On the Use of Stock Index Returns from Economic Scenario Generators in ERM Modeling

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Abstract

The modeling of insurance company enterprise risks requires correlated forecasts of the future values of various economic variables. These forecasts, especially as they pertain to interest rates, inflation, stock market performance and other economic variables needed for asset modeling, are typically obtained from an economic scenario generator (ESG). With respect to stock market performance, third-party ESGs generally provide forecast returns for various market indexes; the output is not tailored to reflect an insurer's own equity portfolio composition. For that reason, ESG stock return scenarios cannot be used for insurer ERM modeling without adjustment to reflect the insurer's own equity portfolio composition and idiosyncratic risk. This paper describes two methods for making the necessary adjustment to the ESG market return scenarios based on the assumption of normally-distributed 1) arithmetic returns, and 2) logarithmic returns.

Keywords. CAPM; correlated sampling; economic scenario generator; enterprise risk management; stochastic modeling.

1. INTRODUCTION

An economic scenario generator (ESG) produces a set of future scenarios for the values of economic and investment variables. The scenarios, typically stochastically generated, are intended to be mutually coherent, meaning that they reflect realistic dependencies and correlations among the modeled variables. The list of modeled variables from commercial ESGs is extensive; the key variables for risk modeling in non-life insurance include interest rate term structures, credit spreads, inflation, equity returns and other economic variables of interest to insurers. For a general overview of economic scenario generators, see Ahlgrim, D'Arcy and Gorvett [1].

The sole focus of this paper is on ESG *equity return* scenarios and how to use them appropriately in insurance company enterprise risk management (ERM) stochastic modeling. The future equity returns modeled by an ESG generally pertain to one or more stock market indexes representing the broad market, e.g., the S&P 500 in the U.S. and comparable international indexes elsewhere. ESG data sets are not typically tailored to reflect an insurer's own equity portfolio composition.

If an insurer holds a common stock portfolio that exactly matches one of the equity indexes for which an ESG provides modeled future market returns, then the ESG output can be used without adjustment to model the risk and return of the insurer's own portfolio. However, unless the insurer invests solely in index funds, it is unlikely that the match would be exact.

In the more likely case in which the insurer's portfolio deviates from the ESG's index portfolio, the ESG returns must be adjusted to reflect the characteristics of the insurer's own equity portfolio before they can be used to model the risk in that portfolio.

2. ADJUSTING ESG EQUITY RETURNS TO REFLECT INSURER PORTFOLIO CHARACTERISTICS

One method for making the necessary adjustment to ESG equity return output is based on the Capital Asset Pricing Model (CAPM),[1] which expresses the expected return $E(r_i)$ on capital asset i (in our case the insurer's equity portfolio) as a function of the risk-free return r_f, the expected market return $E(r_M)$ and a factor β_{iM} (known as "beta"):

$$E(r_i) = r_f + \beta_{iM} \cdot (E(r_M) - r_f), \tag{2.1}$$

where

$$\beta_{iM} = \frac{\sigma_{iM}}{\sigma_M^2} = \rho_{iM} \cdot \frac{\sigma_i}{\sigma_M}, \tag{2.2}$$

and σ_{iM} and ρ_{iM} are, respectively, the covariance and correlation coefficient of the portfolio return with the market return, σ_M is the standard deviation of the market return and σ_i is the standard deviation of the portfolio return.[2]

β_{iM} is frequently described, especially in the non-academic press, as a measure of the volatility of a portfolio relative to the market. For example, according to the Bloomberg terminal guide posted on numerous university websites (and widely echoed elsewhere),

> You can think of beta as the tendency of a security's returns to respond to swings in the market. For example, if a stock's beta is 1.2, then it is theoretically 20% more volatile than the market.[3]

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[1] While there is much criticism of the validity of CAPM, there is also widespread acceptance among and active use by financial professionals. See the CAPM discussion in Bodie, Kane and Marcus [2], particularly pp. 299-300.

[2] Strictly speaking, these should all be defined with respect to the market and portfolio returns *excess* of the risk-free rate, but they are generally expressed in terms of the total rather than excess returns. The origin of that convention is probably due to the fact that, if r_f is a constant, then there is no difference. That is not true if r_f is regarded as variable, but in most practical situations the difference is likely to be too small to matter.

