Market Risk, Interest Rate Risk, and Interdependencies
In Insurer Stock Returns: A System-GARCH Model

James M. Carson
College of Business
Florida State University
Tallahassee, FL 32306-1110
jcarson@fsu.edu

Elyas Elyasiani
School of Business and Management
Temple University
Philadelphia, PA 19122
Elyas@temple.edu

Iqbal Mansur
School of Business Administration
Widener University
One University Place
Chester PA 19013
Iqbal.Mansur@widener.edu

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Abstract

We demonstrate significant interdependencies in stock returns across different segments of the insurance industry. Return interdependency is strongest between property and casualty (P&C) and accident and health (A&H) insurers, and weakest between life (Life) insurers and insurers from the other segments. We do not find empirical support for the existence of significant volatility transmission across the three segments. In terms of market and interest rate betas, we find that market risk is greatest for A&H insurers, followed by Life insurers and P&C insurers, while interest rate sensitivity is greater for Life insurers than that for A&H and for P&C insurers. The findings on stock return interdependencies across insurance segments complement research on diversification and focus strategies, while the results on market and interest rate risk complement the literature on insurer financial strength.

Keywords: Insurance, Stock Returns; Interest Rates; Diversification; System-GARCH

JEL Classification: G22, G34, K23, L11

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1. Introduction

Financial performance of insurers is sensitive to various exogenous shocks such as changes in the overall market, interest rates, and insurance-related legislation.[1] If stock return variations are relatively independent across different segments of the insurance industry (e.g., property-casualty (P&C), accident-health (A&H), and life insurers (Life)), shocks affecting one segment of the industry will have little impact on the return distributions of the firms in the other segments. However, stock returns and risks in different segments of the insurance industry are generally linked through several channels. First, some insurers offer products in multiple segments and often reallocate resources among these segments, engendering co-movements as a result. Some insurers in one segment of the industry may also make investment in affiliates in the other segments. If the size of such investment is large, co-movement will be expected. In addition, as Philips, Cummins, Allen (1998, p. 598) have pointed out, "in a multiple line insurance company, equity capital is held in a common pool. If one or more lines incur deficits or losses over premiums, the line in difficulty can draw upon the full amount of the firm's equity capital, including earnings from the 'solvent' lines." Second, regulatory decisions for different segments of the insurance industry are made with similar objectives in terms of safety and consumer service and tend to affect these segments similarly. Third, industry segments operate within the same economic and financial environments and, consequently, would be expected to move in the same direction. Fourth, insurer assets are comprised primarily of bonds, regardless of the type of insurer (P&C, A&H, or Life) and movements in bonds are highly correlated.

[1] See Browne, Carson, and Hoyt (1999); Scott and Peterson (1986); and Marlett, Pacini, and Hillison (2003); respectively.

Finally, the advent of risk-based capital requirements has led to similar activity on the part of all insurance providers in managing capital via various financial risk management techniques and instruments such as positions in derivatives.

Intra-industry interdependencies constitute an important question for insurer managers, public policymakers and investors. Insurer managerial decisions concerning the optimal avenue for diversification through acquisition are critically dependent on the extent of interdependency between different sectors of the industry because the more strongly these sectors move together, the smaller the diversification gains will be. This issue also has implications on decisions of the insurance companies on entering single versus multiple lines of insurance activity. Public policy makers are interested in the knowledge of inter-sectoral interdependence since shocks to one sector may be transmitted to other sectors resulting in the collapse of the entire industry. Similarly, from the viewpoint of investors in insurer stocks, high co-movement among different segments of the industry will translate into negligible gains in terms of risk diversification.

We introduce a System-GARCH model of stock return movements to simultaneously estimate and contrast the systematic market risk and interest rate sensitivity of property-casualty (P&C), accident-health (A&H), and life insurance companies (Life) and to examine the return and risk spillover among these segments of this industry. We make three primary contributions. First, we provide empirical estimates of the market and interest rate betas of the three examined segments of the insurance industry and demonstrate that these risk measures differ across the segments. Market risk is greatest for A&H insurers, followed by Life insurers and P&C insurers, while interest rate sensitivity is greater for Life insurers than that for A&H and for P&C insurers. These findings are consistent with Allen and Jagtiani (1997) who interpreted differences in risk/return tradeoffs among financial intermediaries as evidence of market segmentation in the financial services industry. Second, we find that the impact of changes in the stock returns in one insurance segment on another is always positive, indicating a direct co-movement of returns across different insurance activities. Finally, our results show a weak linkage of volatility transmission from one category of insurers to the other categories. This feature highlights the presence of stronger return related co-dependence and weaker risk co-dependence of different segments of the insurance industry.

The remainder of the paper is organized as follows. The next section reviews the literature related to market risk, interest rate sensitivity, and interdependency of insurer stock return distributions. Section 3 describes the methodology, hypotheses, sample, and data. Section 4 discusses the empirical results, and section 5 summarizes and concludes.

2. Review of Literature

A large body of literature shows a significant relationship between the stock returns of financial institutions and interest rates. Much of this research has investigated the market risk and interest rate sensitivity of commercial bank equity returns (e.g., Scott and Peterson, 1986; Song 1994, and Elyasiani and Mansur, 1998 and 2003). Another branch of literature similarly investigates the sensitivities of insurer equity returns to the same variables (e.g., Schini, 1999; and Brewer, et al, 2006). The sensitivity results on insurer firms are not always consistent. For example, Yourougou (1990) finds that interest rate sensitivity of life insurance companies varies across the monetary policy regimes. Browne and Hoyt (1995) do not find a significant relationship between property-liability insurer insolvency and interest rates while Browne, et al. (1999) do report a negative relationship between financial performance of life insurers and interest rates. The link between stock returns and interest rates highlights the importance of asset-liability management and dynamic financial analysis, and their effects on the risk exposure of financial firms (Santomero and Babbel, 1997, D'Arcy, et al., 1997).

