

CAPITAL AND RISK REVISITED: A STRUCTURAL EQUATION MODEL APPROACH FOR LIFE INSURERS

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ABSTRACT

The role of risk in the capital structure decision of firms is a vast topic in finance. Commonly, models of the interrelationship between risk and capital enumerate as many risk factors as possible by appropriate proxies, with the goal of detailing their individual effects. In this study of the life insurance industry for 1994 through 2000, we take a broader, holistic view of enterprise risk, identifying two groups of insurer risk factors that arise from the major activities of life insurers: investing and underwriting. We call the group of risk factors associated with investing *asset risk*, and the group associated with underwriting *product risk*. After specifying other important determinants of capital structure as controls, we allow all other risk factors to find expression in residual error. Within this framework, our focus is to compare two candidate measures for the role of proxy for asset-related risks. One measure, called *regulatory asset risk* (RAR), derives from the regulatory tradition of concern with solvency and is related to the C-1 component of risk-based capital. The other measure, called *opportunity asset risk* (OAR), is motivated by traditional finance concerns with market risk and reflects volatility of returns. Product-related risks are proxied by underwriting exposures in different product lines. We employ structural equation modeling (SEM), which uses longitudinal factor analysis. SEM is an innovative technique for such studies, in dealing effectively with multiple structural equations, autocorrelated panel data, unobserved underlying factors, and other issues that are not simultaneously addressed in other methodologies. We find that RAR and OAR are not equivalent proxies for asset risks. Although overlapping to some extent, each illuminates different aspects of the asset risk-capital interrelationship. In particular, RAR does not seem to affect the capital structure decision of small firms, although OAR does. We interpret this to suggest that small firms as a whole are not as sensitive in their capital decisions to the proxy of regulatory concerns as to the proxy of market opportunity. This contrasts with large insurers, for whom both RAR and OAR have significant

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effects on capital that comport with the *finite risk hypothesis*. More detailed analysis suggests that the lack of effect of RAR for small insurers may result from RAR's proxying some factors that induce finite risk for part of the small insurer sample, and other factors that favor the *excessive risk hypothesis*.

INTRODUCTION

The context of this article is the capital structure strategy of U.S. life insurers during the 1990s. Capital structure decisions are made within the framework of a panoply of enterprise risks. For life insurers, there are two major categories of enterprise risks aligned with the two principal activities of life insurers: investing and underwriting. Our study provides a simplified but appropriate framework for imbedding the capital structure decision of life insurers into the spectrum of their investing and underwriting risks. We do not essay a detailed enumeration of various enterprise risks, but keep the categories of risks at a general level. Within this framework, our purpose is to compare two different approaches that purport to measure aspects of investment risk. One measurement approach derives from the traditional regulatory concern with avoiding insolvency. The other approach is oriented toward the risks of optimizing investment opportunities. Each has its proponents in the literature.

For the regulatory-associated approach, we use a measure called *regulatory asset risk* (RAR) that is closely related to the C-1 risk of the life-risk-based capital law. For the investment-opportunity-related approach, we introduce a volatility-of-returns-based measure called *opportunity asset risk* (OAR). We view RAR and OAR neither as potential competitors nor as complementary, but as somewhat overlapping. We expect them to provide different insights into the capital structure decision. We compare RAR and OAR in the same manner as in a controlled scientific experiment: by swapping one for the other in a model in which everything else remains the same—the same response variables, the same predictors, the same data. Thus the differences in model results can be attributed to the swap. We believe this is the first such comparison of proposed proxies in capital structure studies.

To provide a model for our framework, we use *structural equation modeling* (SEM). Introduced into capital structure studies by Titman and Wessels (1988), but subsequently largely neglected, SEM deals appropriately with several methodological issues for our study that are not dealt with simultaneously by other models. In particular, SEM provides for multiple equations to describe insurer behavior, for autocorrelated panel data, and for unobservable latent factors that underlie measured proxies. In addition, as noted by Titman and Wessels, the factor feature of SEM mitigates measurement issues arising from the use of imperfect proxies.

Our major findings are striking and present possible policy and managerial implications: RAR has no effect on the capital structure of small insurers, although it does on large insurers. By contrast, OAR affects the capital structure of both large and small insurers, but has more effect on large insurers. There are also temporal differences, before and during the late bull market.

Insurers are engaged in two major activities: investing and underwriting. Risks from those activities are represented in the balance sheet by assets (investing) and liabilities (underwriting). On the asset side, insurers maintain substantial portfolios generated from premiums collected and capital raised. These portfolios are invested in bonds,

stocks, mortgages, real estate, and other assets of varying risks.¹ On the liability side, risk arises from the nature and volume of products sold. Annuity contracts represent different liability risks than do health and accident policies.

In empirical studies, risks are complex constructs that cannot be measured directly and thus are always proxied. Our focus in this article is on two composite proxy measures of asset risk, distinguished by their orientation. One originates from a regulatory tradition oriented toward insolvency risk, that is, the objective of minimizing the risk of failure or ruin from investing activities. We call this measure RAR. To calculate RAR, we approximate the C-1 component of life risk-based capital. Such measures have been used in capital structure studies by Baranoff and Sager (2002 and 2003) and Shrieves and Dahl (1992) for banks. The other proxy originates from an orientation toward maximizing firm value and reflects the risks of investing to optimize asset returns. We call this risk measure the OAR. Although OAR per se is an innovation of this study, a somewhat similar measure was used by the capital structure study of Cummins and Sommer (1996). OAR measures volatility of an insurer's *potential* investment returns. Actual returns are not used (and are not available). Instead, returns are calculated as though portfolio components were invested in related investment indices. OAR is motivated by the use of returns volatility to calibrate investment risk in portfolio theory.² Given the orientations of RAR and OAR, one might interpret RAR as theoretically intended to reflect downside risks of investing and OAR as intended to reflect opportunity for both gain and loss. But as we shall see, there is considerable empirical overlap.

RAR and/or OAR potentially represent the category of asset risks for life insurers. As potential representatives for the category of product risks, we measure the extent of insurer involvement with annuity and health products, representing relatively less risk (annuities) and relatively more risk (health). These measures were used in some form in Baranoff and Sager (2002, 2003). It could be argued that loss ratios might better represent liabilities-side risks, but loss ratios are not available to us.

To represent elements of the capital structure decision that are not among the primary risks for life insurers, we include the most important controls from previous studies: size, organizational form, and group membership. Size is used both as an explicit control and as a stratum. We stratify the life insurance industry by size to examine potential qualitative differences between large and small insurers that may have significant policy and managerial effects (see Baranoff, Sager, and Witt, 1999). We also compare the years 1994 through 1996 with 1998 through 2000 in order to gauge the potential effects of the great bull market of the late 1990s.

For capital structure, we examine the ratio of book capital to total invested assets. It would be better to use the market value of equity. But since most life insurers are not publicly traded, market value is not available.

An enumeration of the spectrum of enterprise risks to which life insurers are subject would be a long list. Moreover, such risks are not neatly distinct but overlap in ways

¹ Individual life insurer invested assets vary from less than \$400,000 to over \$120 billion in our study period.

² See most basic financial management textbooks.

difficult to depict. The empirical topology of risk is even messier. Any observed risk measure most likely embodies significant components from a variety of enterprise risks. Therefore, any proxy for a portion of the risk spectrum could be viewed as a mixture of underlying theoretical risks, some of which may not be directly measurable (see Titman and Wessels, 1988). By taking a factor view of risk, we mitigate some of these measurement issues.

Moreover, our concern in this article is not with mapping the geography of risk *per se*, but with the relationship of risk to capital structure. Some risks that occupy large territories in risk space may not be especially important for capital structure.³ Our focus is: Given whatever overall role that risks play in capital structure decisions, how do OAR and RAR compare and contrast as proxies for asset risks? If our model failed to represent regions of risk space that are important for capital structure decisions, then it would be appropriate to criticize our findings as potentially misleading on account of the distorting effects of missing variables. *A priori*, we do not know what proportion of the capital effects of various asset risks can be captured by OAR and RAR. Neither do we know what proportion of the capital effects of various product risks can be captured by our measures. *A posteriori*, however, it seems that our framework captures sufficient explanatory power so that the scope for distortion by unenumerated risks is greatly reduced.

The theoretical backdrop for our analysis is the set of capital structure theories that were summarized by Harris and Raviv (1991) in general and more particularly by Cummins and Sommer (1996) for the property and casualty insurance industries and Baranoff and Sager (2002, 2003) for the life and health insurance industries. Harris and Raviv surveyed the body of the theoretical and empirical capital structure studies that include agency theory, asymmetric information, and product/input theories.

As explained later in the hypothesis section, the prior studies of insurers' capital/risk relationship for both the property and casualty and the life and health insurance industries suggest that the industry as a whole operates within the finite risk rather than the excessive risk paradigm. Cummins and Sommer (1996) for the property and casualty insurance industry and Baranoff and Sager (2002, 2003) for the life and health insurance industry showed a positive interrelationship between various risks and capital, in line with the finite risk hypothesis. Their studies were industry-wide, without segmentation. Cummins and Sommer used a combined asset and product risk proxy measure that is based on financial market returns and loss ratios. Baranoff and Sager unbundled the risk measures into asset risk and product risk. For asset risk, they used only the insolvency-oriented RAR; for product risk, they used health writings (2002) and a profile of product writings (2003).