[3] Excerpt from the Bloomberg Guide posted on the Brigham Young University website at the following link: http://guides.lib.byu.edu/content.php?pid=53518&sid=401576. The same language also appears on a number of other university websites, all of which appear to license the Bloomberg terminal. Similar language is widely used elsewhere. See, for example, http://www.thestreet.com/topic/46048/beta.html.

2.1 Using $\boldsymbol{\beta_{iM}}$ to Adjust ESG Market Returns – An Incomplete Solution

Given the conception of β_{iM} as a measure of volatility as expressed at the end of the previous section, it is tempting to model portfolio returns excess of the risk-free rate by simply multiplying the excess portion of the market return $\hat{r}_M$ obtained from the ESG by the portfolio beta β_{iM}:

$$\hat{r}_i - r_f = \beta_{iM} \cdot (\hat{r}_M - r_f), \tag{2.3}$$

where $\hat{r}_i$ represents the modeled portfolio total return, the idea being that the resulting $\hat{r}_i$ values would be used to represent the insurer's equity returns in its ERM modeling .

However, *that would be wrong*, at least if one stopped there. Despite Bloomberg's description, β_{iM} does not fully capture the volatility of the portfolio return, which is *actually* given by σ_i. What β_{iM} captures is only the portion of volatility that is correlated with the market. To see this, consider the following.

The standard deviation of the modeled portfolio excess return from Formula (2.3) is:

$$\sigma(\hat{r}_i - r_f) = |\beta_{iM}| \cdot \sigma(\hat{r}_M - r_f), \tag{2.4}$$

which, if we treat r_f as a constant, simplifies to

$$\begin{aligned} \sigma(\hat{r}_i) &= |\beta_{iM}| \cdot \sigma_M \\ &= \left|\rho_{iM} \cdot \frac{\sigma_i}{\sigma_M}\right| \cdot \sigma_M \\ &= |\rho_{iM}| \cdot \sigma_i. \end{aligned} \tag{2.5}$$

Formula (2.5) shows that using Formula (2.3) to model portfolio returns by simply multiplying the ESG market excess returns by β_{iM} and adding back the risk-free rate results in the understatement of portfolio return volatility whenever $|\rho_{iM}| < 1$.

To illustrate the consequences for ERM modeling, consider the following scenario in which $r_f = 3\%$, $E(r_M) = 7\%$, $\beta_{iM} = 0.9$, $\rho_{iM} = 0.8$, $\sigma_M = 20\%$ and $\sigma_i = 22.5\%$. In this scenario Formula (2.3) implies an expected portfolio return $E(r_i)$ of 6.6%. If equity returns are normally distributed, the one-year portfolio value-at-risk (VaR) at the 99.5% level is given by:[4]

$$VaR(r_i)_{0.995} = -(E(r_i) + N^{-1}(0.005) \cdot \sigma_i) \tag{2.6}$$

$$= -(6.6\% - 2.576 \cdot 22.5\%)$$

$$= 51.36\%$$

In contrast, if we were to model the portfolio returns according to Formula (2.3), the value of σ_i would be replaced by $|\rho_{iM}| \cdot \sigma_i$ and the calculated $VaR(r_i)_{0.995}$ would be only 39.77%, which is 11.59 points (or nearly one-quarter) *lower than the correct amount*.

2.2 Using $\boldsymbol{\beta_{iM}}$ to Adjust ESG Market Returns – More Complete Solution

It is possible to repair the erroneous Formula (2.3) by adding an independent error term ϵ_i with a mean of zero that reflects the portfolio's idiosyncratic risk, i.e., the extent to which it displays additional variation not explained by market movements:

$$\hat{r}_i - r_f = \beta_{iM} \cdot (\hat{r}_M - r_f) + \epsilon_i, \tag{2.7}$$

in which case the corrected formula for the portfolio total return is then given by:

$$\hat{r}_i = r_f + \beta_{iM} \cdot (\hat{r}_M - r_f) + \epsilon_i. \tag{2.8}$$

In order for the required relationship of $\sigma(\hat{r}_i) = \sigma_i$ to hold, the standard deviation of the error term $\sigma(\epsilon_i)$ must be:

$$\sigma(\epsilon_i) = \sqrt{1 - \rho_{iM}^2} \cdot \sigma_i. \tag{2.9}$$

Under these conditions, and again treating r_f as a constant, the standard deviation of the modeled portfolio return $\sigma(\hat{r}_i)$ consistent with Formula (2.8) now matches σ_i as required:

$$\sigma(\hat{r}_i) = \sqrt{0^2 + |\rho_{iM}|^2 \cdot {\sigma_i}^2 + (1 - \rho_{iM}^2) \cdot {\sigma_i}^2}$$

$$= \sqrt{{\rho_{iM}}^2 + (1 - \rho_{iM}^2)} \cdot \sigma_i = \sigma_i.$$

[4] Value-at-risk is a downside risk measure. VaR amounts are generally shown as positive numbers even though they signify losses. For that reason, in Formula (2.6) we must change the sign on the 0.5th percentile result from the return distribution (in which losses are negative numbers). The 99.5th percentile of the resulting distribution is $VaR(r_i)_{0.995}$.

2.2.1 Normal arithmetic return assumption

Let's assume that equity returns r_M and r_i as well as the error term ϵ_i in Formula (2.8) all are normally distributed, and that r_M is modeled accordingly within the ESG.

Then, given a value of $\hat{r}_M$ drawn from the ESG, we can generate a related portfolio return $\hat{r}_i$ as follows:

$$\hat{r}_i = r_f + \beta_{iM} \cdot \left(\hat{r}_M - r_f\right) + z \cdot \sqrt{1 - \rho_{iM}^2} \cdot \sigma_i, \tag{2.10}$$

where z represents a random draw from the standard normal distribution.

To illustrate the application of Formula (2.10), let's again assume the risk-free rate $r_f = 3\%$, $\beta_{iM} = 0.9$, $\rho_{iM} = 0.8$ and $\sigma_i = 22.5\%$. Under those conditions Formula (2.10) simplifies to:

$$\hat{r}_i = 3\% + 0.9 \cdot (\hat{r}_M - 3\%) + 0.135 \cdot z. \tag{2.11}$$

Next, we obtain a market return value $\hat{r}_M$ from the ESG and randomly draw a standard normal random number z. Let's say $\hat{r}_M = 12\%$ and $z = -0.8416$. Then Formula (2.11) yields:

$$\hat{r}_i = 11.10\% + 0.135 \cdot (-0.8416)$$

$$= -0.26\%.$$

A different draw of z would, of course, result in a different value of $\hat{r}_i$. For example, if $\hat{r}_M = 12\%$ and $z = 0.4823$, Formula (2.11) yields:

$$\hat{r}_i = 11.10\% + 0.135 \cdot (0.4823)$$

$$= 17.61\%.$$

Note that Formula (2.10) requires little explicit information about the ESG's market return random variable r_M. All that is needed from the ESG is the market return observation $\hat{r}_M$. For further insight into Formula (2.10), see Section (A.1) of the Appendix.

2.2.2 Normal logarithmic return assumption

As an alternative to the assumption that arithmetic equity returns are normally distributed, market practitioners sometimes use a lognormal model in which *logarithmic* returns (or excess returns) are normally distributed. If the arithmetic market return, for example, is $\hat{r}_M$, the corresponding logarithmic return is given by the expression $\ln(1+\hat{r}_M)$. In a lognormal return model, $\ln(1+r_M)$ is normally distributed, but r_M is not.

If we replace the arithmetic excess returns in Formula (2.10) with the corresponding logarithmic returns and the arithmetic return standard deviation σ_i with the standard deviation of the logarithmic return $\sigma_i(LN)$, and then isolate $\hat{r}_i$, we obtain:[5] [6]

$$\ln\left(1+\hat{r}_i-r_f\right)=\beta_{iM}\cdot\left(1+\hat{r}_M-r_f\right)+z\cdot\sqrt{1-\rho_{iM}^2}\cdot\sigma_i(LN), \qquad (2.12)$$

$$\hat{r}_i=r_f+\exp\left(\beta_{iM}\cdot\ln\left(1+\hat{r}_M-r_f\right)+z\cdot\sqrt{1-\rho_{iM}^2}\cdot\sigma_i(LN)\right)-1 \qquad (2.13)$$

For additional insight into Formula (2.13), see Section (A.2) of the Appendix.

