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THE BASIS RISK OF CATASTROPHIC-LOSS INDEX SECURITIES

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The Basis Risk of Catastrophic-Loss Index Securities

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This paper analyzes the basis risk of catastrophic-loss (CAT) index derivatives, which securitize losses from catastrophic events such as hurricanes and earthquakes. We analyze the hedging effectiveness of these instruments for 255 insurers writing 93 percent of the insured residential property values in Florida, the state most severely affected by exposure to hurricanes. County-level losses are simulated for each insurer using a sophisticated model developed by Applied Insurance Research. We analyze basis risk by measuring the effectiveness of hedge portfolios, consisting of a short position each insurer's own catastrophic losses and a long position in CAT-index call spreads, in reducing insurer loss volatility, value-at-risk, and expected losses above specified thresholds. Two types of loss indices are used – a statewide index based on insurance industry losses in Florida and four intra-state indices based on losses in four quadrants of the state. The principal finding is that firms in the three largest Florida market-share quartiles can hedge almost as effectively using the intra-state index contracts as they can using contracts that settle on their own losses. Hedging with the statewide contracts is effective only for insurers with the largest market shares and for smaller insurers that are highly diversified throughout the state. The results also support the agency-theoretic hypotheses that mutual insurers are more diversified than stocks and that unaffiliated single firms are more diversified than insurers that are members of groups.

The Basis Risk of Catastrophic-Loss Index Securities

1. Introduction

An important recent innovation in financial markets is the securitization of losses from catastrophic (CAT) events such as hurricanes and earthquakes. The development of these instruments has been motivated by a surge in the frequency and severity of catastrophic losses. Hurricane Andrew in 1992 and the Northridge earthquake in 1994 resulted in $30 billion in insured property losses, and recent projections indicate that the losses from a major Florida hurricane or California earthquake could exceed $100 billion.[1] Losses of this magnitude would significantly stress the capacity of the insurance industry, but are manageable relative to the size of U.S. stock and bond markets.[2] Thus, securitization offers a potentially more efficient mechanism for financing CAT losses than conventional insurance and reinsurance (Jaffee and Russell 1997, Froot 1998a). Both insurers and non-insurers such as industrial firms can use these instruments to hedge their exposure to catastrophic losses, in effect permitting the non-insurers to bypass the insurance market.[3] Moreover, because catastrophic losses are "zero-beta" events, CAT-loss securities provide a valuable new source of diversification for investors (Litzenberger, et al. 1996, Canter, et al. 1997).

CAT-risk securities offers a particularly interesting example of a new type of derivative where the underlying is not a traded asset or commodity, so that prices are not observed. In this regard, CAT securities are analogous to other new derivatives with "exotic underlyings," such as weather derivatives (Geman 1999). In the absence of a traded underlying asset, insurance-linked securities have been structured to pay-off on three types of variables – insurance-industry catastrophe loss indices, insurer-specific catastrophe losses,

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[1]Unpublished data from Applied Insurance Research, Boston.

[2]A loss of $100 billion would equal approximately 30 percent of the equity capital of the U.S. insurance industry but would be less than 0.5 of 1 percent of the value of U.S. stock and bond markets.

[3]CAT securities also enable insurers and non-financial firms exposed to CAT risk to hedge losses exceeding the capacity of the international insurance and reinsurance markets and to avoid the market disruptions caused by reinsurance price and availability cycles (Cummins and Weiss 2000).

and *parametric* indices based on the physical characteristics of catastrophic events. The choice of a triggering variable involves a trade-off between moral hazard and basis risk (Doherty 1997). Securities based on insurer-specific (or hedger-specific) losses have no basis risk but expose investors to moral hazard; whereas securities based on industry loss indices or parametric triggers greatly reduce or eliminate moral hazard but expose hedgers to basis risk. In fact, the perception among insurers that CAT index securities are subject to unacceptable levels of basis risk has been identified as the primary obstacle to the more rapid development of the CAT-loss securities market (American Academy of Actuaries 1999).

The most prominent example of CAT securities that settle on an industry-wide loss index are the Chicago Board of Trade (CBOT) call option spreads, introduced in 1992.[4] However, the majority of risk capital raised to date has been generated through the issuance of CAT bonds, which typically settle on the losses of a specific hedger.[5] Nearly all CAT-loss bonds issued to date also are structured as call option spreads. More details on CAT options and bonds are provided below.

Although basis risk is an important concern, there is no comprehensive empirical evidence about the basis risk of index-linked CAT loss securities. The primary objective of this paper is to remedy this deficiency in the existing literature by conducting a comprehensive analysis of the basis risk and hedging-effectiveness of index-linked CAT loss securities. We conduct a simulation analysis of hedging-effectiveness for 255 insurers accounting for 93 percent of the insured property values in Florida, the state with the highest

[4]The current CBOT call option spreads settles on industry-wide catastrophe loss indices compiled by Property Claims Services (PCS), an insurance industry statistical agent. The first catastrophe insurance derivative contracts were introduced by the CBOT in 1992 based upon an industry-wide index compiled by Insurance Services Office (ISO). The ISO-based contract was withdrawn when the PCS contracts were introduced.

[5]CAT bonds differ from the CBOT options in that the bonds are pre-funded by a bond issue, with the proceeds invested in safe securities such as Treasury bonds. If a specified catastrophic event occurs, the hedger can use the bond proceeds to offset catastrophic losses; and there is full or partial forgiveness of the repayment of principal and/or interest.

exposure to hurricane losses. The study is based on data provided by the Florida Insurance Commissioner on county-level insured residential property values for each insurer in the sample.

The study proceeds by simulating hurricane losses for each insurer in the sample using a sophisticated model developed by Applied Insurance Research (AIR), a leading CAT modeling firm.[6] The AIR hurricane model combines actuarial data, vulnerability relationships for various construction types, historical climatological data, and meteorological models of the underlying physical processes that drive the severity and trajectory of hurricanes. We use the AIR model to obtain estimates of insurer losses over a simulation period consisting of 10,000 years of hurricane experience. We then utilize the simulated loss experience to analyze the effectiveness of catastrophic loss hedging strategies for the sample insurers.

The analysis focuses primarily on non-linear hedging strategies where the hedge portfolio consists of a short position in catastrophe losses and a long position in call option spreads on a CAT loss index. Analyzing non-linear hedging is important because the call-spread is the dominant functional form for payoffs on CAT bonds and options as well as for conventional catastrophe reinsurance contracts.[7] Several hedging objectives are investigated, including reduction in loss volatility (variance), value-at-risk (VaR), and the expected loss conditional on losses exceeding a specified loss threshold. The benchmark model of hedging effectiveness is the *perfect hedge*, defined as the risk reduction a hedger could achieve by using its own loss experience as the hedge index. The perfect hedge is equivalent to purchasing reinsurance or issuing hedger-specific CAT bonds. The effectiveness of the perfect hedge is compared with hedges based on a statewide loss index and four intra-state regional indices analogous to the PCS indices used as the basis for

[6]The AIR model has been widely used by insurers and reinsurers since 1987 in monitoring their exposure to catastrophic losses and developing underwriting strategies and was the first model to meet the standards of the Florida Insurance Commission on Hurricane Loss Projection Methodology.

[7]For purposes of comparison with prior work, we also analyze and briefly report on linear hedging strategies where hedge portfolios are formed that linearly combine a short position is CAT losses with a long position in CAT loss futures.

the CBOT CAT call spreads. The analysis measures the degree of basis risk insurers would incur from hedging through CAT loss indices.

A second purpose of the study is to investigate the relationship between potential hedging effectiveness and insurer characteristics. Specifically, we formulate and test hypotheses about the relationship between hedging efficiency and insurer organizational form (stock versus mutual), size, capital structure, and membership in a group of insurers under common ownership versus operating as an unaffiliated insurer. The analysis is important in gauging the risk-taking incentives of insurers with specific size and organizational characteristics. For example, whether mutuals and small insurers are less successful than other firms in diversifying risk is important in determining regulatory policy towards demutualizations and mergers and acquisitions in the insurance industry as well as managerial strategies towards such restructurings.

By way of preview, the principal finding of our study is that insurers in the two largest size quartiles can hedge very effectively using intra-state regional indices. Many insurers in the third size quartile also can hedge effectively using the intra-state indices, but hedging by insurers in the smallest size quartile is significantly less effective. Mutual insurers can hedge <u>more</u> effectively than stock insurers using the intra-state indices – a result that we argue can be explained by agency theoretic considerations. We also find insurers with greater leverage can more effectively hedge with index contracts consistent with the hypothesis the increased use of leverage gives insurers more incentive to diversify their risk geographically. Finally, we although we find many insurers would encounter significant basis risk in hedging with a state-level index, even with this index a high proportion of the total property value exposed to loss in Florida could be hedged efficiently.

The findings are important as a case study in the securitization of a non-traded asset, and thus can provide guidance for the securitization of other unconventional financial exposures. Our methodological approach also has the potential to serve as a model for analyzing the hedging effectiveness of similar securities on exotic underlyings, such as weather derivatives. The results have important implications for insurers, not only with respect to hedge efficiency but also for the management of underwriting exposure. The analysis should be of interest to insurance regulators and policymakers concerned about financing losses from catastrophic events and preventing the destabilization of insurance markets due to catastrophes. Finally, as discussed above, the results have implications regarding the risk taking incentives of insurers with different organizational characteristics.

There have been two previous empirical studies of the basis risk of insurance-linked securities, both using different or less comprehensive study designs. Harrington and Niehaus (1999) conduct a time series analysis of the correlation between state-specific loss ratios for a sample of insurers and the PCS CAT loss index and find that PCS derivatives would have provided effective hedges for many homeowners insurers. In a study more similar to ours, Major (1999) conducts a simulation analysis of insurer CAT losses based on insurer exposures in Florida and finds that hedging with a statewide CAT index is subject to substantial basis risk. Our analysis extends Major's by considering much larger numbers of insurers and storms, testing intra-state indices as well as a statewide index, and evaluating a wider variety of hedging strategies.

The remainder of the paper is organized as follows: Section 2 discusses the catastrophic loss financing problem, provides more details on insurance-linked securities, and discusses our hypotheses about insurer size and organizational form. Section 3 describes the AIR model, our data, and the study design. The results are presented in section 4, and section 5 concludes.

2. Theoretical Background, Catastrophic Losses, and Securitization

In this section, we discuss the catastrophic loss problem and explain the role of securitization in financing catastrophic losses. We then provide more details on insurance-linked securities and formulate hypotheses about insurer organizational form, size, and membership in an insurance group.

The Catastrophic Loss Financing Problem

Both the frequency and the severity of property losses due to natural catastrophes have increased dramatically in recent years. During the period 1970-1985, the number of catastrophes averaged about 35 per year. Beginning in 1986, however, the number of catastrophes increased sharply, and from 1994-1998 more than 125 catastrophes were recorded each year (SwissRe 1999).[8] Insurers have paid more than $150 billion in property losses due to catastrophes since 1986, representing 77 percent of insured CAT losses during the period 1970-1998. Although the largest loss, Hurricane Andrew, resulted in only $18 billion in insured property-losses, modeling firms are predicting that losses from a major California earthquake or Florida hurricane could exceed $100 billion.

At first glance, it might seem that the international insurance and reinsurance markets could easily fund a major property catastrophe. The amount of equity capital in the U.S. property-liability insurance industry is about $350 billion, and the amount of capital in the international reinsurance market is about $125 billion. However, most of this capital is committed to backing insurer promises to pay the relatively small, frequent losses that are covered by the vast majority of insurance and reinsurance policies. Insurance markets are much less efficient in financing large, infrequent events such as natural catastrophes. As a result, the percentage of insured property covered by catastrophe reinsurance is inversely related to the size of the event, and only a small fraction of the property exposure base in hazard prone U.S. states is covered by catastrophe reinsurance (Swiss Re 1997, Froot 1998a). Thus, the capacity of the international reinsurance market is clearly inadequate to fund major catastrophes (Cummins and Weiss 2000). In addition, reinsurance markets are subject to price and availability cycles, often resulting in price increases and supply restrictions following catastrophic events (Froot 1998a, Froot and O'Connell 1999).

Raising additional equity capital in the insurance industry would not be an efficient solution to the CAT loss financing problem because holding capital in an insurer or reinsurer is costly (Jaffee and Russell

[8]SwissRe defines a catastrophe as an event causing at least $32 million in insured property loss.

1997). Capital held in insurers is subject to regulatory and agency costs; and tax and accounting rules also penalize insurers for holding capital to cover infrequent (e.g., once in 50-year) events. Informational asymmetries between insurers and capital markets regarding exposure to catastrophic events and the adequacy of loss reserves are an additional impediment to holding additional equity. Finally, "excess" capital not currently committed to projects with short or intermediate time horizons is likely to attract corporate raiders.

Securitization has been offered as a more efficient approach to solving the catastrophic loss financing problem. Although a $100 billion catastrophe amounts to about 30 percent of the equity capital of the U.S. property-liability insurance industry and about 80 percent of the equity of the international reinsurance industry, a loss of this magnitude amounts to less than one-half of 1 percent of the value of stocks and bonds traded in U.S. securities markets. Securities markets also are more efficient than insurance markets in reducing information asymmetries and facilitating price-discovery. Finally, because natural catastrophes are zero-beta events, CAT securities provide a valuable new source of diversification for investors, shifting the efficient investment frontier in a favorable direction (Litzenberger, et al. 1996, Canter, et al. 1997).

CAT Options and Bonds

To date, the most important CAT securities have been the CBOT CAT call option spreads and CAT bonds. The CBOT's call spreads settle on insurance-industry catastrophe loss indices compiled by Property Claims Services (PCS), an insurance industry statistical agent. There are nine indices – a national index, five regional indices, and three state indices (for California, Florida, and Texas). The indices are based on PCS estimates of catastrophic property losses in the specified geographical areas during quarterly or annual exposure periods.[9]

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[9]The indices are defined as the total accumulated losses divided by $100 million. E.g. a 20/40 Eastern call spread would be in the money for a catastrophic loss accumulation in the Eastern region of more than $2 billion (20 points). Each index point is worth $200 on settlement so that one 20/40 call would pay a maximum of $4,000 (20 points times $200 per point).

The structure of a typical CAT bond is shown in Figure 1. Capital raised by issuing CAT bonds is invested in safe securities such as Treasury bonds, which are held by a single-purpose reinsurer to insulate investors from the credit risk of the bond-issuer. The bond-issuer holds a call option on the principal in the single-purpose reinsurer with triggering or strike conditions usually expressed in terms of the issuing insurer's losses from a defined catastrophic event.[10] If the defined event occurs, the bond-issuer can withdraw funds from the reinsurer to pay claims, and part or all of the interest and principal payments are forgiven. If the defined catastrophic event does not occur, the investors receive their principal plus interest equal to the risk free rate plus a risk-premium.

Index-linked CAT options and issuer-specific CAT bonds can be compared and contrasted in terms of their transactions costs, liquidity, basis risk, and exposure to moral hazard. CAT options are superior to CAT bonds in terms of transactions costs. CAT options can be traded inexpensively on an exchange, whereas CAT bond issues are subject to substantially higher transactions costs for legal, investment, auditing, and tax advice. CAT options also have the potential to generate a very liquid market due to their standardization and the anonymity of traders. Although a liquid market in CAT bonds can also be envisioned, the bonds issued to date have low market liquidity because they are not standardized and not traded on an exchange. Index-linked CAT options also are superior to issuer-specific CAT bonds in terms of exposure to moral hazard. The existence of a CAT bond may give an insurer the incentive to relax its underwriting and claims settlement standards, leading to higher-than-expected losses. CAT options, on the other hand, are relatively free of moral hazard because they settle on industry-wide losses rather than the losses of a specific insurer.[11] The primary advantage of insurer-specific CAT bonds over index-linked CAT

[10]The first successful CAT bond was issued in 1997 by SwissRe to cover earthquake losses (Goldman Sachs 1999); and the first CAT bond issued by a non-financial firm, occurring in 1999, covers earthquake losses in the Tokyo region for Oriental Land Company, Ltd., the owner of Tokyo Disneyland.

[11]Index-linked options are not totally free of moral hazard problems because large insurers may have the ability to manipulate the index by over-reporting losses to the statistical agent. However, because concentration in insurance markets is relatively low, over-reporting by a large insurer is significantly diluted at the index level,

options is that insurer-specific bonds expose the hedger to less basis risk than do the options. The empirical analysis in this paper is designed to provide information on the degree of basis risk that would be faced by insurers in hedging with index-linked CAT loss securities.

Table 1 summarizes all principal-at-risk CAT bonds issued since 1996 as well as a sampling of Florida CBOT call spread transactions. Panel B shows twenty CAT bond issues, ten of which have more than one principal-at-risk tranche (multiple entries for an issuer in the same month indicate multiple tranches). The table shows that a total of $2.6 billion in risk capital has been raised through principal-at-risk CAT bonds. The table also shows the risk premium over the risk-free rate and the expected CAT loss conditional on the occurrence of a loss for each issued tranche.[12] If natural disasters are zero-beta events and significant market imperfections are not present, the rate of return on CAT bonds should approximately equal the risk-free rate plus a risk premium sufficient to compensate investors for the expected loss of principal due to a catastrophe. A CAT bond pricing puzzle, not explored in the present paper due to insufficient market data, is why the risk premia on CAT bonds are several times larger than the expected losses (the median risk-premium to expected-loss ratio is 6.8). Possible explanations for this phenomenon include moral-hazard, the illiquidity of the bonds, uncertainty about expected loss estimates, and investor unfamiliarity with the contracts.[13] The CBOT call spread section of the table shows that Florida calls tend to trade at lower risk-premium to expected-loss ratios than CAT bonds (the median is 2.1), suggesting that the higher premia on CAT bonds may be partly attributable to moral hazard.

