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Interest Rate Risk and Equity Values of Life Insurance Companies: A GARCH–M Model

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Abstract

The importance of managerial decisions related to interest-sensitive cash flows has received considerable attention in the insurance literature. Consistent with the interest-sensitive nature of insurer assets and liabilities, empirical research has shown that insurer insolvency is significantly related to interest rate volatility. We investigate the interest rate sensitivity of monthly stock returns of life insurers based on a generalized autoregressive conditionally heteroskedastic in the mean (GARCH–M) model. We examine three different portfolios (equally weighted, risk-based, and size-based) with binary variables to explicitly account for varying interest rate strategies adopted by the Federal Reserve System. Results based on data for the period 1975 through 2000 indicate that life insurer equity values are sensitive to long-term interest rates and that interest sensitivity varies across subperiods and across risk-based and size-based portfolios. The results complement insolvency research that links insurer financial performance to changes in interest rates.

Introduction

Interest rate risk is an important concern for financial firms, and a large body of literature shows a strong relation between the stock returns of financial institutions and

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interest rates. Much research has investigated the interest sensitivity of commercial bank equity returns (e.g., Lloyd and Shick, 1977; Lynge and Zumwalt, 1980; Chance and Lane, 1980; Flannery and James, 1984; Bae, 1990; Kwan, 1991; Scott and Peterson, 1986; Kane and Unal, 1988, 1990; Elyasiani and Mansur, 1998, 2003). However, excepting the early works of Scott and Peterson (1986) and Bae (1990), little attention has been paid to the interest sensitivity of life insurer equity returns. Santomero and Babbel (1997) state that insurers have a sense of urgency to apply the tools of asset/liability management to manage interest rate risk. Life insurer equity returns that vary with changes in interest rates suggest that the market is accounting for their interest rate exposure. Thus, we investigate the interest rate sensitivities of monthly stock returns of life insurers.

We make four primary contributions. First, we evaluate the systematic factors that generate life insurer common stock returns by utilizing a GARCH–M (generalized autoregressive conditionally heteroskedastic in the mean) model. The model includes several basic capital asset pricing models as its special cases and allows a test of their validity. Although previous research has employed the GARCH–M methodology (Elyasiani and Mansur, 1998) in the analysis of the interest rate sensitivity of depository institution stock returns, to our knowledge the current study is the first application of a GARCH–M model in the analysis of the interest rate sensitivity of life insurer stock returns. Second, the study tests if the interest rate sensitivity of life insurers stock returns and overall stock return volatility of these firms remain constant over time, when the Fed adopts different interest rate strategies, and interest rate volatility changes as a result. Third, the study employs a comprehensive data set for the period from 1975 through 2000. Finally, to examine firm level variation in interest rate sensitivity, the sample is disaggregated and portfolios are formed based on high-beta and low-beta firms as well as small, medium, and large insurers.[1]

Our results provide several insights. First, consistent with research on insurer financial strength (e.g., Browne, Carson, and Hoyt, 1999), we find the equity values of life insurers to be sensitive to long-term interest rates. Second, as in previous studies for depository institutions (e.g., Scott and Peterson, 1986), the stock returns of life insurers are negatively related to changes in interest rates. Third, similar to studies for other financial institutions (e.g., Yourougou, 1990), we find that the interest rate sensitivity of life insurer stock returns varies across the monetary policy regimes. Finally, we find that life insurers with low market betas exhibit significant interest rate sensitivity whereas those with high market beta do not, and that equity returns of smaller life insurers are more sensitive to movements in the stock market than to movements in interest rates.

The remainder of the article is organized as follows. The next section reviews the literature regarding interest rate risk of life insurers and the equity returns model for

[1] Market betas and interest rate betas for each firm are estimated using OLS. Portfolios are formed based on the magnitude of market beta. The high-beta (low-beta) portfolio is represented by $\beta > 1$ ($\beta < 1$). The high-beta portfolio contains 15 insurers and the low-beta portfolio contains 45 insurers. To further address firm-level variation, we also examine three portfolios comprised of small (<\$1b), medium (\$1–\$10b), and large (>\$10b) insurers based on asset size. We thank an anonymous referee for suggesting that we split the data based on various characteristics of firms.

financial institutions. We then describe our sample, data, and methodology. Next we analyze the empirical results, and the final section summarizes and concludes.

REVIEW OF RELATED LITERATURE

Insurers issue stochastic debt instruments for which the amount and timing of loss payments (contingent claims) are unknown at policy issuance, and they invest the proceeds to maximize the risk-adjusted return on capital. By effectively "borrowing" from policy owners, insurers lever ownership capital. Interest rate risk, defined as the degree of exposure, or elasticity, of insurer net worth to changes in the interest rate, is important to life insurers for a number of reasons, as discussed, e.g., by Staking and Babbel (1995) and Briys and Varenne (1997). The importance of interest rate risk is based on (1) the investment portfolio of the typical highly leveraged insurer is concentrated in long-term fixed-income securities; (2) life insurer performance is negatively related to changes in interest rates (Browne, Carson, and Hoyt, 1999, 2001); (3) for insurers whose duration of assets exceeds that of their liabilities, rising interest rates erode the value of surplus, leading to increased leverage and a greater probability of ruin; (4) higher leverage increases the insurer's cost of capital (Cummins and Lamm-Tennant, 1994); and (5) interest rate risk leads insurers to take steps to match asset–liability durations with futures and options (hedge) in order to hedge to protect franchise value (Hoyt, 1989b; Colquitt and Hoyt, 1997).

It is fruitful to explore whether the equity returns of life insurers vary in response to changes in market interest rates, since life insurer equity returns that vary with changes in interest rates would suggest that the market accounts for insurers' interest rate exposure. Interest rate sensitivity also reinforces the importance of asset-liability management (Santomero and Babbel, 1997; Panning, 1995) and dynamic financial analysis (D'Arcy et al., 1997) for insurers.

Research on the general relationship between interest rates and equity returns is extensive. Stone (1974) postulates a two-index market model that includes an interest rate for explaining equity returns of financial firms. Lloyd and Shick (1977) use a two-index market model and find that financial firms' stock values are sensitive to changes in interest rates. However, Chance and Lane (1980) do not find a relationship, whereas Lynge and Zumwalt (1980) do. Flannery and James (1984), Booth and Officer (1985), and Scott and Peterson (1986) all find interest rate sensitivity in the two-index market model for financial firms during an era of high volatility in market rates.

The works of Akella and Chen (1990), Brewer and Lee (1990), Choi, Elyasiani, and Kopecky (1992), Kane and Unal (1988, 1990), Kwan (1991), Neuberger (1991), Wetmore and Brick (1994), and Yourougou (1990) all find that the interest rate dependency of financial stocks is time varying; interest rate sensitivity shifts according to economic conditions and monetary policy strategy (e.g., Brewer and Lee, 1990).

