FINANCIAL IMPLICATIONS OF ENGINEERING DECISIONS

A Dissertation

by

VESYEL ZAFER ASLAN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2012

Major Subject: Civil Engineering

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Approved by:

Chair of Committee,	Ivan Damnjanovic
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ABSTRACT

Financial Implications of Engineering Decisions. (August 2012)

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When society fails to effectively integrate natural and constructed environments, one of the cataclysmic byproducts of this disconnect is an increased risk of natural disasters. On top of the devastation that is the aftermath of such disasters, poor planning and engineering decisions have detrimental effects on communities as they attempt to recover and rebuild. While there is an inherent difficulty in the quantification of the cost of human life, interruption in business operations, and damage to the properties, it is critical to develop plans and mitigation strategies to promote fast recovery.

Traditionally insurance and reinsurance products have been used as a mitigation strategy for financing post-disaster recovery. However, there are number of problems associated with these models such as lack of liquidity, defaults, long litigation process, etc. In light of these problems, new Alternative Risk Transfer (ART) methods are introduced. The pricing of these risk mitigating instruments, however, has been mostly associated with the hazard frequency and intensity; and little recognition is made of the riskiness of the structure to be indemnified. This study proposes valuation models for catastrophe-linked ART products and insurance contracts in which the risks and value

can be linked to the characteristics of the insured portfolio of constructed assets. The results show that the supply side – structural parameters are as important as the demand – hazard frequency, and are in a highly nonlinear relationship with financial parameters such as risk premiums and spreads.

DEDICATION

Dedicated to my family

ACKNOWLEDGEMENTS

I would like to take this opportunity to express my deepest gratitude to my advisor, Dr. Ivan Damnjanovic, and co-advisor, Dr. John Mander for their excellent guidance and continuous support throughout the duration of my doctoral studies. This dissertation would have not been possible without their vision, inspiration, and direction.

I would also like to thank my committee members, Dr. Smith, and Dr. Butenko, for their support and feedback during the course of this research. Thanks also go to my colleagues and the department faculty and staff for making my time at Texas A&M University a great experience.

Above all, I am most grateful to my parents, Dr. Veysi Aslan and Mrs. Nedret Aslan; my younger brother, Oguz Aslan; and my girlfriend, Haley Shields. It would have not been possible to write this dissertation without their endless support, patience, and encouragement.

Last, but by no means least, I would like to thank my friends here in the USA and Turkey for their support and encouragement.

NOMENCLATURE

AL	Annualized loss
ART	Alternative risk transfer
CALTRANS	California Department of Transportation
CAT	Catastrophe
CDF	Cumulative Distribution Function
DBE	Design basis earthquake
DS	Damage state
EAL	Expected annual loss
EDP	Engineering demand parameter
EER	Expected excess return
E(L)	Expected loss
FEMA	Federal Emergency Management Agency
GIS	Geographic information system
GBM	Geometric Brownian Motion
HAZUS	Hazards United States
HAZUS-MH	Hazards United States – Multi hazard
ILS	Insurance Linked Securities
IM	Intensity measure
LIBOR	London interbank offered rate
PDF	Probability density function

PE	Probability of exhaustion
PFL	Probability of first loss
PGA	Peak ground acceleration
P-H	Proportional hazard
RRG	Risk retention groups
SPV	Special purpose vehicle
UBC	Uniform building code
USGS	United States Geological Survey
β	Dispersion
$\beta_{f\|L}$	Dispersion in annual frequency, given loss ratio
$\beta_{L\|f}$	Dispersion in loss ratio given annual frequency
β_{RC}	Randomness in capacity
β_{RD}	Randomness in demand
β_{U}	Uncertainty in modeling
β_{UL}	Uncertainty in loss estimation
f	Annual frequency of earthquake
f_{DBE}	Annual frequency for design basis earthquake
f_{on}	Annual frequency of earthquake at onset of damage
f_{rr}	Annual frequency of earthquake when $L_{\max} = 1$
f_{u}	Frequency of earthquake when loss ratio is L_u

L_{DBE}	Loss ratio for design basis earthquake
L_{on}	Loss ratio at onset of damage
L_u	Loss ratio at collapse
K_x	Standardized Gaussian random variable
θ	Story drift
θ_c	Critical story drift
θ_{DBE}	Story drift for design basis earthquake
θ_{on}	Story drift at onset of damage
Z	Impact factor

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1. INTRODUCTION

Buildings, bridges, and other civil infrastructure must be designed, constructed, and managed to withstand the effects of natural hazards. This ensures public safety and supports the goals and needs of society. The earthquake hazard is paramount among the natural hazards impacting civil infrastructure. The occurrence of major earthquakes such as: San Fernando (1971), Loma Prieta (1989), Northridge (1994), Hanshin-Awaji-Kobe (1995), Izmit (1999), Darfield (2010), Chile (2010), and the very recent Christchurch (2011) and Tohoku (2011) have highlighted the limitations in post-loss financing mechanisms. Such earthquakes have also provided the impetus for significant improvements in engineering practices for earthquake-resistant design and actuarial practices for financial risk hedging.

Notwithstanding the recent advances in earthquake-resistant design paradigm and financial risk mitigation efforts, uncertainties still remain in seismicity, the response of engineering structures, and the capital capacity of the insurance industry to absorb the large financial losses. The potential consequence of these uncertainties is risk that civil infrastructure will fail to perform as intended by the owner, user, or society as a whole, and the reconstruction works cannot be carried out effectively. It is not feasible to eliminate risk entirely; rather, the risk must be managed by engineers, code-writers, insurers and other regulatory authorities for the public's best interest.

The traditional approach to manage seismic hazard risk uses two components.

This dissertation follows the style of *Journal of Structural Engineering*.

The first component is the engineering community which uses structural design and reliability analysis as tools in the decision making process. The second component, on the other hand, is the financial community which evaluates risk mitigation and hedging instruments such as insurance, warranties, and structured products to deal with the financial burden created by seismic hazards. While the connection between the engineering design characteristics and financial losses is apparent, a disconnect between the two branches exists when it comes to pricing risk hedging instruments. Although these instruments are often designed to provide coverage to constructed assets, most current pricing models do not consider the damage potential of underlying assets (Loubergé et al. 1999; Lee and Yu 2002; Gründl and Schmeiser 2002; Vaugirard 2003; Cox et al. 2004; Jaimungal and Wang 2006; Chang and Hung 2009). In fact, available pricing models often use a "black box" approach in which the losses and the claims are estimated using complex simulation models based on statistical distributions and historical data (Damnjanovic et al. 2010). This disconnect creates a significant problem since large constructed assets such as toll roads, power plants, railroads, and bridges represent the major portion of financial losses when a natural disaster occurs. The large constructed assets differ in geometry, material type, design code, age, location, etc.; their seismic performance (and hence loss exposure) can only be captured with engineering analysis.

In order to bridge the gap between the engineering and the financial approaches in decision making process, an integrated approach which provides tools that are easily implementable in both fields is needed. To this aim, this study incorporates an "engineering loss model" into a financial valuation framework for catastrophe insurance and catastrophe linked risk hedging products such as bonds and options.

The remainder of Section 1 provides an introduction to catastrophe risk with an emphasis on earthquake hazard. It continues with an overview of the traditional risk sharing and financing mechanisms such as insurance and re-insurance, and the associated capacity and stability concerns regarding such mechanisms. Section 1 then introduces the concept of Alternative Risk Transfer (ART), history and rationale behind this concept and currently available ART tools in the market. The section concludes with stating the research objectives and presents the organization chart of the dissertation.

1.1. Catastrophe Risk

Natural forces such as earthquakes, hurricanes, and landslides often leave human and economic losses in their wake. Such hazards are considered catastrophes when they lead to extremely large losses, which typically is the case when they affect densely populated areas. They are not very frequent, but their effect on economic life can be devastating, and the consequences result in expensive reconstruction processes.

In the absence of well-functioning insurance markets, post disaster rehabilitation depends on other funding sources. Often, local governments and international charities step in to assist in the recovery process, but this aid tends to reduce incentives to engage in prevention and insurance (Damnjanovic et.al, 2010; Aslan et al. 2011). In addition, post disaster financing efforts may divert funds from public capital budgets and disrupt long-term development investments.

Financial consequences of natural catastrophes reached a new record level in the 1990s (Rode et al 2002). Hurricane Andrew (1992) and the Northridge Earthquake (1994) caused insured losses of about $23 billion and $19 billion respectively (Cummins et al. 2002). More precisely, in nine years (between 1989 and 1997), the U.S. property-casualty industry suffered an inflation-adjusted $80.2 billion in catastrophe losses, $34.2 billion more than what the industry suffered during the 39 years from 1950 to 1988 (Meyers and Kollar 1999). It is estimated that a repeat of an earthquake similar to the one that destroyed Tokyo in 1923 could cause $900 billion to $1.4 trillion in damages (Valery 1995). Similarly a severe earthquake in California could generate losses of $70 billion or more, and a magnitude 8.5 earthquake on the New Madrid Fault in the central U.S. could result in $115 billion or more in insured losses (Meyers and Kollar 1999).

Recently in 2011, there were 253 separate events that caused substantial damage and casualties all over the globe. The aggregated economic loss from these events was $435 billion and insured loss was $107 billion (Aon-Benfield 2011). The year 2011 is now the costliest natural disaster year in terms of economic losses. Insured losses incurred in 2011 are the second highest in the history right after the losses in 2005 ($120 billion in insured losses due to major hurricanes Katrina, Rita, and Wilma).

The most devastating natural disaster of 2011 was the Tohoku Earthquake and the resulting tsunami in Japan. Tohoku alone resulted in an estimated $35 billion insured losses and $210 billion economic losses (Aon-Benfield 2011). Shortly after the Tohoku earthquake, the Christchurch region in New Zealand was hit by two devastating earthquakes leading to economic losses in excess of $30 billion (Aon-Benfield 2011). The importance of earthquake hazard among the other natural phenomena becomes more apparent when the losses are compared with other types of natural disasters. Fig. 1-1 shows the economic and insured losses caused by different natural disaster types in 2011(Aon-Benfield 2011).

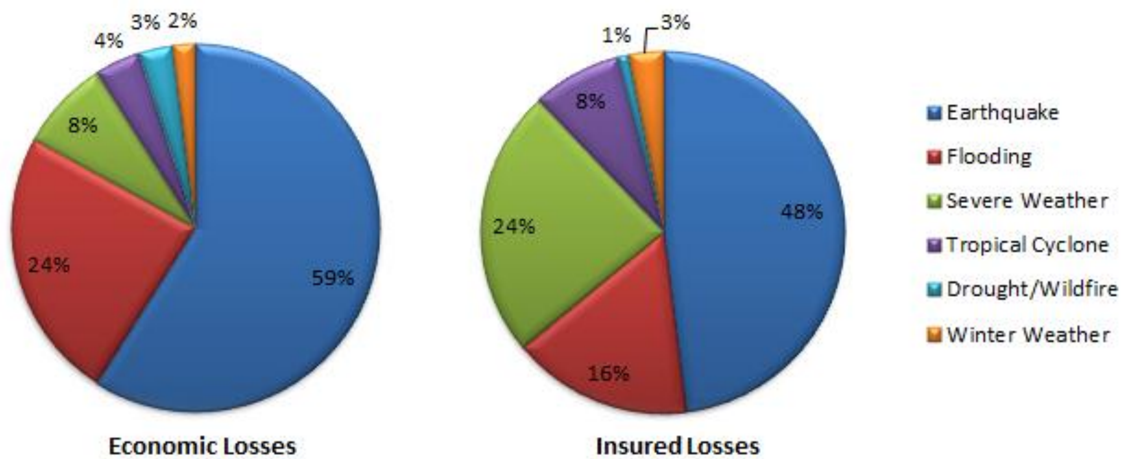

Fig. 1-1: Economic and insured losses by natural disaster type (Aon-Benfield 2011)

The U.S. property liability insurers have a cumulative operating surplus of approximately $300 billion (Cummins et al. 2002). Although reinsurance capital seems to be increasing recently and the supply seems to be adequate to pay for the "big one," potential financial losses at magnitudes of hundreds of billions of USD could severely drain the capital capacity of the insurance industry, affecting not only their policy holders but also their credit (Damnjanovic et al. 2010). Fig. 1-2 shows the trend in reinsurance capital in USD billion for the years 2007 to 2011 based on the data obtained from Aon-Benfield (2011).

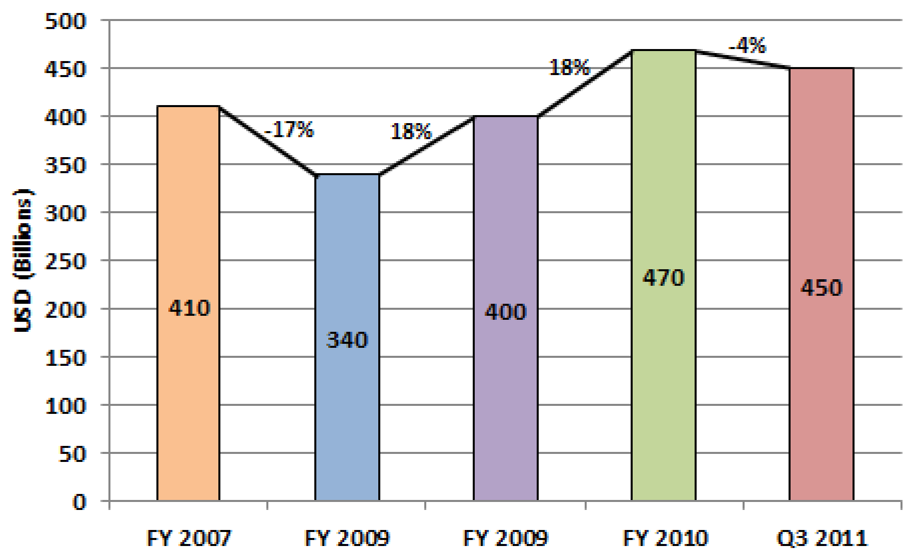

Fig. 1-2: Insurance capital trend 2007-2011(Aon-Benfield 2011)

1.2. Role of Insurance and Reinsurance

Insurance is the most common method of mitigating risks for individuals. By obtaining insurance coverage, individuals spread risks over a diversified portfolio of policy holders so that no single entity receives a financial burden that it cannot normally cope with. The traditional approach to insurance risk management relies on probability distributions of risk causing events that are often predictable and statistically measurable. For such cases, the strong law of large numbers allows insurers to predict future claims with a high level of confidence. Thus, insurers can cover financial losses through collected premiums from policy holders. This method works for well-known and quantifiable risks such as car accidents and personal medical emergencies (Damnjanovic et al. 2010; Aslan et al. 2011). Catastrophic losses due to natural disasters, on the other hand, pose unique problems for insurers because large numbers of those insured can incur large and correlated losses at the same time. The common practice of strong law of large numbers fails for low-probability and high-consequence events such as natural catastrophes (Froot 1997; Meyers and Kollar 1999; Cummins et al. 2002; Banks 2004).

One widely accepted solution to the complex issue of catastrophe insurance is to obtain reinsurance coverage. Reinsurance companies support insurance companies by underwriting specific large risks, increasing capacity, and sharing liability when claims overwhelm the primary insurer's resources (Rode at al. 2000; Banks 2004). This support of course comes at a price (i.e. premium) - a price that is often difficult to assess due to the challenging nature of estimating long tailed[1], severe, and infrequent losses (Cox and Pedersen 2000; Lee and Yu 2002; Vaugirard 2000; Wang 2004).

In spite of the additional benefits of reinsurance in terms of increased capacity and diversification, the problems associated with financing post-disaster recovery still exist. Large catastrophic events have the potential to severely drain capital capacity of (re)insurance industry (Lewis and Davis 1998; Meyers and Kollar 1999; Cummins et al. 2002; Doherty and Richter 2002). Such exhaustion of capital could significantly limit the future availability of catastrophe (re)insurance coverage while the demand from endangered regions is likely to increase after the loss experience (Ermoliev et al. 2000). A decreasing supply in capital capacity and increasing demand in coverage normally results in increased (re)insurance prices. An increasing trend in (re)insurance prices

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[1] The long tail refers to the statistical property that a larger share of data rests within the tail of a probability distribution than observed under a normal or Gaussian distribution

normally attracts investors in the capital markets which in turn increases the supply once again and stabilizes the market for (re)insurance business (Lewis and Davis 1998). Clearly, (re)insurance is largely impacted by the price cycles, a significant concern in catastrophe risk management. The Insurance Services Office of the U.S. (Insurance Services Office 1996) emphasizes the catastrophe risk and its consequences:

"The infrequency and high severity of catastrophes contribute to insufficient capital in the property/casualty industry to absorb losses from mega-catastrophes. The traditional methods of dealing with large losses from catastrophes, such as reinsurance and guaranty funds, are also inadequate. Individual insurer actions to limit their exposure to catastrophe losses have led to availability problems for insureds in high risk areas. Solutions to the shortage of surplus to manage catastrophe risk, and to availability problems, will require access to capital from outside the industry."

The current deficiencies in the insurance industry call for a further examination of funding risks in catastrophe prone areas and economies. Given the cyclic nature of (re)insurance markets and the limited financing capacity, there are incentives to look for alternative means of risk financing and transferring mechanisms.

1.3. Alternative Risk Transfer (ART)

The cyclic nature of the (re)insurance market and the limited capacity of the insurance industry to absorb large financial losses stimulated public and private efforts to address the problem of catastrophe risk (Froot 1997; Canabarro et al. 2000; Cummins et al. 2002). Alternative Risk Transfer (ART) instruments are the outcome of such efforts to provide vehicles for hedging the catastrophe risk. ART instruments can be described as contracts that allow for transferring insurer liabilities to other entities (e.g. capital markets) which have the ability to absorb probable excessive losses. Banks (2004) defines the ART market as the "*combined risk management marketplace for innovative* *insurance and capital market solutions*," while ART is "*a product, channel or solution that transfers risk exposures between the insurance and capital markets to achieve stated risk management goals.*"

The recent trends in the insurance markets and the increased exposure to natural disasters in both developed and emerging economies indicate that the market for ART instruments will only grow with time. Following are the most significant contributing factors to this growth prediction (Damnjanovic et al. 2010; Aslan et al. 2011).

- Highly volatile pricing trends in traditional insurance market due to cyclic nature
- High cost of reinsurance following a catastrophe
- Lack of capital capacity in the insurance industry to pay for the "big one"
- Increased interest from global markets in insurance risk as an investment class

From capacity point of view, the rationale behind employing ART in catastrophe risk management is compelling. Publicly traded stocks and bonds have a total market value of approximately $200 trillion (Roxhburgh et al. 2011). A hypothetical, yet probable, natural catastrophe amounting in $150 billion losses would represent less than 0.1 % of the global market portfolio. Fluctuations of such magnitudes are considered "normal" daily occurrence in capital markets (Rode et al. 2000). While increasing the capacity for the issuers by utilizing the almost inexhaustible capacity of capital markets, ART also offers unique opportunities for investors. Since occurrence of natural catastrophes is not correlated with capital market risks such as: interest rate risk, currency risk, economic risk, etc., investing in ART instruments presents an opportunity for investors willing to increase their portfolio performance through diversification (Litzenberger et al. 1996; Lewis and Davis 1998; Banks 2004).

ART instruments allow pooling and packaging of the insurance risks into marketable financial securities. This pooling mechanism helps spread risks from local disasters across global capital markets. By merging the capital market techniques with insurance structures, ART solutions enable parties to select the most appropriate risk financing mechanisms to acquire needed capital at reasonable cost. Such solutions, however, will only be successful if they simultaneously meet insurers' need to spread risk efficiently while offering investors opportunities to improve the performance of their portfolios. Even though this process comes with a cost, the associated benefits make ART instruments a valuable risk management solution (Cox and Pedersen 2000).

ART instruments have taken several forms, each with different structures, advantages, and disadvantages. To date, the two principal forms include: insurance-linked securities (e.g. catastrophe bonds) and contingent capital financing instruments (e.g. catastrophe options). The next section briefly defines these two classes and their link to catastrophe risk management.

1.3.1. Insurance Linked Securities

The concept of securitizing insurance risks was first born in the mid-1990s due to the limited capacity in the non-life insurance market and an increased focus on capital management across both the life and non-life insurance sectors (Lewis and Davis 1998). Securitization is a financing technique for packing a designated pool of receivables and redistributing these packages to the investors in capital markets. The investors buy these packages in the form of "securities" which are collateralized. These securities of course come with their associated income stream and hence serve as future cash flows. In short, insurance-linked securities (ILS) allow for converting illiquid assets such as insurance liabilities into tradable liquid assets. Moreover, by transferring insurance liabilities to capital markets, ILS provides insurers and reinsurers with new tools for diversifying their risks (Loubergé et al. 1999). Fig. 1-3 illustrates the structure of a simple ILS.

Fig. 1-3: Typical ILS structure (Banks 2004)

The special purpose vehicle (SPV) shown in Fig. 1-3 is created for the sole purpose of covering financial losses due to a catastrophic event defined in the ILS contract. If the pre-defined event does not occur during the term of contract, then the SPV is obligated to pay principal and promised interest to the investors. If the pre-defined event does occur, the SPV is obligated to pay the losses of the insured. For the latter case, investors face the risk of losing their invested capital (Lewis and Davis 1998; Harrington and Niehaus 1999; Banks 2004; Damnjanovic et al. 2010).

The most popular form of ILS is the catastrophe bond (CAT bond), a structure that was developed to broaden reinsurance capacity in the aftermath of Hurricane Andrew in 1992. These bonds are often issued by insurance or reinsurance companies. The underlying risk of the CAT bond is compensated via additional risk premium (spread) paid to investors. The future payments of earned interests and repayment of initial principal invested depends strictly on the occurrence of a pre-defined catastrophic event (Lee and Yu 2002). The structure of the CAT bonds along with the involved parties, current pricing models, and related research is discussed in Section 3.

1.3.2. Contingent Capital

Contingent capital is another ART instrument connecting insurance and capital markets. These instruments are designed to allow for immediate financing of disaster recovery contingent upon the occurrence of a pre-defined catastrophic event. Since traditional means of financing through public and private resources often becomes unavailable after a major loss, contingent capital arrangements provide an additional level of comfort and assurance for the insured (Jamingual and Wang 2006; Aslan et al. 2011).

The financial structure of the contingent capital is based on a contractual commitment to provide capital to the originator (e.g. insurance company) after a pre-defined loss causing event (trigger). Unlike insurance-linked securities, that contain aspects of (re)insurance and securities, contingent capital arrangements are structured strictly as funding agreements with no element of insurance contracting. The contingent capital instruments typically provide for the issuance of shares of stock upon the occurrence of a pre-defined event at an inflated pre-defined price. The economic motivation of the originator (insured) is to have access to capital for post-event recovery financing at a pre-event defined rate, which is often a less expensive alternative to obtaining capital through capital markets or bank loans at post-event conditions (Cox et al. 2004). Fig. 1-4 illustrates the structure of a simple contingent capital agreement.

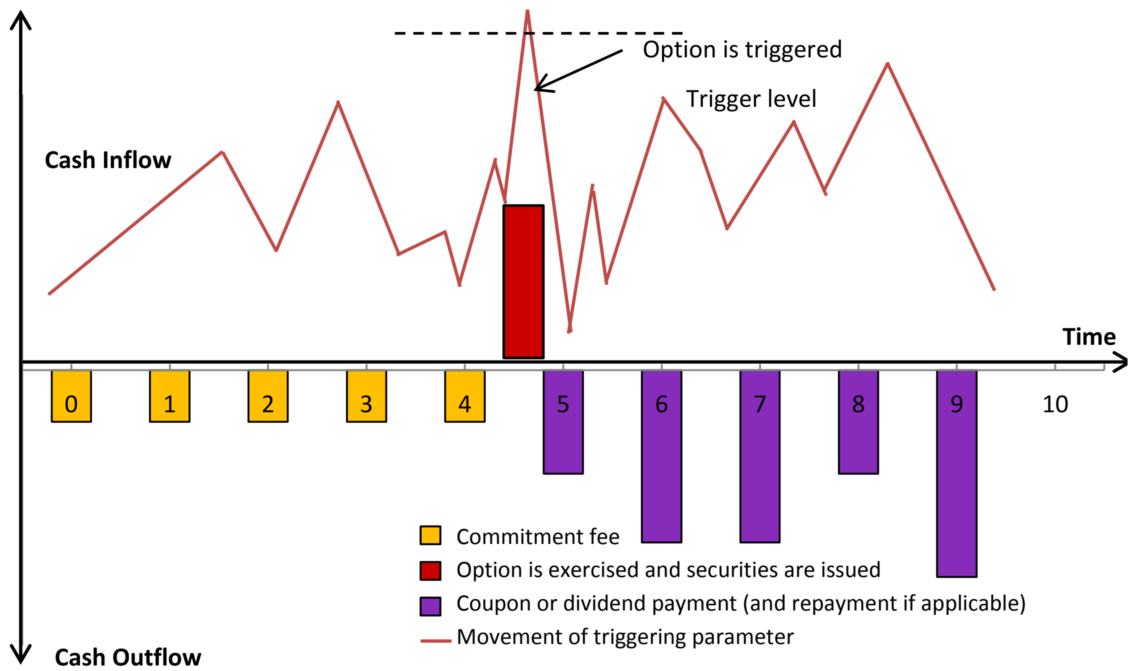

Fig. 1-4: Contingent capital agreement structure (Aon-Benfield,2011)

The most popular form of contingent capital structure is contingent equity, which stands for any post-loss equity financing made available when specific events are triggered. This form of contingent capital instrument is often called as catastrophe equity put option, or CatEPut. The CatEput gives the originator/writer of the option the right to sell a specified amount of its stock to investors at a predetermined price if catastrophe losses surpass a specified loss trigger (Cox et al. 2004). The structure of the CatEPuts along with the involved parties, current pricing models, and related research is discussed in Section 4.

1.4. Problem Statement

Financial valuation of catastrophe-linked ART products and insurance policies is a challenge due to the unpredictable nature of natural disasters and large number of variables in the decision making process. Most of the currently available pricing models use a “black box” approach in which the losses and the claims are estimated by complex simulation models based on assumed statistical distributions of arrival rates and limited historical data of incurred damage. This ambiguous approach can result in higher insurance prices and higher risk premiums (relative to the other tradable securities with similar level of underlying risks) for the ART products.

1.5. Need

A transparent and robust framework that utilizes both demand side (hazard frequency and intensity) and supply side (structural response to natural hazard) parameters is needed for pricing ART instruments and insurance policies. Such a framework can reduce the uncertainty in modeling catastrophe losses. The increased transparency may increase the investor appetite for catastrophe-linked ART instruments and decreases the risk premiums associated with insurance policies.

1.6. Research Objectives

This study aims to develop valuation frameworks for catastrophe-linked ART instruments and insurance policies in which the risk and value can be directly linked to the engineering characteristics of the underlying portfolio of constructed assets.

Recommendations to help increasing efficiency, capacity, and stability in catastrophe risk management solutions will also be provided.

1.6.1. Develop a Pricing Model for Catastrophe Bond (CAT Bond)

The first objective of this study is to develop an integrative pricing model for CAT bond that connects observable engineering design parameters with financial indicators such as spread and bond ratings. Once the pricing model is developed, various trigger mechanisms and term structures of CAT bonds are examined based on the loss-estimation procedure and the valid schemes of operations. Finally, the effectiveness of the proposed pricing model in post-loss financing for public and private infrastructure is illustrated with numerical examples.

1.6.2. Develop a Pricing Model for Catastrophe Equity Put (CatEPut)

The second objective of this study is to develop a pricing model to capture two important aspects of asset-specific CatEPut:

1) a joint stochastic model representing the changes in equity values of insurers due to catastrophic events,

2) a link between the engineering characteristics of the underlying asset and the option price.

The proposed model embeds engineering analysis into the option pricing framework. This joint model creates a link between financial and engineering analyses in the decision making process for financing of catastrophe risk.

1.6.3. Develop a Social Insurance Framework and Conduct Portfolio Analysis

The third and final objective of this study is to propose a "social insurance" framework for communities where insurance coverage against natural hazards is either not offered or offered at a high cost. The proposed framework adopts an interface with access to social networks to reach broader user profiles and reduce transaction costs. The social network access may also help in creating a "viral impact" to increase the participation.

The key step in the social insurance framework is developing the premium model. The premiums need to satisfy the stability and capacity requirements of the insurance company while accounting for structural, geographical, and demographical properties of the insured. The participants/policy holders in this framework are allowed to create groups with other users or to simply join one of the existing groups based on their needs and risk preferences. The rationale behind allowing multiple insurance portfolios (groups) is to promote "recovery as a whole." For instance, individuals living in the same or nearby communities can join the same group or create their community groups to help protect the value of their properties as well as the value of the entire neighborhood. Note that the regain in property value after a catastrophe is largely a function of the regained value of surrounding properties and constructed assets. The details of the engineering models used to develop the insurance framework along with the numerical analysis are provided in Section 5.

1.7. Research Significance

The integrated (financial + engineering + actuarial) approach to risk-based decision making provides stakeholders with a structured framework for evaluating how public safety and economic well-being may be threatened by the failure of constructed assets to perform under a spectrum of disastrous events. The proposed framework in this study may improve the ability to assess the effectiveness of various risk mitigation strategies in terms of risk reduction per dollar invested, and thus provides better allocation of public and private resources for managing risk.

1.8. Section Closure

This study looks into the current valuation models for catastrophe-linked ART instruments and insurance policies, and examines how their values are related to catastrophe risk, damage potential of underlying assets, terms of the contract, and other key elements of these risk management solutions. The valuation approach used in this study accounts for both the financial market parameters and engineering design characteristics of the constructed assets at risk to ensure the most cost effective risk hedging in terms of risk coverage per dollar invested.

The remainder of this dissertation is structured as follows: **Section 2** presents a four-step engineering loss model to quantify expected financial losses to a constructed asset (e.g. bridge) due to a catastrophic event (e.g earthquake). The information obtained from the loss analysis is used in **Section 3** to develop a pricing model for catastrophe bonds (CAT bonds), a risk financing instrument that utilizes bond holders in the capital markets. The model is tested with different numerical examples and results are discussed with both managerial and technical implications. **Section 4** examines the CatEPut option, another catastrophe risk financing tool that utilizes equity holders. A stochastic pricing model is proposed to represent the dynamics of equity value. The model is analyzed by means of simulations and the results are discussed in detail. **Section 5** introduces a new concept, a "social insurance" framework to help cope with the catastrophe risk. A comprehensive loss estimation tool for fair insurance pricing is developed to support the proposed framework. Practical implications of this concept by utilizing internet-based social networks are discussed. Numerical examples are provided to examine capacity and stability performance of the proposed insurance framework and results are discussed in detail. Finally, **Section 6** concludes this study with managerial and technical recommendations, and recommends future study.

2. ENGINEERING LOSS MODEL

Successful use of any risk transfer instrument depends on the ability to accurately and effectively estimate the amount of risk involved. Based on the quantified risks and estimated losses, (re)insurance companies and self-insured entities can assess the risk profile of insurance contracts and risk linked financial instruments (Damnjanovic et al. 2010). Therefore, it is important to be able to quantify potential damage to constructed assets and estimate losses due to natural hazards, and to communicate the risk in a comprehendible way to all stakeholders. To this aim, Section 2 proposes a rapid probabilistic loss estimation model that can be easily integrated in ART valuation and portfolio analysis models.

2.1. Background

Natural hazards such as earthquakes and hurricanes can significantly disrupt economic activity in a region and cause loss of life and limb. If this happens, the extent of damage must be rapidly quantified and financing must be made available for rehabilitation work quickly. Risk management process consists of predicting the catastrophic events and developing financial instruments that limit or reduce financial loss. Efforts have been made to predict the damage to constructed assets due to seismic events and estimate the associated losses. One common method is the Hazards U.S. (HAZUS) approach that classifies the damage severity into five different damage states and expresses this probabilistically in the form of fragility curves for each damage state. The total loss is obtained by aggregating the losses for each damage state for a given intensity measure. (Whitman et al. 1997; Kircher et al. 1997; Mander and Sircar 1999).