Performance of firms in the same industry tends to be highly correlated, as the firms are exposed to somewhat similar economic shocks and even perhaps regulatory changes. Further, insurers are often organized into groups of diverse insurance companies, and hold shares of other firms in their industry, thereby making the firm's value sensitive to product reshuffling within the activity lines and to the movements in the value of these other firms and securities. De Nicola and Kwast (2002) discuss direct and indirect interdependencies across firms. Direct interdependencies may arise through counterparty credit exposures on derivative instruments. For example, Cummins, Phillips, and Smith (1997) indicate that 11 percent of life insurers and 7 percent of property-liability insurers use derivative instruments. Similarly, Colquitt and Hoyt (1997) note that about 13 percent of insurers in Georgia use futures and options contracts to hedge their risk exposures. McCullough and Hoyt (2006) examine the strategies of diversification and focus for insurers in the property-casualty industry. These authors note that previous studies have found evidence that both strategies can be value-enhancing for firms, and that the "benefits of diversification are similar to the benefits of corporate hedging", as in Graham and Rogers (2002).

Indirect interdependencies arise from exposures to the same or similar assets, and from other sources such as underwriting similar types of events. An important example is potential losses incurred by several institutions due to default in the corporate bond market (e.g., junk bonds). Insurers are generally active participants in both the private placement and public corporate debt markets. In addition, failure of one insurer can result in guaranty fund assessments on remaining insurers, thus tying the financial performance of firms to one another. Failure of a reinsurer can also have ripple effects that affect several insurers that had transferred risks to the reinsurer. Another example is sensitivities of numerous insurers to changes in interest rates, market, and other common factors that can bring about a co-movement in their stock returns.

Fenn and Cole (1994) study the interdependencies of insurer stock returns by examining the contagion effects associated with asset write-downs by two large Life insurance companies in 1990 (First Executive Corporation and Travelers Corporation). They investigate several interrelated information-based hypotheses. These hypotheses are based on the idea that an insurer's decision to release adverse information induces investors to expend resources to reevaluate the future cash flows of other firms in the industry. They argue that the announcements are significant to shareholders of other insurance companies, not for what they reveal about the condition of the asset portfolios of the former companies, but because of the anticipated impact of the announcements on the behavior of policyholders, especially guaranteed investment contracts holders of the latter companies. Fenn and Cole note that the announcements concerning investment losses may have a negative impact on other life insurer's profitability by inducing policyholders to exercise their withdrawal options and discouraging new policy sales.

Aharony and Swary (1983) were among the first to differentiate between a "pure" contagion effect and a signaling or information-based contagion effect. An example of a pure contagion effect would be the negative effects of an insurer failure spilling over to other insurers, regardless of the cause of the failure. An example of a signaling contagion effect would be if an insurer failure is caused by problems whose revelation is correlated across insurers, and the correlated insurers are all impacted negatively in accordance to their exposures to the problems (e.g., an adverse ruling in workers compensation).

Lang and Stulz (1992) provide a comprehensive treatment of indirect interdependencies (intra-industry contagion effects) in the literature. They investigate the effects of bankruptcy announcements on the equity value of the bankrupt firm's competitors. They find that at the time of the bankruptcy announcement of a firm, the market value of a portfolio of the stocks of its competitors declines significantly. Lang and Stulz argue that bankruptcy announcements need not necessarily convey bad news for other firms in the industry. Specifically, by redistributing wealth from the bankrupt firm to its competitors, a bankruptcy announcement may, under certain circumstances, have a positive impact on its competitors. They document, empirically, that when industries are more concentrated and firms are less levered, the average value of competitors' equity increases significantly in response to a bankruptcy announcement. This suggests that in some industries, competitors benefit from the difficulties of the bankrupt firms. Similarly, Epermanis and Harrington (2005) provide evidence that property-casualty insurers experience significant declines in premium volume following rating downgrades. Presumably their competitors benefit with increased premium volume.

3. Methodology, Hypotheses, Sample, and Data

3.1 Methodology

We divide insurers into three categories based on their standard industrial classification (SIC) codes: life (Life, SIC=6311), accident-health (A&H, SIC=6321), and property-casualty (P&C, SIC=6331). An eight-equation System-GARCH model is postulated to describe the stock return behavior of the Life, A&H, and P&C categories.[2] The return equations in the model include a market factor, an interest rate factor, and return-spillover effects across different

[2] Much research has been conducted in the investigation of conditional variance models of stock behavior. For a discussion of these models and their applicability to the financial institutions' stock returns, see Elyasiani and Mansur (1998).

