A FORMAL APPROACH TO CATASTROPHE RISK ASSESSMENT AND MANAGEMENT

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ABSTRACT

Insurers paid $1.9 billion on property claims arising from catastrophes in 1983. Researchers have estimated that annual insured catastrophe losses could exceed $14 billion. Certainly, the financial implications for the insurance industry of losses of this magnitude would be severe; even industry losses much smaller in magnitude could cause financial difficulties for insurers who are heavily exposed to the risk of catastrophic losses.

The quantification of exposures to catastrophes, and the estimation of expected and probable maximum losses on these exposures pose problems for actuaries. This paper presents a methodology based on Monte Carlo simulation for estimating the probability distributions of property losses from catastrophes and discusses the uses of the probability distributions in management decision-making and planning.

INTRODUCTION

There were 33 named catastrophes in 1982, and they resulted in an estimated $1.5 billion of insured property damage. Most of these catastrophes were natural disasters such as hurricanes, tornadoes, winter storms, and floods. In 1983, hurricane Alicia caused over $675 million of insured losses; the December storms caused insured damage of $510 million.[1]

Hurricane Alicia barely rated a three on a severity scale ranging from one to five, and destruction from hurricanes increases exponentially with increasing severity. A hurricane that rated a four hit New York and New England in 1938; 600 people died and wind speeds of 183 mph caused hundreds of millions of dollars of damage.

If this storm were to strike again, dollar losses to the insurance industry could amount to six billion given the current insured property values on Long Island and along the New England coast. Estimates of the dollar damages that will result if a major earthquake occurs in Northern or Southern California are even larger in magnitude.

A very severe hurricane or earthquake would produce a year of catastrophic loss experience lying in the upper tail of the probability distribution of annual losses from catastrophes, and it is the opinion of the author that the 1982 catastrophe loss figure lies in the lower end of this distribution. However, the determination of the shape and the estimation of the parameters that describe this distribution are tasks that are not easily performed by standard actuarial methodologies. Yet since insurers need the knowledge of their exposures to catastrophes and the probability distributions of annual catastrophic losses to make pricing, marketing, and reinsurance decisions, the estimation of the distribution and the expected and probable maximum losses pose problems for actuaries.

Standard statistical approaches to estimation involve the use of historical data to forecast future values of variables. However, models based on time series of past catastrophe losses are not appropriate for estimating future losses. Catastrophes are rare events so that the actual loss data are sparse and their accuracy is questionable; average recurrence intervals are long so that many exogenous variables change in the time periods between occurrences. In particular, changing population distributions, changing building codes, and changing building repair costs alter the annual catastrophe loss distribution.

Since most catastrophes are caused by natural hazards and since most natural hazards have associated with them geographical frequency and severity patterns, the population distribution impacts the damage producing potentials of these hazards. A natural disaster results when a natural hazard occurs in a populated area. Changing population patterns necessarily alter the probability distribution of catastrophic losses. Since the average recurrence intervals of natural hazards in any particular area are long, patterns of insured property values may vary between occurrences to an extent that damage figures of historical occurrences have no predictive power. For example, if hurricane Alicia had struck in 1950, dollar damages would have been significantly lower even after adjustment for inflation because of the smaller number of insured residential and commercial structures in the Houston area at that time.

It is primarily the influence of the geographic population distribution that renders time series models inadequate although changing building codes also alter the loss producing potentials of natural hazards. As time passes, building materials and designs change, and new structures become more or less vulnerable to particular natural hazards than the old structures. Of course, changes in building repair costs also affect the dollar damages that will result from catastrophes.

The above issues do not render the estimation problem intractable, but they do produce a need for an alternative methodology to approaches which employ historical catastrophe losses adjusted for inflation to approximate the probability distribution of losses. Even models which adjust these losses for population shifts can give only very rough approximations of expected and probable maximum losses.

This paper presents a methodology based on Monte Carlo simulation, and it focuses on property damage from natural disasters. Part I discusses Monte Carlo simulation and the natural hazard simulation model. A windstorm example is employed to illustrate the approach. Part II outlines the ways in which management may use the model and its output for decision-making and strategy formulation. It discusses how knowledge of the probability distribution of property losses due to catastrophes enables management to make risk versus return trade-offs in marketing, pricing, and reinsurance decisions.

PART I: ESTIMATING THE PROBABILITY DISTRIBUTION OF CATASTROPHE LOSSES

Monte Carlo Simulation

Dramatic decreases in computing costs have led to the increased use of computer simulation in the analysis of a wide variety of problems. Many of these problems involve solutions that are difficult to obtain analytically. For example, computer simulation may be employed to evaluate complex integrals or to determine one or more attributes of complex systems. Law and Kelton state that "Most complex, real-world systems ... cannot be accurately described by a mathematical model which can be evaluated analytically. Thus, a simulation is often the only type of investigation possible." [8, p.8]

The simulation approach is very basically the development of computer programs that describe the particular system under study. All of the system variables and their interrelationships are included. A high speed computer then "simulates" the activity of the system and outputs the measures of interest.

Simulation models may be deterministic or stochastic. Monte Carlo simulation models are stochastic models with random variables from stable probability distributions; they are static, i.e. not time dependent, models.

A Monte Carlo simulation model is an excellent tool for performing sensitivity analyses of the system of interest. Alternative values of input variables may be given; the system may be resimulated and new output produced. This type of simulation may be employed to analyze a variety of insurance related problems. Arata described five areas in which actuaries may employ the simulation approach; one of these is the pricing of difficult or catastrophic exposures. [1]

The Natural Hazard Simulation Model

The natural hazard simulation model is a model of the natural disaster "system". As stated in the introduction, models based on historical catastrophe losses are not appropriate for forecasting future losses.

Standard statistical approaches are found lacking for three reasons. First, since the losses are caused by rare events, there is not much historical loss data available and those that are available are imprecise. Parameters estimated from the historical loss distribution will be subject to much uncertainty because of the small sample size. Secondly, the shape of the distribution itself is not clearly discernible. Finally, the distribution is not stable since many factors that influence it change with time.

The Monte Carlo model described below simulates natural hazards so that the primary variables are meteorological or geophysical in nature. These variables are random variables that have stable probability distributions, and although the historical data on these variables are sparse as are the loss data, their probability distributions may be supplemented with the knowledge of authoritative meteorologists and geophysicists.

This is, therefore, a stochastic yet stable system. The variables that change with time, i.e. the geographic distribution of exposure units, the insured property values, and the building construction types, are inputs into the model and the probability distribution of losses from natural hazards given these inputs is the model output. These inputs may be changed to see how the loss distribution is altered.