Another method called 'assembly based vulnerability' estimates loss ratio after detailed analysis of various assemblies of structural and nonstructural components in the constructed asset (Porter et al. 2001). An assembly is a group of structural or nonstructural components such as pipe fixtures, ceilings, beams, columns etc. Fragility curves are developed for each assembly in the constructed asset based on its damage state and total loss is obtained by summation of losses in each of the individual assemblies.

Dhakal and Mander (2006) developed a financial risk assessment methodology for natural hazards to relate system capacity, demand and financial risk. Losses to constructed assets were estimated in terms of financial risk, by developing a theoretical financial risk assessment methodology.

Mander et al. (2012) developed a four step approach to estimate financial losses for seismically damaged structures. This method simplified the loss estimation procedure bypassing the need for fragility curves. This approach expresses losses in terms of commonly used and observed quantities and can help link the engineering community with the financial community. The four steps can be summarized as:

1) hazard analysis (evaluating the seismic hazard at constructed asset site and generating intensity measures representing local hazard levels),
2) structural analysis (evaluating the structural damage model using engineering demand parameters (e.g. story drifts),

3) damage and repair cost analysis; (estimating damage or repair costs in terms of loss ratio) and,

4) loss estimation (estimating structural and nonstructural damage).

2.2. Modeling Loss

The "Four Step" approach proposed by Mander et al. (2012) is used herein to estimate loss from structural damage. Their approach is an expansion of the concepts derived from the relationships developed by Kennedy (1999) and Cornell et al. (2002). Kennedy (1999) represented seismic hazard recurrence relationship using $f_o(IM) = k_o(IM)^{-k}$. This is a relationship between intensity measure (IM) and annual frequency (f_o) where, k and k_o are best fit empirical constants. Cornell et al. (2002) developed a relation between IM and engineering demand parameter, EDP, (such as column drift) given by $D = aS_a{}^b$ where $D = \theta$ is column drift and S_a is spectral acceleration; 'a' and 'b' are empirical constants.

The four steps are shown in Fig. 2-1. Each graph in Fig. 2-1 is plotted on a log-log scale and represents the above mentioned four-step process (Mander et al. 2012). Each task is referenced to the design basis event (DBE) and each curve plotted in the graph is a median. The four graphs are inter-related because the neighboring two graphs (one beside and one either below or above) have adjacent axes representing the same variable and have the same scales. Starting in the top right, Fig. 2-1(a), local hazard is plotted in terms of an intensity measure (IM) versus annual frequency (f_a). By following the horizontal arrow to the left, it is evident that when a hazard strikes a structure, this imposes an engineering demand parameter, EDP, in the form of structural column deformation, called drifts (θ), as shown in Fig. 2-1(b). Then by following the arrow downward to Fig. 2-1(c), when a certain drift threshold (θ_{on}) is exceeded, financial losses are incurred from the damage that necessitates repairs. Such financial losses can be expressed in terms of a loss ratio (L) which is defined as the ratio of the repair cost to the reinstatement cost of a new constructed asset built under normal conditions. Finally, by following the arrow to the right, losses can be related to the frequency of occurrence of the originating hazard as shown in Fig. 2-1(d). Structural capacities are characterized in terms of inter-story column drifts and related to damage states (quantified in terms of loss ratios) of the structure.

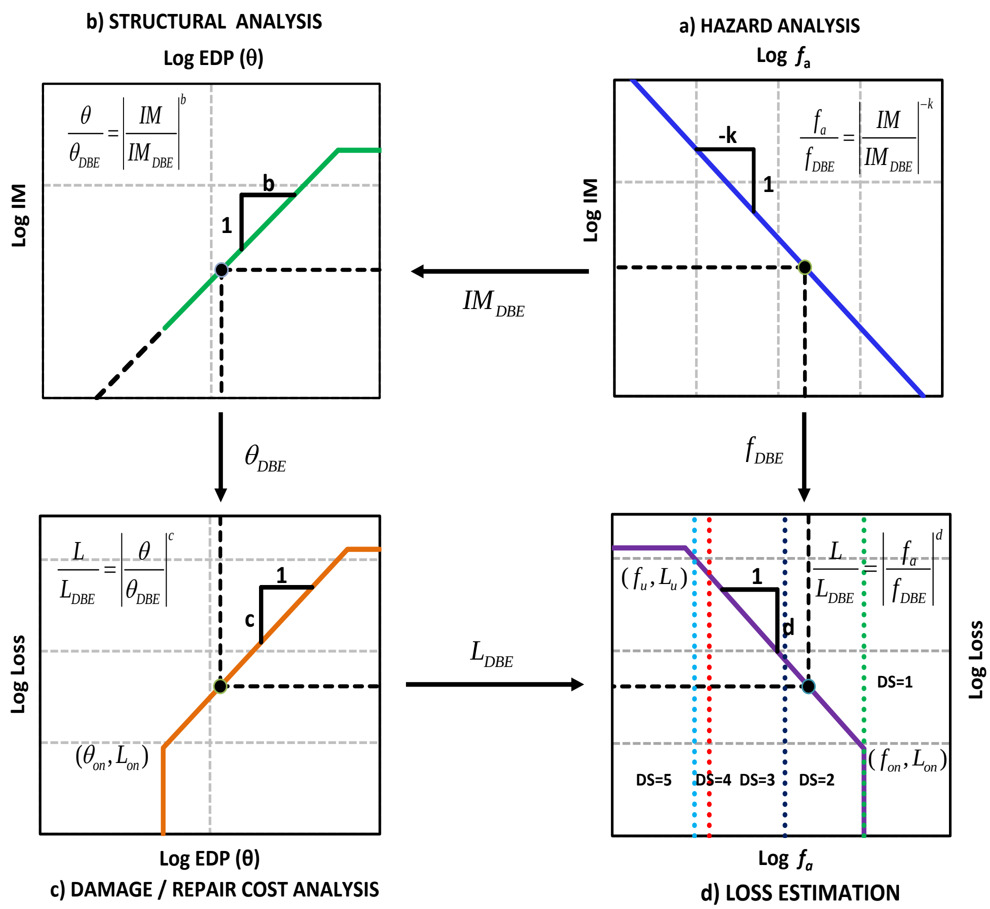

Fig. 2-1: Four step loss estimation procedure (Mander et al. 2012)

where:

- L = loss ratio ($\dfrac{\text{repair cost}}{\text{reinstatement cost}}$)
- θ = interstrory drift, (an engineering demand parameter, EDP, equal to the column deflection with respect to the story height);
- IM = intensity measure (e.g. spectral acceleration, S_a, or PGA for earthquakes or wind speed for hurricanes);
- f_a = annual frequency of an event,

- and the parameters k, b, c are exponents defined by the slopes of the curves in the respective graphs (a), (b), (c) in Fig. 2 such that $d = bc/(-k)$.

The mathematical expression governing the four-step model that defines the mutual relation between four graphs is (Mander et al. 2012):

$$\frac{L}{L_{DBE}} = \left|\frac{\theta}{\theta_{DBE}}\right|^{c} = \left|\frac{IM}{IM_{DBE}}\right|^{bc} = \left|\frac{f}{f_{DBE}}\right|^{d} \tag{2-1}$$

in which:

- DBE = design basis earthquake,
- L_{DBE} = loss ratio for design basis earthquake,
- θ = inter-story drift rate – an EDP
- θ_{DBE} = inter-story drift for the DBE,
- IM_{DBE} = intensity measure for the DBE,
- f_{DBE} = frequency of seismic event for design basis earthquake typically taken as 10 percent in 50 years (Mander and Sircar 2009).

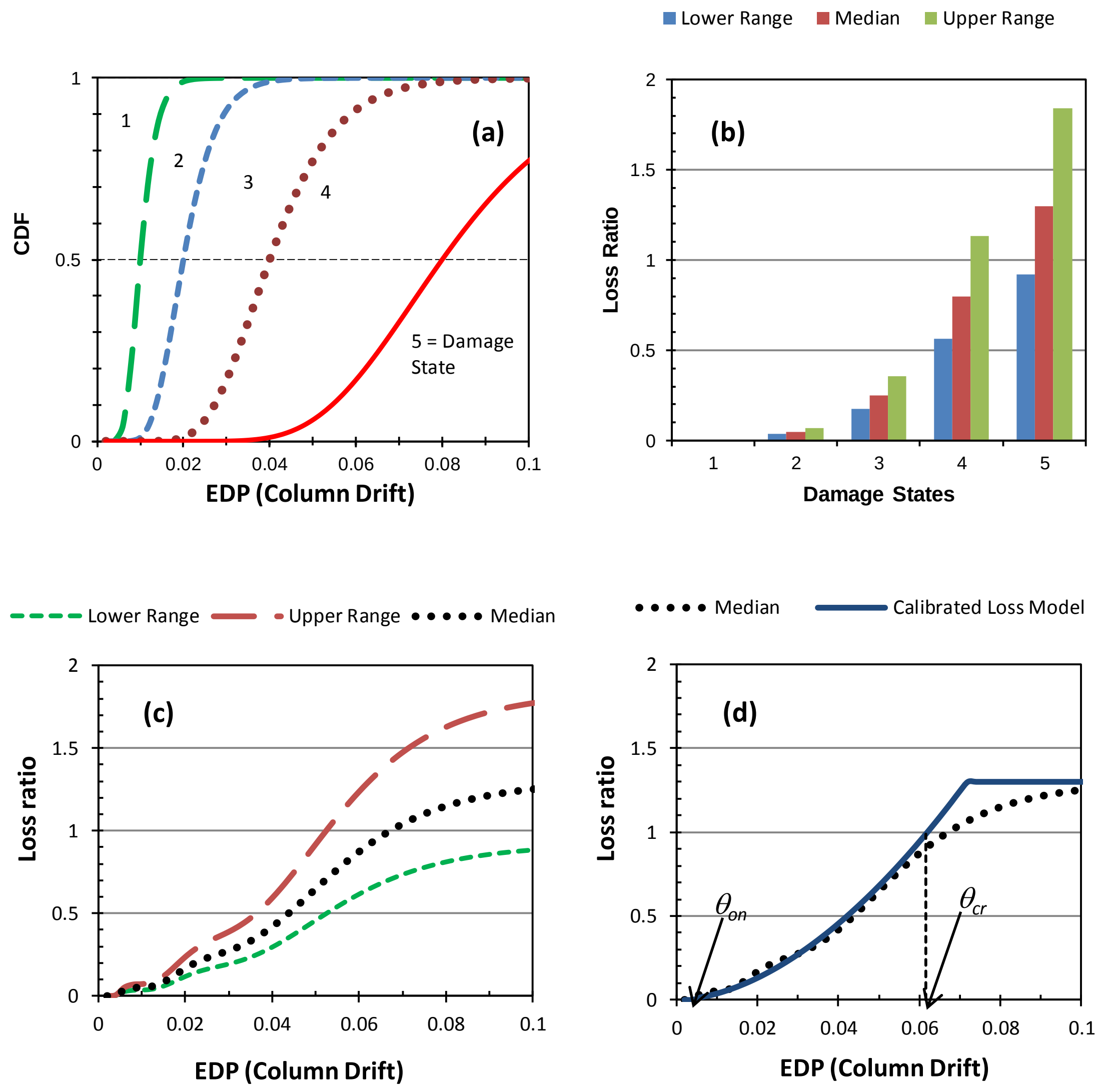

Fig. 2-2: General procedure for estimating loss ratios (Mander et al. 2012)

The intensity of damage, as defined by an EDP, is classified into the five damage states used in HAZUS (Dhakal and Mander, 2006), that is: (1) none, (2) slight, (3) moderate, (4) heavy, and (5) complete-collapse. As shown in Fig. 2-2, for an earthquake that generates a specified EDP, the total probable financial loss is the sum of corresponding values for the damage states and is given by:

$$L[EDP] = \sum_{i=2}^{5} P_i[EDP] L_i \tag{2-2}$$

in which:

- $P_i[EDP]$ is probability of the EDP for the i^{th} damage state,
- L_i is the loss ratio for the i^{th} damage state.

It is possible to use a two-parameter power curve, with upper and lower cutoffs to represent a loss ratio as a function of structural drift (Sircar et al. 2009). Such parametric loss model is based on the capacity-side fragility curves where parameters are estimated from a structure specific non-linear model, and discrete damage states adopted in HAZUS (FEMA 2003). The key benefit of the proposed four-step model is no need for custom demand-side fragility curves. The relationship between intensity measures and engineering demand parameters is used to define the demand model which is compared with the capacity obtained by conducting a non-linear analysis. This is shown in Fig. 2-2(c) and can be expressed through a relationship relating losses with EDPs (e.g interstory drifts) as follows:

$$\frac{L}{L_c} = \left|\frac{\theta}{\theta_c}\right|^c \text{ and; } L_{on} \le L \le L_u = 1.3 \tag{2-3}$$

in which:

- θ_c = critical drift = θ_{DS5} = drift at collapse (Damage State 5),
- L_c = unit loss ratio = 1,
- L_u = loss ratio at ultimate collapse.

Note that $L \leq \tilde{L}_u$ and $L_u > 1$ to account for the expected post-disaster price surge of the repair and rebuilding process (it is suggested a median value of L_u=1.3 be used). Also, when $\theta < \theta_{on}$, $L = 0$ where, θ_{on} = the onset of damage normally taken as "yield" of the structure ($\theta_{on} = \theta_{DS2}$ where $\tilde{\theta}_{DS2}$ = median value for Damage State 2).

2.3. Modeling Uncertainties

Because the loss model developed above is not crisp, it incorporates epistemic[2] and aleatory[3] uncertainties in the loss estimation. The four-step model considers propagation of uncertainty (epistemic and aleatory) from hazard to loss estimation tasks as shown in Fig. 2-3. The model conforms to a lognormal distribution and is described using median values and the lognormal standard deviation or dispersion associated with it.

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[2] Given that an event has occurred, the uncertainty in the amount of loss, distribution of possible outcomes, rather than expected outcome.

[3] Uncertainty of which, if any, event will occur.

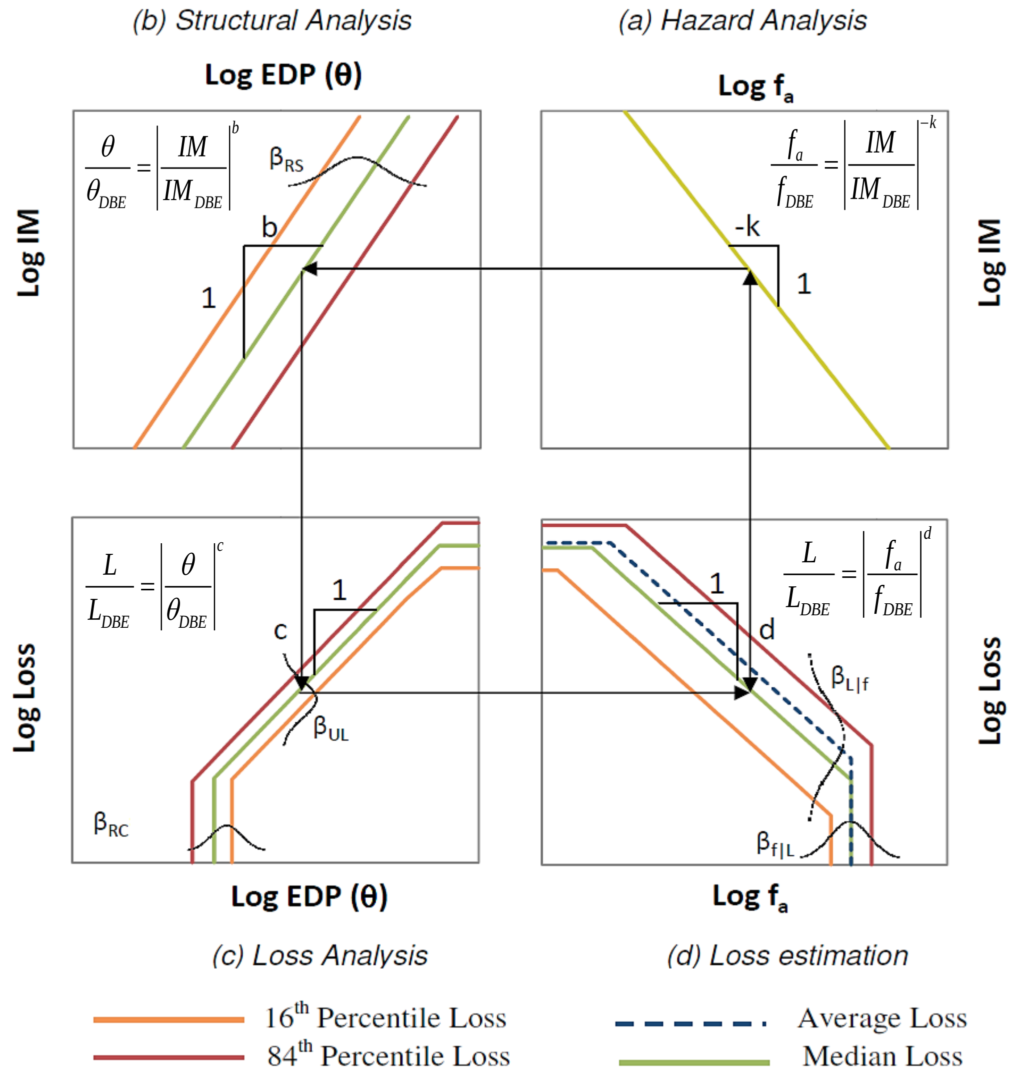

Fig. 2-3: Dispersion of variabilities (Mander et al. 2012)

The dispersion of all combined uncertainty and randomness $\left(\beta_{RS}\right)$ is given by root-sum-squares method (Kennedy et al. 1980; Solberg et al. 2008)

$$\beta_{RS} = \sqrt{\beta_{RD}^2 + \beta_U^2 + \beta_{RC}^2} \tag{2-4}$$

where:

- β_{RC} = randomness in capacity of the structure = 0.2 (Solberg et al. 2008),
- β_{U} = uncertainty in modeling = 0.25 (Kennedy and Ravindra 1984),
- β_{RD} = randomness in demand.

The dispersion in estimation of the annual frequency of event; $\beta_{f|L}$ for a given loss ratio is given by (Mander et al. 2012)

$$\beta_{f|L} = \frac{k}{b}\beta_{RC} \tag{2-5}$$

The dispersion in loss estimation for a given annual frequency of event $\beta_{L|f}$ depends upon uncertainty in predicting capacity of the structure and on uncertainty in estimating losses for that capacity.

$$\beta_{L|f} = \sqrt{\beta_{UL}^2 + c^2 \cdot \beta_{RS}^2} \tag{2-6}$$

where:

- β_{UL} = uncertainty in loss estimation = 0.35 (Mander et al. 2012).

The expected annual loss (EAL) is given by the area under the average loss curve in Fig. 2-3(d), and can be mathematically defined as:

$$EAL = \frac{\bar{f}_{on}\bar{L}_{on} + d\bar{f}_u\bar{L}_u}{1+d} \tag{2-7}$$

where $(\bar{f}_{on}, \bar{L}_{on})$ and $(\bar{f}_u, \bar{L}_u)$ are the mean cut-off co-ordinates and are defined by:

$$\bar{L}_{on} = \tilde{L}_{on}\exp(1/2\,\beta_{L|f}^2) \tag{2-8}$$

$$\bar{f}_{on} = \tilde{f}_{on} \tag{2-9}$$

$$\bar{L}_u = \tilde{L}_u \exp(1/2\,\beta_{UL}^2) \tag{2-10}$$

$$\bar{f}_u = f_{DBE} \cdot \left|\bar{L}_u / \bar{L}_{DBE}\right|^{1/d} \tag{2-11}$$

$$\bar{L}_{DBE} = \tilde{L}_{DBE} \exp(1/2\,\beta_{L|f}^2) \tag{2-12}$$

in which,

- $\bar{f}_{on} =$ the mean frequency of earthquake at onset of damage,
- $L_u = 1.3$ upper bound of loss ratio.

Since a normal distribution in material yield point is assumed with a coefficient of variation of 0.2, the normal standard deviation equivalent becomes $\beta_{RC} = 0.2$ and hence in Eq. (2-9) $\bar{f}_{on} = \tilde{f}_{on}$ (Mander et al. 2012). $L_u \geq 1$ accounts for expected price surge following a catastrophic event where contractors have to compete heavily for labor and materials $(L_{on} < L < L_u = 1.3)$. The list of parameters used in the four-step loss estimation procedure is presented in Table 2-1.

Table 2-1: Summary of four-step estimation parameters (Mander et al. 2012; Sircar et al. 2009)

	Parameters	Non-Seismic	Seismic
a)	IM_{DBE}	0.4	0.4
	f_{DBE}	0.0021	0.0021
	k	3.45	3.45
b)	θ_{DBE}	0.0115	0.0117
	b	1.25	1.25
c)	θ_{on}	0.0053	0.0053
	θ_c	0.025	0.0616
	c	2	2
	L_{DBE}	0.2116	0.03608
Median Parameters	d	-0.725	-0.725
	L_u	1.3	1.3
	L_{on}	0.04	0.0074
	f_u	1.72E-04	1.5E-05
	f_{on}	0.0209	0.0187
Mean Parameters	β_{RD}	0.4	0.42
	β_{RC}	0.2	0.2
	β_{UL}	0.35	0.35
	β_U	0.25	0.25
	β_{RS}	0.512	0.528
	$\beta_{f\|L}$	0.552	0.552
	$\beta_{L\|f}$	1.083	1.112
	L_{DBE}	0.380	0.067
	L_U	1.38	1.38
	f_u	3.54E-04	3.22E-05
	L_{on}	0.0718	0.0137
	f_{on}	0.0209	0.0187

Using the four-step process, it is now possible to assess loss ratios (L) for various hazard scenarios or to obtain a composite loss measure through calculating expected annual losses (EAL).

2.4. Section Closure

This section presents a four-step closed-form loss estimation methodology that relates hazard to response and hence to losses without the need for classic demand-side fragility curves. The closed-form solution is formulated in terms of well understood hazard and structural design and capacity parameters. Structural response can be related to losses through a parameterized empirical loss model in the form of a tripartite power curve. The principal part of that model conforms to a simple power curve relationship relating the L to EDP for that structural system.

When accounting for all variabilities in terms of randomness and uncertainty, the resulting hazard-loss model can be integrated across all possible scenario events to derive the expected annual loss, EAL. To obtain a sense for the upper bound on loss, it is straight forward to formulate losses for other fractiles, such as the 90th percentile non-exceedance probability.

The EAL information obtained from the four-step model plays an essential role in decision making for catastrophe risk management. This information is used in the next sections to assess the risk profile of insurance contracts and risk-linked financial instruments.

3. SHARING THE RISK WITH BOND HOLDERS

CAT bonds can be used to reduce the total cost of post-disaster reconstruction in emerging as well as in developed economies. Insurers, reinsurers, private entities or even governments may issue CAT bonds to obtain an immediate inflow of cash right after a catastrophe when the repair and reconstruction funds are needed the most. The immediate access to the capital reduces the project disruption risk if the emergency funds are not readily available. Considering the devastating impact of recent catastrophes, even if the emergency funds are available, they may be insufficient (Croson and Richter 2003).

Unlike other tradable securities, the valuation of CAT bonds is based on a “black box” approach in which the expected losses are estimated using complex simulation models validated by third-party engineering consulting firms (Damnjanovic et al. 2010). As a result of this lack of transparency, investors have often hesitated to invest in CAT bonds which resulted in larger premium (Aslan et al. 2011). The objective of this section is to develop a more transparent approach to valuating CAT bonds for large constructed assets that play a central role in an owner’s business operations. Examples of these assets include tolled bridges, power plants, airports, high-rise commercial buildings, etc. This section proposes a pricing methodology based on an engineering loss model that provides a closed-form solution for computation of the potential financial losses of engineered structures exposed to seismic risks. The simplified four-step loss model proposed in Section 2 is embedded in the pricing model to link observable engineering design parameters of the constructed assets and the financial parameters of CAT bonds.

The proposed model is illustrated with numerical examples for a seismically designed bridge (the underlying asset) using two unique CAT bond contracts. The results show a nonlinear relationship between engineering design parameters and market-implied spread.

3.1. Background

Natural disasters are examples of societal failure to integrate the natural and the built environment. Poor planning and engineering choices have devastating effects on the affected communities as they attempt to recover and rebuild. While it is inherently difficult to quantify the cost of human life, interruption in business operations, damage to the properties as well as the cost of reconstruction (often measured in terms of tens of billions of dollars), it is critical to develop plans and mitigation strategies to support fast recovery (Damnjanovic et al. 2010; Aslan et al. 2011).

Following Hurricane Andrew in 1992 and the Northridge Earthquake in 1994, property catastrophe reinsurance became scarce and for some insurers unavailable (Cummins et al. 2002). The pricing rose steeply when available at all. These experiences led firms to explore alternative means of financing instruments to pay for the financial consequences of such catastrophic events. The first alternative capital market instrument linked to catastrophe risk called a catastrophe bond, also known as Act of God bond or more commonly, a CAT bond was introduced in 1994 (Andersen 2002).

CAT bonds are structured as coupon paying bonds with a default linked to the occurrence of the trigger event (e.g. when losses after a devastating earthquake exceed a pre-specified level). The financial market variables such as interest rate, firm-specific volatility, managerial decisions, economic downturn or aggregate consumption have no impact on the default risk of CAT bonds (Cox and Pedersen 2000).

The contractual structure of a CAT bond typically involves a ceding party (e.g. Cedant), who seeks to transfer the risk, and investors, who accept the risk for a premium. The cedant can be an insurer, a reinsurer, or the owner of a constructed asset (Sircar et al. 2009; Damnjanovic et al. 2010). The transfer of the risk to the capital markets is achieved by creating a special purpose vehicle (SPV) that provides coverage to the cedant and issues the securities for the investors (Banks 2004). The cedant pays a premium in exchange for the coverage against a pre-specified event, while SPV sells bonds to investors and collects the capital. Raised capital and insurance premium are deposited in a trust account that receives a risk-free interest. The returns generated from this account are swapped for London Interbank Offered Rate (LIBOR) returns that are supplied by a highly rated swap counterparty. Through this swap mechanism, the bond becomes a floating rate note from which interest rate risk is largely removed (Cummins 2008). Fig. 3-1 shows the relationship among the stakeholders when structuring CAT bonds. In this study, the cedant is assumed to be the owner of the constructed asset.

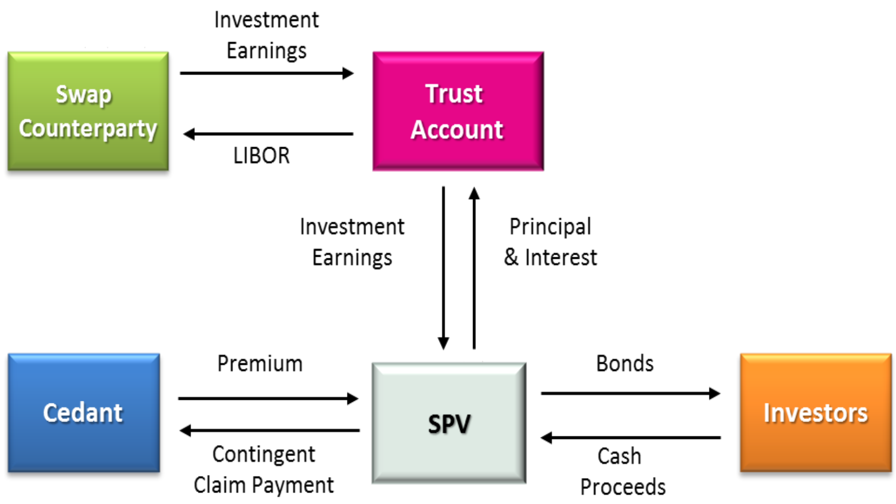

Fig. 3-1: CAT bond structure (Damnjanovic et al. 2010)

If the trigger event does not occur during the term of the CAT bond, investors receive promised coupons and the principal. However, if a catastrophic event occurs and triggers defined default parameter(s) then, the raised capital residing in SPV account is transferred to the ceding company as promised in the bond contract. This results in a partial or total loss of principal to the investors (Cox and Pedersen 2000; Bantwal and Kunreuther 2000).

3.1.1. Triggers

Every catastrophe-linked security has a trigger that determines the conditions under which the ceding company can suspend interest and/or principal payments (either temporarily or permanently). In general, a trigger may be based on single or multiple events and becomes effective after a cedant's losses exceed a particular amount. Triggers can take three different forms: the indemnity trigger, the index trigger, and the parametric trigger (Banks 2004; Sircar et al. 2009; Damnjanovic et al. 2010; Aslan et al. 2011). Each type has its own characteristics, advantages, and disadvantages.

Defining the default-trigger event is essential in structuring CAT bonds. This event must be measurable and easily understood. If the trigger event is based on the level of actual monetary losses suffered by the cedant; the contract is called an "indemnity-based" contract. This contract type is subject to moral hazard risk. This phenomenon occurs when the cedant no longer tries to limit its potential losses as the risk is transferred to investors. Thus, moral hazard occurs due to inadequate loss control efforts by the cedant (Lee and Yu 2002). While suffering from moral hazard risk, indemnity-based contract eliminate basis risk[4] by offering indemnity against modeled perils (Harrington and Niehaus 1999). However, the advantage of eliminating basis risk comes at a price. Structuring and selling indemnity-triggered CAT bonds has been rather difficult due to the lack of transparency. As the catastrophe modeling techniques become more transparent, it is expected that the market will become more receptive.

Another option to relate the trigger event with the actual losses is to specify a loss related index (i.e. total industry loss). "Index-based" contracts help the cedant in avoiding detailed information disclosure to the competitors. However, index-based contracts are subject to basis risk as the cedant's losses may differ from the industry losses. Here, the basis risk relates to the mismatch between the index and the cedant's losses. The quality and hence the benefits of the CAT bond hedge decreases with a

[4] Basis risk relates to the mismatch between the promised coverage (based on the pre-event estimated losses) and the actual losses incurred by the cedant.

decrease in correlation between the cedant's losses and the contract payoff (Harrington and Niehaus 1999).

The triggering event can also be defined based on physical parameters such as peak ground acceleration (PGA) for earthquakes, or wind speed for hurricanes. This is often referred to as "parametric-based" CAT bond contract. Even though a parametric-based CAT bond is subject to basis risk in a similar manner as the index-based contracts, it provides a transparent setting for investors to assess the risks while having a significantly shorter development period compared to indemnity-based contracts (Härdle and Cabrera 2010).

Under indemnity triggered contracts, the cedant reports the actual losses. This creates a situation in which the cedant is incentivized to over-report the losses, so that the trigger event is initiated. However, under both index-based and parametric-based contracts, the cedant has limited to no capability in over-reporting the losses (Damnjanovic et al. 2010). If the trigger loss is based on an industry index then the cedant's ability to initiate the trigger is proportional to its share in the index. For the parametric-based contracts, the cedant has no ability to influence the trigger event as the trigger is based on physical parameters such as location or magnitude (Doherty and Richter 2002). For such triggers, the basis risk can be substantially reduced by appropriately defining the location where the event is measured. Previous studies show that industry loss indices based on narrowly defined geographical areas have less basis risk than those based on wider areas (Cummins et al. 2004). In summary, selection of the bond triggering event involves a trade-off between moral hazard and basis risk. Fig. 3-2 shows the effect of trigger choice over basis risk and transparency.

