insolvent insurers' claims, but the limits of this coverage vary. In Florida, the limit for guaranty fund coverage is $300,000 per claim and in New York this limit is $1,000,000.[24] Thus, unpaid losses above those amounts are not covered by guaranty funds and claimants must attempt to recover these amounts as general creditors against the insurer's estate.[25] This would suggest that consumers with Coverage A limits on their dwelling above these amounts should pay more attention to the financial solvency prospects of their insurers.

We are able to test this hypothesis on the Florida data because there are ample observations of homes with Coverage A limits above $300,000. For the state of New York, our dataset had too

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[24] See http://www.ncigf.org/Publications/Claim%20Parameters.xls for a summary of state fund policy limits for 2001.

few observations of Coverage A limits over $1,000,000 to test this hypothesis.

Table 6 shows the results of our analysis, focusing on an insurer's A.M. Best rating as the measure of its financial strength. These estimates are derived from models like those shown in Table 4, but estimated separately for homes where the Coverage A limit was above or below the Florida guaranty fund limit of $300,000 per claim.[26] Panel A shows the results for homes below the $300,000 policy limit for total demand, catastrophe coverage, and non-catastrophe coverage. Once again, the rating level of A+ and above was omitted. Panel A's results look similar to the overall result shown in Table 4. Generally, total demand is higher for lower rated firms. The same is true for non-catastrophe coverage. For catastrophe coverage, consumers have greater demand for A rated companies and the NR2 rated company over A+ and higher rated companies and insurers in the other rating category. This suggests that consumers who are fully protected by guaranty funds may be willing to pay more for insurers with good ratings but not the additional premium for insurers with a superior rating. As explained earlier, the insurer with the NR2 rating is an anomaly as it is a subsidiary of high-rated insurer.

If a consumer is not fully covered in the event of his insurer's insolvency, then we would expect that he would place a greater value on the insurer's financial strength. Thus, all coefficients should be negative. This is generally what is observed in Panel B. For the total demand equation, all coefficients are negative (except for the anomalous NR2 company and that is not significantly different from zero).

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[25] Coverages in addition to Coverage A triggered by a given claim would be combined with Coverage A losses in the application of the guaranty fund claim coverage limit. For example, if a fire totally destroyed an insured's home with a Coverage A limit of $250,000 and personal property valued at $125,000, the Florida guaranty fund would only cover $300,000, leaving $75,000 in losses not covered by the guaranty fund.

[26] We were not able to estimate a fixed effect model here due to the fact that there were some 2000 observations above the $300,000 level. Given the fact that the A.M. Best Ratings do not change much over this period for individual firms, the rationings and the firm effect are highly collinear. If we had a longer panel and we saw ratings change over the time period, we would be able to separate the ratings effect from the firm effect.

We also see a logical ordering of the coefficients on the various rating categories reflecting

Table 6

Regression Coefficient Estimates for Various A.M. Best Ratings on the Demand for Insurance (Total, Cat, and Non-Cat) for Policies with Coverage A limits above and below Florida's Guarantee fund Policy Limit ($300K).

Panel A. Effect of Ratings on Households Below Guarantee Fund Policy Limit.					
	Rating	Coefficient**	Std. Error	T-stat	Prob
Total Demand	A	-0.2175	0.0252	-8.6300	0.000
	A-	-0.3947	0.0344	-11.4800	0.000
	B+	0.0723	0.0366	1.9800	0.048
	NR2***	0.4643	0.0517	8.9800	0.000
Cat Coverage	A	0.456	0.040	11.440	0.000
	A-	-0.135	0.054	-2.480	0.013
	B+	-0.152	0.058	-2.630	0.009
	NR2	0.379	0.082	4.640	0.000
Non-Cat Coverage	A	-0.222	0.019	-11.620	0.000
	A-	-0.143	0.026	-5.490	0.000
	B+	0.199	0.028	7.160	0.000
	NR2	0.299	0.039	7.610	0.000

