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*The Basis Risk of Catastrophic-loss
Index Securities*

by
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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 provides an analysis of the basis risk of catastrophic-loss (CAT) index options, which securitize losses from catastrophic events such as hurricanes and earthquakes. Interest in these securities has grown due to the recognition that projected catastrophes in the \$30 to \$100 billion range are beyond the capacity of insurance and reinsurance markets but could be financed efficiently in securities markets. Because catastrophic losses are “zero-beta” events, insurance-linked securities also provide a valuable new source of diversification for investors.

The principal trading in CAT securities has been in CAT call option spreads, which settle on industry-wide loss indices, and CAT bonds, where a specified catastrophic event triggers forgiveness of the repayment of principal. Because most CAT bonds settle on the losses of specific insurers, they have very low basis risk but expose investors to moral hazard. Index-linked options, on the other hand, have low moral hazard but expose insurers to an indeterminate amount of basis risk.

Our study provides new information on the basis risk of index-linked CAT securities through an extensive simulation analysis of their hedging effectiveness 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 study the effectiveness of hedge portfolios, consisting of a short position each insurer’s own catastrophic losses and a long position in an insurance-linked security, in reducing insurer loss volatility, value-at-risk, and expected losses above specified thresholds.

The principal finding is that insurers of all sizes can hedge effectively using loss four intra-state regional loss indices. Although many insurers would encounter significant basis risk in hedging with a state-level index, even with this index a high proportion of the total loss exposure in the state could be hedged efficiently. The results should be of interest to insurers, investors, and public policy-makers, and also provide a useful case study of the development of a new asset class to provide guidance for the securitization of other unconventional financial exposures.

The Basis Risk of Catastrophic-Loss Index Securities

1. Introduction

An important recent innovation in financial markets is the securitization of losses from catastrophic events such as hurricanes and earthquakes, which 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 \$40 billion (Applied Insurance Research 1999).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 or reinsurance (Jaffee and Russell 1997, Froot 1998). 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

CAT-risk securitization 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 securities such as weather derivatives (Geman 1999). In the absence of a traded underlying asset, insurance securities have been structured to pay-off on three types of variables – insurance-industry catastrophe loss indices, insurer-specific catastrophe losses, or *parametric* indices based on the physical characteristics of catastrophic events. The choice of a triggering variable involves a

¹Estimates by Applied Insurance Research (1999) indicate that there is a 1 percent probability of losses of about \$45 billion resulting from a Florida hurricane or a California earthquake.

²A 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.

³CAT securitization offers advantages to both hedgers and investors. CAT securities enable both insurers and non-financial firms exposed to catastrophic 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). Investors can benefit from CAT securities because catastrophic losses are “zero-beta” events. Thus, adding such securities to a diversified portfolio permits investors to shift the efficient frontier in a favorable direction (Litzenberger, et al. 1996, Canter et al. 1996).

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 criteria greatly reduce moral hazard but expose hedgers to an indeterminate amount of 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 catastrophic-loss securities market (American Academy of Actuaries 1999).⁴

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 1992.⁵ 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 (Goldman Sachs 1999).⁶ The loss payoff functions of nearly all CAT bonds and

⁴Because the issuance of CAT bonds typically involves the formation of a single purpose reinsurer to hold the bond proceeds and because the bonds are not standardized, CAT options also have a significant advantage over bonds in terms of transactions costs. Thus, solving the basis risk problem has the potential to facilitate the development of a more efficient insurance-linked securities market.

⁵The CBOT introduced catastrophic loss futures and option contracts in 1992. However, the futures contracts failed to generate sufficient interest among insurers or investors and were withdrawn in 1995. The current version of the call option spreads trades on industry-wide catastrophe loss indices compiled by Property Claims Services (PCS), the authoritative insurance industry statistical agent that reports on catastrophes. Contracts based on nine indices are currently traded on the CBOT – a national index, five regional indices, and three state indices (for California, Florida, and Texas).

⁶CAT 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. Investors are rewarded for placing their capital at risk by a premium above the yield on comparable bonds without the CAT contingency feature. The bond proceeds are held by a single-purpose reinsurer to insulate bond holders from the credit risk of the subject insurer. The reinsurer is typically located off-shore (e.g., the Cayman Islands) for regulatory and tax reasons. The coupon is usually stated as LIBOR plus a premium, with 400 to 600 basis points being the typical range for the premium. The triggering event typically involves multiple criteria, e.g., a hurricane of strength 3 or higher on the Saffir-Simpson scale causing losses to the insurer of \$500 million or more in the Southeastern United States. The first successful CAT bond was issued in 1997 to cover the losses of the St. Paul Insurance Group (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.

options issued to date are structured as call option spreads.⁷

Although the potential for basis risk is an important concern, there is no comprehensive empirical evidence about the basis risk of index-linked CAT securities. The 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 catastrophic-loss index CAT derivatives. 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 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.⁸ 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.

For purposes of comparison with prior work, we analyze the traditional hedging strategy based on a hedge portfolio that linearly combines a short position in CAT losses with a long position in CAT loss

⁷There have been approximately 20 CAT bond issues (most with multiple tranches), totaling about \$2.9 billion in proceeds (unpublished data from Goldman-Sachs). Although the open-interest of the CBOT CAT call spreads has increased since the introduction of the PCS contracts, the amount of risk-capital provided has been small, less than \$100 million in any given calendar quarter. To put these figures in perspective, the annual premium volume in the international reinsurance market is about \$120 billion. The slow development of the CAT securities markets is traceable to several factors, including insurer unfamiliarity with the instruments, the current widespread availability of low-cost reinsurance, and the transactions costs of issuing CAT bonds. However, the primary reason for the lack of interest in index-linked CAT options is the basis risk issue explored in this paper.

⁸The AIR model has been widely used by insurers and reinsurers since 1987 in monitoring their exposure to catastrophic losses and developing underwriting strategies and the first model meeting the standards of the Florida Insurance Commission on Hurricane Loss Projection Methodology.

futures. We also analyze 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. The latter analysis is important because the call-spread is the dominant functional form for payoffs on CAT bonds and options as well as for conventional reinsurance contracts.

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 hedging effectiveness a hedger could achieve by using its own loss experience as the hedge index. The perfect hedge is equivalent to purchasing insurance or 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 the CBOT CAT call spreads. The analysis measures the degree of basis risk insurers would incur from hedging through CAT loss indices. An analogous study design could be used to measure basis risk for industrials and other non-insurance hedgers.