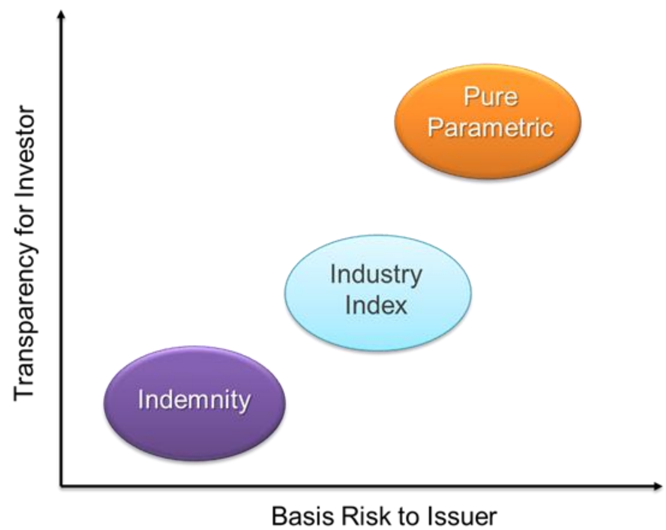

Fig. 3-2: Choice of trigger vs. risk

3.1.2. Coverage

CAT bonds also differ in the level of principal protection and the recovery rates they offer. They are commonly offered in "principal-at-risk" and "principal-protected" types (Banks 2004). If the bond is principal-at-risk type, then in the event of a catastrophe all of the capital raised from the investors will be used to cover cedant's losses. Hence, investors are subject to the risk of losing full principal amount. Coupons can be either protected at the minimum recovery value, or fully lost, much like the principal. The principal protected tranche on the other hand is structured to attract risk-averse investors. In principal protected CAT bonds, the whole principal amount or a pre-specified portion of it is paid back to investors even if the bond defaults. Recent evidence shows that demand for principal protected CAT bonds has significantly decreased as the investors become more familiar with this new asset class (Canabarro et al. 2000)

As there are a number of differently structured CAT bonds on the market, it is important to define the key characteristics of the bonds that are analyzed in this study. The CAT bonds considered for numerical analysis are earthquake-triggered and indemnity-based, but not identical to those offered currently on the market. Nevertheless, they have the same key features such as: default-trigger event, coupons, principal, and contract specifications. The characteristics of the two Cat bonds that are analyzed in this study are defined below.

CAT1 is an indemnity-based principal-at-risk type CAT bond with the attachment point **a**. When the losses to the cedant exceed the attachment point **a** CAT1 defaults.

CAT2 is an indemnity based principal-partially-protected type CAT bond with the attachment point **a** and the exhaustion point **e**. When the aggregated losses to the cedant exceed the attachment point, the investors lose their principal proportionally to the incurred losses exceeding the attachment level. The principal is fully lost when the losses reach the exhaustion point **e**.

3.2. Pricing Models

Litzenberger et al. (1996) used a bootstrap approach to price CAT bonds and compared the results with price estimates obtained by assumed catastrophe loss distributions.

Loubergé et al. (1999) numerically estimated the CAT bond price under the assumptions that the catastrophe loss follows a pure Poisson process, the loss severity is an independently identical lognormal distribution, and the interest rate is driven by a binomial random process.

Lee and Yu (2002) extended the literature and priced CAT bonds with a formal term structure model of Cox and Pedersen (2000). They developed a methodology that incorporates stochastic interest rates and more generic loss processes (compound Poisson) to price default-risky CAT bonds. They also analyzed the value of the bond under the considerations of default risk, moral hazard, and basis risk. Also under an arbitrage-free framework, Vaugirard (2003) evaluates CAT bonds by Monte Carlo simulation methods and stochastic interest rates. The existing literature for valuing Cat bonds is sparse, and contains models that are either too complex or based on equilibrium constructs (Bakshi and Madan 2002; Bantwal and Kunreuther 2000; Dassios and Jang 2003; and Zanjani 2002).

This study contributes to the literature by setting up a new asset-specific framework that considers a joint mechanism for loss arrival and intensity process. This approach fills the gap between the damage potential of the underlying asset and required risk premium of the CAT bond. The next section discusses the methodology for estimating the structural loss.

3.3. Modeling Loss for CAT Bond

When a CAT bond contract is tied to a constructed asset, the connection between the engineering design features and financial losses is highly visible. For such cases, in order to determine the value of a CAT bond contract, one needs to estimate the potential losses to the insured property first. The four-step model presented in Section 2 is used herein to estimate the loss from structural damage and to bridge the gap between engineering and financial analysis in decision making process.

Recall the mathematical expression governing the four-step model as defined in Eq. (2-1):

$$\frac{L}{L_{DBE}} = \left|\frac{\theta}{\theta_{DBE}}\right|^{c} = \left|\frac{IM}{IM_{DBE}}\right|^{bc} = \left|\frac{f_a}{f_{DBE}}\right|^{d} \qquad (2\text{-}1)$$

Eq. (2-1) can be used to compute the annual frequency of the event for which a specific value of loss is exceeded. Note that the developed loss model represents a framework for modeling losses for unique structures rather than portfolio of structures (i.e. seismically or conventionally designed bridges, building, or other constructed assets). Fig. 3-3 summarizes the four-step process and it is provided here for completeness.

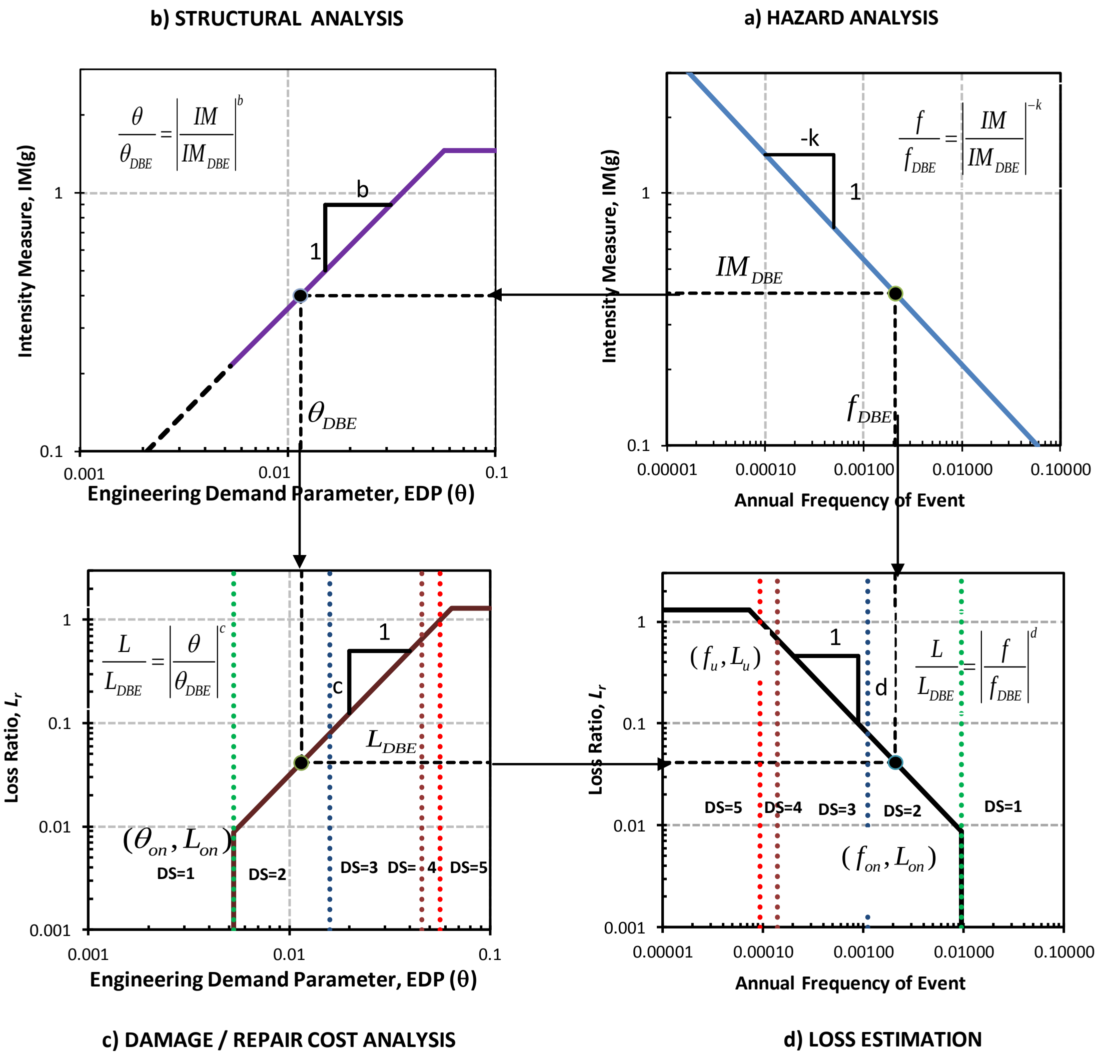

Fig. 3-3: Four step procedure for CAT bond pricing (Damnjanovic et al. 2010)

Annual losses (AL) can be estimated by integrating the area beneath the curve in Fig. 3-3(d) when that curve is plotted to natural scales. Hence, AL can be found by computing the following integration (Sircar et al. 2009):

$$AL = \int_{0}^{f_{on}} L_r df = L_u f_u + \frac{L_{DBE}}{f_{on} f_{DBE}^{\ d}} \int_{f_u}^{f_{on}} f^d df = \frac{L_{on} f_{on} + dL_u f_u}{1+d} \tag{3-1}$$

where f_{on} and f_u are defined by:

$$f_{on} = f_{DBE} \left| \frac{\theta_{DBE}}{\theta_{on}} \right|^{\frac{k}{b}} \tag{3-2}$$

and,

$$f_u = f_{DBE} \left(L_u \right)^{\frac{1}{d}} \left| \frac{\theta_{DBE}}{\theta_c} \right|^{\frac{k}{b}} \tag{3-3}$$

In order to estimate the Expected Annual Losses (EAL), it is essential to transform the median parameters to other fractiles, including the mean values. This can be achieved by quantifying the kind and degree of uncertainty in each of the parameters concerned. Due to the multiplicative (power) nature of the loss model, lognormal distribution is assumed to be an appropriate representation of variability (Sircar et al. 2009; Mander et al. 2012). Thus, in computing a variable *y* the relationship between the mean $\bar{y}$ and the median $\tilde{y}$ is given by (Kennedy et al. 1980):

$$\bar{y} = \tilde{y} \exp\left(\frac{1}{2} \beta^2 \right) \tag{3-4}$$

Consequently, for other fractiles (i.e. *x%* non-exceedance probabilities)

$$y_{x\%} = \tilde{y} \exp(K_x \beta) \tag{3-5}$$

where K_x represents the standardized Gaussian random variable for a given percentile value (i.e. *x*) with a mean value of zero and standard deviation of one. K_x can be obtained by using cumulative distribution tables for the standardized Gaussian random variable for the desired percentile value of *x* (Kennedy et al. 1980).

By using the dispersion equations (Eqs. (2-4), (2-5), and (2-6)) defined in Section 2-3, it is now possible to compute the expected (mean) annualized losses (EAL) by using the aforementioned dispersion factors along with the median coordinates $(\tilde{f}_{on}, \tilde{L}_{on})$ and $(\tilde{f}_u, \tilde{L}_u)$. EAL can be expressed mathematically by utilizing Eq. (3-1) when applying Eq. (3-4) as follows:

$$EAL = \int_0^{\bar{f}_{on}} L df = \bar{L}_u \bar{f}_u + \frac{\bar{L}_{DBE}}{\bar{f}_{on} \bar{f}_{DBE}^{\,d}} \int_{\bar{f}_u}^{\bar{f}_{on}} f^d df = \frac{\bar{L}_{on} \bar{f}_{on} + d\bar{L}_u \bar{f}_u}{1+d} \qquad (3\text{-}6)$$

In Eq. (3-6), the coordinates, $(\bar{f}_{on}, \bar{L}_{on})$ and $(\bar{f}_u, \bar{L}_u)$ are the mean values of the primary loss curve coordinates.

In the following sections the model for estimating seismically-induced losses is related to the model for determining fair market value of the risk premium (spread).The methodology for implementing the structural loss model to the CAT bond pricing is presented and followed by numerical examples to illustrate the findings.

3.4. Methodology

The focus of this section is indemnity based CAT bonds for which the trigger event is based on specified actual monetary losses to the cedant. By using the loss-frequency curve illustrated in Fig. 3-3(d), it is possible to estimate the losses of a constructed asset that is insured with an indemnity-based CAT bond for a specified loss trigger.

It is assumed that the probability of occurrence (or annual occurrence frequency) of a catastrophe in T years is q and the risk free rate on US treasury bills per time period

T is r_f. For simplicity, consider a single period case ($T = 1$ year) where coupons[5] (C) are paid annually and the bond is sold at Par[6] (face value). Since the underlying assets are constructed assets, it is assumed that a SPV is created by the cedant (owner of the constructed asset). To be able to pay the promised coverage (L_{cov}) in case of a catastrophe, the SPV raises the needed capital from the capital market by issuing CAT bonds. If B_p denotes the raised capital from bond issuing, required condition for the loss coverage can be written mathematically as:

$$B_p(1+r_f) = L_{\text{cov}} \tag{3-7}$$

If no catastrophe occurs during the term of the bond, investors get their principal back and the promised coupon payments. For such cases the unit price of the bond in terms of expected discounted cash flow can be expressed as:

$$B_p = (1-q)\frac{C + \text{Par}}{(1+r_f)} \tag{3-8}$$

Fig. 3-4 shows the payoff of the CAT bond to investors and cedant depending on the occurrence of pre-specified catastrophe.

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[5] A coupon payment on a bond is a periodic interest payment that the bondholder receives during the time between when the bond is issued and when it matures.

[6] Par value or face value is the amount of money the investor will receive once the bond matures, meaning that the entity that sold the bond will return to the investor the original amount that it was loaned.

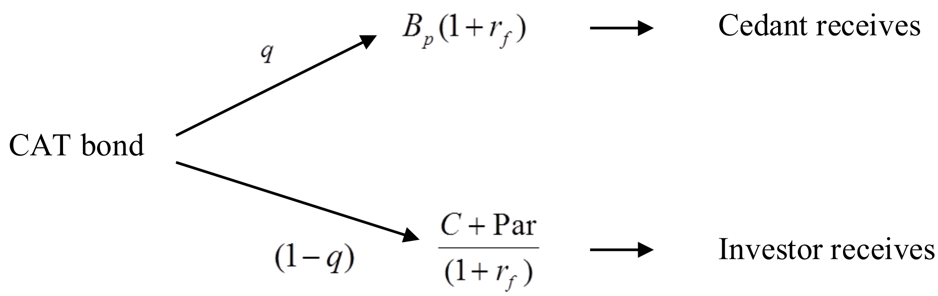

Fig. 3-4: CAT bond payoff diagram

Recall that both Eq. (3-7) and Eq. (3-8) are written for $T = 1$ years. A more general formula for N periods of T years can be defined as:

$$B_p = C\sum_{n=1}^{N}\frac{(1-q)^n}{(1+r)^n} + \frac{(1-q)^T}{(1+r)^T}\text{Par} \tag{3-9}$$

As discussed in Section 2, the annual occurrence probability of a loss variable exceeding a predefined threshold value due to an earthquake can be obtained from the proposed structural loss model. When the bond is priced at par, the coupon is defined by a spread (risk premium) added to risk free rate (LIBOR). Spread (S) is defined as an interest that compensates investors for taking on additional risk (investing in a potentially defaulting entity). As the risk increases, so does the spread (Damnjanovic et al. 2010). Therefore, the key factor in determining the value of CAT bonds is finding the spread value for the underlying risk.

Wang (1995) stated that in the absence of systematic risk[7], the spread corresponds to the market implied value of the expected losses. Based on this approach,

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[7] The risk inherent to the entire market or entire market segment.

well known Wang Proportional Hazard (P-H) transforms are used to transform the annual loss function (obtained by the engineering loss model) and calculate the spread values of CAT bonds. By doing so, a direct link between the observable engineering design parameters and the value of spread is created. The P-H transform methods are used to adjust the best-estimate distribution with respect to the varying levels of uncertainty, portfolio diversification as well as market competition (Wang, 1996).

The losses from catastrophic events are represented by the loss exceedance (survival) curves. For the loss variable X, the survival function of X, given by $S(x)$ is defined as (Wang, 1996):

$$S(x) = P\{X > x\} \tag{3-10}$$

In Eq. (3-10) $S(x)$ refers the probability that loss X will exceed amount x. Clearly, the relation between the survival function and cumulative distribution function $F(x)$ can be constructed as:

$$S(x) = 1 - P\{X \le x)\} = 1 - F(x) \tag{3-2}$$

It can be verified that, for non-negative random variables, the mean value of the loss variable $X, E(X)$, is obtained by integration of the survival curve over the range from zero to infinity (Wang, 1995).

$$E(X) = \int_0^\infty S(x)dx \tag{3-12}$$

However, the current market prices imply quite higher loss estimates (Damnjanovic et al. 2010). In fact, the investors do not account for the risk of high losses due to a relatively low likelihood of a catastrophe event that is equivalent to a small loss resulting event with a high chance of occurrence. The expectation of losses does not accentuate the very nature of catastrophes, their likelihood and consequences (Haimes, 2004). To account for this, Wang (1995) showed that the market implies a direct transform of the objective survival curve, and defined the P-H risk adjusted premium of such contracts with potential losses as the mean of the transformed distribution as:

$$\prod_{\rho}(X) = E\left[\prod_{\rho}(X)\right] = \int_0^{\infty} S^*(x)dx = \int_0^{\infty} \left(S(x)\right)^{1/\rho} dx \qquad (3\text{-}13)$$

The mapping $\prod_{\rho} : S(x) \rightarrow (S(x))^{1/\rho}$ referred to as the P-H transform and $\prod_{\rho}(X)$ is the risk adjusted premium or risk adjusted spread at risk aversion level (RAL) $\rho \geq 1$. This model was further extended to include the Sharpe ratio for risks with skewed distribution (Wang, 1996):

$$S^*(x) = \Phi\left(\Phi^{-1}\left(S(x)\right) + \lambda\right) \qquad (3\text{-}3)$$

where Φ is the standard normal cumulative distribution and $\lambda = (\text{E[R]-r}) / \sigma\text{[R]})$ is the Sharpe ratio.

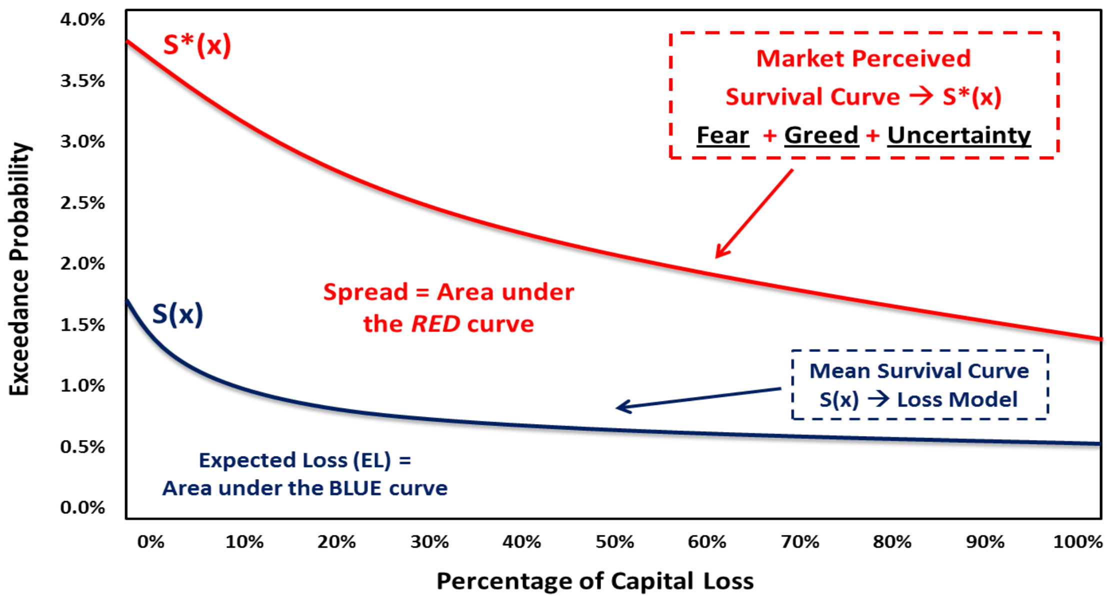


Fig. 3-5: Probability transformation

Fig. 3-5 shows a typical survival function of a loss variable and its transform. The area under the survival curve represents expected loss (EL) and the area under the transformed curve $S*(x)$ gives the spread. Accordingly, the area between two curves is simply the additional risk loading required by investors for taking on the risk. This additional risk loading is also known as expected excess return (EER). In the case of CAT bonds the estimates of probability of first loss (PFL) and the probability of cover exhaustion (PE) have critical importance over determining the spread values. Once the trigger loss value and required coverage is set, both of these probability values can be computed easily with the proposed loss model in Section 2.

However, it is very important to characterize the entire distribution since investors and issuers make decisions not only on the information about distribution's tails and expectation, but full information about event's probability space. The estimates of probability distributions are based on the limited data and hence subject to parameter uncertainty. To adjust the parameter uncertainty, Wang (2004) suggested empirically estimated probability distribution $F(x)$:

$$F^*(x) = Q\left(\Phi^{-1}\left(F(x)\right)\right) \tag{3-15}$$

where, Q is the student-t distribution with degree-of-freedom υ. Eq. (3-15) can be re-written in terms of a survival function as:

$$S^*(x) = Q\left(\Phi^{-1}\left(S(x)\right)\right) \tag{3-16}$$

Combining the transform in Eq. (3-16) and the parameter adjustment in Eq. (3.14), the following two factor model is obtained:

$$S^*(x) = Q\left(\Phi^{-1}\left(S(x)\right) + \lambda\right) \tag{3-17}$$

and hence, the risk adjusted premium of a survival function for a loss variable X becomes:

$$\prod\nolimits_{\lambda}(X) = E\left[\prod\nolimits_{\lambda}(X)\right] = \int_{0}^{\infty} Q\left(\Phi^{-1}\left(S(x)\right) + \lambda\right) dx \tag{3-18}$$

Once the transformation parameters are set, it is critical to select the survival function that gives the most accurate potential loss information for a specific type of asset. It is possible to use the developed annual loss function (frequency-loss curve shown in Fig. 3-3(d) as the survival function for computing the spread values of indemnity-based CAT bond contracts. Thus, the survival function of an indemnity based CAT bond can be defined as:

$$S(L) = f_L = f_{DBE} \left| \frac{\text{L}}{\text{L}_{DBE}} \right|^{1/d} \tag{3-19}$$

The spread value for indemnity based CAT bonds for a particular type of underlying structural asset can be calculated as:

$$\prod_{\lambda}(L) = E\left[\prod_{\lambda}(L)\right] = \int_{0}^{\infty} Q\left(\Phi^{-1}\left(f_{DBE}\left|\frac{\text{L}}{\text{L}_{DBE}}\right|^{1/d}\right) + \lambda\right) dL \tag{3-20}$$

Fig. 3-6 summarizes the methodology followed for calculating spread values of CAT bonds.

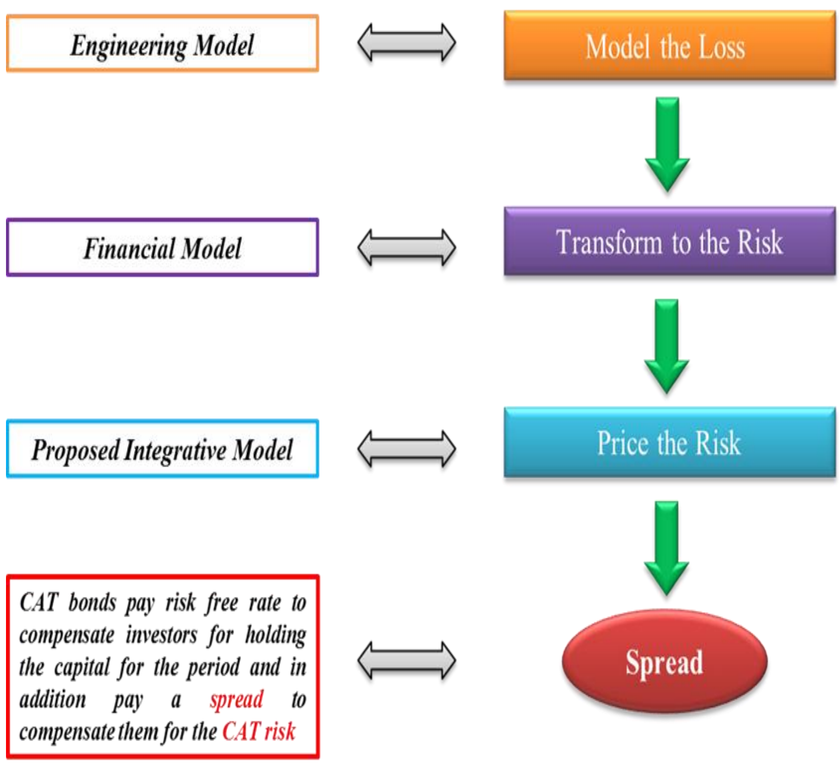


Fig. 3-6: CAT bond valuation process

3.4.1. Losses Given Default

A closed-form solution for the loss distribution of bond investors can be derived by using a risk adjusted survival function $S^*(x)$. Recall the Eq. (3-11) which defines the relationship between the cumulative distribution function and the survival function, that is, $S^*(x)=1-F^*(x)$. Thus, the probability density function (*PDF*) of losses given default $f^*(x)$ is a derivative of $F^*(x)$. However, finding the derivative of $F^*(x)$ can be a challenge with the two factor model. By using the simpler P-H transformation in Eq. (3-17) defined by $S(x)\to(S(x))^{1/\rho}$, the following relationship is obtained:

$$f^*(L)=\frac{-\left(f_{dbe}\times\left|\frac{L}{L_{dbe}}\right|^{1/d}\right)^{1/\rho}}{L\rho d} \quad ; \text{for } L>L_T \tag{3-21}$$

where L_T refers to the default trigger loss.

3.4.2. Market Price of Risk

The CAT bond market has significantly increased in both variety and number of investors over the last decade (Damnjanovic et al. 2010). The attractive spreads offered by these bonds have been considered the main drivers of this increasing trend (Sircar et al. 2009). Due to the weak appetite of investors for CAT bonds and unfamiliarity with this new asset class, the issuers had to offer significantly higher yields than for the similar class of corporate bonds. Table 3-1 summarizes the probability of first loss (*PFL*), probability of cover exhaustion (*PE*) and annual spread values of insurance-linked securities (ILS) issued between 2000 and 2003.

Table 3-1: Data for insurance linked securities issued between 2000 and 2003 (Damnjanovic et al. 2010)

SPV	PFL	PE	S
to March 2000			
Mosaic 2A	1.15%	0.04%	4.08%
Mosaic 2B	5.25%	1.15%	8.36%
Halyard Re	0.84%	0.45%	4.56%
Domestic Re	0.58%	0.44%	3.74%
Concentric Re	0.64%	0.00%	3.14%
Juno Re	0.60%	0.33%	4.26%
Residential Re	0.78%	0.26%	3.71%
Kelvin 1stE	12.10%	0.50%	10.97%
Kelvin 2ndE	1.58%	0.07%	4.82%
Golden Eagle B	0.17%	0.17%	2.99%
Golden Eagle A	0.78%	0.49%	5.48%
Namazu Re	1.00%	0.32%	4.56%
Atlas Re A	0.19%	0.05%	2.74%
Atlas Re B	0.29%	0.19%	3.75%
Atlas Re C	5.47%	1.90%	14.19%
Seismic Ltd	1.13%	0.47%	4.56%
April 2000-March 2001			
Alpha Wind FRN	0.99%	0.38%	4.62%
Alpha Wind Prefs	2.08%	0.99%	7.10%
Residential Re	0.95%	0.31%	4.16%
NeHi	0.87%	0.56%	4.16%
MedRe Class A	0.28%	0.17%	2.64%
MedRe Class B	1.47%	0.93%	5.93%
PRIME Hurricane	1.46%	1.08%	6.59%
PRIME EQEW	1.69%	1.07%	7.60%
Western Capital	0.82%	0.34%	5.17%
Halyard Re	0.84%	0.04%	5.58%
SR Wind ClA-1	1.07%	0.44%	5.83%
SR Wind Cl A-2	1.13%	0.53%	5.32%
NeHi	1.00%	0.87%	4.56%
Gold Eagle 2001	1.18%	1.18%	7.10%
SR Wind Cl B-2	1.13%	1.13%	6.59%
Atlas Re II Class B	1.33%	0.53%	6.84%
Redwood Capital I	0.72%	0.34%	5.58%
Redwood Capital II	0.31%	0.14%	3.04%
Residential Re 2001	1.12%	0.41%	5.06%
St. Agatha Re	1.55%	0.87%	6.84%
Trinom Class A-1	2.42%	0.39%	8.11%
Trinom Class A-2 (Pre)	1.01%	0.43%	4.06%
Redwood Capital I	0.72%	0.72%	7.10%
Trinom (Pre)	3.11%	3.11%	10.14%
April 2002-March 2003			
Fujiyama	0.88%	0.42%	4.06%
Pioneer A Jun-02	1.59%	0.97%	6.08%
Pioneer A Dec-02	1.59%	0.97%	5.32%
Pioneer A Mar-03	1.59%	0.97%	5.58%
Pioneer B Jun-02	1.59%	1.05%	5.07%
Pioneer B Sep-02	1.59%	1.05%	5.32%
Pioneer B Dec-02	1.59%	1.05%	5.32%
Pioneer B Mar-03	1.59%	1.05%	4.82%
Pioneer C Jun-02	1.59%	0.98%	6.08%
Pioneer C Sep-02	1.59%	0.98%	6.08%
Pioneer C Dec-02	1.59%	0.98%	6.08%
Pioneer C Mar-03	1.59%	0.98%	6.08%
Pioneer D Jun-02	0.27%	0.19%	1.77%
Pioneer D Sep-02	0.27%	0.19%	1.77%
Pioneer D Dec-02	0.27%	0.19%	1.77%
Pioneer D Mar-03	0.27%	0.19%	1.77%
Pioneer E Jun-02	1.59%	1.01%	4.31%
Pioneer E Dec-02	1.59%	1.01%	4.82%
Pioneer F Jun-02	1.60%	1.02%	7.60%
Pioneer F Dec-02	1.60%	1.02%	7.60%
Pioneer F Mar-03	1.60%	1.02%	7.60%
Residential Re 2002	1.12%	0.40%	4.97%
Studio Re Ltd.	1.38%	0.22%	5.17%

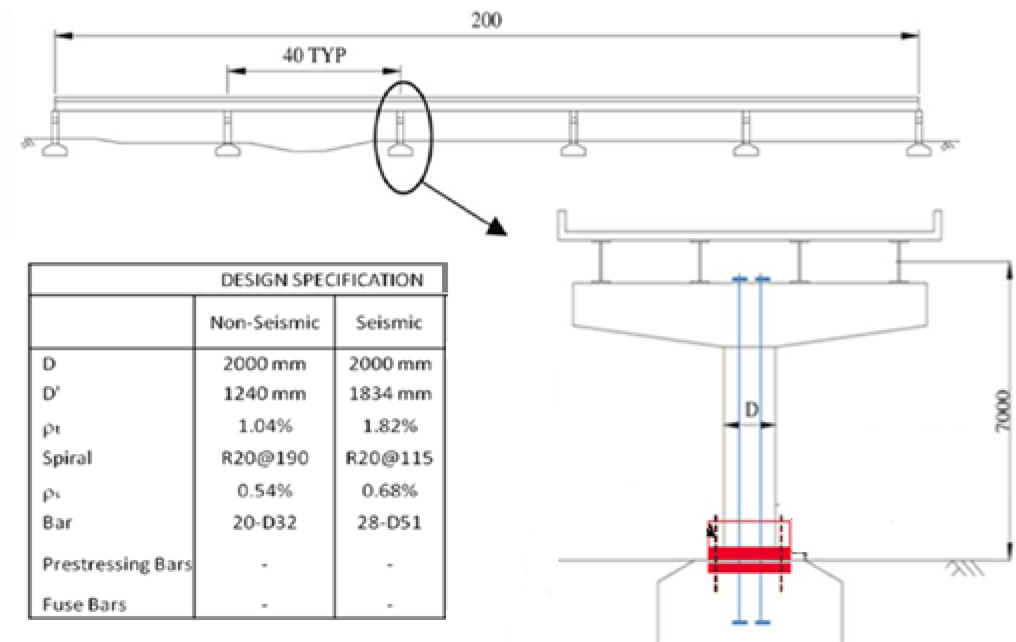
The ILS data presented in Table 3.1 is used to estimate the two factor model parameters defined in Eq. (3-24). Based on minimizing the mean squared error method and by using the genetic algorithms (GA), the best fit two factor model parameters λ and υ are estimated to be 0.75 and 15, respectively.