Maher (1997) finds that the time-varying interest rate sensitivity renders tests over long periods inconclusive. To address the time-varying nature of the stock return generating process for banks, Song (1994) employs an ARCH-type methodology. Elyasiani and Mansur (1998) go further by employing an extended GARCH–M model, which includes an interest rate in the mean and interest rate volatility as an argument in the volatility of the bank stock return generating process. Inclusion of the latter variable reveals that changing interest rate volatility, in turn, leads to changing volatility in financial firms' stock returns and varying expected risk premia.[2]

SAMPLE, DATA, AND METHODOLOGY

Data Description and Diagnostics

The sample consists of all (60) publicly traded insurance companies specializing in life insurance with available data, as described below.[3] Based on 1990 figures, insurers in the sample range in size from $20 million in assets to $89 billion in assets (as shown in Appendix A). Mean (median) assets for the sample equals $8 billion ($2 billion). Total assets of sample firms ($505 billion) in 1990 are approximately one-third of industry assets ($1.4 trillion) for the same year. The data for the study run from January 1975 to December 2000. Monthly return data for life insurers are obtained from the Center for Research in Securities Prices (CRSP) file. Monthly (versus daily) return data provide a longer historical period that better reflects long-term movements in volatility. Settlements and clearing delays are also less problematic with monthly data versus daily returns (Baillie and DeGennaro, 1990).

We follow the approach of Friend, Westerfield, and Granito (1978) and Harrington (1983) in using portfolio data versus individual security data. There is a trade-off between using individual firm data and portfolio data. When individual firm data are used, the noise is high and the results tend to be unduly influenced by individual random shocks. The use of portfolios does mask some of the detailed information provided by individual firm data but produces more reliable results as it washes out the noise. Given the trade-off between these approaches, a middle of the road approach is adopted here as a compromise. Following this strategy, we examine the sample in smaller subsamples sorted by risk (high-beta versus low-beta portfolios) and by asset size (smaller, medium, and large firm portfolios), as well as subsample periods based on changing monetary policy strategy.[4]

The data set for each time period includes each of the 60 life insurers (listed in Appendix A) that were in business during that particular period. It follows that the

[2] Various methods have been used to model the time varying second moment. For a discussion on application of ARCH and GARCH methodology in finance, see Bollerslev, Chou, and Kroner (1992). For a discussion of modeling volatility, see Poon and Granger (2003), Anderson et al. (2003), and McQueen and Vorking (2004).

[3] Life insurers are defined as firms in which assets of life insurance subsidiaries account for more than 60 percent of consolidated assets of the firm. We also included two companies, the Aetna Life & Casualty Corporation and Travelers Corporation, which had less than 60 percent of their consolidated assets in life insurance because they are two of the largest firms in the insurance industry. The list of life insurers used in this study is obtained from Brewer, Mondschean, and Strahan (1997) and is presented in Appendix A. We do not include some large life insurance companies such as Prudential of America, Metropolitan Life, Hartford Life, and Nationwide because their stock market data are unavailable or only available for a short period. Other large life insurance companies such as Aegon USA Inc, Teachers Insurance and Annuity, New York Life, and Equitable Groupare not included because they are not publicly traded in this time period. American International Groupis the only large publicly traded life insurer with sufficient stock market data that we do not include in this study, primarily because AIG is much more diversified than the other firms.

[4] We would like to thank an anonymous referee very much for suggestions on this matter.

TABLE 1
Descriptive Statistics on Monthly Life Insurer Stock Returns

	Life Insurer Stock Returns
No. of observations	312
Mean	0.0165***
Variance	0.002
Minimum	−0.221
Maximum	0.251
Skewness	−0.498***
Kurtosis	3.484***
LM(χ^2)	15.866***
$Q(8)$	16.308**
$Q(16)$	20.316
$Q(24)$	25.880
ADF(4)	−7.650***
ADF(4, t)	−7.672***
PP(4)	−15.065***

Note: LM is a Lagrange multiplier test for normality under the null hypothesis that the coefficients of skewness and kurtosis are jointly equal to zero and three, respectively. This statistic is distributed as a χ^2 with two degrees of freedom. The critical value at the 5 percent level is 5.99. Q is the Ljung–Box statistic at a lag of n, distributed as a χ^2 with n degrees of freedom. Critical values of 8, 16, and 24 degrees of freedom are 15.50, 26.29, and 36.41 at the 5 percent level, respectively. The standard errors for skewness and kurtosis are $(6/T)^{.5} = 0.138$ and $(24/T)^{.5} = 0.277$, respectively, where T is the number of observations. ADF(4) and ADF(4, t) refer to augmented Dickey–Fuller test with four lags and four lags with trend. Both tests include intercepts. The critical values are –3.46 and –3.99, respectively. PP(4) refers to Phillps–Perron test with four lags including intercept. The critical value is –3.46. *, **, and *** represent significance at the 0.10, 0.05, and 0.01 levels, respectively.

sample size and sample membership vary over time. The rationale for this sample selection procedure is to use all the company data available in each period, and thus to minimize survivor bias, and to maximize the membership in the sample, in order to improve estimator efficiency.[5] For the stock market index we employ the S&P 500 equity market index, obtained from CRSP database. The interest rate series, described below, is obtained from Ibbotson Associates (2002). Table 1 contains the descriptive

[5] It is generally accepted that studying only the firms that exist at the end of the sample period induces survivorship bias that could adversely affect the reliability of the results. Various approaches have been utilized to deal with survivorship bias. Bartram (2002) avoids this bias by constructing sample portfolios each sub-period of which includes only the firms traded during that period of time. Flannery et al. (1997) and Chen and Chan (1989) follow similar approaches in constructing their samples. Along the same lines, Brown et al. (1992) have pointed out that disregarding dead mutual funds in sample selection leads to an overestimation of average performance. Hence, the dead funds are included in the sample until they disappear (Cesari and Panetta, 2002; Bauer et al., 2005). Stone (1974), Song (1994), and Elyasiani and Mansur (1998, 2003) also use portfolios in estimation of bank stock return sensitivities. The selection criteria used in the current study are consistent with the methodologies outlined above.

statistics of life insurer stock returns. The summary statistics suggest that the data series is skewed and leptokurtic relative to the normal distribution.[6] Overall, these diagnostics suggest that a GARCH-type process is appropriate for modeling life insurer stock returns.

