

ESTIMATING THE COST OF EQUITY FOR PROPERTY-LIABILITY INSURANCE COMPANIES

Min-Ming Wen
Anna D. Martin
Gene Lai
Thomas J. O'Brien

ABSTRACT

Due to the highly skewed and heavy-tailed distributions associated with the insurance claims process, we evaluate the Rubinstein-Leland (RL) model for its ability to improve the cost of equity estimates of insurance companies because of its distribution-free feature. Our analyses show that there is as large as a 94-basis-point difference in the estimated cost of insurance equity between the RL model and the capital asset pricing model (CAPM) for the sample of property-liability insurers with more severe departures from normality. In addition, consistent with our hypotheses, significant differences in the market risk estimates are found for insurers with return distributions that are asymmetrically distributed, and for small insurers. Third, we find significant performance improvements from using the RL model by showing smaller values of excess return of the expected return of the portfolio to the model return for a portfolio of insurers with returns that are more skewed and for a portfolio of small insurers. Finally, our panel data analysis shows the differences in the market risk estimates are significantly influenced by firm size, degree of leverage, and degree of asymmetry. The implication is that insurers should use the RL model rather than the CAPM to estimate its cost of capital if the insurer is small (assets size is less than \$2,291 million), and / or its returns are not symmetrical (the value of skewness is greater than 0.509 or less than -0.509).

INTRODUCTION

Cost of capital research recognizes that industry factors influence the cost of equity (e.g., Fama and French, 1997). The cost of equity for the insurance industry, in

Min-Ming Wen is Assistant Professor of Actuarial Science, Northern Illinois University, DeKalb, IL 60115. Anna D. Martin is Theis Chair and Professor of Finance, St. John's University, Queens, NY 11439. Gene Lai is Safeco Distinguished Professor of Insurance, Washington State University, Pullman, WA 99 164-4746. Thomas J. O'Brien is Professor of Finance, University of Connecticut, Storrs, CT 06269. The authors can be contacted via e-mail: mwen@niu.edu, martina@stjohns.edu, genelai@wsu.edu, and tomo@business.uconn.edu. They thank two anonymous referees for their insightful and valuable comments. Financial support from the Society of Actuaries and the Alois J. Theis endowment at St. John's University are also gratefully acknowledged.

particular, has received a substantial amount of attention in the literature. For the insurance industry, an accurate cost of equity is important for existing and potential investors, managers, and regulators.

The traditional capital asset pricing model (CAPM), which is justified when equity returns are normally distributed, is commonly used to estimate the cost of equity for insurance firms (Quirin and Waters, 1975; Lee and Forbes, 1980; Harrington, 1983; Cummins and Harrington, 1988; Cummins and Lamm-Tennant, 1994; Lee and Cummins, 1998). However, the distribution of property-liability (P/L) insurance claims at the firm level can be highly skewed and heavy-tailed (Cummins, Dionne, and Pritchett, 1990; McNeil, 1997), implying that equity returns for P/L insurers will not be normality distributed. We therefore test whether the model developed by Rubinstein (1976) and applied by Leland (1999), which captures the skewness, kurtosis, and other higher moments of returns, generates significantly different estimates of equity risk and cost of capital than the traditional CAPM.

To incorporate nonnormal conditions into the pricing of insurance contracts, the literature suggests a three-moment CAPM (Kraus and Litzenberger, 1976) and an N-moment CAPM (Kozik and Larson, 2001). Recent studies by Harvey and Siddique (2000) and Chung, Johnson, and Schill (Forthcoming) empirically examine the effects of co-skewness and higher order of co-moment on the determination of the cost of equity. The adoption of the N-moment insurance CAPM could possibly capture the nonnormal characteristics of the insurance claims process. Unfortunately, the determination of the optimal moment and its finite nature does limit the application of this model.

Using a sample of publicly traded P/L insurers, we compare the equity betas generated from the RL model to those generated by the traditional CAPM. As suggested in Leland (1999), we expect that the equity betas are significantly different for insurers with a greater degree of nonnormal return distributions and for insurers with more asymmetric returns, since their distributions violate CAPM assumptions. Furthermore, based on scale economies, we expect that larger insurers, through the insurance pooling process, reinsurance, and/or the use of financial hedging techniques, are more able to mitigate the asymmetric risk embedded in their insurance policies. Thus, we hypothesize that the differences in the equity betas generated from the two models are significant for small insurers and that the differences are larger for small insurance companies.

Our analyses show that the difference in the estimated cost of insurance equity between the RL model and the CAPM for P/L insurers over 1970–2001 is as large as 94 basis points for the subset of insurers with more severe departures from normality. We also find that the equity betas are significantly different for insurers with returns that depart from the normal distribution, and for relatively small insurers. Finally, for insurers with asymmetric returns, the absolute differences in the equity betas generated from the two models are significantly larger than those of insurers with symmetric returns.

In addition, a multivariate panel data analysis confirms that the discrepancy between the risk estimates is larger for smaller insurers and for insurers with more asymmetric return distributions. Lastly, we conduct a performance comparison based on excess returns and find significant performance improvements from using the RL model for

a portfolio of insurers with returns that are more skewed and for a portfolio of small insurers. The implication of our findings is that P/L insurers should use the RL model rather than the CAPM to estimate its cost of capital if the insurer is small (assets size is less than \$2,291 million) and/or its returns are not symmetrical (the value of skewness is greater than 0.509 or less than -0.509).

The remainder of this article is organized in the following manner. The section “The RL Model Versus CAPM” discusses the RL model and the CAPM and associated research in estimating the cost of insurance equity. The following describes the sample and data. The next presents the empirical examination that includes (1) evaluating whether there are significant differences in the risk estimates generated from the CAPM and RL model (2) analyzing the cross-sectional variation in the differences between the CAPM and RL risk estimates based on univariate analysis as well as on multivariate panel data analysis, and (3) examining the model performance of the CAPM, RL model, and co-skewness model. The last section provides the conclusion.

THE RL MODEL VERSUS CAPM

In a mean-variance framework, the CAPM is derived by maximizing the investor’s expected value of utility subject to the investor’s wealth allocation. For arbitrary preferences, using the mean-variance model can be justified by assuming that rates of return on risky assets are multivariate normally distributed. However, the normality assumption suggests that the distribution is completely described by its mean and variance; thus, the third and higher moments of returns are effectively ignored.

Kraus and Litzenberger (1976) develop a three-moment CAPM under a logarithmic utility assumption. They conclude that asset pricing models should incorporate not only the price of the second moment of risk aversion but also the value of skewness preference. Nevertheless, the CAPM has been applied in the insurance literature to insurance contracts (Fairley, 1979; Hill, 1979; Myers and Cohn, 1987), insurance equities (Harrington, 1983; Cummins and Harrington, 1988; Cummins and Lamm-Tennant, 1994), and insurance reserves (D’Arcy, 1988). Without knowing the precise distribution that most accurately fits insurance equity returns, it is appropriate to apply a model like the RL model that has a distribution-free feature to capture the nonnormally distributed risk embedded in insurance equity. In a similar spirit, Kozik and Larson (2001) have proposed an “N-moment CAPM” to price insurance policies. However, the applications of the RL model are broader in the sense of not limiting the moments of preference and returns to be finite.

