

HOMEOWNERS INSURANCE WITH BUNDLED CATASTROPHE COVERAGE

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ABSTRACT

We estimate the demand for homeowners insurance in Florida and New York with indicated loss costs as our proxy for the quantity of real insurance services demanded. We decompose the demand into the demand for coverage of catastrophe perils and the demand for noncatastrophe 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 noncatastrophe 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 threat of mega-catastrophes striking major population centers has altered the insurance environment over the last decade. Probable maximum losses estimates from a catastrophe striking the United States range up to \$100 billion depending on the location and intensity of the event (Grace, Klein, and Kleindorfer, 2001). While insurers' capital 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, 2002).

We explore insurance markets threatened by natural disasters concentrating on the demand for residential/catastrophe insurance. Among the phenomena, we seek to

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illuminate are the sensitivity of demand to prices, income, and policy features. Further, we examine insurer and consumer decisions in different market and regulatory environments—Florida and New York—over a 4-year period.

Our analysis of the homeowner insurance demand yields a number of interesting results. First, for both New York and Florida, catastrophe coverage is more price elastic than for noncatastrophe coverage. Second, we find that the income elasticities 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 state markets. Further, regulation has had a bigger impact in the Florida market where rate compression has been more severe. We also find evidence consumers consider guaranty fund provisions when purchasing insurance. For Florida, we find high-quality solvency prospects (measured by A. M. Best Ratings) are more important for consumers who may have claims above the Florida guaranty fund coverage limits than for those consumers who would not have claims above the coverage limit.

The article 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

We obtained information from a group of primary insurers writing business in Florida and New York that report premium and exposure data to the Insurance Services Office (ISO). The data set contains homeowners' premium and exposure data for 60 companies, comprising 20 groups, taken as a snapshot in the first quarter of each of the four years, 1995–1998. Each record contains "slightly aggregated" information on similar groups of policies in every zip code where reporting companies operated. The information contains data regarding the characteristics of the policies purchased by homeowners for each company, including premiums, structural information about the insured property, and coverages purchased. Additionally, we have compiled financial and organizational data on the insurers in our sample (from the NAIC and A. M. Best), as well as household economic and demographic data (from the 1990 census) by zip code.

Defining Price and Output

"Price" for insurance is defined on the basis of value-added per unit (in this case, per dollar) of output. 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.¹ Denoting by $L(F, Z)$ the expected losses for a policy h with features F , insurer firm characteristics X , neighborhood characteristics Z , and by $P(F, X, Z)$, its premium, we obtain the following definition of price $P(F, X, Z)$ for a homeowners' policy:

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

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.

¹ Note that we do not consider the effects of taxes in this model.

$L(F, Z)$ is the indicated loss costs (ILCs) per unit of coverage for the policy features (F) and structure and neighborhood features (Z) in question. The ISO data provide 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 ILCs, as computed using ISO filed loss cost manuals and rules, for the policy characteristics (F, Z).²

Using ISO loss cost filing information on catastrophe loss costs and noncatastrophe loss costs, we calculated an expected ILC for each contract in our database. ISO employed Risk Management Services and its CAT model to develop the catastrophe portion of the ILC. The ISO-estimated noncatastrophe ILCs are based on standard actuarial analysis of historical data and cost trends. The database allowed us to compute an expected annual loss for each possible combination of location, policy form, and additional contract terms.

ILCs for a policy are estimates of the expected claims costs (including claims adjustment expenses) of coverage under the terms of a policy for a particular house. Thus, ILCs proxy for the amount of insurance embodied in a specific policy. One could also employ the coverage A limit to proxy for the insurance embodied in a policy. However, while this limit reflects the replacement cost of the home, it does not necessarily reflect the risk of loss to the home. The limit reflects the maximum possible insured loss rather than the expected loss.

We estimate three demand equations. The first is for the catastrophe coverage and the second is for the noncatastrophe coverage. The third is for both coverages combined. These demand equations are all of the following general form:

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

where $L(F, Z)_i$ reflects the quantity demanded of real services measured by the ILCs for catastrophe (C), noncatastrophe (NC), or total coverage (TOT), 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.

Table 1 summarizes the contract features. The HO3 policy is the 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. The HO5 policy offers broader coverage than an HO3 policy. The HO3 policy provides named-perils coverage for personal property; the HO5 policy provides open-perils coverage on personal property.³ 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 contracts, consumers choose to purchase actual cash value or replacement cost coverage on personal property. Ordinance or law coverage is typically chosen as an endorsement on HO3 policies while it is a standard coverage in HO5

² We discuss the ISO procedures briefly in Grace et al. (2003).

³ 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.

TABLE 1
Comparison of Homeowners Contracts Basic Terms

Contract Terms	Policy Form				
	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	×	×	×	×	×
Other attached property and structures	×	×	×	×	×
Personal property	Not covered	Not covered	×	×	×
Loss of use	×	×	×	×	×
Personal liability to others	×	×	×	×	×
Medical payments to others	×	×	×	×	×
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	×	Endorsement available?
Off-premises theft coverage	Endorsement available	Endorsement available	Endorsement available	×	Endorsement available?

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

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

policies.⁴ Finally, there is a wind credit that consumers in Florida can obtain if they install specified mitigation features, such as storm shutters or roof straps.