The model variables may also be classified as frequency or severity variables. The frequency variables indicate the expected number of occurrences of the particular events within a given time period. Severity variables represent the physical components of natural hazards and they do not have a time dimension. Severity variables account for a hazard's force, size, and duration.

A year of natural disasters is simulated thousands of times to generate the probability distribution of annual losses. For each model iteration and for each natural hazard, the following is performed:

1. The annual number of occurrences is generated from the frequency distribution.

2. The exact location of each occurrence is generated.

3. For each occurrence, values for the force and size are generated from the severity distributions.

4. The movement of the event across the affected area is simulated, and dollar damages are calculated and accumulated.

The average of all iterations is the model-generated expected loss estimate; a higher percentile loss is the probable maximum loss estimate.

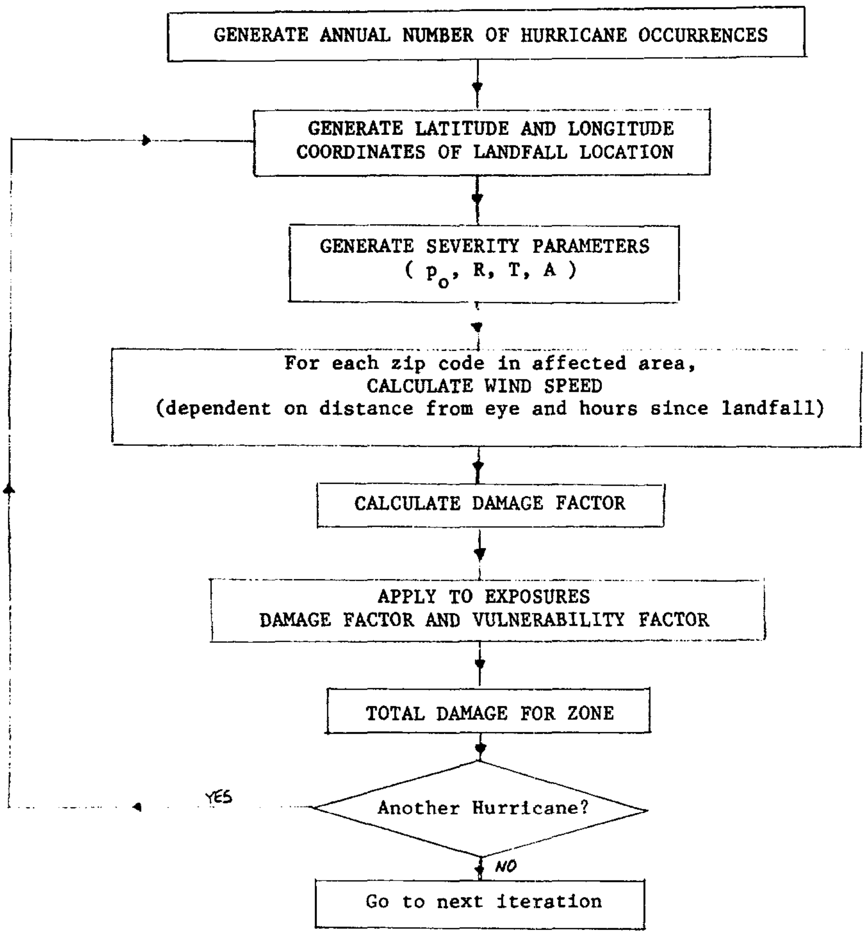
A Windstorm Example

A model of the hurricane hazard has been developed, and this model will be used to illustrate the Monte Carlo simulation approach. Exhibit 1 is a flowchart of the computer model.

All of the storm data used in the development of the model were obtained from the U.S. Department of Commerce. The data had been collected and analyzed by various agencies of the National Weather Service, and they included seventy-nine years of history spanning the period from 1900 to 1978. Complete and accurate data were available for most of the hurricanes that struck the U.S in this time period.

EXHIBIT 1

MODEL FLOWCHART



A hurricane is a closed atmospheric circulation which develops over tropical waters and in which winds move counterclockwise around a center of pressure lower than the surrounding area. It is a severe tropical storm in which the center of pressure is less than or equal to 29 (in.) which causes sustainable wind speeds of 74 mph or more. One hundred and twenty-eight hurricanes either approached and bypassed or entered the U.S. during the sample period.

Referring back to exhibit 1, the first step of the model is the generation of the annual number of landfalling hurricanes. Table 1 shows the numbers of years in which the number of occurrences was 0, 1, 2, and so on. The exhibited data fit a Poisson distribution with mean and variance equal to 1.8, and the model generates the annual frequency from this distribution.

Table 1

ANNUAL NUMBER OF HURRICANES LANDFALLING IN U.S
1900-1978

No. storms per year	Observed occurrence
0	25
1	25
2	14
3	8
4	5
5	1
6	1

The next step of the model is the determination of the landfall location of each storm. Hurricanes enter the U.S. from the Gulf and East Coasts. The map in exhibit 2 shows the U.S. coastline from Texas to Maine divided into thirty-one smoothed 100 nautical mile segments.[2] The number of hurricanes that entered through each segment during the sample period is also shown.

The numbers seem to indicate that there are variations in locational frequencies. In this case, it would not be appropriate to generate the landfall location from a distribution which assigns equal probabilities to all values, i.e. a uniform distribution. However, the limited amount of data precludes one from ascertaining statistically whether there are true frequency differences or whether the variations are caused by randomness within the small samples.