Model and Methodology

The degree of exposure of a life insurance company to interest rate risk is determined by the leverage-adjusted duration gap between its assets and liabilities, and the convexity in the market value of its net worth. The duration gap and net worth convexity can be chosen by the firm managers, subject to a number of limitations. These include the need to accommodate customer demand, and firm's access to, and costliness of, markets for hedging interest rate risk, such as options, futures, and swaps. Santomero and Babbel (1997) note that "measures of interest rate sensitivity that take into account the interest-sensitive cash flows of an asset or liability stream are referred to as 'effective duration and convexity' or, alternatively, 'option-adjusted duration and convexity'" (p. 245). They also report that between the duration measure and convexity, insurers place more confidence in the former and less in the latter. Based on these findings, we limit our attention to the duration gap faced by the life insurers. Moreover, by using portfolios and fixed beta values for the period of study, we are examining the average interest rate sensitivity of the group, rather than the individual firm sensitivity to interest rates. Of course, in practice, these sensitivities are apt to vary across firms and over time.[7]

We use the GARCH–M methodology to model the stock return behavior of U.S. life insurers. The basic model consists of a return equation that includes the market return, the interest rate index, and the volatility measure, and a volatility equation that includes the ARCH and GARCH factors.[8] Analytically, the model can be described as follows:

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[6] The Lagrange multiplier test for joint normality under the null hypothesis that skewness and kurtosis are jointly equal to zero and three, respectively, is rejected. In addition, there is evidence of serial dependence in life insurer stock returns as presented by significant Box–Pierce–Ljung Q statistics. Both the augmented Dickey–Fuller (Dickey and Fuller, 1979) and Phillips–Perron (Phillips and Perron, 1988) tests are utilized to determine whether the life insurer stock return series is stationary. The evidence presented in Table 1 shows that life insurer returns follow an I(0) process and satisfy this condition.

[7] To address the convexity issue, models developed here can be extended to accommodate the nonlinearities due to convexity. Appendix B discusses one such extension. The assumptions of fixity of beta and inconsequentiality of convexity are made frequently in the literature on interest rate sensitivity.

[8] For a discussion of the benefits of utilizing the GARCH–M model see, e.g., Elyasiani and Mansur (1998, 2003). In brief, there are several advantages. First, the GARCH–M procedure addresses the potential problems with heteroskedasticity that would lead to inefficient estimators and possibly incorrect inferences. This phenomenon is especially likely if the variance of the residuals fluctuates significantly during the sample period. During the November 1979 to September 1982 subperiod, both short- and long-term interest rates were at least twice as volatile than they were in the other two subperiods. This property has implications concerning the reliability of inferences on the hypotheses, and in particular the significance and stability of the interest rate risk (Hypotheses H_1 and H_2 below). Second, the GARCH–M model nests a

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 ltr_t + \gamma \log(h_t) + \varepsilon_t \quad (1)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \quad (2)$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t), \quad (3)$$

where R_t is the *ex post* holding period return on a portfolio of life insurer stocks, $R_{m,t}$ is the *ex post* holding period return on an equity market index (S&P 500), and ltr_t is the holding period return associated with long-term (approximately 20 year maturity) U.S. government bonds. Since the interest rate variable is in holding period return format, the coefficient of this variable is expected to be positive. That is, a positive relationship between the holding period return variables and life insurer stock returns implies that equity values are negatively correlated with interest rate changes.[9]

Volatility of life insurer stock returns is measured by conditional variance h_t, which is described as a function of the squared values of the past residuals (ε_{t-1}^2), presenting the ARCH factor, and an autoregressive term (h_{t-1}) reflecting the GARCH character of the model. The parameters β_0, β_1, β_2, γ, α_0, α_1, and α_2 are estimated. The coefficients α_1 and α_2 must satisfy the stationarity conditions such that $\alpha_1 \geq 0$, $\alpha_2 \geq 0$, and $(\alpha_1 + \alpha_2) \leq 1$. The degree of volatility persistence is measured by the sum of α_1 and α_2. The error term, ε_t, is a random variable with a zero mean and conditional variance (h_t) and is dependent on the information set Ω_{t-1}.

The model is extended to examine (1) a shift in the interest rate sensitivity of life insurer stock returns by introducing two binary variables (D_2 and D_3) that distinguish the monetary policy strategies prevailing prior to November 1979, during November 1979 to September 1982, and in the post-September 1982 periods, and (2) the effect of the changes in differing interest rate environments on the volatility of life insurer stock returns using the same binary variables.[10] The extension can be presented as Equations (4)–(6):[11]

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variety of functional forms in stock return modeling including the CAPM, ARCH–M, ARCH, and GARCH, and permits a formal test for the choice of the appropriate model. Hypotheses H_3–H_6, discussed below, carry out these tests. Third, the GARCH–M model allows for a feedback effect between volatility and mean return. Hypothesis H_3 provides a test of prevalence of this intertemporal trade-off or the feedback effect.

[9] A number of other specifications of both the basic and extended models are tested. These models are developed by replacing the long-term interest rate (*ltr*) with (a) short-term interest rate, (b) term structure of interest rate, and (c) various combinations of binary variables in the mean and volatility equations of models a and b. Prior literature suggests that the long-term interest rate is more relevant in modeling stock return behavior of depository institutions. Thus, we include results for the long-term rate here. Results of the other models are available from the authors. In sum, the signs, magnitudes of the coefficients, and degrees of statistical significance are similar among the models, except for the case of the interest rate coefficients. In no case was the short-term interest rate coefficient found to be statistically significant.

[10] Thus, coefficients of D_2 and D_3 are evaluated relative to the 1/1975 to 10/1979 period (Greene, 1997, p. 381).

[11] Other specifications of conditional volatility, such as h and $\sqrt{h}$ are also used in the extant literature. Engle, Lilien, and Robins (1987) find the log(h) specification is a better representation of risk than other specifications.

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 ltr_t + \beta_3 D_2 l\dot{t}r_t + \beta_4 D_3 l\dot{t}r_t + \gamma \log(h_t) + \varepsilon'_t \tag{4}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + g_2 D_2 + g_3 D_3 \tag{5}$$

$$\varepsilon'_t \mid \Omega'_{t-1} \sim N(0, h_t). \tag{6}$$

Hypotheses

The model and the data described above are utilized to test several hypotheses about the returns of life insurer equities. These hypotheses are presented below:

H_1: There are no interest rate effects. Under this hypothesis, the returns on life insurer stocks are not sensitive to changes in market interest rates over the sample period. In the basic model, the null can be formulated as: $\beta_2 = 0$. In the extended model, the null is presented as: $\beta_2 = \beta_3 = \beta_4 = 0$.

H_2: The extent of interest rate sensitivity of life insurer stocks does not change across varying interest rate environments. This hypothesis can only be tested within the extended model and is formulated as: $\beta_3 = \beta_4 = 0$.

H_3: GARCH functional form: this hypothesis can be formulated as $\gamma = 0$. In this specification, return volatility is not a significant factor in life insurer stock returns and, hence, there is no intertemporal trade-off between volatility and return.