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unlike over-reporting on an insurer-specific instrument.

[12]The CAT bond data, including the expected loss, were obtained from the offering circulars. We grateful to Michael Millette of Goldman Sachs & Co. for providing the CAT bond data. The information on the CBOT option trades was obtained from the CBOT web site and correspondence with the CBOT. The expected losses on the CBOT contracts were estimated using output from the AIR model over the 10,000 year simulation and the parameters of each trade.

[13]For further discussion see Kunreuther and Bantwal (1999).

Hypotheses

Our analysis takes as its starting point the geographical exposure to property loss of the insurers in our sample. Insurers that are more diversified geographically will show up in our analysis as having higher hedging efficiency using index-linked CAT securities than insurers whose exposures are more concentrated geographically. Because the geographical exposure to loss is largely under the control of management, it provides an indicator of managerial attitudes toward risk-taking and diversification. In this section, we develop hypotheses about the relationship between managers' revealed preferences for exposure risk and three important firm characteristics – organizational form (stock versus mutual), firm size, capital structure, and being a member of a group of insurers under common ownership versus operating as an unaffiliated, single insurer.

The first hypothesis is that mutuals are likely to be more diversified geographically and hence have higher hedging efficiency than stocks. It is in the interests of both the owners and the managers of a mutual insurer for the firm to be well-diversified. Mutuals are owned by their policyholders, who are averse to insolvency risk. Policyholders purchase insurance in part to shift the burden of catastrophic losses to the insurer, i.e., absent insurance, their personal portfolios are overexposed to catastrophe risk. Therefore, they are not likely to want the insurer to shift part of the CAT risk back to them through sub-optimal diversification. Likewise, managers of mutuals have their human capital committed to the insurer and are less likely to benefit from risk-taking than the managers of stock insurers. Rather, managers of mutuals tend to be more concerned about job security and thus to adopt operating strategies that reduce insolvency risk.[14]

Stock insurers, on the other hand, are owned by shareholders, who prefer higher levels of risk-taking as long as it maximizes firm value. Because the market mechanisms available for stock owners to control mangers are much stronger than those available to mutual owners, stock managers are likely to pursue the owners' interests in maximizing firm value. To the extent that stock managers can increase firm value by

[14]Evidence that stocks take more risk than mutuals is presented in Lamm-Tennant and Starks (1993).

writing insurance in profitable geographical regions and avoiding unprofitable regions, stock insurers will tend to be less geographically diversified than mutuals.

The second hypothesis investigated in this paper is that large insurers will be more diversified than smaller insurers and thus have higher potential hedging efficiency. Besides the obvious rationale that to become large an insurer cannot restrict its operations to a limited number of geographical areas, we argue that it is more efficient for large insurers to incur the fixed and variable costs of acquiring risk management expertise and operating effective exposure management programs.

Our third hypothesis is that insurers with higher leverage have a more limited ability to bear risk than better-capitalized insurers and will therefore be more concerned about diversifying their exposures across the state. Thus, insurers with greater degrees of leverage are expected to be more efficient index hedgers.

The final hypothesis is that insurers that are members of insurance groups under common ownership will be less diversified than insurers operating as unaffiliated single insurers. Insurers that are members of groups are likely to have access to the equity capital of other group members or the group holding company in the event of a major loss shock. Although the group is not obligated to rescue a failing subsidiary, in most cases reputational costs and other factors motivate the group to recapitalize subsidiaries that have suffered capital shocks. The insurance group diversifies across subsidiaries, permitting individual subsidiaries to be less diversified. Although unaffiliated insurers can in principle raise money in capital markets following a loss shock, in reality raising capital following a shock is likely to be expensive or infeasible because of information asymmetries involving the adequacy of reserves. In addition, sustaining a large loss shock constitutes an adverse signal to capital markets about the quality of the firm's management. Hence, to avoid loss shocks, unaffiliated firms are expected to be more diversified than group members.

3. Data and Study Design

The study has five major phases: (1) The identification and analysis of data on the catastrophic loss exposure of a sample of insurance companies. (2) The simulation of catastrophic losses in the geographical area covered by the sample companies. (3) The measurement of basis risk and hedge effectiveness for the insurers in the sample using a variety of hedging strategies and loss indices. (4) Hypothesis tests about insurer characteristics associated with hedging effectiveness. And (5) the development of a parametric index that breaks the linkage between the losses of specific insurers and the payoff trigger of index-linked CAT loss securities. The remainder of this section provides more details on the five phases of the study.

The Data

The data base for the study consists of county-level data, obtained from the Florida Insurance Commissioner, on insured residential property values for 255 of the 264 insurers writing property coverage in Florida in 1998.[15] The insurers in our sample account for 93 percent of the total insured residential property values in the state. Thus, our results can be interpreted as representative of the entire insurance industry. Further details about the sample are provided in the empirical results section below.

Catastrophic Loss Simulations

The simulated catastrophic losses for our sample of insurers are generated using the hurricane model developed by Applied Insurance Research. This section provides a brief description of the model. Further details on the model are provided in Appendix A and in Applied Insurance Research (1999).

The hurricane loss estimation methodology employed by AIR is based on well-established scientific theory in meteorology and wind engineering. The simulation models were developed through careful analyses and synthesis of all available historical information and incorporate statistical descriptions of a large number of variables that define both the originating event (e.g., hurricane) and its effect on insured structures. The models are validated and calibrated through extensive processes of both internal and external peer review, post-disaster field surveys, detailed client data from actual events, and overall reasonability and convergence testing. The AIR hurricane model has been used by the insurance industry since 1987 and is

[15]Data on the nine omitted insurers were not available from the Florida Insurance Commissioner.

well known for its reliability and the credibility of the loss estimates it generates. The AIR model was the first to meet the standards of the Florida Insurance Commission on Hurricane Loss Projection Methodology.

The structure of the simulation model is summarized in Table 2. The process begins with a Monte Carlo simulation of the number of storms per year for a 10,000 year simulation period, generating more than 18,000 simulated events. The landfall and meteorological characteristics are then simulated for each storm, where the meteorological characteristics include central barometric pressure, radius of maximum winds, forward speed, storm direction, and storm track. Once the model generates the storm characteristics and point of landfall, it propagates the simulated storm along a path characterized by the track direction and forward speed. In order to estimate the property losses resulting from the simulated storms, the AIR hurricane model generates the complete time profile of wind speeds, or windfield, at each location affected by the storm.

After the model estimates peak wind speeds and the time profile of wind speeds for each location, it generates damage estimates for different types of property exposures by combining data on insured property values and structure characteristics with wind speed information at each location affected by the event. To estimate building damage and the associated losses, the AIR hurricane model uses damageability relationships, or damage functions which have been developed by AIR engineers for a large number of building construction and occupancy classes. In the last component of the catastrophe model, insured losses are calculated by applying the policy conditions to the total damage estimates. Policy conditions include deductibles, coverage limits, coinsurance provisions, and a number of other factors.

A fundamental component of the model is AIR's insured property data base. AIR has developed databases of estimated numbers, types, and values of properties for residential, commercial, mobile home, and automobile insured values in the United States by five-digit ZIP code. These databases have been constructed from a wide range of data sources and reflect the estimated total replacement cost of U.S. property exposures. In the present study, AIR's zip code level data on insured property values for companies doing business in Florida were used in the simulations and aggregated to the county level using information supplied by the Florida Insurance Department to protect the confidentiality of AIR's data bases. The simulations were also conducted using the AIR zip-code data base exclusively for a random sample of five companies in order to validate the county aggregation approach. The validation tests indicated that aggregating our results to the county level provides an accurate representation of the losses that would have been generated using AIR's zip code data base as the exclusive source of information.

Hedging Strategies and Hedge Effectiveness

In this paper, we seek to determine the effectiveness of hedges based on a statewide loss index and four intra-state regional indices. The four intra-state indices are based on clusters of counties obtained by roughly dividing the state into four quadrants based on horizontal and vertical lines through the center of the state.[16] Four regions were chosen as a subdivision of the state that we hypothesized would be sufficient to enable insurers to create effective hedges without incurring the high transactions costs and lack of liquidity that would likely result from a finer subdivision of the state.[17]

Index-hedge effectiveness is measured relative to the performance of *perfect hedges*, which pay off on the insurer's own losses. The perfect hedge parallels the results the insurer could attain by purchasing conventional reinsurance contracts or issuing insurer-specific CAT bonds, whereas the index hedges are designed to reflect results that could be achieved through trading in index-linked CAT options.

The analysis assumes that insurers are risk-neutral but are motivated to hedge by market imperfections, including direct and indirect costs of financial distress and convex tax schedules.[18] In

[16]The grouping is "rough" in the sense that we did not subdivide counties that intersected with the horizontal and vertical axes but rather placed such counties in the quadrant containing the highest proportion of their property value exposure. The counties included in each cluster are shown in Appendix B.

[17]A 1998 attempt to launch zip-code level index contracts failed to generate interest among insurers and investors and is currently dormant. Chookaszian and Ward (1998) discuss the proposed indices.

[18]For more extensive discussions of the rationale for corporate risk management, see Merton and Perold (1993) and Froot, Scharfstein, and Stein (1993).

addition, because the role of insurance is to indemnify policyholders for insured losses, insurers are motivated to maintain a reputation for having low default risk. In this regard, risk management can be viewed as a substitute for holding costly equity capital.

We consider "buy and hold" hedging strategies covering a single period, because this is the standard approach used by insurers when purchasing excess of loss reinsurance contracts and issuing CAT options and bonds. We focus primarily on non-linear hedges, where the insurer forms a hedge portfolio consisting a short position in unhedged catastrophe losses and a long position in call option spreads. The non-linear analysis is emphasized because the call option spread is the dominant contractual form in both the CAT securities and catastrophe reinsurance markets (see Froot 1998b, Cummins, Lewis, and Phillips 1999). We also analyze and briefly discuss linear hedges, familiar from the hedging literature (e.g., Ederington 1979), which assume that the insurer forms a hedging portfolio consisting of a linear combination of a short position in unhedged catastrophic losses and a long position in the loss index.

Non-Linear Hedging

As discussed above, for the non-linear hedges, the insurer is assumed to form a portfolio consisting of its own unhedged catastrophic losses and a position in call option spreads on a loss index. Defining insurer j's hedged net loss under loss index i as L_j^i, insurer j's loss under the perfect hedge (i = P) is:

$$L_j^P = L_j - h_j^P [Max(L_j - M_j^P, 0) - Max(L_j - U_j^P, 0)] \tag{6}$$

where L_j^P = insurer j's hedged loss under the perfect hedge, L_j = insurer j's unhedged loss, h_j^P = the hedge ratio for the perfect hedge, M_j^P = the lower strike price of the call spread under the perfect hedge, and U_j^P = the upper strike price of the spread.

The perfect hedge is compared to hedges based on loss indices that are not perfectly correlated with the insurer's losses. Insurer j's net loss based on an index consisting of industry-wide, state-level losses is:

$$L_j^S = L_j - h_j^S [Max(L_S - M_j^S, 0) - Max(L_S - U_j^S, 0)] \tag{7}$$

where L_j^S = insurer j's hedged loss using an industry-wide, state-level loss index, h_j^S = the hedge ratio for the state-level hedge, $L_S = \sum_j L_j$ = state-wide losses for the industry, and M_j^S and U_j^S are the lower and upper strike prices for company j's state-level call spread. Insurer j's hedged loss under the intra-state regional hedge is:

$$(8) \qquad L_j^R = \sum_{r=1}^{R} \left[L_{jr} - h_j^r \left[MAX(L_r - M_j^r, 0) - MAX(L_r - U_j^r, 0) \right] \right]$$

where L_j^R = company j's losses under the intra-state regional hedge, L_{jr} = the unhedged losses of insurer j in region r, h_j^r = hedge ratio for insurer j in region r, L_r = industry-wide losses in region r, M_j^r = lower strike price for company j's region r call option spread, and U_j^r = upper strike price for company j's region r call spread, and R = the number of regions (R = 4 in our analysis).

In the general non-linear hedging problem, the insurer is assumed to minimize a function of L_j^i subject to a cost constraint. Defining the objective function for criterion m as $G_m(L_j^i)$, the optimization problem using a state-wide hedge, for example, is given as:

$$(9) \qquad \underset{\{h_j^S, M_j^S, U_j^S\}}{\text{Minimize:}} \quad G_m(L_j^S)$$

$$\text{Subject to:} \quad h_j^S \left[W(L_S, M_j^S) - W(L_S, U_j^S)\right] \le C_j$$

where C_j = the maximum amount available to insurer j to spend on hedging, and $W(L_S,M_j^S)$ and $W(L_S,U_j^S)$ = the prices of call options on industry losses L_S with strike prices M_j^S and U_j^S, respectively. Thus, the insurer optimizes over the hedge ratio and the two strike prices, M_j^S and U_j^S, subject to spending a maximum of C_j on hedging. The optimization problem for the perfect hedge is defined similarly. The optimization problem for the regional hedge is also analogous to expression (9) except that there are twelve decision variables – four hedge ratios and four sets of lower and upper strike prices. By varying C_j, it is possible to generate an efficient frontier based on each optimization criterion and loss index.

Several hedging objectives or criterion functions have been discussed in the literature. We focus on three criteria which are either standard in the hedging literature or likely to be appropriate for insurers: (1) the variance of losses, (2) the value-at-risk (VaR), and (3) the expected exceedence value (EEV). Variance reduction is the most straightforward of the three hedging criteria, giving rise to the objective function: $G_1(L_j^i) = \sigma^2[L_j^i(h_j^i, M_j^i, U_j^i)]$ = the variance of the insurer j's loss net of the payoff on the call option spread using loss index i, where i = P for the perfect hedge, S for the statewide industry hedge, and R for the intra-state regional hedge, where the latter is a function of twelve rather than three variables.

Value-at-risk (VaR) reduction has received considerable attention in the literature as a hedging criterion (e.g., Ahn, et al. 1999, Dowd 1999). VaR is used extensively by financial institutions to measure potential losses or profits from their trading operations and other risky activities (Santomero 1997). Moreover, VaR is similar in concept to the probability of ruin, which has been studied for decades by actuaries. Hence, insurers are likely to find VaR to be a familiar and informative criterion.

The VaR is defined as the amount of loss such that the probability of exceeding this amount during a specified period of time is equal to α, a small positive number ($0 < \alpha < 1$). Stated more formally, defining insurer j's net loss distribution function under hedge index i as $F_{ij}[L_j^i(h_j^i, M_j^i, U_j^i)] = F_{ij}(\cdot)$, VaR is defined as:

$$(10) \qquad VaR_{ij}[\alpha, L_j^i(h_j^i, M_j^i, U_j^i)] = F_{ij}^{-1}(1-\alpha)$$

where $F_{ij}^{-1}(\cdot)$ = the inverse of the net loss distribution function. Using VaR, the optimization function in expression (9) becomes $G_2(L_j^i) = VaR[\alpha, L_j^i(h_j^i, M_j^i, U_j^i)]$.

Although the VaR is an important and useful statistic, in many cases the risk manager would like to know not only the probability that a given loss level will be exceeded but also the expected amount of loss conditional on the loss level being exceeded. This is the quantity measured by our third optimization criterion, the expected exceedence value (EEV). EEV is similar in concept to the insolvency put option discussed in the risk-based capital literature and is essentially the value of a call option on L_j^i with strike price equal to a specified loss threshold.[19] More formally, the EEV is defined as:

$$(11) \qquad EEV_j[L_T, L_j^i(h_j^i, M_j^i, U_j^i)] = \int_{L_T}^{\infty} [L_j^i - L_T]\, dF_j(L_j^i(h_j^i, M_j^i, U_j^i))$$

where L_T = a loss threshold specified by the decision maker, and $L_j^i(h_j^i,M_j^i,U_j^i)$. The EEV criterion function is $G_3(L_j^i) = EEV_j[L_T,L_j^i(h_j^i,M_j^i,U_j^i))]$. Thus, the insurer minimizes the expected excess loss conditional on the loss being equal to or greater than a specified loss threshold. This measure is more informative than the VaR in the sense that the risk manager is likely to care whether the threshold loss level is exceeded by $1 or $1 million.

For each loss index i, we define hedge effectiveness as the proportionate reduction in the unhedged value of the criterion function. We denote the hedge effectiveness measure for insurer j based on loss index i as HE_{jm}^{i}, where m = 1, 2, and 3 for the variance, VaR, and EEV criteria, respectively. Under the EEV criterion function, for example, the hedge effectiveness of the state-wide index is:

$$(12) \qquad HE_{j3}^{S} = 1 - \frac{EEV_j[L_T, L_j^S(h_j^S, M_j^S, U_j^S)]}{EEV_j[L_T, L_j]}$$

The other two hedge effectiveness measures are defined similarly.

Estimation Methodology

In solving complicated non-linear optimization problems such as the one specified in expression (9), it is not unusual for standard optimization algorithms to fail to converge or to converge to a local optimum. We found this to be the case in working with expression (9), particularly when optimizing over the intra-state regional hedges. For example, it was not unusual for hedging with the intra-state contracts to be less

[19] Recent research suggests that EEV-type measures have desirable properties not possessed by value at risk measures. See, for example, Artzner, et al. (1999).

effective than hedging based on the statewide contract – a result that does not make sense in view of the fact that the statewide index can be replicated by summing the intra-state indices. We concluded that this problem arose because the solution algorithms we were using were not powerful enough to find the global optimum.

