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Model Risk Management for Pension Funds Investment Practitioners

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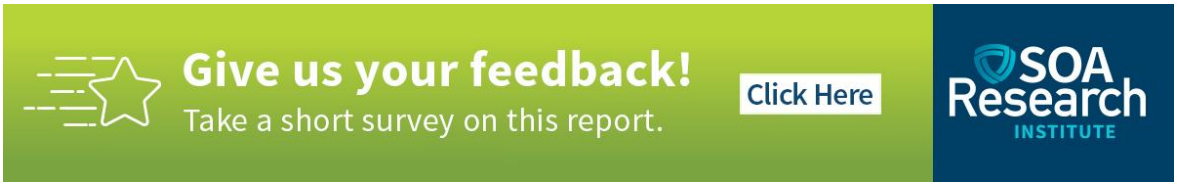
Authors Don Boyd and Gang Chen
Co-Directors
State and Local Government Finance Project
Rockefeller College

Sponsor Aging and Retirement Strategic Research Program



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Model Risk Management for Pension Funds Investment Practitioners

Executive Summary

Financial models are central to the management of pension plans, guiding decisions about contributions, asset allocation, and risk mitigation. Yet, these models are inherently imperfect, and reliance on them introduces model risk—the possibility of adverse outcomes due to inappropriate model selection, inaccurate parameter values, incorrect model implementation, inappropriate use, or poor communication of results. This report aims to help pension fund practitioners understand and manage such risks, with a particular focus on the Economic Scenario Generators (ESGs) that drive investment-return projections in Asset/Liability Management (ALM) models.

Since the Great Recession, model risk management has become a growing priority for financial institutions, spurred by regulatory guidance and actuarial standards. Pension funds face a unique array of risks—investment shortfalls, asset-liability mismatches, contribution volatility, and demographic shifts—that compound the need for robust modeling practices. ESGs play a critical role by generating capital market assumptions that underpin ALM projections. The choice of ESG model and the calibration of its parameters have a profound influence on perceived pension risks and, ultimately, policy decisions.

KEY INSIGHTS

This report examines the impact of ESG model selection and parameter uncertainty on pension fund outcomes based on resources developed by the Society of Actuaries and other organizations and researchers and illustrates selected risks using simulation-based modeling of the assets of a simple pension fund. Key findings include:

- **Model selection risk is substantial.** Different ESG models can yield materially different forecasts. In this report, impacts on risks of asset loss and contribution increases for simple stochastic volatility models with and without skew or leverage effects are illustrated. Models that incorporate leverage—reflecting increased volatility after market downturns—produce more severe downside outcomes than simpler models.
- **Parameter uncertainty compounds risk.** Even within a given ESG model, variations in key parameters such as volatility of volatility (σ_v) can significantly alter projections.
- **Sophisticated models may not always be better.** Complex ESGs can outperform simpler models in some contexts but may also be more fragile when mis-specified. Ensemble approaches that combine multiple models often outperform single-model approaches by averaging out errors.
- **Portfolio composition matters.** High-equity portfolios are more sensitive to modeling assumptions, especially in the tails of the distribution. This reinforces the need for tailored modeling based on asset allocation and funding strategy.
- **Model misuse is a real risk.** Even well-constructed models can mislead if users over-rely on outputs without understanding the underlying assumptions, limitations, and sensitivity to inputs.

For a full understanding of these issues, model users should refer to references discussed in the section on Model Risk Management for Pension Funds.

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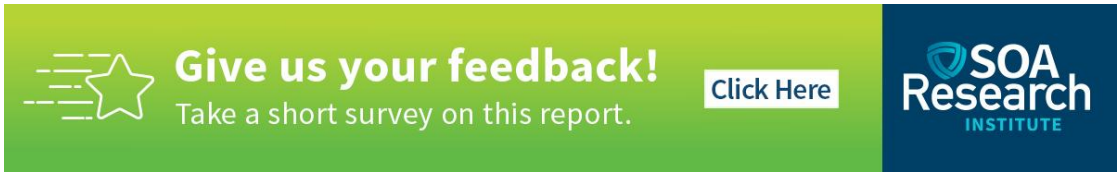
PRACTICAL IMPLICATIONS AND GUIDANCE

To mitigate model risk, pension practitioners can benefit from a disciplined, transparent approach to model development, validation, and use. These include the following considerations:

