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CATASTROPHE MODELING:
A NEW APPROACH TO MANAGING RISK

edited by

Patricia Grossi

Howard Kunreuther

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CATASTROPHE MODELING: A NEW APPROACH TO MANAGING RISK

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CATASTROPHE MODELING: A NEW APPROACH TO MANAGING RISK

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Preface and Acknowledgments

This book had its genesis in June 1996 when the Wharton Risk Management and Decision Processes Center (Wharton Risk Center) co-hosted a conference on “Information Technology and Its Impact on Catastrophic Risks”. It was one of the events that year celebrating the 50th Anniversary of the first computer (ENIAC) at the University of Pennsylvania. The focus of the conference was on the challenges in dealing with natural disasters. There had been two catastrophic events several years before — Hurricane Andrew in 1992 and the Northridge earthquake in 1994 — that had raised grave concerns within the private and public sectors as to what steps should be taken to deal with future losses from these and other natural hazards. The conference featured presentations by scientific experts on assessing these risks, three leading firms [AIR Worldwide, EQECAT and Risk Management Solutions (RMS)] on modeling the risks using information technology, and the development of new strategies by insurers, reinsurers and financial institutions for managing catastrophic risks.

Over the past 8 years, representatives from all these constituencies have worked together as part of the Wharton Managing Catastrophic Risks project to examine the role of catastrophe modeling in assessing and managing natural disaster risk. This book is truly a joint effort with the modeling firms and reflects the critical commentary and evaluations from key individuals in insurance and reinsurance companies as well as financial institutions who provided funds for the research activities.

From 1996 through 2001, the project was a joint venture between the Wharton Financial Institutions Center (WFIC) and the Wharton Risk Center. We want to express our deep appreciation to Anthony Santomero, director of the WFIC during the first five years of the project, Peter Burns, project manager, and Steve Levy, project coordinator, during this period. Thanks also go to Franklin Allen, Richard Herring and Carol Leisenring who assumed leadership positions at the WFIC after Anthony Santomero and Peter Burns moved on from the Wharton School in 2000.

From the outset, our goal was to undertake state-of the-art research on the role of risk assessment in developing meaningful strategies for managing catastrophic risks. Although our focus was on natural hazards, we viewed the project as one that could be applied to a wide variety of extreme events. In fact, since 2002 the Managing Catastrophic Risks project has morphed into the Managing Extreme Events project, which is one of the major ongoing activities at the Wharton Risk Center.

To ensure the highest scientific standards, we formed a Technical Advisory Committee (TAC) whose role was to provide detailed commentary on the models developed by AIR Worldwide, EQECAT and Risk

Management Solutions. For the first few years of the project, this committee met at least once a year and several members attended the semi-annual project meetings. The TAC provided insightful comments on the use of the models as a linkage between risk assessment and risk management and urged the modeling firms to coordinate their efforts to the highest extent possible. They were principally responsible for convincing the three firms that it would be beneficial to all if a comparative study of earthquake risk were completed. As a result, a study in Charleston, South Carolina presented in this book illustrates the opportunities of utilizing these models for estimating risks, while at the same time demonstrating the degrees of uncertainty surrounding loss estimates.

Each of the three firms permitted members of the TAC to examine their models. Subsets of the TAC visited AIR Worldwide, EQECAT and Risk Management Solutions for a full day for this purpose. These TAC members then wrote up reports on the technical accuracy of the models that they shared with each firm as well as with the Wharton team. Through this process and without revealing any confidential information, the TAC members were convinced that all three firms base their models on the best scientific information available. Without this assurance from the TAC we would not be writing this book.

Most of the TAC members also commented on earlier drafts of the chapters in the book. In particular, we want to thank Roger Borcherdt (USGS), William Holmes (Rutherford & Chekene), William Iwan (Cal Tech), and Robert Whitman (MIT), who spent considerable time in going over the material on the book and writing up extensive comments for us. The other members of the TAC who provided us with advice and guidance on the project and to whom we owe a debt of gratitude are: Joe Golden (NOAA), Mark Johnson (University of Central Florida), Ralph Keeney (Duke University), Peter Sparks (University of South Carolina), Kathleen Tierney (University of Colorado, Boulder), and Susan Tubbesing (EERI).

There are numerous other individuals and firms who played a key role in this effort. Jim Tilley from Morgan Stanley and Jerry Isom from CIGNA (now ACE) convinced their organizations to provide initial seed funding for the project. Other sponsors included American Re, General Re, Goldman Sachs, Japan Property and Casualty Association, State Farm, Swiss Re, and Tokio Marine. A number of individuals from these organizations provided us with extremely helpful comments at various stages of the project. They include: James Ament (State Farm), David Durbin (Swiss Re), Carl Hedde (American Re), Robert Irvan (CIGNA/ACE), Jeff Warren (General Re), Gordon Woo (Risk Management Solutions), Yuichi Takeda (Tokio Marine). American Re (Carl Hedde, Mark Bove, and Hjortur Thraisson) provided key information on historic losses. Goldman Sachs (Vivek Bantwal and Ohi Akhigbe) also provided helpful comments on the current state of catastrophe bonds and other new financial instruments.

Special thanks go to the leadership in all three modeling firms for agreeing to share their software with the Wharton team and to open their doors to a dialog with academia: Karen Clark from AIR Worldwide; Dennis Kuzak from EQECAT; and Tom Hutton, Haresh Shah, and Terry van Gilder, who were at Risk Management Solutions when the project started.

The research on this book occurred over a span of almost 9 years, so there have been a number of individuals who have played a key role in helping to undertake the research that forms the basis for each of the chapters. At the beginning of each chapter, we list the principal authors who took the lead in writing the material, but there are others who played a role in providing data for the various chapters. In particular, we want to thank Vivek Bantwal, Jessica Binder and Jaideep Hebbar, three remarkable undergraduate students at Wharton, who were indefatigable in their efforts working with the modeling groups. Without their assistance, Chapters 8 and 9 in the book could not have been written. Paul Kleindorfer, co-director of the Wharton Risk Center, played a key role in providing inputs and guidance on the project from its very outset. He participated in all the meetings of the project and provided invaluable comments and suggests on all aspects of the research. We would also like to thank Neil Doherty and Dave Cummins from Wharton for their helpful comments and suggestions at various stages of the project. Both Neil and Dave were undertaking complementary studies of risk transfer instruments and insurance as part of the Managing Catastrophic Risks project and were also involved in the meetings with the sponsors of the project. We also had helpful discussions with Daigee Shaw of Academia Sinica in Taipei, Taiwan. Erwann Michel-Kerjan of the Wharton Risk Center has reviewed the entire book and provided insightful comments as to how the material on natural hazards linked to other extreme events, notably terrorism.

We both had a wonderful time working with our co-conspirators from the modeling companies, without whose active involvement this book would never have been written: David Lalonde, Beverly Porter, and Mehrdad Mahdyiar from AIR Worldwide, Dennis Kuzak and Tom Larsen from EQECAT, Weimin Dong and Don Windeler from Risk Management Solutions.

Chandu Patel from the Casualty Actuarial Society volunteered to play the role of editor and has gone through every chapter with a fine tooth comb, making a number of extremely helpful suggestions for improving the flow of material. We want to thank Cathy Giordano from ACE and Tara Newman from the Wharton Risk Center for their help in coordinating this effort. We were also fortunate to have Ann Perch from the Wharton School and Hannah Chervitz from the Wharton Risk Center go through the entire book to make sure it was readable to a more general audience and was in final camera-ready form for the publisher.

This has been a long journey that has taken Patricia Grossi through her doctoral dissertation at the University of Pennsylvania, to an Assistant Professor at Southern Methodist University and finally to her current position at Risk Management Solutions. On September 3, 2001, Howard Kunreuther began a one-year sabbatical at the Earth Institute (Columbia University) and has been involved in terrorism research ever since September 11th. The last chapter of the book reflects the broader objectives of catastrophe modeling by applying the concepts from natural hazards to this risk.

Our families have been part of the process from the very beginning and our spouses, Mohan Balachandran and Gail Loeb Kunreuther, deserve special thanks for their encouragement and understanding.

Patricia Grossi
Howard Kunreuther

Prelude

The aftermath of a natural disaster, such as an earthquake, flood, hurricane, can be devastating. There is a tremendous sense of personal as well as economic loss. Immediately following the disaster, the actual devastation as well as media coverage related to the event causes the affected individuals as well the general public to be keenly aware of the risk of catastrophes. Unfortunately, this awareness often fades with time and the importance of being prepared is often forgotten. There are, however, a large number of individuals who spend a great deal of time and energy modeling natural disasters and enlightening others on ways in which their impact can be managed.

The goal of this book is to bring the reader up to date on recent developments in the nature and application of catastrophe models used to manage risk from natural disasters. It describes current and potential future uses of such models. The book emphasizes natural disasters, but also discusses application of the models to the terrorist attacks of September 11, 2001. The book is targeted to individuals concerned with monitoring and managing the impact of catastrophe risks. For example:

- Senior insurance and reinsurance managers can gain insight into the policy implications of competing hazard management strategies.
- Actuaries and underwriters can learn how catastrophe modeling, in its current form of user-friendly software, can facilitate their portfolio analyses.
- Federal, state and local government employees can learn to expand their definition of risk management to include the role that insurance can play in protecting their organizations against loss.
- Structural engineers, proficient in seismic and wind resistant design, can examine the latest approaches to modeling the fragility of a building system.
- Other experts interested in catastrophe modeling, including earth scientists, computer scientists, economists, and geographers, can discover their role in creating the next generation of models.

Roadmap of the Book

Part I of this book provides an introduction to risk management and catastrophe models. Chapter 1 indicates the need to manage risk and describes the key stakeholders involved in the process. Chapter 2 provides an introduction to catastrophe models and insurance. It introduces the components of a catastrophe model and how catastrophe models aid insurers in assessing their portfolio risk. The chapter concludes by introducing a framework for integrating risk assessment with risk management strategies via catastrophe modeling.

Part II of the book delves more deeply into the complex process of linking the science of natural hazards to the output from catastrophe models. Chapter 3 discusses the components of catastrophe modeling in more detail, including the hazard, inventory, vulnerability, and loss modules. This chapter clarifies how data are incorporated into catastrophe models and how modeling techniques facilitate the assessment of earthquake and hurricane risk.

Chapter 4 discusses the treatment of uncertainty in a catastrophe model. Catastrophe modeling is an evolving science; there are assorted interpretations and approaches to the modeling process. Differences in the output from competing catastrophe models are presented for hurricane and earthquake risk. Using the Charleston, South Carolina region as an example, the chapter highlights how uncertainty in modeling risks affects estimates of future losses.

Part III examines how catastrophe modeling currently aids insurers and other stakeholders in managing the risks from natural hazards. After a general overview of current practices used by insurers, specific examples of risk management strategies are discussed in Chapters 5 though 7. Chapter 5 focuses on the actuarial principles for insurance rate making. Special emphasis is given to the role of catastrophe modeling in earthquake risk classification and rate setting for residential structures in the state of California.

Chapter 6 focuses on the role of catastrophe modeling in quantifying an insurer's portfolio risk. One of an insurer's principal concerns when constructing a portfolio of risks is to reduce the possibility of unusually large losses. Special attention is given to ways that models can address uncertainty issues and reduce the chances of highly correlated losses in an insurer's portfolio.

Chapter 7 provides a comprehensive discussion of risk financing for an organization and the regulatory basis for the design of risk transfer instruments. The chapter illustrates the role that catastrophe modeling plays in evaluating these financing schemes and discusses the reasons why there has been limited interest by investors in utilizing new financial instruments.

Part IV illustrates how catastrophe models can be utilized in developing risk management strategies for natural disasters and terrorism. In Chapter 8, insurers consider a specific risk management strategy – requiring homeowners to adopt specific mitigation measures – in determining the pricing of a policy and the amount of coverage to offer. Utilizing data provided by the three leading modeling firms (AIR Worldwide, EQECAT, and Risk Management Solutions), three hypothetical insurance companies are formed to provide earthquake or hurricane coverage to homeowners in Oakland, California, Long Beach, California and Miami/Dade County, Florida. The analyses illustrate the impact of loss reduction measures and catastrophe modeling uncertainty on an insurer's profitability and likelihood of insolvency.

Chapter 9 builds on the analyses presented in Chapter 8 by examining the role of risk transfer instruments in providing protection to insurers against losses from natural disasters. The chapter examines the impact of reinsurance and catastrophe bonds on the profitability of an insurer and the return on assets to investors in the insurance company.

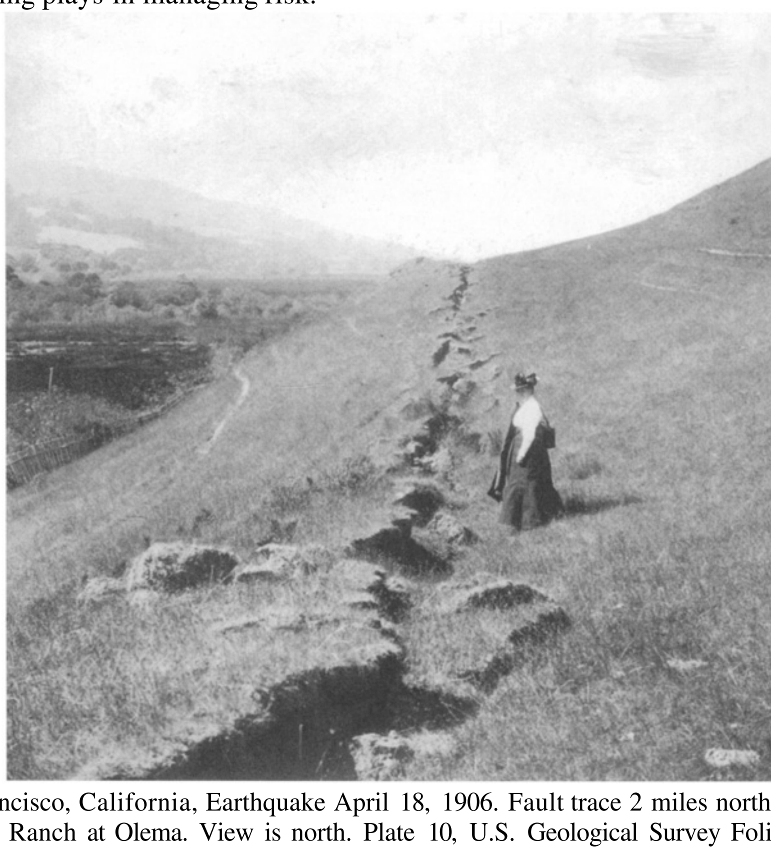
Chapter 10 concludes the book by focusing on how catastrophe modeling can be utilized in dealing with terrorism. The chapter examines the challenges faced by the U.S. in providing terrorism coverage after the September 11th attacks. Given the uncertainties associated with this risk and the potential for catastrophic losses, there is a need for public-private partnerships to reduce future losses and provide financial assistance after a terrorist attack.

A Glossary at the end of the book provides definitions of scientific, engineering and economic terms used throughout the book. This should aid the reader in understanding key words that are often used to characterize and analyze risks.

PART I

FRAMEWORK FOR RISK MANAGEMENT USING CATASTROPHE MODELS

Part I of this book is an introduction to natural hazards and catastrophe risk management. Chapter 1 discusses the history of natural disaster loss and introduces the stakeholders who manage catastrophe risk, along with their motivations and relationships to one another. The chapter also discusses the role of the public and private sectors in managing risk. Chapter 2 turns to the development of catastrophe models and the use of insurance in managing catastrophe risk. The concept of an exceedance probability curve is introduced. This is a key element used throughout the book for communicating risk to a stakeholder. Finally, a conceptual framework is presented that illustrates the critical role that catastrophe modeling plays in managing risk.



San Francisco, California, Earthquake April 18, 1906. Fault trace 2 miles north of the Skinner Ranch at Olema. View is north. Plate 10, U.S. Geological Survey Folio 193; Plate 3-A, U.S. Geological Survey Bulletin 324.

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Chapter 1 – Introduction: Needs, Stakeholders, and Government Initiatives

Major Contributors:
Patricia Grossi
Howard Kunreuther

1.1 Need to Manage Risk

The problem of preparing for a natural disaster is not a new one. Around the world and particularly in the more-developed countries, governments, individuals and corporations know they should prepare for a "big earthquake" or a "large hurricane" or an "extensive flood." Yet, they often do not take the necessary steps to prepare for a disaster. Only after a disaster occurs do they recognize the importance of preparing for these types of extreme events.

A major earthquake or hurricane can result in loss of life and serious damage to buildings and their contents. Bridges and roads can be damaged and closed for repair over long periods of time. Disaster victims may need to be relocated to temporary shelters or reside with friends or relatives for days or weeks. Businesses may have their activities interrupted due to facility damage or lack of utility service. For some businesses, this may result in insolvency. In August and September 2004, these challenges were obvious when Florida and other states as far north as New Jersey and Pennsylvania were deluged by Hurricanes Charley, Frances, Ivan, and Jeanne.

The need to prepare for these types of extreme events is evident when evaluating the economic consequences of natural disasters. Figure 1.1(a) and Figure 1.1(b) depict the losses due to great natural catastrophes from 1950 to 2002 throughout the world. A great natural catastrophe is defined as one where the affected region is "distinctly overtaxed, making interregional or international assistance necessary. This is usually the case when thousands of people are killed, hundreds of thousands are made homeless, or when a country suffers substantial economic losses, depending on the economic circumstances generally prevailing in that country" (Munich Re, 2002). These figures include data on the overall economic and insured losses worldwide (in 2002 dollars) from earthquakes, floods, windstorms, volcanic eruptions, droughts, heat waves, freezes, and cold waves.

Figure 1.1(a) suggests a good deal of variation in losses with time. The figure illustrates that in certain years, such as 1976, 1988, 1995, and 1999, there are peaks in the amount of loss. Furthermore, the amplitude of the peaks seems to be increasing over time. This trend is expected to continue as higher concentrations of population and built environment develop in areas susceptible to natural hazards worldwide. Additionally, worldwide losses during the 1990's exceeded $40 billion dollars each year with the exception of 1997. Losses were as high as $170 billion in 1995, primarily due to the large-scale earthquake that destroyed portions of Kobe in Japan in January of that year. Insured losses matched this growth during the same timeframe.

The volatility and trend in losses can be seen in the United States as well. Figure 1.2(a) and Figure 1.2(b) show the economic and insured losses from significant United States catastrophes from 1950 through 2002 with losses adjusted to 2002 dollars. U.S. catastrophes are deemed significant when there is an adjusted economic loss of at least $1 billion and/or over 50 deaths attributed to the event (American Re, 2002).

There are peaks in losses due to catastrophic events, as in worldwide losses (most prominently in 1989, 1992, and 1994), and the upward trend over the past 50 years is evident when broken down by decade, as seen in Figure 1.2(b). The losses from individual disasters during the past 15 years are an order of magnitude above what they were over the previous 35 years. Furthermore, prior to Hurricane Hugo in 1989, the insurance industry in the United States had never suffered a loss of over $1 billion from a single disaster. Since 1989, numerous disasters have exceeded $1 billion in insured losses. Hurricane Andrew devastated the coastal areas of southern Florida in August 1992, as well as damaging parts of south-central Louisiana causing $15.5 billion in insured losses. Similarly, on the west coast of the United States, insured losses from the Northridge earthquake of January 1994 amounted to $12.5 billion.

Residential and commercial development along coastlines and areas with high seismic hazard indicate that the potential for large insured losses in the future is substantial. The ten largest insured property losses in the United States, including the loss from 9/11, are tabulated in Table 1.1 adjusted to 2001 dollars (Insurance Information Institute, 2001). The increasing trend for catastrophe losses over the last two decades provides compelling evidence for the need to manage risks both on a national, as well as on a global scale.

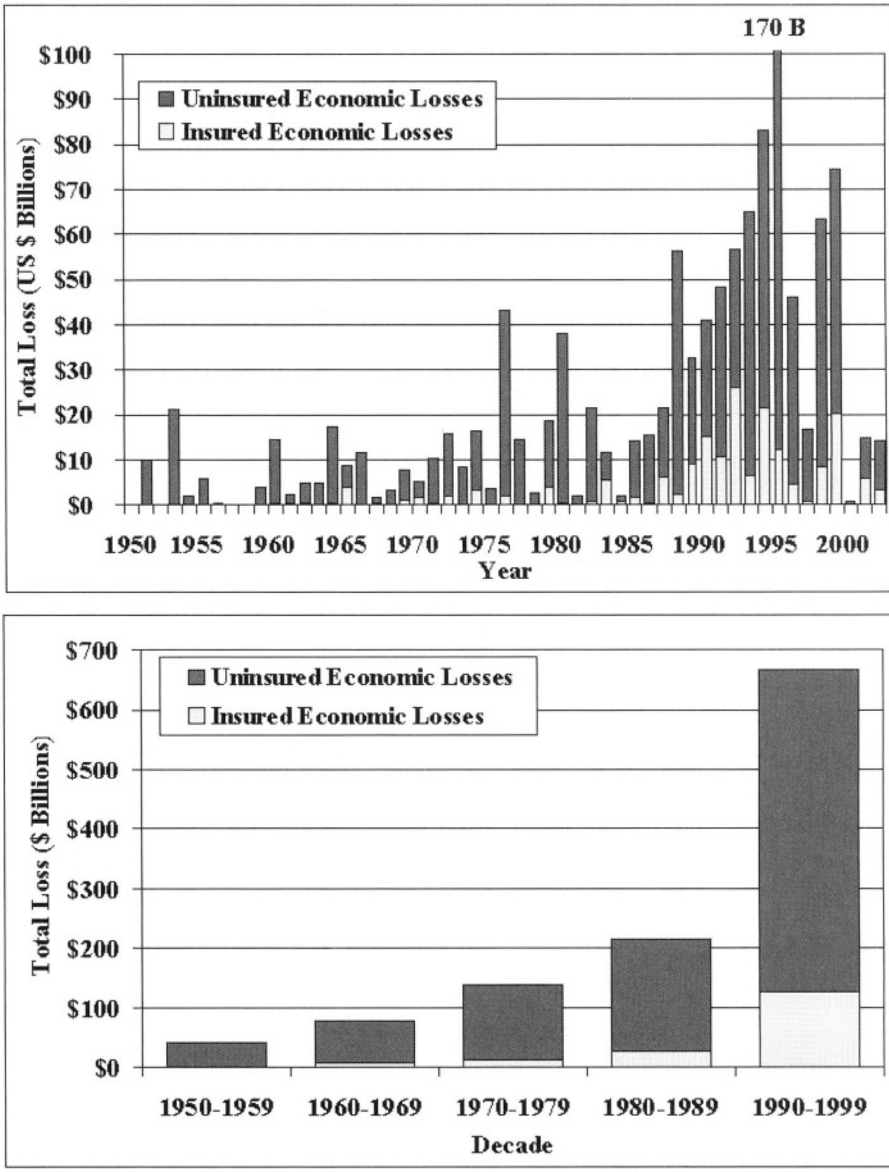

Figure 1.1. Losses due to great natural catastrophes worldwide: (a) by year; and (b) by decade (developed by the Geoscience Division of Munich Re).

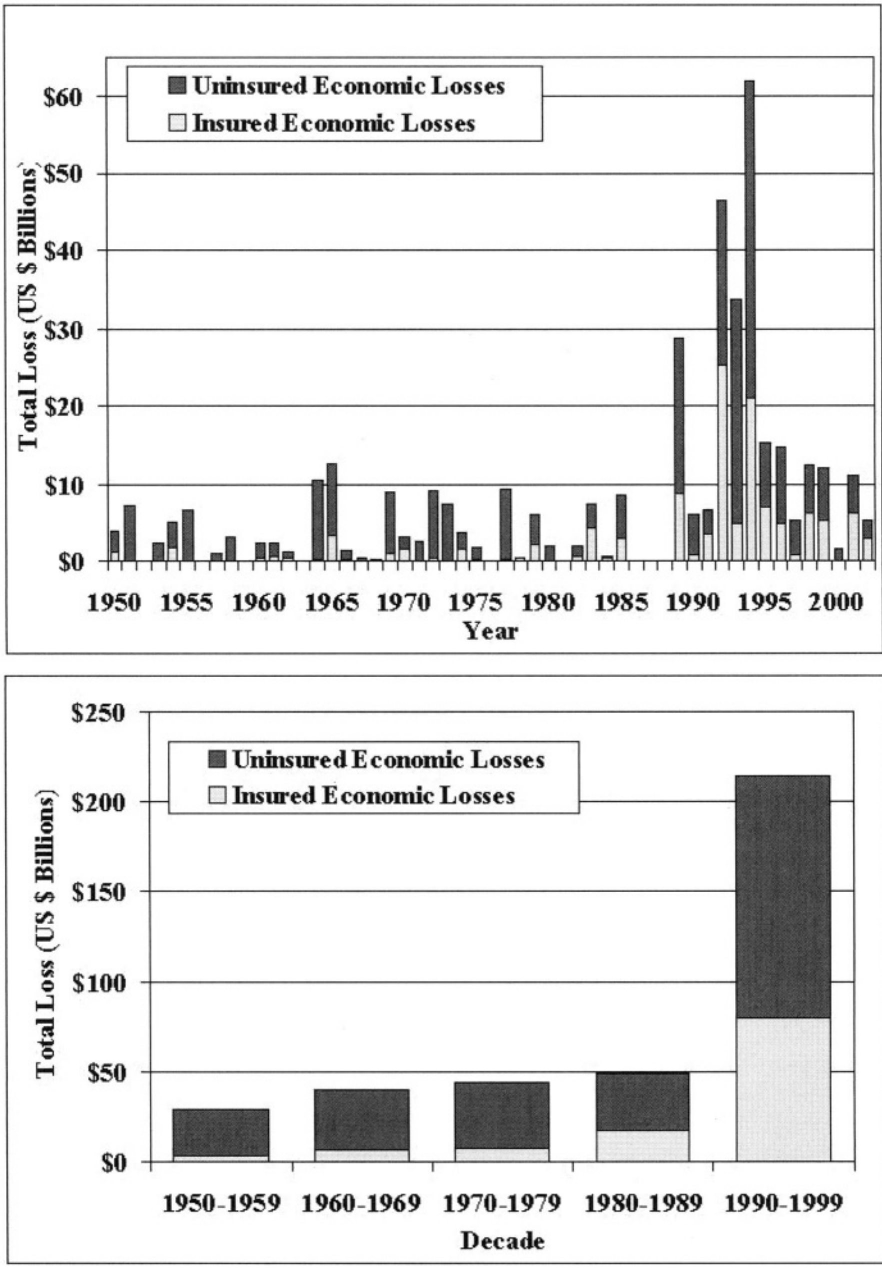

Figure 1.2. Losses due to significant U. S. natural catastrophes: (a) by year; and (b) by decade (developed by the Geoscience Division of American Re).

Table 1.1. Top 10 U.S. insured property losses (US $ billions)

Event	Dollars at year of occurrence	2001 dollars
World Trade Center (2001)	$20.3	$20.3[1]
Hurricane Andrew (1992)	$15.5	$19.6
Northridge Earthquake (1994)	$12.5	$14.9
Hurricane Hugo (1989)	$4.2	$6.0
Hurricane Georges (1998)	$2.9	$3.2
Tropical Storm Allison (2001)	$2.5	$2.5
Hurricane Opal (1995)	$2.1	$2.4
Hurricane Floyd (1999)	$2.0	$2.1
20-state winter storm (1993)	$1.8	$2.1
Oakland Firestorm (1991)	$1.7	$2.2

(Source: Insurance Information Institute)

1.2 Private Sector Stakeholders in the Management of Risk

The magnitude of economic and insured losses from natural disasters raises various questions. Who are the individuals affected by these events? What options are available to them to assess their risk? What factors influence their choices for dealing with these risks and actively managing their risk? By examining the perspectives of these individuals and groups, one can develop more effective risk management strategies for reducing potential losses from such disasters.

Figure 1.3 illustrates the key stakeholders in the management of risk that are discussed in this book. Each of the stakeholders' goals and perceptions of the risk lead them to view natural hazards from a unique perspective.

At the bottom of the pyramid are the property owners who are the primary victims of losses from natural disasters. They have to bear the brunt of the losses unless they take steps to protect themselves by mitigating or transferring some of the risk. Insurers form the next layer of the pyramid. They offer coverage to property owners against losses from natural disasters. Insurers themselves are concerned with the possibility of large claim payments from a catastrophe and turn to reinsurers, the next layer of the

[1] Some major claims are still in dispute; this does not include liability claims. Total insured losses due to the 9/11 attacks (including liability) are estimated around $35 billion as of July, 2004.

pyramid, to transfer some of their risk. At the top of the pyramid are the capital markets, which in recent years have provided financial protection to both insurers and reinsurers through financial instruments, such as catastrophe bonds. Of course, there are exceptions to this pyramid structure. For example, there have been two catastrophe bond issues (Concentric Re, covering Tokyo Disneyland, and Studio Re, covering Universal Studios) that offered direct protection to these property owners in place of traditional insurance arrangements.

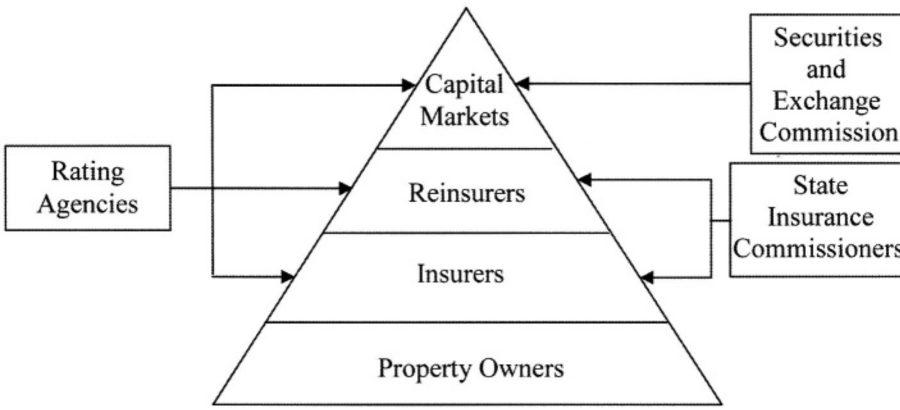

Figure 1.3. Key private sector stakeholders in the management of risk

The insurance rating agencies and state insurance commissioners are the two institutions that regulate the insurance industry. Rating agencies provide independent evaluations of the financial stability of the insurers and reinsurers. State insurance commissioners are primarily concerned that the rates charged by insurers are fair and that insurers in the market will remain solvent following a disaster. The Securities and Exchange Commission (SEC) regulates capital markets and catastrophe bonds are given bond ratings by organizations such as Fitch, Moody's Investor Service, and Standard & Poor's.

In the following sections, risk management strategies are discussed from the perspective of each stakeholder in the pyramid.

1.2.1 Property Owners

Owners of commercial and residential structures have a range of risk management strategies from which to choose. They can reduce their risk by retrofitting a structure to withstand wind or earthquake loading, transfer part of their risk by purchasing some form of insurance, and/or keep and finance their risk.

The ways in which particular individuals decide to manage risk is often a function of their perceptions. Despite a front-line position in facing the financial impacts of natural disasters, the average homeowner is one of the least active stakeholders in the process. For most, the choices are whether or not to buy insurance – if this is an option – and whether to take actions that would make their home more resistant to damage. Many homeowners do not take action even when the risk is abundantly clear and loss-reducing measures are available. It is often the case that these homeowners feel that a disaster will not affect them.

A commercial property owner's risk perception and strategies to manage risk are different from those of residential owners. A commercial establishment must concern itself not only with life safety and insolvency issues, but also with the impact of a natural hazard on the operation of its business. Often, there are extra expenses as a business tries to remain viable after a catastrophe. The company is concerned about business interruption loss – the loss or reduction of income due to the suspension of operations resulting from a natural disaster. Business owners in hazard-prone regions are normally quite interested in purchasing coverage against this type of risk.

1.2.2 Insurers

An insurer provides protection to residential and commercial property owners for losses resulting from natural disasters. Losses due to damage from fires (resulting from lightning during thunderstorms) and wind (resulting from tornadoes and hurricanes) are covered by a homeowner's insurance policy, normally required by lenders as a condition for a mortgage. In the U.S., loss due to water damage (resulting from floods) is covered under the National Flood Insurance Program (NFIP), a public-private partnership between the government and the insurance industry established in 1968. Losses due to damage from ground movement (resulting from earthquakes and landslides) are covered by a policy endorsement or by a separate policy. This separate policy is issued either by the private sector or, in California, through a state-run, privately funded earthquake insurance company, the California Earthquake Authority (CEA) that was created in 1996.

Losses from natural disasters can have a severe impact on an insurer's financial condition. Insurers, therefore, want to limit the amount of coverage they provide to property owners in hazard-prone areas. An important concern for insurers is the concentration of risk. Those who cover a large number of properties in a single geographic area face the possibility of large losses should a natural disaster occur in the area. An insurer views a portfolio with this type of highly correlated (or interrelated) risks as undesirable. Subject to regulatory restrictions, an insurer limits coverage in any given area and/or charges higher premiums in order to keep the chances of insolvency at an acceptable level.

1.2.3 Reinsurers

Reinsurers provide protection to private insurers in much the same way that insurers provide coverage to residential and commercial property owners. They traditionally supply indemnity contracts against unforeseen or extraordinary losses. In this type of arrangement, the reinsurer charges a premium in return for providing another insurance company with funds to cover a stated portion of the losses it may sustain. Most insurers, especially smaller or geographically concentrated firms, purchase reinsurance for covering natural hazard losses. Indeed, the failure to do so will likely adversely affect their financial rating and/or attract the attention of insurance regulators.

Similar to insurers, reinsurers concern themselves with concentration of risk. Hence, they too limit their exposure in catastrophe-prone areas to keep the chances of insolvency at an acceptable level. One way they achieve this is to pool the risks of several different insurers who have independent exposures in different high hazard regions. Thus, a reinsurer could take on Insurer A's hurricane risk in Florida, Insurer B's earthquake risk in California and Insurer C's earthquake risk in Tokyo, Japan. By diversifying across a number of regions and risks, the reinsurer is able to collect sufficient premiums to cover relatively large losses from a single disaster while at the same time reducing the likelihood of a catastrophic loss.

1.2.4 Capital Markets

The capital markets have recently emerged as a complement to reinsurance for covering large losses from disasters through new financial instruments known as catastrophe bonds (see Chapter 9). Several factors have led to this development. The shortage of reinsurance following Hurricane Andrew and the Northridge earthquake made it possible for insurers to offer bonds with interest rates high enough to attract capital from investors. In addition, the prospect of an investment uncorrelated with the stock market or general economic conditions is attractive to capital market investors. Finally, catastrophe models have emerged as a tool for more rigorous estimates of loss, so that disaster risk can be more accurately quantified than in the past.

Catastrophe bonds enable an insurer or reinsurer to access needed funds following a disaster. If the losses exceed a trigger amount, then the interest on the bond, the principal, or both, are forgiven. To justify the risks of losing their principal and/or interest, capital market investors demand a large enough risk-adjusted return to invest in these bonds. These investors include hedge fund managers, pension fund managers, insurers, and others, who concern themselves with the impact of the investment on their portfolio. In turn, the institutions that issue catastrophe bonds worry about their reputation should a major disaster negatively impact their investors' return.

1.2.5 Rating Agencies

Rating agencies, such as A.M. Best Company, Standard & Poor's, Moody's Investors Service, and Fitch, provide independent evaluations of reinsurers' and insurers' financial stability and their ability to meet their obligations to policyholders. The rating assigned to an insurer has significant consequences on how they do business. Many states have minimum rating requirements for an insurer to write business in their territory; similarly, insurers are less willing to cede risk to a poorly rated reinsurer. A poor rating has an impact on the premium a company can charge or the coverage it can sell, and is likely to have a negative effect on the share price of publicly traded firms.

A.M. Best Company, for example, assigns ratings through a quantitative analysis of a company's balance sheet strength, operating performance, and business profile (A.M. Best, 2001). Since at least 1997, A.M. Best Company has required insurance companies to complete a rating questionnaire that includes information on catastrophe exposures. Catastrophes play a significant role in evaluating a company's exposure, since these events could threaten the solvency of a company. Modeled loss results at specified return periods (100-year windstorm and 250-year earthquake), and the associated reinsurance programs to cover them, are important components of the rating questionnaire. A.M. Best Company's approach has been an important step forward in the incorporation of catastrophe risk into a company's capital adequacy requirements.

Investors also rely on the evaluations of catastrophe bonds by those rating agencies. These firms evaluate the quality of the risk analysis used in support of the issuance of a bond and require a variety of stress tests to check the sensitivity of the modeled losses. The resulting ratings influence the marketability and the price of a catastrophe bond. In addition, the rating can limit the potential buyer pool since some institutional investors will not participate in bonds with an unacceptable rating.

1.2.6 State Insurance Commissioners

In the United States, insurance is regulated at the state level with the principal regulatory authority residing with insurance commissioners. For insurers, two important and somewhat conflicting goals of this regulation are solvency regulation and rate regulation. Reinsurers are subject to the solvency regulation; however, they are not subject to rate regulation. Solvency regulation addresses the same concerns as rating evaluation: Is the insurer sufficiently capitalized to fulfill its obligations to its policyholders if a significant event occurs? A primary concern is the authorized control level of risk-based capital, the minimum amount of capital required below which the state has the authority to take action against the company.

Rate or market regulation attempts to ensure fair and reasonable insurance prices, products, and trade practices. Rate regulation focuses on whether insurance rates are equitable and nondiscriminatory. In all states, insurance companies are required to obtain a certificate of authority or license to underwrite policies. A license bureau provides a screening that in principle should protect the public from economic loss caused by misrepresentation, dishonesty, and incompetence of individuals seeking to sell insurance.

Solvency and rate regulation are closely related and must be coordinated to achieve their specific objectives. Regulation of rates and market practices will affect insurers' financial performance; solvency regulation ensures adequate capital. In this regard, the regulator plays a vital role in ensuring that a viable insurance market is functioning with coverage offered to consumers at affordable prices.

1.2.7 Other Stakeholders

Lenders play an essential role in managing natural disaster risk. Except for the uncommon case in which the owner pays for property outright, banks and other financial institutions enable individuals in the United States to purchase a home or business by providing mortgages. The property is the collateral in the event that the owner defaults on the mortgage.

Lenders thus have a vital stake in the risk management process, as they are unlikely to recover the full value of a loan on a piece of property destroyed by catastrophe. The 1994 Northridge earthquake, for example, generated $200-$400 million in mortgage-related losses in the Los Angeles area (Shah and Rosenbaum, 1996). Following Northridge, Freddie Mac experienced an unprecedented number of earthquake-related defaults on condominiums. As a consequence, the company retained a risk modeling firm to develop underwriting criteria that would identify high risk areas. Buyers of condominiums in these areas seeking a mortgage would then be required to buy earthquake insurance (Lehman, 1996). Interestingly enough, in 1996, the California State Legislature sought to bar this requirement, citing an undue burden on condominium owners. As a result, Freddie Mac changed its policy to require that a condominium buyer (a) purchase earthquake insurance; (b) purchase a property located in a low-risk area; or (c) pay an additional fee with the mortgage loan.

Real estate agents, developers, engineers, contractors, and other service providers also play a supporting, yet important role in the management of risk from natural disasters. In hazard-prone regions, federal or state regulations require real estate agents to inform the new owner of potential hazards. Examples include the location of a home relative to an earthquake fault line or within a 100-year flood plain. Unfortunately, it is sometimes unclear how information on natural hazard risk is being used in the purchase process. One study showed that despite the California requirement that purchasers of residential property within a certain distance of a known earthquake fault be told about the hazard, most home buyers did not understand or recall the risk warning (Palm, 1981).

Engineers and contractors can aid in the management of risk in high hazard areas. For example, structures designed and built to high standards, with inspections by reputable building officials during construction, provide good protection against life and property loss in the next earthquake or hurricane. Life and property loss are often attributable to inadequate design and construction practices. The problem of building and selling property in hazard-prone regions is exacerbated when disreputable building contractors bypass costly wind and seismic-resistant designs.

1.3 Government's Role in Management of Risk

Federal, state and local government often take the lead in managing risk from natural disasters. Policy makers at all levels of government have developed a set of programs for reducing risks from these disasters. In addition, they prioritize funding following a severe earthquake, flood, tornado, or other extreme event.

1.3.1 Types of Programs

Federal Level

At the national level, the Federal Emergency Management Agency (FEMA) coordinates many of the planning and response aspects related to catastrophes. Although specific programs come and go, FEMA has historically taken the lead in developing strategies for mitigation. For example, in December 1995, the agency introduced a National Mitigation Strategy with the objective of strengthening partnerships between all levels of government and the private sector to ensure safer communities.

This strategy was developed with input from state and local officials as well as individuals and organizations with expertise in hazard mitigation (FEMA, 1997). One of its key features was to create disaster-resistant communities through the Project Impact program. The program, begun in 1997, encouraged communities to "bring interested parties together to identify their potential natural hazards, assess the community's vulnerability, prioritize hazard risk reduction measures and communicate success to the residents" (FEMA, 2000). In 2001, over 250 communities participated in Project Impact.

Federal legislation that promotes natural disaster mitigation is another way to manage catastrophe risk. The Earthquake Loss Reduction Act of 2001 (HR.2762/S.424) and the Disaster Mitigation Act of 2000 (Public Law 106-380) are two such examples. The Disaster Mitigation Act, the latest amendment to the Robert T. Stafford Disaster Relief and Emergency Assistance Act, seeks to reduce losses to publicly owned buildings following disasters. While the federal government still provides funds to cover the majority of the cost to repair public facilities in the event of a disaster, there is a clause in the Disaster Mitigation Act of 2000 noting that the "President shall promulgate regulations to reduce the Federal share of assistance" if the eligible facility "has been damaged, on more than one occasion within the preceding 10-year-period, by the same type of event; and the owner of which has failed to implement appropriate mitigation measures to address the hazard that caused the damage to the facility." The message from the federal government is clear: local and state government officials are encouraged to mitigate.

The Earthquake Loss Reduction Act of 2001 takes a different approach to encourage mitigation. The legislation aims to "provide a number of incentives, including grants and tax credits, in order to encourage responsible state and local governments, individuals, and businesses to invest in damage prevention measures before an earthquake strikes" (Feinstein Press Release, March, 2001). As of May 2004, the Senate finance committee was still reviewing this legislation. Due to the concern of the federal government over terrorism risk, this legislation may not have the priority it had prior to 9/11.

The federal government also provides financial assistance to natural disaster victims through the Small Business Administration's (SBA) Disaster Loan Program. Over the years, the SBA has provided loans and sometimes forgiveness grants to cover homeowner and business losses from natural disasters. During the period between the Alaska Earthquake of 1964 and Tropical Storm Agnes in June 1972, the SBA was very generous in the type of disaster relief it provided. For example, those suffering uninsured losses after Agnes were eligible to receive $5,000 forgiveness grants and 30-year loans at 1% interest. In recent years, the SBA has not been as generous; disaster loans in 2003 were offered at interest rates just slightly below the existing market rate.

State Level

At the state level, an office of emergency services or a department of public safety promotes natural disaster preparedness. Additionally, seismic safety commissions have been established by earthquake-prone states to prioritize earthquake research and public policy needs. Building codes that include criteria for wind or earthquake resistance and legislation for land use management endeavor to reduce risk.

Incentive programs have been instituted to reduce losses from disaster events, especially in hazard-prone states. A good example of such legislation is California's Proposition 127. Passed in November of 1990, the law states that seismic retrofits to property completed on or after January 1, 1991, and completed on or before July 1, 2000, will not increase the property tax for a homeowner until ownership changes. The state concluded that these improvements constitute such a significant reduction in the risks to life and safety, that they should be exempt from additional property tax.

Local Level

At the local level, communities enforce building codes and have developed economic incentives, such as tax relief, for those who retrofit. Local communities have developed programs to promote awareness, provide training, and encourage self-help actions through neighborhood emergency response teams. For example, the city of San Leandro, California has set priorities to retrofit both unreinforced masonry buildings (URMs) and older wood-frame homes. The Home Earthquake Strengthening Program is a comprehensive, residential seismic strengthening program that provides homeowners with simple and cost-effective methods for strengthening their wood-frame houses for earthquake survival. The program includes earthquake-strengthening workshops for residents, a list of available earthquake contractors, as well as a tool-lending library for homeowners should they wish to do the work themselves.

Table 1.2 provides a set of examples of leadership activities at the different levels of government: for defining and prioritizing risks, for alleviating risks through legislative means, and for encouraging reduction of earthquake risk. These programs bring together diverse groups of people around a common issue, and provide needed encouragement and resources.[2]

1.3.2 Federal Disaster Insurance

The federal and state governments in the United States now play a major role in supplementing or replacing private insurance with respect to floods, hurricanes, and earthquakes. This coverage is limited to certain key stakeholders, mainly residential property owners.

Flood Insurance

Insurers have experimented over the years with providing protection against water damage from floods, hurricanes and other storms. After the severe Mississippi Floods of 1927, they concluded that the risk was too great. With the need for this type of coverage evident, Congress created the National Flood Insurance Program (NFIP) in 1968, whereby homes and businesses could purchase coverage for water damage. The stipulation for this financial protection was that the local community make a commitment to regulate the location and design of future floodplain construction to increase safety from

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[2] See Grossi and Kunreuther (2000) for more details on earthquake programs and Moss (2002, Chapter 9) for a more general discussion of the role of the public sector in providing disaster assistance.

flood hazards. The federal government established a series of building and development standards for floodplain construction to serve as minimum requirements for participation in the program.

Table 1.2. Government leadership in managing earthquake risk (Grossi and Kunreuther, 2000)

	Define and Prioritize Risk	**Legislation to Alleviate Risk**	**Encourage Risk Reduction**
Federal Government	National Earthquake Hazards Reduction Program (NEHRP)	Robert T. Stafford Disaster Relief and Emergency Assistance Act	Federal Emergency Management Agency's Project Impact
State Government	State Seismic Safety Commissions California Earthquake Hazards Reduction Act	California Unreinforced Masonry Building Law	California Proposition 127
Local Government	Home Earthquake Strengthening Program (San Leandro, CA)	Earthquake Hazard Reduction Ordinance (Los Angeles, CA)	Tax Transfer Rebate (Berkeley, CA)

In the NFIP, private insurers market flood policies and the premiums are deposited in a federally operated Flood Insurance Fund, which then pays all legitimate claims. To encourage communities to participate in the program, and to maintain property values of structures, those residing in the area prior to the issuance of a flood insurance rate map (FIRM) have their premiums subsidized. New construction is charged an actuarial premium reflecting the risks of flood as well as efforts in mitigation (Interagency Flood Plain Management Review Committee, 1994). Additionally, the Community Rating System (CRS) was created in 1990 to recognize and encourage flood mitigation activities. The communities that are the most involved in floodplain management activities receive the greatest premium reduction; households or firms located in a community with no active risk management strategies receive no premium reductions (Pasterick, 1998).

Actuarial premiums are charged to property owners living outside the 100-year flood plain (i.e., the area where the annual chance of a flood occurring equals or exceeds 1%) or to those living within 100-year areas who build or substantially improve structures after the federal government provides complete risk information from the flood insurance rate map. Over time, the percentage of homes requiring a subsidy has declined. Whereas 41% of the 2.7 million policies were subsidized in 1993, only 30% of the 4.3 million policies were subsidized in 2000.

SIDEBAR 1: Loss estimation and policy in Oregon

For most of the 20th century, the lack of significant earthquakes in Oregon resulted in the state having minimal seismic requirements in its building code. Since the late 1980's, however, new scientific evidence reveals that massive earthquakes occurred offshore repeatedly before white settlement in the 19th century, most recently in 1700, and will likely reoccur (Clague and others, 2000; Atwater and Hemphill-Haley, 1997). While current building codes now reflect this consensus, the legacy of the older regulations leaves a building stock largely unprepared for significant earthquakes.

The Department of Geological and Mineral Industries (DOGAMI), Oregon's state geological survey, has been active in assessing the potential financial impact from the earthquake hazard. In addition to identifying and assessing sources of earthquake activity, DOGAMI has been using the federal government's loss estimation model, HAZUS, to quantify potential losses due to earthquakes on both the local and statewide levels (Wang and Clark, 1999; Vinson and Miller, 2000).

The HAZUS study was a catalyst for action within the state government. The Department of Administrative Services, which handles risk management for state-owned facilities, increased the level of earthquake insurance coverage following discussions with DOGAMI. With the growing awareness of the earthquake threat, the Oregon State Legislature drafted several bills in 2000 addressing the need for earthquake preparedness (SB 13) and retrofitting of critical structures such as schools (SB 14), hospitals, and fire stations (SB 15). HAZUS-derived statistics from Wang and Clark (1999), estimating $12 billion in losses and 8,000 casualties from a M8.5 offshore earthquake, were quoted in support of these bills. All three bills easily passed the State Legislature in 2001.

An important part of the bill's implementation will be the further incorporation of loss estimation tools. Funding for these propositions is not infinite and ideally should be allocated to targets where it will provide the most quantifiable benefit. DOGAMI will be involved in assessing the loss of life and property in communities most at risk and prioritizing these projects to optimize reduction of these losses (Beaulieu, 2001).

In January of 2003, Congress reauthorized the NFIP through the 2003 fiscal year. Also during this time, other legislation was introduced to amend the National Flood Insurance Act of 1968 to reduce losses to properties for which repetitive flood insurance claim payments have been made. At the time of the legislation's introduction in January of 2003, it was referred to subcommittee.

Hurricane Insurance

The need for hurricane insurance is most pronounced in the state of Florida. Following Hurricane Andrew in 1992, nine property-casualty insurance companies became insolvent, forcing other insurers to cover these losses under Florida's State Guaranty Fund. Property insurance became more difficult to obtain as many insurers reduced their concentrations of insured property in coastal areas.

During a special session of the Florida State legislature in 1993, a bill was enacted to handle the insurance availability crisis. It stipulated that insurers could not cancel more than 10% of their homeowners' policies in any county in one year, and that they could not cancel more than 5% of their property owners' policies statewide for each year the moratorium was in effect. At the same time, the Florida Hurricane Catastrophe Fund (FHCF) was created to relieve pressure on insurers to reduce their exposures to hurricane losses. The FHCF, a tax-exempt trust fund administered by the state of Florida, is financed by premiums paid by insurers that write insurance policies on personal and commercial residential properties. The fund reimburses a portion of insurers' losses following major hurricanes, and enables insurers to remain solvent while renewing most of their policies scheduled for non-renewal (Lecomte and Gahagan, 1998).

Earthquake Insurance

Historical earthquake activity in California convinced legislators that this risk was too great to be left solely in the hands of private insurers. In 1985, a California law required insurers writing homeowners' coverage on one to four unit residential buildings to also offer earthquake coverage. Since rates were regulated by the state, insurers felt they were forced to offer coverage against older structures in poor condition, with rates not necessarily reflecting the risk.

Following the 1994 Northridge earthquake, huge insured property losses created a surge in demand for coverage. Insurers were concerned that if they satisfied the entire demand, as they were required to do by the 1985 law, they would face an unacceptable level of risk and become insolvent following the next major earthquake. Hence, many firms decided to stop offering coverage, or restricted the sale of homeowners' policies in California.

In order to keep earthquake insurance alive in California, the State legislature authorized the formation of the California Earthquake Authority (CEA) in 1996. At the CEA's inception, all claims were subject to a 15% deductible. This meant that with full insurance on a house valued at $200,000, the property owner would have to pay the first $30,000 of repairs from future earthquake damage. In 1999, the CEA began offering wrap around policies, defined as policies with a 10% deductible, or additional contents coverage, or both. As of July 31, 2003, the CEA had 735,909 policies in force with total premiums of $428 million. Approximately 18% of those insured purchased a wrap around policy (California Earthquake Authority, 2003). In 2003, with insurers providing $743 million in cash contributions and up to $3.6 billion in possible future assessments, along with additional layers of funding from the reinsurance industry and lines of credit, the total CEA insurance pool capacity stood at $7 billion.

1.4 Summary of Chapter

This chapter provided an overview of the history of natural disasters and the nature of natural hazard risk, with a focus on the United States. Special emphasis was given to property owners at risk, the capital market, reinsurers, and insurers who provide financial protection, and the role that rating agencies and state insurance commissioners play in regulating these groups. With insured losses expected to grow in the future, this chapter serves as an introduction to the current role catastrophe models can play in helping insurers and other key stakeholders to manage this risk.

As government often takes on the responsibility of providing funds to cover damage from catastrophic disasters, it has an economic incentive to mitigate the risks from these events. While the state and federal governments often play this role, all the supporting entities in the management of risk (reinsurers, regulators, capital markets, lenders, engineers, contractors, real estate agents, and developers) have an opportunity to promote mitigation efforts and assist in the recovery after an event.

Insurers and property owners are the two stakeholders given principal consideration during the remaining chapters of this book. The next chapter presents a framework for characterizing their decision processes in choosing between competing risk management strategies. It is used throughout this book to illustrate existing and emerging solutions for managing catastrophe risk.

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Chapter 2 – An Introduction to Catastrophe Models and Insurance

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This chapter provides an overview of the history of catastrophe models and their role in risk assessment and management of natural disasters. It examines the insurability of catastrophe risk and illustrates how the output from catastrophe models aids insurers in meeting their goals for risk management. Throughout the chapter, there is an emphasis on understanding catastrophe modeling for earthquake and hurricane hazards and how it is used to manage natural hazard risk. In the final section, a framework for integrating risk assessment with risk management via catastrophe modeling is presented.

2.1 History of Catastrophe Models

Catastrophe modeling is not rooted in one field or discipline. The science of assessing and managing catastrophe risk originates in the fields of property insurance and the science of natural hazards. Insurers may well argue that catastrophe modeling's history lies in the earliest days of property insurance coverage for fire and lightning. In the 1800's, residential insurers managed their risk by mapping the structures that they covered. Not having access to Geographic Information Systems (GIS) software, they used tacks on a wall-hung map to indicate their concentration of exposure. This crude technique served insurers well and limited their risk. Widespread usage of mapping ended in the 1960's when it became too cumbersome and time-consuming to execute (Kozlowski and Mathewson, 1995).

On the other hand, a seismologist or meteorologist may well argue that the origin of catastrophe modeling lies in the modern science of understanding the nature and impact of natural hazards. In particular, the common practice of measuring an earthquake's magnitude and a hurricane's intensity is one of the key ingredients in catastrophe modeling. A standard set of metrics for a given hazard must be established so that risks can be assessed and managed. This measurement began in the 1800's, when the first modern seismograph (measuring earthquake ground motion) was invented and modern versions of the anemometer (measuring wind speed) gained widespread usage.

In the first part of the twentieth century, scientific measures of natural hazards advanced rapidly. By the 1970's, studies theorizing on the source and frequency of events were published. Significant analyses include the U.S. Water Resources Council publication on flood hazard (USWRC, 1967), the Algermissen study on earthquake risk (Algermissen, 1969) and National Oceanic and Atmospheric Administration (NOAA) hurricane forecasts (Neumann, 1972). These developments led U.S. researchers to compile hazard and loss studies, estimating the impact of earthquakes, hurricanes, floods, and other natural disasters. Notable compilations include Brinkmann's summary of hurricane hazards in the United States (1975) and Steinbrugge's anthology of losses from earthquakes, volcanoes, and tsunamis (1982).

These two separate developments – mapping risk and measuring hazard – came together in a definitive way in the late 1980's and early 1990's, through catastrophe modeling as shown in Figure 2.1. Computer-based models for measuring catastrophe loss potential were developed by linking scientific studies of natural hazards' measures and historical occurrences with advances in information technology and geographic information systems (GIS). The models provided estimates of catastrophe losses by overlaying the properties at risk with the potential natural hazard(s) sources in the geographic area. With the ability to store and manage vast amounts of spatially referenced information, GIS became an ideal environment for conducting easier and more cost-effective hazard and loss studies.

Around the same time, several new modeling firms developed computer software for analyzing the implications of natural hazard risk. Three major firms emerged: AIR Worldwide was founded in 1987 in Boston; Risk Management Solutions (RMS) was formed in 1988 at Stanford University; and EQECAT began in San Francisco in 1994 as a subsidiary of EQE International. In 2001, EQE International became a part of ABS Consulting.

When introduced, the use of catastrophe models was not widespread. In 1989, two large-scale disasters occurred that instigated a flurry of activity in the advancement and use of these models. On September 21, 1989, Hurricane Hugo hit the coast of South Carolina, devastating the towns of Charleston and Myrtle Beach. Insured loss estimates totaled $4 billion before the storm moved through North Carolina the next day (Insurance Information Institute, 2000). Less than a month later, on October 17, 1989, the Loma Prieta Earthquake occurred at the southern end of the San Francisco peninsula. Property damage to the surrounding Bay Area was estimated at $6 billion (Stover and Coffman, 1993).

These two disasters sent a warning signal to the insurance industry. On the heels of these two events, Hurricane Andrew made landfall in Southern Florida in August of 1992. Within hours of landfall, AIR Worldwide issued a fax to its clients to the effect that losses, as estimated in real time by the AIR Worldwide hurricane model, might reach the astonishing amount of $13 billion. It was not until months later that the final tally, $15.5 billion, was issued by the Property Claim Services Office.

Nine insurers became insolvent as a result of their losses from Hurricane Andrew. Insurers and reinsurers realized that, in order to remain in business, they needed to estimate and manage their natural hazard risk more precisely. Many companies turned to the modelers of catastrophe risk for decision support. The modeling companies grew and catastrophe models increased in number, availability, and capability. By 2001, other organizations joined these front-runners in developing catastrophe models for assisting insurers and reinsurers in pricing their insurance policies and determining how much coverage to offer in hazard-prone areas of the country.

The series of natural disasters in 1989 and 1992 also sent a warning signal to the public sector of the United States. The government recognized the need for an accurate assessment of the impact of disasters for mitigation and emergency planning purposes. In 1992, the Federal Emergency Management Agency (FEMA) funded a study to assess the latest loss estimation methodologies for earthquakes. The agency issued a report in 1994 on the results of this study entitled: Assessment of the State of the Art Earthquake Loss Estimation Methodologies (FEMA 249, 1994).

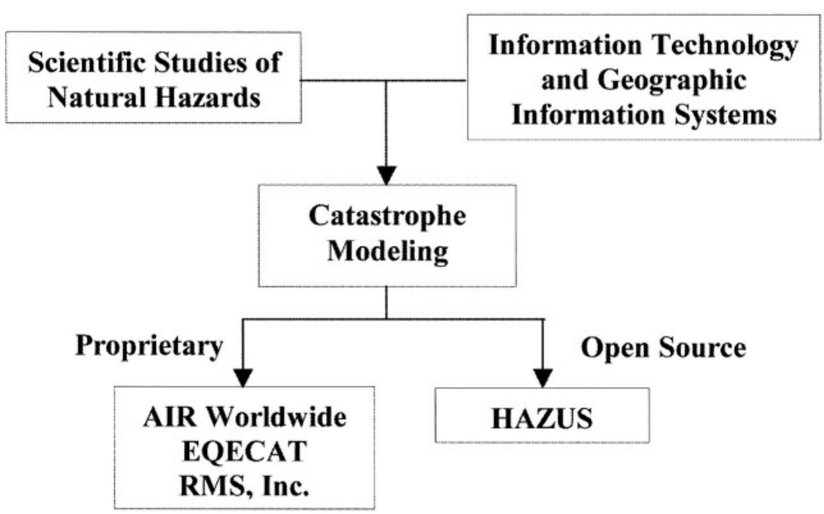

Figure 2.1. Development of catastrophe modeling.

