Essays Surrounding Enterprise Risk Management's Influence on Risk Tolerance, Value and Performance.

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Contents

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Notable Terms and Abbreviations

AM Best – one of the major agencies issuing credit ratings and financial strength ratings

Chief Risk Officer (CRO) – leader or manager of enterprise risk management frameworks, processes and related models

Credit Ratings – a scoring system to denote debt and bonds that have high or low risk of default

Economic Capital Modelling (ECM) – modelling process to estimate necessary capital to support adverse financial stress events during a specified period

Economic Scenario Generator (ESG) – simulation model used to estimate 1,000s of paths of potential economic events

Enterprise Risk Management (ERM) – holistic approach to risk management meant to view all risks across an organization jointly; framework to facilitate links between risk and strategy

Enterprise Risk Management Index (ERMI) – a quantitative proxy to measure the relative strength of ERM across the samples used in this thesis

Financial Strength Ratings – a scoring system to denote a financial institutions ability to service its obligations over time, such as an insurer's ability to pay future claims

Investments – securities purchased with the expectation to generate income or price appreciation over time

Investment Leverage – the amount of total investments divided by common shareholder equity

Multi-Criteria Decision Making (MCDM) – applying and triangulating broad information and multiple factors of consideration to facilitate efficient choice

Reinsurance – an insurance risk transfer mechanism designed to remit a certain amount of insurance underwriting premium and related risk from one insurer to another insurer

Risk Budget Structure (RBS) – the difference between investment leverage minus underwriting leverage; higher positive numbers suggest a risk budget biased towards investments while higher negative numbers suggest a bias towards underwriting

Risk Capacity (RC) – within Chapter 4 Manuscript 2 this includes common shareholder equity capital available plus subordinated debt divided by total assets; Within Chapters 5 Manuscript 3 and Chapter 6 Manuscript 4 this is revised to include total average assets

Risk Capacity Residual (RCR) – the remaining risk capacity available after deducting risk capacity utilization; an inverse relation to risk tolerance

Risk Capacity Utilization (RCU) – the amount of equity capital-at-risk divided by risk capacity, a proxy of a firm's risk tolerance

Risk Tolerance – the amount of equity capital-at-risk divided by risk capacity, estimated by firm's risk capacity utilization

Standard & Poor's – one of the major agencies issuing credit ratings and financial strength ratings

Underwriting – the process that insurers take to assess, select and price insurance policies

Underwriting Leverage – the amount of written premiums net of reinsurance divided by common shareholder equity

Value-at-Risk (VAR) – an estimate of capital that would be lost due to an adverse event or a series of events over the course of a defined period such as a year

Abstract

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Degree Title: Doctor of Business Administration (DBA)

Thesis Title: Essays Surrounding Enterprise Risk Management's Influence on Risk Tolerance, Value and Performance

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Abstract: Enterprise risk management (ERM) has been cited as a framework that fosters a holistic understanding and response to the risks that an organization is exposed to during its normal course of operations. ERM builds on traditional risk management in that risks are managed in a connected fashion, and not simply controlled in separate silos. Theoretically this holistic approach fosters improved decision making across the corporate governance structure, while supporting operational efficiencies, improved performance and enhanced value. The goal of this research is to evaluate if the connection between ERM and value or performance is as evident as its supporters would suggest, and just as importantly to provide insight on the role within these relationships of an organization's risk capacity and the choice to utilize that capacity for risk taking activities. The thesis will follow an alternative format consisting of four manuscripts. The first is a thematic assessment of existing research as respects to how ERM, corporate risk tolerance, value and performance are interlinked. This is followed by three distinct, but interconnected empirical research studies. The first empirical study will use different interaction regression techniques to evaluate how risk tolerance interacts with ERM's influence on value and performance, and if this is consistent over a multiyear period. The second empirical study will establish a two-phased multiple regression modelling process to help estimate optimal risk tolerances for an insurer based on its risk profile and ERM strength, and to assess if assuming a less than optimal risk tolerance detracts from performance. The final empirical study will utilize mixed methods – time-fixed panel regressions and structured interviews – to assess the extent and nature of ERM's role in how insurance companies decide to allocate risk and return specifically between investments and underwriting given a presumed corporate risk tolerance. Collectively, the thematic review of relevant ERM literature and these three empirical studies should benefit efforts to expand existing theoretical and practical understandings of ERM's relationship to value, performance, risk tolerance and risk-based decision making.

Key Words: Enterprise Risk Management, Capital Management, Risk-Based Decisions, Corporate Risk Tolerance, Value, Performance

Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or learning.

Chapter 5, manuscript 3, of this thesis has been published as a research paper entitled: "Enterprise Risk (Mis)Management – Performance Implications of the Misapplication of Risk Capacity", 2016, Journal of Finance and Risk Perspectives - Special Issue of Finance Risk and Accounting Perspectives, v5 (1): 1-21.

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The author currently works as one of the Enterprise Risk and Capital Management professionals at New England Asset Management (NEAM). He joined NEAM in 2012. His focus is on the capital management and corporate development activities for property-casualty insurers. This includes developing and evaluating strategic invested asset allocation, quantitative and financial risk analytics, and risk insights for NEAM insurance clients. The author also helps with marketing support, industry presentations and enterprise risk management research on behalf of NEAM. He has over 20 years of financial risk management and insurance experience. Prior to NEAM he was global head of Aon Benfield's Enterprise Risk Management advisory practice. Before Aon Benfield he worked in risk and financial analysis roles at Standard & Poor's, Citibank, AIG and Chubb.

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Myers, C. R. (2016). "Risk Budget Structures and the Relevance of Enterprise Risk Management (ERM)." University of Manchester DBA Conference 2016. Manchester, England.

Myers, C. R. (2015). "Enterprise Risk (Mis)Management – Value Implications of the Misapplication of Risk Capacity." 23rd International Society on MCDM - Multicriteria Decision Making Conference 2015, Helmut Schmidt Universitat. Hamburg, Germany.

Myers, C. R. (2014). "Enterprise Risk (Mis)Management – Value Implications of the Misapplication of Risk Capacity." University of Manchester DBA Conference 2014. Manchester, England.

Myers, C. R. (2013). "Enhancing Portfolio Risk Analysis - Balancing the Past, the Future, the Objective, the Subjective." 22nd International Society on MCDM - Multicriteria Decision Making Conference 2013, University of Malaga. Malaga, Spain.

Notable Research Awards During The DBA Programme

- University of Manchester DBA Conference 2016 – Honourable Mention (2nd Place) Paper
- University of Manchester DBA Conference 2015 – Best Paper

Dedication

To my Grandmother, Gladys and to my Mother, Maria.

Without you I would not be here and I would not be me.

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Chapter 1.

Introduction

Enterprise risk management (ERM) is a concept that has gained significant traction across multiple industries in recent years, and particularly within the insurance and banking industries. Financial institutions are in the business of assuming risk. Investors pay them to do so and regulators and rating agencies expect them to do so as a good for society. However, these constituencies have differing agendas that present challenges to executives of these firms. The holistic understanding of risk that ERM fosters should help financial institutions manage to the different expectations of these constituencies. Indeed, evidence has shown that some firms with superior ERM are recognized favourably by regulators and investors. However, not all organizations are able to translate what appears to be strong ERM into measurable success such as higher valuations and operational efficiency.

ERM can be viewed as a framework, and like other frameworks can have unique designs that are engineered soundly. However, those frameworks may not be universally suited to all end-users. To use a housing analogy, a high-rise flat recently built with the highest standards located in the centre of London, may not suite the goals and objectives of a large family who enjoy large garden spaces, hiking and backyard cookouts. The preferences of this family do not really align with what the high rise flat is meant to address. The same can be said of ERM frameworks. An organization's risk preferences, goals and objectives should be linked to the ERM framework that the firm utilizes. Part of what allows strong ERM to manifest into organizational success is when this alignment occurs. In contrast companies with risk tolerances that are less optimal, and pursue risks not fully understood, are less likely to reap ERM's full potential.

1.1 What is Enterprise Risk Management (ERM)

Enterprise risk management (ERM) is a holistic, corporate-wide understanding and approach to risk. ERM fosters consistent measurement and language around risk, capital and strategy. Common terminology in this regard includes risk-adjusted returns, earnings-at-risk, and economic value added to name a few, which all look beyond basic accounting measures to gain perspective on the connection of risk and strategy through an economic lens (Crouhy et al 2001), (Culp 2001). Theoretically, via an effective ERM construct, banks and insurers can implement the ideal level of financial capital, what we define as risk capacity, required to keep all constituencies satisfied. The capital modelling frameworks applied by regulators (e.g., BIS 2010, 2011), (EIOPA (F.K.A. CEIOPS) 2009) and rating agencies (e.g., Standard & Poor's 2010) to assess solvency and financial strength respectively imply that regulators and rating agencies prefer banks and insurers to hold excess levels of capital to satisfy obligations, particularly during stress events. However, investors theoretically would rather these same firms leverage equity capital thus increasing returns on equity, particularly during non-stressful periods. ERM affords an intuitive and appealing means for risk managers across all industries, and in particular financial institutions, to jointly satisfy these differing stakeholder preferences. In turn these institutions can put themselves in position to leverage available opportunities that fall within their risk preferences, enhancing value as shown by Hoyt and Liebenberg (2011). Unfortunately evidence suggests that too few firms are able to execute effective risk management on a holistic level in this regard as shown by Standard & Poor's, where less than 25% of rated insurers in the U.S. were deemed to have "strong" or "excellent" ERM, and of those that were publically listed their stock prices outperformed their peers both from overall returns and volatility standpoints (Standard & Poor's 2011b).

1.2 Challenges to Realizing Enterprise Risk Management (ERM) Benefits

The reasons for ERM shortfalls are varied. Internal operational barriers are common frictions of efficient general management. It is reasonable to link such limitations to risk management processes and tools specifically also, such as:

- *Misapplication.* Firms may be highly competent in their ability to assess, price and manage risk, but because of misaligned governance there is resistance to the analysis that results from these competencies. A simple example is the bank trader, and revenue generator, has a view of reward associated with a risky transaction that might be challenged by the risk manager, who is also a cost centre. Due to naive or short-term perspectives the risk taker's view is adopted despite the associated elevated long-term risk. Some (e.g., Valukas 2010) have presented evidence that the fall of Lehman Brothers was at least in part due to this phenomenon. Similar studies have been made for other corporate failures due to weaknesses in applying risk management frameworks (e.g., Rosen 2003). Here again is a situation where satisfying the demands of the shareholder (via revenue growth) goes against the demands of other constituencies such as a counterparties, policy holders, etc. where a stable financial position or liquidity is essential to service financial obligations during expected or unexpected events.

- *Misperception*. Another issue may lie in a misunderstanding of what ERM is meant to accomplish. So despite best intentions, some managers have a misplaced view of ERM's key components such as: risk appetite, risk governance and holistic risk response. Hence, a form of ERM may exist, but it is not appropriate given the firm's risk profile. A common mistake that links to here is defining an ERM process as separate from strategy. For example, equating broader risk management as only a control, compliance or 'check-the-box' exercise overlooks the influence that ERM can have on discovering new business and growth opportunities (Dienhart 2010).

- *Structural limitations.* The risk management process may be prudent in its intentions, but there are structural flaws in the analysis such as model error, bad data or over dependence on such risk management tools some of which were noted by Jarrow (2011). Moreover, with regards to risk management processes specifically, studies and textbooks have focused mostly on the mechanical and technical elements of risk, such as a modelling tool, pricing tool or hedging strategy - such as Hull's (2000) classic derivatives text. Whereas practical limitations (timing, availability, etc.) that may undermine these sophisticated – at times glamorous, though at times theoretical – approaches are sometimes overlooked. Alternatively, some managers may view the near-term costs of implementing a full ERM process as being too high relative to alternative uses of resources. So good risk management suffers over time.

There may also be cultural elements, influenced by behavioural and psychological biases. Much of behavioural finance research has taken the perspective of the investor or consumer (i.e., the risk taker), showing that their decision-making tendencies often deviate from what is assumed in economic theories and related models (Thaler 1980), (Wood 2010), which suggests that certain economic theories underlying asset pricing models in finance are flawed to assume risk takers are always rational. Moreover, some have presented prudent notions of how incentives could have contributed to risk management breakdowns leading to the 2008 financial crisis. Yet less empirical evidence exists demonstrating the impact of behavioural tendencies of the financial institution risk manager herself, or how organizational behaviours can render risk management processes at companies inefficient. Our experience has shown that certain cognitive biases are prevalent at financial institutions that limit risk framework efficiencies. Research of these biases exists; although the focus tends not to be specific to banks and insurance companies nor financial risk management within these institutions. Yet these biases may play a role with challenged risk analysis and related sub-optimal risk decisions of banks and insurers just the same.

An exhaustive review of potential behavioural influences is not intended in this work, as these topics have been explored extensively within social economics research. For example, financial institutions led by highly experienced managers who made their success through traditional risk management methods, may fail to accept where their own limitations are, and resist adopting the modern approaches inherent with an ERM framework. This relates to a common trait of illusory superiority in that most people consciously overestimate their abilities (Kruger 1999), (Dunning et al 2003). Other examples and corresponding notable research include: anchoring (Tversky and Kahneman 1974); framing (Druckman 2001a, 2001b), (Plous 1993); group think (Janis 1982), (McCauley 1989), (Hart 1998); and prospect theory (Kahneman and Tversky 1979), (Fox and Tversky 1995). All are worthy considerations of ERM limitations. And while this research will not explore these behavioural and psychological elements directly, these factors may be deeply embedded in some of the findings presented. We will introduce, empirically, the possibility of limitations around risk management effectiveness within financial institutions being at least partially attributed to these concepts.

1.3 Research Questions

ERM is not always fully effective. Some organizations exhibit characteristics that imply that their ERM is very robust and this shows in attributes such as relatively higher value, stronger performance and reasonable risk profiles. While other organizations can exhibit similar ERM characteristics and struggle to reach these positive attributes. The leading research question is to understand some of the reasons why this is the case. Along the way to that discovery this work will assess for the importance of risk tolerance and its influence on ERM effectiveness, and if risk-based decisions are clearly linked to ERM in practice.

1.4 Expected Findings and Contributions

This research builds upon the understanding of how corporate strategy, corporate governance and risk management have historically interplayed, and can support each other (Brealy et al 2011), (Hillier et al 2008). Given society's complex and evolving financial and economic landscape, banks and insurers must embrace frameworks that seamlessly connect risk, finance, capital and strategy into a cohesive structure. But they must also recognize their risk capacity and operating limitations. Strategists and risk managers should have equal footing and influence throughout the firm and only accept risks for which they fully understand. This is predicated on appropriate risk selection and decision making recognizing associated capital costs (Miles and Ezzell 1980), (Brealy et al 2011), thus avoiding a valuation discount due to questionable risk management.

This research exercise will present new ideas, critique or validate existing approaches, and ultimately provide an additional source of reference for executives, financial market participants and academia. It may not immediately and dramatically shift the way leaders of banks and insurers approach risk specifically, or manage their firms generally. However, it will frame and clarify issues and present perspectives that will enrich the risk acumen of these leaders. The goal of this work is to bring to fore a connected view of different influences on enterprise risk management effectiveness that are often researched separately, or whose conclusions are less comprehensive for the practitioner. This should enable bank and insurance executives, and their boards, to better understand how to approach their risk bearing capacity, and the appropriateness of their ERM frameworks. Moreover, this should help them design, implement and execute more effective enterprise risk management processes, and to identify strategies that are appropriate to their risk appetite and stakeholder expectations.

Ideally this will facilitate an increased likelihood of managers making decisions that reduce agency costs, lead to long-term value, and are appreciated by multiple stakeholders. Over time these value-generating actions may attract more interest by investors to the overall industry, potentially increasing market capitalization on a systematic basis. What is more, society would realize economic benefits as more capital is directed into financial institutions enabling these firms to persist over time and to offer more products and services to society - e.g., more abundant and affordable loans and insurance.

1.5 Thesis Structure

The goal of this research is to evaluate if the connection between Enterprise Risk Management (ERM) and value or performance is as evident as its supporters would suggest, but more importantly to provide insight as to the role that risk tolerance has within these relationships. An alternative format thesis is used to research and articulate these findings. The motivation for this format is multifaceted.

Firstly, a driving theme of this doctoral research is to contribute directly to academic and industry knowledge jointly, and the compartmentalized structure of an alternative format allows that in an efficient way in this instance. The research results of each manuscript is designed as a standalone piece ready for journal submission. Indeed, one of the articles written has been published[1] while other elements have been selected for full presentation at multiple academic conferences. By following an alternative format the practical understanding of article composition and structure is reinforced early, which should help with a more efficient journal submission and publication processes in the future. Preparing the thesis in this structure enables a timely completion of my doctoral studies and immediate contribution to literature.

Secondly, despite conducting research across multiple independent papers, each paper is linked to the other, and their composition coincides with the pace of my doctoral studies. The thematic survey of the literature, the first manuscript, forms the foundation of the overall thesis as respects to defining ERM and the role of risk tolerance within ERM; and this originated as the literature review project of the DBA program curriculum. The second manuscript, which was an expansion of the required doctoral pilot project, and the third both build on the foundations established in the survey of literature. These papers present thoughts on how value and performance are each related to optimal tolerance ranges. Finally the fourth manuscript extracts findings and concepts developed in the first three to show a relationship

[1] Chapter 5, manuscript 3, of this thesis has been published as a research paper entitled: "Enterprise Risk (Mis)Management – Performance Implications of the Misapplication of Risk Capacity", 2016, Journal of Finance and Risk Perspectives - Special Issue of Finance Risk and Accounting Perspectives, v5 (1): 1-21.

between strong ERM and risk-based allocation decisions. In essence, this collection of manuscripts could serve as the first four chapters of a text book on implementing ERM.

Thirdly, at its core the DBA program is designed to encourage research and development of theoretical concepts for practical applicability – i.e., research that can be used in real world business applications. This is different from a traditional theory-driven research doctoral program. The traditional doctoral thesis format is often well-suited for theory-driven research, while the concise and compartmentalized structure of an alternative format thesis can in certain instances be more useful for practical-driven research. In the author's case this jointly facilitated more timely completion of the research as a whole, and was important as some of the findings in certain papers were utilized within the deliverables of advisory mandates on a real-time basis for clients of the author. These outcomes may have been more challenging following a traditional thesis format.

Generally, the alternative format should make the thesis more accessible to readers that may readily make use of the findings and conclusions. Each results chapter (manuscript) is linked to findings from the other results chapters (manuscripts) to show a logical and fluid discussion that might be less effectively demonstrated in a traditional thesis structure. Following this introduction, Chapter 2 provides a summary of research methodologies used for each manuscript. Chapter 3 presents the first manuscript: a thematic review of the literature and foundation for the thesis. Chapter 4 is the second manuscript which evaluates the efficacy of an ERM measure developed by Gordon et al (2009) and how risk tolerances moderate ERM's relationship to value of certain U.S. banks and insurance companies. Chapter 5 is the third manuscript, and expands on the findings of Chapter 4. It introduces the notion of establishing optimal risk tolerances and how performance measures can suffer when insurers deviate from those optimal tolerance ranges. Chapter 6 is the fourth and final manuscript utilizing several findings of Chapters 2, 3 and 4. It employs a mixed method of research including a quantitative time-fixed panel study coupled with a qualitative review of mini case studies, both focused on U.S. insurance companies. This mixed method evaluates how organizations may budget their risk choices in different areas given the nature of their ERM, how ERM interacts with overall risk tolerances while controlling for time and industry effects. Finally, Capter 7 presents a summary and concluding comments.

Chapter 2.

Methodology Review

2.1 Methodology Used for "Framing Enterprise Risk Management and Its Influence on Risk Tolerance, Value and Performance" (Manuscript 1)

Enterprise risk management (ERM) garners a lot of focus and attention for academia and industry. Several bodies of work have been designed to frame what quality ERM should entail, and how this influences a whole host of business administration objections: corporate governance, valuations, performance, etc. Manuscript 1 is meant to consolidate certain themes as respect to ERM into one thematic discussion.

Manuscript 1 develops a thematic review and summary of key literature surrounding ERM with mostly qualitative and some quantitative approaches. Qualitative data analysis is used to assessing findings, to triangulate conclusions and to summarize broad thoughts of ERM expressed within the literature. ERM concepts are categorized into different themes, which helps facilitate a synthesized understanding of what ERM is, how researchers have chosen to evaluate it and where gaps might exist in the literature. Some quantitative analysis is employed also. This is measures different frequencies of research methods used, common publication sources and other trends notable within the literature.

Manuscript 1 serves as a foundation for other researchers to assess certain areas where and how ERM has been evaluated to a point in time. It also acts as a groundwork for the remaining three manuscripts included in this thesis.

2.2 Methodology Used for "Enterprise Risk (Mis)Management – Value Implications of the Misapplication of Risk Capacity" (Manuscript 2)

There are growing numbers of studies that purport a relationship between ERM and value or between ERM and performance. Often these hypothesis apply some sort of multivariate linear regression modelling technique where a proxy for ERM coupled with multiple control variables are used as predictors of value or performance estimates. Some of these approaches show that a statistically significant relationship is evident. However, lacking in those discussions is if or how corporate risk tolerance interacts with any relationship between ERM and value or performance.

The focus of this manuscript is on a sample of U.S. publicly listed insurance companies and U.S. publically listed saving and loans banks, due in part to the greater data availability common to these industries. Data comes from commonly used secondary financial data sources such as CRSP, COMPUSTAT, SNLFinancial, and Bloomberg. The analysis covers a three year period from 2010 to 2012, with the same sample of companies used in each year.

A hierarchical interaction regression technique, using both simple linear and polynomial regression structures are used. This includes moderation and mediation regressions, and response surface analysis. The goal is to assess for evidence where risk tolerance either moderates or mediates ERM's influence on value and performance. Regression variables will include proxies for value, performance, risk tolerance and ERM.

The findings from this study should provide worthy practical consideration for managers of banks and insurance companies as they consider using ERM for operational efficiency and related decision-making, for capital providers as they choose which financial institutions to provide capital to and at what cost, and for regulators as they look to evaluate the solvency of financial institutions for stability within the broader financial systems that they oversee.

2.3 Methodology Used for "Enterprise Risk (Mis)Management – Performance Implications of the Misapplication of Risk Capacity" (Manuscript 3)

Risk tolerance can be defined as the degree of exposure to loss a company choices to accept as part of its operational strategy. A firm that assumes a relatively high risk tolerance might do so given higher expected rewards for the additional risk, or because a company understands certain risks better than others. Yet, determining an optimal risk tolerance may not always be obvious. A goal of this study is to examine the extent of which a strong and integrated ERM framework, coupled with other company-specific factors can be used to determine a company's optimal risk tolerance. Additionally, this research assesses to what degree deviations from this optimal range influences performance characteristics of a company.

The focus will be on a sample of U.S. publicly listed insurance companies given the data availability common to this industry. Data comes from commonly used secondary financial data sources such as CRSP, COMPUSTAT, SNLFinancial, and Bloomberg. Company specific data sourced from annual filings, websites and analysts reports are used as well to establish how integrated a company's ERM process is. The analysis focuses on the 2013 financial reporting year for the sample companies.

Manuscript 3 utilizes a two stage multivariate regression. Stage one uses a stepwise linear regression process to establish and evaluate a multivariate model where a company's ERM measurement and other company risk factors can be used to estimate an optimal risk tolerance. Stage two assesses if deviations from the stage one model – exhibiting a risk tolerance that is too low or too high – are related to performance. The primary regression variables include proxies for performance, risk tolerance, ERM, and control variables such as organizational complexity, age, sector (life or non-life), financial leverage, market share, size, etc.

The two stage regression approach is meant to account for potential non-linear relationships between ERM and performance. Moreover, it is the first attempt at creating a modelling framework to determine optimal risk tolerances for an organization that accounts for a firm's demographics and ERM strength.

This research should contribute to the existing literature in multiple ways. It provides a framework to estimate an appropriate risk tolerance. It links multiple empirical and theoretical works to cohesively demonstrate how and why ERM influences performance. Unlike most existing literature, this research does not presume that ERM is directly linked to performance. Indeed, it shows that ERM's effectiveness is both predicated on its integration as well as its adaptation towards a well-structured risk tolerance.

2.4 Methodology Used for "Risk Budget Structures and the Relevance of Enterprise Risk Management (ERM)" (Manuscript 4)

Insurance companies are in business to assume risk. Their cash flows and earnings are predicated on effective risk selection and pricing for the risks that they select. The primary sources for earnings come from underwriting income (insurance premiums net of insurance claims and operational expenses) plus investment income. The proportion of underwriting income relative investment income will vary by insurer. This split might depend in part on the perceived relative risk for each area in a period. For example, an insurer may elect to assume higher insurance income for those years when investment income is deemed riskier all else equal. This may also be driven by the financial and operational capacity to assume and retain certain risks over others. Collectively, these risk preferences may influence how risk is budgeted within the firm.

This research applies a mixed method approach. Method one is a quantitative study utilizing multiple linear panel regression modelling. Method two is a qualitative study utilizing case-study interviews.

Method one uses a sample of U.S. publicly listed insurance companies. A time-fixed panel multiple regression is applied. The relationship among ERM, risk tolerance and risk budgeting is considered, while using certain control variables. Data comes from commonly used secondary financial data sources such as CRSP, COMPUSTAT, SNLFinancial, and Bloomberg. The time frame used is annual periods from 2008 to 2013. The fixed effects used are the three insurance industry types in the United States – i.e., health, life and property casualty. The goal is to confirm a relationship among ERM, risk tolerance and risk budgets, and if this relationship varies by industry over time.

Method two uses a sample of nine insurance companies. Interviews with senior risk and finance leaders within these firms are used to collect qualitative data on the ERM processes and risk preferences within these firms. This part of the study assesses qualitative data to determine the nature of the relationship among ERM, risk tolerance and risk budgets; while Method one is used to identify if a relationship exits. Method two brings additional insights not readily apparent through quantitative analysis alone.

This study augments existing research evaluating how insurers balance their organizational risk and return profile between investments and underwriting, while considering the potential influence of enterprise risk management over time. It also provides a more recent perspective to this idea, as most research focused on insurer risk management appears to consider data prior to the 2008 financial crisis. Findings adds color regarding how ERM and risk preferences have evolved since the financial crisis.

Chapter 3.

Manuscript 1:

A Thematic Review of Literature Framing Enterprise Risk Management with Risk Tolerance, Value and Performance

3.1 Abstract

Enterprise risk management (ERM) is a research area of growing popularity within academia and industry alike. The pool of literature on the topic grows deeper, but it is still relatively shallow compared to other more seasoned disciplines. What seems particularly absent is a deep review of the relationship between ERM and risk tolerance, and how this relationship impacts the effectiveness of ERM. This paper intends to review and organize some of the applicable literature related to this topic, and across four main themes. First, is a review of works discussing the theoretical components of traditional risk management including how it has been defined, and its relevance to financial institutions. Second is an assessment of literature reviewing ERM from a theoretical and empirical perspective, including elements consistent with effective ERM frameworks, the role of multi criteria decision making, and ERM's value proposition. Third is a review of qualitative and quantitative research methods commonly employed in research linked to ERM. Finally, there will be a summary discussion of the apparent gaps that exist in the current literature relevant to the topic in question. A key finding is that studies in this space are limited, but growing. Findings suggest that effective ERM is a contributing factor to value and performance for financial institutions and perhaps other types of firms. However, the role of risk preferences and tolerances in the ERM dynamic is less obvious in the literature. Such findings highlight the need for further exploration of ERM and its role in the business administration process.

3.2 Key Words

Decision Making, Enterprise Risk Management, Risk Management, Risk Tolerance

3.3 Introduction

The concept of Enterprise Risk Management (ERM) is one where its user utilizes a holistic understanding of the risks and return opportunities inherent to, and across the full spectrum of, the operations of the firm. That holistic understanding enables the user to make better decisions regarding the allocation of resources, such as capital. From a corporate finance or operations research perspective, ERM is a relatively new idea, but its roots are linked to the well established notion of "traditional" risk management based in control or transfer of risk via limit setting, hazard insurance or financial hedging.

Research around the ERM concept is growing, but publications explicitly related to it lag traditional risk management research. Most efforts focused on ERM are motivated by defining the theoretical notions of it, the nature of utilization of ERM, and a few instances of empirical analysis of ERM's effectiveness from a value perspective.

The following review will explore the existing literature as it relates to ERM, including thoughts on:

- Synthesizing the literature as it relates to ERM and its influence on decision making for financial institutions, including notable (in)consistencies
- How different established areas of study connect directly or indirectly to ERM
- Where gaps exist in the literature, particularly from an empirical perspective, and particularly as it relates to the decision-making and resulting financial performance of publicly traded banks and insurance companies within the U.S.
- Research methods commonly used, and some overlooked
- Considerations of which further research should be mindful

The remaining section of this paper is structured as follows. **Section 3.4** focuses on what we define as traditional risk management, where the practitioner's general objective is to reduce, limit or eliminate loss of some sort. **Section 3.5** introduces ERM, how and where it expands on traditional risk management by both controlling downside risks and leveraging risk taking into value generation. **Section 3.6** provides an overview of the research methodologies and techniques often utilized within the risk management research space. **Section 3.7** discusses some relevant gaps in the literature and suggestions for further research in this area. **Section 3.8** is our conclusion

3.4 Traditional Risk Management

3.4.1 Defining Risk and Risk Management

Risk can mean different things to different people. Therefore it is worth level setting a definition for the purposes of this literature review. Webster's New World College Dictionary (2000) includes in its definition of risk the following:

"the chance of injury, damage, or loss; dangerous chance; hazard"

From a corporate finance perspective, particularly with banks and insurance companies, risk can be viewed broadly as something that leads to a loss of value of some meaningful degree. This can be sourced from financial activities or operational activities. However, simply realizing a loss, as noted by Webster's might be within the realm of expectation, and as such is not unusual or risky per se. For example, banks make loans and expect some of those loans to become delinquent at some point, and insurance companies expect to pay some level of insurance claims for the policies that they underwrite. Both the bank and the insurer are structured to realize a certain level of financial loss through the course of normal business. So we must amend the definition of risk for the purposes of the theme within this paper to include the "unexpected" financial loss.

Manufacturing firms, retail and distribution companies, energy supply firms, utility companies and even service providers are exposed to loss of value of some meaningful degree, but the sources of that loss are likely to vary by industry. For example, the economics surrounding energy prices and supply will be a concern for both utilities and energy suppliers, but less so for clothing retailers. Despite these different sources, the end concern is similar - what are the risks across the enterprise that can have a significant impact to the value of the firm. For the purposes of this discussion the focus on risk will be towards the perspective of ERM by banks and insurance companies, but at times other industries will be considered to the extent that relevant literature exists in this regard.

Now that risk has been defined let us reflect on what is meant by the management of risk, and how this will be considered within the review of the literature. In the context of the discussion in this essay, risk management is a means to curb or limit the firm's exposure to adverse events, and to the extent those events occur, the resulting loss levels are kept within tolerable ranges. In this context risk management includes the identification, measurement, mitigation or transfer of specific risks inherent to the firm with the goal that if there are adverse events, management will expect them to occur within the normal course of business. This aligns to definitions posed by most texts and thought pieces focused on risk management at financial institutions.

3.4.2 (Un)Justification of Risk Management

There are different studies that examine the motivations and justifications of risk management. Some considering connections between good risk management and value such as Fairchild (2002) and Smithson and Simkins (2005). Some suggest employing such processes makes for prudent management decision making and useful exercise for the sustainability of the firm over time. Others argue that managers might have access to certain economies of scale or better access to risk management activities than capital providers. Reduced agency costs have also been cited. However, some studies contrast these arguments or present alternative perspectives that imply limitations of risk management or that it is not useful overall.

Let us first examine some of the arguments in favor of or that justify risk management. Financing decisions, including the impact of taxes and their linkage to leverage and capital structure, has been considered in multiple studies. One position by Graham and Rogers (2002) note that firms apply risk management activities when the cost to do so is outweighed by the benefits of tax offsets via increased debt capacity. Indeed reducing tax burdens and financial distress are common reasons cited for risk management practices (Smith and Stulz 1985).

Mayers and Smith (1982) show that in addition to tax motivations and financial distress, risk mitigation via insurance reduces regulatory constraints and address other financial concerns of management. Overall several arguments have been presented that explain risk management's appropriateness in an overall corporate finance context, including: diversification (Mayers and Smith 1990), financial flexibility and internal versus external costs of capital (Froot et al 1993), risk preferences and the incentives of management (Smith and Stulz 1985).

Productivity has also been cited as linked to certain types of risk management activities. For instance Cornaggia (2013) showed that within the U.S. agricultural industry certain financial constraints can be reduced through insurance and hedging, which also allows improved access to financing to fund high productivity projects.

Risk management's justification goes beyond managing the idiosyncratic risks unique to a firm and shared between the firm and its capital providers. There are arguments that look at the aggregate of micro and macro factors that can result when risk taking is left unchecked, and ethical elements come into consideration, which impacts all stakeholders. Petrick (2011) showed exactly this using the global financial crisis of 2008 as the type of global financial disruption that can be avoided through prudent financial risk management practices.

However, there have been theories that suggest risk management is not a necessary practice upon which management should engage, or it is at least questionable to do so given the data. Mian (1996) provides empirical evidence that challenges or undermines any strong claim that some of the risk management benefits outlined above have true value. Although insightful, this study was limited to a set of firms' public disclosures for 1992. By focusing on just one year as opposed to a time series incorporating multiple extreme events where risk management can be more thoroughly tested, making any broad conclusions on this and similarly structured studies would be limiting.

Risk management has been cited as means to reduce agency costs[2]. Some have suggested that risk management is not relevant for this, and that shareholders would be better positioned to manage risk to their own tolerances, then to leave this up to managers acting on their behalf. Leland (2002) showed that certain financial stresses such as bankruptcy costs, faster debt maturity schedules and low cash flows, which theoretically would benefit from certain risk management hedging activities, are often already associated with low agency costs. This raises questions as to why would risk management would be necessary in this regard.

Other studies questioning the purpose and place of risk management have focused on the systemic and structural elements of risk taking and risk managing that permeates in capital markets and insurance markets. These studies suggest that risk management elevates financial market stresses and dislocations. Mergers and acquisitions make firms larger and more global, and potentially increases the level of risks retained by organizations. Moreover, risk management software solutions with similar if not exact model specifications can be used by similar banks and insurers, and if those specifications are wrong this impacts a large group of market participants at the same time. By the nature of banking and insurance, the competitive

[2] Brealey and Myers (2011) define agency costs as those costs incurred by shareholders because management, acting on behalf of shareholders, do not take actions that are designed to maximize shareholder value.

forces of trading within these industries dictate reliance on similar systems, information and processes to trade risk. If these operational elements fail, then potentially the entire financial system realizes the impact. This notion was studied by Coleman and Pinder (2010) where they showed that, at least in Australia, financial executives tended to rely and assume that similar attributes of the financial system (liquidity, asset prices, risk management tools, etc.) would persist in a favorable way leading up to the 2008 global financial crisis. Another related element to this argument surfaces when one considers overdependence on risk management processes or when risk management is misplaced. Huber and Scheytt (2013) follow this theme, particularly as it relates to the financial crisis. They include in their argument that some practices meant to control risk at the micro level can exacerbate risks at the macro level, and that one element of this problem links back to improper or misaligned accountability within the firm. These arguments suggest that even prudent risk management can fail to manage risk properly when everyone is using the same imperfect information or systems underlying risk management frameworks.

Some evidence either in support of or raising doubts of the purpose and relevance of risk management is helpful, but given that some of these studies were done 15 or more years ago, or targeted other narrow data sets, it is worth at least revisiting these empirically based arguments with newer and comprehensive data. The motivation being that the operational and financial landscape of today has evolved since some of the literature was introduced, and the impact of new regulations, mergers and acquisitions, financial crisis lessons learned, information abundance through social medial and the internet, geopolitical influence, and other economic factors warrant consideration.

3.4.3 Traditional Risk Management

Corporate finance research and economic analysis of the firm have traditionally focused on two areas of risk management - 1) theory, methodology and empirical analysis around hedging risk and 2) the motivation for utilization of insurance to address hazard risks.

Hedging for the sake of this discussion is the means to reduce or eliminate one risk through an action or transaction that offsets the risk outcome. This can be through the use of derivative securities, taking offsetting positions with similar securities[3]. In order for hedging to be effective the structure of the hedge must be appropriate and efficient otherwise the instrument used for the hedge may not perform as intended to address the risk it was meant to offset (Crouhy et al 2006).

Several studies exist on hedging utilization and application, with impact across multiple industries. Research shows that agricultural organizations or others that are susceptible to weather might find benefit from the use of weather derivatives (Wang et al 2010). Airlines susceptible to fuel costs have shown to hedge this exposure (Carter et al 2006). Energy producers focused on related supply and demand of their product also can realize value from hedging with financial instruments (Yanbo and Jorion 2006). Banks and insurance companies have interest rates, credit default exposure and other financial risks to contend with on their balance sheets and hedging presents a means to reduce those concerns (Colquitt and Hoyt 1997). Finally, firms with trading partners or operations in other geographies have foreign currency valuations that present risks to earnings (Allayannis and Weston 2001). All of these risks can be managed via hedges to some degree. This is not always a simple process. Hedging costs come in different forms.

The literature makes note that a hedge meant to address one risk may create additional risks. This is common, for example, when over-the-counter derivative securities are used, as these can introduce counter-party exposure, credit exposure, liquidity exposure or operational stresses at the exact time when a hedge outcome is needed, presenting unanticipated operational or financial risks and undermining the intents of the hedge, as noted in Choudhry (2004). There is also potential for basis risk associated with the hedge in that some hedges do not perfectly offset a loss given the structural elements of the hedge, thus leaving some degree of variability not addressed. Moreover, Froot et al (1993) argue that the payoff nature of non-linear instruments such as options are more appropriate for corporate financing decisions than hedges with linear payoffs common with futures and forward derivative contracts. However, derivatives with linear payoffs might be well-suited when considering risks of rising supply costs. Text books focused on financial risk management address many of these topics for a practitioners perspective, e.g., Crouhy et al (2001) or Culp (2004).

[3] For example – interest rate forward agreements or stock options or other derivative structures.

Studies have explored the appropriateness of explicit financial hedging, and if a firm's natural (operational) hedges are a preferred means to manage risk. For example, Allayannis et al (2001) showed that larger global organizations susceptible to foreign currency risks were more likely to use financial hedges (e.g., currency financial instruments) and would do so in conjunction with naturally occurring operational hedges. These risk management actions were shown to be a contributor to shareholder value (Géczy et al 1997), suggesting that certain stakeholders want hedging actions to be in place.

Commercial hazard insurance is the other commonly cited risk management tool for firms. Here loss associated with a whole host of risks or hazards such as weather-related property damage, theft, health costs or liability to products or services can be considered for insurance, but to apply a universal definition to insurance can be challenging. Culp (2002) suggests five attributes for something to qualify as insurance considering among other things an exchange of premium and the notion of risk transfer or risk sharing between the insurer and the insured. Following Culp (2002)'s definition studies show that insurance can transfer risk to those with comparative advantages to assume it, can lower transaction costs of bankruptcy, can make for more effective tax management, and reduced regulatory constraints, among others (Mayers and Smith 1982). Another study considerers the perspective of insurance companies shows that a less diversified ownership structure can lead to relatively higher reinsurance[4] purchases (Mayers and Smith 1990).