By their nature, proxies are not pure measures of the antecedent quantities that they are supposed to represent. *A priori*, we suspect that our measured risk proxies are actually composite effects of a number of underlying risks, some of which are not directly observable. We treat all risks as *factors*, that is, as unobserved constructs that underlie measured quantities. We use factor analysis to estimate the risks through

³ For example, the operational risk of high-tech systems or globalization.

their manifestations in the observable variables. Factor analysis is a methodology that attempts to organize underlying features into similarly grouped composites and thus provides purer proxies than the measured variables. But the methodology must also deal with other challenges.

The major modeling issues for this study are longitudinally autocorrelated panel data over a multiyear period, simultaneous structural equations, and underlying unobservable factors that are hard to proxy. The SEM methodology appropriately deals with these challenges. As noted above, our primary focus is to compare the risk-capital relationship for the two asset risk measures. Therefore, we create two separate models. The models are identical but for the use of the RAR measure in the first and the OAR measure in the second. We run the two models on the same data. Each model has the same control variables and the same health and annuity product risks. The models are run 18 times = 2 asset risk measures $\times$ 3 size segments (large firms, small firms, whole industry) $\times$ 3 time periods (before and during the bull market, and whole time period).

Among other things, our findings suggest a near absence of effect for the regulatory insolvency-based asset risk in the capital structure decisions of small insurers. Another key finding is the validation of prior studies' conclusion (Cummins and Sommer, 1996; Baranoff and Sager, 2002, 2003) that the industry generally operates under the finite risk paradigm, except for small insurers. For small insurers, OAR impacts capital positively, whereas RAR has no effect on capital. Follow-up analysis that incorporates both RAR and OAR in the same equation suggests that the absence of the RAR effect for small insurers may result from the inclusion of both positive and negative influences on capital within RAR. These conflicting influences appear to cancel each other out. For large insurers, both RAR and OAR generally have significant effects on capital structure that operate in the same direction but at different degrees of strength. Although RAR and OAR cover some of the same parts of risk space, they are not identical. Thus, it is useful to consider the insights that each can yield within the broader spectrum of life insurers' risks.

The remainder of the article is structured as follows: The next section explains the observable variables. The "Hypotheses" section discusses the presumed relationships of the predictors with the capital structure. Then the "Model" section explains the methodology of the structural equation model, and is followed by the empirical results. The article concludes with a summary.

KEY OBSERVABLE VARIABLES

The insurer data for this study are taken from the annual statements of life insurers filed with the NAIC for 1993 through 2000. Since all data are from the post-risk-based capital law period, the analysis therefore covers a period of fairly consistent regulation for life insurers. To have a uniform sample for year-to-year comparison, we deleted companies with missing values for one or more years. We further eliminated companies with nonpositive capital or negative health or annuity premiums, and other anomalies such as companies with capital exceeding assets and companies with health or annuity premiums exceeding total premiums. After all of these adjustments,

719 insurers per year remained for the analysis.⁴ Diagnostic checks on the 719 insurers ($\times 7$ years⁵ = 5,033 observations) indicated conformity with the linearity assumptions underlying our model after logarithmic transformation. For most analyses, the data set was split into two subsets of 360 large insurers and 359 small insurers at the median net invested assets for the 719 insurers in the data set.⁶ The entire sample of 719 insurers has about 88.3 percent of total industry-invested assets during the time period. Table 1 summarizes the observable variables used in this study.

Capital Ratio

For capital structure, we take the logarithm of the ratio of adjusted book value of capital to total firm invested assets.⁷ Since most life insurers are not publicly traded, the market value of equity is not generally available. It would have been preferable to use measures of economic capital rather than accounting data. Unfortunately, we could neither find nor construct a credible measure of market capital. This is a limitation of the study. Figure 1 compares the mean capital ratio between the size segments and the two periods.

The Asset Risk Measures

We use two measures of asset risk and two of product risk. The two asset risk measures are summarized and compared in Table 2. RAR is based on the regulatory penalty weights of the insurer investment portfolio, relative to invested assets (see Baranoff and Sager, 2002 and 2003). It equals $\log(R/IA)$, where R is an approximation of the C-1 portion of risk-based capital and IA is insurer invested assets. R is calculated as a "penalty-weighted average" of the values of various asset classes in the portfolio of an insurer, as shown in Figure 2. The "penalty weight" for each asset is based on the default risk of the asset as indicated in the risk-based capital formula. Assets with lower credit ratings have higher "penalty weights." R is a *static* measure of risk that changes from year to year because only the asset mix proportions change as shown in Figure 2, but not the "penalty" weights. The division by invested assets accomplishes the objective of normalizing the measure for comparability with the capital-to-asset ratio.

⁴ Undoubtedly, the requirement of data for every year biases the sample toward large insurers because large insurers tend to report more regularly. In addition, insurers formed by merger or divestiture during the period are not represented. Thus, it is likely that the differences between large and small insurers that we find would be even more pronounced if we had complete data on all insurers. However, we have the same sample throughout the study period, so year-to-year differences cannot be attributed to changes in the sample composition.

⁵ 1993 data are used only to provide lags for 1994.

⁶ For each firm, the mean of its net invested assets was computed over 8 years, from 1993 through 2000. For the purpose of splitting the industry into large and small insurers, the median of these 719 means was used as splitting point.

⁷ The adjusted capital formula is the sum of Capital and Surplus, Asset Valuation Reserve (AVR), Voluntary Investment Reserve, Dividends Apportioned for Payment, Dividends not yet Apportioned, and the Life Subsidiaries AVR, Voluntary Investment Reserves and Dividend Liability less Property/Casualty Subsidiaries Non-Tabular Discount. (Source: page LR022 of the 1996 Life NAIC Risk Based Capital Report Including Overview and Instructions for Companies.)

TABLE 1
Summary Statistics of the Variables Used in the SEM Models by Size and Period

Model Variable	1994–1996						1998–2000						94–96 vs. 98–00**	
	Large Insurers			Small Insurers			Large Insurers			Small Insurers			Large	Small
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N		
													p-value	p-value
Invested assets*	3,731	11,203	37	37	50	50	4,634	13,114	46	46	51	51	0.0000	0.0000
Capital	0.2079	0.2347		0.4669	0.2692		0.2211	0.2435		0.4734	0.2718		0.0006	0.1756
OAR	0.0047	0.0011		0.0055	0.0014		0.0040	0.0032		0.0049	0.0036		0.0000	0.0000
RAR	0.0236	0.0277		0.0238	0.0323		0.0260	0.0301		0.0256	0.0350		0.0000	0.0062
Pannuity	0.3354	0.3397		0.0651	0.1688		0.3350	0.3460		0.0649	0.1817		0.4378	0.0010
Phealth	0.1881	0.2801		0.3478	0.3664		0.1898	0.2928		0.3523	0.3750		0.0349	0.4008
Ntype	0.8296	0.3723		0.9489	0.2176		0.8389	0.3622		0.9536	0.2092		0.1072	0.2500
Ngroup	0.9148	0.2694		0.6007	0.4757		0.9269	0.2461		0.6546	0.4555		0.1023	0.0000

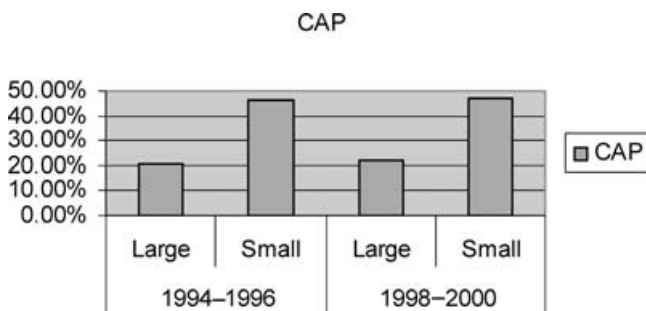
*In million dollars.

**Wilcoxon signed-rank test of H₀: mean 94–96 = mean 98.00.

Note: We omit showing tests for differences between size segments, all of which are significant on all variables, regardless of the time period.

FIGURE 1

Mean Capital Ratio—By Insurer Size and Time Period



The OAR intends to measure the opportunity available in the market for gain or loss presented by the insurer's allocation choices among different asset classes in its portfolio. To do this, we begin by calculating on a monthly basis the hypothetical return that the insurer could have earned by investing each component of its actual portfolio in a related investment index. That is, prevailing monthly exogenous returns (from T-bills, S&P 500 stocks, bonds of various types of issuers, credit classes and duration classes, real estate, mortgages) are applied to the firm's specific asset portfolio values in 14 categories shown in Figure 3 (cash, stocks, 10 types of bonds, real estate, and mortgages) to yield hypothetical estimated portfolio earnings. "Like" indices are applied to "like" asset classes, and the returns are aggregated across the 14 classes that are shown in Figure 3. Then the standard deviation of the 12 monthly returns is calculated for each year for each insurer based on the asset allocation mix of that insurer. Since this standard deviation depends on the size of the insurer, it is normalized by dividing by firm invested assets and then logged. As in the calculation of RAR, the division by invested assets here also recognizes the need to standardize for size. Thus, the observable OAR is a constructed measure $\log(O/IA)$ that equals $\log$ (standard deviation of each insurer's hypothetical monthly returns/invested assets). By choosing its particular allocation of assets among the 14 asset classes, the insurer has created the *opportunity* to earn the returns shown in our calculations and could have earned them by simply investing in our investment indices. Doing so would have exposed the insurer to the corresponding risk of volatility, which is measured by the standard deviation of those hypothetical insurer returns. The *actual* volatility risk that the insurer realizes would be measured by the standard deviation of actual returns. Actual monthly returns data are not available to us, so we cannot assess how well insurers realized the opportunity presented by their asset allocation decisions. However, an insurer could easily calculate its own actual asset risk and compare with OAR as a performance benchmark.