This study convinced FEMA to fund the development of “Hazards U.S.” (HAZUS), a catastrophe model in the public domain. HAZUS is labeled as an open source model in Figure 2.1. From the outset, one of FEMA’s goals was to create a methodology that was the “standard national loss methodology for assessing losses from natural hazards” (FEMA, 2002). The first version of HAZUS was developed with a combination of public and private resources to estimate earthquake losses and was released in 1997 (NIBS, 1997). Updates to the HAZUS earthquake model have been in the form of data and software integration; methodologically, the software remains the same. In 2004, the latest HAZUS multi-hazard methodology, relabeled HAZUS-MH, integrates the earthquake module with two new modules for estimating potential losses from wind and flood (riverine and coastal) hazards.

2.2 Structure of Catastrophe Models

The four basic components of a catastrophe model are: hazard, inventory, vulnerability, and loss as depicted in Figure 2.2. First, the model characterizes the risk of natural hazard phenomena. For example, an earthquake hazard is characterized by its epicenter location and moment magnitude, along with other relevant parameters. A hurricane is characterized by its projected path and wind speed. The frequency of certain magnitudes or frequencies of events also describes the hazard in question.

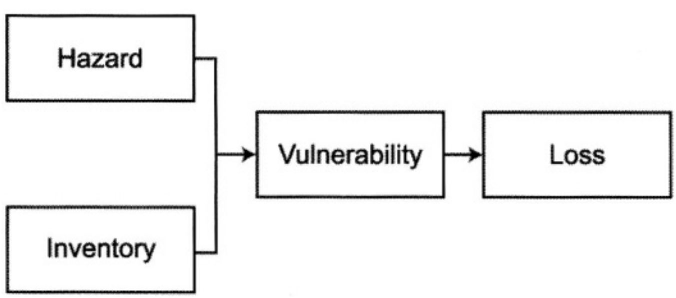

Figure 2.2. Structure of catastrophe models.

Next, the model characterizes the inventory or portfolio of properties at risk as accurately as possible. Arguably, the most important parameter used to characterize the inventory is the location of each property at risk. A process called geocoding is normally used to assign geographic coordinates such as latitude and longitude to a property based on its street address, ZIP code or another location descriptor. With a property’s location in spatial terms, other factors that could aid in estimating the vulnerability of a property are added to its characterization. For a building, these parameters include such features as its construction type, the number of stories in the structure, and its age. If the property is insured, information on the nature of the policy, such as the deductible and coverage limit, is also recorded.

The hazard and inventory modules enable the calculation of the vulnerability or susceptibility to damage of the structures at risk. In essence, this step in the model quantifies the physical impact of the natural hazard phenomenon on the property at risk. How this vulnerability is quantified differs from model to model. For example, the HAZUS model classifies a structure as being in a Slight, Moderate, Extensive, or Complete damage state. Other models construct damage curves and relate structural damage to a severity parameter, such as peak gust wind speed or spectral acceleration. In all models, damage curves are constructed for the building, its contents and time element losses, such as business interruption loss or relocation expenses.

From this measure of vulnerability, the loss to the inventory is evaluated. In a catastrophe model, loss is characterized as direct or indirect in nature. Direct losses include the cost to repair and/or replace a structure. Indirect losses include business interruption impacts and relocation costs of residents forced to evacuate their homes. Proprietary models include the ability to analyze insurance policies, so that the loss can be properly allocated. More details on these elements of a catastrophe model are provided in Chapter 3.

2.3 Uses of a Catastrophe Model for Risk Management

A catastrophe model is employed to assess catastrophe risk and improve risk management decisions. But how is this accomplished? Briefly, the model output is quantified and presented in a way that is useful to the stakeholder. Once these metrics are in hand, alternate risk management strategies, such as mitigation, insurance, reinsurance and catastrophe bonds, can be assessed. Currently, insurers and reinsurers are the stakeholders with the most widespread interest and integrated use of catastrophe models. Reinsurance brokers in particular have enhanced the use of catastrophe models. It is fairly common for a broker to collect data for potential clients, run the models on that data, and provide the output to interested reinsurers.

The capital markets have also been eager users of this technology in order to more accurately price catastrophe bonds. In fact, their recent interest and involvement in natural hazards have been made possible by the quantification afforded by catastrophe modeling. Property owners are less likely to use catastrophe models themselves, but their decision processes are directly or indirectly influenced by the outcomes. At the governmental level, catastrophe modeling presents both a positive opportunity and a political dilemma for regulators and emergency management agencies.

As an example of a positive use of the models, consider the use of HAZUS to measure the impact of an earthquake. One model output option is to create a GIS map of the potential loss. Given the definition of the hazard, including the earthquake's epicenter location, and the concentration of the properties at risk, Figure 2.3 depicts a map of the displaced households for the Charleston, South Carolina region subject to an M 7.3 earthquake. The largest concentration of loss, measured by the number of individuals seeking shelter following the disaster, is near the scenario's epicenter. This map is potentially useful to emergency response and recovery officials responding to a disaster.

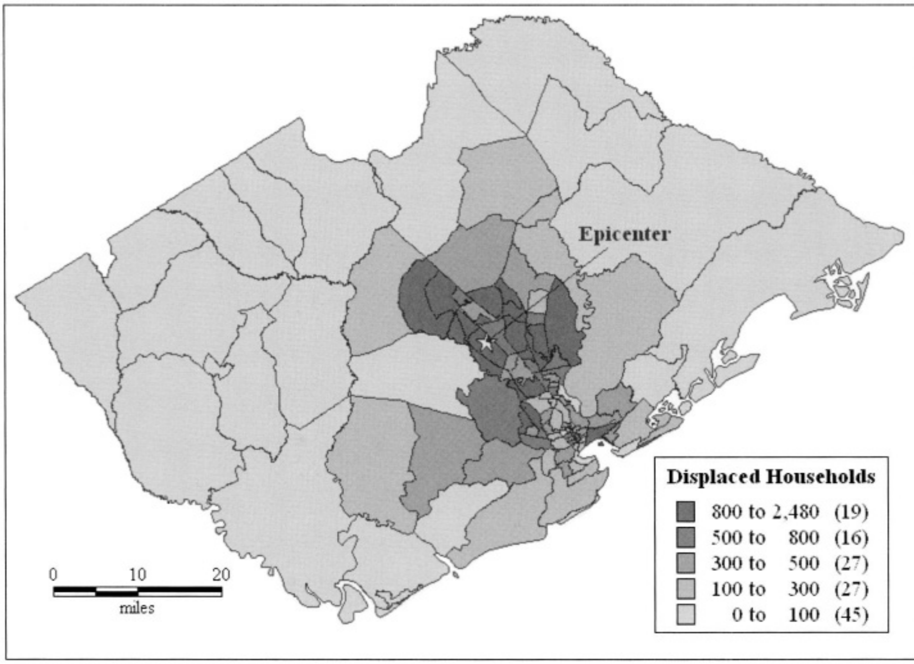

Figure 2.3. Catastrophe model output: Map of shelter requirements predicted by HAZUS for M 7.3 events in Charleston, South Carolina region.

Another output option is the exceedance probability (EP) curve. For a given portfolio of structures at risk, an EP curve is a graphical representation of the probability that a certain level of loss will be surpassed in a given time period. Special attention is given to the right-hand tail of this curve where the largest losses are situated. Figure 2.4 depicts an EP curve for an insurer with a portfolio of residential earthquake policies in Long Beach, California. In contrast to a GIS map of loss, which presents loss in a spatial manner, an exceedance probability curve portrays loss in a temporal manner.

An EP curve is particularly valuable for insurers and reinsurers to determine the size and distribution of their portfolios' potential losses. Based on the EP curve, they can determine the types and locations of buildings they would like to insure, what coverage to offer, and what price to charge. To keep the probability of insolvency at an acceptable level, insurers can also use an EP curve to determine what proportion of their risk needs to be transferred to either a reinsurer and/or the capital markets.

For example, suppose an insurer in Long Beach offers residential earthquake coverage and the insurer's exceedance probability curve for its portfolio is as depicted in Figure 2.4. Further suppose the insurer specifies \$10 million as an acceptable level of loss at a 1% (1-in-100) probability of exceedance. Based on the graph, it can be seen that loss profile of the current portfolio would be unacceptable since the 1-in-100 loss for the portfolio is \$ 15 million. The insurer would need to look for ways to reduce its portfolio, transfer \$5 million of loss to a reinsurer, or purchase a catastrophe bond to cover it.

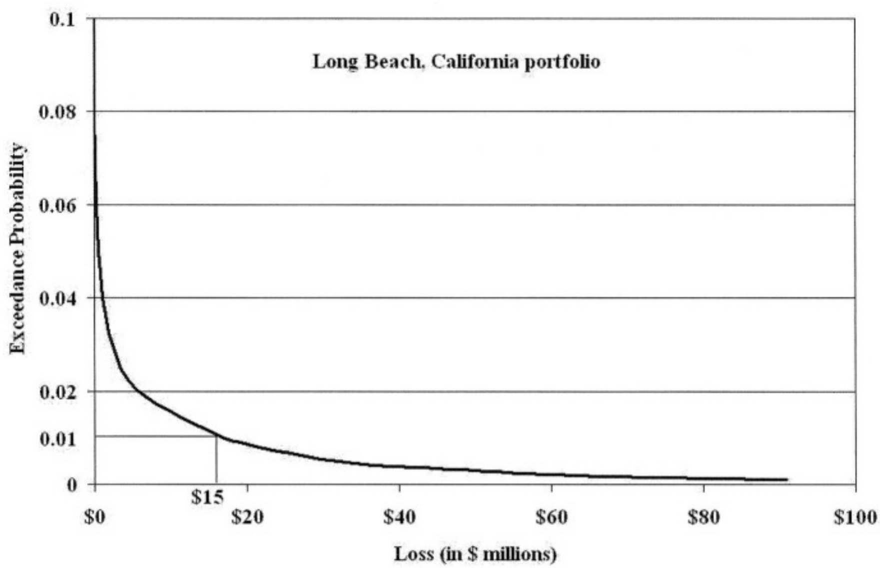

Figure 2.4. Catastrophe model output: Right-hand tail of exceedance probability curve predicted by EQECAT for all possible events.

2.4 Derivation and Use of an Exceedance Probability Curve

Given the importance of how insurers use catastrophe modeling and the EP curve to manage risk, it is essential to understand how the EP curve can be created from the loss output.

2.4.1 Generating an Exceedance Probability Curve

For the purposes of illustration, some simplifying assumptions are made to generate an EP curve. Suppose there is a set of natural disaster events, E_i, which could damage a portfolio of structures. Each event has an annual probability of occurrence, p_i, and an associated loss, L_i. The number of events per year is not limited to one; numerous events can occur in the given year. A list of 15 such events is listed in Table 2.1, ranked in descending order of the amount of loss. In order to keep the example simple and calculations straightforward, these events were chosen so the set is exhaustive (i.e., sum of the probabilities for all of the events equals one).

The events listed in Table 2.1 are assumed to be independent Bernoulli random variables, each with a probability mass function defined as:

$$P(E_i \text{ occurs}) = p_i$$

$$P(E_i \text{ does not occur}) = (1 - p_i)$$

If an event E_i does not occur, the loss is zero. The Expected Loss for a given event, E_i, in a given year, is simply:

$$E[L] = p_i L_i$$

The overall expected loss for the entire set of events, denoted as the average annual loss (AAL) in Table 2.1, is the sum of the expected losses of each of the individual events for a given year and is given by:

$$AAL = \sum_i p_i L_i$$

Assuming that during a given year, only one disaster occurs, the exceedance probability for a given level of loss, $EP(L_i)$, can be determined by calculating:

$$EP(L_i) = P(L > L_i) = 1 - P(L \le L_i)$$

$$EP(L_i) = 1 - \prod_{j=1}^{i} (1 - p_j)$$

The resulting exceedance probability is the annual probability that the loss exceeds a given value. As seen in the equation above, this translates into one minus the probability that all the other events below this value have not occurred. The exceedance probability curve for the events in Table 2.1 is shown in Figure 2.5. Sidebar 1 explains how the EP curve can be used to determine probable maximum loss (PML).

Table 2.1. Events, Losses, and Probabilities

Event (E_i)	Annual probability of occurrence (p_i)	Loss (L_i)	Exceedance probability [$EP(L_i)$]	$E[L] = (p_i * L_i)$
1	0.0020	$25,000,000	0.0020	$50,000
2	0.0050	15,000,000	0.0070	75,000
3	0.0100	10,000,000	0.0169	100,000
4	0.0200	5,000,000	0.0366	100,000
5	0.0300	3,000,000	0.0655	90,000
6	0.0400	2,000,000	0.1029	80,000
7	0.0500	1,000,000	0.1477	50,000
8	0.0500	800,000	0.1903	40,000
9	0.0500	700,000	0.2308	35,000
10	0.0700	500,000	0.2847	35,000
11	0.0900	500,000	0.3490	45,000
12	0.1000	300,000	0.4141	30,000
13	0.1000	200,000	0.4727	20,000
14	0.1000	100,000	0.5255	10,000
15	0.2830	0	0.6597	0
		Average Annual Loss (AAL)	=	$760,000

SIDEBAR 1: PML as a function of the EP Curve

The exceedance probability curve illustrated in Figure 2.5 enables an insurer to determine his PML or Probable Maximum Loss for a portfolio of structures in a given time period. The term PML is a subjective risk metric and is associated with a given probability of exceedance specified by the insurer. For example, suppose that an insurer specifies its acceptable risk level as the 0.4% probability of exceedance. The insurer can use the EP curve to determine how large a loss will occur at this probability level. Often, PML limits are framed in terms of a return period. The return period is simply the inverse of the annual probability of exceedance. In this example, a 1-in-250 year PML is the lower limit on the loss at a 0.4% probability of exceedance on the EP curve. From the inset of Figure 2.5, it can be seen that the PML is approximately $21 million.

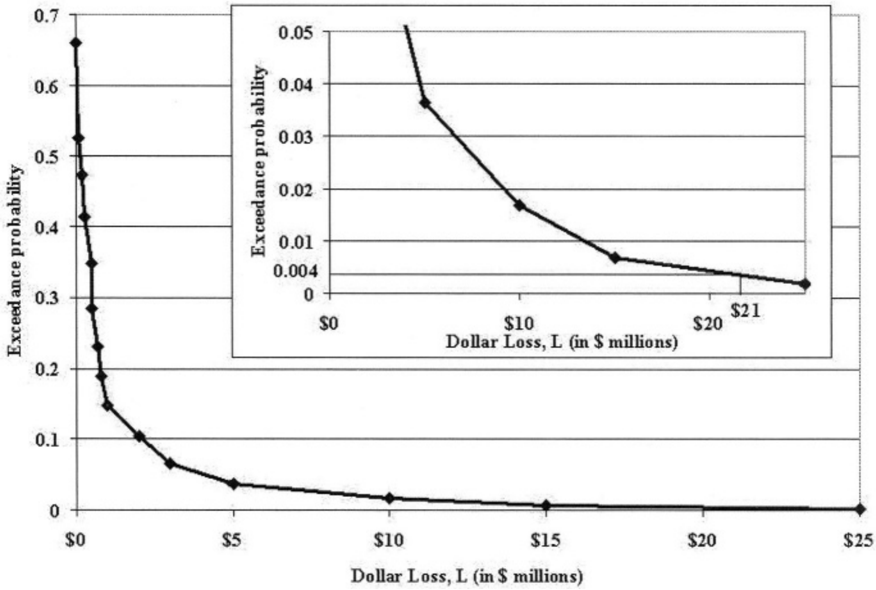

Figure 2.5. Exceedance probability curve

2.4.2 Stakeholders and the Exceedance Probability Curve

The exceedance probability curve can also be used to distribute the losses between stakeholders. Suppose there are three stakeholders who share the losses from a particular disaster. The owner retains the first part of the loss, a second party covers the middle portion and a third party covers the extreme portion. This scenario could represent a portfolio of homes with the homeowners having deductibles on their insurance policies such that they cover the first portion of the loss, an insurer covers the middle portion and a reinsurer handles the losses above a certain amount. Figure 2.6 shows a simple illustrative example. The potential loss for a portfolio with a total value of $100 million is split between three participants: P1, P2, and P3. The first $5 million of loss (L1) would be borne by P1 (homeowners), losses between $5M and $30M (L2) by P2 (insurer), and losses in excess of $30M (L3) by P3 (reinsurer). If the events facing the three parties were those given in Table 2.1, then the reinsurer would never experience any claim payments because the maximum loss would be $25 million.

Now suppose the three parties face the set of events in Table 2.1, but there is some uncertainty associated with the losses from each of the first 14 events (E_{15} has a loss of zero). In other words, the losses in Table 2.1 represent the mean estimates of loss; each event E_i has a distribution of loss associated with it. There is now a range of possible outcomes for each event, and some of these will penetrate the higher layer L3 (Figure 2.7). By combining the loss distributions for all the events, the probability of exceeding a specific loss level can be calculated. This then becomes the basis for developing EP curves for each of the parties with resources at risk.

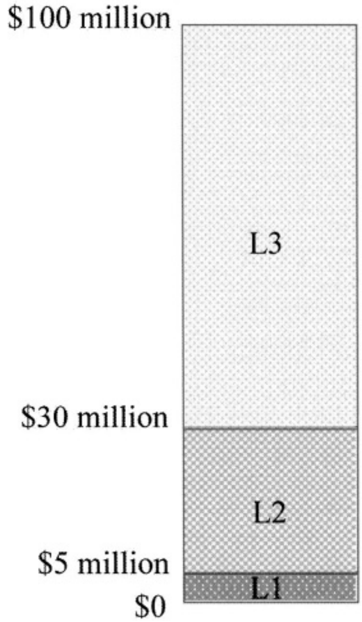

Figure 2.6. Layering for hypothetical portfolio, total value $100 million.

Figure 2.7 shows a set of loss-causing events with a high level of uncertainty in the loss distributions where the coefficient of variation (CV) on the event losses is 1.0.[1] By definition, the coefficient of variation is the ratio of the standard deviation to the mean. The effect of this high uncertainty is clearest on L3. If there were no variability in the losses, L3 would not be affected because no event is capable of reaching a $30 million loss, as previously stated. Based on the assumption (CV = 1.0), there is an annual probability of 0.28% that an event would cause some loss to L3.

This illustrative example shows how catastrophe modeling provides a means of both quantifying risks and allocating them among stakeholders. Using these metrics, it is possible to make rational, informed decisions on how to price risks and determine how much coverage is needed based on an

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[1]Note that the assumption of a constant coefficient of variation for all events is not realistic and is used only for ease of illustration. The CV on the event loss generally decreases as the size of the loss increases; a portfolio CV of 1.0 for the most damaging event in this example is highly unlikely.

acceptable level of risk. However, there are uncertainties inherent in the catastrophe modeling process that can have a large impact on the distribution of risk among stakeholders. The quantification and disaggregation of uncertainty provides opportunities for stakeholders to reduce risk. As will be discussed in Part II, some of this uncertainty can be reduced by better data, but a significant component is an intrinsic part of the physical process.

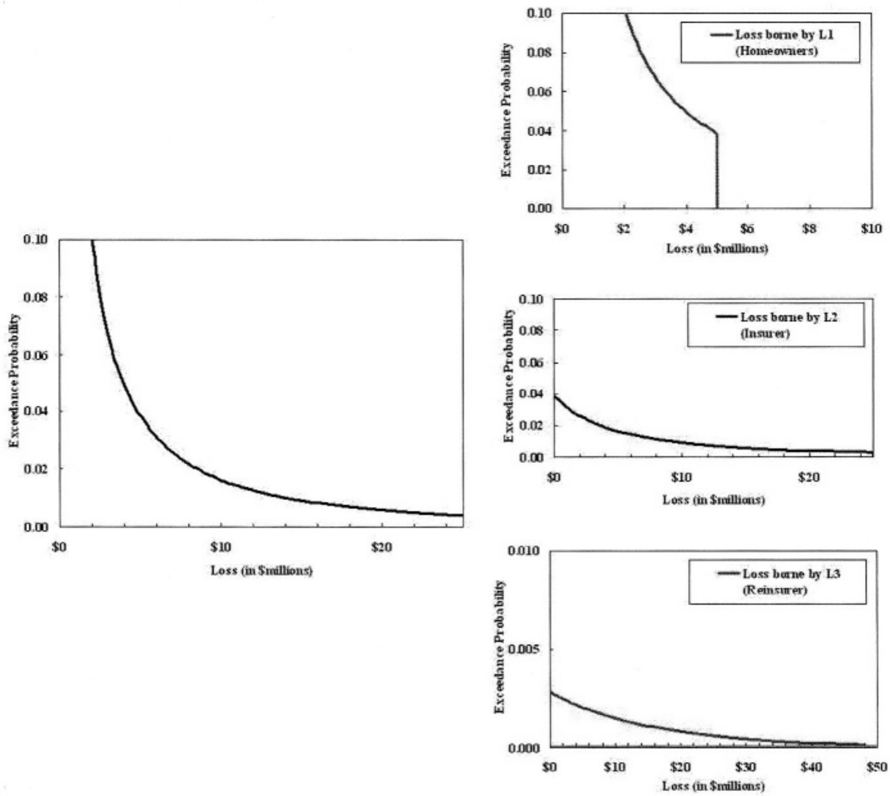

Figure 2.7. Exceedance probability curves for total portfolio and individual participants.

2.5 Insurability of Catastrophe Risks

In most developed countries, insurance is one of the principal mechanisms used by individuals and organizations to manage risk. Insurance allows the payment of a relatively small premium for protection against a potentially large loss in the future. In the United States, some property insurance coverage is required by law or by the lending institution. For example, homeowners normally have to purchase fire coverage as a condition for a mortgage. Automobile liability insurance is also required in most states as a condition for licensing a car. However, earthquake insurance is usually not required by lenders on single-family residences.

Insurance pricing can be a signal of how risky certain activities are for a particular individual. To illustrate, consider automobile insurance. For cars that are the same price, younger, inexperienced drivers of sporty vehicles pay more in premiums than older drivers of more conservative cars. For life and health insurance, smokers pay more for coverage than nonsmokers. This allocation of risk seems appropriate since it is tied to the likelihood of outcomes resulting from the nature of an individual's lifestyle. If one individual is more susceptible to a specific risk, then the cost for coverage against a loss from that risk is greater. Of course, since insurance rates are subject to regulation, the price of the policy may not fully reflect the underlying risk.

The key challenge is how to allocate catastrophe risk among stakeholders in a manner similar to what is done for more frequent, non-extreme events. For automobile coverage, considerable historical data are available and utilized to estimate insurance premiums for individuals with different risk characteristics. The large number of data points and the absence of correlation between accidents allow the use of actuarial-based models to estimate risk (Panjer and Willmot, 1992). With respect to natural disasters, there are limited data available to determine the probabilities of events occurring and their likely outcomes. In the absence of past data, there is a need for insurers to model the risk. Catastrophe models serve this purpose by maximizing the use of available information on the risk (hazard and inventory) to estimate the potential losses from natural hazards.

2.5.1 Conditions for Insurability of a Risk

Consider a standard insurance policy whereby premiums are paid at the start of a given time period to cover losses during this interval. Two conditions must be met before insurance providers are willing to offer coverage against an uncertain event. The first condition is the ability to identify and quantify, or estimate at least partially, the chances of the event occurring and the extent of losses likely to be incurred. The second condition is the ability to set premiums for each potential customer or class of customers.

If both conditions are satisfied, a risk is considered to be insurable. But it still may not be profitable. In other words, it may be impossible to specify a rate for which there is sufficient demand and incoming revenue to cover the development, marketing, operating, and claims processing costs of the insurance and yield a net positive profit over a prespecified time horizon. In such cases, the insurer will opt not to offer coverage against this risk.

To satisfy the first condition, estimates must be made of the frequency of specific events and the likely extent of losses. Such estimates can be based on past data or catastrophe modeling, coupled with data on what experts know about a particular risk. The insurer can then construct an exceedance probability (EP) curve that depicts the probability that a certain level of loss will be exceeded on an annual basis.

With respect to the second condition, if there is considerable ambiguity or uncertainty associated with the risk, insurers may wish to charge a much higher premium than if they had more precise estimates of the risk (Kunreuther, Hogarth and Meszaros, 1995). Moreover, if the capacity of the insurance industry is reduced due to recent large losses, then premiums will rise due to a shortage in supply. The situation will be exacerbated if the recent losses trigger an increase in demand for coverage, as was the case after Hurricane Andrew in 1992 and the Northridge earthquake in 1994 (Kunreuther and Roth, Sr. 1998).

Once the risk is estimated, the insurer needs to determine a premium rate that yields a profit and avoids an unacceptable level of loss. There are a number of factors that influence an insurer's decision on what premium to set. State regulations often limit insurers in their rate-setting process, and competition can play a role in what may be charged in a given marketplace. Even in the absence of these influences, there are a number of issues that an insurer must consider in setting premiums: uncertainty of losses, highly correlated losses, adverse selection, and moral hazard. Neither adverse selection nor moral hazard appears to be a major problem with respect to natural hazard risks. Adverse selection occurs when the insurer cannot distinguish (or does not discriminate through price) between the expected losses for different categories of risk, while the insured, possessing information unknown to the insurer, selects a price/coverage option more favorable to the insured. Moral hazard refers to an increase in the expected loss caused by the behavior of the policyholder. One example of moral hazard is moving unwanted furniture into the basement so an impending flood can destroy it, but this behavior occurs very infrequently. Given the difficulty uncertainty of losses and highly correlated losses pose in setting premiums, they are discussed below.

2.5.2 Uncertainty of Losses

Natural disasters pose a set of challenging problems for insurers because they involve potentially high losses that are extremely uncertain. Figure 2.8 illustrates the total number of loss events from 1950 to 2000 in the United States for three prevalent hazards: earthquakes, floods, and hurricanes. Events were selected that had at least $1 billion of economic damage and/or over 50 deaths (American Re, 2002).

Looking across all the disasters of a particular type (earthquake, hurricane or flood), for this 50-year period, the median loss is low while the maximum loss is very high. Given this wide variation in loss distribution, it is not surprising that there is a need for catastrophe models to aid insurers and reinsurers in estimating the potential loss from events that have not yet occurred but are scientifically credible.

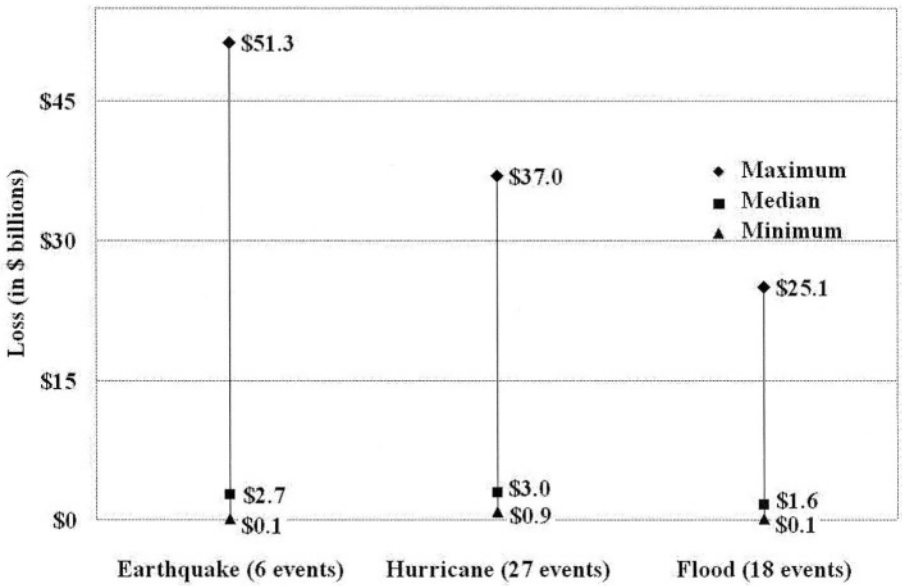

Figure 2.8. Historical economic losses in $ billions versus type of significant U.S. natural disaster. 1950-2000 (Source: American Re)

2.5.3 Highly Correlated Losses

Natural disasters involve spatially correlated losses or the simultaneous occurrence of many losses from a single event. If insurers sell a block of residential policies in a neighborhood, they could potentially experience a large (spatially correlated) loss should a disaster occur in the region. For example, due to their high concentration of homeowners' policies in the Miami/Dade County area of Florida, State Farm and Allstate Insurance paid $3.6 billion and $2.3 billion in claims respectively in the wake of Hurricane Andrew in 1992. Given this unexpectedly high loss, both companies began to reassess their strategies of providing coverage against wind damage in hurricane-prone areas (Lecomte and Gahagan, 1998).

In general, insurance markets flourish when companies can issue a large number of policies whose losses are spatially and otherwise independent. The portfolio follows the law of large numbers, and is thus predictable. This law states that for a series of independent and identically distributed random variables, the variance around the mean of the random variables decreases as the number of variables increases. Losses from natural hazards do not follow the law of large numbers, as they are not independent.

2.5.4 Determining Whether to Provide Coverage

In his study, James Stone (1973) sheds light on insurers' decision rules as to when they would market coverage for a specific risk. Stone indicates that firms are interested in maximizing expected profits subject to satisfying a constraint related to the survival of the firm. He also introduces a constraint regarding the stability of the insurer's operation. However, insurers have traditionally not focused on this constraint in dealing with catastrophic risks.

Following the disasters of 1989, insurers focused on the survival constraint in determining the amount of catastrophe coverage they wanted to provide. Moreover, insurers were caught off guard with respect to the magnitude of the losses from Hurricane Andrew in 1992 and the Northridge earthquake in 1994. In conjunction with the insolvencies that resulted from these disasters, the demand for coverage increased. Insurers only marketed coverage against wind damage in Florida because they were required to do so and state insurance pools were formed to limit their risk. Similarly, the California Earthquake Authority enabled the market to continue to offer earthquake coverage in California.

An insurer satisfies the survival constraint by choosing a portfolio of risks with an overall expected probability of insolvency less than some threshold, p_1. A simple example illustrates how an insurer would utilize the survival constraint to determine whether the earthquake risk is insurable. Assume that all homes in an earthquake-prone area are equally resistant to damage such that the insurance premium, z, is the same for each structure. Further assume that an insurer has $A dollars in current surplus and wants to determine the number of policies it can write and still satisfy its survival constraint. Then, the maximum number of policies, n, satisfying the survival constraint is:

$$\text{Probability [Total Loss} > (n \cdot z + A)] < p_1$$

Whether the company will view the earthquake risk as insurable depends on whether the fixed cost of marketing and issuing policies is sufficiently low to make a positive expected profit. This, in turn, depends on how large the value of n is for any given premium, z. Note that the company also has some freedom to change its premium. A larger z will increase the values of n but will lower the demand for coverage. The insurer will decide not to offer earthquake coverage if it believes it cannot attract enough demand at any premium structure to make a positive expected profit. The company will use the survival constraint to determine the maximum number of policies it is willing to offer.

The EP curve is a useful tool for insurers to utilize in order to examine the conditions for meeting their survival constraint. Suppose that an insurer wants to determine whether its current portfolio of properties in Long Beach is meeting the survival constraint for the earthquake hazard. Based on its current surplus and total earthquake premiums, the insurer is declared insolvent if it suffers a loss greater than $ 15 million. The insurer can construct an EP curve such as Figure 2.4 and examine the probability that losses exceed certain amounts. From this figure, the probability of insolvency is 1.0%. If the acceptable risk level, $p_1 < 1.0\%$, then the insurer can either decrease the amount of coverage, raise the premium and/or transfer some of the risk to others.

2.6 Framework to Integrate Risk Assessment with Risk Management

Figure 2.9 depicts a framework for integrating risk assessment with risk management and serves as a guide to the concepts and analyses presented in this book. The risk is first assessed through catastrophe modeling. Catastrophe modeling combines the four components (hazard, inventory, vulnerability, and loss) to aid insurers in making their decisions on what type of protection they can offer against a particular risk.

The key link between assessing risk via catastrophe models and implementing risk management strategies is the stakeholders' decision processes. The types of information stakeholders collect and the nature of their decision processes are essential in developing risk management strategies. With respect to insurers, catastrophe models are the primary sources of information on the risk. Their decision rule for developing risk management strategies is to maximize expected profits subject to meeting the survival constraint. Property owners in hazard prone areas utilize simplified decision rules in determining whether or not to adopt mitigation measures to reduce future losses to their property and/or to purchase insurance.

For purposes of this book, risk management strategies are broadly classified as either risk reduction measures, such as mitigation, or risk transfer measures, such as reinsurance. For example, strategies for residential property owners often involve a combination of measures, including mitigation, insurance, well-enforced building codes, and land-use regulations. In California and Florida, all these initiatives exist in some form. Strategies for insurers could involve charging higher rates to reflect the uncertainty of the risk, changing their portfolio so they can spread the risk across many areas, or reassigning the risk using risk transfer instruments such as reinsurance and/or catastrophe bonds.

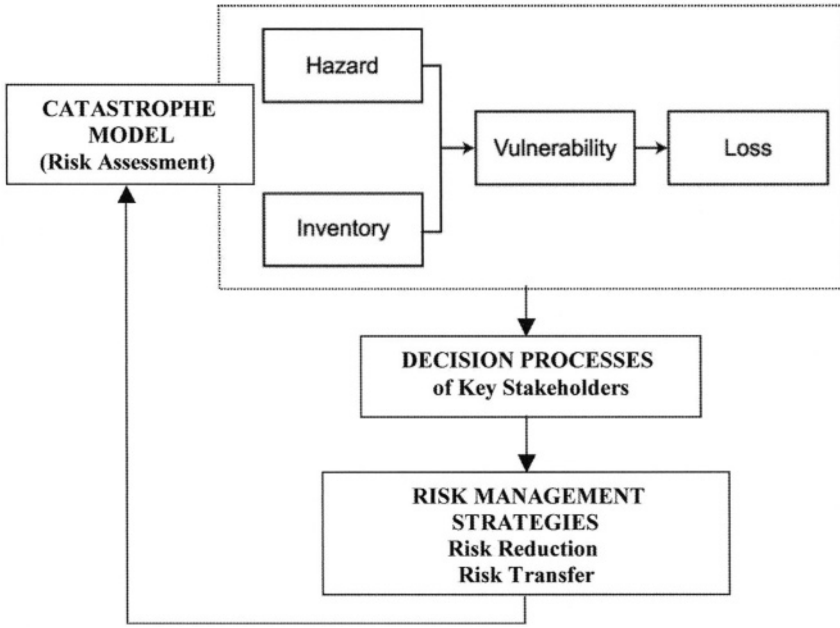

Figure 2.9. Framework for linking risk assessment with risk management.

2.7 Summary and Relationship to Parts II-IV

This chapter examined the history of catastrophe modeling and the role catastrophe models play in making a risk insurable. Part II provides a more detailed discussion of catastrophe modeling for earthquakes and hurricanes. The output from catastrophe models provides important information for insurers to manage their risk. By modeling the risk, insurers can more accurately estimate the premiums to charge for insurance coverage from natural disasters. In addition, insurers and reinsurers are able to tailor their coverage to reduce the chances of insolvency. They can develop new strategies for managing their portfolios so as to avoid losses that might otherwise cause an unacceptable reduction in surplus. These strategies are discussed in Part III of the book.

The impact of insurers' risk management strategies on profitability and probability of insolvency are explored further in Part IV of the book. Exceedance probability curves are constructed using real market data for insurers in Oakland, California, Long Beach, California and Miami/Dade County, Florida and alternative strategies are examined, including requiring mitigation to homes in these disaster-prone areas and using risk transfer instruments to satisfy an insurer's survival constraint. The book concludes with a chapter on the future role of catastrophe models in dealing with the risks associated with terrorism as an extreme event.

2.8 References

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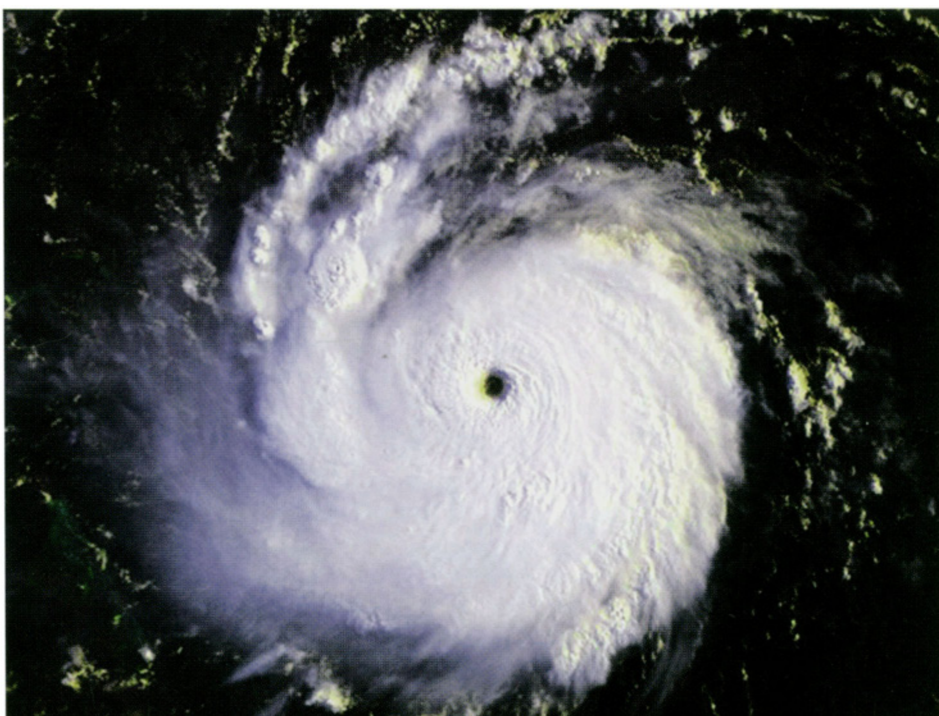
PART II
NATURAL HAZARD RISK ASSESSMENT

Part II of this book discusses the inner workings of catastrophe models and how they assess risk from natural hazards. Readers will learn more about the components of catastrophe models, including the hazard, inventory, vulnerability, and loss modules. In Chapter 3, these components are discussed in detail, and the complexities of the process are illuminated. This chapter also emphasizes the importance of data quality in determining earthquake and hurricane hazards, as well as exposure risk. Chapter 4 turns to the role of uncertainty in catastrophe models by examining the sources, nature, and impact of uncertainty on assessing natural hazard risk. Illustrative examples of assessing hurricane risk in Florida and earthquake risk in South Carolina enable readers to understand how uncertainty in the modeling process affects the allocation of risk between stakeholders.



Hurricane Andrew on its approach to Florida, 1992.

Chapter 3 – The Risk Assessment Process: The Role of Catastrophe Modeling in Dealing with Natural Hazards

Major Contributors:
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3.1 Introduction

Probabilistic risk analysis has long played an important role in engineering design for natural hazards. For example, the lateral loads imposed by hurricanes or earthquakes, and characterized by a specified probability of exceedance, are used by structural engineers to design buildings that minimize injuries and fatalities. More recently, these techniques have been extended to estimate the damage to existing building inventories and, ultimately, to estimate the economic and insured losses that result from the occurrence of natural catastrophes. Catastrophe loss estimation techniques, known collectively as catastrophe modeling, have gained widespread acceptance by the insurance and risk management industries and are now heavily relied upon to support a wide range of financial decisions.

A probabilistic approach to catastrophe loss analysis is the most appropriate way to handle the abundant sources of uncertainty inherent in all natural hazard related phenomena. As pointed out in Chapter 2, the relative infrequency of catastrophe events results in a scarcity of historical loss data. Hence statistical techniques used by actuaries for estimating future losses stemming from automobile or fire insurance policies, for example — techniques that rely on a wealth of available claims data — are not appropriate for estimating future losses from natural catastrophes. Furthermore, the usefulness of the limited historical loss data that do exist cannot be easily extrapolated to estimate the economic impact of disasters because of the ever-changing landscape of properties. Property values change, as do the costs of repair and replacement. Building materials, design and practice change along with building codes. Therefore new structures may be more or less vulnerable to catastrophe events than existing ones.

While it is generally agreed that the probabilistic approach is the most appropriate, it is highly complex and multifaceted. It requires modeling complex physical phenomena in time and space, compiling detailed databases of building inventories, estimating physical damage to various types of structures and their contents, translating physical damage to monetary loss and, finally, summing over entire portfolios of buildings. From the modeler's perspective, the task is to simulate, realistically and adequately, the most important aspects of this very complex system. Risk managers need to familiarize themselves with the underlying assumptions of the models and understand the implications and limitations of their output in order to utilize the results effectively.

Briefly, the hazard component of catastrophe models estimates the probability that the physical parameters that define the hazard will exceed various levels. In the case of earthquakes, for example, the model estimates the probability that parameters such as peak ground acceleration or spectral acceleration (defined as the maximum acceleration experienced by a simple oscillator, used as a representation for building response) will exceed various levels at a particular site. The model's vulnerability component deals with the potential for the hazard to damage structures and their contents. It estimates the probability that building damage will exceed various levels as a result of ground motion. The loss module translates physical damage into monetary loss and estimates the probability of exceeding various levels of loss.

Together, the hazard and vulnerability modules comprise what is traditionally known as probabilistic risk analysis. This approach to modeling earthquake risk is based on the pioneering work of Cornell (1968) and is now well established in the literature. Catastrophe loss models can be thought of as one application of probabilistic risk analysis, characterized by their refinement of the financial loss estimation component. The final result of the catastrophe model, commonly used in financial analysis, is the exceedance probability, or EP, curve introduced in the preceding chapter. At each stage in the process, the model takes into consideration the uncertainty in the various parameters that describe the model.

All catastrophe models require substantial amounts of data for model construction and validation. In addition, the reliability of such models depends heavily on our understanding of the underlying physical mechanisms that control the occurrence and behavior of natural hazards. While no one would claim to have a complete understanding of all of the intricacies of these physical systems, scientists and engineers, aided by increasingly sophisticated instrumentation and computing capabilities, have accumulated vast amounts of information and knowledge in these areas. By incorporating this information and knowledge, the sophisticated theoretical and empirical models currently being developed can reasonably simulate these complex phenomena.

This chapter explores in detail the building blocks of catastrophe models introduced in Chapter 2: hazard, inventory, vulnerability, and loss (see Figure 3.1 below). Chapter 4 focuses on the sources, nature and impact of the uncertainties that characterize each of these modules.

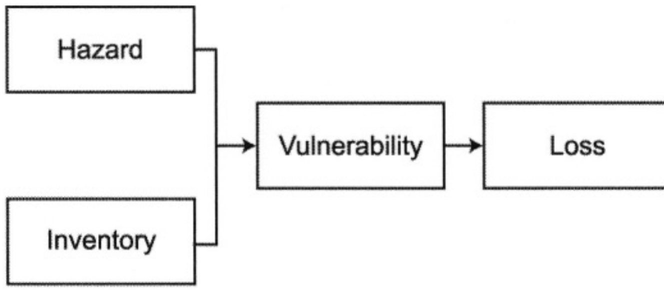

Figure 3.1. Catastrophe model components.

3.2 Hazard Module

All catastrophe models must address three basic issues regarding the source parameters of the hazard: the most likely locations of future events, their frequency of occurrence and their severity. These three elements are closely related and, in many cases, their modeling and validation require very similar sets of data. Probability distributions are developed based on historical data for each variable that defines these elements. The selection and subsequent refinement of these distributions is based not only on the expert application of statistical techniques, but also on well-established scientific principles and an understanding of how natural hazards behave. By sampling from these probability distributions, the model produces a large catalog of simulated events.

Once the model generates the source parameters of each simulated event, it propagates the resulting intensity over the affected area. That is, for each location within the affected area, local intensity is estimated. What follows is a more detailed discussion of each of these elements of the model's hazard module.

3.2.1 Locations of Potential Future Events

To achieve reliable estimates of catastrophe loss, the modeler must first define the model domain, or the region over which the sources of the hazard need to be identified.

Earthquakes

In conducting a catastrophe analysis for earthquakes in southern California, those faults and seismic source zones that have measurable impact on the building inventory of interest must be identified. Much of this information becomes available through direct observation and measurement of the physical parameters of actual earthquakes and their impact upon their environment. Typically, the rate at which ground motion attenuates with distance will determine the appropriate geographical extent of the region to be modeled.

In certain cases, however, the issue becomes more complex. In 1985, an earthquake of magnitude 8.1 occurred at the Pacific coast of Mexico, fully 400 kilometers away from Mexico City. Ordinarily, this distance would be too great to pose any significant threat to that city. Yet this earthquake caused serious damage there and killed some 20,000 people. This happened because the soft soils that comprise the former lake basin over which Mexico City is built, trapped and strongly amplified the very weak incoming ground motion that had traveled from hundreds of kilometers away (Mendez and Anderson, 1991).

This type of information is critical in identifying a model domain that captures all relevant sources of hazard. In this example, physical damage and loss can be better predicted with a thorough knowledge of the region's geological features and an understanding of the physics of wave propagation through soft soils and ground motion-structure interaction.

After defining the boundaries of the model domain, all sources of hazard within those boundaries need to be identified. In the case of earthquakes, that task is greatly facilitated when the locations of faults are known and mapped. In some regions, faults can easily be seen on the surface of the earth — the San Andreas Fault in California is a prime example. For the most part, records of historical seismicity (both instrumental and pre-instrumental), such as those depicted in Figure 3.2, play a key role in the process of identifying active faults. These data are supplemented by information obtained through methods such as fault trenching, subsurface sounding techniques and aerial photography (designed to detect the surface expression of faults). In general, an identified fault that has exhibited no earthquake activity within the current Holocene time period (roughly within the last 10,000 years) can be considered inactive and therefore excluded from earthquake hazard analysis.

Not all earthquakes happen on known faults, however. In such cases, seismicity is often modeled using area (polygonal) source zones rather than faults. The spatial distribution of past earthquakes within the zone is used to estimate the spatial distribution of future earthquakes. However, because of the uncertainty surrounding the exact locations of the underlying faults (which are inferred from the seismic activity of the area), catastrophe models typically allow simulated earthquakes to occur not only where they have occurred in the past, but also, with some probability, anywhere within the seismic source zone. This is accomplished by statistically smoothing the historical data.

For regions where there has been little or no historical seismic activity, larger zones of so-called "background seismicity" are typically defined. Using these concepts, seismic hazard is ultimately modeled as some weighted combination of seismicity as generated by faults, area source zones, and background seismicity. The United States Geological Survey (USGS) seismologists have used this technique to develop the present U.S. Seismic Hazard Maps that are used in the International Building Code (IBC).

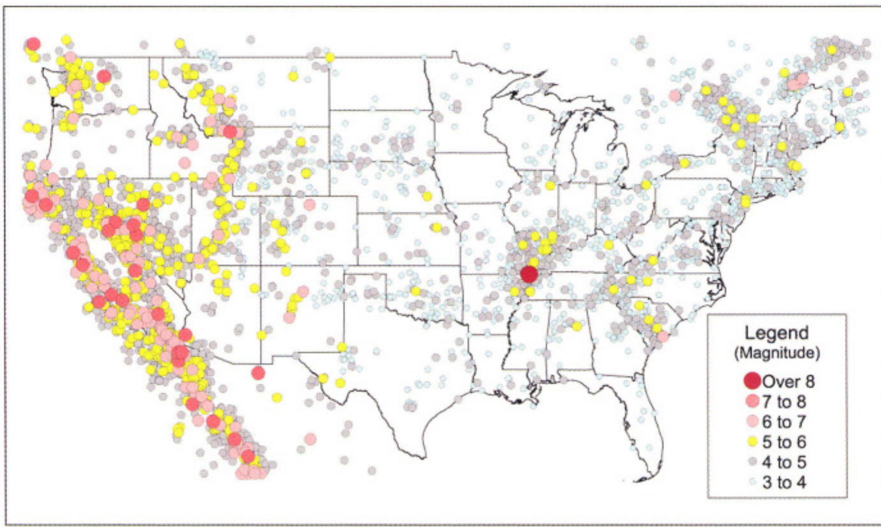

Figure 3.2. Spatial distribution of historical earthquakes since 1700. (Source: USGS)

Historical seismicity catalogs alone cannot identify all regional seismic sources. One reason is that large earthquakes associated with particular faults have sometimes very long recurrence intervals, while our historical and instrumentally recorded earthquake catalogs are of relatively short duration. Thus, in many cases, if the modeler relies only on earthquake catalog data, active faults can remain unidentified because of the lack of any record of earthquakes having occurred there. The historical earthquake catalog can be augmented with other auxiliary information, such as paleoseismic data. Paleoseismology is the study of prehistoric earthquakes, particularly their location, timing and size. Paleoseismologic evidence of prehistoric earthquakes includes offsets in geologic formations found in exhumed fault zones, evidence of rapid uplift or subsidence near coastal areas, laterally offset stream valleys, and liquefaction artifacts such as sand boils.

The principal challenge with this approach is to assign magnitudes to the paleoearthquakes. This requires locating contemporaneous sites exhibiting evidence of paleoseismicity, estimating the total affected area and converting this area to a magnitude. The last step is typically based on empirical relationships derived from the few earthquakes of sufficient size that have occurred historically in the region. Consequently, there is considerable uncertainty regarding estimates of recurrence rates derived from paleoseismic data. Nevertheless, paleoseismology is a major source of data used to estimate return periods of large magnitude earthquakes. For example, paleoseismic studies (Johnston and Schweig, 1996) have provided some of the most compelling evidence for estimating the magnitudes and return periods of large earthquakes in the New Madrid Seismic Zone of the Central United States.

Another more recent technique for identifying potentially active seismic sources is the use of geodetic survey data. Geodetic surveys, and in particular data derived from Global Positioning System (GPS) networks, which reveal relative movements of the earth's crust, provide information that can be used to identify regions under strain (SCEC, 1995). Theory and observation indicate that elastic materials relieve strain by producing earthquakes. In that sense, geodetic data can provide valuable information for identifying regions under strain and thus with high potential for earthquake activity.

Hurricanes

Weather-related sources of potential hazard, like seismic sources, are more prevalent in some regions than in others. Tropical cyclone genesis, for example, requires a large expanse of warm ocean water; therefore these cyclones are most likely to form between 5 degrees and 20 degrees latitude. Hurricanes are the most severe manifestation of tropical cyclones, and are characterized by wind speeds of 74 miles per hour or greater.

Approaches used to quantify the geographical distribution of hurricanes include defining various parameters such as storm tracks, landfall location, and track angle at landfall. Other more sophisticated approaches, such as physically-based numerical weather prediction models, are being used increasingly and may ultimately replace parametric models, particularly for very complex weather events (Kurihara et al., 1992). Storm tracks are the manifestation of the temporal and spatial interaction between complex and dynamic atmospheric systems. Nevertheless, observations of past storm tracks reveal clear patterns and are therefore important pieces of information when constructing stochastic, or simulated, storm catalogs for catastrophe loss analysis.

Scientific and fully probabilistic procedures have been developed to simulate storm tracks for each ocean basin of concern. Historical track data are used to generate probability matrices that answer the question: "If the direction of storm movement at some location is *a,* what is the probability that its next direction will be *a, b, c, d,* etc.?" The advantage of this probabilistic approach is that the storm tracks generated for simulated hurricanes more closely resemble the curving and recurving tracks that are actually observed.

Furthermore, the simulated storm tracks are fully probabilistic, which means that any possible storm track can be generated, not just historical tracks.

Figure 3.3 depicts the observed number of land-falling hurricanes from 1900 to 2000 per 50-mile segment of the Atlantic and Gulf Coasts of the United States. This historical distribution suggests where future hurricanes are most likely to make landfall. Yet, discontinuities in landfall frequency between adjacent coastline segments may occur not for meteorological reasons, but rather due simply to the small size of the historical sample. The historical data are therefore smoothed, using algorithms well established in the meteorological literature, to allow for the possibility of future hurricanes making landfall where none have occurred in the past. This kind of information is used to construct the stochastic storm catalogs that become part of the catastrophe model's hazard module. Also shown in Figure 3.3 are the cumulative probability distributions of both actual and simulated hurricanes making landfall in Florida.

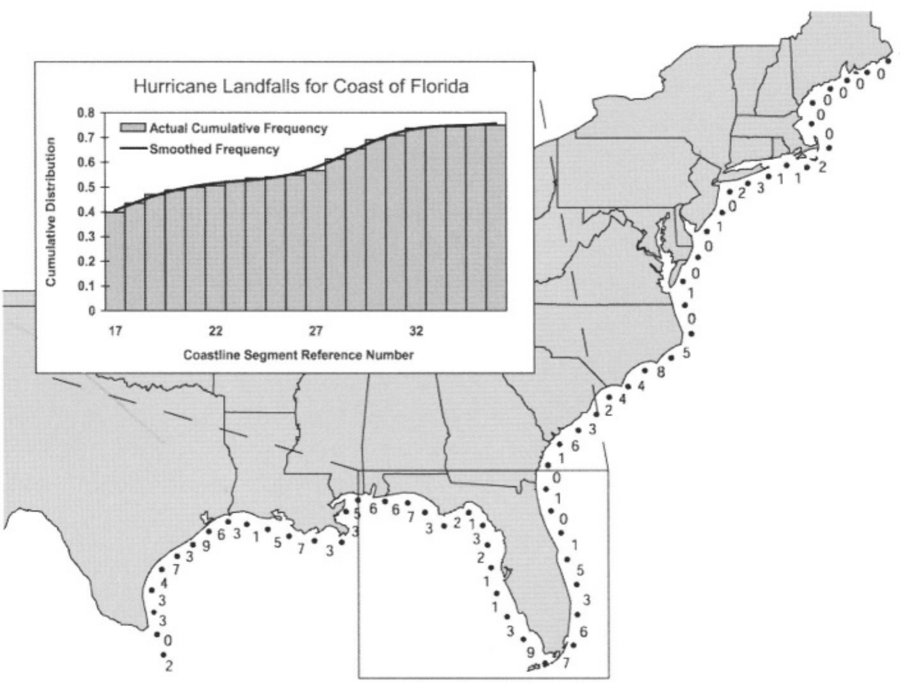

Figure 3.3. Number of Historical Landfalls Per 50-Mile Coastline Segments from 1900 to 2000. (*Source: National Hurricane Center*)

3.2.2 Frequency of Occurrence

Closely related to the likely locations of potential future catastrophe events is their frequency of occurrence. The determination of the annual probability of occurrence of catastrophe events is, in general, the most critical and uncertain aspect of the model's hazard module. It is critical because the damage and loss probabilities are directly related to this value. The uncertainty results, in part, from the scarcity of historical data necessary to construct reliable statistical recurrence models for these events. Furthermore, what really determines the probability of occurrence of natural hazards within any time period are the underlying physical mechanisms and boundary conditions over which, despite enormous advances, scientists still have only a loose grasp.

Earthquakes

The statistical interpretation of past earthquakes on the San Bernardino Mountain segment of the San Andreas Fault in Southern California suggests a mean recurrence interval of about 150 years for large magnitude earthquakes. The last such occurrence was in 1812, or 189 years ago. Using a time-independent model of earthquake occurrence (that is, one that makes no assumption regarding the temporal pattern of earthquake occurrence), the estimated 1/150 annual rate of occurrence on this fault implies a 6.5% probability that another large earthquake will occur in the next 10 years. In fact, the present state of stresses on the fault, and the forces resisting rupture, control the next occurrence of a large magnitude earthquake. The state of stress on a fault can be influenced by the rupture of adjacent faults or, as new findings suggest, even the occurrence of large earthquakes on distant faults. Therefore the stress history of the fault must be known in order to assess its present condition and its rupture potential.

It is a common practice to model the relationship between the frequency of occurrence of earthquakes and their magnitude as a combination of so-called characteristic earthquakes and the Gutenberg-Richter magnitude distribution. When a fault or fault segment ruptures at fairly regular intervals, producing earthquakes of similar magnitude, the fault is said to have a characteristic earthquake. In general, faults do not rupture with such predictability. However, the concept of a characteristic earthquake is a useful tool for formulating a fault's strain accumulation and subsequent release. Characteristic earthquakes can be identified either by a single magnitude or by a magnitude range with some distribution.

The Gutenberg-Richter relationship, which holds over a wide range of magnitudes (M), is depicted in Figure 3.4 and can be written as:

$$log\ (N) = a - b\ M$$

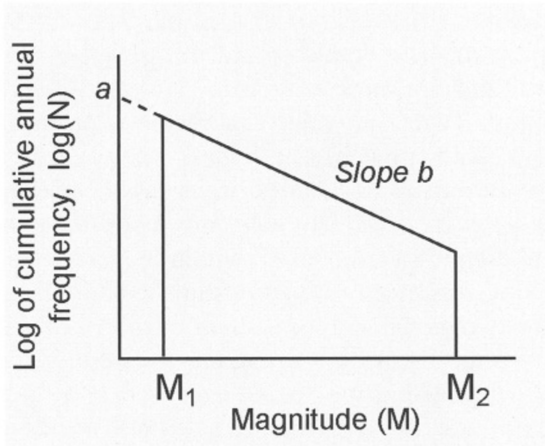

Figure 3.4. Frequency-magnitude relationship of a typical seismic zone.

The defining parameters, which depend upon seismic characteristics of the region under consideration, are:

- Lower and upper bound magnitudes, M_1 and M_2
- The occurrence rate of earthquakes of magnitude greater than or equal to some reference magnitude, characterized by the so-called *a*-value
- The rate at which the log of the cumulative annual frequency of earthquakes decreases as the magnitude increases, characterized by the *b*-value.

The level of effort to determine these parameters varies from region to region, depending on the availability and reliability of various types of data. Where there are long and reliable historical and instramentally recorded earthquake data, parameters can be directly calculated from such information. Where historic and recorded data are not available or are unreliable, the common practice is to estimate this distribution based on relevant physical parameters, such as those obtained from GPS data.

The choice of the upper bound magnitude in the above formulation has an important implication for the frequency-magnitude distribution of earthquakes. A unit increase in earthquake magnitude translates to about 32 times greater energy release. This means, for example, that the occurrence of 32 earthquakes of magnitude 6 release about the same amount of energy as one magnitude 7 earthquake. This is an important consideration in source modeling. An unrealistic choice of upper bound magnitudes for a seismic source could result in the model producing either too few or too many small and moderate magnitude earthquakes, rates that may not be supported by the observed data.

All available earthquake-related data for a source zone are integrated into a coherent representation of seismic hazard. The most recent example of such an effort is the USGS National Seismic Hazard Mapping Project (Frankel, et al., 1996). USGS has compiled geologic, paleoseismic and geodetic data for all major seismic sources in the U.S. Based on the available data, seismic sources were categorized as either faults or as area seismic zones. For certain faults, paleoseismic data were used to estimate the magnitudes and recurrence rates of their characteristic earthquakes. Regional earthquake catalogs were used to calculate both the rates and spatial probability distribution of earthquakes within different geographic areas. Geologic and seismic data were used to estimate fault slip rates. GPS data were used to estimate regional and local strain rates. All of this information is synthesized into seismic hazard maps that show earthquake ground motions that have a specified probability of being exceeded in 50 years. Among the uses of these maps are the creation and update of the seismic design provisions of building codes.

Hurricanes

For a particular weather hazard, frequency of occurrence may reflect the regional climate. Hurricanes form where there is a convergence of the necessary conditions. Two such conditions are a large expanse of warm ocean water (generally, water temperatures must be at least 80 degrees Fahrenheit), and the relative absence of vertical shear, or winds that change appreciably in either magnitude or direction with height. Too great a distance from the equator means that water temperatures will not be sufficiently warm for cyclonic formation.