It is worth noting that not all risk management instruments that can reduce and transfer risk are used only for hedging purposes, some are used for speculation. Even insurance companies are taking a speculative position when they issue an insurance policy, expecting either to make a profit on the policy itself or to earn a net positive rate of return on the cash flows associated with insurance premiums. One study that showed a relationship between derivatives usage and risk levels where extensive derivatives usage can add aggregate risk to the risk profile of a firm (Nguyena and Faff 2010), which implies that not all derivatives transactions result in a hedge or means to reduce or offset risk.

Financial hedging and using hazard insurance have been identified as useful means to manage financial and operational risks of firms. Empirical evidence presented has been

[4] Reinsurance is when an insurance company transfers some or all of its insurance liability to another insurance company. This is traditionally done on a treaty (portfolio risk) basis or on a facultative (individual risk) basis.

compelling. However, some of these studies have focused on narrow or dated time periods (e.g., early 1990s), or focused on broad industry groupings with heterogeneous characteristics which elevate potential for spurious relationships to exhibit themselves (Yanbo and Jorion 2006). This implies that at least a refresh of the analysis, particularly as it relates to risk oriented companies such as banks and insurance companies is relevant.

3.5 Enterprise Risk Management

3.5.1 Review of the Theoretical Components and Structure of Enterprise Risk Management

The concept of managing risks, and how risks can interplay across different sources has been in the business vernacular for several years. Consider the piece "Portfolio Selection" by Markowitz (1952). Here risk and return characteristics and dependency structures of different assets are considered jointly, allowing one to create optimal investment portfolios, which minimize risk for a given amount of return or vice versa.

Enterprise risk management (ERM) is defined in subtly different ways within existing journal articles and text books, but the theme underlying those definitions are becoming more consistent. The premise being that all risks that an enterprise is exposed to should be managed in a collective way, as opposed to traditional, silo-driven risk management where there is only independent focus on specific areas or functions such as financial risks or operational risks. This collective understanding, where risks are viewed in a portfolio context, is argued as more optimal and should lead to more informed decisions as there is greater appreciation of how risks across the enterprise interact and behave on a collective basis. ERM is now the standard means of expression for this concept, but earlier works on the topic include phraseology that are synonymous to ERM such as enterprise-wide risk management (Culp 2001), integrated risk management (Colquitt et al 1999), (Meulbroek 2002) or holistic risk management.

Some of the first research pieces on the concept of ERM surfaced in the early 2000s. These early works often positioned ERM as a governance framework, and sometimes took the perspective of accountants and auditors where limiting or controlling risk was paramount. The work from COSO (2004) outlined a structured and control process covering a joint view of core considerations such as strategy, operations, reporting and compliance and their role in the risk management process. Corporate governance has been a research consideration as to how and when ERM is implemented (Kleffner et al 2003). Moreover, there are multiple works suggesting best practice of how ERM frameworks should be structured and how the risk assessment process within an ERM construct should function. COSO (2012) is one example, with credit rating agencies such as Standard & Poor's (2013a) and AM Best (2013c) offering their views as well. Moreover, any search on amazon.com of books with the words “enterprise risk management” will bring back several options with authors pontificating their views of ERM standards and best practice.

Ownership of the ERM construct has also been considered. Questions and evidence have been assessed surrounding the evolving roles of the various levels of the firm from the board of directors to line level management, as well as functional roles and responsibilities such as internal audit, finance and accounting, and dedicated risk departments (Arena et al 2010). Studies have explored the role of the chief risk officer (CRO) or equivalent, and have shown that this role is becoming more common within the corporate governance structure, and that the need for CROs is often linked to the risk characteristics and preferences of the firm. Firms with more aggressive risk profiles are more likely to have CROs on staff (Pagach and Warr 2011). Indeed, the capital structure, namely leverage, has been an indicator of the desire of a CRO or equivalent position (Liebenberg and Hoyt 2003), (Pagach and Warr 2011). Others suggest that the CRO is now a standard C-Suite level position needed in response to the growing complexity of financial institutions, and whose ongoing role transcends compliance, value and capital management (InsuranceERM 2017).

Credit rating agencies such as Standard & Poor's and A.M. Best, who assess financial strength and claims paying abilities of insurance companies, produced white papers on ERM as well. As mentioned above, these works provide guidance on ERM best practice and how ERM is considered in the ratings process for these rating agencies. Standard & Poor’s views ERM as a collective appreciation of risk culture, risk controls, emerging risk management, risk modeling and strategic risk management (Standard & Poor's 2013a). From AM Best's perspective ERM consists of three primary characteristics: culture, identification and measurement. Moreover, these characteristics are meant to address five key risks: credit risk, market risk, underwriting risk, operational risk and strategic risk (AM Best 2013c).

Research around ERM is not unique to banks and insurers. Indeed, manufacturing firms where logistics is a major risk, or energy providers where supply is a major risk are examples of other industries that could possibly embrace the ERM concept, albeit in a slightly different ways. However, evidence does not always support this theoretical ideal. An example is the work by Blome and Schoenherr (2011) which explored supply chain risk management (SCRM) and how this could be linked with ERM, considering stress events such as the 2008 financial crisis. Their findings (based on case studies) suggest that at the time of their analysis SCRM and ERM were potentially too distinct to be integrated. This was just one study focused on a limited pool, and warrants further exploration prior to formulating any generalized theories.

3.5.2 ERM and Economic Capital Modeling

One attribute of ERM constructs is that it facilitates a better discovery and understanding of the risk profile of the firm. This helps management make better decisions around the source and use of capital. As part of that discovery process many organizations that utilize ERM, particularly financial institutions, use economic capital modeling (ECM)[5] as part of that ERM framework. ECM can be defined as:

". . . the methods or practices that allow banks to consistently assess risk and attribute capital to cover the economic effects of risk-taking activities."

(BIS 2009), p1

The literature offers different ways to measure economic capital, but ECMs are often structured as complex risk modeling systems that tend to use Monte Carlo simulations to generate a distribution of outcomes upon which statistical analysis can be made, such as estimating earnings or capital loss frequencies (Klaassen and Eeghen 2009). This would include measures of downside risk under extreme events such as 1-in-200 year likelihoods (i.e., 99.5 percentile of a probability). Writings on ECM profess it as a process to assess how risks behave in their silos (e.g., equity market risk versus credit risk) and how they interact with other risks at the enterprise level. Therefore, ECMs may start from a ground up process where risks are first assessed individually and then compiled to formulate an enterprise-wide perspective for risk aggregation. Or it may be top down approach where there is a view taken at the enterprise level first, and then that is decomposed by each risk area (De Weert and Ebrary Inc. 2011). Regardless of the starting point, the notion of Value-at-Risk (VAR) or Tail Value-at-Risk

[5] Economic capital modeling is also known as risk capital modeling and risk-based capital modeling. These terms are sometimes used interchangeably.

(TVAR)[6] can be used as a means to support the ECM measurement process (Crouhy et al 2001). See **Section 3.11 Appendix C** for a broader discussion on VAR and TVAR.

At the enterprise level, the output from an ECM might note that management is 99% confident that there would not be a loss that would deplete capital by more than 30% over the course of one year. In other words the risk modeling process predicts that there is only a 1-in-100 chance that there will be a capital loss greater than 30% over the next 12 months. TVAR builds on the VAR concept and says that if you do realize that 1% possible loss, what will be the expected amount of that loss. Both VAR and TVAR are tail risk measures or downside risk measures. Evidence show that banks and insurers commonly use these metrics to measure the type of significant risk of loss that they are exposed to and are concerned about, yet other industries are rarely focused on or even consider such metrics (De Weert and ebrary Inc. 2011).

The output of ECMs is centered around a measure at some degree of confidence of the amount of capital that would be required to absorb extreme financial loss. This is often assessed against available capital within the firm. The greater the amount of your available capital relative to the required capital, the greater the capital strength of the firm. For some organizations such information provides a proxy of a firm's risk profile as well. There have been several articles and text books that examine such theoretical construct of ECMs, how they should be designed, how the information from ECMs should be used, and the role of ECMs within an ERM framework - e.g., Klaassen and Eeghen (2009), Standard & Poor's (2011a), De Weert and ebrary Inc. (2011). But empirical studies assessing the extent of ECM usage and effectiveness are less abundant, perhaps because little is required of banks and insurance companies regarding public disclosure of ECM reporting.

Regulators and rating agencies often use risk-based capital (RBC) models of their own when evaluating the risk profiles of banks and insurers, with a particular focus on solvency and financial strength of these institutions (e.g., AM Best 2013b, EIOPA (F.K.A CEIOPS) 2010). These models use generic and deterministic calculations to measure required capital to absorb the significant risks generated by the operations of the firm. In theory firms with riskier liabilities and assets would be expected to hold more capital than firms with relatively less risky liabilities and assets all else equal. However, RBC models are designed to be "one-size-fits-all" so that users of them can gauge in a consistent way the financial strength and capital

[6] Also known as conditional tail expectation (CTE) or expected shortfall.

risks of several firms. This generic approach may suggest different conclusions than an internal ECM tailored specifically to one firm. Therefore, ERM practitioners must be able to reconcile how their ECMs differ from the RBC models positioned by rating agencies and regulators (e.g. Standard & Poor's 2011a, 2013c). Similar to internal ECMs, RBC models provide some perspective of economic or risk capital of the firm. However, internal models would be tailored to unique attributes and risk preferences of a firm that a generic RBC would overlook. For example, RBCs and ECMs may focus on different reporting horizons (Crouhy et al 2001) or may reflect different risk dependency structures, which can distort comparisons and even motivate different risk management actions (NEAM 2017).

The literature shows how and why an ECM process ultimately enables the risk manager to compare alternatives using a consistent language supporting capital allocation decisions and managing to risk tolerances (Culp 2001). For example, a global insurance company with three potential demands on a limited amount of capital: 1) growing a property insurance operation in the United States, 2) an annuities and life insurance offering in Canada, and 3) an acquisition target in the United Kingdom. These three opportunities would have very different risk characteristics when you consider frequency and severity, while also exhibiting variable profitability profiles, creating challenging decisions to be made as to which of the three are most optimal. Discussions of how net present value and internal rates of return are commonly positioned in corporate finance text books (e.g., Brealey et al 2011) as a means to evaluate such alternatives, but these calculations assumes a consistent definition of risk, which can be over(under)stated particularly give the RBC charges and related capital constraints that also need to be considered. The literature suggests that an ECM framework could address this problem, and reduce the ambiguity of that capital allocation decision. Ai et al (2012) follow this concept where they assume a hypothetical company is primarily focused on maximizing return on capital, and offers a quantitative framework that incorporates various constraints and factors that a firm could consider. Nocco and Stulz (2006) take a purely qualitative approach offering rationale as to why economic capital frameworks enhance the overall decision-making process.

There is research showing that ECMs are used by banks and insurance companies. One can look at the public filings and websites of some banks and insurers and see evidence of this as ECM's are sometimes discussed as part of management's discussion of risk and capital management. Research surveys also show evidence of this with major accounting and consulting firms producing periodic industry surveys on ERM denoting some measure of the extent of ECM usage as part of ERM processes. Some of these surveys are produced annually, allowing one to estimate ECM usage over time. Survey examples include: Deloitte (2012), PricewaterhouseCoopers LLP (2013) and Towers Watson (2013a). These industry surveys note that usage of ECMs are at least partially driven by geography and sector, among other factors, suggesting areas for further exploration within an academic lens to determine why such relationships exist and what could be gleaned from them.

It is worth noting that economic capital helps measure risk capacity. Internally developed ECMs developed by management and external RBC models applied by rating agencies and regulators both represent a view of risk capital, or required solvency capital, to support the risk profile of the firm. When this is measured against available capital the firm measures its risk bearing capacity – higher available capital or lower required capital suggests greater risk bearing capacity all else equal. This idea and the research supporting it will be discussed in more detail below in **subsection 3.5.3** of how ERM supports multi criteria decision-making.

Given the multiple ways to construct ECMs, coupled with inherent differences in the risk profile of one firm to another, there is little consistency from firm to firm regarding ECM processes and their role within ERM constructs. Moreover, there is no requirement for banks or insurers to disclose publically (in any detail that would be useful for empirical studies) how they have constructed, calculated, and allocated economic capital. This presents challenges to researches looking to gain insight on when and where ECM's are effective within an ERM framework, and ultimately with risk-based decision making. Therefore, evidence of the presence of ECMs alone does not provide complete information for the research community to gauge the effectiveness of ECMs, and to ultimately refine ECM approaches and their role within the ERM construct. Some other qualifier needs to come into play. This may eventually become readily available as secondary data such as financial disclosures become more transparent, or this may have to be identified via surveys or other means of primary data extrapolation perhaps via case studies and structured interviews. Many questions regarding the following are mostly unanswered within the literature:

- ECM reliability and predictability – e.g., is there empirical evidence to suggest that certain modeling processes are more robust or less flawed than others in any way

- ECM applicability – e.g., are ECMs more appropriate for firms with stronger ERM; do findings suggest that certain types of ECMs (stochastic, deterministic, blended, etc.) are more appropriate to certain types of organizations (industry, size, age, jurisdiction, etc.)
- ECM necessity – e.g., when is an ECM framework a luxury and when is it ever a requirement in order for ERM, capital management and related decision making to be effective
- ECM exploitability – e.g., evidence that some firms abuse or misuse ECM processes within ERM and capital planning frameworks

What is evident in the literature is that ECMs are a useful element of ERM frameworks for many insurers and banks. However, how these are used are not fully understood from an empirical sense, particularly as it relates to decision-making. Most studies focus on how to develop and implement ECMS, but take a theoretical perspective. Little in the literature discusses empirical analysis of ECMs in practice beyond surveys denoting usage.

3.5.3 ERM and Multi Criteria Decision Making

Brealey et al (2011) show that managers, acting on behalf of shareholders, must decide where and how to allocate resources most effectively throughout the firm. This is part of the capital budgeting process, perhaps the quintessential decision process for a financial institution. Most corporate financial literature will profess that decisions surrounding capital allocation are usually made with the understanding that projects which use capital will generate adequate returns to cover the costs of that capital, satisfying the expectations of shareholders, bond holders and other key capital providers to the firm. However, at issue is that these allocation decisions are not always clear (e.g., return and cost estimation), may be mutually exclusive or at least must reflect the changing expectations of stakeholders. Schrand and Unal (1998) look at U.S. savings and loan institutions that converted from a mutual ownership structure to a stock company. Their findings show that the decisions surrounding the risk management process and the allocation of risk change as the dynamics of the stakeholders change. This is one example of how risk preferences of management adapt to shareholder expectation in order to target a preferred risk profile.

These notions of 1) preferences or expectations and 2) targets, boundaries or constraints are elements considered in multi criteria decision making (MCDM). The basics of MCDM within the literature describe it as a means of determining optimal choices predicated on preferences and boundaries, recognizing that these may have conflicting attributes or tradeoffs. The process employed may be linear, non-linear, subjective, objective or a blend. There may be very advanced mathematical constructs employed using thousands of simulations under a Monte Carlo framework, or a simplified system based on different heuristics. Examples of texts that speak to these ideas more specifically include: Bazerman and Moore (2009), Keeney and Raiffa (1993), Sen and Yang (1998), and there are several others.

Within discussion of MCDM preferences are often the elements which influence decisions. Traditional utility theory, predicated on the assumption that people are always rational in their choices, has been a starting point to explain preferences. Most microeconomic text books will discuss utility theory thoroughly (and we offer our thoughts as respects to utility and preferences in a risk management context in **Section 3.12 Appendix D**). However, some empirical studies show that the reality differs from theory and must be recognized in risk-based decision making. Prospect theory has been a concept to articulate risk-based decision making where there is a better understanding of how people will consider risky prospects. Studies show that sometimes people's choices are counterintuitive where logic suggests risk aversion when the odds are against you, though people become risk seeking at exactly that point, or when the same choice and outcome is presented in alternative ways the decisions are inconsistent - e.g., Kahneman and Tversky (1979), Tversky and Kahneman (1992). Studies on the subject go on to suggest that the pain of losing a certain amount often outweighs the euphoria of an equitable winning, which can be a factor when managers are considering how to use capital or other resources when there is uncertainty associated with costs and benefits of such decisions.

Behavioral economics have grown in importance in the social sciences and builds on such notions of prospect theory. This also influences risk-based decision making and is an additional consideration addressed in the literature. Studies focused on behavioral finance have echoed or elaborated on some of the findings of prospect theorists, where decision making dynamics and tendencies have deviated from core economic assumptions. Thaler (1980) and Wood (2010) are examples of works that challenge the assumptions of rational decision making by consumers, which might be applicable to a range of decisions such as spending money on food, limits of gambling or making investment choices. Indeed, financial risk management would be a logical extension of where consumer choice can be biased by irrational or emotional tendencies. So to the extent that ERM assumes that those overseeing it are making appropriate decisions, we must consider if irrationality within an ERM context can exist, and understand the impact to ERM when this is evident. Moreover, researchers should be aware of the potential instances where stakeholders expect risk managers to make certain choices that would seem irrational to an outsider, but are appropriate from an insider's view. This raises the question of prudency versus rationality in the decision making process.

Perhaps one of the most crucial underpinnings of prudent risk management decision-making that goes beyond rationality is integrity. That is to say, the decision maker is driven to make decisions in part based on how the result of that decision will impact their personal rewards. Here rewards are defined as a combination of financial ones such as incentive compensation and non-financial rewards such as titles, responsibilities, power, etc. Studies by Kirkpatrick (2009) and others have posited arguments that the financial crisis of 2008 was at least partially attributed to misaligned incentives.

Therefore, the literature makes it clear that psychological influence should not to be overlooked within an MCDM context. Such influence is sensitive to cultural dynamics, financial incentives and other factors. Personal awareness is an extension of this idea. Studies show that people generally overstate their abilities and convince themselves of their overstated abilities even if statistically this cannot be true (Kruger 1999). Most prudent hiring managers, when faced with a choice of hiring one of several worker candidates seemingly proficient at performing a certain task, would be less inclined to hire a candidate if that person suddenly admitted that they were below average in the requisite skills (all else equal). Logically job candidates would profess proficiency in this regard, even if their skills were deficient, and studies show that this is not necessarily an intentional deception. There is no reason to think risk managers at banks or insurers would position themselves any differently in their abilities to manage risks. Kruger (1999) and Dunning et al (2003) call the tendency for people to overestimate their abilities, particularly those less skilled relative to others, illusory superiority.

Looking beyond a misinformed view of a person's ability to make decisions, studies covering multiple psychological factors such as anchoring and its impact on heuristics (Tversky and Kahneman 1974); how the factors of a decision are framed, e.g., focusing disproportionately on the potential favorable outcome versus the unfavorable alternative (Druckman 2001b); or "group think" where there is potential for antecedents surrounding the nature and structure of groups can influence how and why people make certain decisions (Janis 1982); collectively show that multiple subjective factors play a role in a person's decision making process. These behavioral or psychological factors might play a significant role in

ERM effectiveness broadly, or MCDM as part of an ERM framework specifically. Yet the literature is limited in examining what role these specific concerns have within an ERM context.

Academic and industry led research surrounding MCDM has been a popular focus within operations research for several years. In finance several studies spanning several decades have focused on investment portfolio optimization. Classic examples include Markowitz (1952) and Sharpe (1964) which focus on mean variance optimization and asset portfolio construction in an investment management context. Here risks (volatility), rewards (asset returns), and covariances across a mix of asset types are considered to determine the optimal combination of securities where investors can achieve the highest level of return for any given amount of risk. And the ideal portfolio is selected based on the risk preferences, or utility, of the investor. Following this reasoning, one can view a financial enterprise as a portfolio itself. It consists of liabilities and assets that have associated risks and returns associated with them, and those assets and liabilities co-vary in some way as well, suggesting that there is an optimal mix to generate high levels of enterprise return for a given level of enterprise risk.

Within Enterprise Risk Management (ERM) processes views of risk tolerances, risk appetites, risk budgets, requirements, etc. must be established. The decision maker must understand how such measures of risk and reward balance considering some view of risk preference. So the MCDM process would apply. Indeed, by the very nature and motivation of the ERM construct organizations must assess a broad array of risks that come from a multitude of sources across the entire enterprise. As discussed in the section above, regulators, among others, suggest that the risk aggregation process and related performance attribution is often accomplished through an economic capital modeling framework. Theory and evidence shows that ERM facilitates improved understanding of the firm's risk and reward landscape. Yet it also identifies potential means to enhance returns given an equivalent enhanced understanding of risk. This insight outlines opportunities (returns) and threats (risks), and underlies management decisions at all levels of the firm. Risk capital, economic capital and the resulting measures of risk-adjusted returns are leading forces in the multi criteria decision-making process of ERM within the literature. Therefore, decisions at banks and insurers focus on capital and returns (or earnings) generated by capital, but with differing levels of importance depending on the stakeholder. See **Figure 3.1** below:

Figure 3.1. Stakeholder Expectations of Financial Institutions

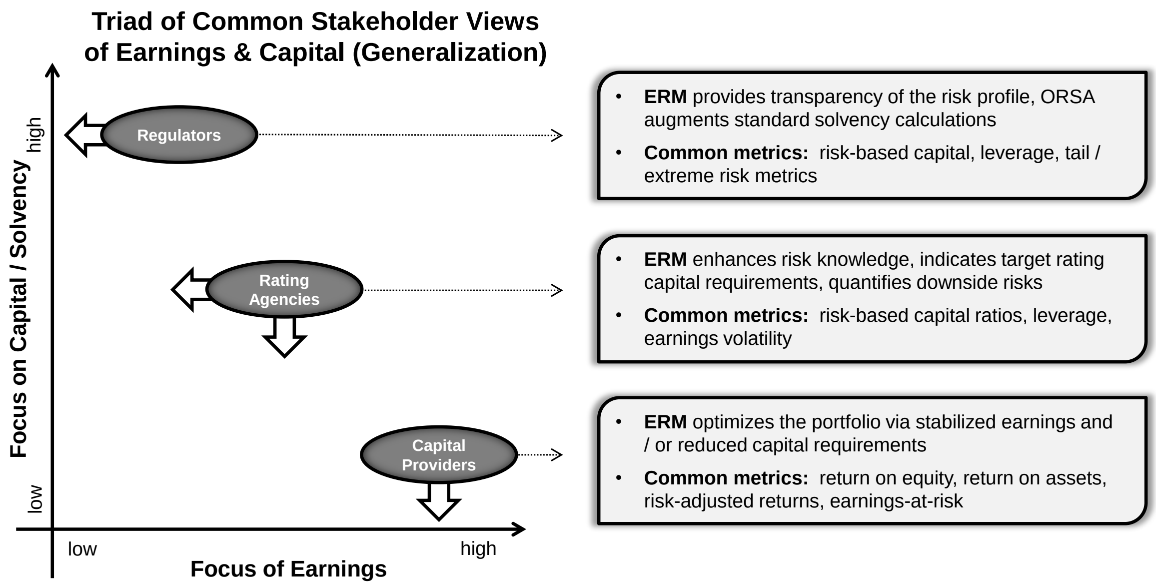


Figure 3.1 is a conceptual visualization of how different stakeholders of financial institutions prioritize the tradeoff between capital and earnings. It also shows how these stakeholders interpret enterprise risk management (ERM) and what common metrics related to ERM that these stakeholders focus upon.

Illustration Source: New England Asset Management Analytics

Not only are there potentially conflicted expectations across stakeholders, but also within a stakeholder. For instance, industry practitioners suggest that regulators have targets regarding the rates that they feel insurers can charge for insurance premiums (Best's News Service 2013) or that banks can charge for loans[7], which effectively limits the amount of capital that can be generated by such products. Yet, as noted above, regulators are setting solvency requirements that establish required capital standards that must be held against those same insurance policies and loans.

Managers of banks and insurance companies are charged with navigating many objectives, and determining how to generate adequate returns measured against appropriate levels of risk is one of them. As noted by Crouhy et al (2006), this concept of seeking actions that generate risk-adjusted returns on capital (RAROC), particularly from an economic capital perspective (Klaassen and Eeghen 2009), is an aspect of prudent operational management and that theoretically should impact value. Moreover, those managers who are able to optimize risk-adjusted returns are able to maximize RAROC given those multiple constraints appropriate

[7] Example is the Unite States Federal Law: "The Credit Card Accountability, Responsibility and Disclosure Act of 2009"

to the risk preference and utility of the firm. These constraints might include earnings volatility thresholds, risk-based capital requirements and other regulator solvency expectations, TVAR / VAR limits, product mix, etc. For example, 'Bank A', a publicly listed stock company may strive to limit the variability of quarterly earnings and stabilize earnings growth to improve prospective valuations and ultimately the level of stock price performance. (The impact that risk management could have in this regard has been considered in the literature (Carson et al 2008), and is explored further in the next section). In contrast, Insurer B, a mutual insurance company, may be less focused on period to period earnings fluctuations, but is concerned with regulatory solvency requirements as it relates to the amount of their capital they must hold, and how much of that capital may be at risk due to significant financial and operational losses. For 'Insurer B' Value-At-Risk (VAR), and other measures of capital at risk, garners heightened focus. However, in the U.S. and certain other countries, both entities will be subjected to certain risk-based capital modeling requirements set forth by rating agencies and regulators (e.g. Standard & Poor's 2011a, 2013c; Bank For International Settlements 2009). The literature suggests that managers at most financial institutions, following the traditions of effective ERM, view the operations within their enterprise as a mix of varied risks with related rewards. Therefore managers strive to balance and control those risks in a way that aligns to utility and risk preferences of the firm (Culp 2001) and the costs or benefits of risk (Nocco and Stulz 2006). Since these risks have different profiles associated with them (e.g., potential returns, degree of volatility), and since these risks may behave with each other in different manners, this portfolio of risks can be structured in optimal ways. The target for this optimization process may be to minimize VAR, to maximize RAROC, or to other thresholds. However, as **Figure 3.1** illustrates, most financial institutions are held accountable to multiple stakeholders (e.g., regulators, rating agencies, debt holders, stock holders, customers, counterparties, etc.), with different expectations, creating multiple criterion for which decisions are made.

This concept is predicated upon or serves to refine risk strategy for the firm. That is to say, in order for an organization to be efficiently and optimally managed, then there must be an understanding of the firm's risk bearing capacity, and an alignment of this capacity to the overall strategy of the firm. This connecting of the known risk strategy by management with that of stakeholders, namely debt and equity capital providers, is explored by some as part of an assessment of agency costs (Leland 2002). An extension of this idea is a study of U.S. life insurance companies in the 1990s (Baranoff et al 2007), where it was found that larger insurers had a significantly different focus than smaller firms with regards to the motivation of capital held considering regulator defined risk capital requirements. Hence it was found that the size of a firm can impact its risk strategy and related decisions.

Utilization of MCDM in a finance context, particularly as it relates to ERM is applicable for further research. At particular interest are the following questions not obviously addressed in the current literature from an empirical perspective: What are the attributes and determinants of a highly effective decision making framework for ERM, and how do stakeholders define "highly effective"? Is such a framework transferable from one organization to another? If not, why? If so, how? Finally, can existing MCDM processes supporting ERM be enhanced in any way?

3.5.4 Empirical Studies on ERM Implementation

As noted above, there are examples of research focused on the components of ERM and what it could accomplish. These take more of a theoretical or illustrative angle to define ERM, but may lack review of how it is used in practice and the results of its implementation. There are some works that look beyond this theoretical context and examined the degree and nature of implementation of these frameworks. Studies utilizing surveys such as Colquitt et al (1999) and Kleffner et al (2003) or those using panel reviews such as Arena et al (2011) are a common means of discovery of the extent of this implementation. These works provide insight into such things as risk governance (e.g., reporting structures and titles), motivations for ERM implementation, types of risks considered for ERM purposes and what areas of focus will organization focus upon for ERM development in future periods, and perspective on cultural or operational frictions for why ERM's implementation might be more advanced in some organization than in others. However, the reach of these surveys are limited to the depth, breadth and timing of the survey. They tend to be a static, point-in-time analysis as opposed to providing insight of variations across a time series. This trend analysis is particularly important since ERM implementation can take an extended period to fully manifest, and may require a cultural shift within an organization for its potential to be fully realized (Institution of Civil Engineers and the Faculty and Institute of Actuaries 2009). Additional research in this space could elevate today's current understanding, perhaps with updates to surveys of similar participant profiles or totally different surveys focused on different regions, industries or other factors.

Case studies assessing ERM implementation have been considered, but are less common relative to surveys. Arena et al (2010) use a seven year longitudinal case study covering 2002 to 2008 consisting of three firms of different industries allowing a deeper exploration of ERM status over time. Their findings show cultural differences and structural dynamics across firms heavily influence the nature, vision and execution of ERM. The findings were insightful in some respects, particularly as it relates to how ERM can develop over time and how it can impact an organization in a true life setting. This deep and narrowly focused study and others like it still leave questions unanswered. Are the findings in this study (in)consistent across industries, across geography, the firm's ownership or capital structure, etc.? Are the findings useful in a general sense or simply insightful? The fact that these questions cannot be answered (fully) is grounds for further research consideration.

The role and impact of the chief risk officer (CRO) has been considered also. One study (Liebenberg and Hoyt 2003) review trends and tendencies of firms that have appointed CROs. This study notes that chief risk officers are typically the owners and pioneers of ERM frameworks within their firms. This study is based on public disclosures noting the appointments of CRO's (or those with similar roles, but different titles) between 1997 to 2001. Across the 26 firms in their study they found that leverage is linked to CRO appointments, suggesting that such appointments provide signals to reduce asymmetric information regarding risk profile characteristics of the firms that have CROs in place. This was an interesting finding, but was limited in the timeframe used and the number of subjects in their study, overlooking more recent geopolitical events and crisis to which ERM using firms might have been subjected.

As noted above ERM was in its early stages of usage prior to 2000, and continues to evolve even today. Further, the extent of implementation of ERM, particularly within banks and insurance companies is much greater now than ever before. For example, it was not until 2005 that Standard & Poor's or AM Best began publishing papers describing their expectations of ERM for the insurance companies that they rate and how this could be considered for financial strength ratings. Moreover, Standard & Poor's began providing an ERM strength score to the insurance companies that they rate in 2005, perhaps signaling that ERM was deemed less relevant until that time. So certain findings and conclusions reached based on results from the late 1990s or early 2000s may not be as relevant or consistent across longer and more current time series.

Another study focuses on the stage of implementation of ERM within firms based in the U.S. versus outside of the U.S., which also considered factors that might influence ERM's presence at organizations generally (Beasley et al 2005). Some findings of this study show that insurers and banks are more likely to have ERM in place relative to other industries. Additionally, corporate governance (e.g., the presence of a CRO, composition of the Board of Directors) and the size of the firm was related to the degree of ERM implementation. 123 firms are considered providing a reasonable, but far from comprehensive coverage of the population of firms using ERM, particularly within the U.S. banking and insurance space where 1000s of such entities exist.

Industry practitioners and trade groups also add thoughts in this space. Some are highlighted in the discussion on ECM above, but another is conducted by Aon Corporation (2010) where survey participants were asked to opine on the stage of maturation of their ERM frameworks as well as to what extent ERM helps to enhance value within the surveyed firms, showing that ERM generally helps in that regard.

Many quantitative studies focused on ERM that are not survey based rely on secondary data, namely public disclosures. From an ERM context such data to support these studies are less than comprehensive. The reporting and disclosure requirements for firms surrounding ERM is extremely limited[8] and at best inconsistent from firm to firm. This makes comparisons among firms within an industry or across industries a challenge. This is in contrast to required disclosures of financial accounting results as prescribed by regulators and accounting boards such as the Securities and Exchange Commission in the United States or the International Accounting Standards Board in Europe. Additionally, the external auditing process typically used to measure the accuracy of those results ensures comparability across time and across organizations. Public disclosures specific to ERM are not nearly as defined and comparable. Therefore, research dependent on secondary data such as disclosures of the specifics of ERM might have been harder to develop in the past. That said, it is becoming more common for financial institutions to provide more transparency regarding their ERM practices. And as noted above, rating agencies such as Standard & Poor's now make specific commentary and assessments on the strength of ERM within financial institutions ratings publications as well as those for corporate ratings. Such insights were less developed or readily available for

[8] For example, no company is required to disclose whether or not that they have a CRO, or that they have an ECM, or how their ECM results have changed from period to period. This is all optional that may or may not be volunteered by the company.

research efforts in the past, suggesting more data exists today than ever before for further research in this area.

3.5.5 ERM's Influence on Value

As noted above, a common theme in the literature is that ERM is meant to manage a company's risk profile to within its risk preferences. Additionally, when ERM is in place it should translate into some value proposition – both value preservation and value enhancement. This is a theoretical or conceptual notion which is discussed in several works in academia and industry alike, but thought pieces that examine this empirically have been relatively limited to this point. In the few cases when ERM is being assessed against value empirically, the authors tend to look at Tobin's Q[9] as a proxy or measurement of value. One example is a work done by Hoyt and Liebenberg (2011). Here the authors examine if the presence of ERM has a meaningful influence on the Tobin's Q of U.S. public stock insurance companies across a specified time period. The results of their study show that firms with ERM in place have better Tobin's Q ratios than the alternative. Their study provides some interesting results gained from prudent statistical and econometric methods, but there are limitations to their research. Since firm's are not required to disclose if they have ERM in place or to describe their ERM framework, the authors rely on word and phrase searches among a firm's public filings for signals of ERM presence (e.g., confirmation of a chief risk officer role or mention of a risk committee). This is a subjective process which only makes note that there are signs that ERM exists or it does not – a binary variable. The study does not distinguish the strength, appropriateness or fit of ERM to a firm, or other characteristics that might play a role in ERM's influence on value. Moreover, the study focuses on a relatively narrow time period of 1998 to 2005, missing the 2007-2008 housing market crash and global financial crisis, two of the most significant economic extreme events faced by insurers and banks in recent time, and an ideal means to evaluate ERM's impact and effectiveness. Moreover, ERM's presence and implementation was in early stages, with limited early adopters (Kleffner et al 2003) during that period of study suggesting that ERM's influence on value might be difficult to fully

[9] There are varying definitions of Tobin's Q in the literature. The idea is that Tobin's Q is a ratio of market value of equity and debt relative to its book value, the lower the ratio - the lower the company valuation. Several authors cite the following paper's included definition of Tobin's Q as it relates to banks and insurers: Cummins et al (2006). "The market value impact of operational loss events for US banks and insurers." Journal of Banking & Finance **30**(10): 2605-2634.

understand at that time. Moreover, there are other definitions of value beyond Tobin's Q that are worthy contenders: return on equity, market price of stock, projected earnings per share, and risk-adjusted valuation metrics are other examples.

A different perspective of ERM and value, also considering excess stock returns, is presented by Gordon et al (2009). Hoyt and Liebenberg (2011), examine the impact of Tobin's Q given the presence of ERM. However, it also considers some elements of appropriateness or fit of ERM, not simply whether or not it exists at a firm. Complementing this theme was work done by Arnold et al (2011) in which they determined that firms that had a well-structured strategic ERM processes reflecting flexible organizational structures were better able to adapt to changing regulatory regimes – a valuable attribute for growth and ongoing performance. That said, one major limitation of the Gordon et al (2009) study is that it only considers a one year time frame – a questionable consideration since more literature on the theoretical elements of ERM, suggest that ERM takes time to implement and to fully vest. This is evident in the studies on the extent of ERM's implementation highlighted above.

Standard & Poor's, a prominent rating agency which scores ERM strength of insurance companies, provides some clarity around the value implications of ERM and what influences it. Their reviews consider stock price volatility of listed insurance companies and if this volatility differed across firms with varying levels of ERM strength or quality (Standard & Poor's 2013b). They show evidence that firms deemed by them to have relatively stronger ERM frameworks also realize lower stock price volatility over time. But their study also has data limitations. It only considered the publicly listed stock U.S. and Bermuda insurance companies that they rate, which isn't a consistent sample year to year. Moreover, insurers that Standard & Poor's rate that are domiciled in other countries were not considered in this study.

Carson et al (2008) explore the interdependencies of financial risks common to public insurance companies and the stock price volatility of these firms. This follows the theme of Standard & Poor's, and also reflects on risk-based capital, a common consideration within ERM frameworks. However, by definition risk management in the Carson et al study follows the more traditional financial risk management description as opposed to enterprise risk management.

However, not all studies show a conclusive cause and effect. In the McShane et al (2011) study firms deemed to have strong or excellent ERM had no discernible higher valuation than firms deemed to have weaker ERM or than firms that followed a traditional risk management framework. The primary data source is limited to 82 U.S. insurance companies rated by Standard & Poor's with public ERM scores. In addition, similar data limitations as outlined above existed in this study and must be considered.

Overall, studies linking ERM to value in some empirical way are less abundant than those speaking to how ERM supports value from a theoretical way. Those that have explored this have offered some insights worth noting, but have done so with certain limitations warranting further consideration. These include source and timeliness of data, definitions of value and other factors.

3.6 Considering Common Research Methodologies Employed

3.6.1 Overview

This review of literature has focused on the merits of Enterprise Risk Management (ERM), the role of Economic Capital Modelling with ERM, and how risk preferences and multi-criteria decision making (MCDM) can play an effective role within an ERM framework. ERM builds on risk management which is a component of finance. MCDM is linked to behavioral science and decision science. Since there are no known journals that specialize in decision science as it relates to effective ERM for financial institutions, it was necessary to explore the literature across multiple disciplines and several journals. This survey of the literature covers five core subject areas[10], and the journal articles under review were catalogued accordingly:

- *Behavioral Science*
- *Decision Science*
- *Finance*
- *Risk Management*
- *Enterprise Risk Management (ERM)*

The landscape of literature for this field of study suggests certain important findings. One, the concept of ERM is a newer extension of a well-established idea of traditional risk management. Most articles that explicitly cite ERM in any way were published after 2000, with

[10] See **Section 3.9 Appendix A** for how these four areas are defined for these purposes

only since 2007 are there publications exploring ERM linkages to value or performance from an empirical perspective. Second, the ERM concept builds on other well-established business management topics. For example, papers written over 50 years ago still show relevance[11] with foundational elements supporting theory related to more recent papers focused on the five areas listed above. Third, topics that relate to ERM cover a full spectrum of journals regardless of quality or discipline.

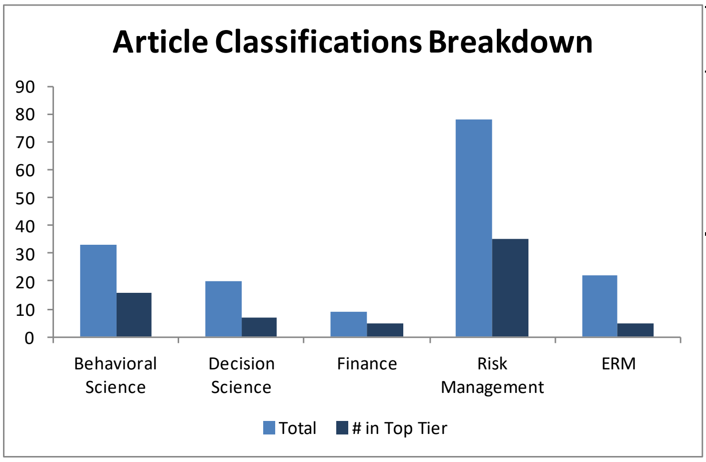
3.6.2 Summary of Research Methods Employed

Roughly 160 articles were considered in this review. The vast majority of these were from peer reviewed academic journals.[12] The content across these sources sometimes overlapped, but attempts were made to classify the articles into categories based on the most prominent of the five areas covered in the research as listed above. This was clearly a subjective process, but it helped the author to gain comfort that applicable disciplines to his research were considered in the right balance. Roughly 60% fall into the risk management or ERM category, a third are either behavioral or decision science based and less than 6% of articles are finance focused. This is viewed as a reasonable distribution of articles by subject matter. **Figure 3.2** shows the distribution.