Table 2 shows descriptive statistics on the contracts in our data. 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 policies account for 71.9 percent followed by HO2 policies which account for 20.3 percent.

In both states, the average premium (total premiums divided by insured house years) by policy form increases with the scope of coverage. This makes intuitive sense. Further, the average price varies by policy form.⁵ 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

We estimate the demand at the level of the zip code using two-stage least squares regression. The ISO data are available for nearly 900,000 house-years in Florida, 220,000 house-years for each of the 4 years studied. In Florida, we have approximately 663,500 usable house years over the 4-year period. Some data are excluded due to incompatible records, the generation of new zip codes over the reporting period (making their

⁴ 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.

⁵ We actually use $PRICE1 = 1 + PRICE = [(1 + r)(\text{Premiums} - \text{ILC})]/[\text{ILC}]$ as our price variable; adding 1 to PRICE simply assures that our price measure in Equation (3) is always positive.

integration with the collateral census data difficult), and missing information on some records. For New York, there are 2,335,000 house-years. By aggregating to the level of the zip code we can obtain data sets that are more easily managed. Further, by matching with census zip code level data we are using the same unit of analysis for all of the data. When these data are aggregated to the contract type, firm, and zip code level, approximately 46,000 observations in Florida and some 70,000 unique observations in New York are obtained.⁶

An issue with our estimation is that the demand for homeowners insurance is derived from the demand for housing. We account for the housing demand 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 are used as instrumental variables in our two-stage least squares estimation below.

Table 3 provides the descriptive statistics for Florida and New York based on the data used in our 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 in Florida could contribute to its lower average price mark-up.

ESTIMATION OF QUANTITY DEMANDED

We estimate the model using company fixed effects using the ILCs (in the logged form) as our proxy of the quantity of insurance demanded and $PRICE1$ in the logged form as our proxy for price. We estimate several endogenous variables. While $PRICE1$ is estimated endogenously, we also account for several other endogenous variables including house value, deductibles, and the choice to invest in wind protection devices.⁷

Since we wish to estimate the demand for catastrophe coverage as well as the demand for noncatastrophe coverage, we computed separately the catastrophe and

⁶ A reviewer raised concerns about the level of aggregation of the analysis. We undertook to examine the data at the level of the individual contract, but the size of the dataset made the problem impossible. To assess the degree of potential aggregation bias, we estimated a model for New York based on a random sample of contracts and found results quite similar to those reported in Table 6. In Florida, we estimated a more parsimonious model and also obtained similar results to those in Table 6. Thus, our results at the zip code level appear robust against aggregation bias.

⁷ In the first stage regression, $\ln price1$ is estimated as a function of type of house (brick, frame, fire resistant), type of contract (HO3, HO5, HO8), year of construction, other contract terms, neighborhood variables such as percent of area that is urban, percent of homes with mortgages, median income, percentage of homes with kitchens, percentage of home with plumbing, percentage of homes using electric or oil heat, percentage of retirees, percentage of homes with city water, and firm specific variables such as A. M. Best rating, four state geographic concentration, the firm's percentage of business in the top four lines written, the ratio of homeowners underwriting expenses to total underwriting expenses, and size of the firm in terms of total assets.

noncatastrophe portions of ILCs for each policy in the sample.⁸ Thus, we think of the homeowners' policy as a joint (or bundled) product where the coverage for the catastrophe peril and the coverage for noncatastrophe perils are typically not always combined in the same contract. Further, consumers can vary or tradeoff the amounts of their catastrophe coverage and noncatastrophe 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.⁹

Before examining the results in detail there are three sets of coefficients from our results in Tables 5 and 6 we wish 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 that it is even more elastic with an estimated coefficient of -1.915 .¹⁰ In contrast, the price elasticity for

⁸ The decomposition ILC 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 RMS catastrophe model in support of ISO loss cost estimations. While proprietary, more information is available at <http://www.rms.com/Catastrophe/Models/>.

⁹ The demand curve is identified by the rank and order conditions. The variables used to estimate the price equation were inadvertently left out from the text and thus some confusion arose about the specification of the model. A further source of confusion is that the author responding to the review misinterpreted the reviewer's comment in the previous round. However, to make it clear we have two equations:

$$\begin{aligned}\log(\text{price1}) &= \alpha + \beta_p X + \gamma G + \eta, \\ \log(Q) &= \delta + \beta_q X + \phi Z + \overline{w}E + \varphi \log(\widehat{\text{price1}}) + \varepsilon,\end{aligned}$$

where $\log(\text{price1})$ is the first stage regression and $\log(\widehat{\text{price1}})$ is the estimate of the $\log(\text{price})$. X is a vector of variables common to both the and quantity and price equations, G is a vector of variables belonging solely to the price equation, Z is a vector of variables belonging solely to the quantity equation, and E are other endogenous variables. Z which is solely in the price equation is {Percentage of homes with full plumbing, percentage of homes with traditional fuel (oil, gas, electric) heat, percentage of homes with city supplied water, the supplying firm's ratio of homeowners expenses to total expenses from the NAIC Insurance Expense Exhibit, 4 line firm concentration ratio, 4 state firm geographic concentration}. W , which is solely for the demand equation, is {the log of premiums written for automobile insurance by the insurer and the log of life premiums written by a sister life insurance company}. E is the set of other endogenous variables {value of coverage A, windstorm device, fire, and wind deductibles}. The set of these endogenous variables is also unique to the demand equation. Using the method suggested by Maddala (1992), we conclude the demand equation satisfies the rank order conditions for identification.