The likelihood of vertical shear increases with distance from tropical latitudes. Neither will hurricane formation occur in very close proximity to the equator because of the absence of the Coriolis Force there, which is required for the spiraling circulation of surface winds. The most active months are when the oceans are at their warmest: August and September in the Northern Hemisphere, and January and February in the Southern Hemisphere. Figure 3.5 indicates average annual frequency of hurricane formation in each of the world's ocean basins. Note that these numbers include all hurricane formations, and not just those storms that make landfall or come close enough to land to cause damage.

3.2.3 Parameterizing Severity at the Hazard's Source

After identifying all regional hazard sources, the model generates the primary characteristics, whether meteorological or seismological, of all simulated events within each source zone. That is, the model quantifies the physical parameters that describe the hazard at its source. The basic parameters for characterizing the severity of hurricanes include central barometric pressure (the primary determinant of wind speed), forward or translational speed, radius of maximum winds and track angle at landfall. For the purpose of seismic hazard analysis, simulated events are typically characterized by earthquake magnitude, focal depth, and various fault-rupture characteristics.

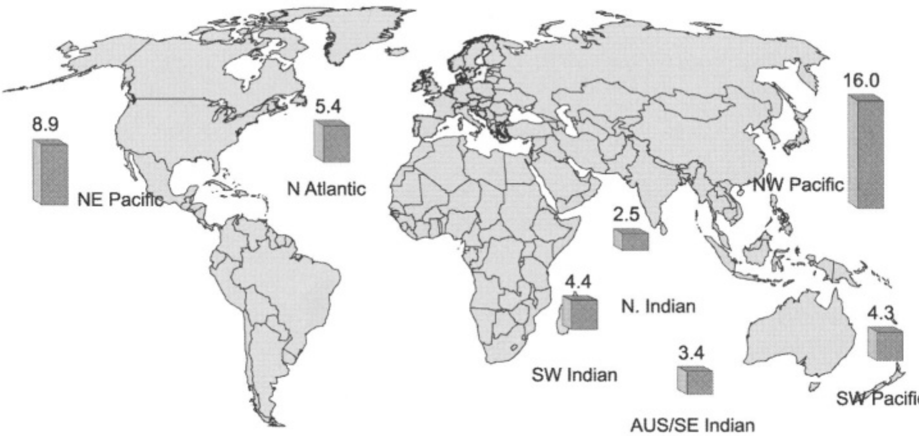

Figure 3.5. Average number of hurricane formations per year by ocean basin.

Earthquake models impose a limiting (upper bound) magnitude for simulated earthquakes on individual modeled faults. This limiting magnitude is usually determined either by examining the magnitudes of historical earthquakes on that fault or by using an estimate of the fault's largest expected rupture dimension. In the latter case, empirical equations that describe the relationship between magnitude and rupture dimension are used to estimate the limiting magnitude.

Determining limiting values for weather hazards involves a similar process. Hurricane models, for example, fit theoretical probability distributions to historical data on central pressure. A lower bound (higher intensity) is determined by analyzing the historical data in conjunction with meteorological expertise regarding what is physically possible.

3.2.4 Parameters for Local Intensity and Site Effects

To estimate the damage potential of natural hazards, the model must estimate their physical parameters not only at the source, but also at the sites of the affected building inventory. This part of the model's hazard module is designed to capture how intensity changes as the simulated catastrophe propagates over the affected area.

Earthquakes

Upon its rupture, a fault releases energy and creates disturbances within its source region. These disturbances propagate away from the source through the region in the form of seismic waves, as illustrated in Figure 3.6.

Damage to structures is sensitive to the amplitude and the frequency content of those waves, parameters that are controlled by the earthquake's source mechanism, characteristics of the intervening geological materials through which the waves travel and, finally, by the complexities of the local soil materials underlying each affected site.

Constructing physical models that realistically simulate variations in earthquake ground motion over a region is difficult. For catastrophe modeling purposes, a common practice is to employ empirical relationships, called attenuation equations, which mathematically describe the rate at which the amplitude of the seismic waves decreases as the waves propagate outward from the source of the rupture. A typical attenuation equation in its general form can be written as:

$$Y = F(f, M, r, Source, Site)$$

where Y is ground motion amplitude at frequency f, M is the earthquake magnitude, and r is the source-to-site distance. The terms Source and Site in the attenuation equation above reflect source rupture mechanisms and the local site effects of soils on ground motion, respectively.

The amplitude of high frequency waves decays faster than that of low frequency waves. The rate of decay is a function of the propagating materials. That is, crustal heterogeneities, such as fractures, and a variety of regional geological complexities all have their effect on attenuation rates. For these and other reasons, empirical attenuation equations are region-specific.

The results of many years of data gathering and interpretation indicate that earthquakes with similar magnitudes but different types of source mechanisms systematically create quantitatively different levels of ground motion. Earthquakes with thrust and reverse faulting mechanisms are, in general, observed to produce higher levels of ground motion than earthquakes with strike-slip and normal faulting mechanisms. Also, the ground motion at sites equidistant from the rupture but with different local soil conditions can be very different, even when the source parameters of the underlying earthquakes are similar.

For example, soft soil materials that lie within a large bowl-like structure of underlying bedrock characterize certain parts of Los Angeles. Such so-called basins of soft soils can trap seismic waves and create very complex amplification and deamplification patterns for low frequency ground motions. The shallow soil materials, on the other hand, mostly affect high frequency components of ground motion. In general, both large-scale basin effects, if present, and shallow soil conditions are important for the estimation of earthquake ground motion at individual sites.

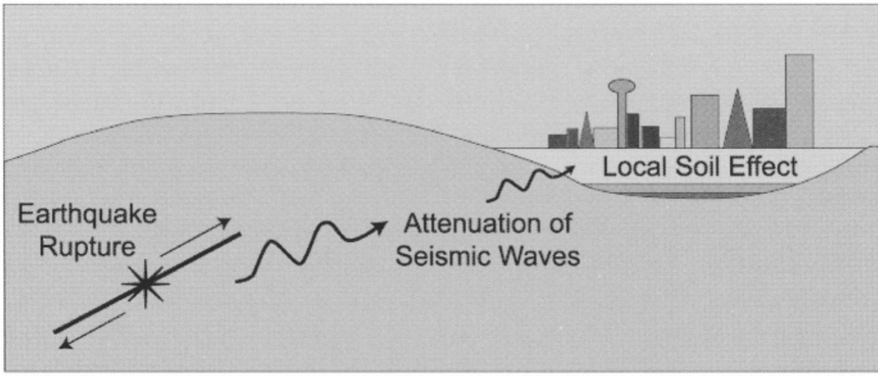

Figure 3.6. Attenuation and local soil/site effects.

Hurricanes

In weather-related hazards, the propagation of intensity across the affected region is determined by the interaction between the source and its environment. In the case of hurricanes, once the model probabilistically generates the storm's source parameters, including its primary meteorological characteristics, it simulates the storm's movement along a track. To generate local windfields, the maximum over-water wind speed is calculated. Adjustments are then made for the effects of storm asymmetry, filling (the rate at which central pressure increases as the storm moves inland), and local surface terrain.

Differences in surface terrain can have a significant effect on wind speeds. Wind velocity profiles typically show higher wind speeds at higher elevations. Winds travel more slowly at ground level because of the horizontal drag force of the earth's surface, or surface friction. The addition of obstacles, such as buildings or trees, will further degrade wind speed. Models often employ a friction coefficient for each location of interest to obtain an estimate of the surface roughness. These estimates are based on digital land use/land cover data, plus exposure information at the site. In general, the rougher the terrain, the more quickly wind speeds dissipate.

Wind duration is also an important consideration in determining local intensity and therefore in damage estimation. Consider the effects of two storms of equal intensity but of different forward speeds and thus different site duration. At any given site, damage resulting from the storm of longer duration (slower forward speed) will be higher because of the cumulative effects of wind. A recent example of this is the 1998 Hurricane Georges, which stalled over the Gulf Coast, battering the area around Biloxi and Gulfport with hurricane and tropical storm force winds over an unusually prolonged period of time resulting in significantly higher losses than might be expected of a hurricane of its intensity (Category 2 on the Saffir Simpson scale).

3.3 Inventory Module

Building inventory is a key input for the catastrophe model to estimate potential future losses to structures and their contents. Catastrophe models can be used to estimate aggregate insured or insurable losses for the entire insurance industry, for individual company portfolios, or for individual buildings.

For aggregate analysis, modelers develop annually updated databases from governmental and private sources that include estimates of total property exposures within the modeled region at the postal code level. The data include the number of properties, or risks, and their values, broken down by line of business (residential, commercial and industrial), by coverage (building, appurtenant structures, contents and time element, or loss of use) and by occupancy and construction type. Building damage is primarily a function of construction type. Masonry buildings, for example, typically perform poorly when subjected to violent ground shaking, but perform quite well in the face of hurricane winds. Engineered buildings typically perform better than non-engineered buildings, whatever the peril. Inventory data should also reflect regional differences in both construction practice and building code. Damage to contents is typically a function of both occupancy class and structural damage. Occupancy class provides insight into the kinds of contents contained in the building and hence their relative vulnerability.

When estimating losses on individual insurance company portfolios, modelers must work closely with clients identifying missing or erroneous data and testing for reasonability. The more detailed the information provided by the client and entered into a catastrophe model, the more detailed and reliable the output. Catastrophe models can take full advantage of risk-specific structural details, such as roof pitch or floor-wall connection, as well as occupancy, age, and height. They can also take advantage of information, if available, on the presence of mitigation devices and retrofit.

For particularly important or valuable buildings, a site-specific analysis may be appropriate. In such cases, the level of detail of the inventory data can increase by an order of magnitude. Typically, engineers make on-site inspections and incorporate information provided in actual design documents, including specifications of the physical dimensions of individual components (beam, column, joints, partitions, etc.) and their material properties. The vulnerability component of the catastrophe model is then developed to mathematically describe the behavior of the building when subjected to the forces imposed by earthquakes or windstorms.

3.4 Vulnerability Module

The vulnerability module estimates the level of building damage expected for different levels of severity of the oncoming external forces imposed, such as earthquake ground motion or high winds. The likelihood that any level of external forces is experienced at any given site identified in the inventory module (Section 3.3) is the result of the hazard module (Section 3.2).

Many different approaches have been devised to link ground motion or wind intensity to the expected level of damage or, more ambitiously, directly to the level of monetary loss. These approaches are based either on engineering judgment or, in more sophisticated models, on building response analyses performed using a wide variety of techniques. The former approach – combining the opinions of experts – is not easily updated when more or new information becomes available. It is, by definition, somewhat arbitrary in nature. The latter approach has been generally recognized by the engineering community to be superior and constitutes one of the most prolific fields of current research. See, for example, the Pacific Earthquake Engineering Research Center website at http://peer.berkeley.edu.

While the most advanced engineering-based techniques can provide a fairly accurate estimate of building response, they are tailored for application to specific buildings at specific locations. Direct application of these techniques to portfolio risk assessment is impractical, at best. For one thing, the information needed for performing any truly sophisticated engineering analysis is usually missing. For most portfolios of insurance companies, the information collected for each property rarely goes beyond its address, the type of construction, the number of stories, and the age. Portfolios of reinsurance companies often contain even less information.

Thus, engineering methods were modified to make possible their application to portfolio risk assessment. The building stock is divided into many typical building classes (e.g., unreinforced masonry building) with different characteristics (e.g., two stories, built between 1976 and 1998). This process may categorize the building stock in the United States into, for example, 50 different building classes. Each class is then subdivided according to different modifiers to account for details that may have an impact on the building response under loads imposed by wind or ground motion (e.g., the presence of a cripple wall in wood frame structures impacts its performance during earthquakes, as does roof pitch during hurricanes).

For each building class, one typical building is analyzed using the structure-specific techniques mentioned above. The response of the typical building for different levels of ground motion or wind intensity is then applied to any property in the portfolio that belongs to that class. Although the performance of any given building within a class may deviate considerably from the performance of the typical building, this approach generally leads to accurate estimates of mean damage (and monetary losses after the loss module is applied) on a portfolio basis. This assumes that typical buildings are appropriately selected to avoid any source of bias. It is important to emphasize that portfolio risk analyses aim at estimating the distribution of potential losses (i.e., the EP curve) to ensembles of large numbers of properties, rather than for any single property.

There are two major steps in the application of such engineering-based vulnerability approaches to portfolio risk analyses:

1) Identification and definition of typical buildings in the modeled region.
2) Calculation of building performance to ground motion or winds of different intensities. This will be referred to here as vulnerability analysis.

3.4.1 Identification of Typical Buildings

In surveying the inventory of buildings in a region, the most important aspect is evaluating the size of the statistical populations of different types of structures within the building stock. Data collection needs to be conducted for all relevant occupancy types such as residential, commercial, industrial, and agricultural, as well as insurance coverages for buildings and contents.

From the perspective of a portfolio analysis, more effort needs to be devoted to estimating the performance of the more widely represented building classes. Other aspects include evaluating the homogeneity of structures within the same building class, addressing construction types unique to the region, adoption and enforcement of regional building codes for the perils of interest, and construction practices. All these aspects lead to the definition of as many building classes as is reasonably practical to represent the statistical population of structures in the region.

The building classes are identified by considering the most important factors affecting structural response to the perils under consideration. These could be building material (e.g., steel or reinforced concrete), structural system (e.g., moment frame versus braced-frame) and height (e.g., two versus 10 stories). Each building class is further subdivided based on parameters sometimes called secondary modifiers (e.g., roof and foundation type).

3.4.2 Evaluation of Building Performance

Building performance is described by a relationship between the intensity of the imposed force, that is, the external excitation, and the level of expected damage caused to the building. Because there is considerable uncertainty in this step, this relationship, besides being a predictive equation for mean damage, also carries a measure of the error of estimation.

Damage to buildings from earthquakes is typically both structural and non-structural in nature and primarily due to the lateral building deformation caused by ground shaking. Engineers have used objective measures of building lateral response, such as the maximum interstory drift (the ratio of the maximum relative lateral displacement of the two adjacent stories to the inter-story height) to predict the level of damage to the components at that story. For earthquakes, structural damage can be severe even for engineered buildings designed according to code. There were examples of this in the Northridge earthquake in California (1994) and the Kobe earthquake in Japan (1995), both places where seismic building codes are among the most advanced in the world. Damage patterns from these two earthquakes revealed that engineers had been overestimating the performance of steel construction.

Wind, on the other hand, results primarily in damage to non-structural elements, involving different components of the building envelope and, in most cases, is localized in nature. The exception to this is mobile homes, where severe roof damage can lead to partial collapse. Structural collapse can occur under extreme wind conditions, but is usually restricted to non-engineered buildings, such as wood frames. In such cases, roofs and openings in the façade (e.g., windows and garage doors) are typically the first elements to be damaged by wind. Loss of the first shingle allows wind to penetrate and lift the next shingle. Unsecured slates may peel off; metal roofs may roll up and off.

Similarly, the loss of the first window, either because of extreme pressure or of wind-induced projectiles, can create a sudden build-up of internal pressure that can blow off roof shingles from inside even if they are properly secured. In structures where the roof provides the lateral stability by supporting the top of the building's walls, the integrity of the entire structure can be compromised. Even if the structure remains intact, once the building envelope is breached, contents are vulnerable either due to the wind itself or to accompanying rain.

Engineered structures, such as those built of commercial reinforced concrete and steel frame, fare relatively well, though they may experience damage to roof coverings, glass, and cladding. At very high wind speeds, these buildings can experience major damage to non-structural elements but rarely to components that would compromise the integrity of the structure.

There is a relative scarcity of test data on component or envelope resistances to wind. Most present-day knowledge of wind damage comes from damage investigations conducted in the aftermath of an event and from wind tunnel data obtained in laboratories around the world. Actual damage investigations are not always reliable, as the final damage state of a house is often caused by the initial failure of windows, doors, or shingles that may not have been properly installed. Furthermore, wind tunnel studies require very expensive testing facilities and are usually obtained by testing structures and/or components built according to high-quality standards rather than actual construction practice. The main drawback of wind damage estimation prediction is the lack of reliable wind recordings at or close to structures that have experienced different levels of damage. The relative scarcity of such observations is therefore often supplemented with engineering experience and knowledge when developing relationships for wind-induced damage.

In the case of earthquakes, the relationship linking the severity of the external excitation to building damage is captured by a fragility curve for given structural damage states (minor, moderate, severe damage, or collapse). A fragility curve for a given damage state provides the probability that the specified damage state will be reached or exceeded as a function of the severity of ground motion at the site. The use of fragility curves started in the 1980s (Kennedy et al., 1980; Kennedy and Ravindra, 1984) with the application of probabilistic risk analysis to nuclear power plants and facilities for the storage of hazardous materials.

In portfolio risk assessment studies, the same information contained in the fragility curve format is typically expressed in a roughly equivalent form called the damage function. A damage function is an equation that relates the expected structural damage state of the entire building to the intensity of the event. The standard deviation divided by the mean, the coefficient of variation, is often used to capture the uncertainty in the prediction of damage.

For financial analysis, building damage is ultimately expressed in terms of a damage ratio, the ratio of repair cost to the replacement cost of the building. The damage ratio can range from 0% to 100%, or total loss. Figure 3.7 shows a typical damage function. The distributions sketched in dotted lines in the figure reflect the fact that both the intensity of the external excitation and the level of damage given the level of excitation are uncertain quantities. Therefore, the damage ratio of the building is an uncertain quantity as well.

The damage state of the entire building for a given level of external excitation is given by the cumulative damage of its structural components, non-structural components, and contents. Structural components are, for example, beams and columns, while non-structural components include items such as cooling and heating systems, partition walls, plumbing, exterior walls, and suspended ceilings. For earthquake excitation, the damage level of most of the building components depends, loosely speaking, on the maximum deformation of the story where the component is located. Contents have instead been found to be more sensitive to maximum floor acceleration than to building deformation.

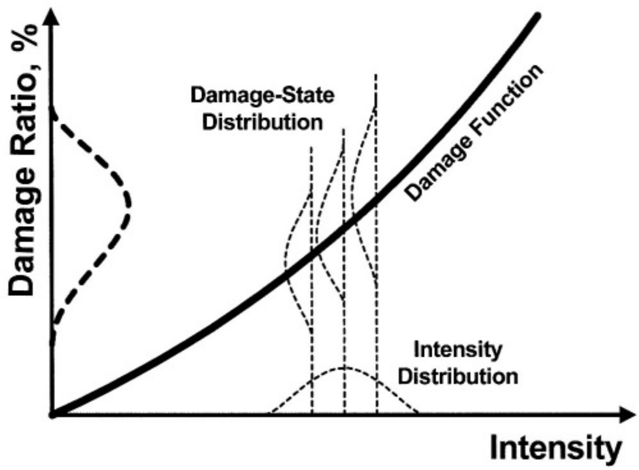

Figure 3.7. Illustration of a typical damage function.

For each typical structure within each building class, engineering analyses are performed to evaluate the level of building deformation and floor acceleration that are imposed on the structure by different levels of ground shaking. The damage inflicted to structural and non-structural components by building deformation and to contents by floor acceleration can be estimated either via a damage survey of instrumented buildings that have experienced past earthquakes or by laboratory tests. The expected damage ratio for the entire building for a certain level of deformation can be computed by considering the sum of the damage ratios of all the components and contents.

The level of physical damage inflicted on each component by a certain level of building deformation can be repaired according to strategies that range from "do nothing" to "complete replacement." Each repair strategy has a cost associated with it. (The next section in this chapter discusses the loss module and describes the process by which physical damage is translated into monetary costs.)

The engineering analyses performed to estimate the level of building deformation for a given level of ground shaking typically entails building a computer model of the structure. The virtual building is then either subjected to ground acceleration recordings of different intensities or pushed in lateral increments until collapse to mimic the lateral response of the building during different size earthquakes. At each increment, the force is redistributed to the elements that remain functional. Figure 3.8 shows a schematic flow of the damage calculation process. The procedure is performed for each site and for each event.

The procedure estimates separate damage states for the building and its contents, as well as a time-element damage state, which determines the amount of loss associated with the loss of use of the building. The structure type is a key element in determining the building damage state. The building's occupancy type is a key element to determine contents damage and time-element damage states. These states of damage are combined to estimate the overall damage to the building as a system.

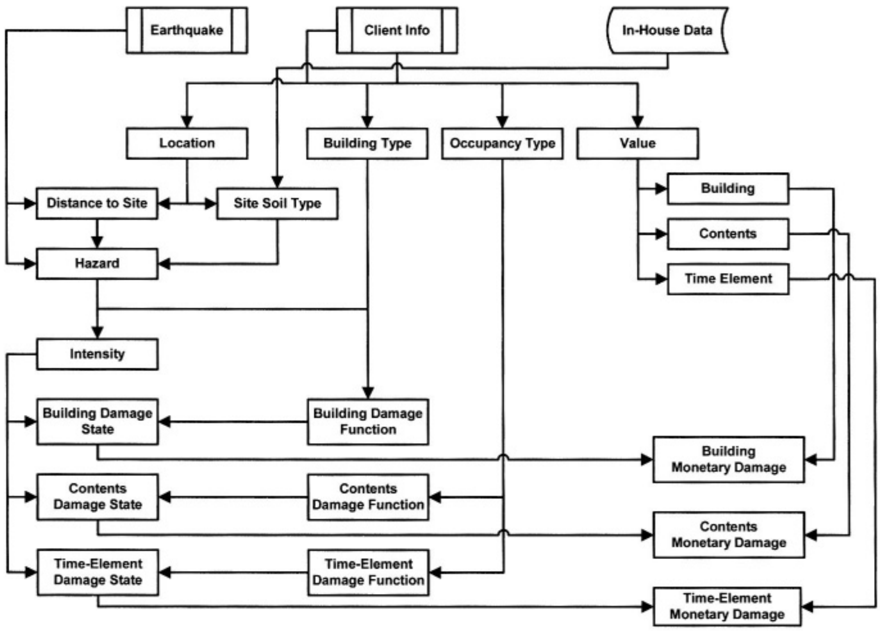

Figure 3.8. Schematic for process of damage calculation.

3.5 Loss Module

As was mentioned in the previous section, one approach taken by catastrophe modelers has been to link ground motion or wind intensity directly to the level of monetary loss. In this case, damage functions are developed based on the opinions of experts and not on actual engineering analysis of building types.

Noted structural engineers from private industry and academia are asked to estimate the damage ratio that would result to a typical building of a specific construction type were that building subjected to a given intensity of earthquake or hurricane. Their responses, which are based on their personal knowledge and experience, are statistically combined. One shortcoming of this approach is that the damage functions based on this method cannot be easily updated to reflect new construction techniques, building codes, repair costs or information gained in the aftermath of actual events.

A recent development in earthquake loss modeling has been the employment of cost models that translate estimates of physical damage into monetary loss. The model produces estimates of the cost of repair or replacement for each damaged structural and non-structural component as identified by the engineering analysis. Repair cost depends on the strategy utilized to replace or restore the structure. This depends, in turn, on the degree of damage to each component. In the case of a reinforced masonry wall with only minor cracks, for example, only cosmetic measures need be taken and the associated costs of repair would be minimal. If cracks are wider, removal and patching of damaged masonry and loose concrete, and injection of cracks with epoxy are needed to restore structural performance. At high levels of damage, full replacement of the affected component may be called for, increasing costs dramatically. The repair costs of each individual component are combined, along with the cost of inspection, set up and debris removal, to achieve an estimate of the monetary loss to the building as a whole.

Once total losses are calculated, estimates of insured losses are computed by applying policy conditions to the total loss estimates. Policy conditions 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. The estimates of insured loss are validated, and damage functions fine-tuned, using loss data from actual events. This is particularly true in the case of wind perils, where loss data are relatively plentiful. Loss data for actual events normally consists of claims and paid losses by ZIP code and by line of business. However, data are also frequently available by construction type, and insurance coverage. Such detailed data, when available, are extremely useful to the modeler who is engaged in a continual process of validation and calibration.

3.6 Summary

Probabilistic catastrophe loss models incorporate detailed databases and scientific understanding of the highly complex physical phenomena of natural hazards, and engineering expertise about how buildings and their contents respond to the effects of those hazards.

Catastrophe models are typically composed of four primary components, or modules. The hazard module estimates the location, severity and frequency of occurrence of potential future catastrophe events. It also propagates the event across the affected region and calculates local intensity at each affected site.

The inventory module consists of detailed databases of property values and the number of structures, broken down by line of business, occupancy, and construction type. The vulnerability module employs mathematical relationships, called damage functions, that describe the interaction between structures and the intensity of the event to which they are exposed. In the loss module, physical damage is translated to total, or ground up (in insurance industry parlance) losses. Insured losses are calculated by applying policy conditions to the estimates of total loss.

After the loss estimations have been completed, they can be analyzed in ways of interest to risk management professionals. For example, the model produces probability distributions of losses, as well as the exceedance probability (EP) curve. As explained in Chapter 2, the EP curve reveals, for a particular portfolio of buildings, the probability that a certain level of loss will be surpassed in a given time period. Output includes probability distributions of total monetary loss, as well as net losses after the application of insurance policy conditions for both annual aggregate and annual occurrence losses. The probabilities can also be expressed in terms of return periods. That is, the loss associated with a return period of twenty years is likely to be exceeded only 5% of the time or, on average, in one year out of twenty.

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 can also provide summary reports of exposures, comparisons of exposures and losses by geographical area, and detailed information on potential large losses caused by the extreme events that make up the right-hand tail of the loss distribution.

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Chapter 4 – Sources, Nature, and Impact of Uncertainties on Catastrophe Modeling

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4.1 Introduction

Catastrophe modeling is a complex tool used to assess the risk from natural hazards. The four components of hazard, inventory, vulnerability, and loss depicted in Figure 3.1 and discussed in detail in Chapter 3 require information from a range of sources and the expertise of an array of professionals. Natural hazard, engineering and economic data are the foundation of catastrophe models. Limitations in data and assumptions about the model's parameters, in the hazard, inventory, and vulnerability modules, affect a catastrophe model's loss estimates and the uncertainty associated with these estimates.

This chapter explores the sources, nature, and impact of uncertainties in a catastrophe model. Prevalent methods to represent and quantify uncertainty through the components of the catastrophe model are discussed. Finally, the impact of uncertainty on exceedance probability (EP) curves used by risk managers to quantify their catastrophe risk potential is illustrated by examining potential losses to residential property from hurricanes in Florida and earthquakes in Charleston, South Carolina. Quantification and classification of uncertainty provides opportunities to reduce risk. With accurate measures of uncertainty, stakeholders can potentially lower the cost of dealing with catastrophe risk. Furthermore, since the risk affects stakeholders in dissimilar ways, the robustness of a risk management strategy can be made clear to each stakeholder if uncertainty is delineated.

4.2 Classifications of Uncertainty

As indicated in Chapter 3, there is a great deal of information needed to develop the hazard, inventory, vulnerability, and loss components of a catastrophe model. Therefore, all stakeholders in the management of risk value new information regarding these modules. For example, an insurer values additional information on the likelihood of disasters and potential damage to properties in its portfolio in order to more accurately manage the risk. Local government officials value a thorough understanding of hazards in their regions in order to plan for emergency response and recovery efforts following a disaster. Model developers value any additional information to validate and calibrate their catastrophe models.

Since catastrophe modeling is a fairly new field of application, there are no historical classifications of catastrophe modeling uncertainty, per se. However, building on the concepts from probabilistic hazard analyses, uncertainty can be characterized as either aleatory or epistemic in nature (Budnitz et al., 1997). Aleatory uncertainty is the inherent randomness associated with natural hazard events, such as earthquakes, hurricanes, and floods. It cannot be reduced by the collection of additional data. In contrast, epistemic uncertainty is the uncertainty due to lack of information or knowledge of the hazard. Unlike aleatory uncertainty, epistemic uncertainty can be reduced by the collection of additional data.

While the advantage of differentiating between aleatory and epistemic uncertainty in an analysis is clear (only epistemic uncertainty can be reduced), the necessity of distinguishing between aleatory and epistemic uncertainty is not. "Epistemic and aleatory uncertainties are fixed neither in space...nor in time. What is aleatory uncertainty in one model can be epistemic uncertainty in another model, at least in part. And what appears to be aleatory uncertainty at the present time may be cast, at least in part, into epistemic uncertainty at a later date" (Hanks and Cornell, 1994). Therefore, developers of catastrophe models do not necessarily distinguish between these two types of uncertainty; instead, model developers concentrate on not ignoring or double counting uncertainties and clearly documenting the process in which they represent and quantify uncertainties.

4.3 Sources of Uncertainty

Limited scientific knowledge, coupled with a lack of historical data, leave open several possible and competing explanations for the parameters, data, and mathematical models underlying each of the components in a catastrophe model. Simply put, the science and impact of natural hazards are not completely understood; in addition, the cross-disciplinary nature of a catastrophe model leads to complexity. Experts in seismology or meteorology who model the hazard must interact with structural engineers who model the vulnerability; similarly structural engineers who model the vulnerability must interact with actuaries who model the loss. Basically, as each discipline's modeling assumptions are added to the process, more uncertainty is added to the estimates.

In catastrophe modeling, both epistemic and aleatory uncertainties are reflected in the four basic components of a model. Aleatory uncertainty is reflected via probability distributions. The frequency of a hazard occurrence and the fragility of a building, as discussed in Chapter 3, are examples of aleatory uncertainty. Since the exact time of occurrence and the precise level of structural damage cannot be known in advance of a hazard event, the recurrence rate and the vulnerability of the inventory exposed to the natural hazard are characterized using probability distributions. Similarly the capacity of individual structural elements of a building during a severe event, and the resulting cost of repair cannot be determined beforehand. Probability distributions are also used to characterize these parameters in a catastrophe model.

A larger issue in quantifying uncertainty is the lack of data for characterizing the four components in a catastrophe model. For example, as discussed in Chapter 3, the recurrence of earthquake events on fault sources can be modeled using a magnitude-frequency model (Richter, 1958), a characteristic earthquake model (Youngs and Coppersmith, 1985), or a combination of both models. In California, estimates of ground shaking probabilities on certain fault segments are established by combining the two recurrence models for earthquake magnitude-frequency distributions (Peterson et al. 1996). Historical earthquake records are used to establish a recurrence curve, or the Gutenberg-Richter relationship, for the smaller magnitude events, while geologic data (most importantly, a fault's slip rate) is used to estimate the recurrence of the larger, characteristic events.

The availability of seismological data describing earthquake occurrence in California for only a few hundred years makes the updating of the recurrence distributions problematic. When more data become available, in the form of fault slip rates or seismograph recordings, these relationships could potentially be improved. Similar issues arise in modeling the recurrence of hurricane events. Past data describing the location and occurrence of hurricanes on the eastern seaboard of the United States are also limited to a few hundred years (Powell and Aberson, 2001).

The deficiency of information regarding repair costs and business interruption costs affect the accuracy of the loss component of a catastrophe model. For example, the increased cost to repair or rebuild after an event is often taken into account using a demand surge adjustment. This is simply the percentage increase in costs due to the limited supply of construction material and labor immediately following a disaster. Further, due to the growing understanding of indirect losses, estimates of business interruption costs to commercial property owners are continually validated and calibrated with the latest loss information.

Another source of epistemic uncertainty in a catastrophe model is the lack of available data to create the Geographic Information Systems (GIS) databases within the modeling software. For any model, recognizing the importance of input data is essential. The “garbage in, garbage out” principle holds irrespective of how advanced or state-of-the-art a model may be. GIS maps of hazard sources, geologic features and topographic landscape characterize hazards. GIS maps of the locations of structures characterize inventory.

An incomplete description of a hazard source, the geology or the topography can cause erroneous results. For example, in earthquake modeling, having accurate information on the underlying soil in a region is very important. A structure built on rock-like material is likely to sustain much lower losses compared to a structure built on soft clay-like material. Inaccurate information on soil conditions can lead to large errors in estimation of loss due to an earthquake.

In fact, past observations from earthquakes confirm that soil condition plays a very important role in building performance. As expected, buildings on soft ground or steep slopes usually suffer more significant damage in comparison to those on firm and flat ground. Since soil condition may vary dramatically within a small area, such as the Marina District in San Francisco (where soil conditions vary from bay mud to rock site), using ZIP code to identify a location may not be sufficiently accurate. At a particular location, high-resolution geocoding should be used as it can more accurately pin down the soil condition.

Partial information on a structure’s characteristics can also result in an inaccurate estimate of future damage. For example, most structural engineers would agree that the construction type, age, height, occupancy, assessed value, and the location of a structure are needed – at a minimum – for the inventory component of a catastrophe model. If more specific information regarding the structure such as its location relative to other structures and previous damage to the structure were available, a more accurate estimate of damage or vulnerability would result.

Lack of accurate data on true market values of the properties under consideration is an additional source of epistemic uncertainty in the modeling process. For determining the appropriate coverage limit, many residential policies use property tax assessment data, which are generally outdated and under-valued. Under-valued exposures will result in under-estimating potential loss. For example, suppose a home’s property value is assessed at $600,000 when its true worth is $1 million. Furthermore, suppose it is insured with a 15% deductible and full coverage based on the lower assessed value. If an earthquake occurs and causes major damage and the cost to repair the structure is 35% of the true value of the home, the resulting monetary loss is $350,000. A $600,000 insurance policy with a 15% deductible translates to the homeowner being responsible for $90,000, with the insurer covering the remaining $260,000 of the loss. If the insurance coverage had been based on the home's true worth of $1 million, the homeowner would have to cover the first $ 150,000 of the loss and the insurer would only have claim payments of $200,000.

Incomplete or inaccurate information on an inventory's description is a concern not only to insurers but also to all risk management stakeholders. To improve on the amount of such information available, an effort to document the types of housing structures worldwide was initiated in 2000 to assess the vulnerability of the world's population to earthquake hazard. Under the guidance of the Earthquake Engineering Research Institute (EERI) and the International Association of Earthquake Engineering (IAEE), the World Housing Encyclopedia has a web-based listing of housing construction types from earthquake-prone countries around the world (EERI, 2003). In addition, the Institute for Business and Home Safety (IBHS) relies on INCAST, a data inventory tool used in conjunction with the HAZUS catastrophe model, to store inventory information on the homes that are a part of their "Fortified...for safer living" program. These homes are reinforced to withstand many natural hazards, including high winds, wildfire, flood, hail, and earthquake.

Epistemic uncertainty is also found in the use of laboratory testing (shake table tests for earthquake hazard or wind-tunnel tests for hurricane hazard) and expert opinion to develop the vulnerability component of a catastrophe model. For a portfolio risk assessment, damage functions such as the one illustrated in Figure 3.7 in Chapter 3, have traditionally been constructed using these sources along with damage surveys of actual structures. Given that laboratory testing has been restricted to certain types of structural materials, there is a limited understanding of how other materials withstand lateral loading.

In the earliest versions of catastrophe models, damage ratios were estimated using the Applied Technology Council report of Earthquake Damage Evaluation Data for California (ATC-13, 1985). This report was generated using the Delphi method of collecting information from a group of experts (Dalkey, 1969). In this method, a series of questionnaires interspersed with controlled opinion feedback resulted in a group judgment. In the ATC-13 study, 71 earthquake engineering experts were asked to indicate their low, best, and high estimates of damage ratios for 78 types of structures subject to earthquakes with Modified Mercalli Intensity (MMI) levels of VI through XII. Catastrophe model developers used these estimates in their earliest versions of their earthquake loss software, skewing estimates of damage due to the use of the Delphi Method and limiting the interpretation of damage due to the use of MMI. More recent models employ cost models that translate estimates of physical damage into direct monetary loss rather than depending on damage ratios.

4.4 Representing and Quantifying Uncertainty

Guidelines do exist for identifying the sources of uncertainty and incorporating them into catastrophe models. The Senior Seismic Hazard Analysis Committee (SSHAC) Report is a comprehensive study addressing this issue and the use of expert opinion in a probabilistic seismic hazard analysis (Budnitz et al., 1997). This report can also be used for the incorporation of uncertainty of other natural hazards. Additionally, guidelines set forth by the Environmental Protection Agency (EPA), requiring that all risk assessments possess the core values of "transparency, clarity, consistency, and reasonableness," are relevant for the modeling of natural hazards (Browner, 1995).

The most common methods for incorporating uncertainty into catastrophe modeling are logic trees and simulation techniques. These two methods are standard approaches for quantifying and propagating uncertainty when there is intrinsic aleatory uncertainty, lack of consensus among experts, and lack of data used to estimate parameters.

4.4.1 Logic Trees

In the logic tree approach, alternative parameter values or mathematical relationships are identified within the catastrophe model, relative weighting schemes are assigned to each alternative, and estimates of parameters or relationships are calculated using a weighted, linear combination of the outcomes. Weighting schemes are numerous, with the weights representing the credibility of that alternative in relation to the available data. For example, one can use equal weights, weights proportional to the ranking of alternatives, or weights based on some comparison of previously assessed estimates with actual outcomes. Weights are often established through the use of expert opinion, and therefore, are biased towards an expert's judgment.

Figure 4.1 depicts a simple example of how a logic tree can be used in a catastrophe model. Suppose that there is an earthquake fault that generates a characteristic magnitude event. This event is estimated using a recurrence model with two alternatives for the fault's slip rate, λ_1 and λ_2, weighted w_1 and $1-w_1$, respectively. Next, suppose a single family residential structure is the only structure to be assessed in the inventory. However, there is a lack of consensus regarding the type of underlying soil at the site. Thus, there are two alternatives for the soil parameter, denoted S_1 and S_2 with respective weights w_2 and $1-w_2$ in Figure 4.1.

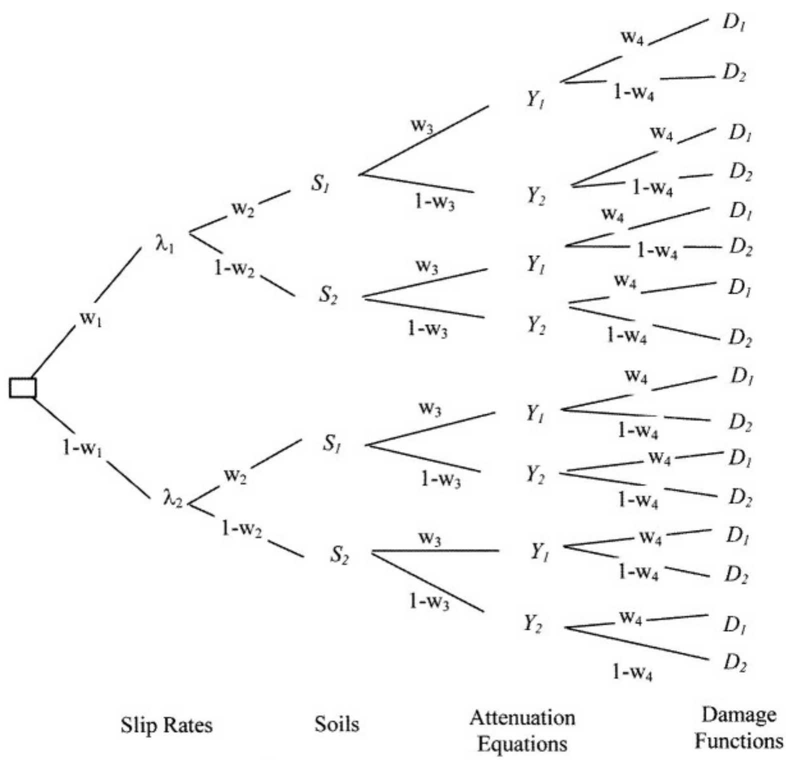

Figure 4.1. Logic tree approach to catastrophe modeling.

In the next branch of the logic tree, the two estimates of recurrence for a characteristic magnitude event and the two alternatives for site-specific soils are combined with two competing attenuation equations describing the rate at which the amplitude of the seismic waves decreases as the waves propagate outward from the source of the rupture. For example, the Frankel, et al. (1996) attenuation relationship and the Toro, et al. (1997) relationship can be used as two competing models of strong ground motion in the Central and Eastern United States. These two models, denoted Y_1 and Y_2 in Figure 4.1 (using similar notation introduced in Chapter 3 for characterizing ground motion attenuation), are weighted w_3 and $1\text{-}w_3$, respectively. This combination results in estimates of earthquake ground motion for certain magnitude events at a certain frequency of occurrence, under certain site conditions, and at certain distances from the event's epicenter.

Finally, these ground motion estimates are combined with two competing models for damage functions, one created using expert opinion and one based on laboratory testing. These functions, D_1 and D_2, relate the expected damage state of the residential building (minor, moderate, severe damage, or collapse) to the level of ground motion at the site. Each is weighted accordingly, denoted w_4 and $1\text{-}w_4$ in Figure 4.1. The final results of this simple example are sixteen calculations of structural damage to a single-family dwelling based on alternative assumptions of characteristic fault slip rates, underlying soils, and empirical attenuation models. As is evident, the costs of repair have not yet been incorporated.

The logic tree approach to incorporating uncertainty is utilized often in practice because of its tractability and its usefulness as a tool to communicate risk to stakeholders. While a set of results grows with each alternative assumption added to the analysis, advances in computing power allow the handling of large databases; therefore, both parameter and model alternatives can be identified within this type of approach. Although the preceding example shows two alternatives at each branch, a larger (yet finite) number of alternatives can be considered, as is typically the case in a catastrophe model.

4.4.2 Simulation Techniques

Simulation is a method for learning about a real system by experimenting with a model that duplicates the essential behavior of the system. It is one of the most widely used quantitative approaches to decision making. In contrast to a logic tree, which requires a set of simplifying assumptions, simulation can model extremely complex processes. An uncertain parameter is represented by a discrete or continuous probability distribution, multiple simulations are run which sample from the distribution, and the analyses are completed using these sample values. The results are statistically analyzed to estimate important performance measures of the system. In the case of catastrophe modeling, a performance measure is, for example, exceedance probability loss.

Although most distributions in catastrophe modeling are continuous, a simulation using a discrete distribution is presented here for simplicity. Suppose that a single-family residential structure is subject to a hurricane hazard and five levels of damage states are defined (none, minor, moderate, severe, or collapse) in a catastrophe model. Suppose further that damage functions are available that represent the probability of being in, or exceeding, a certain damage state level given a certain level of wind speed. Now suppose that the residential insurer wants a probabilistic estimate of being in a certain damage state given that the wind speed is 100 mph.

Simulation can be used to generate this probability distribution. First, the probability of being in one of the five damage states is calculated based on the given set of damage functions, indicated by damage state probability in Table 4.1. For example, there is a 5% probability that there will be no damage and a 7% probability that the building will collapse. In this case, an arbitrary range from 00-99 (100 digits) is used, with 5% representing the probability of having no damage (00-04), 24% representing minor damage (05-28), 48% representing moderate damage (29-76), 16% representing severe damage (77-92), and 7% representing collapse of the structure (93-99). Then the cumulative probabilities are calculated for the ordered damage states and random numbers are assigned in proportion to these cumulative probabilities as shown in Table 4.1.

Table 4.1. Simulation example in catastrophe modeling

Damage State	Damage State Probability	Cumulative Probability	Random Number Lower Bound	Random Number Upper Bound
None	0.05	0.05	00	04
Minor	0.24	0.29	05	28
Moderate	0.48	0.77	29	76
Severe	0.16	0.93	77	92
Collapse	0.07	1.00	93	99

To start the simulation, a random number between 00 and 99 is generated. Based on the resulting value, a damage state is projected. For example, if the random number is 36, the structure has moderate damage; if the random number is 21, the structure sustains minor damage. This random number generation is repeated, for example, 1,000 times, and the levels of damage are stored. At the end of the 1,000 sample runs, a histogram of the sample damage state frequencies is created (Figure 4.2). This histogram is an approximation to the distribution of damage, given a level of wind speed.

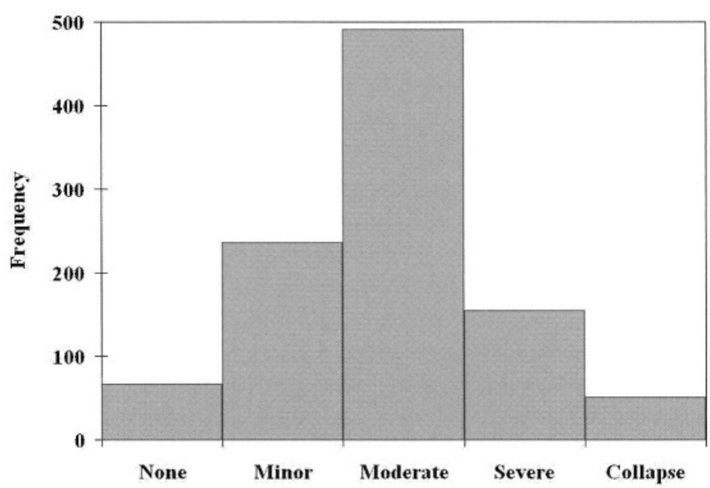

Figure 4.2. Histogram of damage state frequency for 1000 simulation runs.

While this is a simple example of a Monte Carlo simulation (actual simulations in catastrophe modeling are much more complicated), it should be noted that this type of modeling is computationally intensive and requires a large number of samples. If the time and computer resources required to run a full-blown simulation are prohibitively expensive, a degree of computational efficiency can be found through the use of modified Monte Carlo methods, such as Latin Hypercube Sampling, that sample from the input distribution in a more efficient manner (Inman and Conover, 1980). In this way, the number of necessary runs, compared to the Monte Carlo method, is significantly reduced.

4.4.3 Uncertainty and the Exceedance Probability Curve

As defined in Chapter 2, an exceedance probability curve is a graphical representation of the probability that a certain level of loss will be exceeded over a future time period. A widely used technique to create an exceedance probability curve in a catastrophe model is a combination of a logic tree with Monte Carlo simulation. Building on the simple examples presented earlier, each branch of the logic tree represents an alternative that samples from a probability distribution rather than assuming a simple point estimate alternative. For example, consider the competing attenuation equations for ground motion presented earlier, denoted $Y_1 = F_1(f, M, r, Source, Site)$ and $Y_2 = F_2(f, M, r, Source, Site)$. Instead of using the mean estimates of ground motion amplitude based on these functions for each branch of the logic tree, Monte Carlo methods can be used to sample from the attenuation functions along the branches of the tree.

This blended approach allows the creation, in a systematic way, of a set of curves that represent various confidence levels in exceedance probabilities. For example, suppose that there are a set of assumptions, A_1, $A_2 \ldots A_n$, which represent an exhaustive set of all possible assumptions about the parameters, data, and mathematical models needed to generate an exceedance probability curve in a catastrophe model. Further, suppose that each set of assumptions is an alternative on one branch of a logic tree and each logic tree branch results in an EP curve that is generated when the assumptions A_i are made, characterizing the loss L, as shown in Figure 4.3 (i.e., $EP(L,A_i) = P(Loss > L, A_i)$). If each of the sets of assumptions are weighted with subjective probabilities, w_1, $w_2 \ldots w_n$, that add up to one and the assumptions, A_1, $A_2 \ldots A_n$, give rise to a monotonic ordering of their respective EP curves, the mean, median, and a confidence interval for the resulting collection of EP curves, can be defined.

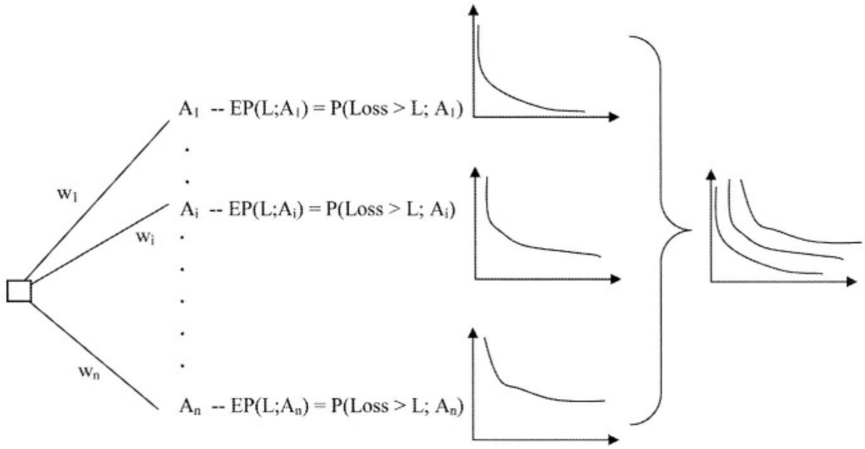

Figure 4.3. Logic tree and simulation to create a set of exceedance probability curves.

4.5 Case Studies in Uncertainty

Given the complexity of catastrophe modeling and the preceding discussion of the sources and techniques to incorporate uncertainty in a model, it is not surprising that competing catastrophe models will generate different EP curves for the same portfolio of structures. When first used in practice, the degree to which these curves could differ is surprising to the users of catastrophe models. With more experience, a user expects a range of possible EP curves.

4.5.1 Hurricane Hazard: Florida

Hurricane losses in Florida provide an interesting example of dissimilar exceedance probability curves for an identical residential inventory. Following the exorbitant losses to the insurance industry after Hurricane Andrew in 1992, the state of Florida resolved to use catastrophe models for residential insurance ratemaking. Prior to Hurricane Andrew, property insurance rates in Florida, including the provision for hurricane losses, were based on historical loss data in combination with the excess wind procedure developed by the Insurance Services Office (ISO), the primary property insurance rating organization in Florida (Florida Insurance Council, February, 1998). This procedure relied on the examination of the prior 30 years wind loss experience in the state and produced an average loss cost to be used in the rate filing application by the insurer.

Prior to Hurricane Andrew, ISO estimated a required catastrophic wind premium for Florida homeowners totaling $80 million using the excess wind procedure. The premium structure proposed by ISO would have required over 100 years to pay for the losses from Hurricane Andrew alone - without considering any other hurricanes that could make landfall. In retrospect, ISO's rate setting process grossly understated the actual risk, shocking the insurance and reinsurance industry with losses far greater than they ever imagined.

In 1995, in response to the insurance crisis in the state and to use a more appropriate procedure to calculate property rates, the Florida Legislature authorized the creation of the Florida Commission on Hurricane Loss Projection Methodology (FCHLPM). The commission consisted of eleven experts, independent of the insurance industry and the Department of Insurance, with responsibility to review the commercially available catastrophe models with regard to their accuracy and reliability (FCHLPM, November 2001). This supported the Legislature's findings that "reliable projections of hurricane losses are necessary to assure that rates for residential insurance are neither excessive nor inadequate, and that in recent years computer modeling has made it possible to improve upon the accuracy of hurricane loss projections" (FCHLPM, 2001).

To be certified for use in establishing residential insurance rates, a catastrophe model undergoes a rigorous yearly review process. Prior to the yearly review and approval by the FCHLPM, a professional team conducts on-site audits of the models. This team consists of five members, including a statistician, an actuary, a computer scientist, a civil engineer and a meteorologist. This professional team is under the authority of the FCHLPM, which is mandated by the state to "consider any actuarial methods, principles, standards, models or output ranges that have the potential for improving the accuracy of or reliability of the hurricane loss projections used in residential property rate filings" (FCHLPM, 2001).

In 1996, AIR Worldwide was the first model certified. In 1997, a total of three models were certified -- AIR Worldwide, EQECAT, and Risk Management Solutions. Since 1997, additional models such as Applied Research Associates have been certified. The Florida Hurricane Catastrophe Fund (FHCF), a residual risk wind pool established in 1993 to maintain insurance availability following Hurricane Andrew, utilizes rate calculations based on computer models that have been certified for use in Florida by the FHCLPM. Typically, rates are based on averaging the outputs from multiple models. In 1999, for example, three models were used, with 50% weight to the middle result, and 25% weight to the high and low results.

While the FHCF must use the Commission's findings regarding models in establishing rates, individual insurers are not required to do so in their own rate filings. If they do, the findings are admissible and relevant in rate filings, arbitration, and judicial proceedings. However, the Department of Insurance has the authority to review and approve rate filings using any methodology, and is not obligated to approve filings based on model-based analyses. The use of models in Florida rate filings is increasing, but public and regulatory acceptance is still far from universal. In fact, some insurers have stated their objection to model based rates, and the public opposition to model rates is especially high in the coastal areas of Broward and Dade County.

As part of a model's certification process, each firm must submit an exceedance probability curve from its catastrophe model for a portfolio of residential structures in Florida. The portfolio includes one $100,000 building for each of three construction types (wood frame, masonry, and mobile home) in each ZIP code in Florida. Additional insured values are added for appurtenant structures, contents, and additional living expense. Table 4.2 and Figure 4.4 present a summary of this information for three competing catastrophe models, denoted Model A, Model B, and Model C, submitted to the Florida Commission in 2001. All models must submit estimates of expected loss for eleven exceedance probability levels, ranging from 0.01% (0.0001) to 20% (0.20). Additionally, a model may or may not present a loss estimate for a top event, defined by the modeler to be the largest exceedance probability/loss combination that can possibly occur. In this case, Model A did not present a top event while Models B and C did, as shown in Table 4.2.

In Table 4.2, a weighted linear combination of the three competing loss estimates for each exceedance probability level is shown to illustrate how all of the information can be used to make an informed decision on setting insurance rates. In this example, a 50% weight is given to the middle result, and 25% weights are given to the high and low results. Thus, the expected loss for this residential portfolio for the 1-in-100 year event could be estimated as: (0.25*$28.5 + 0.50*$31.7 + 0.25*$39.1) = $32.75 million. Other weighting schemes such as equal weights could be utilized to estimate the expected losses for each event.

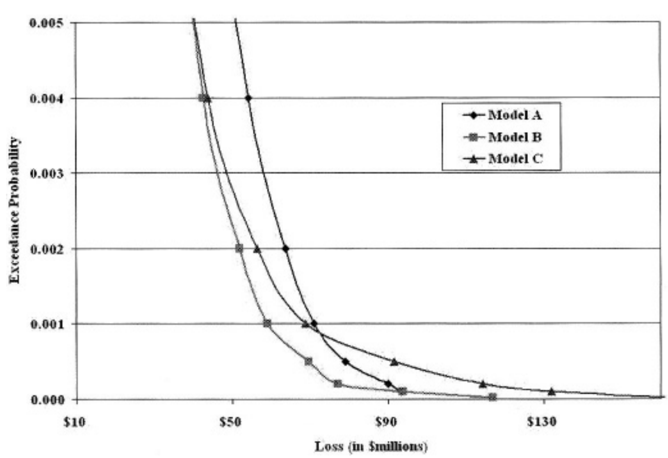

Figure 4.4. Exceedance probability curves from competing models (Source: Florida Loss Commission Data, Form E, 2001).

Table 4.2. Exceedance probabilities versus estimated loss (in millions) across models

Return Time (years)	Exceedance Probability	Estimated Loss Model A	Estimated Loss Model B*	Estimated Loss Model C**	Weighted Linear Combination***
Top Event	---	---	$116.8	$165.9	---
10,000	0.01%	$93.3	$93.7	$131.9	$103.15
5,000	0.02%	89.9	77.1	114.3	92.80
2,000	0.05%	79.0	69.7	91.6	79.83
1,000	0.10%	71.0	59.0	68.8	66.90
500	0.20%	63.7	52.0	56.5	57.18
250	0.40%	54.2	42.7	43.9	46.18
100	1.00%	39.1	31.7	28.5	32.75
50	2.00%	27.8	22.8	18.6	23.00
20	5.00%	16.3	12.5	9.4	12.68
10	10.00%	8.7	6.6	4.7	6.65
5	20.00%	2.9	2.4	1.7	2.35

* top event exceedance probability = 0.002% (Return time of 50,000 years)
** top event exceedance probability = 0.001% (Return time of 100,000 years)
*** 50% weight on middle result and 25% weight on high and low results (no result shown for top event due to differences in exceedance probability and limitations of data)

Looking more closely at the data provided, at the 1-in-20 year event or 5% annual probability of exceedance, the loss estimates range from about $9.4 million to $16.3 million. At the 1-in-1,000 year event or annual probability of exceedance of 0.1% (0.001), loss estimates range from $59 million to $71 million. In this example, as the probability of exceedance increases, the absolute range of losses across the competing model curves consistently decreases. This trend is often seen in the development of exceedance probability curves in high hazard areas. Of course, with the lower dollar figures, the percentage difference can be much higher than at the larger, catastrophic loss levels.

4.5.2 Earthquake Hazard: Charleston, South Carolina

While hurricane risk in Florida is useful to understand the range of differences in loss between competing catastrophe models in the expected or mean case, a different approach must be used to represent confidence levels for various loss/probability combinations on an EP curve. In the summer of 1999, a meeting was held among representatives of Risk Management Solutions, EQECAT, AIR Worldwide and the Wharton School to discuss a sensitivity analysis regarding catastrophe models' estimates of earthquake loss (Grossi, et al., 1999). In this section, a case study of earthquake hazard in Charleston, South Carolina is presented using data from four catastrophe models: models developed by each of the three modeling firms involved in this study (similarly denoted Model A, Model B, and Model C as in the earlier hurricane example), along with FEMA's catastrophe model, HAZUS. A list of the common assumptions were specified for each modeling firm to conduct an assessment of the Charleston region, along with the key elements of uncertainty for the Wharton team to consider in an analysis they would undertake using the HAZUS model.

Composite Model Curves

The first goal of this case study was to discover not only the range of differences between results generated by the three competing catastrophe models, but also to compare a set of exceedance probability curves that represent the 5th percentile, mean, and 95th percentile level of loss. With these curves, a 90% confidence interval on loss is created. In other words, each model created three EP curves for comparison: a best estimate of loss, defined by its mean exceedance probability curve, and two additional curves representing a symmetric 90% confidence level about the mean loss.

As in the case of the hurricane hazard in Florida, the exceedance probability curves produced were expected to be dissimilar, given the degree of uncertainty associated with earthquake recurrence in the Charleston, South Carolina region. In fact, the degree of uncertainty amongst the models was expected to be greater than in the Florida case due to the lack of understanding of the seismic sources in this region. Charleston region is a low earthquake hazard area and the moment magnitude 7.3 earthquake event in 1886 is the only known historical event of note.

The assumptions for the analysis are summarized in Table 4.3. Four counties in the southeastern region of South Carolina, which surround the city of Charleston, comprised the study region. One hundred and thirty four census tracts are contained within the counties of Berkeley, Dorchester, Charleston, and Colleton. The HAZUS database of structures, as defined by the HAZUS97 release (NIBS, 1997), was assumed for the inventory at risk. This database consists of seven occupancy classes of structures, namely residential, commercial, industrial, agricultural, religious, government, and educational occupancies. There were roughly 170,000 buildings in the data set, with approximately 97% of them classified as residential structures.

Table 4.3. Charleston, South Carolina earthquake hazard analysis assumptions

Component	Assumptions
Hazard	o Fault and area sources defined by model o Recurrence defined by model o Site specific characteristics defined by model
Inventory	o 134 census tracts containing 170,000 structures o 97% residential structures
Vulnerability	o Damage functions/fragility curves defined by model
Loss	o Repair costs defined by model o Building damage loss only

Using this common inventory database, each catastrophe model was run unaltered. In other words, no additional common information was used to define the hazard component, the vulnerability component, and the loss component of each model; the proprietary portion of each model remained as such for the study. The generated exceedance probability curves with the relevant confidence intervals were constructed by each of the modeling firms for the loss associated with building damage only (i.e., ground-up loss); no insurance parameters were considered in the analysis.

Given the proprietary nature of the competing models, each model's set of curves is not presented here. Instead, composite curves developed by the Wharton research team are shown[1]. In Figure 4.5, a composite EP curve for the mean loss is shown that represents an equally weighted linear combination of the data (1/3 of each). For example, suppose an estimate of the probability of exceeding a loss of \$1 billion (EP(L) = P(Loss > \$1 billion) is needed for the study area. Model A's probability of exceedance of 0.0091 is combined with Model B's exceedance probability of 0.0051 and Model C's exceedance probability of 0.0053 to estimate: P(Loss > \$1 billion) = (0.0091 + 0.0053 + 0.0051)/3 = 0.0065 or 0.65% probability of exceedance (a 1-in-154 year return period), as seen in Figure 4.5.