- **Diversify modeling approaches.** Where possible, consider use of ensemble modeling or compare outputs from different models to capture a more complete range of risks.
- **Validate and test models rigorously.** Back-testing, stress-testing, and benchmarking against other models to understand strengths and weaknesses adds rigor to the analysis.
- **Perform sensitivity analysis.** Identify which parameters have the greatest influence on outcomes and prioritize accuracy in their estimation.
- **Document assumptions and limitations.** Clear documentation ensures users and stakeholders understand how a model works and where caution is warranted.
- **Update regularly.** Economic and financial conditions evolve, and it is helpful for models used to reflect this.
- **Engage expert oversight.** Collaboration involving actuaries, investment professionals, and independent reviewers in the modeling process can lead to better results.

CONCLUSION

Model risk in pension fund management is unavoidable but manageable. Effective model risk governance—especially around ESGs—can improve the reliability of investment and funding decisions and enhance the long-term sustainability of pension plans. By applying best practices in validation, calibration, and diversification, pension fund practitioners can make more informed choices that account for both average outcomes and extreme scenarios.



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Introduction

This report aims to help pension fund practitioners understand the risks of using financial models for investment, funding, and benefit decision-making.[1] It describes risks ranging from model selection to communication of results, with a particular focus on how choices of models and parameter values in economic scenario generators (ESGs) can affect pension model outputs and, consequently, pension investment and funding decisions.

Since the Great Recession, financial industry regulators, practitioners, and researchers have increasingly emphasized model risk management. Federal Reserve SR Letter 11-7 cautions that "use of models invariably presents model risk, which is the potential for adverse consequences from decisions based on incorrect or misused model outputs and reports," calling on banks and insurance companies to "identify the sources of risk and assess the magnitude." Actuarial Standard of Practice (ASOP) No. 56 similarly defines model risk as the "risk of adverse consequences resulting from reliance on a model that does not adequately represent that which is being modeled, or the risk of misuse or misinterpretation."

Pension plans rely on financial models to inform decision-making. Risks may arise in model selection, data input, model development, validation, use, and communication. Inaccurate inputs, oversimplified theories, or poor assumptions can produce unreliable outputs, while misunderstanding a model's limitations can lead to misapplication of results. Asset-liability management models (ALMs) examine both the asset and liability sides of a pension fund. ESGs provide investment-return inputs to ALMs and play a central role in informing pension fund investment and funding decisions.

Alternative economic and financial theories and assumptions lead to different ESG models, introducing model-selection risk. Even after choosing a model, varying parameters and assumptions about investment features such as volatility, correlation, and mean reversion create further layers of risk. Misuse of these outputs can, in turn, result in inappropriate investment choices or insufficient pension contributions.

Although defined benefit plans are used to illustrate certain kinds of model risk in this report, several universal principles apply across defined contribution, cash balance, and other hybrid plans. Any retirement plan that projects investment outcomes to inform policy decisions should be mindful of model selection risk, parameter uncertainty, and tail risk. Regulatory and professional guidance pertains to non-DB plans as well as DB plans: Federal Reserve SR 11-7 and ASOP No. 56 call for identifying and managing model risk in any significant financial model. While originally developed with banks, insurance, and actuarial modeling in mind, the core lessons relating to governance, validation, and transparency also apply to DC plan providers and hybrid plan sponsors.

This report is organized as follows:

1. A review of pension fund risks and model risk.
2. An examination of how ESG model choice and parameter values can affect practitioners' assessments of pension funding risks.
3. Guidance for pension fund practitioners on managing model risk—particularly ESG model risk.

[1] The illustrations in the report relate to investment and funding decisions, but understanding model risk is also important for benefit decision-making.

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Pension Fund Risks, Model Risk, and Risk Measures

PENSION PLAN RISKS

ASOP 51 defines risk as "the potential of actual future measurements deviating from expected future measurements."[2] It identifies several key risks for defined benefit pension plans:

- **Investment risk**, arising from the volatile, yield-seeking assets in which most pension funds invest. Shortfalls in actual vs. expected returns can threaten solvency if assets become insufficient to cover liabilities.
- **Asset-liability mismatch risk**, where returns fall below the discount rate used for valuing liabilities, leading to unfunded obligations.
- **Interest rate and demographic risks**, including the impact of fluctuating rates on liability valuations and demographic shifts such as unexpected longevity improvements.
- **Contribution risk**, which arises when actual contributions fall short of required amounts due to the sponsor's financial constraints, changes in contribution policy, and/or the emergence of unfunded liabilities.