H_4: Return volatility is time invariant. In the basic model, this hypothesis can be formulated as $\alpha_1 = \alpha_2 = 0$. In the extended model, the null is presented as: $\alpha_1 = \alpha_2 = g_2 = g_3 = 0$. Under this hypothesis, the return distribution is homoskedastic and no ARCH or GARCH effects exist.

H_5: ARCH-M functional form: the ARCH-M specification can be formulated as $\alpha_2 = 0$. Under this specification, return volatility follows an ARCH (time variant and short memory), rather than a GARCH (time variant and long memory) pattern and a trade-off between return and volatility does exist.

H_6: ARCH functional form: the ARCH specification can be formulated as: $\alpha_2 = \gamma = 0$. Under this hypothesis, volatility is time variant, it has a short memory, and no intertemporal effects exist between volatility and return.

Empirical Results and Discussion

The Basic GARCH (1,1)–M Model

Empirical results based on the basic GARCH (1,1)–M model for the "All Firm" portfolio are reported in Table 2. The market index coefficient (β_1) is significant, positive, and less than unity. The coefficient (β_2) for the long-term interest rate variable is positive and significant, indicating that life insurer equity values are positively (negatively) related to holding period returns (interest rates). This finding is consistent with Browne et al. (1999) who suggest that long-term interest rates have a greater impact on insurer performance (financial distress) than short-term interest rates, and that insurer financial strength is significantly negatively related to long-term interest rates.

The magnitude of the trade-off between the mean and the volatility of stock returns in the life insurance industry is determined by the trade-off parameter (γ), as specified in H_3. This parameter has a positive sign, indicating that increased volatility is compensated for by a higher average return, and it is statistically significant. It follows

TABLE 2
GARCH (1,1)–M Results of the "All Firm" Portfolio

Parameters	Variables	Basic All Firm	Extended All Firm
β	Intercept	0.049	0.049
		(2.31)**	(1.64)*
β_1	Market index	0.765	0.776
		(24.30)***	(23.74)***
β_2	Interest rate	0.123	0.494
		(2.12)**	(2.98)**
β_3	Binary 1979–82		−0.338
			(−1.62)
β_4	Binary post 1982		−0.437
			(−2.41)**
γ	Log(Volatility)	0.005	0.005
		(2.03)**	(1.40)
α_0	Intercept	0.0001	0.0001
		(3.52)***	(2.05)**
α_1	ARCH	0.118	0.128
		(2.53)**	(2.76)***
α_2	GARCH	0.749	0.771
		(11.72)***	(9.90)***
g_2	Binary 1979–82		−0.00004
			(−0.45)
g_3	Binary post 1982		−0.0001
			(−2.05)**
Log likelihood		911.75	917.74
Model diagnostic statistics			
Mean		−0.02	−0.04
Variance		1.00	1.00
Skewness		−0.15	−0.17
Kurtois		0.66**	0.30
J–B		7.04**	2.73
$Q(24)$		39.32***	39.26***
$Q^2(24)$		34.07**	35.93**

Note: The basic and extended GARCH (1,1)–M models of all firm portfolio returns are presented as follows:

Basic Model

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 ltr_t + \gamma \log(h_t) + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

Extended Model

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 ltr_t + \beta_3 D_2 ltr_t + \beta_4 D_3 ltr_t + \gamma \log(h_t) + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + g_2 D_2 + g_3 D_3$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t),$$

where R_t is the *ex post* holding period returns; R_m is the return on the S&P 500 index, and ltr_t is the holding period returns associated with a long-term U.S. government bond (approximately 20 year maturity). ε_t is the error from the mean and is distributed with a zero mean and conditional variance of h_t. Ω_{t-1} is the information set at time $t - 1$. D_2 and D_3 are monetary policy binary variables. Diagnostic statistics are based on standardized residuals ($\varepsilon_t/\sqrt{h}$). $Q(24)$ and $Q^2(24)$ are Ljung–Box statistics for standardized residuals and squared standardized residuals of order 24. J–B refers to the Jarque–Bera's normality test statistic for the regression residuals. t-values are in parentheses. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

that, in this specification, returns will vary in response to changes in the stock return volatility (h_t). It is noteworthy that volatility (h_t) is the overall (total) risk (the sum of systematic and unsystematic risk). Finance theory suggests that only the former component should be priced by the market. Note also that many GARCH–M studies in banking and other sectors find γ to be zero or negative. The zero value reduces the GARCH–M specification to its special case GARCH, where no trade-off between volatility and return prevails. A negative γ is theoretically possible but harder to justify (see Elyasiani and Mansur, 1998).

We examine whether volatility is time invariant as purported by the traditional models. Empirical significance of the estimates for the ARCH and GARCH coefficients in the volatility equation is tested using t-tests ($\alpha_1 = 0, \alpha_2 = 0$), as well as a composite χ^2 test ($\alpha_1 = \alpha_2 = 0$). All tests (not shown in Table 2) are found to be significant (the $\chi^2(2)$ test statistic takes the value of 385.34, with the corresponding probability of less than 1 percent). According to these tests, parameters α_1 and α_2 are statistically different from zero. Hence, stock return volatility is time varying. Specifically, volatility evolves over time as a function of its own lagged value, as well as the intensity of the shock that occurred in the last period. The use of squared past residuals implies a specific pattern of volatility; if the current period innovation is large (small) in absolute value, there is a good chance that it will also be large (small) in future periods. It follows that volatility will manifest itself as clusters, taking a sequence of high values followed by a sequence of lower values.

The null hypothesis of ARCH functional form versus the GARCH–M model is tested as a composite hypothesis: $\alpha_2 = \gamma = 0$. This hypothesis is also rejected ($\chi^2(2) = 138.84$, probability of less than 1 percent), indicating the inadequacy of the simpler ARCH specification. Based on these findings for the ARCH and GARCH parameters and the above tests, the basic constant-variance capital asset pricing models appear to be inappropriate for describing life insurer stock returns.

The measure of volatility persistence given by the sum ($\alpha_1 + \alpha_2$) is found to be less than unity for both basic and extended models indicating that these models are second order stationary. The magnitude of persistence is in the range of 0.8 and is consistent with the findings from the banking sector (see Elyasiani and Mansur, 1998). This implies that the volatility decay in the insurance sector also takes place at a slow pace and that undesirable shocks will continue to exert their influence for many periods after they occur.

Model Diagnostics for the Basic Model

Model diagnostic statistics for the basic model are based on the standardized residuals ($\varepsilon_t/\sqrt{h}$). Under the null hypothesis of normality, the conditional mean and variance are expected to be zero and unity, respectively, and the variance is to be serially uncorrelated and homoskedastic. In addition, kurtosis is asymptotically distributed normally with mean 3 and variance $24/T$, where T, the sample size, is 312. The diagnostic statistics indicate that the values of mean, variance, and skewness are as expected. The GARCH–M process reduces the sample kurtosis, but fails to fully account for leptokurtosis. The Ljung–Box statistics of standardized residuals of order 24, $Q(24)$, and of squared standardized residuals, $Q^2(24)$, fail to reject the null hypothesis of the residuals being uncorrelated. According to these statistics, as in most studies (e.g., Bollerslev, 1987; Lastrapes, 1989; Elyasiani and Mansur, 1998), the distributional assumption of conditional normality is not fully satisfied.