We illustrate the application of Formula (2.13) using the same values for r_f, β_{iM}, ρ_{iM} and σ_i assumed in Section 2.2.1, which together imply a value for the lognormal sigma parameter $\sigma_i(LN)$ of 21.47%. Given the same ESG market return of $\hat{r}_M=12\%$ and the same $z=-0.8416$, the lognormal model yields a slightly different value for the portfolio return $\hat{r}_i$ of -0.04% (vs. -0.26%):[7]

$$\hat{r}_i=3\%+\exp(0.9\cdot\ln(1.09)+(-0.8416)\cdot(0.6)\cdot(21.47\%))-1$$

$$\hat{r}_i=3\%+\exp(7.755\%-10.841\%)-1$$

$$=-0.04\%.$$

For the second draw of $z=0.4823$ used in Section 2.2.1, with everything else being equal, Formula (2.12) produces the following value of $\hat{r}_i$:

$$\hat{r}_i=3\%+\exp(7.755\%+6.213\%)-1$$

$$=17.99\%.$$

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[5] As a first step the r_f term is moved from the right side to the left side of the equal sign in Formula (2.10).

[6] $\sigma_i(LN)=\text{sqrt}[\ln(CV^2+1)]$, where $CV=\sigma_i/\left(1+E(r_i)-r_f\right)$ refers to the coefficient of variation. Strictly speaking, the values of β_{iM}, ρ_{iM} should also be recalculated, but the differences are typically small and thus we omit that step from our illustration.

[7] The insurer's ERM team must make a decision about whether the normal or lognormal return model is more appropriate, in light of what is known about the characteristics of the ESG's market equity return distribution.

3. SUMMARY

In this paper we have demonstrated that ESG data as it pertains to equity market index returns cannot be used without adjustment in the modeling of an insurer's enterprise risks, except in that rare instance in which the insurer only invests in equity indexes. Having identified that problem, we have described two methods for making the necessary adjustment, one based on the assumption that arithmetic equity returns are normally-distributed and the other based on the assumption that logarithmic equity returns are normally distributed. The decision about which, if any, of these two methods is most appropriate depends on the distributional assumptions underlying the ESG supplying the market return scenarios.

APPENDIX

A.1 Normal Arithmetic Return Model – Additional Information

If we assume that the excess return $r_M - r_f$ is normally distributed with mean:

$$\mu_{MX} = E(r_M) - r_f, \tag{A.1}$$

and standard deviation σ_M, then the market return scenario $\hat{r}_M$ can be expressed as a function of the standard normal random number z_1 corresponding to that scenario:

$$\hat{r}_M = r_f + \mu_{MX} + \sigma_M \cdot z_1, \tag{A.2}$$

and Formula (2.10) from Section 2.2.1 can be restated in terms of independent standard normal random numbers z_1 and z_2 (where z_2 is the same as the z in Formula (2.10) but now with a subscript to distinguish it better from z_1):

$$\hat{r}_i = r_f + \beta_{iM} \cdot (\mu_{MX} + z_1.\sigma_M) + z_2 \cdot \sqrt{1 - \rho_{iM}^2} \cdot \sigma_i,$$

$$= r_f + \beta_{iM} \cdot \mu_{MX} + z_1 \cdot \rho_{iM} \cdot \sigma_i + z_2 \cdot \sqrt{1 - \rho_{iM}^2} \cdot \sigma_i. \tag{A.3}$$

We can write Formula (A.3) more succinctly as:

$$\hat{r}_i = r_f + \mu_{iX} + z_2^* \cdot \sigma_i, \tag{A.4}$$

where

$$z_2^* = z_1 \cdot \rho_{iM} + z_2 \cdot \sqrt{1 - \rho_{iM}^2}, \tag{A.5}$$

is a standard normal random number correlated with z_1,[8] and

$$\mu_{iX} = \beta_{iM} \cdot \mu_{MX}. \tag{A.6}$$

Circling back to the illustration in Section 2.2.1, let's assume the mean market excess return embedded in the ESG is $\mu_{MX} = 4\%$. From our other assumptions we can infer $\sigma_M = 20\%$ by using Formula (2.2). Then, given ESG market return scenario $\hat{r}_M = 12\%$, we can use Formula (A.3) to solve for the corresponding value of z_1:

$$\begin{aligned} z_1 &= \frac{(\hat{r}_M - r_f) - \mu_{MX}}{\sigma_M} \\ &= \frac{9\% - 4\%}{20\%} \\ &= 0.25. \end{aligned} \tag{A.7}$$