MODEL RISK IN PENSION FUNDS

Pension funds rely on actuarial and financial models—particularly Asset and Liability Management (ALM) models—to project liabilities (using workforce demographics, salary growth, and mortality assumptions) and assets (based on contributions, investment returns, and cash flows) (Andrew et al., 2021). These models enable stress testing (e.g., market shocks) and sensitivity analysis (e.g., discount rate variations) (Blome et al., 2007).

NATURE OF MODEL RISK

The sophistication of ALM and ESG models can become a source of risk if not managed properly. Model risk may manifest in:

- **Data input** (if data are incomplete or incorrect),
- **Model selection** (choosing an unsuitable model),
- **Coding errors** (bugs or inaccuracies in software),
- **Testing and refinement** (insufficient validation or calibration),
- **Ongoing updates** (failing to adjust for market or demographic shifts),
- **Documentation** (lack of clarity about assumptions or limitations).

In addition, comprehensive pension plan models—incorporating both liability and asset modeling—often combine economic scenarios, workforce projections, benefit rules, and asset and liability calculations. Errors or omissions in any of these components can substantially skew results—especially when the outputs guide major policy decisions such as changing a plan's contribution strategy.

[2] Pension Committee of the Actuarial Standards Board. *Assessment and Disclosure or Risk Associated with Measuring Pension Obligations and Determining Pension Plan Contributions (ASOP 51)*. Actuarial Standards Board, September 2017. https://www.actuarialstandardsboard.org/wp-content/uploads/2017/10/asop051_188.pdf.

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All models carry model risk. Even well-designed models are imperfect approximations of reality. This inherent risk stems from:

- Structural uncertainty: Models simplify complex systems, omitting nonlinear interactions or regime shifts (e.g., market structural breaks) (Cont, 2006; Derman, 1996).
- Parameter uncertainty: Inputs (e.g., equity returns) are estimated with error and may lack stationarity (Blake et al., 2001).
- Tail risk: Extreme events (e.g., pandemics, financial crises) are inherently difficult to model (Taleb, 2020).

Risks are also introduced by flaws in model design, implementation, or use:

- Design flaws: Oversimplified theories or coding errors (Rebonato, 2002).
- Assumption errors: Overoptimistic return expectations.
- Misuse: Overreliance on outputs without expert judgment or misapplication in stress testing .

DETERMINISTIC VS. STOCHASTIC MODELING

ALM models rest on multiple assumptions about interest rates, inflation, equity, and other asset-class returns, volatilities, correlations, and more, which may differ markedly from actual future experience.

- Deterministic models rely on fixed assumptions (often derived from historical averages) to produce easily understood projections. While deterministic models do not provide direct information about risk, they can help users understand risks through simulations of alternative scenarios.
- Stochastic models introduce variability by drawing key assumptions from probability distributions (e.g., Monte Carlo simulations), thus offering a distribution of possible outcomes rather than a single forecast (Blome et al., 2007).

When assumptions or inputs are flawed, even sophisticated approaches can lead to faulty conclusions about contributions or investment strategies. Consequently, pension funds increasingly adopt stochastic methods to capture a broader array of economic scenarios.

Economic Scenario Generators (ESGs) produce stochastic projections of economic and financial variables that are used as inputs to asset models. The most common of these variable is investment returns, but some pension plans incorporate ESG-generated inflation estimates and interest rates into COLA projections. ESGs produce capital market assumptions (CMAs) that guide asset allocation, portfolio optimization, and pension contributions. ESG outputs also feed into common risk measures, including Value at Risk (VaR). These projections help pension managers estimate probabilities of critical events or explore adverse conditions such as market crashes or prolonged low returns.

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EXAMPLES OF RISK MEASURES IN STOCHASTIC ASSET MODELING

Stochastic asset modeling typically employs specific risk indicators to illuminate a plan's vulnerability under different market conditions. For instance, the California Public Employees Retirement System (CalPERS) conducts periodic risk analysis focusing on asset and contribution risks that tracks:[3]

- The probability of funded status dipping below 50% over 30 years,
- The probability of higher contributions in prolonged low-return environments,
- The likelihood of a significant one-year contribution spike following "investment shocks."