Panel B. Effect of Ratings on Households Above Guarantee Fund Policy Limit.					
	Rating	Coefficient	Std. Error	T-stat	Prob
Total Demand	A	-0.1247	0.0495	-2.5200	0.012
	A-	-0.4268	0.0686	-6.2200	0.000
	B+	-0.5281	0.2543	-2.0800	0.038
	NR2	0.1192	0.1472	0.8100	0.418
Cat Coverage	A	-0.12107	0.086471	-1.4	0.162
	A-	-0.6943	0.119737	-5.8	0.000
	B+	-1.06289	0.443832	-2.39	0.017
	NR2	0.405322	0.256869	1.58	0.114
Non-Cat Coverage	A	-0.12228	0.026882	-4.55	0.000
	A-	-0.18532	0.037223	-4.98	0.000
	B+	-0.17548	0.137977	-1.27	0.204
	NR2	-0.12237	0.079855	-1.53	0.126

*Regression Coefficients estimates obtained using models like those in Table 4.
**Note that the coefficients are relative to Rating of A+ and Above.
***NR2 represents one large company in Florida that is a subsidairy of a well known national company with a current A++ rating. The company was rated NR2 due to its lack of experience. It is currently ranked A by AM Best.

lexiographic preferences (A+ > A> A-> B+) based on the ratings. For the catastrophe demand and non-catastrophe demand equations, we see the same relationships. Thus, we find evidence that consumers do pay greater attention to financial strength when exposed to insolvency risk, as well as evidence of the (not so subtle) moral hazard created by guaranty funds for consumers who do not have this exposure.[27]

This result is similar to that found by Phillips, Cummins, and Allen (1998). While we focus on consumer reaction to perceived risk of default (as measured by the rating), Cummins, Phillips and Allen focused on how insurers pricing decisions are influenced by the presence of guaranty funds, that is firms with higher default risks had lower prices especially in lines of business (long tail commercial) that are more likely not to be covered by the guaranty fund or that are more likely to have claims above any guaranty fund claim limit.

SUMMARY AND CONCLUSIONS

Our analysis seeks to illuminate factors affecting homeowners insurance transactions in markets subject to different levels of catastrophe risk and regulatory pressure. We estimated the demand for homeowners' insurance coverage in Florida and New York using two-stage least squares regression and data on insurance contracts, housing and demographic variables, and firm characteristics. Our models estimate the demand effects of standard variables, such as price and income, as well as variables more specific to homeowners insurance transactions under catastrophe risk, such as coverage options and an insured's risk characteristics. We find that the demand for catastrophe coverage is more price elastic than the demand for non-catastrophe coverage. This was true in both Florida and New York. However, the Florida price elasticities were higher in absolute value than New York's estimated price elasticities, suggesting that price elasticity increases with the cost or price of insurance.

We also found that income elasticities differed between the two states. In Florida, the income elasticity of demand was positive and between .25 and .37. In New York, we found that the income elasticity was negative for total coverage and for non-catastrophe coverage, implying

[27] We should also note that insurance agents exposed to lawsuits in the event of an insolvency may urge consumers to purchase insurance from higher-rated insurers when the consumers have some exposure to insolvency risk.

that these are inferior goods. For catastrophe coverage, the income elasticity in New York was positive and approximately .3, which is close to the Florida result.

We also found that regulatory rate suppression/compression increased the demand for insurance in both states. However, the effect of regulatory price constraints was greater in Florida where a given percentage rate inadequacy (e.g., 10 percent) results in a higher absolute subsidy to the insured. Needless to say, such subsidies in insurance markets come at a high price in terms of their incentives for decreasing the incentives for efficient mitigation and location choices.

Generally, options that expand coverage tend to increase demand, suggesting that consumers are willing to pay the incremental cost of additional coverage. Interestingly, higher deductibles also are associated with higher demand. Our explanation is that consumers tend to follow experts' advice to increase their deductibles and use the premium savings to purchase additional coverage that offers a better value in terms of protection against risk.