Bounding the composite mean EP curve are composite symmetric 90% confidence interval curves: a lower bound on loss, representing the 5th percentile loss, and an upper bound on loss, representing the 95th percentile loss. Since the range of exceedance probabilities varied greatly for a particular loss level for these bounded curves, an equally weighted linear combination was not used (as it was in the mean case). Instead, the extreme value points across the three models were utilized in constructing the

[1] The individual and composite curves were reviewed by Professor Robert Whitman of the Massachusetts Institute of Technology, as part of the Technical Advisory Committee input to the project.

confidence intervals. Thus, the tendency to favor one model over the other two models was avoided.

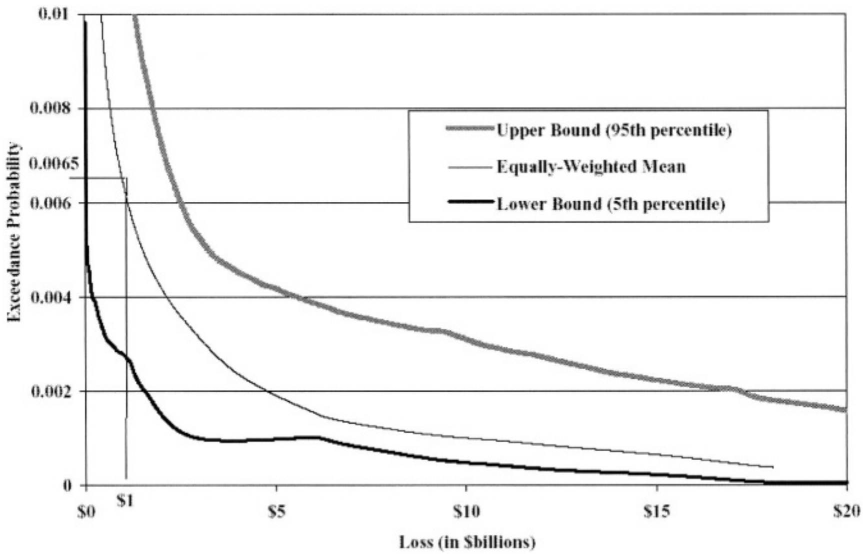

Figure 4.5. Composite exceedance probability curves for Charleston region.

To illustrate the difference between the two approaches, consider the following example. Suppose that the 5th percentile of exceeding a loss of $15 billion (EP(L) = P(Loss > $15 billion)) is required to determine a risk management strategy, which represents a large loss on the right-hand tail of the EP curve. Model A estimates a return period of 5,080 years, Model B estimates a return period of 1,730 years, but Model C's curve does not extend beyond 1,000 years because there is too much modeling uncertainty beyond this point. If the weighted linear combination of these two estimates were calculated equally, ignoring Model C, the result would be a return period of 3,405 years or 0.029% (0.00029) probability of exceedance.

Using the extreme value points for the lower and upper bound curves, the 5th percentile loss of $15 billion has a return period of 5,080 years or approximately 0.02% (0.0002) probability of exceedance rather than the average of 0.029% (0.00029). In this way, the 90% confidence level on the mean curve is an envelope of the three model curves, capturing the true bounds on the uncertainty across the three models.

Reconsidering the loss levels presented earlier for these curves, the probability that the loss to the inventory of structures in the Charleston region will exceed $1 billion or EP(L) = P(Loss > $1 billion) is, on average, 0.0065 or 0.65% with lower and upper bounds of 0.27% (0.0027) and 1.17%

(0.0117), respectively. The mean probability that the loss to the inventory of structures will exceed \$15 billion = P(Loss > \$15 billion) = 0.064% (0.00064) with a lower bound of 0.02% and an upper bound of 0.22%.

A specific loss level for the region could be determined, given a probability of exceedance, using the same data. Using the example of the range of losses for the 0.2% (0.002) probability of exceedance or the 1-in-500 year event, it can be determined from Figure 4.5 that the mean loss to these structures is \$4.6 billion with a lower bound of \$1.5 billion and an upper bound of \$17.1 billion. It should be clear that in dealing with catastrophe modeling, there is a wide variation in the probability of exceedance given a level of monetary loss and a wide variation in loss given a probability of exceedance.

HAZUS Analysis

A related objective of the Charleston analysis was to generate an exceedance probability curve utilizing the HAZUS model and to test the sensitivity of the loss output to a few key assumptions in the model. (For more details and the complete analysis, see Grossi and Windeler, 2000.) While the HAZUS methodology is more transparent than the approaches used in the three competing proprietary models, it requires the development of additional software to create an EP curve (Grossi, 2000). The 1997 HAZUS earthquake model, in its basic form was not designed to create an exceedance probability curve (NIBS, 1997). It could create either an estimate of loss based on one scenario event or based on a probabilistic seismic hazard map, such as the ones created by a USGS team of researchers (Frankel, et al., 1996).

The software tools that enable the creation of an exceedance probability curve using the HAZUS model consist of a pre-processor, designated Scenario Builder and a post-processor, designated HAZUS-EP. As shown in Figure 4.6, Scenario Builder defines a finite set of earthquake events, $j = 1,2...N$, which represent a minimum set of data points needed to create an EP curve. Each event j is defined by its source, magnitude, rupture location, recurrence and attenuation (the hazard component of a catastrophe model). The data and assumptions used to develop the stochastic event set generally follow those described in the USGS National Seismic Hazard Mapping project (Frankel et al., 1996). Notably, the attenuation relationship to describe the rate at which ground motion decays from source to site is an equally weighted linear combination of the Frankel et al., (1996) and the Toro et al., (1997) empirical equations. In this way, all information available is incorporated into the model.

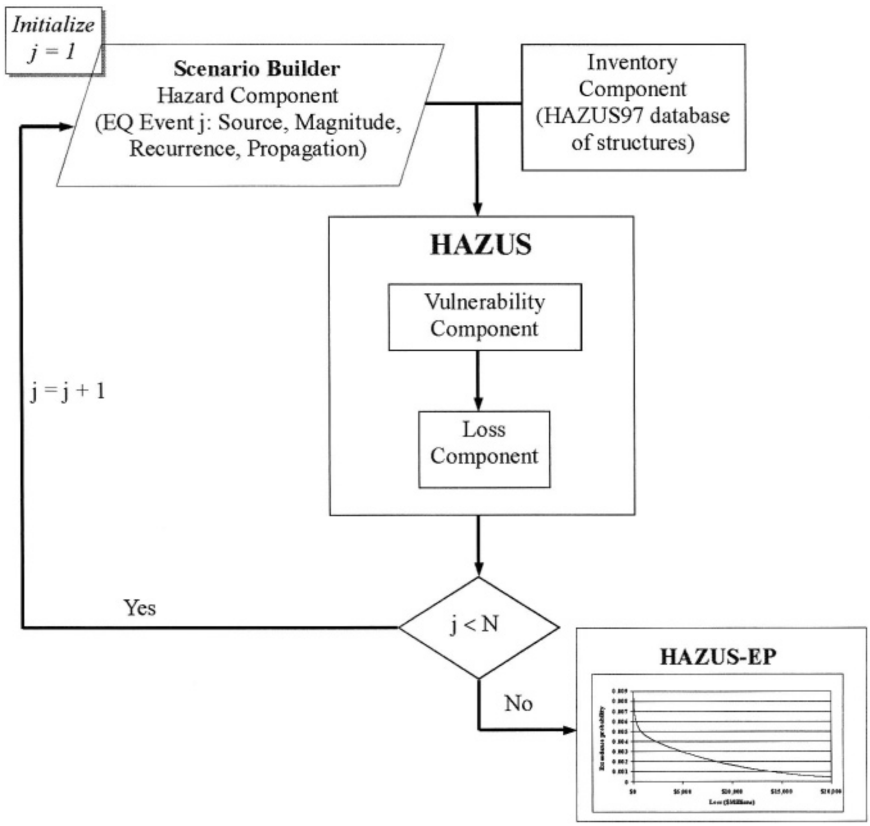

Figure 4.6. Scenario Builder-HAZUS-HAZUS-EP to create an exceedance probability curve.

The total set of events, N = 156, was chosen so that there was a wide enough spectrum of events capable of affecting the Charleston study region. The operative assumption in defining events was that variation in losses would decrease with distance from the study area. Therefore, the greatest number of events would be required within the study counties; the seismicity of progressively larger areas outside these counties could be represented by single events. Similarly, smaller magnitude events were eliminated with increasing distance. As in the earlier analysis to create the composite set of EP curves from Models A, B, and C, the database of inventory structures are defined by the HAZUS97 release (NIBS, 1997), consisting of approximately 170,000 buildings of various occupancy classes.

With the portfolio of structures in Charleston, South Carolina, the HAZUS model is run for each event *j* with *j* = 1,2,...156. The model calculates the damage to the structural and nonstructural building components and the resulting direct economic losses, as defined by the HAZUS methodology (the vulnerability and loss components of a catastrophe model). The results of each run, including losses by census tract and by occupancy type, are stored in a database file for input into the post-processor, HAZUS-EP. HAZUS-EP consolidates the losses to form an exceedance probability curve for the region.

In the complete analysis of the Charleston region using HAZUS, a collection of exceedance probability curves was generated under various assumptions in the hazard and inventory components of the model (Grossi and Windeler, 2000). In this sensitivity analysis, such things as the occupancy mapping of structures, the attenuation relationships, the earthquake duration, and the soils mapping schemes were analyzed. Since a sensitivity analysis of every assumption in a catastrophe model cannot be presented here due to the large number of parameters, a single example demonstrating the sensitivity of loss to a site's underlying soil conditions is discussed. The underlying soils across the entire region are classified as stiff soils or soil class D, as defined by the NEHRP provisions (FEMA, 1997) and assumed in the default mode of HAZUS. To test the sensitivity of this assumption, a different GIS map was used which showed underlying soils in the region to be rock, stiff soils, and soft soils (soil classes B through E in the NEHRP provisions). This latter scheme, which considers varying soil classes, can be considered as a reduction in epistemic uncertainty due to the addition of new data on the geology of the region.

The two curves presented in Figure 4.7 are the mean exceedance probability curves assuming stiff soils and assuming a range of soil types (rock, stiff soils, and soft soils). Interestingly, for a given probability of exceedance, the loss assuming all stiff soils in the region is greater than the loss assuming a range of soil types. It is therefore a conservative assumption in the default mode of HAZUS. For example, at the 0.2% (0.002) probability of exceedance or the 1-in-500 event, the stiff soils mean loss is \$8.4 billion and the mean loss assuming other soil types is \$6.7 billion. Therefore, the assumption of stiff soils everywhere in the region serves to establish a conservative estimate of loss. These curves show no expected loss above the 1% probability of exceedance level.

Finally, the probability of exceeding a loss of \$1 billion using the HAZUS model can be compared with the probability of exceeding this same loss calculated from the equally weighted linear combination of the three competing catastrophe models. The HAZUS analysis, assuming stiff soils everywhere in the region, estimates P(Loss > \$1 billion) = 0.0048 or 0.48% or 1-in-208 year event. As noted earlier and shown on Figure 4.5, the composite mean EP curve has P(Loss > \$1 billion) = 0.0065 or 0.65% probability of exceedance or a 1-in-154 year return period. These two return periods are not very different, a surprising result given the uncertainty in the seismicity of the Charleston region.

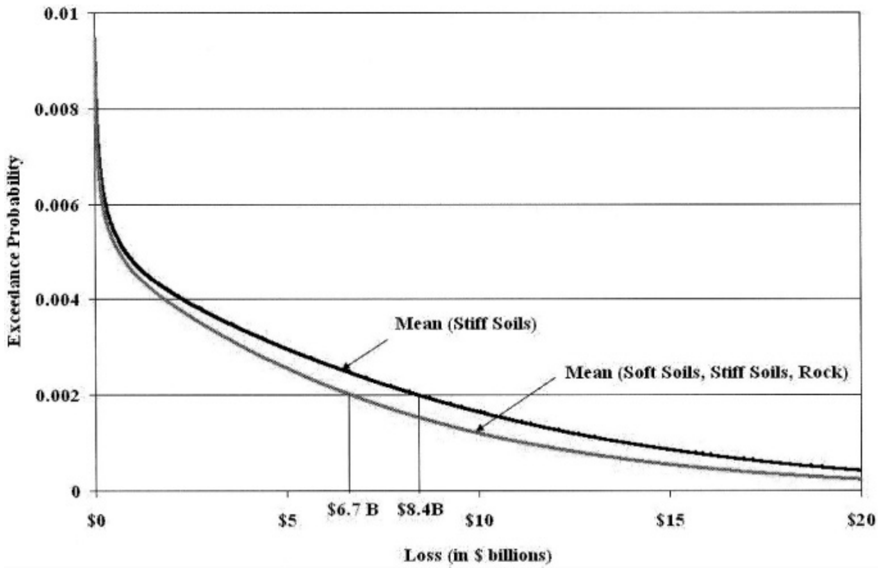

Figure 4.7. HAZUS mean exceedance probability curves for Charleston region.

4.6 Summary and Conclusions

This chapter examined the complexities of catastrophe modeling, mathematical constructs that allow the generation of exceedance probability curves, and the uncertainties inherent in the modeling process. By introducing the concepts of epistemic and aleatory uncertainty, the chapter explored how to quantify uncertainty through the use of logic trees and simulation techniques. Two case studies in Florida and South Carolina indicated the importance of understanding where uncertainty lies in a catastrophe model and how it can be captured and utilized in the risk assessment process. By constructing exceedance probability curves with confidence intervals, the degree of uncertainty associated with natural hazard events, such as an earthquake in Charleston or a hurricane in Florida, can be appreciated.

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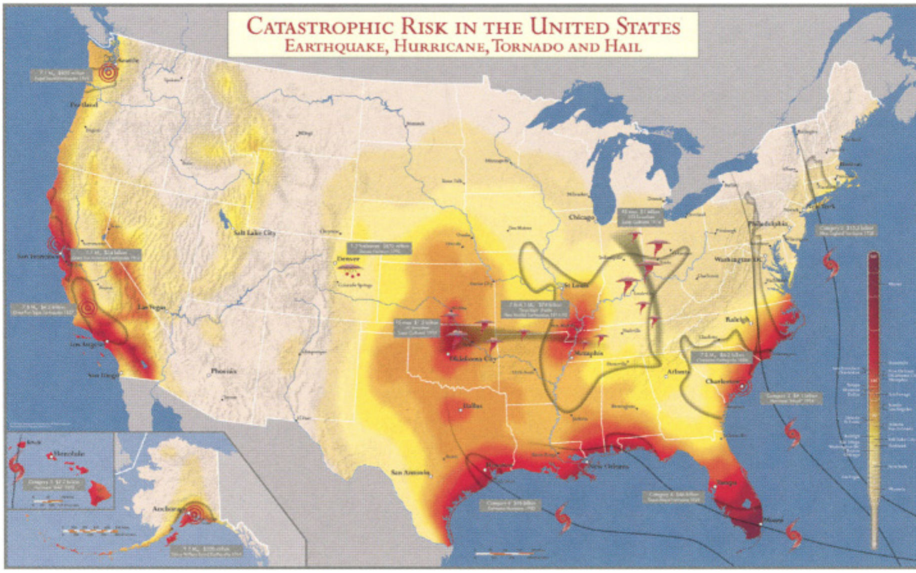

PART III

LINKING RISK ASSESSMENT WITH INSURANCE

Part III of this book explores applications of catastrophe modeling tools by linking the risk assessment process discussed in Part II, with the risk management strategies practiced by insurers. More specifically, the next three chapters address how insurers can take advantage of the scientific advances in evaluating the risks of earthquakes, hurricanes and other natural disasters, to develop strategies for reducing their losses. These strategies should help insurers avoid insolvency or significant loss of surplus following future catastrophic events.

Insurers' risk management strategies are designed to increase their expected profits, while at the same time meeting an acceptable level of risk, characterized in Chapter 2 as a survival constraint. Part III examines how catastrophe models can be used to support insurers in this regard.

As a way of introducing the topic of risk management, a set of EP curves is presented in Figure III for a hypothetical insurer's catastrophe risk. This company is assumed to have $100 million in surplus to cover hurricane losses, and would like this loss level to have an annual probability of 0.4%

(250-year return period) or less. A risk analysis for their portfolio yields an EP curve depicted in Figure III(A), indicating that the likelihood of exceeding $100 million under the insurer's current risk management plan is approximately 0.6%. What options does this company have to improve its situation? More formally, what options does this company have to meet its survival constraint while still maintaining a high expected profits?

Three possible strategies are shown in Figures III(B) through III(D), each one reflecting a topic covered in one of the next three chapters and ordered with an increasing degree of external involvement: rate making, portfolio management, and risk financing. It should be noted that the examples presented are highly simplified and do not consider how the cost of a strategy might reduce the capital available to pay out losses. Some strategies require time to implement and thus are long-term solutions rather than immediate fixes.

Rate Making (Chapter 5)

The rate-making process is concerned with the most basic of insurance questions: when the company decides to provide coverage for a given risk, how much should it charge? The insurer must first consider whether the rates are adequate to cover expected annual losses, plus other administrative expenses. The insurer must then decide whether the premiums are adequate to cover the possible losses following a catastrophic disaster. The answer to this question depends on the nature of the insurer's portfolio.

An alternative to raising premiums is exposure reduction, so that the insurer's EP curve shifts downward as shown in Figure III(B). The two most common ways of doing this are by increasing the deductible or reducing the maximum coverage limits. In either case, if there is a large-scale disaster that destroys many structures, the insurer will have smaller amounts to pay.

Portfolio Management (Chapter 6)

It is the role of an insurer's portfolio manager to examine the scope of the company's risks and determine the likelihood that losses from a catastrophic disaster will exceed $100 million. Through an analysis of its portfolio, the insurer may find that a significant fraction of its loss curve is driven by events affecting one geographic area. By redistributing its exposure such that potential losses are less correlated, the insurer can maintain the total value of its portfolio while reducing the potential for any single event to exceed its surplus. Over time, the firm can develop a plan to strategically shrink its concentrations of exposure contributing to large loss events, and expand coverage in other parts of the country.

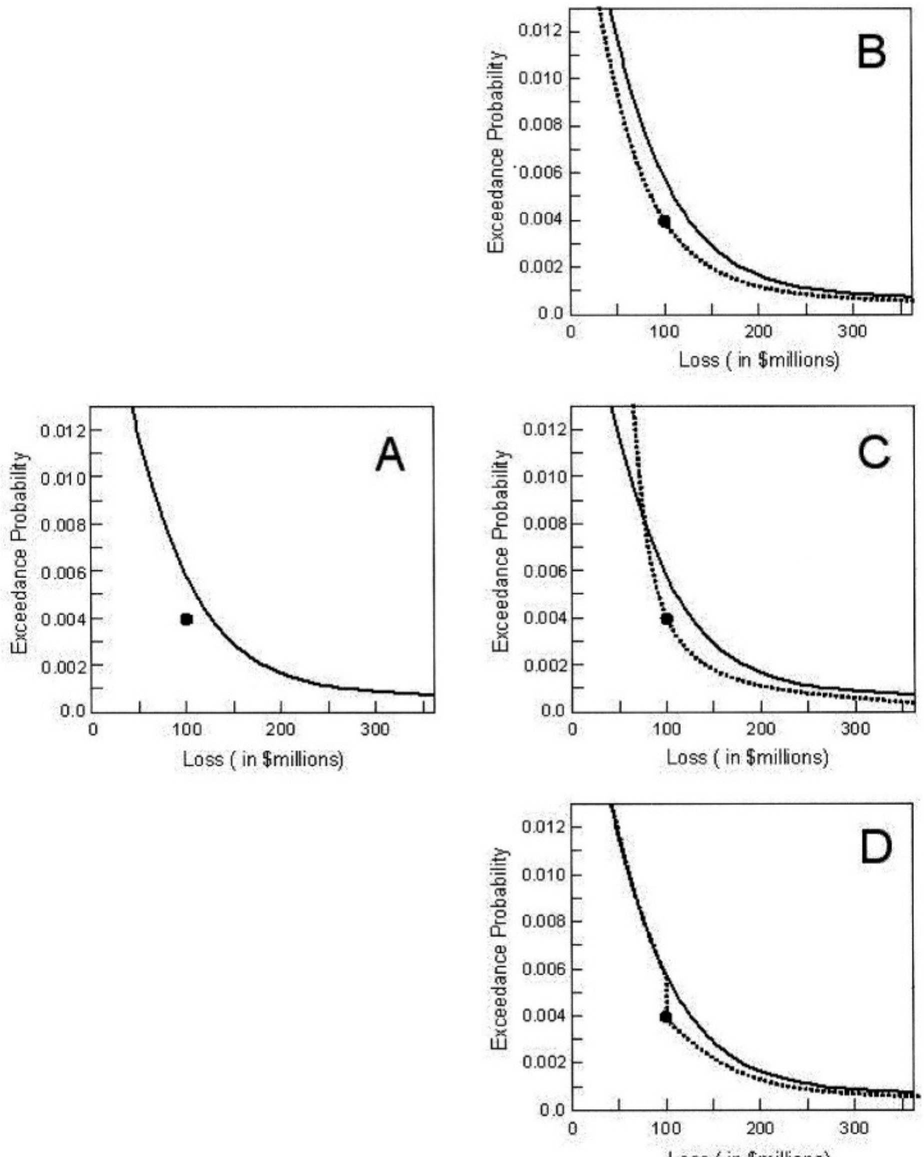

Figure III. Illustrating the effects of alternative strategies for risk. Base case (A) shows the loss curve relative to the company portfolio prior to implementation of any strategy. Dotted lines show modified EP curve relative to original after (B) exposure reduction through an increased deductible, (C) diversification, and (D) transfer. Note that the effects of most management strategies have been exaggerated for display and that the costs of implementation have not been reflected.

Diversification need not only be geographic, however. In Figure III(C), the insurer has arranged a swap with a company writing earthquake insurance, exchanging some of its policies for another risk with identical loss probabilities, but uncorrelated with the existing portfolio. This swap reduces the EP curve so that the likelihood of a loss of $100 million or more is below 0.4% --- the acceptable level of risk specified by the firm.

Risk Financing (Chapter 7)

The traditional method for reducing risk by an insurer has been to transfer it to another party for a fee through reinsurance. In Figure III(D), the insurer purchases a reinsurance treaty that covers the first $30 million of loss above $100 million, reducing its 250-year loss to an acceptable target value. In determining how much reinsurance to purchase, the insurer has to take into account the impact that the costs of this coverage will have on its surplus. More recently, insurers have begun to transfer risk by investing in new financial instruments such as catastrophe bonds.

Summary

The examples highlighted here illustrate how risk assessment tools, via the EP curve, can be used to quantify the effectiveness of different management strategies discussed in the next three chapters. In practice, insurers are likely to utilize some combination of the strategies presented: rate making, portfolio management, and risk financing.

An important value of catastrophe modeling is its ability to examine an appropriate mixture of these three risk management strategies. Thus, an underwriter can link into a company-wide database and not only determine what premium it should charge for a new account, but also how this risk correlates with others in the company's portfolio. The portfolio manager can implement underwriting guidelines to determine what premiums to charge for new policies as a function of their location and potential hazards. Different risk transfer programs can be priced and evaluated in conjunction with an existing portfolio of risk. Decisions can then be made as to whether it is advisable for the company to reduce its exposure, raise its premiums, purchase a catastrophe bond, and/or transfer some of its risk to a reinsurer.

Chapter 5 – Use of Catastrophe Models in Insurance Rate Making

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5.1 Introduction

This chapter explores the use of catastrophe models in insurance rate making. Before examining the use of models, a brief discussion of the rate-making process and the actuarial principles underlying rate making is presented. The chapter then discusses how catastrophe models are utilized in both setting rates and differentiating between risks as a function of structure attributes, location and hazard conditions. The chapter concludes with a discussion of some of the regulatory aspects associated with catastrophe modeling and rate making, using the determination of rates for the California Earthquake Authority (CEA) as a case study.

The chapter concentrates on how modeling is used in the rate-making process, but it is not about rate making per se. However, in order to see how modeling can play its supporting role, a brief review of the rate-making process is presented. Insurance rates are, as all economic products, the result of supply and demand forces. On the demand side, the rates must be sufficiently attractive relative to the insured's estimate of the expected loss such that buying insurance is an attractive option.

On the supply side, the premium must be sufficiently high for investors to expect an acceptable return on their invested capital given the risk characteristics of the insurer. Moreover, the rates must be sufficient to ensure that the insurer has an acceptably low ruin probability and high credit rating so that demand is not eroded by credit risk. Catastrophe modeling provides the technical inputs into a wider planning process associated with financial management. Figure 5.1 illustrates how catastrophe modeling can be used in conjunction with data on capital allocation to undertake financial modeling for an insurance company. For example, the exceedance probability curve developed through catastrophe modeling can be integrated with a capital allocation analysis and run through a financial model of the firm, such as Enterprise Risk Management (ERM) in which the implications of risk-financing strategies can be evaluated using risk versus return criteria.

Figure 5.1. Role of catastrophe modeling in an insurance company's financial management.

5.2 Actuarial Principles

According to the Actuarial Standard of Practice (ASOP), rate-making is "the process of establishing rates used in insurance or other risk transfer mechanisms" and "is prospective because ...rates must be developed prior to the transfer of risk" (Actuarial Standards Board, 1991). While the definition is short, the process of rate making can be long and complex, dictated by the determination of numerous costs associated with risk transfer including claims and claims settlement expenses, operational and administrative expenses, and the cost of capital.

Catastrophe risk models provide significant inputs into the process of determining rates by providing estimates of future claims costs or loss costs. These are the expenditures arising directly from the occurrence of a catastrophic event and are a function of the underlying frequency and severity of the disaster.

Actuarial principles and practice dictate that insurance rates for a catastrophe hazard be based on estimated future costs that are determined in a manner that is fair and equitable. To the extent possible, these rates should reflect individual risk characteristics. The following is a summary of the relevant actuarial principles for determining whether a rate is actuarially sound, reasonable and not unfairly discriminatory (Actuarial Standards Board, 1991).

> ***Principle 1:*** A rate is an estimate of the expected value of future costs.
> Rate making should provide for all costs so that the insurance system is financially sound.
>
> ***Principle 2:*** A rate provides for all costs associated with the transfer of risk.
> Rate making should provide for the costs of an individual risk transfer so that equity among insureds is maintained. When the experience of an individual risk does not provide a credible basis for estimating these costs, it is appropriate to consider the aggregate experience of similar risks. A rate estimated from such experience is an estimate of the costs or the risk transfer for each individual in the class.
>
> ***Principle 3:*** A rate provides for the costs associated with an individual risk transfer.
> Rate making produces cost estimates that are actuarially sound if the estimation is based on Principles 1, 2, and 3. Such rates comply with four criteria commonly used by actuaries: reasonable, not excessive, adequate, and not unfairly discriminatory.
>
> ***Principle 4:*** *A* rate is reasonable and not excessive, adequate, or not unfairly discriminatory if it is an actuarially sound estimate of the expected value of all future costs associated with an individual risk transfer.

Additional commentary on rate setting that has special significance to catastrophe modeling is the suggestion by the Actuarial Standards Board that "the determination of an appropriate exposure unit or premium basis is essential" and that such units should vary with the hazard and should be practical and verifiable. In this context, practical and verifiable means that the exposure unit is directly related to the underlying catastrophic loss potential and that it can be measured objectively in a transparent manner.

Accordingly the criteria used to determine an earthquake or hurricane residential rate should include such factors as the location of the property, size of the home, age of the home, type of construction, replacement cost and mitigation measures. Catastrophe models can also show the effect on losses due to differences in proximity to hazards, construction materials and methods, occupancy, and line of business. If information for an individual risk is insufficient, data for a group of risks with similar risk characteristics can be used. Catastrophe models thus have the ability to estimate future costs based on these actuarial principles and therefore have become a valuable tool in establishing insurance rates.

5.3 Use of Catastrophe Models in Rate Making

Although catastrophe models facilitate the application of actuarial principles to rate making, the process is not a simple one. In contrast to standard perils such as fire and automobile, natural hazards challenge the role of insurance as a means to efficiently transfer risk between parties. Perhaps the most notable feature is highly correlated losses resulting in significant financial hardship to the insurer.

A comprehensive rate-making exercise involves the identification of all of the relevant costs to determine sufficient and equitable rates. In this regard, catastrophe models are essential for the calculation of two components: the Average Annual Loss (AAL) and the Surplus Cost. To adequately insure a basket of risks, an insurer must maintain sufficient liquid assets or surplus to cover potential catastrophic losses. The surplus can take the form of cash and liquid securities, reinsurance (indemnification) contracts, catastrophe bonds, or contingent debt offerings. The insurer will want to charge a higher premium to reflect the opportunity cost associated with holding surplus capital in a more liquid form than normal. This additional premium is the surplus cost or the cost of capital component.

5.3.1 A Simple Rate Making Model

The price or premium that the insurer should charge to policyholders is based on the sum of the following three components:

Premium = AAL + Risk Load + Expense Load

The AAL reflects the actuarial principle that the rate be based on risk. As discussed in Chapter 2, AAL is calculated as:

$$AAL = \sum_i p_i L_i$$

where p_i is the probability that an event occurs and L_i is the associated loss. The Risk Load is determined by the uncertainty surrounding the AAL. While several measures of risk exist, the standard deviation (σ) of the EP curve is used as an example. The risk load is an important component of the pricing equation. It reflects the insurer's concern with the survival constraint and the need for additional surplus capital. The Expense Load reflects the administrative costs involved in insurance contracts and is comprised of factors such as loss adjustment expense, processing fees, premium taxes, commissions and profits.

There are numerous methods that can be used to calculate the standard deviation of the loss, but a computationally efficient form is:

$$\sigma = \sqrt{\sum_i (L_i^2 p_i) - AAL^2}$$

Table 5.1 shows the loss rates for homeowners' risks within the state of Florida using the above formulation. As an example, the table shows the mean and standard deviation from the EP curves for each county within the state.

Table 5.1. AAL and standard deviation rate calculations.

County	**AAL Rate (\$AAL / \$1000 Value)**	**Standard Deviation**
Monroe	\$ 9.02	\$ 45.98
Dade	6.56	33.98
Palm Beach	5.38	28.38
Okeechobee	1.67	9.41
Hillsborough	1.10	6.69
Dixie	0.36	2.21
Duval	0.32	2.05
Sarasota	2.18	15.46

Based on the data in Table 5.1, estimated insurance rates can be constructed for homeowners (i.e., single family dwelling occupancy) in each county as shown in Table 5.2. These rates are derived using a theoretical basis for pricing described in Kreps (1998), where the derived premium is calculated considering the expected loss, its volatility, as well as administrative costs. As noted by Kreps, these rates can be viewed as an upper, but useful, bound on what insurers should charge assuming investment returns based on current financial market conditions and portfolio composition. It does not take into account the benefits of diversifying risks through portfolio selection across counties. The table shows the tremendous range in rates that can exist across counties, reflecting the underlying catastrophe potential.

Table 5.2. Annual homeowner insurance rates by county.

County	Insurance rate per $1000 value (no expenses or credits)
Monroe	$ 32.01
Dade	$ 23.55
Palm Beach	$ 19.57
Okeechobee	$ 6.37
Hillsborough	$ 4.45
Dixie	$ 1.47
Duval	$ 1.35
Sarasota	$ 9.91

5.3.2 Differentiating Risk

There are many risk factors that are important to the calculation of equitable rates. These factors can be characterized as directly related to the inputs of a catastrophe model. Two of the most critical factors in differentiating risks for rate setting are the structure attributes of a portfolio (the inventory component of a catastrophe model) and the location attributes of a portfolio (proximity or susceptibility to hazard). Each of these is now considered in turn.

Structure Attributes

Structure attributes are those features of the insured risk related to the physical performance of a building in an extreme event. Structural materials, building codes, year of construction modification, and occupancy fall under this category and impact the rates charged for insurance.

First, construction plays a major role in determining susceptibility to natural hazard risk. Construction materials and structural systems determine how a building responds to the hazard. Some materials perform better for some hazards and worse for others. For example, wood frame construction is generally thought of as superior for earthquake resistance due, in part, to its light weight and flexibility. During an earthquake, masonry is considered inferior due to its high weight and non-ductile behavior. With respect to the hurricane peril, masonry is superior to wood frame due to its mass and resistance to projectile damage.

Building codes in existence at the time of construction are a reflection of potential building performance. Newer codes reflect the latest advances in science, research, and loss experience. The 1933 Long Beach, California earthquake highlighted the risks to life and property from collapsing unreinforced masonry buildings. The inelastic nature of the masonry-mortar connection makes these structures prone to catastrophic collapse. Similarly, the partial collapse of the brand new Olive View Hospital from the 1971 San Fernando, California earthquake revealed inadequate design of large open areas on the first floor and demonstrated the need for ductile framing connections in structures subjected to earthquake forces. The lessons learned in this earthquake triggered substantial changes to future building codes.

Revised codes apply only to new construction and to those structures that are undergoing voluntary retrofits. For this reason, the year of construction offers insights into the design and detailing methods for particular structures. For example, riveted steel buildings in the 1800's gave way to welded structures in the late 1900's. Higher standards of living led to houses with larger rooms (i.e., fewer crossing walls added stability to structures), changing the way that buildings respond to earthquakes (Bertero, 1989). In recognition of age-related earthquake response, the state of California Department of Insurance approved insurance rates that varied by year of construction as well as by construction materials with the formation of the CEA in 1996. Similarly, in hurricane-prone areas, higher standards of living also led to houses with larger windows and doorways, increasing the exposure to wind borne hazards.

Finally, building occupancies can indicate how susceptible a structure is to damage. Experience with natural catastrophe claims, and engineering reviews of risks, demonstrate the varying damage patterns expected, based on occupancy. Building occupancy effectively changes the layouts of buildings, types of contents and values, and their locations within and outside buildings.

The effect of occupancy is greatest in estimating business interruption losses. Natural catastrophes impact not only the business, but also its suppliers and customers in the region. For example, a processing plant that requires significant amounts of water to operate chillers is effectively interrupted if the water supply is cut off by an earthquake that caused significant damage to underground utilities. Another example is the vulnerability of many retailers to communications outages. Many communications lifelines rely on above-ground distribution, which is susceptible to damage from high winds.

Occupancy can also affect the layout of walls, windows, doors, and equipment within a building. This layout can affect building performance. For example, manufacturing facilities with assembly lines will tend to have long spans with significant amounts of equipment suspended from the ceiling, which increase the potential loss from a catastrophe.

Location Attributes

Location attributes reflect the degree to which structures are subject to damage from hazards as a function of where they are built. For example, one very commonly understood underwriting tool for flooding is whether or not the building is in a 100-year flood plain. Other examples include proximity to known earthquake faults, distance from the coast with respect to hurricane hazard, local soil conditions as they relate to ground motion during an earthquake, and surface roughness and topography as they relate to wind speed during a hurricane.

One important aspect of the differentiation of risk is a structure's proximity to known sources of hazard. As shown in Figure 5.2, the AAL for an idealized risk situated in various locations throughout Southeastern Florida would have a varying loss rate directly related to its proximity to the coastline. The state of Florida Wind Underwriting Authority (FWUA) allows wind insurance rates in southern Florida to vary based on distance from the coastline. This is also done in other states, most notably Texas. The coastal counties in Texas are designated as catastrophe areas by the Texas Department of Insurance. These zones define what construction criteria a structure must meet to be considered for windstorm insurance. Similarly, the State of California identified special earthquake zones in the Alquist-Priolo Act of 1990.

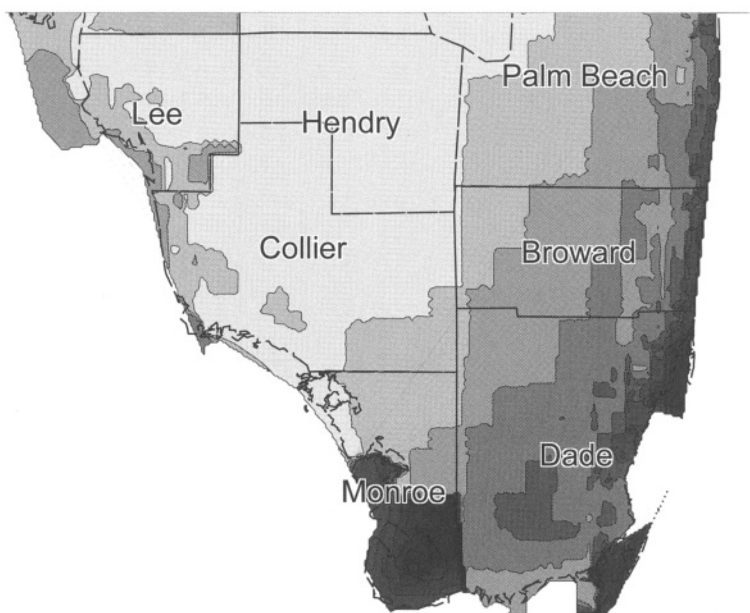

Figure 5.2. Expected annual damage rate contours, State of Florida. (Dark shading is high risk, light shading is low risk)

Local soil conditions play a key role in the determination of risk from earthquakes. One notable type of soil failure is landslide, where a building collapses because its foundation loses its ground support. Ground failure is often excluded from earthquake insurance policies due to its potential catastrophic impact.

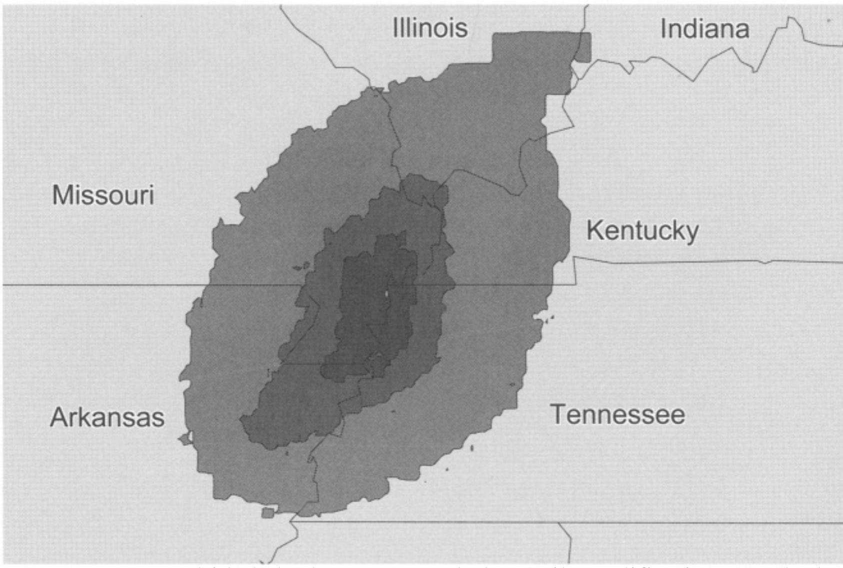

Figure 5.3. New Madrid shake loss rates *excluding* soil amplification. (Dark shading indicates high loss rates, light shading indicates low loss rates)

The 1989 Loma Prieta, California earthquake demonstrated very clearly the effects of soil amplification upon building performance. Although approximately 70 miles from the epicenter of the earthquake, several areas within the city of San Francisco experienced significant levels of damage. One of the most notable pockets of damage was the San Francisco Marina district, where the structures that suffered the highest losses were located in the area of a lagoon that was filled in for the San Francisco World's Fair in the early 1900's (EQE International QuickLook Report, 1989).

Comparing Figure 5.3, which shows the loss rates for the New Madrid Seismic Zone *excluding* soil amplification, to Figure 5.4, which shows the loss rates *including* soil amplification, one can see the significant difference in the Average Annual Loss in the New Madrid region using local soils amplification factors. Both figures depict a very strong dependence in loss rates with distance to the largest source zone in the area. However, the New Madrid region overlays a portion of the Mississippi River and associated tributary streams. Alluvial river valleys such as these are characterized by large depositions of unconsolidated silty and sandy soils (soft soils), which will result in increased earthquake ground shaking similar to the soft soils in the San Francisco Marina District. Hence, as demonstrated in Figure 5.4, losses are much greater when soil amplification is taken into account.

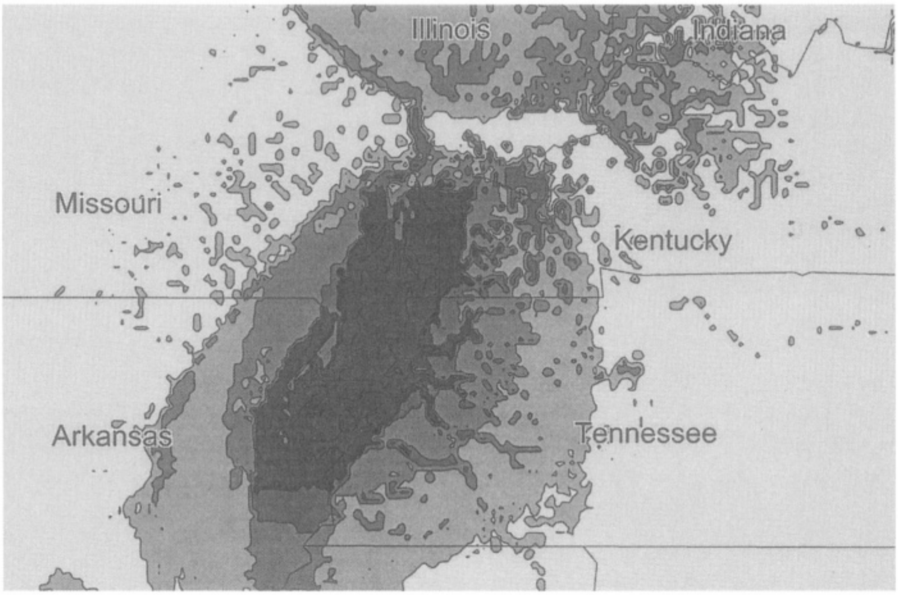

Figure 5.4. New Madrid shake loss rates *including* soil amplification. (Dark shading indicates high loss rates, light shading indicates low loss rates)

5.4 Regulation and Catastrophe Modeling

This book is not directly concerned with the details of the regulatory process. However, catastrophe modeling can play an extremely important role in educating regulators and their constituents of the rationale behind their expected loss costs and the resulting premium structures. Because of intense economic and political pressures, state governments have intervened in catastrophe insurance markets in significant ways.

Insurers and insurance markets are regulated primarily at the state level (Klein, 1998). Hence, the laws and regulations governing insurance transactions are set by the individual state legislatures and insurance commissioners, with legal disputes generally adjudicated by state courts. Regulatory policies vary among states based on market conditions, differing regulatory philosophies, and political factors. As a result, state regulatory authorities respond differently to the use of catastrophe modeling in support of rate making. This is evident in the California case study described in the next section.

To date, regulators have not been supportive of having model-generated information introduced in support of the regulatory process, possibly because it imposes an additional constraint on their already difficult job of finding acceptable recipes for rate regulation. At the same time, they have to develop an understanding of catastrophe models, as insurers increasingly integrate these tools into their day-to-day operations. These models present a conflict for the regulators. On the one hand, they provide a scientifically rational approach for quantifying an insurer's risk. By requiring insurers to report modeled loss estimates, the regulator can assess whether the company has been responsible in controlling their accumulations. Rates can be based on an integration of all possible events, not just a limited historical record. On the other hand, the regulator may view a model with some suspicion if they perceive it as a tool for justifying higher rates.

Catastrophe models are complex products that require specialized expertise to evaluate thoroughly and, for competitive reasons, modeling firms usually want to protect proprietary aspects of their models. This is particularly true for states with sunshine laws that require government documents be publicly available. Differences in model assumptions can cause loss results to vary considerably between modeling firms, as indicated in the case studies presented in Chapter 4. Each model may be reasonable given the data constraints, but the range of uncertainty can be disconcerting when compared to estimates for lines such as life or automobile insurance.

As the states most at risk from earthquakes and hurricanes, California and Florida have been in the forefront with respect to the role that catastrophe models play regarding rate setting. As discussed in Chapter 4, the state of Florida has developed a review process by which modeling firms must show that their products meet a set of technical criteria. Insurers submitting modeled rates must do so using a model certified for use in Florida. This chapter discusses the case of the California Earthquake Authority, in which results from catastrophe models formed the basis of a state-organized insurance program. In both Florida and California, the issue of modeling as a basis for rate-setting has become politicized and been subject to criticism by public interest advocates.

Other states have followed their own path. Texas initially disallowed any rates filed on the basis of computer models. However, the Texas Department of Insurance later modified its stance by allowing information developed from models to be included in rate filings. The Department expressed continued concern about differences in results between modeling firms and noted that they would request additional data to determine the reasonableness of these filings (Mah, 2000).

The National Association of Insurance Commissioners (NAIC) has a working group focused on the use of computer models for rate filings. In February 1999, department of insurance representatives from several states in the region surrounding the New Madrid seismic zone requested presentations from the major modeling firms on earthquake loss estimation. Its goal was to gain an understanding of how these tools were being used to develop rates, with particular emphasis on the validation of results for areas with little historical loss experience. One product of this working group is that states can request insurers to submit with their rate filings a form that describes the scientific basis of their model results.

Recognizing that these models involve technical expertise outside their traditional knowledge base, regulators have looked elsewhere in the government for support. For example, the California Geological Survey explored the process of calculating earthquake insurance loss costs with publicly available models (Cao and others, 1999). These results can then become a baseline for comparison with results from private firms.

5.5 Case Study of Rate-Setting: California Earthquake Authority (CEA)

The rate structure of the CEA formed in 1996 was significantly influenced by the application of catastrophe modeling. Prior to the Northridge Earthquake in January 1994, most residential insurers based their earthquake rates on past experience. With very few losses in the prior 20 years (San Fernando earthquake in 1971, Whittier earthquake in 1987 and Loma Prieta earthquake in 1989), average residential rates were approximately $2.00 per $1,000 of coverage for a policy that had a deductible of either 5% or 10%, along with generous limits for contents and loss of use.

5.5.1 Formation of the CEA

The Northridge earthquake resulted in approximately $12.5 billion of insured losses and almost $40 billion of total damage. Total residential losses exceeded the total earthquake premiums collected in the previous 20 years. Fearing insolvency, over 90% of the homeowners' insurers in California either refused to write or severely restricted issuance of new residential policies in order to avoid offering earthquake coverage.

In response, the California State Legislature designed a policy which permitted insurers to offer a basic policy consisting of a 15% deductible plus much reduced contents coverage ($5,000) and living expense ($1,500). Catastrophe modeling indicated that this policy, if it had been offered in place of the standard 10% deductible policy, would have reduced industry losses by half following the Northridge earthquake. However, the industry was still concerned about insolvency and continued to threaten to leave the California market.

In response, the Legislature established the CEA in 1996, creating a unique publicly managed stand-alone residential earthquake insurance company. Catastrophe modeling was used to estimate the loss probabilities to the reinsurance layers, thereby assisting in the largest catastrophe reinsurance placement (over 100 global reinsurers) ever consummated.

SIDEBAR 1: Modeling and solvency regulation in Canada

In Canada, the property and casualty market is more fragmented than in the U.S., with a large number of companies vying for premiums. In the mid- to late 1990's, many of the firms using modeling tools for earthquake portfolio management felt they were being placed at a competitive disadvantage. By being responsible in their surplus accumulations, they were losing business to insurers that were attempting to capture market share with lower rates.

The Office of the Superintendent of Financial Institutions (OSFI) Canada stepped in with guidelines for managing earthquake exposure. OSFI (1998) required companies with exposure in British Columbia or Quebec to report gross and net PMLs based on a computer model. Guidelines were set for PML return periods (250 and 500 years) and treatment of deterministic or probabilistic models. If a company chose not to use a model, they would have to report precompiled damage factors per CRESTA zone (i.e., a bounded geographic area designated by the Catastrophe Risk Evaluation And Standardizing Target Accumulation organization; the aim of the zones is to establish a globally uniform system for the accumulation risk control of natural hazards). These were relatively draconian, having been derived from the highest losses from the major modelers, with an additional factor for conservatism.

5.5.2 Rate-Setting Procedures

The CEA began to write policies in late 1996, with rates determined through the use of a catastrophe model. A rate application was filed in early 1997, and immediately challenged by consumer groups. Under California insurance law, rate applications submitted to the Department of Insurance can be challenged through a formal public hearing process, similar to a civil court trial but with an appointed Administrative Law Judge. (Sidebar 2 indicates which factors the CEA took into account when establishing rates for earthquake insurance.)

The legislature clearly indicated that rates must be risk based, using the best available scientific information, and that the use of a catastrophe risk model to estimate the rates was anticipated. And the risk factors identified in item 1 of Sidebar 2 were specifically incorporated into the model in estimating loss costs at the ZIP code level.

The public rate hearing commenced in May of 1997, with testimony lasting over four months and culminating in over 7,000 pages of testimony (California Department of Insurance, 1998a). This was the most complex and lengthy insurance rate filing case in California, with rates challenged by four

SIDEBAR 2: Rate-Setting Considerations For The California Earthquake Authority

The CEA's legislative creation (Insurance Code 10089.40) was accompanied by a series of considerations for the establishment of rates, as stipulated in the code:

1. Rates established by the Authority shall be actuarially sound so as to not be excessive, inadequate, or unfairly discriminatory. Rates shall be established based on the best available scientific information for assessing the risk of earthquake frequency, severity, and loss. Rates shall be equivalent for equivalent risks. Factors the Board shall consider in adopting rates include, but are not limited to, the following:
   (a) Location of the insured property and its proximity to earthquake faults and to other geological factors that affect the risk of earthquakes or damage from earthquakes.
   (b) The soil type on which the insured dwelling is built
   (c) Construction type and features of the insured dwelling
   (d) Age of the insured dwelling

2. If scientific information (and/or modeling assumptions) is used in setting rates, such information must be consistent with the available geophysical data and the state of the art of knowledge within the scientific community.

3. Scientific information that is used to establish different rates between the most populous rating territories in northern and southern California cannot be used unless that information is analyzed by experts, such as the U.S. Geological Survey or the California Geological Survey, and they conclude that such information shows a higher risk of loss to support those rate differences.

4. The legislature does not intend to mandate a uniform statewide flat rate for residential policies.

5. Rates established shall not be adjusted to provide rates lower than are justified for classifications of high risk of loss or higher than are justified for classifications of low risk of loss.

6. Policyholders who have retrofitted homes to withstand earthquake shake damage shall receive a 5% premium discount, as long as it is determined to be actuarially sound.

consumer organizations, one insurer, plus the California Department of Insurance. The case was separated into actuarial and earthquake modeling sessions to facilitate expert testimony. Because of the statutory language requiring rates to be consistent with the scientific state of the art, the model was held to both actuarial as well as scientific standards.

Actuarial issues focused on aggregate cost allocations, territorial rating plans, and risk classification based pricing. Discussions on modeling issues centered on definitions of what is the best available scientific information on such elements as ground motion and damage estimates. Because of the public perception of a proprietary "black box" model, considerable challenges to model assumptions and outputs were made. Major modeling issues raised in the hearing included a number of items, as discussed below.

Earthquake Recurrence Rates

Since historical earthquake data in California is limited to a maximum of 150 years, determining the long-term rate of earthquakes, especially medium and large events, is critical. Catastrophe model assumptions based on published scientific information were reviewed and challenged, and compared with models produced by the California Division of Mines and Geology (CMDG).[1] It was determined that the model results compared favorably with such state of the art examples as the CDMG's model. One of the most significant issues was that all the models produced earthquake frequencies that were more than twice the historical record. This finding challenged the acceptability of the CEA model's frequency estimates based on past data.

Uncertainty Values in Estimating Time Dependent Probabilities

Certain earthquake faults or fault segments have been studied in sufficient detail to estimate the likelihood of future rupture, based on geological investigations. This time-dependent probability of rupture differs from the conventional assumption that earthquakes are a random process characterized by a Poisson distribution (Stein, 2003).

At issue in the hearing was the use of time-dependency and the uncertainty factor (σ) associated with the recurrence interval between historical events. A smaller value of σ implies a lower level of uncertainty in the historical recurrence pattern, and hence, the greater weight given to a time-dependent recurrence estimate. Conversely, the larger the value of σ, the less weight given to the time dependent estimate. If σ approached a value near 1.0, then the estimate is essentially time independent and it would be the

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[1] Since the hearings the CDMG has been renamed the California Geological Survey (CGS).

same as a Poisson distribution estimate. Hence, differences in σ would affect both recurrence rates and loss costs.

Since neither the CDMG nor the USGS had produced seismic hazard models that were based on time-dependency, the CEA felt that these models were not state of the art. However, since both the CDMG and USGS have produced working group reports using time-dependency to estimate earthquake probabilities as early as 1988, the Administrative Law Judge ruled that their models were consistent with the state of the art. The Insurance Commissioner noted that this was another area of scientific dispute yet to be resolved.

Damage Estimates

Model-based damage estimates are derived by associating a given level of ground shaking severity at a site with the vulnerability to shaking damage for a specific class of structure defined by age, type of construction, number of stories, etc. Prior to the Northridge Earthquake, earthquake damage curves were based on engineering opinions and judgments published by the Applied Technology Council (ATC). However, the model based its curves on over 50,000 claims from the Northridge quake. It was argued that the ATC-13 curves, which were in the public domain since 1985, should be relied upon as opposed to model-based proprietary curves, which were derived from principally one event. Testimony from representatives of the ATC itself supported the use of claims-based curves as the best available source of information for the link between shaking intensity and damage.

Underinsurance Factor

Model-based damage estimates are expressed as a percent of the building's value. Accordingly, if the value used is less than the replacement cost, damage and loss estimates are understated. In addition, the policy deductible is likely to be understated since it is typically defined as a percent of the policy limit.

Because of inflation and lack of accurate valuation, the insurance to value ratio for most buildings is usually less than 1.0. In other words, most buildings are underinsured. Since the residential insurers in California did not readily have an estimate of the degree of underinsurance, consumer groups challenged the initial model assumptions of 13% derived from surveys of insurance actuaries in the state. They claimed that there was 0% underinsurance and that the properties were fully insured. Ultimately, a 6% underinsurance figure was agreed to and rates were lowered from the initial projections to reflect this compromise.

Demand Surge

Following a major natural disaster, increases in demand for construction material and labor can result in increased claims settlement costs. Settlement costs may also rise from large events such as Hurricane Andrew or the Northridge earthquake due to the demands upon insurers to settle hundreds of thousands of claims in a short time. Based on actuarial principles, it is reasonable to include these additional costs in establishing the appropriate rate. However, determining a demand surge factor is difficult since limited data are available to measure the impact of this phenomenon on claims costs.

The CEA testified that insurers estimated a 20% impact for demand surge following the Northridge earthquake. Since the vulnerability curves were based on Northridge data, the curves used were adjusted and initially reduced by 20% to eliminate the demand surge effect. Then the curves were increased by an adjustable factor, relating demand surge to the size of loss from each stochastic event in the model's probabilistic database. Although interveners argued that demand surge does not exist, the CEA actuarial group's testimony was accepted as reasonable even though little empirical data exists to support this assertion.

Policy Sublimits

Although a catastrophe model was used to establish the loss costs through such risk factors as location, soil conditions, age and type of structure, the model could not determine the contribution to losses from certain CEA policy features such as sublimits on masonry chimney damage, walkways, awnings, etc., because insurance claims data do not identify sources of loss from these categories. Hence, actuaries had to reduce the modeled loss costs to account for the specific CEA policy sublimits which were not reflected in the claims data used in the damage estimates produced by the model.

Rating Plan-Deviation

The statewide loss cost is derived from the sum of loss costs from approximately 1,700 ZIP codes containing residential exposures. From these detailed loss costs by ZIP, the CEA constructed a rating plan consisting of 19 contiguous territories based on modeled loss costs, four housing types (single family, mobile home, condominiums, and rentals), two construction types (wood frame and other) and age (three groups).

Interveners challenged the plan since they claimed it was unfairly discriminatory. According to the insurance code (10089.40(a)), "rates shall be equivalent for equivalent risk," but the CEA capped the rates in two territories because of affordability issues, and spread the capped costs to other territories. One insurer challenged these rates, claiming that they were not actuarially sound, adversely impacting other policyholders. The insurer argued that capped rates did not reflect true costs, with the CEA undercharging in high hazard areas and overcharging in low hazard areas. This had the potential of causing adverse selection problems with only the highest risk individuals purchasing policies at subsidized rates to them. This could leave the CEA as the main insurer in high hazard areas and with few individuals purchasing policies in low hazard areas. In response to the challenge, the commissioner ruled that a rating plan does not have to base premiums on risk in view of the affordability issues, and that the plan was still actuarially sound and not unfairly discriminatory.

Retrofit discount

The CEA statutory language requires a premium discount of at least 5% if policyholders have retrofitted their homes for earthquake shake damage, and the discount is determined to be actuarially sound. The CEA offers discounts for three mitigation measures: bolting the walls to the house foundation, cripple wall bracing, and water heater tie-down (which minimizes fire following risk, which is not covered by the CEA policy). Based on conversations the CEA actuary had with structural engineers, he concluded that losses would be reduced. With no empirical or scientific guidance on the loss reduction, the statutory minimum of 5% was used as the premium discount. Interveners challenged the discount, claiming more studies were needed to actuarially justify the discount. In response, the Commissioner ruled that the discount was appropriate since the actuary had relied on input from engineering experts.

Changing Deductibles and Coverage Limits

Typically, various combinations of deductibles and limits have been used to reduce the amount of earthquake loss to an insurer. In its initial rate filing, the California Earthquake Authority proposed a policy that combined the effects of a relatively high deductible (15% of the coverage amount) with strict limits on the payouts of contents ($5,000) and additional living expense ($1,500). Testimony given during the rate hearing supported the assertion that the insurance cost for the proposed CEA policy was one-half the cost of the previous standard earthquake policy form, which had a 10% deductible, with much higher limits for contents and additional living expense.

Conclusion

The Commissioner (California Department of Insurance, 1998b) ruled in favor of the CEA loss estimates based on catastrophe modeling on almost all major issues. This demonstrates the contribution of catastrophe modeling for rate setting with respect to meeting actuarial standards and legislative requirements. However, many scientific and technical issues still remain.

5.5.3 Future Research Issues

The hearings associated with CEA rate-setting procedures raised a number of questions that require future research. The scientific community and stakeholders utilizing catastrophe models could profitably work together to improve state-of-the-art knowledge for use in policy decisions in the following areas: scientific uncertainty, additional claims data, retrofit discounts, and demand surge.

First, the hearing highlighted the significant disagreement among earth scientists on frequency estimates, maximum magnitudes, and time dependent calculations. Given the high level of seismic research undertaken by academics and researchers in government agencies such as the USGS, and the inherent uncertainty in the estimation process, disagreements are likely to persist. The challenge is to select credible and representative research, and in some cases to include more than one methodology in the catastrophe models.

Additionally, insurance claims data from catastrophic loss events are by nature very limited. Yet, it is the single best source from which to estimate future losses. Insurers need to capture and preserve loss data and portfolio exposures for each loss event. Because of the legal and commercial aspects, release of this data to third parties needs to be carefully managed to protect the insurance companies' interests.

Mitigating future catastrophic losses via structural retrofits, with commensurate insurance premium reductions, is strongly desired by politicians and the public. Models have the ability to quantify the benefits of various wind or earthquake mitigation applications, but are hampered by the lack of detailed loss data, since insurers typically do not distinguish losses by structural component, such as roof, chimney, foundations, or non-load-bearing walls. The states of Florida, California, and Hawaii are encouraging research and studies to assist in estimating such benefits. Results of these efforts will undoubtedly find their way into model analysis in the development of actuarially sound retrofit discount programs.