To solve the optimization problem while avoiding local minima, we adopted a *differential evolutionary genetic algorithm* (Goldberg 1989).[20] Genetic algorithms provide a robust search procedure to solve difficult non-linear or non-smooth optimization problems. Unlike conventional deterministic algorithms that will always yield the same solution when started from the same point, evolutionary algorithms rely on random sampling and hence will reach different solutions in different runs of the model. Because of the evolutionary feature, the model is less likely than conventional algorithms to get stuck at a local optimum and will generally locate the global optimum.

The genetic algorithm is based on the principles of genetics and the process of natural selection. The algorithm starts with a population of initial trials for the parameter vector to be estimated and interprets the value of the objective function at each of the trials as a measure of these points' "fitness" as an optimum. A new population is developed from the initial trial values by following three steps: First, the "fittest" members of the old population are selected for reproduction, defined according to the optimization criterion. Second, analogous to the mating process in genetics, new parameter combinations are created from the components of the existing solution vectors, according to a set of recombination rules. Third, the solution vectors are given the opportunity to mutate, potentially increasing the "fitness" of the population. The process continues until a solution is reached that satisfies the specified convergence criteria. We found this method to be very effective in solving the intra-state optimization problem; and for consistency, we also used it to solve the statewide optimization problem.

[20]See Engle and Manganelli (1999) for another application of genetic algorithms to optimize non-differentiable objective functions in financial risk management.

Insurer Characteristics and Hedge Effectiveness

Following the measurement of hedging effectiveness for the insurers in the sample, we seek to determine firm characteristics that tend to be associated with effective hedging. The objective is to test the three hypotheses discussed above and to identify other insurer characteristics associated with effective index hedging. In addition to providing a better understanding of hedging effectiveness, this analysis can also provide information that should be helpful to insurers in managing their exposure distributions.

Regression analysis is used to analyze the relationship between firm characteristics and <u>hedging efficiency</u>, where efficiency is defined as the ratio of hedging effectiveness (see equation (12)) using index hedges to hedging effectiveness using the perfect hedge. That is, the dependent variable for insurer j is: HE_{jm}^{i}/HE_{jm}^{P}, where i = S (for the statewide index hedge), R (for the regional index hedge), and P for the perfect hedge, and m indicates the hedging criterion.

To test our hypotheses, we include in the regressions a dummy variable equal to 1 for mutuals and 0 for stocks, and a dummy variable equal to 1 for unaffiliated single companies and 0 for affiliated insurers. As size measures, we include in the models dummy variables for the three largest size quartiles, where size is defined as the insurers' total assets. To test our capital structure hypothesis, we include a leverage variable equal to the insurer's liabilities-to-assets ratio. As explained above, the mutual and unaffiliated firm dummy variables and the leverage variable are all predicted to be positively related to hedging efficiency. The larger size quartile variables are more likely to have positive signs than smaller quartile dummies.

Also included in the model are dummy variables for the three largest Florida market share quartiles, where the company's market share in the state defined as S_j/S, where S_j = the dollar value of insurer j's exposure to loss in Florida and S = the total insured property value in the state. The size quartile variables are expected to be positively associated with hedging efficiency because companies with higher market shares have more impact on the value of the loss index, ceteris paribus. We also test as a diversification variable the coefficient of variation of the insurer's market share define as $s_{jk} = S_{jk}/S_j$, where S_{jk} = insurer j's total insured property value in county k, and $S_j = \sum_k S_{jk}$ = insurer j's total insured property value in the state.[21] The diversification measures is hypothesized to be inversely associated with hedge efficiency because more geographically diversified portfolios will have low coefficients of variation.

An additional variable included in the regression models is the proportion of an insurer's total insured property value located in ocean front counties. This variable is of obvious importance in an analysis of catastrophic risk because ocean front counties tend to sustain the highest degree of damage from hurricanes. Insurers with high proportions of their insured property value in ocean front counties might be expected to be able to hedge more efficiently using loss index hedges because the loss indices tend to be driven by losses in ocean front counties rather than losses in inland counties. Finally, dummy variables also are included in the regressions for the levels of the cost constraints.

A Proposed Parametric Index

As our discussion of the insurer market share variable suggests, even industry-wide loss indices are not totally free of moral hazard. It would be possible for a large insurer to materially increase the amount of its payoff from an index hedge by overstating its catastrophe losses to the statistical agent who compiles the index. Although the effects of its over-reporting would be diluted in comparison with the impact of over-reporting on a perfect (insurer-specific) hedge, the possibility of over-reporting by large insurers could discourage some investors from participating on the short side of the CAT call-spread market and/or lead to higher risk premia for index-linked products than would be the case if no moral hazard were present. Consequently, it seems relevant and important to develop a parametric index based on our simulation data.[22]

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[21]We also tested the Herfindahl index of county market shares, defined as $\sum_k s_{jk}^2$. The results using the Herfindahl index are similar and hence not shown.

[22]A few CAT loss security offerings have included parametric triggers as the sole criterion for determining the payoffs on the securities. The most prominent parametric contract was issued in 1998 by a single-purpose reinsurer appropriately named Parametric Re. The beneficiary of the Parametric Re bond issue is Oriental Land Company, Ltd.. Debt forgiveness on the Parametric Re bond is triggered solely by Richter Scale readings for an earthquake in the Tokyo metropolitan area – the monetary value of loss resulting from the earthquake is irrelevant in determining the payoff of the bond.

Our proposed parametric index for hurricane losses in Florida is based on a regression model with monetary hurricane damages as the dependent variable and storm characteristics as independent variables. Specifically, we regress the natural log of the dollar value of statewide (or regional) simulated losses from storms on three physical measures of storm severity – the natural logs of (1) 30 minus the central pressure at the eye of the storm, (2) the forward velocity of the storm, and (3) the radius to maximum wind speed. The variable "30-central pressure" is expected to be positively associated with storm damages since wind speeds are typically greater as the difference between the barometric pressure at the eye of the storm and the pressure on the periphery of the storm increases. The forward velocity of the storm is hypothesized to be negatively related to the amount of storm damage since fast moving storms have less time to cause damage in any given region. Finally, we hypothesize that the radius to maximum wind speed variable will be positively associated with storm damages because larger storms impact a wider area, thus exposing more structures to the damaging effects of wind. Also included in the regressions are dummy variables for each 50-mile segment of coastline where the storm is predicted to make landfall. These variables are designed to proxy for the value of property directly exposed to the storm as it makes landfall.

Our estimated regression equation could be used to generate a parametric index of storm damages to serve as the payoff trigger for index-linked CAT options. The procedure would be to compute a fitted value of the predicted loss from a hurricane by inserting the three storm severity indicators into the regression equation. This would produce a storm severity index that would be independent of insurer-reported storm damage estimates.

4. Results of the Empirical Tests

In this section, we present the results of our empirical analysis of hedging effectiveness using index-linked CAT securities, the regression analysis of the determinants of hedging effectiveness, and the proposed parametric index. We begin the section by providing a more detailed discussion of the sample, the hurricane simulation results, and the loss indices.

The Sample

As mentioned above, the first step in our empirical analysis was to obtain data on the value of property exposed to catastrophic loss in Florida. The data we use in the study are provided by the Florida Insurance Commissioner and reflect exposures in 1998. The data base includes 255 of the 264 property insurers operating in Florida in that year, accounting for 93 percent of the insured residential property values in the state.[23] Thus, the study applies to hedging effectiveness for residential property insurance.[24] The total value of insured residential property exposed to loss in Florida in 1998 was $764 billion.

More details on the sample are provided in Table 3. The table shows that the distribution of exposures across the companies in the industry is highly skewed, with the top quartile of insurers accounting for 88 percent of insured exposure in the state. This is important from a public policy perspective because larger insurers are expected to be able to hedge more effectively than smaller firms. Thus, even though some individual firms may not be able to reduce risk significantly by trading in index-linked derivatives, a high proportion of the total exposure in the state is likely to be subject to effective hedging.

Larger firms tend to have their exposures dispersed across a wider range of counties than smaller firms, an indicator of better diversification. On average, firms in the top quartile have exposures in 58 of the 67 counties in Florida, compared with 44, 29, and 12 counties for insurers in the second, third, and fourth size quartiles. Larger firms also tend to be more diversified in terms of the coefficient variation of the market share across counties and in terms of the county market share Herfindahl index. This provides further evidence suggesting that larger firms will be able to hedge more effectively than smaller insurers**.**

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[23]The residential data include coverage under the following types of property insurance policies: apartment buildings, condominium associations, condominium unit owners, dwelling fire and allied line, farmowners, homeowners, mobile homes, and tenants policies. Data were not available on commercial property exposures.

[24]This is the type of insurance with the most significant catastrophic risk problem because business firms are better able to search the market for insurance coverage and have access to alternative hedging mechanisms such as captive insurance companies.

Simulation Results and CAT Loss Indices

The second step in the analysis is to simulate county-level losses for the insurers in the sample using the AIR model. We initially simulated 10,000 years of hurricane experience. In order to reduce the time required to perform the optimization analysis, we base most of the analysis on a random sample of 1,000 years of experience from the simulated 10,000 year data base. Robustness checks based on conducting the optimization using the full 10,000 years of experience for a random sample of 10 insurers revealed that virtually no accuracy is lost by basing most of the analysis on the 1,000 year random sample of events.

The simulations produce the variables L_{jkrt} = hurricane losses for company j, in county k, located in intra-state region r, for simulation year t, where j = 1, . . . , 255, k = 1, . . . , 67, r = 1, . . . , 4, and t = 1, . . . , 10,000 (as indicated, the maximum value of t equals 1,000 for most of the analysis). The simulated losses are then used to construct the following loss indices:

$$\text{(13)} \qquad The\ \text{"}Perfect\text{"}\ Index = L^{P}_{j\cdot\cdot t} = \sum_{r=1}^{R} \sum_{k=1}^{K_r} L_{jkrt}$$

$$\text{(14)} \qquad The\ Regional\ Indices = L^{R}_{\cdot\cdot rt} = \sum_{j=1}^{N} \sum_{k=1}^{K_r} L_{jkrt}$$

$$\text{(15)} \qquad The\ State\ Index = L^{S}_{t} = L_{\cdot\cdot\cdot t} = \sum_{r=1}^{R} \sum_{k=1}^{K_r} \sum_{j=1}^{N} L_{jkRt}$$

where N = the number of insurers (255), R = the number of regions (4), K_r = the number of counties in region r, and a dot in place of a subscript means that a summation has been taken over that subscript. Hedge portfolios are formed for each insurer to determine the basis risk for each index.

Non-Linear (Call Spread) Hedging

The non-linear hedging analysis assumes that insurers form hedge portfolios consisting of their own losses and a position in call option spreads on loss indices. The hedge ratios and option strike prices are then chosen to minimize a criterion function subject to a cost constraint. I.e., insurers form portfolios with payoff functions specified in equations (6), (7), and (8) and solve the optimization problem given in expression (9). The objective criteria to be minimized are the variance, the value at risk (VaR), and the expected exceedence value (EEV) of the insurer's net loss liabilities, where net loss liabilities are defined as unhedged loss liabilities minus the payoff on the hedge. The cost constraints are specified as percentages of the insurer's expected Florida homeowners losses, ranging from 5 percent to 50 percent. By varying the cost constraint, an efficient frontier is generated based on each of the criteria. To focus purely on basis risk, most of the analysis is conducted under the assumption that hedging contracts are available at prices equal to the expected losses under the contracts, i.e., the expected recovery from the hedge. We also report robustness tests based on the assumption that the options are available at expected cost plus a risk premium.

We first consider the effect of non-linear hedging on the variance of the insurer's net loss. Before presenting the results for the overall sample, we give examples of hedging effectiveness for a diversified insurer and an undiversified insurer. The diversified insurer has an exposure distribution across the state very similar to the industry-wide exposure distribution. The undiversified insurer has 92 percent of its exposure to loss concentrated in two of the four intra-state regions. The variance reduction of the diversified insurer is shown in Figure 2A. This insurer can hedge with about 91 percent efficiency (defined as the variance reduction of the index hedge divided by the variance reduction of the perfect hedge) using the statewide index and with about 96 percent efficiency using the regional indices, showing the benefits of holding a diversified underwriting portfolio. The variance reduction for the undiversified insurer is shown in Figure 2B. This insurer can hedge with only about 23 percent efficiency using the statewide index, but it can hedge with about 97 percent efficiency using the regional indices. Thus, even relatively undiversified insurers can benefit from intra-state hedging.

Figure 3 shows the variance-reduction frontiers based on non-linear hedges for the insurers in the largest size quartile, obtained by varying the cost constraint. Each point on the frontier is obtained as an unweighted average of the percentage variance reduction across the firms in the top quartile for each specified cost constraint. The figure compares frontiers based on the perfect hedge, the state hedge, and the regional hedge. The results confirm that hedging with the regional loss indices is more effective than hedging using the state loss index. In fact, the variance reduction using the regional hedge is closer to that given by the perfect hedge than to the variance reduction based on the statewide hedge. For example, an expenditure of 10 percent of expected losses reduces the net loss variance by 28 percent using the statewide hedge, 38 percent using the regional hedge, and 40 percent using the perfect hedge. Thus, the basis risk of the regional hedge is not very large and might be worth incurring in order to avoid the moral hazard inherent in the perfect hedge.

The average variance reduction frontiers for insurers in the four size quartiles based on the regional hedge are shown in Figure 4. Perhaps the most surprising result is that the frontiers in the two largest size quartiles are almost indistinguishable. Thus, the insurers in the top two quartiles can hedge with about equal effectiveness using the regional loss indices, and the quartile 3 results are almost as good. Again, this suggests that it is not size per se but rather diversification that determines hedging effectiveness, at least for insurers in the top three size quartiles. As expected, the degree of variance reduction is noticeably less for insurers in the fourth size quartile.

To provide additional information on basis risk for the sample insurers, Figure 5 shows the frequency distribution of the variance-reduction hedge efficiency for an expenditure of 25 percent of expected losses.[25] The most striking result is that the regional hedge is at least 90 percent as effective as the perfect hedge in terms of reducing loss volatility for 152 of the 255 firms in the sample and at least 85 percent efficient for 189 of the 255 sample firms. These results provide further evidence that the degree of basis risk from index

[25]The results for other expenditure levels are comparable and thus not shown. Recall that hedge efficiency is defined for the variance reduction criterion as the ratio of the variance reduction using the statewide and regional hedges to the variance reduction under the perfect hedge.

hedging may be sufficiently small to make index hedging attractive for the majority of Florida insurers.[26] The statewide hedge is at least 80 percent as effective as the perfect hedge for 87 of the 255 firms.[27]

We next consider the other two hedging criteria – the value at risk (VaR) and expected exceedence value (EEV). Since the analyses of these two criteria lead to the similar conclusions and the EEV has more desirable theoretical properties than the VaR (Artzner, et al. 1999), we focus the discussion on the EEV.[28] Recall that the EEV is the expected loss, conditional on losses exceeding a specified threshold (see equation (11)). To calculate the EEV, we selected a threshold for each insurer equal to 97.5-th percentile of its unhedged loss distribution. Hence, our analysis is equivalent to minimizing the EEV above the $VaR_j(0.025,L_j)$, i.e., above the 2.5 percent VaR for the jth insurer's unhedged loss distribution. Although the choice of an EEV threshold is inevitably somewhat arbitrary, the 97.5 percentile is likely to be relevant because it corresponds to an industry loss in Florida of about $13.5 billion. Thus, the assumption in using this threshold is that insurers are hedging large losses, in the range of Hurricane Andrew and above. This seems to be an appropriate objective given the general lack of availability of reinsurance for losses of this magnitude (SwissRe 1997). The value of the expected CAT loss above the 97.5 percentile to the total expected CAT loss ranges monotonically from 19 percent for firms in the first quartile to 31 percent for firms in the fourth quartile. Thus, hedges based on this threshold also have the potential to significantly reduce the insurers' overall expected losses from catastrophes.

The expected exceedence value (EEV) reduction frontiers for the firms in the largest size quartile are shown in Figure 6.[29] The results again support the conclusion that insurers in the top size quartile can

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[26]These 152 firms account for 93.7 percent of the total property exposure of the sample insurers.

[27]These 87 firms account for 76.9 percent of the total property exposure of the sample insurers.

[28]The VaR results are available from the authors on request.

[29]Given the loss threshold for the largest insurers, the EEV using the perfect hedge is reduced to zero at an expenditure of approximately 25 percent of the expected loss for all insurers in the top size quartile. This does not imply that these insurers can suffer no loss from large events because the EEV is an expected value criterion

hedge effectively using the regional loss indices. For example, a 50 percent reduction in the EEV can be obtained at a cost of about 7.5 percent of expected losses with the perfect hedge and about 8.5 percent of expected losses for the regional index hedge. A comparable reduction costs about 12.5 percent of expected losses under the statewide hedge.