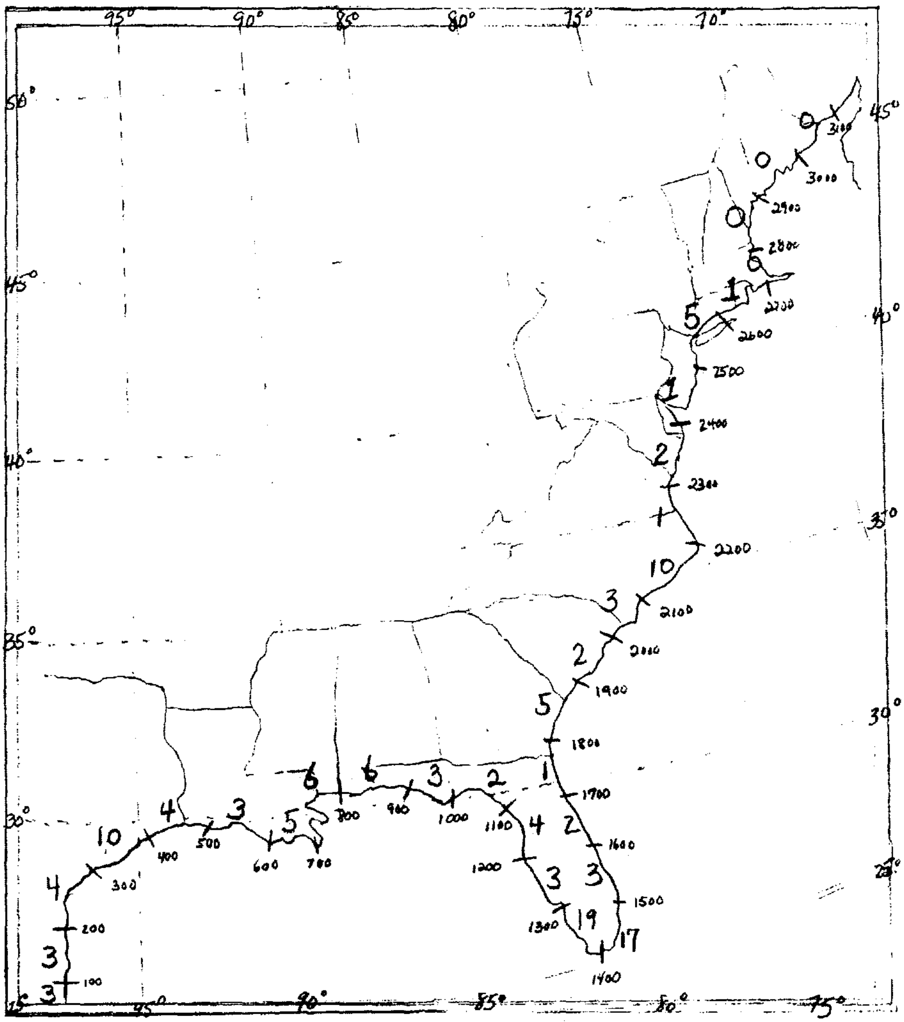
The actual number of storm occurrences within each segment is not employed by the model to develop the relative frequency distribution. It is not clear, first of all, if 100 nautical mile segments are the appropriate lengths of coastline to use for the calculations. Additionally, although several segments are completely free of historical storm occurrences, it is not clear that the probability of hurricane landfall is zero in these areas.

The relative frequency may be estimated by correlating it with another variable for which the value is known or may be estimated for each segment. Alternatively, the causal relationship between a variable(s) and the frequency of landfall may be employed if such a relationship

[2] The coastline is smoothed for irregularities such as inlets and bays.

Exhibit 2

HURRICANES ENTERING THE U.S. 1900-1978



exists. Of course, if one knew all of the conditions favoring landfall, one could assign probabilities based on the existence or absence of these conditions at each coastal location.

The way in which hurricanes are formed as well as the process by which energy is supplied to the circulating winds determine the likely paths of these storms. To illustrate, "hurricanes obtain kinetic energy from latent heat from the condensation and precipitation of water vapor. Therefore, hurricanes develop over warm tropical ocean areas where evaporation rates are very high and vast quantities of water vapor are stored in the atmosphere. The general movement of air over most of the Tropics is from the east while in higher latitudes it is usually from the west. Consequently, most hurricanes move initially to the west and may drift slightly northward. However, as they continue to drift toward higher latitudes, they come under the influence of westerly winds and recurve to the east" [4, p.3]. Wind patterns, therefore, provide an explanation for the lower frequencies at higher latitudes.

To derive the model locational frequency distribution, the following approach was adopted. First, the hurricane data were supplemented with data on all tropical storms. Tropical storms are closed atmospheric circulations with less intense winds than those of hurricanes. The assumption here is that the atmospheric conditions that favor the occurrence of a tropical storm are the same conditions that favor the occurrence of a hurricane. The additional data eliminate the problem of long coastal segments with no historical occurrences.

Next, the raw data on numbers of occurrences were smoothed using a procedure that was selected on the basis of its ability to capture turning points in the data while smoothing slight variations. The coastline was redivided into 50 nautical mile segments, and the number of occurrences for each segment was set equal to the weighted average of 11 successive data points centered on that segment. The smoothed frequency values are obtained as follows:

$$F_i = \frac{\sum_{n=-5}^{5} W_n C_{i+n}}{\sum_{n=-5}^{5} W_n}$$

where C_i = the number of historical hurricane occurrences for the ith segment

F_i = the smoothed frequency value for the ith segment

W_n = .300, .252, .140, .028, -.04, -.03

for n = 0, ±1, ±2, ±3, ±4, ±5, respectively

This is the preferred smoothing procedure in climatological analyses because the weighting scheme maintains the frequency and phase angle of the original series of numbers. The endpoints of the series were approximated so that each segment of the coast was assigned a relative frequency. The landfall location of each storm is generated from the thus derived locational frequency distribution.

Step three of the model is the generation of values for the severity variables. There are four primary variables which account for hurricane severity. These variables are: the minimum central pressure, the radius of maximum winds, the forward speed, and the wind inflow angle.

Central pressure (p_o) is defined as the sea-level pressure at the hurricane center or eye. This variable is the most important for computing hurricane windspeeds, and it is a universally accepted index of hurricane intensity. All else being equal, the square of the wind speed varies directly with Δp ($\Delta p = p_w - p_o$) where p_w is the peripheral pressure, i.e. the sea level pressure at the periphery of the storm.

The radius of maximum winds (R) is the radial distance from the hurricane center to the band of strongest winds. Forward speed (T) refers to the rate of translation of the hurricane center from one geographical point to another. Track direction (A) is the path of forward movement along which the hurricane is traveling and is measured clockwise from north.

The empirical data on each severity variable cannot be fit to standard theoretical distributions as were the annual frequency data. There appears to be a geographical hurricane severity pattern as there was a locational frequency pattern so that the probability density functions of the severity variables vary by location, and there are not enough data points at each location to estimate these functions. Additionally, the available data indicate that the severity variables are not independent. Linear correlation coefficients are positive between most pairs of variables. However, it is not possible to test the significance of the correlation coefficients unless it is assumed that pairs of variables form bivariate normal distributions.

If the variables are not independent, their correlations must be explicitly formulated within the model since the correlations will impact the variance of the model output, i.e. the estimated hurricane loss distribution.