The RL Model

Assuming a power utility function, Rubinstein (1976) derives the equilibrium price of any asset as Equation (1):¹

¹ Rubinstein (1976), Brennan (1979), and He and Leland (1993) show that a power utility function can be used to describe the representative investors’ preferences if the market portfolio’s rate of return is identically and independently distributed and if markets are assumed to be perfect. In addition, Friend and Blume (1975) evaluate cross-sectional data on household asset holdings to assess the nature of households’ utility functions and conclude that the assumption of constant relative risk aversion (CRRA) for households is a fairly accurate description of the marketplace. Based on these prior studies, we believe that it is reasonable to assume a power utility function.

$$P_0 = \frac{E(X_1) - \frac{\text{Cov}(X_1, -(1+r_m)^{-b})}{E(1+r_m)^{-b}}}{1+r_f}, \quad (1)$$

where:

P_0 = price of an asset,

X_1 = terminal payoff of the asset,

r_m = return of the market portfolio,

b = degree of risk aversion of the assumed power utility,

$\text{Cov}(u, v)$ = covariance of variables u and v , and

$E(\cdot)$ = expected value.

In addition, b can be derived as described below in Equation (2) by assuming lognormality of the market returns.

$$b = \frac{1}{2} + \frac{E[\ln(1+r_m)] - \ln(1+r_f)}{\text{Var}[\ln(1+r_m)]}. \quad (2)$$

Therefore, b can be related to the market excess return per unit of risk.

Following Rubinstein (1976), Leland (1999) demonstrated a linear relation between risk and return for any asset i as shown in Equation (3):

$$E(r_i) = r_f + B_i[E(r_m) - r_f], \quad (3)$$

where:

$E(r_i)$ = required return for asset i ,

r_f = risk-free rate,

$E(r_m) - r_f$ = market risk premium, and

$$B_i = \frac{\text{Cov}[r_i, -(1+r_m)^{-b}]}{\text{Cov}[r_m, -(1+r_m)^{-b}]}$$

The empirical applications of the RL model require an estimate of b , the degree of risk aversion. To utilize a theoretical comparison between the risk estimates from the RL model and the CAPM, we primarily assume that $b = 4$ and use a risk-free rate of 3 percent and a market risk premium of 5 percent.² Nevertheless, we derive the estimate of b using actual return data when we conduct the performance comparison.

² The degree of risk aversion of the representative investor can be related to the market risk premium. Leland (1999) viewed it as a "market price of risk": the market's instantaneous excess rate of return divided by the variance of the market's instantaneous rate of return. The possible values of the risk aversion parameter have raised significant discussions in extant literature among which we summarize here. Friend and Blume (1975) have attempted to measure b from empirical surveys of consumer wealth allocation. Campbell (1996) takes into

THE CAPM

Except for the definition of the risk measure, Equation (3) above is similar to the CAPM, which is shown below in Equation (4):

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f] \quad (4)$$

where:

$$\beta_i = \frac{\text{Cov}(r_i, r_m)}{\text{Var}(r_m)}$$

and $E(r_i)$, r_f , and $[E(r_m) - r_f]$ were previously defined in Equation (3). As when estimating the RL cost of equity, we use a risk-free rate of 3 percent and a market risk premium of 5 percent to estimate the CAPM cost of equity.³

Comparisons of the RL Model and the CAPM

Leland (1999) showed that the CAPM and the RL model will give results that are nearly the same for assets that are symmetrically distributed. However, for asymmetrically distributed returns induced by an asymmetric claims process, the error in using the CAPM may be substantial.

The RL model can capture all elements of risk including skewness, kurtosis, and higher moments. The risk measure of the CAPM, β_i , is easier to estimate than the risk measure of the RL model, B_i . However, B_i incorporates the effects of preferences and aversions toward higher moments, given that the market's representative investor has a power utility function with parameter b .

Quirin and Waters (1975) provide empirical evidence indicating that CAPM is inadequate to describe the insurance equity returns due to the unique characteristics embedded in the quasi-debt (written policies) of an insurance company. They conclude that either insurance companies are able to "beat the market" or there is a third factor, in addition to mean and variance, determining the costs of insurance equity.

account the effects of human capital and the mean aversion character of the stocks index to estimate the parameter b as 3.63. Bliss and Panigirtzoglou (2002) provide a summary of the estimates of b from the literature. To simplify, we specify an integer four based on Campbell (1996) as the preference parameter on which value the analyses and discussions are based. In addition, this study conducts sensitivity analysis of the difference between the estimates from the two models to different value of b . Results for $b = 1, 4$, and 10 are summarized in the Appendix and results for other scenarios of b are available upon request.

³ The Appendix provides the results of the two models based on different scenarios for the assumed market risk premium, such as $E(r_m) = 11$ percent, $r_f = 6$ percent, and $E(r_m) = 10$ percent, $r_f = 6$ percent. Note that the difference between the costs of equity from the two models is mainly dependent on the difference in risk estimates and market risk premium, i.e., $E(r_i^{CAPM}) - E(r_i^{RL}) = (\beta - B) \times (E(r_m) - r_f)$, but is independent of the choice of risk-free rate. As a result, under the scenarios of $E(r_m) = 11$ percent, $r_f = 6$ percent and $E(r_m) = 8$ percent, $r_f = 3$ percent, both have the same values of $E(r_i^{CAPM}) - E(r_i^{RL})$ and its absolute values.

Using CAPM, Harrington (1983) tests whether beta is the sole determinant of the cost of equity for a sample of life insurance firms. Cummins and Harrington (1988) investigate whether CAPM is adequate to reflect the returns generating process for P/L insurers and conclude that co-skewness and unsystematic risks should be included in estimating cost of equity. Recent studies by Harvey and Siddique (2000) and Chung, Johnson, and Schill (Forthcoming) find better performance with asset pricing models that consider the factors of co-skewness and higher-order co-moments.⁴

SAMPLE AND DATA

The monthly stock return data over the period 1970–2001 of P/L insurers with the four-digit Standard Industrial Classification (SIC) code 6331 are retrieved for firms publicly listed and included in the Center for Research in Security Prices (CRSP) database. In selecting the sample, we employ standard screening rules from the cost of capital estimation literature that exclude firms with estimated CAPM beta coefficients greater than five in absolute value (e.g., Cummins and Phillips, 2003) and exclude firms without five consecutive monthly returns in a year (e.g., Cummins and Harrington, 1988). Overall, these screening rules allow us to generate a reasonable sample of 111 P/L insurers over the period 1970–2001.

Returns on the CRSP value-weighted index of S&P 500 stocks are used as a proxy for market returns, and rates of return on 3-month U.S. Treasury bills are used to represent the risk-free rates. Firm-specific characteristics of total assets and total liabilities to measure firm size and leverage are from Compustat.⁵ When we merge the Compustat and CRSP data, our sample size is reduced to 97 insurers from 111 insurers.

EMPIRICAL EXAMINATION

In this section, three sets of analyses are conducted. First, we evaluate whether there are significant differences in the risk estimates generated from the CAPM and RL model, and assess whether the differences depend on the degree to which the normality assumption underlying the CAPM is violated, the degree to which return distributions are skewed, and/or firm size. Second, panel data analyses are utilized to further evaluate the influence of firm-level characteristics and return distribution

⁴ Cochrane (2001) shows the CAPM to be a special case of the stochastic discount factor (SDF) approach; in addition, Fletcher and Forbes (2004) summarize the nine asset pricing models, that are under the SDF framework. Examples are CAPM, labor CAPM, quadratic CAPM, cubic CAPM, Campbell's discrete-time version of the intertemporal CAPM, and APT. The RL model used in this study can also fit within the SDF framework in the cases when the RL model is equivalent to the CAPM, such as when the power utility function degenerates to a quadratic utility, or when a lognormal distribution can be used to describe the joint distribution of the market and asset returns. We have shown that the RL model, in general, can be represented under SDF framework. The proof is available upon request. We are indebted to an anonymous referee for this comment.

⁵ We also gather data on net premiums written and policyholders' surplus from the *Best's Aggregates/Averages Property & Casualty* (henceforth *Aggregate Reports*) to calculate alternative measures of firm size and insurance leverage ratio, respectively. While we report the results associated with the measures that use financial data from Compustat, robustness checks are conducted using these alternative measures that use insurance-specific data.

characteristics on the cross-sectional differences in risk estimates. Third, we examine the model performance of the CAPM, RL model, and co-skewness model.