Further information on EEV reduction is provided in Figure 7, which shows the frequency distribution of insurers based on EEV-reduction hedge efficiency for a cost constraint equal to 25 percent of expected losses. The results show that the regional index hedge is at least 95 percent efficient for 66 of the 255 insurers in the sample and at least 90 percent efficient for 109 insurers. The state index hedge is at least 90 percent as effective as the perfect hedge for 31 of the insurers in the sample. Insurers that can hedge with at least 90 percent efficiency account for 78.9 percent of the total insured residential property value in Florida for the regional hedge and 48.2 percent for the statewide hedge. Hence, even the statewide hedge, which is relatively inefficient for the majority of insurers, still seems viable if the objective is to hedge the CAT risk for a high proportion of the exposed value in the state.

Linear Hedging

In the linear hedging analysis, we follow the standard approach of forming a hedge portfolio consisting of a linear combination of the insurer's own prospective catastrophe losses (analogous to a cash position) and an appropriate loss index (analogous to a futures position). The insurer is assumed to form a hedge portfolio at time 0 which settles at time t = 1 year. We solve for the hedge ratio that minimizes the variance of the hedge portfolio. The hedge effectiveness for the insurers in the sample is then compared for alternative loss indices. The analysis uses the standard variance minimizing hedge ratio (Ederington 1979), i.e., $h_i = Cov(L_{it},I_t)/Var(I_t)$ and the standard measure of variance reduction $(Cov(L_{it},I_t)^2/[Var(Li_t)Var(I_t)]$, where h_i = the variance minimizing hedge ratio for insurer i, I_t = the index, L_{it} =losses of insurer i, and Cov(.)

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and losses obviously can occur that exceed the expected value. A similar result occurs for insurers in the second-largest size quartile but not for insurers in the two smallest size quartiles. The reason is that the loss distributions of smaller insurers are relatively more skewed because they are not as well diversified as larger firms.

and Var(.) are the covariance and variance operators, respectively. We solve simultaneously for four hedge ratios when the intra-state loss indices are used.

The linear hedging analysis shows that insurers in the top three size quartiles can reduce their loss variance by 93 percent, 92 percent, and 85 percent, respectively, using the intra-state loss indices, but by only 65, 59, and 49 percent, respectively, using the statewide index. Thus, insurers in the top three size quartiles can hedge effectively using the intra-state indices but not the statewide index. Hedging is significantly less effective for insurers in the smallest size quartile – these firms can reduce loss variance by 67 percent using the intra-state indices and by only 37 percent using the statewide index. Thus, hedging effectiveness is positively related to firm size and may not be viable for firms in the smallest size quartile.

Insurer Characteristics and Hedge Effectiveness

The regressions to analyze the determinants of hedging effectiveness are presented in Table 4. The dependent variable in the regressions is hedge efficiency using non-linear hedge portfolios, i.e., the ratios of the effectiveness of index hedges to the effectiveness of perfect hedges, $HE_{jmk}^{i} / HE_{jmk}^{P}$, where i = S for the statewide hedge and R for the regional hedge and HE_{jmk}^{i} is hedging effectiveness (see equation (12)) for insurer j using criterion m for cost constraint k. Thus, the variables differ across insurers and across cost constraints. Regressions based on the variance reduction and EEV reduction criteria are shown in the table.[30]

To test the hypotheses specified above, the equations include a dummy variable equal to 1 for mutuals and 0 for stocks, a dummy variable equal to 1 for unaffiliated single insurers and 0 for members of groups, a leverage variable equal to the insurer's liabilities-to-assets ratio, and dummy variables representing Florida size quartiles (based on insured value exposed to loss), and overall firm size quartiles (based on assets). Other independent variables in the equations include the proportion of loss exposure in ocean front counties and the coefficient of variation of the insurer's county market shares. As control variables, we include dummy variables for the ten cost constraints (ranging from 5 to 50 percent in increments of 5

[30]The VaR results are similar and are available from the authors.

percent). Because a dummy variable is included for each cost constraint, the intercept in the equations is suppressed. All regressions are estimated using the maximum likelihood Tobit procedure because the dependent variable ranges between 0 and 1.

The regression results provide support the hypothesis that mutuals can hedge more efficiently than stocks. Although the mutual dummy variables are insignificant in the statewide index regressions, they are positive and significant in the regional regressions. We consider the regional regressions to be more relevant than the state regressions because it is clear that the statewide index provides a less effective hedge than the regional indices. The leverage variable is positive and significant in all regressions, providing strong support for the hypothesis that insurers with greater degrees of leverage have a stronger incentive to diversify geographically across the state. The results are mixed for the unaffiliated single insurer dummy variable. The variable is negative and significant in both the statewide variance and statewide EEV reduction regressions. However, this dummy variable is positive and significant in both regional regressions. Again, because we consider the regional regressions more relevant, on balance the results tend to support the hypothesis that unaffiliated firms are more diversified.

Florida market share quartile dummy variables are included for the three largest size quartiles, based on exposure to loss. These variables are all positive and significant, implying that firms in the three largest quartiles can hedge more efficiently than firms in the smallest size quartile using both statewide and regional hedges. Thus, firms in the smallest quartile may not be economically viable in the long-run.

The dummy variables for the two largest asset size quartiles are positive and significant in the statewide EEV regressions but insignificant in all others. The third asset size quartile variable is insignificant in all regressions. Thus, we find only limited support for the hypothesis that larger firms practice more effective risk management.

The results provide consistent support for the hypotheses about other determinants of hedging effectiveness. The percentage of exposures in ocean front counties is statistically significant with a positive coefficient in all four regressions shown in Table 4, consistent with the hypothesis that insurers with relatively high ocean front exposure can hedge more effectively. The coefficient of variation of county market share has a significant negative coefficient in all four equations, consistent with the hypothesis that more diversified insurers can hedge more effectively.

Entering dummy variables for all cost constraints in effect estimates a separate intercept for each cost constraint. The first issue to be investigated using the intercepts is whether regional hedges are more efficient than statewide hedges, other things equal. The intercepts are about twice as high in the regional regressions than in the statewide regressions, providing strong evidence that regional hedges are more efficient than statewide hedges, other things equal.

The second issue to be investigated using the intercepts is whether hedge efficiency is a function of the level of expenditure on the hedge. (Recall that our efficiency measure compares index hedge performance to the performance of the perfect hedge, conditional on the level of expenditure on hedging.) To analyze this question, we conducted likelihood ratio tests of the null hypothesis that the intercepts within each equation are equal across cost constraints. The test statistics are shown in the last line of Table 4. The hypothesis that the intercepts are equal is rejected at the 5 percent level in the statewide variance efficiency regression and at the 1 percent level in both the statewide and regional EEV efficiency regressions. The hypothesis is not rejected in the regional variance efficiency regression. Thus, it appears that hedge efficiency is significantly related to the level of expenditures for variance and EEV hedging with the statewide index and for EEV hedging using the intra-state indices, with the largest expenditure levels generally being the most efficient.

Hedging at Recent Market Prices

The analysis so far has been conducted under the assumption that call spread contracts are available at actuarially fair prices equal to the expected loss under the contracts. The rationale for this approach is that catastrophic loss contracts should be priced close to their actuarial value in informationally efficient, liquid securities markets, provided that catastrophic losses do not have systematic risk.[31] However, because most catastrophic risk derivatives issued to date have been sold at prices in excess of the expected actuarial losses, we also conduct our non-linear hedging analysis under the assumption that CAT security prices are actuarially unfair. We base the analysis on the recent market prices for CAT bonds and CBOT call spreads shown in Table 1.

The contractual forms in the non-actuarial analysis are identical to those used in the non-linear hedging analysis above, the only difference being that the contracts analyzed in this section are priced at a markup over the expected loss. The perfect hedge contracts are analogous to CAT bonds, whereas the index hedge contracts are analogous to CBOT options. Accordingly, the perfect hedge contracts are assumed to be sold at a premium-to-expected-loss ratio of 6.8 and the index hedge contracts are assumed to be sold at a premium-to-expected-loss ratio of 2.1, matching the median risk premia shown in Table 1.

The results of the non-actuarial hedging analysis are shown in Table 6. The table shows the ratios of hedge effectiveness using market price contracts to the hedge effectiveness that could be achieved using actuarially priced contracts, for each of the ten cost constraints used in our analysis. The ratios in the table are unweighted averages based on a stratified (by size quartile) sample of the firms in our data base. A sample of size twelve was selected, with three firms chosen randomly from each size quartile. Because the results under different hedging strategies lead to the same conclusions, only the expected exceedence value (EEV) results are shown in Table 6.

The results in show that insurers can still significantly reduce their EEVs using index hedging even when option pricing is non-actuarial. However, as expected, hedge effectiveness is reduced in comparison with actuarially fair pricing. For example, if expenditures on hedging are constrained to 25 percent of expected losses, the market priced perfect hedge reduces the EEV by only 20 percent of the perfect hedge

[31] Evidence that catastrophic risk contracts do not have systematic risk is presented in Litzenberger, Beaglehole, and Reynolds (1996).

EEV reduction that could be obtained with actuarial prices. The results with the state and regional hedges are better because the markup over the actuarial price is significantly less than for the perfect hedge contracts. With the 25 percent cost constraint, the market price hedge reduces the EEV by 63 percent of the reduction that could be achieved using actuarially priced contracts, and the comparable reduction for the regional hedge is 65 percent.

The size of the markup over expected losses is obviously critical in determining the hedging effectiveness of insurance derivative contracts. Such contracts must compete with excess of loss reinsurance - the traditional hedge for insurers facing CAT loss exposure. Interestingly, the markups on the insurance derivative contracts shown in Table 1 are consistent with markups on catastrophe reinsurance contracts. Froot and O'Connell (1999) show that price-to-loss ratios during the late 1980s and early 1990s for excess of loss property reinsurance contracts ranged from about 1.5 in 1987, to 3.0 in 1992, and to 7.0 in 1994, all in the same range as the price-to-loss ratios in Table 1. Thus, CAT derivatives may be price-competitive with reinsurance even with the relatively high markups in today's CAT derivatives market.

The price-to-loss ratios on insurance derivatives can be expected to decline relative to reinsurance as the market becomes more mature. Reinsurance is sold by firms that have limited capital and are averse to insolvency risk; whereas CAT loss derivatives are closer to being pure financial instruments, not dependent upon the solvency or capitalization of any specific firm or industry. Consequently, CAT loss securities are more likely to approach actuarial fairness than reinsurance, particularly for mega-CATs that would significantly stress the capacity of world insurance markets.

There are three primary conclusions from the non-actuarial pricing analysis: (1) Hedging with CAT options and bonds is less effective under non-actuarial pricing, but the non-actuarial hedges still lead to significant reductions in insurer risk. This conclusion is reinforced by observing that price-to-expected loss ratios in the CAT securities market are comparable to those in the reinsurance market. (2) If index contracts continue to be priced significantly lower than insurer-specific contracts, index contracts may come to dominate CAT bonds as CAT securities markets become more liquid. The net result will depend upon the tradeoff between moral hazard and transactions costs (disadvantages of insurer-specific contracts) versus basis risk (the principal disadvantage of index-linked contracts). If, as our results show, intra-state regional contracts can be used to construct hedges with low basis risk for most insurers, the argument for index-linked contracts becomes compelling. (3) The insurance-linked securities market is likely to dominate the reinsurance market for the hedging of mega-CATs if the price-to-loss ratios approach actuarial fairness.

A Parametric Index

As discussed above, our proposed parametric index is based on a regression model with dependent variable equal to the log of storm damages and independent variables consisting of the logs of three physical measures of storm characteristics. The regression model, shown in Table 5, was estimated using data on the 867 hurricanes resulting from the 1,000 simulated years used in most of the analysis. As hypothesized, the "30 minus central pressure" variable is positively associated with the amount of damage caused by a storm, consistent with the hypothesis that the difference in barometric pressure between the eye and periphery of the storm is associated with higher wind speeds. Likewise, the forward wind speed variable is negatively associated with storm damage, as expected if storms that move more rapidly through a geographical area cause less damage. Finally, the log of the radius to maximum wind speed of the storm is positively associated with the degree of storm damage, consistent with the hypothesis that larger storms expose more structures to wind damage.[32]

The regression model provides an excellent fit to the storm damage data, explaining more than 90 percent of the variability in the hurricane damages. The goodness-of-fit of the model is illustrated in Figure

[32]Also included in the regression but not shown are dummy variables for the area along the coast where the storm first makes landfall. All but two of the landfall segment dummy variables are statistically significant and an F-test leads to rejection of the hypothesis that the landfall segment variables are jointly equal to zero. There are 20 landfall segments in Florida. However, there are 31 landfall segments in our sample because storms can make landfall in another state such as Georgia and cause damage in Florida as the storm moves inland. Therefore, thirty landfall segment dummy variables are included in the regression.

8, which plots the log of the predicted value of storm damage from the model against the storm damage amounts. The plotted points adhere closely to the 45° line representing equality between the actual and predicted storm damage. As expected given the goodness-of-fit of the model, linear and non-linear hedges using the predicted values from the model as the loss index perform almost identically with the statewide loss index. Hedging with parametric models fitted to losses by region comes equally close to replicating the results with the actual regional loss indices.

The principal advantage of a parametric model is to reduce the possibility of moral hazard.[33] Because the predicted loss values from our regression model depend only upon physical characteristics of the storm and the regions where it makes landfall, there is no incentive for insurers to over-report losses in an attempt to increase recoveries if the parametric model were used to determine option settlements. The goodness-of-fit of the model indicates that insurers could hedge almost as effectively using the model as they could using monetary loss indices.[34]

5. Conclusions

The securities market has responded to the dramatic increase in catastrophe losses over the last decade by developing innovative new derivative securities to finance catastrophic loss. The introduction of insurance-linked securities also has been driven by the increasing recognition that conventional insurance

[33]Another potential advantage of contracts with payoffs based on parametric criteria is that they settle sooner following an event to the extent that the parametric measurements are available prior to the end of the loss development periods of contracts based on monetary losses. Although most parametric measures (such as the Richter scale magnitude of an earthquake) are available almost immediately following an event, others, such as the radius of maximum wind speed of a hurricane, take longer to resolve, potentially blunting the settlement-time advantages of some parametric contracts.

[34]Of course, like the other tests conducted in this paper, the parametric index tests are subject to "model risk," i.e., the risk that the AIR model results will not perfectly correlate with actual storm damage, thus creating an additional source of basis risk. We do not believe that this additional basis risk is sufficient to prevent the effective use of our parametric model, due to the extensive reliability testing the AIR model has undergone and its widespread acceptance by insurers. Given the number of actual catastrophic events that have occurred since the first version of the model was introduced in 1987, it would be unlikely that insurers and other users of the model would still have confidence in it if the model risk were significant.

and reinsurance markets do not provide efficient mechanisms for financing losses from low frequency, high severity events. CAT-risk securities are a particularly interesting example of a new type of derivative where the underlying is not a traded asset or commodity, so that prices are not observed. Thus, CAT securities are analogous to other new derivatives with "exotic underlyings," such as weather derivatives.

The two most prominent types of CAT securities are the CBOT CAT option call spreads and CAT bonds. The call spreads settle on indices of industry-wide catastrophic property losses in various regions of the U.S., while most CAT bonds settle on the losses of specific insurers. CAT options are superior to CAT bonds in having lower transactions costs and less exposure to moral hazard. However, hedgers have been skeptical about CAT options because the resulting hedges are exposed to an unknown degree of basis risk. This paper responds to this concern by providing new information on the basis risk of CAT index options. In addition, we test hypotheses about the relationship between insurer characteristics and revealed-preferences for geographical diversification of exposure to loss.

The study proceeds in five principal stages: (1) We obtained data on the country-level exposure to catastrophic property loss for 255 insurers accounting for 93 percent of insured residential property exposure in Florida in 1998. (2) We simulated 10,000 years of catastrophic property losses by county for each insurer in the sample using a sophisticated catastrophic loss model developed by Applied Insurance Research (AIR). (3) Hedge portfolios are specified for the insurers in the sample and hedge effectiveness is analyzed for a statewide catastrophic loss index and four intra-state regional indices. (4) Regression analysis is conducted to test hypotheses about the relationship between insurer characteristics and hedging effiency. And (5) a parametric index is developed that breaks the link between the losses of specific insurers and the payoff trigger of insurance-linked security contracts.

In our hedging analysis, we form portfolios consisting of a short position in insurer loss liabilities and a long position in call option spreads on loss indices. Three indices are analyzed – a "perfect" index consisting of the insurer's own losses, a statewide industry loss index, and four intra-state regional industry loss indices obtained by dividing the state into four quadrants. Three criterion functions are minimized, subject to cost constraints – the variance of the insurer's net (of hedging) losses, the value at risk (VaR), and the expected exceedence value (EEV), defined as the expected catastrophic loss conditional on the loss exceeding a specified threshold. We gauge hedging effectiveness by comparing hedges based on the statewide and intra-state indices with perfect hedges based on each insurer's own losses and define *hedge efficiency* as the ratio of the risk reduction obtained using industry loss index options to the risk reduction obtained using the perfect index.

The principal finding is that firms in the three largest Florida market-share quartiles can hedge almost as effectively using intra-state index contracts as they can using perfect-hedge contracts. For example, the hedges based on intra-state index contracts are at least 90 percent as effective as the perfect hedge in terms of reducing loss volatility for 152 of the 255 firms in the sample and at least 85 percent as effective for 189 of the 255 sample firms. Hedging with the statewide contracts, on the other hand, is effective only for insurers with the largest state market shares and insurers that are highly diversified throughout the state. Thus, the intra-state contracts hold significant promise for the development of a more liquid market for insurance-linked securities. Hedging with intra-state contracts also offers insurers and policy makers a solution to the catastrophic risk financing problem in Florida because the 152 firms that can hedge with at least 90 percent efficiency account for 93.7 percent of the residential property exposure in the state. The findings with regard to the intra-state contracts are also important because an index-contract market based on smaller geographical areas such as counties or zip codes would likely encounter high transactions costs and low liquidity in comparison with our more broadly defined intra-state indices.