The Product Risk Measures

For our two product risk proxies, we take the logarithms of the proportions of firm premiums derived from health lines and from annuity lines. We do not maintain that health and annuity products constitute the only product risks for life insurers, only that they represent the most and least risky products. Figure 4 and Table 1 show that large insurers are more in the annuity business across the two periods, whereas small

TABLE 2

Side-by-Side Summary Comparison of the Asset Risk Measures

	Regulated Asset Risk (RegARisk – RAR)	Opportunity Asset Risk (OppARisk – OAR)
Computational process	Calculate raw regulatory asset risk measure based on C-1 component of risk-based capital: Bond quality classes 1–6 $\times$ (.003, .01, .04, .09, .20, .30, respectively) + common stocks $\times$.30 + preferred stocks $\times$ 0.023 + total mortgages $\times$.03 (an average between .001 and .06) + real estate occupied, acquired, and invested $\times$ (.1, .15, .1, respectively) + (total short-term investments and cash) $\times$.003. (See asset mix in Figure 2.) Since this penalty-driven portfolio measure depends on the size of the insurer, it is normalized by dividing by firm invested assets. Regulatory asset risk measure = $\log(\text{C-1 measure of risk-based capital} / \text{total invested assets})$	Prevailing monthly exogenous indices returns (from T-bills, S&P 500 stocks, bonds of various credit and duration classes, real estate, mortgages, etc.) are applied to the firm's specific asset portfolio values in 14 asset classes to yield constructed portfolio earnings for each month based on the proxy returns. (See asset mix in Figure 3.) The standard deviation of the 12 constructed monthly earnings is calculated for each year for each insurer—this is the raw <i>opportunity asset risk</i>. Since this standard deviation depends on the size of the insurer, it is normalized by dividing by firm invested assets Opportunity asset risk measure = $\log(\text{standard deviation of insurer's constructed monthly returns} / \text{total invested assets})$
Similarities	Broad asset mix of insurers Based on weighted average of asset portfolio Portfolio changes annually	Broad asset mix of insurers Based on weighted average of asset portfolio Portfolio changes annually
Differences	Oriented toward the objective of minimizing insolvency—assets with lower credit rating have higher “penalty” weights. Weights are static throughout the years Risk measure is the weighted average of estimated (potential) losses of the portfolio	Oriented toward the objective of maximizing the value of the firm—volatility risk showing both gain and loss variability—depends on exogenous returns in the market Weights are dynamic from year to year Risk measure is the variability in the weighted average of potential earnings (or losses) of the portfolio.

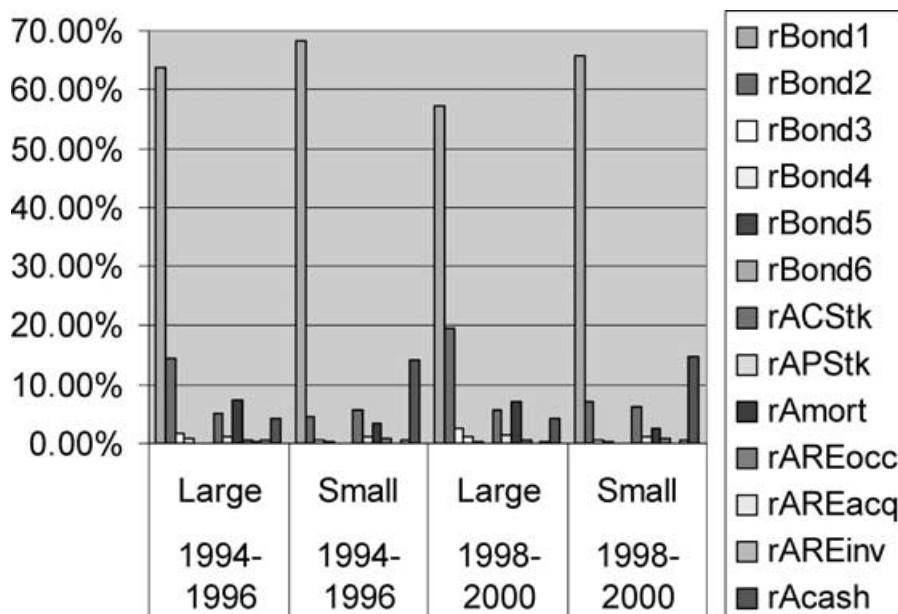
insurers are more in the health business across the two periods. (See further discussion later, under “Impact of Product Risk on Capital Structure.”)

Control Variables

Because of the generally recognized importance and possible confounding effect of firm size, we elected to control for the effect of size explicitly even when we segment the industry into two size groups. For a size measure, we took the 8-year mean of the logarithm of invested assets (the log of the geometric mean).

FIGURE 2

Regulated Asset Risk—Mix of Assets by Size and Period*



Note: Vertical axis is proportion of the total represented by the various asset classes. Index: rBond1–6 represent the ratio of bonds to invested assets for NAIC bond credit rating classes 1–6, respectively. The lowest rating is rBond6. rAmort = ratio of mortgages to invested assets. rACStk = ratio of common stocks to invested assets. rAPStk = ratio of preferred stocks to invested assets. rAREocc = ratio of occupied real estate to invested assets. rAREacq = ratio of acquired real estate to invested assets. rAREinv = ratio of investment real estate to invested assets. rAcash = ratio of cash and short-term investments to invested assets. The left-to-right order of the vertical bars in each of the four size x period blocks corresponds to the top-to-bottom order of the variable legend at the right of Figure 2.

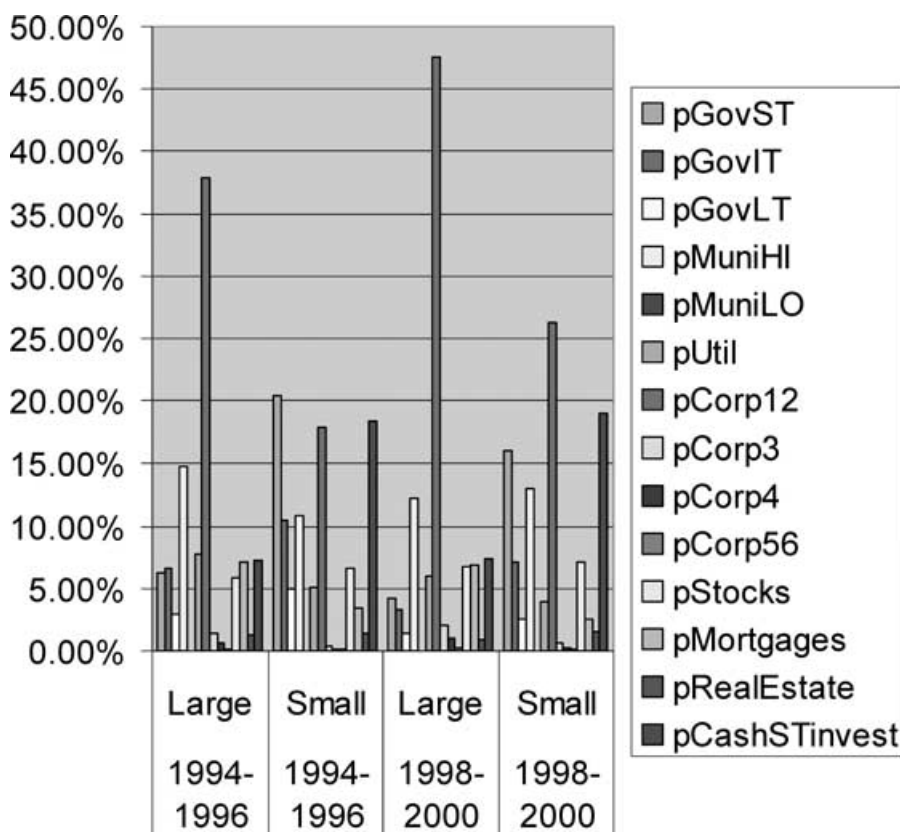
*For each insurer, the ratio of the value of each asset class to the total value of all asset classes is computed for each year. These ratios are averaged by insurer for each asset class over the time period shown in the figure. The vertical scale in the figure displays the mean of these period averages across the size segment indicated.

Other control variables that are often used in capital structure studies of financial institutions and that we elected to include explicitly are indicators for the governance structure (NTYPE—mutual or stock) and for affiliation with a group of companies (NGROUP—yes or no). Under agency theory, risk taking is inversely related to the degree of separation of ownership from management. This implies that managers of mutual insurance companies take less risk than do those of stock companies. Additionally, insurers that are part of a larger group may have superior access to investment opportunities and may have different mechanisms for monitoring or controlling managerial performance.