Given $z_2 = -0.8416$, we can first use Formula (A.5) to obtain the value of z_2^*=0.0864 and then Formula (A.4) to calculate the portfolio return $\hat{r}_i = -0.26\%$ (matching the result in Section 2.2.1) as follows:

$$z_2^* = 0.25 \cdot 0.8 + (-0.8416) \cdot 0.6$$

$$= -0.3050.$$

$$\hat{r}_i = 6.6\% + (-0.3050) \cdot 22.5\%$$

$$= -0.26\%.$$

As we have just illustrated, Formula (A.4), like Formula (2.10), gives us the means to generate the correlated portfolio return $\hat{r}_i$ in cases where we have already obtained the $\hat{r}_M$ scenario from the ESG. However, Formula (A.4) has the further advantage that it can address circumstances in which we do not yet have a known value of $\hat{r}_M$ as well as cases in which we simply prefer to sample from both of the market and portfolio return

[8] For a complete discussion of correlated sampling of two or more standard normal random variables, see Rubenstein [3] (pp. 65-67), which rests on the use of the Cholesky decomposition of the correlation or covariance matrix to transform a set of independent standard normal random numbers into a set of correlated normal random numbers (which might be *standard* normal or not, depending on whether the correlation or covariance matrix is used).

distributions simultaneously. By randomly selecting independent standard normal random numbers z_1 and z_2, and computing z_2^*, we can then obtain correlated random observations $\hat{r}_M$ and $\hat{r}_i$.

For example, if we draw $z_1 = 0.4309$ and $z_2 = -0.3572$, which together with $\rho_{iM} = 0.8$ imply z_2^*=0.1304, we can use Formulas (A.2) and (A.4) to obtain the following values for $\hat{r}_M$ and $\hat{r}_i$, respectively:

$$\hat{r}_M = 3\% + 4\% + 0.4309 \cdot 20\%$$

$$= 15.62\%.$$

$$\hat{r}_i = 3\% + 3.6\% + 0.1304 \cdot 22.5\%$$

$$= 9.53\%.$$

A.2 Normal Logarithmic Return Model – Additional Information

If the ESG equity returns are based on a logarithmic return model, then the market return scenario $\hat{r}_M$ can be expressed as:

$$\hat{r}_M = r_f + \exp\big(\mu_{MX}(LN) + z_1 \cdot \sigma_M(LN)\big) - 1, \qquad (A.8)$$

where $\mu_{MX}(LN)$ and $\sigma_M(LN)$ are the mean and standard deviation, respectively, of the logarithmic excess market return $\ln(1 + \hat{r}_M - r_f)$, and z_1 is a random draw from the standard normal distribution.

The argument of the exponential function in Formula (A.8) can be expressed as the natural logarithm of the accumulated value of the market excess return:

$$\mu_{MX}(LN) + z_1 \cdot \sigma_M(LN) = \ln(1 + \hat{r}_M - r_f) \qquad (A.9)$$

If, in Formula (2.13), we substitute the expression on the left side of Formula (A.9) for the expression $\ln(1 + \hat{r}_M - r_f)$, we see that the portfolio return $\hat{r}_i$ can then be modeled as:

$$\hat{r}_i = r_f + \exp\left(\beta_{iM} \cdot (\mu_{MX}(LN) + z_1 \cdot \sigma_M(LN)) + z_2 \cdot \sqrt{1 - \rho_{iM}^2} \cdot \sigma_i\right) - 1$$

$$= r_f + \exp\left(\mu_{iX}(LN) + z_1 \cdot \rho_{iM} \cdot \sigma_i(LN) + z_2 \cdot \sqrt{1 - \rho_{iM}^2} \cdot \sigma_i\right) - 1, \qquad (A.10)$$

$$\hat{r}_i = r_f + \exp\left(\mu_{iX}(LN) + z_2^* \cdot \sigma_i(LN)\right) - 1, \qquad (A.11)$$

where $\mu_{iX}(LN) = \ln\left(1 + E(r_i) - r_f\right) - 0.5 \cdot \sigma_i(LN)^2$ and z_2^* defined by Formula (A.5).