The analysis of the determinants of hedging efficiency supports the hypotheses that mutual insurers can hedge more efficiently than stock firms and that unaffiliated single firms can hedge more efficiently than insurers that are members of groups. We argue that mutuals are more diversified than stocks because both the owners and managers of mutuals are averse to insolvency risk. Unaffiliated firms are more diversified than members of groups because they do not have access to the capital of other group members if they suffer a loss shock and do not have the benefit of diversifying risk with other affiliated firms. Finally, highly leveraged firms tend to be more diversified than better-capitalized firms consistent with the hypothesis highly leveraged firms have less capacity to bear risk. The evidence also supports the hypothesis that large firms practice more effective risk management than smaller firms, consistent with the view that it is more efficient for large insurers to incur the fixed and variable costs of acquiring risk management expertise. Firms in the three largest Florida market share quartiles can hedge more efficiently than firms in the smallest market share quartile, raising doubts about the long-run viability of the fourth-quartile insurers.

As expected, hedging with contracts that are sold at mark-ups over the expected loss is less efficient than hedging using contracts sold at actuarially fair prices. Even at the current markups in the CAT securities market, however, insurance-linked securities are competitive with conventional reinsurance in terms of price and hedging effectiveness. Moreover, mark-ups in the CAT securities market can be expected to decline as investors acquire more experience with these contracts and the market becomes more liquid. CAT loss securities could come to dominate reinsurance for hedging low frequency, high severity events if prices converge towards actuarial fairness.

Because there is still some concern about moral hazard in the use of loss-indexed securities, we also estimate a parametric loss index by regressing losses from the hurricanes in our sample against three physical measures of storm severity. The resulting model explains more than 90 percent of the variation in hurricane losses and appears to be unbiased for losses of all magnitudes. Either this index or similar indices could be used to reduce insurer and investor concerns about moral hazard.

Overall, our analysis suggests that insurance-linked securities based on exchange-traded, index-linked contracts could be used effectively by insurers in hedging catastrophic risk. This is important given the inefficiency of the global reinsurance market in dealing with this type of loss. Hedging of catastrophic risk has the potential to avoid the destabilization of insurance markets resulting from a major event; and with more widespread trading, insurance-linked securities would play a price-discovery role, potentially smoothing the reinsurance underwriting cycle. The more widespread trading of insurance-linked securities would allow investors to shift the efficient frontier in a favorable direction by further diversifying their portfolios using these zero-beta assets.

A final conclusion has to do with the management of insurers. It is clear from our analysis that a significant proportion of firms in the industry are well-positioned to avoid costs of financial distress by hedging the risk of catastrophic loss. However, it is also clear that too many firms are poorly diversified and in the position to be hit hard by a major catastrophe. Diversification of the underwriting portfolio is equally important as diversification of the investment portfolio, and the managers of many insurers needs to pay more attention to the former type of diversification.

Table 1

Premium to Expected Payout: Florida CBOT Options and CAT Bonds

A. Florida CBOT Call Spreads

Date	Contract	Premium	Lower Strike	Upper Strike	No. of Contracts	Prem to E[Payout]
Feb-96	Sept/Dec	10,000	80	100	10	6.30
Aug-96	Sept	3,600	40	60	10	1.64
Aug-96	Sept	2,400	40	60	10	1.09
Jul-97	Sept/Dec	69,120	80	100	216	2.01
Jul-97	Sept/Dec	13,600	80	100	40	2.14
Jul-97	Sept/Dec	13,600	80	100	40	2.14
Jul-97	Sept	2,200	100	120	10	2.80
Jul-97	Sept	1,200	100	120	5	3.06
Aug-97	Sept/Dec	8,500	80	100	25	2.14
Sep-97	Sept	1,300	100	120	5	3.31
Dec-97	Dec	600	80	100	30	0.42
Dec-97	Dec	700	80	100	30	0.49
					Average	2.30
Source: Chicago Board of Trade and Applied Insurance Research					**Median**	2.14

B. Catastrophe (CAT) Bond Issues

Date	Transaction Sponsor	Spread Premium	Prob of 1st $ of Loss	E[L | L >0]	Expected Loss	Prem to E[Loss]	Risk
Mar-00	SCOR	2.7%	0.19%	57.89%	0.11%	24.55	Eathquake, Windstorm
Mar-00	SCOR	3.70%	0.29%	79.31%	0.23%	16.09	Eathquake, Windstorm
Mar-00	SCOR	14.00%	5.47%	59.23%	3.24%	4.32	Eathquake, Windstorm
Mar-00	Lehman Re	4.50%	1.13%	64.60%	0.73%	6.16	Earthquake
Nov-99	American Re	2.95%	0.17%	100.00%	0.17%	17.35	Hurricane & Earthquake
Nov-99	American Re	5.40%	0.78%	80.77%	0.63%	8.57	Hurricane & Earthquake
Nov-99	American Re	8.50%	0.17%	100.00%	0.17%	50.00	Hurricane & Earthquake
Nov-99	Gerling	4.50%	1.00%	75.00%	0.75%	6.00	Earthquake
Jun-99	Gerling	5.20%	0.60%	75.00%	0.45%	11.56	Hurricane: Multiple Event
Jun-99	USAA	3.66%	0.76%	57.89%	0.44%	8.32	Single Hurricane
Jul-99	Sorema	4.50%	0.84%	53.57%	0.45%	10.00	Earthquake, Typhoon
Jul-98	Yasuda	3.70%	1.00%	94.00%	0.94%	3.94	Typhoon
Mar-99	Kemper	3.69%	0.58%	86.21%	0.50%	7.38	Earthquake
Mar-99	Kemper	4.50%	0.62%	96.77%	0.60%	7.50	Earthquake
May-99	Oriental Land	3.10%	0.64%	66.04%	0.42%	7.35	Earthquake
Feb-99	St. Paul/ F&G Re	4.00%	1.15%	36.52%	0.42%	9.52	Aggregate Cat
Feb-99	St. Paul/ F&G Re	8.25%	5.25%	54.10%	2.84%	2.90	Aggregate Cat
Dec-98	Centre Solutions	4.17%	1.20%	64.17%	0.77%	5.42	Hurricane: Multiple Event
Dec-98	Allianz	8.22%	6.40%	56.41%	3.61%	2.28	Windstorm and Hail
Aug-98	X.L./MidOcean Re	4.12%	0.61%	63.93%	0.39%	10.56	Cat: Multiple Event
Aug-98	X.L./MidOcean Re	5.90%	1.50%	70.00%	1.05%	5.62	Cat: Multiple Event
Jul-98	St. Paul/ F&G Re	4.44%	1.21%	42.98%	0.52%	8.54	Aggregate Cat
Jul-98	St. Paul/ F&G Re	8.27%	4.40%	59.09%	2.60%	3.18	Aggregate Cat
Jun-98	USAA	4.16%	0.87%	65.52%	0.57%	7.30	Single Hurricane
Mar-98	Centre Solutions	3.67%	1.53%	54.25%	0.83%	4.42	Hurricane: Multiple Event
Dec-97	Tokio Marine & Fire	2.09%	1.02%	34.71%	0.35%	5.90	Earthquake
Dec-97	Tokio Marine & Fire	4.36%	1.02%	68.63%	0.70%	6.23	Earthquake
Jul-97	USAA	5.76%	1.00%	62.00%	0.62%	9.29	Single Hurricane
Aug-97	Swiss Re	2.55%	1.00%	45.60%	0.46%	5.59	Earthquake
Aug-97	Swiss Re	2.80%	1.00%	46.00%	0.46%	6.09	Earthquake
Aug-97	Swiss Re	4.75%	1.00%	76.00%	0.76%	6.25	Earthquake
Aug-97	Swiss Re	6.25%	2.40%	100.00%	2.40%	2.60	Earthquake

Source: Goldman Sachs & Co. **Premium/E[Loss] Average = 9.00; Median = 6.77.**

Table 2
Simulating Insured Losses Using the AIR Model

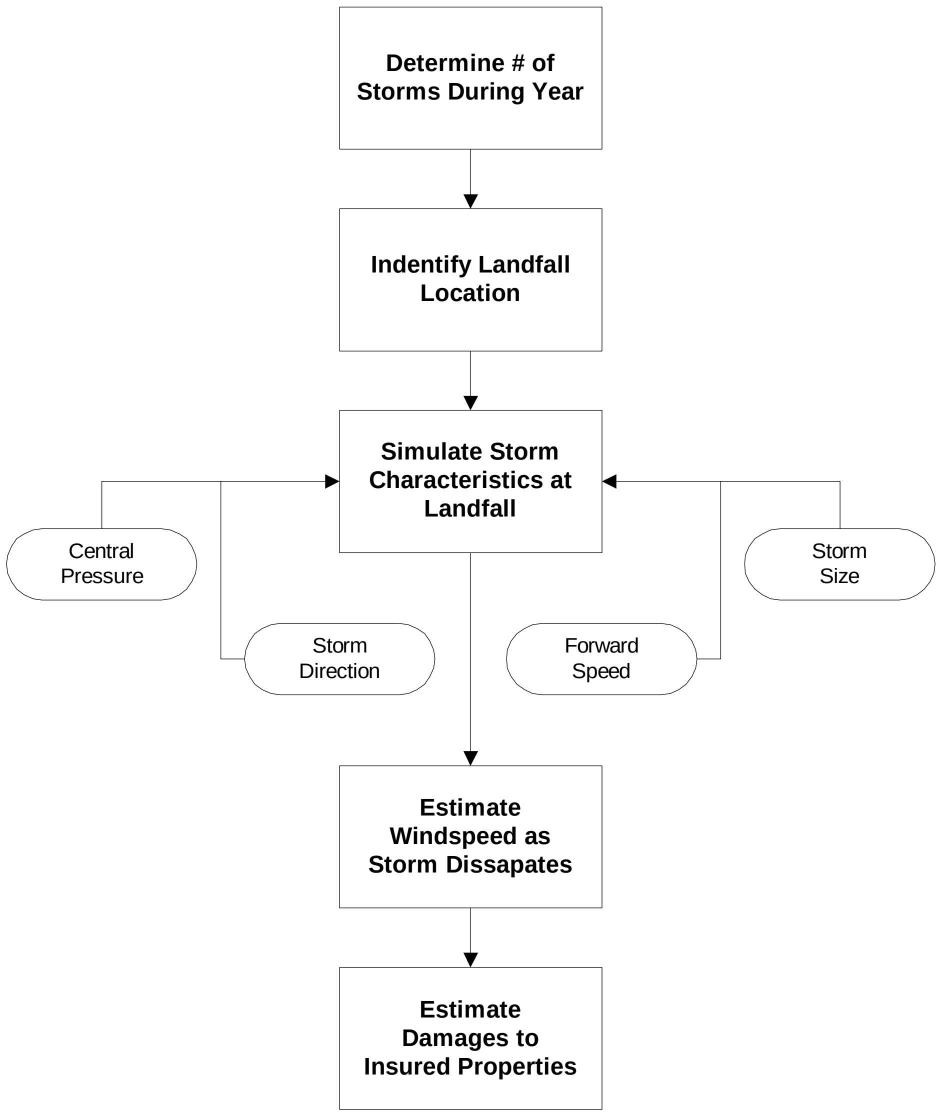


Table 3
Summary Statistics 1998 Florida Insurer Exposure Database

Variable	Size Quartile	Average	Std. Deviation	Minimum	Maximum
Statewide Exposure Limits	1	10,488,076,940	27,023,882,691	947,613,000	197,123,513,015
	2	489,399,825	209,101,097	212,101,944	917,368,990
	3	87,212,264	55,098,625	21,396,000	206,663,000
	4	6,603,762	7,059,451	1,000	21,090,000
	All Insurers	2,778,651,509	14,183,583,447	1,000	197,123,513,015
Statewide Market Share	1	1.373%	3.538%	0.124%	25.810%
	2	0.064%	0.027%	0.028%	0.120%
	3	0.011%	0.007%	0.003%	0.027%
	4	0.001%	0.001%	0.000%	0.003%
	All Insurers	0.364%	1.857%	0.000%	25.810%
Number of Counties with Exposure	1	58.344	11.360	15.000	67.000
	2	44.234	14.777	9.000	67.000
	3	29.203	19.145	3.000	67.000
	4	12.476	16.264	1.000	67.000
	All Insurers	36.157	23.095	1.000	67.000
% of Counties with Ocean Exposure	1	47.104%	9.248%	25.000%	100.000%
	2	52.657%	8.741%	38.636%	81.818%
	3	60.400%	17.039%	26.471%	100.000%
	4	70.612%	26.259%	0.000%	100.000%
	All Insurers	57.642%	18.931%	0.000%	100.000%
% of Exposures in Ocean Counties	1	70.150%	16.715%	23.198%	100.000%
	2	71.446%	18.197%	18.563%	99.657%
	3	70.092%	27.229%	8.702%	100.000%
	4	73.570%	31.800%	0.000%	100.000%
	All Insurers	71.306%	24.169%	0.000%	100.000%
County Market Share CoV	1	1.365	0.607	0.363	3.414
	2	2.204	1.143	0.720	5.983
	3	3.353	1.515	0.931	7.765
	4	5.380	2.165	1.316	8.185
	All Insurers	3.066	2.096	0.363	8.185
County Market Share Herfindahl	1	0.084	0.055	0.024	0.262
	2	0.126	0.116	0.030	0.649
	3	0.240	0.203	0.025	0.892
	4	0.448	0.315	0.035	1.000
	All Insurers	0.224	0.242	0.024	1.000

Note - Data obtained from Florida Department of Insurance regulatory filings. 264 insurer have exposure to losses due to hurricanes of which 255 insurers have usable data. The data set includes 92.8 percent of exposures in Florida subject to windstorm loss. Insurers in quartile 1 had 87.9% of exposure limits in the state. Quartiles 2, 3, and 4 had 4.1%, 0.73% and 0.054% of the exposure limits in the state, respectively.

Table 4
Determinants of Hedging Effectivess
Dependent Variable = Risk Reduction Index/Perfect Hedge

	Variance Reduction		EEV Reduction	
Variable	**Statewide**	**Regional**	**Statewide**	**Regional**
% of Exposures in Ocean Front Counties	0.505	0.106	0.527	0.137
	(28.347)	(8.937)	(28.661)	(10.158)
Coeff. of Variation of County Market Share	-0.048	-0.037	-0.045	-0.034
	(16.549)	(19.574)	(15.200)	(15.679)
Mutual Organization Form Indicator	0.009	0.019	0.009	0.036
	(0.823)	(2.601)	(0.827)	(4.338)
Single Unaffiliated Insurer Indicator	-0.054	0.024	-0.036	0.034
	(3.280)	(2.244)	(2.136)	(2.638)
Liabilities-to-Assets Ratio	0.068	0.045	0.050	0.037
	(2.996)	(2.994)	(2.130)	(2.115)
First Quartile Florida Exposure Indicator	0.061	0.083	0.075	0.110
	(3.677)	(7.475)	(4.351)	(8.583)
Second Quartile Florida Exposure Indicator	0.047	0.115	0.049	0.133
	(3.102)	(11.482)	(3.162)	(11.592)
Third Quartile Florida Exposure Indicator	0.052	0.096	0.058	0.091
	(3.907)	(10.901)	(4.216)	(9.064)
First Quartile Total Assets Indicator	0.017	-0.011	0.039	-0.010
	(1.145)	(1.107)	(2.577)	(0.836)
Second Quartile Total Assets Indicator	0.023	-0.011	0.038	0.002
	(1.609)	(1.153)	(2.583)	(0.141)
Third Quartile Total Assets Indicator	-0.019	0.007	0.003	0.017
	(1.441)	(0.802)	(0.225)	(1.622)
5% Cost Constraint	0.282	0.804	0.289	0.839
	(10.452)	(44.870)	(10.402)	(40.892)
10% Cost Constraint	0.305	0.791	0.255	0.762
	(11.340)	(44.176)	(9.195)	(37.326)
15% Cost Constraint	0.320	0.793	0.229	0.699
	(11.886)	(44.299)	(8.254)	(34.262)
20% Cost Constraint	0.329	0.792	0.240	0.696
	(12.200)	(44.217)	(8.649)	(34.130)
25% Cost Constraint	0.334	0.794	0.269	0.711
	(12.405)	(44.339)	(9.687)	(34.876)
30% Cost Constraint	0.337	0.793	0.309	0.747
	(12.506)	(44.316)	(11.109)	(36.527)
35% Cost Constraint	0.339	0.794	0.344	0.781
	(12.582)	(44.331)	(12.374)	(38.054)
40% Cost Constraint	0.340	0.794	0.375	0.805
	(12.637)	(44.335)	(13.467)	(39.122)
45% Cost Constraint	0.341	0.795	0.401	0.833
	(12.675)	(44.408)	(14.397)	(40.336)
50% Cost Constraint	0.343	0.797	0.426	0.860
	(12.748)	(44.532)	(15.280)	(41.347)
Log Likelihood Function Value	388.000	1409.312	198.411	663.604
Likelihood Ratio Test Statistic	20.650	1.590	135.140	316.500

Note: z-statistics shown in parentheses. Estimation conducted using the Tobit procedure.
The intercept term has been supressed since the model includes cost constraint dummy variables.
The null hypothesis for the likelihood ratio test is that all cost constraint dummary variables are equal.
Critical values for the chi-squared distribution with nine degrees of freedom at the one and five percent levels are 21.67 and 16.92, respectively.