insurer segments. The volatility equations allow for risk spillover across different insurance company categories, ARCH and GARCH factors, and a binary variable for the passage of the Gramm-Leach-Bliley Act of 1999 (GLBA), also known as the Financial Services Modernization Act. Analytically, the model can be described as follows:

$$R_{1,t} = \beta_{10} + \beta_{11} RM_t + \beta_{12} I_t + \beta_{13} R_{2,t-1} + \beta_{14} R_{3,t-1} + \varepsilon_{1,t} \quad (1)$$

$$h_{11,t} = \nu_{10} + \alpha_{11} h_{11,t-1} + \lambda_{11} \varepsilon^2_{1,t-1} + \varphi_{11} h_{22,t-1} + \varphi_{12} h_{33,t-1} + \varpi_{11} D_1 \quad (2)$$

$$R_{2,t} = \beta_{20} + \beta_{21} RM_t + \beta_{22} I_t + \beta_{23} R_{1,t-1} + \beta_{24} R_{3,t-1} + \varepsilon_{2,t} \quad (3)$$

$$h_{22,t} = \nu_{20} + \alpha_{21} h_{22,t-1} + \lambda_{21} \varepsilon^2_{2,t-1} + \varphi_{21} h_{11,t-1} + \varphi_{22} h_{33,t-1} + \varpi_{21} D_1 \quad (4)$$

$$R_{3,t} = \beta_{30} + \beta_{31} RM_t + \beta_{32} I_t + \beta_{33} R_{1,t-1} + \beta_{34} R_{2,t-1} + \varepsilon_{3,t} \quad (5)$$

$$h_{33,t} = \nu_{30} + \alpha_{31} h_{33,t-1} + \lambda_{31} \varepsilon^2_{3,t-1} + \varphi_{31} h_{11,t-1} + \varphi_{32} h_{22,t-1} + \varpi_{31} D_1 \quad (6)$$

$$\varepsilon_{i,t} | \Omega'_{t-1} \sim N(0, h_{i,t}) \quad (7)$$

$$h_{ij,t} = \rho_{ij} h_{i,t} h_{j,t} \qquad (-1 < \rho_{ij} < 1),\ i \neq j \quad (8)$$

In this model, $R_{i,t}$ is the return on the stocks of insurance company of category i (i=1, 2, 3 for Life, A&H, and P&C categories, respectively), RM is the market return, and I_t is the change (first difference) in the interest rate. To account for the impact of the passage of the Financial Services Modernization Act on stock return volatility, following Elyasiani, Mansur, and Pagano (2006), a binary variable, D_1, is introduced into the model. D_1 takes the value of zero prior to the passage of the bill by the Senate (1/2/91-11/3/99) and the unit value afterwards (11/4/99-12/31/2001). The variable $h_{ii,t}$ is the volatility of returns on the stocks of insurance company of category i, $\varepsilon_{i,t-1}$ is the error term, and β_{i0}, β_{i1}, β_{i2}, β_{i3}, β_{i4}, ν_{i0}, α_{i1}, λ_{i1}, φ_i , φ_{i2}, ϖ_{i1} (i=1,2,3) are the parameters to be estimated. The ten-year Treasury constant maturity bond yield is used as the long-term interest rate. The long-term asset mix of insurers is likely to make these firms more sensitive to the long-term rate. Browne, Carson, and Hoyt (1999) find that long-term interest rates are more important than short-term interest rates for life insurer solvency. Choi and Park

(2003) also show that, at least for part of their sample period, property-casualty firms were more sensitive to long-term interest rates. Similarly, Elyasiani and Mansur (2004) find the long rate exerts a stronger effect on banks than the short rate does. Hence, a long-term rate is employed here in our model specification.

The multivariate GARCH specification offers several advantages. First, it accounts for intra-industry transmission of stock returns and stock return volatilities. This feature allows for tests of significance of interdependence across insurance company categories and allows the relative explanatory power of each category for other categories to be determined. Second, this specification allows the asymmetry of the spillover effects across insurance company categories to be investigated and tests of linear relationships among the parameters within and across the model equations to be carried out. This property is highly convenient for addressing research issues such as the equality of insurance company stock return sensitivities among Life, A&H, and P&C insurers to macroeconomic variables such as interest rates and market returns. Finally, the joint estimation of a multivariate system has an advantage, over the univariate GARCH, as it permits the errors in the mean equations to interact, and allows a more efficient set of estimates to be obtained. Multivariate GARCH also receives support from the empirical literature (e.g., Karolyi (1995), Laux and Ng (1993)). [3]

The Berndt, Hall, Hall, and Hausman (1974) (BHHH) algorithm, a nonlinear maximum likelihood technique, is used to carry out the estimation of the System-GARCH model. One advantage of this algorithm is that it does not require any computations beyond those needed to solve the likelihood equation. Moreover, if the function examined is not the true log likelihood function, the algorithm typically still ends up at the correct maximum. In addition, this algorithm

[3] For application of GARCH modeling to the banking industry, see e.g., Elyasiani and Mansur (1998, 2003), Flannery, Hameed, and Harjes (1997), and Song (1994).

has the virtues that it is always “non-negative definite" and is highly likely to produce convergence.[4]

3.2 Hypotheses

Several sets of hypotheses are tested within the model developed above. Specific formulations of the hypothesis tests will be described in the results section. We examine hypotheses concerning:

- H_{1i}: Equality of systematic risk across insurer segments
- H_{2i}: Significance of interest rate sensitivity of insurers
- H_{3i}: Equality of interest rate sensitivity across insurer segments
- H_{4i}: Prevalence of return spillover across insurer segments
- H_{5i}: Symmetry of return spillover effects across insurer segments
- H_{6i}: Prevalence of volatility spillover across insurer segments
- H_{7i}: Symmetry of volatility spillover across insurer segments
- H_{8i}: Significance of the effects of Gramm-Leach-Bliley Act (1999) on insurer volatility

3.3 Sample and Data

Based on the SIC values, firms are classified as Life, A&H, or P&C insurers, and are used to form three equally-weighted portfolios. The sample for each trading day includes only those firms whose stocks were actively traded on that particular day. Due to factors such as mergers and acquisitions, spin-offs and IPOs, the sample membership (size) for each portfolio varies over time. The sample size for the portfolios is between 17 to 37 for Life, between 5 to 11

[4] See Green (2003) and RATS V5.0 User’ Guide (2000) for further discussion of the advantages of and the application of the BHHH algorithm.

for A&H, and between 21 to 46 for P&C portfolios.[5] This procedure limits survivorship bias by allowing the use of all available data in each period, and thus maximizes the sample size for each portfolio.