Formula (A.11), like Formula (2.13), supports correlated sampling of r_i in cases where we have already obtained the $\hat{r}_M$ scenario from the ESG. In addition, however, Formula (A.11) has the feature that it can address cases in which we do not already know $\hat{r}_M$ as well as those situations in which we prefer to sample from both of the market and portfolio return distributions simultaneously. By randomly selecting numbers z_1 and z_2, and computing z_2^* using Formula (A.5), we can then obtain correlated random observations $\hat{r}_M$ and $\hat{r}_i$ using Formulas (A.8) and (A.11).

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Abbreviations and Notations

β_{iM}	CAPM beta of portfolio *i* with respect to the market index *M* .
CAPM	Capital Asset Pricing Model.
ϵ_i	Random variable for an independent error term reflecting the idiosyncratic variability of the return on portfolio *i*.
ERM	Enterprise risk management.
ESG	Economic scenario generator.
μ_{iX}	Mean of arithmetic portfolio *i* return excess of risk-free rate: $E(r_i - r_f)$; mu parameter of normal distribution of arithmetic (excess) portfolio *i* return.
μ_{MX}	Mean of arithmetic market index *M* return excess of risk-free rate: $E(r_M - r_f)$; mu parameter of normal distribution of arithmetic (excess) market index *M* return.
$\mu_{iX}(LN)$	Mean of logarithmic portfolio *i* return excess of risk-free rate: $E(\ln(r_i - r_f))$; mu parameter of the lognormal distribution of logarithmic (excess) portfolio return.
$\mu_{MX}(LN)$	Mean of logarithmic market index *M* return excess of risk-free rate: $E(\ln(r_M - r_f))$; mu parameter of the lognormal distribution of logarithmic (excess) market return.
$N^{-1}(z)$	Inverse distribution function of the standard normal distribution evaluated at *z*, where *z* is a standard normal number.
r_f	Risk-free rate of return, treated as a constant.
r_i	Random variable representing the arithmetic return on portfolio *i.*
$\hat{r}_i$	One modeled or observed arithmetic return on portfolio *i*
r_M	Random variable representing the arithmetic return on market index *M.*

$\hat{r}_M$	One modeled or observed arithmetic return on market index *M.*
ρ_{iM}	Correlation coefficient between portfolio *i* and market index *M* returns.
σ_{iM}	Covariance between portfolio *i* and market index *M* equity returns.
σ_i	Standard deviation of r_i; sigma parameter of normal distribution of arithmetic portfolio *i* return.
$\sigma(\epsilon_i)$	Standard deviation of the idiosyncratic portion of the arithmetic return on portfolio *i*.
$\sigma_i(LN)$	Standard deviation of portfolio *i* logarithmic return; sigma parameter of the lognormal distribution of logarithmic portfolio *i* return.
σ_M	Standard deviation of r_M; sigma parameter of normal distribution of arithmetic market index *M* return.
$\sigma_M(LN)$	Standard deviation of market index *M* logarithmic return; sigma parameter of the lognormal distribution of logarithmic market index *M* return.
$VaR(r_i)_{0.995}$	Value-at-risk of portfolio *i* return at the 99.5th percentile, where negative returns are expressed as positive numbers. It corresponds to the 0.5th percentile of the unadjusted return distribution multiplied by -1.
z	A standard normal random number; sometimes given with a subscript (z_1 and z_2).
z_2^*	A standard normal random number correlated with z_1; determined from a pair of independent standard normal random numbers and a correlation coefficient.

Biography of the Author

Michael G. Wacek is Executive Vice President and Chief Risk Officer of Odyssey Re Holdings Corp., based in Stamford, CT. Over the course of more than 35 years in the insurance / reinsurance industry, including nine years in the London Market, he has seen the business from the vantage point of a primary insurer, reinsurance broker and reinsurer in actuarial, underwriting, risk management and executive management roles. He has a BA from Macalester College (Math, Economics), is a Fellow of the Casualty Actuarial Society, a Chartered Enterprise Risk Analyst and a member of the American Academy of Actuaries. He is the author of a number of actuarial papers on insurance, reinsurance and enterprise risk management issues.