By way of preview, the principal finding of our study is that insurers of all sizes can hedge CAT loss efficiently using the intra-state regional indices. Thus, contrary to the contention of some prior researchers, it is not necessary for an insurer to be large in order to hedge effectively using index-linked contracts. Although 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 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. Finally, the results should be of interest to insurance regulators and policymakers concerned about preventing the destabilization of insurance markets due to catastrophes.

There have been two previous studies of the basis risk of insurance-linked securities, both of which use 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 over the period 1974-1994. They find that state-specific PCS derivatives would have provided effective hedges for many insurers, especially those focusing on homeowners insurance. In a study more similar to ours, Major (1996) conducts a simulation analysis of insurer CAT losses using data on insurer exposures in Florida. He finds that hedging with a statewide catastrophe index is subject to substantial basis risk. Our analysis expands on Major's by considering significantly larger numbers of insurers and storms as well as evaluating a wider variety of hedging strategies.

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

2. Solving the Catastrophic Loss Problem Through Securitization

This section reviews the catastrophic loss problem and the role of securitization in financing catastrophic risk. We then provide some additional details on insurance-linked securities and discuss the advantages and disadvantages of the primary types of insurance-linked securities.

The Catastrophic Loss Problem

The magnitude of the worldwide catastrophic loss problem is illustrated in Figures 1, 2, and 3. Figure 1 shows that the number of catastrophes, defined as events causing at least \$32 million in insured losses, has increased dramatically in recent years.⁹ The increase in catastrophic property events is primarily attributable to the rapid growth in insured property values in catastrophe-prone areas on the East and West coasts of the U.S., especially in California and Florida. Figure 2 shows that total insured catastrophic losses also have increased significantly. During the period 1970 through 1988, there were only three years in which

⁹The data for Figures 1, 2, and 3 are from SwissRe (1999) and Figure 4 is based on unpublished data from SwissRe. The \$32 million threshold for a catastrophic loss is the one used in SwissRe (1999).

total catastrophic losses equaled or exceeded \$5 billion. Beginning in 1989, however, insured catastrophic losses have equaled or exceeded \$5 billion in every year, reaching a peak of \$25 billion in 1992. A graph of the cumulative insured losses from the top 40 events since 1970, shown in Figure 3, reveals that more than 80 percent of the total dollar value of CAT losses has occurred since 1988.

Until recently, reinsurance was the only mechanism available for insurers to hedge catastrophic risk. However, the capacity of the international reinsurance industry is inadequate to handle large catastrophes (Swiss Re 1997, Cummins and Weiss 2000). Insurance and reinsurance markets function well for relatively small, frequent events, but are not efficient mechanisms for financing large, infrequent events (Jaffee and Russell 1997). The total resources of the international reinsurance industry from 1993-1998 are shown in Figure 4. Although the industry has about \$300 billion in premiums and equity capital, most of the coverage provided by the industry is for relatively small events and only a fraction of the exposure base in hazard prone U.S. states is covered by reinsurance (Swiss Re 1997).

In addition to their limited capacity, reinsurance markets are subject to price and availability cycles, which often lead to price increases and supply restrictions following catastrophic events. The reinsurance price cycle is illustrated in Figure 5, which shows price levels in the international reinsurance market from 1989-1998 (Froot 1998a). The graph shows an index of the *rate on line*, a common measure of reinsurance pricing defined as the ratio of the reinsurance premium to the maximum amount payable under the reinsurance contract. Also shown is a price index, which adjusts the rate on line for the quantity of reinsurance available in the market. Both indices increased dramatically following Hurricane Andrew in 1992 and remained high due to the Northridge Earthquake in 1994. Price levels declined in the latter part of the 1990s, probably because no catastrophes comparable to Andrew or Northridge have occurred.

It might appear that the CAT loss financing problem could be solved by inflows of new equity capital into the reinsurance market. However, because holding capital in an insurer is costly, an infusion of new capital is not likely to be an efficient solution to the CAT problem (Jaffee and Russell 1997). Costly capital arises due to the regulatory and agency costs of operating an insurance company as well as accounting and

tax rules that penalize the accumulation of equity capital. Securitization provides a potentially much more efficient approach to financing catastrophic losses. Although a \$100 billion catastrophe amounts to about 30 percent of the capital of the U.S. insurance industry, a loss of this magnitude is less than one-half of 1 percent of the value of stocks and bonds in U.S. securities markets. Securities markets also are more efficient than insurance markets in reducing information asymmetries and facilitating price-discovery, potentially smoothing or eliminating insurance price cycles. Moreover, insurance-linked securities cover zero-beta events and thus are valuable to investors for diversification purposes. Thus, securitization is a promising approach to solving the catastrophic risk problem.

Insurance-Linked Securities

To date, the most important CAT securities have been the CBOT CAT call option spreads and CAT bonds. The CBOT's CAT call spreads settle on 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 cumulative catastrophic property losses in the specified geographical areas during quarterly or annual exposure periods. 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 6. Capital raised by issuing CAT bonds is invested in safe securities such as Treasury bonds, which are held by a single-purpose reinsurer, usually located off-shore for regulatory and tax reasons. The use of the single-purpose reinsurer also insulates the investors from the credit risk of the issuing insurer or non-insurance hedger. The CAT bond instrument defines the structure of the transaction – most importantly, the agreed-upon interest payments to investors and the contingencies that trigger partial or total forgiveness of the interest and/or principal of the bond. If the defined catastrophic event does not occur, the investors receive their principal plus interest, with the

interest payment usually defined as LIBOR plus a risk-premium ranging from 350 to 600 basis points for an event with a probability of triggering a principal loss of approximately 1 percent. However, if the defined event occurs, the insurer can withdraw funds from the reinsurer to pay claims, and part or all of the interest and principal payments are forgiven. Thus, the insurer holds a call option on the principal in the single-purpose reinsurer. In most CAT bonds, the trigger can be based upon single or multiple criteria – e.g., a hurricane of Saffir-Simpson magnitude 3, 4, or 5 that causes the insurer to lose at least \$500 million in the Southeastern United States. A co-payment mechanism is usually used to control moral hazard, e.g., the subject insurer bears 10 percent of the losses in excess of the trigger amount.¹⁰

CAT options and hedger-specific CAT bonds can be compared and contrasted in terms of their transactions costs, liquidity, and exposure to moral hazard and basis risk. The comparison is illustrated in Table 1. 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. Although the costs of issuing CAT bonds are expected to decline as the bonds become more standardized and market participants acquire more experience with insurance-linked securities, it is likely that index-linked options will continue to have a transactions cost advantage over CAT bonds for the foreseeable future.