The strongest correlations seem to be between the severity variables and latitude. In general, as latitude increases, average hurricane severity decreases as does frequency. When a hurricane moves over cooler waters, its primary source of energy is reduced so that the intensity of circulation decreases in the absence of outside forces. "The reasons for the increase in central pressure[3] from south to north include: the inability of hurricanes to carry their warm, moist, tropical atmosphere into temperate latitudes and the entrance of colder and drier air at low levels, which ... decreases the amount of energy available to the storm." [7, p.39]

The data, however, indicate a more direct relationship between severity and latitude than that between frequency and latitude, and the mathematical expressions which describe the relationships between the hurricane severity components and latitude were estimated and employed

[3]Central pressure is inversely related to severity so that high central pressures result in less severe storms.

by the simulation model in the following manner: Given the latitude and longitude coordinates of the landfall location, the latitude coordinate is entered into the equations to obtain initial values of the severity variables. Stochastic elements are added to the initial values and the sums become the simulated values. The stochastic elements are generated from the distribution of the error term for each equation.

Linear transformations of exponential, power, hyperbolic, and other special functions were fit to the empirical data for each severity variable using the ordinary least squares estimation procedure. Simple linear equations provided the best fits of the relationships between R and latitude and T and latitude.

Exhibit 3 shows a plot of the latitude, radius of maximum winds pairs for the 128 hurricanes in the data sample. Exhibit 4 shows the linear regression residuals plotted against latitude. Although the dispersion of the residuals is wide, i.e. the standard deviation is 10.10, the errors are distributed normally with expected value equal to zero. This statistical distribution is employed to generate the values e_i for the following equation:

$$R_i = a + b(L_i) + e_i$$

where R_i = the ith simulated value for R

L_i = the latitude coordinate for the ith hurricane

a,b are the estimated regression coefficients

Exhibit 3

LATITUDE VS. RADIUS OF MAXIMUM WINDS

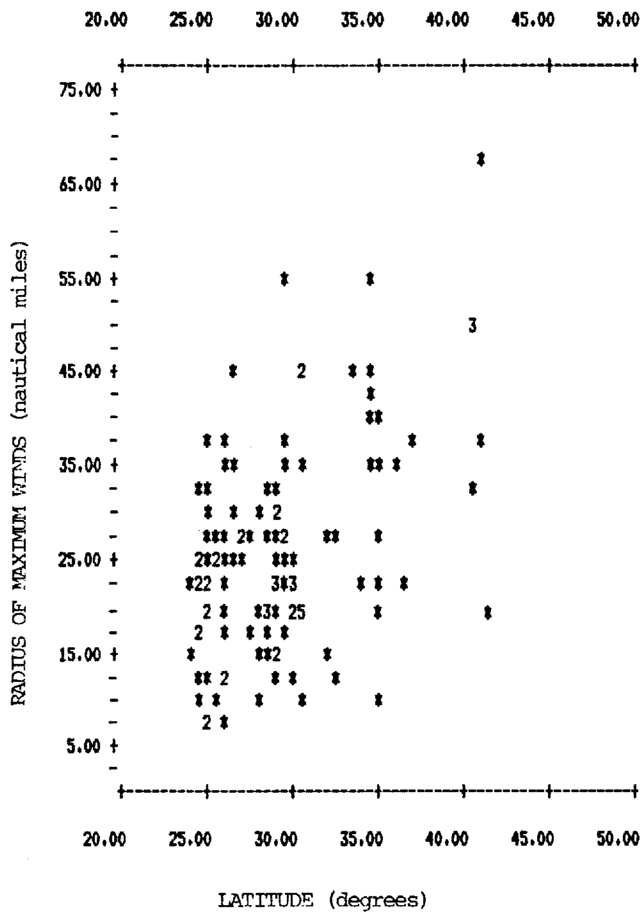
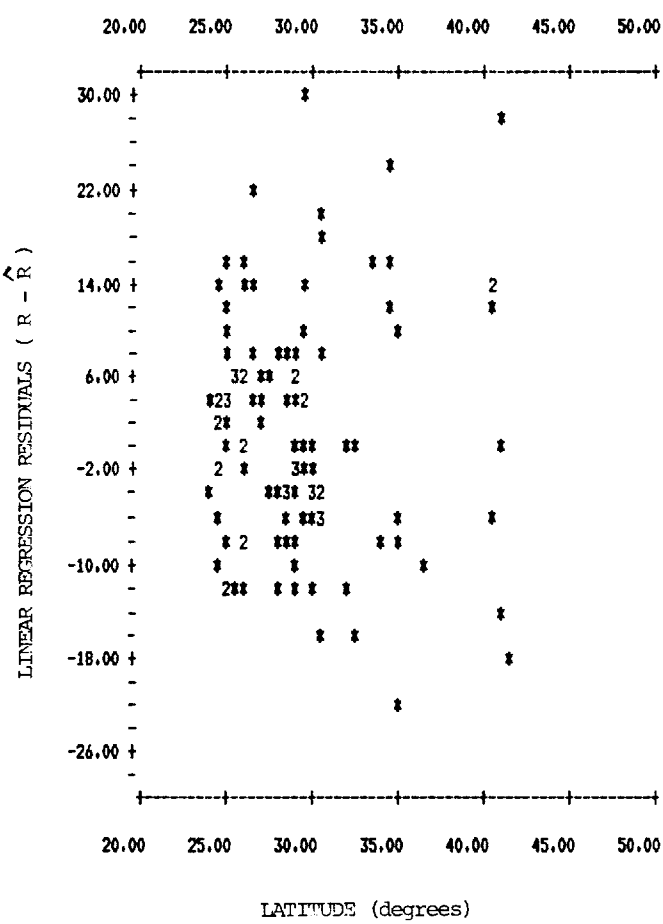


Exhibit 4

LATITUDE VS. LINEAR REGRESSION RESIDUALS ($R - \hat{R}$)



The distribution of the simulated values of R is then bounded by meteorological estimates of lowest and highest possible values.

The strength of the linear relationship between latitude and forward speed is even greater than that between latitude and the radius of maximum winds as shown by exhibit 5. However, the regression residuals shown in exhibit 6 seem to be heteroskedastic, i.e. the variance of the residuals increases with latitude. A basic assumption of the linear regression model is that the distribution of the error term has a constant variance, and the violation of this assumption leads to least squares estimators that are not efficient, i.e. minimum variance, or asymtotically efficient.

For the simulation model, it is also important that the distribution of the error term from which values are generated is stable for all values of latitude. If this is not the case, the simulated values of the particular variable will not form probability distributions that match the true underlying distributions, and the model-generated probability distribution of losses will not provide an accurate estimate of the true probability distribution of losses.