The Extended GARCH (1,1)–M Model (Subperiod Specific Interest Rate Sensitivity)

The basic model is extended to allow for the subperiod-specific interest rate sensitivity.[12] In this section, three subperiods are distinguished by introducing two binary variables. The first binary variable (D_2) will take the value of unity for November 1979 through September 1982 period and zero otherwise, whereas the second binary variable (D_3) will take the value of unity after September 1982 and zero otherwise. This will allow a test of the hypothesis that interest rate sensitivity of the life insurers was identical across the whole sample period versus the alternative that this sensitivity was subsample specific. The size and the signs of the binary variables also will allow the magnitude and the direction of the change in the relevant coefficients to be determined for each subsample period.

The estimation results for this model are also presented in Table 2. The coefficient estimate (β_1) for market risk is positive and significant, similar to that for the basic model. As in the basic model, the coefficient (β_2) for the interest rate variable is positive and significant. The ARCH and GARCH parameters also take values similar to those for the basic model. The trade-off parameter (γ), however, is found to be statistically insignificant in the extended model, reducing it to a GARCH, rather than the more general GARCH–M specification. It appears that in this case, the binary variables for the different interest rate environments, which are correlated with interest rate and market volatility, understandably pick up some of the effect of the volatility measure ($\log(h_t)$) in the mean equation, rendering γ insignificant.

Tests of functional forms are also conducted in the context of the extended model. The composite hypotheses of time-invariant return volatility ($\alpha_1 = \alpha_2 = 0$) and ARCH ($\alpha_2 = \gamma = 0$) are again rejected (at less than 1 percent) confirming the dominance of the more general GARCH–M specification.[13] The main question, however, is whether the interest rate sensitivity of life insurers is fixed over the three subperiods considered, or time varying and responsive to changes in the monetary policy strategy. The null hypotheses of $\beta_3 = 0$, $\beta_4 = 0$, and $\beta_3 = \beta_4 = 0$ are all rejected, indicating that the binary

[12] During the sample period chosen (1975–2000), the Federal Reserve System (the Fed) changed its policy strategy to fulfill its objectives of fighting inflation and promoting full employment and economic growth. The sample period covers three distinct subperiods in this regard. In the pre-1979 period, the Fed followed the policy of interest rate targeting. During this period, any deviation of the federal funds rate from the Fed target would lead to open market operations in order to bring the rate back to the target level. As a result, in this period, interest rates exhibited a moderate level of volatility. During October 6, 1979, to September 1982, the Fed deemphasized the federal funds rate as a target, in order to fight inflationary pressures, allowing the fed funds rate to fluctuate according to market conditions. This period is known as one with a high degree of interest rate volatility. As inflation was gradually brought under control, the Fed switched back to smoothing interest rates, in October 1982. This third period (post October 1982) witnessed a lower degree of interest rate turbulence.

[13] Note that the results of simple and composite tests may differ, as is the case here. This is because in a joint test two different relationships constitute the null, and rejection of either relationship may lead to rejection of the composite test.

variables are significant and, hence, the interest rate sensitivity of life insurers is time varying (the level of significance for the composite test is less than 1 percent).

Results of these tests suggest that the overall degree of interest rate volatility (monetary policy strategy) exert a significant influence on the life insurer's sensitivity to interest rate risk. The coefficient estimates for the binary variables indicate that, although the sensitivity of life insurer stock returns to the long-term interest rate did not change in the 1979–1982 period compared to the 1975–1979 period, it did decline in the post-1982 period. It is likely that to counter the greater interest rate volatility of the 1979–1982 period, life insurers began to take a more active approach to asset-liability management in the post-1982 period, reducing their exposure to interest rate risk as a result (see Hoyt, 1989a; Colquitt and Hoyt, 1997).[14] Carson and Hoyt (1992) show that demand for policy loans decreased significantly in the early 1980s when life insurers shifted from offering policies with fixed loan rates to policies with variable loan rates, thereby reducing their exposure to interest rate risk. Also likely at play is the fact that the mix of life insurer activity changed during this period toward a position of less interest rate risk exposure. For example, the widespread acceptance of universal life and variable life insurance products that shifted much investment risk from the insurer to the policy owner throughout the 1980s is consistent with this notion. Although the results reported here indicate that the equity returns of life insurers have become less sensitive to changes in interest rate over time, results are not inconsistent with those of Browne, Carson, and Hoyt (1999, 2001) that changes in long-term interest rates are significantly related to insurer financial strength.

Changing interest rate environments likely impact the level of stock return volatility (h_t), and overlooking this possibility could lead to model misspecification and consequent erroneous conclusions. To examine this matter, the two period-specific binary variables discussed above are included in the volatility equation as shift parameters corresponding to the 1979–1982 and the post-1982 periods, respectively. The coefficient (g_2) on the binary variable D_2, corresponding to the 1979–1982 period is not significant, whereas the coefficient (g_3) on the binary variable D_3, corresponding to the post-1982 period, is negative and significant. These results indicate that the overall riskiness of life insurer stocks did not alter in the 1979–1982 period compared to the 1975–1979 period, whereas overall riskiness declined in the post-1982 period, parallel with the decline in general interest rate volatility. The composite hypotheses concerning functional forms ARCH ($\alpha_2 = \gamma = 0$) and ARCH–M ($\alpha_2 = g_2 = g_3 = 0$), and interest-rate insensitivity ($\beta_2 = \beta_3 = \beta_4 = 0$) are all tested within this extended model and the tests are found to be highly significant.

The parameter restrictions between the extended and basic models are also tested using the following likelihood ratio (LR) test statistic:

$$LR = -2\{\log L(\tilde{\theta}_R) - \log L(\tilde{\theta}_U)\} \sim \chi_q^2,$$

[14] Choi and Elyasiani (1997) show that interest rate risk exposure of banks is impacted by their derivatives positions. Studies by Brewer, Minton, and Moser (2000) and Brewer, Jackson, and Moser (1996) find that depository institutions that utilized interest rate derivatives experienced greater growth in their lending activity than institutions that did not use these financial instruments.

where $L(\tilde{\theta}_U)$ and $L(\tilde{\theta}_R)$ denote the values of the maximized likelihood functions under the alternative and null hypotheses, respectively. The LR statistic is statistically significant for four degrees of freedom at the 5 percent level. This finding suggests that the extended model is a better representation of the return generating process for portfolios of life insurers.