Another important difference between CAT options and bonds involves market liquidity. CAT options have the potential to generate a very liquid market due to their standardization and the anonymity of traders. The CAT bonds issued to date, on the other hand, have low market liquidity because they are not standardized and not traded on an organized exchange and there is a limited investor base.

Index-linked CAT options also are superior to insurer-specific CAT bonds in terms of exposure to

¹⁰As a further control of moral hazard, at least one CAT bond has been issued with a *parametric trigger*, defined as an earthquake of a given Richter Scale magnitude in a specified geographical area; and CAT bonds also could settle on industry-wide loss indices. Because parametric and loss-index bonds are subject to basis risk, we focus the discussion on bonds with insurer-specific monetary triggers, to illustrate the basis risk contrast between this type of CAT bond and index-linked options.

moral hazard. The existence of the CAT bond may give an insurer the incentive to relax its underwriting and exposure management strategies, leading to an increase in exposure to loss in hazard prone areas. CAT bonds also may give insurers the incentive to settle claims more liberally than might be appropriate and to over-report losses to increase the amounts withdrawn from the single-purpose reinsurer. Although loss co-payment provisions provide at least some control over the moral hazard, it is unlikely that co-payment can be completely effective in eliminating moral hazard concerns. 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 disadvantage of index-linked options over insurer-specific contracts is the potential for basis risk. By linking payoffs to the losses of a specific insurer, insurer-specific CAT bonds virtually eliminate basis risk. However, CAT options, which pay-off on a loss index rather than the losses of a specific hedging insurer, are subject to an indeterminate amount of basis risk. A recent study by the American Academy of Actuaries (1999) reveals that the potential for basis risk is the most important reason for the lack of interest among insurers in the CBOT call spreads (see also Foppert 1993 and Himick 1997).

The issue of basis-risk remains a problem in part because defining hedge effectiveness is perceived by insurers as complex and in part because there is almost no publicly available information available about the degree of basis risk posed by index-linked options. Because of the advantages of index-linked contracts in transactions costs, market liquidity, and moral hazard, providing additional information on basis risk has the potential to promote a greater degree of interest among insurers and other hedgers in using index-linked options to hedge the risk of catastrophic losses. Greater liquidity in the CAT options market in turn can improve the efficiency of insurance and reinsurance markets by providing an additional source of risk-bearing capacity as well as reducing risk premia in reinsurance and CAT securities markets. The remainder of this paper is devoted to an analysis of the basis risk of index-linked CAT securities.

¹¹Index-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, unlike over-reporting on an insurer-specific instrument.

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) The identification of insurer characteristics that are associated with hedging effectiveness. And (5) the development of a parametric index that breaks the link between the losses of specific insurers and the payoff trigger of insurance-linked security contracts. 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 1998.¹² 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 reasonably representative of the entire insurance industry. The total exposure to property loss of the insurers in the sample is \$764 billion.

More details on the sample are provided in Table 2. 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

¹²Data on the nine omitted insurers were not available from the Florida Insurance Commissioner.

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 and that a high proportion of the exposure base in the state may be able to benefit from index-linked hedging.

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 (1999b).

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 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.

The structure of the simulation model is summarized in Table 3. 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. Index-hedge effectiveness is measured relative to the performance of perfect hedges, which pay off

on the insurer's own losses.¹³ 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 market price penalties for riskier insurers, direct and indirect costs of financial distress, and convex tax schedules.¹⁴ We consider “buy and hold” hedges 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 analyze two principal types of hedges: (1) 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; and (2) 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 linear hedging analysis is important for comparison with prior hedging studies; and the non-linear analysis is important because most insurance-linked securities and reinsurance contracts are structured as call option spreads.

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 . 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.

To define the linear hedge, let L_t = losses of a specified insurer at time t (a random variable which

¹³The counties in the four regions are specified in Appendix B.

¹⁴For more extensive discussions of the rationale for risk management at the firm level, see Merton and Perold (1993), Froot, Scharfstein, and Stein (1993), and Cummins, Phillips, and Smith (1999).

is unknown at time 0), and $E(L_t)$ = the expected value of the insurer's losses to be paid at time t , based on information available at time 0.¹⁵ The industry loss index at time t is I_t (also a random variable), with time 0 expected value = $E(I_t)$. The net payoff on the linear hedge is:

$$(1) \quad H_t = [E(L_t) - L_t] + h [I_t - E(I_t)] - h \pi_I E(I_t)$$

where H_t = the net payoff on the hedge, h = the hedge ratio, and π_I = the hedge premium or per-dollar price of the hedge.¹⁶ Defining the *basis* as $B_t = I_t - L_t$, the hedge payoff also can be written as:

$$(2) \quad H_t = [B_t - E(B_t)] - (1 - h) [I_t - E(I_t)] - h \pi_I E(I_t)$$

Hence, the variance of the hedge can be expressed in terms of basis risk, as:

$$(3) \quad \text{Var}(H_t) = \text{Var}(B_t) + (1 - h)^2 \text{Var}(I_t) - 2(1 - h) \text{Cov}(B_t, I_t)$$

The variance of the hedged position is positively related to basis risk and the risk of the index and negatively related to the correlation between the index and the basis.

Differentiating with respect to h yields the variance-minimizing hedge ratio:

$$(4) \quad h = 1 - \frac{\text{Cov}(B_t, I_t)}{\text{Var}(I_t)} = \frac{\text{Cov}(L_t, I_t)}{\text{Var}(I_t)}$$

Substituting equation (4) into equation (3), it is straightforward to calculate the reduction in variance as the result of executing the hedge. Expressing the variance reduction as a proportion of the unhedged variance yields the familiar expression for variance reduction or **hedge effectiveness** through linear hedging:

$$(5) \quad \text{Variance Reduction} = \frac{\text{Cov}(L_t, I_t)^2}{\text{Var}(I_t) \text{Var}(L_t)} = R^2(L_t, I_t)$$

where $R^2(L_t, I_t)$ = the coefficient of determination between the insurer's losses and the index.

Non-Linear Hedging

¹⁵Company subscripts are suppressed here for simplicity.