Table 5
Parametric Index Regression
Dependent Variable = Log(Storm Damages)

Variable	**Coefficient / (t-Ratio)**
Intercept	2.147
	(5.30)
Log(30 - Central Pressure)	4.617
	(46.17)
Log(Fwd. Windspeed)	-0.172
	(2.18)
Log(Radius)	1.163
	(14.19)
R^2	90.50%
Adjusted R^2	90.13%

Note - t-statistics shown in parentheses. Landfall segment dummy variables are included but not shown. All but two are landfall variables are significant at the 1% level or higher. The F statistic testing the null hypothesis that all landfall segment dummy variables are jointly equal to zero is equal to 1785.648. The number of simulated hurricane over the 1000 year simulation period = 867.

Table 6

Expected Exceedence Value (EEV) Reduction:
Market Price EEV Reduction/Actuarial EEV Reduction

Cost	Market/Actuarial		
(% of EV)	Perfect	State	Regional
5.0%	0.9%	49.3%	50.5%
10.0%	12.9%	50.7%	54.6%
15.0%	15.7%	56.4%	58.4%
20.0%	20.3%	63.0%	64.5%
25.0%	24.6%	69.5%	70.0%
30.0%	29.2%	74.7%	75.7%
35.0%	34.0%	77.9%	81.5%
40.0%	38.9%	80.6%	84.4%
45.0%	43.7%	82.3%	88.4%
50.0%	48.6%	83.9%	90.8%

Note: The percentages are the ratio of the EEV reduction using hedge contracts with median market risk premia divided by the EEV reduction that is obtained using hedges priced at the expected loss. The price-to-expected-loss ratio for the perfect hedge contracts 6.8, and the price-to-expected-loss ratio for the state and regional contracts are 2.1. These ratios are the median ratios for the CAT bond and CBOT option contracts, respectively, shown in Table 1.

Figure 1
CAT Bond With Single Purpose Reinsurer

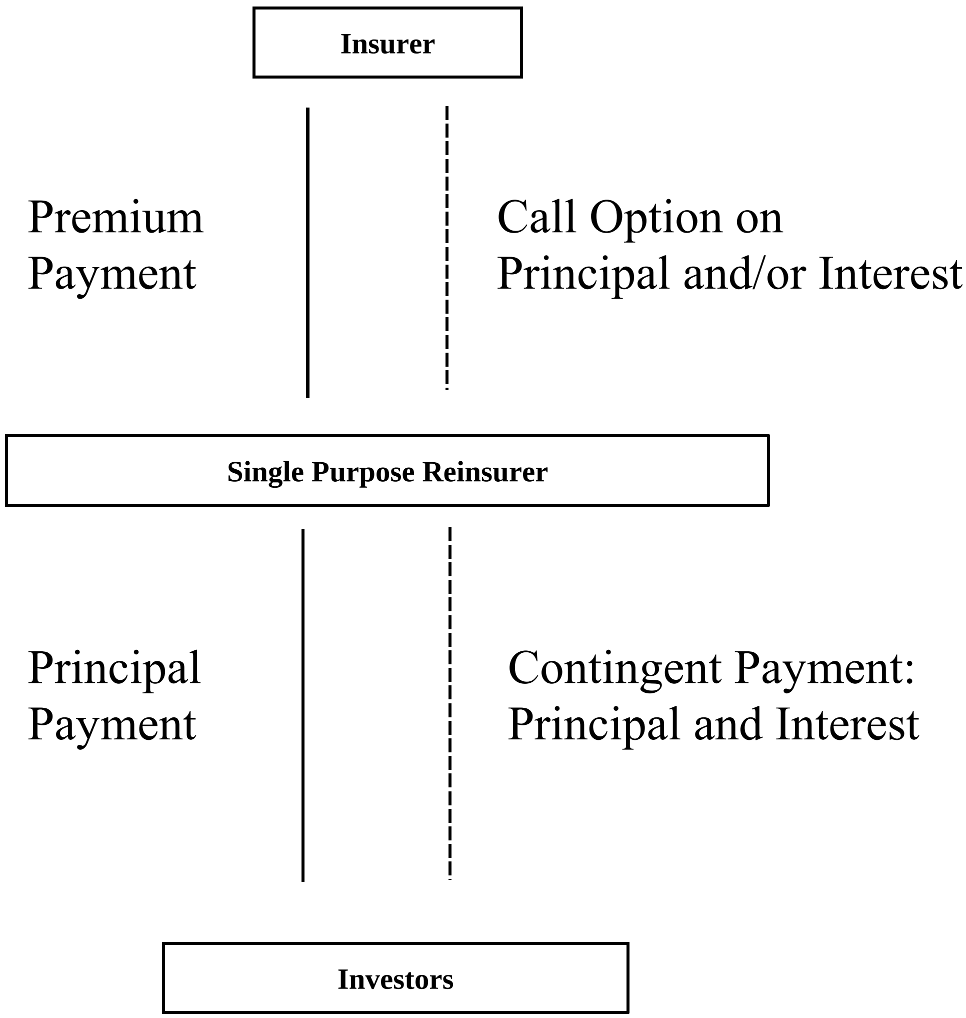


Figure 2A
Variance Reduction Using Non-Linear Contracts: Highly Diversified Insurer

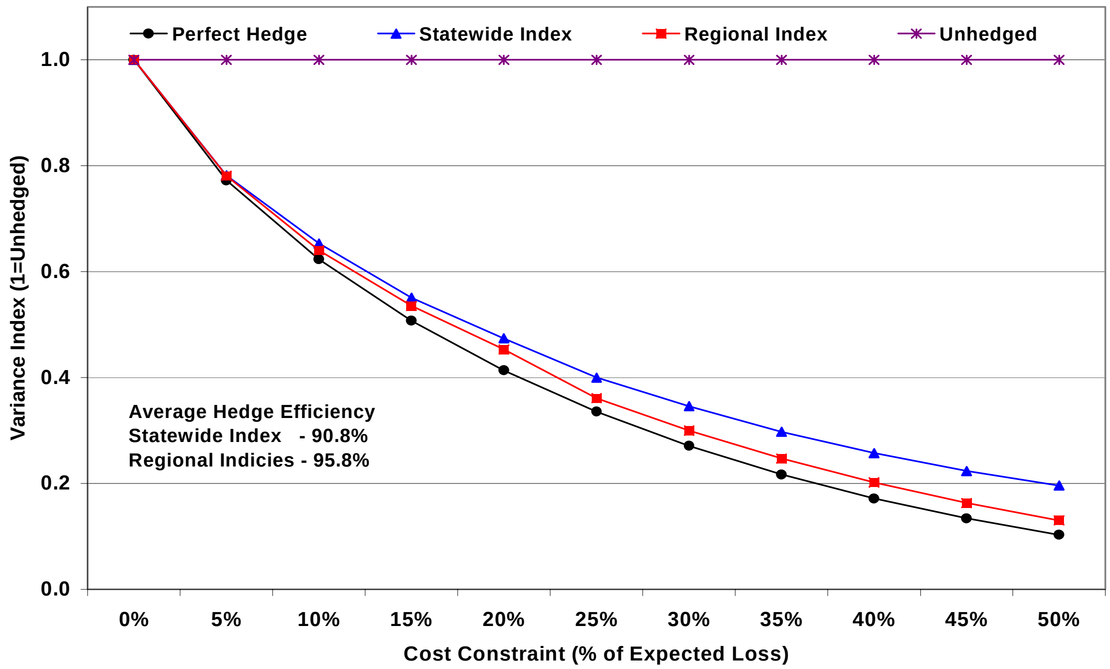


Figure 2B
Variance Reduction Using Non-Linear Contracts: Undiversified Insurer

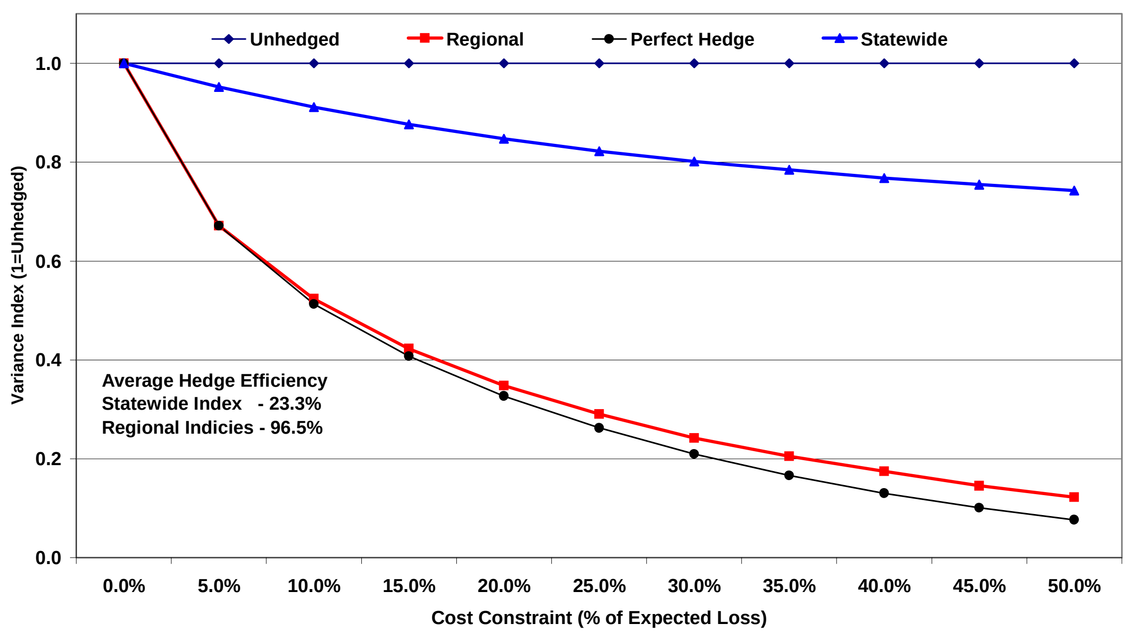


Figure 3
Variance Reduction Frontiers: Average For Insurers in Largest Size Quartile

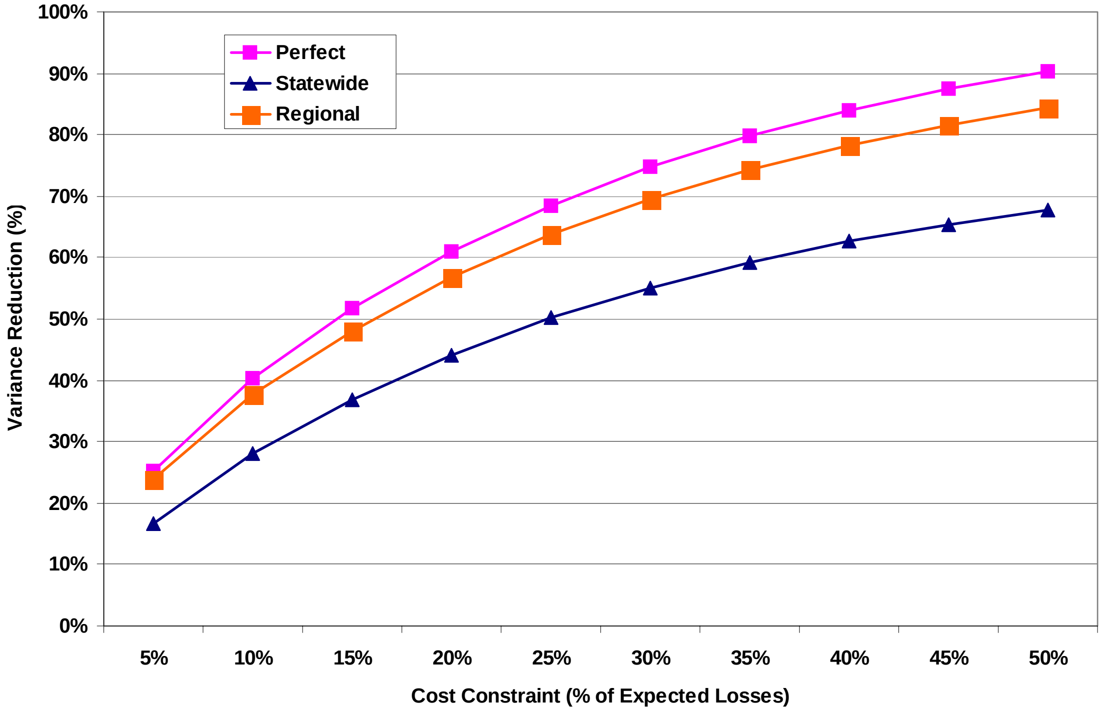


Figure 4
Variance Reduction Frontiers Using Non-Linear Contracts & Regional Indices
By Insurer Size Quartile

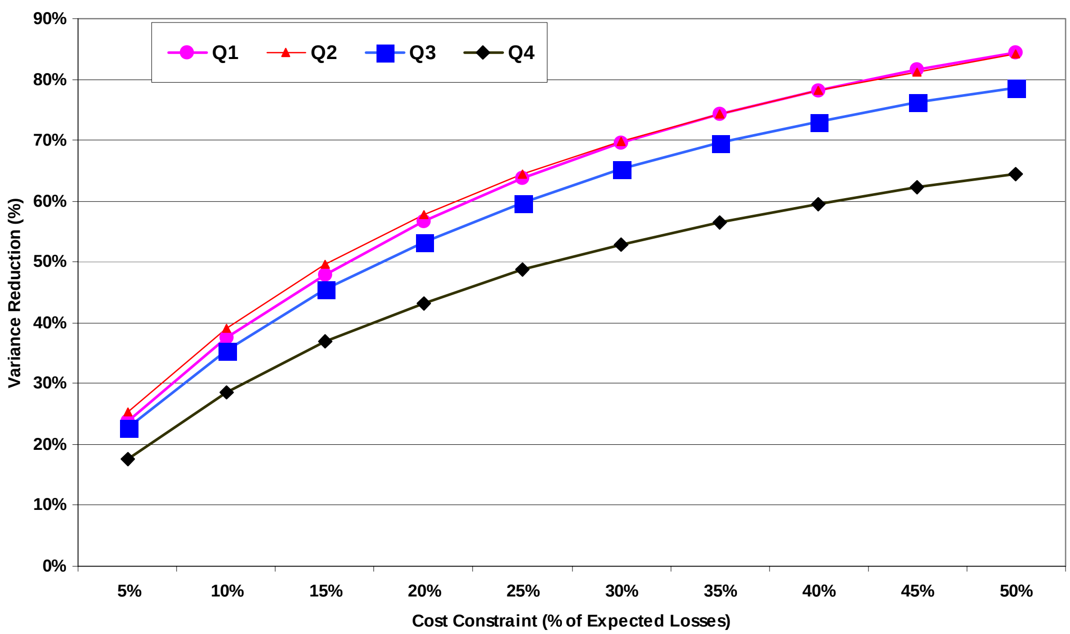


Figure 5
Variance Reduction Hedging Efficiency: Non-Linear Contracts
Hedging Cost Constraint = 25 Percent of Expected Annual Losses

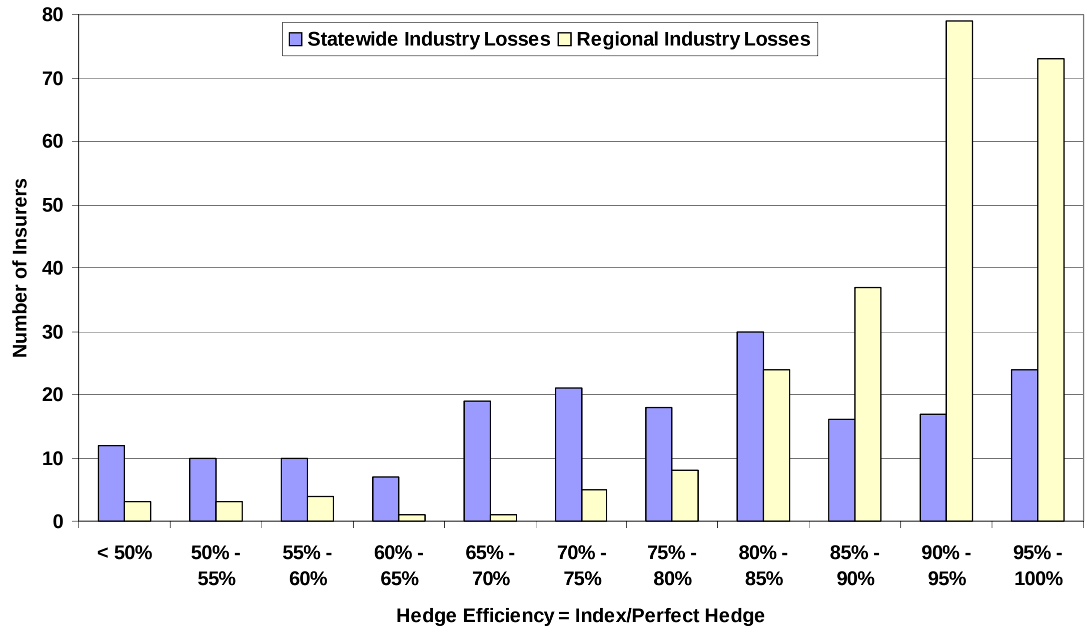


Figure 6
Expected Exceedence Value Reduction: Non-Linear Contracts
Average For Insurers In Largest Size Quartile