Table 1 displays summary statistics for all explicitly observable variables used in the SEM models. We used the robust Wilcoxon test to assess significance of differences. The table shows the Wilcoxon *p* values for differences between the years 1994 through 1996 and 1998 through 2000 time periods. The two time periods are statistically significantly different on a majority of variables, whether for large firms or for small firms. We omit

FIGURE 3

Opportunity Asset Risk—Mix of Assets by Size and Period*



Note: Vertical axis is proportion of the total represented by the various asset classes. *Index:* pGovST = ratio of short-term government bonds to invested assets. pGovIT = ratio of intermediate-term government bonds to invested assets. pGovLT = ratio of long-term government bonds to invested assets. pMuniHi = ratio of high-quality municipal bonds to invested assets. pMuniLo = ratio of low-quality municipal bonds to invested assets. pUtil = ratio of utility bonds to invested assets. pCorp12 = ratio of high-quality corporate bonds to invested assets. pCorp3 = ratio of quality-3 corporate bonds to invested assets. pCorp4 = ratio of quality-4 corporate bonds to invested assets. pCorp56 = ratio of lowest-quality corporate bonds to invested assets. pStocks = ratio of common stocks to invested assets. pMortgages = ratio of mortgages to invested assets. pRealEstate = ratio of all real estate to invested assets. pCashSTinvest = ratio of cash and short-term investments to invested assets. The left-to-right order of the vertical bars in each of the four size x period blocks corresponds to the top-to-bottom order of the variable legend at the right of Figure 3.

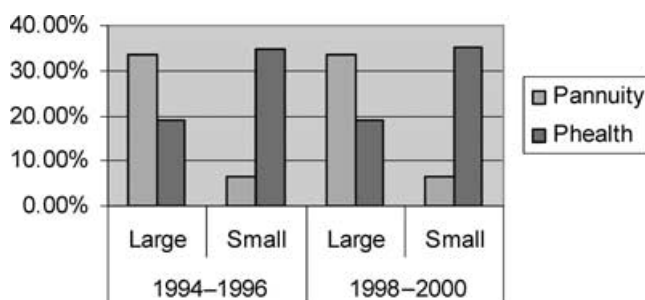
*The computations for Figure 3 are similar to those for Figure 2. Note the difference in the composition of the asset mix used for calculation of the opportunity asset risk in comparison to that of the regulated asset risk.

showing tests for differences between large and small firms, all of which are significant on all variables, regardless of the time period.

From Figures 1–4 and Table 1, a few pertinent observations can be made for future reference: Compared with large insurers, small insurers tend to have higher capital ratios, more cash, more bonds of top quality, fewer lower-grade bonds, more short-term government bonds, and fewer corporate bonds—all of which are consistent with

FIGURE 4

Product Risk—By Size and Period (Vertical Axis is Mean Proportion of Total Written Premiums)



a lower investment risk posture. At the same time, small insurers tend to write more health business and less annuity business—consistent with a higher product risk orientation.

HYPOTHESES

Impact of Regulatory Asset Risk on Capital Structure

We first provide an overview of the expected impact of the RAR on the capital structure based on prior research. (See summary in Table 3, based on Baranoff and Sager, 2002, 2003.) Overall, the prevailing finite risk and excessive risk hypotheses underlie the expected signs in the relationship between regulated asset risk and the capital ratio.

For the relation between capital and RAR, the literature entertains the distinct and conflicting theories that are summarized as (or culminate in) the hypotheses of finite risk vs. excessive risk taking. Under transaction-cost economics theory, agency theory, and the bankruptcy and regulatory costs hypotheses, adoption of a more risky strategy in assets is associated with holding more capital. The competing hypothesis of excessive risk taking is entrenched in the risk-subsidy hypothesis, which suggests that a risky asset strategy leads directly to greater risk taking in capital (leverage risk) and asset risk. The excessive risk taking stems from having the security of guarantee funds or deposit insurance. Formally, these hypotheses are depicted in the left-hand column of Table 3.

Impact of Opportunity Asset Risk on Capital Structure

The expected impacts of OAR on capital are summarized in Table 3. The same theories leading to finite risk (transaction-cost economics theory, agency theory with monitoring, regulatory and bankruptcy costs) also predict a positive relationship between the OAR and capital, just as between the RAR and capital, and through the same theoretical mechanisms. Similarly, excessive risk theories predict a negative relationship. But one can buttress both arguments in the case of OAR by appealing to theories that link capital and asset risk through *returns*.⁸ Our discussion borrows from and extends

⁸ This is especially important as the OAR is computed using the variability in returns. Returns are the core foundation of this asset risk measure.

TABLE 3

Comparison of the Underlying Theory for the Impact of the Two Asset Risk Proxy Measures on the Capital Ratio

RAR $\geq$ Capital	OAR $\geq$ Capital
H1: Positive interrelationship	H1: Positive interrelationship
Theoretical support: Solvency/preservation subject to agency theory and transaction-cost economics, asymmetric information, bankruptcy cost theory, and regulatory cost hypotheses (finite risk hypothesis)	Theoretical support: Value maximization subject to agency theory and transaction-cost economics theory, asymmetric information, bankruptcy cost and regulatory cost hypotheses (finite risk hypothesis), and augmented by retained earnings (Berger, 1995): higher OAR $\Rightarrow$ higher returns $\Rightarrow$ higher capital
H2: Negative interrelationship	H2: Negative interrelationship
Theoretical support: "Go for broke" subject to the risk-subsidy hypothesis (excessive risk).	Theoretical support: Value maximization subject to the risk-subsidy hypothesis (excessive risk): higher OAR $\Rightarrow$ lower capital

Berger (1995), who studied the relationship between capital and returns for banks. Obtaining high investment returns is one aspect of the drive to maximize firm value. But portfolio theory posits that high expected returns correlate positively with high volatility of returns.⁹ OAR reflects the potential volatility of returns for each insurer's asset portfolio, with respect to the yields of benchmark indices. In the framework of value maximization, an important question is, what is the relationship between the capital structure and the risk of returns as represented by their volatility? Berger (1995) points out that if a firm gains high returns and it retains those returns, then capital increases. To this observation, we add that higher returns are correlated with higher volatility in the form of higher OAR. Thus the linkage is that higher volatility of returns (higher OAR) would be expected to lead to higher returns, which in turn would lead to higher capital if the earnings are retained.

Impact of Product Risk on Capital Structure

Theoretical support for the impact of product risk is found also in transaction-cost economics, agency theory (the monitoring hypothesis), bankruptcy cost avoidance, and regulatory cost hypotheses.¹⁰ In transaction-cost economic theory, the level of

⁹ See basic portfolio theory in basic financial management textbooks.

¹⁰ The life insurer annual statements do not provide the loss ratios and loss development data as the property-casualty annual statements do. Thus, a comparable quantifiable risk measure for each product is not available. Therefore, we resort to using theoretical tools to evaluate the risk level embedded in each life product and use the proportion of writing for each as the quantifiable variable for predetermined more risky versus less risky products.

transaction costs and the risk embedded in the products largely determine the capital structure (Williamson, 1988, with further explanation in Baranoff and Sager, 2002, 2003). Products that involve large potential contractual disputes and uncertainties (Williamson, 1985) are considered riskier and would not lend themselves to financing by debt. Therefore, for firms specializing in higher risk products, the method of financing would tend to favor capital rather than debt. Thus, it can be inferred that an emphasis on higher risk products is associated with higher capital.

But which insurance products are riskier? Among the primary insurance products sold by life insurers (annuity, health, life, and reinsurance contracts), health contracts are the least *complete*, in transaction-cost economics terms, and hence least certain. Of all four products, health writings receive the highest “penalty” weight by the life risk-based capital law, and health insurers incur much higher legal expenses than life insurers.¹¹ On the other hand, annuity contracts are the most complete in transaction-cost economics terms, and hence most certain. They offer calculable payouts with well-defined endpoints and uncertainties subject to actuarial control via mortality tables. We therefore view health products as the riskiest and annuities as least risky. Life products are in between. (See Baranoff and Sager, 2002, 2003, for further discussion.)

THE SEM MODEL

As noted in the “Introduction,” this study uses a statistical methodology known as structural equation modeling, embodying longitudinal factor analysis. The methodology enjoys three main advantages over ordinary least-squares (OLS) regression: (1) multiple interacting equations can be modeled simultaneously, (2) time-dependent correlation can be explicitly modeled, and (3) unobservable latent variables can be included in the model. To be sure, simultaneous equation models also enjoy point (1), time series models treat point (2), and factor analysis handles point (3). But SEM incorporates all three features, thus making the other methodologies special cases of SEM. Roughly speaking, if simultaneity, autocorrelation, and latent factors are stripped out of SEM, one has OLS regression. Add back simultaneity and one has the simultaneous equation models that are familiar from econometrics. Then in addition, add back autocorrelation and one has autoregressive forms of simultaneous equations. Finally, add back latent factors and one has SEM.¹²

All three features are essential to our study. Since the study is concerned with the interrelationships among measures of a life insurer’s capital ratio, asset risk, and two types of product risk exposure, we therefore construct four simultaneously interacting descriptive equations for these four quantities. The capital ratio can be observed directly, but the four risks cannot be measured directly. The risks must be assessed

¹¹ For our sample, the legal expenses of health specialists are about 3 times those of any other specialty segment—about 0.3 percent of net invested assets per year, on average.