¹⁶In an efficient market, the hedge premium should equal zero, provided that catastrophes are "zero beta" events. However, actual insurance-linked securities and reinsurance markets, the hedge premiums tend to be greater than zero, due to information asymmetries and other factors (see Froot and Stein 1999, Goldman-Sachs 1999).

The non-linear hedges considered in this paper involve hedging through the use of call option spreads. The call option spread is the dominant contract form in the market for catastrophic loss reinsurance as well as for CAT bonds and options (see Froot 1998b, Cummins, Lewis, and Phillips 1999). The insurer is assumed to hold 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 is:

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

where L_j^P = insurer j 's hedged loss under the perfect hedge, L_j = insurer j 's unhedged loss, h_j = the hedge ratio, M_j = the lower strike price of the call spread, and U_j = the upper strike price of the spread. The perfect hedge, based on an index consisting of the insurer's own losses, is the result that would be obtained under excess of loss reinsurance or an insurer-specific CAT bond.

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:

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

where L_j^S = insurer j 's hedged loss using an industry-wide, state-level loss index, and $L^S = \sum_j L_j$ = state-wide losses for the industry. Insurer j 's hedged loss under the regional hedge is:

$$(8) \quad L_j^R = \sum_{r=1}^R \left[L_{jr} - h_{jr} [\text{MAX}(L_r^R - M_{jr}, 0) - \text{MAX}(L_r^R - U_{jr}, 0)] \right]$$

where L_j^R = company j 's losses under the regional hedge, L_{jr} = losses of insurer j in region r , h_{jr} = hedge ratio for insurer j in region r , L_r^R = industry-wide losses in region r , M_{jr} = lower strike price for company j 's region r option spread, and U_{jr} = upper strike price for company j 's region r spread, and R = the number of regions

($R = 4$ in our analysis).

In the general non-linear hedging problem, the insurer is assumed to optimize 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:

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

$$\text{Subject to:} \quad h_j [W(L^S, M_j) - W(L^S, U_j)] \leq C_j$$

where C_j = the maximum amount available to insurer j to spend on hedging, and $W(L^S, M_j)$ and $W(L^S, U_j)$ = the prices of call options on industry losses L^S with strike prices M_j and U_j , respectively. Thus, the insurer optimizes over the hedge ratio and the two strike prices, M_j and U_j , 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: $G_1(L_j^i) = \sigma^2[L_j^i(h_j, M_j, U_j)]$ = 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 regional hedge.

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 ($0 \leq \alpha \leq 1$). Stated more formally, defining insurer j 's net loss distribution function under hedge index i as $F_{ij}[L_j^i(h_j, M_j, U_j)] = F_{ij}(\cdot)$, VaR is defined as:

$$(10) \quad \text{VaR}_{ij}[\alpha, L_j^i(h_j, M_j, U_j)] = F_{ij}^{-1}(1 - \alpha)$$

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

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.¹⁷ More formally, the EEV is defined as:

$$(11) \quad \text{EEV}_j[L_T, L_j^i(h_j, M_j, U_j)] = \int_{L_T}^{\infty} [L_j^i - L_T] dF_j(L_j^i(h_j, M_j, U_j)) = \int_{L_T}^{\infty} [1 - F_j(L_j^i)] dL_j^i$$

where L_T = a loss threshold specified by the decision maker, and $L_j^i(h_j, M_j, U_j)$ has been abbreviated as L_j^i in the last term of equation (11). The EEV criterion function is $G_3(L_j^H) = \text{EEV}_j[L_T, L_j^i(h_j, M_j, U_j)]$. 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 be interested not only in the probability of exceeding a given loss level but also in how large the excess loss is likely to be, i.e., it matters whether the threshold loss level is exceeded by \$1 or \$1 million.

¹⁷Recent research suggests that EEV-type measures have desirable properties not possessed by value at risk measures. See, for example, Artzner, et al. (1999).

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:

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

The other two hedge effectiveness measures are defined similarly.

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 determine why some insurers can hedge effectively using index-linked contracts and others cannot. 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 to enhance their ability to hedge.

Regression analysis is used to analyze the relationship between firm characteristics and hedging effectiveness. Two types of dependent variables are employed in the analysis. The first set of tests considers the hedging effectiveness ratios defined in equation (5), for linear hedging, and equation (12), for non-linear hedging. The second set of tests considers only non-linear hedging effectiveness. The dependent variable in these models is a relative hedging effectiveness or **hedge efficiency** variable that compares index hedging with perfect hedging. These variables consist of the hedge efficiency ratios HE_{jm}^i / HE_{jm}^P , where $i = S$ (for statewide index hedging), R (for regional index hedging), and P for perfect hedging, and m indicates the hedging criterion.

Three variables are hypothesized to be related to hedging effectiveness and efficiency – (1) the proportion of an insurer's total insured property value located in ocean front counties, (2) the overall diversification of an insurer's insured property value exposure across the state, and (3) the insurer's size as

measured by its market share of total insured property values in the state. The proportion of insured property value in ocean front counties is of obvious importance in an analysis of catastrophic risk as these 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 effectively using loss index hedges because the loss indices tend to be driven by losses in ocean front counties rather than losses in inland counties.

The overall diversification of exposures across the state is measured for each company based on its county market shares. The market share for company j in county k is defined 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. The county market shares are used to calculate two measures of diversification – the coefficient of variation of s_{jk} and the market share Herfindahl Index, which equals $\sum_k s_{jk}^2$. Both diversification measures are hypothesized to be inversely associated with hedging effectiveness because losses from a more geographically diversified portfolio would have a low coefficient of variation and Herfindahl index and thus should be more highly correlated with the loss indices than losses from more concentrated portfolios.

The third variable used to test for the determinants of hedging effectiveness is the insurer's statewide market share $s_j = S_j/S$, where S = total insured property value in the state. This variable is expected to be positively associated with hedging effectiveness because companies with higher market shares have more impact on the value of the loss index, *ceteris paribus*.

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.¹⁸

Our proposed parametric index is for hurricane losses in Florida. The index 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 - 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 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.

¹⁸Only a handful of insurance-linked 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.

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 development of the proposed parametric index. We begin the section by providing some additional discussion of the hurricane simulation results and the definition of the indices.

Simulation Results and CAT Loss Indices

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 92.8 percent of the insured residential property values in the state.¹⁹ Thus, the study applies to hedging effectiveness for residential property insurance. This is considered to be 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. The total value of insured residential property exposed to loss in Florida in 1998 was \$764 billion.