Daily data are obtained from the Center for Research on Securities Prices (CRSP). All insurers traded on the NYSE, ASE, and NASDAQ are included for the sample period 1/2/1991 to 12/31/2001. The S&P 500 index is utilized as the market index and also is obtained from CRSP database. Finally, the ten-year Treasury constant maturity bond yield, used as the long-term interest rate, is obtained from the Federal Reserve Bank of St. Louis Web site. The summary statistics for the data appear in Table 1.

To identify whether the returns and interest rate series are stationary, several tests are performed. The test procedures include the Augmented Dickey Fuller test with trends and 4 lags [ADF (T,4)], Augmented Dickey Fuller test with 4 lags [ADF(4)], Phillips-Perron test with zero lag [PP(0)], and Phillips-Perron test with four lags [PP(4)]. The results, presented in Panel A of Table A1 in the appendix, indicate that all return series follow an I(0) process. The interest rate series follow an I(1) but the first difference of interest rate series reverts to an I(0) process. The explanatory variables in the return equations are also checked for multicollinearity using the conditional index measures. These measures include the returns on the Life, A&H, and P&C portfolios, the return on the market index (S&P500), and changes in the interest rates. The conditional index values are found to be less than the critical value of 10 (See Gujarati, 2003, p.362) indicating that multicollinearity is not a concern and is unlikely to affect the reliability of the estimated coefficients. The values are presented in Panel B of Table A1 in the appendix.

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[5] This approach follows that of Friend et al. (1978) and Harrington (1983) in using portfolio data versus individual security data. The use of portfolios masks some information provided by individual firm data but produces more reliable results as it washes out noise. The list of insurers included in each portfolio is available upon request.

4. Empirical Results

The coefficient estimates based on the system-GARCH model and the related t-statistics are displayed in Table 2. The hypothesis test results are presented in Table 3 through Table 5. We will discuss the results in terms of the hypotheses stated above.

4.1 Systematic Risk (Market Betas) and Interest Rate Sensitivity

As shown in Table 2, systematic risk in all three portfolios ($\beta_{11}, \beta_{21}, \beta_{31}$) is positive and highly significant. In terms of magnitude, the market betas are all below unity with A&H insurers having a higher market beta (0.866), than the Life (0.714) and the P&C (0.508) insurers. Using these betas as measures of systematic risk, the insurers in the sample, considered collectively, are less risky than the average market portfolio. Tests of equality of systematic risk across all three portfolios of insurers, as well as pair-wise equality of systematic risk between each pair of insurance segments, are carried out. Based on the test statistics reported in Table 3, the null hypothesis of equal systematic risk (H_{1i}) is rejected in all cases, providing empirical evidence that market beta does vary across the three insurance segments examined. By comparison, Hoyt and Trieschmann (1991) found market betas of 0.52 for Life-Health insurers and 0.95 for P&C insurers for the 1973 to 1987 period. Thus, as measured by beta, the relative risk of Life insurers has increased and the relative risk of P&C insurers has decreased since the earlier time period.

The interest rate sensitivities of the three portfolios ($\beta_{12}, \beta_{22}, \beta_{32}$) are found to be negative, as expected, and significant in all cases (Table 2). Simple and composite tests of insignificance of the interest rate sensitivities (H_{2i}) are all rejected, confirming the prevalence of insurer exposure to interest rate risk. In terms of magnitude, Life insurers show a stronger sensitivity (-0.879) to interest rates than the P&C (-0.198) and the A&H insurers (-0.132). Bonds account for the single largest asset in the asset portfolios both of Life and P&C insurers. Thus, their stock returns are, not surprisingly, susceptible to changes in interest rates. This finding is consistent with Browne et al., (1995, 1999) for Life and P&C insurers.

Tests are also carried out to determine whether the differences in the magnitudes of the interest rate coefficients do indeed reflect statistically significant differences between them (H_{3i}). Tests of equality of interest rate betas across all insurers and on a pair-wise basis are all rejected at the 1% level, except the pair-wise test between A&H and P&C, supporting statistical dissimilarity of interest rate risk exposure between Life insurers and the other two segments. Differences in interest rate sensitivity across segments of the insurance industry are likely to stem not only from dissimilarity in asset composition, but also from the greater leverage of Life insures.