A simple linear model, as shown in Eq. (3-22), is fitted to the presented data to observe the sensitivity of offered spread values to *PFL* and *PE* (R^2 adjusted = 0.888). The statistical results for transactions between 2000 and 2003 indicate that the spread values are much more sensitive to the *PFL*, occurrence probability of the event that causes first loss; than *PE*, the probability of the event that causes the ultimate loss (loss of entire investment).

$$S = 5.15(PFL) + 0.90(PE) \tag{3-22}$$

3.5. Numerical Examples

Assume that the cedant (owner of the constructed asset) seeks financial coverage against earthquake risk for his revenue-generating structural asset (e.g. bridge). The bridge under consideration is designed with the current California Department of Transportation (CALTRANS) seismic design codes and shown in Fig. 3-7.



DESIGN SPECIFICATION	Non-Seismic	Seismic
D	2000 mm	2000 mm
D'	1240 mm	1834 mm
ρ_t	1.04%	1.82%
Spiral	R20@190	R20@115
ρ_s	0.54%	0.68%
Bar	20-D32	28-D51
Prestressing Bars	-	-
Fuse Bars	-	-

Fig. 3-7: The five-span prototype bridge used and design attributes

The proposed loss model is illustrated with the following parameters: $f_{DBE} = 0.0021$, $L_{DBE} = 0.05$, $d = -0.6522$ and $k = 3.45$. These parameters are typical for a seismically designed bridge structure located in California (Sircar et al. 2009; Damnjanovic et al. 2010; Aslan et al. 2011; Mander et al. 2012).

3.5.1. Example CAT1

The cedant requires coverage if the actual monetary losses to the underlying asset (i.e. bridge) exceed 10% of the replacement cost (attachment point, $a = 10\%$) and issues CAT1. Losses up to the attachment level are covered by either primary insurance or private funds. This region is also known as deductible and shown by the area with diagonal stripes (A1) in Fig. 3-8.

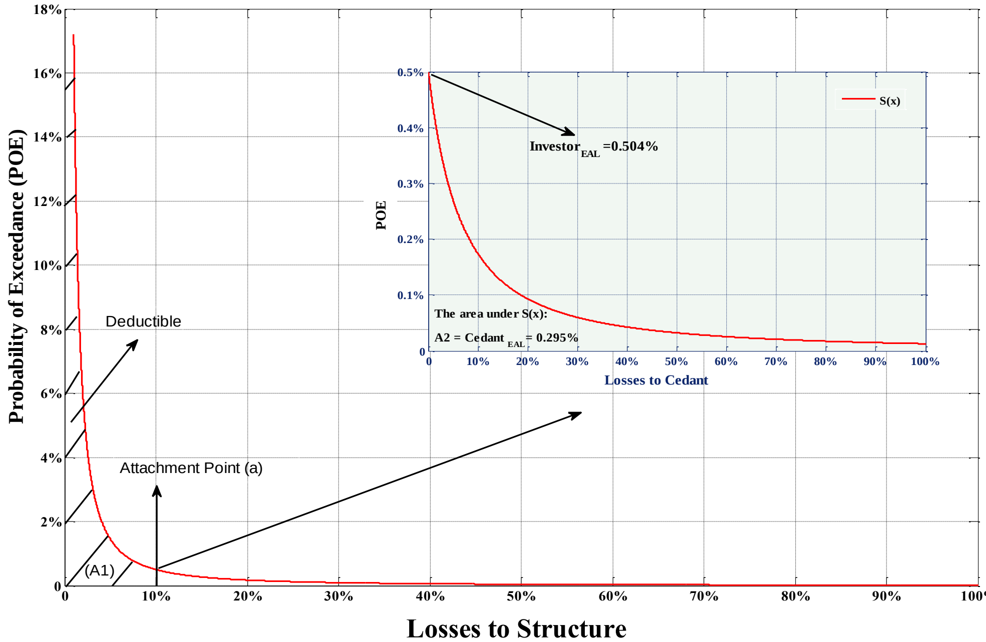


Fig. 3-8: Losses to the cedant and to the investors with CAT1

Since investors of CAT1 lose the whole principal in case of default, investors' expected annual losses ($E(L)_I^{CAT1}$) per invested principal is simply the probability value that losses exceed the attachment point ($a = 10\%$), and hence $E(L)_I^{CAT1} = 0.504\%$. To compute the spread value, the market adjusted survival curve for CAT1 investors is constructed and shown in Fig. 3-9.

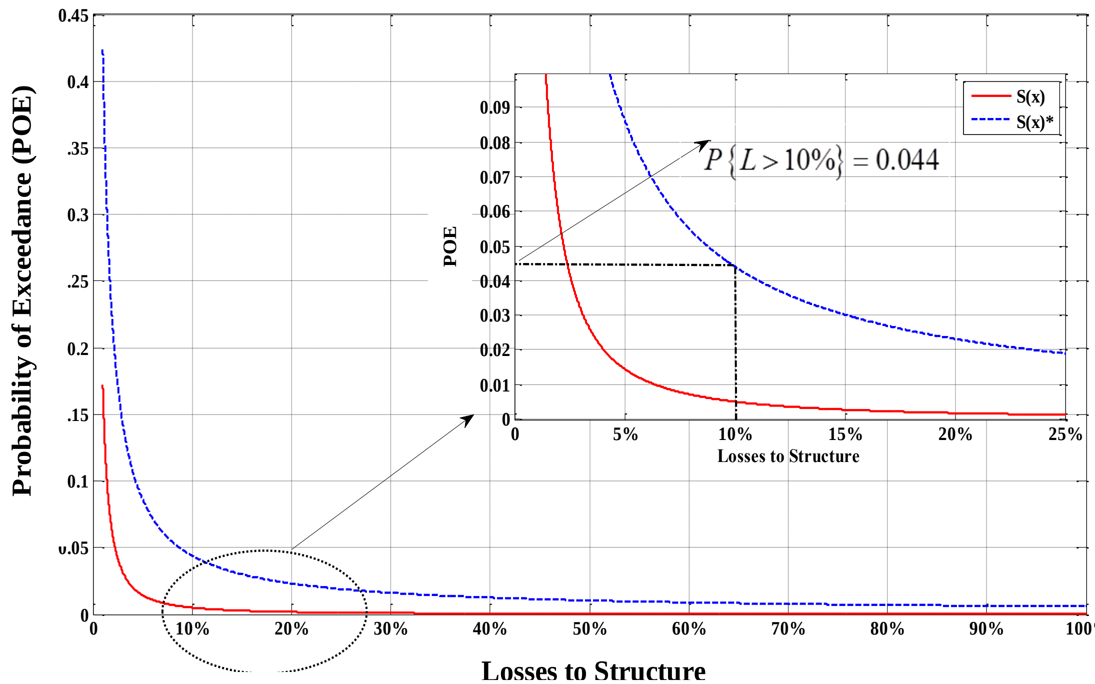


Fig. 3-9: $S(x)$ and $S^*(x)$ with CAT1 coverage

Recall that all probability values used in the analyses are the exceedance probabilities, $P\{X > x\}$. By using the risk adjusted survival curve $S^*(x)$, $P\{L > 10\%\}$ is calculated as 4.4%. This value is related to the perceived risk, or in case of CAT1 bond, its default probability implied by the market and hence the market-implied risk premium (spread) is estimated to be $S_{CAT1} = 4.4\%$ or 440 basis points[8].

3.5.2. Example CAT2

Now consider the case where the cedant issues CAT2 for the same coverage requirement defined in CAT1 example with a = 10% (attachment point) and e = 100%

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[8] In the bond market, the smallest measure used for quoting yields is a basis point. Each percentage point of yield in bonds equals 100 basis points. Basis points also are used for interest rates.

(exhaustion point where the investors lose entire principal). Fig. 3-10 shows the survival curve of the cedant, $S(x)$, and the risk adjusted transform, $S^*(x)$, for investors.

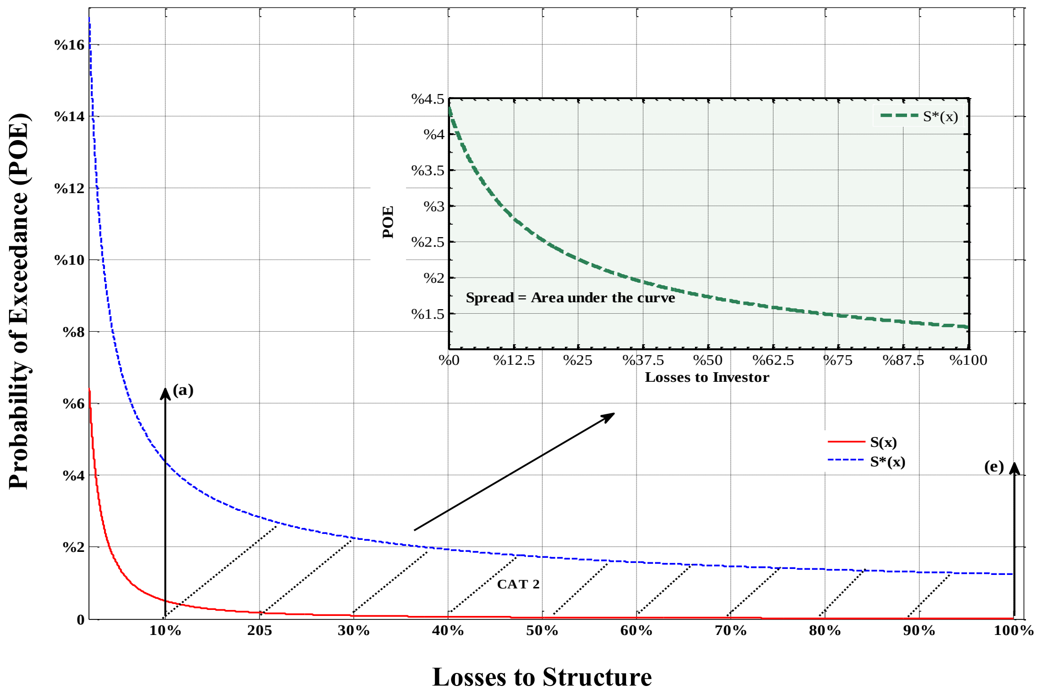

Fig. 3-10: $S(x)$ and $S^*(x)$ with CAT2 coverage

The following are the numerical findings for CAT2 investors: $E(L)_I^{CAT2} = 0.0668\%$ and $S_{CAT2} = 1.197\%$ = 119.7 basis points. Notice the significant decrease in $E(L)_I^{CAT2}$ compared to $E(L)_I^{CAT1}$. This is the consequence of increased recovery rate (level of principal protection) provided to CAT2 investors.

3.5.3. Managerial Implications

CAT bonds are highly attractive securities for investors in terms of returns (Bantwal and Kunreuther 2000). Using the results obtained from the numerical examples presented in previous section, it is possible to compare spreads of analyzed CAT bonds and corporate bond with respect to the underlying risk. Fig. 3-11 illustrates annualized expected losses and offered spreads for CAT bonds and corporate bonds with common ratings (see Hamilton et al. 2006 for more information on bond ratings).

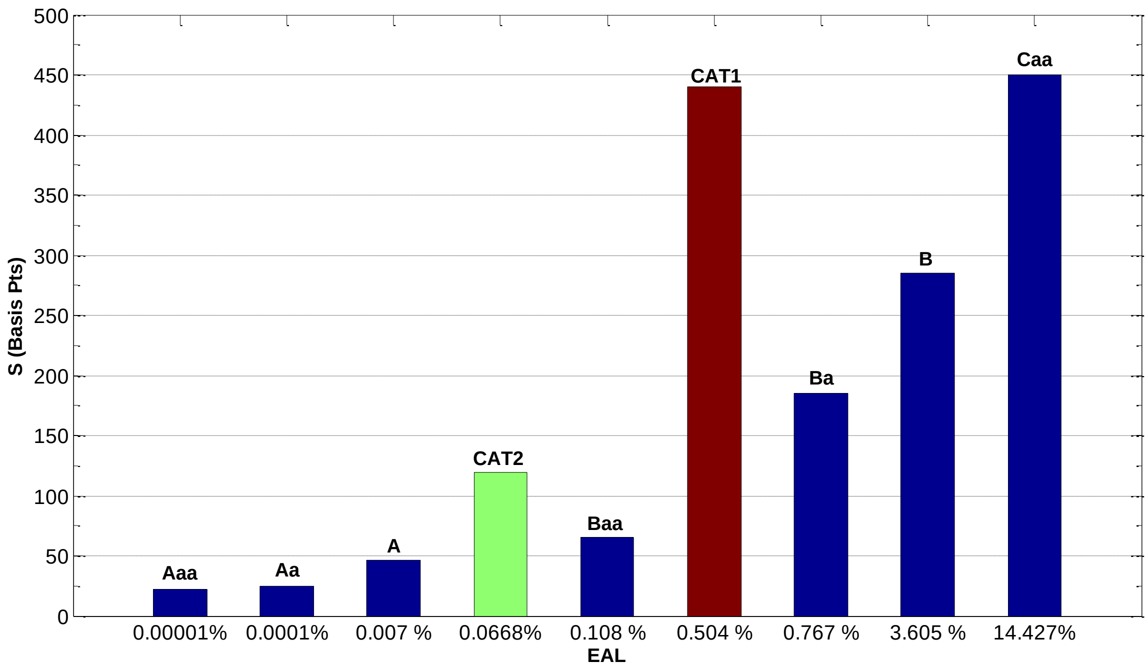

Fig. 3-11: EAL vs. spread (Corporate bond data from Damnjanovic et al. 2010)

Fig. 3-11 clearly indicates that both CAT1 and CAT2 offer higher spreads than corporate bonds with similar underlying risk (in terms of expected loss). In fact, the engineering loss analysis shows that the estimated expected losses do not support the rating. The hypothesis of the study is that this discrepancy can be eliminated if more information and transparency existed in how engineering parameters are mapped into the expected losses. The current "black-box" approach results in inflated risks and make this class of insurance linked securities less liquid.

A key component governing both expected loss, $E(L)$, and spread, S, estimates is the value of the default trigger loss, or the attachment point (**a**). This point can act as a deductible limit to adjust the risk profile of the bond. In fact, the issuers can adjust it based on needed coverage and available funds. Fig. 3-12 presents the sensitivity of $E(L)$ and S to changes in the value of default trigger (attachment point). It can be observed from Fig. 3-12 that both $E(L)$ and S decrease as the attachment point increases. For a 100% increase in attachment point (from 10% to 20%), $E(L)$ decreases by 40 percent and S decreases by 25 percent.

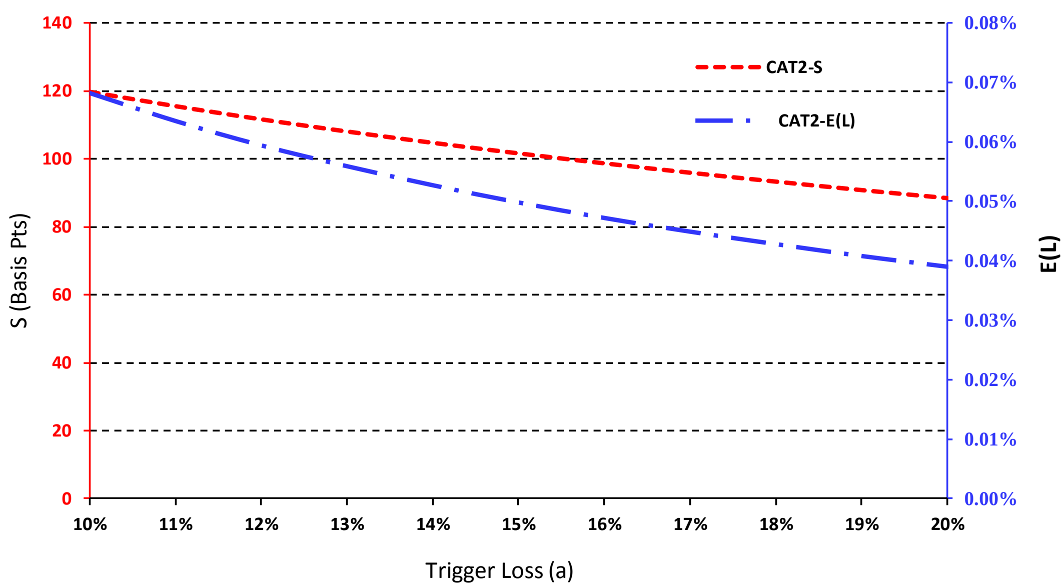

Fig. 3-12: CAT2 bond spread sensitivity to trigger loss

Further, the impact of time to maturity (duration of CAT bonds) on market-implied spread values is analyzed. Fig. 3-13 illustrates the theoretical term structure of the CAT2 bond. When compared to term structure of corporate bonds, the CAT2 bond shows similar behavior (Damnjanovic et al. 2010).

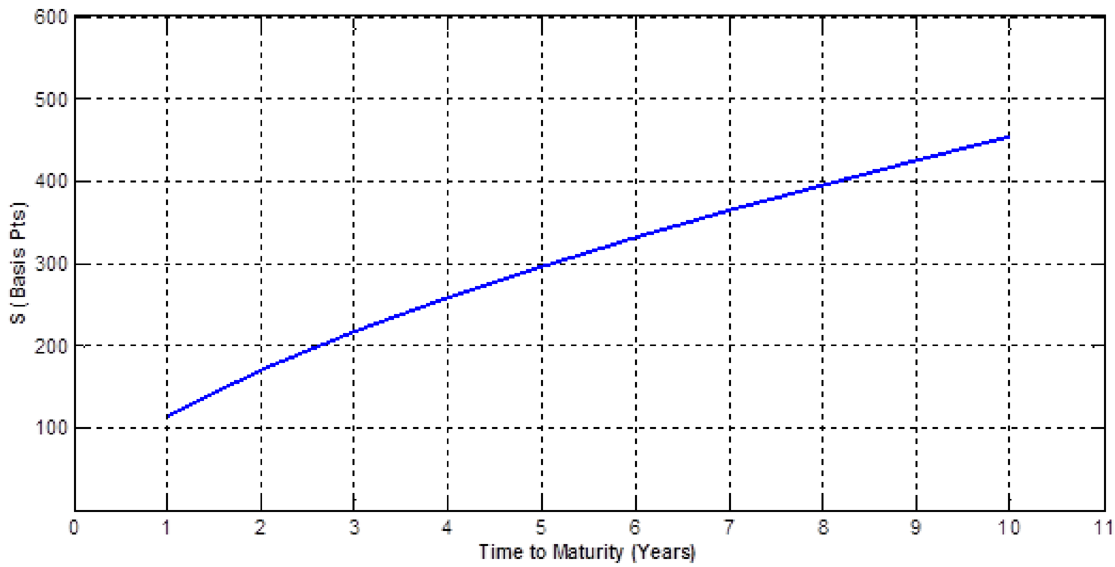

Fig. 3-13: Term structure of the CAT2 bond

Fig. 3-14 illustrates the comparison of annualized expected losses (EAL) of corporate bonds (for given bond ratings) and CAT2 over the 5 years range (For corporate bond data, see Hamilton 2006). Evidently from Fig. 3-14, CAT2 should be rated as either A or Baa whole letter grade according to the Moody's rating standard. It is notable that the marginal increase in EAL over time is very similar to higher investment grade bonds (e.g. Aaa, Aa and A rated corporate bonds) rather than the Baa class.

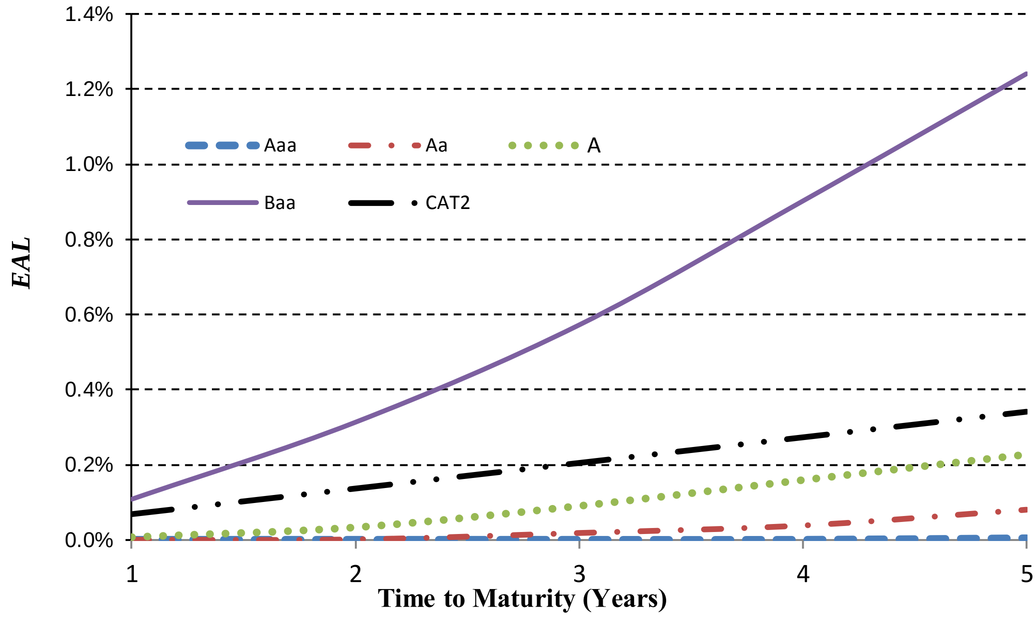

Fig. 3-14: Expected loss vs. time to maturity

Finally, one of the most important aspects of this study is determining how engineering parameters affect CAT bonds' risk loading (e.g. spread). Traditional seismic design philosophy puts little emphasis on design solutions that go beyond legal and code-imposed requirements. However, as insurance cost can be a significant component of life-cycle costs for the constructed assets in hazard-prone areas, seismic design philosophy needs to be changed to consider the optimal level of design variables that minimize not only the first (i.e., construction) cost, but also the total life-cycle cost including insurance cost.

Fig. 3-15 shows the impact of changes in engineering design variables on the spread of CAT bonds issued for the bridge structure. Six parameters showed changes markedly higher than the 10% variation, namely; IM_{DBE}, *b, k, c,* θ_{DBE}, and θ_{c}. These parameters can be grouped to represent seismic hazard demand (IM_{DBE}, k), structural response demand (b, θ_{DBE}) and structural damage capacity (c, θ_c). Thus, it is critical to have dependable local hazard data and specific structure behavioral models to accurately predict the expected losses and market-implied spread.

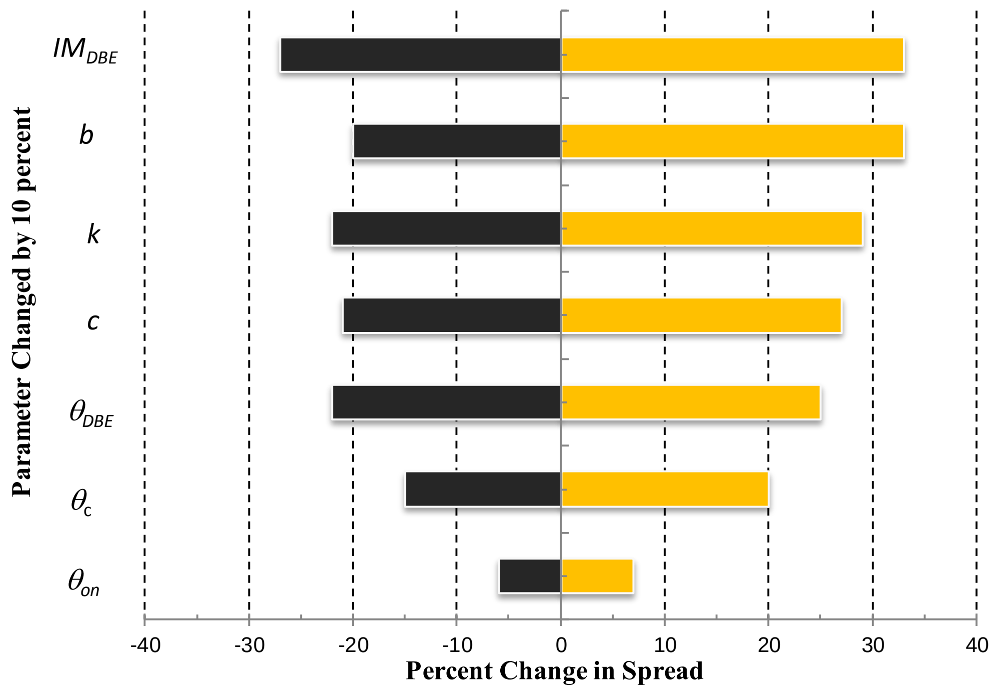

Fig. 3-15: Sensitivity analysis for engineering design parameters

The results show that specific design types and structural material characteristics can significantly help reduce the cost of mitigating structural losses from earthquakes. The impact of structural response and damage potential parameters (*b* and *c*) is almost as important as the ground motion parameters. This demonstrates that structural designers should exercise special attention when evaluating designs and developing specifications for constructed assets.

3.5.4. Barriers and Role of Education

The issuers of CAT bonds often state that this type of securitization is very costly, and investors are reluctant to purchase catastrophe-linked securities despite the offered attractive premiums that are sometimes more than 500 basis points over the LIBOR[9] (Damnjanovic et al. 2010). The lack of liquidity and relative novelty may have substantially contributed to this high premium demand. This highly risk averse behavior raises the question whether the problem is about the current offerings or if there are some psychological barriers associated with the risks of catastrophe-linked securities.

Froot (1997) states that the global catastrophe risk distribution system fails to spread the risks of major catastrophes and hence high costs appear due to the consequent inefficient risk sharing. He also summarizes the major barriers that prevent risks from being properly spread as:

1) Insufficiency of capital within the global reinsurance industry,
2) inefficiency of the corporate form for reinsurance,
3) presence of moral hazard at the insurer level, and basis risk at the investor level,
4) behavioral factors associated with catastrophic events.

Utilizing capital markets via securitization would address the first barrier. As to the second barrier, ILS may provide a lower cost of managing catastrophe risk than raising large amounts of equity capital. For the third barrier, to the point that perceived basis risk is too large by some hedgers, the reinsurers can overcome this problem by creating

[9] The LIBOR is the average interest rate that leading banks in London charge when lending to other banks, it is an acronym for London Interbank Offered Rate.

a diversified portfolio of primary insurance contracts and hence hedge the residual risk in the CAT-linked derivatives markets (Cummins et al. 2004). Alternatively, the residual risk due to the difference between the estimated amount of loss and the actual claims suffered by the issuer can be either retained by the issuer or hedged with a customized reinsurance contract (Croson 2000). As far as overcoming the moral hazard risk is concerned, the straightforward and simple CAT-loss estimation models can create a transparent link between the potential losses to the issuers and resulting investor risks.

However, addressing the fourth barrier is difficult because it requires understanding the risk preferences of investors. The ambiguity aversion of the investors is one of the behavioral barriers that remarkably increase the cost of catastrophe-linked securitizations (Rode et al. 2000). The investors demand higher spreads if there is significant ambiguity associated with the risk which is often the case with the natural hazards and "black box" approaches for estimating losses. Further, investors may overweight small probabilities (i.e. statistically rare events like catastrophes). Several studies showed that two alternative investments having the same expected loss values, preference is given to a sure small loss rather than a very small chance of a relatively large loss (Rode et al. 2000). In a conventional pricing model, a potential risk with a very small probability would result in a comparably small risk loading and hence premium; however, as the decision weighing function of the investors overweighs the small probabilities, investors demand a higher return.

Typically investors are reluctant to invest the effort and time required to understand the potential risks of the new securities (Sircar et al. 2009). Not surprisingly the cost of learning increases as the complexity of the products increases. In this setting, the simplified asset-specific engineering approach presented earlier addresses this barrier because it creates a straightforward linkage between engineering design characteristics and damage potential of the underlying asset. This modeling feature enables investors to analyze the risks based on the observable physical parameters of the underlying structure.

3.6. Section Closure

This section has introduced an asset-specific engineering approach for determining the market-implied spread of CAT bonds. The implementation of a simplified closed-from engineering model to the bond valuation process creates a transparent procedure that should increase the confidence in the estimates of potential losses and the interest in securitization of natural hazards. Further, being able to determine the value of CAT bond for a particular structure type improves the life cycle design considerations and more effective management practices for the underlying asset.

The results demonstrated that the four-step engineering model can be integrated into financial valuation methods to compute financial indicators such as spread, rating, and others. However, this integration is a two way sheet. The structural engineers can use the developed model to support evaluation of design alternatives to make sound life-cycle analysis decisions including possible risk transfer strategies for different types of assets and coverage needs. The owners of the constructed assets on the other hand, may compare available risk transfer instruments such as; primary insurance, re-insurance, and others by utilizing the loss information obtained from the four-step model.

As verified in the analysis, well-designed structures reduce the required spread values. The analysis also showed that the current spreads are significantly higher relative to the expected annual losses and are very conservative.

Even though CAT bond markets have showed a growing trend, there are myriad of remaining issues requiring the attention of the research community. Some of the remaining issues are:

1) from the investor's perspective, the basis risk, adverse selection and moral hazard are important factors and should be further investigated,
2) the demand surge such as demand for building material and labor after catastrophes should be considered in the analysis for a better estimation of needed funds,
3) the initial wealth and the expected future cash flow of the both investors and issuers influence the decision making process. Such impacts should be modeled and included in pricing framework and,
4) while this work considers the structural component of financial losses for computing market-implied spread, it does not account for losses on non-structural elements.

The loss model presented in the study has the capability of incorporating non-structural component and can therefore be extended. All of these are subject for future work.

4. SHARING THE RISK WITH EQUITY OWNERS

The subject of this section in another ART product, the Catastrophe Equity Put (CatEPut). The CatEPut is a contingent equity arrangement used in catastrophe risk management. In essence, a CatEPut is a modified put option contract that gives the right to the option buyer to sell a given number of their shares to the issuer at a predetermined fixed price when a specific catastrophe threshold is exceeded (Banks 2004). The threshold value can be defined in terms of actual monetary losses suffered by the option holder or a physical parameter (e.g. peak ground acceleration, PGA) for earthquakes, or wind speed for hurricanes) and is specified in the option contract (Cox et al. 2004). This innovative concept combines different financial and insurance risks into one product and results in lower transaction costs compared to purchasing separate coverages. Furthermore, a CatEPut reduces post-loss market behavior and offers more stable premiums by providing multiple period contracts in contrast to reinsurance, which is usually priced annually (Cox et al. 2004). Another important advantage of a CatEPut option is the unique investment opportunity. Catastrophe linked ART products are zero-beta[10] assets and help investors to reduce their portfolio risks (Banks 2004; Cox et al. 2004).

For a better understanding of how the CatEPut option can be used for risk management practices, consider a self-insured company with all the underlying physical assets located in a seismically active area. Further, assume that the operations of those

[10] An asset is called zero-beta if its returns change independently of changes in the market's returns.

assets create the major, if not the only source of the company revenue (e.g. toll road companies\commissions). Under these conditions, a catastrophic event (e.g. earthquake) is likely to result in severe interruption in business operations and thus, a decline in equity value. For such scenarios, an “asset-specific” CatEPut option could be used to provide access to additional capital for immediate repair actions in order to allow prompt recovery of the business operations, as well as to protect the equity value of the company. This scenario is not far from reality especially for industries such as energy and transportation where the major part of the revenue is generated by underlying physical assets (e.g. oil rigs, power plants, toll roads, high speed rails, etc.), and self-insurance is a common form of post-loss financing method. However, an asset-specific CatEPut option differs from a regular CatEPut option and needs meticulous designing while considering not only the actuarial data but also the unique design characteristics of the underlying physical assets (Aslan et al. 2011).