¹² Although all the three main features of SEM are theoretically necessary, we also ran our models without one or more key features in order to test the robustness of our results to alternative specifications. We removed all three features and ran OLS, then added back simultaneity, then autoregression. In general, we saw similar explanatory power and results. The main difference was that the results for models without autoregression were even more significant. This is because models that assume independence (OLS, simultaneous equations) tend to overstate significance in the presence of positive autocorrelation.

TABLE 4
Serial Autocorrelations, Controlling for Size

Variable	Large Insurers	Small Insurers
Log(capital ratio)	0.9487	0.9152
Log(regulatory asset risk)	0.9478	0.8940
Log(opportunity asset risk)	0.8380	0.5836
Log(health product risk)	0.9813	0.9709
Log(annuity product risk)	0.9617	0.9356

through proxies that imperfectly reflect the effects of the true risks and other variables. That is, observable risk proxies are actually composite manifestations of unobservable underlying true risks (factors) and other variables.¹³ In contrast to other studies, we do not accept the observable proxies as direct surrogates for the true risks. Instead, we use the factor feature of SEM to estimate the underlying risks and thus obtain purer proxies for them. Since the data track individual firms from 1994 through 2000, there will be a significant degree of longitudinal autocorrelation, which is estimated and adjusted for by the model. Indeed, Table 4 shows high serial autocorrelation for our key variables, even after adjusting for size, empirically emphasizing the need for the methodology to address this feature of the data. Thus, we utilize all three main features of SEM.

More specifically, the SEM model can be described both analytically and graphically, as discussed further. Analytically, the structural model is specified by a set of functional relationships and a set of distributional assumptions. The functional equations for the SEM model comprise a static specification and a dynamic specification:

$$\text{Static specification } \left\{ \begin{array}{l} C_t = \beta^{(c)} S + \delta^{(c)} T + \kappa^{(c)} G + \lambda^{(a)} F_t^{(a)} + \lambda^{(p_h)} F_t^{(p_h)} \\ \quad + \lambda^{(p_{an})} F_t^{(p_{an})} + \varepsilon_t^{(c)} \end{array} \right. \quad (1)$$

$$A_t^{(a)} = \beta^{(a)} S + \delta^{(a)} T + \kappa^{(a)} G + F_t^{(a)} + \varepsilon_t^{(a)} \quad (2)$$

$$P_t^{(h)} = \beta^{(p_h)} S + \delta^{(p_h)} T + \kappa^{(p_h)} G + F_t^{(p_h)} + \varepsilon_t^{(p_h)} \quad (3)$$

$$P_t^{(an)} = \beta^{(p_{an})} S + \delta^{(p_{an})} T + \kappa^{(p_{an})} G + F_t^{(p_{an})} + \varepsilon_t^{(p_{an})} \quad (4)$$

$$\text{Dynamic specification } \left\{ \begin{array}{l} F_t^{(a)} = \gamma^{(a)} F_{t-1}^{(a)} + d_t^{(a)} \end{array} \right. \quad (5)$$

$$F_t^{(p_h)} = \gamma^{(p_h)} F_{t-1}^{(p_h)} + d_t^{(p_h)} \quad (6)$$

$$F_t^{(p_{an})} = \gamma^{(p_{an})} F_{t-1}^{(p_{an})} + d_t^{(p_{an})} \quad (7)$$

$$\varepsilon_t^{(c)} = \gamma^{(\varepsilon^{(c)})} \varepsilon_{t-1}^{(c)} + d_t^{(\varepsilon^{(c)})} \quad (8)$$

¹³ In SEM terminology, observable variables are called *manifest* variables because they may be the measurable manifestations of underlying unmeasurable *factors*.

In all equations, the subscript t indicates the year (1994 through 2000).

$T = \text{NTYPE}$ = number of years in which NTYPE has the value 1 (so T takes values from 0 to 7)

$G = \text{NGROUP}$ = number of years in which NGROUP has the value 1 (so G takes values from 0 to 7)

The Static Specification (Equations (1)–(4))

The static component defines the functional relationship between the observable variables capital ratio C_t , asset risk proxy A_t , health and product risk proxies $P_t^{(h)}$ and $P_t^{(an)}$, on the one hand, and the three underlying factors $F_t^{(a)}$, $F_t^{(ph)}$, and $F_t^{(pan)}$, on the other hand.¹⁴ We propose a single factor $F_t^{(a)}$ that manifests itself with error as the firm's asset risk exposure. The observable asset risk proxy A_t and corresponding underlying asset risk factor $F_t^{(a)}$ will be either the RAR proxy and factor, or the OAR proxy and factor. We compare the effects of swapping the regulatory pair for the opportunity pair. We shall call $F_t^{(a)}$ the (*regulatory* or *opportunity*) *asset risk factor*. Similarly, we propose two factors $F_t^{(ph)}$ and $F_t^{(pan)}$ underlying the firm's product risk exposure. We shall call $F_t^{(ph)}$ the *health product risk factor*, and $F_t^{(pan)}$ the *annuity product risk factor*. In Equations (2), (3), and (4), the coefficients of $F_t^{(a)}$, $F_t^{(ph)}$, and $F_t^{(pan)}$ are restricted to be 1.0, without loss of generality, in order to provide identifiability of parameters. The capital ratio C_t , size variable S , organizational type T , and group membership G are directly observed, not as proxies, but for what they are—so factors are not needed for them.

It is important to note that the asset risk proxy and corresponding factor ($A_t, F_t^{(a)}$) used in the model are either regulatory or opportunity. Both RAR and OAR are not used together in the same model for our main results.¹⁵ For our model, RAR and OAR are treated as alternatives because our major objective is to compare their *holistic* roles in capital structure *under similar conditions*. Thus, each instance of our model is run twice—once with RAR and again with OAR. We expect some overlap between the two asset risks. If both were used in the same equation, then their coefficients would be interpreted as net effects, as in OLS—the effect of the overlap would be removed from each. On the other hand, whichever asset risk is used, it is used together with the two product risks. Therefore, the measured asset risk and product risk proxies are (partially) cleansed of their mutual overlapping effects, as well as of the control variables.

The role of the factors in the model is significant and merits further discussion. Conceptually, the factors are *latent*, in the sense that they are not directly measured in themselves, but they underlie observed phenomena. Latent variables appear as theoretical

¹⁴ Customary factor-analytic considerations indicate that three factors are sufficient: The sum of the squares of the first three eigenvalues of the size-adjusted correlation matrix of the observable variables indicates that the first three factors explain 85 percent to 93 percent of the observable variation for all of our model runs.

¹⁵ In the "Results" section, we comment on the additional insights provided by having both asset risk factors in the same equation.

constructs in almost all sciences. Examples of such variables in economics are the real rate of interest, the natural rate of unemployment, the business cycle, seasonality, and measurement error. In comparison with other forms of modeling, latent variable models can be characterized as simpler and more conceptual because the number of examined variables is reduced. Latent variables can be estimated from observed variables and used in SEM to simplify and clarify otherwise complex and dynamic relationships. When the observable variables are themselves proxies, as here, then the latent variables can be considered purer estimates of the proxied constructs than the measurable proxies themselves. In the more familiar multiple regression methodology, the independent variables are often proxies for unobservable constructs. But a construct often manifests itself in multiple independent variables, which overlap in ways that interfere with assessment of relative importance. Use of factors reduces (but does not eliminate) such problems (also observed by Titman and Wessels, 1988).¹⁶ Moreover, multiple regression studies of capital structure often attempt to enumerate and assess the importance of as many risks as possible. Detailing all possible risks is not our objective. We wish to compare two asset risks in context. Our approach is minimalist, in a sense. We include only those predictors essential to our study and those controls that appear to have great significance in all insurance studies (size, organizational type, and group membership).

Thus the main factors may be used explicitly as higher-level proxies for the details of more complicated relationships that, for our purposes, are not necessary to specify or understand. We point out that our version of the SEM model also allows complicated relationships to survive *implicitly* through the dynamic part of the model, in lag form via the factors: As can be seen in Equations (5)–(8) or the Path Diagram (Figure 5), last year's risk factors are inputs into the estimation of the current year's risk factors. Last year's risk factors are not observed, but are estimated from last year's observables, which include capital. Factors must be estimated since they cannot be observed directly. They are estimated from the observables. Thus, through the factors, last year's capital and other observables are already included in the estimation of the current year's risk factors. The dynamic portion of the model provides an avenue for preserving the effects on capital of other risks and variables that we have not explicitly enumerated.¹⁷

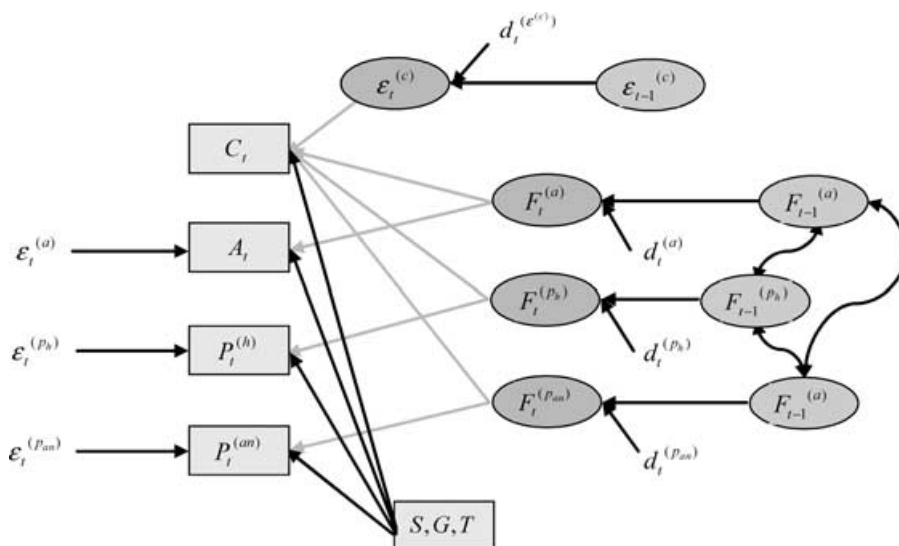
Longitudinal factor analysis was considered first by Corballis and Traub (1970) and applications in education were illustrated by Corballis (1973) and McDonald (1980).