[11] As denoted by the article references, bibliographies and citations considered for this review

[12] Text books and industry / trade / news articles were considered for the broader thematic review or literature, but are not included in this assessment of research methodologies.

Figure 3.2. Journal Article Classifications Breakdown, Including Journal Tier



Classification	Total	# in Top Tier	Percentage Top Tier
Behavioral Science	33	16	48%
Decision Science	20	7	35%
Finance	9	5	56%
Risk Management	78	35	45%
ERM	22	5	23%

Where Top Tier = 2010 ABS Journal Rank of 4 or 3

This figure provides distribution characteristics of the articles used in this thesis by theme and journal article ranking. Five themes were chosen and articles were assigned to one of the five based on where most of the content in the article seemed to focus. It also shows the number of articles within top tier ABS Journal rankings as of 2010 by each category.

Approximately 70 were published in high quality (tiers '4' or '3') academic journals (as ranked by the 2010 ABS Journal Guide[13]). Approximately 90 were in journals ranked lower quality journals (tiers '2' or '1')[14]. And the remaining were working papers that had yet to be or were being considered for publication at the time of the review. Although the majority of articles were from lower tier journals, there was a healthy representation across all tiers. Note **Figure 3.3**.

[13] See **Section 3.1 Appendix B** for how the ABS Journal Quality Guide scoring is defined

[14] There were approximately 15 articles published in journals or on websites, including industry publications, not listed in the ABS listing or other similar listings. These were all classified as tier 1 for this analysis

Figure 3.3. Journal Quality Breakdown - Count of Articles by Journal Tier

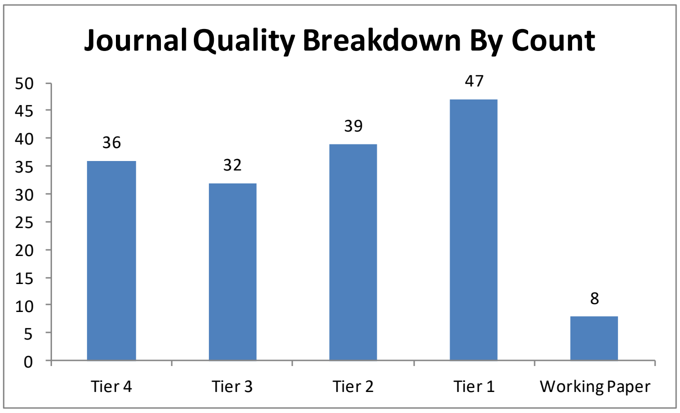
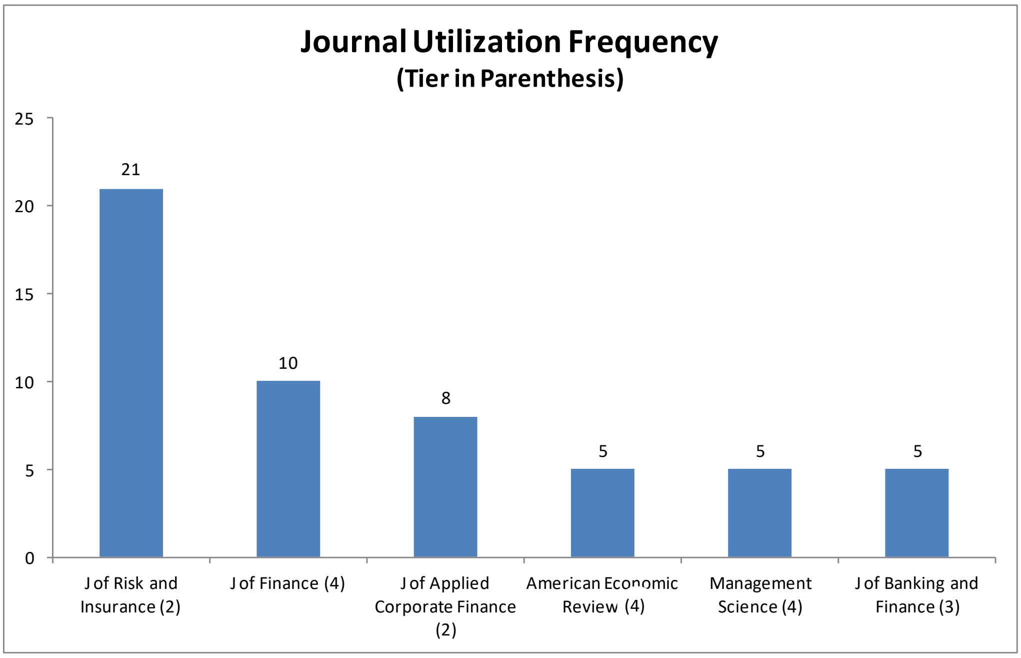


Figure 3.3 shows the overall journal quality distribution for articles reviewed in this manuscript. Journal quality categories are defined by the 2010 ABS Journal rankings.

For perspective of the number of journals used and the frequency note **Figure 3.4**. This shows the distribution when a journal was used at least five times. By far the most frequently used journal was the Journal of Risk and Insurance, accounting for 21 of the 160+ considered. This was followed by the Journal of Finance and the Journal of Applied Corporate Finance, accounting for 18 collectively. The remaining were evenly split across 35+ different journals.

Figure 3.4. Journal Utilization Frequency For Those Journals Used Five Times or More

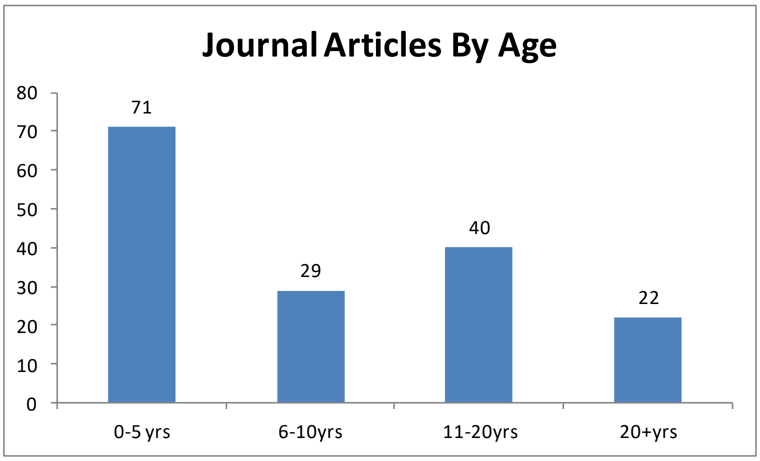


This figure considers those journals where articles included in this review were published at least five times. It provides perspective of how often ERM-related articles were included in a particular journal.

The age of articles was also a consideration. Works from several years ago may be useful in certain theoretical respects, but may lack relevance in others, particularly if the data or method(s) or research employed is dated. Ideally, a balanced pool of new and older literature would be preferred. **Figure 3.5** below shows the distribution of articles discovered during the review by age of publication. Four classifications are shown: 1) published within the past five years, 2) six-to-ten years ago, 3) 11-20 years ago, and 4) those published over 20 years ago. Although most articles of relevance are current, there are a number of articles that still hold some relevance that are much older. For example, Portfolio Selection, by Harry Markowitz published in the Journal of Finance in 1952 was mentioned above. This piece has not been without its challengers over the years, but at its core it presented a framework to evaluate optimal risk and return decision making in a financial context that forms a fundamental principle for much of current risk management and decision science applications for financial institutions today.

Overall this review maintains a balance of relevance, timeliness and quality of articles and the journals they were published within.

Figure 3.5. Journal Articles By Age



This table provides a distribution of the journals considered in this review by the age of the article.

Across all articles considered there was a fairly balanced split between qualitative and quantitative methods employed. Those using qualitative techniques tended to follow a case-study design focusing on a small group of companies for the analysis. Those articles focused on quantitative analysis followed one of two paths: 1) statistical or econometric methods applied to primary or secondary data or 2) mathematical finance to explain or demonstrate a theory or concept where no observed data was used or simulated data was employed for illustrative purposes. In the later mathematical proofs using calculus, differential equations or a hypothetical scenario was often applied to justify a position. There were no notable instances where a mixed-method of qualitative and quantitative techniques was used.

When non-simulated data is used, researchers tend to rely on one of three sources: 1) financial databases (e.g., CRSP, Compustat, Bloomberg, etc.), 2) surveys, or 3) results from conducting experiments where subjects were asked questions or are asked to take certain actions in a live setting[15]. Of these three sources, financial databases were used the most, where information on financial performance and governance structures of corporations were the usual data analyzed.

Sample sizes[16] across these articles varied significantly. As **Figure 3.6** below demonstrates, most articles have sample sizes in the 200-250 range. However, data samples ranged from 25 to over 800,000. Some articles have better discussions of the applicability of data, including how well the data sample represented a certain population, but this was mostly when the data is sourced from financial databases. When financial databases are used the sample sizes are much larger than other sources, providing indications of accepted sample sizes by data source[17] for researchers in this space. See **Table 3.1**.

[15] It is also worth noting that just about all live setting experiments were centered around a psychological or behavioral study where volunteers were asked to make choices to evaluate for risk preferences and risk taking tendencies – e.g., when or when not to take part in games of chance.
[16] For instances when financial data or corporate disclosure was cited as the data source, the number we counted as the amount of data was the different number of companies used in a study as opposed to the frequency of reporting of any form of data from one corporation. For example, some authors would have returns on equity for 200 companies across ten years of annual data and others across five years of quarterly data. In this case the data set is counted as 200, not 2,000 or 4,000 respectively. This is to assure consistency across journal articles for comparison purposes, and also to level set expectations for my pending research.
[17] There are a couple instances where extreme outliers of unusually high sample sizes were ignored

Figure 3.6. Data Analysis of Typical Sample Sizes Employed

Descriptive Statistic	Value	Natural Log
Mean	13147	5.7
Median	241	5.5
Standard Deviation	100410	1.7
Minimum	25	3.2
Maximum	828516	13.6

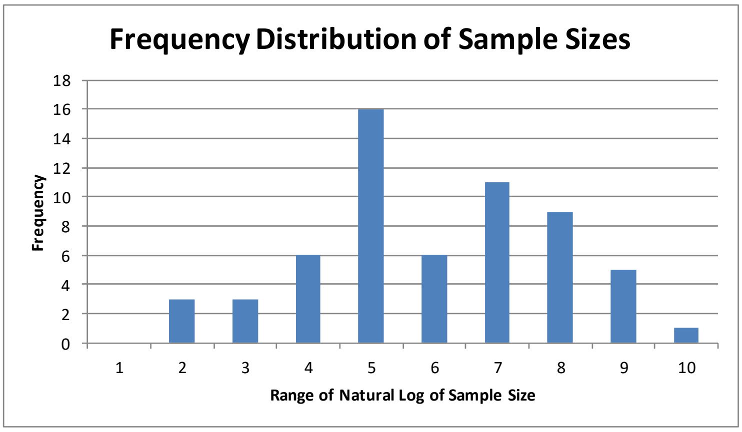


Figure 3.6 provides a perspective of the sample sizes used by article when data analysis was applied. Natural Logs are shown to provide an easier assessment of the data given then vast differences at both ends of the spectrum.

Table 3.1. Descriptive Statistics of Sample Count by Data Source

Data Source	Number of Articles	Descriptive Statistics For Sample Sizes				
		Mean	*Median*	*StDev*	*Min*	*Max*
Financial Database	34	788	311	1346	25	6888
Questionnaire	11	356	227	421	60	1881
Live Setting / Experiment	6	179	146	124	34	399

Table 3.1 provides perspective of how data was commonly sourced across the quantitative focused articles considered for this review.

3.6.4 Takeaways Regarding Quantitative Methods Employed

Across all the quantitatively focused articles each author employ multiple methods to evaluate their data or to test hypothesis, with some employing more extensive statistical analysis than others. Furthermore, deductive reasoning, where an established theory was being evaluated, was employed in approximately 56% of the articles. Most researchers use a combination of some sort of least squared regression coupled with significance testing via t-statistics, p-values or chi-squared tests. Regressions include simple linear or multiple linear regressions, and a small portion using logistical regressions. Descriptive statistics were also assessed, but not in all cases. Interestingly, in very few instances were results presented to test for (ab)normality[18] of the data – either visually or otherwise. Analysis of Variance (ANOVA) was applied in 66% of these papers, often to test if the average result of some characteristic between two or more firms were statistically different. In roughly 40% of the papers were other quantitative methods employed. These might include Monte Carlo simulation, factor analysis, structural equation analysis, another method, or a combination, with no one approach used more frequently than another. See **Figure 3.7**.

Figure 3.7. Frequency of Quantitative Method Employed Out of 62 Articles

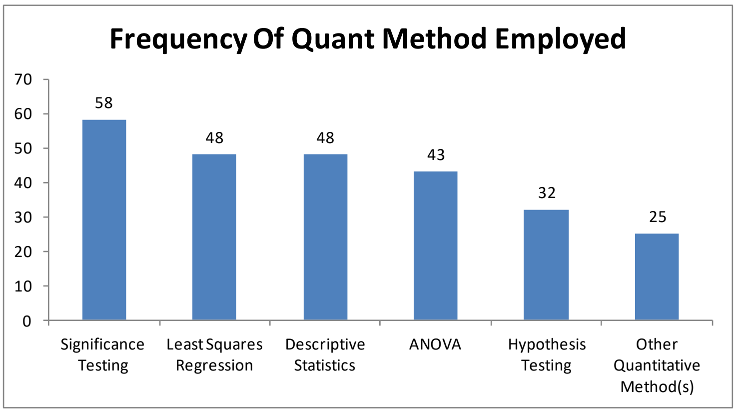


Figure 3.7 provides perspective of the research method commonly used across the quantitative focused articles considered for this review.

3.6.5 Visualization of Data and Results

Across the quantitative articles reviewed, tables were the primary and often sole means to discuss data or results. Graphs showing certain descriptive statistics, a concept or an illustration were used, but this was a rare exception and too often overlooked by researchers in this space. Indeed, quantitative-focused journals, most of which seemed to target topics related banking, insurance, corporate finance, and financial risk management are less likely to use graphs of any nature to describe data or results. When questionnaires are used to generate data there was a greater use of fundamental statistical methods to assess the data, and in those cases

[18] It seemed that most researchers were eager to apply regression analysis but rarely commented on any testing or evaluation of the data or data results to assure regression model assumptions were not breached.

there is greater likelihood of such visuals as histograms, scatter plots, or other creative means to showcase data tendencies. See **Table 3.2** for a summary of the tables versus graphs usage.

Table 3.2. Frequency Table of Table and Graph Usage

Tables vs Graphs	Frequency	Percent
Tables Only	40	47%
Tables and Graphs	25	29%
Graphs Only	7	8%
No Graphs or Tables Used	13	15%
Total	85	100%

Table 3.2 provides perspective of how data was commonly presented across the quantitative focused articles considered for this review.

3.6.6 General Research Method Takeaways

Across the selected literature covering the research areas that are of consideration (excluding text books) several quantitative methods and limited qualitative methods have been employed. From a quantitative methods perspective most approaches were used. Additionally, and several authors used a combination of statistics and econometrics. Sample sizes are large, particularly when considering secondary data sources from public disclosures of performance and corporate governance. That said, more processes considering analysis of a financial time series would seem a logical focus for further studies given the longer duration for ERM to develop. In contrast to the broad range of quantitative analysis within the literature, qualitative methods are less common and generally have been limited to case studies. Methods including grounded theory, ethnography or action research, for example, are not obvious choices in this space indicating that researchers either do not find such methods insightful or applicable to the topics in question, or have simply undervalued the relevance of such methods. Finally, a mixed-methods approach is lacking and could present a fresh look at even already established researched conclusions. These gaps in research methodology are worthy considerations; however, there are journals that tend to appreciate a certain type of research methodology and this also must be contemplated to the extent publication is a primary consideration

3.7 Gaps in the Literature

3.7.1 New and Popular Field of Study

ERM and the research surrounding it is relatively limited compared to other established disciplines in the economic social sciences such as finance, operations research or accounting. ERM tends to borrow elements from several disciplines both in theory and in practice. It was only in the year 2000 did theoretical and empirical publications focused on ERM best practice start appearing in the literature. This contrasts to the field of finance where there are several related works published as far back as the 1950s and 1960s. The fact that it is a relatively new area of research is one reason that it warrants ongoing attention. ERM is a new field in development in an of itself, and the idea of linking risk-based decisions and risk preferences to an ERM construct is an area of study that is far from fully developed.

Multiple stakeholders have expressed their ongoing focus with ERM as well. Documentation produced by regulators and rating agencies cite Own Risk and Solvency Assessment and ERM as key ingredients to prudential standards and financial strength. Also, industry practitioners fully embrace the concept as can be seen with websites and periodicals dedicated to the topic such as ‘InsuranceERM’, qualifications on the topic such as ‘Chartered Enterprise Risk Analyst (CERA)’, and conferences on the topic such as the annual ‘Enterprise Risk Management Symposium.’ These are just a few examples of how ERM is permeating in the finance and risk management vernacular.

3.7.2 Limited Empirical Analysis

Existing research has brought to light some interesting findings and theories for consideration. Some of these are based on theory alone, and others apply some empirical evaluations. However, most of the empirical statistical analysis focused on ERM effectiveness has assumed a direct or linear relationship between ERM and value or performance, not contemplating the notion of risk preferences, risk tolerance and related risk-based decision-making, or how these can interact with ERM’s relation to value / performance. Other studies are limited in scope due to small or narrow time series data. Some are devoid data post 2010 and major risk events that would test the efficacy of ERM in a stress environment such as the 2008 global financial crisis. Some studies are based almost entirely on surveys and questionnaires, which can only offer a point in time assessment based on the opinions and responses of survey participants.

3.7.3 Routine Research Methodologies

There are examples where the methodology to address certain research questions could be expanded. There are some instances where case studies were applied, and others have taken a broader view across hundreds of firms via quantitative analysis. Qualitative studies could augment or challenge the conclusions gleaned from quantitative approaches or vice versa through mixed methods for even further robustness tests. For example, some have used surveys exclusively thus positioning findings predicated on primary data, while others have considered secondary data sources from one or more years of public disclosures. Limited research exists that combined these two.

3.8 Conclusion

The literature defines what Enterprise Risk Management (ERM) is meant to accomplish. We have findings that demonstrate what companies are doing with their ERM constructs. Less clear is the empirical evidence of cause and effect of decision-making, ERM execution and performance. Some studies show ERM enhances value, while others show mixed results to the contrary. Still left to be determined is how can ERM be structured such that management can not only be more effective, but to optimize risk tolerance and risk-based decisions for that effectiveness. Are ERM structures fully appreciative of the expectations of external stakeholders? For example, can a Multi-criteria Decision Making (MCDM) process be formally embedded into an ERM framework resulting in optimal risk-based decision-making predicated on the unique risk preferences and risk bearing capacity of a firm? Can this be done in a way that builds upon an economic capital modeling (ECM) structure, or even considers reasonable alternatives to ECM? If so, how? Within an ERM or MCDM context are there special circumstances to be mindful of that are specific to banks and insurance companies that have yet to be understood, which can pose a meaningful influence on ERM and MCDM effectiveness? These are a few questions needing resolution in order to elevate ERM from an elegant theoretical concept to one that is relevant from the most rigorous empirical perspectives, thus filling certain gaps in the academic literature and providing insight for the ERM practitioner and decision-maker.

Chapter 3 Appendices

3.9 Appendix A - Five core subject areas considered for this review

Behavioral Science: This can cover topics of choice and psychology, but these articles are generally more specific to individual human behavior in settings outside of the workplace. The articles selected in this category include ideas around risk preferences between genders, age, income levels, the impact of stress or the environment on behavior and rational or irrational actions

Decision Science: This includes studies of how managers apply choice in a business context. Articles selected in this context include studies of optimization, decisions under uncertainty, use of tools to support the decision-making process, and criteria and methodology upon which choices are predicated

Finance: Within financial institutions the preservation of capital and capital structure is a major focus, and decisions and risk management processes are often focused upon capital management. Articles with this theme are classified as finance with regards to my review of the literature

Risk Management: This covers processes, procedures, frameworks, constructs, etc. that constitute methods to identify, measure, control or transfer risk within a corporation. Articles selected included oversight and cultural awareness of risk management (e.g., governance structures) as well as discussions of tactical risk management actions (e.g., hedging interest rate risks with derivatives)

Enterprise Risk Management (ERM): This builds on the definition of traditional risk management above. The primary difference is that risks are considered jointly and holistically across and organization. Moreover, ERM constructs are often deemed to contribute to strategy, value and operational efficiency. However, traditional risk management may lack this direct or indirect linkage. Articles that discuss ERM in this context, including those that do not use the words ERM explicitly are considered in this regard.

3.10 Appendix B – ABS Academic Journal Quality Guide Scoring System

Figure 3.8. ABS Academic Journal Quality Guide Scoring System Excerpt

Table 2: Specification of Journal Quality Standards

Quality Rating	Meaning of Quality Rating	No. and (%)
4*	World Elite Journals. There are a small number of grade four journals that are recognized worldwide as exemplars of excellence within the business and management field broadly defined and including economics. Their high status is acknowledged by their inclusion as world leading in a number of well regarded international journal quality lists.	22 (2.7%)
4	All journals graded 4, whether included in the world elite or not, publish the most original and best executed research. As top journals in their field, these journals typically have high submission and low acceptance rates. Papers are heavily refereed. Top journals generally have the highest citation impact factors within their field.	72 (8.7%)
3	Three rated journals publish original and well executed research papers and are highly regarded. These journals typically have good submission rates and are very selective in what they publish. Papers are heavily refereed. Highly regarded journals generally have fair to good citation impact factors relative to others in their field, although at present not all journals in this category carry a citation impact factor.	230 (27.9%)
2	Journals in this category publish original research of an acceptable standard. A well regarded journal in its field, papers are fully refereed according to accepted standards and conventions. Well regarded journals have modest citation impact factors or do not have one at all.	295 (35.8%)
1	These journals, in general, publish research of a recognized standard. They are modest standard journals within their field. Papers are refereed relatively lightly according to accepted conventions. Few journals in this category carry a citation impact factor.	204 (24.8%)

The table excerpt is taken from p. 5 of the ABS Academic Journal Quality Guide, version 4 (2010). It provides the quality rating definitions used for its ranking process.

3.11 Appendix C – Thoughts on Value at Risk and Tail Value at Risk

Value at risk (VAR) is a downside risk metric used to estimate potential loss to a portfolio or an enterprise resulting from one or several significant adverse events happening over a specified period. It is often articulated with three components: 1) a value or percentage of a value expected to be at risk, 2) a time horizon, and 3) a statistical confidence interval or degree of confidence.

With an expectation such as expected earnings or change in value, there is a distribution of outcomes that surround that expectation. Some of these outcomes are favourable and some are unfavourable. Furthermore, some outcomes are more likely to happen than others. VAR is meant to estimate the impact from those least favourable outcomes which are usually very unlikely to happen, but when they do occur the result is a significant loss of value. VAR can be measured at a micro level such as for the value of an investment portfolio or for a project's expected discounted cash flows. This impact can also be measured at a macro level such as for the shareholder's equity of the entire enterprise. As an example, a risk manager may go through a financial risk modelling process to estimate the expected profits for her firm in the coming year. After assessing the various favourable and unfavourable outcomes the firm could face she determines that at a 95% confidence level she would not expect to lose more than 25% of shareholder's equity over the coming twelve months as a result of adverse events. The 25% is the VAR impact, which is qualified by the 12 month time horizon and 95% statistical confidence.

Since the risk manager in this case is not 100% confident and as a result there is still a 5% probability of losses exceeding 25% over the period. Tail value at risk (TVAR) considers the expected losses in the tail of the distribution of outcomes, akin to an average of those most adverse or least favourable outcomes if the VAR threshold was breached - i.e., the mean of those adverse events with loss values greater than 25%.

VAR and TVAR are commonly used metrics in financial risk management, measuring and expressing corporate risk tolerances and with assessing the financial strength and solvency of financial institutions. The reader is encouraged to consider different references such as Crouhly et al (2001), Culp (2001), Jorion (2001) and others that dedicate significant discussion on VAR and TVAR for further clarification.

3.12 Appendix D – Thoughts on Utility and Risk Preferences

Traditional microeconomic theory suggests individual or organizational consumers will assign higher values to those goods or services that offer greater pleasure, and all else equal will prefer consuming those greater pleasure items relative to lesser pleasure items. From a risk management perspective the organizational consumer positions the firm in a way such that the goods and services that the firm consumes collectively exhibit preferred utility characteristics. For a certain bank this may include lending to high credit quality borrowers. For a certain insurer this may include underwriting higher premium auto insurance contracts for high risk drivers. For some energy produces this may include digging oil wells in remote locations perceived to be rich in oil. Other industries have other relevant examples and in each instance organizational consumption provides utility for each respective firm. However, these sources of utility all have inherent risks. Borrows may default on their loans, auto drivers may have terrible accidents, and drilling oil wells may not produce much oil.

One aspect of risk management is to direct the consumption activities of the firm such that there is appropriate utility associated with that activity despite the potential risks of said consumption. Risk preferences of the firm determine that direction. These preferences also can be viewed as risk tolerance. Organizational consumers with relatively high risk tolerances may seek (or prefer) utility from high risk sources, but may view and expect high utility from these sources as a result. Other organizations with relatively low risk tolerances may seek (or prefer) to target lower sources utility where the underlying risks are less. These notions of utility, risk preferences and risk tolerances are central to optimal risk management for organizations.

Chapter 4.

Manuscript 2:

Enterprise Risk (Mis)Management – Value Implications of the Misapplication of Risk Capacity

4.1 Abstract

Enterprise risk management (ERM) is a modern holistic approach to managing risks within financial institutions. Recent studies have explored the relationship between ERM and value (or performance), but have done so with an assumption that the ERM and value relationship is a linear one. While understanding that this type of relationship is a warranted exploration, absent in the research is a consideration of an organization's capacity for risk, and how this capacity interacts with the aforementioned relationship. Indeed, an underlying premise of executing prudent ERM is that it facilitates an improved awareness of a company's risk appetite and risk capacity, those targets to which risk management is meant to manage towards. The following study will consider how risk capacity interacts with ERM and how these two factors jointly impact value. Specifically, we will show through a moderation regression process, coupled with a response surface analysis framework, that when North American financial institutions make overuse or little use of their risk bearing capacity, in part due to misapplied risk appetites, the relevance of ERM on value suffers.

4.2 Key Words

Enterprise Risk Management, Moderation, Risk Capacity, Tobin's Q

4.3 Introduction

Risk management is a key aspect of the operational success of financial institutions, such as banks and insurance companies, since their business model is predicated on taking risk for profit. Banks make loans using the deposits given to them by their customers, resulting in assumed interest rate risk and credit risk. Insurers are paid premiums which eventually fund claims payments for the risks that they underwrite. When these institutions make prudent risk decisions profits are earned and valuations are raised. Traditional risk management frameworks help with that decision making process. Enterprise risk management (ERM), founded on a holistic understanding of risks across all aspects of a company's operations, is an evolution of these traditional risk management frameworks (Brehm 2007), (Nocco and Stulz 2006). Given the interaction between risk management and decision making it is not unreasonable to presume that ERM could influence value and performance. Additionally, it is not unreasonable to presume that this influence could vary as organizations with operations deemed riskier than others are also deemed to have stronger (or weaker) ERM frameworks.

Three elements come to mind as a result of managing the inherent risks of a financial institution's operations: risk capacity, risk capacity utilization, and risk capacity residual. Risk capacity is a concept that we define as an organization's ability to withstand risks associated with sustaining their operations at desired levels. For financial institutions a common source for this ability is financial capital (Towers Watson 2013b)[19]. For example, a bank may have to maintain minimum capital requirements in order to meet regulatory standards or to keep the quality of their bonds at a certain credit rating, but may choose to maintain capital levels above those minimums to avoid regulator interventions or threats of credit default due to a sensitivity to severe or adverse financial conditions inherent to their operating activities. The next element is risk capacity utilization. Aven (2013) defines risk appetite as "the willingness to take on risky activities in pursuit of values", p467. Risk-based decision making also has been linked to risk appetite frameworks (Hillson and Murray-Webster 2012). The decision-making within financial institutions determines what mix of those activities that these companies will pursue; a particular mix translates into future earnings to shareholders and long-term value (Tower's Watson 2013). In this study we use the term risk capacity utilization as an estimate of an

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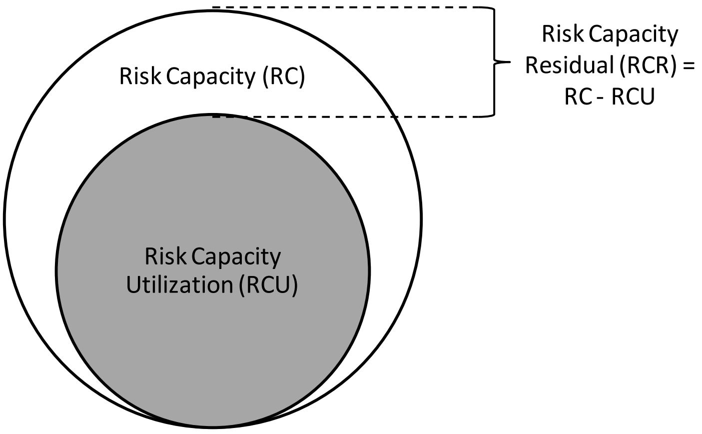
[19] Towers Watson (2013b) use the term "adaptive buffer" to describe the resources that are available to adapt to and withstand an insurer's operational and financial stressors. They suggest that these can be financial or non-financial. What I call risk capacity is the same thing as an adaptive buffer.

organization's risk appetite, where risk capacity utilization is assumed to be some value less than risk capacity itself. The third element is risk capacity residual, which is the remaining risk capacity after subtracting risk capacity utilization from risk capacity. (See **Figure 4.1**). Firms with high risk appetites have high risk capacity utilization and lower risk capacity residual, or vice versa.

Figure 4.1. Risk Capacity Decomposition



Risk capacity is a concept that we define as an organization's ability to withstand risks associated with sustaining their operations at desired levels. For financial institutions we can measure this with available capital. This figure is a Venn diagram illustrating how risk capacity utilization is a fraction of risk capacity.

The combination of ERM, risk capacity, risk capacity utilization and risk capacity residual are central to the analysis within this study. Our theory suggests that organizations can influence their value to the extent that they are able to use ERM to understand and prudently utilize risk capacity. It is worth noting that the focus of this study is on measurable, financial risk capacity and risk capacity utilization. However, Power (2009) argued that using financial capital as measurement of risk capacity and risk appetite [i.e., risk capacity utilization], may be too narrow of a measurement and overlook broader ethical and behavioral elements that underlie these risk concepts. So conceivably, this study may only shape part of a full understanding of how risk capacity and risk capacity utilization interacts with ERM's influence on value.

4.4 Review of the Literature

Several works have discussed enterprise risk management (ERM) over the past several years. As an example, Meulbroek (2002) describes the fundamentals of ERM, which includes the notion that ERM is a holistic risk management process where risks across an organization are viewed, measured and managed in an aggregated manner. Meulbroek's work suggests that practitioners of ERM should exhibit better performance and generate higher value relative to non-practitioners. This view coincides with several other research pieces on the topic originating in industry trade groups and academia – e.g., COSO (2012, 2004), CAS ERM Committee (2003), Culp (2001), Colquitt et al (1999) and others. Those articulating the merits of ERM also make note that ERM helps organizations determine risk appetites or target risk profiles, e.g., Nocco and Stulz (2006). Pagach and Warr (2011) find that companies with more aggressive risk profiles, attuned to an aggressive risk appetite, are more likely to have chief risk officers on staff to help manage those risks. Moreover, capital structure, namely leverage, and a way of expressing risk capacity, has been an indicator of the desire of a CRO or an equivalent risk oversight process (Liebenberg and Hoyt 2003), (Pagach and Warr 2011). Therefore, it is prudent to think of risk appetite, risk capacity and ERM as interlinked concepts.

The idea that ERM can impact value or performance has been assessed empirically and most studies show a positive linear relationship. One example is work done by Hoyt and Liebenberg (2011), where the authors show that U.S. public stock insurance companies with a developed ERM framework in place have higher valuations relative to their peers. Gordon et al (2009) provide a method to calculate an ERM index based on publically available data, and showed how ERM effectiveness, where an ERM framework is properly suited to the operational characteristics of a company, has a positive influence on performance. Complementing this theme is work done by Arnold et al (2011), in which they determine that firms with well-structured strategic ERM processes reflecting flexible organizational structures are better able to adapt to changing regulatory regimes – a valuable attribute for growth and ongoing performance. Standard & Poor's provide some thoughts around the value implications of ERM as well. Their reviews consider stock price volatility of listed insurance companies and if this volatility differs across firms with varying levels of ERM strength as defined by them (Standard & Poor's 2011b, 2013a, 2013b). They show evidence that insurers deemed by them to have relatively stronger ERM frameworks also realize lower stock price volatility over time. In contrast McShane et al (2011) studies firms deemed to have strong or excellent rated ERM by Standard & Poor's and found that they had no discernible higher valuation relative to firms deemed to have weaker ERM, or relative to firms that followed a traditional risk management framework. However, most studies support the theory that strong ERM and value share a positive linear relationship.

The existing literature provides some insight on how to define and measure value, risk capacity and ERM. However, and despite a general theme of a positive relationship between ERM and value, there has been little in the literature to show if or how the use of an organization's risk capacity or risk profile impacts the relationship between ERM and value. This is a worthy consideration for managers of banks and insurance companies as they consider using ERM for operational efficiency and related risk-based decision-making, for capital providers as they choose which financial institutions to provide capital to and at what cost, and for regulators as they look to evaluate the solvency of financial institutions for stability within the broader financial systems that they oversee.

4.5 Research Design

The theory being assessed is that ERM's impact on the value of financial institutions is at least partially influenced by the institution's capacity to withstand the risks it assumes. For example, consider two companies that are similar in every way except that one decides to exercise greater risks in its operations relative to the other. One consideration is if the importance of ERM for the company with a higher risk appetite is different than for the company with a lower risk appetite. Hierarchical regression analysis is applied to determine when and how ERM relates to value. The base regression uses linear multivariate analysis where a proxy for value is regressed on proxies for enterprise risk management and risk capacity residual (RCR). (These proxies are explained and defined below.) Next an interactive term between the predictors is added to the regression to test for moderation effects of risk capacity on ERM's influence on value. Finally, quadratic terms of the predictors are added for a response surface analysis, which looks to understand if alignment or divergence between the relative strength of ERM and the relative expected risk capacity utilization has an impact on value. The regression hierarchy is as follows:

Value = Intercept + B1(ERM) + B2(RCR) + error term

Value = Intercept + B1(ERM) + B2(RCR) + B3(ERM x RCR) + error term

Value = Intercept + B1(ERM) + B2(ERM squared)+ B3(RCR) + B4(RCR squared + B5(ERM x RCR) + error term

4.5.1 Regression Variables Discussion

ERM is measured in part using a proxy defined by Gordon et al (2009), which includes variables to measure four components of ERM advocated by COSO (2004, 2012) - strategy, operations, reporting, compliance. We extend Gordon et al's ERM definition to include a measure for risk modelling capabilities, a characteristic particularly relevant to the evaluation of a financial institution's ERM strength (e.g., AM Best 2013c, Standard & Poor's 2013a). By applying this measurement of ERM it is assumed that all companies within the sample have some form of ERM in place, even if the efforts around its execution is apparently weak, not fully developed or not apparent at all. See **Section 4.13 Appendix C** for further discussion of the ERM proxy calculation.

In this study risk capacity utilization is considered a moderating variable of ERM as respects to value. A financial institution's available capital is the usual metric that regulators and credit rating agencies use to benchmark solvency, claims paying ability, and overall financial strength against, e.g., AM Best (2013b), BIS (2011). Generally, companies with higher capital levels are in a greater position to remain solvent, pay future claims, service debt, etc. In essence, firms with higher levels of capital can assume higher degrees of risk, all else equal. Following this perspective available capital is used as a proxy of risk capacity. For the purposes of this study available capital includes shareholder equity and long-term subordinated debt.[20] To account for company size, assets are used for scaling purposes. Therefore, risk capacity (RC) is the ratio of available capital to total assets:

RC = (Shareholder's Equity + Subordinated Debt) / Total Assets

Ideally, over the course of a year for-profit organizations will generate and grow earnings, and doing so is not without costs. Specifically, financial institutions' growth and profits have underlying risks associated with them. For example, a fire insurer generates premiums for home insurance, but it has to pay property damage claims when fires happen.

[20] Subordinated debt is often considered to exhibit similar characteristics as equity and is included as available capital by regulators and rating agencies when they consider financial strength of financial institutions that they evaluate (e.g., Standard & Poors 2013b).

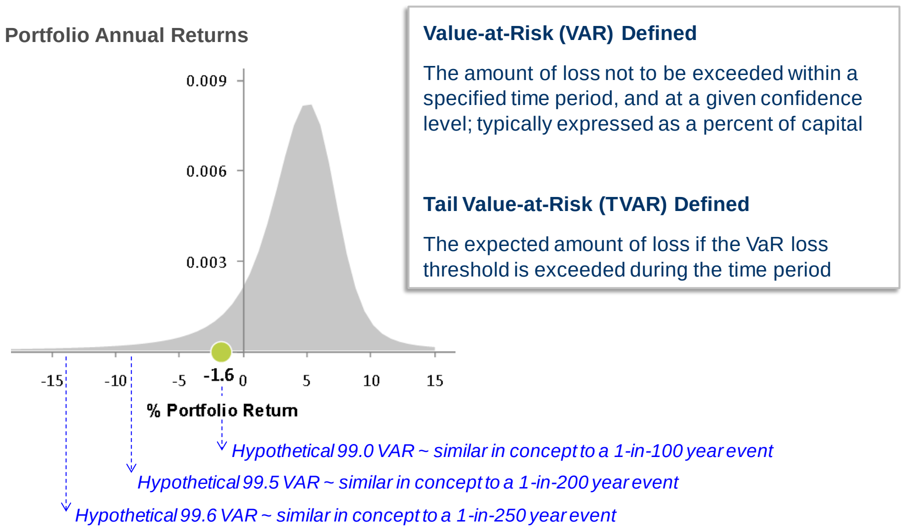
Moreover, there is the risk that premiums and actuarial reserves for such insurance may not be sufficient to pay these claims, adversely impacting earnings and ultimately the consumption of RC. To estimate this risk capacity utilization we first determine the volatility of earnings, which is measured as the annual standard deviation of returns on equity (ROE) over the prior five years:

$$\textit{Earnings Volatility} = \textit{Standard Deviation of ROE}$$

$$\textit{Where Standard Deviation} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2}, \textit{ and } x\text{=}ROE \textit{ and } i = year$$

The final determination of risk capacity utilization is based on the downside risk metric called value-at-risk (VaR). This metric is used by financial institutions to gauge risk of loss to their financial portfolios under extreme or highly infrequent events, e.g., a 1-in-200 year loss event, over a certain time-period (Jorion 2001). VaR or similar metrics are considered by financial institutions as a means to articulate risk appetite (Shang and Chen 2012). So when considering a distribution of potential earnings outcomes, the focus of VaR is on the tail of the distribution, particularly the negative earnings tail (See **Figure 2**). VaRs can cover various time periods from days to years. For this study we always assume a 12 month VaR. VaR is often estimated through Monte Carlo simulations or can be estimated parametrically[21].