Finally, we found some evidence that a consumer's exposure to an insurer's insolvency risk (as measured by the amount of a potential total loss that would not be covered by the guaranty fund) affects his valuation of financial strength. Using A.M. Best ratings as a measure of a firm's solvency prospects, we found evidence that consumers with contractual limits below the state guarantee fund policy limit prefer a lower price than higher financial strength. In contrast, consumers with contractual limits above the guaranty fund coverage limit appear to place greater value on higher rated companies. These results are potentially important for consumer welfare. If guarantee policies are such that financial strength and other quality indicators are not rewarded in the market place, then the overall quality of the insurance industry supporting risk coverage in a state will suffer and high-risk firms will replace high-quality firms. The consequences for sustainability of the state insurance industry would clearly be deleterious.

REFERENCES

Arrow, Kenneth J., 1971, *Essays in the Theory of Risk Bearing* (Chicago: Markham Publishing Co.).

Bartlett, Dwight K., Robert W. Klein, and David T. Russell, 1999, Attempts to Socialize Insurance Costs in Voluntary Insurance Markets: The Historical Record, *Journal of Insurance Regulation* 17: 478-511.

Briys, Eric, Georges Dionne, and Louis Eeckhoudt, 1989, More on Insurance as a Giffen Good, *Journal of Risk and Uncertainty*, 2: 415-420.

Cleeton, David, and Bruce Zellner, 1993, Income, Risk Aversion, and the Demand for Insurance, *Southern Economic Journal*, 60-1: 146-56.

Collins Center for Public Policy, 1995, *Final Report of the Academic Task Force on Hurricane Catastrophe Insurance* (Tallahassee, Fla.).

Cummins, J. David, 1988, Risk Based Premiums for Insurance Guaranty Funds, *Journal of Finance,* 43: 823-839.

Cummins, J. David, 1990, Multi-Period Discounted Cash Flow Ratemaking Models in Property-Liability Insurance, *Journal of Risk and Insurance* 57: 79-109.

Cummins, J. David, Neil A. Doherty and Anita Lo, 1999, Can Insurers Pay for the 'Big One'? Measuring the Capacity of an Insurance Market to Respond to Catastrophic Losses, Working Paper, The Wharton School, University of Pennsylvania, Philadelphia.

Cummins, J. David, Mary Weiss, and Hong Min Zi, 1999, Organizational Form and Efficiency: The Coexistence of Stock and Mutual Property-Liability Insurers, *Management Science* 45: 1254-1269.

Froot, Kenneth A. and Paul G. J. O'Connell, 1999, On the Pricing of Intermediate Risks: Theory and Application to Catastrophe Reinsurance, in Kenneth Froot, ed., *The Financing of Catastrophe Risks* (University of Chicago Press).

Grace, Martin, Klein, Robert W. and Kleindorfer, Paul R., 1999, The Supply of Catastrophe Insurance under Regulatory Constraints, Working Paper, Wharton Managing Catastrophic Risks Project, University of Pennsylvania, Philadelphia.

Grace, Martin, Klein, Robert W. and Kleindorfer, Paul R., 2000, The Supply and Demand for Residential Property Insurance with Bundled Catastrophe Perils, Working Paper, Wharton Managing Catastrophic Risks Project, University of Pennsylvania, Philadelphia.

Grace, Martin, Klein, Robert W., Kleindorfer, Paul R. and Michael R. Murray, 2001, Catastrophe Insurance: Supply, Demand and Regulation, unpublished paper, Wharton Managing Catastrophe Risks Project, University of Pennsylvania, Philadelphia.

Green, William, 2000, *Econometric Analysis*, (Prentice Hall: Upper Saddle River, NJ).

Greenwald, Bruce C. and Stiglitz, Joseph E., 1990. Asymmetric Information and the New Theory of the Firm: Financial Constraints and Risk Behavior, *American Economic Review*, 80: 106-165.