4.2. Return Spillover

An interesting result is the evidence in favor of prevalence of stock return transmission among the insurers in the Life, A&H, and P&C segments of the industry. The coefficients for the spillover of returns from other lines of activity are always positive, indicating a direct co-movement of returns across different activities. It is noteworthy, however, that while the effect of Life insurers on the other two categories is strongly significant, the latter do not exert a statistically significant effect on Life insurance companies. Between A&H and P&C insurers, they do exert a significant impact on one another. Formal statistical tests of prevalence of return spillover (H_{4i}) in Table 4 confirm these basic estimation results on the asymmetry of the spillover effects. The joint test of the null hypothesis of no spillover of returns from A&H and P&C to Life cannot be rejected. On the contrary, however, all tests of the hypotheses postulating no spillover from Life to the A&H and P&C insurers are strongly rejected. This finding establishes a leadership position for the Life insurers versus a follower position for the latter two segments of insurers.

In terms of magnitudes of the effects, the coefficient estimates in Table 2 indicate that the P&C insurers have a larger effect on the A&H insurers (0.120) than Life insurers do (0.025), while the Life insurers have a bigger effect on the P&C insurers (0.071) than A&H insurers do (0.046). A pair-wise comparison between P&C and A&H insurers shows a bigger effect running from P&C to A&H (0.120) than the effect in the reverse direction (0.046). This result provides P&C insurers a more dominant position between the two segments of activity. Asymmetry of the spillover effects is also confirmed by the statistical tests in Table 4, but only partially. The hypotheses of symmetry in spillover of returns (H_{5i}) cannot be rejected between Life insurers and the other two categories while symmetry in spillover of returns is rejected between A&H and P&C (in contrast to the t-tests in Table 2).

4.3. Volatility Spillover

The coefficient estimates for the parameters of volatility equations, presented in Table 2, demonstrate that a GARCH specification is indeed the appropriate model for describing the stock return behavior of the insurers. All ARCH and GARCH parameters for the three portfolios have the theoretically expected positive signs, are statistically significant, and satisfy the stability condition of adding up to less than the unit value. The persistence of volatility, captured by the sum of ARCH and GARCH parameters, is the highest for Life (0.73) compared to A&H and P&C that are in the range of 0.30. The longer-term asset-liability structure and the relatively higher level of return volatility for Life insurers contribute to this elevated level of volatility persistence. Confirmation of the GARCH functional form indicates greater reliability of the results reached here relative to those from traditional constant variance asset pricing models.

Volatility spillover prevails but is limited in scope. Coefficient estimates in Table 2 for the volatility spillover across lines of insurance activity is significant only from A&H to Life. Based on this result, volatility spillover prevails only between A&H and Life insurers, and it is unidirectional. No volatility spillover is found between Life and P&C, nor between A&H and P&C (H_{6i}). Increasingly, Life insurers are offering health insurance products. Life insurers may also be holding shares of the A&H companies. These two channels are likely to have contributed to the volatility transmission between these institutions**.** The direction of the effect from A&H to life insurers is negative, indicating that increased uncertainty in the A&H market will lead to a decline in volatility in the life insurer returns. This may be an indication that disquiet in A&H markets drives the A&H customers to seek the same products from life insurers when offered, enhancing the latter's risk profile as a result.

The lack of spillover of volatility between Life and P&C and between P&C and A&H is an indication of non-substitutability of the product and services that these institutions provide. By virtue of their businesses, the P&C policies are short-term in nature while the Life policies are long-term. In addition, P&C insurers insure events that are varied in scope and more difficult to predict than mortality risks. The potential losses arising from such events are also difficult to predict compared to the losses in life insurance. These characteristics cause P&C insurers to hold more liquid assets than their Life counterparts. The divergence in the underlying risk characteristics of these assets impedes any volatility co-movement between these institutions.[6]

We also test whether the spillover in volatility across lines of activity is symmetric in nature. Formal test results of the symmetry hypotheses are reported in Table 5 (H_{7i}). The null of symmetry in volatility transmission between different segments of the insurance industry cannot

[6] Elyasiani, Mansur, and Pagano (2006) find that return spillover prevails across smaller banking, investment banking, and insurance companies while volatility spillover is the predominant mode of behavior among the larger ones.

be statistically rejected. In other words, although the t-tests of coefficient significance in Table 2 indicate that volatility of the A&H stock returns affects Life insurers, while the reverse fails to be true, symmetry tests lack the power to confirm these findings. Thus, volatility transmission across Life, A&H, and P&C can be said to be statistically similar (symmetric). Overall, these results show a weak risk linkage across insurers and point to sources of risk that are more idiosyncratic in nature.

4.4. The Effect of Gramm-Leach-Bliley Act (GLBA)

The passage of GLBA in 1999 had the potential to alter the return and/or volatility of insurer stock returns because it allowed banks, investment banks, and insurers to combine into a single entity in the form of a financial services holding company (FSHC). Theoretically, GLBA had the potential to decrease or increase riskiness of those insurers not forming FSHCs. This is because in the post GLBA period these insurers face a new source of competition from some giant rivals such as Citigroup (see Saunders, 1997; and Hendershott, et al., 2002) but they may also be left alone to enjoy their particular niche of activity. Insurers forming FSHCs with other financial institutions may become safer due to diversification but this may embolden them to seek riskier projects.

We test the effect of GLBA on risk by including a binary variable in the volatility equation. This variable takes the unit value after the passage of the GLBA and zero otherwise.[7] As shown in Table 5, the GLBA binary variable for the effect on volatility is found to be positive and significant for A&H and P&C insurers, and insignificant for Life insurers (H_{8i}). This indicates that stock return volatility increased significantly for A&H and P&C insurers following

[7] The effect of GLBA on returns was also investigated and found to be insignificant. Hence, the GLBA dummy variable was dropped from the returns equation.

the GLBA of 1999. This finding follows discussion in Marlett et al. (2003) whereby investors were less certain of the likely effects of GLBA on P&C insurers than on Life insurers.