Figure 4.2. Value-at-Risk Illustration



[21] Parametric VaR is used when the corresponding variable is assumed to follow a normal distribution. For the sake of this we make a very strong assumption that the five year return on equity value for each case in each sample is normally distributed.

Illustration Source: New England Asset Management Inc.

A parametric VaR is calculated using the expected volatility of returns to a portfolio, the inverse normal cumulative distribution factor (i.e., standard normal critical value) corresponding to the confidence level in question, and the portfolio value (Jorion 2001, p.109). For each case in this study we use the previously defined available capital used in the risk capacity calculation as the basis for portfolio value. Earnings volatility defined above is used for expected portfolio volatility. The confidence level is at 99.5% over a 12 month period, which aligns to confidence levels and time periods used by regulators to calibrate their solvency and statutory tests (e.g., EIOPA (F.K.A CEIOPS) 2010). A 99.5% confidence translates into a 2.56 critical value. Therefore, each case's VaR in U.S. dollars is calculated as:

VaR = Earnings Volatility x 2.56 x Available Capital

This VaR is scaled by assets of each firm, which determines the overall risk capacity utilization ratio (RCU):

Risk Capacity Utilization (RCU) = VaR / Total Assets

The net of Risk Capacity (RC) and Risk Capacity Utilization (RCU) determines the Risk Capacity Residual (RCR):

RCR = RC – RCU

Value is the dependent variable used in this study. Hoyt and Liebenberg (2011) advocate that Tobin's Q is a favourable metric because, among other favourable factors, it is a forward looking measure capturing expectations of future performance. Tobin's Q is formally defined as market value of equity plus the market value of liabilities relative to the book value of assets.

Tobin's Q = (Market Value of Equity + Market Value of liabilities) / Market Value of Assets

However, since assets and liabilities of financial firms are not readily traded and their respective market values are not readily reported, for this study we use the book value of liabilities and assets as reported on company balance sheets as proxies for their respective market values. Market value of equity is determined from common stock market capitalization. Generally speaking, a Tobin's Q ratio greater than 1.0 indicates high value and when less than 1.0 indicates low value (Brainard and Tobin (1968), Bodie et al (2013)).

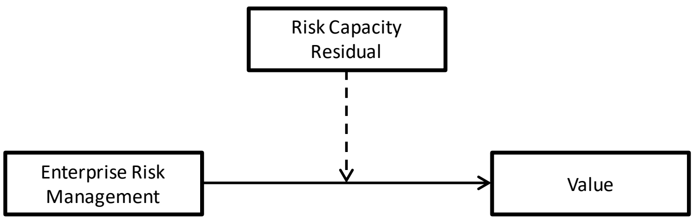
4.5.2 Regression Processes

This study uses the SPSS statistical package to regress Tobin's Q on different combinations of ERM and RCR to understand how ERM impacts value across a stepwise regression process. The first regression, model (1), tests for a linear relationship by applying the following equation to each company across the samples used in the study (see **Section 4.6** for a discussion on data and sample composition):

$$\textit{Tobin's } Q = \textit{Intercept} + B1(ERMI) + B2(RCR) + \textit{error term} \qquad (1)$$

The next regression, model (2), will be a moderation regression to assess if the introduction of a term capturing interaction of ERM and risk capacity utilization plays a role in this influence, i.e., does the risk capacity residual moderate when ERM influences value (See **Figure 4.3**).

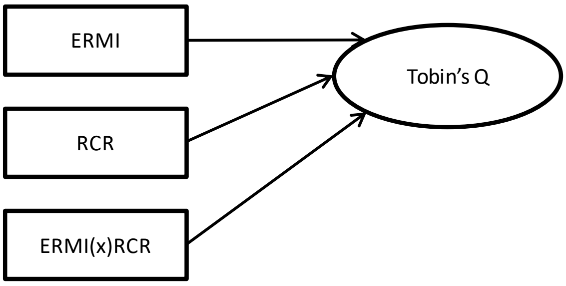
Figure 4.3. Moderation Diagram Where Risk Capacity Residual Moderates Enterprise Risk Management's Relationship with Value



This figure illustrates that enterprise risk management's influence on value is moderated by its risk capacity residual. Where risk capacity residual is a proxy of how much risk capacity (i.e., capital) an organization's risk tolerance is expected to consume.

The moderation model combines the variables ERMI, RCR and Tobin's Q defined above. The interactive variable is the product of ERMI and RCR, following the methodology prescribed in Baron and Kenny (1986). (See **Figure 4**).

Figure 4.4. Model Representation of the Moderation Diagram Model with Respect to ERM, Risk Capacity Residual and Tobin's Q



This figure illustrates the explanatory variables enterprise risk management index (ERMI), risk capacity residual (RCR) and their interaction (ERMI(x)RCR) collectively influence the proxy for value, Tobin's Q.

The moderation equation under evaluation:

Tobin's Q = Intercept + B1(ERMI) + B2(RCR) + B3(ERMIxRCR) + error term (2)

With one moderating variable there are three interaction effect possibilities and interpretations. These are shown by the sign of the moderator and interactive term's regression coefficients. See **Table 4.1** below.

Table 4.1. Moderation Model Influence Interpretations (Cohen et al., 2003, pp. 285–286)

Influence Type	Sign of Moderator Coefficient	Sign Interactive Term Coefficient	Interpretation
Enhancing	Positive (negative)	Positive (negative)	• Increasing the moderator will increase the effect of the predictor
Buffering	Negative (positive)	Positive (negative)	• Increasing the moderator will decrease the effect of the predictor
Antagonistic	Negative	Negative	• Increasing the moderator reverses the effect of the predictor
None	Coefficient of interactive term is not statistically different from zero		• No evidence of interaction

This table provides perspective on how to interpret the coefficients of a moderation regression model as defined by Cohen et al (2003).

Response surface analysis (RSA) rounds out the study. RSA will expand the moderation analysis by assessing if diversions or alignment of enterprise risk management (i.e., ERMI) and net risk taking (i.e., RCR) play a role in their joint effects on value (i.e., Tobin's Q). For example, if a company is considered to have above average ERM, but also is deemed to have a higher than average risk profile, does that type contradiction or divergence influence the relationship between ERM on Tobin's Q. Moreover, is that influence similar or not to other levels of ERM and risk profile combinations. To apply an RSA model we follow instructions outlined by Shanock et al (2010), where quadratic terms of the initial predictor variables from model (1) are added to model (2). This forms the RSA model in this study, which is the third regression or model (3). The RSA equation is then (applied to each sample):

$$\textit{Tobin's Q} = \textit{Intercept} + B1(ERMI) + B2(ERMI^2) + B3(RCR) + B4(RCR^2) + B5(ERMI x RCR) + \textit{error term} \quad (3)$$

Across all models the intent is to understand how interactions between ERM and RCR influence ERM's impact to value. To the extent that there are "hidden" relationship characteristics that cannot be identified through linear regression, the moderating and response surface regressions should provide insight on those hidden characteristics. However, there are several micro- and macro-economic factors that determine a company's value. So it is not expected that ERM, or its relationship with RCR, will explain a significant portion of Tobin's Q's variation – e.g., very high r-squareds. However, it is expected that the variation that is explained in this regard is statistically different from zero.

Note that all remaining figures and tables referenced in the sections below are placed in **Sections 4.11 Appendix A Additional Figures** and **4.12 Appendix B Additional Tables** respectively.

4.6 Data Review and Analysis

Data was collected across 305 publicly listed stock[22] insurance companies and saving and loan banks based in the United States, Canada and Bermuda[23] as captured by SNL Financial's database[24]. From the initial 305, roughly one third were deemed to have too many missing or not meaningful data points to provide reliable support to the analysis and were removed. Ultimately 189 companies (128 banks and 61 insurers) were judged to have sufficient data to support the analysis[25]. Separate samples were created for 2012, 2011 and 2010 calendar

[22] Publicly listed stock insurance companies were chosen given the transparency and availability of reported financial data, including market capitalization, for those firms listed on U.S. stock insurance exchanges. These include savings & loans standard industry classification (SIC) codes: 6035, 6141, 6036; and insurer SIC codes: 6311, 6321, 6351.
[23] These three countries are often linked as the North American insurance industry given their proximity to each other.
[24] SNLFinancial is highly regarded by banks and insurance companies. It is a subscription data service providing an abundance of financial and operational data related to financial institutions in Bermuda, Canada and the United States. See http://www.snl.com/Sectors/Fig/Default.aspx.
[25] There were a few companies where meaningful estimates were used in place of a missing observation - e.g., an average from multiple years to measure assets for a missing year. There were six cases whose Tobin's Q data was deemed too much

years, but used the same 189 companies in each year. In total these 189 firms represented approximately 21% of the assets associated with the included industries in the study (see **Table 4.2**). This percentage is deemed a reasonable sample of the population upon which to evaluate the aforementioned theory. Indeed, the collective sample size is well above the range suggested by Field (2009) for regression model validity. Field notes that the recommended minimum sample size to test such validity is dependent on the number of predictors in the model. Specifically the target sample size = 50 + 8k, where k is the number of predictors. Model (3) has five predictors and the most of the three models, so the target sample size is 50 + 8(5) = 90, which is below my sample of 189.

A Tobin's Q ratio was calculated for each case in each sample. Since this variable will be used as the dependent variable in all regressions we tested each sample's distribution of this ratio for normality. The graphs in **Figure 4.4** showing reasonable bell shape curves supporting assumptions of normality for Tobin's Q in each sample year.

For each sample, descriptive statistics were calculated for means, standard deviations and correlations. Difference in means when separately controlling for ERMI and RCR were calculated for each sample as well (see **Table 4.3**). In both instances the difference in means for the predictor variables was statistically significant. For instance, at higher RCR levels companies' ERMI score were generally higher, and at low ERMI scores their RCR levels were generally lower. There were no discernible differences in mean Tobin's Qs when controlling for RCR or ERMI. Additionally, correlation coefficient calculations showed that positive or negative linear relationships between ERMI or RCR and Tobin's Q were low. Correlations between ERMI and RCR were moderate and statistically different from zero, and were generally consistent across each year in the sample. (See **Table 4.4**)

However, one reason to support the notion of a moderating effect on ERM's relationship with Tobin's Q is evidence of correlation "drift" between ERM and Tobin's Q as RCR changes. **Table 4.5** shows how correlations vary at different ranges of RCR levels. Existing research evaluating ERM's relationship with value posits that it is positive and linear. This implies a positive relationship between ERM and Tobin's Q regardless of RCR. Particularly notable is

of an outlier, i. e., more than three standard deviations from the mean, and probably unrepresentative of the population. An adjustment was made to these cases following Field (2009, p 153).

that the correlations were negative at the highest levels of risk capacity residual for each year, while generally positive at other RCR levels.

4.7 Moderation Regression Analysis

Prior to evaluating for a moderation regression process we considered the possible singular influence of ERMI on Tobin's Q by viewing scatter plots of these two variables for each sample, shown in **Figure 4.5**. These plots did not indicate strong evidence of a pure linear relationship between these variables. However, a non-linear relationship could still be possible and not obvious in such scatter plots. Anticipating that the relationship on value by ERM could be moderated by risk capacity utilization, we began with a regression process testing for any linear relationship between Tobin's Q and the predictors ERMI and RCR. For this, model (1) was run for each of the three samples.

$$\textit{Tobin's Q} = \textit{Intercept} + B1(\textit{ERMI}) + B2(\textit{RCR}) + \textit{error term} \qquad (1)$$

The findings from these regressions showed no meaningful influence of ERMI or RCR on the variation of Tobin's Q. In each year the r-squareds were less than 0.01 and the p-values for the F-statistic were at least 0.50. Moreover, T-tests results of the coefficients for ERMI and RCR in model (1) were not statistically different from zero in each sample. See the regression outputs in **Table 4.6**. This was counter intuitive and went against findings from other research showing that ERM did influence value as measured by Tobin's Q (e.g., Hoyt and Liebenberg, 2011).

Several works, such as Baron and Kenny (1986), explore moderator variable influences in least squares regressions. In Baron and Kenny's work they suggest that a moderator variable be added to a linear regression when there is an unexpectedly weak relationship between the predictor variable and the outcome variable, such as what was identified above. To account for possible interaction between RCR and ERMI as it relates to Tobin's Q, a moderating variable was introduced to model (1) to form model (2):

$$\textit{Tobin's Q} = \textit{Intercept} + B1(\textit{ERMI}) + B2(\textit{RCR}) + B3(\textit{ERMIxRCR}) + \textit{error term} \qquad (2)$$

As most works describing the moderating regression process will suggest, e.g., Fairchild and MacKinnon (2009), a key test for moderation is if the coefficient of the interaction term is statistically significant from zero. Also, it is not necessary for the coefficients of the other variables to be statistically significant if the interaction term is. Another test is that the increase in the r-squareds in the models with the interactive term versus those without this term is statistically significant (Baron and Kenny 1986). A third test measures to what degree of effectiveness, if any, does the moderating variable have on the linear regression process (Cohen 1988), (Aiken and West 1991).

The regression results for the 2012 sample produced coefficients of 0.002 (0.205 p-value), 0.121 (.083 p-value) and -0.030 (.005 p-value) for the ERMI, the RCR moderator and the interactive term respectively. Thus, the interactive term's coefficient was statistically significant. Moreover, given the positive sign of the moderator (RCR) coefficient and the negative sign of interactive term (ERMIxRCR) coefficient, a buffering moderating influence is evident (see **Table 4.1** of **subsection 4.5.2** above). The increase in the r-squared going from model (1) to model (2) was 0.042 and significant from zero (0.027 p-value). Moreover, the test for the effectiveness of the moderator variable, as measured by the Cohen's f-squared variable (Cohen 1988), showed an effect size of 0.044 for 2012. This suggested a small effect size as prescribed by Aiken and West (1991) and using thresholds outlined by Cohen (1988). The 2011 and 2010 samples yielded similar results for each test with growing f-squared effectiveness levels from 2010 to 2012 (See **Table 4.6**).

Regression assumption diagnostics were evaluated for model (2). Variance inflation factors are shown in **Table 4.6** and were low for each sample suggesting little concern of multicollinearity. **Figure 4.6** shows the graphs of the regression residuals and provides no strong indication of regression assumption violations.

Using the coefficients established within the model (2) regressions, graphs were developed showing the Tobin's Q-to-ERM relationship when the risk capacity residual is relatively high or relatively low (see **Figure 4.7**). These graphs show for each sample that only when the RCR level is low (i.e., high risk capacity utilization due to high risk) will ERMI have a positive influence on Tobin's Q. Moreover, when the RCR level is expected to be high (i.e., low risk capacity utilization or low risk tolerance) ERM can have negative influence to Tobin's Q all else equal. We can interpret the regression results as follows - while ERM has an influence on value, the extent of this influence varies at different RCR levels. Even a company with strong enterprise risk management may not realize a positive impact to value if risk capacity is not utilized at optimal levels. To expand on this consider the earlier discussion of how capital providers of financial institutions contribute towards the risk capacity that these institutions use to support the risk taking inherent to their operations. Risk bearing capacity shapes the value generating capabilities that capital providers expect banks and insurers to utilize. One can equate risk bearing capacity as a firm's tolerance towards opportunity. And while ERM can enhance value, the extent of this relationship is predicated on the company's understanding and optimal utilization of its risk capacity, its opportunities. Therefore, when financial institutions make sub-optimal use of their risk capacity, such as with unexpectedly low risk capacity utilization, the benefits and influence of ERM come into question for these firms. In this case an underutilized risk capacity firm is a firm whose risk tolerance is too low.

4.8 Response Surface Analysis

The findings from the above moderation regression process provide useful insight. It showed how the interaction between the strength of a financial institution's ERM framework capabilities and expected risk capacity utilization can influence value. When the expected risk consumption of an organization is high (low), translating into a lower (higher) risk capacity residual, then ERM has a positive (negative) influence on the Tobin's Q value metric. This interaction is overlooked if one isolates ERM, the risk capacity residual measure, or views these two only linearly. Although this interaction makes economic sense, it was not obvious when considering scatter plots of Tobin's Q and ERM (**Figure 4.5**). However, others (e.g., Shanock et al 2010) have demonstrated that traditional moderating regressions may miss certain non-linear relationship nuances that can exist between two predictors and an outcome. Response surface analysis (RSA) is a regression technique that builds on the notion of moderation, allowing further insight into such nuances (e.g., Box and Draper, 1987; Shanock et al 2010). Specifically, a quadratic term for each predictor variable is added to the existing moderation model, upon which analysis focuses on the significance of slope and curvature along the "response surface pattern" of outcomes produced from the RSA model, as opposed to traditional significance tests of multiple regression analysis (Edwards 1994; Harris et al 2008).

As a reminder, the moderation regression model (2) is shown again:

Tobin's Q = Intercept + B1(ERMI) + B2(RCR) + B3(ERMIxRCR) + error term (2)

The proposed RSA model expands model (2) by considering the square of variables ERMI and RCR as defined above. The new equation becomes model (3):

$$Tobin's\ Q = Intercept + B1(ERMI) + B2(ERMI^2) + B3(RCR) + B4(RCR^2) + B5(ERMIxRCR) + error\ term \quad (3)$$

Relevant questions that can be answered by an RSA process include: 1) To what extent does an alignment or diversion between the two predictors impact the outcome of the dependent variable?; 2) Does the magnitude of diversion play a role in the outcome?; 3) Does the direction of diversion of one or both of the predictors impact the outcome? (Shanock et al 2010); and 4) Is there an optimal balance between the predictor variables that translates into the greatest influence on the outcome variable? The moderation regression shown above indicated that the linear relationship between ERMI and Tobin's Q changed significantly depending on the expected level of the risk capacity residual (RCR), where low (high) RCR suggests a high (low) risk tolerance. The RSA process adds further insight to this interaction by showing if other nonlinear interdependencies between RCR and ERMI play a role in Tobin's Q, beyond simply the level of RCR.

For response surface analysis to be useful there must be evidence to support a reasonable frequency of divergence between the two predictor variables used in the analysis. In this case we assess if there are frequent instances across the sample that show companies with relatively high (low) ERMI scores coupled with relatively low (high) RCR scores. Shanock et al (2010) suggested a threshold of 10% or more of the sample with such tendencies as a useable frequency. To assess this we followed Fleenor et al (1996) by first standardizing the ERMI score and the RCR values to level set the units. Companies that had ERMIs and RCRs at similar relative levels to each other were considered aligned (e.g., average range ERMI coupled with average range RCR). While companies that had ERMIs and RCRs of at least one half of a standard deviation from the other were considered divergent (e.g., very low ERMI coupled with very low RCR). The frequency of divergence was tallied for each sample year, and in each case these divergences accounted for at least 10% of more of the sample (see **Table 4.7**).

Next the regression model (3) defined above was run in SPSS for each sample using the standardized variables for ERMI and RCR. The results are outlined in **Table 4.9**. The f-stats for each regression show a reasonable amount of significance (i.e., p-values < 0.10), with the strongest result in 2011 (r-squared of 0.071, f-test p-value of 0.018).[26] Tests for non-normal residuals, heteroscedasticity and multicollinearity were evaluated as well. The 2010 regression results show some elevated concerns for multicollinearity as indicated by the variance inflation factors of 8.024 and 6.360 for the RCR^2 and ERMIxRCR variables respectively. As these values approach ten multicollinearity becomes a concern, Field (2010). This potential issue was also confirmed with the high and statistically significant Pearson correlations for these two variables (see **Table 4.4**). Ultimately we did not think this was such a concern to change or reject the model. Other regression assumptions were deemed valid across all samples.

A key feature of the Response Surface Analysis (RSA) is that coefficient significance tests are not essential to the analysis. Hence, the precision of the prediction of the dependent outcome is not under evaluation per se (Shanock et al 2010). What is being assessed is how the relationship between the predictor variables relate to the dependent outcome. This is done through a response surface tests using the coefficients and corresponding standard errors from the RSA regression to formulate four test values: A1, A2, A3 and A4. Each test value prescribes a directional impact on the dependent variable (i.e., Tobin's Q) as the predictor variable values (i.e., ERMI and RCR) change, while also showing the shape of that impact (i.e., linear or nonlinear). The coefficient's p-value denotes the significance of this relationship. For instance, a positive (negative) A1 indicates that the dependent variable will increase (decrease) as the predictor variables increases. A2 indicates either a linear (high p-values) or nonlinear (low p-values) nature of increase or decrease of the dependent outcome from a joint increase in the predictors. For example, a statistically significant positive (negative) A2 indicates a convex (concave) relationship between the two predictors and the dependent outcome variable. A3 focuses on how divergence between the two predictors impacts the outcome. A statistically significant positive (negative) A3 suggests that as the two predictor variables diverge, the dependent outcome increases (decreases). A4 expands upon the divergence relationship to indicate either a linear (high p-values) or nonlinear (low p-values) nature of increase or decrease of the outcome variable from a divergence between the predictors (Shanock et al 2010). **Table 4.8** shows the results of these values and **Section 4.14 Appendix D** provides the formula to calculate the test statistic to measure statistical significance for these values. Also, **Figure 4.8** gives an indication of how the ERMI and RCR variables showcase a slight

[26] It is worth noting that, unlike with a moderation regression, a statistically significant interactive term is not required for response surface analysis (Shanock et al, 2010).

curvilinear interaction at different levels of their standardized scores, which the RSA process can take into consideration.

Focusing on the 2012 sample we see that A1 is positive and significant (0.017, p-value 0.019), which indicates that Tobin's Q will increase as both ERMI and RCR increase. However, A2 is negative and significant (-0.008, p-value 0.004), which indicates that the rate of increase in Tobin's Q will slow as the predictor variables increase. The impact and nature of any divergence between ERMI and RCR on Tobin's Q is not deemed meaningful for 2012 (A3 = -0.007, p-value 0.435; A4 = -0.002, p-value 0.734). Overall, 2012's results suggest that the strength of a firm's ERM and the degree of that firm's risk capacity utilization have a joint impact to value, particularly when a firm exhibits relatively weak ERM coupled with a relatively high risk capacity utilization (i.e., low RCR and high risk tolerance) the associated company value (Tobin's Q) is low. The 2011 and 2010 sample years show slightly different degrees of the relationships identified within the 2012 sample year, but directionally this statement still holds. For example, there is a statistically significant negative impact on Tobin's Q in 2011 due to divergent ERM and RCR (A3 = -0.016, p-value 0.045). One consistency across all years was a statistically significant positive A1 and negative A2. See **Table 4.8** for a summary of the response surface analysis regression tests across each year.

These results show that at certain levels of ERMI and RCR these two jointly have a positive or negative impact on Tobin's Q, particularly when ERMI and RCR are deemed low (i.e., weak ERM with a high risk profile relates to low Tobin's Q values). This is shown visually in the response surface diagrams in **Figure 4.9**. Focusing on the 2012 sample, the concave, dome-like diagram shows two things: 1) the impact on Tobin's Q when ERMI and RCR are at different levels of divergence or alignment, and 2) how the rate of change varies for the impact on Tobin's Q noted in 1. For example, Tobin's Q will decrease at an increasing rate as firms demonstrate lower ERMI and lower RCR levels. So like the earlier moderation regression analysis, there is evidence to support the notion that organizations can preserve or enhance value when they are able to optimally utilize risk capacity and align this with the strength of their ERM frameworks.

4.9 Standardized Risk as an Alternative Moderator and the Consideration of Mediation

An alternative research consideration is that risk capacity utilization without reference to the amount of available capacity (hence ignoring available assets) is sufficient to evaluate for reasonable interaction with ERM, and that this alternative interaction influences value. Considering this, the same regression models (1) and (2) defined above are run, but risk capacity utilization as illustrated in **Figure 4.1** above is used instead of risk capacity residual as a predictor variable. The premise of this alternative view is that higher expected risk can dampen value for an organization, but a good ERM process can offset that dampening. In essence, ERM now becomes the moderator.

The Model (2) regression becomes Model (2a):

$$\textit{Tobin's } Q = \textit{Intercept} + B1(RCU) + B2(ERMI) + B3(RCUxERMI) + \textit{error term} \qquad (2a)$$

The Model (3) regression becomes Model (3a):

$$\textit{Tobin's } Q = \textit{Intercept} + B1(RCU) + B2(RCU^2) + B3(ERMI) + B4(ERMI^2) + B5(RCUxERMI) + \textit{error term} \qquad (3a)$$

Following the same process of standardization of the RCU variable and the ERM index used in the initial hierarchical regressions, a multivariate linear-, moderation- and response surface regression was run for each sample year. The results are in **Table 4.9**. The strength of the moderation models was inconsistent relative to the originals. For example, the findings for the 2010 sample support a potential moderation process (r-squared 0.07, p-value < 0.01) and a response surface analysis process (r-squared 0.08, p-value 0.01). The results for the 2011 and 2012 samples suggest moderation was not an appropriate model given the lack of statistical significance for the respective moderation coefficients (p-values were at 0.28 for the 2011 sample and 0.97 for 2012). However, response surface analysis might be useful as f-tests for each year's RSA model yielded p-values < 0.05. Further analysis is warranted before any conclusions are made as a result of this alternative modelling structure.

We also evaluated for potential mediation of ERM's influence on value by risk capacity utilization as an alternative to moderation. The resulting models with the sample used showed no significances to suggest mediation was evident.

4.10 Conclusions

The results of this study supports the theoretical positive relationship between ERM (as we defined using a combination of concepts and related proxies developed by COSO (2004) Gordon et al (2009)) and value (as proxied by Tobin's Q). However, the extent and the nature of that relationship is at least partially dependent on an organization's understanding and utilization of its risk bearing capacity. This is intuitive because if financial institutions are assuming and managing risks, but do not fully understand to what extent they should be managing those risks towards (e.g., optimal risk tolerances), then even the best risk management frameworks are misplaced. This supports Gordon et al's (2009) findings that when ERM frameworks are properly aligned to the individual dynamics of an organization, that organization will realize relatively higher performance benefits accordingly.

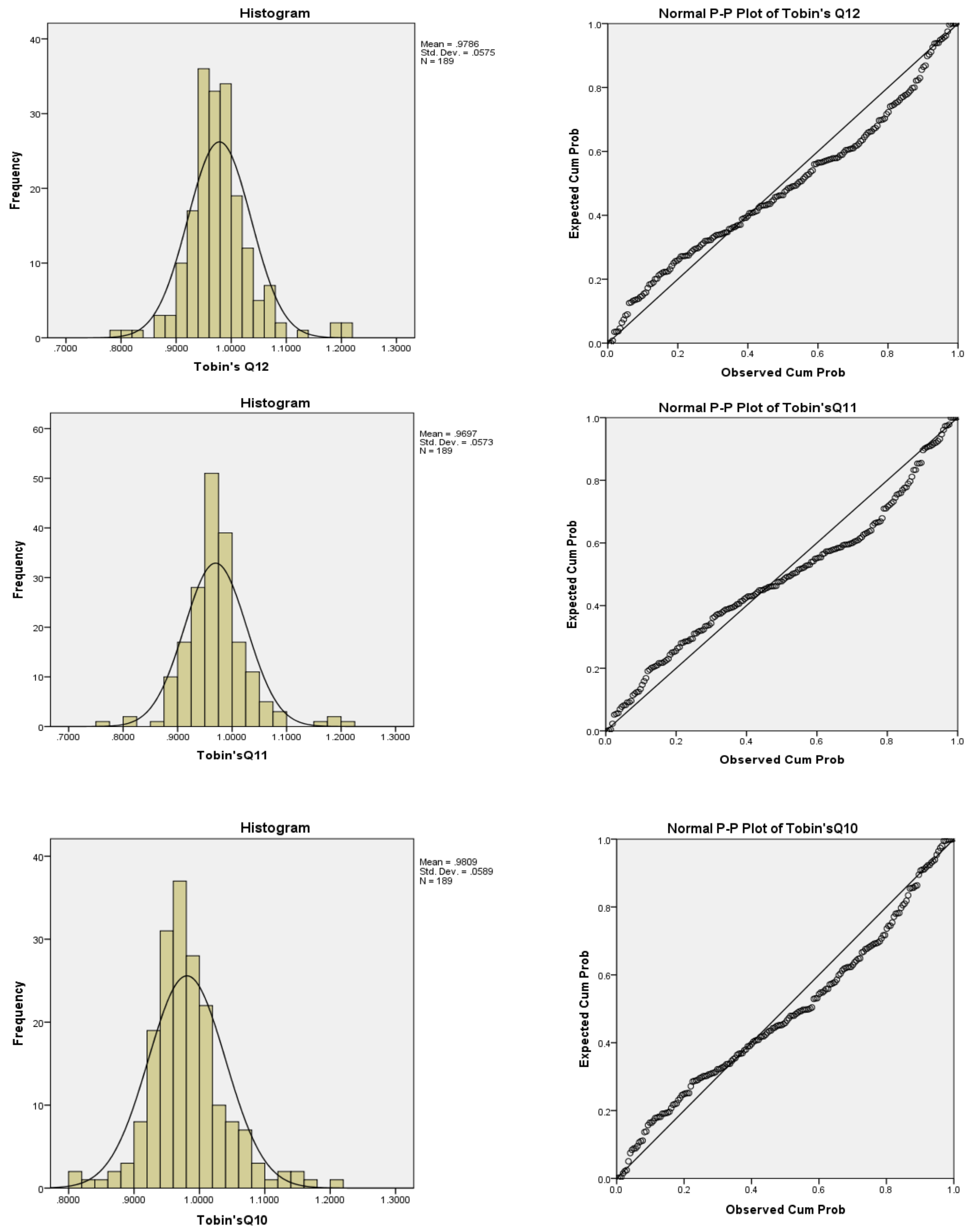
Different types of analysis are used to understand the relationship between ERM and value. Tobin's Q is shown by Hoyt and Liebenberg (2011) to be a good value metric, particularly when considering the relationship between ERM and value for certain types of financial institutions. Gordon et al (2009) demonstrates that the strength of a firm's ERM process could be measured from a series of variables following four ERM components suggested by COSO (2004), which collectively define an ERM index or ERMI. The methodology introduced by Gordon et al for the ERMI is generally followed for this study; however, we made a modification to account for risk modelling capabilities, which are critical to the risk management processes for banks and insurance companies. Risk capacity (RC) is measured as a ratio of shareholder equity plus subordinated debt to total assets. Higher ratios imply greater RC. We also estimate an expected risk capacity utilization (RCU) using a value-at-risk estimate based on expected volatility of return on equity. The remaining RC after accounting for RCU we define as risk capacity residual (RCR), which is an implied corporate risk tolerance. When Tobin's Q is regressed on ERMI and RCR there is limited evidence that a linear relationship exists, which contradicts existing theory and research. However, when an interaction term between ERMI and RCR is added to the regression there is reasonable evidence of a relationship between ERMI and Tobin's Q, but that this is moderated by RCR. Response surface analysis (RSA) is used as an extension of the moderation analysis. The RSA findings reconfirm or extend the understanding of the moderation relationship, albeit from a non-linear perspective, by showing how divergence between enterprise risk management and risk capacity residual can also play a role in the value proposition measured by Tobin's Q. Overall, the study shows that ERM can have an impact on a financial institution's value, but the degree and direction of that impact is predicated on how risk capacity and risk capacity utilization is viewed and measured for that financial institution. This is most pronounced when considering the downward influence on value when a bank or insurer has relatively weak ERM coupled with relatively a high risk tolerance. This relationship was strongest in the 2012 sample, but directionally similar results are evident in 2011 and 2010.

There are limitations to this study that are worth mentioning. There may be other relevant metrics to gauge value, risk, risk capacity or ERM. Moreover, other model structures where different combinations of factors and predictors may also moderate (or mediate) ERM's relationship with value. Therefore, modelling frameworks beyond those applied in this study may be worth exploring in future research such as including multiple moderating variables, interactions with a combination of mediation and moderation, etc. Structural equation modelling might offer additional insight in this regard. Also, we define risk bearing capacity with observable quantitative variables. However, risk awareness, risk acumen and ethical considerations are parts of a firm's "qualitative" risk capacity and risk appetite. These qualitative elements are difficult to observe and were not directly reflected in this study. To the extent that a reasonable proxy of these qualitative aspects can be assessed, perhaps through surveys or other means of discovery, it would bode well to include this information in future research. Additionally, we assume that a firm's exhibited risk capacity utilization is its targeted risk tolerance, which may not be the case. Also, we estimate ERM using a proxy, and such estimates are subject to error or incompleteness. Finally, samples from other time periods beyond 2010 to 2012, while also considering other companies, may exhibit different relationships of worthy consideration before generalizations are made. Overall, the results are insightful and useful but deeper and expanded analysis is encouraged.

Chapter 4 Appendices

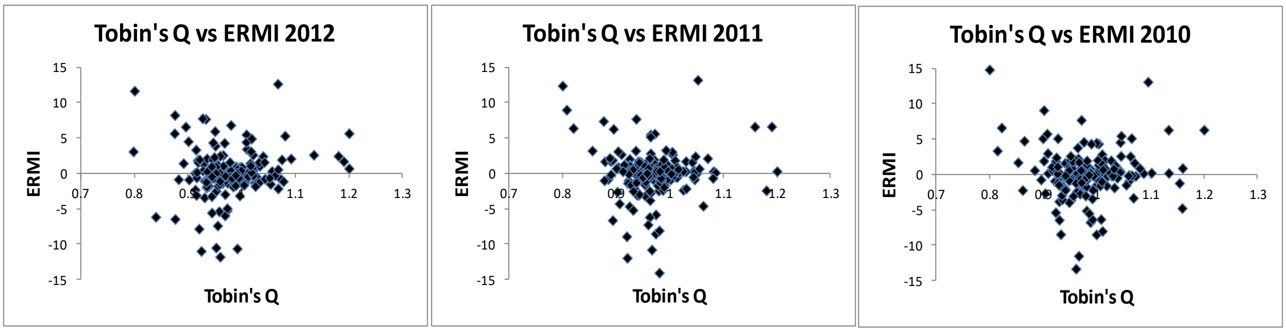
4.11 Appendix A – Additional Figures

Figure 4.5. Tobin's Q, A Valuation Metric, Normality Evaluation Graphs



The graphs in this figure show the distribution of Tobin’s Q, a proxy of value, for the sample year’s 2012, 2011 and 2010.

Figure 4.6. Tobin's Q relative to ERMI Scatter Plots



Tobin’s Q is a valuation metric. Tobin’s Q values below 1.0 suggest undervalue and values above 1.0 suggest overvalued. ERMI is an index to proxy the strength of enterprise risk management. For the sample, ERMI ranged between -15 and 15 for 2012, 2011 and 2010. Higher ERMI scores indicate stronger ERM.

Figure 4.7. Model (2) Regression Line Graphs When Controlling For RCR Levels

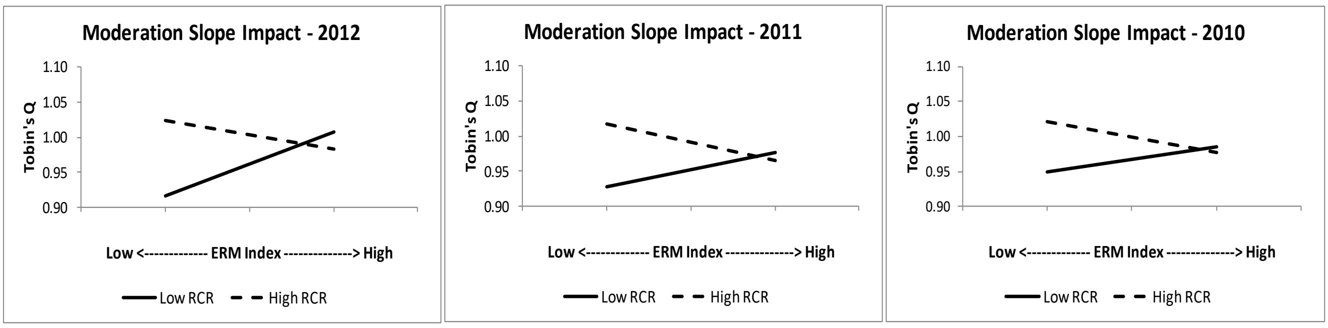


Figure 4.7 provides a visual interpretation of the effects low versus high risk capacity residual (RCR) variable moderating the impact of enterprise risk management (ERM) on Tobin’s Q for the sample years 2012, 2011 and 2010.

Figure 4.8. ERMI Relative to RCR Scatter Plots

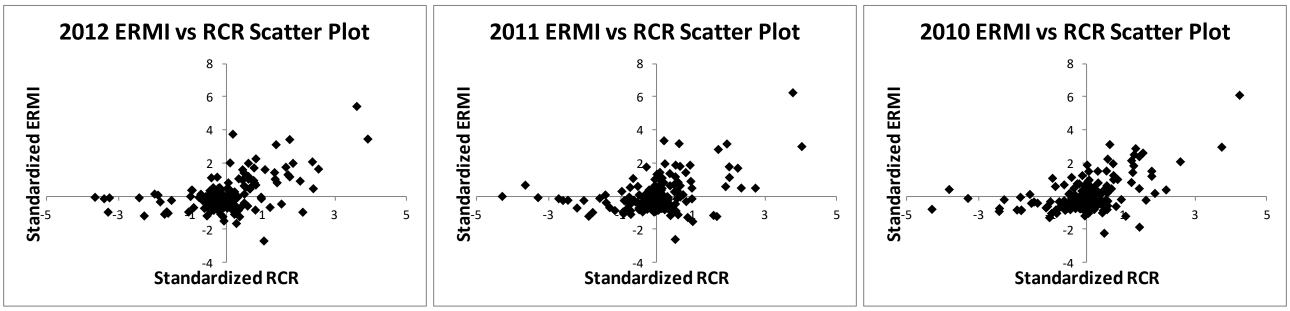
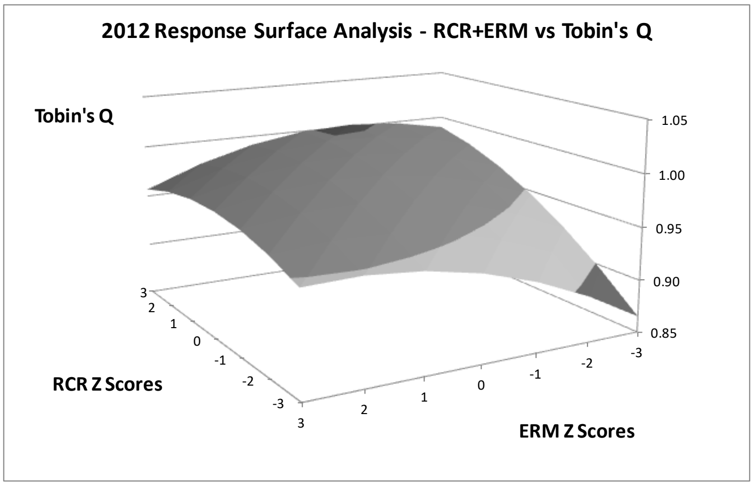
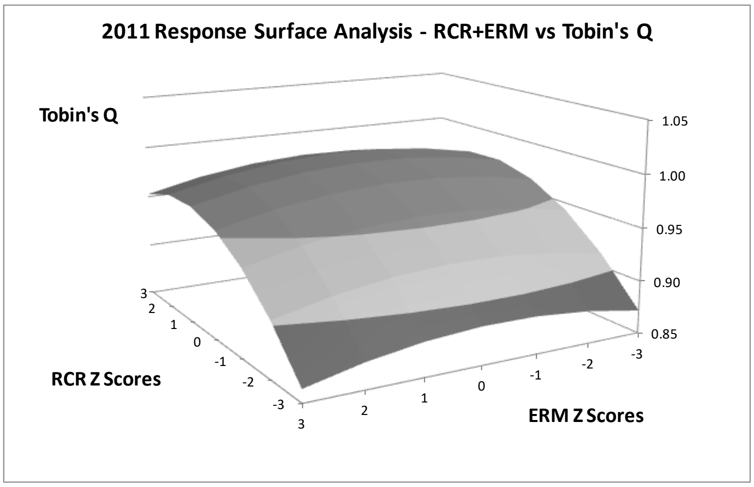


Figure 4.8 shows a scatter diagram of the standardized ERMI (Enterprise risk management proxy) relative to standardized risk capacity residual (RCR). RCR is remaining capital after expected utilization of capital. RCR is a proxy for risk tolerance for each firm across the sample years 2012, 2011 and 2010.