The factors discussed above, along with the movement toward more active asset-liability management used by life insurers to manage their interest rate exposure, help to explain the empirical results based on the extended model. Namely, the overall riskiness of life insurer stocks did not alter in the 1979–1982 period compared to the 1975–1979 period, whereas overall riskiness declined in the post-1982 period.[15]

Interest Sensitivity of Portfolios Based on Beta and Insurer Size

Although our primary analysis is based on portfolios as opposed to individual insurers, important differences with respect to interest sensitivity may exist across firms. To provide some indirect evidence on interest sensitivity at the firm level, Table 3 presents results based on portfolios composed of high market betas ($\beta > 1$) and low market betas ($\beta < 1$) insurers, and Table 4 presents results based on portfolios composed of small (<\$1b), medium (\$1b–\$10b), and large (>\$10b) insurers. From Table 3, we see that life insurers with low market betas exhibit significant interest rate sensitivity, whereas life insurers with high market betas do not. The opposite is true for the intertemporal trade-off coefficient (γ) between risk and return; the trade-off coefficient is significant for the high market beta portfolio but not for the low market beta portfolio. The insignificant trade-off coefficient for the low-beta portfolio suggests that the volatility risk premia are portfolio specific and sensitive to the level of market risk. As pointed out by Engle, Lilien, and Robins (1987), the direction and the magnitude of the trade-off parameter (γ) is dependent on the utility function of the investors. Moreover, the persistence of volatility is also found to be high for the high-beta portfolio, compared to the low-beta counterpart. Similar findings also hold true for the extended model. As in the case with the "All firm portfolio," the coefficients pertaining to D_3 binary variable are significant for both the return and volatility equations, with the coefficient of D_2 showing significance in the mean equation. In addition, the LR values favor the extended model for the low-beta portfolio but not for the high-beta portfolio.

Table 4 indicates that equity returns among smaller life insurers are more sensitive to movements in the stock market than to movements in interest rates. The result also suggests that market risk is directly related to asset size with the "large firm" portfolio beta being larger than those of "medium" and "small" firms and closer to unity. This may reflect the more aggressive attitude of the large firm managers toward risk and their confidence due to liberal access to financial markets in cases of financial need. The intertemporal trade-off parameters are portfolio specific across size portfolios. Shock persistence in return volatility ($\alpha_1 + \alpha_2$) is high and similar in magnitude for "medium," and "large" firm portfolios (0.9), whereas it is somewhat lower (0.8) for the

[15] As pointed out earlier, interest rate exposure is related to duration and nonlinearity in stock prices resulting from convexity in the market value of a life insurer's net worth. To address the nonlinearity in pricing, we estimated the models shown in Table 2 with the addition of a squared interest rate term. The coefficient for the squared interest rate term is insignificant in all of the GARCH–M specifications. Results are shown in Appendix B.

TABLE 3
GARCH (1,1)–M Results of High- and Low-Beta Portfolios

Parameters	Variables	Basic High Beta ($\beta > 1$)	Basic Low Beta ($\beta < 1$)	Extended High Beta ($\beta > 1$)	Extended Low Beta ($\beta < 1$)
β	Intercept	0.071	0.060	0.079	0.067
		(2.94)***	(1.59)	(2.55)**	(1.58)
β_1	Market index	1.079	0.629	1.086	0.637
		(17.53)***	(19.06)***	(16.86)***	(18.24)***
β_2	Interest rate	0.096	0.142	0.396	0.571
		(0.96)	(2.44)**	(1.44)	(3.08)***
β_3	Binary 1979–82			−0.289	−0.387
				(−0.88)	(−1.81)*
β_4	Binary post 1982			−0.324	−0.511
				(−1.12)	(−2.60)***
γ	Log(Volatility)	0.008	0.007	0.010	0.007
		(2.42)**	(1.23)	(2.09)**	(1.26)
α_0	Intercept	0.0002	0.0001	0.0002	0.0002
		(3.39)***	(2.38)**	(2.71)***	(2.20)**
α_1	ARCH	0.183	0.090	0.180	0.116
		(3.30)***	(1.75)*	(3.70)***	(2.04)**
α_2	GARCH	0.764	0.723	0.778	0.736
		(13.89)***	(6.65)***	(15.40)***	(6.16)***
g_2	Binary 1979–82			−0.00002	−0.00006
				(−0.18)	(−0.85)
g_3	Binary post 1982			−0.0001	−0.0001
				(−1.55)	(−1.90)*
Log likelihood		773.77	919.72	776.39	925.68
Model diagnostic statistics					
Mean		0.004	−0.02	−0.009	−0.002
Variance		1.00	1.00	1.00	1.00
Skewness		0.07	0.23*	0.07	0.06
Kurtois		1.44***	1.50***	1.47***	0.69**
J–B		27.20***	31.84***	28.53***	6.46**
$Q(24)$		23.67	31.70*	23.40	32.76**
$Q^2(24)$		29.96*	14.71	33.02**	21.25

Note: The basic and extended GARCH (1,1)–M models of high-beta ($\beta > 1$) and low-beta ($\beta < 1$) portfolio returns are presented as follows:

Basic Model

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 ltr_t + \gamma \log(h_t) + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

Extended Model

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 ltr_t + \beta_3 D_2 ltr_t + \beta_4 D_3 ltr_t + \gamma \log(h_t) + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + g_2 D_2 + g_3 D_3$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t),$$

where R_t is the *ex post* holding period returns; R_m is the return on the S&P 500 index, and ltr_t is the holding period returns associated with a long-term U.S. government bond (approximately 20 year maturity). ε_t is the error from the mean and is distributed with a zero mean and conditional variance of h_t. Ω_{t-1} is the information set at time $t-1$. D_2 and D_3 are monetary policy binary variables. Diagnostic statistics are based on standardized residuals ($\varepsilon_t/\sqrt{h}$). $Q(24)$ and $Q^2(24)$ are Ljung–Box statistics for standardized residuals and squared standardized residuals of order 24. J–B refers to the Jarque–Bera's normality test statistic for the regression residuals. t-values are in parentheses. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