5. Summary and Conclusions

The stock return behavior of insurance companies in three main segments—life (Life), accident and health (A&H), and property and casualty (P&C)—is modeled using a System-GARCH specification. This framework allows for return spillover and volatility spillover across the three primary types of insurers investigated. This framework also allows tests of equality of market risk, equality of interest rate sensitivity, and prevalence and symmetry of return and risk spillover across different segments of the insurance industry to be carried out through system-wide cross-equation restrictions. The findings show that GARCH is the appropriate framework for describing return and risk behavior of the insurers. The ARCH and GARCH parameters are all positive, statistically significant and of the theoretically acceptable magnitude.

We demonstrate significant interdependencies in stock returns across different segments of the insurance industry. Interdependency is strongest between P&C and A&H insurers, and weakest between Life insurers and firms from the other segments. The results also indicate a weak presence of volatility spillover among insurers. Only the A&H stock return volatility is found to affect Life insurers.

Our results also demonstrate that insurers from all three segments are exposed to market risk. Coefficient estimates for market betas and tests of their equality across different lines of activity reveal that A&H insurers are exposed to a greater extent, followed by Life, and then P&C insurers. Further, insurer stock returns in all three segments are found to be negatively related to long-term interest rates, with Life insurers demonstrating a much greater exposure than

A&H insurers and P&C insurers. This finding is similar to that for banks that have positive duration gaps as they borrow short and lend long. The negative and differential interest rate effect for the Life and P&C insurers is consistent with findings by Browne et al. (1995 and 1999**).**

The choice of insurers to offer products in multiple segments, the choice of those segments, and insurer managerial decisions to diversify through acquisition are made taking into account the extent of interdependency between different segments of the industry. Thus, the levels of these interdependencies are important concerns for insurer managers. Public policymakers are also interested in this issue because the probability of a collapse in the overall industry is influenced by intersegment shock sensitivities. The gains from diversification will be greatest among those lines of business for which the interdependency of stock returns is weakest: results indicate that return interdependency is weakest between Life insurers and the A&H and P&C segments. The findings on interdependencies across insurance segments complement research on diversification and focus strategies, and the results on market and interest rate risk complement the literature on insurer financial strength.

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Table 1

Summary Statistics of Insurance Company Stock Returns

	Life	**A&H**	**P&C**
No. of Observations	2869	2869	2869
Mean	0.0012	0.0004	0.0006
Standard Deviation	0.0097	0.0120	0.0081
Minimum	-0.0513	-0.0878	-0.0698
Maximum	0.0619	0.0631	0.0523
Skewness	0.2276***	-0.1161**	0.0498
Kurtosis	2.3892***	5.1744***	4.8653***
Jack-Bera Statistics (Normality)	707.182***	3206.885***	2830.970***
Ljung-Box (Serial Correlation)			
Ljung-Box Q(8)	8.855	7.204	30.264***
Ljung-Box Q(16)	14.888	12.147	37.164***
Ljung-Box Q(24)	30.498	19.798	44.277***
Ljung-Box $Q^2(8)$	24.209***	24.575***	30.598***
Ljung-Box $Q^2(16)$	36.057***	33.287***	54.338***
Ljung-Box $Q^2(24)$	48.692***	41.105***	68.830***

Life, A&H, and P&C refer to Life insurance, Accident & Health, and Property & Casualty portfolios, respectively. The Jack-Bera measure is the Jarque-Bera joint normality test statistic. $Q(n)$ and $Q^2(n)$ are the Ljung-Box test statistics for the 8th, 16th, and 24th order serial correlation in returns and squared return series. The critical values for 8, 16, and 24 degrees of freedom are 15.50, 26.29, and 36.41 at the 5 percent level, respectively. ***, **, and * represent significance at the 1% , 5%, and 10% levels, respectively.

Table 2

Estimation Results for System-GARCH Model of Insurer Stock Returns

Coefficients		LIFE (i = 1)	A&H (i = 2)	P&C (i = 3)
β_{i0} x (10^{-3})	Intercept	1.324	0.023	0.035
		(5.591)***	(0.078)	(0.258)
β_{i1}	Market beta	0.714	0.866	0.508
		(28.688)***	(29.549)***	(33.733)***
β_{i2}	Interest rate beta	-0.879	-0.132	-0.198
		(-37.867)***	(-3.134)***	(-10.882)***
β_{i3}	Return spillover	0.004	0.025	0.071
		(0.183)	(0.691)***	(4.692)***
β_{i4}	Return spillover	0.050	0.120	0.046
		(1.515)	(2.868)***	(3.690)***
ν_{i0} x (10^{-3})	Volatility intercept	0.048	0.123	0.030
		(3.891)***	(4.896)***	(6.316)***
α_{i1}	GARCH	0.617	0.123	0.140
		(7.816)***	(1.688)*	(1.865)*
λ_{i1}	ARCH	0.114	0.178	0.171
		(5.171)***	(6.538)***	(6.300)***
φ_{i1}	Volatility spillover	-0.061	-0.029	0.007
		(-4.317)***	(-0.252)	(0.316)
φ_{i2}	Volatility spillover	0.101	0.041	-0.019
		(0.548)	(0.123)	(-1.053)
ϖ_{i1} x (10^{-3})	GLBA binary	0.026	0.105	0.069
		(1.548)	(2.779)***	(6.915)***

The model described in section 3.1 is the basis for the results presented here. Asymptotic *t*-values are in parentheses. i= 1, 2, and 3 represent Life, A&H, and P&C insurer portfolios, respectively. ***, **, * represent significance at the 1%, 5%, and 10% levels, respectively. Error diagnostic results are presented in the Appendix in Table A2.

