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ENTERPRISE RISK (MIS)MANAGEMENT – PERFORMANCE IMPLICATIONS OF THE MISAPPLICATION OF RISK CAPACITY

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***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.*

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, Scharfstein 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 appetite or risk tolerance is not aligned to a firm's ERM process. One exception is a study by Myers (2014), who used hierarchical moderation regression techniques to discuss how ERM processes within banks and insurance companies that are not anchored with an established risk appetite can be ineffective. Their findings showed how the strength of an ERM framework, coupled with risk tolerance estimates, impacted value. However, that study assumed that different organizational risk profiles (e.g., complexity, risk management leadership) were not factors, and assumed that all companies practiced ERM to some degree. This study will build on that approach, but present an alternative methodology 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 two explores additional relevant literature and background related to the underlying argument of the study. Section three presents the research design. Section four includes a discussion of the data used in the study. Section five provides an overview of the empirical results. Section six presents concluding comments.

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 management 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) 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 have used 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 (2010), AM Best (2013). 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.

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 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 optimal 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 follows other studies that have shown 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).

Our view of risk tolerance is linked to an insurer's financial position as measured by the size of its balance sheet. 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 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. 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. We suggest that insurers who strike the ideal balance among complexity, leverage and ERM, and in turn operate within an optimal risk tolerance range, generate relatively higher performance. 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 evaluate for a possible relationship.

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

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 deviation increases 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
Where $|+\varepsilon_i|$ is the absolute value of company i's residual if above an optimal risk tolerance
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.

Discussion and Evaluation of Data

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 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[1].

It was also necessary to identify companies that had integrated ERM frameworks. There are no formalized reporting requirements as respects to ERM for U.S. insurance companies. In order to track this information we followed 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, reviewed each company's 2013 annual report, 10K, and website[2] for language indicative of ERM. Example catch phrases included "Enterprise Risk Management", "Holistic Risk Management", "Corporate Risk Management" and similar. We then assessed the context of the phrase to assess if the company was currently practicing ERM, and not simply defining it or were noting future plans for implementation. Additionally, 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

[1] 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 below my sample of 110.

[2] Website data was reviewed as of month-end February 2015 across all 110 companies in the study for consistency of timing.

suggestions of integrated ERM[3]. 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 reinsurance for natural catastrophe risk) these alone were not considered characteristics of an integrated ERM framework. See Appendix A for examples of commentary used to confirm integrated ERM.

Variable Calculation and Measurement

Ten research 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 1 provides a quick reference for how these variables are defined. Table 2 provides some corresponding descriptive statistics and correlation data. These will be discussed in turn and its relevance to this study.

Table 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	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 company or non-life company.	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 operations. Note any firm with global operations is considered to have an additional segment.	COMPUSTAT
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

[3] 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 S&P were also deemed to have integrated ERM for the purposes of our study.

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	RCAP	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 2. Descriptive Statistics and Correlations of key variables used in the study. Correlations above 0.50 are denoted in bold.

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			

	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

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 Appendix B.

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 section 4.1 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.

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.

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".

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.

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 was 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 were classified as elevated. Those with six or more segments and had global operations were 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 was classified as medium complexity instead. These classifications resulted with most insurers in either the medium to elevated categories, with smaller clusters in the low or high category. Table 3 provides the count in each category for the COMPLX variable.

Table 3. This shows 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.

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.

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. 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. See Figure 1.

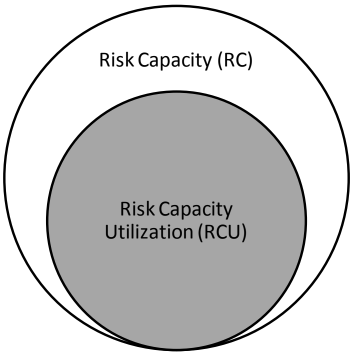

Figure 1. Risk Capacity Utilization Venn Diagram

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

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

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[4] is calculated as:

Earnings Volatility = ROE Standard Deviation

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

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

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.

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.

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[4] 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.

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 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 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.

Empirical Results

A multi staged 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.

Model Evaluation

The first regression assessed the relationship across complexity (CMPLX), leverage (LEV), enterprise risk management (ERMI) and risk capacity utilization (RCU), where RCU is our proxy for risk tolerance:

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

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[5]. Hence dummy variables of 0 or 1 were assigned for each company to identify the category to which that company belonged. Model (1) becomes:

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

The results of the model (1a) regression are shown in Table 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

[5] See Field (2009).

expect. However, the ERMI variable seems to not have any relevance in determining an optimal risk tolerance in this model.

Table 4. Regression model (1a) results. Risk capacity utilization is regressed on complexity dummy variables, leverage and the ERM proxy.

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			

Gordon et al's (2009) ERMI score 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 was made to the ERMI score by accounting for those insurers assessed to have integrated ERM (INTEG) versus those that do not as defined in section 4.4 above. An interactive variable was 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 showed how evidence of ERM interaction and implementation impact risk profiles and valuation. Model (1a) is modified to model (1b):

$$Risk\ Tolerance\ = \beta_0 + medComplexity + \beta_{1b}elevComplexity + \ \beta_{1c}hiComplexity + \beta_2Leverage + \beta_3ERM + \beta_4ERMI * INTEG + \ Residual \tag{1b}$$

Table 5. Regression model (1b) results. Risk capacity utilization is regressed on complexity dummy variables, leverage, the ERM proxy, and a variable that recognizes if ERM is integrated within the firm.

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	

The results of the model (1b) regression are shown in Table 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: 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. To account for this weighted least squares was applied to adjust for higher variation in RCU as leverage increased. Model (1b) then becomes model (1c):

$$Risk\ Tolerance\ = \beta_0 + medComplexity + \beta_{1b}elevComplexity + \ \beta_{1c}hiComplexity + \beta_2Leverage + \beta_3ERM + \beta_4ERMI * INTEG + \beta_6MS + \beta_6AGE + \beta_7LIFE\ + Residual \qquad (1c)$$

The results of regression model (1c) are shown in Table 6.

Table 6. Weighted least squares regression model (1c) results. 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.

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
Market Share	-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			

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 ERMI is removed. The revised RCU regression becomes model (1d):

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

The results of regression model (1d) are in Table 7.

Table 7. Weighted least squares regression model (1d) results. Risk capacity utilization is regressed on complexity dummy variables, leverage, an integrated ERM variable and a life dummy control variable.

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	

The final regression 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. 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 6**. The results support 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 6. Regression Model (2) results. Risk adjusted ROA and risk adjusted ROE are regressed on the absolute value of the negative and positive residuals from model (1d).

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

	ROAz		**ROEz**		
Coefficient Name	**Coefficient Value**	**P-Value**	**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		

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 not perfectly normal, but not so much to be of concern. Significant outliers were assessed prior to the regression models being run. These were removed from the original dataset. As mentioned in section 5.1 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.

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 more directly 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, given 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.

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 S&P Financial Strength Rating Report, 19 December 2013, S&P 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."

ACRN Oxford Journal of Finance and Risk Perspectives
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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. Any differences in calculations from Gordon et al are denoted in bold below.

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

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