Finally, increases in settlement costs following a major catastrophe have been noted in Hurricane Andrew, the Northridge Earthquake and Typhoon Mirielle (1991) in Japan. Actuaries estimated a 20% increase in Northridge with similar levels for the hurricane events. Unfortunately, little research has been conducted to identify the sources of these losses and what size events would evidence such behavior.

5.6 Open Issues for Using Catastrophe Models to Determine Rates

In the last five to ten years, the use of catastrophe models for insurance rate making has become common practice in states with the potential for severe catastrophic insured losses. There are still a set of open questions that need to be resolved with respect to their use in rate-making decisions.

Regulatory Acceptance

Proprietary sophisticated models create a problem for regulators, who are unlikely to have the technical expertise to judge the reasonableness of the inputs, assumptions, and outputs. Some states, such as Florida, have created independent commissions consisting of technical experts who certify models for use in insurance rate-setting situations in Florida. However, the State insurance commissioner has publicly criticized all models as biased in favor of the insurers.

In California, the Insurance Commission relied on the rate hearing process with experts provided by the interveners as well as by the Department of Insurance to examine model details and assumptions. However, regulators have a dual responsibility in setting rates. Rates need to be acceptable and affordable to the general public, but also actuarially sound to preserve the financial integrity of the insurers.

Public Acceptance

As expected, public acceptance of the models has been low, principally because their use resulted in substantial increases in wind or earthquake rates. No one likes a rate increase. The problem is that previous rate making approaches based on historical experience fail to capture the potential severity and frequency of these loss events. Rate estimates from models are not precise due to the uncertainty in the science, but they provide considerably more insight than extrapolations based on past loss experience.

Actuarial Acceptance

Rate filings are usually the responsibility of a casualty actuary, who needs to comply with actuarial practice and principles. The catastrophe model is a tool that can be used by an actuary in meeting his/her obligations to determine the fair and equitable rates to charge an insured. Since the models are outside an actuary's usual professional expertise, it is necessary for them to become familiar with the model components.

More recently, the Actuarial Standards Board has published Standard of Practice No. 38 that requires actuaries to (a) determine appropriate reliance on experts, (b) have a basic understanding of the model, (c) evaluate whether the model is appropriate for the intended application, (d) determine that appropriate validation has occurred, and (e) determine the appropriate use of the model (Actuarial Standards Board, 2000).

Model-to-Model Variance

Given the inherent uncertainty in catastrophe loss estimates, significant differences in loss estimates from one model to another do occur. Often models are dismissed for this reason, with claims that models are good only if they agree with each other. However, models are based on inputs from varying scientific data and engineering information, which may differ because of uncertainty in the understanding of hazards. The modeler is required to use one or more sub-models of hazard or severity defined by a reputable scientific researcher, which may result in different loss results. That is the inherent nature of the modeling process. Risk, and uncertainty in estimating the risk of loss, derives not only from the randomness of the event occurrence, but also from the limits in knowledge and different interpretations by experts. It is unlikely that science will provide us all the answers, thus leading to continued differences in model results.

5.7 Summary

Catastrophe models are playing an important role in managing the risk of natural hazards through the establishment of risk-based insurance rates. These rates provide price information and economic incentives to mitigate and manage risks from low probability events that otherwise would be ignored until the disaster has occurred. This chapter has detailed the actuarial principles on which rates are based. It then illustrated how the four components of catastrophe modeling play a role in the rate setting process.

By focusing on an actual hearing in the context of rate setting by the California Earthquake Authority as a case study, the challenges of linking science with policy were highlighted. The chapter concluded by discussing future research issues and open questions related to the use of catastrophe models for rate-setting purposes.

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Chapter 6 – Insurance Portfolio Management

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6.1 Introduction

Per standard insurance terminology, a portfolio refers to an ensemble of individual policies. Each policy, in turn, may cover a number of individual assets, for example buildings, which may or may not be spread out geographically. The use of the term portfolio is not restricted to primary insurers; it applies to reinsurers as well. In this chapter, the focus is on how catastrophe modelers can aid primary insurers in managing their book of business, but the approach is also relevant to reinsurers.

Insurers who issue policies to cover catastrophe losses are concerned with the maximum loss they might experience. Hence, the risk of a portfolio is important to understand. It is an aggregation of the risks of the individual policies, which, in turn, are the aggregation of the risks at various locations. However, the aggregation is not simply one of addition or summation. Unlike events, such as fires, where each accident is normally localized and independent of one another, a catastrophe casts a large footprint, which is likely to affect a number of assets covered by a portfolio.

Essential for good portfolio management is a thorough understanding of risk and the instruments that are available to reduce the likelihood and magnitude of catastrophic losses. The combination of new engineering knowledge, advances in loss modeling, and innovations in the insurance and financial industries, have increased the effectiveness in managing catastrophe risk significantly compared to a decade ago. Quantification of the contributing losses and their associated uncertainties is now possible.

After presenting an overview of an insurance portfolio, the chapter describes how portfolio risk can be quantified using catastrophe modeling. This is followed by an illustration of how optimal portfolio risk management can be achieved by better underwriting and risk selection. The chapter concludes with a discussion of the features of the risk quantification process that affect the nature of an insurer's portfolio, such as data quality, uncertainty modeling, and impact of correlation.

6.2 Portfolio Composition and Catastrophe Modeling

6.2.1 Portfolio Composition

Insurance companies who issue coverage for natural hazard events usually have portfolios that consist of many individual policies, either residential, commercial or both. Residential properties and assets that are insured are often physically located in a single location while commercial properties are often distributed across many regions. The insurance policy stipulates how properties located at a group of locations are to be covered.

Most residential policies have a simple insurance structure: one policy for building, contents, and additional living expenses with a deductible and coverage limits. A portfolio of such policies may be in the hundreds of thousands. Most primary insurance companies collect relatively detailed data for each of their policies with the data including building type, year built, street address (or ZIP code) and market values. Some insurers record building-specific features, such as the number of stories, presence of cripple walls, past retrofits, and/or site-specific geologic conditions.

Within a commercial portfolio, an insurance policy may insure a large corporation against losses to its facilities in many locations. Some policies, for example a fast food chain, may cover a number of nearly uniform buildings in different parts of the country. Since the insured value for a commercial building is much greater than a residential structure, detailed information about the property is normally required by the insurer to underwrite these policies. An engineer may inspect construction plans or be sent to the site to examine particularly valuable risks.

In most cases, there will be a location-level deductible and coverage limit for building, contents, and business interruption. There may also be a policy-level deductible and coverage limit to protect against excessive insurance losses for that policy. For example, a policy may cover 100 locations, each with \$1 million coverage limit. If there was no aggregate limit on the policy and all locations suffered total damage from an event, the insurer would have to pay \$100 million. In order to avoid excessive loss, the insurer may impose a policy coverage limit of \$20 million, for example. In that case, if the sum of losses for all 100 locations was greater than \$20 million, the loss to the insurer would be capped at \$20 million.

The resulting collection of policies constitutes a portfolio. To illustrate, suppose the portfolio depicted in Figure 6.1 contains commercial structures covered by a single insurer. There are a total of m policies, each with its own structure (e.g., deductible and limit level) for different types of coverage (e.g., building and contents). Moreover, for each policy, there are n locations covered. If this were a residential portfolio, there would be m different policies at individual locations, with the number of policies per location allowed to vary.

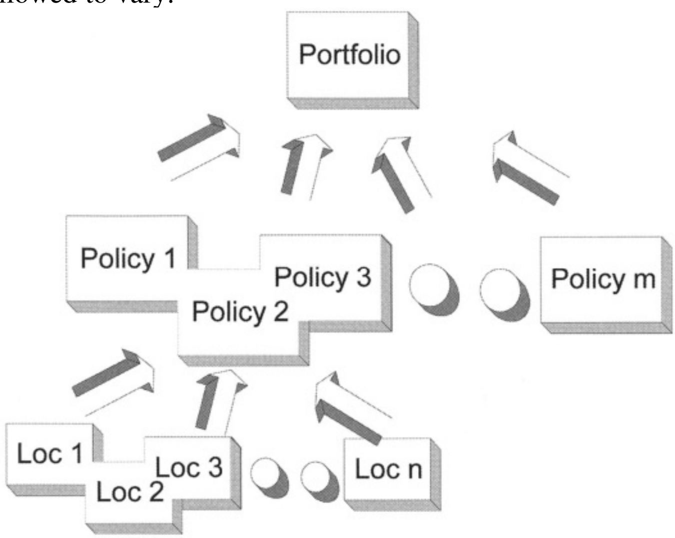


Figure 6.1. Depiction of an insurance portfolio.

6.2.2 Catastrophe Modeling – Bottom-up approach

The development of catastrophe models that can generate a loss exceedance probability curve for a portfolio greatly expands the underwriting options available to insurers. A portfolio manager could use a catastrophe model to calculate the probability that the portfolio loss will exceed a given level (e.g., 1%) or to calculate the probability of experiencing a loss that exceeds the company's survival constraint. The insurer could also examine the effect of changing deductibles and coverage limits on the existing portfolio.

An underwriter's decision to write a new account is based on the magnitude of the risk, its correlation with the existing portfolio, and the highest acceptable price that a client is willing to pay for insurance. In addition, there are factors related to what is being insured (e.g., flammability or fragility of contents, performance of the structure type under wind or earthquake loads), where it is located (e.g., distance from the coast or to active faults, potential for ground failures such as landslides), and how much can be charged (i.e., regulatory constraints and competitive impacts on rates for a given policy form).

Suppose a hypothetical insurer has a corporate policy of maintaining sufficient surplus to withstand a 250-year loss corresponding to a survival constraint with an annual probability of exceedance of 0.4% (0.004). This constraint is currently satisfied, but the insurer would like to increase his exposure in a hurricane-prone state without significantly increasing the potential 250-year loss. In order to achieve this objective, the insurer can perform a hurricane analysis and identify and rank tiers of ZIP codes by their contribution to events causing losses in excess of the 250-year value.

New business in the ZIP codes with the largest loss contribution would be eliminated from consideration unless the structure had a sufficiently high enough score on the basis of wind-resistance structural features. In this case, its potential loss from a major disaster in the area would be low enough for it to qualify as a candidate for the portfolio. Other factors, such as the age of the structure or its size, might assume less importance in ranking ZIP codes because they contribute less risk to the portfolio.

Given an event, a catastrophe model is used to calculate a ground-up loss for each location in the portfolio. Stepping through the levels of the model allows one to allocate this ground-up loss to each of the participating parties: insured, insurer, and reinsurer. Since the event is random, an annual rate of occurrence is associated with it and, by extension, with the calculated losses. For all possible events with their occurrence rates, calculations of all losses associated with each event can be completed; an event loss table is compiled as illustrated in Table 6.1.

Table 6.1. Conceptual event loss table.

Event (E_i)	**Annual probability of occurrence (p_i)**	**Loss (L_i)**
1	p_1	L_1
2	p_2	L_2
:	:	:
i	p_i	L_i
:	:	:
N	p_N	L_N

From the table, various portfolio risk metrics are computed for any or all of the participants. For example, the average annual loss, AAL, is the expected loss for the portfolio, calculated as the product of loss from an event and its annual rate, summed over all events that cause a loss. Based on cumulative rates of occurrence, an exceedance probability (EP) curve is generated such as the one shown in Figure 6.2. For example, there is a 1% chance that the loss will exceed $50 million.

The bottom-up approach provides the most robust means to quantify portfolio risk. That is, losses are first calculated for insured and insurer at the location level based on deductible and coverage limit. The next step is to aggregate all location losses in a policy to find the gross loss to the insurer for this policy. Finally, losses are aggregated over all policies in the portfolio.

Figure 6.2. Exceedance probability curve for portfolio.

A valuable graphic tool in characterizing the role of insurance in managing portfolio risk is the loss diagram. The loss diagram is a two-dimensional representation of loss that is the backbone of the insurance model (Figure 6.3). The y-axis of a loss diagram measures the loss. Three thresholds are of fundamental importance in loss modeling. They are, in increasing order of magnitude: deductible, coverage limit, and total exposure. The deductible is the first portion of the loss absorbed by the policyholder or insured. The insurer will absorb the loss above the deductible up to the coverage limit. The total exposure refers to the replacement value of the property if it is completely destroyed. If the actual loss is greater than the coverage limit, then the remaining portion will be borne by the insured.

The x-axis runs from 0% to 100%, which corresponds to 0% to 100% proportionality, which is only applicable in the case of reinsurance (See Sidebar 1). Since there is no reinsurance on this portfolio, the insurer assumes the entire loss above the deductible amount and capped at the coverage limits as shown in Figure 6.3. For this sample loss, the insurer covers the entire loss above the deductible.

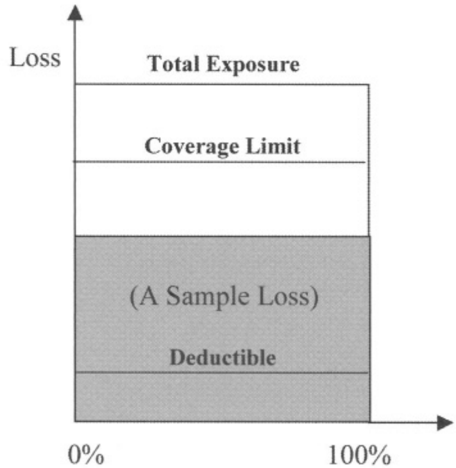


Figure 6.3. Loss diagram.

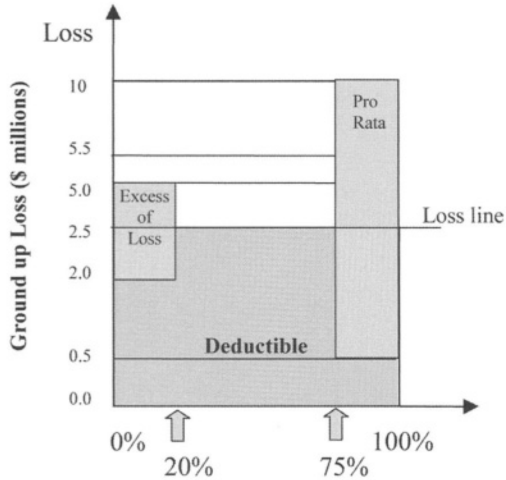
6.2.3 Portfolio Aggregation

By constructing event loss tables for the different portfolios that comprise the insurer's book of business, it is easy to combine these portfolios to generate the aggregated EP curve. Table 6.2 shows a simple example of how such an aggregation procedure could be performed. It is apparent that the total loss is simply the sum of losses across portfolios for the same event. If one examines the figures for each event across the three portfolios in the table, it is evident that Portfolio 1 and Portfolio 2 are positively correlated with each other and that Portfolio 3 is not. Based on this visual examination, if the insurer needed to reduce its risk, then the obvious candidates to eliminate would be either Portfolio 1 or 2. The aggregate risk will be more highly diversified when either 1 and 3 or 2 and 3 are combined than if 1 and 2 make up the total portfolio.

Table 6.2. Aggregation of Event Loss Tables From Three Portfolios

Event (E_i)	Probability (p_i)	Loss for Portfolio 1	Loss for Portfolio 2	Loss for Portfolio 3	Total Loss
1	p_1	$100,000	$80,000	$0	$180,000
2	p_2	60,000	50,000	10,000	120,000
3	p_3	50,000	40,000	30,000	120,000
..	..	..	..	..	..
i	p_i	30,000	25,000	50,000	105,000
..	..	..	..	..	..
..	..	..	..	..	..
N	p_N	10,000	8,000	120,000	138,000

SIDEBAR 1: Loss Diagram with Reinsurance



The figure to the right shows a more complex loss diagram with two traditional reinsurance contracts: one pro-rata contract and one excess-of-loss contract (See Chapter 7 for more details). In general, reinsurance contracts have an attachment, a limit and a participation level (in a percentage). In conventional shorthand, this is written % Limit X Attachment. In the case shown here, the insurance policy has deductible of $0.5 million and a coverage limit of $10 million. The excess-of-loss contract is 20% of $3 million excess of $2.0 million (or, in conventional shorthand, 20% 3M X 2.0 M). In other words, the reinsurer pays 20% of the portion of the loss that is between $2 million and $5 million once the deductible is taken into account. The pro-rata contract is 25% of $9.5 million above the deductible, so the reinsurer pays 25% of any loss between $0.5 and $10 million. If the ground-up or economic loss is $2.5 million as shown by the loss line, then the insured loss will be $2 million. In this event, the excess-of-loss amount is 0.2*($2.5 - $2.0) million or $0.1 million and the pro-rata contract covers 0.25*$2 million or $0.5 million.

6.3 Portfolio Management Example

A portfolio manager faces two critical questions with regard to dealing with catastrophic risks: What is the average annual loss (AAL) and what is the likelihood that the company may become insolvent? The first question is linked to the premium rate. A proper rate enables a company to operate smoothly while making reasonable profits for its shareholders. The second question relates to the company's ability to survive and ensure that the risk of insolvency remains acceptable. To address both of these issues, it is critical to adequately model the right hand tail of the EP curve where the loss is large and there is a significant amount of uncertainty.

In broad terms, there are two levels of portfolio risk management: micro and macro. Micromanagement addresses individual policies or even locations, while macro management considers the aggregate portfolio.

6.3.1 Understanding risk

The first step to managing a portfolio is to quantify the risk. Computer-based modeling and loss estimation are important tools in this process. Based on currently available models, a probabilistic risk analysis can identify the key drivers of loss by business unit, by peril, by geographic region, or by account. This can be used to manage the level of risk of a portfolio.

Consider a company that wants to limit its 250-year loss to be less than $100 million; that is, the annual probability of exceeding $100 million should be less than 0.4%. Based on its current book of business, the losses from various events with their annual occurrence rate are calculated and listed in descending order in Table 6.3. For each event, HU indicates a hurricane event and EQ indicates an earthquake event. From the table, it is found that the probability of exceeding $100 million is approximately 0.557%.

Table 6.3. Event Loss Table for an insurer's portfolio

Event (E_i)	**Loss (L_i)**	**Annual probability of occurrence (p_i)**	**Exceedance probability ($EP(L_i)$)**
HU_1	$279,707,730	0.0079%	0.008%
...	...	...	...
HU_{20}	$106,945,669	0.0098%	0.232%
EQ_1	105,964,573	0.0586%	0.290%
HU_{21}	105,821,572	0.0127%	0.303%
HU_{22}	103,944,373	0.0068%	0.310%
HU_{23}	103,428,541	0.0079%	0.318%
HU_{24}	102,631,772	0.0267%	0.344%
EQ_2	102,438,481	0.0659%	0.410%
HU_{25}	101,664,120	0.0529%	0.463%
EQ_3	101,056,232	0.0888%	0.552%
HU_{26}	100,329,263	0.0052%	0.557%
HU_{27}	99,526,987	0.0220%	0.579%

Scanning all events whose losses are greater than $100 million in Table 6.3, there are three earthquake events (EQ_1, EQ_2, EQ_3) whose losses barely exceed $100 million. In the aggregate, however, the annual rate of occurrence of these three events is 0.213%, or approximately 38% of 0.557%. As a potential strategy, if the earthquake exposure is reduced such that the aggregate loss for each earthquake scenario is lowered by 6%, then losses from all three earthquake events will be less than $100 million. This will result in a portfolio with the probability of exceedance at 0.344% for a loss threshold of $100 million (Table 6.4).

Table 6.4. Event Loss Table for an insurer's revised portfolio

Event (E_i)	Loss (L_i)	Annual probability of occurrence (p_i)	Exceedance probability ($EP(L_i)$)
HU_1	$279,707,730	0.0079%	0.008%
…	…	…	…
HU_{20}	$106,945,669	0.0098%	0.232%
HU_{21}	105,821,572	0.0127%	0.245%
HU_{22}	103,944,373	0.0068%	0.251%
HU_{23}	103,428,541	0.0079%	0.259%
HU_{24}	102,631,772	0.0267%	0.286%
HU_{25}	101,664,120	0.0529%	0.339%
HU_{26}	100,329,263	0.0052%	0.344%
EQ_1	99,606,700	0.0586%	0.403%
HU_{27}	99,526,987	0.0220%	0.425%
EQ_2	96,292,172	0.0659%	0.491%
EQ_3	94,992,858	0.0888%	0.579%

6.3.2 Underwriting and Risk Selection

Catastrophe modeling is also a valuable tool for underwriting and pricing. By quantifying risk, the impact of adding another policy to a portfolio becomes transparent. If the potential loss from adding the policy to the portfolio is too large, then the underwriter can decide not to provide coverage for this risk. Certain types of structures, like unreinforced masonry buildings in earthquake-prone areas, may then not be eligible for coverage. The insurer will also avoid areas with soils that have a high potential for landslide or liquefaction. By estimating potential losses and their variability, catastrophe models provide a means to determine the appropriate actuarial premium for a particular insurance policy. Given the concern with aggregate losses, the insurer can examine the impact on portfolio losses by varying the deductibles as well as coverage limits on insurance contracts.

6.4 Special Issues Regarding Portfolio Risk

There are three important issues that insurers must take into consideration when managing their portfolio risk from natural disasters: data quality, uncertainty modeling, and impact of correlation. While each of these issues has been raised in other parts of this book, they are revisited here due to their unique impact on a portfolio.

6.4.1 Data Quality

Amongst all the data elements that are necessary for input into a catastrophe model, insurers must pay special attention to the inventory component. In defining as accurately as possible the composition for their portfolio, they can reduce the degree of epistemic uncertainty. Specifically, past natural disaster events have shown that the building construction type, the age of the building, the soil data (for earthquake events) and exposure data are important elements for estimating loss. Having this information available on each structure will enable the insurer to estimate the risk of claims exceeding certain amounts more accurately.

The type of construction and the age of a building are two key components in assessing the vulnerability of a structure. While this point may seem evident since different construction types respond to load differently, and older buildings have more wear and tear, the impact of construction type, and age of a building sometimes play out in subtle ways. For example, after the 1989 Loma Prieta earthquake, a portfolio for an insurance company covering industrial facilities had an incurred loss that was much less than the projected loss. An extensive investigation and field inspection of the buildings in the portfolio revealed that a number of the structures had been coded incorrectly as unreinforced masonry buildings.

With each new natural disaster event, the structural engineering community learns more about how different construction types respond to lateral loads. For example, until the 1994 Northridge earthquake in Southern California, steel structures were thought to perform well under earthquake loading. However, inspections following this earthquake revealed that a large number of steel moment-frame buildings experienced fractured or cracked connections.

Earthquakes provide engineers with the opportunity to gradually improve the building design code. In California there were two major revisions to the building code: one after the Long Beach Earthquake in Los Angeles in 1933 and another after the San Fernando Earthquake in 1971. Buildings constructed before 1933 did not consider earthquake resistance and are consequently more vulnerable. The San Fernando earthquake pointed out deficiencies in concrete tilt-up structures built before 1971. They often lacked proper connection between the roof and tilt-up panels. Consequently, the walls of a number of tilt-ups separated from the roof diaphragm and collapsed outward on strong ground shaking. In general, building age can be used to infer the design code used to construct it and therefore to select the appropriate vulnerability function for use in loss prediction.

Besides construction and age of a building, other factors that are important in assessing vulnerability are the geology and geography of the site and the value of the covered policy. Accurate classification of underlying soils for earthquake loss modeling and surrounding surface terrain for hurricane loss modeling can aid an insurer in estimating expected loss. Furthermore, residential policies often use tax assessor data, which are generally outdated and under-valued. As discussed in Chapter 4, under-valued exposure will result in under-estimating potential insurer's loss.

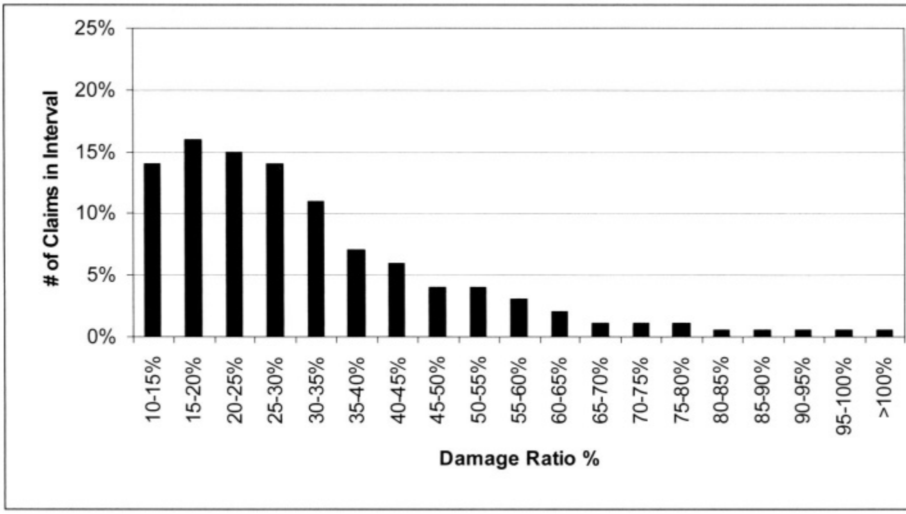


Figure 6.4. Dwelling loss experience for the 1971 San Fernando earthquake.

6.4.2 Uncertainty Modeling

The uncertainty surrounding a loss estimate from a catastrophe model is of paramount importance. One cannot properly allocate losses to different parties simply by using the expected or mean value of the potential ground-up loss. The entire loss distribution needs to be considered in the process. For example, a review of empirical data on building performance reveals that for a given event magnitude, a great deal of variability exists in damage to the same type of structure. Figure 6.4 highlights the variability in building performance for wood frame dwellings, normalized to similar levels of ground motion and soil conditions (Algermissen and Steinbrugge, 1990).

To illustrate the importance of the variability in a loss estimate, suppose the estimated damage to a building has a probability density distribution as depicted in Figure 6.5, with a mean damage ratio (ratio of dollar loss to replacement value of the structure) of 7%. In addition, suppose the deductible on each individual insurance policy is 10% of the structure's value. A loss allocation based on the mean damage can be compared to one based on the damage ratio distribution. In the former, because the mean damage of 7% is less than the deductible (10%), it appears as if the policyholder incurs all of the loss. In the latter, a random damage ratio is sampled from the distribution curve, and the loss is allocated based on the sampled damage and the deductible.

All of the sampled losses that are below the deductible must be paid by the policyholder. For sampled losses above the deductible, the first 10% is covered by the policyholder and the excess is paid by the insurer. If all losses are then weighted by the appropriate probability of occurrence, the resulting net mean loss allocations are 5.2% for client, and 1.8% for insurer (Table 6.5). Thus, if only the mean damage is used to estimate loss, the loss allocation to the policyholder and insurer can be inaccurate. In general, deductibles influence the allocation of losses between insurer and insured at the low end and coverage limits affect the allocation of losses at the high end.

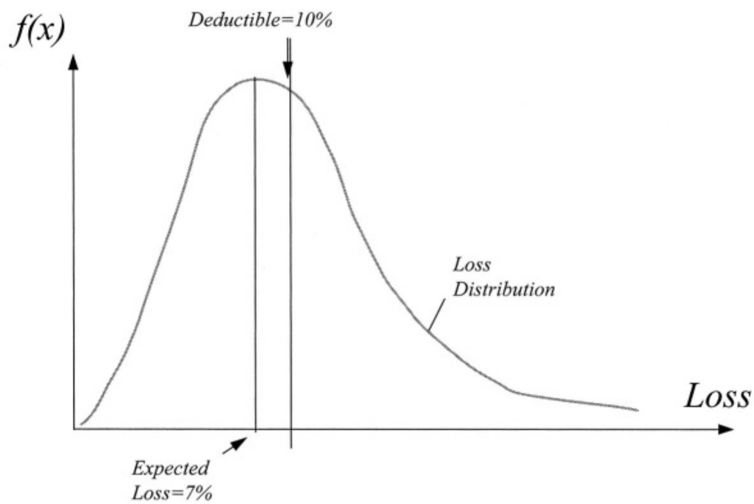


Figure 6.5. Simple example of the difference between expected and distributed loss allocations. (Source: Shah and Dong, 1991)

Table 6.5. Uncertainty in catastrophe modeling.

Allocation Method	Client Loss	Insurer Loss
Point-estimate	7%	0%
Distributed	5.2%	1.8%

6.4.3 Impact of Correlation

An important consideration in portfolio risk management is correlation between losses from different policies. Since most portfolios contain policies at multiple locations and the losses at each location are random variables, the aggregate loss to the portfolio has to incorporate the loss correlation between geographic regions. If losses across regions are independent of one another and the number of locations in a portfolio is large, then the aggregate loss for the portfolio will be highly diversified with a sharp peak at the mean and low variability. On the other hand, if losses across some or all regions are highly correlated, then the aggregate loss for the portfolio will have a large variation and there is a greater chance that claims payments will penetrate the higher levels of loss, thus exceeding the survival constraint.

Currently there are few published studies that investigate the factors influencing loss correlation from a given event. Major factors affecting loss correlation include geographic and site condition concentration, parameter uncertainty in vulnerability modeling, and model uncertainty for hazard attenuation. As discussed in earlier chapters, geographic concentration of a portfolio will normally increase the chances of a large loss from a single disaster. Post-event surveys for both earthquakes and hurricanes have pointed out the existence of local pockets in which all structures suffered more (or less) severe damage as a group than similar buildings in neighboring areas.

For earthquakes, this high correlation is usually due to local conditions that can focus ground motion. Such localized effects are not usually included in general attenuation models. For hurricanes, such effects are observed with the presence of localized tornados within the broad affected area, with affected buildings suffering much higher damage than other structures subject solely to hurricane wind and waves. These localized effects are generally not considered in the general wind field model.

Concentration of locations subject to certain site conditions, such as subsurface geology for ground motion or terrain roughness for wind, will impact loss correlation. If buildings in a portfolio are all located in the vicinity of an area with common geology or terrain, there will be a higher loss correlation within such a portflio. This phenomenon is most important from an earthquake perspective. While a geographically concentrated portfolio could clearly suffer site condition concentration, it is quite possible for a portfolio to have a strong site condition concentration while being geographically distributed.

Finally, if the mean damage ratio for a particular building class is underestimated by the model, then the calculation of losses to all such buildings will be lower than the actual figures, as was the case for wood frame buildings after the Northridge earthquake. If all buildings in a portfolio are located at the same distance from the rupture of an earthquake fault, there is a good chance that all ground motion estimates may be off simultaneously using a particular attenuation model than if the portfolio of buildings were located at a wide range of distances from the rupture. A recent study has tried to quantify the spatial correlation of probabilistic earthquake ground motion and loss (Wesson and Perkins, 2000). This type of risk quantification can improve the portfolio risk management process.

6.5 Summary

An overview of how the insurance sector manages catastrophe risks from natural hazards using a portfolio approach has been presented. A portfolio manager needs to balance pricing with exposure. Pricing is related to the expected annual loss and its uncertainty. Likewise exposure is related to the loss exceedance probability: the likelihood of a crippling loss must be kept at an acceptably low level. The framework based on engineering modeling addresses these and related requirements.

Several points are worth repeating. Adequate portfolio risk quantification involves not only the expected level of loss, but also the associated uncertainty and correlation. Major sources of loss correlation are geographic concentration, site condition, attenuation and vulnerability. In the quantification process, it is also important to recognize that data quality is important; uncertainty or lack of information on the property, site and exposure must be incorporated and accounted for in the risk estimate. The risk modeling framework discussed in the chapter is an essential tool. Reinsurance is an important tool for portfolio risk management and is discussed in the next chapter.

6.6 References

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Chapter 7 – Risk Financing

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7.1 Introduction

Natural hazard risks are associated with high severity, low frequency events. The significant losses caused by these events can lead to earnings volatility and drain the economic value of organizations. There are many ways of financing these shock losses to alleviate the disruptions they cause.

The focus of this chapter is to discuss alternative methods for dealing with the financial impact associated with natural hazards. Risk assessment deals with understanding a company's current risk profile through the use of catastrophe modeling and the creation of exceedance probability (EP) curves. Once it is determined, for example, that a company's 1–in–100 year loss is unacceptably high, the question becomes: what actions can be taken to address this risk? Risk transfer is one approach to financing risk and deals with techniques to change the shape of the EP curve with the goal of achieving a risk profile consistent with management's objectives and tolerance for risk.

The next section discusses which risks should be financed. Section 7.3 provides an overview of various funding mechanisms and how they respond to losses from natural hazards. Starting with a review of traditional reinsurance products and their evolution to customized products such as triggers, carve-outs and multi-year contracts, a discussion of the emergence of insurance-linked securities as a risk transfer mechanism follows along with an exploration of the key role that catastrophe models play in the crafting of such transactions.

The structure of these instruments is explored in Section 7.4 and techniques are introduced for dealing with the uncertainty introduced by basis risk, a measure of the extent to which the cash flow provided by the financial instrument may not reflect the actual losses experienced by the issuer. The chapter concludes by developing an evaluation framework that companies can use to assess alternative options and make sound strategic risk financing decisions.

7.2 What Risks Should Be Financed?

There is a significant lack of relevant historical experience regarding natural hazard events and other such catastrophes. As a result, companies do not have access to reliable historical loss data to assess their likelihood of sustaining future losses or to assess the effectiveness of various risk financing schemes. In the absence of historical data, catastrophe models that simulate potential catastrophe experience for over thousands of years can be helpful. In addition to modeling random events, the parameters of known historical events can be used to estimate the potential current impact if similar events were to occur today. These models produce exceedance probability (EP) curves that estimate the likelihood that losses will be greater than a given level as shown in Figure 7.1. By using models to look at risk probabilistically the company can appropriately quantify the impact of financing various risks.

A thorough assessment of the current risk profile including the risk from catastrophes combined with the company's tolerance for risk and available resources will determine the level of risk the company is comfortable retaining. As a starting point, the company will want to answer the following questions:

- How will peer companies be affected by similar events? Losing 20% of company surplus is a devastating event; however its impact on the ongoing viability of the company will be much worse if peer companies only lose 5-10% of their surplus.
- What level of retention and limits of loss are rating agencies and regulators concerned about? Historically, both have focused on 100-year hurricanes and 250-year earthquakes.
- What is the single largest loss that could be sustained without leading to financial impairment? After a certain level of loss the company will be facing a rating downgrade that may affect its competitive position. The company can review various rating and regulatory ratios to see how much of a loss would cause concern.
- What is the impact of multiple losses within a short period of time? In addition to a single large loss, the company must also be concerned about the aggregate loss that may arise from smaller catastrophes over the year. Losses from such catastrophes may come from a single peril or a combination of perils.
- What is the appropriate time horizon to consider in determining which risk financing strategy to pursue? The company will need to analyze the impact of catastrophic losses over a period of time – for example, over a five-year period. Similar to the case of accumulation of losses in a single year, the company needs to consider the possibility of multiple years of abnormal levels of catastrophe losses.

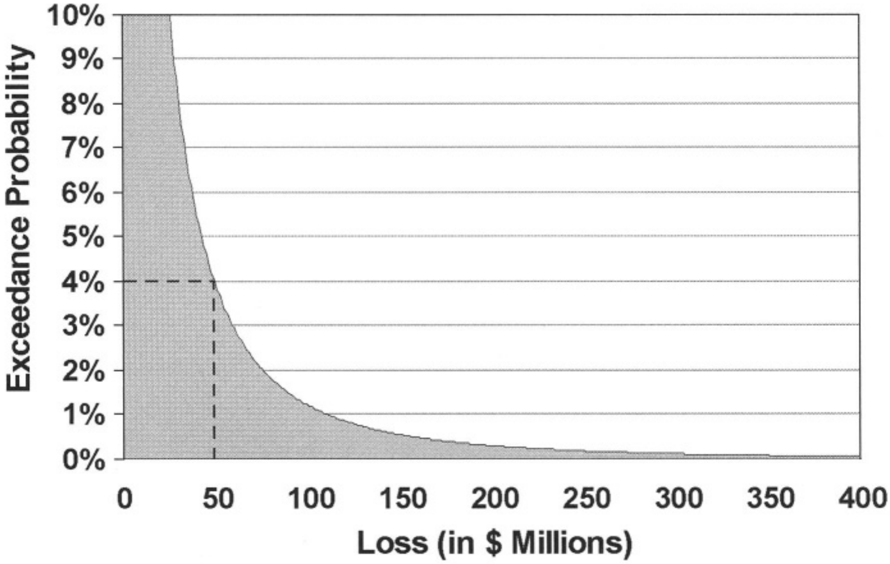

Figure 7.1. Exceedance probability curve.

7.2.1 Level of Risk

The first step in determining an appropriate risk financing strategy is to undertake a risk assessment based on the company's current portfolio. As demonstrated in Part II of the book, catastrophe models provide the probability of exceeding any given level of loss, as well as measures of uncertainty. The goal is to devise strategies to optimize expected return given the company's risk profile and subject to satisfying various constraints. Besides the obvious survival constraint, the company must consider constraints such as the difficulty of changing an existing portfolio, the prevailing conditions and regulatory issues. Figure 7.1, for example, shows a 4% probability per year that gross losses (losses before any risk transfer) will exceed $50 million – a level of risk that the insurer may decide is unacceptable.

One of the constraints faced by the company is that, in order to write business, it must hold an acceptable level of capital. While minimum capital requirements are set by regulation, the true amount required depends on the risk profile of the underlying business. Catastrophe models, which depict the full distribution of potential losses, can be helpful in this regard. There are costs associated with holding capital; higher amounts of capital reduce company leverage. In the example above, consider the strategy of transferring the layer of potential loss between $50 and $100 million to another party, rather than holding surplus to cover the loss directly. These potential losses are represented by the darker shaded area in Figure 7.2. By removing, or ceding, that part of exposure, the company can successfully change the shape of the EP curve and its risk profile.

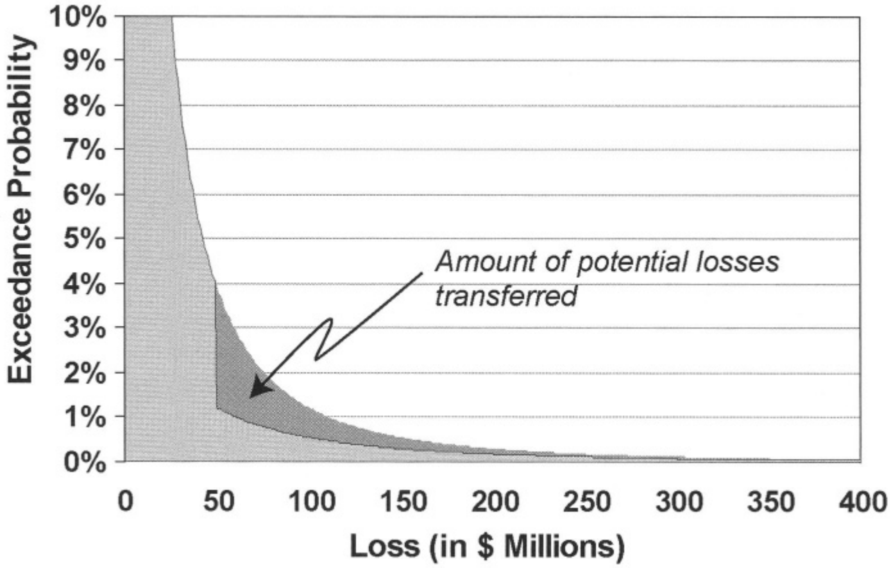

Figure 7.2. The shape of the exceedance probability curve, and therefore the risk profile, is altered by the transfer of risk.

Although the layer discussed above is amenable to risk transfer, in the extreme tail of the EP curve, there is a point at which the cost associated with transferring the risk can be prohibitive. For this layer, the company will be forced to retain the risk. For ease of analysis, the risk profile illustrated by the EP curve above can be segmented into losses that the company can handle through normal operations, losses that require some level of risk transfer/financing and losses that are not economically feasible to finance.

7.2.2 Probable Maximum Loss (PML)

Once the insurer has determined at what point along the EP curve consideration of risk financing options should start, the next question is to determine the amount of financial protection desired. Companies often determine the amount of risk to retain and which risks to finance based on the concept of probable maximum loss (PML). As discussed briefly in Chapter 2, PML is a measure of risk corresponding to the largest loss the entity can reasonably be expected to experience. Often, PML is defined as a return period, which is the inverse of the probability that losses will exceed a dollar threshold.

A 500-year return period loss of $100 million, for example, implies that losses above this amount have a probability of 0.2% of occurring in any given year. Should an insurance company worry about protecting itself against levels of catastrophe loss with a 0.2% probability of occurrence? What about a 1-in-1000 year loss, or 0.1% probability? How large a loss along the EP curve is it economically viable to protect against?

These questions can only be answered in the context of the level of other risks facing the enterprise. For example, if a company purchases reinsurance to protect against a 250-year return period loss (probability 0.4%) and files for bankruptcy after an economic downturn that had a probability of 1%, it has deployed its capital inefficiently. Using catastrophe models to measure the impact of risk financing strategies to alter the EP curve yields the changes in risk. The costs and impact of other company operations must also be considered. These questions are addressed through the evaluation framework discussed at the end of the chapter where catastrophe models are integrated into enterprise risk management. The scenario that maximizes the company's return given their level of risk tolerance will yield the answer as to which risks should be financed.

7.3 Risk Financing Mechanisms

Natural hazard events can lead to concurrent losses on multiple exposures. Continuation of operations depends upon a company's ability to meet its obligations to policyholders and have sufficient resources remaining to pay operating expenses. How a company weathers the event will have an impact on the perception of those in the market and its financial ratings. There is usually an immediate need to pay losses after an event. In fact, quick payment of obligations can have a mitigating effect on total loss. In the following pages, the many financing mechanisms available to pay for catastrophe losses are explored, as well as the implications of employing each. The mechanisms can be classified under two broad categories: generating funds internally or transferring risk.

7.3.1 Generating Funds Internally

When the company chooses to retain risk, it must generate funds internally to pay for losses resulting from a catastrophe. Options available include the following: maintaining funds on hand, borrowing, issuing debt, and issuing equity.

Maintaining Funds on Hand

Funds on hand are usually in the form of physical assets or investments. First, consider funds that can be generated internally by selling physical assets. This can be problematic in that physical assets may not be very liquid and the likelihood exists that the realized value of the assets can be reduced due to the urgency of the liquidation. Additionally, selling assets may impede the company's ongoing operations. On the other hand, the financial benefit of asset liquidation is immediate and there is no lingering debt to affect future earnings.

Funds can also be generated internally by selling investments. An issue of concern here and with the liquidation of physical assets is that the portfolio will have a market gain or loss associated with the sale. If the portfolio has an embedded gain, the catastrophe loss may offset this and reduce the tax burden associated with selling investments that have been profitable. If the portfolio has an embedded loss, the catastrophe will compound the situation, resulting in further impairment of the company.

Funds can also be generated internally by maintaining a catastrophe reserve that finances potential losses in advance over time. In the U.S., this entails the accumulation of after-tax profits into a dedicated account. However, this capital could perhaps be used more advantageously elsewhere, depending upon alternative investment opportunities. The advantage of the reserving approach is that the cost of future events is spread out over time, resulting in more stable earnings.

Borrowing

Companies can choose to borrow funds to cover catastrophic losses. The amount required, however, is likely to be quite large. It will be difficult to arrange for an appropriate level of funds quickly, and because there will be simultaneous demands for funds from other parties, the cost of borrowing can be driven up significantly. Since the cost of borrowing funds to finance losses is unknown until the catastrophe event actually occurs, it is very difficult to plan for this financially. However, options do exist for establishing a line of credit with a preset interest rate spread.

Issuing Debt

The issuance of debt into the market is another form of borrowing. Mutual companies can also issue surplus notes. Again, however, if many parties are trying to place debt simultaneously and the company's financial position is compromised, the rate of return required to attract investors can be artificially high.

Issuing Equity

By issuing equity, the company's current shareholders forfeit some level of ownership and future profitability in exchange for the funds required to finance current obligations. Furthermore, in the immediate aftermath of a catastrophe event, the company's stock price may fall, thus raising the implicit cost of issuing equity.

In general, it is beyond the means of most insurance companies to generate internally the funds necessary to absorb catastrophic losses, though such a strategy may be appropriate for normal operational risk or to absorb small shock losses. In managing catastrophe risk, there is usually a need for some element of risk transfer.

7.3.2 Risk Transfer – Reinsurance

In anticipation of catastrophic events, companies transfer risk by arranging for the right to some level of reimbursement or indemnification when losses actually occur. In all cases, however, the company retains ultimate responsibility for the payment of losses; thus the credit worthiness of the entity to which risk is transferred is an important consideration. Traditionally, risk transfer has been accomplished through reinsurance. In exchange for a premium, the company transfers to a reinsurance company the risk of part of their loss from a given set of exposures. Over the years, the level of sophistication in the reinsurance market has grown as companies have become better able to identify and quantify their risk. The most common form of reinsurance for catastrophes is to protect against losses between a minimum and a maximum amount, with refinements for specific lines of business and geographic regions.

Traditional Reinsurance

The topic of traditional reinsurance is covered in many texts on reinsurance (for example, Carter, 2000). There are two main types: pro rata reinsurance, in which premium and loss are shared on a proportional basis, and excess of loss reinsurance, for which a premium is paid to cover losses above some threshold. Figure 7.3 illustrates how these types of reinsurance contracts relate to the whole of risk transfer. While a certain amount of pro rata reinsurance is used for catastrophe protection, excess of loss reinsurance is the predominant form.

Custom Features in Reinsurance Contracts

The increased sophistication and resolution of models used to analyze catastrophe risk have enabled reinsurers to offer many custom features in their products to meet the growing demands of insurers. Some examples include: carveouts, triggers, multi-year contracts, industry loss warranty, and dual trigger products.

Carving out exposures – Carveouts involve excluding a certain region from the reinsurance program, such as a particularly vulnerable group of counties. Some reinsurers have offered protection at a lower cost when certain areas (where the reinsurer may have already accumulated exposures) are excluded. Carveouts can also apply to particular lines of business or perils. In a carveout arrangement, the insurer retains the riskiest part of the exposure and must find an alternative financing mechanism if it wants to transfer this risk.

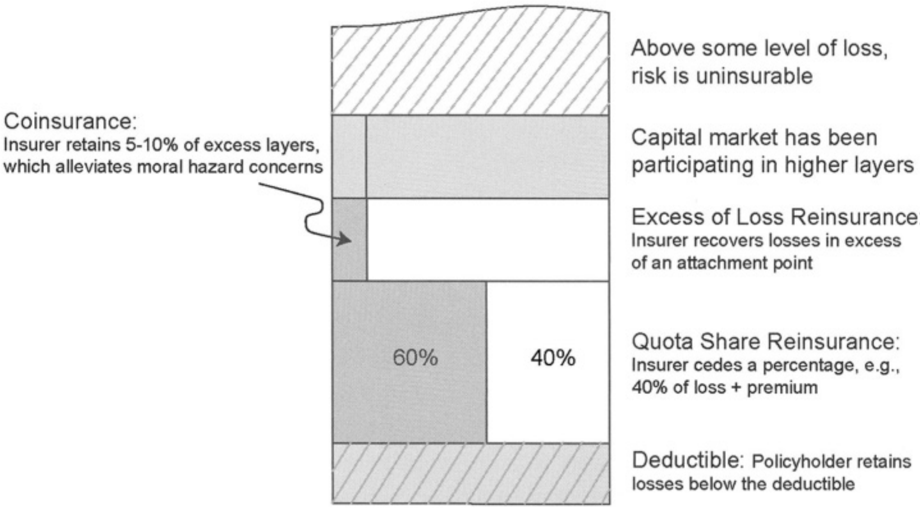

Figure 7.3. Overview of transfer risk: policyholder, insurer, reinsurer, capital market.

Triggers – Reinsurance programs can be activated as the result of triggering events, such as a threshold industry loss, a second catastrophe event, or a threshold loss ratio. An insurer may be able to finance internally a single catastrophe but may need protection should a second or multiple events occur in the same time period. Catastrophe models generate many years of catastrophe activity and can be used to determine the probability of one, two, or more catastrophe losses in a given year. Hence, they can be utilized to design a reinsurance program with a trigger that is most appealing to the primary insurance company.

Multi-year contracts – Companies may want the guarantee of coverage at fixed or indexed variable costs over a longer time horizon. Multi-year reinsurance contracts can be used to achieve these objectives. Most multi-year contracts are two to three year deals and include cancellation provisions.

Industry Loss Warranty – These contracts pay out only if total industry losses arising from the catastrophe event are greater than some specified amount; they do not, therefore, require a detailed analysis of an individual company's exposures. In addition, they do not require a detailed assessment of the company loss once a catastrophe occurs. From a primary company perspective, industry loss warranties carry basis risk. This concept is discussed in more detail later in this chapter.

Dual Trigger Products – Companies may be able to pay catastrophe losses out of their investment portfolio. If interest rates have risen, however, their bond portfolio could contain significant unrealized capital losses.

Realization of these losses at the same time that a catastrophe loss is experienced would be devastating to the financial performance of the company. Buying reinsurance wastes capital because the protection is not needed unless the company faces catastrophe and investment losses simultaneously. This scenario has led to the development of dual trigger reinsurance products that pay only if both a reinsurance retention and an economic trigger have been breached.

Contingent Products – Some innovative products have been developed that provide the right to generate funds if an event happens. These include contingent debt, contingent equity (CatEputs™), and even contingent future reinsurance availability. In the latter, for a premium, the company has the right to purchase reinsurance protection at a prearranged price, if a predefined event occurs.

7.3.3 Risk Transfer – Securitization

Immediately after Hurricane Andrew occurred in 1992, reinsurance rates became expensive and availability was restricted. This event led companies to take a more focused look at determining which risks drive their catastrophe exposure and to restructure traditional reinsurance contracts to address specific areas of concern. Catastrophe models, with their detailed level of output, have been instrumental in the refinement of this market by providing the tools for insurers to structure their contracts and for reinsurers to price and manage them within their broader portfolios of catastrophe exposures.

While the reinsurance market is the traditional venue for risk transfer contracts, insurance-linked securities that transform reinsurance contracts into securities are now being sold in the capital markets. The securitization of catastrophe risk is an increasingly popular route as both insurance and reinsurance companies seek alternative sources of capital.

The capital markets are many times larger than the reinsurance market and experience daily fluctuations in value greater than the largest contemplated catastrophe. In addition, catastrophe risk is potentially attractive to the capital markets due to its demonstrated lack of correlation with other investments. Insurance-linked securities offer a means of diversification in capital market portfolios and thus, theoretically, allow the capital markets to accept catastrophe risk with a lower risk load than reinsurers.

Most reinsurance contracts are indemnity based; that is, they pay losses in accordance with the insured's actual underlying losses. The capital markets have introduced derivatives, whereby payments are tied to an underlying indicator, such as an index of industry losses or the occurrence of a disaster of a given magnitude in a particular location.

The securitization of insurance risk is still evolving as new twists are added to find an effective balance between the needs of the issuers (the insurer) and those of the investors. The issuer desires risk transfer with minimal basis risk so that the amount of the payment from the risk transfer instrument reflects the actual losses for which it has contracted. The issuer would also like broad coverage, competitive pricing, and no counterparty credit risk. Investors want transparency, limited or no moral hazard and maximum yield.

Securitization is more involved than traditional reinsurance in terms of the time and expenses needed to implement each transaction. These costs include underwriting fees plus additional legal, rating agency, and modeling fees. The time commitment on the part of senior management is also significant, as potential investors need to be educated on the assessment of catastrophe risk.

Traditional reinsurance treaties are usually of one-year duration. Through multi-year securitization, the issuer can achieve multi-year risk transfer capacity while avoiding fluctuations in the price of reinsurance and, at the same time, lowering the marginal transaction costs associated with the securitization itself. The process involved in issuing a catastrophe bond can be divided into four basic steps: loss estimation, ratings, prospectus, and investor education.

Loss Estimation

The risk analysis performed by the catastrophe modeler is fundamental to the very structure of the transaction and to its pricing strategy. The underlying risk assessment involves validation and mapping of exposure data and analysis through the catastrophe model. This analysis produces detailed output used to assess the risk and structure the transaction. The key output is the exceedance probability (EP) curve. The attachment point corresponds to the level of loss where the investor will start to lose principal. The exhaustion point is the level of loss at which the investor has lost all of his or her principal. Further analyses of loss probabilities, by peril, line of business, and geography help investors understand how the catastrophe bond may correlate with other securities in their portfolio.

Ratings

Ratings assigned by agencies such as Standard & Poor's, Moody's Investors Service, and Fitch, allow investors to compare the offered insurance-linked security with other corporate bonds with which they are more familiar. Investors do not have the insurance and catastrophe modeling experience and resources of reinsurance companies. They rely, in part, on the research and due diligence performed by the securities rating agencies, which subject the underlying exposure data, the catastrophe models, and the transaction's structure to extensive scrutiny.

The modelers present the results of detailed sensitivity analyses of all major components of the model. Independent experts are also used by the rating agencies to perform stress tests for model robustness. Since catastrophe bonds made their debut in 1996, rating agencies and, to an increasing degree investors, have become quite sophisticated with respect to catastrophe modeling technology.

Prospectus

The prospectus describes the details of the model results. It contains language on the limitations of the analysis and risk factors designed to alert investors of the variability inherent in the catastrophe modeling process. It contains all available information related to the transaction. Over time, disclosure of exposure data and results has become increasingly detailed and the presentation of results is becoming more standardized, allowing investors to better compare transactions.

Investor Education

Investor education has been an important feature in the early development stages of the insurance linked securitization market. Road shows, conference calls, and other investor meetings are required to explain the catastrophe modeling process. There are numerous interactions with investors who require a more careful analysis of the correlation between transactions and real time information on actual events.

7.3.4 Securitization Structures

Figure 7.4 illustrates the typical structure of a catastrophe bond issued in a securitization transaction. The issuing company enters into a reinsurance agreement with a special purpose vehicle (SPV), which transforms insurance risk into investment risk. The issuer pays a premium to the SPV in exchange for loss payments should a covered event occur. The SPV in turn issues securities to finance the coverage. The investors, or noteholders, who purchase the securities are essentially putting up the principal and they receive interest payments equal to a risk free rate, such as LIBOR (London InterBank Offered Rate) and a risk premium. Additionally, they receive the return of their principal investment less any loss payments that may be made.

The funds raised from the issue are deposited into a collateral account and invested in high-grade securities. By entering into a total return swap with a highly rated counterparty, the return on the collateral account is converted to LIBOR and the assets in the collateral account are guaranteed. This feature is used to provide an enhanced return to the collateral account.

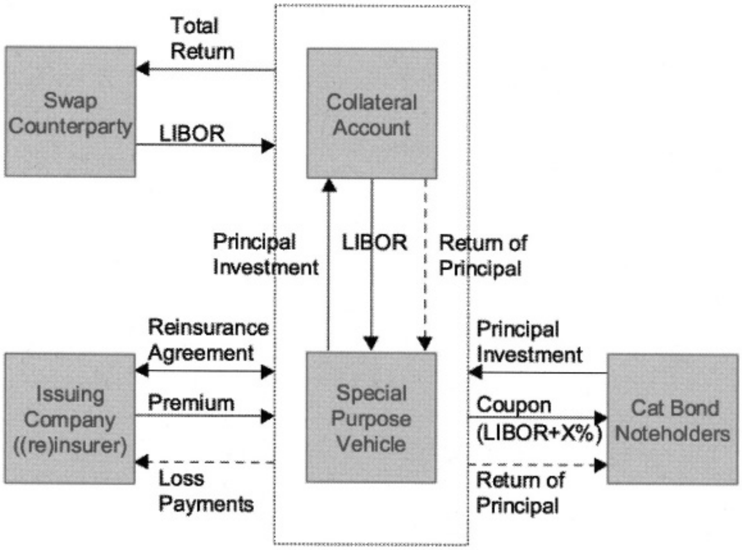

Figure 7.4. Typical securitization structure.

The catastrophe modeling undertaken in support of the transaction reveals the probability that investors will recover their principal in full, in part, or that they will forfeit their principal altogether. The yield on the notes depends on these probabilities, as does their rating. Any default on the notes is triggered by the occurrence of an actual event or events during the period of coverage. The principal, which has been held in trust, is then used to pay the losses of the issuer, or cedant (i.e., the party ceding risk).

The nature of the modeling undertaken to determine these probabilities will depend on the type of transaction, of which there are four principal types that are now discussed (indemnity, index, parametric, and notional portfolio).

Indemnity-based Securitizations

Indemnity-based securitization transactions most closely resemble reinsurance than any type of new financial instrument. Losses from a catastrophe are paid on the basis of actual company losses. The indemnity transaction is suited to situations where certainty of full recovery is critical.

Investors examine individual transactions independently; reinsurers, on the other hand, are familiar with the underwriting process and have long-term relationships and other non-catastrophe business with their clients. The questions and concerns of the investor and the reinsurer will thus differ significantly. A company undertaking a securitization transaction will need to perform a very detailed review of its underwriting processes and data handling.

The quality of the exposure data is critical to the process. In the case of indemnity-based transactions, data should include location, construction type and occupancy; it may also include age, building height, and other information. If more detailed data are available on individual risk characteristics, such as the presence of storm shutters, these can be used in the analysis. Both the purchaser of the bond and the modeler spend considerable effort in evaluating the data and determining whether they meet logical and reasonability tests.

A key concern of the investor is moral hazard, the extent to which the purchaser of the bond is able and willing to control losses. For this reason alone, the investor will want to thoroughly understand the company's motivation for the transaction. This is an area where reinsurers have greater efficiency than investors. In indemnity-based transactions, mechanisms to reduce moral hazard can be built in. Such mechanisms include deductibles, coinsurance, co-participation in the losses or the use of a triggering event, such as restricting recovery to losses from a Category 3 or greater hurricane. The company has no control over these events.

The first truly successful catastrophe bond issues came in 1997. The largest of these was a transaction by which the United Services Automotive Association (USAA) ceded $400 million of hurricane risk to Residential Re, a special purpose vehicle (SPV) set up for the sole purpose of this transaction (Froot, 1999). Funds raised from investors by Residential Re were held in trust for the purpose of paying USAA for claims against it resulting from hurricane losses along the Gulf and East Coasts of the United States. Residential Re has renewed its issue at different amounts every year and in 2002 expanded coverage to include Hawaii hurricanes. Catastrophe modeling was a key component in supporting the transaction and was used to estimate expected losses on USAA's book of business (Figure 7.5).

Figure 7.5 specifies USAA's exposure and policy conditions for insured losses, as well as the detailed output and reports needed for the issue. Insured losses are calculated by applying the specific policy conditions to the total damage estimates. Policy conditions may include deductibles by coverage, site-specific or blanket deductibles, coverage limits and sublimits, coinsurance, attachment points and limits for single or multiple location policies, and policy-specific reinsurance terms. Explicit modeling of uncertainty in both intensity and damage calculations enables a detailed probabilistic calculation of the effects of different policy conditions.

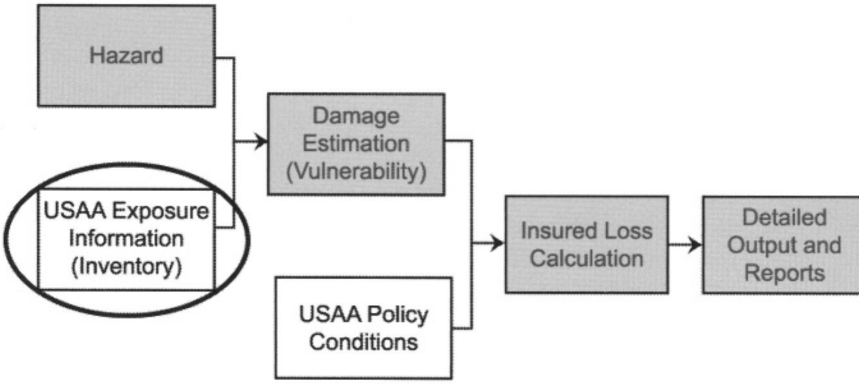

Figure 7.5. Catastrophe modeling components for an indemnity-based transaction.