Table 3

Hypotheses Related to Systematic Risk and Interest Sensitivity Among Insurers

Hypothesis Description	D.F.	χ^2 Values
H_{1i}: Hypotheses Concerning Equality of Systematic Risk Across Segments		
Joint test of equality of systematic risk Across Groups: H_{11}: $\beta_{11} = \beta_{21;}\ \beta_{11} = \beta_{31;}\ \beta_{21} = \beta_{31}$	2	143.49***
Equality of systematic risk between Life & A&H: H_{12}: $\beta_{11} = \beta_{21}$	1	16.73***
Equality of systematic risk between Life & P&C: H_{13}: $\beta_{11} = \beta_{31}$	1	51.52***
Equality of systematic risk between A&H & P&C: H_{14}: $\beta_{21} = \beta_{31}$	1	124.06***
$H_{2\,i}$: Hypotheses Concerning Interest Rate Sensitivity		
No interest rate sensitivity for any IC category: H_{21}: $\beta_{12} = \beta_{22} = \beta_{32} = 0$	3	1494.89***
No interest rate sensitivity for Life & A&H: H_{22}: $\beta_{12} = \beta_{22} = 0$	2	1450.02***
No interest rate sensitivity for Life & P&C: H_{23}: $\beta_{12} = \beta_{32} = 0$	2	1475.53***
No interest rate sensitivity for A&H & P&C: H_{24}: $\beta_{22} = \beta_{32} = 0$	2	123.59***
No interest rate sensitivity for Life: H_{25}: $\beta_{12} = 0$	1	1433.91***
No interest rate sensitivity for A&H: H_{26}: $\beta_{22} = 0$	1	9.82***
No interest rate sensitivity for P&C: H_{27}: $\beta_{32} = 0$	1	118.41***
H_{3i}: Hypotheses Concerning Equality of Interest Rate Sensitivity Across Segments		
Joint test of equality of IR sensitivity across Segments: H_{31}: $\beta_{12} = \beta_{22;}\ \beta_{12} = \beta_{32;}\ \beta_{22} = \beta_{32}$	2	702.95***
Equality of IR sensitivity between Life & A&H: H_{32}: $\beta_{12} = \beta_{22}$	1	287.95***
Equality of IR sensitivity between Life & P&C: H_{33}: $\beta_{12} = \beta_{32}$	1	601.73***
Equality of IR sensitivity between A&H and P&C: H_{33}: $\beta_{12} = \beta_{32}$	1	2.23

Table 4
Hypotheses Related to Stock Return Spillover
Among Insurance Company Segments

Hypothesis Description		D.F.	χ^2 Values
$H_{4\,i}$: Hypotheses Concerning Prevalence of Return-Spillover Across Segments			
No Return Spillover:	H_{41}: $\beta_{13} = \beta_{14} = \beta_{23} = \beta_{24} = \beta_{33} = \beta_{34} = 0$	6	95.54***
No Spillover between Life & A&H:	H_{42}: $\beta_{13} = \beta_{14} = \beta_{23} = \beta_{24} = 0$	4	19.03***
No Spillover between Life & P&C:	H_{43}: $\beta_{13} = \beta_{14} = \beta_{33} = \beta_{34} = 0$	4	73.33***
No Spillover between A&H & P&C:	H_{44}: $\beta_{23} = \beta_{24} = \beta_{33} = \beta_{34} = 0$	4	90.65***
No Spillover from A&H & P&C to Life:	H_{45}: $\beta_{13} = \beta_{14} = 0$	2	2.88
No Spillover from Life & P&C to A&H:	H_{46}: $\beta_{23} = \beta_{24} = 0$	2	16.67***
No Spillover from Life & A&H to P&C:	H_{47}: $\beta_{33} = \beta_{34} = 0$	2	67.63***
No Spillover from Life (to P&C & A&H):	H_{48}: $\beta_{23} = \beta_{33} = 0$ (LIC not a leader)	2	56.49***
No Spillover from A&H (to P&C & Life):	H_{49}: $\beta_{13} = \beta_{34} = 0$ (ACH not a leader)	2	13.63***
No Spillover from P&C (to Life & A&H):	H_{410}: $\beta_{14} = \beta_{24} = 0$ (FMC not a leader)	2	9.65***
H_{5i}: Hypotheses Concerning Symmetry of Return-Spillover Effects Across Segments			
Symmetric Return-Spillover between Life & A&H:	H_{51}: $\beta_{13} = \beta_{23}$	1	0.22
Symmetric Return-Spillover between Life & P&C:	H_{52}: $\beta_{14} = \beta_{33}$	1	0.32
Symmetric Return-Spillover between A&H & P&C:	H_{53}: $\beta_{24} = \beta_{34}$	1	2.71*

Table 5
Hypotheses Related to Volatility Spillover and GLBA Among Insurer Stock Returns