¹⁶ An analogy may help explain the proxy-purification aspect of factors. One can think of an observable variable as a mixture of factors, as a restaurant dish is a mixture of flavors. The taste of the food is a combination of five basic factors: sweet, sour, salty, bitter, and the recently discovered *umami*. One does not ordinarily encounter a restaurant dish purified of all but one taste factor. Perhaps a dessert may be sufficiently sweet to be a plausible proxy for sweetness, or a snack to be a reasonable proxy for saltiness. But sweet-and-sour stir-fry is a blend. So are most observable variables. Factor analysis can take imprecise proxies and distill their essences into purer, but still imperfect, proxies, in the same way that a restaurant patron might separate stir-fry into pieces that are sweet and pieces that are sour. We obtain a sweeter sweet and sourer sour than the mixture.

¹⁷ As we just discussed, these other effects enter the model implicitly in lag form. To enter them as contemporaneous variables, Equations (2)–(4) could be modified to include capital explicitly on the right-hand side, as in Baranoff and Sager (2002).

FIGURE 5

Path Diagram Graphical Portrayal of the SEM Model



Note: The observable variables are represented by rectangles: capital ratio (C_t), asset risk (A_t), health and annuity product risks ($P_t^{(h)}$ and $P_t^{(an)}$), size (invested assets S), group membership (G), and organizational type (T). Unobservable factors are represented by ovals, and error terms appear without enclosures. Arrows indicate a modeled structural relationship, that is, either functional dependence (straight arrows) or correlational dependence (curved arrows). For more details see the explanation in the text.

Watson and Engle (1983) introduced two estimation methods based on the method of scoring and the Expectation Maximization (EM) algorithm. A method for the analysis of multivariate time series was introduced by Molenaar (1985) for stationary time series, and then for nonstationary time series by Molenaar, Gooijer, and Schmitz (1992). A simple and robust method for deviations from multivariate normality for unbalanced longitudinal data was proposed by Papadopoulos and Amemiya (2005), and it can be applied in this data set. For a general methodology of longitudinal models with latent variables see Dunn, Everitt, and Pickles (1993) and Anderson (1989). Such models have been applied to economics by Melvin and Schlagenhauf (1986) and Biorn and Klette (1999). Titman and Wessels (1988) appear to be the first to use SEM models to study capital structure.

The four ε_t terms in the static specification are residual error (disturbance) terms. As in OLS, the effects of all other predictors not explicitly expressed on the right-hand side of these equations show up in overlap with the enumerated predictors or in the residual errors. We expressly point out that this applies to all other risks with which Enterprise Risk Management is concerned. The right-hand side of the capital equation is always a complete accounting of capital—all risks are there, if not explicitly enumerated, then present through overlap with the enumerated predictors or present in the residual error. We caution that as in regression, the inadvertent omission of key explanatory variables can result in distorted coefficient estimates. But we observe that our models have quite good measures of fit, and the factors explain 85 percent

to 95 percent of observable variation. Thus, an omitted variable is not likely to distort the results significantly because it is unlikely that the omitted variable would bring significant *new* explanatory power to the equation. Bringing these omitted variables into the model would overlap with included predictors. Our focus is on comparing our two asset risks as wholes, rather than on comparing their net effects after adjusting for numerous other predictors. For these reasons, we do not consider omitted variables to be an issue for our study.

The Dynamic Specification (Equations (5)–(8))

The dynamic component defines the temporal relationships among the factors. The three factors are assumed to depend linearly on their year-preceding values F_{t-1} . The four γ coefficients are time-independent. The four d_t terms are time-dependent error terms. Thus, the factors are assumed to follow a first-order autoregressive process. In Equation (8) we fit autoregressive errors by an innovative technique. Since the current versions of the statistical packages SAS and EQS do not allow for modeling nonindependent error structure explicitly, we accomplished the same objective implicitly by declaring the errors to be latent factors (permitted to have autoregressive structure), and we defined additional variables to be zero-variance errors. Otherwise, we would be limited to fitting independent errors or compelled to develop new special-purpose computer programs.

The Distributional Specification

For the distributional specification of the SEM model, we assume all of the e_t and d_t error terms are independent, except that $\varepsilon_t^{(c)}$ is first-order autoregressive, as mentioned. The factors $F_t^{(a)}$, $F_t^{(ph)}$, and $F_t^{(pan)}$ are assumed to be possibly correlated in every year. The factor and error variances are not assumed to remain the same from year to year.

In general, to make statistical inferences, we need the assumption of multivariate normal distribution. However, under the parameterization of the structural model given above, the maximum-likelihood estimates of parameter values are consistent and their asymptotic standard errors are robust to deviations from multivariate normality (see Browne, 1987; Anderson and Amemiya, 1988; Anderson, 1989; Papadopoulos and Amemiya, 2005). The variables that we consider in this article have distributions with very long tails, and it is necessary to apply methods robust to departures from normality, even after the use of logarithms.

Standardization

All of the independent and dependent variables and factors in Equations (1)–(8) are standardized to mean of 0 and variance of 1 prior to estimation of parameters, both within years and separately, for large and small companies to adjust for time fixed effects and time heteroscedasticity. This facilitates direct comparison of coefficients, which would otherwise not be as transparent because of the differences in the units in which the variables are measured. One consequence of such standardization is that the intercepts are all 0. Thus, without loss of generality, Equations (1)–(8) contain no intercept terms. The variables $\lambda^{(a)}$, $\lambda^{(ph)}$, and $\lambda^{(pan)}$ are (standardized) coefficients that

assess the effects of the three factors on capital; these coefficients are interpreted much as coefficients are interpreted in regression.¹⁸ But because of variable standardization, these coefficients are dimensionless and so are directly comparable. Each is interpreted as the number of units of change in the dependent variable that result from an increase of 1 unit in the independent factor, *ceteris paribus*, but where the "unit" in each case is the value of the standard deviation of the corresponding variable. Larger standardized coefficients represent more substantial impacts, in that a given change within the distribution of the independent factor results in a relatively greater change within the distribution of the dependent variable. The coefficients are time independent. That is, they are constrained to remain the same over the study period.

Path Diagram

The SEM model can be displayed graphically in the form of a path diagram, shown in Figure 5. In the diagram, observables are denoted by rectangles, factors by ovals, and error terms appear without enclosures. Straight arrows indicate relationships modeled directly by the eight equations; curved arrows indicate relationships induced by the model.

The static specification of the model (Equations (1)–(4)) is represented by the left and center portions of the diagram. For example, the capital ratio equation (Equation (1)) represents the dependent observable variable C_t as a function of observables (size, organizational type, group membership), the three unobservable factors, and an autoregressive error term, innovatively treated as a factor. Thus, the C_t rectangle at the left in the diagram receives arrow inputs from the three main factor ovals in the center, the three observables, and the error oval at top. Similarly, the asset risk equation (Equation (2)) shows asset risk as a function of observables, the unobservable asset risk factor, and error, represented in the diagram by the arrows leading into the A_t rectangle from the appropriate sources. The product risk equations are similar.

The dynamic specification (Equations (5)–(8)) is represented by the center and right portions of the diagram. For example, the asset risk factor equation (Equation (5)) shows the asset risk factor as a function of the asset risk factor for the preceding year and error. In the path diagram, this relationship is represented by the asset risk factor oval in the center receiving input arrows from the year-preceding asset risk factor at right and an unenclosed error. The two product risk factors (Equations (6) and (7)) are similar. Equation (8) models the capital ratio equation error term autoregressively as a function of its year-preceding value and error. This is represented in the diagram by the error oval at center top receiving inputs from the year-preceding error oval at right and from an unenclosed error.

¹⁸ Technically, standardized coefficients result when factor analysis uses the correlation matrix of the observable variables as input. Factor analysis ordinarily uses the covariance matrix. An alternative is to use the covariance matrix of the standardized observables. Since the correlation matrix is the covariance matrix of the standardized observable variables, the resulting coefficients are called standardized. There is a parallel in OLS: if the variables are standardized to zero mean and unit variance prior to the regression, one gets standardized regression coefficients.