Probability distributions of losses and their complement, the exceedance probability curve, are estimated for potential levels of annual aggregate and occurrence losses that the insurer may experience given their book of business. The curves also provide the probabilities of attachment for various reinsurance layers and therefore the probabilities that investors will suffer a loss of interest on, or all or part of the principal amount of, the notes.

In the 1997 Residential Re transaction, which was a one-year term, actual losses could be triggered by the occurrence of any single Gulf or East Coast hurricane of Saffir Simpson Category 3 or greater that resulted in losses to USAA in excess of $1 billion. Concern about moral hazard was ameliorated, at least in part, by a 20% coinsurance arrangement by USAA in the securitized reinsurance layer. The structure of that initial issue is shown in Figure 7.6. This structure has remained largely the same in subsequent years, though the size of the issue has varied.

The results of the risk analysis performed for this transaction indicated that the probability that USAA's hurricane losses would exceed $1 billion and that the holders of the notes would suffer a loss was 1%. Further, the probability that it would suffer a complete default was 0.39%. The transaction was the first to be rated by all four rating agencies in existence at the time (Moody's Investors Service, Standard & Poor's, Fitch, and Duff & Phelps).

Index-based Transactions

In index-based transactions, the model estimates losses on estimated industry exposures with the trigger based on actual industry losses resulting from an event. Industry-wide losses are typically used for catastrophe indices. Based on the industry losses from an event, a formula is used to derive payment to the company.

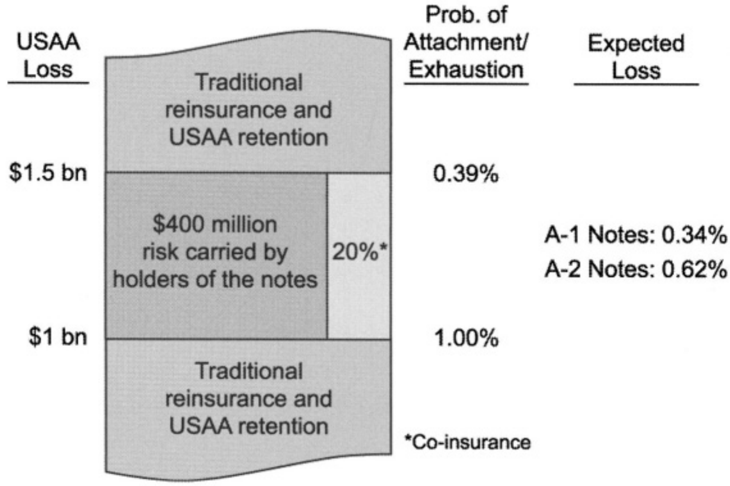

Figure 7.6. 1997 Residential Re (USAA) summary features.

Two issues that need to be addressed to accommodate the increasing use of such derivatives are pricing and basis risk. Specifically, is pricing competitive with that of traditional reinsurance products, including any additional monitoring and educational costs? Is there strong correlation between the underlying variable and the variable being hedged so that there is limited basis risk? A third issue, availability, requires the first two issues to be settled.

Index-based contracts are attractive to investors because they only have to understand and evaluate the index, not underwrite individual companies. In order to minimize basis risk, companies must assess what their loss would be given a particular industry loss. Reviewing market share, as well as correlation with past industry losses can help accomplish this.

From an investor's point of view, index-based transactions are attractive because they reduce moral hazard, since an individual cedant has little control over industry losses. To estimate expected losses on the notes, a catastrophe model is utilized. Modelers have developed, in house, detailed databases of property values. These annually-updated databases include estimates of total property exposures, typically at ZIP code resolution. Data include the number of risks and their values broken down by line of business, by coverage, by occupancy, and by construction type. The modeling process is illustrated in Figure 7.7 on the next page. The hazard components of the model operate in the same manner as for the indemnity-based transaction. The hazard is superimposed on industry exposures and damages are estimated, as before. Insured losses are calculated by applying industry average policy conditions.

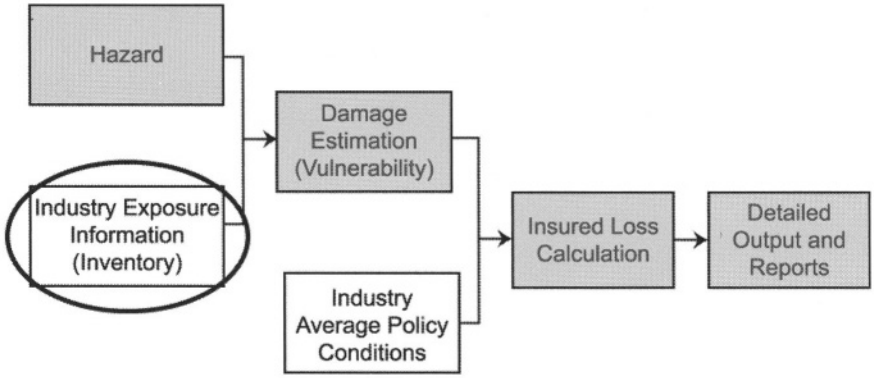

Figure 7.7. Catastrophe modeling components for an industry index-based transaction.

In February 2001, Swiss Re ceded $ 100 million of earthquake risk to Western Capital, an SPV. Western Capital, in turn, issued $97 million in notes and $3 million in preference shares. Funds raised are held in trust for 23 months to pay claims resulting from industry earthquake losses in California.

This type of transaction is called a transformer, since Swiss Re was ceding the residential risk they underwrote for the California Earthquake Authority (CEA) into the capital markets via an industry loss measure. Swiss Re thus transformed CEA residential losses into industry losses, accepting the basis risk. The reporting agent of industry losses is Property Claim Services (PCS). PCS develops its estimate of industry loss by conducting surveys of insurers after the occurrence of a catastrophe event. The structure of the Western Capital transaction is illustrated in Figure 7.8. If industry losses from an earthquake in California between February of 2001 and January of 2003 were less than $22.5 billion, then investors in this contract would pay nothing. If these industry losses exceeded $31.5 billion, they would pay $97 million to Swiss Re. No earthquakes of any sizeable magnitude occurred in California during this 23-month period.

One advantage of the index-based transaction from the point of view of the cedant is that there is no need to disclose details of its book of business, since losses to the notes are triggered by industry losses and not the cedant's book. From the investor's point of view, this also alleviates the problem of asymmetry of information; because the investor does not need to understand the details of the issuer's business or its risk profile, the risk inherent in the notes is easier to evaluate. Therefore, concerns about moral hazard, as well as adverse selection, are reduced.

The primary disadvantage associated with an index-based transaction is that the cedant is exposed to basis risk to the extent that its own exposures – and therefore losses – differ in kind and geographical distribution from that of the industry's, or from that of the index used to determine the payoff of the contract. It should be noted, however, that the modeler can help the cedant assess and minimize the basis risk by quantifying the correlation between the potential losses from the cedant's book of business and industry-wide exposures.

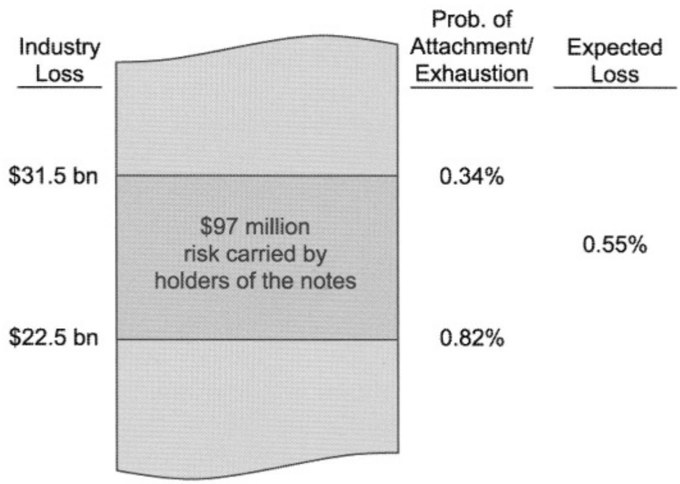

Figure 7.8. 2001 Western Capital summary features.

Another disadvantage is that the index of industry losses may require a long time to develop. Preliminary surveys are conducted in the immediate aftermath of an event, but results are revised as actual claims data come in. This may take months, particularly in the case of earthquakes. In order to alleviate this issue, if a triggering event or events occur during the covered period, the maturity date on the notes can be extended so that a more accurate value of the index can be determined. In this case, however, investors must be compensated with a higher return for the potential delay in receiving their payment.

Parametric Indices

This type of transaction uses a catastrophe model to estimate the likelihood that an event of or above a given intensity will occur in a given location during the covered period. Any payment to the cedant is triggered not by a loss amount, but rather by the physical parameters of the actual event, should one occur. More specifically, parametric index involves measuring an intensity measure at multiple locations in proximity to the portfolio risk sites, and weighting each recording by the values at risk and the vulnerabilities of each insured risk.

Payment depends on the intensity of an event as measured by an independent and objective third party, such as earthquake magnitude as measured by the United States Geological Survey (USGS) or a category hurricane issued by the National Oceanic and Atmospheric Association (NOAA). The basis risk from this type of contract depends on the correlation between the parameters of an event and the level of loss. The basis risk will be high if a large event produces limited damage or a mild event causes severe losses.

From the point of view of the investor, losses on the notes are no longer connected to the cedant's losses, thus obviating any need for the investor to understand details of the cedant's business – or of the industry's, for that matter. From the investor's point of view, only the hazard probability needs to be assessed and the catastrophe modeling process undertaken in support of the transaction only works with the hazard component of the model.

This is misleading, however. It is true that once the transaction has been structured and priced, the potential investor need only be concerned with gauging the modeler's expertise in estimating event frequencies and intensities, rather than in their ability to determine the vulnerability of structures and estimate probable losses on some book of business. From a cedant's point of view, however, the modeler must determine the most appropriate trigger – one that mitigates, as much as possible, basis risk. That determination will very likely involve a catastrophe loss analysis of the cedant's exposures. In the end, however, some degree of basis risk will remain, which can be quantified by the modeler.

Again, from the investor's viewpoint, both adverse selection and moral hazard are no longer issues, and risk on the notes is independent of the quality of exposure data. In January 2000, PRIME Capital issued two separate security offerings of $306 million based on parametric indices. Funds raised are held for three years to cover claims against Munich Re resulting from earthquakes in California, hurricanes in the Miami and New York City areas of the eastern seaboard, and European windstorm. The three-year deal protects Munich Re from fluctuations in the price of reinsurance and the parametric nature of the transaction provides transparency to the investor.

The epicenter of a triggering earthquake, for example, must be located within one of eight boxes, or seismic source zones, four around the San Francisco area (as shown in Figure 7.9) and four around Los Angeles. The reporting agent of epicentral location is the USGS. The moment magnitude (M_w) of a covered earthquake must be equal to or greater than certain defined magnitudes for each source zone for Munich Re to receive payments from the notes.

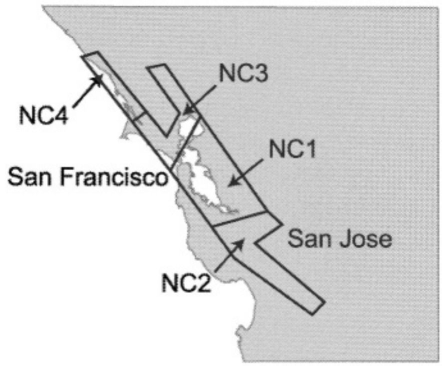

Figure 7.9. 2000 PRIME Capital (Munich Re).

Losses to the notes stemming from the occurrence of hurricanes are triggered by central pressure within certain defined landfall zones. The reporting agency here is the National Hurricane Center. For European windstorms, losses to the notes are triggered by a weighted parametric index calculated from wind speeds measured at stations across Western Europe, as reported by various governmental meteorological organizations. These transactions can be quite complex in structure.

In the case of parametric transactions, scrutiny by rating agencies and investors is focused on the hazard components of the catastrophe model. Here the scientific, rather than engineering, expertise of the modeler's professional staff of seismologists, meteorologists and climate scientists is of paramount importance.

Notional portfolio

Utilization of a notional portfolio is another form of indexing in which payments are based on loss to a fixed hypothetical, or notional, portfolio. This reference portfolio typically stays fixed during the period of coverage. The trigger is based on modeled losses on the notional portfolio.

A notional portfolio can be structured to closely resemble the issuing company's portfolio, minimizing basis risk. By virtue of a fixed portfolio, the investor is protected from changes in or differences from the underlying actual portfolio of an indemnity transaction.

Insurance-linked securities based on losses to a notional portfolio are among the more interesting transactions. They also put the highest demand on the catastrophe modeler for, in this case, not only does the modeler quantify the risk inherent in the notes, but is also the reporting agent in determining losses to the notes after the occurrence of a covered event. That is, the trigger is based not on actual realized losses, but rather on modeled losses.

The risks that comprise the notional portfolio are typically on the books of the cedant, though, theoretically, a notional portfolio could be an entirely synthetic construct. To minimize basis risk, it is structured to be representative of the cedant's exposures at risk from the covered peril(s). The model estimates expected losses by superimposing local intensity on the notional portfolio' exposures, damage functions are applied and estimates of insured loss are calculated by applying the policy conditions of the notional portfolio (Figure 7.10).

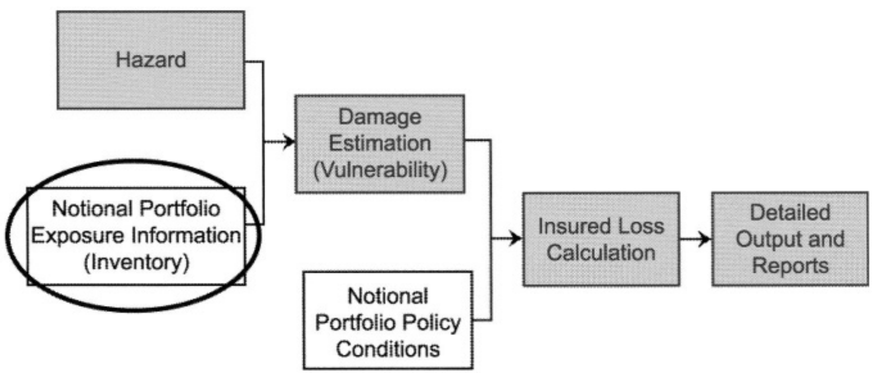

Figure 7.10. Catastrophe model for a notional portfolio.

The model and the notional portfolio then go into escrow for the duration of the covered period. If a qualifying event occurs, the model is pulled out of escrow and losses on the notional portfolio are estimated by inputting the actual physical parameters of the event into the model. Results will indicate whether the attachment point has been reached and what losses, if any, noteholders will experience.

From the point of view of the investor, the risk of moral hazard and the risk of portfolio growth are eliminated, since the notional portfolio stays fixed during the period of coverage. Uncertainty regarding data quality, vulnerability of the exposures and other variables is also eliminated in both the prospective risk assessment and the post-event loss determination. The cedant need not disclose as much information about its business as in the case of an indemnity-based transaction, but does face more basis risk because payments are based on modeled rather than actual losses.

Another issue with this type of transaction is the potentially complex nature of the loss calculation that takes place in the aftermath of an event. In order that it is as transparent as possible to all concerned parties, the catastrophe modeler must develop, in writing, a step-by-step post-event calculation procedure, also held in escrow. The parameters used as input into the model are named, as are the reporting agencies, and alternatives to those parameters are listed in order of priority if the preferred parameter is not readily available. The exact lines of computer code used to run the model are specified. The cedant, placement agency, and modeler work closely together to develop the procedure so that the post-event calculation will go as quickly and as seamlessly as possible (Figure 7.11).

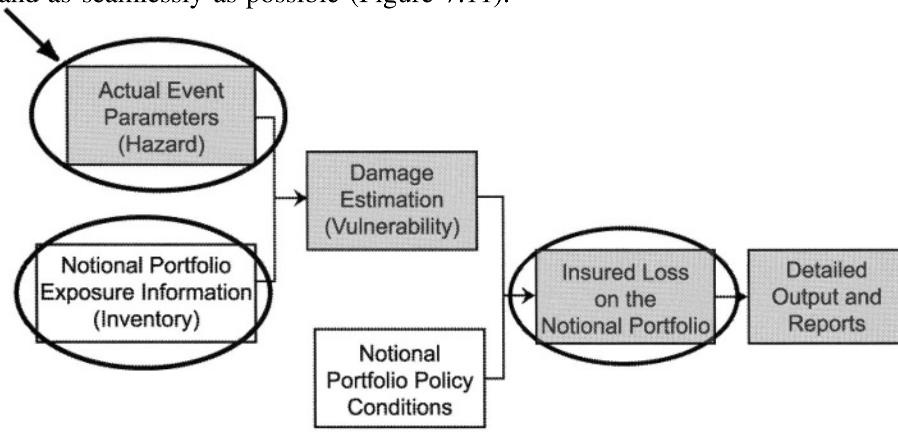

Figure 7.11. Catastrophe model for a notional portfolio after the occurrence of a trigger event.

In July 2001, Trinom Ltd. issued $200 million in notes and preference shares with a three-year maturity to provide protection for Zurich Re against hurricane, earthquake, and windstorm losses. A risk analysis was performed using catastrophe modeling on three separate notional portfolios structured by Zurich Re to match specific books of its European windstorm, California earthquake, and U.S. East Coast hurricane exposures. Figure 7.12 illustrates one small part of this multi-faceted transaction: Class A-1 Notes covering European windstorm.

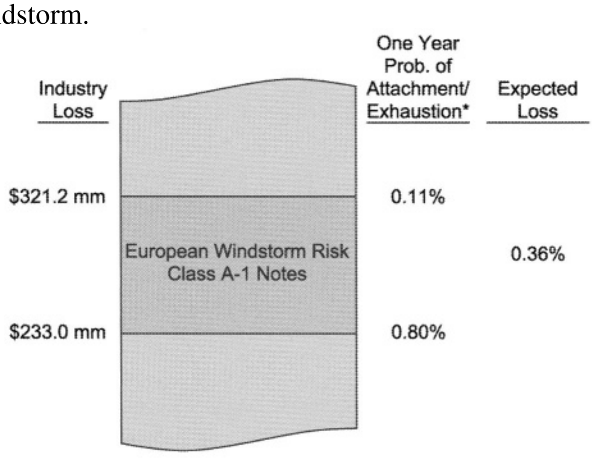

Figure 7.12. 2001 Trinom Ltd. (Zurich Re) summary features.

7.3.5 Dealing with Basis Risk

Basis risk arises in derivative products as a result of uncertainty associated with ability of the cash flows of the hedging instrument to exactly offset the cash flows from the instrument being hedged. Although there are several factors that may be present which lead to basis risk, the main concern for insurance companies using an industry-based index to hedge the company's catastrophe losses is the cross basis risk.

This arises when the company's losses will not be perfectly correlated with industry losses. This correlation will vary depending on the layer of loss and the region being examined. It is necessary, therefore, to ensure that correlation is being calculated between similar variables, e.g. losses within a specific layer. Examining the correlation of a company's past loss experience with industry losses may not be a good indicator of future correlation. Catastrophe models can provide estimates of both company and industry losses so one has the ability to examine correlation under a wide range of potential scenarios.

Table 7.1. Determining Basis Risk for the Layer $50M Excess of $100M

Event ID	Company Loss	Recovery with Reinsurance	Industry Loss Based Index	Index-based Recovery	Basis Risk
1	8	0	75	0	0
2	42	0	101	1	-1
3	153	50	140	40	10
4	156	50	139	39	11
5	200	50	250	50	0
6	133	33	130	30	3
⋮	⋮	⋮	⋮	⋮	⋮
10000	141	41	150	50	-9

The value of derivative transactions depends on how well the company's losses are correlated with the relevant index-based recovery. Catastrophe models are used to derive both the company loss and the underlying index. For the example in Table 7.1, the company wants to recover losses over $100 million up to a limit of $150 million. A reference contract is defined here as traditional reinsurance for $50 million excess of $100 million. Under this reference contract, the company will achieve full recovery (ignoring co-insurance). The index is defined as some function of industry losses. A hedge contract is set up to pay $1 million for every point the index reaches above 100, with a cap of 150. Company losses are not perfectly correlated with industry losses due to differences in geographic distribution and mix of business. Therefore index-based recoveries under the hedge contract will not exactly match the full recovery under the reference contract. The difference between the full or reference recovery and the index-based recovery is known as basis risk.

As seen in Table 7.1, the basis risk can be positive or negative, reflecting over- and under-recovery. The graph in Figure 7.13 illustrates the recovery under each scenario where the reference and hedge are defined above.

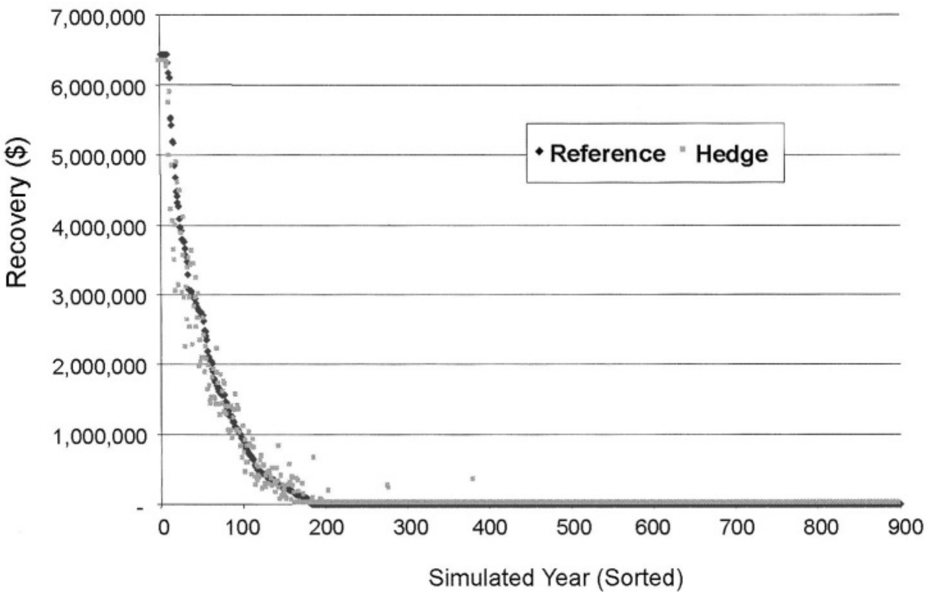

Figure 7.13. Recovery under reference and hedge scenarios.

Figure 7.14 compares basis risk in the above hedge contract with the losses to insurers using a traditional reinsurance product with 20% co-insurance. Insurers have always been exposed to some losses from coinsurance, which in some cases may be greater than the basis risk in index-based products. Some level of basis risk may be acceptable; the company's goal is not to eliminate basis risk, but to maximize expected return for a given level of risk.

Once management has made the decision to consider derivatives, they must determine what to buy. There is not a unique solution to this question and management will need to impose constraints and have tools available to address the goals of maximizing expected return and minimizing basis risk.

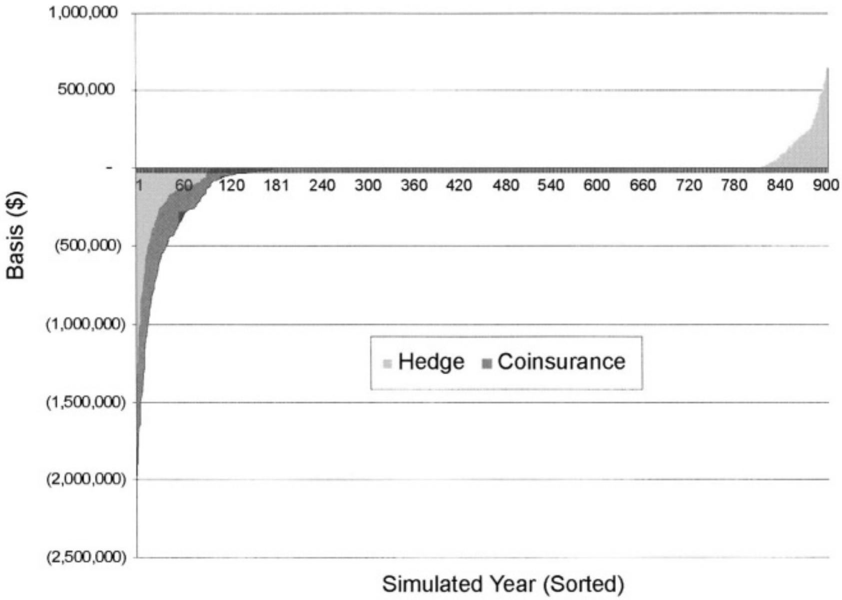

Figure 7.14. Basis risk vs. coinsurance.

7.4 The Costs of Risk Transfer

Decisions regarding how much risk to transfer and which form of risk transfer to use involve pricing the various strategies and checking availability. Securitization transactions to date have typically provided protection above traditional catastrophe reinsurance layers, attaching at probabilities around 0.4 to 1.25%. Pricing will consider the true underlying cost, as well as availability capacity and other market conditions; market prices will be a function of supply and demand. The first step involves using the catastrophe model to assess the underlying theoretical cost of each option.

The theoretical cost of risk transfer consists of three components: the expected losses, expenses associated with the transaction, and a risk load. The differences in market pricing between the reinsurance and capital markets are based on expenses and risk load. Models help quantify the risk load, but the uncertainty in the models used to evaluate the risk needs to be considered. To the extent risk can be quantified, it can be priced commensurately.

The pricing of securities involves detailed analysis of the cash flows and contingencies and is driven by the underlying catastrophe loss distribution as determined by the model. Investors often look for comparable securities to gauge price adequacy. Although there are no direct comparison products in the financial markets, the prices can be compared to prices for traditional reinsurance. Use of the reinsurance markets, which often participate in the transactions, provides important price validation for investors.

The usual operational efficiency of the capital markets, which also could reduce the cost of transferring catastrophe risk, has not as yet materialized due to high legal costs and costs of educating the investors about these transactions. This will surely change as investors become more sophisticated in assessing catastrophe risk and understanding the models that support these transactions. In the meantime, multi-year deals are gaining popularity because they allow the amortization of certain costs over a longer time period, thereby reducing the annualized cost.

There are many more issues to be addressed for management to pursue a derivative strategy. Even after the issue of basis risk has been addressed, there remains the issue of index estimation error, overhead costs, timing of premium payments, loss recoveries, and reinstatement options.

7.5 Evaluation of Risk Financing Schemes

Catastrophe risk dominates the risk profile of most property casualty insurance and reinsurance companies. While the level of sophistication of traditional catastrophe models has been evolving, so too has the industry's view of the risks they face when writing insurance exposures. Questions no longer focus exclusively on the magnitude of a potential loss from a natural disaster, but more broadly on what is the overall financial impact of such a loss on earnings. For example, aside from the direct property loss, what are the ancillary types of losses that may affect the corporation? What other lines may be affected? Is stock market performance really uncorrelated with cataclysms, events that strain worldwide insurance and reinsurance industry reserves (Cutler and Zeckhauser, 1999)? Enterprise Risk Management (ERM) can help answer these and other questions relating specifically to catastrophe risk.

Integrating catastrophe models with ERM models provides a robust context for managing the entire enterprise risk profile in general, and for evaluating risk transfer options and other management questions regarding pricing and underwriting guidelines in particular. Today, companies are using ERM to assess the impact of a catastrophe treaty not only on the catastrophe loss curve, but also on overall financial results. Just as catastrophe models derive the risk profile in terms of an exceedance probability curve, ERM models are producing full probabilistic distributions of the enterprise-wide risk profile.

The way companies view risk is changing. The tragic events of 9/11 opened the eyes of many companies as to the nature of the risks to which they are exposed. Just as Hurricane Andrew was a wake-up call to the industry in terms of managing accumulations of property exposures, the terrorist attacks of 9/11 have companies concerned about the potential combination of losses across multiple lines of business (see Chapter 10). Insurers and reinsurers are taking a much broader view of catastrophe risk, realizing they have not adequately addressed the financial exposure faced by companies writing business across multiple lines, companies, and regions. The insurance industry is revisiting existing processes with the goal of improving knowledge of accumulated exposures and potential enterprise-wide financial losses that could result.

To evaluate properly all alternatives, a framework is needed to put them into the same context and integrate the natural hazard risk into an ERM strategy. Only then can a systematic comparison be made and incorporated into a risk management decision. Such a framework will encompass the steps outlined next.

7.5.1 Analyze Current Risk Profile

Natural hazard risks should not be considered in isolation of the total enterprise risk profile. There are many other sources of risk that may offset or compound the company's overall risk profile. This first step integrates the EP curve from catastrophe risk with other company risks from other lines of business, investment risk, and operational risk to develop an enterprise-wide EP curve. The level of risk tolerance should not depend on the source of risk. A company is not rationally managing its risk if it manages the risk of a 1-in-100 year catastrophe without contemplating the risk of a 1-in-100 year investment return or expense ratio. Catastrophe models are evolving to address the issue of extreme event risk in general.

7.5.2 Customize Decision Model

The decision models should incorporate the current risk profile and how the components of risk interact under multiple economic, business, and catastrophe scenarios. ERM provides a way of integrating all sources of risk so that the interaction of risks can be evaluated. Catastrophe models or their output are being integrated into ERM and the interaction with other risks such as liquidity can be measured. These models also allow for a better understanding of how the risk from various lines of business may react to a catastrophe.

7.5.3 Establish Performance Measures, Constraints, Critical Function

For any type of risk management, the company needs to determine the key measures of performance. These may include profitability, growth, and operating ratios. Consideration must be given to time horizons as well. Qualitative measures are used to set the framework, but in order to effectively evaluate the impact of various risk transfer alternatives, they must be put into quantitative terms. Constraints, such as the ability to significantly change a book of business, need to be considered. A critical function is a measure of risk associated with the quantification of those items of most concern to the company. These may include a rating downgrade, loss of x percent of surplus, and minimum profitability levels. By establishing a risk-return framework the company can answer questions in the same context and be able to systematically evaluate the effect of potential strategies.

7.5.4 Develop Risk Management Alternatives

Each alternative will have benefits, drawbacks, and varied impacts on return as well as on the corporate risk profile. Some alternatives may work better for high layers and others are useful for filling gaps in coverage. A review of the company's risk management alternatives involves not just a simple evaluation of each; instead, the company needs to consider the interaction of various combinations. The bases of selecting the best alternate will be cost, availability, and the monitoring requirements of each component. In addition to the EP curve, catastrophe models can also provide detailed loss data by geography and line of business. From this information, the company can explore the areas that drive their risk and obtain customized transfer mechanisms to address these risks specifically. This can also ensure they are not purchasing unneeded protection.

7.5.5 Evaluate Alternative Strategies

Evaluating alternative strategies involves establishing a measurement of risk and reward, and evaluating the tradeoffs relative to the company's tolerance for risk. For each alternative under consideration, the impact of the risk/reward tradeoff on the company's enterprise-wide risk profile must be compared.

The various alternatives for financing the natural hazard risk will, of course, have associated costs and differing impacts on the risk profile. The risk appetite of the company will determine the optimal shape of the company's risk profile. The company must employ a systematic evaluation of the countless combinations of available alternatives to move toward the target balance between risk and return. Catastrophe models are used to measure the costs and risk in each of the alternatives. To evaluate the alternatives, the results can be plotted on a risk-return graph, such as in Figure 7.15.

In Figure 7.15, each point represents one potential alternative for risk financing, with Alternative A representing no risk financing. Returns may be high year after year until there is a large catastrophe, which would result in significant losses. This variability in return is one measure of risk that can easily be assessed within a catastrophe model. Purchasing reinsurance, such as the $50 million excess of $100 million coverage in the earlier example, would decrease risk. At the same time the cost of the reinsurance would lower return (this is reflected in Alternative B). Alternative C reduces both risk and return significantly. It is clearly sub-optimal to Alternative D which reduces risk the same amount but at a lower cost. The points on the line reflect the efficient frontier along which the company will strive to balance risk and return (a so-called efficient frontier of risk management strategies); points below the line are sub-optimal.

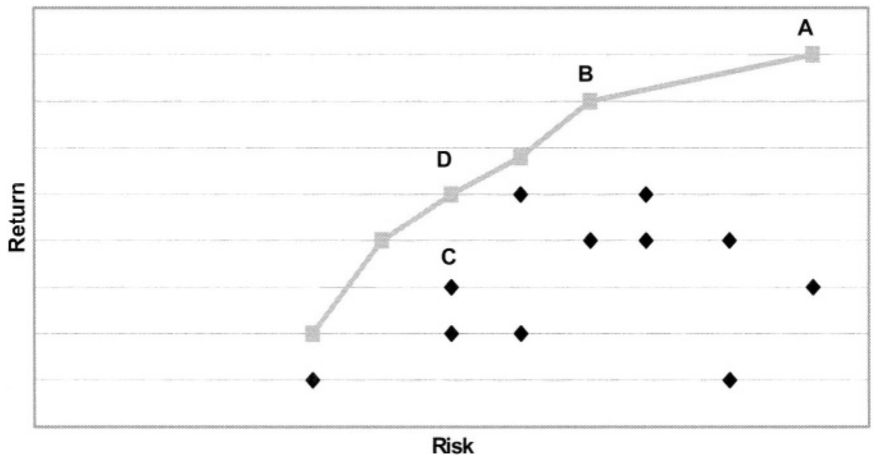

Figure 7.15. Risk vs. Return.

Because many risk-financing alternatives have been developed to address specific issues and to have different impacts on the risk profile, the company can create a highly tailored solution to its risk-financing program. By evaluating the alternatives in a risk versus return context, the company will be able to eliminate many sub-optimal structures. The scenario that maximizes the company's return for its given level of risk tolerance will yield the best strategy.

7.5.6 Select, Implement, and Monitor Strategy

Once a strategy is selected based on the company's risk/return preference, the risk management program needs to be implemented. The capacity and costs assumed in the evaluation must be confirmed and deviations from the strategy can be fed into the evaluation framework to ensure the selected strategy is still optimal. Over time, the strategy is monitored and rebalanced as assumptions are realized or altered. Catastrophe models have become an integral part of insurance company operations, as they continuously monitor natural hazard risk and test new strategies.

7.6 Summary

Catastrophe models generate the full EP curve reflecting natural hazard risk. This information is used to evaluate risk transfer and financing schemes in the context of an overall risk versus return evaluation. As new approaches arise, the modeling framework produces the information to price and manage the risk without the direct need for details of the insurance market.

A catastrophe model plays a critical role in the issuance of insurance-linked securities. The risk analysis performed is fundamental to the very structure of the transaction and to its pricing strategy. The modeler must perform a detailed analysis of loss probabilities by peril, line of business, and geography up front and, in the case of notional portfolio transactions, a post-event calculation after a triggering event has occurred. In multi-year deals involving loss triggers, the modeler must perform an annual reset of attachment and exhaustion amounts to maintain a constant probability of expected loss. They can also assist the cedant in understanding and even reducing their basis risk.

Originally used for gauging an insurance company's likely maximum loss from natural hazards, catastrophe modeling is now a critical tool for the development of finely crafted pricing, underwriting, and risk-transfer strategies, leading to overall portfolio optimization and integrated risk management.

7.7 References

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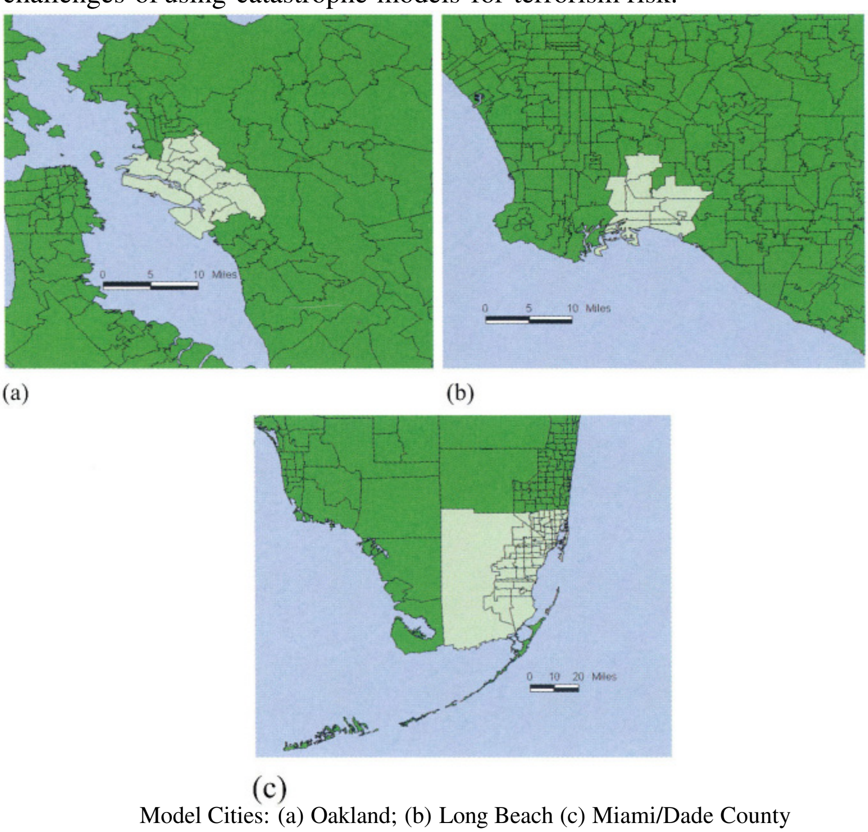
PART IV

RISK MANAGEMENT STRATEGIES USING CATASTROPHE MODELS

Part IV examines risk management strategies for three model cities completed at the Wharton School under the guidance of three leading catastrophe loss modeling firms: AIR Worldwide, EQECAT, and Risk Management Solutions (RMS). The three cities are Oakland, California (subject to earthquakes), Long Beach, California (subject to earthquakes), and Miami/Dade County, Florida (subject to hurricanes). The analysis illustrates how an insurer can more effectively manage catastrophe risk. Chapter 8 analyzes how residential mitigation measures in high hazard areas can reduce losses to property owners and insurers. Chapter 9 then considers the impact of reinsurance and catastrophe bonds, in conjunction with mitigation measures, on an insurer's profitability and solvency. Chapter 10 examines the challenges of using catastrophe models for terrorism risk.



(a) (b) (c)

Model Cities: (a) Oakland; (b) Long Beach (c) Miami/Dade County

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Chapter 8 – The Impact of Mitigation on Homeowners and Insurers: An Analysis of Model Cities

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8.1 Introduction

This chapter focuses on the evaluation of the economic impact of specific loss reduction measures to property owners and insurers in the event of a natural disaster. After discussing the impact of such measures on insurers offering coverage to residential property owners, the tradeoffs that property owners face in deciding whether or not to invest in mitigation are examined. The results presented here include the impact of mitigation measures on damage to residential structures in three model cities: Oakland, California (subject to earthquakes), Long Beach, California (subject to earthquakes), and Miami/Dade County, Florida (subject to hurricanes). The analysis also shows how uncertainty in catastrophe risk impacts the effectiveness of different mitigation measures. The primary focus of the chapter is to examine the potential benefits of mitigation to property owners in the form of reduced losses and lower insurance rates. The chapter also includes a discussion of the interaction of mitigation and policy design, underwriting strategies, profitability, and solvency of insurers that provide coverage for catastrophe risk.

The discussion begins with the study of the impact of mitigation on the losses to the homeowner and the insurer using exceedance probability (EP) curves. If a mitigation measure is to be effective, it should produce sufficient expected benefits in the form of reduced losses to the property owner so that investing in the measure makes financial sense.

Sharing these benefits between the property owner and the insurer is, however, a more complex matter. Benefits from a particular mitigation measure affect different parts of an insurer's EP curve (low-end, mid-range, or right hand tail), as shown in Figure 8.1. The precise location of these effects will determine the impact of deductible levels, coverage limits, and premium structures on the insurer's retained risks, profitability, and solvency. In addition, the net benefits to the insurer of mitigation measures will depend on the cost of the various risk bearing and risk transfer methods the insurer uses for each part of the EP curve.

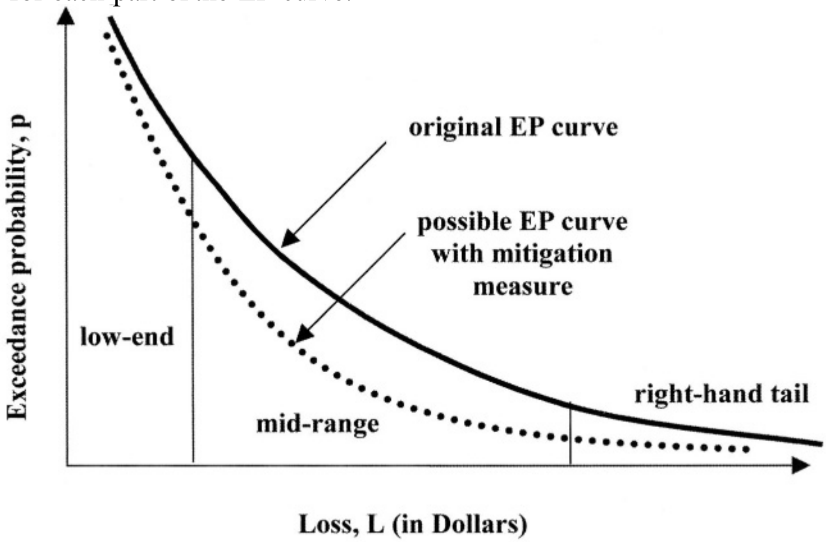

Figure 8.1. An insurer's exceedance probability curve.

The following interdependent issues arise from these observations. First, it is not a foregone conclusion that policyholders will adopt mitigation measures even when they are shown to be effective and properly priced by the insurer. Second, determining the proper pricing of insurance to ensure that all aspects of the cost of risk are properly accounted for requires a detailed assessment of the impact of each mitigation measure on the insurer's entire exceedance probability curve. This impact is dependent on the full characteristics of the insurer's book of business, its strategies for risk bearing and risk transfer, as well as the number of policyholders who adopt the measure.

To keep matters relatively simple, two issues are discussed here: (1) the decision by a property owner to invest in a mitigation measure, and (2) the interaction of mitigation, premium setting, and deductible levels on profitability and solvency of an insurer assuming the insurer retains all the risk. Both issues are presented within a framework of uncertainty regarding the mitigation measure's effectiveness over time. The more complex scenario including the additional impact of risk transfer and the use of reinsurance and catastrophe bonds is considered in the next chapter.

8.2 Framework of Analysis

Figure 8.2 depicts a framework for analyzing the themes discussed earlier. It builds on concepts developed in a report by the Heinz Center (1999) and by Kleindorfer and Kunreuther (1999), and is analogous to the framework depicted in Chapter 2. Using a catastrophe model and taking into account the decision processes of insurers and homeowners, the performance of insurance and other risk transfer mechanisms on future losses, with and without mitigation measures in place, can be evaluated. The discussion here is focused on building structural damage and the related losses. Any disruption of infrastructure, such as loss of the water supply or electric power that can cause indirect losses to residents, is not considered here.

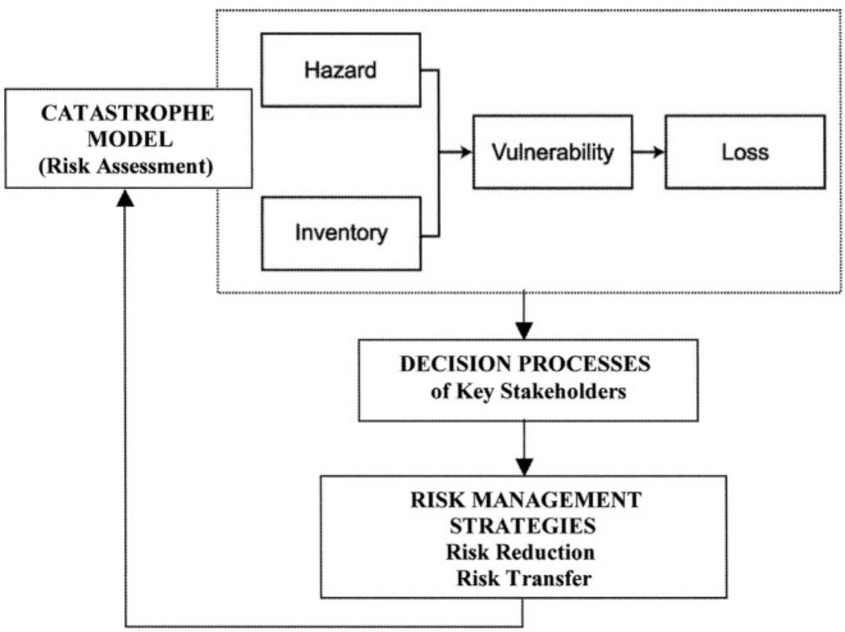

Figure 8.2. Framework for analysis.

As discussed in more detail in earlier chapters, the main ingredients for evaluating the vulnerability of an insurer's book of business to catastrophes are the nature of the hazard and the inventory of buildings at risk. The probability of events of different intensities occurring within a certain proximity of the building inventory specifies the nature of the hazard. Such features as location, construction class, occupancy class, and year of construction characterize the building inventory. An EP curve describes the resulting loss curve for the insurer's book of business.

The key link between the risk assessment process as described above, and the risk management process, is the stakeholders' decision processes. What impacts the homeowner's decision as to whether or not to retrofit his home to reduce his future losses from a severe earthquake or hurricane? What information does he need on the natural hazard and the potential damage with and without a mitigation measure? What type of decision rule(s) does the property owner utilize in determining whether or not to invest in this mitigation measure? What type of data and decision rules do insurers utilize in evaluating the effectiveness of different mitigation measures? In order to get support for specific risk reduction programs, the nature of the decision processes of these interested parties must be understood. Sidebar 1 presents information on how corporate risk mitigation measures reduced disaster losses.

SIDEBAR 1: Corporate "wins" from mitigation

Cost-benefit analysis of risks from natural disasters and potential benefits from mitigation may prompt a company to reduce these risks through mitigation measures. Two FEMA publications, 294 and 331, describe case studies of corporations, utilities, and homeowners that have taken this route to protect themselves against catastrophic losses (FEMA, 1997; 1998). Discussed below are examples of several businesses that experienced catastrophic events after mitigation measures were put into place and thus could compare actual versus potential losses:

- *Anheuser-Busch brewery (Los Angeles, California).* Seismic reinforcement to buildings and critical equipment saved the company an estimated $300 million in direct and business interruption losses from the 1994 Northridge earthquake.
- *Warner Brothers Studio (Burbank, California.)* Nonstructural mitigation such as bracing of building contents prevented an estimated $ 1 million in damages from the 1994 Northridge earthquake.
- *Andritz, Inc. (Muncy, Pennsylvania).* Losses from two similar levels of hurricane-related flooding dropped from $3.4 million in 1972 to $0.23 million in 1975 following flood-proofing measures implemented between the two events (1979 dollars).

Based on an understanding of the vulnerability of the book of business and the decision processes of the key interested parties, strategies can be developed and evaluated for reducing losses and providing financial protection to those subject to risk. As expected, these measures will differ across regions within the United States and between countries, depending on the current institutional arrangements, the science and engineering infrastructure available, and existing legislation and laws.

8.3 Construction of Model Cities

This section sets the stage for evaluating the impact of mitigation on the property losses in the three model cities. For modeling purposes, two broad assumptions are made. The first assumption is that the homeowner is willing to implement mitigation measures. The second assumption is that all residents desire some form of hazard insurance and have the financial ability to purchase coverage. With respect to the second assumption, it should be noted that although all homeowners desire coverage, if an insurance company is concerned with the possibility of insolvency, the amount of coverage it provides may be limited so some property owners may be unprotected.

8.3.1 General Model Structure

The general structure of the analysis is as follows. First, scenario variables that describe the set of hazard events and their associated probabilities are set. Next, the Model City is specified according to the number and types of residential structures characteristic of the region, the type of mitigation measures applicable to these structures, and the types of residential insurance policies offered. The set of hazard events and residential structure characteristics for Oakland (referred to hereafter as Model City 1 or MC1) was provided by Risk Management Solutions, the Long Beach (referred to as MC2) data was provided by EQECAT and the Miami/Dade County (referred to as MC3) data was provided by AIR Worldwide.

The variables that describe the nature of the hazard and characteristics of the buildings at risk are used in conjunction with a catastrophe model to generate an EP curve for the insurer's book of business. For an individual residential property owner, the EP curve is a function of the set of natural hazard events that are used in the model, the impact of mitigation (risk reduction) and the amount and structure of the residential insurance purchased (risk transfer). For a given insurance company, the EP curve is a function of the amount and nature of insurance sold, the number and types of properties insured, overall adoption of mitigation measures, and the natural hazard events that are used to generate loss exposures. For the modeling exercise, all these parameters and decisions must be specified. The EP curves for the residential property owners and the insurance companies provide the foundation for evaluating expected and worst-case consequences of a set of scenarios, as well as the shares of the losses borne by each stakeholder. Each of these elements is now considered in more detail.

8.3.2 Mitigation Measures

Each model city was evaluated to determine the appropriate residential mitigation measure to consider. Based on feedback from structural engineers in California, the mitigation measure used in MC1 and MC2 was bracing a wood-frame structure's cripple wall (the wall/crawl space between the structure's foundation and its first-floor diaphragm) and securing the structure to its foundation with additional anchor bolts. This only applies to wood-frame structures built before or immediately after World War II in California, since a large portion of these were built without adequate cripple wall bracing (due to the sparse supply of plywood). The mitigation measure used in MC3 was partial roof mitigation, which leads to better uplift resistance and an improved ability to withstand lateral loads in a hurricane. This can be accomplished without removing the roof covering, which is assumed to be wind resistant and in good condition. Partial roof mitigation includes bracing roof trusses and gable end walls, applying wood adhesive where the roof decking and roof supports meet, installing hurricane straps or clips where the roof framing meets the top of the studs, and anchoring the walls to the foundation.

The proportion of structures in each model city that adopted a mitigation measure was assumed to vary from 0% to 100%. For illustration purposes, the extreme points 0% and 100% are considered here. Full adoption of mitigation (100%) assumes that all eligible structures in the model city utilize the mitigation measure. In MC1 and MC2, the mitigation costs are based on a data survey undertaken by Grossi (2000), which revealed that the estimated average cost of bracing a wood-frame structure's cripple wall was approximately $5,000 (1998 dollars). In MC3, for a typical single-family dwelling in the Miami metropolitan area, the estimated average mitigation cost was assumed to be $3,000 (1998 dollars) based on an estimate provided by AIR Worldwide.

8.3.3 Books of Business for the Insurance Companies

For each Model City, 5,000 residential structures were randomly selected to represent the maximum exposures that an insurance company could write. Companies could insure fewer than 5,000 structures to maintain an acceptable probability of insolvency (1%).

It is assumed that all structures in MC1 and MC2 are wood frame, single-family residences. The distribution of structures is given in Table 8.1. In MC1, the structures were picked randomly from over 62,000 wood frame, single-family residences in the model city and all pre-1940 structures were considered eligible for mitigation. Structures whose age was unknown are assumed to fall into the pre-1940 or post-1940 category with the same likelihood as the known structures. Based on the ratio of pre-1940 homes in the group of homes with known ages, it was assumed that 172 of the 259 structures with unknown age were constructed prior to 1940. Thus, 3,263 homes or 65.3% of the structures were eligible for mitigation in MC1. In MC2, only the low-rise homes built prior to 1949 with unbraced cripple walls are considered eligible for mitigation. Thus, only 409 homes or 8.2% of the structures, were eligible in the analysis.

Table 8.1. Composition of books of business in the model cities

MC1 (Oakland) Structure by Year of Construction	
Unknown	259
Pre-1940	3,091
Post-1940	1,650
Total	**5,000**
MC2 (Long Beach) Structure by Type and Year of Construction	
Low Rise Average	704
Low Rise pre-1949 braced cripple walls	1448
Low Rise 1949-78 braced cripple walls	1616
Low Rise post-1979 braced cripple walls	823
Low Rise pre-1949 unbraced cripple walls	409
Total	**5,000**
MC3 (Miami/Dade County) Structure by Type	
Wood Frame	496
Masonry Veneer	1,005
Masonry	3,117
Semi-Wind Resistive	260
Wind Resistive	122
Total	**5,000**

The properties selected in MC3 are also single-family residences that reflect the general distribution of structures in the entire model city. All homes were considered eligible for roof mitigation. It was assumed that the five structure types listed in Table 8.1 had similar expected mean damage reduction ratios if mitigation measures were undertaken.

8.3.4 Insurance Company Premium and Asset Levels

Table 8.2 specifies the parameters for the insurance companies in each Model City. Full insurance coverage against damage from the disaster is available, with a deductible of 10% in MC1 and MC2 and 1% in MC3.

Since insurers are concerned with insolvency, they focus on worst-case scenarios in determining the portfolio of risks to which they offer coverage. For this analysis, a Worst-Case Loss (WCL) is defined as a loss corresponding to a target ruin probability (TRP) of 1%. This implies they would like to limit their book of business such that they have at least a 99% chance of avoiding insolvency (see Table 8.2). The asset levels for each company are set such that each firm's insolvency probability is roughly 1 percent when mitigation is present.

Table 8.2. Base case insurance company parameters

Parameter	MC1 Company	MC2 Company	MC3 Company
Assets	$57 million	$20 million	$24 million
Deductible	10%	10%	1%
Target Ruin Probability (TRP)	1%	1%	1%

8.3.5 Incorporating Uncertainty into Analysis

For each of the model cities, the analysis uses mean estimates for all of the hazard parameters. In order to incorporate uncertainty into the study, two parameters are varied from each mean estimate and the sensitivity of the resulting losses to these changes is presented. For the earthquake hazard, the annual frequency of seismic events, F_E, and the vulnerability of the building inventory, V_E, are subjected to variation. For hurricane hazard, the filling rate, F_H, and the structural vulnerability, V_H, are varied. Specifically, high and low estimates of these parameters are determined such that they encompass a 90% confidence interval for each parameter in question. In other words, these high and low estimates are selected such that they cover the true estimates of the model parameters with a probability of 90%. The high estimate (95th percentile) is conservative since it produces a parameter estimate that will be exceeded only 5% of the time. The low estimate (5th percentile) is optimistic in that it produces a parameter estimate that will be exceeded 95% of the time.

Furthermore, based on the assumption that (a) the two curves for the F and V parameters are on the high side, and (b) the two curves for the F and V parameters are on the low side, two more 90% confidence intervals using the joint distribution for these parameters were generated. The values for the F and V parameters based on the joint distribution, assuming they are independently distributed, are less extreme than the earlier ones to yield the joint confidence interval[1]. These joint curves are the ones utilized in this chapter.

8.4 Insurer Decision Processes

Literature in economics in recent years suggests that insurers and other firms are risk-averse due to their concern with the consequences of financial distress. Hence, they pay particular attention to non-diversifiable risks such as catastrophic losses from disasters (Mayers and Smith, 1982). Insurers are also likely to be averse to ambiguity in their risk. The term "ambiguity averse" denotes an insurer's reluctance to make decisions based on imprecise probabilities of loss occurrence. Both actuaries and underwriters utilize decision-making processes that reflect an aversion to excessive risk and ambiguity (Kunreuther, Hogarth, and Meszaros, 1993).

The actuarial premium is based on the value of expected annual loss loaded for uncertainty and fixed costs. A commonly used formula for determining premium is:

$$z = (1+\lambda_I)E[L]$$

where E[L] = expected loss and λ_I = an insurance "loading" factor. The loading factor reflects administrative costs as well as an additional provision to reflect uncertainty in loss estimates. The loading factor used here is 1.0.

8.4.1 Impact of Mitigation on Losses and Insurer Behavior

First, the effects of mitigation and uncertainty on total losses to the insurer are considered. The statistics presented here are the insurer's expected loss, worst-case loss, and probability of insolvency. These results are shown assuming coverage was offered to all 5,000 residential property owners for each of the three books of business in Table 8.1. The expected and worst-case losses to the insurer are determined using the full book of business for levels of mitigation of 0% and 100%. The mean values of these losses are displayed in Table 8.3 (mean) along with the bounds, denoted as low (5th percentile) and high (95th percentile).

The mean expected loss, E[L], is the loss borne by the insurer after the deductible is applied to each policy. In MC1 and MC2, this deductible level is 10%; in MC3, there is a 1% deductible level. The worst-case loss, WCL, is the loss at the 1% probability of exceedance level. Finally, the

[1] It is assumed that the joint probability of both parameters being at their designated confidence levels is the product of their marginal probabilities. For example, at the 5th percentile, $P\{F < f_{5\%}$ and $V < v_{5\%}\} = P\{F < f_{5\%}\} \times P\{V < {}_{5\%}\} = 5\%$. There are an infinite number of ways to pick $f_{5\%}$ and $v_{5\%}$ to make this equality true. Arbitrarily, $f_{5\%}$ and $v_{5\%}$ are chosen so that $P\{F < f_{5\%}\} = P\{V < v_{5\%}\} = 22.36\%$. (For more information, see Grossi, et al, 1999.)

Probability of Insolvency is the likelihood that the insurer's losses will exceed the sum of its premiums and assets. Two other statistics are shown in Table 8.3: the percentage of Properties Insured and the Expected Profits of the insurer. Properties Insured is the percent of the full book of business that each insurer can cover without having its probability of insolvency exceed 1%; expected profits are equal to the sum of the premiums minus the losses and administrative costs.

Table 8.3. Effects of mitigation on insurer ($ in $1000s)

MC1 (Oakland)	**0% Mitigation**			**100% Mitigation**		
	Low	Mean	High	Low	Mean	High
E[L]	$770	$1,700	$3,140	$460	$1,000	$1,740
WCL	$40,020	$92,940	$141,580	$25,080	$58,660	$85,460
Probability of Insolvency (%)	0.74%	1.35%	1.84%	0.70%	1.00%	1.57%
Properties Insured (%)	100%	66.1%	42.8%	100 %	100%	70.9%
Expected Profits	$2,590	$1,100	$90	$1,510	$1,000	$160
MC2 (Long Beach)	**0% Mitigation**			**100% Mitigation**		
	Low	Mean	High	Low	Mean	High
E[L]	$230	$760	$2,230	$230	$730	$2,150
WCL	$6,720	$22,220	$59,840	$6,560	$21,430	$57,970
Probability of Insolvency (%)	0.44%	1.03%	2.94%	0.43%	0.99%	2.86%
Properties Insured (%)	100%	98.0%	34.5%	100%	100%	35.6%
Expected Profits	$1,280	$740	-$250	$1,240	$730	-$250
MC3 (Miami/Dade)	**0% Mitigation**			**100% Mitigation**		
	Low	Mean	High	Low	Mean	High
E[L]	$1,570	$1,920	$2,300	$1,060	$1,300	$1,550
WCL	$34,030	$42,490	$51,430	$22,360	$27,620	$33,530
Probability of Insolvency (%)	1.33%	1.84%	2.29%	0.77%	1.04%	1.38%
Properties Insured (%)	80.3%	62.6%	50.7%	100.00%	97.1%	78.3%
Expected Profits	$1820	$1,200	$780	$1,530	$1,260	$820

As expected, the analysis shows that mitigation reduces losses to the insurer in each of the three model cities - with a more pronounced impact on worst-case loss than expected loss. For MC1 and MC3, the reduction in annual expected loss is $700,000 or 41% and $620,000 or 32%, respectively. In comparison, for MC2, mitigation is not as significant in reducing losses and the reduction in expected annual loss is only $30,000 or 4%. This is primarily due to the extremely small number of homes eligible for mitigation in MC2 (approximately 8%).