Corrections for heteroskedasticity were made by assuming that the variance of the error term is proportional to latitude. The re-estimated regression equation residuals are shown in exhibit 7; they form a normal distribution with mean equal to zero and standard deviation equal to 4.9.

Exhibit 5

LATITUDE VS. FORWARD SPEED

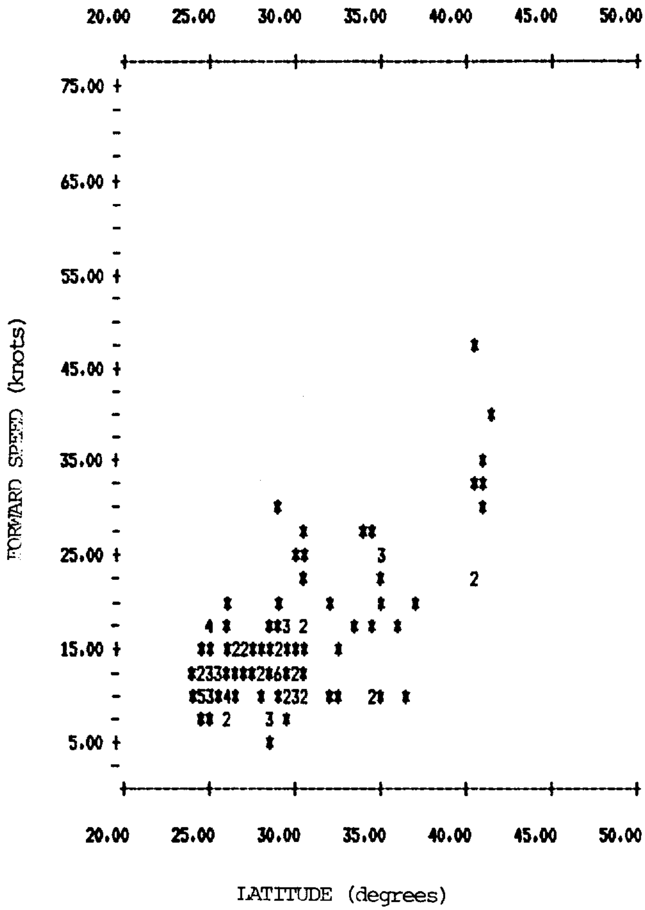


Exhibit 6

LATITUDE VS. LINEAR REGRESSION RESIDUALS ($T - \hat{T}$)

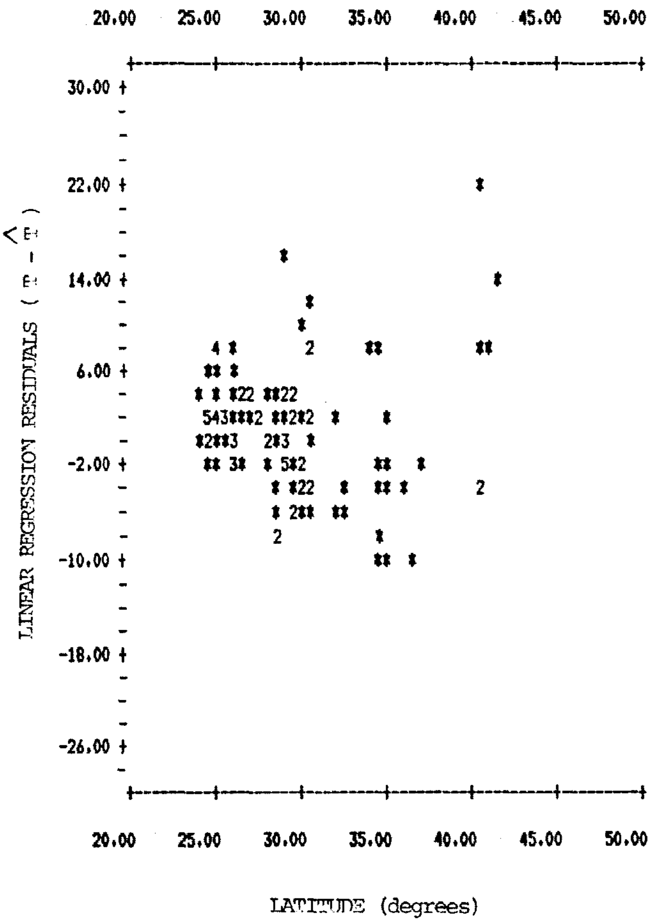
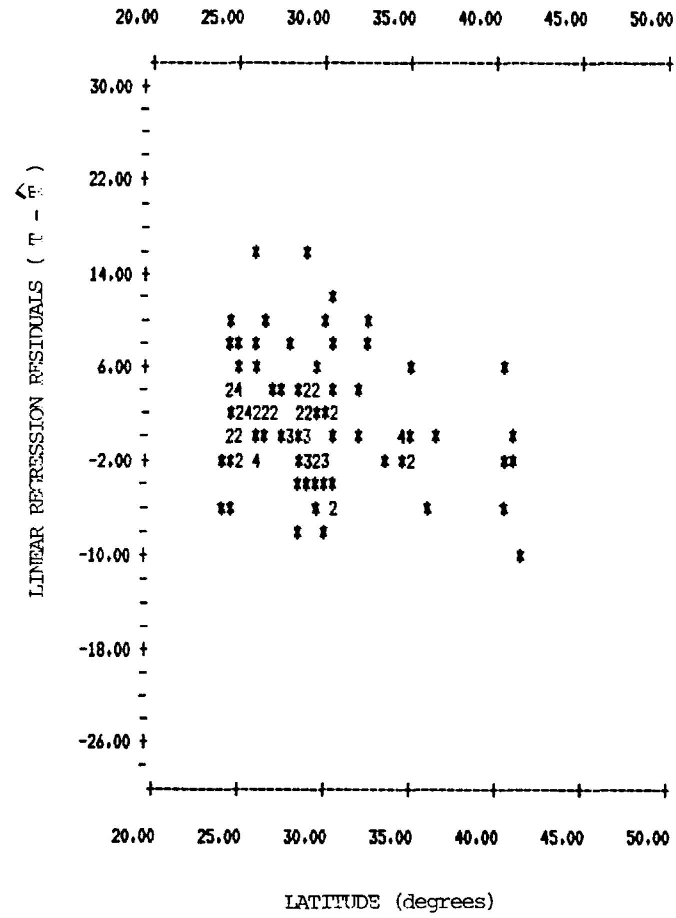


Exhibit 7

LATITUDE VS. LINEAR REGRESSION RESIDUALS (T - $\hat{T}$)
AFTER CORRECTION FOR HETEROSKEDASTICITY



Although hurricane central pressure and track direction are both correlated with latitude, the relationships between p_o and latitude and A and latitude were more difficult to estimate statistically. For these variables, the simulated values are generated from the empirical distributions. Outliers are first removed so that the simulated values for each coastal location are within the lower and upper bounds that have been developed by meteorologists.