Figure 4.9. Response Surface Results Graphs





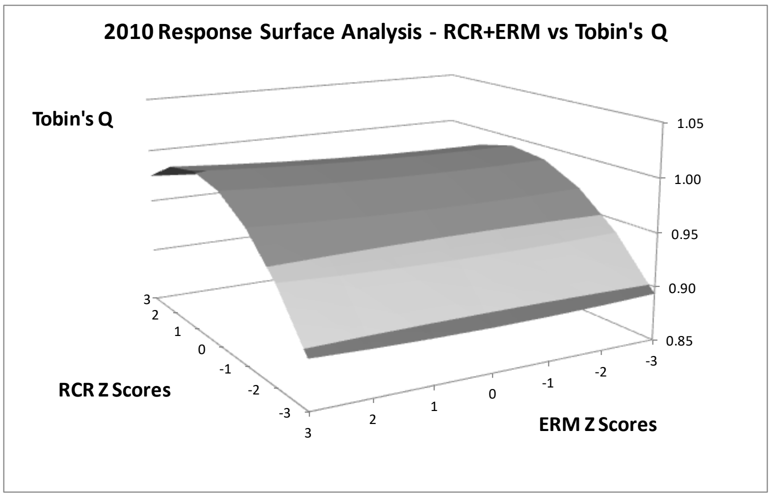


Figure 4.9 shows response surface diagrams to give a three dimensional perspective of the non-linear relationship among the dependent variable Tobin's Q (the valuation proxy), the explanatory variable standardized ERMI (Enterprise risk management proxy) and the explanatory variable standardized risk capacity residual (RCR). RCR is remaining capital after expected utilization of capital. RCR is a proxy for risk tolerance for each firm across the sample years 2012, 2011 and 2010.

4.12 Appendix B – Tables

Table 4.2. Industry Asset Representation

	Total Assets (000s)	Sample Assets (000s)	Percent Represented
U.S. Savings Banks	629,287,356	286,977,504	46%
U.S. Insurers	7,293,959,439	4,614,826,548	63%
Total	7,923,246,795	4,901,804,052	62%

Table 4.2 shows the total assets in the U.S. universe of savings and loans banks and insurance companies, and the sample assets for those sectors represented in this study. Bank data does not include commercial banks. Data is as of year-end 2012 as reported in SNL Financial.

Table 4.3. Descriptive Statistics Difference in Means

Controlling for RCR

Year 2012	Total Sample		>/= Median RCR		< Median RCR		Difference in Means	
Variable	Mean	StDev	Mean	StDev	Mean	StDev	Difference	p-Value
Tobin's Q	0.979	0.058	0.980	0.071	0.977	0.040	0.003	0.724
ERMI	-0.001	3.232	0.633	3.881	-0.641	2.252	1.274	<0.01
RCR	0.139	0.084	0.195	0.084	0.083	0.030	0.112	<0.01

Year 2011	Total Sample		>/= Median RCR		< Median RCR		Difference in Means	
Variable	Mean	StDev	Mean	StDev	Mean	StDev	Difference	p-Value
Tobin's Q	0.970	0.057	0.972	0.072	0.967	0.036	0.005	0.554
ERMI	-0.003	3.281	0.449	4.002	-0.460	2.270	0.909	0.056
RCR	0.138	0.088	0.196	0.089	0.080	0.031	0.115	<0.01

Year 2010	Total Sample		>/= Median RCR		< Median RCR		Difference in Means	
Variable	Mean	StDev	Mean	StDev	Mean	StDev	Difference	p-Value
Tobin's Q	0.981	0.059	0.983	0.070	0.979	0.045	0.004	0.667
ERMI	-0.003	3.496	0.984	3.852	-1.000	2.777	1.983	<0.01
RCR	0.137	0.091	0.197	0.092	0.076	0.028	0.121	<0.01
Observations	*189 (100.0%)*		*95 (50.3%)*		*94 (49.7%)*			

Controlling for ERMI

Year 2012	Total Sample		>/= Median ERMI		< Median ERMI		Difference in Means	
Variable	Mean	StDev	Mean	StDev	Mean	StDev	Difference	p-Value
Tobin's Q	0.979	0.058	0.983	0.070	0.974	0.042	0.009	0.269
ERMI	-0.001	3.232	1.995	2.555	-2.017	2.518	4.012	<0.01
RCR	0.139	0.084	0.166	0.105	0.112	0.040	0.054	<0.01

Year 2011	Total Sample		>/= Median ERMI		< Median ERMI		Difference in Means	
Variable	Mean	StDev	Mean	StDev	Mean	StDev	Difference	p-Value
Tobin's Q	0.970	0.057	0.968	0.067	0.971	0.046	-0.003	0.763
ERMI	-0.003	3.281	1.938	2.492	-1.965	2.783	3.903	<0.01
RCR	0.138	0.088	0.159	0.111	0.117	0.050	0.042	<0.01

Year 2010	Total Sample		>/= Median ERMI		< Median ERMI		Difference in Means	
Variable	Mean	StDev	Mean	StDev	Mean	StDev	Difference	p-Value
Tobin's Q	0.981	0.059	0.981	0.069	0.981	0.048	0.000	0.956
ERMI	-0.003	3.496	2.146	2.606	-2.174	2.892	4.321	<0.01
RCR	0.137	0.091	0.169	0.111	0.105	0.047	0.065	<0.01
Observations	*189 (100.0%)*		*95 (50.3%)*		*94 (49.7%)*			

Table 4.4. Model Variables Correlation Matrix

2012	Tobin's Q	ERMI	RCR	$ERMI^2$	RCR^2	ERMI(x)RCR
Tobin's Q	1	0.072	0.046	-0.137	0.040	-0.006
ERMI	0.077	1	**0.359**	0.000	**0.356**	0.009
RCR	0.047	**0.502**	1	**0.231**	-0.094	**0.211**
$ERMI^2$	**-0.175**	-0.025	**0.340**	1	**0.274**	**0.443**
RCR^2	-0.088	**0.456**	**0.658**	**0.445**	1	**0.440**
ERMI(x)RCR	-0.115	**0.425**	**0.658**	**0.646**	**0.822**	1

2011	Tobin's Q	ERMI	RCR	$ERMI^2$	RCR^2	ERMI(x)RCR
Tobin's Q	1	**-0.027**	0.047	**-0.254**	0.065	-0.048
ERMI	-0.034	1	**0.237**	0.033	**0.274**	**0.17**
RCR	0.027	**0.395**	1	0.028	-0.088	**0.262**
$ERMI^2$	-0.129	-0.099	**0.329**	1	**0.178**	**0.347**
RCR^2	**-0.172**	**0.414**	**0.659**	**0.408**	1	**0.231**
ERMI(x)RCR	**-0.151**	**0.420**	**0.642**	**0.539**	**0.869**	1

2010	Tobin's Q	ERMI	RCR	$ERMI^2$	RCR^2	ERMI(x)RCR
Tobin's Q	1	0.024	0.032	**-0.146**	0.079	-0.089
ERMI	-0.027	1	**0.404**	0.024	**0.164**	-0.089
RCR	0.008	**0.507**	1	0.132	**-0.084**	**0.173**
$ERMI^2$	-0.081	-0.095	**0.330**	1	**0.233**	**0.468**
RCR^2	**-0.170**	**0.463**	**0.665**	**0.512**	1	**0.329**
ERMI(x)RCR	-0.141	**0.397**	**0.638**	**0.652**	**0.906**	1

Peasons' correlations on the lower diagonal; Spearman's Rho on the upper diagonal
All predictors were standardized prior to calculations
Bold indicates significance at the .05 level

Tobin's Q is a proxy for value. ERMI is a proxy for enterprise risk management. RCR is a proxy for risk capacity residual, which is an estimate of the remaining capacity to absorb risk once the expected tolerance for risk is utilized. We are showing both Pearson's and Spearman's for perspective only. Pearson's correlations were used for modelling purposes.

Table 4.5. ERMI Versus Tobin's Q Correlation Drift

Pearson's Correlations Between ERMI and Tobin's Q ***(expected sign would be positive regardless of range)***

	2012		2011		2010	
RCR Level	Correlation	Significance	Correlation	Significance	Correlation	Significance
Overall	0.077		-0.034		-0.027	
> Median	0.082		-0.063		-0.081	
< Median	0.046		0.024		0.060	
Top 25	-0.133		-0.187	*	-0.148	
75th	0.300	**	0.060		-0.095	
50th	0.019		0.018		0.041	
Bottom 25	0.075		0.031		0.078	

** .10 significance; **.05 significance (one tailed)*

This table is evaluating how correlations between ERMI (enterprise risk management proxy) and Tobin's Q (a valuation proxy considering the sum of market value of equity plus the market value of liabilities divided by total assets) varied at different ranges of RCR (risk capacity residual and remaining capital after expected utilization of capital to support risk tolerance).

Table 4.6. Model (1) and Model (2) Regression Outputs

		2012			2011			2010		
		Coeffcient	*Sig*	VIF	Coeffcient	*Sig*	VIF	Coeffcient	*Sig*	VIF
Model (1)	Intercept	0.979	*0.000*		0.970	*0.000*		0.981	*0.000*	
	ERMI	0.001	*0.399*	1.337	-0.001	*0.511*	1.185	-0.001	*0.629*	1.347
	RCR	0.008	*0.893*	1.337	0.031	*0.552*	1.185	0.019	*0.735*	1.347
	R-Squared	0.006			0.003			0.001		
	F Test Significance	0.568			0.754			0.884		
Model (2)	Intercept	0.983	*0.000*		0.972	*0.000*		0.983	*0.000*	
	ERMI	0.002	*0.205*	1.366	<0.001	*0.977*	1.261	<0.001	*0.811*	1.367
	RCR	0.121	*0.083*	1.972	0.111	*0.065*	1.657	0.088	*0.175*	1.883
	ERMIxRCR	-0.030	*0.005*	1.802	-0.022	*0.013*	1.698	-0.016	*0.046*	1.663
	R-Squared	0.048			0.036			0.021		
	F Test Significance	0.005			0.078			0.235		
Impact	R-Squared Increase	0.042			0.033			0.020		
	F-Sig	0.027			0.013			0.046		
	f-Squared	0.044			0.034			0.020		
	Moderation Effect Size*	Small			Small			Small		

* Moderation effect sizes looks at the ratio of the increase in R-Squared over 1 - the initial R-Squared. Higher values imply a greater effect by the moderating variable. The effect sizes are small, but growing year over year.
f2 = .02: small effect
f2 = .15: medium effect
f2 = .26: large effect

Table 4.7. Frequency of Divergence Table for Suitability of Response Surface Analysis

	2012		2011		2010	
	count	*Percentage*	count	*Percentage*	count	*Percentage*
ERMI more than RCR	31	*16%*	62	*33%*	56	*30%*
In Agreement	118	*62%*	79	*42%*	89	*47%*
ERMI less than RCR	40	*21%*	48	*25%*	44	*23%*
Total	189	*100%*	189	*100%*	189	*100%*

For response surface analysis (RCR) to be useful there must be evidence to support a reasonable frequency of divergence between the two predictor variables used in the analysis. In this case we assess if there are frequent instances across the sample that show companies with relatively high (low) enterprise risk management index (ERMI) scores coupled with relatively low (high) RCR scores. Shanock et al (2010) suggested a threshold of 10% or more of the sample with such tendencies as a useable frequency. To assess this we followed Fleenor et al (1996) by first standardizing the ERMI score and the RCR values to level set the units. Companies that had ERMIs and RCRs at similar relative levels to each other were considered in agreement (e.g., average range ERMI coupled with average range RCR, low range ERMI with high range RCR, high range ERMI with low range RCR), which ranges from 42-62% depending on the year. While for each year more than 35% of the sample showed ERMI that was not in agreement with RCR; units of ERMI were at least one half a standard deviation higher or lower than an otherwise in agreement unit of RCR on a standardized basis (e.g., average ERMI with low/high range RCR, low range ERMI with low range RCR, high range ERMI and high range RCR).

Table 4.8. Model (3) Response Surface Regression Outputs

		2012			2011			2010		
		Coeffcient	*Sig*	VIF	Coeffcient	*Sig*	VIF	Coeffcient	*Sig*	VIF
Response Surface	Intercept	0.985	*0.000*		0.977	*0.000*		0.987	*0.000*	
	ERMI	0.004	*0.446*	1.652	-0.001	*0.775*	1.536	0.001	*0.831*	1.821
	$ERMI^2$	0.011	*0.064*	2.076	0.015	*0.008*	1.892	0.012	*0.042*	2.021
	RCR	-0.003	*0.241*	2.147	-0.002	*0.303*	1.757	0.000	*0.880*	2.400
	RCR^2	-0.003	*0.516*	5.120	0.000	*0.993*	5.463	0.000	*0.943*	8.024
	ERMIxRCR	-0.002	*0.432*	3.448	-0.005	*0.050*	4.473	-0.007	*0.062*	6.360
	R-Squared	0.058			0.071			0.056		
	F Test Significance	0.053			0.018			0.061		
Surface Tests on Tobin's Q*										
Joint Directional Impact	A1	0.015	*0.028*		0.014	*0.048*		0.014	*0.051*	
Direction Linear or Non-Linear	A2	-0.008	*0.004*		-0.007	*0.007*		-0.006	*0.022*	
Divergence Impact	A3	-0.007	*0.435*		-0.016	*0.045*		-0.011	*0.243*	
Divergence Linear or Non-Linear	A4	-0.002	*0.734*		-0.007	*0.115*		-0.007	*0.231*	

*The moderation surface tests defined: A1) If there is a direction impact on Tobin's Q as ERMI and RCR jointly increase (P-value < .05) and that it is positive (A1 > 0) or negative (A1 < 0); A2) determines if the direction is linear (p-value >.05) or curvilinear (p-value < .05), and if non-linear, convex (A2 > 0) or concave (A2 < 0); A3 determines if Tobin's Q is sensitive to diverging paths of ERMI and RCR (P-value < .05) and that divergence increases Tobin's Q (A3 > 0) or decreases Tobin's Q (A3 < 0); A4 determines if the impact of divergence on Tobin's Q is linear (p-value >.05) or curvilinear (p-value < .05), and if non-linear, convex (A4 > 0) or concave (A4 < 0).

Table 4.9. Model (2) and Model (3) Regression Results Considering Risk Capacity Utilization with ERMI as the moderator instead of Risk Capacity Residual.

	2012			2011			2010		
Regression Model	R-Squared	F-Test's P-Value	Moderator P-Value	R-Squared	F-Test's P-Value	Moderator P-Value	R-Squared	F-Test's P-Value	Moderator P-Value
Multivariate Linear	0.03	0.08		0.04	0.02		0.04	0.02	
Moderation	0.03	0.16	0.97	0.05	0.02	0.28	0.07	0.00	0.02
Response Surface	0.06	0.03		0.07	0.03		0.08	0.01	

Predictor Variables: ERMI, Estimated Risk Capacity Utilization (as estimated by Value-at-Risk)

This table provides some regression model strength statistics using a different model construct than the one proposed originally. The same regression models (1) and (2) defined above are run, but risk capacity utilization as defined in **Section 4.3** above is used instead of risk capacity residual as a predictor variable. The premise of this alternative view is that higher expected risk can dampen value for an organization, but a good ERM process can offset that dampening. In essence, ERM now becomes the moderator. The results show that this alternative model structure is weaker than the original.

4.13 Appendix C – Calculating the Enterprise Risk Management (ERM) Effectiveness Index

The ERM index was calculated closely following the specifications developed by Gordon et al (2009). They adhered to the premise that effective ERM is comprised of strengths across four elements as prescribed by COSO (2004, 2012) – strategy, operations, reporting, and compliance. They defined two variables for each element. COSO's prescription of ERM is relevant; however, credit rating agencies evaluate the ERM prowess of financial institutions and they make note that risk modelling is a key factor in their evaluation of ERM for these firms (Standard & Poor's 2013a), (AM Best, 2013c). As such add a fifth element to the ERM index to account for risk modelling.

Banks and insurance companies maintain reserves for expected future loan losses and insurance losses. Extensive risk modelling is necessary in order to set these reserves appropriately. Firms that do this well should have reserve balances that are at appropriate levels to support the eventual losses that they were meant to support. It is likely that these balances will show some degree of natural variation as companies' operations and revenues expand or contract. However, when these balances are not appropriately estimated, firms will either have reserves that are too high (creating unexpected reserve reductions) or are too low (creating unexpected reserve additions). This has the potential of creating additional volatility beyond typical yearly reserve balance variation. Therefore, as a proxy of risk modelling uses the ratio of the five year standard deviation of reserves over the five year standard deviation of revenues. Relatively lower (higher) ratios indicate relatively higher (lower) risk modelling abilities.

Each variable of each element was separately standardized first and then subsequently added to create the ERM index for each company in the sample. Following the tradition of Gordon et al (2009), equal weighting was applied to each of the five elements.

Aside from the risk modelling component, most of the variables used in this study were calculated as prescribed by Gordon et al (2009). However, there were a few exceptions to these calculations due to certain limitations of available data within the SNL Financial database and reasonable proxies were used instead. Any differences in calculations from Gordon et al are denoted in bold below.

Table 4.10. Enterprise Risk Management Effectiveness Index Calculation Methodology

Variable Description	**Components**
Strategy	
Component 1 =	(company sales – average industry sales) / standard deviation of industry sales
Component 2 =	(change in company's beta from prior year – mean change in betas from prior year for the industry) / standard deviation of change in betas from prior year for the industry
Operations	
Component 1 =	company sales / company total assets
Component 2 =	company sales / company number of full time employees
Reporting	
Component 1 =	reinstatement for the year? (yes = -1; no = 0) + qualified auditors opinion? (yes = -1; no = 0) + material weakness? (yes = -1; no = 0) (assumed 0 because this is not reported in SNL Financial)
Component 2 =	|company normal accruals| / (|company normal accruals| + |company abnormal accruals|)
Compliance	
Component 1 =	company auditor's fees / company total assets (only the most recent year (2012) was reported in SNL Financial, so assumed the ratio for 2012 was constant for 2011 and 2010)
Component 2 =	company settlement net gain / company total assets (assumed 0 because this is not reported in SNL Financial)
Risk Modelling	
• Component 1 =	One less the ratio of the five year standard deviation of reserves to fiver year standard deviation of revenues: $1-\left(\frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_i-\bar{r})^2}}{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(s_i-\bar{s})^2}}\right)$ where *r* equals year-end reserve balance, *s* equals year-end revenues, and *i* equals years

4.14 Appendix D – Response Surface Analysis Statistical Tests Formulas for A1, A2, A3 and A4 (Shanock et al 2010)

In each case SE = standard error of the coefficient in question and Cov = the covariance of the predictors in question

A1 Test Statistic:

$$t = \frac{a_1}{\sqrt{(SE^2 b_1 + SE^2 b_2) + 2Cov b_1 b_2}}$$

A2 Test Statistic:

$$t = \frac{a_2}{\sqrt{(SE^2 b_3 + SE^2 b_4 + SE^2 b_5) + 2Cov b_3 b_4 + 2Cov b_4 b_5 + 2Cov b_3 b_5}}$$

A3 Test Statistic:

$$t = \frac{a_3}{\sqrt{(SE^2 b_1 + SE^2 b_2) - 2Cov b_1 b_2}}$$

A4 Test Statistic:

$$t = \frac{a_4}{\sqrt{(SE^2 b_3 + SE^2 b_4 + SE^2 b_5) - 2Cov b_3 b_4 + 2Cov b_4 b_5 - 2Cov b_3 b_5}}$$

Chapter 5.

Manuscript 3:

Enterprise Risk (Mis)Management – Performance Implications of the Misapplication of Risk Capacity

5.1 Abstract

The study assesses the relationship between enterprise risk management (ERM) and risk tolerance to determine if there is evidence of operational efficiencies as a result of implied well structured, optimal risk tolerances. Current ERM research suggests that firms which adopt ERM obtain a holistic perspective of their risk profile, and make better decisions with resource allocation and risk strategy in contrast to companies that have not fully adopted ERM. However, these studies generally lack a discussion of how risk tolerances and ERM are related, and that this relationship can determine the effectiveness of ERM. Using a sample of 110 US publicly listed insurance companies, a two stage step-wise regression process is used to provide evidence to support this idea. We show that one reason for ERM user successes is that their ERM frameworks facilitate an alignment of risk tolerances to risk capacity, a subtle, yet essential aspect of the ERM process. When this alignment is established we see stronger operational efficiencies across ERM-user firms with well-structured risk tolerances relative to those firms where such structures are in question.

5.2 Key Words

Enterprise Risk Management, Operational Efficiency, Risk Tolerance, Risk-adjusted Performance

5.3 Introduction

Public corporations through the course of normal business operations are expected to generate earnings for their shareholders. Doing so is not without risk. Unforeseen events can disrupt income, or unexpected economic or environmental factors can limit financial forecasts from coming to fruition. Managers of these firms that are able to make strategic and operational decisions which generate consistent earnings while controlling for risk can add value. Several studies show that risk management can improve performance such as reducing the costs of financial distress and certain tax liabilities (Smith and Shultz 1985; Graham and Rogers 2002), reduced regulatory constraints (Mayers and Smith 1982), enhanced diversification (Mayers and Smith 1990), enhanced financial flexibility and reduce the costs of capital (Froot et al 1993) among others. More recent studies have shown that a holistic understanding and approach to managing risk can lead to operational efficiencies and higher valuations - e.g., Gordon et al (2009), Hoyt and Liebenberg (2011). This holistic approach, called Enterprise Risk Management (ERM), builds on the merits of traditional risk management practices and facilitates a cohesive, strategic management of risks that permeate across an organization (Nocco and Stulz, 2006). Hence, ERM is meant to not only assess and control risks, but also to understand how they interact with each other. When done effectively ERM supports strategy and operational efficiency. However, ERM is not a "one size fits all" concept. Factors such as graphical foot print, leverage, operational strategy and organizational complexity will vary by company, and effective ERM frameworks are tailored to these differences (Gordon et al 2009).

Perhaps one of the most basic, yet most critical, elements of any ERM construct is for a firm to have established risk preferences - namely risk appetite and risk tolerance - upon which ERM can function towards. One definition proposed for risk appetite is by Aven (2013), p. 476: “the willingness to take on risky activities in pursuit of values”. For the sake of this study we define risk appetite and risk tolerance separately in turn. Risk appetite covers those risks that an organization wishes to attract and get paid to assume in support of operational and strategic objectives. Risk tolerance measures the extent of which those risks an organization has an appetite will remain on the balance sheet. For all intents and purposes risk appetite is a high level qualitative expression, where risk tolerance is a quantitative metric that measures risk appetite. Both appetite and tolerance combine to form an organization's risk preferences. Undeveloped or misapplied risk preferences undermine the prudent risk-based decisions and objectives of an otherwise solid ERM framework (Hillson and Murray-Webster 2012).

While, the existing literature has shown that well-structured ERM does influence value, few empirical studies exist that have explored how this influence changes when risk tolerance is not aligned to a firm's ERM process. One exception is a study by Myers (2014), who use moderation regression techniques to discuss how ERM processes within banks and insurance companies that are not operating with an appropriate risk appetite can be ineffective. Their findings show how the strength of an ERM framework, coupled with risk tolerance estimates, impacted value. However, that study did not account for different factors to determine organizational risk profiles (e.g., complexity, risk management leadership), and assumed that all companies practiced ERM to some degree. This study will build on that approach, but present an alternative methodology in part by introducing the impact of factors unique to an organization such as graphical foot print, leverage, organizational complexity, and ERM integration and how these factors jointly influence risk tolerance.

The goal of this study is to examine the extent of which an integrated ERM framework influences an insurer's risk preferences, and to see if optimal risk preferences influence performance. We will do so by combining elements of the research designs of two recent ERM studies. We will measure ERM strength following a methodology developed by Gordon et al (2009), and we will evaluate ERM integration based on a methodology presented by Hoyt and Liebenberg (2011). Our argument is that when ERM is both strong and integrated into the firm, insurers are able to operate towards an optimal or well-structured risk tolerance. Furthermore, as that optimal risk tolerance is determined, improved operational efficiencies are realized.

This research should contribute to the existing literature in multiple ways. It links multiple empirical and theoretical works to cohesively demonstrate how and why ERM influences performance. Unlike most existing literature, this research does not presume that ERM is directly linked to performance. Indeed, it shows that ERM's effectiveness is predicated on its integration as well as its adaptation towards a well-structured risk tolerance.

The remainder of this paper is organized in five additional sections. **Section 5.4** explores additional relevant literature and background related to the underlying argument of the study. **Section 5.5** presents the research design. **Section 5.6** includes a discussion of the data used in the study. **Section 5.7** provides an overview of the empirical results. **Section 5.8** presents concluding comments.

5.4 Review of the Literature

Traditional risk management has been identified historically as a means to support operational efficiencies - e.g. Smith and Stulz (1985), Mayers and Smith (1982, 1990), (Froot, Scharfstein et al 1993). Enterprise risk management is a framework that takes traditional risk management to a point where the management of risk goes beyond a control mechanism to that where performance and valuation is enhanced via holistic risk management processes (Nocco and Stulz 2006). Meulbroek (2002) describes the fundamentals of ERM reflecting a holistic and aggregated process to manage risk across an enterprise. COSO (2012, 2004) goes as far as defining four components that define ERM - efficiencies with strategy, operations, reporting and compliance; and that practitioners of strong and integrated ERM should exhibit better performance and generate higher value relative to non-practitioners. These notions have been explored empirically by Gordon et al (2009), Hoyt and Liebenberg (2011), McShane et al (2011), Standard & Poor's (2013b), Myers (2014) and others. Additionally, it has been shown that operational costs can be reduced and efficiencies increased through effective ERM (Eckles et al 2014). Moreover, ERM has been cited as a means for organizations to better adapt to changing regulatory standards (Arnold et al 2011).

Determining if a company has an ERM framework in place, and in turn measuring the effectiveness of ERM is not without challenges. Such disclosures are voluntarily and inconsistently communicated across companies, making relative comparisons and data collection difficult. Some studies use announcements of chief risk officer appointments as an indicator of ERM - e.g., Liebenberg and Hoyt (2003). Indeed, more complex organizations may have a need for stronger ERM frameworks. This may be signalled through the hiring of chief risk officers or similar roles to oversee the integration of these frameworks (Pagach and Warr 2011). Gordon et al (2009) developed an ERM index score based on COSO's (2012, 2004) definition of ERM. Additionally, certain credit rating agencies publish opinions on the strength of ERM, but only for the companies they rate (Standard & Poor's 2013a).

ERM also facilitates a better understanding of, and decisions surrounding, ideal risk preferences and ideal risk profiles, e.g., Nocco and Stulz (2006). Hillson and Murray-Webster (2012) explore how risk-based decision making is linked to risk preferences. Risk profiles are a reflection of risk capacity. One way to frame risk capacity is via a financial context; for instance, using the size and scope of a company's balance sheet. Regulators and rating agencies incorporate risk-based capital models which gauge the risk profile of an insurer relative to its financial position - e.g. EIOPA (F.K.A CEIOPS) (2010), AM Best (2013a, 2013b). This might consider all assets, liabilities and equity of the firm. However, there may be other aspects of risk capacity that are not measured with these approaches. For example, Power (2009) argued that using financial capital as measurement of risk capacity and risk appetite may be too narrow of a measurement and overlook broader ethical and behavioral elements that hold no quantitative measure yet are important considerations in risk management.

5.5 Research Design

There are two hypothesis at the center of the argument in this paper. One is that insurers with strong integrated ERM suited to their complexity[27] and degree of leverage, are able to achieve better performance relative to those with weaker or non-existent ERM frameworks. The other is that the aforementioned achievement is predicated on insurers operating within an optimal risk tolerance, ideally suitable to their target risk profile. Hence:

$$Optimal\ Risk\ Tolerance = f(Complexity, Leverage, ERM) \qquad \textit{(Hypothesis I)}$$

$$Performance = f(Optimal\ Risk\ Tolerance) \qquad \textit{(Hypothesis II)}$$

Both aspects are tested through linear regression. This argument shows that ERM's influence on performance and value is not necessarily due to a direct link such as what McShane et al (2011) argued against, but that ERM's influence is predicated on other interactions, such as the suitability of ERM not simply the apparent strength of ERM (e.g., Gordon et al, 2009), (Myers 2014).

Our view of risk tolerance is linked to an insurer's financial position as measured by the size of its balance sheet. A firm's balance sheet size (or balance of total assets) defines the overall financial capacity that can be used to assume risk, and the portion of that capacity which is utilized determines a firm's risk tolerance.[28] Firms with high risk tolerances will expose more of its balance sheet to potential earnings losses than other firms. As an organization becomes more complex, more things can go wrong or need to be unaccounted for, thus inherent risks become more apparent. Similarly, high leverage acts a multiplier of good or bad outcomes, thus it increases an insurer's inherent risk profile. Since complexity and leverage reduce the margin of error as managers execute risk strategies, intuition suggests that these factors should

[27] Here complexity is a measure of how operationally complicated a firm is. We proxy this by the number of operating segments and global exposure of the firm. This is discussed in more detail in **Section 5.6.8**.
[28] This is discussed in more detail in **Section 5.6.10**.

act inversely to an operational risk tolerance. Specifically, as organizations become more complex or increase leverage they should seek lower risk tolerances.

Enterprise risk management may offset or reduce the likelihood of adverse earnings outcomes associated with complexity or leverage. But this assumes that the ERM framework is well designed and fully integrated into the organization. All else equal we expect that increases to ERM strength can support increases to risk tolerance.

By striking the right balance across complexity, leverage and ERM an optimal risk tolerance can be identified for the insurer, which generate relatively higher performance. Existing ERM research state that companies which are ERM users benefit from lower costs, higher risk adjusted performance and increased valuations (e.g., Nocco and Stultz 2006; Gordon et al 2009; Hoyt and Liebenberg 2011). However, the role of risk tolerance in how these benefits come to fruition warrants further exploration. Hence we confirm that the link between ERM and performance is not necessarily a linear one.

We will assess this by first regressing risk tolerance on complexity, leverage and ERM and other control variables to confirm that a relationship exists.

$$Risk\ Tolerance_i = \beta_0 + \beta_1 Complexity_i + \beta_2 Leverage_i + \beta_3 ERM_i + \beta_x Control\ Variables_i + \varepsilon_i \qquad (1)$$

If there is predictive power found in model (1), then the regression equation will suggest an optimal risk tolerance level for each insurer in our sample. Riskier profiles garner lower risk tolerances so it is important to recognize the signs of the coefficients in model (1). We expect complexity and leverage to put downward pressure on the ideal risk tolerance since these elevate an insurer's risk profile, and we expect strong and integrated ERM to allow a higher risk tolerance since this reduces the risk profile. The signs for the control variable coefficients will vary.

Next we will assess how each company's residual in model (1), ε_i , relate to that company's performance. Performance will be measured by return on assets and return on equity both on a risk adjusted basis. The expectation is that as the absolute value of the residual increases, a company's existing risk tolerance range is further removed from its optimal risk tolerance range and performance suffers as a result. We take the absolute value, because existing risk tolerances can be too high or too low relative to optimal levels. We also separate negative residuals from positive residuals to isolate any potential differences in influence by either an overly conservative (negative ε_i) or overly aggressive (positive ε_i) risk tolerance relative to optimal levels. This residual is inversely related to performance, so as the absolute value of the residual increases in either direction performance should decrease. See model (2).

$$Performance_i = \beta_0 + \beta_1|-\varepsilon_i| + \beta_2|+\varepsilon_i| + e_i \quad (2)$$

Where Performance is risk adjusted ROA or risk adjusted ROE

Where $|-\varepsilon_i|$ is the absolute value of company i's residual if below an optimal risk tolerance, otherwise zero

Where $|+\varepsilon_i|$ is the absolute value of company i's residual if above an optimal risk tolerance, otherwise zero

Each company has only one of either a residual below, above or equal to its optimal risk tolerance

Holding all else constant if the regression coefficients of model (2) are statistically greater than zero, then model (2) supports our argument that an optimal risk tolerance contributes to performance. The next section will review the data used in this study and how the variables for models (1) and (2) are estimated.

5.6. Discussion and Evaluation of Data

5.6.1 Data Sources

The initial data set was sourced from SNL Financial and included its listing of 145 publicly traded stock insurance companies based in the United States. The focus was narrowed to insurance organizations since risk management is normally their strategic focus. U.S. Insurers were used to avoid the potential for regional differences and influences, and also because more public data is readily available for U.S. entities compared to most other regions. The choice to use publically traded companies allowed greater opportunities to extrapolate the necessary qualitative and quantitative data than what would typically be available from private firms, while also considering the impact to stock price performance.

The core data for the analysis included financial performance, operational statistics and stock price returns. SNL Financial, CompuStat and CRSP were the primary sources for this information. The 2013 reporting year was the primary year of focus for each company. However, for certain metrics in our research design we required multiple years of data going back to 2008 (e.g., return on equity volatility). Some of the initial 145 companies in the study were missing data for certain years or reported data would not produce meaningful results (e.g., a negative shareholders equity balance). After review of the initial sample it was determined that 110 of the 145 had sufficient financial and operational data to be included within the study. This sample size of 110 is deemed reasonable. It is well above the range suggested by Field (2009) for regression model validity[29].

It was also necessary to identify companies that had integrated ERM frameworks. There are no formalized reporting requirements as respects to ERM existence or quality for U.S. insurance companies. In order to track this information we follow a similar method employed by Hoyt and Liebenberg (2011), Eckles et al (2014) and others that track signals in the commentary of public disclosures of a company to determine the presence of integrated ERM. Firstly, we reviewed each company's 2013 annual report, 10K, and website[30] for language indicative of ERM. Example search phrases included "Enterprise Risk Management", "Holistic Risk Management", "Corporate Risk Management" and similar. We then assessed the context surrounding the phrase to assess if the company was currently practicing ERM, and not simply defining it or were noting future plans for implementation. Secondly, as shown by Liebenberg and Hoyt (2003), Beasley et al (2005) and Pagach and Warr (2011), companies with Chief Risk Officers, Heads of ERM or equivalent positions tend to have integrated ERM frameworks. Thus if ERM framework descriptions were not readily evident in a company's public disclosures, those companies with CRO-equivalent positions listed on websites or within financial statements were deemed to have integrated ERM frameworks for this study. Thirdly, in those instances where no CRO was present and there was no indication of ERM otherwise, we reviewed available rating agency reports to find suggestions of integrated ERM[31]. Finally, if a company only described a risk management practice that was focused on one specific risk type (e.g., managing interest risk through derivatives hedges; utilizing hazard insurance for natural catastrophe risk) these alone were not considered characteristics of an integrated ERM

[29] Field notes that the recommended minimum sample size to test such validity is dependent on the number of predictors in the model. Specifically the target sample size = 50 + 8k, where k is the number of predictor variables. Our sample size exceeds this value.
[30] Website data was reviewed as of month-end February 2015 across all 110 companies in the study for consistency of timing.
[31] For instance, the credit rating agency Standard & Poor's produces an annual financial strength rating and corresponding rationale report. Within these reports are commentary regarding the strength of the insurer's ERM framework. Companies deemed to have stronger ERM assessments by Standard & Poor's were also deemed to have integrated ERM for the purposes of our study.

framework. See **Section 5.9 Appendix A** for examples of commentary used to confirm integrated ERM.

5.6.2 Variable Calculation and Measurement

Ten variables were tracked for this study using data captured as described above. Eight of these were continuous, non-categorical variables. Two were discrete, categorical variables. **Table 5.1** provides a quick reference for how these variables are defined. **Table 5.2** provides some corresponding descriptive statistics and correlation data. These will be discussed in turn and its relevance to this study.

Table 5.1. Description of variables used in the study

Variable	Abbreviation	Definition	Data Source
Enterprise Risk Management Index	ERMI	Score that measures the strength of a firm's ERM considering COSO's four pillars: strategy, operations, reporting and compliance. See **Section 5.9 Appendix B.**	COMPUSTAT, CRSP, SNL
Integrated ERM	INTEG	A categorical variable denoting if a company shows evidence that their ERM framework is formalized and integrated into their operational lexicon. 1 = yes; 0 = no.	Financial statements, websites, rating agency reports
Leverage	LEV	Average assets for the year divided by average equity for the year.	SNL
Life Insurer	LIFE	Dummy variable to capture if an insurer was a life insurance company or non-life insurer.	COMPUSTAT, SNL
Market Share	MS	Market share takes each insurer's 2013 revenues divided by total revenues generated that year by that insurer's industry (life, health or property casualty) in the United States.	COMPUSTAT, SNL
Organizational Complexity	COMPLX	A categorical variable denoting the degree of complexity of a firm. Low: < 4 Segments, Medium: 4-6 Segments, Elevated: > 6 Segments, High: > 6 Segments with global	COMPUSTAT

		operations. Note any firm with global operations is considered to have an additional segment.	
Return on Assets	ROA	Earnings before interest and taxes over average assets for the year.	SNL
Return on Assets (risk adjusted)	ROAz	ROA divided by the five year annual standard deviation of ROA.	SNL
Return on Equity	ROE	Earnings before interest and taxes over average equity for the year.	SNL
Return on Equity (risk adjusted)	ROEz	ROE divided by the five year annual standard deviation of ROE.	SNL
Risk Capacity	RC	The size of insurers balance sheet as measured by average assets for the year.	SNL
Risk Capacity Utilization	RCU	A proxy of a firm's risk tolerance. It is Average Equity times ROE VAR% divided by Risk Capacity.	SNL
ROE Value at Risk	VAR	Five year standard deviation of ROE multiplied by the 99.5% confidence statistical table factor of 2.56 applied to average equity.	SNL
Years in Business	AGE	The number of years that an insurer has been in business.	COMPUSTAT, SNL, websites

Table 5.2. Descriptive Statistics and Pearson Correlations of key variables used in the study.