The second step in the analysis is to simulate county-level losses for the insurers in our 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_{jkt} = hurricane losses for company j , in county k , located in

¹⁹The 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.

region r , for simulation year t , where $j = 1, \dots, 255$, $k = 1, \dots, 67$, $r = 1, \dots, 4$, and $t = 1, \dots, 10,000$ (as indicated, the maximum value of t equals 1,000 for most of the analysis). The counties are roughly grouped into regions by dividing the state into quadrants based on horizontal and vertical lines through the center of the state.²⁰ The simulated losses are then used to construct the following loss indices:

$$(13) \quad \text{The "Perfect" Index} = L_{j..t}^P = \sum_{r=1}^R \sum_{k=1}^{K_r} L_{jkr t}$$

$$(14) \quad \text{The Regional Indices} = L_{..rt}^R = \sum_{j=1}^N \sum_{k=1}^{K_r} L_{jkr t}$$

$$(15) \quad \text{The State Index} = L_t^S = L_{...t} = \sum_{r=1}^R \sum_{k=1}^{K_r} \sum_{j=1}^N L_{jkr t}$$

where N = the number of insurers (255), R = the number of regions (4), K_r = the number of counties in region r (approximately 15), and a dot in place of a subscript means that a summation has been taken over that subscript. The indices are then used to form hedge portfolios for each insurer to determine the degree of basis risk for each type of index.

Linear Hedging

In this analysis, we form hedge portfolios for each insurer in the sample consisting of a short position in its own catastrophic losses and a long position in an index (see equations (1) and (2)). The variance minimization or hedge effectiveness for the state and regional hedges are then given by:

$$(16) \quad R_S^2(L_{j..t}, L_t^S) = \frac{Cov(L_{j..t}, L_t^S)^2}{Var(L_{j..t}) Var(L_t^S)}$$

$$(17) \quad R_R^2(L_{j..rt}, L_t^R) = \frac{Cov(L_{j..rt}, L_t^R)^2}{Var(L_{j..rt}) Var(L_t^R)}$$

²⁰The 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. Appendix B summarizes the counties included in each cluster.

where $R_S^2(L_{j,t}, L_t^S)$ = the variance reduction for insurer j using the state index, and $R_R^2(L_{j,t}, L_t^R)$ = the variance reduction for insurer j using the regional indices. The coefficient of determination defined by equation (16) is taken across the T simulated years, while the coefficient of determination in equation (17) is across R regions for each of T simulated years.

The results of the linear hedging analysis are presented in Table 4. Table 4 shows the average variance reduction from linear hedging for insurers in the four size quartiles (the largest firms are in quartile 1) for the statewide and regional loss indices. Average variance reduction using the statewide index ranges from 64.8 percent for insurers in the largest size quartile to 37.4 percent for insurers in the smallest size quartile. Thus, by this measure there is substantial basis risk for insurers in the smaller size quartiles when the statewide index is used. The results are significantly better for the regional loss indices. Insurers in the two largest size quartiles could reduce their loss volatility by more than 90 percent using the regional loss indices, and insurers in quartile 3 could reduce loss volatility by 85 percent. Even in the smallest size quartile, loss volatility could be reduced by about two-thirds using regional indices. Thus, there are substantial hedging gains by moving from a statewide index to regional indices.

Additional information on the effectiveness of linear hedging is provided in Figure 7. This figure adjusts for the skewness of exposures across companies doing business in the state by showing the percentage of exposures in companies that could reduce their loss volatility by various percentages. The graph reveals that almost 80 percent of the exposures in the state are insured by companies that could hedge with at least 95 percent effectiveness using regional loss indices and that 97 percent of exposures are insured by companies that could reduce loss volatility by at least 90 percent using regional hedges. The skewness-adjusted results are relevant from a public policy perspective because they show that a very high proportion of the total state exposures reside in companies that could hedge very effectively using regional hedging strategies. Figure 7 also shows that hedging based on the statewide index is less effective than hedging using the regional indices. Using the statewide index, 50 percent of the exposures in the state are insured by

companies that could reduce their loss volatility by at least 75 percent.

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 functions 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 losses, ranging from 5 percent to 50 percent. By varying the cost constraint, an efficient frontier is generated based on each of the criterion functions. The perfect, statewide, and regional loss indices defined in equations (13), (14), and (15) are used to form hedge portfolios.

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 8A. 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 8B. 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 9 shows the non-linear variance-reduction frontiers 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 10. 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. 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 11 shows a frequency distribution of the variance-reduction hedge efficiency for an expenditure of 25 percent of expected losses.²¹ 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 using an index hedge may be sufficiently small to make index hedging attractive for the majority of Florida

²¹The 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.

insurers.²² The statewide hedge is at least 90 percent as effective as the perfect hedge for 41 of the sample and at least 80 percent as effective for 87 of the sample firms.²³

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.²⁴ 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 $\text{VaR}_j(0.025, L_j)$, i.e., above the 2.5 percent VaR for the j th 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 or the Northridge earthquake. This seems to be an appropriate objective given the general lack of availability of reinsurance for losses of this magnitude. 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 12. The results again support the conclusion that insurers in the top size quartile can 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

²²These 152 firms account for 93.7 percent of the total property exposure of the sample insurers.

²³These 87 firms account for 76.9 percent of the total property exposure of the sample insurers.

²⁴The VaR results are available from the authors on request.

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 13, 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 ineffective for the majority of insurers, still seems quite effective if the objective is to hedge the CAT risk for a high proportion of the exposed value in the state.

Insurer Characteristics and Hedge Effectiveness

The regressions to analyze the determinants of hedging effectiveness are presented in Table 5. The dependent variables in the regressions are hedge efficiencies, 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.²⁵ The independent variables in the equations include the proportion of loss exposure in ocean front counties, the coefficient of variation of the insurer's county market share, and the firm's statewide market share. Also included as control variables are dummy variables for the ten cost constraints (ranging from 5 to 50 percent in increments of 5 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

²⁵The VaR results are similar and are available from the authors.

dependent variable ranges between 0 and 1.