The movement of the storm is next simulated by the computer model, and the property damage inflicted by the circulating winds is calculated for each geographic location. The particular geographical unit for which the damages are accumulated is determined by the model input. Insured property values are input along with the construction types and ages of the insured buildings and locational information such as zipcodes and counties. Wind speeds and dollar damages are calculated for each zipcode, but the damages may be accumulated by larger units to provide more meaningful output.

The dollar damages are calculated by applying damage and vulnerability factors to the dollar amounts of liability. The damage factors are based on the results of engineering studies of the relationship between wind speeds and structural damage. The vulnerability factors account for the variability in inflicted damage due to construction type and age. The dollar damages are accumulated by the selected geographical units.

Two thousand years of hurricane experience are simulated by the model. These two thousand model iterations provide a complete probability distribution of annual hurricane losses from which the expected loss and probable maximum loss estimates are derived.

Exhibit 8 shows the expected losses as well as the 80%, 90%, 95%, and 99% confidence level losses calculated as the 80th, 90th, 95th, and 99th percentile losses, respectively, for a given geographical distribution of exposures. These confidence level losses may be interpreted in two ways. A given confidence level loss shows the loss amount for which the probability of experiencing losses above that amount is 1.0 minus the particular confidence level. For the loss distribution in exhibit 8 the probability of experiencing losses above $10 million is .20. The confidence level loss also shows the loss amount for which losses greater than that amount will be experienced on average once in every 1.0/(1.0 - confidence level) years. Again, from exhibit 8 losses greater than $10 million will be experienced once in every five years on average. The loss distribution is highly skewed with a median value which is much below the mean and a high proportion of zero values.

The model output provides management with information that may be used in the formulation of pricing, marketing, and reinsurance strategies. Before the uses of the model output are discussed, the next section will summarize the Monte Carlo simulation approach.

Exhibit 8

MODEL-GENERATED LOSS ESTIMATES

LIABILITIES	EXPECTED LOSS	CONFIDENCE LEVEL LOSSES 80%	90%	95%	99%
7,170,753,024	9,011,808	10,003,715	24,179,636	44,827,623	117,946,980

Summary of the Methodology

The Monte Carlo simulation approach to the estimation of the probability distribution of catastrophe losses involves the development of models to simulate catastrophes. Each model is developed around the probability distributions of the random variables of the loss-producing "system."

Ideally, the model builder will have an a priori theory on the shape of the probability distribution underlying each random variable. For the results of the Monte Carlo simulation to be valid, the underlying model assumptions must be true. The empirical distribution formed by the raw data may be compared to standard statistical distributions using appropriate goodness-of-fit tests, and if the data do fit a well-known probability distribution, the moments of the distribution may be estimated and employed by the simulation model. In the windstorm example, the Poisson distribution was used to generate the annual number of hurricanes.

Alternatively, the expressions which describe the relationships between model variables may be estimated and employed by the model to generate simulated values of variables. This approach was adopted for some of the hurricane severity components.

Finally, the empirical distribution may be employed for the generation of values for a particular model variable. This procedure, however has a few drawbacks. First, since the sample is a collection of random data, a different sample could yield a very different empirical distribution. Secondly, the generation of random variables from an empirical distribution precludes the possibility of generating a value of the variable outside of the observed range, and the observed range may not include all possible values of the variable. Finally, the generation of values from empirical distributions is, in general, less efficient from the standpoint of computing time than the generation of values from theoretical distributions. Nevertheless, in some cases generation from the empirical distribution is either necessary or preferred for various reasons, and in these cases, the empirical distribution can be programmed into the model.

The testimony of experts may be employed along with the statistical data to build the model. Physical scientists who have studied extensively the phenomena of interest can provide information on the ranges of possible values of particular variables as well as on the most likely value or values. This information may enable the model builder to substitute theoretical distributions for empirical distributions, to identify outliers in the data, and/or to determine appropriate points at which to bound the probability distributions.

Once the model is built, i.e. the important variables have been identified and their probability distributions and interrelationships have been programmed into the computer, the system is simulated many times to provide a range of all possible annual loss amounts. There is no standard formula that gives the number of model iterations necessary to produce output with a given level of precision for this type of Monte

Carlo simulation model. The necessary number of iterations is endogenous, i.e. model-dependent.

Given that the variable of interest is annual dollar losses from catastrophes, one hopes to derive accurate estimates of annual expected losses and maximum probable losses. Assuming that the model has been specified correctly, the expected loss estimate will converge to the true expected loss and the model generated loss distribution will converge to the true loss distribution as the number of iterations increases. Very basically,

$$E(X) = \lim_{n \to \infty} \frac{\sum_{i=1}^{n} X_i}{n}$$

where $E(X)$ = expected annual loss

X_i = annual loss from ith model iteration

and,

$$F(X) = \lim_{n \to \infty} F_n(X)$$

where $F(X)$ = the distribution function of annual losses

$F_n(X)$ = distribution function of n model generated annual loss figures.

The larger the variance of the probability distribution of annual losses, the larger the value of n needed to produce loss estimates with a given level of precision. The variability of the model generated annual losses is determined by the variability of the model variables, i.e. the frequency and severity variables, and their correlations. If the model variables are positively correlated, the variance of the loss distribution will be greater than it would be in the absence of this correlation.

Although there is no straightforward procedure for calculating the value of n needed for specified precision levels, there are a few procedures that may be employed to develop confidence intervals for E(X) if certain assumptions are made. These procedures will not be discussed here, and the interested reader is referred to Chapter 8 of Law and Kelton. [9]

The recommendation of this author is to perform at least 1000 model iterations if possible. This should not present a problem given the low costs of computing time on high speed computers; however, development time may be well spent on writing efficient computer programs that minimize the computing time, particularly if the model is to be run frequently. If each iteration is still expensive, certain variance reduction techniques may be employed to reduce the number of iterations needed to reach convergence. The model builder may perform tests to see how quickly the loss distribution is converging. Iterations may be performed in groups of 100 so that the changes in the loss distribution may be monitored. A stable loss distribution indicates that convergence has been reached.