¹⁰ 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 catastrophic coverage (or noncatastrophic coverage).

TABLE 3
Descriptive Statistics for Florida (Panel A, N = 40,971) and New York (Panel B, N = 66,426)

Panel A

Variables	Mean	Std. Dev.	Min	Max
<i>Insured Risk Characteristics</i>				
% 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
<i>Contract Terms</i>				
Total ILCs	\$884.51	1102.030	\$121.93	\$26,567.09
Catastrophe-related modeled ILCs	\$509.73	859.337	\$0	\$21,962.30
Noncatastrophe ILCs	\$374.78	290.342	\$87.63	\$5,548.80
Log(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	88.90%	0.261	0.00%	100.00%
% of HO5 policies in zip code	11.75%	0.266	0.00%	100.00%
% of HO8 policies in zip code	0.05%	0.016	0.00%	100.00%
% of policies with wind exclusion (FL only)	1.58%	0.106	0.00%	100.00%
% of policies with replacement cost coverage	91.00%	0.199	0.00%	100.00%
% of policies with ordinance or law coverage	52.50%	0.463	0.00%	100.00%
Coverage A limit	\$140,527	91,715.950	\$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
Percent of total indicated lost costs that are due to CAT costs	42.36%	0.228	0.00%	91.06%
Percent with wind protection device credit (FL)	6.20%	0.206	0.00%	100.00%

<i>Neighborhood Characteristics</i>					
Percent of implemented loss costs to ILCs	69.04%	0.065	47.80%	92.04%	
Median year of construction in zip code	1974.320	8.008	1943.000	1988.000	
% of homes in zip code with a mortgage	87.05%	0.0821	0.00%	100.00%	
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	
Average age of pop. in zip code	39.370	7.158	19.651	71.907	
Percent of households in urban areas	75.90%	0.3566	0.00%	100.00%	
Percent of persons in zip code aged 65 or over	17.76%	0.112	0.00%	82.42%	
Median income	\$29,629.40	\$9,650.77	\$7,890.00	\$78,668.00	
<i>Firm Characteristics</i>					
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	\$0	\$181,509,056	
Life premiums written by sister company	\$30,078,038	56,541,230	\$0	\$182,655,744	
Total assets of company selling policy	\$3,125,676,695	4,307,150,626	\$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	
<i>Time Indicators</i>					
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	

(Continued)

TABLE 3
(Continued)

Panel B

Variables	Mean	Std. Dev.	Min.	Max.
<i>Insured Risk Characteristics</i>				
Percent of homes with frame construction	88.69%	0.229	0.00%	100.00%
Percent of homes with brick construction	11.18%	0.228	0.00%	100.00%
Protection code (1 is highest)	643.65%	2.370	100.00%	10.000
<i>Contract Terms</i>				
Total ILCs	\$448.43	262.123	\$102.82	\$4,309.08
Catastrophe-related modeled ILCs	\$41.33	102.178	\$0.14	\$1,909.33
Noncatastrophe ILCs	\$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)	0.40%	0.032	0.00%	83.3%
% of HO2 policies in zip code	17.75%	0.271	0.00%	100.0%
% of HO3 policies in zip code	73.61%	0.316	0.00%	100.0%
% of HO5 policies in zip code	8.24%	0.213	0.00%	100.0%
% of HO8 policies in zip code	0.00%	0.004	0.00%	100.0%
% of policies with replacement cost coverage	67.21%	0.335	0.00%	100.0%
% of policies with ordinance or law coverage	35.24%	0.444	0.00%	100.0%
Coverage A limit	183.562	104.966	5.000	1009.090
Wind deductible	327.023	160.558	0.000	1200.000
Fire deductible	342.208	162.506	50.000	1200.000
Percent of total indicated lost costs that are due to CAT costs	6.86%	12.36%	0.02%	63.28%
Percent with off-premises theft coverage	2.82%	12.01%	0.00%	100.00%

<i>Neighborhood Characteristics</i>					
Percent of implemented loss costs to ILCs					
Median year of construction in zip code	91.95%	0.109	0.00%	110.74%	
	1955,720	10.615	1939,000	1988,000	
Percent of homes in zip code with a mortgage	79.60%	0.114	0.00%	100.00%	
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 value	0.007	0.002	0.000	0.037	
Average age of pop. in zip code	36.650	3.600	20.759	61.767	
Percent of households in urban areas	55.16%	0.497	0.00%	100.00%	
Percent of persons in zip code aged 65 or over	13.51%	0.050	0.00%	67.74%	
Median income	\$40,004.39	16663.760	\$4,999.00	\$150,001.00	
<i>Firm Characteristics</i>					
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	40,809,184	\$526	\$152,694,176	
Life premiums written by sister company	\$193,270,586	289,152,435	\$3,436	\$904,290,112	
Total assets of company selling policy	\$3,120,947,934	3,750,565,022	\$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	
<i>Time indicators</i>					
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	