A principal reason for investigating the impact of mitigation on the worst-case loss is to understand how mitigation reduces the probability of insolvency. Based on Table 8.3, one can see that for MC3, for the mean scenario, the probability of insolvency is reduced significantly from 1.84% to 1.04% with mitigation. For MC1, the corresponding reduction is from 1.35% to 1.00%.

Since mitigation shifts the EP curve downward (as illustrated in Figure 8.1), it will also increase the percentage of structures for which the insurer can provide coverage and still maintain an annual probability of insolvency of 1%. In other words, insurers can provide coverage to more homes if each homeowner is required to adopt mitigation as a condition for insurance. Consider the mean scenario in Table 8.3. When no mitigation is adopted, the insurance company in MC1 will only be able to provide coverage for 66% of those property owners who would like to buy a policy. As the percentage of homes adopting mitigation increases, so does the percentage of homes for which the insurer can provide coverage. When all of the homes have adopted the mitigation measure, the insurer is willing to provide coverage to all of the structures, a significant increase over the percentage covered when no mitigation is in place. Similarly, in MC3, the percentage of homes that the insurance company is willing to cover increases from approximately 63% to 97% with mitigation.

A good representation of the findings for the mean loss estimates and changes in insolvency probability with mitigation is shown via the exceedance probability curve for the insurer in MC3 (Figure 8.3). As one can see, the EP curve shifts downward when all homes are mitigated and the insurer's losses are reduced significantly. In particular, at the 1% probability of exceedance, the loss to the insurer shifts from $42.5 million to $27.6 million.

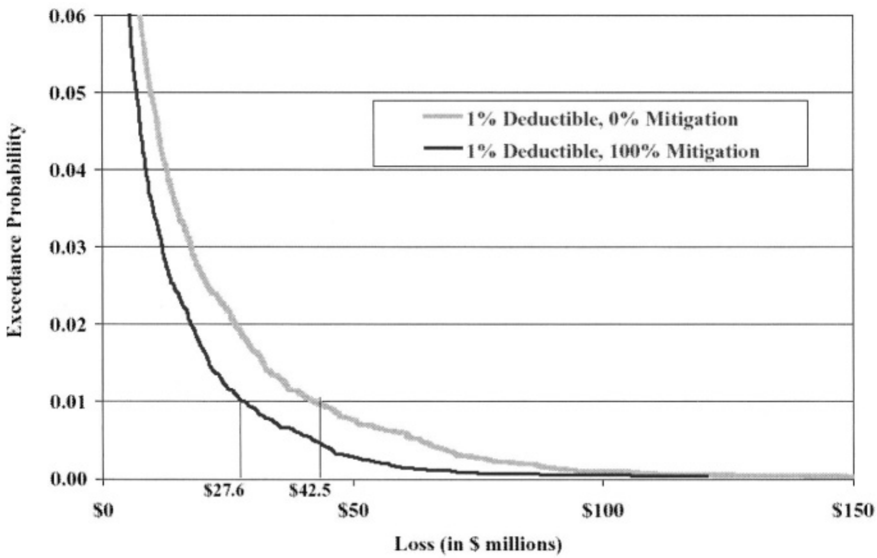

Figure 8.3. Example of exceedance probability curve shift with mitigation in MC3 (Miami/Dade).

8.5 Homeowner Decision Processes

Studies suggest that individuals are not willing to invest funds for mitigation even if they are residing in highly hazard-prone areas (Mileti, 1999). Simple steps, such as strapping a water heater with plumbers' tape, can normally be done by residents at a cost of under $5 in materials and one hour of their own time (Levenson, 1992). This measure can reduce damage from gas leaks and fire by preventing the heater from toppling during an earthquake. Yet residents in earthquake-prone areas are not adopting such simple and other loss-reduction measures unless they are required to do so. This section provides a more detailed analysis of the factors that influence the decision to adopt protective measures and an illustration of how the adoption of mitigation measures can reduce the cost of insurance for homes in the three model cities.

8.5.1 Factors Influencing Mitigation Adoption Decisions

Basically there are four principal reasons why homeowners do not want to invest in mitigation measures: myopia, desire for a quick return on investment, budget constraints, and lack of perception of added economic value. Individuals want to recoup their investment in a mitigation measure, in general, on a relatively short time horizon. Even if the expected life of the house is 25 or 30 years, the person may only consider the potential benefits from the mitigation measure over the next 3 to 5 years. This may be based on their expected length of stay in the current residence. A related reason why mitigation is often unattractive is that individuals expect a quick return on their investment. Financially this is consistent with using a high discount rate for evaluating potential future payoffs.

Third, many individuals perceive the probability of a disaster causing damage to their property as being so low that an investment in protective measures is deemed unnecessary. Even if there is some concern with the potential of a hazard, budget constraints lead homeowners to place mitigation as a low priority item. In fact, many residents in hazard-prone areas feel they simply cannot afford these measures. It is not unusual for one to hear the phrase "We live from payday to payday" when asked why a household has not invested in protective measures (Kunreuther, et al., 1978).

Finally, individuals may have little interest in investing in protective measures if they believe that the measures will provide limited added economic value to them. For example, homeowners may not consider an investment to be cost effective if they believe it will not increase the resale value of their property. If they are financially responsible for only a small portion of their losses should a disaster occur, the measure would be even less attractive. In addition, if they have limited assets at stake, they may feel they can walk away from their destroyed property without much financial harm. Similarly, if residents anticipate liberal government disaster relief, they have even less reason to invest in a mitigation measure.

In analyzing a homeowner's decision to mitigate or not to mitigate, the fixed mitigation costs are converted to an annual expenditure based on a time horizon of 30 years. This allows a comparison of these costs to annual insurance premiums and expected annual losses to the homeowner. In this way, the robustness of the mitigation measure can be viewed in terms of an average homeowner's decision process.

The results are presented in Table 8.4 for the homeowners in the three model cities when no insurance is purchased. The expected loss is the annual mean loss to the average property owner. The cost of mitigation is the annual average cost discounted at a 7% rate over a 30-year time horizon, applicable only to those homeowners who mitigate. This corresponds to 3,263 homeowners in MC1, 409 homeowners in MC2, and 5,000 homeowners in MC3. The worst-case loss is the average homeowners' loss at the 1% probability of exceedance level.

From Table 8.4, it can be seen that mitigation reduces losses in each of the model cities. But, it is not cost-effective in most cases. More specifically, when one adds the annualized cost of mitigation to the expected loss with mitigation, this total is larger than the expected loss without mitigation. One exception is the high case in MC1. For this one case, the potential loss to the homeowner is $1,550 without mitigation. With mitigation, including the cost of mitigation, the total potential cost is lower and equal to $1,480. These results imply that for most scenarios, for the eligible structures in the three model cities, the disaster risk is not serious enough to justify investing in mitigation based solely on the mean potential loss and the costs of the measure combined.

A basic point to recognize from these results is that whether particular mitigation measures will be viewed as worth adopting by a homeowner is not a foregone conclusion, but requires a detailed assessment of the costs and benefits under various hazard scenarios. It is important to note as well that only the direct property losses are evaluated in this analysis. Mitigation could have additional real and perceived benefits for homeowners in reducing the risk of fatalities, stress and interruption of home life. These are not considered here, but are discussed in more detail in the Heinz Center report (1999).

If the homeowner's worst-case loss (WCL) is examined, a different picture emerges. In MC1 and MC3, there is a significant decrease in the WCL when homes are mitigated. If a homeowner is concerned with a potential catastrophic loss, these results suggest that the homeowner has an incentive to invest in mitigation. Furthermore, to the extent that insurers are risk averse and concerned with reducing their probability of insolvency, they will require mitigation measures to be implemented for structures that they insure.

Table 8.4. Effects of mitigation on average homeowner (No Insurance)

MC1 (Oakland)	**0% Mitigation**			**100% Mitigation**		
	Low	Mean	High	Low	Mean	High
Expected Loss	$430	$910	$1,550	$310	$640	$1,070
Mitigation Cost	--	--	--	$410	$410	$410
Total	$430	$910	$1,550	$720	$1,050	$1,480
Worst-Case Loss	$14,850	$30,100	$40,700	$11,280	$20,390	$27,170
MC2 (Long Beach)	**0% Mitigation**			**100% Mitigation**		
	Low	Mean	High	Low	Mean	High
Expected Loss	$110	$280	$640	$110	$270	$630
Mitigation Cost	--	--	--	$410	$410	$410
Total	$110	$280	$640	$520	$680	$1,040
Worst-Case Loss	$3,340	$8,370	$17,600	$3,300	$8,260	$17,290
MC3 (Miami/Dade)	**0% Mitigation**			**100% Mitigation**		
	Low	Mean	High	Low	Mean	High
Expected Loss	$360	$440	$520	$250	$300	$360
Mitigation Cost	--	--	--	$240	$240	$240
Total	$360	$440	$520	$490	$540	$600
Worst-Case Loss	$7,560	$9,230	$11,080	$5,120	$6,230	$7,400

8.5.2 The Interaction of Mitigation Decisions and Insurance Decisions

Turning to the relationship between insurance and mitigation, some interesting findings emerge from recent surveys undertaken by Risa Palm and her colleagues. Palm and Carroll (1998) report that individuals who adopt mitigation measures were also more likely to buy earthquake insurance. This raises the question as to whether certain types of individuals want protection for reasons that have less to do with their perception of the risk than their intrinsic worries and concerns.

In analyzing a homeowner's decision to purchase insurance or adopt a mitigation measure in the three model cities, the time horizon is once again set at 30 years with a discount rate of 7%. Total expected loss and worst-case loss for insured homeowners are computed for the property owners under the assumption that the insurer is providing coverage to the full book of business. In this case, the homeowner expected loss corresponds to the average deductible loss. Worst-case loss is the loss borne by the homeowner at the 1% exceedance probability level, and costs of mitigation are the same as those noted in Table 8.4.

The results of this analysis are presented in Table 8.5. They suggest that when insurance is purchased, the earthquake mitigation measure is cost-effective for both the mean and high scenarios in MC1. By lowering the cost of insurance, mitigation becomes a financially feasible option even for the mean scenario. In MC1, the total mean annual costs are $1,240 and $1,250 with and without mitigation, respectively.

For the average homeowner in MC2, the results suggest mitigation is not cost-effective under any scenario. However, when insurance is purchased, the WCL is $3,930 for the mean scenario compared to $8,370 when the homeowner is uninsured (See Table 8.4). These findings suggest that if a homeowner is risk averse and is concerned with the impact of a catastrophic loss, purchasing insurance makes sense.

8.6 Implications for Workable Public-Private Partnerships

Suppose homeowners were to voluntarily adopt mitigation measures and insurers were to set premiums that reflected the reduction in losses resulting from the mitigation. Under these ideal conditions, there would be a reduction in losses to residents as well as a reduction in the probability of insolvency for the insurers.

Table 8.5. Effects of mitigation on average homeowner (with Insurance)

MC1 (10% Deductible) (Oakland)	**0% Mitigation**			**100% Mitigation**		
	Low	Mean	High	Low	Mean	High
Expected Deductible Loss	$280	$580	$920	$220	$440	$720
Insurance Premiums	$670	$670	$670	$390	$390	$390
Cost of Mitigation	--	--	--	$410	$410	$410
Total	$950	$1,250	$1,590	$1,020	$1,240	$1,520
Worst-Case Loss	$6,850	$11,510	$12,390	$6,630	$8,660	$10,080
MC2 (10% Deductible) (Long Beach)	**0% Mitigation**			**100% Mitigation**		
	Low	Mean	High	Low	Mean	High
Expected Deductible Loss	$70	$130	$190	$60	$120	$190
Insurance Premiums	$300	$300	$300	$290	$290	$290
Cost of Mitigation	--	--	--	$410	$410	$410
Total	$370	$430	$490	$760	$820	$890
Worst-Case Loss	$2,000	$3,980	$5,690	$1,990	$3,930	$5,630
MC3 (1% Deductible) (Miami/Dade)	**0% Mitigation**			**100% Mitigation**		
	Low	Mean	High	Low	Mean	High
Expected Deductible Loss	$50	$55	$60	$40	$45	$50
Insurance Premiums	$770	$770	$770	$520	$520	$520
Cost of Mitigation	--	--	--	$240	$240	$240
Total	$820	$825	$830	$800	$805	$810
Worst-Case Loss	$760	$730	$790	$640	$705	$700

In reality, as pointed out above, most property owners have limited interest in investing in these measures. Furthermore, insurers have little reason to encourage mitigation in hazard-prone areas if they are not forced to provide coverage and the rates they are allowed to charge are inadequate. In this case, insurers would want to do everything they could to reduce their exposure and encourage the policyholder to seek coverage from another insurer. Insurers may have an interest in mitigation if they have no choice in providing coverage to individuals in hazard-prone areas. If rates in these hazard-prone areas were risk-based, insurers would want to encourage mitigation, reduce overall losses, and charge lower premiums for those who adopted the measures. If, on the other hand, they are forced to charge the same maximum premium for all the risks, they have no incentive to charge lower premiums for homeowners that mitigate. This would enable them to collect as much premium as possible.

In the following subsections, three types of public-private partnership programs that can encourage mitigation are explored: (1) building codes and other legislation, (2) premium reductions linked with long-term loans for mitigation, and (3) insurers offering lower deductibles for those investing in mitigation. In evaluating these programs, it is assumed that there has already been an attempt to use market-based mechanisms to encourage the different interested parties to take action[2].

8.6.1 Role of Building Codes

Building codes require property owners to meet standards on newly built structures. Often such codes are necessary, particularly when property owners are not inclined to adopt mitigation measures on their own. One way to encourage the adoption of mitigation measures is for banks and financial institutions to provide a seal of approval to each structure that meets or exceeds building code standards. Under the Institute for Business and Home Safety's (IBHS) "Fortified for Safer Living" program, structures that meet predefined criteria receive a certificate of disaster resistance. Upon receipt of that certificate, there are a set of incentives provided by banks (e.g., lower mortgage rates), contractors, and insurers. The success of such a program requires the support of the building industry and a cadre of qualified inspectors to provide accurate information as to whether existing codes and standards are being met. Such a certification program can be very useful to insurers who may choose to provide coverage only to those structures that are given a certificate of disaster resistance.

Cohen and Noll (1981) provide an additional rationale for building codes. When a building collapses, it may create externalities in the form of economic dislocations and other social costs that are beyond the economic loss suffered by the owners. These may not be taken into account when the owners evaluate the importance of adopting a specific mitigation measure. For example, if a building topples off its foundation after an earthquake, it could break a pipeline and cause a major fire that would damage other homes not structurally damaged by the earthquake in the first place. Additionally, if a family is forced to vacate its property because of damage that would have been prevented had a building code been in place, then avoiding relocation costs is an additional benefit of mitigation.

The latest in the battle to encourage individuals to adopt mitigation measures is the Earthquake Loss Reduction Act of 2001. If the U.S. Congress passes this Act[3], the government would offer incentives for commercial and residential property owners to adopt mitigation measures. Residential property

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[2] See the report issued by the Earthquake Engineering Research Institute (1998), which indicates the challenges facing property owners in improving the seismic performance of their structures and suggests ways to encourage cost-effective investments.

[3] This legislation is still under review in the Senate finance committee as of May 2004.

owners would receive a 50% tax credit for a qualified seismic retrofit expense (limited to $6,000 per year). Further, businesses will be allowed to depreciate expenses associated with earthquake mitigation over a period of five years.

8.6.2 Long-Term Mitigation Loans

If homeowners are reluctant to incur the upfront cost of mitigation due to budget constraints, then a long-term loan may provide a financial incentive for adopting cost-effective measures. The bank holding the mortgage on the property could provide funds for this purpose through a home improvement loan with a payback period identical to the life of the mortgage. For example, a $1,500 loan with a 20-year term at an annual interest rate of 10% would result in payments of $145 per year. If the annual insurance premium reduction due to the adoption of the mitigation measure is greater than $145 per year, the insured homeowner would have lower total payments by investing in mitigation (Kunreuther, 1997).

One additional factor to consider is that many poorly constructed homes are owned by low-income families who cannot afford the costs of mitigation measures or the costs of reconstruction should their house suffer significant damage from a natural disaster. Social considerations suggest providing this group with low interest loans and grants for the purpose of adopting mitigation measures or to relocate them to a safer area. Such subsidies can be justified from an economic perspective as well since low-income victims are more likely to receive federal assistance after a disaster.

8.6.3 Lower Deductibles Tied to Mitigation

An alternative way to encourage consumers to mitigate is to change the nature of their insurance coverage. More specifically, the insurer could offer a lower deductible to those who adopt mitigation. Such a program is likely to be very attractive given the empirical and experimental evidence that suggests that consumers appear to dislike high deductibles even though they offer considerable savings in premiums. (See Braun and Muermann, in press, for a summary of the empirical evidence on preference for low deductibles).

Table 8.6 examines the impact of lowering the deductible on insurance policies for earthquake and hurricane protection if the property owner adopted a mitigation measure on his property. This table compares the total expected costs to the homeowner (labeled HO in Table 8.6) who mitigated with those who did not mitigate for two different levels of deductibles: 0% and 10% for those in MC1 and MC2 and 0% and 1% for those in MC3.

Table 8.6. Effects of mitigation on homeowner losses and insurer insolvency probabilities

	0% Mitigation			100% Mitigation		
MC1 (10% Deductible)	Low	Mean	High	Low	Mean	High
HO Deductible Loss	$280	$580	$920	$220	$440	$720
Insurance Premium	$670	$670	$670	$390	$390	$390
Cost of Mitigation	--	--	--	$410	$410	$410
Probability of Insolvency	0.74%	1.35%	1.84%	0.70%	1.00%	1.57%
	0% Mitigation			**100% Mitigation**		
MC1 (0% Deductible)	Low	Mean	High	Low	Mean	High
Insurance Premium	$1820	$1820	$1820	$1270	$1270	$1270
Cost of Mitigation	--	--	--	$410	$410	$410
Probability of Insolvency	1.06%	1.75%	2.58%	0.91%	1.47%	1.97%
	0% Mitigation			**100% Mitigation**		
MC2 (10% Deductible)	Low	Mean	High	Low	Mean	High
HO Deductible Loss	$70	$130	$190	$60	$120	$190
Insurance Premium	$300	$300	$300	$290	$290	$290
Cost of Mitigation	--	--	--	$410	$410	$410
Probability of Insolvency	0.44%	1.03%	2.94%	0.43%	0.99%	2.86%
	0% Mitigation			**100% Mitigation**		
MC2 (0% Deductible)	Low	Mean	High	Low	Mean	High
Insurance Premium	$560	$560	$560	$540	$540	$540
Cost of Mitigation	--	--	--	$410	$410	$410
Probability of Insolvency	0.74%	1.82%	3.87%	0.73%	1.80%	3.85%
	0% Mitigation			**100% Mitigation**		
MC3 (1% Deductible)	Low	Mean	High	Low	Mean	High
HO Deductible Loss	$50	$55	$60	$40	$45	$50
Insurance Premium	$770	$770	$770	$520	$520	$520
Cost of Mitigation	--	--	--	$240	$240	$240
Probability of Insolvency	1.33%	1.84%	2.29%	0.77%	1.04%	1.38%
	0% Mitigation			**100% Mitigation**		
MC3 (0% Deductible)	Low	Mean	High	Low	Mean	High
Insurance Premium	$880	$880	$880	$600	$600	$600
Cost of Mitigation	--	--	--	$240	$240	$240
Probability of Insolvency	1.62%	2.19%	2.51%	0.90%	1.23%	1.64%

The results are interesting in two ways. First, insurers tend to be better off when homeowners mitigate than when they fail to adopt mitigation measures. In MC1, at the same deductible level, insurer insolvency probability fell measurably with mitigation in place. There was further reduction with the higher deductible in place and, in fact, it moved from an unacceptable level of 1.75% when the homeowners did not mitigate and had a 0% deductible level to an acceptable 1.00% when mitigation was in place and the homeowners were subject to a 10% deductible. Similar results apply to the companies in MC2 and MC3. In general, the effects of mitigation are sufficiently positive in these three model cities so that insurers, looking for ways of decreasing the chances of insolvency, can profit from mitigation.

Second, homeowners are better off in terms of their insurance premiums after they invest in mitigation. Thus, residents in MC1 who bought insurance would have their premiums reduced from $670 to $390. This result is not surprising since insurance premiums would benefit from a reduction in claims costs as well the associated loading costs. As pointed out above, however, it may be difficult to convince property owners of the merit of the higher deductible since they may focus on their out-of-pocket expenses following a disaster when they buy coverage. As would be expected, those who undertake mitigation have considerably lower worst-case loss than those who do not invest in loss reduction measures. In summary, homeowners, who are risk averse and hence concerned with the consequences of a catastrophic loss, are likely to have an interest in these measures.

8.7 Conclusions

Scientific and modeling uncertainties play an important role in accurately assessing natural hazard risk. If one focuses solely on reductions in property damage, mitigation measures may not be cost-effective for a homeowner in earthquake and hurricane-prone areas. However, if one includes indirect benefits of protective measures such as reduction in injuries and fatalities as well as avoiding the costs and stress of having to relocate after a disaster, then mitigation may be viewed as an attractive option. As seen in the sensitivity analysis, mitigation measures can be cost-effective. While the risk perceptions of homeowners often lead them to overlook these strategies, mitigation and insurance are effective tools in reducing worst-case losses to homeowners. Building codes, premium reductions linked to long term mitigation loans, and lower deductibles tied to the adoption of mitigation are several strategies that could be pursued to encourage homeowners to adopt these measures.

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Chapter 9 – The Impact of Risk Transfer Instruments: An Analysis of Model Cities

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9.1 Introduction

This chapter builds on the analyses completed in Chapter 8 and focuses on the impact that risk transfer instruments, such as reinsurance and catastrophe bonds, have on the performance of insurers. As it is throughout the book, the exceedance probability (EP) curve is utilized in structuring the analysis. A typical insurance company's goal is to operate under two somewhat conflicting constraints: a safety first constraint and a return on assets constraint. The first relates to both a target ruin probability level and a target insolvency level; the second is to satisfy the firm's shareholders and investors.

Of particular interest is how the homeowners' adoption of mitigation measures impacts the need for risk transfer instruments by insurers. This chapter should thus be viewed as a supplement to the analyses on mitigation and residential property insurance undertaken in Chapter 8. After characterizing the types of strategies that an insurance company can pursue to meet its profit maximization goal while still satisfying a number of constraints, an example using the model city of Oakland illustrates how an insurer makes its portfolio decisions. The chapter concludes by exploring the potential impact of multiple region catastrophe bonds for increasing the profitability of an insurer while meeting a solvency constraint.

9.2 Framework for Evaluating Alternative Strategies

The framework for analysis used here is similar to Chapter 8 (Figure 8.2), but the focus is on how reinsurance and other financial instruments can play a role in meeting an insurer's objectives. The insurance company's principal goal is to maximize expected profits, denoted $E(\pi)$, but it must also take into account the needs of its shareholders who require a positive minimum Return On Assets (ROA), defined as the ratio of expected profits to assets, in any given year.

As indicated in Chapter 8, an insurer sets a Target Ruin Probability (TRP) based on its appetite for risk and uncertainty. The safety first constraint reduces the company's expected profits from what they could have been had it been risk neutral. More specifically, if a firm cannot meet a predetermined level of insolvency risk with a given strategy, then it must take steps to reduce the amount of risk in its portfolio. This is likely to lower the firm's ROA since the insurer will typically either hold additional funds to maintain an acceptable level of claims-paying capacity (increasing the denominator of ROA) or purchase reinsurance or catastrophe bonds at prices exceeding the expected value of the risk transferred (thus decreasing the numerator of ROA). Alternatively, the company may need to limit its insurance exposure by insuring only a fraction of the available book of business.

In some cases, it may be impossible for the insurer to meet its TRP and desired ROA even when risk transfer instruments are utilized. For example, purchasing a catastrophe bond can reduce an insurer's insolvency probability to its target level, but it may be so costly that it results in an ROA below the level desired by the insurance company's shareholders. A risk would be considered uninsurable if there is no feasible strategy to meet the two relevant constraints. For an insurer, strategies to achieve both sets of objectives involve a combination of the following different options: (1) charging a higher premium, (2) varying deductibles and coverage levels, (3) employing underwriting strategies which limit the insurer's book of business in hazard-prone areas, (4) utilizing risk transfer instruments, or (5) requiring that the homeowner adopt specific mitigation measures as a condition for insurance.

The insurer's model can be expressed mathematically as follows. Given j different risk management strategies associated with the use of the above factors:

$$\text{Maximize } E(\pi_j) = (1+\lambda_I)E(L_j) - E(L_j) + E(B_j) - E(C_j)$$

Subject to:

$$\Pr\{ WCL_j > CPC_j \} \leq TRP \qquad \text{(Safety First Constraint)}$$

$$ROA_j \geq ROA^* \qquad \text{(Return on Assets Constraint)}$$

$E(L_j)$ and $E(\pi_j)$ are the expected loss and expected profits under strategy j, where loss L_j is a function of mitigation and underwriting elements of strategy j. $E(B_j)$ and $E(C_j)$ are the expected benefits and costs of risk transfer instruments under strategy j; and λ_I is the insurance loading factor for determining the premiums to charge homeowners. The insurance loading factor, as discussed in Chapter 8, reflects the administrative costs, profits, and costs of accumulating and maintaining capital in liquid form to pay for large losses.

In the first constraint, CPC_j is the available Claims Paying Capacity under strategy *j* to cover losses incurred and WCL_j is the associated Worst-Case Loss, which depends on the TRP. The claims paying capacity, CPC_j, is defined as the insurer's initial assets, A_j, plus premium revenues (both of which may generate interest income, although neglected here) minus the sum of ultimate losses incurred, the net payouts of any risk transfer instruments and administrative costs, C_j, and profits, B_j. In the notation of the above model:

$$CPC_j = A_j + (1+\lambda_I)\, E(L_j) - L_j + B_j - C_j$$

In the second constraint, ROA_j [i.e., $E(\pi_j)/A_j$)] is the expected return to the firm on initial assets for strategy *j*. ROA^* is the minimum ROA required by insurance company shareholders. The values of ROA depend on the nature of the risk involved and degree of uncertainty associated with it.

9.3 Evaluating Different Strategies for the Insurer

Suppose an insurance company is considering whether to provide earthquake coverage to homes in Oakland, California and has to determine what level of initial assets (A) are necessary to meet the target ruin probability of 1% and investor's minimum return on assets, ROA*, while still earning a positive expected profit based on an insurance loading factor of $\lambda_I = 1$.

One way to meet this goal is to impose a 10% deductible on all insurance policies and to use underwriting standards that assure that all eligible homes in the insurer's book of business have been appropriately mitigated. This implies all pre-1940 wood-frame homes are required to adopt mitigation as a condition for insurance.

Suppose the asset level A_1 associated with Strategy 1 is set so that the safety first constraint is exactly satisfied. Figure 9.1 shows the EP curve based on the portfolio of homes this company insures in the Oakland region. Based on the curve, WCL_1 is approximately \$59 million. For Strategy 1, A_1 equals \$57 million, the expected profits, $E(\pi_1)$, are approximately \$1 million and the return on assets, ROA_1, is approximately 1.75% (See Table 9.1). If the insurer utilized other strategies, such as lowering its deductible levels and/or not requiring mandatory mitigation measures, the company would need a higher level of assets to meet the target ruin probability of 1%. On the other hand, the expected profits would increase due to the collection of more premiums. The ROA could either increase or decrease depending on the change in profits relative to the required level of assets.

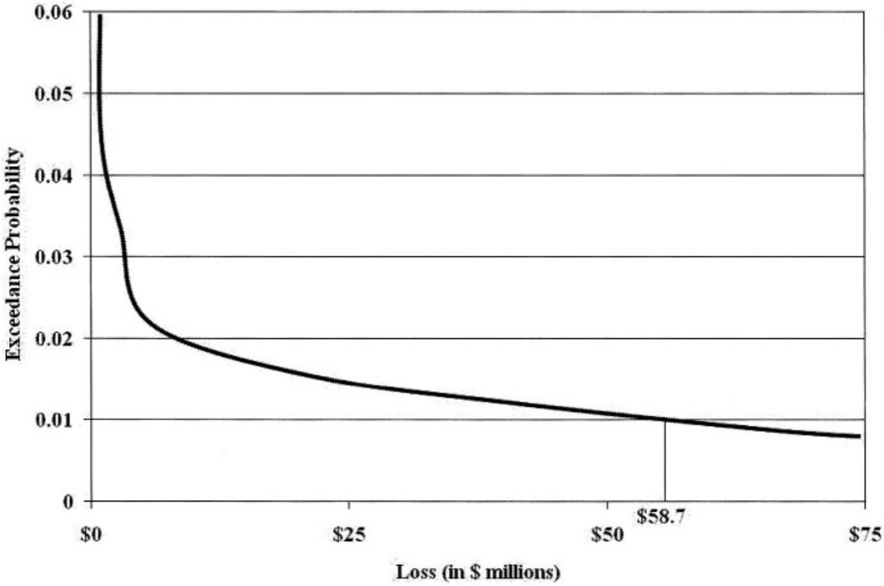

Figure 9.1. Loss exceedance probability curve (10% Deductible, 100% Mitigation)

In order to evaluate Strategy 1, the insurer can investigate the effects of varying deductibles and mitigation levels on E(π) while still meeting the TRP of 1%. Three other strategies are considered here. Strategies 1 and 2 assume all applicable homes undertake mitigation measures and Strategies 3 and 4 assume no residential homeowners mitigate. The deductible levels can be one of two levels: 10% (Strategies 1 and 3) or 0% (Strategies 2 and 4) of the value of the structure. In each case, the level of assets A_j is set at the minimum required to meet the safety first constraint at TRP of 1%. Table 9.1 shows A_j, E(π_j), and ROA_j for these four strategies.

Table 9.1. Performance of strategies to meet safety-first constraint

Strategy j (Deductible, Mitigation)	**Asset (A_j) (in \$1000s)**	**E(Profits) E(Π_j) (in \$1000s)**	**Return on Assets (ROA_j)**
1 (10%, 100%)	$57,000	$1,000	1.75%
2 (0%, 100%)	96,000	3,350	3.50%
3 (10%, 0%)	89,000	1,700	1.91%
4 (0%, 0%)	135,000	4,720	3.50%

From Table 9.1, it is clear that there are tradeoffs between these strategies with respect to the insurer's objectives. Strategy 1, with the highest deductible and required mitigation, necessitates considerably fewer assets for the insurer to meets its TRP than Strategy 4, which has no deductible and no required mitigation. On the other hand, expected profits and ROA levels are highest for insurance policies with the lowest deductible levels and no mitigation requirements. This is because the insurer collects considerably more in premiums and is compensated for the additional risk it assumes.

9.4 Impact of Indemnity Contracts on Insurer Performance

One of the principal ways for an insurer to reduce the asset level required to meet a prescribed value of TRP is through the use of risk transfer mechanisms. In this section, the role of reinsurance and its impact on the insurer's expected profits and ROA is explored. The typical reinsurance contract is an excess-of-loss policy that provides coverage against unforeseen or extraordinary losses. A typical excess-of-loss reinsurance contract requires the primary insurer to retain a specified level of risk with the reinsurer covering all losses between an attachment point, L_A, and exhaustion point, L_E on the EP curve (See Figure 9.2). In the analysis of the insurer's strategy in this section, it is assumed that the exhaustion point, L_E, corresponds to the worst-case loss, WCL and is defined by the target ruin probability (TRP) of 1%. The layer of reinsurance, $L_E - L_A$, is denoted as Δ.

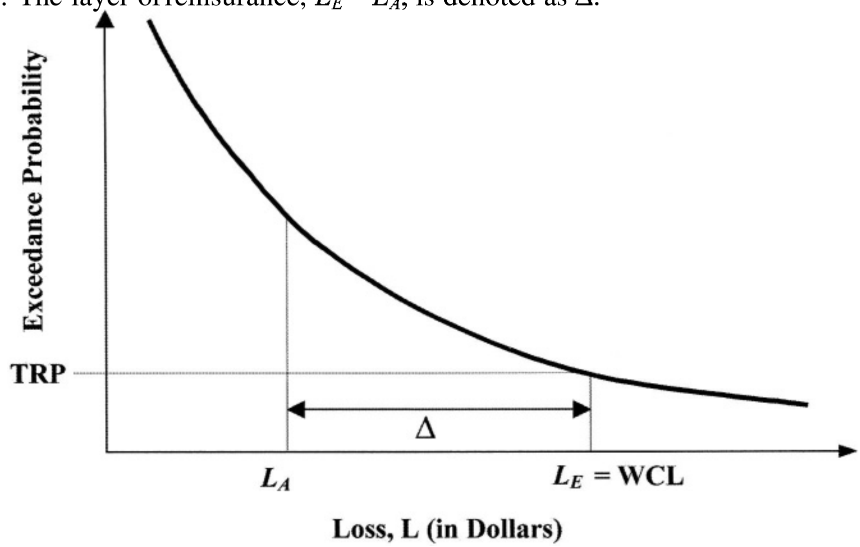

Figure 9.2. Excess-of-loss reinsurance contract

Excess-of-loss reinsurance contracts have the following features: the reinsurer pays all losses in the interval L_A to L_E with a maximum payment to the insurer of Δ. In return for this protection, the insurer pays the reinsurer a premium that reflects the expected loss, as well as a loading factor, λ_R. Thus, if $E(\Delta)$ = the expected losses for Δ units of reinsurance, and the loading factor is λ_R, then the insurer pays a premium to the reinsurer of $E(\Delta)(1+\lambda_R)$. In practice, of course, the reinsurance loading factor λ_R will vary as the attachment points of the reinsurance contract vary. For simplicity, λ_R is held constant here.

Prior to utilizing reinsurance as a strategy, the insurer needs to know how Δ and λ_R impact TRP, $E(\pi)$ and ROA. In the analysis that follows, it is assumed that there is sufficient capacity in the reinsurance market to provide the amount of excess-of-loss protection that the insurer desires.

9.4.1 Excess-of-Loss Reinsurance Using Strategy 1

Suppose that the company follows Strategy 1 in Table 9.1 and wants to explore the impact of an excess-of-loss reinsurance contract on TRP, $E(\pi)$ and ROA. As expected, the level of assets required to meet a TRP of 1% decreases as the reinsurance layer, Δ, increases as shown in Table 9.2 since the reinsurer absorbs more of the risk. Thus, for a reinsurance loading factor of λ_R =1, the required asset level (A_1) decreases from \$57 million with no excess-of-loss reinsurance in place to approximately \$18 million with a reinsurance layer of \$40 million. Table 9.2 also shows that the impact on A_1 is negligible for all values of Δ as λ_R increases, since this change only impacts the premium that the insurer pays to the reinsurer. This is a small dollar figure relative to potential losses from earthquakes.

Table 9.2. Required asset level (A) to meet safety first constraint (TRP = 1%) for Strategy 1 (in \$1000s)

Reinsurance Layer	**Reinsurance Loading Factor (λ_R)**			
Δ	**1**	**1.5**	**2**	**2.5**
\$ 0 million	\$ 57,000	\$ 57,000	\$ 57,000	\$ 57,000
\$ 10 million	46,900	46,900	47,000	47,000
\$ 20 million	37,100	37,100	37,200	37,300
\$ 30 million	27,300	27,500	27,600	27,700
\$ 40 million	17,700	17,900	18,100	18,300

The picture changes considerably when one looks at the impact that changes in Δ and λ_R have on expected profits earned by the insurer. Table 9.3 shows the values of $E(\pi)$ for the same values of Δ and λ_R shown in Table 9.2 under the assumption that assets are set as in Table 9.2 to just satisfy the required solvency constraint. Expected profits decrease significantly when one changes Δ due to the smaller amount of premiums collected by the insurer. As λ_R increases, the expected profits decrease even further because the insurer is required to pay the reinsurer more for protection. In fact, when λ_R = 2.5 and the maximum reinsurance layer is $40 million, the company experiences an approximate loss of $40,000.

Table 9.3. Expected profits [$E(\pi)$] while meeting safety first constraint (TRP = 1%) for Strategy 1(in $1000s)

Reinsurance Layer	**Reinsurance Loading Factor (λ_R)**			
Δ	**1**	**1.5**	**2**	**2.5**
$ 0 million	$ 1,000	$ 1,000	$ 1,000	$ 1,000
$ 10 million	950	920	900	870
$ 20 million	860	790	720	650
$ 30 million	740	600	470	340
$ 40 million	580	370	170	-40

Finally, the data from Tables 9.2 and 9.3 enable one to determine how changes in the amount of reinsurance affect the return on assets to the insurer. Table 9.4 considers the same sets of policies as previously considered. One sees that if the loading factor is sufficiently low, then the insurer obtains a higher ROA as it increases the size of its reinsurance layer. To illustrate, if $\lambda_R = 1$, then the ROA increases from 1.75% without any reinsurance to 3.29% if the reinsurance layer is $40 million. On the other hand, if λ_R = 2.5, the ROA is at its highest level when reinsurance is $10 million and decreases monotonically as the reinsurance layer increases. As a result, the insurer experiences negative expected profits, and hence a negative ROA, when the reinsurance layer is $40 million.

Table 9.4. Return on assets (ROA) given safety first constraint (TRP = 1%) for Strategy 1

Reinsurance Layer	**Reinsurance Loading Factor (λ_R)**			
Δ	**1**	**1.5**	**2**	**2.5**
$ 0 million	1.75%	1.75%	1.75%	1.75%
$ 10 million	2.02%	1.96%	1.91%	1.85%
$ 20 million	2.32%	2.13%	1.94%	1.75%
$ 30 million	2.69%	2.20%	1.72%	1.24%
$ 40 million	3.29%	2.09%	0.92%	-0.23%

The above analysis clearly shows that there are tradeoffs associated with any decision that the insurer makes regarding its choice of a reinsurance contract. The larger the reinsurance layer, the fewer the assets required to satisfy a predetermined safety first constraint. On the other hand, expected profits may decrease as the reinsurance layer increases, particularly if λ_R is relatively high. If the safety constraint is satisfied, then it is natural for the insurer to focus attention primarily on ROA. As discussed next, every aspect of the insurer's strategy, from mitigation and underwriting criteria, to choice of reinsurance contract terms, becomes important in attempting to maximize ROA.

9.4.2 Comparison of Performance Across Insurer's Strategies

Consider an insurance company that can purchase reinsurance with a loading factor $\lambda_R = 1$. It wishes to compare the impact that different values of the reinsurance layer Δ would have on its performance for Strategies 1 through 4. More specifically, the insurer is interested in the optimal level of reinsurance to purchase when the deductible levels and mitigation requirements change. Tables 9.5 through 9.7 compare the required asset level, the expected profits and the ROA for the four different strategies that the insurer is considering.

Table 9.5. Required asset level (A) to meet safety first constraint (TRP= 1%) with Reinsurance Loading Factor ($\lambda_R = 1$) (in $1000s)

	Strategies (Deductible, Mitigation)			
Δ	**1 (10%, 100%)**	**2 (0%, 100%)**	**3 (10%, 0%)**	**4 (0%, 0%)**
$ 0 Million	$ 57,000	$ 96,000	$ 89,000	$ 135,000
$ 10 Million	47,000	86,000	79,000	126,000
$ 20 Million	37,000	76,000	69,000	112,000
$ 30 Million	27,000	66,000	59,000	105,000
$ 40 Million	18,000	56,000	49,000	96,000

Table 9.6. Expected Profits [$E(\pi)$] to Meet Safety First Constraint (TRP= 1%) with reinsurance loading factor ($\lambda_R = 1$)

	Strategies (Deductible, Mitigation) Expected Profits E(Π) in $1,000's			
Δ	**1 (10%, 100%)**	**2 (0%, 100%)**	**3 (10%, 0%)**	**4 (0%, 0%)**
$ 0 Million	$ 1,000	$ 3,350	$ 1,700	$ 4,720
$ 10 Million	950	3,300	1,640	4,660
$ 20 Million	860	3,220	1,560	4,580
$ 30 Million	740	3,120	1,460	4,490
$ 40 Million	580	2,990	1,330	4,380

Table 9.7. Return on assets (ROA) to meet safety first constraint (TRP= 1%) with reinsurance loading factor ($\lambda_R = 1$)

	Strategies (Deductible, Mitigation)			
Δ	**1 (10%, 100%)**	**2 (0%, 100%)**	**3 (10%, 0%)**	**4 (0%, 0%)**
$ 0 Million	1.75%	3.50%	1.91%	3.50%
$ 10 Million	2.02%	3.85%	2.08%	3.72%
$ 20 Million	2.32%	4.25%	2.26%	3.98%
$ 30 Million	2.69%	4.72%	2.46%	4.26%
$ 40 Million	3.29%	5.31%	2.70%	4.58%

In comparing the four strategies, two principal conclusions can be drawn regarding the role of reinsurance in satisfying the company's objectives. First, it is possible to reduce the required assets to a relatively small figure if one requires mitigation as a condition for insurance and incorporates a deductible in the policy. As shown in Table 9.5, Strategy 1 (10% deductible; 100% mitigation) requires $27 million in assets to achieve the safety first constraint if the insurer has a $30 million layer of reinsurance. This is approximately one-fourth of the assets required by the insurer when utilizing Strategy 4 (0% deductible; 0% mitigation).

As shown in Table 9.6, $E(\pi)$ is highest when there is no mitigation and no deductible (Strategy 4). However, the required assets to support this strategy range from $135 million when there is no reinsurance to $96 million when the reinsurance layer is $40 million. Consistent with the inherent risk, the capital requirements and the ROA (Table 9.7) for this strategy are significantly higher. However, this strategy would only be feasible if the insurer could raise the required capital at reasonable interest rates.

9.5 Catastrophe Bonds As Additional Sources of Funding

To avoid the possibility of insolvency or a significant loss of claims-paying capacity, insurers have traditionally utilized reinsurance contracts as a source of protection. While the reinsurance market is a critical source of funding for primary insurers, the magnitude of catastrophic losses makes it implausible for them to adequately finance a mega-catastrophe. Cummins, Doherty and Lo (2002) have undertaken a series of analyses that indicate that the U.S. property-liability insurance and reinsurance industry could withstand a loss of $40 billion in practice with minimal disruption of insurance markets. According to their model, a $100 billion loss would create major problems by causing 60 insolvencies and leading to significant premium increases and supply side shortages.

The losses from Hurricane Andrew and the Northridge earthquake were signals to the insurance industry that they could face major problems from a future catastrophic disaster. It stimulated financial institutions to market new types of insurance-linked securities known as catastrophe bonds for providing protection against large-scale disasters. This solution looks promising given the fact that the $26.1 trillion U.S. capital market is more than 75 times larger than the property/casualty industry (Insurance Services Office, 1999). Thus the capital markets clearly have the potential to enhance the risk-bearing capacity of the insurance industry and allow them to spread risks more efficiently on a broader level.

Though the market for risk-linked securities is still in its early stages, insurers and reinsurers have over $4.3 billion in catastrophe bonds outstanding at the end of 2003, an increase in more than 50% over 2002. The total amount of risk-linked securities since its inception in 1996 is over $9.5 billion (Swiss Re, 2004). This section illustrates the performance of a catastrophe bond in interaction with other policy variables. Only the simplest type of catastrophe bond is treated here, where the trigger and payouts are anchored on aggregate losses of the insurer issuing the bond. This type of bond is useful for illustrative purposes and it is similar to the first hurricane-related catastrophe bond issued by USAA in June 1997.

Other catastrophe bonds being issued today are tied to an industry or parametric index as discussed in Chapter 7. These bonds cover damage from a certain natural peril based on insurance industry losses or the physical parameters of the actual event (e.g. hurricane wind speed, earthquake magnitude) within a specified region rather than to the insurer's actual losses.[1] Since these parameters are normally independent of the firm's actual losses, payments can be made to the firm immediately after the disaster occurs rather than being subject to the time delay necessary to compute actual losses, as in the case of the catastrophe bond considered in this section. Hence indexed catastrophe bonds reduce the amount of moral hazard in loss estimation. On the other hand, such an indexed catastrophe bond creates basis risk. Basis risk refers to the imperfect correlation between the actual losses suffered by the firm and the payments received from the bond. In contrast, excess-of-loss reinsurance has very little basis risk because there is a direct relationship between the loss and the payment delivered by the reinsurance instrument.

9.5.1 Structure of Catastrophe Bond for Oakland

Suppose that the insurer who is providing coverage against 5,000 homes in Oakland is considering issuing a catastrophe bond to reduce its chances of insolvency. Naturally, those investing in the bond would require an

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[1] For more details on the challenges in marketing catastrophe bonds, see U.S. General Accounting Office (2003).

appropriate return (greater than the risk-free rate of interest) to assume the additional risk of loss of principal and interest which might occur should a disaster trigger payouts from the bond.

The specific pricing model is as follows. An insurer issues a catastrophe bond that pays investors an interest differential in exchange for guaranteed funds based on the occurrence of a disaster. For this analysis, the bond is priced assuming that investors demand a Sharpe Ratio of 0.6. The Sharpe Ratio measures the amount of excess return required by investors for an additional unit of risk. In other words, the Sharpe Ratio = $(r - r_f)/\sigma$, where r is the return on the catastrophe bond, r_f is the risk free return (in this case assumed to be 5.5%) and σ is the standard deviation of bond returns. The Sharpe Ratio of 0.6 represents the average historical Sharpe Ratio for catastrophe bonds issued prior to 1999 (Bantwal and Kunreuther, 2000) and approximates the Sharpe ratio for more recent cat bonds.[2] It should be noted that in practice, a bond is not priced solely on the basis of a Sharpe Ratio. Investors often think about many other metrics, including spread as a multiple of expected loss.

Suppose a catastrophe bond is issued with face value, B, of \$10 million. The payout, PO, from the bond to the insurer is calculated as follows:

$$PO(\alpha, L, T, K) = \text{Minimum}\ [\alpha\ (L - T)^{+}, K]$$

where α is a fraction between 0 and 1 representing the co-payment rate borne by the bondholders (the fraction of losses paid by the bond holders in excess of the trigger T). The co-payment rate α is usually less than 1 to provide incentives to the insurer to accurately estimate claims even when these are in the range covered by catastrophe bond payouts. L represents the random variable of losses in the region in question, T is the trigger point for the catastrophe bond, and K is the maximum payout from the catastrophe bond, with $K \leq B$. Finally, $(L - T)^{+}$ is defined as the maximum of either $(L - T)$ or zero.

To illustrate, suppose the trigger, T, is \$20 million, $\alpha = 0.9$ and the maximum payout, K, is \$10 million. Then the payouts to the insurer, PO(0.9, L, \$20, \$10), from the catastrophe bond are 90% of losses in excess of the trigger level of \$20 million, until the maximum payout of \$10 million

[2] The average Sharpe ratio for a sample of six recent cat bonds analyzed by Swiss Re was 0.64 (Swiss Re, 2003, p. 19).

has been reached at a loss of L = \$31.11 million.[3]

The actual dollar payout from the catastrophe bond to the bondholder or investor, PB, at the end of the period (assumed here to be a year) is defined as:

$$PB(\alpha, L, T, K, B) = B - PO(\alpha, L, T, K)$$

The structure of the catastrophe bond is as follows: at the beginning of the year, investors would provide the insurer an amount of capital, $B/(1+r)$, where r is the promised rate of return on the zero-coupon catastrophe bond. The investors are then paid $PB(\alpha, L, T, K, B)$, as given above, at the end of the year. Sidebar 1 details the formulae for calculating the rate of return to investors from this catastrophe bond. This involves considering the ratio of the payout, $PB(\alpha, L, T, K, B)$, to what investors provide at the beginning of the year.

The insurer's actual profits at the end of the year are defined as:

$$\pi = (1+\lambda_I)E(L) - L - [rB - PO(\alpha, L, T, K)]$$

where, as in the earlier model, λ_I is the insurer's loading factor, so that $(1+ \lambda_I)*E(L)$ represents premiums collected, L represents the loss, and $[rB - PO(\alpha, L, T, K)]$ represents the payouts to the bondholders net of any triggered payments to the insurer from the bond. The insurer's basic performance measure, expected ROA, is computed as $E(\pi)/A$, where A represents the assets needed to achieve the desired solvency level, as measured by the TRP.

The above valuation process was used to evaluate various catastrophe bonds from the perspective of a primary insurer. As with reinsurance, the insurer pays investors for the potential protection from the catastrophe bond whether or not the insurer actually collects from it. The rates demanded by investors for catastrophe bonds marketed to date have suggested that investors perceive these bonds to be very risky implying very high rates of return for the bonds. Similar to reinsurance, the key question is whether the high price the insurer has to pay to sell these bonds is compensated for by their ability to substitute investor capital for insurer's capital for a desired level of solvency. The price of the catastrophe bond clearly reduces the insurer's expected profits, but it also reduces the insurer's own capital requirements to achieve a desired level of solvency.

[3] For this simple example, the maximum payout of \$10 million occurs at a loss of \$31 million because the investor is only responsible for losses if they exceed T = \$20 million and the insurer absorbs 10% of any loss above this amount since $\alpha = 0.9$. Therefore, at L = \$31.11 million, the insurer absorbs \$1.11 million of the loss above \$20 million and the investor pays \$10 million.

SIDEBAR 1: Calculating the Rate of Return to Investors from a Catastrophe Bond

The normal structure for a catastrophe bond is for investors to provide the insurer an amount B/(1+r) at the beginning of the year, where r is the promised rate of return on the zero-coupon catastrophe bond. The rate of annual return to investors from this arrangement is computed as:

$$R(\alpha, L, T, K, B) = \frac{B - PO(\alpha, L, T, K)}{\frac{B}{(1+r)}} - 1 = (1+r)\left(1 - \frac{PO(\alpha, L, T, K)}{B}\right) - 1$$

$$= r - \frac{(1+r)PO(\alpha, L, T, K)}{B}$$

This return is a random variable depending on the loss distribution (or exceedance probability) associated with L with a mean and standard deviation denoted by E{R} and σ(R), respectively. From the equation just above, E{R} and σ (R) clearly depend on all the parameters of the catastrophe bond, and in particular on the bond's face interest rate, r. Fixing the other parameters (α, L, T, K, B) and the insurer's underwriting and mitigation screening policies that determine the loss distribution for L, the required rate of return, r, for an investor with Sharpe ratio of 0.6, is then determined as follows:

$$\frac{E\{R\} - r_f}{\sigma(R)} = 0.6$$

where r_f is the risk-free rate.

9.5.2 Impact on Insurer's Performance in Oakland

Now, consider the performance of catastrophe bond for the 5,000 Oakland region homes analyzed earlier. The following bond parameters are fixed across all scenarios: α = 0.8; the face value, B, is $20 million; T is set so that the probability of the bond triggering a payout to the insurer is 2% corresponding to a trigger of approximately $ 10 million for all the scenarios considered. The maximum payout level, K, from the bond to the insurer is set at various levels, as shown in Tables 9.8 – 9.10. As expected, the results show that as K increases, the level of assets required decrease since more of the risk is transferred to the bond holders. As with reinsurance, assets levels correspond to a target ruin probability of 1%.

Using the same four strategies by the insurer as for the case of reinsurance, the required assets are shown in Table 9.8, the net expected profits of the bond payments are presented in Table 9.9, and the corresponding ROA is depicted in Table 9.10. These tables are comparable to Tables 9.5 through 9.7 for the reinsurance case. The reader should note, however, that a straightforward comparison between reinsurance and catastrophe bonds is not possible, since a reinsurance loading factor of $\lambda_R = 1$ is assumed in Tables 9.5 - 9.7 and a Sharpe ratio of 0.6 is assumed in Tables 9.8 - 9.10. The answer to the question of which of these instruments, reinsurance or catastrophe bonds, or both, is preferable will depend on their relative pricing in the market (as represented by the reinsurance loading factor and the Sharpe ratio), and in practice would require a thorough analysis of actual reinsurance rates and investor preferences. As expected, the first row of Tables 9.8 through 9.10 reproduces the corresponding row of Tables 9.5 through 9.7, since the case of K = 0 represents no effective coverage.

Table 9.8. Assets (to the nearest $1000s)

K	Strategies (Deductible, Mitigation)			
	1 (10%, 100%)	2 (0%, 100%)	3 (10%, 0%)	4 (0%, 0%)
$ 0 million	$57,000	$96,000	$89,000	$135,000
$ 10 million	47,000	86,000	85,000	132,000
$ 20 million	37,000	76,000	75,000	122,000

Table 9.9. Expected Profits (in $1,000s)

K	Strategies (Deductible, Mitigation)			
	1 (10%, 100%)	2 (0%, 100%)	3 (10%, 0%)	4 (0%, 0%)
$ 0 million	$1,000	$3,350	$1,700	$4,720
$ 10 million	-1,410	1,150	-706	2,500
$ 20 million	-2,300	150	-2,190	1,280

Table 9.10. Return on Assets

K	Strategies (Deductible, Mitigation)			
	1 (10%, 100%)	2 (0%, 100%)	3 (10%, 0%)	4 (0%, 0%)
$ 0 million	1.75%	3.50%	1.91%	3.50%
$ 10 million	-2.98%	1.33%	-0. 83%	1.89%
$ 20 million	-6.15%	0.20%	-2.93%	1.05%

As seen in Tables 9.8 through 9.10, based on the parameters assumed in the model, catastrophe bonds are not a good option for an insurer providing coverage for homes in Oakland alone. The only strategies for which ROA is positive are for Strategies 2 and 4 where there are no deductibles. In these situations, the insurer experiences higher expected losses and the insurer is able to make positive returns even with the expense associated with the bond.

Of course, if different levels of solvency (TRP) were chosen or if higher premiums were charged in Oakland (for example, $\lambda_I = 1.5$ or 2.0, rather than the level used earlier of 1.0), then the insurer might have a positive ROA even with a 10% deductible. Similarly, if investors in the catastrophe bond were less risk averse than assumed here (Sharpe Ratio lower than 0.6), they would require a lower interest rate and insurers could find these instruments to be more attractive.

9.5.3 Performance of Catastrophe Bonds Across Different Regions

For comparison purposes, the previous exercise is repeated for MC2 (Long Beach) and MC3 (Miami). The catastrophe bonds considered for these regions have the same features as the bond considered for Oakland: $\alpha = 0.8$; B = \$20 million and T is set so that the probability of the bond triggering a payout to the insurer is 2%; target ruin probability (TRP) is set at 1%; Sharpe Ratio is 0.6; and two different loading factors $\lambda_I = 1.0$ and $\lambda_I = 2.0$ are used.

Only Strategy 3 is analyzed (with 10% deductible and 0% mitigation). The values of ROA for different face values of catastrophe bonds issued for the three different regions are compared. Table 9.11 shows the results for $\lambda_I = 1.0$. With this loading factor, the bond is not attractive in any of the three model cities. Even with relatively low coverage, the price of the bond is too high for the insurer to make positive profits if they issue it.

Table 9.12 shows the results for $\lambda_I = 2.0$. Even with this relatively high loading factor, a catastrophe bond is not attractive for either Oakland or Long Beach. For Miami, the issuance of a catastrophe bond yields a positive ROA when K = \$5 million. This analysis reinforces a point that insurers have made in recent years: single region catastrophe bonds are generally priced too high for them to be an attractive option.

Table 9.11. ROA for catastrophe bonds in Oakland, Long Beach and Miami/Dade for Strategy 3 ($\lambda_I = 1.0$ and K as shown)

	Region		
K	**Oakland**	**Long Beach**	**Miami/Dade**
\$ 0 million	1.91%	1.81%	7.59%
\$ 5 million	-0.08%	-6.37%	-7.92%
\$ 10 million	-0.83%	-16.25%	-32.09%

Table 9.12. ROA for catastrophe bonds in Oakland, Long Beach and Miami/Dade for Strategy 3 (λ_I = 2.0 and K as shown)

	Region		
K	**Oakland**	**Long Beach**	**Miami/Dade**
$ 0 million	3.86%	3.68%	16.44%
$ 5 million	1.86%	-0.97%	4.57%
$ 10 million	1.21%	-9.49%	-5.65%

9.5.4 Multi-Region Catastrophe Bonds

By constructing a catastrophe bond that combines several uncorrelated hazards, the risk is diversified resulting in lower required investor interest rates due to diversification of risk. Insurers can clearly profit from improved exposure management which geographical diversification brings. Investors in catastrophe bonds are willing to accept a lower interest rate since they have a smaller chance of losing a given amount of principal if the maximum amount that the bond pays out is now spread across the uncorrelated risks in different regions, or across different types of hazards. A multi-regional catastrophe bond should cost less due to lower variance, increased ROA, and expected profits for a given target ruin probability TRP and investor sharpe ratio.

Recently, there have been several such parameterized catastrophe bonds issued. SCOR, the French reinsurer, issued a three year multi-peril bond that covers earthquakes and fires following an earthquake in Japan, earthquakes in the U.S. and windstorms in seven different European countries (Standard & Poor's, 2000). In June 2002 Swiss Re issued a four-year bond (PIONEER) that covers three types of perils in different parts of the world — hurricanes in the North Atlantic, windstorms in Europe and earthquakes in California, the central US and Japan --- based on five parametric indices tied to each of these natural perils using physical trigger mechanisms. There is also a multi-peril tranche that is linked to all five of these perils (Swiss Re, 2003).

To illustrate the impact of multi-region catastrophe bonds, consider the scenario in which a single insurer owns all three books of business in Oakland, Long Beach and Miami. Table 9.13 compares the ROA for the three single-region catastrophe bond in Table 9.11 with a multi-region bond for the entire portfolio of all three books of regional business for various levels of K. The same bond parameters as before are used with an insurance loading factor of λ_I = 1.0. Assets are specified so as to achieve a TRP = 1%.

From these results, two observations are made. One is the overall pooling effect of placing the three books of business together in one company. The superior returns to the Miami portfolio and the normal diversification effect allow a significantly higher ROA on the combined portfolio than on the average of the separate portfolios. Additionally, the multi-region catastrophe bond provides a mechanism for risk transfer for all three portfolios and can improve the performance of the ROA over that of all three of the separate regional portfolios, as in the case of K = \$5 million. In 2003, many catastrophe bonds are actually priced below similarly rated corporate bonds as there has been a significant widening of spreads in the bond market (due to deteriorating credit quality) while catastrophe bond spreads have remained fairly steady. Note, however, that these bonds continue to be a poor investment in risk transfer by the insurer relative to reinsurance, given the rates of return assumed to be required by investors (namely those implied by a Sharpe ratio of 0.6).

Table 9.13. ROA for Single-Region and Multi-Region Catastrophe Bonds for $\alpha = 0.8$; B = \$20 million; TRP = 1%; Sharpe Ratio = 0.6; $\lambda_I = 1.0$

	Region Covered by Catastrophe Bond			
K	**Oakland**	**Long Beach**	**Miami/Dade**	**Multi-region**
\$ 0 million	1.91%	1.81%	7.59%	4.19%
\$ 5 million	-0.08%	-6.37%	-7.92%	1.58%
\$ 10 million	-0.83%	-16.25%	-32.09%	-0.29%

9.6 Extensions of the Analysis

The framework presented in this chapter can be applied to many different hazards and many types of firms in different situations. The Oakland insurer example presented illustrates a firm concerned with the impact of a catastrophe on its ability to operate. However, it is important to keep in mind that these results for a single model city may themselves have idiosyncratic characteristics. For example, the effect of different risk management strategies may yield rather different payoffs than the Oakland results presented here if one changes the assumptions in the catastrophe model utilized for analysis.

The above analysis does indicate the importance for insurers to integrate risk transfer strategies with risk bearing strategies, underwriting strategies, and mitigation strategies. Each of these strategies has rather different impacts on the EP curve and on the associated profitability and insolvency levels. For some insurers and some books of business, mitigation measures will suffice to satisfy the safety first constraint and yield an attractive return on assets while maintaining demand for the product. Other insurers will require reinsurance and/or catastrophe bonds to deal with their constraints.