TABLE 4
GARCH (1,1)–M Results of Large, Medium, and Small Firm Portfolios

Parameters	Variables	Basic Large Firm	Basic Medium Firm	Basic Small Firm	Extended Large Firm	Extended Medium Firm	Extended Small Firm
β_0	Intercept	0.066	0.074	0.028	0.059	0.075	0.049
		(2.41)**	(3.14)***	(0.50)	(1.78)*	(2.44)**	(0.48)
β_1	Market index	0.955	0.779	0.665	0.946	0.793	0.663
		(16.77)***	(17.78)***	(13.43)***	(16.70)***	(16.51)***	(13.56)***
β_2	Interest rate	0.313	0.111	−0.002	0.777	0.635	0.047
		(3.55)***	(1.51)	(−0.025)	(3.07)***	(3.04)***	(0.17)
β_3	Binary 1979–82				−0.506	−0.476	−0.126
					(−1.66)*	(−1.88)*	(−0.03)
β_4	Binary post 1982				−0.498	−0.601	−0.085
					(−1.88)*	(−2.73)**	(−0.28)
γ	Log(Volatility)	0.008	0.009	0.001	0.007	0.009	0.004
		(2.16)**	(2.70)***	(0.08)	(1.53)	(2.06)**	(0.37)
α_0	Intercept	0.0002	0.0001	0.0004	0.0003	0.0002	0.0002
		(3.46)***	(2.80)***	(1.73)*	(2.51)**	(2.50)**	(1.52)
α_1	ARCH	0.227	0.165	0.096	0.233	0.166	0.066
		(3.94)***	(3.52)***	(2.90)***	(4.21)***	(3.44)***	(1.83)*
α_2	GARCH	0.684	0.743	0.711	0.692	0.751	0.742
		(10.16)***	(11.82)***	(5.65)***	(10.59)***	(10.39)***	(4.77)***
g_2	Binary 1979–82				−0.0001	−0.00006	−0.0003
					(−0.58)	(−0.58)	(−1.25)
g_3	Binary post 1982				−0.0001	−0.0001	−0.0003
					(−1.01)	(−1.77)***	(−1.58)
Log likelihood		822.03	867.04	797.62	824.98	873.83	800.58
Model diagnostic statistics							
Mean		−0.007	−0.10	−0.01	−0.01	−0.02	−0.007
Variance		1.00	1.00	1.00	1.00	1.00	1.00
Skewness		0.16	−0.02	0.42***	0.12	−0.15	0.41***
Kurtosis		1.35***	0.95***	1.29***	1.28***	0.73***	1.03***
J–B		24.93***	11.78***	31.10***	21.98***	8.26***	22.95***
Q(24)		27.75	37.66**	50.33***	26.70	36.13**	50.09***
Q^2(24)		50.30***	31.57*	18.68	47.57***	34.72**	16.35

Note: The basic and extended GARCH (1,1)–M models of large, medium, and small sized firm portfolio returns are presented as follows:

Basic Model

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 ltr_t + \gamma \log(h_t) + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

Extended Model

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 ltr_t + \beta_3 D_2 ltr_t + \beta_4 D_3 ltr_t + \gamma \log(h_t) + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + g_2 D_2 + g_3 D_3$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t),$$

where R_t is the *ex post* holding period returns; R_m is the return on the S&P 500 index, and ltr_t is the holding period returns associated with a long-term U.S. government bond (approximately 20 year maturity). ε_t is the error from the mean and is distributed with a zero mean and conditional variance of h_t. Ω_{t-1} is the information set at time $t-1$. D_2 and D_3 are monetary policy binary variables. Diagnostic statistics are based on standardized residuals $(\varepsilon_t/\sqrt{h})$. Q(24) and Q^2(24) are Ljung–Box statistics for standardized residuals and squared standardized residuals of order 24. J–B refers to the Jarque–Bera's normality test statistic for the regression residuals. t-values are in parentheses. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

"small firm" portfolio. The direction of the effect of the binary variable coefficients is similar to that obtained in other models examined here. The binary variables in the volatility equation are insignificant, with the exception of D_3 binary variable for the medium firm portfolio. The implication is that return volatility declined in the post-1982 period when the Fed switched back to interest rate targeting and markets calmed. Only in the case of medium firm portfolio, the LR test value for parameter restrictions suggests the use of the extended model over the basic model.

Overall, these findings indicate that the interest rate sensitivities can vary across individual firms or subsets of firms sorted by size or risk. As discussed, these sensitivities change over time and across varying interest rate environments. This feature, which is common to most studies of financial firm stock return behavior, supports the need for the additional empirical analysis beyond the results shown in Table 2.[16]

SUMMARY AND CONCLUSIONS

This study extends previous research on insurance company stock return behavior in four primary ways. First, we introduce a generalized autoregressive conditionally heteroskadastic in the mean (GARCH–M) model of stock returns, which includes the asset pricing models traditionally used in the literature as its special cases and allows a test of their validity. Second, we test whether the interest rate sensitivity of life insurers remained constant over time or varied in response to changing interest rate risk environments. Third, we employ a comprehensive data set that encompasses different monetary policy regimes dating back to 1975 in order to draw more reliable results. Finally, we examine several additional models to test for differences between low-beta and high-beta insurers, as well as small, medium, and large insurers.

We find that, as in previous studies of depository institutions, the stock returns of life insurers are negatively correlated with changes in interest rates. This finding is also consistent with research on insurer financial strength (e.g., Browne, Carson, and Hoyt, 1999) and research by Staking and Babbel (1995) and Briys and Varenne (1997). Moreover, the coefficients in the volatility of stock returns equation show that volatility is time varying and evolves over time as a function of its own lagged value, as well as the intensity of the innovation that occurred in the market in the previous period. In other words, volatility displays a cluster pattern. It follows that the basic fixed-variance capital asset pricing models generally used to describe stock returns of life

[16] Another interesting extension of the model develops if we hypothesize that insurers set their level of interest rate exposure (β_2) in response to changes in the degree of volatility in the firm's stock returns (h_t) or an affine transformation of it such as $\log(h_t)$. In this case, β_2 would change every period as well as cross-sectionally, rather than being fixed. To see this, we define β_2 as a function of $\log(h_t)$ and substitute for it in the initial model. The resulting model can be written as $R_t = \beta_0 + \beta_1 R_{m,t} + \delta_0 ltr + \delta_1 \log(h_t) ltr_t + \gamma \log(h_t) + \varepsilon_t$.

A test of this hypothesis is a test of significance of δ_1. We estimated the above model, with and without binary variables for shifts in monetary policy startegy. The null of $\delta_1 = 0$ cannot be rejected in either specification. Moreover, the value of the likelihood function does not increase to indicate a better fit. Hence, we conclude that this extension does not improve the model and is unnecessary. One explanation may be that, due to the GARCH–M nature of the model, the volatility variable $\log(h_t)$ is already included in the model and accounts for the manager response to market volatility. In a simpler GARCH model, which does not include the volatility variable in the mean equation, this hypothesis may receive stronger support. We would like to thank an anonymous referee for raising this point.

insurance companies are suspect and the coefficient estimates and inferences based on these models may be biased.

Our conclusion that the equity values of life insurers are sensitive to long-term interest rates and that the interest rate sensitivity varies across subperiods complements insolvency research that links insurer financial performance to changes in interest rates, as well as asset/liability management research that emphasizes the importance of interest rate movements to insurers. Evidence presented in this study suggests that life insurers with low market betas exhibit significant interest rate sensitivity, and that equity returns among smaller life insurers are more sensitive to movements in the stock market than to movements in interest rates. A natural extension of this study for future research is to focus more specifically on firm level variation in asset/liability management to provide greater insight into the relation between interest rate risk and equity returns.