TABLE 4
Demand Elasticity Estimates

Price Elasticity	Absolute Value of Elasticity	Citation
Life	0.26–0.49	Babbel (1985)
Long-term care	0.75–1.25	Cohen and Weinrobe (2002)
Individual health	0.17	Marquis and Long (1995)
Auto	0.57	Jaffee and Russell (1996)
Home		Grace, Klein, and Kleindorfer (current study)
Florida	1.08	
New York	0.86	
National flood insurance	0.32	Browne and Hoyt (2000)
Crop insurance	0.14–0.33	Barnett and Skees (1996)
Income Elasticity	Actual Value of Elasticity	Citation
Life	0.006–0.008	Babbel (1985)
Long-term care	None estimated	
Individual health	0.15	Marquis and Long (1995)
Auto	0.16–1.71	Sherden (1984)
Home		Grace, Klein, and Kleindorfer (current study)
Florida	0.06	
New York	–0.03	
National flood insurance	3.00	Browne and Hoyt (2000)
Crop insurance	None estimated	

noncatastrophe coverage (column 9) is approximately -0.40 , which is inelastic. We see this same pattern in Table 6 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.

DISCUSSION OF INCOME ELASTICITY

Table 4 compares our estimated elasticities with published results for other lines of insurance. Our price elasticities are generally higher than those reported for other lines of insurance. In terms of income elasticity our results seem to be in the same range as those reported by previous research. However, these results are not necessarily comparable. None of these studies, with the exception the individual health insurance study (Marquis and Long, 1995), use a relatively fully specified model with endogenously determined prices. In addition, each study uses different definitions of price and output, which further reduces direct comparisons.

In our sample, we have 60 companies over the 4 years. In Florida, this represents about 30 percent of the total homeowners' premiums written in each year. In New York, our sample companies 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. This

selection model employs firm specific characteristics to determine whether the firm is an "ISO Reporter."¹¹

From this regression, we obtain the inverse Mills ratio for each observation (λ) from the estimates of the probit regression (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 not reporting to ISO, all other things being equal.

For our Florida results, in Table 5, the selection indicator (λ) is significantly negative for catastrophe coverage, thus implying that consumers are less likely to demand catastrophe coverage from ISO reporting companies than from non-ISO reporting companies. However, our selection indicator is significantly positive for noncatastrophe, implying that consumers are more likely to demand noncatastrophe coverage from ISO reporting companies. Overall, we see that the selection indicator is not significantly different from zero. Thus, the opposing effects of selection are netted-out in the overall demand for homeowners' insurance in Florida. In Table 6, we see the same results for New York—the selection parameter is negative for catastrophe demand and positive for noncatastrophe coverage catastrophe and noncatastrophe coverage combined. For the overall level of demand for catastrophe and noncatastrophe coverage combined, the coefficient for pour selection variable takes a positive sign for both Florida and New York, but is only significant for New York.

FLORIDA RESULTS

Insured Risk Characteristics

First, we construct variables based upon the standard base loss costs for a particular type of home with a given set of coverages in a zip code. This base loss cost is employed to provide an index for the level of risk in the zip code. We calculate four indicator variables based 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 that higher risk areas will have higher demand for coverage, all other things being equal. We see this is true for those zip codes that have above median costs for both CAT and non-CAT risks. The HL and LH indicator variables are not significant for overall demand. However, we see that all three "risk" variables are significantly related to the demand for catastrophic coverage. In contrast, for

¹¹ The regression we estimate is: Probit [(ISO Reporter and Participant) = 1, 0 otherwise] = $f(\log$ of total assets, log of Florida homeowners premiums, Best's Capital Adequacy Ratio, business concentration ratio (top four lines), geographical four state concentration ratio, percent of claims paid within 2 years, percent of claim value paid within 2 years, Stock Dummy, Direct Writer Dummy, and year dummies).

TABLE 5
Two-Stage Least Squares Results: Florida Contract Demand Equations for Total Loss Costs, Catastrophic Loss Costs, and Noncatastrophic Loss Costs (N = 40,971)

Variables	Endogenous Variable	Hypothesized Sign	Total Indicated Loss Costs				Catastrophic ILCs				Noncatastrophic ILCs			
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			Coefficient	Std. Error	t-Stat	Prob	Coefficient	Std. Error	t-Stat	Prob	Coefficient	Std. Error	t-Stat	Prob
Intercept		?	8.767	0.936	9.360	0.000	-6.797	3.229	-2.100	0.036	14.872	0.769	19.340	0.000
Selection Variable		?	0.018	0.021	0.880	0.379	-0.628	0.072	-8.720	0.000	0.104	0.017	6.080	0.000
<i>Insured Risk Characteristics</i>														
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	0.000
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	0.000
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	0.000
Percent 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	0.000
Percent 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	0.000
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	0.000
<i>Contract Terms</i>														
Log(price + 1)	×	-	-1.079	0.013	-80.070	0.000	-1.915	0.046	-41.210	0.000	-0.404	0.011	-36.490	0.000
Percent 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	0.000
Percent 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	0.080
Percent 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	0.000
Percent 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	0.000
Percent of policies with ordinance 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	0.000
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	0.000
Log of wind deductible	×	+/-	-0.015	0.009	-1.670	0.095	0.114	0.031	3.640	0.000	-0.102	0.007	-13.640	0.000
Log of fire deductible	×	+/-	0.500	0.044	11.340	0.000	2.670	0.152	17.580	0.000	-0.403	0.036	-11.160	0.000
Percent with wind protection device credit (FL)	×	?	0.286	0.073	3.910	0.000	-1.588	0.252	-6.310	0.000	0.540	0.060	9.010	0.000