Enterprise Risk Management Index (ERMI) Subgroup Comparison

Variables	**Total Sample**		**Integrated ERM**		**Not Integrated**		**Difference In Means**	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Difference	p-Value
ERMI	0.157	2.622	0.701	2.240	-0.497	2.907	1.198	0.016
LEV	6.114	6.008	6.818	7.284	5.268	7.284	1.550	0.179
MS	0.018	0.042	0.019	0.047	0.016	0.034	0.003	0.711
ROA	0.034	0.034	0.035	0.031	0.034	0.038	0.000	0.969
ROAz	3.581	3.965	3.670	2.977	3.474	4.927	0.196	0.797
ROE	0.134	0.133	0.134	0.090	0.135	0.172	-0.001	0.979
ROEz	3.215	3.908	3.329	2.554	3.079	5.107	0.250	0.740
RCU	0.053	0.053	0.050	0.053	0.057	0.053	-0.007	0.498
VAR	0.230	0.253	0.234	0.289	0.224	0.204	0.010	0.840
AGE	52.982	44.033	51.017	44.900	55.340	43.304	-4.323	0.610
Sample Size	110		60		50			

Pearson Correlations across the sample

	ERMI	XS	LEV	ROA	ROE	RCU	VAR	ROAz	ROEz	AGE	MS
ERMI	1										
XS	-0.110	1									
LEV	0.077	-0.232	1								
ROA	-0.048	0.167	-0.378	1							
ROE	-0.118	0.016	-0.026	**0.765**	1						
RCU	-0.074	-0.027	-0.303	0.129	-0.101	1					
VAR	-0.011	-0.338	0.016	-0.175	-0.219	**0.829**	1				
ROAz	0.045	0.055	-0.085	0.044	-0.031	-0.049	-0.085	1			
ROEz	0.078	0.066	-0.139	0.097	-0.034	0.001	-0.061	**0.741**	1		
AGE	-0.063	0.033	-0.088	-0.087	-0.041	-0.074	-0.105	0.126	0.037	1	
MS	0.138	0.046	-0.092	0.127	0.073	0.022	-0.044	0.243	0.370	0.192	1

Correlations above 0.50 are denoted in bold.

5.6.3 Enterprise Risk Management Effectiveness Index (ERMI)

This variable captures the strength of an organization's ERM framework following the tradition of COSO (2004, 2012), and measured using a process introduced by Gordon et al

(2009). Strategy, operations, reporting and compliance are the four components of the ERMI. Data used to measure these components are extracted from annual financial disclosures, standardized and equally weighted to form the ERMI for each insurer in the study. All else equal a higher score is indicative of a stronger ERM framework for a given company. Details of the data used and the process applied to generate the ERMI calculation are explained in **Section 5.9 Appendix B**.

5.6.4 Integrated ERM (INTEG)

Gordon et al's ERMI score is indicative of how strong an ERM framework appears based on available public information. However, the score on its own makes an assumption that ERM is practiced readily, without any adjustment to account for non-ERM users that coincidentally might have a high indicative ERM score. In order to determine if the insurers in the sample were true practitioners of integrated ERM each organization's available financial and operational disclosures were reviewed, as well as credit rating agency reports if necessary, to make subjective determinations of ERM integration. This was described in further detail in **subsection 5.6.1** above. To the extent evidence was apparent that an insurer practiced ERM "1" was assigned to that company. All other firms were assigned "0". 60 of the 110 firms, or approximately 55% of the sample were deemed to have integrated ERM.

5.6.5 Leverage (LEV)

It is assumed that as an organization's leverage increases so does the inherent risk of its balance sheet and operational profile all else constant. This was calculated as average total assets divided by average total equity for the 2013 period.

5.6.6 Life Dummy (LIFE)

Life insurers may have certain operational characteristics that are different from their non-life counterparts. These may influence their risk profiles. To capture this influence all life insurers, as denoted as such by COMPUSTAT, were assigned a dummy variable of "1".

5.6.7 Market Share (MS)

Market share takes each insurer's 2013 revenues divided by total revenues generated that year by that insurer's industry (life, health or property casualty) in the United States.

5.6.8 Organizational Complexity (COMPLX)

COMPLX provides an indication of how complex an organization is based on a combination of operating segments and global foot print. The rationale for this follows that as presented by Ge and McVay (2005), Doyle et al (2007), and employed by Eckles (2014), which all argue that as the number of segments for a firm increases so does its complexity. COMPUSTAT data was used to capture the number of operating segments for a firm and if it had global operations. Each insurer is assigned into one of four categories based on this data. Insurers with less than four operating segments were considered low complexity. Those with four to six segments were deemed medium complexity. Those with over six segments are classified as elevated. Those with six or more segments and had global operations are considered of high complexity. Having global operations was considered as having an additional operating segment. For example, a firm with three operating segments would ordinarily fall in the low complexity category, but if that firm also operated globally it is classified as medium complexity instead. These classifications results with most insurers in either the medium to elevated categories, with smaller clusters in the low or high category. **Table 5.3** provides the count in each category for the COMPLX variable.

Table 5.3. The distribution of companies across the four categories of complexity used in this study.

Complexity Category	Operating Segments*	Count	Percent
Low	less than four	12	11%
Medium	four to six	41	37%
Elevated	greater than six	47	43%
High	greater than six plus global	10	9%
Total		110	100%

* Having global operations was equivalent to having one additional operating segment.

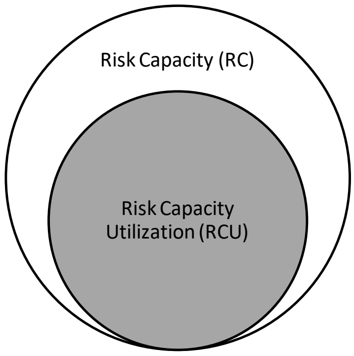
5.6.9 Return on Assets (ROA), Return on Equity (ROE) and Risk-adjusted ROA / ROE

A common measure of operational performance is to assess the amount of earnings a company is able to generate from its assets. This was calculated as earnings before interest and taxes generated over the period divided by average assets for the period. And similar to ROA, but focused on returns that are generated for shareholders, ROE is earnings before interest and taxes divided by average equity. These are risk adjusted by dividing ROA and ROE by their respective five year standard deviations, which is denoted as ROAz and ROEz.

5.6.10 Risk Capacity (RC), Risk Capacity Utilization (RCU) and ROE Value-at-Risk (VaR)

An insurance company is in the business of exposing itself to risk with an expectation of generating value. Following Aven (2013), an organization's willingness to expose its balance sheet to financial loss is what is defined as risk capacity utilization for the purposes of this study. Myers (2014) introduced the concept of a firm's risk capacity (RC) using total equity plus subordinated debt divided by total assets. We follow a similar approach but assume a company’s entire balance sheet (total average assets), is available as capacity to support risk. This reflects the idea that all stakeholders that an organization is accountable to have claim to the balance sheet, and are impacted by returns on assets. While stock holders are the only stakeholders with direct claims on equity capital. Risk capacity utilization (RCU) is measured by taking a portion of RC estimated to support downside risk associated with an insurer's normal course of business over a one year period. See **Figure 5.1.**

Figure 5.1. Risk Capacity Utilization Venn Diagram



Introduced by Myers (2014) Risk capacity (RC) is a concept defined as an organization’s ability to withstand risks associated with sustaining their operations at desired levels. Myers (2014) used equity divided by total assets to define RC. For our study we measure RC with the size of a company’s entire balance sheet, or total assets. Our rational is that performance has a direct impact on a broader set of stakeholders, not simply stock holders as Myers (2014) was evaluating. Hence looking beyond equity capital is allows a more appropriate proxy of risk capacity.

Equation *(ii)* formally defines the calculation for RCU consistent with Myers (2014).

$$\text{RCU}_i = \frac{ROE\ VaR_i * Equity_i}{Total\ Assets_i} \qquad (ii)$$

Where for firm i, RCU equals the equity value-at-risk (VaR) expected over a one year period divided by the total assets of the firm. Downside risk metrics such as value-at-risk are considered by financial institutions as a means to articulate risk appetite (Shang and Chen 2012). A parametric VaR is calculated using the expected volatility of returns to a portfolio, the inverse normal cumulative distribution factor (i.e., standard normal critical value) corresponding to the confidence level in question, and the portfolio value (Jorion 2001, p.109). A 99.5% confidence level is assumed for this paper, which has been used by regulators as the confidence level to which they calibrate their solvency and statutory tests (e.g., EIOPA (F.K.A CEIOPS) 2010). A 99.5% confidence translates into a 2.56 critical value. Therefore, each case's ROE VaR[32] is calculated as:

Earnings Volatility = ROE Standard Deviation

$$ROE\sigma_i = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(ROE_{i,j} - \overline{ROE_i})^2}, \text{ where } i = \text{firm } i,\ j = \text{year} \qquad (iii)$$

$$ROE\ VaR = ROE\sigma_i \ x\ 2.56\ x\ Equity \qquad (iv)$$

It was assumed that firms exhibit high RCUs due to implied high risk tolerances. However, high RCUs are not necessarily bad, nor are low RCUs necessarily good. What is argued is if a firm's RCU is too high or too low relative to its risk profile, i.e. less than optimal, then its performance can suffer. A strong and integrated ERM framework helps establish an appropriate RCU level for a given firm.

5.6.11 Years of Operation (AGE)

AGE takes the total years of existence for each insurer as denoted by COMPUSTAT. It is assumed that younger firms would be more risky relative to older established firms.

5.6.12 Data Review and Analysis

The initial review of the data included assessing differences in means of the eleven continuous variables across the integrated and non-integrated ERM subgroup. These are shown in part in **Table 5.2.** There were 60 insurers identified with integrated ERM and 50 without integrated ERM. Comparing the two groups shows no obvious linear differences in the means

[32] VAR can be estimated in various ways, including parametrically. A parametric VaR is usually used when the corresponding variable is assumed to follow a normal distribution. For the sake of this analysis we make a strong assumption that the five year return on equity value for each case in each sample is normally distributed.

across all variables other ERMI. Correlations were generally low across all variables except between ROA and ROE, between ROAz and ROEz, and between RCU and VAR. ROA and ROE use the same return values. The RCU metric is directly impacted by a company's VAR. ERMI exhibits no obvious linear positive or negative linear relationship with any other variable. The empirical results of this study are presented in the next section, which show how on a non-linear basis ERMI's influence becomes more apparent.

5.7 Empirical Results

A multistage regression was applied to examine the role that enterprise risk management plays with performance. The argument is that ERM's influence on performance is not necessarily direct or linear. A key outgrowth of strong and integrated ERM is that ERM users can identify and work towards an optimal use of their risk bearing capacity, i.e., risk tolerance. As management decisions facilitate movement towards and within optimal risk tolerance levels, they are able to improve performance. All regression analysis is done within the SPSS statistical software environment.

5.7.1 Model Evaluation

The first stage regression process evaluates influence for the influence of an optimal risk tolerance. The initial regression in this first stage assesses the relationship across complexity (CMPLX), leverage (LEV), enterprise risk management (ERMI) and risk capacity utilization (RCU), where RCU is our proxy for risk tolerance:

$$Risk\ Tolerance = \beta_0 + \beta_1 Complexity + \beta_2 Leverage + \beta_3 ERM + Residual \qquad (1)$$

The complexity variable was based on an assigned category of either low, medium, elevated or high. There is no perceived difference in the scale or magnitude between low to medium, medium to elevated or elevated to high. The only assumption is that 'high' suggests higher complexity relative to 'elevated' and so on. Given that these are categories as opposed to continuous variables to define complexity, traditional statistical methods were followed for regression with categorical variables[33]. Hence dummy variables of 0 or 1 were assigned for each company to identify the category to which that company belonged. Model (1) becomes:

---

[33] See Field (2009).

$$Risk\ Tolerance = \beta_0 + \beta_{1DummyA} medComplexity + \beta_{1DummyB} elevComplexity + \beta_{1DummyC} hiComplexity + \beta_2 Leverage + \beta_3 ERM + \ Residual \quad (1a)$$

The results of the model (1a) regression are shown in **Table 5.4.** The r-squared and F-stat imply that the model has some explanatory value. The COMPLX coefficient shows statistical significance at the 95% confidence level. Additionally, as complexity increases the corresponding coefficient values also increase. Both results support the notion that higher organizational complexity puts greater downward pressure on an optimal risk tolerance. The leverage coefficient is also statistically significant and negative and inline to what we would expect. However, the ERMI variable seems to not have any relevance in determining an optimal risk tolerance in this model.

Table 5.4. Regression model (1a) results.

Model (1a) Regression Result

Optimal RCU reflecting Complexity, Leverage and ERM

Coefficient Name	Coefficient Value	Expected Sign	P-Value	VIF
Intercept	0.102		0.000	
Dummy: medCOMPLX	-0.032	-	0.060	2.871
Dummy: elevCOMPLX	-0.038	-	0.023	2.885
Dummy: hiCOMPLX	-0.055	-	0.014	1.742
LEV	-0.003	-	0.002	1.021
ERMI	0.000	+	0.997	1.050
F-Statistic	3.767		0.004	
R-Squared	0.153			
Adjusted R-Squared	0.113			

Risk capacity utilization is regressed on complexity dummy variables, leverage and the ERM proxy.

Gordon et al's (2009) ERM index score (ERMI) methodology was used, which includes four equally weighted standardized values across strategy, operations, reporting and compliance. These four areas are consistent with COSO (2004, 2012). However, this score on its own only captures the strength of ERM. It does not recognize that some organizations have integrated ERM and others do not. For example, an insurer may practice one or more elements of traditional risk management very well, while not on a holistic or integrated basis. This may look like it practices certain characteristics of strong ERM (e.g., very effective operations), but these elements may not be interlinked as defined by COSO (2004, 2012). To account for these potential false impressions an adjustment is made to the ERMI score by accounting for those insurers determined to have integrated ERM (INTEG) versus those that do not as defined in **Section 5.6** above. An interactive variable is added to model (1a) by multiply ERMI by their INTEG score. This follows methods used by Eckles et al (2014), Hoyt and Liebenberg (2011), which shows how evidence of ERM interaction and implementation impact risk profiles and valuation. Model (1a) is modified to model (1b):

$$Risk\ Tolerance = \beta_0 + medComplexity + \beta_{1b}elevComplexity + \beta_{1c}hiComplexity + \beta_2 Leverage + \beta_3 ERMI + \beta_4 ERMI * INTEG + Residual \quad (1b)$$

Table 5.5. Regression model (1b) results.

Model (1b) Regression Result

Optimal RCU reflecting Complexity, Leverage, ERM and Integrated ERM Qualifier

Coefficient Name	Coefficient Value	Expected Sign	P-Value	VIF
Intercept	0.096		0.000	
Dummy: medCOMPLX	-0.029	-	0.077	2.884
Dummy: elevCOMPLX	-0.033	-	0.047	2.944
Dummy: hiCOMPLX	-0.051	-	0.020	1.753
LEV	-0.003	-	0.001	1.022
ERMI	-0.004	-/+	0.133	1.881
ERMIxINTEG	0.009	+	0.026	1.831
F-Statistic	4.117		0.001	
R-Squared	0.193			
Adjusted R-Squared	0.146			
R-Square Change	0.193		0.026	

Risk capacity utilization is regressed on complexity dummy variables, leverage, ERMI (the enterprise risk management proxy), and a variable that recognizes if ERM is integrated within the firm.

The results of the model (1b) regression are shown in **Table 5.5**. The r-squared and F-stat imply that the model has some explanatory value. Moreover, the r-squared improvement to 0.194 from 0.150 by including the ERMIxINTEG variable is statistically significant compared to the results of the model 1a regression. The COMPLX coefficients shows reasonable statistical significance at just below the 95% confidence level or better, and similar to model (1a) there is a progression in the coefficient as its value gets more negative going from medium to high complexity. Leverage is negative and statistically significant as with model (1a). ERMI shows more relevance in this model, but still falls short of even the 90% confidence level. However, when we consider the interactive variable ERMIxINTEG which captures the strength and integrated nature of ERM, we see it is positive and statistically significant. Considering each variable in turn the results are aligned to our expectations: 1. Complexity and leverage add to the risk profile resulting in downward pressure on the optimal risk tolerance; 2. Integrated and strong enterprise risk dampens the risk profile facilitating upward pressure on the optimal risk tolerance. When an insurer is able to strike the optimal mix of complexity, leverage and ERM, and assuming that ERM is integrated, an optimal risk tolerance, as measured by risk capacity utilization, can be achieved.

As an additional model refinement we introduce other risk profile control variables that might influence risk capacity utilization or risk tolerance: market share (MS), years of operation (AGE) and a life (LIFE) insurer dummy variable. Moreover, model tests showed evidence of heteroskedasticity with regards to leverage where we notice higher variation in RCU as leverage increased. To account for this weighted least squares was applied within SPSS. Model (1b) then becomes model (1c):

$$Risk\ Tolerance \ = \beta_0 + medComplexity + \beta_{1b}elevComplexity + \ \beta_{1c}hiComplexity + \beta_2 Leverage + \beta_3 ERMI + \beta_4 ERMI * INTEG + \beta_6 MS + \beta_6 AGE + \beta_7 LIFE \ + Residual \tag{1c}$$

The results of regression model (1c) are shown in **Table 5.6** below.

Table 5.6. Weighted least squares regression model (1c) results.

Model (1c) Regression Result

Optimal RCU reflecting Complexity, Leverage, ERM, Integrated ERM Qualifier, control variables: market share, years of operation and life industry designation and weighted least squares.

Coefficient Name	Coefficient Value	Expected Sign	P-Value	VIF
Intercept	0.102		0.000	
Dummy: medCOMPLX	-0.029	-	0.060	0.382
Dummy: elevCOMPLX	-0.029	-	0.063	3.738
Dummy: hiCOMPLX	-0.037	-	0.061	2.104
LEV	-0.001	-	0.010	1.764
ERMI	-0.003		0.277	2.324
ERMIxINTEG	0.008	+	0.028	2.512
MS	-0.001	-	0.699	1.394
Age	0.000	+	0.140	1.223
Dummy: Life	-0.031	-/+	0.001	1.362
F-Statistic	6.336		0.000	
R-Squared	0.363			
Adjusted R-Squared	0.306			

Risk capacity utilization is regressed on complexity dummy variables, leverage, the ERM proxy, an integrated ERM variable while also considering other control variables - market share, the age of the company and if the company is a life insurer.

While MS and AGE show no meaningful influence to RCU, being a life insurer does. ERMI in isolation continues to not play a role. Hence, as one last model revision the life control variable is included as an additional predictor of RCU and insignificant predictors, including ERMI, are removed. The revised RCU regression becomes model (1d):

$$Risk\ Tolerance\ = \beta_0 + medComplexity + \beta_{1b}elevComplexity + \beta_{1c}hiComplexity + \beta_2 Leverage + \beta_3 ERMI * INTEG + \beta_4 LIFE\ + Residual \quad (1d)$$

The results of regression model (1d) are in **Table 5.7.**

Table 5.7. Weighted least squares regression model (1d) results.

Model (1d) Regression Result With Weighted Leaset Squares (WLS)

Optimal RCU reflecting Complexity, Leverage, ERM, Integrated ERM Qualifier and Life dummy

Coefficient Name	Coefficient Value	Expected Sign	P-Value	VIF
Intercept	0.100		0.000	
Dummy: medCOMPLX	-0.032	-	0.039	3.743
Dummy: elevCOMPLX	-0.036	-	0.019	3.548
Dummy: hiCOMPLX	-0.046	-	0.016	1.912
LEV	-0.001	-	0.009	1.755
ERMIxINTEG	0.006	+	0.022	1.278
Dummy: Life	-0.034	-	0.000	1.328
F-Statistic	8.666		0.000	
R-Squared	0.335			
Adjusted R-Squared	0.297			
R-Square Change Significance Versus Model (1b)			0.000	

Risk capacity utilization is regressed on complexity dummy variables, leverage, an integrated ERM variable and a life dummy control variable.

The second stage regression process evaluates how an optimal RCU relates to performance as measured by return on assets and return on equity both on a risk adjusted basis - denoted as ROAz and ROEz respectively. To evaluate this the absolute values of the residuals from model (1d) are collected for each company in the sample and categorized as a positive (i.e., higher than optimal risk tolerance), or negative (i.e., lower than optimal risk tolerance). These were labelled as ABSRESID+ and ABSRESID- respectively. Next ROAz and ROEz are each regressed on ABSRESID+ and ABSRESID-. The regression equation is noted as model (2).

$$Performance = \beta_0 + \beta_1 ABSRESID_+ + \beta_2 ABSRESID_- + error\ term \qquad (2)$$

If there is a positive relationship between optimal risk tolerance and performance one would expect model (2)'s result to show an R-squared and beta coefficients to be statistically different from zero. To interpret this result consider Company A, who has an optimal RCU. If this is so than Company A's ABSRESID would be zero, and the net impact on the performance measure is the regression intercept β_0, which should be positive. In contrast, Company B has an RCU that is above an optimal level, then Company A's ABSRESID+ would be relatively high resulting in negative pressure on performance.

The regression results of Model (2) are shown in **Table 5.8**. The results support elements of the argument. The r-squared is positive, the intercept and the ABSRESID+ regression coefficient has the expected signs, and the p-values indicate statistical significance when considering aggressive risk appetites. Insurers with RCUs above optimal levels suffer with regards to risk adjusted performance. Yet insurers with conservative risk appetites, hence RCUs below optimal levels, show no meaningful lag in performance. This could suggest that it is better to be conservative than aggressive with regards to risk capacity.

Table 5.8. Regression Model (2) results.

Model (2) Regression Result of ROAz and ROEz versus deviations from optimal RCU. Deviations tracked from residuals of Model (1d)

Coefficient Name	ROAz Coefficient Value	P-Value	ROEz Coefficient Value	P-Value	Expected Sign
Intercept	3.962	0.000	3.340	0.000	+
ABSRESID-	16.847	0.393	26.691	0.172	-
ABSRESID+	-35.041	0.003	-29.696	0.010	-
F-Statistic	7.580	0.001	7.267	0.001	
R-Squared	0.124		0.120		

Risk adjusted ROA (ROAz) and risk adjusted ROE (ROEz) are regressed on the absolute value of the negative and positive residuals from model (1d). The results suggest that higher than optimal risk tolerances (ABSRESID+) have a statistically significant adverse impact on risk adjusted performance, while the impact of lower than optimal risk tolerances (ABSRESID-) is unclear.

5.7.2 Diagnostics and Robustness Checks

Since the analysis employs linear regression most diagnostics focused on verifying the traditional linear regression assumptions. Multicollinearity was not deemed an issue given the low variance inflation factors in any of the models. The regression residuals were within acceptable ranges to not rule out normality. Significant outliers were assessed prior to the regression models being run. A few were removed from the original dataset. As mentioned above heteroskedasticity was identified with regards to leverage - as leverage increased variation in RCU levels increased. This was confirmed visually and through a White's Test. As such the regressions were re-run using weighted least squares (WLS). The results were consistent under this approach as with the un-weighted least squares model but with higher r-squareds. There is a risk of our model over fitting our sample data using WLS so we refrain from making strong generalizations to a population at this time.

There are performance or valuation measures beyond what was used for this study that may be worth consideration such as economic value added, Tobin's Q, and price-to-book. However, valuation metrics generally consider the perspective of shareholders. Moreover there are other factors that might influence risk tolerance levels or indeed other measures of risk tolerance. Further research are encouraged to test such considerations. However, notwithstanding these points, and as it relates to the sample in question, the results of this study provides evidence of how strong and integrated ERM frameworks support ideal risk tolerances for a given risk profile, and how this support is ultimately positively related to common performance measures.

5.8 Conclusions

The results of this study demonstrate a plausible, indirect relationship between Enterprise Risk Management and risk-adjusted performance. Using Gordon et al's (2009) measure of ERM, while applying similar methods employed by Eckles et al (2014), Hoyt and Liebenberg (2011) to evaluate the role of integrated ERM, an indirect influence of ERM on performance can be identified. An organization's risk-adjusted performance is defined as the unit of return on assets per unit of risk associated with those returns. Strong and integrated ERM can eventually lead to improvements in organizational performance, but ERM's role is linked to an insurers risk profile and risk capacity utilization. Higher leverage, organizational complexity and simply being life insurer can elevate an insurer's risk profile, but strong and integrated ERM reduce that risk profile. Risk capacity utilization is defined as the range of an insurer's balance sheet that is at risk of loss due to its normal course of operations. Insurers that are able to operate within optimal risk capacity utilization ranges that align to their risk profile, are able to realize higher performance compared to those who operate outside of optimal ranges. This linkage has not been fully explored in prior ERM studies. The notion of ERM integration is a critical element of these findings. Exhibiting characteristics of prudent ERM involves a framework that is well structured, but also embraced by the organization's leadership and culture. When this integration is evident ERM's role in supporting risk profiles and ultimately risk adjusted performance can be seen. When this integration is not clear, then ERM's role is in doubt. The results shown are limited to a sample of U.S. publically listed insurance companies, focused primarily on their reported financial and operational results as of year-end 2013. While the findings are meaningful, the data and methods employed are not without their limitations. These are preliminary, yet encouraging, results whose insights support and add to earlier theories and studies surrounding the role of ERM in performance. Further exploration of this idea is encouraged.

5.9 Appendix A. Examples / Excerpts of Disclosures Used to Confirm Integrated ERM.

Aetna 2013 Annual Report, Page 67

"We continue to devote resources to further develop and integrate our enterprise-wide risk management processes. Failure to identify, prioritize and appropriately manage or mitigate these risks, including risk concentrations across different industries, segments and geographies, can adversely affect our operating results, our ability to retain or grow business, or, in the event of extreme circumstances, our financial condition or business operations."

Chubb's Standard & Poor's Financial Strength Rating Report, 19 December 2013, Standard & Poor's Global Credit Portal

"We regard Chubb's ERM framework as strong. Positive scores for risk culture, risk controls, emerging risks management, and strategic risk management along with a neutral score for risk models contribute to the overall assessment."

"Our positive score for Chubb's risk management culture reflects management's emphasis on underwriting risk management, risk identification and a seasoned committee structure that deals with risks proactively."

Travelers Inc. 2013 Annual Report, Page 36

“ERM at the Company is an integral part of its business operations. All risk owners across all functions, all corporate leaders and the board of directors are engaged in ERM. ERM involves risk-based analytics, as well as reporting and feedback throughout the enterprise in support 0f the Company’s long-term financial strategies and objectives.”

5.10 Appendix B. Calculating the Enterprise Risk Management (ERM) Effectiveness Index

The ERM index was calculated closely following the specifications developed by Gordon et al (2009). They adhered to the premise that effective ERM is comprised of strengths across four elements as prescribed by COSO (2004, 2012) – strategy, operations, reporting, and compliance. They defined two variables for each element. Each variable of each element was separately standardized first and then subsequently added to create the ERM index for each company in the sample. Following the tradition of Gordon et al (2009), equal weighting was applied to each of the five elements. Most of the variables used in the study were calculated as prescribed by Gordon et al (2009) using multiple data sources: SNL Financial, Compustat and CRSP.

Table 5.9. Enterprise Risk Management Effectiveness Index Calculation Methodology

Variable Description	Components
Strategy	
Component 1 =	(company sales – average industry sales) / standard deviation of industry sales
Component 2 =	(change in company's beta from prior year – mean change in betas from prior year for the industry) / standard deviation of change in betas from prior year for the industry
Operations	
Component 1 =	company sales / company total assets
Component 2 =	company sales / company number of full time employees
Reporting	
Component 1 =	reinstatement for the year? (yes = -1; no = 0) + qualified auditors opinion? (yes = -1; no = 0) + material weakness? (yes = -1; no = 0) (assumed 0 because this is not reported in SNL Financial)
Component 2 =	|company normal accruals| / (|company normal accruals| + |company abnormal accruals|)
Compliance	
Component 1 =	company auditor's fees / company total assets
Component 2 =	company settlement net gain / company total assets

Chapter 6.

Manuscript 4:

Risk Budget Structures and the Relevance of Enterprise Risk Management (ERM)

6.1 Abstract

Insurance companies are in business to assume risk. However, there is a limit to how much risk an insurer can assume. Once this total capacity for risk is determined, insurers must effectively choose how to utilize and distribute that capacity and align it to its operational strategy and stakeholder expectations. Operational strategies will influence the proportion of an insurer's total earnings sourced from underwriting income versus investment income, the two primary earnings sources for most insurers. Some insurers operational strategy are biased towards underwriting, some towards investments, and others may be balanced between the two. Furthermore, some insurers practice a holistic and strategic risk management process, called Enterprise Risk Management (ERM), which can influence the risk taking choices between underwriting and investments. We call this choice setting a risk budget structure. Through a mixed method research process this study evaluates to what extent the role of an ERM framework influences an insurer's choice to allocate more or less of its overall risk budget towards underwriting or investments. The first method employs a panel regression using financial and operational data for a sample of 108 U.S. publicly listed insurance companies. This panel considers select company characteristics over the 2008-2013 period, while also controlling for industry and time fixed effects. Augmenting this is an assessment of qualitative data obtained through interviews and supportive research of nine insurance companies' approach and utilization of ERM in risk allocation and strategy. The mixed method will provide different perspectives: 1) confirming a link between ERM and risk budget structuring, and 2) insight as to the nature of this linkage.

6.2 Key Words

Capital, Du Pont, Enterprise Risk Management, Risk-based Decisions, Risk Budget

6.3 Introduction

This study evaluates to what extent an insurance company's budgeting of risk between investment sources and underwriting sources is influenced by the strength of their enterprise risk management frameworks. Mixed methods of quantitative regression analysis and qualitative interview-gathered data analysis are used for the evaluation.

Insurance companies are in business to assume risk. Their cash flows and earnings are predicated on effective selection and pricing for the risks that they assume. For most property / casualty insurers their two primary earnings sources come from underwriting activities and investment activities. Underwriting profit margins depends on collecting more premium inflows than claims expense outflows. Investment activities generate returns as accumulated cash assets collected from operating activities are invested into various securities, and generate returns as those securities pay a yield and appreciate in price. Both can contribute to income, but they have different risk profiles.

Capital is an essential resource for insurance companies and serves as a key factor for their overall risk capacity. They must retain appropriate levels of capital, and overall balance sheet strength, to satisfy solvency requirements of regulators and to maintain financial strength ratings by rating agencies. Hence, risk capacity is a boundary within which an insurer must operate or otherwise face insolvency, default or other factors that will prevent that insurer from operating as a going concern. Most insurers will conservatively utilize a portion of their overall risk capacity on an ongoing basis. This portion is defined as risk capacity utilization and can be considered an organization's risk tolerance. Each insurer has an optimal risk capacity utilization or risk tolerance target based on their operational and geographical characteristics (Myers 2014, 2016).

Within a specified risk capacity utilization insurers can choose the types and degree of risks to assume. This choice is structuring a risk budget. Underwriting and investments are two primary sources of revenue and risk for an insurer. Some insurers prefer underwriting risk. They assign a significant portion of their risk budget to underwriting and significant resources to maintain positive underwriting margins over a period. Others have a bias towards investment risk. They will assume investment strategies expecting investment returns and profits, on a risk-adjusted basis, that are relatively higher than those from underwriting. While some insurers will maintain a relative balance of risk allocated between underwriting and investments. We define risk budget structure as established choice to allocate more or less underwriting risk relative to investments, while staying within a pre-determined risk capacity (tolerance). See **Sections 6.11 Appendix A** and **6.12 Appendix B** for an illustration and further explanation of risk capacity and risk budget structures.

Preference to maintain either an underwriting risk bias, an investment risk bias or a neutral bias might depend on the perceived relative risk or return profile for each area in a period, or because an insurer has a better understanding of one risk area over another. Enterprise risk management (ERM), a process where risks and risk-adjusted returns are assessed holistically across an organization, may play a role in evaluating insurance and investment strategies, or with budgeting the amount of risk to be assumed between these strategies (Cummins et al 1997).

This study evaluates selected available data to assess the extent to which having a strong and integrated ERM framework matters to risk budget structures. Based on ERM theory a reasonable presumption is that having a stronger and integrated ERM framework supports optimal risk selection and efficient allocation of risk within organizations versus those with weaker ERM (e.g., Standard & Poor's 2013a). Through a time fixed effect panel regression consisting of 108 companies across six years (2008-2013), we show evidence that ERM, its interaction with risk tolerance and other factors influence how an insurer's risk is distributed between investments and underwriting. Additionally, through qualitative analysis of data gathered through interviews with risk and financial management leaders of nine insurers, we discover that as their ERM becomes more advanced it is used more as a means to enhance returns (offensive positioning). This compares to early-stage ERM adaptors where limiting risk (defensive positioning) is the focus. Collectively this presents a mixed method approach to evaluating the role of ERM in risk budgets.

Findings from this research contribute to existing studies of the role that ERM plays in operational decisions and allocation of capital resources. It utilizes measures of ERM suggested by Gordon et al (2009). It evaluates ERM effectiveness using insights presented by Hoyt and Liebenberg (2011). It applies findings presented by Myers (2014, 2016) which showed how ERM and optimal risk tolerance are linked to performance and value. It also expands on Myers (2014, 2016) by looking within risk tolerance to understand its components. This subtle yet crucial aspect of the risk management process goes beyond addressing the question of how much risk is an entity willing to take overall. We evaluate how a company's ERM strength, risk tolerance, complexity, size and other characteristics influence which types of risks an entity is willing to assume – i.e., establishing risk budget structures. A modified DuPont return on equity decomposition, similar to what Smith (1999) proposed, will be utilized to assess risk budget structures.

These elements collectively evaluate for the potential influence of enterprise risk management on a company's risk-based decision making of capital allocation between underwriting and investments, two major contributions to an insurers earnings profile. In doing so this study builds upon existing studies that have evaluated for ERM's influence on performance and value, but going further to show how ERM influences the decision making process of firms to allocate and budget risk. We discuss the relevance of leverage as a key component of the risk allocation and budget decision-making process, as opposed to assessing risk transfer such as derivatives hedging effectiveness common to the literature. Finally, these notions are assessed via a mixed method of quantitative and qualitative techniques to offer a broader perspective, taking a top down deductive approach to confirm a relationship exists and a bottom up inductive approach to assess the nature of that relationship.

The remainder of this paper is organized in seven additional sections. **Section 2** explores additional relevant literature and background related to the underlying argument of the study. **Section 3** presents the quantitative research (Method (1)) and qualitative research (Method (2)) designs. **Section 4** includes a discussion of the data used in Method (1). **Section 5** provides an overview of the empirical results of Method (1). **Section 6** includes a discussion of the data used in Method (2). **Section 7** provides an overview of the empirical results of Method (2). **Section 8** presents our summary and concluding comments.

6.4 Review of the Literature

Modern approaches to risk management that compliment traditional risk controls with strategic and holistic perspectives are elements of enterprise risk management (Nocco and Stulz 2006), Meulbroek (2002). ERM can be useful with evolving regulatory requirements (Arnold et al 2011). Enterprise risk management also is linked with risk preferences and risk-based decision-making (Shang and Chen 2012).

The Committee of Sponsoring Organization of the Treadway Commission (COSO) (2012, 2004) outlined four dimensions of ERM – strategy, operations, performance and compliance – for companies to consider. Moreover, rating agencies (AM Best 2013c), (Standard & Poor's 2013a) and regulators (NAIC 2015) have produced standards for prudent ERM that insurers could be measured against.

However, companies within the United States are not obligated to employ ERM nor disclose information regarding any ERM frameworks in place, making identification, measurement and comparisons of ERM across companies difficult (Lundqvist 2014). The inconsistency in data available and the subjectivity surrounding ERM effectiveness makes these studies useful, but far from complete. Indeed, McShane et al (2011) showed that certain measures of strong ERM, as determined by a third party like Standard & Poor's may not be indicative of a firm's ability to achieve notable improvements in performance and value. Although Baxter et al (2013) showed that the Standard & Poor's ERM score was a relevant indicator of strong corporate governance and accounting performance. This inconsistency may be attributed to the application of that particular ERM metric beyond its intended usage, which is to support a financial strength rating assessment (Standard & Poor's 2013a) and not necessarily to indicate value. However, despite certain difficulties in the evaluation of ERM via standard financial disclosures, most research has demonstrated a relationship between ERM and performance, value and operational efficiencies.

Gordon et al (2009) presented a framework to measure ERM effectiveness based on the COSO definition, which showed a relationship between ERM and valuation. Myers (2016, 2014) followed that discussion to show how Gordon's ERM score is linked to firms' risk tolerance and risk-adjusted performance. Hoyt and Liebenberg (2011), Standard & Poor's (2011b, 2013b) and Eckles et al (2014) produced similar studies touting ERM effectiveness.

Ideal risk appetites, tolerances and budgets also may be linked to ERM. Hillson and Murray-Webster (2012), Shang and Chen (2012) and others discussed how ERM facilitates a better understanding of, and decisions surrounding, risk choices and ideal risk profiles. Myers (2016) showed that an optimal risk tolerance might act as a buffer between strong ERM and superior risk-adjusted performance. Operating within a targeted risk profile may include hedging and transferring risks in support of a holistic risk management process (Aven 2013). McShane et al (2012) showed that there are tradeoffs between insurance risks and financial risks within insurance firms, and indicated that integrated risk management might play a role in evaluating those tradeoffs. Dhaene et al (2012) and Ai et al (2012) showed how banks and insurance companies can allocate capital optimally to align portfolio risks to their risk tolerances and capital needs. Baranaoff et al (2007) showed that company-specific considerations, namely size, can influence how risk opportunities are chosen across investments and insurance products. And Mikes (2011) showed how cultural biases can impact how the risk management process evolves and how quantitative or qualitative preferences are used with assessing risk appetites within a financial firm.

ERM is still relatively new to the risk management vernacular compared to well-established disciplines such as portfolio theory or derivatives hedging. Further insight of how ERM can influence balance sheet risk budget structure, where corporate finance, risk management and capital management are interlinked would be useful to academics and to practitioners. This is particularly so for insurance firms where adequate capital and financial strength are essential to operate, and where the focus on ERM is particularly high. The research presented in this manuscript will add to that insight.

6.5 Research Design

The research question under evaluation is whether evidence exists that indicates enterprise risk management (ERM) influences the risk budget structure of investment earnings and underwriting earnings by insurance companies, and the nature of that influence. We define ERM as a process where risks and risk-adjusted returns are assessed holistically across an organization to enhance corporate risk management, to improve risk-based decision-making, and to support strategy. We define risk budget structure as the choice an insurer makes to assume a degree of investment risk relative to underwriting risk while staying within a pre-determined aggregate risk capacity utilization level. **(**See **Section 6.11 Appendix A** and **Section 6.12 Appendix B)**

This study employs two methods of analysis for this evaluation. Method (1) applies quantitative techniques including data analysis and a fixed effects panel regression using publically available financial and operational data of publically listed insurance companies. Method (2) applies qualitative techniques using data gathered through interview responses with nine insurance companies, some of which are included in the sample used in Method (1). Method (1) uses public available information to proxy ERM, risk tolerance and risk budgets. These uniformly developed proxies are reasonable metrics to evaluate the relationship between ERM and risk allocation decisions considering certain controls, but they are not perfect measures. A company's risk cultural and behavioral tendencies are examples of data points not always transparent via public disclosure, but may influence the risk management process. Method (2) compliments the findings of Method (1) by offering additional insight into the nature of ERM at firms using certain information not readily apparent in the public domain. Combining these two methods broadens the researcher's understanding of the nature of influence that ERM has in the risk budgeting and allocation process. Findings will support the hypothesis that ERM plays a role in risk budget structuring between investments and underwriting at insurance companies.