APPENDIX A

TABLE A1

Publicly Traded Life Insurance Holding Companies

Life Insurance Company	Total Assets* December 31, 1990 (U.S. $ millions)	Life Insurance Company	Total Assets* December 31, 1990 (US $ millions)
Academy Life	332.6	Jefferson Pilot Corp	4,454.9
Acceleration International Corp	196.3	Kansas City Life Ins	1,589.7
Aetna Life & Casualty Corp	89,300.7	Kemper Corp	13,587.8
Alfa Corporation	515.7	Kentucky Central Life Ins	2,182.8
American Bankers Ins Group	1,260.2	Laurentian Capital Corp	879.2
American Family Corp	8,034.8	Liberty Corp	1,536.5
American General Corp	33,808.0	Lincoln National	27,598.0
American Heritage	780.6	Manhattan National Corp	563.2
American National Ins Co	4,754.2	MCM Corp	180.7
Amvestors Financial Corp	1,623.3	Monarch Capital Corp	206.0
AON Corp	10,432.2	National Security Ins Co	62.0
Atlantic American Corp	162.2	National Western Life Corp	2,288.3
Broad Inc	10,078.6	NWNL Companies Inc	8,473.6
Capital Holding Corp	16,668.5	Penn Treaty American Corp	76.7
Central Reserve Life Corp	69.0	Presidential Life Corp	2,492.3
CIGNA Corporation	63,691.0	Protective Life Corp	2,331.2
Citizens Ins Co of America	55.9	Provident Life & Accident Ins	18,446.7
Colonial Companies Inc	549.8	Reliable Life Corp	420.2
Conseco Group	8,284.1	Reliance Group Holdings	10,983.3
Cotton States Life & Health	94.8	Statesman Group	2,598.4
Durham Corp	844.0	Torchmark Corp	5,535.9
Equitable of Iowa Corp	3,650.1	Transamerica Corp	31,783.5
Financial Benefit Group	641.3	Travelers Corp	56,430.0
First Capital Holding Corp	9,452.8	United Companies Financial Corp	1,419.2
First Centennial Corp	19.6	United Ins Companies Inc	283.1
First Executive Corp	15,193.4	Universal Holding Corp	64.4
Home Beneficial Corp	1,159.8	Unum Corp	9,513.6
ICH Corp	5,493.0	USLICO Corp	2,717.9
Independent Ins Group	1,437.0	USLIFE Corp	4,573.3
Intercontinental Life	1,323.2	Washington National Corp	2,685.3

Note: Total assets for this date are shown since all firms have values at this point during the time period 1975–2000.

Source: *Moody's Bank and Finance Manual*, 1992 and A.M. Best: *Best's Insurance Reports*, 1991.

APPENDIX B: DURATION AND CONVEXITY

Interest rate risk exposure of insurance firms, in theory, is determined by the leverage-adjusted duration gap between their assets and liabilities and the degree of convexity of their net worth. However, the relative importance of each of these two factors is an empirical matter. Duration is the slope (first derivative) of the price–yield relationship, measuring the elasticity of a fixed-income security to variations in the interest rate. Convexity is the second derivative of the same relationship. Fixed-income securities without special option features are all convex (Saunders and Cornett, 2006). The McCauley concept of duration provides a linear approximation to the true concept, resulting in overestimation of capital losses when interest rates rise, and underestimation of capital gains when interest rates fall. The net worth of life insurers is convex because many life insurer assets and liabilities are fixed-income securities.

The relevance of convexity for a particular life insurer depends on how convex its portfolio is and how high the interest rate changes are. As convexity deepens and the magnitude of the changes in interest rates becomes bigger, the error in approximation of the interest rate risk exposure by the basic duration concept grows larger. Hence, although for some life insurers, and for certain periods of large interest rate changes, convexity may be a significant issue, for other life insurers and/or other time periods, it may not be of much concern. Based on information from on-site visits to financial services firms, Santomero and Babbel (1997) provide a unique perspective of risk management practices employed by life–health and property–liability insurers both in the United States and abroad. Their survey reveals the extensive use of duration and convexity by insurers in assessing risk, with more emphasis placed on the duration measure and less on convexity. Santa-Clara (2004) also provides a review of findings on the relationship between duration and equity returns.

Although not directly attributable to convexity, we attempt to address nonlinearity in pricing by generalizing our basic GARCH–M model and the extended GARCH–M model to include an additional squared interest rate variable in the mean equation. We have estimated these generalized models using the "All Firm Portfolio" returns and present the results in Table B1. The coefficient (s_1) associated with the squared interest rate term is found to be insignificant, and the results are found to be similar between all models with and without the squared error term.

TABLE B1
GARCH (1,1)–M Results with Squared Interest Rate

Parameters	Variables	Basic All Firm	Extended All Firm
β_0	Intercept	0.048	0.051
		(2.26)**	(1.68)*
β_1	Market index	0.761	0.775
		(24.21)***	(23.41)***
β_2	Interest rate	0.157	0.489
		(2.62)***	(2.90)***
s_1	Sq. interest rate	−1.017	−0.777
		(−0.843)	(−0.572)
β_3	Binary 1979–82		−0.284
			(−1.31)
β_4	Binary post 1982		−0.412
			(−2.20)**
γ	Log(Volatility)	0.005	0.006
		(1.95)*	(1.43)
α_0	Intercept	0.0001	0.0001
		(3.46)***	(3.02)***
α_1	ARCH	0.119	0.128
		(2.53)**	(2.76)***
α_2	GARCH	0.745	0.769
		(11.40)***	(9.86)***
g_2	Binary 1979–82		−0.000
			(−0.70)
g_3	Binary post 1982		−0.0001
			(−2.04)**
Log likelihood		912.34	918.05

Note: The models estimated are as follows:

Basic:

$$R_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 ltr_t + s_1(ltr_t)^2 + \gamma \log(h_t) + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$$

Extended:

$$R_t = \beta_0 + \beta_1 R_{\mathrm{m},t} + \beta_2 ltr_t + s_1(ltr_t)^2 + \beta_3 D_2 ltr_t + \beta_4 D_3 ltr_t + \gamma \log(h_t) + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + g_2 D_2 + g_3 D_3$$
$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t),$$

where R_t is the *ex post* holding period returns, R_m is the return on the S&P 500 index, and ltr_t is the holding period returns associated with a long-term U.S. government bond (approximately 20 year maturity). ε_t is the error from the mean and is distributed with a zero mean and conditional variance of h_t. Ω_{t-1} is the information set at time $t-1$. D_2 and D_3 are monetary policy binary variables. t-values are in parentheses. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

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