Neighborhood Characteristics													
Percent of implemented loss costs to ILCs	-	-0.282	0.022	-12.590	0.000	-0.438	0.077	-5.660	0.000	-0.292	0.018	-15.870	0.000
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	0.000
Percent 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	0.061
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	0.000
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	0.646
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	0.000
Percent 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	0.000
Percent 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	0.007
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	0.000
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	0.000
Stock company	?	-0.571	0.172	-3.310	0.001	-0.892	0.594	-1.500	0.134	-0.218	0.142	-1.540	0.124
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	0.000
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	0.000
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	0.000
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	0.000
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	0.000
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	0.038
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	0.005
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	0.803
1997 indicator	+	0.091	0.029	3.170	0.002	0.355	0.099	3.570	0.000	0.096	0.024	4.050	0.000
1998 indicator	+	0.094	0.032	2.890	0.004	0.452	0.112	4.030	0.000	0.077	0.027	2.880	0.004
R ²		0.937				0.797				0.891			

TABLE 6
Two-Stage Least Squares Results: New York Contract Demand Equations for Total Loss Costs, Catastrophic Loss Costs, and Non-Catastrophic Loss Costs (N = 66,426)

Variables	Endogenous Variable	Hypothesized Sign	Total Indicated Lost Costs				Catastrophic ILCs				Noncatastrophic ILCs			
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			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
<i>Insured Risk Characteristics</i>														
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
Percent 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
Percent 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
<i>Contract Terms</i>														
Log(price +1)	×	-	-0.857	0.047	-18.380	0.000	-2.064	0.110	-18.720	0.000	-0.331	0.063	-5.260	0.000
Percent 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
Percent 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
Percent 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
Percent 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
Percent of policies with ordinance 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	×	+	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	×	+/-	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	×	+/-	0.299	0.068	4.410	0.000	-1.124	0.161	-7.000	0.000	0.780	0.092	8.510	0.000
Percent 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

<i>Neighborhood Characteristics</i>													
Percent of implemented loss costs to LLCs	–	–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
Percent 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
Percent 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
Percent 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
<i>Firm Characteristics</i>													
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
<i>Time Indicators</i>													
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
R ²		0.819				0.691				0.731			

noncatastrophic coverage all three are significant, but the HL (above median for CAT and below median for non-CAT) is negatively related to the demand for coverage.

In estimating the effect of the construction type, superior fire resistant (SFR) homes are treated as the base case in our specification of dummy variables (i.e., SFR is omitted to avoid multicollinearity with indicators for other construction types). *A priori*, one would expect demand to be lower for the SFR homes if fire risk was a major component of the insurance demand. Thus, we would hypothesize that consumers with wooden frame homes would have a higher demand for insurance than consumers with SFR homes. Our results support this hypothesis. Further, this relationship is strong and significant for both catastrophe and noncatastrophe coverage.

For brick construction, we see a positive and significant relationship for the overall demand and for demand both catastrophe and noncatastrophe coverage. Relative to owners of SFR homes, owners of brick homes tend to have a higher demand for insurance.

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. We find 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 reflecting 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. If HO5 policies are preferred to other policies, then there should be negative coefficients on the percentages of HO3 and HO8 policies in a zip code. Our results are partially consistent with this hypothesis as the percentage of HO3 policies in a zip code is negatively related to the demand for coverage. This is true across the various types of coverage: catastrophe, noncatastrophe, and combined. However, our estimations yield a positive coefficient for the percentage of HO8 policies in the total demand equation. One explanation for this result is that HO8 policies tend to be written in older urban neighborhoods where the risk of noncatastrophe perils such as fire and theft can be very high.

In Florida, insureds can elect to exclude windstorms from their policy (presuming they are not prevented from doing so their mortgage agreement). We would expect wind exclusions would negatively affect demand. However, our results yield a positive coefficient for this variable. This is true for both the catastrophe coverage and noncatastrophe coverage equations and may be due to the fact that the zip codes with a high percentage of excluded policies are in higher risk zip codes where the Florida wind pool provides low cost coverage against windstorms. This availability of low cost protection against hurricanes may have increased demand for insurance overall.

If consumers value policy options such as replacement cost coverage on contents, then the addition of these options should be associated with higher levels of demand if the benefits of the options outweigh their incremental cost. For replacement cost coverage, we see this is true only for noncatastrophe coverage. The coefficient on replacement cost coverage is not significant for overall demand or for catastrophe

coverage. This implies consumers do not value it in excess of its cost. This suggests that 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.¹²

Ordinance or law coverage increases demand for both noncatastrophe coverage and overall coverage. This is not surprising, as Florida has significantly strengthened its building codes since Hurricane Andrew, increasing the value of this additional coverage for homeowners. However, we see that ordinance or law coverage is not valued for the catastrophe coverage.