Risk Estimates

Equation (3) describes how we estimate the RL risk, B , and Equation (4) describes how we estimate the CAPM equity risk, β . For insurer i , we examine whether the differences between the two risk estimates B and β are significant. Specifically, we evaluate the following null hypothesis using a paired t -test:⁶

$$H_0: \beta_i - B_i = 0.$$

We report the results of the paired t -test and various summary statistics for the overall sample and various subperiods in Table 1 and for subsets of insurers defined by the degree of nonnormality, degree of asymmetry, and firm size in Table 2.

Table 1 includes summary statistics of the mean parameter estimates for β and B , and the paired t -test that evaluates the above hypothesis for the overall sample of 111 P/L insurers over 1970–2001, and for subsamples over 5-year subperiods.⁷ The mean and median values of $|\beta_i - B_i|$ are also provided in Table 1. In addition, to infer the cost of equity implications, the mean values of the absolute difference between the costs of equity generated from RL and CAPM (Equations (3) and (4), respectively) are displayed in the last column.

We do not detect statistically significant differences in the equity betas over 1970–2001. However, we are able to reject the null hypothesis that the risk estimates from the CAPM and RL model are the same when they are estimated over subperiods 1980–1984, 1985–1989, and 1990–1994.⁸ Specifically, Table 1 shows the mean absolute difference in equity betas between the two estimates for the full examination period is 0.066.⁹ The evidence also shows that the largest discrepancy, 0.122, occurs in the period 1970–1974 and the smallest discrepancy, 0.042, occurs in the period 1990–1994.

Over the entire period, the average difference between the estimates of equity cost is 33 basis points (0.33 percent). We find that the largest discrepancy in cost of equity (0.61 percent) also corresponds with the 1970–1974 subperiod and the smallest discrepancy (0.21 percent) also corresponds with the 1990–1994 subperiod.¹⁰

⁶ By assuming that the paired differences are independent and identically normally distributed under the null hypothesis, we can employ a two-tailed paired t -test.

⁷ We use the available monthly return data over each subperiod to estimate the corresponding parameters.

⁸ The analyses based on period analysis provide an insight that even if the true distribution of insurer returns is skewed, it is possible that the observed distribution of actual returns is not skewed in any given sample period. In other words, the data could suffer from the “peso problem.” In this case, we may not empirically detect any difference in the two models over every subperiod, when in fact one exists. We thank an anonymous reviewer for making this point.

⁹ For the entire sample analysis, the monthly return over the entire period is used to estimate the corresponding parameters.

¹⁰ In order to evaluate the effects of the risk-aversion parameter, b , on the theoretical differences between β and B , we report the same statistics in the Appendix as Table 1 using various

TABLE 1

Summary of Risk Estimates, Differences in Risk Estimates, and Differences in Cost of Equity

Period	No. of Insurers	Mean β	Mean B	t -test $\beta = B$	Mean $ \beta - B $	Median $ \beta - B $	Mean $ \Delta E(R_i) $
1970–2001	111	0.696	0.705	−1.59	0.066	0.048	0.33%
1970–1974	22	0.982	0.936	1.38	0.122	0.096	0.61%
1975–1979	29	0.804	0.824	−1.44	0.059	0.060	0.30%
1980–1984	27	0.888	0.931	−2.59**	0.075	0.056	0.37%
1985–1989	24	0.665	0.705	−2.34**	0.077	0.065	0.38%
1990–1994	35	0.770	0.787	−1.83*	0.042	0.032	0.21%
1995–1999	56	0.607	0.621	−1.54	0.049	0.035	0.25%
2000–2001	56	0.490	0.476	1.02	0.072	0.052	0.36%

Notes: The market risk parameters are estimated from the CAPM and RL model. In the results presented here, the assumptions for both models are that r_f = the risk-free rate of 3% and $E(r_m) - r_f$ = the market risk premium of 5%. Using the CAPM, $\beta_i = \frac{\text{Cov}(r_i, r_m)}{\text{Var}(r_m)}$ and $E(R_i^{\text{CAPM}}) = r_f + \beta_i[E(r_m) - r_f]$. Using the RL model, $B_i = \frac{\text{Cov}[r_i, -(1+r_m)^{-b}]}{\text{Cov}[r_m, -(1+r_m)^{-b}]}$ with the additional assumption that $b=4$, and $E(R_i^{\text{RL}}) = r_f + B_i[E(r_m) - r_f]$. $|\Delta E(R_i)| = |E(R_i^{\text{CAPM}}) - E(R_i^{\text{RL}})|$. The paired t -test evaluates the hypothesis that $\beta_i = B_i$, where ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

While we are not able to reject the null hypothesis that the risk estimates from the CAPM and the RL model are the same in every subperiod, this is not surprising. The reason is that these results are based on the full sample, which includes insurers with normally distributed and symmetrical returns, and large insurers. Leland (1999) suggests that the RL model outperforms the CAPM when returns are not symmetrically distributed. Thus, we next evaluate the two models based on the return characteristics (degree of asymmetry and normality) and firm characteristics (firm size).¹¹

Differences in Risk Measures for Nonnormally Distributed and Skewed Equity Returns

The RL model theoretically provides an advantage over the CAPM when equity returns are nonnormally or asymmetrically distributed. In other words, as long as the assumption of normality is rejected, the application of the CAPM is likely to be invalid and the RL model is likely to be more appropriate. The model developed by Rubinstein (1976) embeds a distribution-free feature as compared to the normality assumption underlying the CAPM, while Leland (1999) specifically examined an asymmetric distribution to compare the Rubinstein model against the CAPM. In order to have

values for b ($b = 1, 4$, and 10 ; see Tables A.1 and A.2). To conserve space, the additional analyses based on other scenarios of b are not reported here but are available upon request.

¹¹ We use the p -values from the Shapiro-Wilk tests (Shapiro and Wilk, 1968) to measure the degree of normality, use the significance levels of skewness (see Snedecor and Cochran, 1989; Sheskin, 2000; Taylor and Cihon, 2004) to measure the degree of asymmetry, and use asset value to measure firm size. More details of each measure are discussed in later sections.

TABLE 2

Summary of Risk Estimates and Differences in Risk Estimates

Panel A: Subsets of Insurers Based on Degree of Normality (1970–2001)

Subsets	No. of Insurers	Mean β	Mean B	t -test $\beta = B$	Mean $ \beta - B $	Median $ \beta - B $
$p < 0.01$	47	0.709	0.725	-1.93*	0.0684**	0.0670*
$p < 0.05$	60	0.655	0.667	-1.28	0.0728***	0.0673***
$p < 0.20$	69	0.644	0.654	-1.20	0.0711**	0.0670***
$0.01 < p$	64	0.617	0.622	-0.42	0.0611	0.0482
$0.05 < p$	51	0.656	0.662	-0.58	0.0550	0.0404
$0.20 < p$	42	0.675	0.682	-0.64	0.0534	0.0333

Panel B: Subsets of Insurers Based on Degree of Symmetry (1970–2001)

$p < 0.01$	44	0.622	0.637	-1.34	0.0729**	0.0673**
$p < 0.05$	59	0.662	0.672	-1.02	0.0708**	0.0670**
$0.01 < p$	67	0.683	0.688	-0.65	0.0586	0.0450
$0.05 < p$	52	0.655	0.664	-0.87	0.0565	0.0450

Panel C: Subsets of Insurers Based on Total Assets (1970–2001)