Validation of simulation models often presents a problem if there are no historical data on the variable that the model is designed to measure. In the case of natural hazard simulation models, the historical data are sparse. Past occurrences may be simulated, nevertheless, if the geographical distribution of exposures that is input to the model corresponds precisely to the geographical distribution of exposures that existed at the time of the occurrence. Insured values, construction types, and ages of exposure units should also match precisely. Values for the variables which account for the severity components of the hazard are input to the model, the model is simulated, and the model-generated loss estimate is output. This estimate is compared to actual dollar damages to test the validity of the model and its underlying assumptions.

There are several advantages of the simulation approach. First of all, it is able to capture the effects on the loss distribution of changes in variables over time. Secondly, this estimation procedure provides management with a complete picture of the probability distribution of losses rather than just estimates of expected and probable maximum losses. And finally, the Monte Carlo simulation approach provides a framework for performing sensitivity analyses and "what-if" studies. The model uses will be described in the following sections.

PART II: MANAGING EXPOSURE TO CATASTROPHES

A methodology for estimating the probability distribution of annual catastrophe losses given a particular geographical distribution of exposures was described and illustrated in Part I. Knowledge of the probability distribution of losses enables insurers to manage their exposures to catastrophes. With respect to these exposures, management has several options:

1. Write no business in catastrophe prone areas.

2. Exclude coverage for losses caused by natural hazards.

3. Plan to recover losses after a catastrophe occurs by retrospective pricing.

4. Spread property business so that it is not concentrated in catastrophe prone areas.

5. Add loadings to premiums and build up reserves to cover catastrophe losses when they occur.

6. Reinsure property business.

Option 1 does not present a very viable strategy since most areas of the continental U.S. are prone to natural disasters of at least one type.

For example, the Gulf and East Coast states are prone to hurricanes while the Great Plains and Midwestern states are highly prone to tornadoes. Earthquakes are natural hazards with the greatest damage producing potential in California, Nevada, Washington, and parts of Indiana, Missouri, Tennessee, Arkansas, South Carolina, and Massachusetts. [3]

Option 2 may also not be feasible. If an industry-wide attempt is made to exclude coverage for losses resulting from a particular hazard, legislation may be passed to prevent effective exclusion. Recent legislation in California concerning concurrent causation is a case in point. On the other hand, if a single company or group of companies attempt to exclude coverage, business will certainly be lost to competitors who do provide coverage unless the policy premiums are reduced sufficiently.

The insurance industry has traditionally priced its products retrospectively since expected costs are estimated from past costs. Policy premiums are determined by the most recent historical loss experience so that larger than expected losses in year t will lead to higher prices in year t+1. As long as the individual firm's loss experience is better than or equal to the industry average, the firm may set premiums in relation to its own loss experience (in the absence of regulatory barriers.) However, if the individual firm's loss experience is worse than the industry average, competition will force the firm to price below its costs.

Retrospective pricing cannot be used to recover losses from catastrophes. If an individual firm experiences a disproportionate share of total industry losses from the occurrence of a catastrophic event in year t, competition will prevent the firm from increasing its rates enough to recover all of its losses in year t+1. Additionally, the industry as a whole is prevented from increasing rates dramatically after the occurrence of a catastrophe by the threat of new entry.

The barriers to entry into the insurance industry are high enough to allow retrospective pricing of normal insurance covers; however, a financial need of existing firms to raise prices by a significant amount would provide a competitive advantage for new entrants that are free of the financial burden.

Accordingly, option 3 is an inferior strategy as were options 1 and 2. The last three alternatives, however, are all viable strategic options, and each one will be discussed in turn under the headings of marketing, pricing, and reinsurance.

Marketing

The windstorm simulation model output as illustrated in exhibit 8 shows the probability distribution of annual countrywide losses from the hurricane hazard. For marketing purposes, however, it may be more useful to divide the country into zones so that the specific areas of high windstorm risk are clearly identifiable.

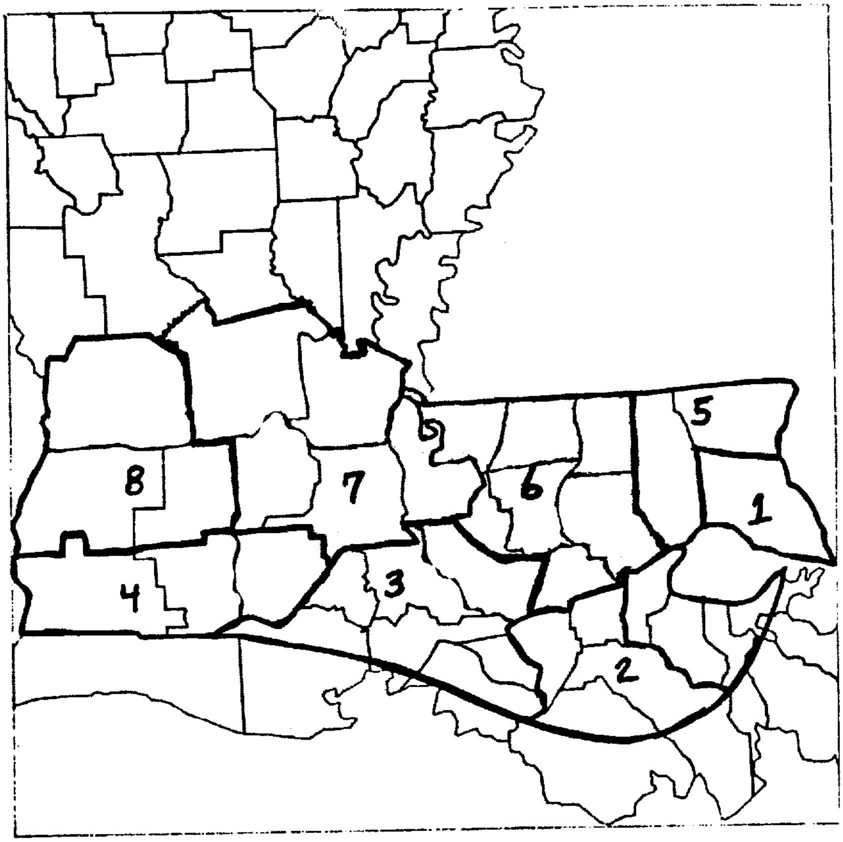
The computer model may be designed to accumulate dollar damages by state, by county, or by any other geographical configuration. Exhibit 9 shows the state of Louisiana divided into eight zones. The dollars of liability, i.e. exposure, the expected loss, and various confidence level losses[4] are shown for each zone. The loss figures show clearly that the higher risk areas are the coastal zones. The hurricane is at maximum force just as it crosses overland; as it travels inland, the storm dissipates because of the elimination of its primary energy source i.e. kinetic energy derived from the sea, and because of frictional effects.