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.¹³ One would expect that demand would increase as the replacement cost of the home increases, all other things held constant. Our results are generally consistent with this expectation. As the value of the home increases, the quantity of insurance demanded increases. An interesting exception is for catastrophe coverage. In this case, we see that demand does not rise with housing values, perhaps because the incremental cost of additional coverage exceeds its perceived utility.

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. Whether the price falls depends on the ratio of premium reductions to loss cost reductions (see Equation (3)). In any case, the homeowner may use the premium savings to purchase additional coverages, such as higher policy limits. Indeed, insurance experts commonly advise trading higher deductibles for higher limits. In addition, as the deductible increases, the value of the coverage decreases and the consumer bears more risk. Demand for the 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 overall demand, we see that the coefficient for the wind deductible is negative but just barely significant at the 10 percent level. This implies that the coverage effect dominates. Increases in deductibles 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 and quite significant, implying consumers value a higher wind deductible for catastrophe coverage because the premium-reduction effect dominates. Higher deductibles imply lower premiums, and this encourages consumers to purchase more insurance. Thus, as consumers facing greater catastrophe risk may be more concerned about

¹² Indeed, in areas with a high catastrophe risk (and high catastrophe loadings in the cost of insurance), insureds may forgo replacement cost coverage on personal property in order to afford and purchase more adequate structural coverage for catastrophe losses.

¹³ Insurers typically require a homeowner to carry coverage A limit equal to at least 70–80 percent of the replacement cost of the 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. The first stage regression has instruments like those for the $\ln(\text{price1})$ first stage regression.

having adequate coverage to cover large losses than absorbing a larger deductible in the event of a hurricane.¹⁴ For the noncatastrophe coverage equation, the wind deductible is negative indicating that the coverage effect dominates. This is also plausible, as noncatastrophe perils tend to involve more frequent and smaller losses not related to wind.

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 also positive and significant. Catastrophes (hurricanes) are not fire related, and thus the higher fire deductible's effect on premium leaves more funds available to purchase other coverage. However, in column 9, we see that, for noncatastrophe coverage, the coefficient on the fire deductible is negative, suggesting that coverage effect dominates the premium-reduction effect in the demand for noncatastrophe coverage.

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 overall demand for insurance but the presence of such devices could lead to increases in demand for noncatastrophe 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.¹⁵

Neighborhood Characteristics and Regulation

In this section we discuss a subset of the neighborhood characteristics and their effect on demand.¹⁶ In fact, we focus on two important variables. The first neighborhood characteristic is the ratio of implemented loss costs to ILCs. 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. This ratio may be viewed as a regulatory indicator 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. We think of this ratio as a measurement of rate suppression. As the implemented loss costs are reduced by regulation (relative to the expected or indicated loss costs), the consumer obtains a lower price for coverage. As the ratio increases, the price reduction diminishes. Thus one would expect that a higher ratio would reduce the demand for coverage. As regulatory price suppression

¹⁴ 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.

¹⁵ Once again, the first stage regression contains those instruments employed in the regression for $\ln(\text{price1})$ and the deductibles.

¹⁶ For a more thorough treatment of these neighborhood control variables and their effect on demand for homeowners insurance in Florida and New York, see Grace et al. (2003).

is reduced, price rises, and as price rises, the quantity demanded falls. In fact, we find this to be the case for all the three demand functions.

Next, 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 this analysis 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 income 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.¹⁷

If we look at Table 4, we see that most insurance demand studies obtain relatively low demand estimates. Our results are consistent with most of the reported income elasticities.

Firm Characteristics

In Florida, consumers tend to buy coverage from agency writers and mutual companies. For all the three demand equations, there is a negative relationship between

¹⁷ 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 (approximately) $-.04$ we would expect to see a positive elasticity between income and the amount of insurance purchased.

the demand for insurance and being a direct a writer, although it is not significant in the case of catastrophe insurance. Similarly, for all the three demand equations, there is a negative relationship between demand for insurance and being a stock company, although it is only significant in the equation for overall demand. We included auto premiums written by the insured's homeowners' carrier to account for potential consumer transactions cost savings from discounts for buying multiple policies from the same provider. We find that the coefficient on auto premiums is positive, which implies that consumers' value being able to purchase homeowners insurance and auto insurance from the same carrier. Further, we see a significantly positive relationship for life premiums written by a sister company and the demand for catastrophe insurance and the demand for noncatastrophe insurance. Again, we conjecture that consumers like the ability to deal with one insurance company. There is also a positive relationship between life premiums and overall demand for homeowners insurance, but it is not significant.

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 perceived to be financially stronger and are able to take advantage of economies of scale. For our sample companies, company size has a positive effect on all the three demands.

Another indication of firm solvency quality is its A. M. Best Rating of its claims paying ability. 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 5 that the coefficients for companies with ratings lower than the omitted category are generally positive and significant, paradoxically suggesting that consumers prefer to purchase insurance from companies that are less financially secure.¹⁸ One interpretation of this perverse result is that insurers' Best ratings are correlated with other factors omitted from this analysis. We also note that, while guaranty fund coverage is not widely publicized, consumers may know that they will receive some protection in case of 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, e.g., Cummins, 1988) and we explore this further in the last part of our analysis.