Assets < Q_1	24	0.6290	0.6737	-5.13***	0.0658*	0.0599**
Assets < Q_2 (median)	49	0.5901	0.6230	-5.12***	0.0607*	0.0510**
Assets < Q_3	73	0.5837	0.6084	-4.93***	0.0540	0.0453*
$Q_1 < \text{Assets}$	73	0.6564	0.6606	-0.93	0.0452	0.0340
Q_2 (median) < Assets	48	0.7091	0.7046	0.96	0.0400	0.0289
$Q_3 < \text{Assets}$	24	0.8389	0.8275	1.83*	0.0379	0.0287

Notes: The summary statistics are reported in Panel A for subsets of insurers with equity returns that violate and do not violate the normality conditions, in Panel B for subsets of insurers whose equity returns are more and less skewed, and in Panel C for subsets of small and large insurers. The p -value of the Shapiro-Wilk statistic is used for forming the subsets in Panel A, with significance levels of 1%, 5%, and 20% as benchmarks. We form subsets in Panel B on the basis of statistically significant skewness at the 1% and 5% levels. The subsets on the basis of firm size are formed using total assets. Across all panels, we report the corresponding average risk estimates from the RL model (B) and the CAPM (β), the mean and median absolute differences between B and β , $|\beta - B|$. The paired t -test evaluates the hypothesis that $\beta_i = B_i$, where ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The Kruskal-Wallis test and median one-way analysis evaluate the hypotheses that the means and medians, respectively, between two groups are equal. One-tailed tests are used to compare the means and medians between two groups. ***, **, and * in the columns of Mean $|\beta - B|$ and Median $|\beta - B|$ indicate significant differences between the group comparisons at the 1%, 5%, and 10% levels, respectively.

a direct comparison between Rubinstein's model and the CAPM, we focus on the degree of normality and, following Leland, we also specifically focus on the asymmetry characteristic. Thus, we investigate the importance of using the RL model by evaluating the previously stated null hypothesis for subsets of insurers whose stock returns are nonnormally distributed and for subsets of insurers with asymmetric

equity returns. We use Shapiro and Wilk (1965) to test the normality assumption and we use the value of skewness to identify the degree of asymmetry.¹²

Panel A of Table 2 examines subsets of insurers that have been formed on the basis of nonnormally distributed equity returns, Panel B examines subsets of insurers that have been formed on the basis of return asymmetry degree, and Panel C examines subsets of insurers that have been formed on the basis of firm size measured by total assets. All panels also include the full sample of P/L insurers with estimates generated throughout the 1970–2001 time period and provide the mean β , mean B , and the mean and median absolute difference in the risk estimates. Again, we use the two-tailed paired t -test to evaluate, for a given subset of insurers, whether there is a significant difference between the two risk estimates (i.e., $H_0 : \beta_i - B_i = 0$). Due to the fact that the absolute differences will all be positive, we employ nonparametric measures of differences between groups. The Kruskal-Wallis (K-W) test and median one-way analysis are used to evaluate whether mean and median absolute differences, respectively, between two groups are equal.¹³ These evaluations are conducted using one-tailed tests since we hypothesize that the absolute differences should be larger with nonnormal, skewed, and small firms. The reason that we conduct the analyses based on the absolute difference is that Leland (1999) does not predict whether the estimate of the RL model is larger or smaller than that of the CAPM.

The subsets of insurers based on the degree of normality in Panel A are formed based on the p -values of 1 percent, 5 percent, and 20 percent from the Shapiro-Wilk tests.¹⁴ The Shapiro-Wilk test shows that 47, 60, and 69 of the insurers reject the null hypothesis that their equity returns are normally distributed at the 1 percent, 5 percent,

¹² Details of the tests for normality are found in Shapiro and Wilk (1965), Shapiro, Wilk, and Chen (1968), and Royston (1982). The details of the test of skewness can be found in Snedecor and Cochran (1989), Sheskin (2000), and Taylor and Cihon (2004). Skewness is a parameter that describes asymmetry in a random variable's probability distribution. Following Snedecor and Cochran (1973) and Taylor and Cihon (2004), we standardize the skewness by σ^3 and use the value of $\frac{\sum (r_i - \mu)^3}{n\sigma^3}$ to represent the skewness level, where μ and σ are the mean and standard deviation of returns, r_i . As one might expect, the standardized skewness takes on a positive value if returns are positively skewed and a negative value if returns are negatively skewed. In addition, hypothesis testing is based on the comparison of this value of skewness to the critical values of skewness. Because the stock returns can be skewed to the right or to the left, we use the absolute value of skewness to indicate the asymmetry feature. For example, the critical value of skewness at the 5 percent significance level is 0.509. That is, the asymmetry group at the 5 percent significance level is the group of insurers with skewness level larger than 0.509 or less than -0.509 .

¹³ Details on the K-W test can be found in Maritz (1995) and details on the median one-way analysis can be found in Hollander and Wolfe (1973).

¹⁴ One might consider using the W -statistic for the degree of nonnormality. The general rule is $0 < W < 1$, and the smaller W -value, the smaller p -value, thus leading to the rejection of the normality hypothesis. However, as mentioned in Shapiro and Wilk (1968), the distribution of W is highly skewed, and therefore seemingly large values of W (such as 0.9) may be considered small and lead to the rejection of the null hypothesis depending on the sample size. As a result, using the p -value is a better benchmark than the W -statistic.

and 20 percent significance levels, respectively.¹⁵ For example, the subset of insurers with p -values less than 0.01 includes 47 insurers with return distributions that reject the normality null hypothesis at the 1 percent level. The mean and median absolute differences in the risk estimates for this subset of 47 insurers are compared to the mean and median absolute differences for the subset with the remaining 64 insurers that do not reject the normality at the 1 percent level.

It can be seen in Panel A that the risk estimates are significantly different (t -value = -1.93) for the subset of insurers with returns that reject the null hypothesis of normal distribution at the 1 percent significance level. On the other hand, the risk estimates do not show significant difference for the subset of insurers with returns considered to be normally distributed at the significance level larger than 1 percent. This finding provides evidence that RL risk estimates are significantly different for insurers with nonnormal return distributions, because we are able to reject the hypothesis that $\beta = B$.

Further evidence is provided with the K-W test and median one-way analysis that show the mean and median absolute differences in risk estimates are significantly larger at the 5 percent and 10 percent levels, respectively, for subsets of firms with larger departures from normality compared to the subsets of firms with smaller departures from normality. More specifically, the absolute differences in the risk measures are significantly larger for the $p < 0.01$ group compared to the $p > 0.01$ group, and for the $p < 0.05$ group compared to the $p > 0.05$ group.

In Panel B of Table 2, the subsets of insurers are formed according to the significance of the degree of skewness. We use 1 percent and 5 percent significance levels of skewness (see Snedecor and Cochran, 1989; Sheskin, 2000; Taylor and Cihon, 2004) to divide the sample into subsets. On this basis, there are 44 and 59 insurers that reject the null hypothesis that their equity returns are symmetric at the 1 percent and 5 percent levels, respectively. While the paired t -test does not reject the hypothesis that $\beta = B$, the K-W test and median one-way analysis show that the mean and median $|\beta - B|$ for insurers with significantly skewed returns are larger than those for insurers without significantly skewed returns. More specifically, the mean value of $|\beta - B|$, 0.0729, and the median value of $|\beta - B|$, 0.0673, for the subset of insurers with skewed returns at the 1 percent level are significantly larger than the mean value of $|\beta - B|$, 0.0586, and median value of $|\beta - B|$, 0.0450, at the 5 percent level. The absolute difference in the risk estimates is also significantly larger at the 5 percent level for the comparison of the $p < 0.05$ group to the $p > 0.05$ group.

¹⁵ We also obtain a sample of nonfinancial firms to judge the extent to which nonfinancial firms may benefit by using the RL model. We randomly choose non-financial firms from CRSP, while applying the same screening criteria used with the insurance companies in this sample that was previously described in the "Sample and Data" section. The findings over the full examination period of 1970–2001 indicate that the average discrepancy in the risk estimates for the nonfinancial firms is even larger than the average discrepancy for the insurance firms. Accordingly, applying the RL model also appears to be more appropriate than CAPM for nonfinancial firms. However, the standard deviation in the discrepancy is smaller for the insurance firms, which suggests that the asymmetry or nonnormality characteristics are more persistent in the insurance firms.