The regression results provide consistent support for two of the three hypotheses about the 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 5, consistent with the hypothesis that insurers with relatively high ocean front exposure can hedge more effectively. Likewise, 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. The regressions provide mixed support for the hypothesis that hedging efficiency is related to insurer size, as measured by statewide market share. The market share variable is positive and significant in the statewide variance and EEV efficiency models but insignificant in the regional variance efficiency model and significant only at the 10 percent level in the regional EEV model. These results suggest that insurers of all sizes can hedge effectively using the regional indices, provided that their other characteristics are consistent with efficient hedging.

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 significantly higher for the regional regressions than for the statewide regressions, providing additional 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. 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 5. 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. In the three equations where the null hypothesis is rejected, the efficiencies tend to be higher for the higher expenditure levels. The coefficients differ only slightly in the statewide variance efficiency regression, and in the regional EEV efficiency model the

difference between the largest and smallest intercept is modest (about 20 percent). However, in the statewide EEV efficiency model, the largest intercept is about 60 percent higher than the smallest. Thus, the expenditure level is important for the statewide EEV models but less important in the variance models and the regional EEV model.

A Parametric Index

As discussed above, our proposed parametric index is based on a log-linear regression model with dependent variable equal to the log of storm damages and independent variables consisting of three physical measures of storm characteristics as well as landfall segment dummy variables (not shown). The regression model, shown in Table 6, was estimated on the basis of a sample consisting of the yyys hurricanes resulting from the 1,000 simulated years used in most of the analysis. As hypothesized, the “30-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 is negatively associated with storm damage, as expected if storms that move more rapidly through a geographical area cause less damage. Finally, 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. 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.²⁶

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 14, which plots the log of the predicted value of storm damage from the model against the storm damage

²⁶There 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.

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 regional loss indices.

The principal advantage of a parametric model is to reduce the possibility of moral hazard.²⁷ 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 presented above indicates that insurers could hedge almost as effectively using the model as they could using monetary loss indices.

The most serious potential criticism of our parametric model is that it is essentially a model of AIR's simulated storm damage. Thus, it is a "model of a model," i.e., it shows that a high proportion of the variation in simulated storm damage from AIR's complex model can be replicated using a few physical storm variables. But this does not necessarily mean that the AIR model is a perfect representation of actual storm damage. In effect, because the AIR model is not a perfect representation of reality, using our parametric model introduces additional basis risk. However, 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.

Hedging at Recent Market Prices

The analysis so far has been conducted under the assumption that call spread contracts are available

²⁷Another 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.

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.²⁸ 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 hedging analysis under the assumption that CAT security prices are actuarially unfair.²⁹ The results are reported in this section. In conducting the analysis, we base the prices for the contracts on recent market prices for CAT bonds and CBOT call spreads.

Pricing statistics for Florida CBOT call spreads and CAT bonds are presented in Table 7. Panel A of the Table 7 focuses on CBOT call spreads and shows all trades which have taken place in the September and December CBOT call-spread contracts over the last four years. The table shows the month and year of the trade, the exposure period, the total premium paid by the investor, the lower and upper strike prices of the call spread, and the number of contracts purchased. The expected loss on each contract was estimated using output from the AIR model over the 10,000 year simulation and the parameters of each trade. The final column in panel A shows that the option premia are substantially in excess of the estimated expected losses. The average ratio of option premia to expected payouts is 2.3 and the median ratio is 2.1, indicating pricing in excess of 100 percent above the expected loss.

Pricing information on CAT bond issues is provided in panel B of Table 7.³⁰ The transactions we display are all principal-at-risk catastrophe linked securities that have been issued since 1996. Column 3

²⁸Evidence that catastrophic risk contracts do not have systematic risk is presented in Litzenberger, Beaglehole, and Reynolds (1996).

²⁹Among the reasons that have been advanced for non-actuarial pricing of catastrophic loss securities are investor unfamiliarity with the contracts, investor concern about moral hazard, uncertainty about the accuracy of expected loss estimates provided by modeling firms, and the current illiquidity of the CAT securities market. For further discussion see Kunreuther and Bantwal (1999).

³⁰The information on CAT bonds reported in Table 7 were obtained from the offering circulars. We are grateful to Michael Millette of Goldman Sachs & Co. who provided us the CAT bond data. The information on the CBOT option trades was obtained from the CBOT web site and correspondence with the CBOT.

shows the spread above LIBOR paid on each issue. Columns 4 through 6 show the probability of the first dollar of loss, the expected loss on the security given there is a triggering event, and the ex-ante expected loss on the security, respectively, with the expected loss expressed as a percentage of the value of the bond issue. The premium-to-expected payout ratio equals the spread above LIBOR divided by the expected loss on the security and is substantially higher than those of CAT options – the average ratio of price to expected loss is 9.1 and the median ratio is 6.8. The most likely explanation for the difference between the premium-to-expected-loss ratios of CBOT options and CAT bonds is investor concern about moral hazard – CAT bonds, most of which settle on the losses of specific insurers, are potentially subject to significant moral hazard whereas moral hazard is a relatively minor concern for the CBOT options.

To analyze the effects of non-actuarial pricing on the ability of insurers to hedge using CAT bonds and options, we repeated our non-linear hedging analysis using non-actuarial prices. The contractual forms 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. As above, the contracts studied include a “perfect hedge” contract, which pays off on the losses of individual insurers, and index contracts, which pay off on industry-wide losses. Also as above, two types of index contracts are used – a statewide index contract and four regional index contracts. 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 9.0 and the index hedge contracts are assumed to be sold at a premium-to-expected-loss ratio of 2.0, roughly matching the pricing statistics shown in Table 7.

The results of the non-actuarial hedging analysis are shown in Table 8. Panel A of Table 8 shows the hedging results under market prices, and panel B shows the results under actuarially fair prices for purposes of comparison. The results in the table are 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 8.

As expected, the results in Table 8 show a significant reduction in hedging effectiveness under non-actuarial pricing. For example, if expenditures on hedging are constrained to 20 percent of expected losses, the perfect hedge reduces the EEV by 95.7 percent with actuarially fair pricing but only by about 19.4 percent with non-actuarial pricing (price-to-loss ratio of 9.0). The analogous comparisons for the statewide and regional hedges show that these hedges lead, respectively, to EEV reductions of 66.5 and 81.7 percent at actuarially fair prices but only 41.9 and 52.7 percent with market prices (price-to-loss ratio of 2.0). Because the index contracts have a lower price-to-loss ratio than the perfect hedge contracts (2 versus 9), the statewide and regional index contracts provide significantly better hedges than the perfect hedge contracts.