NEW YORK RESULTS

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

¹⁸ The company with a NR2 rating appears to be an anomaly. Category NR2 is a not rated category. One firm is in the data set with an NR2 rating. The reason the firm was not rated is because 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.

Island, face a moderate degree of catastrophe risk. Regulatory constraints on insurers' rates appear to have been less severe in New York as cost pressures have been more moderate. We would not expect the risk of noncatastrophe 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 adjustments to reflect coverage options specific to New York.

Insured Risk Characteristics

For New York, in Table 6, we see some differences compared to the results that we obtained for Florida after controlling for selection bias and whether the zip code is an area with above median CAT and noncatastrophic losses. Relative to SFR structures, owners of brick homes have a lower demand for insurance, but the effect is only significant for catastrophe insurance. We also see that, while owners of wood frame homes have a significantly higher demand for catastrophe coverage, they have a significantly lower demand for noncatastrophe insurance. The reason for the negative effect of brick and frame 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 quality of public protection services declines (i.e., as public protection grades rise from best to worst), the demand for overall coverage and noncatastrophe coverage increases.

We also undertake to examine the ILCs above and below the median. 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 New York, the HH area is Long Island, while the LL area is most of the remainder of New York State and again serves as the omitted category. As is the case with our results for Florida, being in an HH location has a significantly positive effect in all the three demand equations. Our results for LH and HL locations are somewhat ambiguous.

Contract Terms

If we examine the policy choices in New York in Table 6, we see that HO2 and HO3 policies have negative coefficients for overall and noncatastrophe demand, implying that they are not valued as highly as HO5 policies, which is the omitted category. In turn, HO2 and HO3 policies have positive coefficients in the demand for catastrophe coverage. These findings likely reflect the fact that HO2 and HO3 policies provide less protection against noncatastrophe losses than HO5 policies but similar protection against catastrophe losses. Further, we see that HO1 policies are preferred to HO5 policies for overall coverage and catastrophe coverage but not noncatastrophe coverage, perhaps because of the limited protection that HO1 policies provide against noncatastrophe perils.

Replacement cost coverage on personal property has a negative sign for total demand. This suggests that the average consumer does not value this option. If we look at CAT demand, we see that replacement cost coverage is positive and is valued by the average consumer. However, for non-CAT cover, it is again negative.

Ordinance or law coverage has positive signs for all coverages, suggesting that the average consumer does value this additional policy option, all else being equal. 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. Thus, including ordinance or law coverage probably does not add as much to the overall cost of coverage as it does in Florida.

As in Florida, we see that the coverage A limit is positively related to overall demand and demand for noncatastrophe insurance in New York. However, unlike Florida, we see that coverage A limit is also positively related to demand for catastrophe insurance in New York. Thus, the higher value of the home as measured by the coverage A limit, the more insurance is demanded by New York consumers.

As is the case for Florida, the coefficients on the wind deductible are positive for catastrophe insurance but negative for noncatastrophe insurance (albeit insignificant in New York). Unlike Florida, the coefficient for the wind deductible in the equation for overall demand is positive in New York.

Also as the case in Florida, the coefficients for fire deductibles for New York are generally positive. In New York, however, the coefficient for the fire deductible is negative in the equation for catastrophe insurance, whereas in Florida, it is negative in the equation for noncatastrophe demand.

Nonetheless, it is generally the case in New York that, as wind and fire deductibles rise, consumers purchase more insurance. Increases in wind deductibles that are associated with increases in demand for catastrophe insurance suggests consumers use their savings from higher wind deductibles to purchase additional protection against catastrophes, while the positive relationship between fire deductibles and demand for noncatastrophe insurance suggests that consumers use the savings from higher fire deductibles to buy additional protection against noncatastrophe losses.

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 except in the equation for noncatastrophe demand, 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

Neighborhood Characteristics and Regulation

Again, we focus on two neighborhood variables: the ratio of implemented loss costs and median income. Looking at the regulatory subsidy variable—the ratio of the implemented loss costs to the ILCs (our measure of price suppression)—we generally obtain 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. Recall that rate suppression and compression in Florida was much more severe than in New York.

Finally, we see that in New York, insurance is generally an inferior good. As income increases, the demand for total coverage and noncatastrophe coverage decreases. In contrast, increases in income are associated with 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 overall demand for insurance. However, there is a significant negative relationship between the direct writers and the demand for catastrophe coverage. Thus, it appears that the use of independent agents is associated with higher sales of catastrophe insurance, all other things held constant.

Insurer ownership appears to have a significant effect on demand for insurance in New York. All else being equal, consumers seem to prefer to purchase insurance in general and catastrophe insurance in particular from stockholder-owned insurers, although our regression results indicate that consumers have a preference for purchasing noncatastrophe coverage from mutuals.

Further, the ability to purchase home and other insurance coverages from the same company appears to positively influence demand in a manner largely consistent with what we found in Florida.

Also largely consistent with our findings for Florida, firm size does seem to be positively related to the demand for insurance in New York, although the effect is insignificant in the equation for noncatastrophe demand.