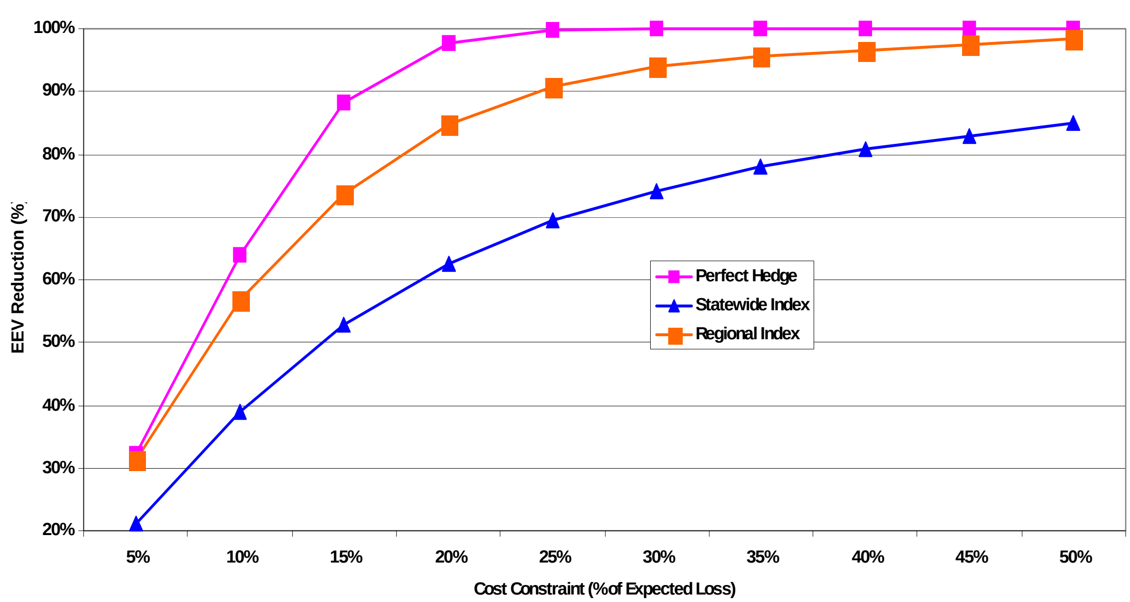


Figure 7
Expected Exceedence Value Reduction Efficiency: Non-Linear Contracts
Hedging Cost Constraint = 25 Percent of Expected Annual Losses

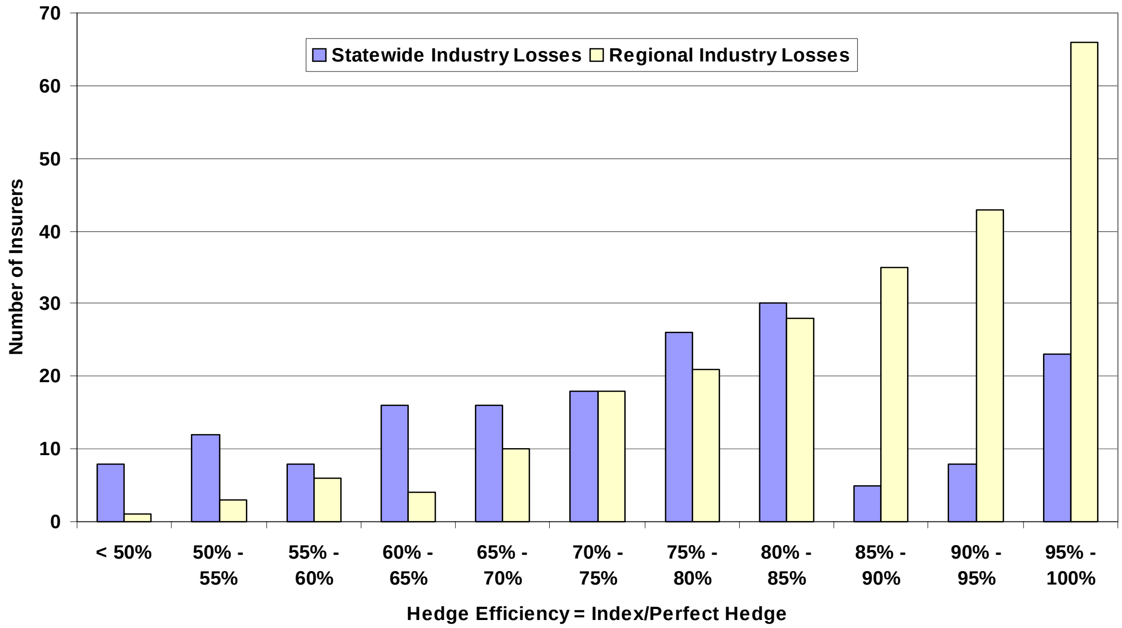
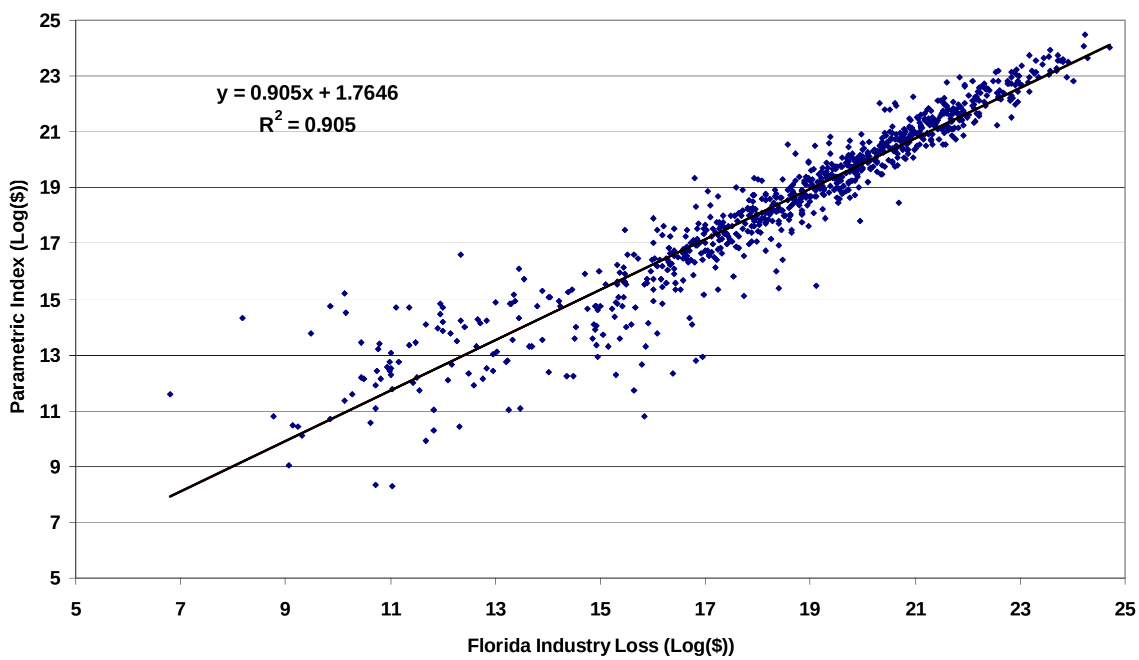


Figure 8
Parametric Index vs. Florida Industry Loss Amounts



Appendix A

The Applied Insurance Research (AIR) Catastrophe Simulation Models

In this Appendix, we describe AIR's approach to the modeling of natural catastrophes, with a focus on hurricanes. We then discuss how catastrophe modeling technology is used to estimate both index values and individual company loss. A more detailed technical description of the model is available from the authors.

AIR catastrophe models use sophisticated simulation techniques to estimate the probability distribution of losses that result from potential natural catastrophes. A simplified flow chart of the model is shown in Figure A.1. The model first generates the frequency with which events occur, their location and magnitude. After simulated events are generated, they are propagated over the affected area. Local intensity is calculated for every site affected by the event. Next, using detailed information on property locations, values and construction characteristics, the AIR models estimate the probabilities of losses of various sizes. Insured losses are calculated by applying policy conditions to the total damage estimates. This information is then synthesized and further analyzed to assist in risk management.

The AIR Hurricane Model

The hurricane loss estimation methodology employed by AIR is based on well-established scientific theory in meteorology and wind engineering. The simulation models were developed through careful analyses and synthesis of all available historical information and they incorporate statistical descriptions of a large number of variables that define both the originating event (e.g., hurricane) and its effect on structures. The models are validated and calibrated through extensive processes of both internal and external peer review, post-disaster field surveys, detailed client data from actual events and overall reasonability and convergence testing. The AIR hurricane model has been used by the insurance industry since 1987 and is well known for its reliability and the credibility of the loss estimates it generates.

AIR employs Monte Carlo simulation, a well-known statistical technique, to generate simulated storms. Monte Carlo simulation involves an iterative process using, in each simulation, a set of values stochastically drawn from the probability distributions governing each of the random variables being analyzed. In the AIR hurricane model, the random variables being analyzed are landfall location and hurricane frequency, as well as the primary meteorological parameters of each simulated storm (see "Hurricane Event Generation" below). Theoretical probability distributions are fit to the historical data using goodness-of-fit tests and AIR's meteorological expertise. By repeating the simulation process, a sample of more than eighteen thousand storms is generated, each corresponding to a different set of random values assigned to the storm parameters. A sample from a Monte Carlo simulation can be analyzed in ways similar to the ways in which a sample of experimental observations can be analyzed. In particular, a sample from a Monte Carlo simulation can be analyzed statistically to generate probability distributions of losses for individual buildings or portfolios of buildings, given the characteristics of each simulated event.

To estimate the hurricane loss potential, 10,000 annual scenarios of potential hurricane experience were simulated, incorporating over 18,000 simulated events. The first step of the AIR hurricane model is to generate the number of hurricanes estimated to make landfall in the simulated year. The model allows for the possibility of multiple events occurring within a single year. That is, each simulated year may have no, one, or multiple events, just as might be observed in an actual year. For each simulated hurricane, the model first assigns a landfall location and values for each of the modeled meteorological characteristics. It then estimates the potential property damage on the basis of a complete time profile of wind speeds, or windfield, at each location affected by each simulated storm. (The AIR hurricane model also estimates losses from storms that bypass the coast without making actual landfall.)

Data Sources and Analysis

The meteorological sources used to develop the AIR model are databases, information, and publications available from various agencies of the U.S. National Oceanic and Atmospheric Administration (NOAA), including the U.S. National Weather Service (NWS) and the National Hurricane Center. These agencies gather original data on historical hurricanes from such sources as barograph traces from land stations and ships, actual wind records from NWS stations, aircraft reconnaissance flight data, radar data and other pressure and wind reports. These original data are not necessarily consistent. NWS scientists analyze these raw data and use them, along with their professional judgment, to synthesize the primary meteorological characteristics of each historical storm. This final synthesized data are used in developing the AIR model.

AIR then uses statistical estimation techniques to fit various probability distributions to the available meteorological data on historical hurricanes. The distributions employed by the AIR hurricane model are standard statistical distributions that are representative of the underlying historical distributions of the meteorological data. It is not likely, however, that the fitted distributions will duplicate the true underlying distribution of the meteorological data.

Hurricane Event Generation

The first component of the AIR hurricane model provides for the generation of simulated hurricanes. Many thousands of scenario years are generated to produce the complete and stable range of potential annual experience of hurricane activity. For each scenario year, the model generates the fundamental characteristics of each simulated storm, including frequency of occurrence, landfall location and track, and the intensity variables of central pressure, radius of maximum winds and forward speed.

Hurricane Frequency. The model generates the number of hurricanes making landfall for each simulated year from an annual frequency distribution. AIR estimates the parameters of this distribution using the actual hurricane occurrences for the 99 years from 1900 to 1998. The sample includes all landfalling and bypassing hurricanes, where bypassing storms are defined as storms passing sufficiently close to land to cause significant damage.

Landfall Location. Because the values of property exposures vary along the coast, loss estimates can also vary greatly depending on where a hurricane makes landfall. The AIR hurricane model identifies 3,100 landfall points along the coast from Texas to Maine—one for each nautical mile of "smoothed" coastline—and groups these points into sixty-two 50-nautical mile segments of coastline in order to develop a cumulative probability distribution of landfall locations. After tabulating the actual number of historical hurricanes for each 50-nautical mile segment, the actual number of occurrences for each segment is smoothed using a statistical smoothing method used in climatological studies and meteorological judgment. This results in a probability distribution governing landfall location for each segment of modeled coastline.

For illustrative purposes, Figure A.2 shows the number of hurricanes that, since 1900, have made landfall along the Florida coast at each of the twenty 50-nautical mile segments from the Alabama to the Georgia borders. The smoothed frequency distribution ensures that each coastal segment has a non-zero probability of hurricane occurrence (except a few where meteorological or geographical factors prevent hurricanes from making landfall). Therefore, the fact that no hurricane has made landfall at a particular segment in the past does not mean that the AIR hurricane model will simulate no hurricanes for such a segment. Accordingly, the AIR hurricane model allows for the possibility of a hurricane making landfall almost anywhere along the Gulf and Atlantic coasts.

Key Meteorological Characteristics. Once a landfall location is generated for the simulated storm, values are generated for each of the storm's key meteorological characteristics at landfall. For purposes of estimating the probability distributions of these other variables, the coastline from Texas to Maine has been divided into thirty-one 100 nautical mile segments, and each geographic segment has a distinct distribution associated with each variable. Historical storm data corresponding to each of these segments (along with adjacent segments) and each of the variables is fit to theoretical probability distributions. These distributions are used to generate values for each of the simulated storm's key meteorological characteristics, which are:

Central Barometric Pressure. This variable is the lowest sea level barometric pressure at the center of the hurricane. It is the primary determinant of hurricane wind speed. Wind speeds typically increase as the central barometric pressure decreases or, more precisely, as the difference between central pressure and peripheral pressure increases.

Radius of Maximum Winds. The strongest winds in a hurricane are typically found at some distance from the center of the storm. This distance is known as the "radius of maximum winds," and it can range from 5 to over 50 nautical miles. Very intense storms typically have a small radius of maximum winds. A storm making landfall at higher latitudes will typically have a larger radius of maximum winds than one making landfall at lower latitudes.

Forward Speed. This is the rate at which a hurricane moves from point to point. Faster moving storms typically go further inland and are therefore likely to result in losses over a larger area. On the other hand, a faster moving storm will subject any given building to high wind speeds for a shorter duration. In some areas, particularly along the coast, this can lead to lower losses than might otherwise be the case. Both effects are taken into account in the AIR hurricane model.

Storm Track. This is the path the storm takes after landfall, important in determining the properties and structures that are in the path of a hurricane. AIR generates simulated storm tracks based on conditional probability matrices. These allow simulated storm tracks to more closely resemble the curving and recurving tracks that are actually observed.

Local Intensity

Once the model generates the storm characteristics and point of landfall, it propagates the simulated storm along a path characterized by the track direction and forward speed. As the storm moves inland at the forward speed generated as described above, wind speeds begin to diminish due to filling and surface terrain effects. In order to estimate the property losses resulting from the simulated storms, the AIR hurricane model first generates the complete time profile of wind speeds, or windfield, at each location affected by the storm.

Windfield generation requires the following steps:

Maximum Wind Speed. he maximum over-water wind speed is calculated for each simulated hurricane.

Asymmetry Factor. An asymmetry factor, which captures the combined effects of the counter-clockwise motion of hurricane winds and the storm's forward speed, increases wind speeds on the right of the hurricane track, and decreases wind speeds on the left of the track.

Filling Equations. After a hurricane makes landfall, the pressure in the eye of the storm begins to increase, or "fill," causing wind speeds to dissipate. The AIR hurricane model filling equations are a function of geographic region, distance from the coast, and time since landfall. The wind speed at the eye of the storm at any point in time is thus dependent upon the number of hours since landfall.

Adjustment of Wind Speeds for Surface Friction. Each location is assigned an adjustment factor, or friction coefficient, to account for the effects of the local terrain. The horizontal drag force of the earth's surface reduces wind speeds. The addition of obstacles such as buildings will further degrade winds. Friction coefficients are based on digital land use/land cover data.

Estimation of Damages

Once the model estimates peak wind speeds and the time profile of wind speeds for each location, it generates damage estimates for different types of property exposures by combining the exposure information with wind speed information at each location affected by the event.

To estimate building damage and the associated losses, the AIR hurricane model uses damageability relationships, or damage functions. These damageability relationships have been developed by AIR engineers for a large number of different construction and occupancy classes, each designed to provide insight into the wind resistivity of a building.

AIR engineers have developed separate damageability relationships for building contents, with contents damageability a function of the building damage. A third set of functions is used to estimate time element damageability, a function of damage to the building, the time needed to repair or reconstruct the building to usable condition, and the *per diem* expense incurred as a result of the building being unusable or uninhabitable.

Separate damageability relationships for each of building and contents provide estimates of the mean, or expected, damage ratio corresponding to each wind speed as well as probability distributions around such mean. In the case of building damageability, the damage ratio is the dollar loss to the building divided by the corresponding replacement value of the building. For contents, it is the dollar loss to the contents divided by the replacement value of the contents. For time element, the number of calendar days that the building is uninhabitable or unusable is estimated based on the building damage ratio. To calculate business interruption losses, the number of calendar days of effective downtime is multiplied by a *per diem* factor. For both mean damage ratios, the probability distribution of damage ranges from no damage to complete destruction, with probabilities assigned to each level of damage in between. The model estimates non-zero probabilities of zero and one hundred percent loss, as is consistent with empirical observation. A high degree of variability in damage is sometimes observed even within a very small geographic area. AIR damageability relationships attempt to capture this variability.