The objective of this section is to provide a valuation framework to capture two important aspects of asset-specific CatEPuts:

1) a joint stochastic model representing the changes in equity values due to the catastrophic events and,
2) a link between the engineering characteristics of the underlying asset and option value.

To do so, an engineering loss model is integrated in the option valuation framework. This approach provides a relatively transparent method in which the risks and value can be directly linked to the characteristics of the insured portfolio of large constructed assets. The section is illustrated with examples of constructed assets exposed to seismic risk.

4.1. Background

The first CatEPut option was issued in 1996 on behalf of RLI Corporation to serve as an alternative to reinsurance treaties. Centre Re, a reinsurance subsidiary of Zurich Centre Group underwrote this option. The CatEPut gave RLI the right to issue up to $50 million in convertible preferred shares in the event that a California earthquake exhausts its reinsurance program, and the agreement was for a three year period (Chang et al 2011). In 1997, Horace Mann Educators Corporation purchased an option to issue $100 million in convertible preferred shares. Centre Re again underwrote this option. Also in 1997, LaSalle Re purchased a CatEPut that would allow it to issue $100 million in convertible preferred shares in the event of a major catastrophe or series of large catastrophes that adversely impact LaSalle Re. The writers of this option were identified as a syndicate of highly rated purchasers. The annual premium on the option was $2.35 million (Culp 2009).

The cash flow of a typical CatEPut option along with a simplified relationship among the parties involved in the option contract is illustrated in Fig. 4-1.

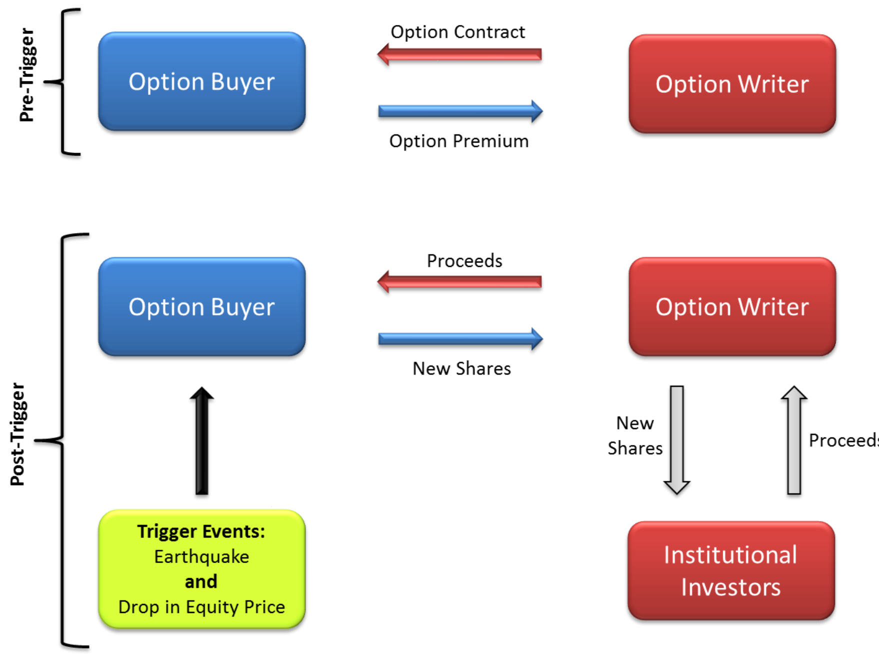

Fig. 4-1: CatEPut structure (Banks 2004)

As can be observed from the Fig. 4-1, the option writer purchases the shares or the surplus notes with a cash payment at pre-event terms and make post-event capital available. The option writer could be an insurance company, a reinsurer, another financial institution, an investment bank, or any other entity with sufficient economic resources. Note that the investor (option writer) is ultimately responsible for taking up new shares and delivering promised proceeds when the option is exercised. In practice the option writer typically turns to its base of institutional investors to distribute the shares (Banks 2004). The option can only be exercised after the occurrence of a qualifying natural catastrophe. In contrast to CAT bonds, investors of CatEPut option provide their capital only after a loss event, where in the case of CAT bonds the capital is made available by investors before the loss event.

The benefits of a CatEPut include providing balance sheet recovery for regulatory and rating agency consideration and the availability of funds after a loss that would allow the company to return to normal operations in a timely fashion. The funds are generated from equity sales, and not from a loan that must be repaid. Similar to (re)insurance, this contract provides protection for the shareholders in the company that purchases the CatEPut. Another advantage of the CatEPut is that the option buyer can tailor the triggers to meet its needs much like an individual (re)insurance contract. However, the CatEPut has its drawbacks as well. CatEPut dilutes the ownership following a loss. The amount of equity increases when the put option is exercised thereby reducing the existing shareholder's ownership. Moreover, as it is the case with many ART methods, investors typically need large amounts of information to analyze the underlying risk, which causes relatively high transaction costs for option buyers. Investors' appetite for information and resulting transaction costs can be reduced by using the triggers based on the physical parameters of catastrophic events (Meyers and Kollar, 1999).

4.2. Pricing Models

Due to the complexity of catastrophe derivatives, only a few studies have focused on valuing such structured products. Loubergé et al. (1999), Lee and Yu (2002), and Vaugirard (2003) priced catastrophe-linked insurance products with the assumption that arrival times of catastrophic events follow a Poisson process. Gründl and Schmeiser (2002) analyzed double trigger reinsurance contracts in terms of a valuation framework (financial versus actuarial approach). These studies show that it is critical to develop a valuation model that considers the joint dynamic relationship between incurred losses and the equity value process for a better evaluation of catastrophe-linked financial products. Such a model for the CatEPut option was first investigated by Cox et al. (2004). The assumption was that the equity value process follows Geometric Brownian Motion (GBM)[11] with additional downward jumps of a specific size in the event of a catastrophe. However, the model considered only the impact of the occurrence of the catastrophe to the equity values while the severity of the catastrophe was not included.

Jaimungal and Wang (2006) investigated the valuation of the CatEPut option by considering stochastic interest rates with losses generated by a compound Poisson process. With this approach, the equity value is assumed to be influenced by the level of total incurred losses rather than the total number of claims. Recently, Chang and Hung (2009) analyzed CatEPut under deterministic and stochastic interest rates while the underlying equity value was modeled through a Levy process.

None of the previous studies have considered the damage potential of the underlying constructed assets in the valuation process. In fact, this disconnect represents a significant problem for particular cases where the large constructed assets play an important role in the option buyer's business operations. The large constructed assets are uniquely built structures (i.e. there is no other Bay Bridge, Hoover Dam, or Empire State Building). These assets may differ in geometry, material type, design code, age, location, etc.; their performance (and hence loss exposure) can only be captured with engineering analysis. Using only statistical distributions without considering the unique

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[11] See Trigeorgis (1996) for detailed explanation of Geometric Brownian Motion process.

design characteristics of these structures does not realistically capture the loss potential. A more accurate, "asset specific" model that takes into account the observable engineering design parameters is needed for fair pricing of the CatEPut when the option contract is tied to large constructed asset or a portfolio of large constructed assets.

This section presents a CatEPut valuation model that adopts a joint mechanism for loss arrival and size, and equity value. The proposed valuation model is based on an engineering loss model that is capable of computing probable financial losses over a full range of damage states for constructed assets. The proposed model is used to determine the fair value of a CatEPut option (tied to a constructed asset) for different hazard intensities and structural responses.

4.3. Modeling Loss for CatEPut

The four-step engineering approach discussed in Section 2 is used herein to model financial losses to underlying structural asset due to seismic hazard. The loss information is then conveyed to key stakeholders to aid decision making process for financing of the post-disaster recovery. The four-step model presented in Section 2 is summarized here for the sake of completeness, and it involves the following sequential tasks: (i) hazard analysis; (ii) structural analysis; (iii) damage and repair-cost analysis; and (iv) loss estimation. Recall the mathematical expression governing the four-step model that is given in Eq. (2-1)

$$\frac{L}{L_{DBE}} = \left|\frac{\theta}{\theta_{DBE}}\right|^{c} = \left|\frac{IM}{IM_{DBE}}\right|^{bc} = \left|\frac{f_a}{f_{DBE}}\right|^{d} \tag{2-1}$$

Equation (2-1) can be used to determine the annual frequency of the event for which a specific value of loss is exceeded. Note that the annual frequencies considered in this study are exceedance frequencies; $P(X > x)$. An indirect relationship exists between the frequency of the hazard and its intensity (the lower the frequency, the higher the PGA in case of an earthquake). This relationship can also be obtained from "probabilistic hazard curves" provided by the U.S. Geological Survey, USGS[12]. This helps define a parametric threshold value for the CatEPut option and compute the corresponding frequency of the hazard. If for example, $IM_{DBE} = PGA_{DBE}$ then Eq. (2-1) can be reconstructed in terms of a parametric trigger event such that:

$$L_{tr} = L_{DBE} \left| \frac{IM_{tr}}{IM_{DBE}} \right|^{bc} = L_{DBE} \left| \frac{PGA_{tr}}{PGA_{DBE}} \right|^{bc} \tag{4-1}$$

where

- L_{tr} = trigger loss,
- IM_{tr} = trigger value of the intensity measure (parametric threshold value),
- PGA_{tr} = the peak ground acceleration of the trigger earthquake.

Using the four-step process, it is now possible to assess loss ratios (L) for various hazard scenarios, or to obtain a composite loss measure through calculating expected annual losses (EAL). In the following section a pricing model for the fair value of CatEPut option that considers the dynamic relationship between seismically-induced losses and the equity value process is presented. To illustrate the impact of engineering

[12] The USGS database for probabilistic hazard curves can be accessed from: http://earthquake.usgs.gov/hazards/designmaps/

decisions on financial implications, numerical analysis is conducted considering both conventionally-designed and seismically-designed bridge structures (constructed assets) exposed to earthquake risk in a highly seismic California zone.

4.4. Methodology

The CatEPut option payoff is conditional upon two trigger events (Cox et al. 2004). The first trigger occurs if the market value of the equity at maturity falls below the exercise price. The second trigger relates to a specific type of catastrophe defined in the option contract that has to occur during the term of the option. Thus, the payoff of CatEPut option at maturity can be expressed as:

$$Payoff = \mathrm{I}_{\{IM \geq IM_{tr}\}} \left(K - S_T\right)_+ = \begin{cases} K - S_T & \text{if} \quad S_T < K \quad \text{and} \quad IM \geq IM_{tr} \\ 0 & \text{if} \quad S_T \geq K \quad \text{or} \quad IM < IM_{tr} \end{cases} \tag{4-2}$$

where

- S_T = the equity value at maturity,
- IM_{tr} = the specified level of ground shaking (PGA) at site above which the option becomes in-the-money,
- $\mathrm{I}_{\{\cdot\}}$ = the indicator function: $\mathrm{I}_{\{IM \geq IM_{tr}\}} = 1$ if $IM \geq IM_{tr}$ and = 0 if $IM < IM_{tr}$,
- K = the exercise price.

The proposed valuation model for the CatEPut assumes that the value of the option buyer's equity, S, is driven by a Geometric Brownian Motion (GBM) model and the loss process, L_t, is driven by the proposed structural loss model. GBM time series are commonly used for modeling in finance (Trigeorgis 1996). It is used particularly in the field of option pricing because a quantity that follows a GBM may take any positive value, and only the fractional changes of the random variate are significant. A stochastic process , S_t , is said to follow a GBM if it satisfies the following stochastic differential equation (SDE):

$$\begin{aligned} dS_t &= \mu S_t dt + \sigma S_t dW_t \\ dW_t &= \varepsilon \sqrt{dt} \end{aligned} \tag{4-4}$$

where,

- S_t = the equity value at time t,
- dW_t = generalized Wiener process,
- ε = Normal (0,1) distribution,
- μ = the percentage drift,
- σ = the volatility.

The value of the buyer's equity while considering the drops due to a catastrophe occurrence is defined by the following stochastic equation:

$$S_t = S_0 \exp\left(\sigma W_t + \left[\mu_S - \frac{1}{2} \sigma_S{}^2 \right] t - Z L_t \right) \tag{4-5}$$

and,

$$L_t = L_{DBE} \left| \frac{j}{IM_{DBE}} \right|^{bc} \tag{4-6}$$

where

- S_0 = the initial equity value,
- S_t = the equity value at time t,

- $\{W_t : t \geq 0\}$ = a standard Brownian Motion with respect to the physical measure P,
- μ = market equilibrium rate of expected return on the equity,
- σ = market volatility of the equity ,
- L_t = the loss process of the option buyer's underlying asset driven by the four-step engineering model during [0, t),
- j = the peak ground acceleration, PGA, of the exposed earthquake at the site,
- $Z \geq 0$ = the impact factor that measures the influence of the catastrophe (earthquake) over the market value of the option buyer's equity.

In essence the model states that the option buyer's equity value at time t is increased by the expected return, μ, but meanwhile it is also exposed to random shocks due to market volatilities and catastrophic events. Fig. 4-2 illustrates the dynamic relationship between equity value, market volatility, and negative jumps due to catastrophic events with a discrete time model.

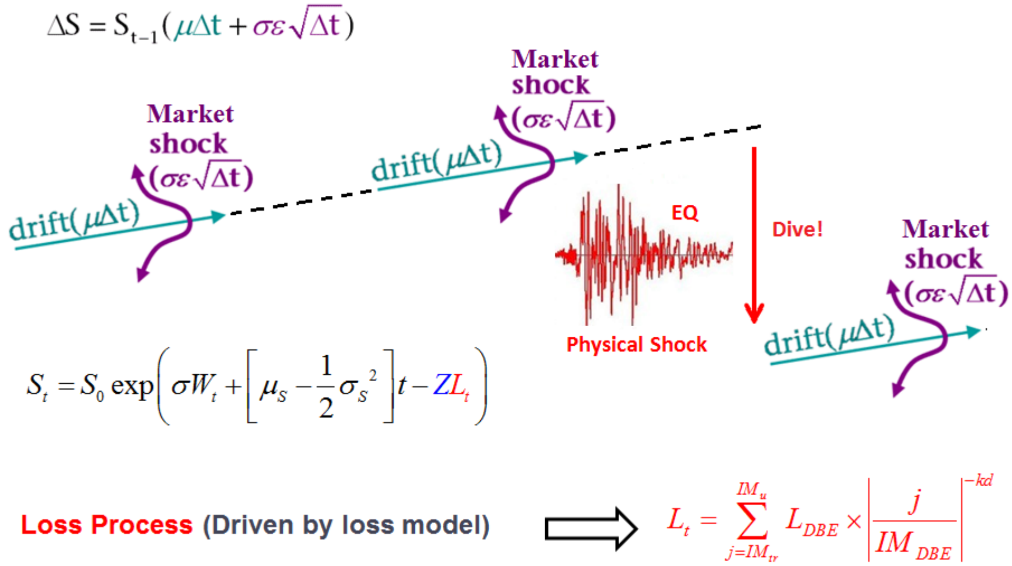

Fig. 4-2: Dynamics of the CatEPut pricing model

The impact factor, Z, is left as a user defined parameter because there are other measures other than earthquake frequency and intensity that may influence the equity value. For example, the option buyer may have more than one structural asset to which the option contract is tied. In such cases the cumulative impact over the equity value differs from the impact caused by having a single asset exposed to earthquake risk. Alternatively, consider a single asset such as a bridge that connects two other toll roads. Potential damage to this bridge will disable the operations of both toll roads as well. Clearly, the bridge is vital for the continuation of the adjoining businesses and their operations. The option writer must consider the marginal value of the bridge while pricing and this can be achieved using the impact factor, Z (Aslan et al. 2011). Possible ways for evaluating the impact factor, Z, include: discrete even simulation, regression analysis, strategic value analysis, and economic value added analysis.

The price of the CatEput at time t is the expected discounted value:

$$\mathrm{E}_t^Q\left[e^{-rT}\mathrm{I}_{\{IM \ge IM_{tr}\}}(K-S_T)_+\right] \tag{4-7}$$

The expectation is calculated under risk-neutral measure Q which is equivalent to the original measure P and for which $\left\{e^{-rT}S_t : t \ge 0\right\}$ is a martingale[13] (Cox et al. 2004). If a new Brownian Motion is now defined as: $\tilde{W}_t = W_t + \frac{\mu - r}{\sigma}t$, then Girsanov's theorem states that there exists a measure Q under which $\tilde{W}_t$ is a Brownian motion. Here, the underlying assumption is that the form of the measure change from P to Q does not alter the jump process (as the jumps are non-diversifiable), nor does it affect the considered pricing methodology of the CatEPut (Jaimungal and Wang 2006). Thus, the joint asset and loss process under the Q measure can be re-written as:

$$S_t = S_0 \exp\left(-ZL_t + \sigma\tilde{W}_t + \left[r - \frac{1}{2}\sigma_S{}^2\right]t\right) \tag{4-8}$$

The price of the CatEPut option with a physical trigger of an earthquake with $IM = j$ is given below by the Black-Scholes formula. Note that the payoff is zero if $j < IM_{tr}$ and for $j \ge IM_{tr}$ as follows:

$$\mathrm{E}_t^Q\left[e^{-rT}\mathrm{I}_{\{IM \ge IM_{tr}\}}(K-S_T)_+ \middle| IM = j\right] = Ke^{-rT}\Phi(dj) - S_0 e^{-ZL_{DBE}\left|\frac{j}{IM_{DBE}}\right|^{bc}}\Phi(dj - \sigma\sqrt{T}) \tag{4-9}$$

where:

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[13] A martingale is a sequence of random variables (i.e., a stochastic process) for which, at a particular time in the realized sequence, the expectation of the next value in the sequence is equal to the present observed value even given knowledge of all prior observed values at a current time. For further details please see Trigeorgis (1996).

$$dj = \frac{\log(K/S_0) - rT + ZL_{DBE}\left|\frac{j}{IM_{DBE}}\right|^{bc}}{\sigma\sqrt{T}} + \frac{1}{2}\sigma\sqrt{T} \tag{4-10}$$

The change in the buyer's equity value can be calculated for any potential earthquake scenarios by using the loss model, and hence the price of the CatEput option can be re-written for $IM_u \geq j \geq IM_{tr}$ as:

$$\mathrm{E}_t^Q\left[e^{-rT}(K-S_T)_+\right] = \sum_j (Ke^{-rT}\Phi(dj) - S_0 e^{-ZL_{DBE}\left|\frac{j}{IM_{DBE}}\right|^{-kd}}\Phi(dj-\sigma\sqrt{T}))\, f_{DBE}\left|\frac{j}{IM_{DBE}}\right|^{-k} \tag{4-11}$$

$$IM_u = IM_{DBE}\left|\frac{f_{DBE}}{f_u}\right|^{1/k} \tag{4-12}$$

4.5. Numerical Examples

The developed model is illustrated using numerical examples. First, the capability of the proposed model to capture the joint dynamic relationship between incurred losses to the underlying constructed asset and the option buyer's equity value process is presented. Next, sensitivity analyses are conducted to evaluate the effects of both financial and engineering design parameters on the CatEPut option value. Note that during the analysis the CatEPut option payoffs are calculated conditionally on occurrence of the earthquake

4.5.1. Insured Constructed Asset Example

Company X owns a toll bridge located in a seismic area of California and is concerned about a potential earthquake. Company X is self-insured and wants to enter a CatEPut contract to have additional coverage and to protect its share value. The CatEPut contract has a parametric trigger of ground shaking (PGA) which is recorded by an accelerograph nearby the asset.

The proposed loss model is implemented with the parameters shown in Table 2-1. To isolate effects of only the engineering design parameters on the option value, the interest rate, i, and volatility, σ, are assumed to be constant.

4.5.2. Joint Dynamic Process and CatEPut Price

The Monte Carlo simulation method is now used to predict potential equity value paths for the Company X. The following parameters are used in the simulations: $S_0 = \$100$, $r = 0.05$, $T = 1$year, $IM_{tr} = 0.2$ g, $\sigma_S = 0.05$, $\mu = 0.05$, and $Z = 1$. Fig. 4-3 presents the results for 10,000 iterations; the blue lines plot the equity values when the earthquakes do not occur, while the red and green lines plot the equity values when earthquakes occur during the term of the option contract. Red lines represent the potential scenarios for underlying assets of seismically designed bridges, while the green lines represent scenarios for conventionally (non-seismically) designed bridges.

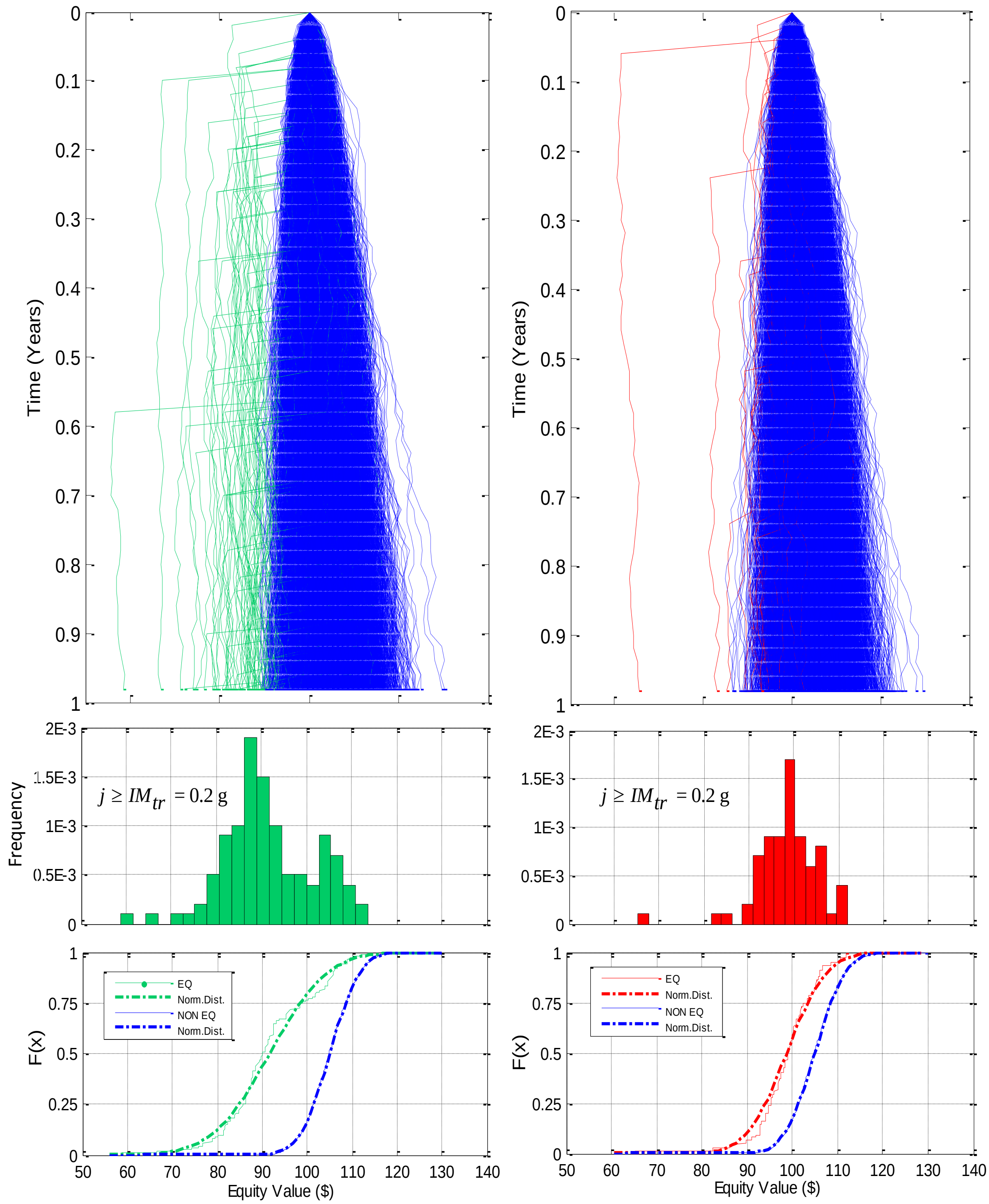


Fig. 4-3: Joint stochastic process representing option buyer's equity value for different design characteristics

As it can be observed from Fig. 4-3, the proposed valuation model captures the dynamic relationship between the incurred losses and the equity value process. The magnitude of the drop in equity values varies based on the intensity of the exposed earthquake. Large (but rare) earthquakes lead to greater damage and hence losses (i.e. the drop in the equity value is correspondingly greater for these severe events). In Fig. 4-4, the cumulative distribution function (CDF) of Company X's equity value for each case where the underlying assets are conventionally-designed bridge structures, and seismically-designed bridge structures, are plotted along with the cdf of Company X's equity value where no earthquakes occur. Evidently design characteristics (seismically or conventionally-designed) of the underlying assets affect the equity value of Company X as much as the intensity of the exposed earthquake.

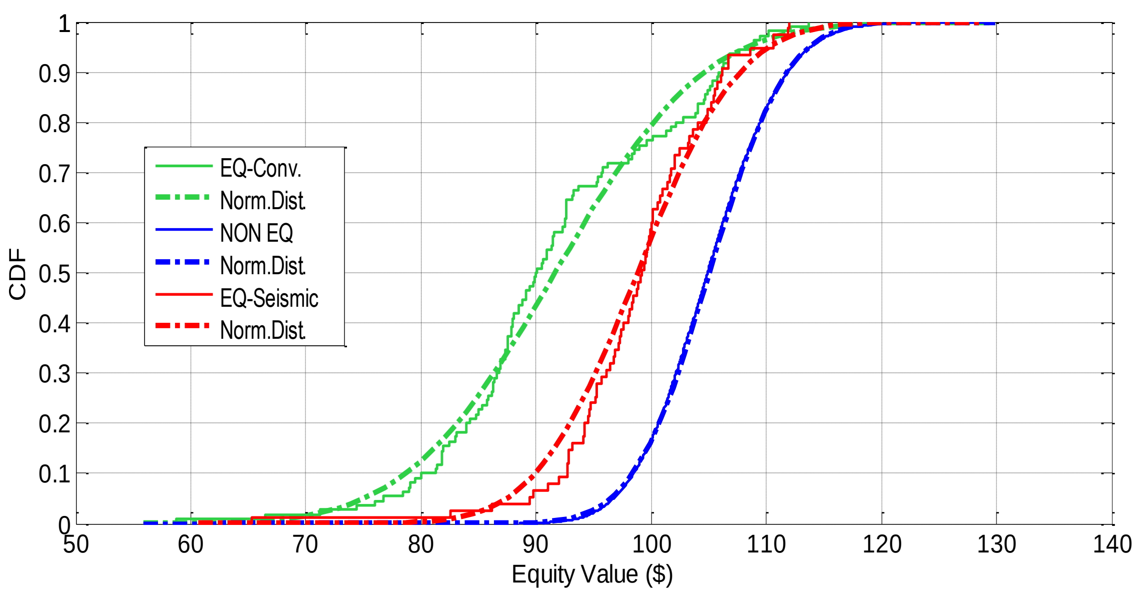


Fig. 4-4: CDF of company X's equity value for different design characteristics

Fig. 4-4 emphasizes the impact of vulnerability of the underlying asset over the value of owner's equity. Here, the vulnerability is considered as the susceptibility of the bridge structures to the potential impact of earthquake hazard. As it can be seen from the Fig.4-4, the median drop in the option buyer's equity value for seismically-designed structures in one year due to earthquakes is at the level of 3% (final equity value of $101 as opposed to final equity value of $105 for no-earthquake case) whereas it is at the level of 15% (final equity value of $89) for a conventionally (non-seismically) designed structure. This is an important finding that both option buyer and option writer need to consider. The EAL to option buyers whose underlying assets are seismically-designed structures is significantly less than the one for conventionally-designed structures and so is the price of the CatEPut option. Option writers may reflect this difference in EAL to their premiums and consequently encourage option buyers to retrofit (for their existing constructed assets) or better build (for their new projects).

Distribution of the CatEPut option values at exercise price, K = $150, for different earthquake scenarios is illustrated in Fig. 4-5. K is set at $150 (a much higher value than the initial equity value, $S_0 = \$100$) to better illustrate the variation of conditional price (option value) for different PGA values. The constructed asset under consideration (the toll bridge) is considered to be seismically-designed. This figure can help both option writers and buyers to determine how the option can be used and how the triggers can be tailored to transfer the risk more effectively.

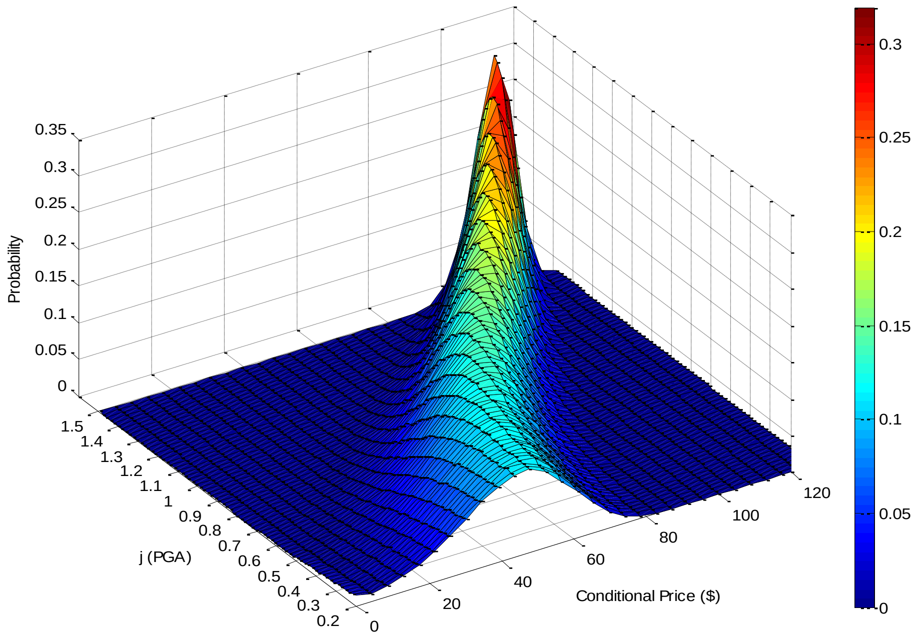


Fig. 4-5: Probability distribution of conditional CatEPut price

It can be observed from the Fig. 4-5 that the CatEPut option value increases as the exposed earthquake's intensity increases. This result is expected as the value of the option buyer's equity is likely to decrease as the severity of the catastrophe increases. It is important to note that the variance of the option price at higher intensity (PGA) levels is significantly smaller than the one at lower intensity levels. This is due to the dominance of losses related to the catastrophe intensity over the other financial parameters. Another analysis is conducted for the same parameters to examine the impact of earthquake intensity over the mean value and standard deviation of the CatEPut option price. The results are illustrated in Fig. 4-6.