This empirical finding is consistent with the argument by Leland (1999) that larger differences in the risk estimates should result from greater degree of asymmetry. In a later section, we will conduct panel data analysis to specifically evaluate the relationship between the degree of asymmetry and the absolute difference between the risk estimates.

Differences in Risk Measures for Smaller Insurers

Based on scale economies, larger insurers can employ reinsurance, pooling, and other financial hedging tools to manage the extreme values of policy losses. Hedging to manage extreme values of policy losses should reduce the asymmetric risks embedded in insurance claims, thus insurance equity returns.¹⁶ In addition, we conjecture that larger insurers tend to have less asymmetric equity returns due to their ability to diversify across insurance lines (Shelor and Cross, 1990) and across geography, due to their ability to facilitate economies of scale not only in hedging activities (Cummins, Phillips, and Smith, 1997; Cummins, Phillips, and Smith, 2001) but also in underwriting insurance policies (Hammond, Melander, and Shilling, 1971), due to their ability to operate more efficiently (Cummins and Weiss, 1993) relative to their cost frontier, and due to their ability to maintain a stable growth variability (Harhoff, Stahl, and Woywode, 1998; Hardwick and Adams, 2002). Taken together, the results of these studies lead us to hypothesize that larger (smaller) insurers are more (less) able to mitigate the asymmetric risk embedded in their insurance policies. Thus, we expect to find significant differences in the market risk measures generated from the two models for smaller insurance companies and the differences are larger for smaller insurers.

Panel C of Table 2 examines subsets of insurers that have been formed on the basis of size as measured by total assets. From the full sample of 111 P/L insurers, there are 97 that have available data from Compustat to compute firm size. We form subsets of insurers based on quartile values of total assets. Relatively small (large) insurers are those with total assets less than the median of the entire group (\$2,291.31 million) and are denoted by $\text{Assets} < Q_2$ ($\text{Assets} > Q_2$). The smallest insurers are those in the first quartile and are denoted as $\text{Assets} < Q_1$, whereas the largest insurers are those in the fourth quartile and are denoted as $\text{Assets} > Q_3$.

Consistent with our expectations, it can be seen in Panel C that the risk estimates are significantly different at the 1 percent level for the subsets of relatively small insurers. Since we are able to strongly reject the hypothesis that $\beta = B$, this is evidence that RL and CAPM risk estimates are significantly different for relatively

¹⁶ The discussions of the association between firm size and hedging activities can be found in several studies. Cummins, Phillips, and Smith (1997) conclude that derivatives usage is more widespread in the largest insurers. Cummins, Phillips, and Smith (2001) empirically examine the relationship between risk management and firm value-maximization using a sample of P/L insurance companies. Geczy, Minton, and Schrand (1997) conclude that, due to the fixed start-up costs associated with hedging, economies of scale are an important factor of hedging use and that the benefits increase with extensive exposure. The survey results of Bodnar, Hayt, and Marston (1998) suggest that large firms are more likely to hedge than small firms.

small insurers. Also consistent with our expectations, both the K-W test and median one-way analysis show that the mean and median absolute differences in risk estimates are significantly larger for relatively small insurers.¹⁷ More specifically, the absolute differences in the risk measures are significantly larger for the Assets < Q₂ group compared to the Q₂ < Assets group.

Factors That Influence CAPM and RL Risk Measures to Differ Across Insurers

Results based on univariate analysis as shown above have provided evidence that the absolute difference in the risk estimates is larger for the smaller insurers and for insurers with asymmetrical returns. In this section, under a multivariate framework, we investigate whether firm-return and firm-level characteristics impact the market risk measures by conducting panel data analyses using a random effects model.¹⁸

The analysis and results are based on the full sample that includes 97 insurers and data measured over 1970–2001. The following regression is estimated:

$$|\beta_i - B_i|_t = \alpha_0 + \alpha_1 \text{Size}_{i,t} + \alpha_2 \text{Leverage}_{i,t} + \alpha_3 \text{Asymmetry}_{i,t} + \alpha_4 \text{Nonnormality}_{i,t} + e_{i,t}, \quad (5)$$

where:

$|\beta_i - B_i|_t$ = absolute difference in risk estimates for insurer i at time t ,

α_0 = intercept,

$\alpha_1 \sim \alpha_4$ = regression coefficients,

$\text{Size}_{i,t}$ = natural log of inflation-adjusted asset for insurer i at time t ,

$\text{Leverage}_{i,t}$ = the ratio of total liabilities to total assets for insurer i at time t ,

$\text{Asymmetry}_{i,t}$ = the absolute value of skewness for insurer i at time t ,

$\text{Nonnormality}_{i,t}$ = the p -value from the Wilk-Shapiro test of normality for insurer i at time t , and

$e_{i,t}$ = residual for insurer i at time t .

Firm Size. To the extent that larger (smaller) insurers are more (less) able to mitigate the asymmetric risk embedded in their insurance policies, we hypothesize that there are larger differences in the market risk measures generated from the two models for

¹⁷ A robustness check is conducted by using a more refined measure of firm size for an insurer, net premium written. When we separate the sample using this measure of firm size, our results confirm that firm size influences the discrepancy between the risk estimates. More specifically, the paired t -test shows a significant difference between the estimates at the 1 percent level for the subset of 50 leading insurers (larger net premium written), which belong to the leading firm category defined by A.M. Best, and the subset of 24 nonleading insurers (i.e., smaller net premium written). Furthermore, the K-W test and median one-way analysis show the mean and median absolute differences are significantly smaller for the larger insurers compared to the smaller insurers, respectively.

¹⁸ The model specification depends on both the cross-section and the time series; the Hausman test suggests that the random effects model is the better choice (Greene, 2003, p. 301).

smaller insurance companies. Thus, we project the sign on the α_1 coefficient to be negative. To take into account the inflation effect on firm size, we use the Consumer Price Index (CPI) as an adjustment factor and measure firm size as natural log of asset over CPI, i.e., $\text{Ln}(\text{Assets}_t/\text{CPI}_t)$.

Financial Leverage. For an insurer, a large portion of liabilities consists of loss reserves and unearned premiums, the distributions of which are more likely to be asymmetric. Thus, we conjecture that an insurer with a high degree of financial leverage relative to its assets is also likely to have a high degree of asymmetry in equity. As such, one may expect larger differences in the market risk measures for insurers with greater leverage, which corresponds to a positive sign on the α_2 coefficient.

Asymmetry. As suggested by and shown in Leland (1999), the larger degree of asymmetry, the larger discrepancy between the risk estimates from the CAPM and the RL model; thus, a positive sign on the α_3 coefficient is expected. To test whether the degree of asymmetry helps explain the cross-sectional variation in the differences between the CAPM and RL risk estimates, we include the value of skewness as a measure of asymmetry. The skewness for a normal distribution is zero; thus, symmetric data should exhibit a skewness value near zero. A measure of the amount of skewness is given by the third moment about the mean, i.e., $\frac{\sum (r - \mu)^3}{n}$. In order to render the measure independent of the scale, we standardize the value of skewness by σ^3 by following Snedecor and Cochran (1989) and Taylor and Cihon (2004), where μ and σ are the mean and standard deviation of returns. We use the absolute value of skewness to represent the asymmetry level since either extreme negative or extreme positive value indicates asymmetry.