Insurance companies issuing policies in a given region may also have to selectively choose the risks they include in their books of business. In another area where catastrophe risks are not as prevalent, an insurer might choose to be stricter in setting the target probability of insolvency. This could be done without incurring huge capital costs associated with assuring sufficient reserves to satisfy their safety first constraint. In a city like Oakland, the problem is significantly more difficult due to the highly correlated risks associated with earthquake losses for the homes in the insurer's portfolio.

It is also worth noting that for certain risks, there are no market solutions, in spite of the existence of reinsurance and cat bonds as risk transfer mechanisms. For these situations, there is a role for the public sector to play in providing financial protection against large losses. California earthquakes are one such example. As described in Chapter 5, the reluctance of the insurance industry to cover losses from earthquakes in California led to the formation of the California Earthquake Authority which is a limited liability state-run insurance company funded by the insurance and reinsurance industry.

9.7 Conclusions

This and the previous chapter explored the relevance of mitigation – with and without the aid of reinsurance and catastrophe bonds – for homeowners and insurers interested in managing catastrophic risk. Two broad themes emerge from the analyses. First from a homeowner's perspective the need to mitigate is not clear-cut. In many cases the long-term benefits of mitigation may not justify the upfront cost of mitigating the structure. In addition, the expected profits for an insurer are higher when mitigation measures are not adopted due to the larger premiums required to cover the higher losses and the associated administrative costs. Hence, if an insurance company is solely interested in maximizing expected profits, it may not be inclined to encourage homeowners to adopt mitigation measures. On the other hand, mitigation measures can significantly reduce the required amount of assets an insurer needs in order to maintain a desired level of solvency. This increases the ROA and limits the downside risk.

Second, when one considers either reinsurance and/or catastrophe bonds as ways to transfer risk – whether or not mitigation is utilized - a more complex story emerges. If insurers have difficulty raising capital at reasonable interest rates, then a strategy requiring mitigation of homes would be a desirable one on their part in combination with some type of risk transfer instrument. These risk transfer instruments increase insurers' return on assets but at the expense of profits.

The two risk transfer instruments considered in this chapter are reinsurance and catastrophe bonds. The relative cost of these two instruments varies according to the insurance underwriting cycle with prices of reinsurance rising after a major disaster when industry capital is in short supply and falling when there is excess supply in the industry (Swiss Re, 2003).

Catastrophe bonds at relatively high interest rates reduce both an insurer's expected profits and ROA. One way to make these instruments more attractive and reduce the interest rates demanded is by issuing a multi-region catastrophe bond that has lower risk than a single-region bond. The yield required by investors in these bonds should be lower due to lower variance of returns associate with them. If the catastrophe bond is a multi-year instrument, insurers can rely on a fixed price in setting premiums and coverage limits that presents more challenge when they protect themselves against catastrophic losses with traditional single-year reinsurance policies. The challenge is to explain the statistical properties of these instruments so that investors understand the nature of the financial risks they face. The recent offering of the multi-year multi-hazard catastrophe bond, PIONEER, suggests that investors are beginning to appreciate the benefits of diversifying their portfolios in this way.

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Chapter 10 – Extending Catastrophe Modeling To Terrorism

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10.1 Introduction

Since the idea for this book was first conceived, the insurance industry and world were rocked by the events of September 11, 2001. While previous chapters have focused on the risk associated with natural disasters, at the core of this book is a more general problem: how to assess and manage risk associated with extreme events. This final chapter examines the unique challenges of extending catastrophe modeling to these types of risks by focusing on terrorism as well as the new challenges faced by the U.S for providing terrorism risk coverage after 9/11.

Section 10.2 discusses the impact of the 9/11 attacks on the insurance industry and the uncertainty regarding future terrorist activities. After discussing the nature of terrorism coverage in Section 10.3 and the differences between terrorism and natural disaster risk in Section 10.4, Section 10.5 turns to the passage of the U.S. Terrorism Risk Insurance Act of 2002 (TRIA). Section 10.6 discusses recent developments in terrorism modeling that can aid insurers and reinsurers in assessing insurance premiums and coverage limits, including a discussion of how models are used to establish insurance rates nationwide. Section 10.7 analyzes why the current demand for terrorism coverage has been at a low level since TRIA was passed. The chapter concludes with directions for future research for dealing with terrorism and other extreme events.

10.2 September 11, 2001: Impacts on Terrorism Insurance

Prior to the 9/11 attacks, terrorism coverage in the United States was included in most standard commercial policy packages without considering the risk associated with these events. The private insurance market had functioned effectively in the U.S. because losses from terrorism had historically been small and, to a large degree, uncorrelated. Attacks of a domestic origin were isolated and carried out by groups or individuals with disparate agendas.

None of these events created major economic disruption nor produced many casualties. The 1993 bombing of the World Trade Center (WTC) killed 6 people and caused $725 million of insured damages (Swiss Re, 2002). The Oklahoma City bombing of 1995, which killed 168 people, had been the most damaging terrorist attack on domestic soil, but the largest losses were to federal property and employees that were covered by the government. As a result, insurers and reinsurers did not have to pay close attention to their potential losses from terrorism in the United States prior to 9/11.

The terrorist attacks that day on the World Trade Center resulted in the death of nearly 3,000 people and inflicted damage estimated at nearly $80 billion. Approximately 40% of this amount was insured, resulting in the most costly event in the history of insurance (Lehman, 2004). The insurance industry was now confronted with an entirely new loss dimension. Reinsurers, who were liable for the lion's share of the claims, were for the most part unwilling to renew coverage and the few who did charged extremely high rates for very limited protection. Insurers unable to obtain reinsurance, or to raise sufficient capital either internally or from the capital markets, began to offer policies that explicitly excluded terrorism coverage.

The lack of available terrorism coverage had an immediate impact by delaying or preventing certain projects from going forward. For example, the U.S. General Accounting Office (GAO) noted a construction project that could not be started because the firms could not find affordable terrorism coverage (U.S. GAO, 2002). Several years after the event, the larger question being debated is whether terrorism is an insurable risk. That is, can insurers offer coverage at an affordable premium to potential insureds? If so, how does one go about determining how much to charge? Can one estimate the chances of another terrorist event occurring and the severity of insured losses?

Spectacular as were the 9/11 losses to the WTC and the Pentagon, do they represent a worst-case scenario? If some predictions concerning a possible chemical or biological attack become a reality, the answer is probably "no." Since March 2003, the U.S. government has issued clear warnings that additional terrorist attacks are likely, and indeed several have occurred including the deadly explosion at a nightclub in Bali that killed close to 200 people in October 2002 and the large-scale attacks on trains in Madrid, Spain on March 11, 2004 that killed more than 200 people and injured more than 1,500 others (Kunreuther and Michel-Kerjan, in press).

10.3 The Nature of Terrorism Coverage

Another key question triggered by the events of 9/11 is the appropriate role of the private and public sectors in reducing losses and offering insurance protection against the impacts of terrorism (Kunreuther, Michel-Kerjan, and Porter, 2003). In Congressional testimony five months after the 9/11 attacks, Richard J. Hillman of the U.S. General Accounting Office indicated “both insurers and reinsurers have determined that terrorism is not an insurable risk at this time” (U.S. General Accounting Office, 2002).

The following scenario (with fictitious names) illustrates the challenges confronting private industrial companies in obtaining terrorism coverage prior to the passage of the Terrorism Risk Insurance Act (TRIA) in November 2002[1]:

> Over the past 10 years, the AllRisk (AR) Insurance Company has provided $500 million in coverage to Big Business (BB) Inc. against risks to its building, including those due to terrorism at a total premium of $13 million. AR covers $100 million itself and has purchased an excess-of-loss reinsurance contract from Reinsurance Enterprise (RE) to cover the remaining $400 million. Given the events of 9/11, RE has decided that terrorism will no longer be included in its coverage because of the uncertainties associated with the risk. BB needs terrorism coverage since the bank that holds its mortgage requires this as a condition for the loan. AR must decide whether or not to continue providing BB with the same type of insurance as it has had previously and, if so, how much coverage it is willing to offer and at what price.

This scenario raises the following questions regarding terrorism coverage:

- What factors determine whether the risk is insurable?
- How much capital will AR require in order to provide protection against terrorism?

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[1] This scenario and the analysis of insurability issues associated with terrorism insurance are based on Kunreuther (2002).

10.3.1 Insurability Issues

As discussed in Chapter 2, insurers would be willing to provide insurance coverage if two conditions are met. First, they must be able to identify and quantify, or estimate at least partially, the risk (e.g., probability of an event occurring and the associated losses). Second, they must be able to set premiums for different classes of customers so the risk of insolvency is deemed acceptable.

In quantifying the risk from terrorist attacks, insurers can utilize an exceedance probability (EP) curve. However, it is considerably harder to construct an EP curve for terrorist activities than it is for natural disasters due to the difficulty in determining the likelihood of a terrorist attack. A potential target that may appear to have a high likelihood of attack, such as a trophy building, may also have a high level of protection and security which makes it less likely to be chosen by terrorists (Woo, 2002). So rather than trying to construct an EP curve, insurers normally turn to a scenario-based approach, by considering a range of terrorist-related events and estimating the likelihood of their occurrence and the resulting losses. Section 10.6 illustrates how catastrophe modeling can be utilized for constructing such scenarios.

10.3.2 Expanding Capacity Through Catastrophe Bonds

For insurers to provide their clients with the level of coverage offered prior to 9/11, they need to find new sources of capital. If the cost of this capital is high, the insurance premium will be prohibitively expensive and demand for coverage will dry up. To illustrate this point, it is useful to consider the scenario involving the AR Insurance Company providing terrorism coverage to BB Inc.

Now that RE has decided to eliminate terrorism coverage in its reinsurance treaties, AR has to determine how much protection it can offer BB and what price to charge for this coverage. The first concern of the underwriters at AR is to keep the firm's chance of insolvency below an acceptable risk level; profit maximization is of secondary interest. For AR to offer BB $500 million in coverage, it now has to raise an additional $400 million in capital.

One possibility would be for an investment bank to issue AR a $400 million catastrophe bond to cover the losses from a potential terrorist attack. As discussed in Chapter 7, a catastrophe bond requires the investor to provide upfront money that will be used by AR if a prespecified event, such as a terrorist attack, occurs. In exchange for a higher return than normal, the investor faces the possibility of losing either some or the entire principal invested in the catastrophe bond.

The amount paid out to AR depends on the design of the catastrophe bond. If investors are concerned with the ambiguity associated with terrorism risk, they will require a much larger than average return on their investment in order to compensate them for the possibility of losing their principal. To determine the costs to AR of a cat bond one needs to specify the annual return on investment (ROI) required by investors of a catastrophe bond and compare it with the normal annual return on AR investments, which for illustrative purposes will be assumed to be 8%. The annual cost, C, to AR of obtaining $400 million through issuing a catastrophe bond would then be:

$$C = (ROI - 0.08)\$400$$

Suppose AR believes that the expected annual loss for providing $500 million of coverage is $ 1 million. Assuming a loading factor of $\lambda_{AR} = 0.5$, AR would have to charge an annual premium (in millions) of P = ($1 + C) (1.5). Table 10.1 shows how C and P are affected by different required ROIs of investors.

Table 10.1. Changes in return on investment (ROI) on catastrophe bond cost (C) and insurance premiums (P) (in millions)

ROI	Catastrophe Bond Cost (C)	Premium (P)
10%	$8	$13.5
12%	$16	$25.5
14%	$24	$37.5
16%	$32	$49.5
18%	$40	$61.5
20%	$48	$73.5

In the above example, it should be noted that the high premium is principally due to the cost (C) of borrowing money from the bond investors. During the fall of 2001, it was not unusual for an ROI to be as high as 20% on capital provided to insurers and reinsurers. The ROI has since declined, but even if it were only 12%, insurers would have to charge $25.5 million to BB for $500 million in terrorism coverage. This is almost twice the $13 million that BB was paying prior to 9/11.

10.3.3 Potential Role of Catastrophe Bonds

It is interesting to speculate as to why with the exception of a few issuances a market for catastrophe bonds to cover losses from terrorist attacks has not emerged since 9/11. Consider the case where an investment banker was issuing a one-year catastrophe bond for covering terrorism losses. Let p represent a conservative estimate of the probability of a terrorist attack during a given year that would destroy BB's building, in which case the investor would lose the principal invested in a cat bond. If the normal annual rate of return is 8%, a risk neutral investor who committed \$Y to a catastrophe bond would require a ROI such that:

$$(1-p)(ROI)Y - pY = 0.08Y$$

Let p_i be the annual probability of a terrorist attack where an investor is indifferent between receiving an annual ROI = i % on a catastrophe bond knowing it would lose its entire investment should the attack occur. Substituting i for ROI and p_i for p in the above equation and rearranging terms, p_i becomes:

$$p_i = \frac{(i-0.08)}{(1+i)}$$

Thus, if i = 10%= 0.10, then $p_{0.10}$ = 0.02/1.10 = 0.018 or 1.8%. If a risk neutral investor believes the annual probability of a terrorist attack is less than .018, an ROI of 10% would be an attractive investment. If i = 20%= 0.20, then $p_{0.20}$ = 0.12/1.20 = 0.10 or 10%. This implies that if $p < .10$, a risk neutral investor would invest in a catastrophe bond if it returned 20% in the case of no terrorist attack. These indifference probabilities would be slightly lower if the investor were risk averse. Yet it is still hard to comprehend why the investment community has not viewed catastrophe bonds as a viable option for dealing with terrorism, particularly if the bond comprised only a small portion of the investor's portfolio.

In a recent paper, Bantwal and Kunreuther (2000) specified a set of factors that might account for the relatively thin market in catastrophe bonds in the context of natural hazard risks. They point out that spreads in this market are too high to be explained by standard financial theory, suggesting that they are not just a consequence of investor unfamiliarity with a new asset, but signal some deeper issues that need to be resolved before the catastrophe bond market can fully develop. In particular, the authors suggest that ambiguity aversion, myopic loss aversion, and fixed costs of education might explain the reluctance of institutional investors to enter this market.

Four additional factors may help explain the lack of interest in catastrophe bonds covering terrorism risk. There may be a moral hazard problem associated with issuing such bonds if terrorist groups are connected with financial institutions having an interest in the U.S. In addition, investment managers may fear the repercussions on their reputation of losing money by investing in an unusual and newly developed asset. Unlike investments in traditional high yield debt, money invested in a terrorist catastrophe bond can disappear almost instantly and with little warning. Those marketing these new financial instruments may be concerned that if they suffer a large loss on the catastrophe bond, they will receive a lower annual bonus from their firm and have a harder time generating business in the future. The short-term incentives facing investment managers differ from the long-term incentives facing their employers.

A third reason why there has been no market for these catastrophe bonds is the reluctance of reinsurers to provide protection against this risk following the 9/11 attacks. When investors learned that the reinsurance industry required high premiums to provide protection against terrorism, they were only willing to provide funds to cover losses from this risk if they received a sufficiently high interest rate.

Finally, most investors and rating agencies consider terrorism models to be too new and untested to price a catastrophe bond. Reinsurers view terrorism models as not very reliable in predicting the frequency of terrorist attacks, although they provide useful information on the potential severity of the attacks under a wide range of scenarios. Furthermore, one of the major rating firms noted that the estimates derived from the models developed by AIR Worldwide, EQECAT and Risk Management Solutions could vary by 200% or more. Without the acceptance of these models by major rating agencies, the development of a large market for terrorist catastrophe bonds is unlikely (U.S. General Accounting Office, 2003).

10.4 Comparison of Terrorism Risk with Natural Disaster Risk

Although both terrorist activities and natural disasters have the potential to create catastrophic losses, there are some significant differences between these two risks. Two features of terrorism – information sharing and dynamic uncertainty – make it difficult for the private sector to provide insurance protection without some type of partnership with the public sector.

The sharing of information on the terrorism risk is clearly different than the sharing of information regarding natural hazard risk. In the latter case, new scientific studies normally are common knowledge so that insurers, individuals or businesses at risk, as well as public sector agencies, all have access to these findings. With respect to terrorism, information on possible attacks or current threats is kept secret by government agencies for national security reasons. One justification for government intervention in insurance markets relates to the asymmetry of information between buyers and sellers and the problems this may cause, such as adverse selection. In the case of terrorism, there is symmetry of non-information on the risk between those insured and insurers where government is the most informed party.

A principal terrorist goal is to destabilize a region or country by attacking certain targets that disrupt normal activities and create fear. Since terrorists will adapt their strategy as a function of available resources and their knowledge of the vulnerability of the entity they are attacking, the nature of the risk changes over time, leading to *dynamic uncertainty* (Michel-Kerjan, 2003b). This feature, which translates into considerable ambiguity of risk, reflects an important difference from estimating natural hazards risks. Damage due to a future large-scale earthquake in Los Angeles can be reduced through adoption of mitigation measures; however, it is currently not possible to influence the occurrence of the earthquake itself. On the other hand, the likelihood of specific terrorist attacks will change over time as a function of the constellation of protective measures adopted by those at risk and actions taken by the government to enhance general security.

These characteristics of terrorism, along with the difficulty for insurers in finding new capital for covering this risk, raise the question as to how the government and the insurance industry can work together in providing protection and reducing future losses from these risks. The need for public-private partnerships was actually recognized in November 2002 when the Terrorism Risk Insurance Act of 2002 (TRIA) was passed.

10.5 Terrorism Risk Insurance Act of 2002

In the aftermath of the 9/11 attacks, many insurers warned that another event of comparable magnitude could do irreparable damage to the industry. By early 2002, 45 states permitted insurance companies to exclude terrorism from their policies, except for workers' compensation insurance policies that cover occupational injuries without regard to the peril that caused the injury. On the one-year anniversary of the 9/11 attacks, the U.S. remained largely uncovered (Hale, 2002). The President and the U.S. Congress viewed such a situation as unsustainable. If the country suffered future attacks, it would inflict severe financial consequences on affected businesses deprived of coverage. As a result, the U.S. Congress passed the Terrorism Risk Insurance Act of 2002 (TRIA).

10.5.1 Public-Private Risk Sharing under TRIA

While the passage of TRIA may have been welcome news for the business community, it was a mixed blessing for insurers who were obligated to offer coverage against terrorism to all their clients. The commercial establishments have the choice of either purchasing this coverage or declining it. Insured losses from property and contents damage and business interruption are covered under TRIA under the following conditions: 1) if the event is certified by the U.S. Treasury Secretary as an "act of terrorism" carried out by foreign persons or interests and 2) results in aggregate losses greater than $5 million.

Under TRIA's three-year term (ending December 31, 2005), there is a specific risk-sharing arrangement between the federal government and insurers[2] that operates in the following manner. First, the federal government is responsible for paying 90% of each insurer's primary property-casualty losses during a given year above the applicable insurer deductible (ID), up to a maximum of $100 billion. The insurer's deductible is determined as a percentage of the insurer's direct commercial property and casualty earned premiums for the preceding year. This percentage varies over the three-year operation of TRIA as follows: 7% in 2003, 10% in 2004, and 15% in 2005. The federal government does not receive any premium for providing this coverage.

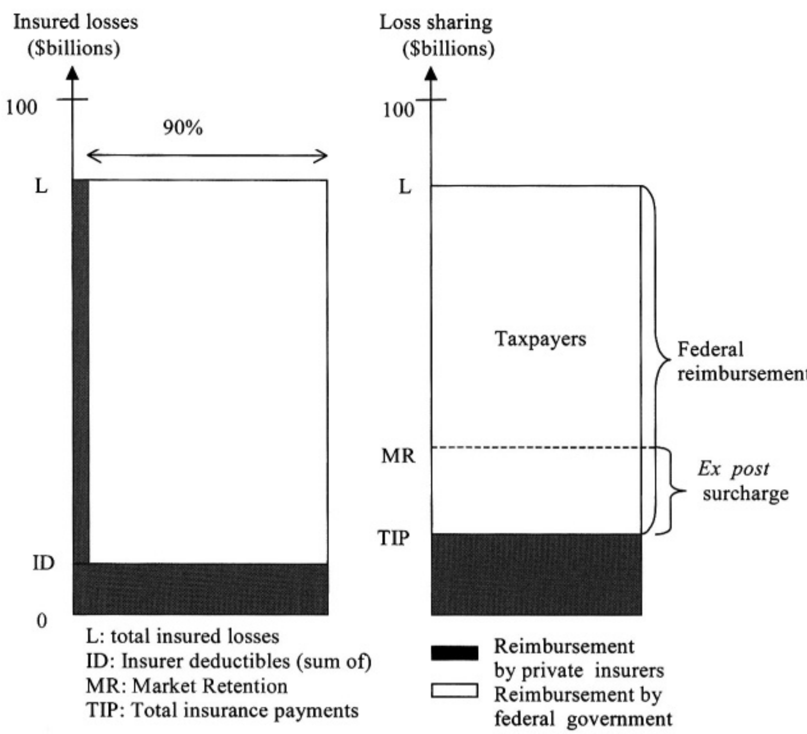

Figure 10.1. Loss sharing under TRIA.

Second, if the insurance industry suffers losses that require the government to cover part of the claims payments, then these outlays shall be partially recouped *ex post* through a mandatory policy surcharge. This

[2] Reinsurers are not part of TRIA but can provide coverage to insurers against their losses from terrorist attacks.

surcharge is applied on all property and casualty insurance policies whether or not the insured has purchased terrorism coverage, with a maximum of 3% of the premium charged under a policy. The federal government will pay for insured losses above a specific insurance marketplace retention amount (MR), as depicted in Figure 10.1. That amount evolves as follows: $10 billion in 2003, $12.5 billion for 2004, and $15 billion for 2005.

10.5.2 Challenge for Insurers and Firms: Quantifying the Residual Risk

Under TRIA, insurers were given 90 days after the legislation was enacted on November 26, 2002 to develop and disclose to policyholders new premiums and coverage terms. Many insurance companies found themselves in the situation of having to set a price for a risk they would rather not write. Although their exposure to terrorism risk is much reduced through the public-private partnership created by TRIA, it is still significant. Over the course of these 90 days, insurance companies followed a variety of strategies. Some determined that their exposures were not in high-risk locations and chose to leave existing premiums unchanged. Others with portfolio concentrations in major metropolitan areas deemed at high risk, such as New York, Washington, D.C., Chicago, and San Francisco, set very high premiums. In this situation, many businesses chose not to insure (Hsu, 2003; Treaster, 2003).

At the same time, many insurers and reinsurers have taken advantage of newly available tools designed to help them estimate their potential losses and therefore make rational and informed pricing decisions. Catastrophe modelers, leveraging their considerable experience and expertise in modeling natural hazard events, released the first generation of models to provide insurers with estimates of loss across multiple lines from terrorist attacks. The value of such models is in their ability to reduce uncertainty in risk estimates. One effect of that reduced uncertainty should be a lowering of premiums for terrorism insurance.

10.6 Catastrophe Models for Terrorism Risk

Insurance markets function best when losses are relatively small, random and uncorrelated, and when there is an abundance of historical loss data to which statistical techniques can be applied to predict future losses. As has been discussed throughout this book, when it comes to natural catastrophes, losses can be of catastrophic proportion and are often highly correlated. Furthermore, because such events occur infrequently, loss data are relatively scarce, making reliance on traditional actuarial techniques dubious at best.

As limited as the data is for nature catastrophes, there is much less information available on terrorist attacks for risk estimation purposes. To the extent that historical data do exist and are available from such sources as the Federal Bureau of Investigation (FBI), the U.S. Department of State, the Center for Defense and International Security Studies (CDISS), and the Central Intelligence Agency (CIA), they may not be representative of current threats.

To explore the alternative approaches that modelers have used to overcome the challenges of quantifying terrorism risk, it is useful to begin with the simple modeling framework introduced in Chapter 2 and reproduced here as Figure 10.2.

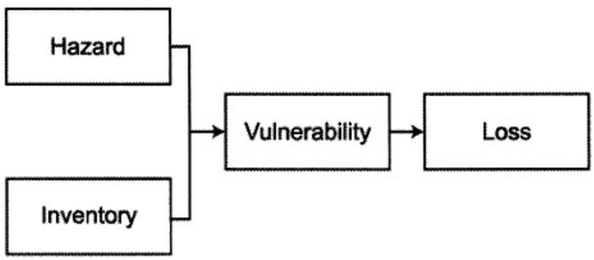

Figure 10.2. Catastrophe model components.

10.6.1 Terrorism Hazard

A terrorism model must first address three basic issues regarding the hazard itself: frequency of occurrence, the most likely locations of future terrorist attacks, and their severity in terms of insured loss. In undertaking this analysis, the different potential targets plus the interdependencies among networks and systems must be taken into account (Pate-Cornell and Guikema, 2002). For example, the loss of electric power or contamination of the water supply could create long-term business interruption risks and require residents in the affected areas to relocate.

The management of international terrorism risks has traditionally relied upon the experience and judgment of a specialist underwriter. For certain individual risks, recourse might be made on the advice of security professionals. For a portfolio, maximum loss would be carefully capped, but the overall risk assessment procedure would remain essentially qualitative and subjective. The most basic terrorism risk model is thus one encoded within the working experience of an underwriter and dependent on his personal expert judgment.

To cover rare catastrophic acts of terrorism, beyond the experience of even the most seasoned underwriter, the judgment of external terrorism experts might be invoked. Terrorism risk management would still be judgment-based, but the underwriter would be supported by the greater knowledge of terrorism experts. Recognizing that experts' risk estimates are based on their own set of assumptions and may reflect a set of biases, the challenge is to evaluate these figures carefully in modeling terrorism risk. Terrorism models incorporate the judgment of teams of experts familiar both with available data and current trends. These experts have operational experience in counterterrorism at the highest national and international levels, with many specializing in terrorism threat assessment. Because each expert is privy to his own sources of intelligence and has his own security clearances, there is no common database of information upon which all experts can form their judgments. In fact, much of the crucial information is confidential.

Determining Likelihood of Attacks

To elicit expert opinion on the likelihood of attacks, several different approaches have been utilized. Some modeling firms employ the Delphi Method; others convene a conference of experts to capture and statistically combine various opinions into a useful and cohesive form that can be used to generate probabilities. For complex problems not governed by scientific laws, the judgment and intuition of experts in their field is not only an appropriate ingredient in any model, but a critical one.

The Delphi Method is a well-known and accepted approach developed by the RAND Corporation at the start of the Cold War. Among its first applications was the forecasting of inter-continental warfare and technological change. The Delphi Method comprises a series of repeated interrogations, usually administered by questionnaire, where the responses are anonymous. Direct interaction between the participants is precluded to eliminate the natural bias of following the leader. After an initial round of interrogation, individuals are encouraged to reconsider and, when appropriate, to change their views in light of the replies of all the others that are shared with everyone in the group (Adler and Ziglio, 1996). While the methodology is highly structured, the final estimates by each participant still only represent opinions, informed by other members of the group.

Experts are asked to weigh in on several aspects of event frequency and intensity: the number of attacks per year, the type of target, the attack mode or weapon type, and finally the specific target of each potential attack. Each of these issues depends in part on the nature of the terrorist organization originating the attack. Critical to the results is the team's operational understanding of the likely terrorist actions in the context of the current state of security countermeasures. Targets and attack methods that were once undefended may now be more vigorously protected by federal homeland security, state and local policy, and private security resources.

An alternative to the Delphi Method is using a conference of experts where participants can exchange views. The agenda is usually topics, such as the kind of weapons a specific terrorist group is more likely to use or what areas/countries are more susceptible to attack. When some experts are unable to attend the conference, their judgment can be elicited separately and fed back to others using the Delphi Method.

The lack of historical data makes the use of experts the only way for modelers to determine the likelihood of new attacks. However, experts have their own limitations in forecasting future behavior, as each of them has specialized knowledge. Some are much more focused on a given terrorist group and disregard dangers from others. Others are specialized on a given type of weapon or on a very specific kind of biological or chemical agent. In other words, each expert can be accurate within his or her small window of expertise, but the whole group of experts can be wrong about the reality of the global threats -- a kind of illusory expertise (Linstone and Turoff, 1975).

Another pitfall is the possible optimism/pessimism bias of experts. For instance, if a terrorist attack recently occurred, a natural trend would be to overestimate the likelihood of new attacks in the short run. Conversely, if a governmental agency arrested leaders of a terrorist group, a natural bias could be to concentrate only on that group and overlook other terrorists, resulting in misconceptions of the likelihood of other attacks.

Identifying Likely Targets and Attack Modes

Obviously target types vary depending on the nature and goals of the individual terrorist groups or organizations, not only because of differences in the resources at this group's disposal, but because of its different political agenda.

Once the target types are identified, databases of individual potential targets are developed. In the case of terrorism, targets within the U.S. might include high profile skyscrapers, government buildings, airports, chemical plants, nuclear power plants, dams, major tunnels and bridges, large sports stadiums, major corporate headquarters, and marine terminals. Trophy targets normally represent a higher value to the terrorists due to the publicity associated with them, and they therefore have a higher probability of attack, other things being equal. Target databases can comprise tens of thousands or even hundreds of thousands of structures.

In the simulations developed by modelers, the terrorist group receives value or utility from the damage inflicted on its adversaries. The expected loss is determined by the probability of success in carrying out the attack and the economic and psychological value of the target. In turn, the probability of success is determined not only by the amount of resources the terrorist group allocates to the attack, but also by the resources its opponent allocates to detecting terrorist activity and defending the target. Both parties are constrained by the funds and people-power at their disposal and the "model" becomes one of strategic decisions as to how to deploy those resources, i.e. which targets to attack and with what weapons, and which to defend. Game theory can thus be used to analyze likely targets and attack modes.

The severity of the attack is a function of the weapon type. Modeled weapon types include so-called conventional weapons, such as package, car and truck bombs, as well as aviation crash. In light of Al Qaeda's clearly expressed interest in acquiring and deploying weapons of mass destruction, models also account for the possibility of non-conventional weapon attacks including chemical, biological, radiological, and nuclear (CBRN) weapons (Central Intelligence Agency, 2003).

10.6.2 Inventory

The 9/11 attacks revealed that not only are the terrorist targets themselves at risk, but so are the surrounding buildings. Nevertheless, the effects of terrorist attacks with conventional weapons are likely to be highly localized compared to natural disasters such as hurricanes and earthquakes. The resulting damage depends on such things as the kind of explosive material used, the amount of material, and the density and verticality of the surrounding buildings. For non-conventional weapons, the spatial extent of damage depends on the delivery mechanism and on external factors such as wind speed and wind direction.

Terrorism models can estimate total losses as well as aggregate insured or insurable losses for individual buildings, insurance company portfolios, and/or the entire insurance industry. While the large losses resulting from natural catastrophes have historically been to property, terrorist attacks can affect multiple insurance lines that include life, liability, workers' compensation, accident, and health, as was the case on 9/11. They can also result in severe stress on the psyche of a nation under siege.

The databases that are utilized in natural catastrophe models are also relevant for terrorism models. Modelers have developed industry databases of employees by building occupancy and construction type at the ZIP code level. These can be supplemented with state payroll and benefit information, generally available to insurance companies, to create an inventory at risk. Since 9/11, modelers are emphasizing to insurers the importance of gathering detailed data on the buildings they insure and the employees who work in them (Insurance Accounting, 2003).

10.6.3 Vulnerability

Research on the impact of explosives on structures has been ongoing since the 1950s. The Department of Defense and the Department of State have examined blast loading in the course of developing anti-terrorism designs for U.S. embassies. In addition, research activity has surged since the bombing of the Alfred P. Murrah Federal Office Building in Oklahoma City (1995) and the U.S. military housing facilities in Dhahran, Saudi Arabia (1996) (Olatidoye et al., 1998).

Modelers have developed damage functions that incorporate historical data from actual events combined with the results of experimental and analytical studies of how different building types respond to such attacks. In the case of a terrorist attack using conventional and nuclear weapons, buildings sustain damage as a result of a variety of assaults on their structural integrity and their non-structural components. In the case of non-conventional weapons, the structure of the building is likely to be unaffected, but the resulting contamination may render it unusable for long periods and result in extensive cleanup costs. In either case, the damage functions determine loss to building, contents, and loss of use.

Conventional Weapons

In terrorism modeling, damage is a function of the attack type and building type. The type of attack, whether package, car or truck bomb, can be expressed as a TNT-equivalent. The size of this charge can be thought of as the intensity of the event. Damage to the target building results from the shock wave, the subsequent pressure wave, and fire.

The target building may sustain total damage from the point of view of insured loss even if it remains standing. If the building collapses, however, it would increase the number of fatalities. Furthermore, different modes of collapse, such as an overturn versus a pancake collapse, will affect the degree of damage to surrounding buildings and thus the total area affected by the event. The buildings surrounding the target building are also likely to be damaged by the resulting shock and pressure waves and/or by falling or flying debris.

Non-conventional Weapons

The effects of nuclear weapons on both structures and populations have been the subject of extensive research for decades (Glasstone and Dolan, 1977). Chemical, biological and radiological (CBR) attacks are more problematical and only a few accidental releases of chemical agents, such as the one that occurred at the Union Carbide chemical plant in Bhopal, India (1984) have been analyzed. Other events include the 1995 sarin attack in the Tokyo subway and the more recent distribution of anthrax through the mail in autumn 2001 in the U.S. (U.S. Department of State, 2003). These examples provide data for empirical analysis and research. Fortunately, those attacks have been extremely rare so there is limited historical data.

Some modelers have developed relationships between the use of non-conventional weapons and potential damage; others employ models developed for various government agencies that follow what is known as a source/transport/effects approach. The "source" refers to how a hazard agent originates, including the type, yield, effectiveness, and other properties of the agent. Various attack types are simulated, including chemical agents such as sarin, VX, tabun, biological agents such as anthrax and smallpox. Nuclear and radiological agents such as cesium, cobalt and plutonium are also simulated (Central Intelligence Agency, 2003).

"Transport" refers to the means by which the agent disperses or moves from the source to the people or facilities presumed to be the targets. A full range of mechanisms is considered ranging from mail-borne dispersal to wide area dissemination via aerosol spraying and conventional bomb blast. "Effects" refers to the physical, performance, and psychological impact of the attack on humans as well as on the environment. While even a small suitcase nuclear device can cause extensive physical damage to buildings over a relatively large geographical area, the primary effects of other non-conventional weapons is contamination, which may render the structures unusable for long periods of time as discussed. In fact, in some cases, the most cost-effective way of dealing with badly contaminated buildings may be demolition under very cautious and well-defined procedures.

10.6.4 Workers' Compensation Loss

In addition to property damage, terrorism models estimate fatalities under both workers' compensation and life insurance policies, as well as losses from injuries arising from personal accident and other casualty lines. The number of injuries and fatalities, as well as the severity of injuries, is a function of the nature of damage sustained by the structural and non-structural components of buildings and their contents. Figure 10.3 illustrates the process for computing workers' compensation loss.

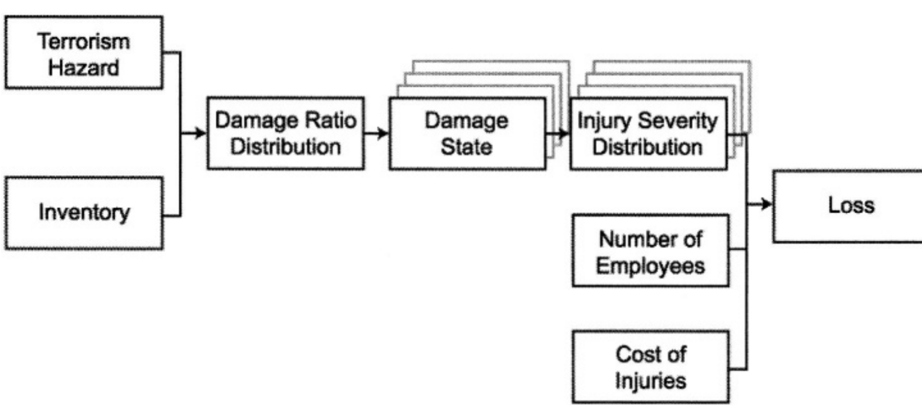

Figure 10.3. Modeling workers' compensation loss.

In estimating workers' compensation loss, models account for variability in damage to individual buildings so that one can estimate the extent of injuries and fatalities. For each level of severity, a mean damage ratio is calculated along with a probability distribution of damage. Because different structural types will experience different degrees of damage, the damage functions vary according to construction materials and occupancy. A distribution of damage for each structure type is mapped to different damage states. These may be, for example, slight, moderate, extensive and complete, as shown in Figure 10.4 for a specific building.

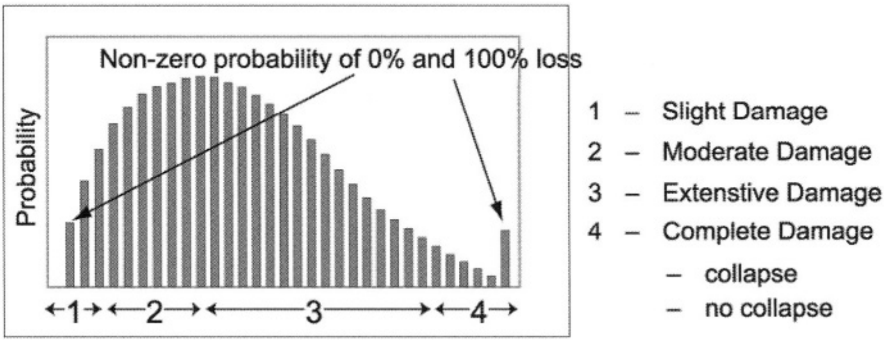

Figure 10.4. Building damage distribution mapped to different damage states.

At the level of complete damage, the building may or may not have collapsed. Complete damage means that the building is not recoverable. Collapse will typically result in more severe injuries and larger numbers of fatalities than if the building is still standing. Estimates of workers' compensation (and other casualty lines) loss are based not only upon the number of people injured, but also on the severity of the injuries, such as minor, moderate, life threatening and fatality. Distributions of injury severity are then developed for each damage state for each building and occupancy type.

By combining information on the number of employees in each damaged building and the cost of injuries, the model generates the total loss distribution for a particular structure. Losses are calculated based on the number of employees in each injury severity level and on the cost of the injury as shown in Figure 10.5. To calculate losses arising from life insurance and personal accident claims, potential losses are calculated for both residential and commercial buildings. These calculations use assumptions about the distribution of the population between these two types of structures at the time of the attack.

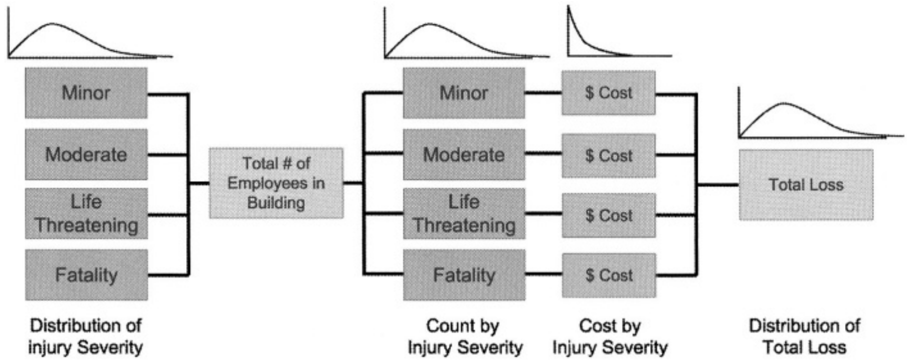

Figure 10.5. Calculation of workers' compensation loss for an individual building.

10.6.5 The ISO Advisory Loss Costs

Loss estimates generated by terrorism models are of interest to all parties. The insureds would like a better understanding of their exposure to potential terrorist attacks in order to determine whether to purchase coverage. Insurers can use model output to develop their pricing, reinsurance needs, and fashion policy conditions such as deductibles, exclusions, and coverage limits. Model output is also of interest to policy makers. In New York City for example, modeled loss estimates have been used to support a request for a larger share of federal funding for homeland security.

Since these terrorism models have been applied to thousands of potential targets, they can provide a picture of the relative risk by state, city, ZIP code and even by individual location. The Insurance Services Office (ISO) used the estimates provided by one of its subsidiaries, AIR Worldwide, to file commercial property advisory average loss costs with the insurance commissioner for each state at the end of 2002.[3] ISO defined three tiers for the country, with certain areas within Washington, DC, New York, Chicago and San Francisco in the highest tier, with assigned loss costs of approximately $0.10 per $100 of property value. A second tier consisted of Boston, Houston, Los Angeles, Philadelphia and Seattle as well as other portions of the highest rated cities; the rest of the country fell into the third tier.

In pre-filing discussions with regulators, ISO's advisory loss costs were challenged by some regulators who felt that such premiums would

[3]A *loss cost* is defined by ISO as that portion of a rate that does not include provision for expenses (other than loss adjustment expenses) or profit. It may be used by ISO companies as a starting point to set insurance rates, after reflection of company-specific expenses and profit. Once an ISO advisory loss cost has been approved by a state, an ISO participating insurance company can usually adopt it without having to undertake its own often lengthy and expensive rate filing process.

lead businesses to relocate to other areas (Hsu, 2003). Negotiations ensued and compromises were made. ISO filed loss costs for first-tier cities based on zip code level model results, which differentiated between the higher risk of downtown city centers and the lower risk of properties on the outskirts. But nowhere did the filed loss costs exceed \$0.03 per \$100 of property value.[4] Thus, while the new official advisory average loss costs no longer adequately reflected the risk in the eyes of the modelers, they became more palatable to other stakeholders. The Departments of Insurance in all 50 states eventually approved these ISO advisory loss costs that covered the years 2003, 2004, and 2005.

10.7 Low Insurance Demand for Terrorism Coverage

When Congress passed the Terrorist Risk Insurance Act (TRIA) in November 2002, the expectation was that it would ease insurers' concerns about suffering large losses from another extreme attack and then enable buyers at risk to purchase coverage at reasonable prices. However, the demand for coverage has been much lower than anticipated even though insurance is now available nationwide under the TRIA requirement (Hsu, 2003; Treaster, 2003).

10.7.1 Empirical Evidence

The Council of Insurance Agents and Brokers (CIAB) undertook the first national survey on the level of demand for terrorism coverage at the beginning of 2003 (CIAB, 2003a). At the time, almost half of its members that handle the largest accounts (customers who pay more than \$100,000 annually in commission and fees to the broker) indicated that less than 1 in 5 of their customers had purchased terrorism insurance. The low demand was even more pronounced for smaller companies (less than \$25,000 in commission and fees to the broker). Only 65% of the brokers indicated that less than 1 in 5 customers were purchasing insurance against terrorism.

According to another national survey by the CIAB undertaken during the spring of 2003, 72% of the brokers indicated that most of their commercial customers were still not purchasing terrorism insurance coverage even in locations like New York City (CIAB, 2003b). A survey by Marsh Inc. of 2400 of its policyholders revealed that 29.3% of them had purchased terrorism insurance in 2003 (Marsh, 2004). If this level of demand continues, a severe terrorist attack will likely have a more devastating effect on business continuity today than after 9/11.

Although TRIA limits the potential losses to the insurance industry, some insurers are still concerned about the impact of a large terrorist attack on

---

[4]The second tier (third tier) settled at \$0.018 (\$0.001) per \$100 of property value.

the solvency of their firms and their ability to pay. Some businesses are concerned not only with acts of terrorism certified by the federal government, but also by the prospect of “domestic terrorism”, such as an attack similar to the Oklahoma City bombings in 1995, which would not be covered by TRIA. The market for domestic terrorism is still mixed with some insurers offering coverage (sometimes at no cost if the risk is perceived to be low) while others simply excluding it (CIAB, 2003a). In the latter case, businesses may prefer not to buy any terrorism coverage than partial protection.

10.7.2 Heuristics and Biases

Since most businesses have little or no information on terrorism risk and no new attack since 9/11 has occurred on U.S. soil at the time this book goes to press, firms may perceive the chances of another event to be extremely low. This behavior has been well documented for natural hazards where many individuals buy insurance after a disaster occurs and cancel their policies several years later if they have not suffered a loss It is hard to convince them that the best return on an insurance policy is no return at all. In other words, there is a tendency for most people to view insurance as an investment rather than as a form of protection (Kunreuther, 2002).

A few years after 9/11, concern with damage from terrorism appears to have taken a back seat. In 2003, most firms believed that if a terrorist attack occurred, it would not affect them, whereas in the first few months after 9/11, they had the opposite belief. The aforementioned CIAB study indicated that more than 90% of the brokers said that their customers eschew terrorism insurance because they think they don’t need it (CIAB, 2003b). These firms consider insurance, even at relatively low premiums, to be a bad investment. The expectation that government may financially aid affected businesses whether or not they are covered by insurance, as illustrated by the airline industry following 9/11, may also contribute to limited interest in spending money on coverage.

There seems to be a large difference in the perception of the seriousness of the terrorist threat by those who are potential buyers of insurance and those who are supplying coverage. In these circumstances, TRIA will not solve the problem. To create a market for terrorism insurance, both buyers and sellers need to do a more systematic analysis of the relationship between the price of protection and the implied risk. There is no guarantee that firms will be willing to pay more for coverage or that insurers will greatly reduce their premiums. But there is a much better chance that a larger market for terrorism coverage will emerge than if the status quo is maintained (Kunreuther and Michel-Kerjan, in press).

The U.S. Treasury Department is required by Congress to undertake studies of the supply and demand for terrorism coverage so that more informed decisions on the renewal of TRIA in 2005 may be made. Those studies, launched in December 2003, should contribute to better understanding the current level of demand for terrorism insurance, as well as to suggest possible improvements in the partnership to create a more stable insurance market should another attack occur.

10.8 Future Research Directions

This concluding section suggests future research for dealing with terrorism and other extreme events, such as natural disasters, by focusing on three areas: vulnerability analyses, risk perception and interdependencies.

10.8.1 Vulnerability Analyses

Risk assessment needs to be supplemented by vulnerability analyses that characterize the forms of physical, social, political, economic, cultural, and psychological harms to which individuals and modern societies are susceptible. Modeling events with considerable uncertainty and ambiguity creates discomfort in undertaking risk assessments. Constructing scenarios that may lead to the occurrence of specific events is a useful first step.

A meaningful example of work in this regard is a study undertaken over 25 years ago by Warner North and his colleagues on estimating the likelihood of microbial contamination of Mars from the first Viking mission, where a landing on the planet was planned on July 4, 1976. They first constructed a series of scenarios characterizing how microbes could contaminate Martian soil based on the possible location of microbes on the spacecraft and Martian environmental conditions. They then assigned probabilities of contamination to each of these scenarios and undertook extensive sensitivity analyses to determine how changes in the inputs to these scenarios would lead to changes in these probabilities. On the basis of these analyses, they determined that the probability of contamination was more than one order of magnitude below the predetermined acceptable level of risk of 1 in 10,000. Scientists who had initially expressed concern about the risk of contamination agreed that the mission should proceed without the need for further steps to reduce the microbial burden on the Viking. The Viking successfully landed on Mars in the summer of 1976.

10.8.2 Risk Perception

The terrorist attacks of 9/11 have raised the question as to what should be done to mitigate the consequences of future catastrophes and aid the recovery process should another disaster occur. In order to develop a strategy, incorporating the growing knowledge of how individuals process information on extreme events and then make choices regarding mitigation is necessary.

As illustrated by the examples of Hurricane Andrew and the Northridge earthquake, people are not very concerned about the possibility of catastrophe events before they occur. They want to take protective action only after the event and this concern dissipates over time. To reduce the consequences of natural disasters, safer structures can be built and/or people can move out of harm's way. To mitigate the consequences of chemical accidents, the inventory level and/or production of specific toxins can be reduced to lower the risk of another mishap occurring.

Taking steps to reduce the risk of future terrorist activities is more difficult than for natural disasters or industrial accidents. Considerable uncertainty exists with respect to who the perpetrators are, their motivations, the nature of their next attack and where it will be delivered. Terrorist groups can attack anything, anywhere, at any time, and not everything can be protected. Additionally, there are challenges associated with allocating resources for dealing with terrorism risk. The government may be tempted to invest huge sums of money in protection to provide reassurance for its citizens (i.e., reassuring expenditures). Educating the public on the current likelihood of attacks might reduce such costs. On the other hand, actions taken by government services to curb terrorism might not be publicly revealed to protect national security.

10.8.3 Interdependencies

The antecedents to catastrophes can be quite distinct and distant from the actual disaster, as in the case of the 9/11 attacks, when security failures at Boston's Logan airport led to crashes at the World Trace Center (WTC), Pentagon, and rural Pennsylvania. The same was true in the case of recent power failures in the northeastern US and Canada, where the initiating event occurred in Ohio but the worst consequences were felt hundreds of miles away.

Future research should address the appropriate strategies for dealing with situations where there are interdependencies between agents (persons, organizations, countries). In these situations, there may be a need for the public sector to take the leading role with respect to providing protective measures because the private sector may have few economic incentives to take these steps on their own. Kunreuther and Heal (2003) have addressed this issue by asking the following question: What economic incentives do residents, firms or governments have for undertaking protection if they know that others are not taking these measures and that their failure to do so could cause damage to them?

To illustrate this point, suppose Airline A is considering whether to institute a sophisticated passenger security system knowing that passengers who transfer from other airlines may not have gone through a similar screening procedure and could cause damage to its airplane. If there is no screening process for passengers who transfer from one airline to another and there is a relatively high probability that these dangerous passengers could get on board Airline A due to the failure of other airlines to adopt screening systems, then Airline A will also not want to invest in such a system. The interdependent risks across firms may lead all of them to decide not to invest in protection.

The 9/11 events and the anthrax attacks during the fall of 2001 also demonstrated a new kind of vulnerability. Terrorists can use the capacity of a country's critical infrastructures to have an immediate large-scale impact on the nation by reversing the diffusion capacity of the networks and turn them against the target population so that every aircraft and every piece of mail now becomes a potential weapon (Michel-Kerjan, 2003a). During the anthrax episode, the attackers used the U.S. Postal Service to spread threats throughout the country and abroad. The entire network was potentially at risk as any envelope could have been considered to be contaminated by anthrax (Boin, Lagadec, Michel-Kerjan and Overdijk, 2003).

The emerging vulnerabilities in critical infrastructures raise challenging questions related to strategies for mitigation given the large operating networks associated with the water supply, electricity, transportation networks, telecommunications, banking and finance, energy, emergency, and defense services. The social and economic continuity of a nation's activities critically depend on their operation (OECD, 2003; Michel-Kerjan, 2003a; White House, 2003).

Future research should examine the nature of these interdependencies as well as the appropriate role of regulations, standards, third party inspections, and insurance to encourage individuals and firms to take protective actions. Without some type of coordinating mechanism, or economic incentives such as a fine, subsidy or tax, it may be difficult to convince any individual group to invest in mitigation because they know others may contaminate them.

To better understand these interdependencies at a managerial level, it would be meaningful to organize international strategic debriefings much more systematically after an extreme event or a large-scale threat occurred with senior-executives who were in charge and with academic experts. Every threat offers an opportunity to learn and be collectively prepared (Lagadec and Michel-Kerjan, 2004).

While launching such initiatives requires expertise and commitment by the top-management of organizations, it would help to learn more about these emerging risks and to examine more adequate global security strategies given limited resources. By developing trusted public-private partnerships to deal with interdependencies associated with extreme events substantial benefits can be provided to the affected individuals and firms as well as improving the social welfare.

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Glossary

AAL:	Average Annual Loss, defined as the average or expected loss for an insurance policy or a set of policies per year.
Aleatory Uncertainty:	Inherent randomness associated with a future catastrophe; it cannot be reduced by the collection of additional data.
Basis Risk:	The imperfect correlation between the actual losses suffered by a company or individual and the payments received from a risk transfer instrument designed to cover these losses.
Blind Thrust Fault:	A type of earthquake fault that terminates before it reaches the Earth's surface.
Capital Markets:	The markets in which corporate equity and longer-term debt securities are issued and traded.
Capacity:	The total limit of liability that a company or the insurance industry can assume, according to generally accepted criteria for solvency.
Catastrophe:	An unexpected or unanticipated natural or man-made event that has wide ranging negative socioeconomic impacts; also known as a disaster.
Catastrophe Bond:	A corporate bond that requires the purchasers to forgive or defer some or all payments of interest or principal if the actual catastrophe loss surpasses a specified amount or trigger.
Catastrophe Loss:	Economic loss resulting from a large-scale disaster.
Catastrophe Model:	A computer-based model that estimates losses from natural or man-made hazards, such as earthquakes, floods, hurricanes and acts of terrorism.
Catastrophe Risk:	Potential economic loss or other negative impact associated with large-scale disasters.
CEA:	The California Earthquake Authority. Established in 1996, it is a state-run agency that manages a fund that provides earthquake insurance coverage to homeowners in California.
Cedant:	An insurer transferring all or part of a risk to another party, such as a reinsurer.
Claim:	A request by a policyholder for payment for losses covered by insurance.
Coinsurance:	The sharing of the losses by an insured party as a way of reducing moral hazard.

Coriolis Force:	A force that results from the Earth's rotation, causing moving objects to be deflected to the right in the Northern Hemisphere and to the left in the Southern Hemisphere.
Correlated Losses:	The simultaneous occurrence of many losses from a single catastrophe or disaster.
Credit Risk:	Risk associated with a reinsurer unable to pay its obligation to a ceding insurance company.
CV:	Coefficient of Variation, an attribute of a probability distribution, calculated as its standard deviation divided by its mean.
Damage Function:	An equation relating the expected damage state of a building to the intensity of an event.
Damage Ratio:	The ratio of repair cost to the replacement cost of a building.
Deductible:	The proportion of an insured loss that the policyholder agrees to pay before any recovery from the insurer.
Demand Surge:	Term used to refer to the sudden increase in construction costs following a natural disaster event.
EERI:	Earthquake Engineering Research Institute, a non-profit organization that strives to improve the understanding and reduce the impact of earthquakes.
Exceedance Probability (EP) Curve:	A graphical representation of the probability that a certain level of risk will be surpassed during a future time period. The most common form of an EP curve is the probability that an economic loss will be surpassed on an annual basis.
Epistemic Uncertainty:	The lack of knowledge associated with a future catastrophe; it can be reduced by the collection of additional data.
Excess of Loss Reinsurance:	A type of reinsurance in which a premium is paid to an insurer to cover losses above a certain threshold or retention.
Exposure:	In a catastrophe model, the properties at risk from a natural or man-made hazard.
FEMA:	The Federal Emergency Management Agency, a U.S. federal agency responsible for developing strategies for mitigation, preparedness, response and recovery from disasters. On March 1, 2003, FEMA became part of the U.S. Department of Homeland Security.
FHCF:	Florida Hurricane Catastrophe Fund. Authorized in 1993, it is a tax-exempt trust fund that covers a portion of natural disaster losses to insurers covering policies in the state of Florida. A

retention level is specified for each year and insurers are reimbursed for losses in excess of that level.

Geocoding: The process by which one assigns geographic coordinates (latitude and longitude) to a location on the Earth. In catastrophe modeling, geocoding is used to assign coordinates to an exposure at risk, often based on its street address, ZIP code or another location descriptor.

Ground-up Loss: The total amount of loss sustained by an insurer before any policy deductibles or reinsurance is applied.

Hazard: One of four catastrophe model components, defining the source, propagation, and site effects for natural perils or defining the likelihood of attacks and attack modes of terrorist activities.

HAZUS: Hazards, U.S., the U.S.'s nationally applicable standardized methodology and software program for analyzing catastrophes (the federal government's catastrophe model). The model was first introduced in 1997, estimating loss from earthquakes. In 2004, the model was renamed HAZUS-MH (multi-hazard) and wind and flood loss estimation models were added.

Homeowners Insurance: A comprehensive insurance policy covering an owner-occupied residence for liability, theft, and physical perils.

Indemnity Contract: A contract in which one insurance company charges a premium to provide funds to another insurance company to cover a stated portion of the loss it may sustain under its insurance policies. See Reinsurance.

Insolvency Risk: The probability of not having sufficient financial resources to meet financial obligations.

Insurability: Acceptability to a company of an applicant for insurance, based on certain criteria for an insurable risk.

Inventory: One of four catastrophe model components, defining exposures at risk from a natural or man-made hazard.

ISO: Insurance Services Office, Inc. Created in 1971, this company is the leader in supplying industry information to the property/casualty insurance industry in the U.S. It also functions as an insurance advisory organization.

LIBOR: London Interbank Offered Rate, A risk-free rate that enables one to determine the risk premium associated with securities, such as catastrophe bonds.

Loss: One of four catastrophe model components, defining the amount of reduction in the value of an asset due to a natural or man-made hazard.

Mitigation:	Loss reduction measure taken to reduce or eliminate damage or loss due to a natural or man-made hazard.
Moral Hazard:	Intentionally careless behavior that increases the risk from an event because the loss is insured. For example, setting a house on fire as a way of collecting an insurance claim is an example of moral hazard.
Natural Disaster:	An event that results in the need for physical and economic assistance from outside sources. A U.S. natural disaster is deemed significant when the economic loss is at least $1 billion and/or over 50 deaths are attributed to the event.
NEHRP:	National Earthquake Hazard Reduction Program, established by the Earthquake Hazards Reduction Act in October of 1977 to reduce the risks to life and property from future earthquakes in the United States.
NFIP:	The National Flood Insurance Program, which provides federal insurance to residents of flood-prone regions.
NOAA:	National Oceanic and Atmospheric Administration. Established in 1970, this federally run organization monitors and predicts the state of the Earth, the oceans and their living resources, and the atmosphere.
Peak Ground Acceleration (PGA):	The maximum absolute magnitude of a ground acceleration time series, as measured during an earthquake event; PGA is often used as an indicator of damage in a catastrophe model.
PML:	Probable Maximum Loss, representing the largest economic loss likely to occur for a given policy or a set of policies when a caatastrophic event occurs.
Portfolio:	The full set of policies covered by an insurance company.
Pro Rata Reinsurance:	A type of reinsurance in which premium and loss are shared by cedant andinsurer on a proportional basis.
Rate Making:	The process by which insurance rates, or the cost per unit of insurance purchased, are established.
Reinsurance:	Purchase of insurance by an insurance (ceding) company from another insurance (reinsurance) company for purpose of spreading risk and reducing the loss from a catastrophe event.
Return Period:	The expected time between a certain magnitude of loss event, defined as the inverse of the annual exceedance probability. For example, a return period of 100 years corresponds to an annual exceedance probability of 1%.

Risk Transfer:	A method by which an individual or company reduces its risk from a natural or man-made hazard by reassigning the risk to another entity.
ROA:	Return on Assets, an indicator of profitability. It is the ratio of net income to total assets.
SBA:	Small Business Administration. Established in 1953 by the U.S. Congress to protect the interests of small businesses and by financially aiding their recovery from natural disasters.
Securitization:	The process by which the economic loss resulting from a catastrophe is guaranteed to be paid. One example of Securitization is issuing a catastrophe bond.
Sharpe Ratio:	A relative measure of a portfolio's return-to-risk ratio. It is calculated as the return above the risk-free rate divided by its standard deviation. It is often used to determine the amount of excess return required by investors for an additional unit of risk.
Slip Rate:	The rate at which each side of a fault plane moves relative to the other, in millimeters per year.
Spectral Acceleration:	A measure used as a representation for building response to an earthquake in a catastrophe model.
Underwriting:	The process of selecting risks to insure and determining in what amounts and on what terms the company will accept the risk.
USGS:	United States Geological Survey, an agency of the federal government that collects, monitors, analyzes and provides information about natural resources.
Vulnerability:	One of four catastrophe model components, defining the susceptibility of an inventory to a natural or man-made hazard. Other terms that are often used to characterize vulnerability are damage and fragility.

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