RESULTS

Table 5 displays the estimated capital models for 18 different runs.¹⁹ There are three time periods (the whole period, 1994 through 2000; the period before the bull market, 1994 through 1996; and the period during and at the end of the bull market, 1998 through 2000) $\times$ three industry size segments (all, large, and small firms) $\times$ two different asset risk factors (regulatory, opportunity). The coefficients shown are standardized coefficients, which facilitate direct comparison of predictors, both within the same model and between models, in terms of their impacts on the dependent variable.

As discussed in the previous section, a standardized coefficient is a dimensionless quantity that assesses the expected change in the dependent variable in response to a unit change in the independent variable, *ceteris paribus*, when both dependent and independent variables are measured in units equal to their respective standard deviations. For example, consider the coefficients for the OAR factors in the models for large and small companies during 1994 through 2000. For the large company model, the coefficient of the OAR factor is 0.5114 (see Table 5). This means that if the standardized OAR factor of Large Company A is one more than that of Large Company B, then A is expected to have standardized capital ratio 0.5114 greater than B, *ceteris paribus*. On the other hand, in the model for small companies during 1994 through 2000, the coefficient of the OAR factor is 0.2951. This means that if the standardized OAR factor of Small Company A is one more than that of Small Company B, then A is expected to have standardized capital ratio 0.2951 greater than B, *ceteris paribus*. Thus, a unit change of position within the distribution of OAR of large insurers results in a greater change of position within the distribution of capital ratio than does a unit change of position within the distribution of OAR of small insurers.

We now elaborate the most important findings from Table 5 with respect to the asset risk factors. Table 6 assists in highlighting some of these features:

1. RAR does not appear to be statistically important for capital structure decisions of small insurers, throughout the study period, before, and during the bull market period. Since we associate RAR with the objective of minimizing the risk of insolvency, we interpret this finding to suggest that small insurers may not place much weight in their capital structure decisions on the insolvency risk due to their assets. The profile of small insurers depicted in Table 1 and Figures 1–3 may shed light on this and other aspects of insurer behavior related to size. These figures show that small insurers have substantially higher capital ratios and hold more low-risk assets (high-grade bonds, cash, etc.) than do large insurers. It could therefore be anticipated that the less risky profile of smaller insurers might dispose them toward less sensitivity to asset-insolvency concerns in their capital decisions. But we did not anticipate finding them immune to such concerns. This result may be of critical importance to policymakers.
2. RAR is important for capital structure decisions of large insurers, throughout the study period, before, and during the bull market period. This is striking in contrast with the small insurers. Large insurers hold less capital, less cash, more lower-grade bonds, and more corporate and less government bonds. Thus, when

¹⁹ All modeling is done with SAS/CALIS and EQS software.

TABLE 5
The Capital Ratio Equation Estimates From SEM Model

Panel A: Model Using Regulatory Asset Risk as Asset Risk Factor									
Model Run		Size	Ntype	Ngroup	RAR Factor	Hrisk Factor	AnRisk Factor	NFI and GOF	
94-00, All	Coefficient	-0.4209	-0.0631	0.1203	0.2484	0.1302	-0.2984	0.9978	
	<i>t</i> -value	-12.2787	-1.8687	3.5073	7.7048	4.2132	-8.5422	0.9961	
94-00, Large	Coefficient	-0.4393	-0.1612	0.1369	0.4989	0.0831	-0.3091	0.9978	
	<i>t</i> -value	-9.0955	-3.2892	2.7508	13.0417	2.1940	-7.3261	0.9952	
94-00, Small	Coefficient	-0.4134	0.0399	0.1382	0.0097	0.1124	-0.2935	0.9965	
	<i>t</i> -value	-8.4318	0.8215	2.7831	0.2004	2.6164	-5.7795	0.9943	
94-96, All	Coefficient	-0.4137	-0.0200	0.1401	0.1789	0.1348	-0.3427	0.9968	
	<i>t</i> -value	-12.0469	-0.5908	4.0758	5.5555	4.3161	-9.8732	0.9940	
94-96, Large	Coefficient	-0.4535	-0.1174	0.1581	0.4174	0.0770	-0.3631	0.9959	
	<i>t</i> -value	-9.4557	-2.4134	3.2001	10.4297	1.9782	-8.3519	0.9911	
94-96, Small	Coefficient	-0.3817	0.0810	0.1514	-0.0604	0.1189	-0.3246	0.9953	
	<i>t</i> -value	-7.7228	1.6531	3.0230	-1.3502	2.6586	-6.5541	0.9920	
98-00, All	Coefficient	-0.4330	-0.1021	0.0986	0.3043	0.1378	-0.2486	0.9966	
	<i>t</i> -value	-12.7262	-3.0436	2.8964	9.6548	4.7466	-7.1831	0.9939	
98-00, Large	Coefficient	-0.4277	-0.1990	0.1152	0.5717	0.1068	-0.2369	0.9981	
	<i>t</i> -value	-8.8508	-4.0595	2.3140	16.0786	3.0305	-6.0587	0.9958	
98-00, Small	Coefficient	-0.4508	0.0038	0.1217	0.0591	0.1147	-0.2661	0.9925	
	<i>t</i> -value	-9.3253	0.0796	2.4858	1.2874	2.6494	-5.2132	0.9884	

(Continued)

TABLE 5
(Continued)

Panel B: Model Using Opportunity Asset Risk as Asset Risk Factor									
Model Run		Size	Ntype	Ngroup	OAR Factor	Hrisk Factor	AnRisk Factor	NFI and GOF	
94-00, All	Coefficient	-0.4203	-0.0632	0.1201	0.4129	0.1353	-0.2730	0.9974	
	<i>t</i> -value	-12.2634	-1.8709	3.5021	11.0660	4.7442	-8.1323	0.9957	
94-00, Large	Coefficient	-0.4402	-0.1594	0.1367	0.5114	0.1210	-0.2856	0.9977	
	<i>t</i> -value	-9.1291	-3.2594	2.7527	12.1143	3.1582	-6.5967	0.9954	
94-00, Small	Coefficient	-0.4125	0.0398	0.1379	0.2951	0.1287	-0.2640	0.9960	
	<i>t</i> -value	-8.4092	0.8178	2.7758	4.5280	3.0135	-5.3412	0.9943	
94-96, All	Coefficient	-0.4117	-0.0212	0.1401	0.3774	0.1368	-0.3420	0.9955	
	<i>t</i> -value	-11.9764	-0.6247	4.0719	8.1406	4.4993	-10.0874	0.9927	
94-96, Large	Coefficient	-0.4522	-0.1158	0.1575	0.3746	0.1289	-0.3741	0.9940	
	<i>t</i> -value	-9.4547	-2.3867	3.1963	8.1806	3.1871	-8.2129	0.9885	
94-96, Small	Coefficient	-0.3801	0.0809	0.1512	0.4056	0.1427	-0.3057	0.9947	
	<i>t</i> -value	-7.6827	1.6505	3.0167	3.5127	3.2371	-6.1855	0.9924	
98-00, All	Coefficient	-0.4332	-0.1021	0.0988	0.4538	0.1368	-0.2011	0.9960	
	<i>t</i> -value	-12.7369	-3.0442	2.9033	13.9331	4.9470	-6.1177	0.9931	
98-00, Large	Coefficient	-0.4273	-0.1992	0.1148	0.6591	0.1184	-0.1594	0.9983	
	<i>t</i> -value	-8.8495	-4.0673	2.3078	17.1575	3.4526	-4.1126	0.9965	
98-00, Small	Coefficient	-0.4510	0.0041	0.1217	0.2675	0.1218	-0.2315	0.9914	
	<i>t</i> -value	-9.3461	0.0851	2.4895	5.3069	2.8886	-4.7029	0.9875	

Notes: Each row displays the capital ratio equation (Equation (1) from the model) for a different model run, identified by years included and size segment (all = 719 firms, large = 360 firms, small = 359 firms). Standardized coefficients in first line, and *t*-values based on asymptotic standard error in second line of cell. RAR = regulatory asset risk; OAR = opportunity asset risk; HRisk = health product risk; AnRisk = annuity product risk. Measures of fit: NFI = normed fit index, GOF = goodness-of-fit index.

TABLE 6
Selected Coefficients From Table 5

Model Run	RAR Factor	OAR Factor
94–96, Large	0.4174	0.3746
94–96, Small	*	0.4056
98–00, Large	0.5717	0.6591
98–00, Small	*	0.2675

*Not statistically significant.

looking at the larger insurers' profile in comparison to the smaller insurers, it may be that the significant role for RAR in capital decisions of large insurers is not unexpected. The positive signs of the coefficients are consistent with prior findings that large insurers operate in accord with the paradigm of finite risk, as far as RAR is concerned. Moreover, the coefficient of RAR for large insurers before the bull market (0.4174) is a bit less than that during the bull market (0.5717).

3. OAR is important for the capital structure decisions of both large and small insurers, throughout the study period, before, and during the bull market. We find it interesting that the coefficient of this asset risk factor increased substantially during the bull market for larger insurers (from 0.3746 to 0.6591), whereas it declined substantially for the smaller insurers (from 0.4056 to 0.2675). Since the changes in the asset portfolios of large and small insurers from the prebull market to the bull market period were not substantial, although many were statistically significant, the most likely explanation is a realignment of capital ratio decisions during the bull market period to accord more with value maximization criteria for large insurers and to accord less for small insurers.²⁰ The positive signs for OAR are also consistent with the claim that large and small insurers operate under the paradigm of finite risk, as far as OAR is concerned.