Nonnormality. One fundamental assumption underlying the CAPM is that the distributions of equity returns follow a normal distribution; on the other hand, the RL model has a distribution-free feature. As a result, for insurers with nonnormally distributed returns, we expect a larger difference between the estimates from the CAPM and the RL model leading us to project the sign on the α_4 coefficient to be negative. We include the p -value from the Wilk-Shapiro test of the normality as a proxy for the degree of departure from normality. A larger (smaller) p -value indicates a lower (higher) possibility of rejecting the normality null hypothesis, thereby suggesting a greater (lesser) degree of normality.

Summary statistics of the variables used in the analyses for the entire period are reported in Panel A of Table 3. The insurers included in the analysis have, on average, an absolute difference in β and B of 0.049, log (assets / CPI) of \$3.04 million, leverage ratio of 0.75, value of skewness of 0.70, and p -value from the Wilk-Shapiro test of 0.35.

Panel B of Table 3 provides the results from estimating Equation (5).¹⁹ We find the coefficient on *Size* is negative and statistically significant at the 5 percent level. This result is consistent with the hypothesis that larger firms have a smaller discrepancy between the risk measures and attributed to the economies of scale in hedging. Hence,

¹⁹ When firm size and leverage are measured using insurance-specific measures of net premium written and ratio of net premium written to policyholders' surplus, respectively, from the *Aggregate Reports*, we find qualitatively similar results.

TABLE 3
Panel Data Analysis of Firm Characteristics That Influence Differences in Betas

Panel A: Summary Statistics of Variables (Period 1970–2001)					Panel B: Panel Data Analysis Results	
	Mean	Median	Minimum	Maximum	Standard Deviation	
$ \beta - B $	0.0494	0.0377	0.0001	0.2197	0.0434	Intercept
Size	3.0395	2.8151	0.0277	7.7359	1.8326	Size
Leverage	0.7481	0.7738	0.1515	0.9744	0.1495	Leverage
Asymmetry	0.6983	0.5422	0.0056	3.2591	0.6593	Asymmetry
Nonnormality	0.3545	0.2789	0.0000	0.9936	0.3092	Nonnormality
						R^2
						N
						Coefficient Estimates (t-value)
						0.0197 (0.79)
						−0.0053 (−2.09**)
						0.0605 (1.91*)
						0.01315 (1.69*)
						−0.0194 (−1.2)
						0.1197
						97

Notes: Panel A reports the summary statistics for the variables used in the cross-sectional analysis. Panel B reports the results of the estimated using a random effects panel data model for insurers with firm-level data available in Compustat:

$$|\beta_i - B_i|_t = \alpha_0 + \alpha_1 Size_{i,t} + \alpha_2 Leverage_{i,t} + \alpha_3 Asymmetry_{i,t} + \alpha_4 Nonnormality_{i,t} + e_{i,t}$$

where $|\beta_i - B_i|_t$ is the absolute difference in risk estimates, $Size_{i,t}$ is the natural log of total assets divided by consumer price index (CPI), $Leverage_{i,t}$ is the ratio of total liabilities to total assets, $Asymmetry_{i,t}$ is the absolute value of skewness, and $Nonnormality_{i,t}$ is the p -value from the Wilk-Shapiro test of normality. T -values are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

larger insurers are able to mitigate the effects of extreme values of losses and achieve less asymmetrically distributed claims process and equity returns.

The *Leverage* factor is found to be positive and significant at the 10 percent level. This result is consistent with our conjecture that the differences in risk estimates can be attributed to the asymmetrical characteristics of liabilities of an insurer.

We find the coefficient on *Asymmetry* to be positive and statistically significant at the 10 percent level. This finding shows that the variation in the discrepancy between the CAPM and the RL model can be attributed to the degree of asymmetry. This result is consistent with the findings in Leland (1999). Lastly, the *Nonnormality* factor is not found to be significant, though the negative α_4 coefficient is consistent with expectation.

Performance Comparison of the RL Model, CAPM, and Co-Skewness Model

Both univariate and multivariate analyses provide the evidence that the absolute difference between the two risk estimates is larger for small insurers and insurers with larger degree of asymmetry of returns. In this section, we investigate whether those insurers mentioned above can benefit from employing the RL model over the CAPM by comparing model performance. In the illustrative examples, Leland (1999) uses the excess return (alpha) of the expected return over the respective models' return to measure the model "accuracy" or performance of the CAPM and the RL model defined as:

$$\alpha_p^{\text{Model}} = E(r_p | M) - E(r_p)^{\text{model}}, \quad (6)$$

where $E(r_p | M)$ is defined as an expected return to the portfolio conditioned by the information used by the manager and $E(r_p)^{\text{model}}$ is the return generated from the specified model.

Following the empirical technique employed in Leland (1999) we use the value of α from Equation (6) as our measurement of model accuracy to indicate how close the model return, $E(r_p)$, is to approaching to the return based on all available information, $E(r_p | M)$.²⁰ Smaller value of α suggests that the underlying model is comparatively more appropriate than the other models. Specifically, we compare the values of α of portfolios that are formed based on the degree of nonnormality, the degree of asymmetry, and firm size, respectively.

In addition to the CAPM and RL model, we evaluate a co-skewness model described by Chung, Johnson, and Schill (Forthcoming), in our comparisons. The co-skewness model includes the third-order co-moment in the CAPM and is written as:

$$E(r_i) = r_f + \beta_i [E(r_m) - r_f] + \beta_{i,skw} [E(r_m) - r_f]^2, \quad (7)$$

²⁰ Leland (1999) provides the details for the calculations of $E(r_p | M)$ and α .

where

$$\beta_{i,skw} = \frac{\sum_t (r_{it} - \bar{r}_i)(r_{mt} - \bar{r}_m)^2}{\sum_t (r_{mt} - \bar{r}_m)^3} \quad (8)$$

and $E(r_i)$, r_f , β_i , and $[E(r_m) - r_f]$ were previously defined in Equation (4)

Excess returns under the CAPM, the RL model, and the co-skewness model can be written as follows:

$$\alpha_p^{CAPM} = E(r_p/M) - [r_f + \beta_{CAPM} \times (E(r_m) - r_f)] \quad (9)$$

$$\alpha_p^{RL} = E(r_p/M) - [r_f + B_{RL} \times (E(r_m) - r_f)] \quad (10)$$

$$\alpha_p^{SKW} = E(r_p/M) - [r_f + \beta_{SKW} \times (E(r_m) - r_f)]. \quad (11)$$

Table 4 reports the values of excess returns under the RL model, the CAPM, and co-skewness model, respectively. Panel A displays the excess returns of the models based on period analysis—the full period of 1970–2001 as well as the seven subperiods. The major objective of this study is to evaluate whether smaller insurers and insurers with asymmetrical return can benefit from the use of the RL model. To this aim, Panels B, C, and D display the excess returns for the subsets of insurers based on the degree of normality, degree of skewness, and firm size, respectively.²¹

As reported in Panel A of Table 4, the performance comparison shows significant results in one subperiod, 1985–1989. Specifically, $\alpha_p^{CAPM} = 0.082$ percent is significantly larger than $\alpha_p^{RL} = 0.047$ percent at the 5 percent level. Finding the excess returns of RL to be statistically significantly different from those of CAPM in only one subperiod is not troublesome because this analysis uses the full sample. The full sample includes insurers with normally distributed and symmetrical returns, and large insurers. Thus, using the full sample, one may not necessarily always observe that the RL model outperforms the other two models. We anticipate that insurers with asymmetrically or nonnormally distributed returns and small insurers to benefit from using the RL model.

Panel B shows that the excess returns using the CAPM or the co-skewness model are either greater than or equal to those of the RL model, although none of the results are statistically significant.

²¹ In addition, we also test whether α values are significantly different from zero. For the period analysis, the values of α from the three models are significantly different from zero at the 1 percent level in the periods of 1995 to 1999. For the analysis based on firm size, the values of α from the three models are also significantly different from zero at the 1 percent level for the smallest firm portfolio that is the subset of insurers with asset values less than the first quartile asset value Q_1 .