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 to avoid multicollinearity. For the overall demand equation, there are significant differences among the rating categories and, as was the case with our results for Florida, consumers prefer lower rated companies to the A+ or higher rated category. When we look at the equation for catastrophe demand, we see that A+ or higher is significantly valued over the A companies, but is no different than the A–. One would expect that, if solvency of the company were of paramount concern to the consumer, then we would see both significantly negative coefficients for A and A– companies. This is, in fact, the pattern we see in the noncatastrophic demand equation.

Guaranty Funds

Finally, we examine the effects of guaranty fund coverage 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 fund coverage is \$300,000 per claim and, in New York, this limit is \$1,000,000.¹⁹ Thus, unpaid losses above those amounts are not covered by the funds, and claimants must attempt to recover these amounts as general creditors against an insurer's estate.²⁰ This suggests consumers

¹⁹ See <http://www.ncigf.org/Publications/Claim%20Parameters.xls> for a summary of state fund policy limits for 2001.

²⁰ 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,

TABLE 7

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)

	Rating	Coefficient*	Std. Error	t-Stat	Prob
Panel A. Effect of Ratings on Households Below Guarantee Fund Policy Limit					
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					
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.

**NR2 represents one large company in Florida that is a subsidiary 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 A. M. Best.

Note that the coefficients are relative to rating of A+ and above.

with coverage A limits on their dwellings above these fund limits should pay more attention to their insurers' solvency prospects. We are able to test this hypothesis on the Florida data, as there are ample observations of homes with coverage A limits above \$300,000. For New York, our data set had too few observations with coverage A limits over \$1,000,000 to test this hypothesis.

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.

Table 7 shows our results, 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 5, but estimated separately for homes where the coverage A limit was above or below the Florida fund limit of \$300,000 per claim.²¹ Panel A shows the results for homes below the \$300,000 policy limit for total demand, catastrophe coverage, and noncatastrophe coverage. Once again, the rating level of A+ and above was omitted. Panel A's results for overall demand differ from the results shown in Table 5, as that panel A indicates that consumers prefer A+ companies to A and A- companies. The same is true for noncatastrophe coverage and is consistent with our findings as shown on Table 5. For catastrophe coverage, panel A suggests that consumers prefer A-rated companies to both A+ companies and those rated lower. This suggests that consumers who are fully protected by the funds may be willing to pay more for catastrophe insurance from insurers with good ratings but not the additional premium for insurance from insurers with superior ratings. As explained above, 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 strength. Thus, all coefficients should be negative. This is generally what is observed in panel B. For the total demand equation, all coefficients are significantly negative (except for the anomalous NR2 company and that is not significantly different from zero).

For the overall demand equation, panel B also shows a logical ordering of the coefficients for the various rating categories reflecting lexicographic preferences ($A+ > A > A- > B+$). For the catastrophe demand and noncatastrophe demand equations, we see that consumers generally prefer A+-rated companies to other companies, but there are some cases where the coefficients are either insignificant or violate the logical ordering discussed above. Overall, we find evidence that consumers pay greater attention to insurer's financial health when exposed to insolvency risk, as well as evidence of the (not so subtle) moral hazard created by guaranty funds for consumers without this exposure.

This result is similar to that found by Phillips, Cummins, and Allen (1998). While we focus on consumer reaction to perceived solvency risk (as measured by the rating), Cummins, Phillips, and Allen focused on how insurers' pricing decisions are influenced by the presence of guaranty funds. Firms with higher default risks had lower prices especially in lines of business (long tail commercial) and 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 illuminates factors affecting insurance transactions in residential markets subject to different levels of catastrophe risk and regulatory pressure. We estimated the demand for insurance coverage in Florida and New York. We find that the demand

²¹ 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 ratings and the firm effects 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.

for catastrophe coverage is more price elastic than the demand for noncatastrophe coverage. This is true in both Florida and New York. However, the estimated price elasticities for Florida were generally higher in absolute value than the estimated price elasticities for New York, 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 inelastic, but positive. In New York, we found that the income elasticity was negative for total coverage and for noncatastrophe coverage, implying that these are inferior goods. For catastrophe coverage, the income elasticity in New York was positive and approximately 0.25, which is close to the Florida result of 0.32.

We also found that regulatory rate suppression/compression generally increased the demand for insurance in both states but, for New York, the effect was only significant in the equation for catastrophe insurance. Further, 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 negative effect on incentives for efficient mitigation and location choices.

Some options that expand coverage tended to increase demand, but others tended to lower demand, suggesting that consumers are willing and able to gauge incremental costs against incremental benefits and make the decisions perceived to be in their best interests. Interestingly, higher deductibles were often 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 guaranty fund policy limit sometimes prefer to purchase coverage from lower rated insurers. In contrast, consumers with contractual limits above the guaranty fund coverage limit appear to consistently prefer buying coverage from higher rated insurers. These results are potentially important for consumer welfare. If state policies with respect to guaranty funds were such that financial strength and other quality indicators were not rewarded in the market place, then the overall quality of the insurance industry providing coverage in a state would suffer and high-risk firms would displace high-quality firms. The consequences for sustainability of the state insurance industry would clearly be deleterious.

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