The central part of this study is the notion of risk budget structure. We define an insurer's risk budget structure as the amount of capital being leveraged for underwriting relative to investments. To capture this we employ the well understood DuPont return on equity (ROE) decomposition framework[34], but modified for insurers. Under this modified DuPont equation ROE is decomposed into four primary elements – underwriting return, underwriting leverage, investment return and investment leverage. Borrowing from ideas positioned by Smith (1999), and others since (e.g., Chang et al 2014), we apply a modified DuPont ROE decomposition that is appropriate for insurers derived as follows:

$$Return\ on\ Equity\ (ROE) = Net\ Profit\ margin\ x\ Kenney\ ratio^{35} \quad \text{(I)}$$

$$ROE = \frac{Net\ Income}{Premiums}\ x\ \frac{Premium}{Capital} \quad \text{(II)}$$

$$ROE = \left(\frac{Underwriting\ Income}{Premiums} + \frac{Investment\ Income}{Premiums}\right) x\ \frac{Premium}{Capital} \quad \text{(III)}$$

$$ROE = \left(\frac{Underwriting\ Income}{Premiums}\ x\ \frac{Premium}{Capital}\right) + \left(\frac{Investment\ Income}{Premiums}\ x\ \frac{Premium}{Capital}\right) \quad \text{(IV)}$$

$$ROE = \left(Underwriting\ Return\ x\ \frac{Premium}{Capital}\right) + \left(\frac{Investment\ Income}{Capital}\right) \quad \text{(V)}$$

$$ROE = \left(Underwriting\ Return\ x\ \frac{Premium}{Capital}\right) + \left(\frac{Investment\ Income}{Invested\ Assets}\ x\ \frac{Invested\ Assets}{Capital}\right) \quad \text{(VI)}$$

$$ROE = \left(Underwriting\ Return\ x\ \frac{Premium}{Capital}\right) + \left(Investment\ Return\ x\ \frac{Invested\ Assets}{Capital}\right) \text{(VII)}$$

$$ROE = (Underwriting\ Return\ x\ Premium\ Leverage) + (Investment\ Return\ x\ Investment\ Leverage) \quad \text{(VIII)}$$

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[34] Corporate finance textbooks, such as Brealy et al (2011), often provide a full discuss of the DuPont framework.

[35] Per Smith (1999) the Kenny ratio is defined as premium divided by capital, and this ratio acts as a financial leverage multiplier.

Equation (VIII) shows that premium leverage and investment leverage act as multipliers to underwriting returns and investment returns respectively. These leverage effects increase or decrease the contribution to an insurer's equity returns[36] coming from underwriting or investment earnings. The difference between premium leverage and investment leverage is what we define as risk budget structure (RBS)[37]:

$$Risk\ Budget\ Structure = Investment\ Leverage - Underwriting\ Leverage \quad \text{(IX)}$$

Holding all else constant, insurers that have a strong investment bias will have a relatively higher investment leverage, and a risk budget structure greater than zero. This value will be less than zero for those with an underwriting bias. While those with a perfectly balanced risk budget structure will see RBS values close to zero.

We assume firms are motivated to structure their risk budgets in ways that are appropriate to reach strategic and operational objectives and stakeholder expectations, electing to choose a structure that produce stronger risk-adjusted returns for their organization relative to a less effective risk budget structure. We also assumed that a risk budget structure is bounded by a firm's risk capacity utilization. Hence a firm cannot have an infinite premium leverage or infinite investment leverage.

6.5.1 Method (1) Quantitative Analysis

The first method evaluates for a statistically significant relationship between the variation in risk budget structures and a series of economically related explanatory variables. Descriptive statistics, correlation analysis and a multiple linear panel regression model will constitute the components of Method (1).

Numerous factors may contribute to risk budgets. We consider nine explanatory variables for the regression analysis used within this study as shown below:

[36] For simplicity we ignore the impact of taxes and any extraordinary contributions to return on equity.
[37] We feel the absolute difference between investment leverage and underwriting leverage makes for a stronger model than a relative difference of say investment leverage divided by underwriting leverage. When you take the relative Risk Budget Structure (RBS) the leverage effect cancels so it gets lost in the model, but the absolute RBS retains this leverage effect. See **Section 6.13 Appendix C** for further discussion.

$$\textit{Risk Budget Structure} = \quad f\left(\begin{array}{l}\textit{Risk Tolerance}\\ \textit{Enterprise Risk Management (ERM)}\\ \textit{Risk Tolerance x ERM (interaction)}\\ \textit{Years of Operation}\\ \textit{Type of Ownership}\\ \textit{Firm Size}\\ \textit{Organizational Complexity}\\ \textit{Industry Fixed Effects}\\ \textit{Time Fixed Effects}\end{array}\right)$$

Risk tolerance and enterprise risk management are selected as it seems logical and economically justified that risk choices are influenced by a tolerance for risk as well as the ability to manage risk, indeed this is the core of our research question. Our focus on ERM is driven by the notion that ERM helps insurers identify opportunities to enhance their risk-adjusted returns, and to allocate risk and capital accordingly as suggested by (McShane et al 2012). Gordon et al (2009) showed that strong ERM contributes to excess returns across different industries. Myers (2016) showed that ERM and Risk tolerance can interact, and insurers operating at optimal risk tolerance levels see relatively higher risk-adjusted performance. Myers (2014) showed that ERM and risk tolerance contributes to insurer value. Hence, a relationship between an insurer's risk budget structure and its ERM strength and risk tolerance is a logical next step.

We feel that the other explanatory variables listed above are relevant factors of risk budget decisions as well. A corporation's years of operation is relevant as we assume that more mature firms could be better managers and selectors of risk given more experience in doing so relative to younger firms. Years of operation was also cited in Myers (2016) as a contributing factor to establish optimal risk tolerance levels for insurers. We choose ownership percentage, which focuses on the proportion of institutional ownership, because institutional investors are more likely to question, challenge or influence a company's risk management decisions than individual investors (Hoyt and Liebenberg 2011). Size is relevant because larger firms have larger balance sheets and more capital, which may influence how much risk an entity is willing to assume. Size has also been a common factor cited in several recent ERM-related studies (e.g., McShane et al (2011), Hoyt and Liebenberg (2011), Gordon et al (2009), etc.) to show a positive relationship with organization size and ERM adoption. Organizational complexity is selected because there is potential for organizations that are more complex to have more inherent risk, which might factor into how risk is allocated across the enterprise. Finally, we employ a panel regression to control for unobserved industry and time specific effects hence these factors are included in the analysis.

6.5.2 Method (2) Qualitative Analysis

The second method collects and assesses data gathered from interviews with a select group of finance or risk leaders of nine insurance organizations that are known to have ERM frameworks. Interview topics focus on how ERM and related risk models are used within these organizations, and if these uses included capital allocation, setting risk budgets and risk tolerances. Each participant is subjected to the same interview questions, and his or her responses are collected and organized in a similar fashion. These responses served as the data for Method (2). As data is collected and organized we evaluate for themes that are (in)consistent across these entities, or for any (in)consistencies with findings extrapolated from Method (1). We expect to discover findings of how ERM frameworks support decision making that would not be obvious through quantitative techniques alone.

6.6 Discussion and Evaluation of Data used in the Method (1) Quantitative Analysis

6.6.1 Data Sources

The data set applied for Method (1) borrows from much of the same data used in Myers (2016). The initial set started with the full pool of 145 United States public underwriting insurance companies as classified by SNL Financial with reported financial results through year-end 2013. Our focus was on publicly listed U.S. insurers since they are in the business of assuming risk, they often have a particular focus on enterprise risk management and because data is readily available for these companies.

Most data points focused on operational and financial statistics found in balance sheets and income statements. Valuation measures such as stock price, stock price multiples and stock return volatily were also captured. In addition to SNL Financial, Compustat, and CRSP were used as data sources. Myers (2016) used the same initial 145 companies and filtered them down to 110 by removing companies that had several instances of missing or not meaningful data. We apply those same filters, but removed two additional insurers that appeared to have unusual and inconsistent outliers over the 2008-2013 time period. All data collected for the 108 observations by Myers (2016) for the 2013 data set were tracked for each year back to 2008 using annual results for each year for each company. Thus our total sample includes six years of data (2008-2013) or 648 observations in total across 108 insurers. See **Section 6.15 Appendix E** for the listing of insurers used in the analysis.

We start with 2008 since this was the heart of the Great Recession[38]. This period and the three years following 2008 were also associated with the global financial crisis[39] and the wave of financial market stresses occurring in conjunction with the bankruptcy of Lehman Brothers in September of 2008, and the failure of other financial institutions during the crisis period. Insurers, like most in the financial services sector, faced significant losses in value to their investment portfolios due to these events. To some these losses may have been outside of their range of acceptance or expectation as respects to risk preferences. As the recovery transpired over the years following these events we evaluate how time can play a role in how ERM, among other factors, influence risk budgeting between investments and underwriting within insurance companies. We choose a five-year period as this seems an appropriate duration for companies to identify needed improvements with operational strategy, ERM and risk preferences, and to implement and realize the benefits of executing on these changes.

6.6.2 Variable Calculation and Analysis

Nine variables are tracked for this study using data captured as described above. Six of these were continuous, non-categorical variables. Three are discrete, categorical variables where dummy codes were used. All variables are tracked for 108 firms for each year between 2008-2013 making for 648 observations for each variable.

Three are worth highlighting – Risk Budget Structure, Risk Capacity Utilization (RCU) and Enterprise Risk Management (ERM). Risk Budget Structure (RBS), the primary dependent variable, measures the difference between investment leverage and underwriting leverage. RBS is a proxy of how an insurer chooses to allocate risk between investments and underwriting. Higher positive values suggest a preference for investment risk and return, while higher negative values suggest a preference for underwriting risk and return. RBS exhibited excess

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[38] The National Bureau of Economic Research defines the Great Recession period as December 2007 to June 2009.

[39] There are different timelines for the global financial crisis. We follow the Federal Reserve Bank of St. Louis's time line of February 2007 to April 2011 as noted on their website as of 20 September 2016: https://www.stlouisfed.org/financial-crisis/full-timeline

kurtosis and modest skewness that is worth explaining. The RBS data showed some very high values on both ends of the distribution for a small number of observations. We found that these observations were associated with a few life insurers (highly positive RBS) or health insurers (highly negative RBS), and these extremes are most pronounced in the 2008 and 2009 periods (See **Section 6.16 Appendix F**). Also interesting was that from 2008 to 2013 these extreme RBS values did revert towards ranges similar to other life insurers (less positive over time) or health insurers (less negative over time) respectively. We were tempted to exclude some of these potential outliers or to attempt some sort of data transform to force pure data normality, but we felt that this phenomenon was worth retaining explicitly in our model. Indeed, the panel data regression itself was designed to capture meaningful contribution from industry or time fixed effects over the six-year period under review.

RCU is a proxy of a firm's risk tolerances proposed by Myers (2016). There are multiple parts to this calculation, and **Section 6.11 Appendix A** provides a full description of how the RCU calculation is developed. ERM is a proxy score of a firm's enterprise risk management strength proposed by Gordon et al (2009). There are multiple parts to the ERM calculation as well, and Section **6.14 Appendix D** provides a full description of how the ERM score is calculated. **Table 6.1** provides a quick reference for how all variables are defined. **Table 6.2** provides some corresponding descriptive statistics for each continuous variable (except the RCUxERM interaction term) aggregated across the 2008 to 2013 period. **Table 6.3** shows differences in means in the RBS calculation by subindustry groups. **Table 6.4** shows correlation data.

The mean risk budget structure of 2.336 is not zero, meaning as a starting point insurers generally have higher investment leverage relative to underwriting leverage. Our interpretation of this is not that all insurance companies assume more investment risk than underwriting risk, but this does provide a benchmark to compare when and how the RBS is significantly higher or lower to the mean depending on influential factors impacting specific companies uniquely, or fixed effects impacting all companies similarly. This is particularly evident when you consider life, health and property / casualty insurer groups, which have meaningful differences among each other in their mean risk budget structures (see **Table 6.3**).

Table 6.1 Description of variables used within the quantitative methods analysis of Method (1) of the study.

Variable	Abbreviation	Definition	Data Source
Risk Budget Structure	RBS	The sum of investment leverage minus underwriting leverage. All else equal, high positive values mean more investment risk bias. While high negative values mean more underwriting risk bias.	SNL
Investment Leverage	INV_LEV	Invested assets divided by equity	SNL
Underwriting Leverage	UW_LEV	Insurance premiums and insurance-related revenues divided by equity	SNL
Risk Capacity Utilization	RCU	A proxy of a firm's risk tolerance. It is average equity multiplied by Return on Equity (ROE) Value at Risk (VAR)^ divided by Risk Capacity. ROE VAR is the five-year standard deviation of ROE multiplied by the 99.5% confidence statistical table factor of 2.56 applied to average equity. Risk Capacity is the size of an insurer's balance sheet as measured by average assets for the year. See **Section 6.11 Appendix A** for further description on how Risk Capacity was calculated	SNL
Enterprise Risk Management	ERM	Score that measures the strength of a firm's ERM contingent on evidence that ERM is integrated while considering COSO's four pillars: strategy, operations, reporting and compliance. See **Section 6.14 Appendix D** for further description on how the ERM score was calculated.	COMPUSTAT, CRSP, SNL, Financial statements, websites, rating agency reports
Years in Business	AGE	The number of years that an insurer has been in business	COMPUSTAT, SNL, websites
Institutional Ownership	OWNER	A firm's percentage of shareholder owners deemed as institutional owners	SNL
Asset Size	SIZE	Total assets standardized to account for units	SNL

Organizational Complexity	COMPLEX_x	A categorical dummy variable denoting the degree of complexity of a firm. -Low: < 4 Segments, -Medium: 4-6 Segments, -Elevated: > 6 Segments, -High: > 6 Segments with global operations. Note any firm with global operations is considered to have an additional segment.	COMPUSTAT
Insurer Type	INSTYPE_x	Industry fixed effect dummy variables to denote if a company was classified as a -Life-life insurer, -Health-health insurer, or -Property/Casualty insurer to account for factors unique to these industries	SNL
Reporting Year	YEAR_x	Reporting year fixed effect dummy variables to account annual time effects from 2008 to 2013	

^Value at Risk is a measure of risk of loss to a portfolio typically measured at a certain confidence level, such as a 99% confidence, over a certain period, such as one year. This confidence implies a low likelihood of exceeding the loss amount, such as a 1% likelihood of exceeding the loss amount if one is 99% confident of not exceeding the amount. The same Jorion (2001) and others have explored this concept with extensive detail.

Table 6.2. Descriptive statistics of key variables used in the study.

Variable	Observations	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis
RBS	648	-8.107	22.680	2.336	3.242	1.044	5.800
RCU	648	0.002	0.511	0.077	0.082	2.232	5.996
ERM	648	-7.291	13.077	0.049	2.213	0.213	3.387
AGE	648	1.000	203.000	51.176	44.002	1.329	1.026
OWNER	648	0.000	1.068	0.666	0.304	-0.724	-0.713
SIZE	648	-0.429	7.762	0.006	1.031	4.112	19.177
COMPLEX	648						
COMPLEX_Low	58						
COMPLEX_Medium	204						
COMPLEX_Elevated	327						
COMPLEX_High	59						
INSTYPE	648						
INSTYPE_Property/Casualty	390						
INSTYPE_Life	144						
INSTYPE_Health	114						

Variables in **Table 6.2** are fully defined in **Table 6.1**.

Table 6.3. Comparing Risk Budget Structure (RBS) by Industry.

Variable	Obervations	Mean	Difference In Mean Variable vs All Other	Difference In Mean P-value
RBS_TOTAL	648	2.336		
RBS_Property/Casualty	390	1.804	-1.402	<.001
RBS_Life	144	5.367	3.896	<.001
RBS_Health	114	0.156	-2.587	<.001

RBS_TOTAL = risk budget structure across the entire sample; RBS_Property/Casualty = risk budget structure across property/casualty insurers within the sample; RBS_Life = risk budget structure across life insurers within the sample; RBS_Health = risk budget structure across health insurers within the sample.

Table 6.4. Pearson correlations of non-categorical variables used in the study.

	RBS	RCU	ERM	AGE	OWNER	SIZE
RBS	1					
RCU	-0.244	1				
	(<.001)					
ERM	-0.112	-0.024	1			
	(0.004)	(0.540)				
AGE	0.249	-0.175	0.016	1		
	(<.001)	(<.001)	(0.677)			
OWNER	-0.056	-0.015	0.063	0.111	1	
	(0.152)	(0.695)	(0.109)	(0.005)		
SIZE	0.383	-0.154	0.156	0.407	0.028	1
	(<.001)	(<.001)	(<.001)	(<.001)	(0.479)	

P-values shown in parenthesis. Variables in **Table 6.4** are fully defined in **Table 6.1**.

6.7 Empirical Results for Method (1) Quantitative Analysis

6.7.1 Model Design and Strength

Three panel regressions are run in stepwise fashion to assess how the differential between investment leverage and underwriting leverage, i.e., risk budget structure (RBS), is influenced by risk capacity utilization (RCU), enterprise risk management (ERM), company specific characteristic variables and variables to account for industry and time fixed effects. The first regression excludes the fixed effects dummy variables. The second adds industry fixed effects and the third adds time fixed effects. The stepwise panel regression design follows regression (1), (2) and (3) models defined below:

$$Y_i = \beta_0 + \beta_1 X_{ij} + \ldots + \beta_n X_{ij} + \gamma C_i + \varepsilon_i \qquad \text{Regression (1)}$$

$$Y_i = \beta_0 + \beta_1 X_{ij} + \ldots + \beta_n X_{ij} + \gamma C_i + f_I I_I + \varepsilon_i \qquad \text{Regression (2)}$$

$$Y_i = \beta_0 + \beta_1 X_{ij} + \ldots + \beta_n X_{ij} + \gamma C_i + f_I I_I + f_t T_t + \varepsilon_i \qquad \text{Regression (3)}$$

Where

Y_i	= Dependent variable RBS
β_0	= Intercept
$\beta_{1\ to\ n}$	= Coefficients of explanatory variables RCU, ERM, RCUxERM (interactive term), AGE, OWNER, and SIZE
$X_{1to\ n,ij}$	= Explanatory variables RCU, ERM, RCUxERM (interactive term), AGE, OWNER, and SIZE for each company (i) across the years 2008 to 2013 (j)
γ_i	= Coefficients of complexity explanatory binary dummy variables (COMPLEX_), with n-1 dummies for low, medium, elevated and high complexity
C_{ij}	= Complexity explanatory binary dummy variables (COMPLEX_), with n-1 dummies for low, medium, elevated and high complexity for each company (i) across the years 2008 to 2013 (j)
f_I	= Coefficients of industry fixed effect explanatory binary dummy variables (INSTYPE_) with n-1 dummies for Life, Health and Property/Casualty insurer types
I_I	= Industry fixed effect explanatory binary dummy variables (INSTYPE_) with n-1 dummies for Life, Health and Property/Casualty insurer types
f_t	= Coefficients of time fixed effect explanatory binary dummy variables (YEAR_) with n-1 dummies for 2013, 2012, 2011, 2010, 2009, 2008 years
T_t	= Time fixed effect explanatory binary dummy variables (YEAR_) with n-1 dummies for 2013, 2012, 2011, 2010, 2009, 2008 years
ε_i	= Error term

Table 6.5 provides a summary of the regression results[40].

Table 6.5. Panel regression output and summary statistics.

	Response Variable = RBS								
	Regression (1)			Regression (2)			Regression (3)		
	Coefficient	P-Value	VIF	Coefficient	P-Value	VIF	Coefficient	P-Value	VIF
Intercept	4.040	<.001 ***		1.936	<.001 ***		2.357	<.001 ***	
RCU	-7.680	<.001 ***	1.077	-4.821	<.001 ***	1.285	-5.593	<.001 ***	1.330
ERM	-0.282	<.001 ***	2.162	-0.169	0.012 ***	2.311	-0.198	0.003 ***	2.355
RCUxERM	0.607	0.230	2.105	0.419	0.343	2.135	0.527	0.232	2.152
AGE	0.005	0.058 *	1.292	0.008	0.003 ***	1.296	0.008	0.002 ***	1.298
OWNER	0.626	0.093 *	1.027	1.605	<.001 ***	1.272	1.585	<.001 ***	1.273
SIZE	1.255	<.001 ***	1.445	0.815	<.001 ***	1.558	0.817	<.001 ***	1.558
COMPLEX_Medium	-0.896	0.037 **	3.155	-0.818	0.028 **	3.163	-0.841	0.023 **	3.168
COMPLEX_Elevated	-0.755	0.071 *	3.483	-1.086	0.003 ***	3.507	-1.167	0.001 ***	3.532
COMPLEX_High	-2.184	<.001 ***	2.125	-2.099	<.001 ***	2.144	-2.141	<.001 ***	2.149
INSTYPE_Life				3.306	<.001 ***	1.522	3.264	<.001 ***	1.526
INSTYPE_Health				-2.026	<.001 ***	1.213	-2.032	<.001 ***	1.215
YEAR_2013							-0.776	0.023 **	1.730
YEAR_2012							-0.549	0.103 *	1.696
YEAR_2011							-0.371	0.268	1.687
YEAR_2010							-0.396	0.237	1.678
YEAR_2009							0.367	0.272	1.676
Durbin-Watson Statistic	2.135			2.174			2.225		
Regression Significance									
F-Statistic	22.71	<.001 ***		43.773	<.001 ***		31.439	<.001 ***	
R-Squared	0.243			0.431			0.444		
Adjusted R-Squared	0.232			0.421			0.429		
Change in R-Squared Significance									
R-Squared Increase				0.188			0.013		
F-Statistic				105.179	<.001 ***		2.880	0.014 ***	

This table provides a summary of our panel regression statistics showing how company-specific characteristics and fixed effects (explanatory variables) influence a firm's risk budget structure (RBS) (dependent variable). Regression (1) excludes any fixed effects. Regression (2) shows the impact of industry type fixed effects dummy variables. Regression (3) shows the impact of time fixed effects dummy variables. *** Significant at the .01 level; ** Significant at the .05 level; *Significant at the .10 level.

We expect the model's explanatory power to increase as fixed effects were added for two reasons. Firstly, life, health and property / casualty insurers provide distinctly different insurance offerings with different risk characteristics. For example, life insurance products tend to be very long-tail in nature, are written for individuals, and often include investment-like features such as annuity products that pay a prescribed amount periodically to the annuity holder over his or her lifetime. Health insurer products can be priced for individuals or groups, and are generally short-tail in nature. Property / casualty insurers offer products for businesses or individuals as well, and their products include short tail (e.g., fire insurance) and long tail

[40] The model results of **Table 6.5** reflect an 'absolute' Risk Budget Structure (RBS). **Section 6.13 Appendix C** shows how the absolute RBS model results compare to relative RBS.

(e.g., worker's compensation) lines. Hence, there are characteristics unique to different insurer types that may explain how risk budget structures are determined. These impacts are evident as the predictive power of the regression model improved significantly with an r-squared of 0.431 including industry fixed effects vs and r-squared of 0.243 without these variables.

Time is another fixed effect that we want to account for in the model. Insurers are heavily regulated entities, accountable to multiple stakeholders (policyholders, regulators, rating agencies, capital providers, etc.). To the extent an insurer wants to implement change to operational strategies and ERM, given changes to risk preferences (RBS), these changes are likely to take extended time to become effective. For example, filing and obtaining approvals of rate changes for insurance premiums take significant time and must be done separately for each state a U.S. insurer operates. Moreover, understanding any capital market implications as fiscal and monetary policy and geopolitical factors influence the economic environment can take extended time as well. When annual time fixed effects are accounted for, the model's R-squared improves by 0.013 to 0.444. This improvement is statistically significant at the 0.01 P-value level. Also, as time fixed effects are added coefficient signs and significance levels are consistent with the model not including these effects.

Model diagnostics show no major concerns with regression assumption violations. Variance inflation factors indicate a low concern of multicollinearity. Durbin-Watson statistics showed low concern for autocorrelation. Regression residual plots did not appear to suggest concerns with heteroskedasticity, any notable skew, or discernible evidence of a non-linear relationship.

6.7.2 Coefficient Interpretation

Table 6.5 lists key panel regression statistics in a step-wise fashion for each regression coefficient, first showing no fixed effects and then showing industry and time fixed effects in succession. Across all regressions, RCU and ERM are significant predictive variables (P-values < .001). Risk capacity utilization, an indication of risk tolerance, and ERM have negative coefficients suggesting that both reduce the net value of the risk budget structure. Hence, as risk capacity utilization increases and ERM strength increases risk budget structures gravitate towards more underwriting risk relative to investments, all else equal. This is expected since insurance companies are generally in the business of underwriting insurance coverages as a primary goal. We also would have expected the interaction between RCU and ERM to play a meaningful role as risk tolerance and risk management are logically linked. However, the interaction between these two variables do not appear to be statistically significant (P-values >/= .20) in predicting RBS variation in this model. We evaluated the models with and without this interactive term and found no meaningful difference in the regression results across all three panel regressions. That said, given theoretical precedents outlined in prior ERM research (e.g., Myers 2014) we feel this interaction is still a relevant consideration for our model, which suggests that as RCU and ERM increase risk preferences towards underwriting there are instances where that preference is less pronounced as RCU and ERM interact. (See **Section 6.17 Appendix G** for a visual interpretation of the interactive term RCUxERM).

All other predictive variables relating to company-specific characteristics show statistical significance (P-values </= .05). AGE, OWNER and SIZE all had positive coefficients. We are neutral theoretically as to the signs of these three coefficients – e.g., more mature firms appear not to have an economic predisposition to assume more or less investment risk relative to insurance risk compared to younger firms – but we would expect them to be statistically significant to the model overall. Offsetting this would be organizational complexity. Each COMPLEX variable's coefficient is negative, and is progressively more negative with greater complexity as fixed effects are added to the model. We defined complexity as the number of operating segments and global footprint – i.e., having more operating segments and global operations suggests relatively higher complexity. Generally an insurer's operating segment is offering insurance products so it would be expected as more insurance is offered by an organization, as measured by its number of operating segments, that organization's RBS is biased towards underwriting (all else equal).

Regression (2) include industry fixed effects, which are statistically significant (P-value </= .001) and have coefficients that aligned with expectations. We classify insurers into one of three industry groups: life, health and property / casualty. Life insurers tend to assume higher investment risk as indicated by higher investment leverage relative to other insurers, and in contrast health insurers generally assume more underwriting risk as indicated by higher underwriting leverage (see **Table 6.3** to see impact of leverage on industry mean RBS). The regression results echo this. INSTYPE_Life has a positive coefficient and INSTYPE_Health has a negative coefficient, increasing RBS (investment bias) and decreasing RBS (underwriting bias) respectively.

Regression (3) adds time fixed effects to the panel regression to account for year-over-year factors that might contribute to RBS changes from 2008 to 2013. This is of particular interest since insurers faced significant investment stress events with the global financial crisis of 2008-2011, which might have changed investment risk preferences during and after this time-period. Concurrently there was the great recession for all of 2008 and part of 2009, which could jointly affect investment performance and underwriting revenues and associated margin. Moreover, we would expect insurers to make improvements to their ERM process after learning from a significant loss event like the financial crisis. However, such improvements may take time to come to fruition. The panel regression suggests that for the years 2009 to 2011 there are no meaningfully different change in RBS compared to 2008, since each coefficient for these years are not statistically significant. These years overlap with the timeframes of the global financial crisis, which many suggest permeated until 2011. However, we do see time becoming a modest factor in 2012 (P-value </= .10), and a significant factor in 2013 (P-value </= .05). Perhaps this suggests that it takes multiple years for firms to redefine risk preferences and to modify their operational structure accordingly to align with stakeholder expectations. This may hold true for implementing changes and improvements to ERM as well. There also may have been financial market or general economic dynamics associated with the global financial crisis that slowed the course of risk budget change.

6.8 Discussion and Evaluation of Data used in the Method (2) Qualitative Analysis

Method (2) involves collection and assessment of data gathered from structured interviews with a select group of finance or risk leaders of nine insurance organizations. These are selected out of a potential 100+ insurance companies that the author has relationships with as a risk and capital management advisor. The only requirement for companies to participate in the interviews are that the companies had an enterprise risk management process in place. Otherwise several companies were considered and requested to participate, and the first nine to agree to these interviews were included as interviewees. Information sourced through structured interviews are supplemented with information gathered through review of websites, any publicly available financial reports and notes gathered from applicable advisory projects.

Finance and risk leaders include those individuals with direct influence over, or otherwise lead, the enterprise risk management and related modelling frameworks within these companies. Representative titles include head of risk, head of capital modelling / planning, chief risk officer, chief financial officer, chief actuary, etc. Interviews with these individuals last between 40 to 60 minutes conducted over the phone. Five of the interviews include one or two additional participants, but these participants are generally silent observers. The remaining four are conducted on a one-to-one basis. Participants are not given any questions prior to the interviews, but are advised of the general themes of the questions ahead of the interviews to allow for any necessary preparations.

The interviews are conducted over the course of six months between October 2015 and March 2016. There are common topics discussed and questions asked for each interview participant. Half of the questions focus on how ERM frameworks were developed and overseen within each firm, including the role of ERM within risk tolerance development and risk allocation. The other half inquires about the risk modelling tools that are used to support ERM, such as economic capital models. (See **Section 6.18 Appendix H** for an example interview template).

The companies represented are all classified as non-life insurers. Some have operations exclusive to the United States or United Kingdom and others are multinational. **Table 6.5** provides some summary demographics. It also includes a very basic composite score adding the scores of the last six columns of the table; this provides a very simple means of comparability across the interviewee set. Larger, more complex and more established organizations have a larger composite score. Five firms are publicly traded stock companies and the others are privately held or mutual insurance companies. Some have been in business for less than 25 years, while others are well-established insurers with over 100 years of operations. They range in size in just under $1 Billion equivalent assets or revenues to well over $50 Billion. The UK entities have higher financial leverage than their US or global counterparts. Company names are removed for anonymity.

All companies interviewed have established risk preferences usually linked to an acceptable loss of capital due to significant operational loss. However, some risk preferences are more definitive than others. For example:

e.g., definitive: Maintaining a 1% chance of 20% loss of capital due to any event or series of events over an annual period

e.g. less definitive: Avoid a significant capital loss that could threaten a financial strength rating

ERM is practiced at each firm interviewed, but how these ERM processes worked varied. Some organizations follow a central approach where a chief risk officer oversaw the process. Others are decentralized where risk managers oversaw ERM practices and related risk models at local subsidiary or business unit levels.

Table 6.6. Demographics and scoring key of the companies used for the qualitative study.

Demographics

Firm Code	Domicile	Stock Firm?	Age	Revenues	Total Assets	Financial Leverage	Risk Tolerance	Firm Complexity	Composite Score
A	U.S.	Y	4	3	4	2	n/a (0)	4	17
B	U.S.	Y	2	2	4	2	2	4	16
C	U.K.	N	1	2	2	4	2	1	12
D	U.K.	N	1	2	1	4	2	1	11
E	U.S.	N	3	2	2	2	1	2	12
F	U.S.	Y	3	4	4	2	2	4	19
G	U.S.	Y	2	2	3	2	2	4	15
H	U.S.	Y	2	2	2	3	2	3	14
I	U.S.	N	4	1	2	2	4	1	14

The composite score is a sum of the firm's Age, Revenues, Total Assets, Financial Leverage, Risk Tolerance and Firm Complexity scores.

Scoring Key

Score	Age	Revenues ($)	Total Assets ($)	Financial Leverage (assets / equity)	Risk Tolerance (capital loss)	Firm Complexity
1	0-25yrs	<0.5 Billion	<0.5 Billion	<2	1% chance of 10% loss	<4 segments
2	25-49yrs	.5-4 Billion	.5-4 Billion	2-5	1% chance of 20% Loss	4-6 segments
3	50-74yrs	5-10 Billion	5-10 Billion	5-6	1% chance of 30% Loss	>6 Segments
4	75+yrs	>10 Billion	>10 Billion	>6	1% chance of 40% Loss	>6 Segments and Global

Scoring example: Company A is a US entity, has been operating for over 75 years, has annual revenues between $5B-10B, has total assets over $10B, has financial leverage (total assets divided by equity) in the range of 2 to 5, does not have a specific capital loss amount defined within their risk tolerance, has over six segments and operates globally. Adding these scores uniformly, assigning zero for the lack of formal risk tolerance definition, yields a composite score of 17.

6.9 Empirical Results of Method (2) Qualitative Analysis

6.9.1 Distinguishing ERM Qualitatively

Method (2) involves collection and assessment of data gathered from structured interviews with multiple insurance organizations and from certain publicly available information described in **Section 6.6**. NVivo qualitative data coding software and Excel are used to synthesize and organize data into thematic structures and hierarchies. At first, several potential themes are identified including risk culture, risk awareness, risk measurement, risk allocation, risk modelling and others. Interview responses coupled with excerpts obtained from other public data sources (inline to those public secondary data described in **Section 6.6)** are categorized into one or more of the potential themes within Excel tables, and then evaluated through thematic coding within NVivo.

Enterprise risk management (ERM) appeared part of the cultural construct of each firm included in the analysis. However, following the first pass of data coding, it was determined that some of the themes overlapped or had very little influence in the overall findings. Some of the initial themes were combined forming three major themes as a result. These three high-level ERM themes we call ERM traits. Trait one was how ERM supports strategic risk management and planning. Trait two was ERM's role with risk tolerance and risk allocation. Trait three focused on the developmental stage of the ERM framework and structure. (See **Table 6.7**).

One observation related to traits one and two is the difference in how ERM is culturally positioned within the firm. Some interviewees described their ERM framework as an offensive tool, where ERM proactively contributes to strategy development and decisions of risk allocation. With these firms ERM is used to evaluate new product development, merger or acquisition opportunities, how to allocate risk and generally identifying ways to find upside potential for the enterprise. In contrast other interviewees position ERM as a defensive construct. Here ERM governs and controls strategy, planning and risk budgets. For example, defensive ERM users prioritize ERM to assure their solvency ratio or credit rating is adequate, to development risk reports, and generally to preserve capital by control downside risks for the enterprise.

The third trait is the development stage of the ERM framework at a firm. Some organizations are much more advanced. The advanced users appear to have ERM processes that have been in place for several years. They are also heavier users of centralized risk modelling tools, relative to their less advanced peers. To the extent improvements are expected for these advanced users, these would include updating risk models, refining technical documents, or introducing new stress scenarios, but these were largely marginal refinements and maintenance of well-established frameworks. Conversely, those firms with developing ERM processes expect significant improvements to one more elements of ERM over the next year or more, or otherwise are heavily dependent on external advisors for ERM processes. Users with developing ERM often have no formalized risk modelling process, and the few of these users with risk models often relied on a less formal spreadsheet environments or ad-hoc calculations for such efforts relative to their advanced ERM peers.

Table 6.7. Summary of three ERM traits that firms appeared to exhibit, as well as two dimensions for each trait.

	Trait One: Strategic Risk Management & Planning	Trait Two: Risk Tolerance & Risk Allocation	Trait Three: ERM Framework & Structure
Offensively or Advanced Explained	ERM is used offensively; ERM is mostly a contributor to: • New product development • Planning, forecasting and capital management • Mergers and acquisition decisions	ERM is used offensively; ERM is mostly a contributor to: • Risk retention and risk transfer evaluation • Establishment of risk tolerances and risk appetites • Assessment of investment and underwriting strategies and related trade-offs	Exhibits an advanced ERM framework mostly supported by: • Fully developed risk and economic capital models • A team approach inclusive of multiple functions; culturally aware • Systematic processes; minimal or marginal improvements needed
Defensively or Developing Explained	ERM is used defensively; ERM is mostly a governor of: • Risk reporting and control processes • Risk-adjusted return contribution hurdle rates • Compliance and regulatory requirements	ERM is used defensively; ERM is mostly a governor of: • Financial strength assessment (e.g. solvency ratios, credit ratings) • Adherence to risk tolerances • Stress testing and scenario testing	Exhibits a developing ERM framework mostly supported by: • A notable dependence on a spreadsheet environment • Dependence on vendors and consultants for model results general enhancements • Ad-hoc processes; anticipate meaningful enhancements to ERM models and processes

The above provides a summary grid of the data coded as sourced from exploratory interviews and other qualitative data collected across nine insurance companies. The questions explored how each firm's ERM framework was designed and supported risk-based decision-making. Three traits were identified during this coding process. Trait one considers ERM's role within strategy and planning with some firms using ERM offensively and others more defensively. Trait two considers ERM's role with risk tolerance and risk allocation, similarly with some using ERM in an offensive manner to support risk allocation and others using ERM more as a defensive construct. Trait three considers the developmental stage of ERM, with some firms having very advanced ERM frameworks and others with ERM in the developmental stages.

6.9.2 Key Empirical Findings

Interviewees describe ERM in different ways. Some focus on their modelling processes and technology systems. Others focus on staff and how risk decisions traverse through their organization. Notable is the difference in maturity of the ERM frameworks; five have mostly advanced ERM processes and four have mostly developing ERM processes. Interestingly there is no obvious relationship with the age of the organization and the development stage of its ERM. It is worth highlighting that a firm's age did have influence in the quantitative part of this study as noted in **Section 6.7** above. Also notable is that some firms view ERM as an offensive process to support upside return potential, and others characterize ERM as a defensive process to control or limit downside risk. These different views of ERM are anecdotal links to the maturity stage of ERM. Firms whose ERM is advanced tends to position their ERM process as supportive to setting strategy and allocating capital to enhance earnings. While an ERM framework that is developing tends to be used for governance and control of downside risk, particularly with the preservation of capital. There are quantitative and qualitative differences in ERM structures as well, similar to findings by Mikes (2011) often associated with a cultural preference with risk modelling versus risk judgment. Note **Table 6.7** for a summary of these findings.

Table 6.6 lists certain demographics of the companies interviewed, including a composite score. The respective firm codes and composite scores are listed again in **Table 6.8** ranked by composite score. Also shown are designations of firms exhibiting characteristics of mostly offensive or mostly defensive approaches of ERM within areas of strategic risk management and risk tolerance. Finally, we denote which firms have advanced or developing ERM processes.