A few features of Table 5 are worth pointing out in regard to other variables. All models show that the health product risk factor always has a positive and significant impact on capital and the annuity product risk factor always has a negative and significant impact. This accords with expectations under the finite risk hypothesis. Size remains an extremely important predictor, even after absorbing some of its explanatory power by splitting the industry into large and small segments; there is still much variation in size within the large and small segments. Size always has a strong negative effect on capital ratios. The larger the firm, the lower is its capital ratio—perhaps a consequence of the relatively greater stability of large firms. Figures 2 and 3 show that large insurers tend to hold riskier assets than small insurers. Being a member of a group of affiliated companies is always associated with relatively higher capital ratios. Having a stock form of organization always has a significant negative relationship with the capital ratio for large companies, but is not significant for small companies. This result for large insurers is in accordance with the expectation that stock insurers take more risk

²⁰ The most substantial change in asset portfolios was that large insurers moved about 10 percent of their bonds from Quality Category 1 to Category 2 during the bull market.

TABLE 7

Partial Correlations Among Certain Observable Variables, Controlling for Size

Variable	Large Insurers		Small Insurers	
	Log(Capital Ratio)	Log(Regulatory Asset Risk)	Log(Capital Ratio)	Log(Regulatory Asset Risk)
Log(Regulatory asset risk)	0.6355	—	0.0566	—
Log(Opportunity asset risk)	0.6113	0.7623	0.2649	0.5047

to satisfy the stockholders in response to monitoring mechanisms. The insignificance of organizational form for small insurers may therefore provide some insight into the lack of significance of RAR in the capital structure. Finally, the models show good fits for all runs since the normed fit index and the goodness-of-fit index are close to 1.²¹

We think these findings can be useful to policymakers. Small insurers are positioned differently than larger insurers and may have different objectives. In part, these differences may be related to differences in the inherent riskiness of large- and small-insurer portfolios. But also in part, as shown by comparison of prebull market analysis and that during the bull market, the differences may be attributed to how closely large and small insurers align their capital ratios with their asset portfolios.

We omit discussion of the results for Equations (2)–(4) since their roles are auxiliary for Equation (1). Equations (2)–(4) have no inherent interest for our study and are included in the model in order to link the manifest risk variables with their latent factors.

We think it worthwhile to point out that simple descriptive statistics support the major findings. Table 7 shows size-adjusted partial correlations among the observable variables for the capital ratio and the two asset risk measures. For larger companies, the correlations between both asset risk measures and capital are strong and very similar. For small companies, the correlation between capital and the regulatory measure is low, but stronger for the opportunity measure. Table 8 shows ordinary correlations among all manifest variables in our models. These also support our findings.

Finally, we ran our model including both asset risk factors in the capital equation to see what additional insights might be gained for the behavior of small and large insurers. To do this, we retained the two versions of our model—one using RAR and the other using OAR—but added to each version the other of the two risks as a *net factor*. That is, in the model that used RAR as the asset risk, we partialled RAR out of OAR and included the remainder of OAR (as *net OAR*) on the right side of the capital equation. Net OAR is essentially OAR, minus its overlap with RAR. This partialling treatment parallels the standard treatment of predictors in OLS, which partials all other predictors out of each predictor. The model was adjusted so that the partialling would occur as a seamless part of model optimization, rather than as an

²¹ For definition, see Bollen (1999).

TABLE 8

Ordinary Correlations Among the Manifest Variables, Pooled Data 1994 Through 2000

	Capital	RAR	OAR	Health	Annuity	Size	Type	Group
Capital	*	0.5689	0.6400	0.3853	-0.5375	-0.3936	-0.0946	0.0043
RAR	0.0084	*	0.7304	0.3594	-0.1814	0.0379	-0.2672	-0.0127
OAR	0.2761	0.4904	*	0.2934	-0.3115	-0.2398	-0.1359	-0.0646
Health	0.1030	0.0678	-0.0053	*	-0.3947	-0.0441	-0.1977	0.0389
Annuity	-0.3905	-0.0750	-0.1163	-0.2375	*	0.4343	-0.0062	-0.0015
Size	-0.3913	0.1110	-0.0847	0.1826	0.2673	*	-0.0949	0.1975
Type	0.1042	-0.0750	0.0188	-0.0446	-0.0650	-0.1101	*	0.2570
Group	0.0442	-0.0371	0.0507	0.0926	0.0448	0.2326	0.1935	*

Note: Correlations for large insurers are above the main diagonal and small are below.

ad hoc preliminary step. Similarly, a *net RAR* factor was included on the right side of the capital equation in the model that used OAR as asset risk.

The results were enlightening. For all runs, we found that model coefficients of the other predictors remained much the same as before adding the net factors. For large firms, the included net factor had positive coefficients that were statistically significant in all but one case (for added net RAR in 1998 through 2000). The statistical significance of both net factors implies that OAR and RAR are empirically distinct in their effects on capital structure. Each adds new explanation not covered by its overlap with the other asset risk factor. Moreover, the added net factor exerts its effects on capital in the same positive direction.

For small firms, the results are more complex. Recall from our main results that OAR has a significant positive effect on capital for small insurers, but that RAR is insignificant. Interestingly, when net RAR is added to OAR for small firms, OAR remains significant and positive, but net RAR becomes significant and negative in every case. Why? One explanation that is consistent with these results is that RAR may capture risk elements that act both positively and negatively. For small insurers, net RAR may represent the negative elements, whereas the part of RAR that overlaps OAR affects capital positively, as does OAR. When combined into RAR as a whole, the positive and negative parts tend to neutralize each other. Since the finite risk hypothesis is associated with positive effects on capital and the excessive risk hypothesis with negative effects, our results would be consistent with the existence of both finite risk and excessive risk behaviors among small insurers. On the other hand, when net OAR is included with RAR for small firms, there is no corresponding paradoxical switch of signs: RAR remains insignificant, and net OAR exerts a positive and significant effect on capital in every case.

SUMMARY AND CONCLUSION

This is the first academic study of capital structure in the life insurance industry to compare the effects of two different perspectives of asset risk, represented by two different proxies, and for two size segments of the industry in two separate periods of the roaring 1990s. We introduce a new measure of asset risk, OAR, which assesses volatility in potential returns that can be earned on an insurer's invested assets. We can

associate OAR with the financial objective of maximization of firm value, in distinction to the objective of insolvency avoidance, which we can associate with RAR, a penalty-weighted average of risky holdings. The two risks are compared by swapping them for each other in otherwise identical models that use the same data. Thus, any differences between the runs may be attributed to the swapping of asset risks between runs. The models also include two measures of product risk to represent the liabilities side of the balance sheet and major control variables for insurer size, organizational form, and membership in an affiliated group of companies. We use an SEM model that treats the four risks as unobservable factors to be estimated through their observable manifestations. This permits the extraction of purer proxies for the risks. The SEM model also deals appropriately with simultaneous descriptive equations and time series autocorrelation in our panel data set.

Our most important finding is that large life insurers and small life insurers differ substantially in the importance of the two asset risks to their capital structure decisions. For large life insurers, the two asset risks exert strongly positive and approximately equal effects on the capital ratio. But for the smaller life insurers, the RAR fades to insignificance, whereas the OAR remains strong and positive—about as important in the prebull market period as for large insurers, although much less important during the bull market period. An interpretation consistent with this finding is that, in their capital decisions, small insurers may not be attending to the insolvency protection criteria devised by regulators. This is potentially an important finding for policymakers. The finding becomes more explicable when the asset profile of small life insurers is examined. Compared with large insurers, small insurers have relatively more of their holdings in less risky asset classes and hold relatively more capital. Conversely, large insurers may attend more to regulatory concerns because they hold more assets in risky classes and have lower capital.

We also find relatively few differences in our models between the years 1994 through 1996 and 1998 through 2000, except in the asset risk coefficients of the capital ratio equation. The coefficients of both asset risks increased for large insurers; the coefficient of OAR declined for small insurers. Both large and small life insurers edged their portfolios somewhat toward slightly riskier bonds during the bull market, with large insurers moving more than small insurers. But that movement was quite modest, and the proportion of stocks barely changed at all for either size segment. At the same time, the yields from all asset classes except real estate and stocks became more stable during the bull market.²² The decrease in the coefficient of OAR for small insurers may be related to the interperiod stability of small-insurer portfolios as yields became more stable.

The signs of most coefficients are consistent with the finite risk hypothesis, the view that various theoretical mechanisms lead firms to balance an increase in risk in one area with a reduction in risk in another. Thus, all but one of the asset risk coefficients are positive, indicating that an increase in asset risk is accompanied by an increase in capital. However, in a follow-up analysis in which RAR was added as a net factor to the capital equation alongside OAR, net RAR was significantly negative for small insurers. This suggests the presence of excessive risk tendencies in RAR for small

²² Although it is not shown in the article, the variation in unweighted monthly yields (not returns) of most of our benchmark investment vehicles declined during the bull market.

insurers, along with finite risk affinities. The health product risk signs are positive, and the annuity product risk signs are negative. This is as expected in transaction-cost economics, since the annuity business has lower contractual risk. Size has a negative coefficient, indicating that managers of large firms are more comfortable with lower capital ratios.

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