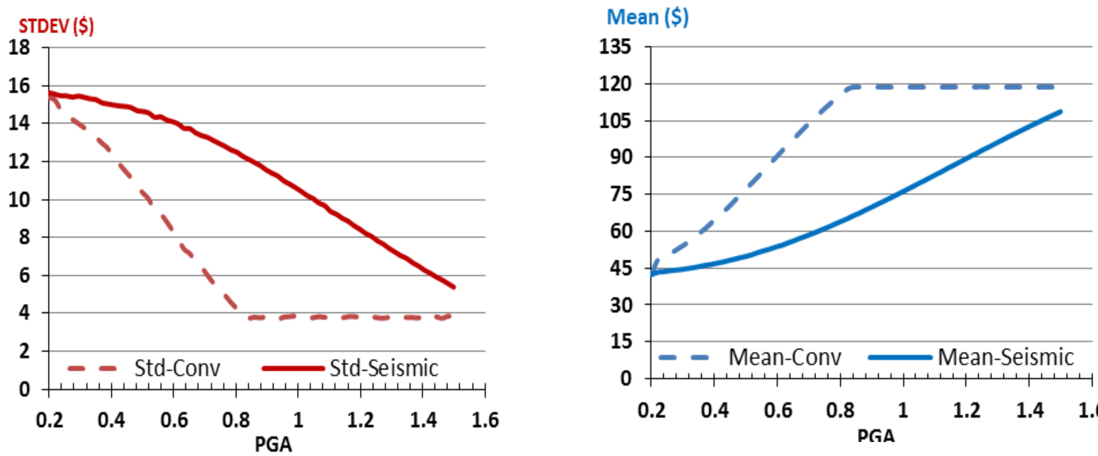


Fig. 4-6: PGA vs. standard deviation and mean

Fig. 4-6 shows that the possibility of large upside benefits of the CatEPut option increases with higher intensities. This result is no surprise since the toll bridge is the only source of Company X's revenue. In such settings, the equity value of Company X is remarkably more vulnerable to severe earthquakes than fluctuation in equity markets. Since earthquakes with high intensities are very rare events, the CatEPut option with high intensity triggers becomes more valuable and appealing relative to the coverage it provides. Note that under the same circumstances the CatEPut price is significantly lower for seismically-designed structures. Moreover, the CatEPut option price for conventionally-designed structures reaches its maximum value (structure collapses) at significantly smaller PGAs compared to seismically-designed structures as they perform relatively poorly (Aslan et al. 2011; Mander et al. 2012).

4.5.3. Model Sensitivity

The conditional price of a 1-year CatEPut option contract is analyzed for different values of the financial contract parameters as well as the underlying asset's engineering design parameters. Here, option value is conditional upon the occurrence of the earthquake and the underlying asset of the option buyer is considered to be seismically-designed bridge structures. The following parameters are fixed; $S_0 = \$100$, K = \$100, $r = 0.05$, $\sigma_S = 0.1$, $\mu = 0.05$, and $Z = 1$. Note that the sensitivity analysis is conducted while paying specific attention to correlated parameters to prevent inconsistent and unreliable results. To ensure accuracy in the analysis, only the un-correlated parameters are used in the following sensitivity analysis.

Fig. 4-7 helps option holders to acquire an insight into the impact of both physical and financial parameters for valuing the CatEPut option for different catastrophe scenarios. It provides essential information that, when the option contract is tied to a parametric trigger (PGA in this case) and the underlying asset is an engineered structure, the option payoff is highly correlated with the design characteristics as well as the financial parameters. This information may be valuable for investors as they could tailor the triggers to reduce portfolio risks.

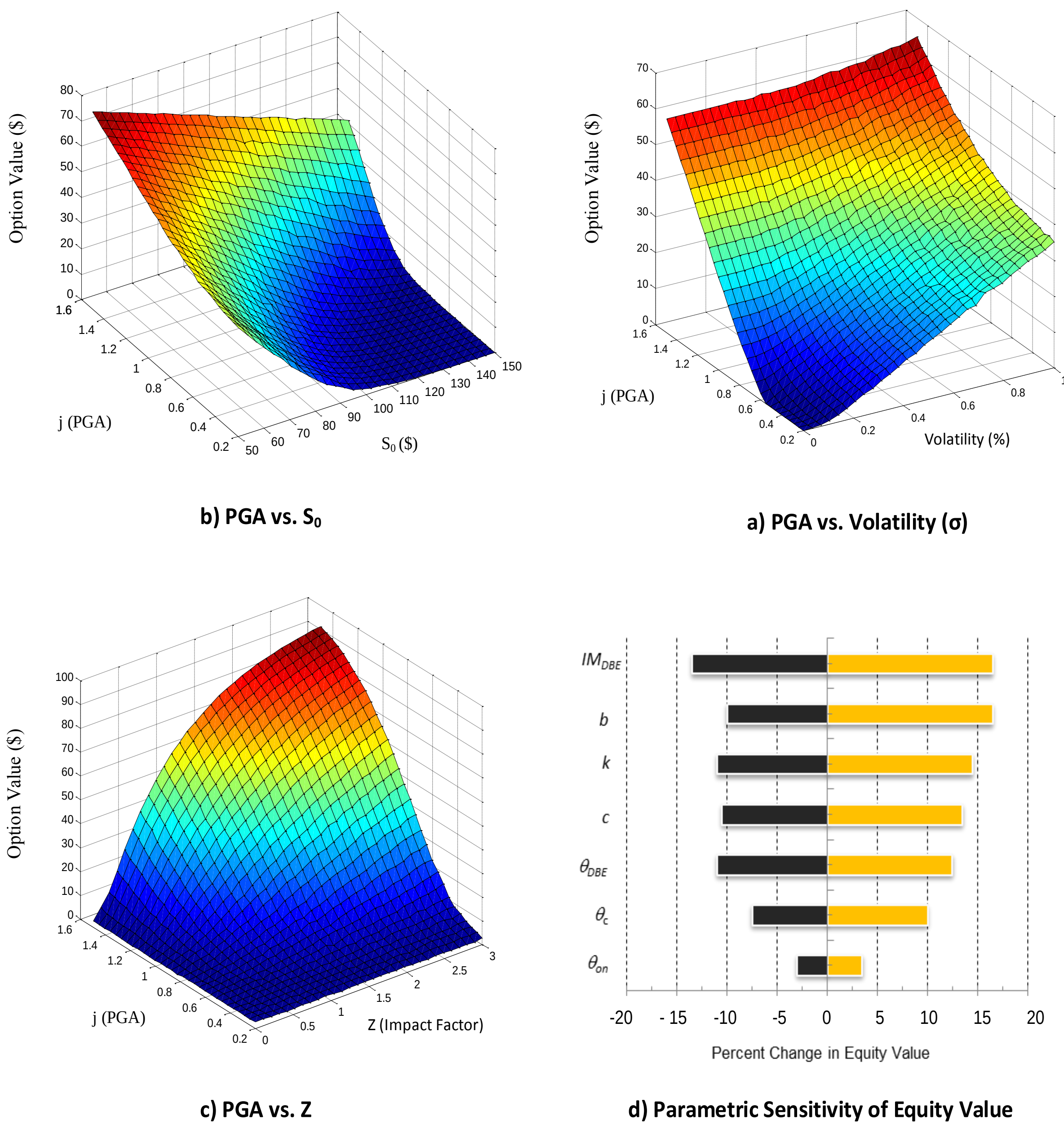


Fig. 4-7: Sensitivity analysis

Fig. 4-7(a) illustrates the CatEPut option payoffs for various levels of PGA, and equity volatility, σ. As shown, increased volatility can significantly affect the option value. Holders of the CatEPut option benefit when the equity price decreases given that the trigger earthquake occurred. Hence, the volatility is positively correlated with

CatEPut option payoff and price. Fig. 4-7(a) also shows that for the earthquakes with lower intensity levels, volatility is the major factor that drives the changes in option payoff. For such cases, option payoff increases with volatility which is consistent with previous findings. However, for the high intensity levels, the impact of volatility over option payoff is negligible. Fig. 4-7(b) illustrates CatEPut option payoffs with respect to change in the trigger PGA level, and the initial price of the option buyer's equity, S_0. Clearly, the CatEPut option payoff is a decreasing function of S_0. This result is consistent with intuition as the payoff at maturity is likely to decrease with an increase in initial equity value. This characteristic of the CatEPut option is similar to a traditional put option.

Fig. 4-7(c) demonstrates that the CatEPut payoff increases as the impact factor *Z* increases. If the underlying constructed assets create the major portion of the option buyer's cash flow, then the value of its equity is strongly affected by earthquake intensity. The impact factor *Z* is considered to take the values from 0 to 3 ($0 \le Z \le 3$) as the *Z* = 0 causes no drop in equity value and *Z* = 3 results in a drop of 98% in equity price for the ultimate collapse case. As shown in Fig. 4-7(c), for small values of *Z* (well diversified assets or, some risk mitigation measures already in place, such as seismic isolators, might result in lower Z values) the earthquake intensity has a negligible impact over the option payoff.

Finally, a swing analysis is conducted to determine how the engineering design parameters influence the price of the option buyer's equity. This highlights an aspect of the engineering implications on financial practice. The swing analysis is conducted to evaluate the impact of the changes in engineering design variables over the equity value, and results are presented in Fig. 4-7(d). Six considered parameters showed changes markedly higher than the 5% variation, namely: IM_{DBE}, b, k, c, θ_{DBE}, and θ_{c}. It is possible to group these parameters to represent: the seismic hazard demand $(IM_{DBE},\ k)$; the provided structural strength capacity $(b,\ \theta_{DBE})$; and the structural deformation capacity which leads to damage potential $(\mathrm{c},\ \theta_{\mathrm{c}})$. The results show that it is critical to have dependable local hazard data and specific structure behavioral models to accurately predict the expected losses and the subsequent drop in equity value.

4.6. Section Closure

This section has introduced a structure-specific engineering approach for developing a continuous time model for pricing the CatEPut option. The model considers a joint dynamic relationship between incurred losses to the underlying structural asset of the option buyer and option buyer's equity value process. Hence, the model introduces the observable (quantifiable) engineering design parameters to the option pricing and creates the necessary linkage. It also considers the unique structural performance of underlying large constructed assets and accounts for that throughout the option valuation process. It is important to note that large constructed assets create the major financial portion of losses in case of a catastrophe, and the financial losses associated with such structures can only be captured with engineering analysis. Incorporating the closed-form stochastic engineering model for the option valuation process provides a transparent procedure that can increase the confidence in the estimates of potential losses and the interest in securitization of natural hazards.

The proposed model suggests that engineering parameters need to be considered along with the financial and actuarial parameters when pricing structured catastrophe derivatives. The results show that specific design types and structural material characteristics may have a significant influence on reducing the cost of mitigating structural losses due to earthquakes and hence lower the CatEPut option price. In fact, the impact of structural response and damage potential parameters (b and c) is essentially as important as the option triggering hazard parameter (IM). This is an important implication for the financial analysts when evaluating option contracts tied to a constructed asset. Further, being able to determine the value of a CatEPut option tied to a single constructed asset or to a portfolio of assets improves life-cycle considerations and more effective risk management practices for constructed assets.

The developed model has limitations, and it is possible to extend this study in several ways. For instance, the present work considers the structural component of financial losses for computing the fair price of CatEPut option. However a comprehensive assessment of losses must also incorporate the non-structural component of losses. The loss model presented in the study has the capability to incorporate non-structural components and can therefore be applied for pricing CatEPut options that can be the subject of future work. The impact factor Z can be mathematically modeled for particular cases where there is sufficient data, but this aspect also needs to be developed in future work. The model studied in this study considers the European CatEPut option.

As an extension, an early exercise condition or an American CatEPut option can be developed.

This study permits an update of knowledge on pricing methodologies for catastrophe linked financial products. It differs from actuarial data-dependent black box approaches and supports more robust and transparent yet simple solutions. This study integrates different approaches (financial, actuarial, and engineering) into one pricing framework to capture the potential losses and resulting financial consequences as accurately as possible. This study approach can be further investigated and extended to account for broader types of hazards, structures, and losses (e.g. death and downtime), but at present it represents a key step forward in introducing engineering analysis for the pricing of catastrophe linked ART products.

5. SHARING THE RISK WITH SOCIAL NETWORKS

Natural disasters such as earthquakes cause rare and highly correlated insurance claims. The number and the size of these claims vary based on the provided coverage to the policy holders. It is impractical to analytically define the loss claims with a joint probability distribution due to the lack of historical data and high correlation coefficients. Rather, a feasible solution for modeling the loss estimates employs numerical methods and explicit simulations of catastrophic events (Ermoliev et al. 2000). It is possible to analyze the problem of catastrophe insurance, or more commonly "insurability of catastrophe risk," with a systems approach. The similarities between a catastrophe risk management problem and a complex system problem becomes more visible when diverse user portfolios and a wide range of risk profiles are considered (Amendola et al. 2000).

The goal of this Section is to develop a catastrophe insurance framework using a systems approach that considers the combined use of engineering analysis, Monte Carlo simulations, and internet-based social networks to help decision making in designing optimal risk portfolios. The proposed framework uses Monte Carlo Simulations for its hazard module, engineering analysis for damage module, and internet-based social networks for enhanced risk diversification. A dynamic stochastic model with performance measures such as "insolvency risk", "pool reserve," and "recovery rate" is proposed.

5.1. Introduction

Risks of natural hazards such as earthquakes require unique portfolio selection strategies since the strong law of large numbers does not apply for such low-frequency and high-consequence events (Amendola et al. 2000). The most promising method for estimating catastrophe related losses for different combinations of decision variables (e.g. deductible, location, structural characteristics of underlying asset, and etc.) involves explicit simulations of catastrophic events and engineering analysis for damage assessments (Ermoliev et al. 2000).

The Monte Carlo Simulation is a widely accepted and highly effective method to generate lifelike catastrophic event scenarios, but it is not the primary concern of this study. The damage modeling for insurance portfolios on the other hand is a key element in successful risk management applications, and is the focus of this study. The four-step loss model proposed in Section 2 is a powerful and reliable model for estimating losses for individual constructed assets, but the model currently does not capture the damage potential of a portfolio of assets. In fact, it is not feasible to develop a deterministic loss model for a portfolio of insured assets due to the large number of decision variables (e.g. different deductibles chosen for different assets by users, different asset-specific characteristics such as number of stories, structure age, dwelling type, and locations). Instead, separate loss estimations for every insured property within the insurance portfolio need to be done to effectively analyze capacity and stability concerns of the insurance company.

The remainder of this section introduces a new insurance framework in which the premiums and loss estimations are conducted via engineering analysis for each individual policy holder. The individual estimates are then used in a comprehensive portfolio analysis to evaluate the stability and capacity measures of the insurance portfolio. A computational algorithm is developed to demonstrate the practicality of the proposed framework.

5.2. Modeling Loss for Insurance Portfolios

It should be noted that successful use of risk transfer instruments depends on the ability to effectively estimate the amount of risk involved. Once the risks and losses are estimated, insurance companies then can assess the "fair" or "pure" price of insurance contracts and risk-linked financial instruments for further mitigation.

The key element of catastrophe insurance pricing is the computation of expected annual losses, EAL (Ermoliev et al. 2000). Once quantified, the EAL becomes the foundation for premium determination and risk management. The state-of-the-art four-step engineering loss estimation model proposed in Section 2 is herein modified to be used in insurance portfolio analysis. How each step in the "four-step" approach is re-addressed for portfolio analysis is explained next.

5.2.1. Hazard Module

Since earthquake ground shaking varies from site to site, the premium calculation for users (policy holders) of any earthquake insurance scheme starts with determining the demand side parameters such as earthquake frequency and intensity for the location of the insured asset. This information is often provided by a "hazard curve." A hazard curve is a plot of the annual frequency of exceedance versus peak ground acceleration (PGA) or a spectral acceleration (Mander and Sircar 1999). A sample hazard curve for a specific location is given in Fig. 5-1. The data used to generate the hazard curve is also shown along with the plot. This dataset is provided by the U.S. Geological Survey (USGS) and it is available on the internet (http://geohazards.cr.usgs.gov/eq/).

Conterminous 48 States - 2002 Data
Hazard Curve for PGA
Zip Code = 90210
Zip Code Latitude = 39.520199
Zip Code Longitude = -122.206001
Ground Motion = 0.5122 g
Return Period = 475 years
Frequency of Exceedance =2.1053E-03
Probability of Exceedance = 10%
Exposure Time = 50 years

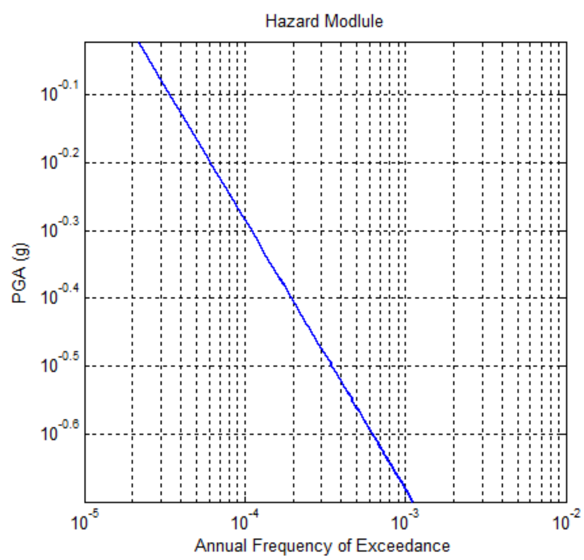


Fig. 5-1: Hazard module output

The frequency of exceedance values of 0.0021, 0.00103, and 0.000404 correspond to probabilities of exceedance of 10% in 50 years, 5% in 50 years, and 2% in 50 years, respectively. These values are stored in a data base for each grid point (defined by a set of longitude and latitude coordinate) for each ground motion parameter. This gridded data is used in the hazard module of this study to generate probabilistic hazard curves for each policy holder in the study region. In short, the hazard module of the four-step process is now capable of producing seismic hazard curves for any location in the forty-eight states of the United States, based on the data from the 2002 USGS National Seismic Hazard Mapping Project. In fact, Fig. 5-1 provided above is an output of the proposed loss module for the location defined by the zip code: 90210 (Beverly Hills, CA). Note that the zip code information is the only user input required to generate such a plot.

5.2.2. Response Module

The second step in the four-step process is to develop the response module. For any site of interest, the loss estimation process starts with selecting the model building types. Here model building type refers to the materials of construction (wood, steel, reinforced concrete, etc.), the system used to transmit earthquake forces from the ground through the building (referred to as the lateral force-resisting system), and sometimes, height category (low-rise, mid-rise, and high-rise, which generally correspond to 1-3, 4-7, and 8+ stories, respectively). The model building types defined by HAZUS-MH MR3 is given in Table 5-1 below (FEMA 2003).

Table 5-1: HAZUS-MH earthquake model building types (FEMA 2003)

No.	Label	Description	Hei			
			Range		Typical	
			Name	Stories	Stori	Feet
1 2	W1 W2	**Wood, Light Frame (≤ 5,000 sq. ft.)** **Wood, Commercial and Industrial (>5,000 sq. ft.)**		1 - 2 All	1 2	14 24
3 4 5	S1L S1M S1H	**Steel Moment Frame**	Low-Rise Mid-Rise High-Rise	1 - 3 4 - 7 8+	2 5 13	24 60 156
6 7 8	S2L S2M S2H	**Steel Braced Frame**	Low-Rise Mid- Rise High-Rise	1 - 3 4 - 7 8+	2 5 13	24 60 156
9	S3	**Steel Light Frame**		All	1	15
10 11 12	S4L S4M S4H	**Steel Frame with Cast-in-Place Concrete Shear Walls**	Low-Rise Mid-Rise High-Rise	1 - 3 4 - 7 8+	2 5 13	24 60 156
13 14 15	S5L S5M S5H	**Steel Frame with Unreinforced Masonry Infill Walls**	Low-Rise Mid-Rise High-Rise	1 - 3 4 - 7 8+	2 5 13	24 60 156
16 17 18	C1L C1M C1H	**Concrete Moment Frame**	Low-Rise Mid- Rise High-Rise	1 - 3 4 - 7 8+	2 5 12	20 50 120
19 20 21	C2L C2M C2H	**Concrete Shear Walls**	Low-Rise Mid-Rise High-Rise	1 - 3 4 - 7 8+	2 5 12	20 50 120
22 23 24	C3L C3M C3H	**Concrete Frame with Unreinforced Masonry Infill Walls**	Low-Rise Mid-Rise High-Rise	1 - 3 4 - 7 8+	2 5 12	20 50 120
25	PC1	**Precast Concrete Tilt-Up Walls**		All	1	15
26 27 28	PC2L PC2M PC2H	**Precast Concrete Frames with Concrete Shear Walls**	Low-Rise Mid-Rise High-Rise	1 - 3 4 - 7 8+	2 5 12	20 50 120
29 30	RM1L RM2M	**Reinforced Masonry Bearing Walls with Wood or Metal Deck Diaphragms**	Low-Rise Mid-Rise	1-3 4+	2 5	20 50
31 32 33	RM2L RM2M	**Reinforced Masonry Bearing Walls with Precast Concrete Diaphragms**	Low-Rise Mid-Rise High-Rise	1 - 3 4 - 7 8+	2 5 12	20 50 120
34 35	URML URMM	**Unreinforced Masonry Bearing Walls**	Low-Rise Mid-Rise	1 – 2 3+	1 3	15 35
36	MH	**Mobile Homes**		All	1	10

The response module needs to take into account the design-code of each building type selected. There are four generic design-codes defined by HAZUS: 1) High code, 2) moderate code, 3) low code, and 4) pre-code. These codes reflect important changes in design forces or detailing requirements that affect the seismic performance of a building. The choice of design code is a function of both construction era and site location. Since the location of the insured structure under consideration is an input parameter provided in the hazard module, the response model can be run with only two user inputs: 1) building type, and 2) era of construction. This provides a user-friendly framework for both insurer and insured.

Table 5-2 below shows the change in design-code as a function of construction era and site location (in terms of seismic zone). Fig. 5-2 illustrates the 1997 edition Uniform Building Code (UBC) seismic zone map which is used in the response module to assign appropriate design codes based on the seismic zones.

Table 5-2: Effective design codes

UBC Seismic Zone (NEHRP Map Area)	**Post-1975**	**1941 - 1975**	**Pre-1941**
Zone 4 (Map Area 7)	High-Code	Moderate-Code	Pre-Code (W1 = Moderate-Code)
Zone 3 (Map Area 6)	Moderate-Code	Moderate-Code	Pre-Code (W1 = Moderate-Code)
Zone 2B (Map Area 5)	Moderate-Code	Low-Code	Pre-Code (W1 = Low-Code)
Zone 2A (Map Area 4)	Low-Code	Low-Code	Pre-Code (W1 = Low-Code)
Zone 1 (Map Area 2/3)	Low-Code	Pre-Code (W1 = Low-Code)	Pre-Code (W1 = Low-Code)
Zone 0 (Map Area 1)	Pre-Code (W1 = Low-Code)	Pre-Code (W1 = Low-Code)	Pre-Code (W1 = Low-Code)

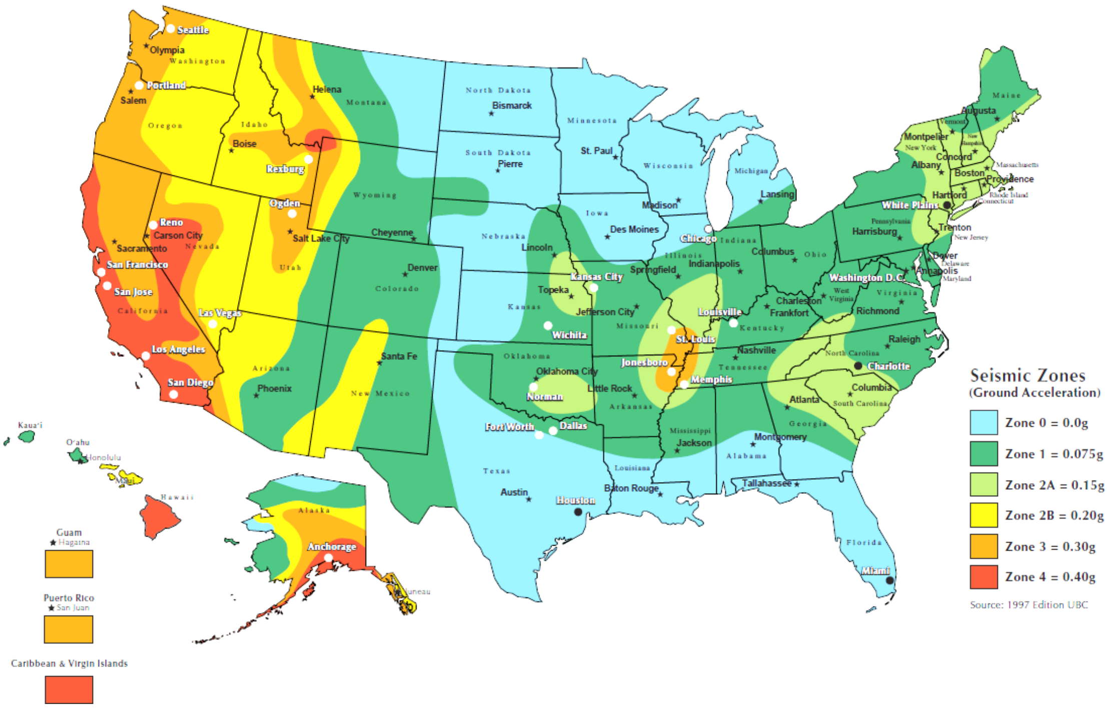


Fig. 5-2: UBC seismic zone map of the U.S. (FEMA, 2003)

Once the database of design codes is created for different generic building types in different locations, it is important to link ground motion parameters with engineering demand parameters, such as inter-story column drifts (Mander et al. 2012). Since it is possible to define damage states with inter-story drift ratios (e.g. Damage State 2 $= \theta_{DS2} = \theta_{on}$), it is also possible to relate the inter-story drift ratios at each damage state with ground motion parameters (e.g. $\theta_{on} = PGA_{on}$) by utilizing the HAZUS tables for "equivalent PGA structural fragility" and "average inter-story drift ratio of structural damage states" (FEMA 2003). These tables are provided in the Appendix.

All of the aforementioned steps, interrelationships between input parameters, and provided datasets are included in the proposed response module and embedded in a computer code to speed up the process for modeling structural responses. Fig. 5-3 shows a sample output generated by the response module for provided user parameters (building type and construction era) for a given site.

Conterminous 48 States - 2002 Data

Hazard Curve for PGA

Zip Code = 90210

Zip Code Latitude = 39.520199

Zip Code Longitude = -122.206001

Ground Motion = 0.5122 g

Return Period = 475 years

Frequency of Exceedance =2.1053E-03

Probability of Exceedance = 10%

Exposure Time = 50 years

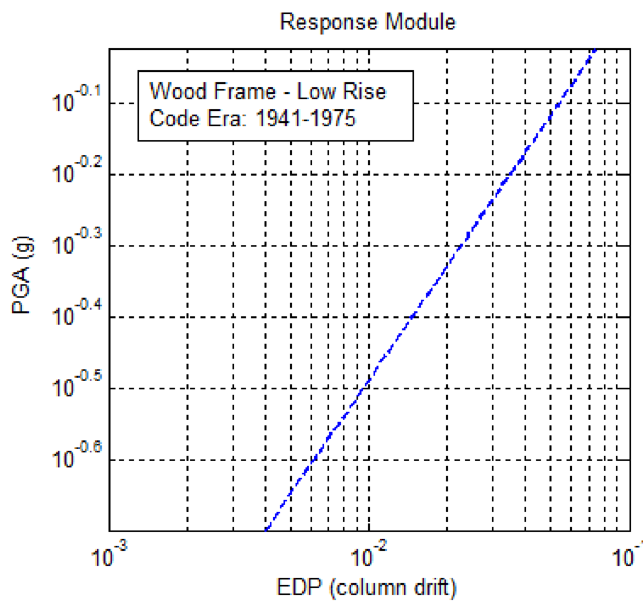


Fig. 5-3: Response module output

5.2.3. Damage Module

The third step in the four-step comprehensive loss estimation process is developing the damage module. Evidently, when a hazard strikes a structure, this imposes a so-called engineering demand parameter (EDP) in the form of column deformation, called inter-story drifts. It is possible to identify damage to components of a structural system in terms of such drifts which represents the lateral displacement of the structure due to the exposed hazard. Here, average inter-story drift ratio refers to the roof displacement divided by structure height. Although it is expected to have different drift ratios for individual stories of a multi-story building, the average inter-story drift is considered to be a convenient and reliable measure of building response (FEMA 2003). The average inter-story drift ratios at different structural damage states (i.e., slight, moderate, extensive, and complete) for each generic building type are listed in Table 5.3.

Table 5-3: *HAZUS* average inter-story drift ratio of structural damage states (FEMA 2003)

Model Building Type		Structural Damage States			
		Slight	Moderate	Extensive	Complete
Low-Rise Buildings – High-Code Design Level					
W1, W2		0.004	0.012	0.040	0.100
S1		0.006	0.012	0.030	0.080
C1, S2		0.005	0.010	0.030	0.080
C2		0.004	0.010	0.030	0.080
S3, S4, PC1, PC2, RM1, RM2		0.004	0.008	0.024	0.070
Low-Rise Buildings – Moderate-Code Design Level					
W1, W2		0.004	0.010	0.031	0.075
S1		0.006	0.010	0.024	0.060
C1, S2		0.005	0.009	0.023	0.060
C2		0.004	0.008	0.023	0.060
S3, S4, PC1, PC2, RM1, RM2		0.004	0.007	0.019	0.053
Low-Rise (LR) Buildings – Low-Code Design Level					
W1, W2		0.004	0.010	0.031	0.075
S1		0.006	0.010	0.020	0.050
C1, S2		0.005	0.008	0.020	0.050
C2		0.004	0.008	0.020	0.050
S3, S4, PC1, PC2, RM1, RM2		0.004	0.006	0.016	0.044
S5, C3, URM		0.003	0.006	0.015	0.035
Low-Rise (LR) Buildings – Pre-Code Design Level					
W1, W2		0.003	0.008	0.025	0.060
S1		0.005	0.008	0.016	0.040
C1, S2		0.004	0.006	0.016	0.040
C2		0.003	0.006	0.016	0.040
S3, S4, PC1, PC2, RM1, RM2		0.003	0.005	0.013	0.035
S5, C3, URM		0.002	0.005	0.012	0.028
Mid-Rise Buildings					
All	Mid-Rise Building Types	2/3 * LR	2/3 * LR	2/3 * LR	2/3 * LR
High-Rise Buildings					
All	High-Rise Building Types	1/2 * LR	1/2 * LR	1/2 * LR	1/2 * LR

The tabulated values in Table 5-3 are used to develop the damage module of the four-step process. Once the average inter-story drift values are assigned to each building type, it is then possible to create the relationship between damage states (in terms of loss ratios) and drift rates for each building type. Table 5-4 provides as a general guidance for selection of structural damage state medians in terms of loss ratios. One needs to bear in mind that the presented loss ratios should not be used to develop building specific loss functions, unless the user has used the same values during the development of damage-state medians.

Table 5-4: General guidance for selection of damage-state medians (FEMA 2003)

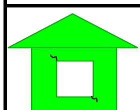
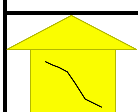
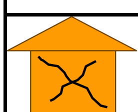
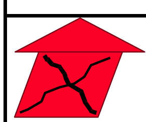
Damage State		Loss Ratio	Description
	**Slight**	**0% - 5%**	Small plaster cracks at corners of door and window openings and wall- ceiling intersections. Small cracks are assumed to be visible with a maximum width of less than 1/8 inch (cracks wider than 1/8 inch are referred to as “large” cracks).
	**Moderate**	**5% - 25%**	Large plaster or gypsum-board cracks at corners of door and window openings; small diagonal cracks across shear wall panels exhibited by small cracks in stucco and gypsum wall panels; large cracks in brick chimneys; toppling of tall masonry chimneys.
	**Extensive**	**25% - 100%**	Large diagonal cracks across shear wall panels or large cracks at plywood joints; permanent lateral movement of floors and roof; toppling of most brick chimneys; cracks in foundations; splitting of wood sill plates and/or slippage of structure over foundations.
	**Complete**	**100%**	Structure may have large permanent lateral displacement or be in imminent danger of collapse due to cripple wall failure or failure of the lateral load resisting system; some structures may slip and fall off the foundation; large foundation cracks.

Fig. 5-4 shows a sample output generated by the damage module for provided user parameters for a given site.