Herring, Richard J. and Prashant Vankudre, 1987, Growth Opportunities and Risk-Taking by Financial Intermediaries, *The Journal of Finance* 52: 583-599.

Insurance Information Institute, 2001, *The Fact Book 2001: Property/Casualty Insurance Facts* (New York, NY).

Insurance Services Office, 1994a, *The Impact of Catastrophes on Property Insurance* (New York, N.Y.).

Insurance Services Office, 1994b, *Catastrophes: Insurance Issues Surrounding the Northridge Earthquake and Other Natural Disasters* (New York, N.Y.).

Insurance Services Office, 1996a, *Managing Catastrophe Risk* (New York, N.Y.).

Insurance Services Office, 1996b, *Homeowners Insurance: Threats from Without, Weakness Within* (New York, N.Y.).

Joskow, Paul L., 1973, Cartels, Competition and Regulation in the Property-Liability Insurance Industry, *Bell Journal of Economics* 4: 375-427.

Klein, Robert W., 1998, Regulation and Catastrophe Insurance, in Howard Kunreuther and Richard Roth, Sr., eds., *Paying the Price: The Status and Role of Insurance Against Natural Disasters in the United States* (Washington, D.C.: Joseph Henry Press): 171-208.

Kunreuther, Howard, Jacqueline Meszaros, Robin Hogarth, and Mark Spranca, 1995, Ambiguity and Underwriter Decision Processes, *Journal of Economic Behavior and Organization* 26: 337-352.

Kunreuther, Howard, 1996, Mitigating Disaster Losses through Insurance, *Journal of Risk and Uncertainty* 12: 171-187.

Kunreuther, Howard, 1998a, Insurability Conditions and the Supply of Coverage, in Howard Kunreuther and Richard Roth, Sr., eds., *Paying the Price: The Status and Role of Insurance Against Natural Disasters in the United States* (Washington, D.C.: Joseph Henry Press): 17-50.

Kunreuther, Howard, 1998b, The Role of Insurance in Dealing with Catastrophic Risks from Natural Disasters, in Robert W. Klein, ed., *Alternative Approaches to Insurance Regulation* (Kansas City, Mo.: National Association of Insurance Commissioners).

Kleindorfer, Paul and Howard Kunreuther, 1999, Challenges Facing the Insurance Industry in Managing Catastrophic Risks, in Kenneth Froot, ed., *The Financing of Catastrophe Risks* (University of Chicago Press).

Lecomte, Eugene and Karen Gahagan, 1998, Hurricane Insurance Protection in Florida, in Howard Kunreuther and Richard Ross, Sr., eds., *Paying the Price: The Status and Role of Insurance Against Natural Disasters in the United States* (Washington, DC: Joseph Henry Press): 97-123.

Marlett, David C. and Alan Eastman, 1998, The Estimated Impact of Residual Market Assessments on Florida Property Insurers, *Risk Management and Insurance Review*, 2: 37-49.

Mossin, Jan, Aspects of Rational Insurance Purchasing, *Journal of Political Economy* 76 July (1968): 553-68.

Myers, Stewart and Richard Cohn, 1987, Insurance Rate Regulation and the Capital Asset Pricing Model, In J. David Cummins and Scott E. Harrington, eds., *Fair Rate of Return in Property-Liability Insurance* (Norwell, MA: Kluwer Academic Publishers).

Phillips, Richard D., J. David Cummins, and Franklin Allen, 1998, Financial Price of Insurance in the Multiple Line Insurance Company, *Journal of Risk and Insurance* 65:597-636.

Risk Management Solutions, Inc. and Insurance Services Office, Inc., 1995, *Catastrophe Risk* (Menlo Park, C.A. and New York, N.Y.).

Rothschild, Michael and Joseph Stiglitz, 1976, Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information, *Quarterly Journal of Economics* 90: 629-650.

Russell, Thomas and Dwight M. Jaffee, 1997, Catastrophe Insurance, Capital Markets, and Insurable Risk, *Journal of Risk and Insurance* 64: 205-230.