A few findings are noteworthy from the companies captured in **Table 6.8** which highlight the nature of ERM within each firm. First, a relatively high composite score (associated with longer years in business, greater size or greater complexity) is not indicative of whether a firm took an offensive or defensive risk management trait with ERM. However, four of the five firms (firms A, B, F and G) with high composite scores do exhibit characteristics of advanced ERM. Additionally, as these advanced ERM firms exhibited characteristics of offensive ERM usage, generally this was consistent whether considering our other two ERM traits: strategic risk management and planning, or risk tolerance and risk allocation. For instance, firms A, B, C and G were each advanced ERM users who used ERM offensively (See **Table 6.7**). These four firms discuss instances where the ERM process supports the development of their risk tolerance generally, and with decisions surrounding which areas to assume risk specifically. They cite examples of how ERM supports the annual planning and forecasting process. For these firms ERM support evaluation of the viability of investment strategies and reinsurance treaties[41] often with vetting through their ERM models. Some examples of vetting from this group of four:

- *"The company uses the [ERM model] for both strategic and capital adequacy measurement purposes. From a strategic basis the [ERM model] will be used to allocate risk capital to different business lines, to evaluate strategic planning, expanding / retracting growth, etc." – Company A*
- *"Each planning period we contemplate growing certain business lines. Sometimes this puts us close to or exceeds our risk tolerance thresholds as measured through the ERM process. In those instances we will assess the implications at the company level, and ultimately this would need to be presented and approved by the board of directors' risk committee." – Company B*
- *". . . the [ERM modelling] process is used to support decision making as well. It is used for treaty purchase decisions, to evaluate operational plans, and to evaluate alternative investment strategies." – Company C*
- *"The board sets the risk tolerance and this is measured / tracked against exposure with the [ERM model]. . . We prefer to take more risk, allocate more of the risk budget, to underwriting. This dates back to the early years of the organization culture and this is an underlying theme in what's been communicated to shareholders" – Company G*

In contrast here are two examples of feedback provided by Developing ERM users and their approach to risk budget structuring:

- *"Risk and capital modeling was not meant to support strategic decisions such as setting investment strategy . . . the word 'strategy' was not a consideration with the [ERM model]" – Company H*
- *"We have explored developing our own [ERM model], but the resource costs outweigh the perceived benefits . . . Planning and forecasting of earnings and capital are updated regularly internally, but output from advisors helps to fine-tune assumptions" – Company I*

[41] A reinsurance treaty is a financial structure where one insurance carrier transfers a portion of its insurance risk exposure to another insurance carrier for a defined period and specified cost.

Within this sample, the nature of ERM and risk budget structures is contingent on the traits exhibited by ERM, particularly the ERM framework and structure development stage. Advanced ERM users are more model dependent in their decision-making, but their choices are geared more towards ways to enhance capital, value and assessing risk tradeoffs. Advanced users were more likely to use their ERM framework to help determine what degree they would assume investment risk relative to insurance risk. Developing ERM users are less model dependent, but the defensive nature of their ERM frameworks are primarily about capital preservation and limiting downside loss. That said, all nine companies mentioned that modelled results are evaluated against human intuition, even heavy ERM model users do not manage their business by models alone.

Table 6.8. Summary table of ERM traits by company and their composite score.

Firm Code	Composite Score	Trait 1: Strategic Risk Management & Planning		Trait 2: Risk Tolerance & Risk Allocation		Trait 3: ERM Framework & Structure	
		Offensively	*Defensively*	*Offensively*	*Defensively*	*Advanced*	*Developing*
F	19		✓		✓	✓	
A	17	✓		✓		✓	
B	16	✓		✓		✓	
G	15	✓		✓		✓	
H	14		✓		✓		✓
I	14		✓		✓		✓
C	12	✓		✓		✓	
E	12	✓			✓		✓
D	11		✓		✓		✓

Listed by order of composite score explained in **Table 6.6**, this table summarizes each interviewed firm's tendency towards either offensive or defensive usage of ERM for traits one and two explained in **Table 6.7**. As respects to trait 3, the table outlines whether these firms exhibited advanced or developing ERM frameworks.

6.10 Conclusions

Enterprise Risk Management (ERM) is a holistic risk management framework that goes beyond risk control processes typical of traditional risk management. This study assesses if ERM influences choice between an insurer's two primary sources of earnings and underlying risks. Specifically, we evaluate if ERM influences risk-based decisions between underwriting and investments. We show how underwriting leverage and investment leverage are indicative components of an insurer's risk budget. Some insurers choose to allocate more risk to underwriting (investments) and by doing so have a relatively higher underwriting (investment) leverage. This choice we define as a risk budget structure (RBS).

A two-part mixed method is used for the evaluation. The first part is a quantitative analysis using a time fixed effect panel regression to demonstrate a linkage between ERM and RBS. This measures how much ERM, risk tolerance and other company characteristics influence risk budgeting between underwriting and investments. A sample of 108 U.S. publicly listed insurance companies and their financial data from 2008 to 2013 is used for this part of the study. The findings show that ERM does influence risk budget structures. This is evident even when controlling for other influencers such as organizational complexity, size, and ownership. Moreover, this relationship is consistent even when controlling for fixed effects of insurer type and time effects. Our model is able to explain a little over 40% of the variability of RBS. While reasonable, there may be other considerations worth reflecting in future studies to add clarity to insurer risk budget structuring. Indeed, there may be other ways to measure or proxy ERM, risk capacity utilization and risk budgeting other than those outlined in our study. Additionally, our sample of 108 insurers is a small portion of several hundred that comprise of the public and private consolidated insurance groups in the U.S., and the 1000s across the global population of insurers.

The second part of the study is a qualitative analysis of data gathered from structured interviews of nine insurers. This explores the nature the ERM-to-RBS linkage identified in the first part of the study. Findings suggest that insurers have different levels of ERM development regardless of how long these insurers were in business. Those firms with advanced (developing) ERM are more likely to use ERM offensively (defensively) to generate returns (limit risk). Moreover, some of the advanced ERM firms cited instances where ERM-related models are used to support the decision-making process to assess different risk levels and to determine how much risk to allocate between underwriting and investments.

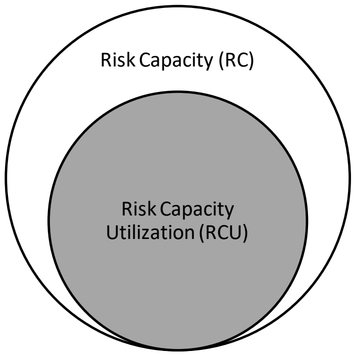
The mixed method approach provides insight for two perspectives: 1) to what extent does ERM influence risk allocation within insurance firms, and 2) what is the nature of this influence? The triangulation of data gathered from public and privately available sources provides rich and unique insight that could be missed with one method alone. Quantitative analysis shows that ERM influences risk allocation, and this is at least partially contingent on industry and time fixed effects. Qualitative analysis augments this understanding. It shows that ERM's influence on risk budget structures is evident, but how that influence materializes depends on whether firms have advanced ERM processes, particularly fully developed and centralized risk models. Moreover, users of advanced ERM utilize their processes in an offensive way to support risk allocation decisions to find ways to enhance value, as opposed to less developed ERM users where capital preservation is often the primary objective.

Overall, our findings are encouraging. And while it may be premature to make strong generalities at this stage, we view our findings as a positive contribution nonetheless, and will hopefully motivate future studies to expand on the concepts presented. Most existing ERM research looked to directly link ERM to value or performance. This research goes deeper by exploring how ERM is linked to the risk-based decision-making process, the stage preceding those actions leading to any increases to performance or value. In particularly we show that narrowly focused studies of ERM that ignore the strength, years of development, degree of cultural integration and offensive / defensive positioning of ERM may not provide a comprehensive understanding of ERM's role in the risk and finance dynamic of business administration. Moreover, companies currently are not required to discuss and report publicly on their ERM frameworks, and those that choose to do so tend not to follow a consistent measurable standard. ERM must be proxied, but existing quantitative proxies of ERM will have limitations, perhaps only capturing part of the story behind a firm's ERM framework. A deeper understanding of the unique ERM characteristics at each company, explored through multiple methods, may provide a richer perspective of ERM's role. Policy makers, company leaders and other stakeholders could also benefit from such broad findings. Whereas ERM is generally a voluntary effort today, it may be prudent for certain ERM standards to exist across all firms (not just insurers), and comprehensive research in this area could help frame some of those standards.

6.11 Appendix A – Background on the Risk Capacity Utilization Calculation. Commentary Borrowed from Myers (2016)

An insurance company is in the business of exposing itself to risk with an expectation of generating value. Following Aven (2013), an organization's willingness to expose its balance sheet to financial loss is what is defined as risk capacity utilization for the purposes of this study. A firm's risk capacity (RC) is measured by its total assets. Risk capacity utilization (RCU) is measured by taking a portion of RC estimated to support downside risk associated with an insurer's normal course of business over a one-year period.

Figure 6.1. Risk Capacity Utilization Venn Diagram



Equation *(i)* formally defines the calculation for RCU.

$$\text{RCU}_{\text{i}} = \frac{ROE\ VaR_i\% * Equity_i}{Assets_i} \qquad (i)$$

Where for firm i, RCU equals the value-at-risk (VaR) as a percentage of equity expected over a one-year period divided by the total assets of the firm. Downside risk metrics such as value-at-risk are considered by financial institutions as a means to articulate risk appetite (Shang and Chen 2012). A parametric VaR is calculated using the expected volatility of returns to a portfolio, the inverse normal cumulative distribution factor (i.e., standard normal critical value) corresponding to the confidence level in question, and the portfolio value (Jorion 2001, p.109). A 99.5% confidence level is assumed, coinciding with regulators as the confidence level for solvency test calibration. A 99.5% confidence translates into a 2.56 critical value. Therefore, each case's ROE VaR[42] is calculated as:

[42] VAR can be estimated in various ways, including parametrically. A parametric VaR is usually used when the corresponding variable is assumed to follow a normal distribution. For the sake of this analysis we make a strong assumption that the five year return on equity value for each case in each sample is normally distributed.

$$Earnings\ Volatility = ROE\ Standard\ Deviation$$

$$ROE\sigma_i = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(ROE_{i,j} - \overline{ROE_i})^2},\ where\ i = firm\ i,\ j = year \qquad (ii)$$

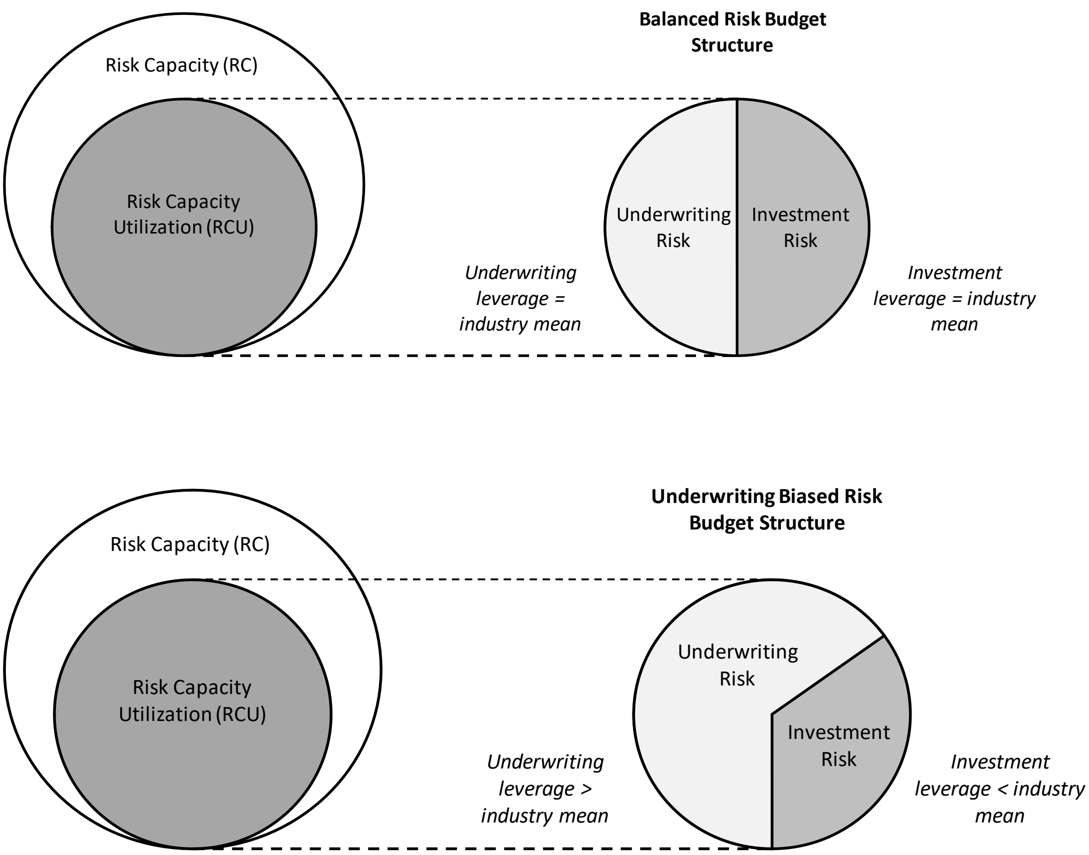
$$ROE\ VaR = ROE\sigma_i\ x\ 2.56\ x\ Equity \qquad (iii)$$

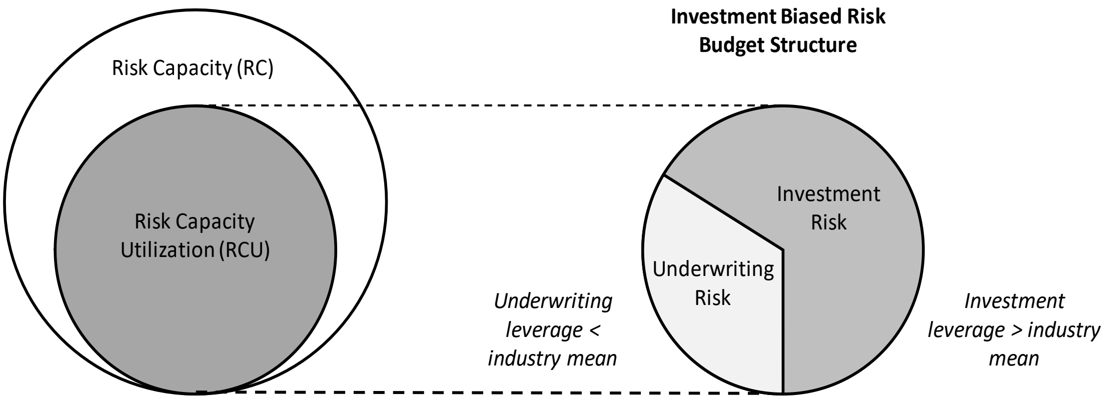
It was assumed that firms exhibit high RCUs due to implied high risk tolerances.

6.12 Appendix B – Illustration of Different Risk Budget Structures, the Components of Risk Capacity Utilization.

All insurers have a risk capacity boundary in which they can operate. Most choose to utilize a fraction of that capacity; this fraction is risk tolerance. Risk tolerance is allocated (budgeted) between underwriting and investments; this allocation or budgeting process is Risk Budget Structuring.

Figure 6.2. Illustration of Different Risk Budget Structures, the Components of Risk Capacity Utilization.





6.13 Appendix C – Absolute Versus Relative Risk Budget Structure (RBS) Model Results

Insurance companies are accountable to regulators and must show their financial strength and risk management capabilities are supportive to their inherent operating risks. NAIC (2015) outlines one example of this accountability for insurers operating in the United States. Additionally, most U.S. insurers use a financial strength rating by one of the major credit rating agencies to show counter parties that they will be able to service claims and other liabilities over time. Rating agency criteria (e.g., AM Best 2013a, Standard & Poor's 2013a) outline standards of risk management and balance sheet strength needed to achieve strong ratings. Financial leverage ratios are elements of the review process that regulators and rating agencies employ to gauge prospective solvency and financial strength. The author's prior experience in advising insurers on risk and capital management matters confirm this as well. Hence, we feel that an absolute measure of risk budget structure that explicitly accounts for leverage effects is stronger than a relative measure. For perspective in the table below we include the results of Regression (3) using the absolute RBS measure and the relative RBS measure.

Table 6.9. Model Regression Results When Considering a Relative Risk Budget Structure (RBS) as Opposed to the Proposed Absolute RBS.

	Regression (3) Current RBS Asbolute (Inv lev - UW lev)			**Regression (3) Alternative** RBS Relative (Inv lev / UW lev)		
	Coefficient	P-Value	VIF	Coefficient	P-Value	VIF
Intercept	2.357	<.001 ***		0.349	0.721	
RCU	-5.593	<.001 ***	1.330	-1.827	0.483	1.357
ERM	-0.198	0.003 ***	2.355	0.025	0.796	1.374
RCUxERM	0.527	0.232	2.152	5.257	<.001 ***	1.355
AGE	0.008	0.002 ***	1.298	0.015	0.002 ***	1.316
OWNER	1.585	<.001 ***	1.273	2.444	<.001 ***	1.331
SIZE	0.817	<.001 ***	1.558	-1.184	<.001 ***	1.581
COMPLEX_Medium	-0.841	0.023 **	3.168	-1.145	0.101 *	3.150
COMPLEX_Elevated	-1.167	0.001 ***	3.532	-0.978	0.152	3.513
COMPLEX_High	-2.141	<.001 ***	2.149	-1.949	0.036 **	2.149
INSTYPE_Life	3.264	<.001 ***	1.526	4.659	<.001 ***	1.523
INSTYPE_Health	-2.032	<.001 ***	1.215	-1.659	0.002 ***	1.201
YEAR_2013	-0.776	0.023 **	1.730	1.164	0.071 *	1.738
YEAR_2012	-0.549	0.103 *	1.696	1.303	0.041 **	1.691
YEAR_2011	-0.371	0.268	1.687	1.087	0.087 *	1.680
YEAR_2010	-0.396	0.237	1.678	1.544	0.015 **	1.675
YEAR_2009	0.367	0.272	1.676	1.039	0.101 *	1.677
Durbin-Watson Statistic	2.225			2.052		
Regression Significance						
F-Statistic	31.439	<.001 ***		9.036	<.001 ***	
R-Squared	0.444			0.186		
Adjusted R-Squared	0.429			0.166		

This table provides a summary of our panel regression statistics showing how company-specific characteristics and fixed effects (explanatory variables) influence a firm's risk budget structure (RBS) (dependent variable). Regression (3) Current shows the RBS on an absolute basis. Regression (3) Alternative shows the RBS on an relative. Both regressions shows the impact of time fixed effects dummy variables. *** Significant at the .01 level; ** Significant at the .05 level; *Significant at the .10 level.

6.14 Appendix D – Calculating the Enterprise Risk Management (ERM) Effectiveness Index

The ERM index was calculated closely following the specifications developed by Gordon et al (2009). They adhered to the premise that effective ERM is comprised of strengths across four elements as prescribed by COSO (2004, 2012) – strategy, operations, reporting, and compliance. They defined two variables for each element. Each variable of each element was separately standardized first and then subsequently added to create the ERM index for each company in the sample. Following the tradition of Gordon et al (2009), equal weighting was applied to each of the five elements. Most of the variables used in my study were calculated as prescribed by Gordon et al (2009) using multiple data sources: SNL Financial, Compustat and CRSP.

Table 6.10. Enterprise Risk Management Effectiveness Index Calculation Methodology.

Variable Description	**Components**
Strategy	
Component 1 =	(company sales – average industry sales) / standard deviation of industry sales
Component 2 =	(change in company's beta from prior year – mean change in betas from prior year for the industry) / standard deviation of change in betas from prior year for the industry
Operations	
Component 1 =	company sales / company total assets
Component 2 =	company sales / company number of full time employees
Reporting	
Component 1 =	reinstatement for the year? (yes = -1; no = 0) + qualified auditors opinion? (yes = -1; no = 0) + material weakness? (yes = -1; no = 0) (assumed 0 because this is not reported in SNL Financial)
Component 2 =	|company normal accruals| / (|company normal accruals| + |company abnormal accruals|)
Compliance	
Component 1 =	company auditor's fees / company total assets
Component 2 =	company settlement net gain / company total assets

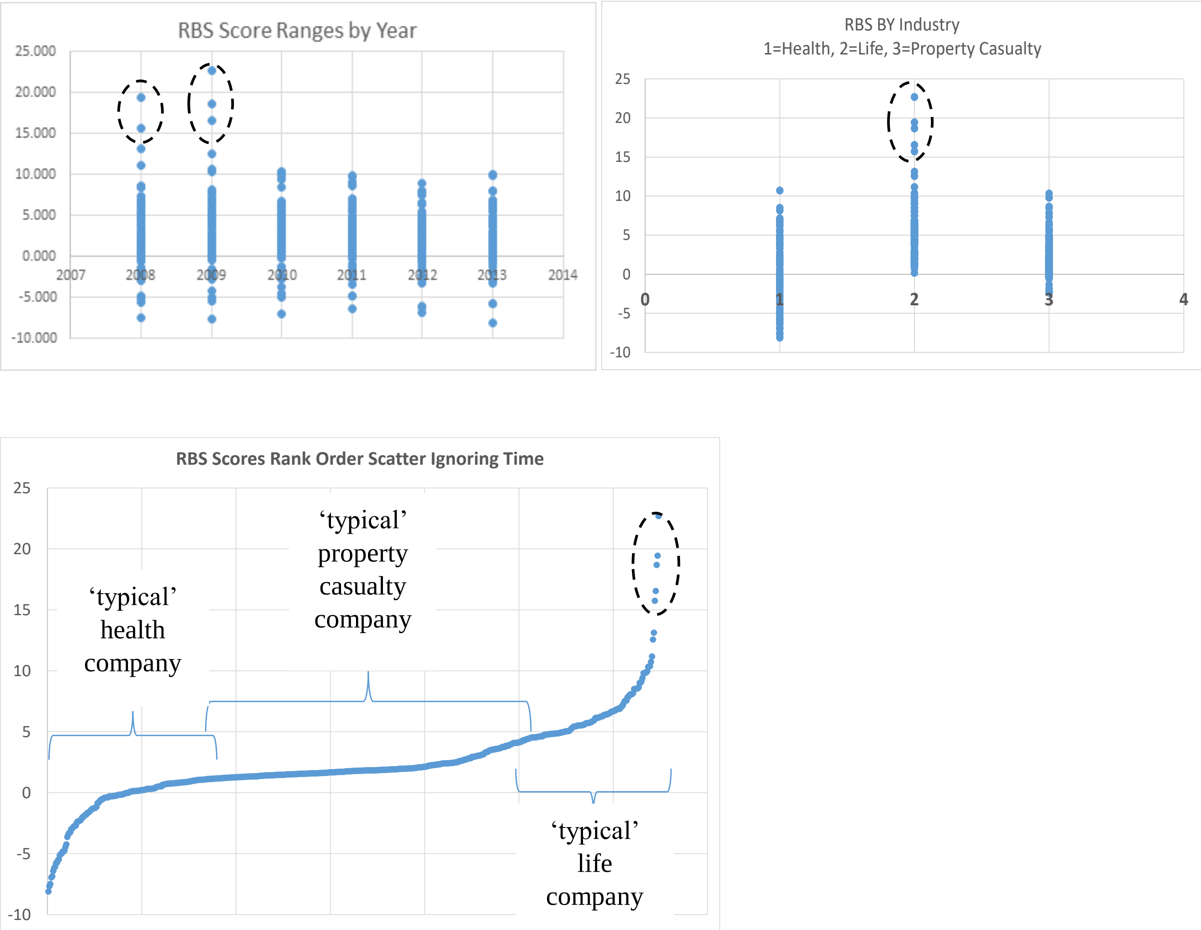
6.15 Appendix E – Listing of Companies Used in the Analysis

Table 6.11. Listing of Companies Used in the Analysis

Company	Insurer Type
Aetna Inc.	Health
Aflac Incorporated	Health
Alleghany Corporation	Prop/Cas
Allstate Corporation	Prop/Cas
American Financial Group, Inc.	Prop/Cas
American Independence Corp.	Health
American International Group, Inc.	Prop/Cas
American Overseas Group Limited	Prop/Cas
Ameriprise Financial, Inc.	Life
AMERISAFE, Inc.	Prop/Cas
AmTrust Financial Services, Inc.	Prop/Cas
Arch Capital Group Ltd.	Prop/Cas
Argo Group International Holdings, Ltd.	Prop/Cas
Aspen Insurance Holdings Limited	Prop/Cas
Assurant, Inc.	Health
Assured Guaranty Ltd.	Prop/Cas
Atlantic American Corporation	Life
AXIS Capital Holdings Limited	Prop/Cas
Baldwin & Lyons, Inc.	Prop/Cas
Berkshire Hathaway Inc.	Prop/Cas
Centene Corporation	Health
Chubb Corporation	Prop/Cas
Cigna Corporation	Health
Cincinnati Financial Corporation	Prop/Cas
Citizens, Inc.	Life
CNA Financial Corporation	Prop/Cas
CNO Financial Group, Inc.	Health
Donegal Group Inc.	Prop/Cas
EGI Financial Holdings Inc.	Prop/Cas
E-L Financial Corporation Limited	Life
EMC Insurance Group Inc.	Prop/Cas
Employers Holdings, Inc.	Prop/Cas
Endurance Specialty Holdings Ltd.	Prop/Cas
Erie Indemnity Company	Prop/Cas
Everest Re Group, Ltd.	Prop/Cas
Fairfax Financial Holdings Limited	Prop/Cas
FBL Financial Group, Inc.	Life
Federated National Holding Company	Prop/Cas
Fidelity National Financial, Inc.	Prop/Cas
First Acceptance Corporation	Prop/Cas
First American Financial Corporation	Prop/Cas
GAINSCO, INC.	Prop/Cas
Genworth Financial, Inc.	Life
Great-West Lifeco Inc.	Life
Hallmark Financial Services, Inc.	Prop/Cas
Hanover Insurance Group, Inc.	Prop/Cas
Hartford Financial Services Group, Inc.	Prop/Cas
HCC Insurance Holdings, Inc.	Prop/Cas
Health Net, Inc.	Health
Horace Mann Educators Corporation	Prop/Cas
Humana Inc.	Health
Independence Holding Company	Life
Industrial Alliance Insurance and Financial Services Inc.	Life
Infinity Property and Casualty Corporation	Prop/Cas
Intact Financial Corporation	Prop/Cas
Investors Heritage Capital Corporation	Life
Investors Title Company	Prop/Cas
Kansas City Life Insurance Company	Life
Kemper Corporation	Prop/Cas
Kingstone Companies, Inc.	Prop/Cas
Kingsway Financial Services Inc.	Prop/Cas
Lincoln National Corporation	Life
Loews Corporation	Prop/Cas
Manulife Financial Corporation	Life
Markel Corporation	Prop/Cas
MBIA Inc.	Prop/Cas
Meadowbrook Insurance Group, Inc.	Prop/Cas
Mercury General Corporation	Prop/Cas
MetLife, Inc.	Life
MGIC Investment Corporation	Prop/Cas
Molina Healthcare, Inc.	Health
Montpelier Re Holdings Ltd.	Prop/Cas
National Interstate Corporation	Prop/Cas
National Security Group, Inc.	Life
National Western Life Insurance Company	Life
Navigators Group, Inc.	Prop/Cas
Old Republic International Corporation	Prop/Cas
OneBeacon Insurance Group, Ltd.	Prop/Cas
PartnerRe Ltd.	Health
Platinum Underwriters Holdings, Ltd.	Prop/Cas
Power Financial Corporation	Life
Principal Financial Group, Inc.	Health
ProAssurance Corporation	Prop/Cas
Protective Life Corporation	Life
Prudential Financial, Inc.	Life
Radian Group Inc.	Prop/Cas
Reinsurance Group of America, Incorporated	Life
RenaissanceRe Holdings Ltd.	Prop/Cas
RLI Corp.	Prop/Cas
Safety Insurance Group, Inc.	Prop/Cas
Security National Financial Corporation	Life
Selective Insurance Group, Inc.	Prop/Cas
StanCorp Financial Group, Inc.	Health
State Auto Financial Corporation	Prop/Cas
Stewart Information Services Corporation	Prop/Cas
Symetra Financial Corporation	Life
Torchmark Corporation	Life
Travelers Companies, Inc.	Prop/Cas
Unico American Corporation	Prop/Cas
United Fire Group, Inc.	Prop/Cas
UnitedHealth Group Incorporated	Health
Universal American Corp.	Health
Universal Insurance Holdings, Inc.	Prop/Cas
Unum Group	Health
UTG, Inc.	Life
W. R. Berkley Corporation	Prop/Cas
WellPoint, Inc.	Health
White Mountains Insurance Group, Ltd.	Prop/Cas

6.16 Appendix F – Selected Data Plots

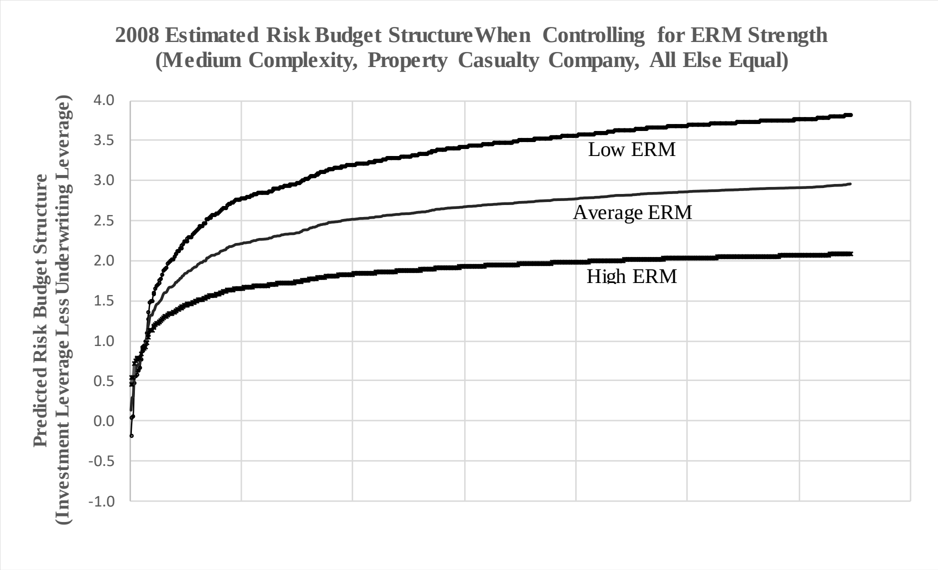
Figure 6.3. Selected Data Plots

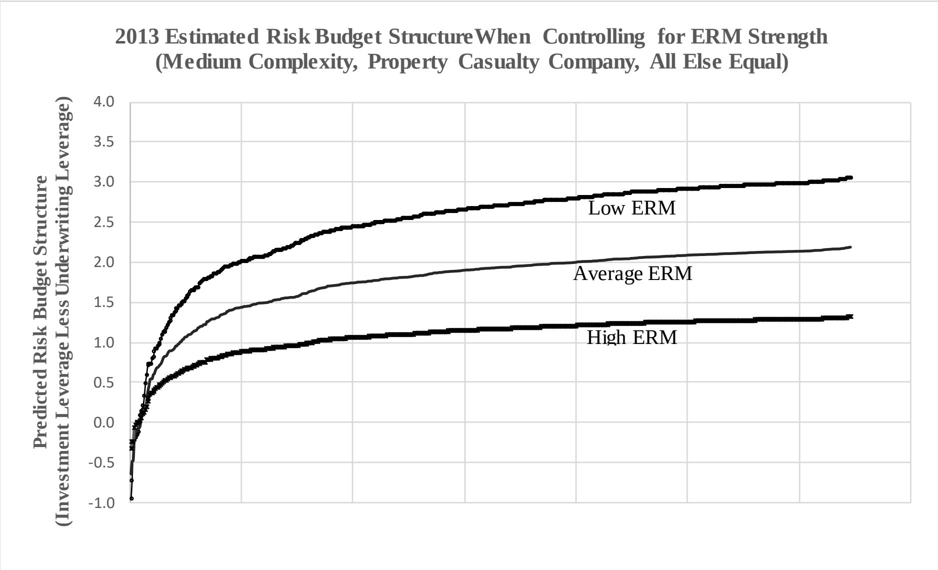


The graphs above show the risk budget structure (RBS) ranges considering time and industry. RBS is defined as investment leverage minus underwriting leverage. Potential outliers are noted in ovals. In each case the "outlier" company, as well as most other companies, reverted towards their respective industry average over time. This is one key reason why we elected to retain these companies across our sample.

6.17 Appendix G – Impact of the RCUxERM Interactive Term

Figure 6.4 Impact of the RCUxERM Interactive Term.





The graphs above illustrate how changing levels or Risk Capacity Utilization (RCU), Enterprise Risk Management (ERM) and their interaction (RCUxERM) translates visually comparing the beginning (2008) and ending (2013) years of the panel regression period. We focus on medium complexity, property / casualty insurance firms and hold all other factors constant. The graphs shows three curves of RBS levels conditional to different ERM levels. We show low ERM (two standard deviations below the mean ERM score), average ERM (the mean ERM score) and high ERM (two standard deviations above the mean). Firms with low or average ERM exhibit wider ranges of RBS, indicating some are very underwriting focused (negative RBS) and others are investment focused (positive RBS) as risk tolerances increase. However, firms with high ERM scores are predicted to maintain a relatively stable and balanced risk budget between investments and underwriting at all risk tolerance levels. This holds for 2013 and 2008, but predicted RBS levels were notably higher in 2008 relative to 2013. Where higher positive levels suggest a greater tolerance for investment risk relative to underwriting.

6.18 Appendix H – Interview Question Template

The interviews were conducted in a conversation manner. Generally, each of the questions below were addressed either directly or indirectly through answers provided from other questions.

Enterprise Risk Management Development and Oversight

- Who has ownership over the ERM process
- Please explain how your enterprise risk management process has developed in recent years
- What are the drivers or motivators for your ERM process ("getting it right"; regulators, etc)
- Do you have a formalized risk tolerance or risk appetite
- How does ERM determine what strategic risks you take
- Discuss how your ERM process supports strategy and planning
- How does ERM influence decisions to allocate risk and capital
- How are ERM findings communicated within the firm and at the board of directors

ERM Risk Modelling, including Economic Capital Modelling

- What tools do you currently employ to support your enterprise risk management framework
- Who has oversight and primary use of the tools (CRO group; CFO group; etc)
- To what extent do you rely on vendors for risk data or risk modelling
- What is the current level of economic capital modelling (ECM) activity within your firm
- Who is the sponsor of the ECM activity
- Do you have an economic scenario generator (ESG)
- How long have you used your ESG
- Who "signs-off" on your risk modelling tool output
- To what degree is your ECM used for financial statement reserving or pricing; Who "signs-off on reserving / pricing

7. Conclusions and Summary

The goal of this research is to evaluate if the connection between Enterprise Risk Management (ERM) and value or performance is as evident as its supporters would suggest, but just as importantly to provide insight as to the role that risk tolerance has within these relationships. An alternative format thesis is used to research and articulate these findings. The thesis is comprised of four studies focused on different elements of the aforementioned connection. The first is a thematic review of the literature as respects to the aforementioned connection, forming a foundation upon which the other three empirical studies build. Using data mainly from publicly listed insurance companies and certain banks the three empirical studies focus on: how risk tolerance interacts with ERM and value, how optimal risk tolerances lead to better risk-adjusted performance, and how ERM is linked to risk budgeting across the balance sheet.

The first study is a thematic perspective of literature related to what enterprise risk management is meant to accomplish and how it has been studied. This shows how ERM builds on traditional risk management concepts and theories, and by focusing on a holistic understanding of risk across the enterprise the practitioner has a more comprehensive perspective of both threats and opportunities to the firm. Some theoretical research says this can facilitate better and optimal risk-based decision making over time; firms with strong ERM will benefit their stakeholders with attributes such as stronger performance and higher valuations. However, empirical evidence shows ERM is not always symbolic of such attributes. Researchers have attempted to understand why using different quantitative methods to measure ERM and evaluate its relationship with value and performance. Considering works on behavioral science, decision science, finance, risk management and ERM we evaluate how quantitative techniques were used in literature, and how this is linked to risk-based decision making and risk tolerance. Statistical analysis, regression techniques using data from surveys or financial disclosures are typical quantitative methods employed. While others use a qualitative approach such as evaluating ERM dynamics and effectiveness via case studies. Unfortunately ERM disclosure requirements and consistency are not part of accounting standards, and qualitative methods are often very company-specific. These approaches are reasonable and often insightful, but because of limited data, timeframes and samples, still lack a full or general understanding of how ERM, value and performance are interlinked. Moreover, there is limited evidence of a mixed method approach to triangulate multiple data and analysis on this topic. Beyond the historic data challenges, we find that empirical research overlooks the role and impact of risk tolerance within a firm's ERM construct and related risk-based decision making process.

The second study evaluates the notion of a direct relationship between ERM and value, which is the common way empirical studies have tested the efficacy of ERM. We accept the theoretical perspective that as ERM strengthens firms may realize higher stock prices and valuation multiples among other benefits. However, we posit that this relationship is not a simple and direct one, and should consider the influence of risk tolerance, particularly as respects to banks and insurance companies. We test the appropriateness of a standardized ERM measure, developed by Gordon et al (2009). We also discuss a method to quantify risk tolerance for organizations when considering earnings volatility and capital. Using measures for risk tolerance, ERM and value, within an interaction regression and response surface analysis, we demonstrate that ERM's influence on value is at least partially moderated by a firm's risk tolerance.

The third study builds on the findings from the prior two by presenting a framework to identify an optimal risk tolerance range for insurers, and to assess how adhering to or deviating from that range impacts risk-adjusted return performance. It uses a two-stage multiple linear regression process. The first stage structures a regression model to predict optimal risk tolerance given an insurer's strength and integration of ERM, its degree of complexity, its amount of financial leverage and type of insurer. The second stage assess the impact of risk-adjusted performance when insurers' practiced risk tolerance deviates from its optimal risk tolerance. Findings show when ERM is fully integrated within an organization that integration can help align risk preferences with risk profiles. Additionally, insurers that are able to operate within optimal risk tolerance ranges are able to realize higher performance compared to those who operate outside of optimal ranges.

The final study utilizes findings presented in the prior three with respects to the relevance of ERM, ERM's interaction with risk tolerance, organizational characteristics and how these impact risk allocation. While the other studies focused on the role of risk tolerance in its aggregate this study focused on the elements that comprise that tolerance for insurance companies. Through a mixed method research process of quantitative and qualitative approaches this study evaluates to what extent the role of an ERM framework influences an insurer's choice to allocate more or less of its overall risk budget towards investment activities or underwriting activities, what we define as a risk budget structure. The first method uses a time-fixed panel regression to assess for a relationship among risk allocation and the effects of time and fixed industry characteristics unique to health insurers, life insurers and non-life insurers within the Unites States. The second method applies small case studies with data gathered mostly from interviews with company risk and finance leaders to understand the nature of the relationship established in the first method. Our findings show some evidence that the years during and immediately following the financial crisis may have influenced insurer's risk budget structure, but changes to this structure may take multiple periods to come to target levels. Moreover, there are meaningful variations across insurer types as respects to their biases towards investments or underwriting. The nature of how ERM influences risk budget structures also varied. Organizations with advanced (developing) ERM are more likely to use ERM offensively (defensively) to generate returns (limit risk). Moreover, some of the advanced ERM firms cited instances where ERM-related models are used to support the decision-making process to assess different risk levels and to determine how much risk to allocate between underwriting and investments.

The four studies of this work discuss the benefits and challenges of ERM broadly, but highlighting factors unique to financial institutions. This includes the role of risk tolerance in strong ERM frameworks. There is ongoing discussion of ERM's benefits across academic and industry forums, and what was once considered best practice may soon become standard practice. We explore these benefits offering additional insight to how, when and why strong ERM can facilitate strong value and performance. We assessed why misplaced risk tolerances may hinder these benefits from apparent strong ERM being fully realized. An organization that strives for strong ERM, but lacks a well-suited and well-articulated risk tolerance nay not fully realize ERM's theoretical benefits. Moreover, ERM coupled with clearly understood risk preferences supports better risk-based decision making over time. Ideally this work will motivate further discussion in this area in academic circles, while acting as a reference for practitioners looking to refine or develop good ERM practices within their organizations.

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