Conterminous 48 States - 2002 Data

Hazard Curve for PGA

Zip Code = 90210

Zip Code Latitude = 39.520199

Zip Code Longitude = -122.206001

Ground Motion = 0.5122 g

Return Period = 475 years

Frequency of Exceedance =2.1053E-03

Probability of Exceedance = 10%

Exposure Time = 50 years

Building Type = W1-LR

Code Era = 1941-1975

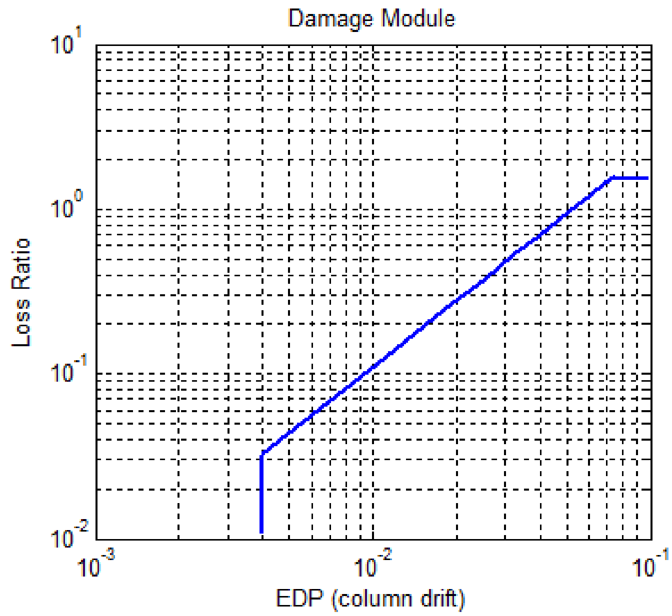


Fig. 5-4: Damage module output

5.2.4. Loss Module

The last step in the four-step process for developing a comprehensive loss estimation tool involves communicating the hazard, response, and damage modules with each other to create the loss module. Since each module is interrelated with each other (i.e. each plot generated in sequential tasks shares a common axis with one another) it is possible to create the relationship between the frequency of the event and the incurred losses on the structure as illustrated in Fig. 5-5.

Conterminous 48 States - 2002 Data

Hazard Curve for PGA

Zip Code = 90210

Zip Code Latitude = 39.520199

Zip Code Longitude = -122.206001

Ground Motion = 0.5122 g

Return Period = 475 years

Frequency of Exceedance =2.1053E-03

Probability of Exceedance = 10%

Exposure Time = 50 years

Building Type = W1-LR

Code Era = 1941-1975

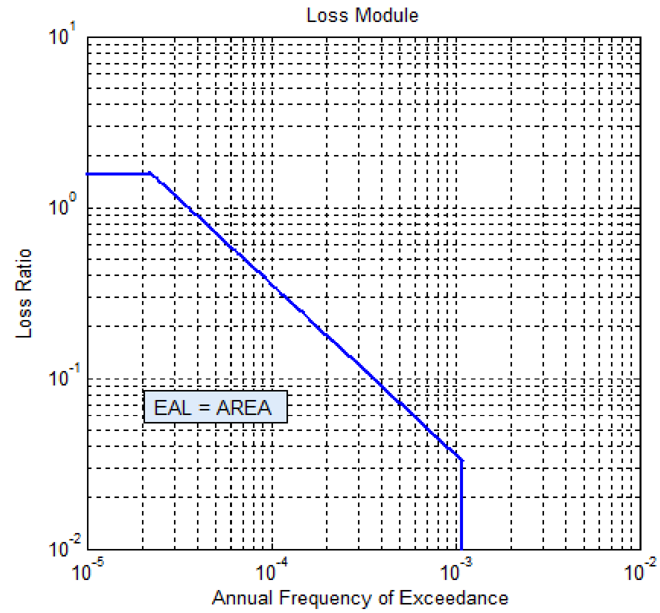


Fig. 5-5: Hazard module output

Expected annual losses (EAL), and hence the "pure premiums" can be estimated by simply integrating the area beneath the curve in Fig. 5-5 when that curve is plotted on natural scales. Convolution of the four sequential tasks and the resulting loss curve is plotted in Fig. 5-6.

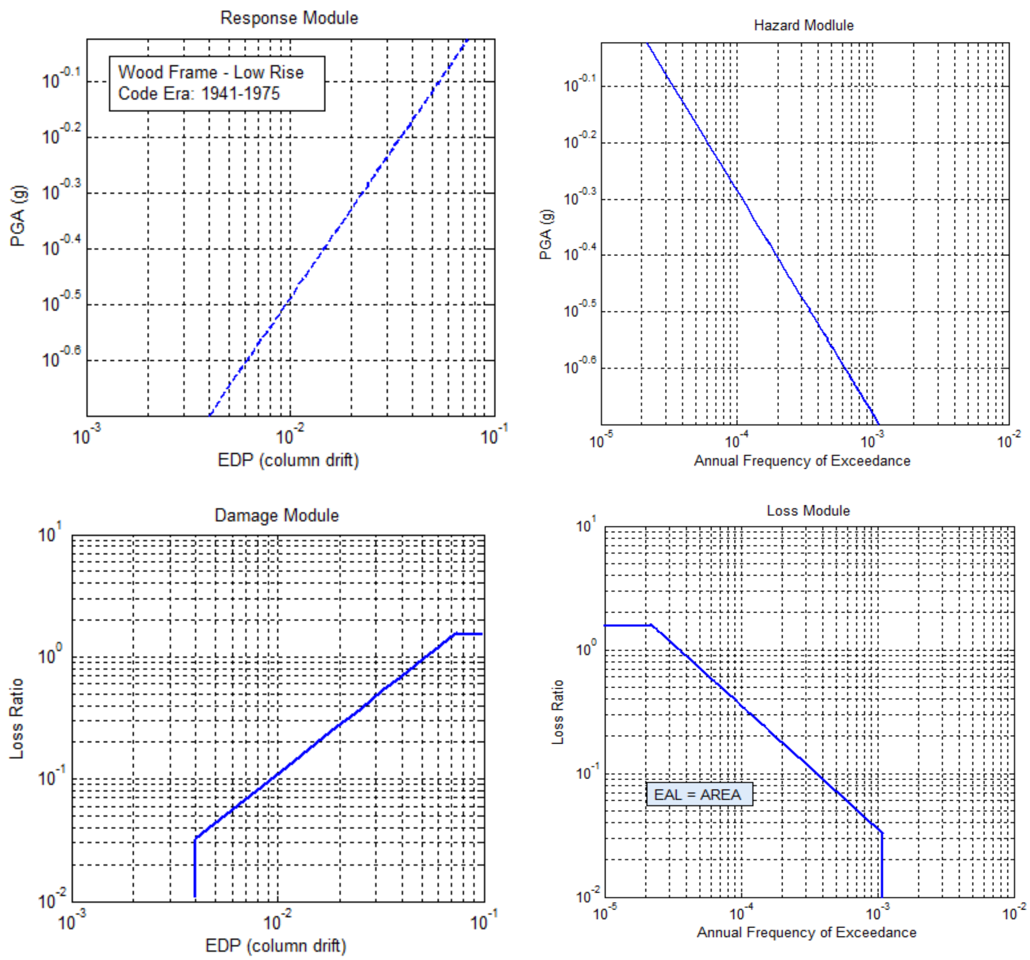


Fig. 5-6: Computational four-step loss analysis

5.3. Optimizing Insurance Portfolios

The financial consequences of natural catastrophes depend on numerous variables. The most important of which are: site specific ground motion parameters, geographical patterns, structure specific parameters (e.g. dwelling type, building height, code era, etc.), distribution of property values and demographics in the region, the variation of insurance coverages among different individuals, etc. Therefore, it is of paramount importance to have effective tools that takes into such variables and their impact over portfolio of insureds in endangered regions. The interdependencies among the variables and how they affect the overall portfolio performance also need to be considered while conducting portfolio analysis to determine economic efficiency and stability. Fig. 5-7 shows the aforementioned insurance modeling process which is followed by portfolio analysis.

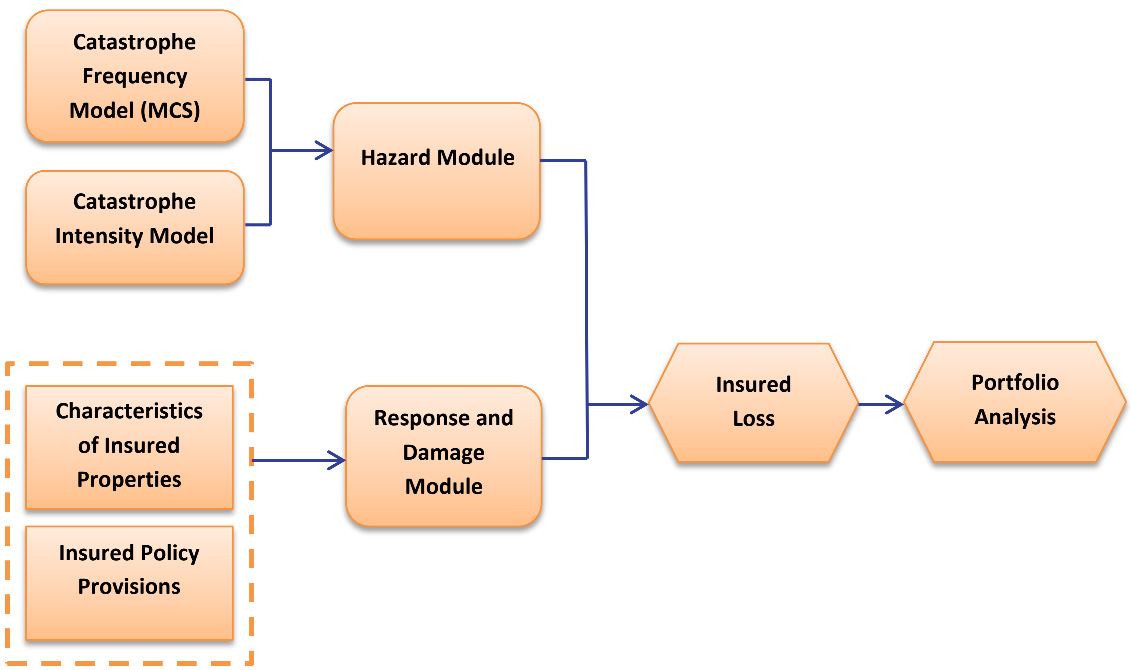


Fig. 5-7: Large-scale insurance modeling steps

Utilizing computer simulations with engineering models to capture both the demand and supply side of the catastrophe risk problem is becoming an increasingly important approach for insurance companies (Damnjanovic et al. 2010). This approach also allows for further integration with insurance portfolio analysis as stakeholders make decisions on the allocation and values of contracts and premiums. This integration is realized by using the information provided by the "insurance loss model" to analyze the impact of various combinations of decision variables (e.g. deductible, risk mitigation measures, etc.) on the capacity and stability of insurance portfolios.

5.3.1. Stochastic Portfolio Analysis

The traditional approach to portfolio analysis focuses on economic activities such as profits and costs (Ermoliev et al. 2000a). The models for insurance portfolio analysis, however, need to focus on the "hit risk" associated with catastrophic events also. Here, the hit risk relates to the risk of instantaneous large financial losses. The hit risk component must be treated equally important with the economic components as it represents the possibility of highly correlated losses occurring at the same time. The outcome of involving the hit risk in insurance portfolio analysis is often a non-smooth distribution with a rather complex jump process, which is a challenge to model (Amendola et al. 2000).

Let us consider a typical insurance scenario where claims occur at random times $t_1,\ t_2,\ t_3,\ ...$ with random sizes $L_1, L_2, L_3 \ldots$ In such cases, the available capital in the insurance pool account (aka risk reserve or pool reserve) at time t can be mathematically defined as:

$$P(t) = P_0 + \rho(t) - L(t),\ t > 0 \qquad (5\text{-}1)$$

where $p(t)$ is the accumulated premium collected from policy holders, R_0 is the initial capital reserve in the insurance pool at $t = 0$, and $L(t)$ is the aggregated claims due to catastrophic events. Fig. 5-8 depicts the dynamics of a typical insurance pool for the above given scenario.

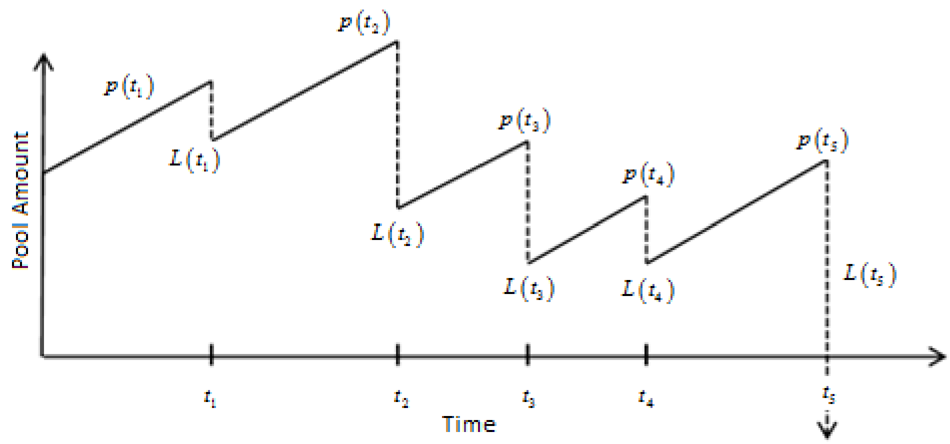


Fig. 5-8: Typical trajectory of insurance pool

In Fig. 5-8, insolvency occurs when the claims size at time t exceeds the available capital in the insurance pool (e.g. at time t_5). Clearly, insolvency risk is a function of initial risk reserve, premium rate, claim size and the time.

Insolvency risk is a key performance measure for portfolio analysis as it represents the "insurability" of the risk under consideration (Ermoliev et al. 2000b). Insurers provide different coverages to various policy holders at different locations based on their risk preferences (reflected as the choice of deductible). To avoid insolvency, insurers try to add policies from different geographical locations to increase diversification and hence decrease correlation between claims. Clearly, the analysis of insolvency risk needs to consider decision variables for both insurers (i.e. location and structure specific risk parameters of the underlying properties) and policy holders (i.e. premium rates, amount of coverage requested, etc.). Thus, in general the insurance pool amount $P(t)$ that leads to computation of insolvency risk is a complex dynamic stochastic process. The shape of the probability distribution for the insurance pool amount changes depending on the various decision variables as defined earlier (Amendola et al. 2000; Ermoliev et al. 2000a).

5.3.2. Model Description

The lower forty eight states of the U.S (Continental U.S.) is adopted as the study region and divided into sub regions to allow for simultaneous occurrences of catastrophic events. For analysis and illustration purposes, the risk causing natural phenomena is selected as earthquakes and the study region is divided into sub regions based on earthquake fault locations and seismic zones defined in HAZUS and UBC. Fig. 5-9 shows the considered regions with associated %g contours, as well as the fault locations based on the 2008 USGS database (http://earthquake.usgs.gov/).

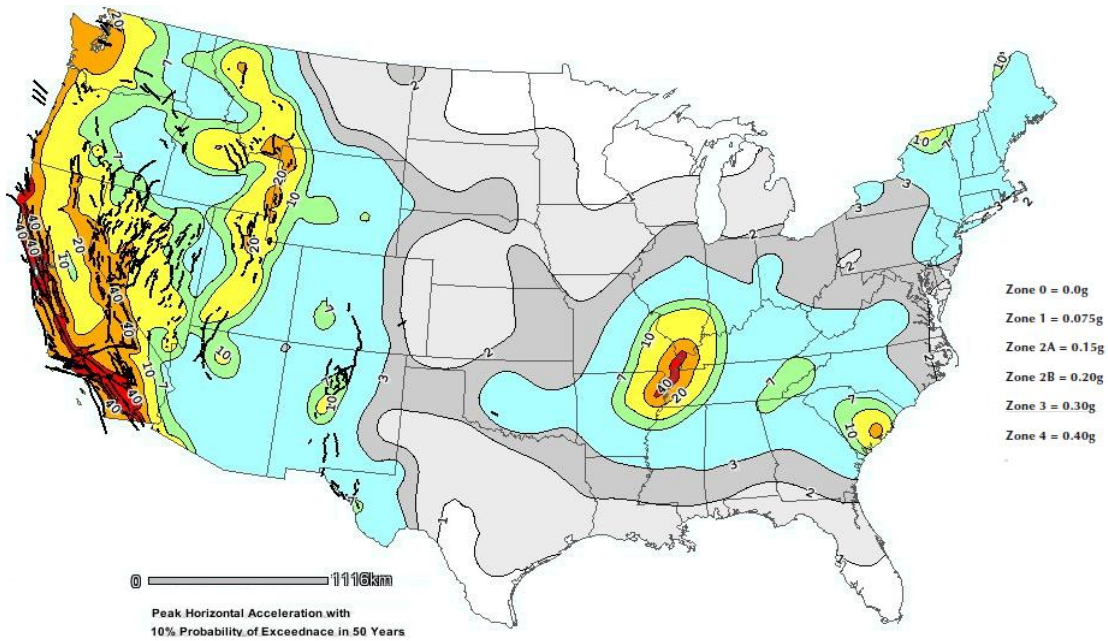


Fig. 5-9: Study region (http://gldims.cr.usgs.gov/website/nshmp2008/viewer.htm)

Assume that there are $n = 1, 2, \ldots$ different insurance portfolios or insurance groups in the study region. Each group has policy holders $i = 1, 2, \ldots$from different sub-regions with different properties and different risk preferences. For each group n there exists a $W(n)$ defining the accumulated property values of the policy holders in group n. Further, assueme that each group has an intial deposit in their pool defined as P_n^0. This initial amount can be raised via join-in fees or insurance guaranty funds, etc. Each insurance group receives premiums $\rho_n(i)$ from the policy holders as defined in their contracts. The dynamics of insurance pool for each group n can be mathematically expressed by the following equation

$$P_n = P_n^0 - \sum_i L_n(i)c_n(i) + \sum_i \rho_n(i)c_n(i) - \sum_i K_n(i) \qquad (5\text{-}2)$$

where

- $L_n(i)$ = random loss claimed by the policy holder "i" in group "n",
- $c_n(i)$ = coverage provided to the user,
- $K_n(i)$ = transaction cost.

Here coverage is defined as the fraction of loss $L_n(i)$ promised to be covered by the insurance pool *n*, and it is a function of the deductible chosen by the policy holder *i*.

Each insurance pool or insurance group n in the study region is primarily concerned with the pool amount P_n^t at time $t = 0, 1, 2, ...$ Clearly, premiums ρ_n^t push up the trajectory of the pool amount at a certain rate over the time while transaction costs K_n^t push it down. It is rather simple to model the impact of both ρ_n^t and K_n^t over the pool amount as the progression of these components is linear. The challenge is to model the random arrival of the loss claims L_n^t at random magnitudes. When a sequence of catastrophic events $w = \left(w_t,\ t = 0,\ 1,\ \ldots\right)$ occurs, each group $n = 1,\ 2, \ldots$ experiences a different loss $L_n^t(w)$ based on the group members' geographical distributions and property types. These losses result in instantaneous negative jumps (drops) in the pool amount.

For non-catastrophic (traditional) mutually independent risks, the probability distribution of loss claims can be derived using historical data (Meyers and Kollar 1999). However, for catastrophic risk this method is not applicable as the potential losses at a certain site are highly correlated with each other. Since it is not feasible to analytically define the joint probability distribution of catastrophic loss claims, it is assumed that claim arrivals can be generated via Monte Carlo Simulation while the claim sizes are quantified via the proposed engineering model, and fed to the trajectory algorithm. The loss process due to claims can be written as:

$$L_n^t(w) = \sum_{i \in S_n(t,w)} L_i^t c_i^t \tag{5-3}$$

where $S_n(t,w)$ identifies the subset of policy holders affected by the catastrophic event w until time t while the insurance group n is still operable.

By using Eq. (5-2) and Eq. (5-3), the capacity of insurance pool n at any time t is modeled as:

$$P_n^{t+1} = P_n^t + \sum_i^m \left[\rho_i^t c_i^t - K_i^t \right] - \sum_{i \in S_n(t,w)} L_i^t(w) c_i^t \tag{5-4}$$

where:

- $i = 1, 2, \ldots .m,$
- $t = 0, 1, .., T-1,$
- $P_n^0 =$ initial $(t = 0)$ deposit in the pool n.

The risk of insolvency (probability of ruin) is a performance measure that is used to represent the long-term stability of the insurance pool capacity. Assume that the probability $\underline{\mu} \le \mu \le \bar{\mu}$ of a catastrophe at any time t is unknown and defined by a probability distribution. In such cases, the risk of insolvency for the first catastrophic event (causing the insolvency) can be mathematically expressed as the expectation:

$$\xi_n = +E \sum_{t=1}^{T} \mu (1-\mu)^{t-1} \Pr\left[P_n^t - L_n^t \right] \tag{5-5}$$

where L_n^t is the loss claim generated in group *n* due to a catastrophe. For the ease of computations, it is assumed that insolvency occurs once (by one catastrophe) and the stochastic probability values are calculated at that discrete time.

This section now continues with introducing potential optimization methods for adjusting premiums and setting stability constraints for the insurance portfolios. In general, these methods are used when pure premiums (premiums based solely on loss estimations with no additional risk loading) are not considered to be profitable enough for the insurance company to take on catastrophe risk, or too expensive for policy holders to afford. This is often the case with poor communities and for-profit insurance companies.

Let us consider the case where the insurance group *n* is exposed to losses due to natural disasters at any time, L_n^t. These losses are paid in full or partially based on the purchased insurance coverage by members *i*, c_i. If W_n^0 denotes the initial wealth of the group *n*, then the wealth at any time $t+1$ can be expressed as:

$$W_n^{t+1} = W_n^t + \sum_i^m \left(L_i^t - \rho_i^t\right)c_i^t - L_n^t \qquad (5\text{-}6)$$

Each member in group *n* aims to maximize his/her wealth and the maximization depends of the choice of coverage. This is also known as deductible policy, V_n^t, and defined as:

$$V_n^t = \sum_{t=0}^{t}\left(\sum_i^m c_i^t\left(L_i^t - \rho_i^t\right)\right) \qquad (5\text{-}7)$$

Thus, the deductibles (and hence the coverages) are selected based on the maximization of the expected value:

$$F_n(x) = Ef_n^{t_r}(x,w),\ f_n^{t_r} = E\left[V_n^{t_r-1} + \alpha_n \min\left\{0,\ V_n^{t-1} - EV_n^{t-1}\right\}\right] \qquad (5\text{-}8)$$

subject to:

$$c_{ni}^t \le 1,\ i = 1,2,..,m.,\ t = 0,1,...T\text{-}1 \text{ and } t \le tr \qquad (5\text{-}9)$$

where

- α_n = risk coefficient of underestimating,
- t_r = time of insolvency and $t_r = \min\left\{t : W_n^t \le 0, t \le T-1\right\}$.

In a similar fashion, insurer n seeks to maximize his expected wealth:

$$Z_n^t = \sum_{t=0}^{t-1}\left(\sum_i^m \left[\rho_i^t c_i^t - K_i^t\right] - \sum_{i \in S_n(t,w)} L_i^t(w) c_i^t\right) \qquad (5\text{-}10)$$

The major difference in the decision making process for insurers as opposed to policy holders is that, he needs to consider risk of overestimating the profits due to premium income, and risk of insolvency, $P\left\{P_n^t < 0\right\},\ [0,t)$. Insurer's decisions x can be chosen from maximization of the expected value

$$F_n(x) = Ef_n^{t_r}(x,w),\ f_n^{t_r} = E\left[Z_n^{t_r-1} + \beta_n \min\left\{0,\ Z_n^{t-1} - EZ_n^{t-1}\right\} + \gamma_n \min\left\{0, P_n^{t_r}\right\}\right] \qquad (5\text{-}11)$$

and subject to Eq. (5-9).

The maximization of the expected value $F(x)$ is a rather difficult stochastic optimization problem with some unique features. This is mainly because of the unpredictable nature of the catastrophe risk and high number of decision variables associated with insurance portfolios. For instance, the time of insolvency, t_r may be an implicit random function of x this alone results in non-smooth complex functions. Moreover, the risk function $F_n(x) = E\{0,\ Z_n^{t-1} - EZ_n^{t-1}\}$ is nonlinear in probability measure and adds non-smooth features to the expectation function. Although developing stochastic optimization functions is not the primary objective of this study, doing so helps to illustrate deficiencies of deterministic models. For in-depth analysis of advanced optimization techniques for insurance portfolios under catastrophe risk, see Ermoliev et al. (2000a).

Large scale models with high a number of decision variables are needed to realistically analyze the catastrophe risk and its ramifications in decision making process (Amendola et al. 2000). Such models involve simulating random occurrences of catastrophic events, their geographical location, and their timing. These models also include regional parameters, characteristics of structures, distribution of current and possible new coverage, etc. Advances in computational programing and internet-based social networks create a stage for such large scale models. The computational power can be used to run simulations with a high number of decision variables and social-networks set the ground for study region as well as building inventory. Scenario events can then be analyzed over the exposed regions and the losses can be computed. Histograms of marginal loss distributions, risk of insolvency, and effective capital capacity (pool amount) for each insurance portfolio within the study region can be computed for any combination of decisions.

The next section presents the large scale model developed in this study for a catastrophe insurance scheme. The model uses pure premium rates to avoid complexities associated with optimization of additional risk loading. Another benefit of using pure premium rates is the ability to evaluate how the modeled loss estimates perform in a non-profit business model with respect to the stability and capacity requirements. These premiums are calculated by using the modified four-step approach defined in Section 5.2 and hence account for uncertainties at primary (uncertainty of which, if any, event will occur) and secondary (given that an event has occurred, the uncertainty in the amount of loss and distribution of possible outcomes, rather than expected outcome) levels.

5.4. Numerical Examples

Integrating engineering models into internet-based applications in actuarial settings improves utilization of risk mitigation instruments in various ways. The most significant improvements may occur in availability, stability, affordability, and capacity areas. A large scale non-profit insurance model is herein presented with numerical examples to illustrate the potential real-world applications. The Continental United States is the study region for the illustrative examples.

The users (policy holders) in this framework are allowed to create their own portfolios and act as small risk retention groups (RRG) where policy holders are also stockholders. The information regarding actuarial performance measures such as risk of insolvency and recovery rate, as well as capacity measures such as pool amount (risk reserve) is made publicly available to help decision making process. Here, risk of insolvency refers to the probability that aggregated loss claims of the insurance group exceed the available deposit in the group's pool reserve. The recovery rate, on the other hand, is the ratio of the paid losses to the actual incurred losses in case of insolvency.

The users are asked to provide a minimum amount of information to compute their insurance premiums and run portfolio analysis. These input parameters are: 1) Zip code, 2) insured value, 3) building type, 4) construction era, 5) deductible, and 6) choice of group. The built in algorithm generates the site specific hazard parameters and structure specific response parameters automatically as the user enters his/her primary input values (i.e. zip code, building type, and construction era). These parameters are used in the loss estimation process defined in Section 5.2. to compute the pure premiums. Once the premiums are calculated for each policy holders, this information is stored in a local database to run portfolio analysis as described in Section 5.3. A scenario case is presented below to demonstrate possible real-world applications of the proposed insurance model.

5.4.1. Insurance Group Example

The individual "Aggie" lives in a seismic prone are and decides to create an insurance group with his former college mates who also live in endangered areas. Aggie and forty five friends of him agreed to create an insurance group of their own. Geographical distribution of group members within the study region is given in Fig. 5-10.

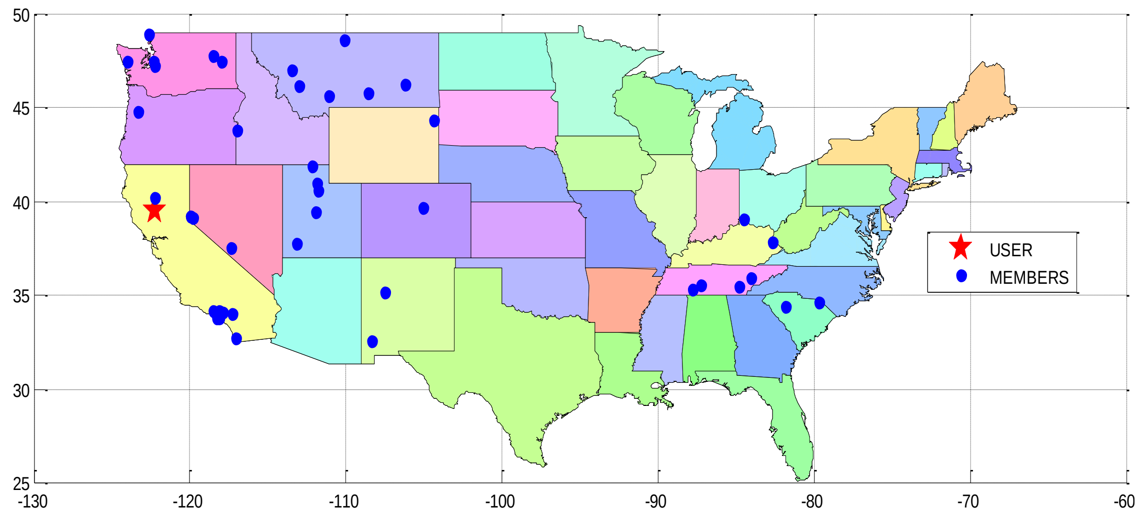


Fig. 5-10: Geographic distribution of Aggie group members

Aggie owns a low-rise wood frame house valued at $100,000 in Willows, California (zip code: 95988). First, he wants to know how much he needs to pay as a premium for his property and choice of coverage if he stays in this insurance group. Next, he wants to know how risky (i.e. risk of insolvency) it is to be in this particular group. The proposed insurance model makes it possible to access all of the information stated above in one step.

The portfolio analysis for any risk retention/insurance group is conducted via computer simulations on a daily basis to provide information about group performance measures such as pool amount and trajectory, risk of insolvency, and recovery rate. Fig. 5-11 depicts the trajectory of a sample insurance group, in this case the Aggie Insurance Group, by means of simulation runs for a ten year period. The blue lines in the plot represent the simulated paths and the red line represents the no-event case where the pool amount is simply the accumulated value of collected premiums over the time period.

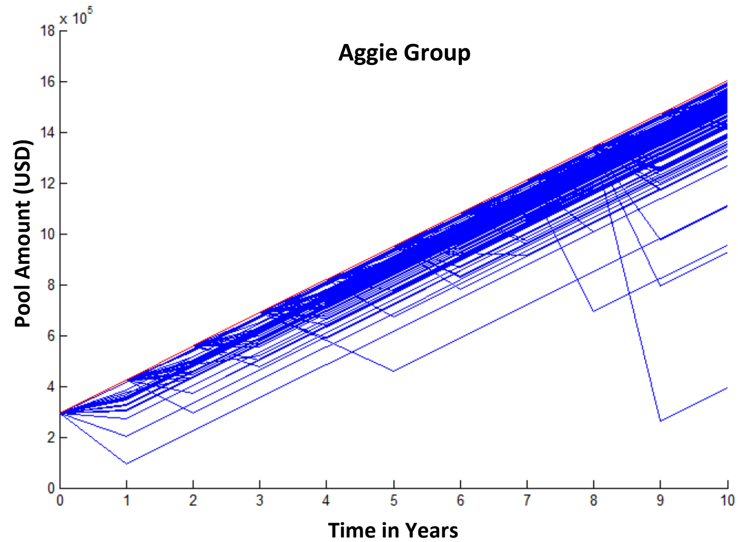


Fig. 5-11: Trajectory of Aggie group pool

The distribution of loss claims for Aggie Group is provided as an output, and plotted in Fig. 5-12. The three dimensional plot shows the cumulative loss claims for each simulation path at each time step. By using the information obtained from Fig. 5.11 and Fig. 5-12, performance measures such as risk of insolvency and recovery rate are calculated for each group. This information is stored in the database and made available for users to help decide which group to join or leave.