Because all natural hazards have associated with them geographical frequency and severity patterns, they will produce gradations of damage or pockets of high risk and low risk. Management will want to avoid concentrations of property exposures in high risk areas, and the model output enables the development of marketing plans that are based on the long term profit potentials of various markets.

Property business in high risk areas may be very profitable in years of no natural hazard occurrences. As years pass and no catastrophes occur, insurers may begin to compete for the business in a high risk area. The competition may drive the profits as well as the catastrophe loading to zero so that there are no resources available to cover the catastrophic losses when they occur. Knowledge of the probability distributions of losses from natural hazards in these areas enables insurers to resist the temptation to write business based on the very recent loss experience in these areas.

[4] It is interesting to note that for small geographic areas, the confidence level losses may be zero since the frequencies of hurricances in specific locations are low.

Exhibit 9



Louisiana Windstorm Zones

zone		$ exp	expected loss	confidence level losses 80%	90%	95%	99%
LOUIS	1	90417112.	256512.	0.	276770.	1947396.	4938375.
LOUIS	2	9210113.	25540.	0.	12932.	213693.	537371.
LOUIS	3	56674660.	94866.	0.	31306.	653101.	2098500.
LOUIS	4	50672900.	71042.	0.	0.	234088.	1722377.
LOUIS	5	79796656.	80965.	0.	0.	547837.	2021005.
LOUIS	6	176149552.	231604.	0.	0.	598946.	6823092.
LOUIS	7	40664716.	47598.	0.	0.	193227.	1309985.
LOUIS	8	33114748.	16552.	0.	0.	5991.	772278.

The natural hazard simulation model is an excellent tool for evaluating the exposure to natural hazards resulting from alternative marketing plans. If marketing plans alter the geographic distribution of exposures, the alternative distributions of exposures may be input to the model and new loss distributions generated.

Pricing

The model-generated expected loss figures may be used to calculate appropriate catastrophe premium loadings. The loadings may be expressed as percentages of insured values by dividing the expected loss figures by the dollars of liability for each of the established zones, i.e. the geographical units into which the country is divided.

Theoretically, if an insurer establishes a reserve for catastrophe losses and makes annual contributions equal to the annual expected losses, the insurer will break even with respect to catastrophe losses over the long run. The model-generated output enables management to fine tune the catastrophe loadings in particular locations. Presumably, premiums charged in catastrophe prone areas include loadings for catastrophe losses, but these loadings may be subjective and may not correspond closely with expected catastrophe losses. Since the model can be programmed to accumulate dollar damages by any geographical configuration, expected loss estimates may be derived for any unit of area, and premiums that are in line with costs may be established.

Clearly, competitive factors dictate the amount of freedom that management has to set prices. If demand is very elastic, small increases in price will lead to large decreases in market share. Price changes may be tempered to result in the desired distribution of premium volume.

An additional caveat is that pricing in accordance with expected loss does not eliminate the risk of large losses since it is possible that catastrophes will occur when the loss fund is at a level that is not sufficient to cover all of the losses. The losses could then lead to financial difficulties for the insurer. Insurers may, however, transfer part or all of this risk through reinsurance agreements.

Reinsurance

To evaluate alternative reinsurance proposals, management needs the following:

1. An estimate of the probability distribution of losses for which the reinsurance contracts are to provide cover.

2. Knowledge of the reinsurance market and the types of contracts that are available.

3. A methodology for performing risk versus return trade-offs and obtaining preference orderings.

Part I of this paper provided a methodology for estimating the probability distribution of property losses from catastrophes. From the cumulative distribution function, one may determine the probability of experiencing losses in excess of any dollar amount.

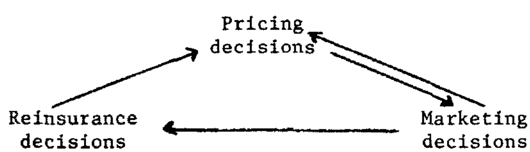
There are two broad categories of reinsurance contracts: proportional and nonproportional. Each type of treaty performs certain functions for the reinsured. Proportional or quota share treaties provide capacity and financing as well as reductions in the variance of the loss distribution. Non proportional or excess-of-loss treaties provide catastrophe and stop loss covers.

Borch [2] has shown that the "most efficient" reinsurance contract from the viewpoint of the ceding company is the stop loss contract. The type of treaty leads to the greatest reduction in variance for a given price if the premium paid to the reinsurer is proportional to the expected loss of the ceded portfolio and not to its variance. From the viewpoint of the reinsurer, the quota share treaty that gives a ceded portfolio with the same expected loss is superior because the variance of the ceded portfolio will be smaller.

In general, the reinsurer will charge a premium that compensates for the variability as well as the expected loss of the ceded portfolio. Accordingly, the premium will be lower for a quota share treaty that gives the reinsurer a portfolio with the same expected loss as the excess-of-loss treaty. The specific premium that the reinsurer will charge for a particular contract depends on the risk profile of the company.

The estimated probability distribution of losses shows the benefits that will be derived from particular reinsurance agreements, and these benefits may be compared to the costs. The reinsuring company will rank order the alternatives that are available in the reinsurance market using its own risk profile. The derivation of the risk profile relies on utility theory and will not be discussed here.

The pricing, marketing, and reinsurance decisions are not independent and as such should be evaluated simultaneously in the planning process. Obviously, pricing policies impact marketing plans which influence the geographical distribution of property exposures. This is a two-way relationship since marketing decisions also impact pricing decisions. The geographical distribution of property exposures will affect the probability distribution of catastrophe losses which in turn will influence the price of reinsurance since the reinsurer will demand a higher premium to cover exposures in high risk areas. Finally, the reinsurance covers influence the loss distribution and change the expected losses which drive the catastrophe loadings. The diagram below illustrates the decision triangle.



Summary

Catastrophic events can affect significantly the results of property and casualty insurance companies. Since the losses resulting from the occurrences of catastrophes could affect adversely the financial condition of a company, management must plan for these events. The first part of this paper described an estimation methodology based on Monte Carlo simulation. A windstorm example illustrated the approach and its primary advantages. These advantages are: It estimates the full probability distribution of losses, it captures the effects on this distribution of changes in population patterns, building codes, and repair costs, and it may be used to perform sensitivity analyses. The second part of the paper outlined how knowledge of the probability distribution of losses enables management to evaluate the effects on the probabilities of severe losses of alternative marketing, pricing, and reinsurance strategies.

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