AIR engineers have developed and refined the damageability relationships over a period of several years. They incorporate documented studies by wind engineers and other experts both within and outside AIR. They also incorporate the results of post-hurricane field surveys performed by AIR engineers and others, and by the analysis of actual loss data provided to AIR by client companies.

Insured Loss Module

In this last component of the catastrophe model, insured losses are calculated by applying the policy conditions to the total damage estimates. Policy conditions may include deductibles by coverage, site-specific or blanket deductibles, coverage limits and sublimits, loss triggers, coinsurance, attachment points and limits for single or multiple location policies, and risk specific reinsurance terms.

Model Output

After all of the insured loss estimations have been completed, they can be analyzed in ways of interest to risk management professionals. For example, the model produces complete probability distributions of losses, also known as exceedence probability curves. Output includes probability distributions of gross and net losses for both annual aggregate and annual occurrence losses. The probabilities can also be expressed as return periods. That is, the loss associated with a return period of 10 years is likely to be exceeded only 10 percent of the time or, on average, in one year out of ten.

Output may be customized to any desired degree of geographical resolution down to location level, as well as by line of business, and within line of business, by construction class, coverage, etc. The model also provides summary reports of exposures, comparisons of exposures and losses by geographical area, and detailed information on potential large losses caused by extreme "tail" events.

Validation and Peer Review of the AIR Models

AIR scientists and engineers validate the models at every stage of development by comparing model results with actual data from historical events. The simulated event characteristics parallel patterns observed in the historical record and resulting loss estimates correspond closely to actual claims data provided by clients. Internal peer review is a standard operating procedure and is conducted by the AIR professional staff of over 50 scientists and engineers, one third of whom hold Ph.D. credentials in their area of expertise. AIR models have also undergone extensive external review, beginning with Dr. Walter Lyons' systematic review of the AIR hurricane model in 1986. Dr. Lyons is an expert meteorologist and consultant with over 24 years of experience and over 130 published book chapters and articles.

Probably the most extensive catastrophe model approval process established to date is that of the Florida Commission on Hurricane Loss Projection Methodology. This Commission was established in 1995 with the mission to "assess the effectiveness of various methodologies that have the potential for improving the accuracy of projecting insured Florida losses resulting from hurricanes and to adopt findings regarding the accuracy or reliability of these methodologies for use in residential rate filings." The Commission has established 40 standards that need to be met before a catastrophe model is acceptable for ratemaking purposes in the state of Florida. The AIR hurricane model was the only model approved under the 1996 standards, and it has consistently been approved under the standards of subsequent years.

Recent years have witnessed a transfer of catastrophe risk to the capital markets through the issuance of catastrophe, or "cat", bonds. AIR models have been used in the majority of the transactions that have been based on catastrophe modeling. In fact, of the nearly $2 billion of risk capital raised in the last few years, close to 70 percent has been raised in transactions based on AIR catastrophe modeling technology, including modeling of earthquakes, hurricanes, other windstorms. Investors have relied on the research and due diligence performed by the securities rating agencies – Standard & Poor's, Moody's Investors Service, Fitch Investors Service, and Duff & Phelps – to make their investment decisions. As part of the due diligence process, the AIR models and their underlying assumptions undergo extensive scrutiny by outside experts hired by these rating agencies as well as by their own experts. Detailed sensitivity analyses of the major components of the model are performed, stress testing each for model robustness.

Estimating Industry Losses

A fundamental component of AIR analysis is the "industry loss file," which is a set of estimates of insured industry losses resulting from the events simulated by the AIR catastrophe models. To create the industry loss file, the AIR models estimate the impact of each peril by applying event characteristics to industry-wide exposure data (as opposed to data for a specific insurer). AIR's estimated property values (see "AlR's Database of Insured Property Values," below) for commercial, residential, mobile home and automobile properties are entered into these models and insured losses are estimated. This analysis results in an industry loss file, which consists of the estimated industry losses by county for each of the four business lines, for each simulated event and for each year of simulated events. This industry loss file forms the basis for estimating index values.

For industry loss based indexes, the industry loss file contains the event by event and year by year simulated industry loss values needed to construct both occurrence and aggregate index values. Additionally, the industry loss file contains descriptive information in the form of the simulated parameters such as central pressure, radius of maximum winds and forward speed for each event, which are used in the construction of the parametric indexes studied herein. By running underlying exposure through the model, any index can be simulated. For example the exposures that underlie the GCCI can be quickly analyzed and the index values estimated.

AIR's Database of Insured Property Values

AIR has developed databases of estimated numbers, types, and values of properties for residential, commercial, mobile home, and automobile insured values in the United States by five-digit ZIP code. These databases have been constructed from a wide range of data sources and reflect the estimated total replacement cost of U.S. property exposures. They are used to estimate total insured property losses. Insured loss estimates are based on assumptions as to the level of deductibles, and how many of the total properties are insured.

The numbers of properties, estimated property values, and other assumptions underlying the database are based on annually updated information. Assumptions specifically regarding insurance policies and trends are based on insurance industry sources including clients, industry organizations, and government studies. The property value databases are developed, maintained and enhanced through an ongoing process of data collection, synthesis and analysis. Much of the information required to develop the estimated values is acquired each year from governmental statistical agencies and private firms that specialize in this type of information. For example, primary data sources in the United States include the U.S. Census Bureau, Dun & Bradstreet, Claritas, the Insurance Information Institute and R.S. Means.

Most data sources supply updated information on an annual basis. While such data sources contain extensive information, AIR has developed internal procedures that select and transform collected data into the required exposure data estimates. These procedures include combining the data from multiple sources and performing appropriate allocations or aggregations of data. For purposes of this analysis, the industry exposure database information is as of July 31, 1998 and no adjustments have been made to reflect the effects of inflation or any other factor since that time.

Estimating Company Losses

For each company in this study, AIR received information on the exposures as described earlier. Where detailed classifications were not provided, AIR assumed industry average characteristics. This exposure information was input into the model described above and, using the same catalogue of events that generated the industry losses, individual company losses were determined. The results are individual company losses, industry loss and event characteristics for each simulated event.

Figure A.1
Flow Chart of the AIR Model

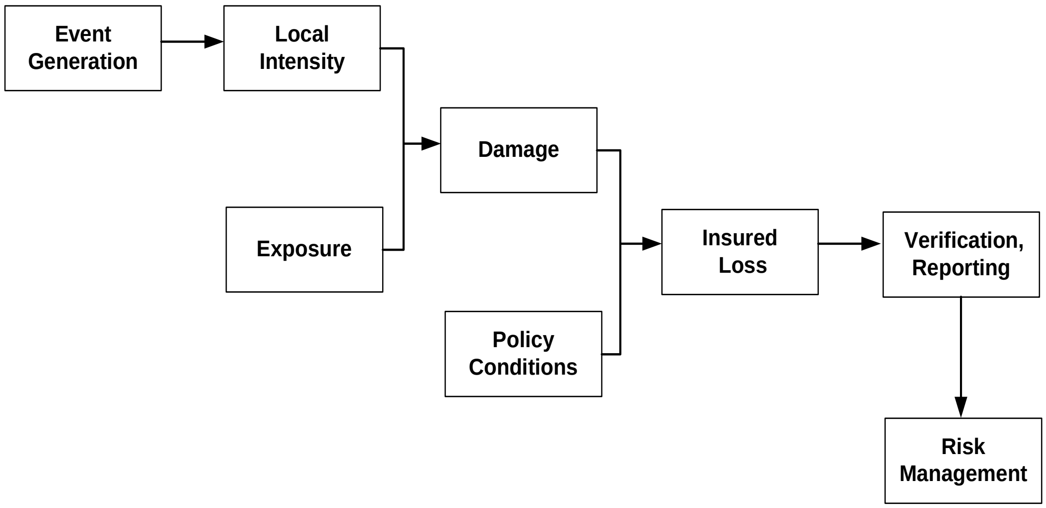
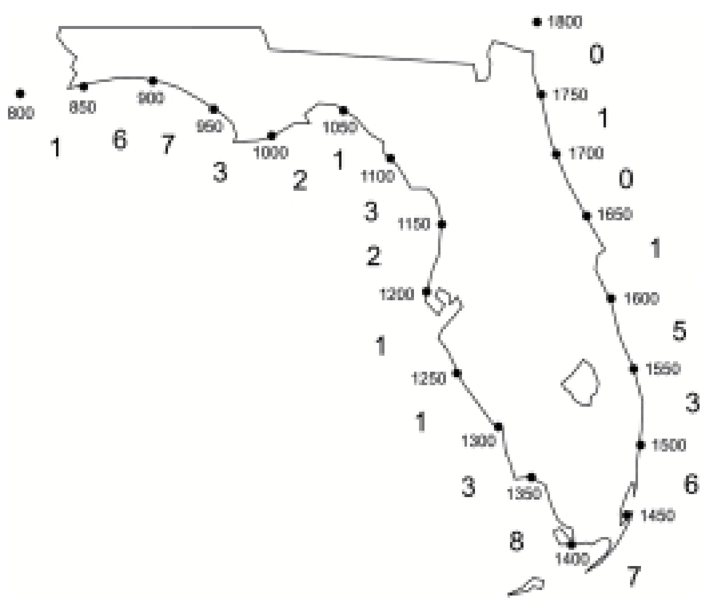
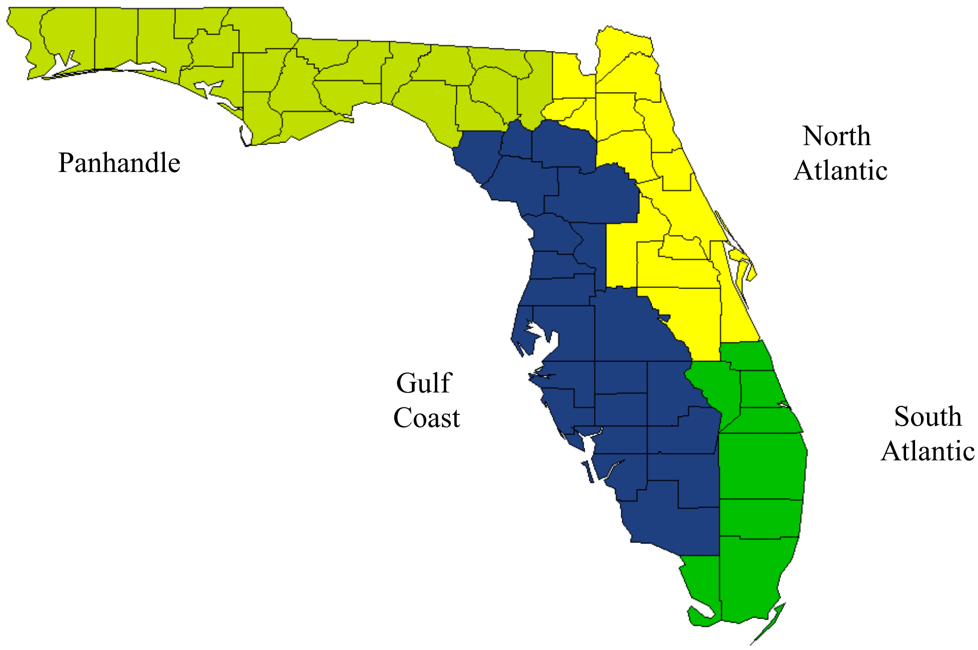


Figure A.2
Number of Hurricanes Making Landfall in Florida: 1900-1998



Appendix B
Counties Composing Each Region in Florida



References

Ahn, D., et al., 1999, "Optimal Risk Management Using Options," *Journal of Finance* 54: 359-375.

American Academy of Actuaries, 1999, "Evaluating the Effectiveness of Index-Based Insurance Derivatives in Hedging Property/Casualty Insurance Transactions," Report of the Index Securitization Task Force (Washington, DC).

Applied Insurance Research, 1999, *AIR Tropical Cyclone Model: United States Region*, Technical Document TCUS 9904 (Boston).

Artzner, Philippe, Freddy Delbaen, Jean Marc Heber, and David Heath, 1999, "Coherent Measures of Risk," *Mathematical Finance* 9: 203-228.

Canter, Michael, Joseph B. Cole, and Richard L. Sandor, 1997, "Insurance Derivatives: A New Asset Class for the Capital Markets and a New Hedging Tool for the Insurance Industry," *Journal of Applied Corporate Finance,* 10(3): 69-83.

Chookaszian, Jeffrey and Thomas Ward, 1998, "Risk Securitization Products On The Rise," *National Underwriter (Property & Casualty/Risk & Benefits Management)* 102(20): 9, 23.

Cummins, J. David, Christopher M. Lewis, and Richard D. Phillips, 1999, "Pricing Excess of Loss Reinsurance Against Catastrophic Loss," in Kenneth A. Froot, ed., *The Financing of Catastrophe Risk* (Chicago: University of Chicago Press).

Cummins, J. David and Mary A. Weiss, 2000, "The Global Market for Reinsurance: Consolidation, Capacity, and Efficiency,"*Brookings-Wharton Papers on Financial Services* (2000), forthcoming.

Doherty, Neil A., 1997, "Financial Innovation in the Management of Catastrophe Risk," *Journal of Applied Corporate Finance* 10: 84-95.

Dowd, Kevin, 1999, "Financial Risk Management," *Financial Analysts Journal* 55: 65-71.

Ederington, Louis, 1979, "The Hedging Performance of the New Futures Markets," *Journal of Finance* 34 (March): 157-170.

Engle, Robert F., and Simone Manganelli, 1999, "CAViaR: Conditional Value at Risk by Quantile Regression," NBER Working Paper No. W7341, Cambridge, MA.

Figlewski, Stephen, 1985, "Hedging With Stock Index Futures: Theory and Application in a New Market," *Journal of Futures Markets* 5: 183-199.

Froot, Kenneth A., 1998a, *The Evolving Market for Catastrophic Event Risk* (New York: Marsh and McLennan Securities).

Froot, Kenneth A., 1998b, "Mid Ocean Limited – Trading Catastrophe Index Options," Harvard Business School Case 9-278-073 (Boston: Harvard Business School Publishing).

Froot Kenneth A. and Paul J. G. O'Connell, 1999, "The Pricing of U.S. Catastrophe Reinsurance," in

Kenneth Froot, ed., *The Financing of Catastrophe Risk* (Chicago: The University of Chicago Press).

Froot, Kenneth A., David S. Scharfstein, and Jeremy C. Stein, 1993, “Risk Management: Coordinating Investment and Financing Policies,” *Journal of Finance,* 68: 1629-1658.

Geman, Hélyette, ed., 1999, *Insurance and Weather Derivatives: From Exotic Options to Exotic Underlyings* (London: Risk Books).

Goldberg, D.E., 1989, *Genetic Algorithms In Search, Optimization and Machine Learning* (Reading: Addison-Wesley.

Goldman-Sachs, 1999, “Practical Challenges In Accessing the Capital Markets for Catastrophic Risk,” Presentation at Wharton Catastrophic Risk Project Meeting, Philadelphia, PA.

Harrington, Scott E. and Greg Niehaus, 1999, “Basis Risk with PCS Catastrophe Insurance Derivative Contracts,” *Journal of Risk and Insurance* 66: 49-82.

Jaffee, Dwight M. and Thomas Russell, 1997, “Catastrophe Insurance, Capital Markets, and Uninsurable Risks,” *Journal of Risk and Insurance 64: 205-30.*

Kunreuther, Howard and Vivek Bantwal, 1999, “A CAT Bond Premium Puzzle,” working paper, Wharton Financial Institutions Center, The University of Pennsylvania, Philadelphia.

Lane, Morton N. and Oleg Y. Movchan, 1999, “Risk Cubes or Price Risk and Ratings (Part II),” *Journal of Risk Finance* 1: 71-86.

Lamm-Tennant, Joan and Laura Starks, 1993, "Stock vs. Mutual Ownership Structures: The Risk Implications," *Journal of Business* 66: 29-46.

Litzenberger, R.H., D.R. Beaglehole, and C.E. Reynolds, 1996, “Assessing Catastrophe Reinsurance-linked Securities as a New Asset Class,” *Journal of Portfolio Management* (December): 76-86.

Major, John A., 1999, “Index Hedge Performance: Insurer Market Penetration and Basis Risk,” in Kenneth A. Froot, ed., *The Financing of Catastrophe Risk* (Chicago: University of Chicago Press).

Mayers, D. and C.W. Smith, Jr., 1992, "Executive Compensation in the Life Insurance Industry," *Journal of Business* 65: 51-74.

Merton, Robert and Andre Perold, 1993, “The Theory of Risk Capital in Financial Firms,” *Journal of Applied Corporate Finance*.

Santomero, Anthony M., 1997, “Commercial Bank Risk Management: An Analysis of the Process,” *Journal of Financial Services Research* 12: 83-115.

SwissRe, 1997, “Too Little Reinsurance of Natural Disasters in Many Markets,” *Sigma* 7: 3-22.

SwissRe, 1999, “Natural Catastrophes and Man-Made Disasters 1998: Storms, Hail, and Ice Cause Billion-Dollar Losses,” *Sigma* 1: 1-38.