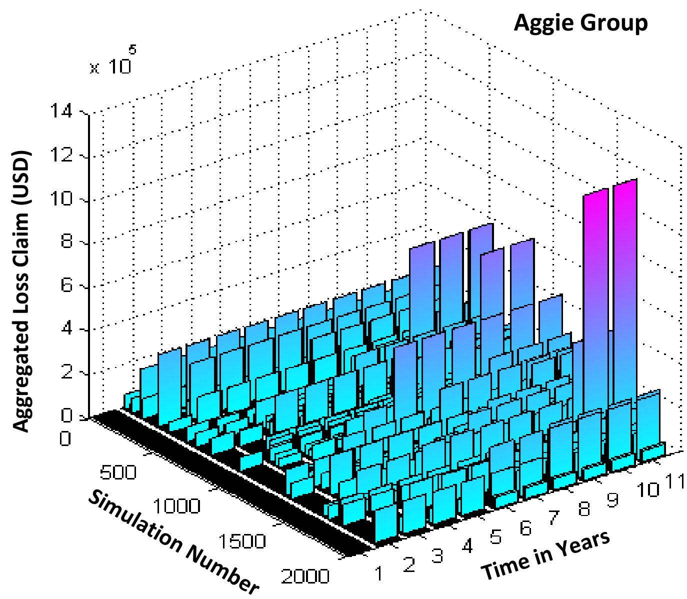


Fig. 5-12: Loss distribution of Aggie group

The case study is extended to provide more insight about the functionality and applicability of the proposed insurance model. A dataset of random user profiles with random locations, building types, construction eras, and coverage needs is generated. This dataset consists of 500 users (policy holders) and ten risk retention/insurance groups (insurance groups). Fig. 5-13 shows the policy holders that are plotted on the study region (USA) map with respect to their group colors and location parameters (zip codes).

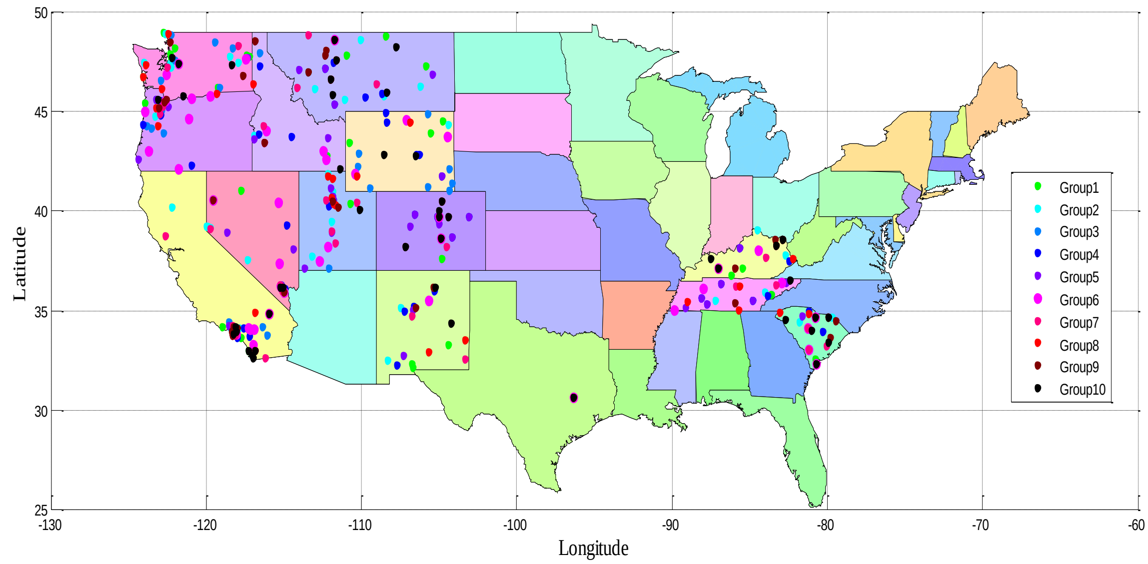


Fig. 5-13: Geographic distribution of group members

The portfolio analysis is conducted for the aforementioned ten groups by running Monte Carlo Simulations for M = 2000 iterations for T = 10 years period. The simulation outputs are used to generate Fig.5-14 and Fig. 5-15 which contain pool trajectory and loss claim distribution plots of each group respectively.

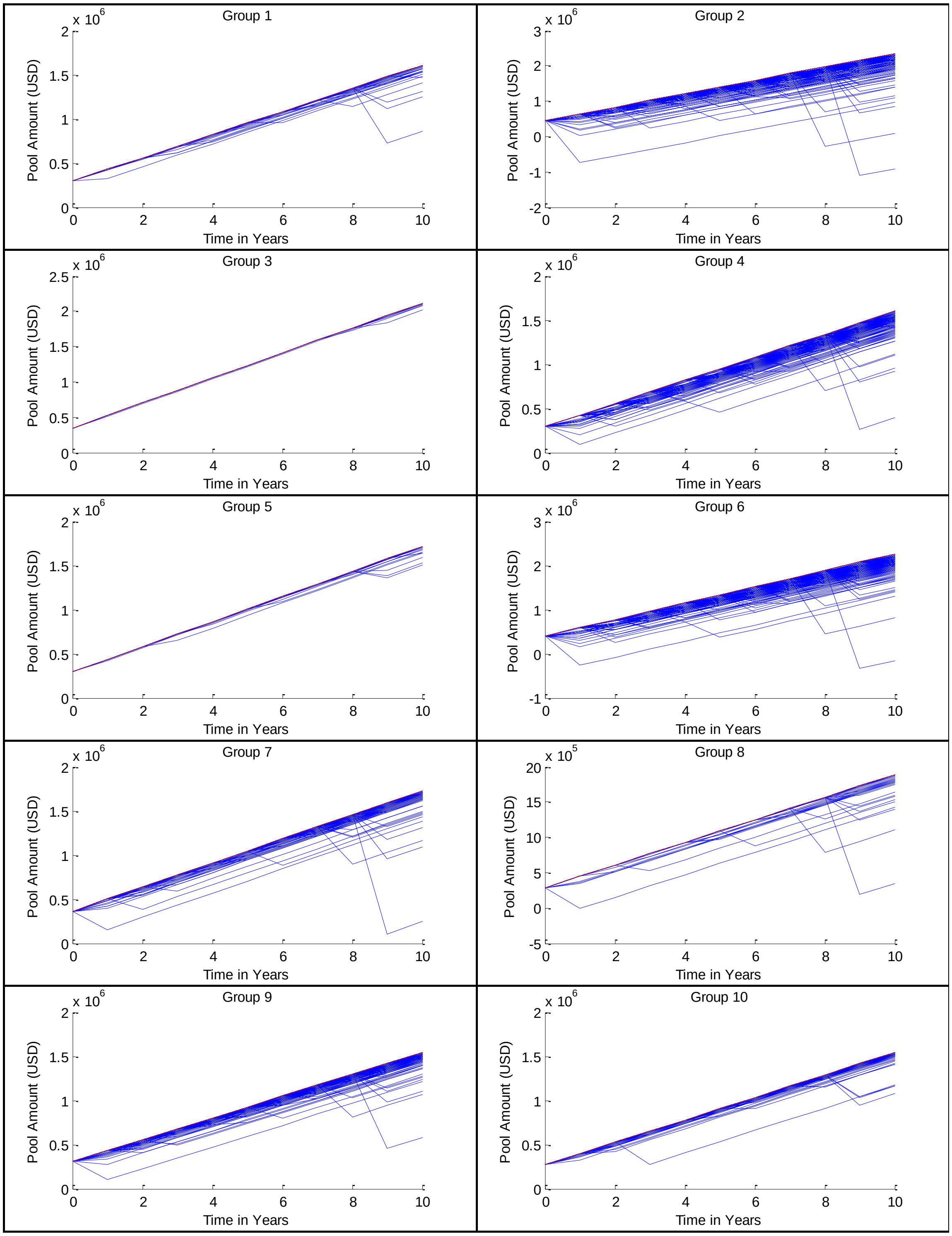


Fig. 5-14: Trajectory of each insurance pool

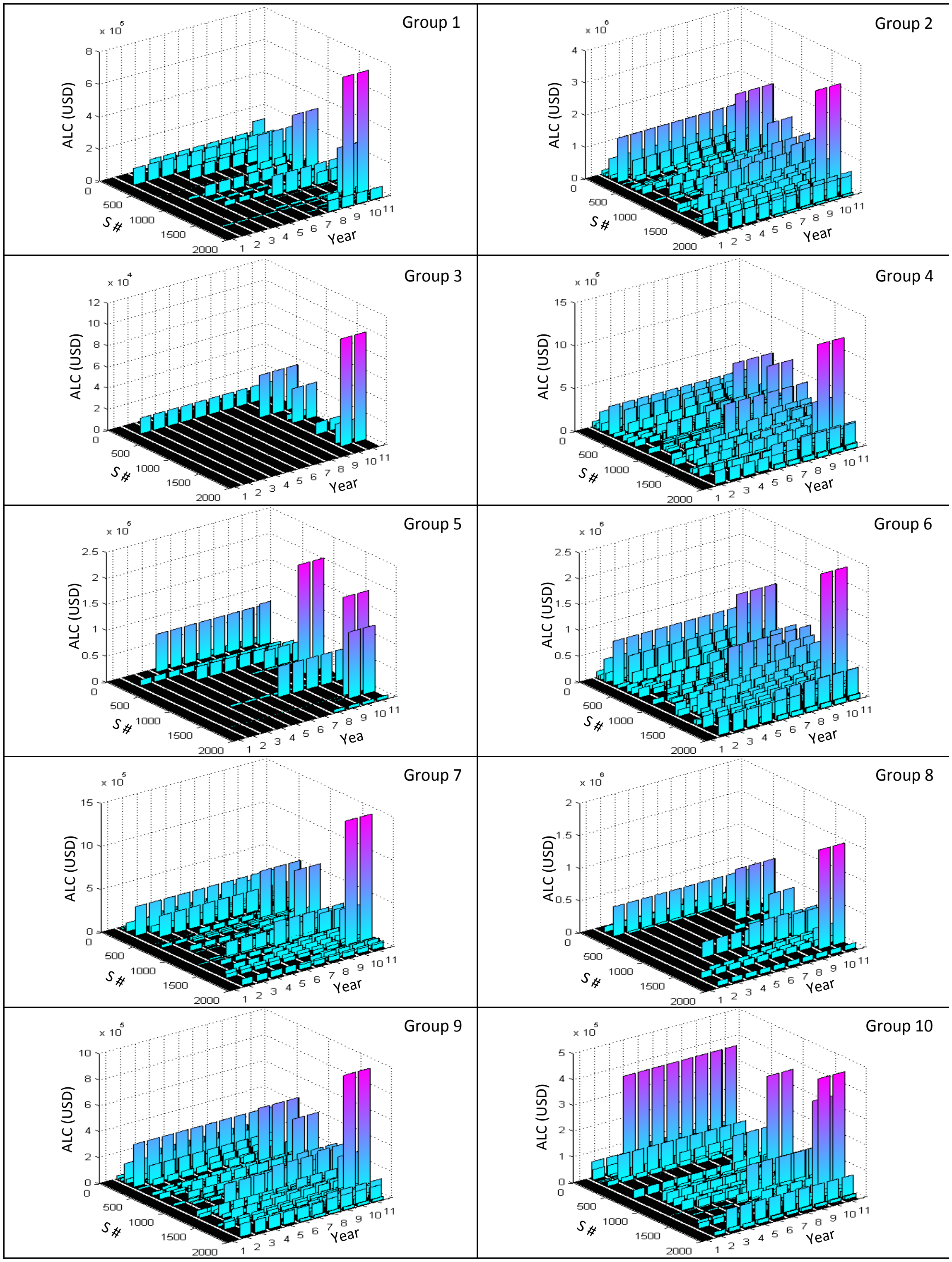


Fig. 5-15: Loss distribution of each insurance pool

Fig. 5-14 and Fig. 5-15 depict that the proposed large-scale insurance model successfully captures the dynamic relationship between supply and demand parameters, as well as user risk preferences.

5.5. Section Closure

This section has demonstrated an application of a systems approach to decision making in catastrophe risk management by setting up a novel framework utilizing a web-based loss estimation tool that employs computer simulations and engineering analysis. This framework is designed to serve societies' best interest and can be easily adopted by both private and public sectors. The framework permits the use of demand (hazard) and supply (vulnerability) information systems in conjunction with financial and actuarial analysis. It provides a quick access to reliable information about loss distribution among the insurance groups and helps decision making in regards to resource allocation and risk mitigation investments.

The framework takes advantage of modern day tools including the computational power to run Monte Carlo Simulations, a web-based interface to reach more diversified user portfolios, and publicly available geospatial datasets to reach site specific hazard parameters. Furthermore, it allows decision makers to define or modify the performance measures or goal functions based on their risk preferences and policy strategies. Thanks to the modular design of the social insurance framework, the decision makers are able to incorporate different sub-models for catastrophe analysis. It is also possible to incorporate a business-model via defining incentives or penalties for group members, originators, or external funding agencies who are willing to be a part of the system by providing additional capital (in terms of initial risk reserve) at a pre-defined cost.

The current framework is developed for a single hazard (i.e. earthquake) however; it is possible to expand the framework for additional hazards by simply modifying the hazard and response modules of the four-step loss estimation process. The proposed framework can be utilized by either a single risk retention group (insurance group), $n = 1$, or a pool of different insurance groups, $n > 1$. The barebones of the framework can be easily modified to include other decision variables such as risk mitigation measures, warranties, capital budgeting strategies, and regulations.

The major benefit of the proposed framework over existing insurance strategies is that it provides policy makers in endangered regions information by presenting them a range of policy options with tradeoffs in terms of risk and value. Also, it presents an opportunity for groups to evaluate their risk-related decisions without running complex analysis. With the ease of simple "what-if" analysis and transparent "risk" information provided, this framework may significantly increase the level of commitment and contribution to social-insurance model.

6. CONCLUSIONS AND RECOMMENDATIONS

Pricing catastrophe–linked risk transfer instruments such as insurance policies, catastrophe bonds and catastrophe options must account for unique characteristics. Since catastrophes are rare occurrences with high consequences at social and economic levels, the very limited historical database does not support for lessons-learned practices. Moreover, past loss experiences are unlikely to realistically represent the loss exposure of modern society due to the constant changes in the demographic distributions and built environment.

This dissertation describes how engineering models can be integrated into financial valuation analysis of risk transfer instruments while utilizing modern day tools such as a web-based loss estimation calculators and geospatial databases. It supports robust, comprehensive, and transparent solutions for decision makers. The major benefit of such an approach is the improved ability to assess the effectiveness of various risk mitigation strategies in terms of risk reduction per dollar invested. The proposed valuation models for ART instruments and insurance portfolio analysis account for the important interaction between catastrophe loss, damage potential of the underlying assets, and survival and stability characteristics of the exposed risk retention group.

The Cat bond analyses demonstrated that the four-step engineering loss model can be integrated into financial valuation methods to compute financial indicators such as spread and bond rating. However, this integration is a two way sheet. The engineering community can use the developed model to support evaluation of design alternatives to make sound life-cycle analysis decisions including possible risk transfer strategies for different types of assets and coverage needs. The owners of the constructed assets on the other hand, may compare available risk transfer instruments such as; primary insurance, re-insurance, and others by utilizing the loss information obtained from the four-step model.

The CatEPut analyses showed that specific design types and structural material characteristics may have a significant influence on reducing the cost of mitigating structural losses due to earthquakes and hence lower the CatEPut option price. In fact, the impact of structural response and damage potential parameters (b and c) is essentially as important as the option triggering hazard parameter (IM). This is an important implication for the financial analysts when evaluating option contracts tied to a constructed asset. Further, being able to determine the value of a CatEPut option tied to a single constructed asset or to a portfolio of assets improves life-cycle considerations and more effective risk management practices for constructed assets.

The transfer of catastrophe risk to the capital markets by means of bonds and options may significantly improve the current deficiencies at capacity level. The proposed pricing models for CAT bonds and CatEPuts (in Section 3 and Section 4 respectively) allow for customization to obtain tailored financing options to meet insured's unique needs. Although the customization often results in inflated transaction costs, the straightforward four-step engineering model which serves as the building blocks of the pricing models may minimize the additional risk premium and the transaction costs by providing improved transparency at the analysis level.

This study also demonstrated an application of a systems approach to decision making in catastrophe risk management by setting up a novel framework utilizing a web-based loss estimation tool that employs computer simulations and engineering analysis. The analysis depicted that the proposed framework can be effectively used to quantify the loss exposure of individual policy holders, the aggregate loss exposure of a portfolio, and the insolvency risk (ruin probability) of the insuring company for credible scenarios. By using engineering analysis, the proposed model converts loss information at the individual or portfolio level and risk preferences (decision variables) into a pricing framework. This framework permits a quick access to reliable information about loss distribution among the insurance groups and helps decision making in regards to resource allocation and risk mitigation investments.

In conclusion, this study recommends using a mix of capital market instruments (ART products) with social insurance mechanisms to effectively manage catastrophe risks. This approach may not only help ease dealing with the financial burden of the catastrophic aftermath but also could provide cost effective means of spreading risks to help promote recovery as a whole.

6.1. Future Research

While this work considers the structural component of the insured losses for, it does not account for the losses on non-structural elements. The portfolio loss model presented in this study is modular in design and has the capability for incorporating non-structural loss component (death and downtime) and can therefore be extended.

From the investor's perspective, the basis risk, adverse selection and moral hazard are important factors in financial valuation analysis, and these factors should be further investigated for analysis of catastrophe-linked financial instruments. Moreover, initial wealth and expected future cash flow of both investors and issuers could influence the decision making process. Such decision variables should be modeled and included in pricing framework. An early exercise option for CatEPut analysis could also be added for completeness. All of these are subject for future work.

This study will be further investigated and extended to account for broader types of hazards and structures but at present it represents a key step forward in introducing engineering analysis for the pricing of insurance policies and insurance-linked financial products.

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APPENDIX

Table 6-1: HAZUS average inter-story drift ratio of structural damage states (FEMA 2003)

Model Building Type		Structural Damage States			
		Slight	Moderate	Extensive	Complete
Low-Rise Buildings – High-Code Design Level					
W1, W2		0.004	0.012	0.040	0.100
S1		0.006	0.012	0.030	0.080
C1, S2		0.005	0.010	0.030	0.080
C2		0.004	0.010	0.030	0.080
S3, S4, PC1, PC2, RM1, RM2		0.004	0.008	0.024	0.070
Low-Rise Buildings – Moderate-Code Design Level					
W1, W2		0.004	0.010	0.031	0.075
S1		0.006	0.010	0.024	0.060
C1, S2		0.005	0.009	0.023	0.060
C2		0.004	0.008	0.023	0.060
S3, S4, PC1, PC2, RM1, RM2		0.004	0.007	0.019	0.053
Low-Rise (LR) Buildings – Low-Code Design Level					
W1, W2		0.004	0.010	0.031	0.075
S1		0.006	0.010	0.020	0.050
C1, S2		0.005	0.008	0.020	0.050
C2		0.004	0.008	0.020	0.050
S3, S4, PC1, PC2, RM1, RM2		0.004	0.006	0.016	0.044
S5, C3, URM		0.003	0.006	0.015	0.035
Low-Rise (LR) Buildings – Pre-Code Design Level					
W1, W2		0.003	0.008	0.025	0.060
S1		0.005	0.008	0.016	0.040
C1, S2		0.004	0.006	0.016	0.040
C2		0.003	0.006	0.016	0.040
S3, S4, PC1, PC2, RM1, RM2		0.003	0.005	0.013	0.035
S5, C3, URM		0.002	0.005	0.012	0.028
All	Mid-Rise Building Types	2/3 * LR	2/3 * LR	2/3 *	2/3 *
All	High-Rise Building Types	1/2 * LR	1/2 * LR	1/2 *	1/2 *

Table 6-2: Equivalent-PGA structural fragility for high-code seismic design level (FEMA 2003)

Building Type	Median Equivalent-PGA (g) and Log-standard Deviation (Beta)							
	Slight		Moderate		Extensive		Complete	
	Median	Beta	Median	Beta	Median	Beta	Median	Beta
W1	0.26	0.64	0.55	0.64	1.28	0.64	2.01	0.64
W2	0.26	0.64	0.56	0.64	1.15	0.64	2.08	0.64
S1L	0.19	0.64	0.31	0.64	0.64	0.64	1.49	0.64
S1M	0.14	0.64	0.26	0.64	0.62	0.64	1.43	0.64
S1H	0.10	0.64	0.21	0.64	0.52	0.64	1.31	0.64
S2L	0.24	0.64	0.41	0.64	0.76	0.64	1.46	0.64
S2M	0.14	0.64	0.27	0.64	0.73	0.64	1.62	0.64
S2H	0.11	0.64	0.22	0.64	0.65	0.64	1.60	0.64
S3	0.15	0.64	0.26	0.64	0.54	0.64	1.00	0.64
S4L	0.24	0.64	0.39	0.64	0.71	0.64	1.33	0.64
S4M	0.16	0.64	0.28	0.64	0.73	0.64	1.56	0.64
S4H	0.13	0.64	0.25	0.64	0.69	0.64	1.63	0.64
S5L								
S5M								
S5H								
C1L	0.21	0.64	0.35	0.64	0.70	0.64	1.37	0.64
C1M	0.15	0.64	0.27	0.64	0.73	0.64	1.61	0.64
C1H	0.11	0.64	0.22	0.64	0.62	0.64	1.35	0.64
C2L	0.24	0.64	0.45	0.64	0.90	0.64	1.55	0.64
C2M	0.17	0.64	0.36	0.64	0.87	0.64	1.95	0.64
C2H	0.12	0.64	0.29	0.64	0.82	0.64	1.87	0.64
C3L								
C3M								
C3H								
PC1	0.20	0.64	0.35	0.64	0.72	0.64	1.25	0.64
PC2L	0.24	0.64	0.36	0.64	0.69	0.64	1.23	0.64
PC2M	0.17	0.64	0.29	0.64	0.67	0.64	1.51	0.64
PC2H	0.12	0.64	0.23	0.64	0.63	0.64	1.49	0.64
RM1L	0.30	0.64	0.46	0.64	0.93	0.64	1.57	0.64
RM1M	0.20	0.64	0.37	0.64	0.81	0.64	1.90	0.64
RM2L	0.26	0.64	0.42	0.64	0.87	0.64	1.49	0.64
RM2M	0.17	0.64	0.33	0.64	0.75	0.64	1.83	0.64
RM2H	0.12	0.64	0.24	0.64	0.67	0.64	1.78	0.64
URML								
URMM								
MH	0.11	0.64	0.18	0.64	0.31	0.64	0.60	0.64

Table 6-3: Equivalent-PGA structural fragility for moderate-code design level (FEMA 2003)

Building Type	Median Equivalent-PGA (g) and Log-standard Deviation (Beta)							
	Slight		Moderate		Extensive		Complete	
	Median	Beta	Median	Beta	Median	Beta	Median	Beta
W1	0.24	0.64	0.43	0.64	0.91	0.64	1.34	0.64
W2	0.20	0.64	0.35	0.64	0.64	0.64	1.13	0.64
S1L	0.15	0.64	0.22	0.64	0.42	0.64	0.80	0.64
S1M	0.13	0.64	0.21	0.64	0.44	0.64	0.82	0.64
S1H	0.10	0.64	0.18	0.64	0.39	0.64	0.78	0.64
S2L	0.20	0.64	0.26	0.64	0.46	0.64	0.84	0.64
S2M	0.14	0.64	0.22	0.64	0.53	0.64	0.97	0.64
S2H	0.11	0.64	0.19	0.64	0.49	0.64	1.02	0.64
S3	0.13	0.64	0.19	0.64	0.33	0.64	0.60	0.64
S4L	0.19	0.64	0.26	0.64	0.41	0.64	0.78	0.64
S4M	0.14	0.64	0.22	0.64	0.51	0.64	0.92	0.64
S4H	0.12	0.64	0.21	0.64	0.51	0.64	0.97	0.64
S5L								
S5M								
S5H								
C1L	0.16	0.64	0.23	0.64	0.41	0.64	0.77	0.64
C1M	0.13	0.64	0.21	0.64	0.49	0.64	0.89	0.64
C1H	0.11	0.64	0.18	0.64	0.41	0.64	0.74	0.64
C2L	0.18	0.64	0.30	0.64	0.49	0.64	0.87	0.64
C2M	0.15	0.64	0.26	0.64	0.55	0.64	1.02	0.64
C2H	0.12	0.64	0.23	0.64	0.57	0.64	1.07	0.64
C3L								
C3M								
C3H								
PC1	0.18	0.64	0.24	0.64	0.44	0.64	0.71	0.64
PC2L	0.18	0.64	0.25	0.64	0.40	0.64	0.74	0.64
PC2M	0.15	0.64	0.21	0.64	0.45	0.64	0.86	0.64
PC2H	0.12	0.64	0.19	0.64	0.46	0.64	0.90	0.64
RM1L	0.22	0.64	0.30	0.64	0.50	0.64	0.85	0.64
RM1M	0.18	0.64	0.26	0.64	0.51	0.64	1.03	0.64
RM2L	0.20	0.64	0.28	0.64	0.47	0.64	0.81	0.64
RM2M	0.16	0.64	0.23	0.64	0.48	0.64	0.99	0.64
RM2H	0.12	0.64	0.20	0.64	0.48	0.64	1.01	0.64
URML								
URMM								
MH	0.11	0.64	0.18	0.64	0.31	0.64	0.60	0.64

Table 6-4: Equivalent-PGA structural fragility for low-code seismic design level (FEMA 2003)

Building Type	Median Equivalent-PGA (g) and Log-standard Deviation (Beta)							
	Slight		Moderate		Extensive		Complete	
	Median	Beta	Median	Beta	Median	Beta	Median	Beta
W1	0.20	0.64	0.34	0.64	0.61	0.64	0.95	0.64
W2	0.14	0.64	0.23	0.64	0.48	0.64	0.75	0.64
S1L	0.12	0.64	0.17	0.64	0.30	0.64	0.48	0.64
S1M	0.12	0.64	0.18	0.64	0.29	0.64	0.49	0.64
S1H	0.10	0.64	0.15	0.64	0.28	0.64	0.48	0.64
S2L	0.13	0.64	0.17	0.64	0.30	0.64	0.50	0.64
S2M	0.12	0.64	0.18	0.64	0.35	0.64	0.58	0.64
S2H	0.11	0.64	0.17	0.64	0.36	0.64	0.63	0.64
S3	0.10	0.64	0.13	0.64	0.20	0.64	0.38	0.64
S4L	0.13	0.64	0.16	0.64	0.26	0.64	0.46	0.64
S4M	0.12	0.64	0.17	0.64	0.31	0.64	0.54	0.64
S4H	0.12	0.64	0.17	0.64	0.33	0.64	0.59	0.64
S5L	0.13	0.64	0.17	0.64	0.28	0.64	0.45	0.64
S5M	0.11	0.64	0.18	0.64	0.34	0.64	0.53	0.64
S5H	0.10	0.64	0.18	0.64	0.35	0.64	0.58	0.64
C1L	0.12	0.64	0.15	0.64	0.27	0.64	0.45	0.64
C1M	0.12	0.64	0.17	0.64	0.32	0.64	0.54	0.64
C1H	0.10	0.64	0.15	0.64	0.27	0.64	0.44	0.64
C2L	0.14	0.64	0.19	0.64	0.30	0.64	0.52	0.64
C2M	0.12	0.64	0.19	0.64	0.38	0.64	0.63	0.64
C2H	0.11	0.64	0.19	0.64	0.38	0.64	0.65	0.64
C3L	0.12	0.64	0.17	0.64	0.26	0.64	0.44	0.64
C3M	0.11	0.64	0.17	0.64	0.32	0.64	0.51	0.64
C3H	0.09	0.64	0.16	0.64	0.33	0.64	0.53	0.64
PC1	0.13	0.64	0.17	0.64	0.25	0.64	0.45	0.64
PC2L	0.13	0.64	0.15	0.64	0.24	0.64	0.44	0.64
PC2M	0.11	0.64	0.16	0.64	0.31	0.64	0.52	0.64
PC2H	0.11	0.64	0.16	0.64	0.31	0.64	0.55	0.64
RM1L	0.16	0.64	0.20	0.64	0.29	0.64	0.54	0.64
RM1M	0.14	0.64	0.19	0.64	0.35	0.64	0.63	0.64
RM2L	0.14	0.64	0.18	0.64	0.28	0.64	0.51	0.64
RM2M	0.12	0.64	0.17	0.64	0.34	0.64	0.60	0.64
RM2H	0.11	0.64	0.17	0.64	0.35	0.64	0.62	0.64
URML	0.14	0.64	0.20	0.64	0.32	0.64	0.46	0.64
URMM	0.10	0.64	0.16	0.64	0.27	0.64	0.46	0.64
MH	0.11	0.64	0.18	0.64	0.31	0.64	0.60	0.64

Table 6-5: Equivalent-PGA structural fragility for pre-code seismic design level (FEMA 2003)

Building Type	Slight		Moderate		Extensive		Complete	
	Median	Beta	Median	Beta	Median	Beta	Median	Beta
W1	0.18	0.64	0.29	0.64	0.51	0.64	0.77	0.64
W2	0.12	0.64	0.19	0.64	0.37	0.64	0.60	0.64
S1L	0.09	0.64	0.13	0.64	0.22	0.64	0.38	0.64
S1M	0.09	0.64	0.14	0.64	0.23	0.64	0.39	0.64
S1H	0.08	0.64	0.12	0.64	0.22	0.64	0.38	0.64
S2L	0.11	0.64	0.14	0.64	0.23	0.64	0.39	0.64
S2M	0.10	0.64	0.14	0.64	0.28	0.64	0.47	0.64
S2H	0.09	0.64	0.13	0.64	0.29	0.64	0.50	0.64
S3	0.08	0.64	0.10	0.64	0.16	0.64	0.30	0.64
S4L	0.10	0.64	0.13	0.64	0.20	0.64	0.36	0.64
S4M	0.09	0.64	0.13	0.64	0.25	0.64	0.43	0.64
S4H	0.09	0.64	0.14	0.64	0.27	0.64	0.47	0.64
S5L	0.11	0.64	0.14	0.64	0.22	0.64	0.37	0.64
S5M	0.09	0.64	0.14	0.64	0.28	0.64	0.43	0.64
S5H	0.08	0.64	0.14	0.64	0.29	0.64	0.46	0.64
C1L	0.10	0.64	0.12	0.64	0.21	0.64	0.36	0.64
C1M	0.09	0.64	0.13	0.64	0.26	0.64	0.43	0.64
C1H	0.08	0.64	0.12	0.64	0.21	0.64	0.35	0.64
C2L	0.11	0.64	0.15	0.64	0.24	0.64	0.42	0.64
C2M	0.10	0.64	0.15	0.64	0.30	0.64	0.50	0.64
C2H	0.09	0.64	0.15	0.64	0.31	0.64	0.52	0.64
C3L	0.10	0.64	0.14	0.64	0.21	0.64	0.35	0.64
C3M	0.09	0.64	0.14	0.64	0.25	0.64	0.41	0.64
C3H	0.08	0.64	0.13	0.64	0.27	0.64	0.43	0.64
PC1	0.11	0.64	0.14	0.64	0.21	0.64	0.35	0.64
PC2L	0.10	0.64	0.13	0.64	0.19	0.64	0.35	0.64
PC2M	0.09	0.64	0.13	0.64	0.24	0.64	0.42	0.64
PC2H	0.09	0.64	0.13	0.64	0.25	0.64	0.43	0.64
RM1L	0.13	0.64	0.16	0.64	0.24	0.64	0.43	0.64
RM1M	0.11	0.64	0.15	0.64	0.28	0.64	0.50	0.64
RM2L	0.12	0.64	0.15	0.64	0.22	0.64	0.41	0.64
RM2M	0.10	0.64	0.14	0.64	0.26	0.64	0.47	0.64
RM2H	0.09	0.64	0.13	0.64	0.27	0.64	0.50	0.64
URML	0.13	0.64	0.17	0.64	0.26	0.64	0.37	0.64
URMM	0.09	0.64	0.13	0.64	0.21	0.64	0.38	0.64
MH	0.08	0.64	0.11	0.64	0.18	0.64	0.34	0.64

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