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, which is the traditional hedge for insurers facing CAT loss exposure. Interestingly, the markups on the insurance derivative contracts shown in Table 7 are not out-of-line with markups on reinsurance contracts covering similar risks. 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 7.0 in 1994, all in the same range as the price-to-loss ratios in Table 7. 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 contracts 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 reinsurance market are comparable to price-to-loss ratios for CAT securities. (2) If index contracts continue to be priced significantly lower than insurer-specific (perfect hedge) contracts, these contracts may come to dominate CAT bonds as catastrophic risk markets become more liquid and investors become more familiar with this type of security. However, 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 securities market is likely to dominate the reinsurance market for the hedging of mega-CATs if the price-to-loss ratios converge towards actuarial fairness.

5. Conclusions

The securitization of CAT losses has been driven by an increase in the frequency and severity of property losses from catastrophes and the recognition that conventional insurance and reinsurance markets do not provide efficient mechanisms for financing losses from low frequency, high severity events. 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.

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. The simulations are based on a sophisticated catastrophic loss model developed by Applied Insurance Research (AIR). (3) Linear and non-linear hedge portfolios are specified for the insurers in the

sample and hedge effectiveness and basis risk are analyzed for a statewide catastrophic loss index and four regional indices. Three hedging criterion functions are used in the non-linear analysis – the variance of insurer losses, the value-at-risk (VaR), and the expected exceedence value. (4) Regression analysis is conducted to determine the insurer characteristics that are associated with hedging effectiveness. 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 the linear hedging analysis we form hedge portfolios consisting of a short position in insurer loss liabilities and a long position in the industry-wide loss indices. Although there is a significant amount of basis risk for most insurers when hedging with the statewide index, insurers in the three largest size quartiles could hedge with at least 85 percent effectiveness using the regional loss indices. Because of the skewness of Florida exposures across insurers, however, the proportion of exposures that could be hedged effectively is much larger than the proportion of insurers that can hedge effectively – 97 percent of exposures are insured by companies that could hedge with at least 90 percent effectiveness.

In the non-linear hedging analysis, we form hedge 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 index, and four regional industry indices. 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, defined as the expected catastrophic loss conditional on the loss exceeding a specified threshold. We gauge hedging effectiveness by comparing the success of the statewide and regional indices in achieving the specified objectives with the effectiveness of hedges based on the perfect index. The statewide hedge is found to be 90 percent as effective as the perfect hedge in reducing variance for 41 of the 255 firms in the sample, while the regional hedge is 90 percent as effective as the perfect hedge for 152 firms and 85 percent as effective for 189 firms. Similar results are obtained for the VaR and the EEV. Thus, the regional hedges could be used effectively by a high proportion of firms in the sample, and, as with the linear hedge, a high proportion of the exposures

in the state could be hedged effectively by either the statewide or the regional indices. This is an important finding, among other reasons, because an index-contract market based on smaller geographical areas such as counties or zip codes would likely encounter higher transactions cost and liquidity problems in comparison with our more broadly defined sub-state indices.³¹

The analysis of the determinants of hedging effectiveness reveals that hedge effectiveness is positively related to the proportion of an insurer's exposures in ocean front counties and the diversification of its exposures across the state. With the statewide hedges, hedging effectiveness is positively related to insurer statewide market share, but for the regional indices, hedging effectiveness is not significantly related to market share. Thus, even relatively small insurers can hedge effectively using the regional indices.

We 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 losses caused by the hurricanes and appears to be unbiased for losses of all magnitudes. Thus, either this index or similar indices could be introduced to significantly reduce insurer and investor concerns about potential moral hazard with indices based on post-event losses reported by insurers.

The final part of the analysis tests the robustness of the results by repeating the non-linear hedging analysis under the assumption that CAT options and bonds are priced at a markup over their actuarially fair expected values. The markups used in the analysis are based on actual price-to-expected-loss ratios for the CBOT option contracts and CAT bond issues. Even at the current markups in the CAT securities market, these securities are competitive with conventional reinsurance in terms of price and hedging effectiveness. Because the price-to-loss ratios of CAT bonds are about twice as high on average as for the CBOT options, the options provide more effective hedges than bonds, even though the former settle on loss indices while the latter settle on the losses of specific insurers. This is suggestive evidence that moral hazard may be a

³¹A 1998 attempt to launch zip-code level index contracts failed to generate interest among insurers and investors and is currently dormant. For a discussion of the proposed market see Chookaszian and Ward (1998).

more serious problem than basis risk, but any more definite conclusions on this point await the development of more mature and liquid CAT securities markets than exist at present.

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 management of many insurers needs to pay more attention to the former type of diversification.

Table 1
Index-Linked vs. Insurer-Specific CAT Securities

Criterion	Index-Linked	Insurer-Specific
Moral Hazard	Low	High
Transactions Costs	Low	High
Liquidity	Potentially High	Relatively Low
Basis Risk	?	Low

Table 2
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 3
Structure of the Applied Insurance Research Simulation Model

Table 4
Variance Reduction Using Linear Hedging

Index	Quartile 1	Quartile 2	Quartile 3	Quartile 4	All Quartiles
Statewide Industry Loss	64.8%	59.0%	49.0%	37.4%	52.6%
Regional Industry Loss	93.2%	92.2%	84.9%	66.8%	84.4%

Table 5
Determinants of Hedging Efficiency
Dependent Variable = Risk Reduction Index/Perfect Hedge

Variable	Variance Reduction		EEV Reduction	
	Statewide	Regional	Statewide	Regional
% of Exposures in Ocean Front Counties	0.522 (30.280)	0.111 (9.424)	0.538 (30.302)	0.138 (10.310)
Coeff. of Variation of County Market Share	-0.054 (-26.753)	-0.050 (-36.269)	-0.052 (-24.757)	-0.050 (-31.501)
Market Share	1.123 (4.943)	0.004 (0.027)	1.926 (6.312)	0.317 (1.644)
5% Cost Constraint	0.366 (19.693)	0.941 (74.419)	0.387 (20.265)	1.003 (68.910)
10% Cost Constraint	0.389 (20.953)	0.928 (73.459)	0.353 (18.494)	0.926 (64.233)
15% Cost Constraint	0.404 (21.743)	0.930 (73.622)	0.327 (17.139)	0.863 (60.150)
20% Cost Constraint	0.412 (22.197)	0.928 (73.496)	0.338 (17.722)	0.860 (60.005)
25% Cost Constraint	0.418 (22.490)	0.930 (73.660)	0.368 (19.254)	0.875 (60.958)
30% Cost Constraint	0.420 (22.635)	0.930 (73.640)	0.407 (21.299)	0.911 (63.104)
35% Cost Constraint	0.422 (22.746)	0.930 (73.659)	0.443 (23.123)	0.945 (64.901)
40% Cost Constraint	0.424 (22.825)	0.930 (73.663)	0.474 (24.699)	0.970 (66.104)
45% Cost Constraint	0.425 (22.879)	0.932 (73.764)	0.500 (26.018)	0.998 (67.314)
50% Cost Constraint	0.427 (22.983)	0.934 (73.938)	0.525 (27.253)	1.026 (68.048)
Log Likelihood Function Value	378.498	1352.441	196.013	600.190
Likelihood Ratio Test Statistic	20.147	1.570	230.765	297.470