TABLE 4
Performance Comparison Between the RL Model, CAPM, and Co-Skewness Model

Panel A: Portfolios of Insurers Based on Time Period

Period	No. of Insurers	Excess Return α^{CAPM}	Excess Return α^{SKW}	Excess Return α^{RL}
1970–2001	111	–0.034%	–0.066%	–0.041%
1970–1974	22	–1.463%	–1.538%	–1.412%
1975–1979	29	1.873%	1.872%	1.873%
1980–1984	27	0.551%	0.546%	0.551%
1985–1989	24	0.082%**	0.086%***	0.047%
1990–1994	35	–0.007%	–0.008%	–0.008%
1995–1999	56	–0.831%	–0.944%	–0.884%
2000–2001	56	–0.034%	–0.035%	–0.018%

Portfolios	No. of Insurers	Excess Return α^{CAPM}	Excess Return α^{SKW}	Excess Return α^{RL}
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Panel B: Portfolios of Insurers Based on Degree of Normality (1970–2001)

$p < 0.01$	47	1.21%	1.19%	1.19%
$p < 0.05$	60	1.11%	1.06%	1.06%
$p < 0.20$	69	0.95%	0.92%	0.93%
$0.01 < p$	64	0.47%	0.47%	0.46%
$0.05 < p$	51	0.39%	0.40%	0.39%
$0.20 < p$	42	0.28%	0.29%	0.27%

Panel C: Portfolios of Insurers Based on Degree of Symmetry (1970–2001)

$p < 0.01$	44	0.40%	0.40%	0.38%
$p < 0.05$	59	0.33%**	0.32%	0.30%
$0.01 < p$	67	0.90%	0.89%	0.90%
$0.05 < p$	52	0.92%	0.92%	0.92%

Panel D: Portfolios of Insurers Based on Quartile Value of Total Assets (1970–2001)

Assets < Q ₁	24	0.476%***	0.452%	0.393%
Assets < Q ₂ (median)	49	0.721%*	0.721%	0.684%
Assets < Q ₃	73	0.586%	0.593%	0.560%
Q ₁ < Assets	73	0.572%	0.576%	0.581%
Q ₂ (median) < Assets	48	0.378%	0.371%	0.386%
Q ₃ < Assets	24	0.435%	0.401%*	0.455%

Notes: The excess returns are reported for various portfolios based on time period in Panel A, based on degree of normality in Panel B, based on degree of symmetry in Panel C, and based on total assets in Panel D. The excess return is defined as $\alpha_p^{\text{Model}} = E(r_p | M) - E(r_p)^{\text{model}}$, where $E(r_p | M)$ is defined as an expected return to the portfolio conditioned by the information used by the manager and $E(r_p)^{\text{model}}$ is the return generated from the specified model—the CAPM, the co-skewness model, or the RL model. The p -value of the Shapiro-Wilk statistic is used to form portfolios based on degree of normality using significance levels of 1%, 5%, and 20% as benchmarks. We form portfolios on the basis of degree of symmetry on the basis of statistically significant skewness at the 1% and 5% levels. The portfolios on the basis of firm size are formed using quartile value of total assets. ***, **, and * indicate that the excess returns from the CAPM (co-skewness model) are significant larger than the RL model at the 1%, 5%, and 10% levels, respectively.

The results from Panel C show that the measure of excess return, α , is significantly statistically smaller in the RL model compared to the CAPM and the co-skewness model in the case where the portfolios are formed based on the significance of asymmetry at the 5 percent level, but the economic significance is limited. More specifically, we find that $\alpha_p^{CAPM} = 0.33$ percent, $\alpha_p^{SKW} = 0.32$ percent, and $\alpha_p^{RL} = 0.30$ percent.

The discrepancy in performance is quite strong when the portfolios are formed based on firm size. As shown in Panel D, for the portfolio of insurers with assets $< Q_1$ (i.e., the smallest firm portfolio), α_p^{CAPM} (0.476 percent) is significantly larger than α_p^{RL} (0.393 percent) at the 1 percent level. In addition, for the portfolio of insurers with assets $< Q_2$, α_p^{CAPM} (0.721 percent) is also significantly larger than α_p^{RL} (0.684 percent).

The above results support our argument that the use of RL model is more appropriate than the CAPM or the co-skewness model for smaller insurers and for insurers with asymmetrical returns.

CONCLUSIONS

This study evaluates the applicability of the RL model for estimating the cost of equity for a sample of publicly traded P/L insurers over the period of 1970–2001. Given the potential for nonnormally distributed equity returns in the insurance industry, the RL model is in principle more appropriate than the CAPM, which thus far has been the predominant asset pricing model applied to insurance companies.

We empirically test whether the RL model is more appropriate than the CAPM. The evidence indicates that there are significant differences in the market risk estimates between these two models over the 1980–1984, 1985–1989, and 1990–1994 subperiods, when all insurers are included in the full sample. We also find the estimates of risk measures are significantly different for insurers with returns that strongly depart from the normal distribution, with returns that are not symmetrical, and for small insurers.

We also conduct multivariate analyses by using random effect panel data models. The evidence shows that smaller insurers and insurers with asymmetrical returns have larger discrepancy in risk estimates between the two models. Moreover, performance comparisons between the RL model, CAPM, and co-skewness model show that the excess returns are significantly smaller for the RL model compared to those of the CAPM and co-skewness model for a portfolio of insurers with returns that are asymmetric and for a portfolio of small insurers.

The results of our study provide some important implications. It may be appropriate to estimate the beta and cost of capital using the CAPM when an insurer is large and its returns are symmetrical. The implication is that insurers should use the RL model rather than the CAPM to estimate its cost of capital if the insurer is small (assets size is less than \$2,291 million), and / or its returns are not symmetrical (the value of skewness is greater than 0.509 or less than -0.509).

APPENDIX

TABLE A1

Summary of Estimates of Risk (β , B), and Differences in Risk ($\beta - B$) and in Costs of Equities ($|E(R_i^{CAPM}) - E(R_i^{RL})|$): The Sensitivity of Parameter Estimates Under Different Scenarios of Risk Aversion Parameter, b

Panel A: $b = 1$

Period	Number of Insurers	Mean β	Mean B	Paired t -test $\beta = B$	Mean $ \beta - B $	Median $(\beta - B)$	Mean $ \Delta E(R_i) $
1970–2001	111	0.696	0.699	−1.25	0.027	0.0192	0.13%
1970–1974	22	0.982	0.965	1.22	0.0510	0.0391	0.26%
1975–1979	29	0.804	0.811	−1.25	0.0240	0.0230	0.12%
1980–1984	27	0.888	0.905	−2.55	0.0303	0.0223	0.15%
1985–1989	24	0.665	0.680	−2.30	0.0297	0.0254	0.15%
1990–1994	35	0.770	0.777	−1.88	0.0169	0.0125	0.08%
1995–1999	56	0.607	0.612	−1.47	0.0192	0.0137	0.10%
2000–2001	56	0.490	0.484	1.11	0.0293	0.0212	0.15%

Period	Number of Insurers	$\bar{\beta}$	$\bar{B}$	Paired t -test $\beta = B$	Mean $ \beta - B $	Median $ \beta - B $	Mean $ \Delta E(R_i) $
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Panel B: $b = 4$

1970–2001	111	0.696	0.705	−1.59	0.0663	0.0479	0.33%
1970–1974	22	0.982	0.936	1.38	0.1215	0.0963	0.61%
1975–1979	29	0.804	0.824	−1.44	0.0593	0.0604	0.30%
1980–1984	27	0.888	0.931	−2.59	0.0747	0.0561	0.37%
1985–1989	24	0.665	0.705	−2.34	0.0766	0.0649	0.38%
1990–1994	35	0.770	0.787	−1.83	0.0418	0.0315	0.21%
1995–1999	56	0.607	0.621	−1.54	0.0493	0.0352	0.25%
2000–2001	56	0.490	0.476	1.02	0.0723	0.0524	0.36%