Hypothesis Description	D.F.	χ^2 Values
$H_{6\,i}$: Hypotheses Concerning Prevalence of Volatility-Spillover Across Segments		
No Volatility Spillover: H_{61}: $\varphi_{11} = \varphi_{12} = \varphi_{21} = \varphi_{22} = \varphi_{31} = \varphi_{32} = 0$	6	36.75***
No Volatility Spillover between Life & A&H: H_{62}: $\varphi_{11} = \varphi_{21} = 0$	2	19.37***
No Volatility Spillover between Life & P&C: H_{63}: $\varphi_{12} = \varphi_{31} = 0$	2	0.38
No Volatility Spillover between A&H & P&C: H_{64}: $\varphi_{22} = \varphi_{32} = 0$	2	1.12
$H_{7\,i}$: Hypotheses Concerning Symmetry of Volatility-Spillover Effects Across Segments		
Volatility-Spillover is Symmetric between Life & A&H: H_{71}: $\varphi_{11} = \varphi_{21}$	1	0.07
Volatility-Spillover is Symmetric between Life & P&C: H_{72}: $\varphi_{12} = \varphi_{31}$	1	0.25
Volatility-Spillover is Symmetric between A&H & P&C: H_{73}: $\varphi_{22} = \varphi_{32}$	1	0.03
$H_{8\,i}$: Hypotheses Concerning the Effect of GLBA on Volatility		
GLBA had No Effects on Volatilities: H_{81}: $\varpi_{11} = \varpi_{21} = \varpi_{31} = 0$	3	70.39***
GLBA had No Effects on Volatility of Life: H_{82}: $\varpi_{11} = 0$	1	2.39
GLBA had No Effects on Volatility of A&H: H_{83}: $\varpi_{21} = 0$	1	7.72***
GLBA had No Effects on Volatility of P&C: H_{84}: $\varpi_{31} = 0$	1	47.82***

Appendix A

Table A1

Panel A: Results of Stationarity Tests

Variables	ADF(4)	ADF(T,4)	PP(0)	PP(4)
LIFE	-22.64	-22.79	-60.51	-60.38
A&H	-22.53	-22.57	-50.28	-50.28
P&C	-21.21	-21.29	-47.06	-46.84
LTR	-2.00	-2.50	-1.92	-1.96
ΔLTR	-25.78	-25.78	-50.37	-50.32
$R_{M\,t}$	-25.67	-25.69	-51.70	-51.67

ADF (T,4) is the Augmented Dickey-Fuller unit root test with trend and lags of 4. PP (0) and PP (4) are the Phillps-Perron test with 0 and 4 lags, respectively. The total number of observations is 2869. Critical values for ADF (4), PP (0) and PP (4), ADF (T,4) are-3.43 and –3.93 at the 5% and 1% levels, respectively. LIFE, A&H, and P&C refer to Life Insurance, Accident & Health, and Property & Casualty portfolios, respectively. LTR is the 10-Year Treasury Constant Maturity rate, ΔLTR is the change in the LTR, and $R_{M\,t}$ is the return on the S&P 500 index.

Panel B: Conditional Index Values for Diagnosis of Multicollinearity

Dependent Variable	**Independent Variables**				**Conditional Index Values**
Life	RSP	ΔLTR	A&H	P&C	9.983
A&H	RSP	ΔLTR	Life	P&C	9.984
P&C	RSP	ΔLTR	Life	A&H	8.143

The conditional index values are used to detect the presence of multicollinearity. These values are calculated as ((maximum eigen value)/(minimum eigen value). In the regressions reported in the Table, RSP is the return on the SP500 index, LTR is the long-term interest rate and ΔLTR is the change in the LTR.

Appendix

Table A2
(Diagnostics for Results in Table 3)
Estimation Results for System-GARCH Model of Insurer Stock Returns

Coefficients	**LIFE (i = 1)**	**A&H (i = 2)**	**P&C (i = 3)**
Based on ($\varepsilon_{i,t}/\sqrt{h_{ii}}$)			
Skewness	0.094**	-0.197***	0.272***
Kurtosis	1.173***	5.398***	3.631***
Jarque-Bera (MSL)	0.00	0.00	0.00
Ljung-Box Q(8)	14.22**	11.55**	8.57
Ljung-Box Q(16)	21.58*	22.88**	17.64
Ljung-Box Q(24)	38.13**	37.02**	30.06*
Based on ($\varepsilon_{i,t}/\sqrt{h_{ii}}$)^2			
Skewness	5.20***	17.165***	12.596***
Kurtosis	47.96***	504.104***	262.32***
Jarque-Bera (MSL)	0.00	0.00	0.00
Ljung-Box $Q^2(8)$	8.77	32.48***	58.14***
Ljung-Box $Q^2(16)$	20.64*	89.63***	78.04***
Ljung-Box $Q^2(24)$	43.83***	129.38***	154.78***
Correlation ρ_{12}	0.178 (4.73)***		
Correlation ρ_{13}	0.266 (5.07)***		
Correlation ρ_{23}	0.196 (5.34)***		
Likelihood value (LL)	35844.54		

Q(*n*) and $Q^2(n)$ are the Ljung-Box test for the 8th, 16th, and 24th order serial correlation in standardized and squared standardized residuals. The critical values for 8, 16, and 24 degrees of freedom are 15.50, 26.29, and 36.41 at the 5 percent level, respectively. Sk and Ku represent skewness and kurtosis, respectively. J-B is the Jarque-Bera joint normality test statistic. LL is the log-likelihood value. MSL stands for Marginal Significance Level. ρ_{ij} is the estimate of the constant correlation term. ***, **, * represent significance at the 1% , 5%, and 10% levels, respectively.