Note: z-statistics shown in parentheses. Estimation conducted using the Tobit procedure.

The intercept term has been suppressed since the model includes cost constraint dummy variables.

The null hypothesis for the likelihood ratio test is that all cost constraint dummy 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 6
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 7
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
Median						2.14

Source: Chicago Board of Trade and Applied Insurance Research

B. Catastrophe (CAT) Bond Issues

Date	Transaction Sponsor	Spread Premium	Prob of 1 st \$ of Loss	Expected E[L L > 0]	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 8
Expected Exceedence Value Reduction: Market Price Contracts

A. Hedging Results at Market Prices

Cost (% of EV)	EEV - to - Exp Loss Ratio				EEV Reduction		
	Unhedged	Perfect	State	Regional	Perfect	State	Regional
5.0%	16.6%	16.5%	14.7%	14.2%	0.3%	11.5%	15.4%
10.0%	16.6%	15.3%	13.0%	11.9%	8.5%	22.2%	30.1%
15.0%	16.6%	14.5%	11.3%	10.0%	14.0%	32.7%	42.3%
20.0%	16.6%	13.6%	9.9%	8.3%	19.4%	41.9%	52.7%
25.0%	16.6%	12.9%	8.6%	6.8%	24.3%	49.9%	61.6%
30.0%	16.6%	12.1%	7.5%	5.6%	29.2%	56.5%	68.8%
35.0%	16.6%	11.4%	6.7%	4.4%	34.0%	61.2%	75.6%
40.0%	16.6%	10.6%	6.1%	3.7%	38.9%	65.1%	79.6%
45.0%	16.6%	9.9%	5.6%	2.9%	43.7%	68.2%	84.2%
50.0%	16.6%	9.2%	5.2%	2.4%	48.6%	70.7%	87.0%

B. Hedging Results at Fair Prices

Cost (% of EV)	EEV - to - Exp Loss Ratio				EEV Reduction		
	Unhedged	Perfect	State	Regional	Perfect	State	Regional
0.05	16.6%	11.6%	12.8%	11.9%	32.9%	23.3%	30.5%
10.0%	16.6%	6.6%	9.6%	7.9%	65.8%	43.7%	55.2%
15.0%	16.6%	2.7%	7.3%	5.0%	89.1%	58.0%	72.5%
20.0%	16.6%	1.2%	5.9%	3.4%	95.7%	66.5%	81.7%
25.0%	16.6%	0.4%	5.0%	2.2%	98.6%	71.8%	88.1%
30.0%	16.6%	0.0%	4.3%	1.7%	100.0%	75.7%	90.9%
35.0%	16.6%	0.0%	3.9%	1.3%	100.0%	78.6%	92.8%
40.0%	16.6%	0.0%	3.5%	1.0%	100.0%	80.8%	94.3%
45.0%	16.6%	0.0%	3.2%	0.8%	100.0%	82.9%	95.3%
50.0%	16.6%	0.0%	3.0%	0.7%	100.0%	84.3%	95.8%

Figure 1
Number of Property Catastrophe Losses: 1970-1998

Figure 2
Insured Catastrophe Losses (Amounts): 1970-1998

Figure 3
Top 40 Insured CAT Losses: Cumulative Loss Amount 1970-98

Figure 4
Total Resources: The Global Reinsurance Industry

Figure 5
Reinsurance Price Levels: Rate on Line and Price Index

Figure 6

CAT Bond with Single Purpose Reinsurer

Figure 7
Variance Reduction Using Linear Hedging: By Percentage of Exposures
Statewide vs. Regional Indices

Figure 8A
Variance Reduction Using Non-Linear Contracts: Highly Diversified Insurer

Figure 8B
Variance Reduction Using Non-Linear Contracts: Undiversified Insurer

Figure 9
Variance Reduction Frontiers: Average For Insurers in Largest Size Quartile

Figure 10
Variance Reduction Frontiers Using Non-Linear Contracts & Regional Indices
By Insurer Size Quartile

Figure 11
Variance Reduction Hedging Efficiency: Non-Linear Contracts
Hedging Cost Constraint = 25 Percent of Expected Annual Losses

Figure 12
Expected Exceedence Value Reduction: Non-Linear Contracts
Average For Insurers In Largest Size Quartile

Figure 13
Expected Exceedence Value Reduction Efficiency: Non-Linear Contracts
Hedging Cost Constraint = 25 Percent of Expected Annual Losses

Figure 14
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. The 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 “AIR’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.

Appendix B
Counties Composing Each Region in Florida

North Atlantic	Pan-Handle	South Atlantic	Gulf Coast
Baker	Bay	Broward	Alachua
Bradford	Calhoun	Dade	Charlotte
Brevard	Columbia	Indian River	Citrus
Clay	Escambia	Martin	Collier
Duval	Franklin	Monroe	Desoto
Flagler	Gadsden	Okeechobee	Dixie
Lake	Gulf	Palm Beach	Gilchrist
Nassau	Hamilton	St. Lucie	Glades
Orange	Holmes		Hardee
Osceola	Jackson		Hendry
Putnam	Jefferson		Hernando
St. Johns	Lafayette		Highlands
Seminole	Leon		Hillsborough
Union	Liberty		Lee
Volusia	Madison		Levy
	Okaloosa		Manatee
	Santa Rosa		Marion
	Suwannee		Pasco
	Taylor		Pinellas
	Wakulla		Polk
	Walton		Sarasota
	Washington		Sumter

Figure A.1
Flow Chart of the AIR Model

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

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