Panel C: $b = 10$

1970–2001	111	0.696	0.718	−1.75	0.1419	0.1003	0.71%
1970–1974	22	0.982	0.871	1.70	0.2343	0.1686	1.17%
1975–1979	29	0.804	0.857	−1.79	0.1282	0.1313	0.64%
1980–1984	27	0.888	0.983	−2.71	0.1580	0.1228	0.79%
1985–1989	24	0.665	0.758	−2.46	0.1709	0.1566	0.85%
1990–1994	35	0.770	0.803	−1.69	0.0887	0.0676	0.44%
1995–1999	56	0.607	0.641	−1.68	0.1132	0.0798	0.57%
2000–2001	56	0.490	0.464	0.88	0.1545	0.1068	0.77%

Notes: Table displays the effects of risk aversion parameters (b) on the estimates of equity costs from the RL model ($E(R_i^{RL})$) and the CAPM ($E(R_i^{CAPM})$), and their difference ($\Delta E(R_i) = E(R_i^{CAPM}) - E(R_i^{RL})$), and $|\Delta E(R_i)| = |E(R_i^{CAPM}) - E(R_i^{RL})|$ by assuming 3% as the risk-free rate and 5% as the market risk premium. The values of b are specified as 1, 4, and 10. The estimation equations are:

The RL model: $E(R_i^{RL}) = r_f + B_Q[E(r_m) - r_f]$, where $E(R_i^{RL})$ = the required return for equity under the RL model, r_f = the risk-free rate = 3%, B_Q is the risk estimate from the RL model, $B_Q = \frac{\text{Cov}[r_Q, -(1+r_m)^{-b}]}{\text{Cov}[r_m, -(1+r_m)^{-b}]}$, and $E(r_m) - r_f$ = the market risk premium = 5%, $b = 1, 4$, and 10.

The CAPM: $E(R_i^{CAPM}) = r_f + \beta_Q[E(r_m) - r_f]$, where $E(R_i^{CAPM})$ = the required return for equity under the CAPM, and β_Q is the risk estimate from the CAPM, $\beta_Q = \frac{\text{Cov}(r_Q, r_m)}{\text{Var}(r_m)}$. $|\Delta E(R_i)| = |E(R_i^{CAPM}) - E(R_i^{RL})|$. As one expected, the estimates from the CAPM are insensitive to the change of b value.

TABLE A.2
Cost of Equity From CAPM and RL Model

Period	Number of Insurers	Panel A: $r_f = 3\%$, $E(r_m) - r_f = 5\%$				Panel B: $r_f = 6\%$, $E(r_m) - r_f = 4\%$			
		$E(R_i^{CAPM})$	$E(R_i^{RL})$	Mean $\Delta E(R_i)$	Mean $ \Delta E(R_i) $	$E(R_i^{CAPM})$	$E(R_i^{RL})$	Mean $\Delta E(R_i)$	Mean $ \Delta E(R_i) $
Panel A: $b = 1$									
1970–2001	111	6.48%	6.50%	−0.02%	0.13%	8.78%	8.80%	−0.01%	0.11%
1970–1974	22	7.91%	7.82%	0.08%	0.26%	9.93%	9.86%	0.07%	0.20%
1975–1979	29	7.02%	7.06%	−0.04%	0.12%	9.22%	9.25%	−0.03%	0.10%
1980–1984	27	7.44%	7.53%	−0.09%	0.15%	9.55%	9.62%	−0.07%	0.12%
1985–1989	24	6.32%	6.40%	−0.08%	0.15%	8.66%	8.72%	−0.06%	0.12%
1990–1994	35	6.85%	6.89%	−0.03%	0.08%	9.08%	9.11%	−0.03%	0.07%
1995–1999	56	6.04%	6.06%	−0.02%	0.10%	8.43%	8.45%	−0.02%	0.08%
2000–2001	56	5.45%	5.42%	0.03%	0.15%	7.96%	7.94%	0.03%	0.12%
Panel B: $b = 4$									
1970–2001	111	6.48%	6.52%	−0.05%	0.33%	8.78%	8.82%	−0.04%	0.27%
1970–1974	22	7.91%	7.68%	0.23%	0.61%	9.93%	9.74%	0.18%	0.49%
1975–1979	29	7.02%	7.12%	−0.10%	0.30%	9.22%	9.30%	−0.08%	0.24%
1980–1984	27	7.44%	7.66%	−0.22%	0.37%	9.55%	9.73%	−0.17%	0.30%
1985–1989	24	6.32%	6.53%	−0.20%	0.38%	8.66%	8.82%	−0.16%	0.31%
1990–1994	35	6.85%	6.93%	−0.08%	0.21%	9.08%	9.15%	−0.07%	0.17%
1995–1999	56	6.04%	6.10%	−0.07%	0.25%	8.43%	8.48%	−0.05%	0.20%
2000–2001	56	5.45%	5.38%	0.07%	0.36%	7.96%	7.90%	0.06%	0.29%
Panel C: $b = 10$									
1970–2001	111	6.48%	6.59%	−0.11%	0.71%	8.78%	8.87%	−0.09%	0.57%
1970–1974	22	7.91%	7.36%	0.55%	1.17%	9.93%	9.48%	0.44%	0.94%
1975–1979	29	7.02%	7.29%	−0.27%	0.64%	9.22%	9.43%	−0.21%	0.51%
1980–1984	27	7.44%	7.92%	−0.47%	0.79%	9.55%	9.93%	−0.38%	0.63%
1985–1989	24	6.32%	6.79%	−0.46%	0.85%	8.66%	9.03%	−0.37%	0.68%
1990–1994	35	6.85%	7.02%	−0.17%	0.44%	9.08%	9.21%	−0.13%	0.35%
1995–1999	56	6.04%	6.20%	−0.17%	0.57%	8.43%	8.56%	−0.13%	0.45%
2000–2001	56	5.45%	5.32%	0.13%	0.77%	7.96%	7.85%	0.11%	0.62%

Notes: Table displays the estimates of equity costs from the RL model ($E(R_i^{RL})$) and the CAPM ($E(R_i^{CAPM})$), and their difference ($\Delta E(R_i) = E(R_i^{CAPM}) - E(R_i^{RL})$, and $|\Delta E(R_i)| = |E(R_i^{CAPM}) - E(R_i^{RL})|$) under different scenarios of risk aversion parameters ($b = 1, 4$, and 10) and two scenarios of risk-free rate ($r_f = 3\%$ and 6%) and market risk premium ($E(r_m) - r_f = 5\%$ and 4%). The estimation equations are:

The RL model: $E(R_i^{RL}) = r_f + B_Q[E(r_m) - r_f]$, where $E(R_i^{RL})$ = the required return for equity under the RL model, B_Q is the risk estimate from the RL model, $B_Q = \frac{\text{Cov}[r_{Q,-(1+r_m)^{-b}}]}{\text{Cov}[r_{m,-(1+r_m)^{-b}]}$.

The CAPM: $E(R_i^{CAPM}) = r_f + \beta_Q[E(r_m) - r_f]$, where $E(R_i^{CAPM})$ = the required return for equity under the CAPM, and β_Q is the risk estimate from the CAPM, $\beta_Q = \frac{\text{Cov}(r_Q, r_m)}{\text{Var}(r_m)}$.

Panel A of each table presents the results by assuming $r_f = 3\%$ and $E(r_m) - r_f$ = the market risk premium = 5% , and Panel B shows the results by assuming $r_f = 6\%$ and $E(r_m) - r_f$ = the market risk premium = 4% .

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