Value at Risk (VaR) and related measures complement these probabilistic measures by quantifying downside risk under worst-case or adverse scenarios, highlighting tail risk (Andrews et al., 2022 and Blome et al., 2007). In pension plans, VaR measures are often used to show how much pension assets would be expected to fall short and how much pension funding costs would be expected to increase when market returns are at the bottom 1% or 5% of all scenarios (Blome et al., 2007).

Stress testing analysis that examines multiple alternative scenarios helps decision-makers focus on events that could imperil plan solvency or necessitate sharp contribution increases.

EMPIRICAL EVIDENCE ON MODEL CHOICE AND PARAMETER UNCERTAINTY

Research illustrates that **model selection** and **parameter uncertainty** in ESGs can have large impacts on asset outcomes. The papers noted below illustrate some of the important conclusions from this extensive research.

Ahlgrim et al. (2008) compared two major financial scenario generators—the CAS-SOA (Casualty Actuarial Society-Society of Actuaries model) and the AAA RBC C-3 (American Academy of Actuaries' Risk-Based Capital C-3 model)—and identified significant differences in the mean, standard deviation, and skewness of the interest rates and equity returns generated by these models.

Lee (2013) demonstrated that three key assumptions in Monte Carlo simulations can yield significantly different model outputs, thereby affecting decision-making in pension fund management. These assumptions include the distribution of stock returns, mean reversion in returns over time, and the uncertainty of return parameters.

Collins et al. (2015) used several risk models to compare bankruptcy risk in a retirement income portfolio. They demonstrated that predictions of bankruptcy risk varied significantly based on the parameters used in these models, including those related to skewness, fat tails, autocorrelation, volatility clustering, and dynamic correlations, highlighting the need for investors to better understand the limitations of using risk models to inform their decisions.

Andrews et al. (2019) used VaR measures in stochastic models to assess the risks associated with pension plans. Comparing VaR outputs from two ESGs, the Wilkie model and the Graphical model, they found that the Graphical ESG model produced a longer left tail than the Wilkie ESG model, underscoring that ESG model choice influences risk measures.

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[3] California Public Employees' Retirement System. *2024 Annual Review of Funding Levels and Risks*. California Public Employees' Retirement System, November 2024. https://www.calpers.ca.gov/sites/default/files/spf/docs/board-agendas/202411/financeadmin/item06a-01_a.pdf.

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Bégin (2019) demonstrated that parameter uncertainty has a significant impact on the outcomes of economic scenario generators (ESGs). When parameter uncertainty is accounted for in the Wilkie model, loss-related risk measures—such as VaR—are at least 12% higher than when deterministic parameters are used.

Bégin (2021) showed that complex ESGs tended to outperform simpler models within the sample period over which they were estimated. However, when the models were used for other purposes, including forecasting and estimating ranges of possible outcomes, the story was more complicated: complex models outperformed simpler models for interest rates and stock returns, but simpler ESGs matched or surpassed complex models for inflation and dividend yield. Bégin conducted a preliminary analysis that combined models and found it to be a good compromise: "if one model is off at times, the other models compensate and bring the ensemble to decent levels." This is consistent with a long line of research in other domains that finds ensemble models can help reduce model risk.[4]

Bégin (2023) examined ensemble models more deeply, combining eight different ESGs. This ensemble model significantly outperformed weaker models and is comparable to stronger models, reducing model risk when applied to asset allocation. However, determining the optimal weights for the ensemble presents challenges, with optimal model weights varying over time and across economies.

Collectively, these findings confirm that model selection and calibration are critical choices with far-reaching implications for asset allocation, funding policy, and overall risk strategy. They show that no single model can be assumed to be correct, and that combining models can reduce overall model risk.

MODEL RISK MANAGEMENT FOR PENSION FUNDS

Pension plan risks, including investment risk, asset-liability mismatch risk, interest rate and demographic risks, and contribution risk, are deeply entwined with model risk, given the reliance on actuarial and financial models for crucial decisions. Deterministic and stochastic ALM approaches each have roles in projecting future asset and liability values, but inaccuracies or misinterpretations can lead to suboptimal outcomes. By following established model risk management practices—covering development, testing, validation, and documentation—pension funds can better navigate the complexities of ESG modeling and safeguard against unintended consequences in investment and funding decisions. This report summarizes many of these practices, but for a deeper understanding users should refer to resources discussed below.

Comprehensive pension plan models typically consist of several main components, such as economic scenarios, workforce construction, application of benefit rules, and the calculation of future liabilities and assets. Model risk can occur in any of these areas during model development and use, and it tends to increase with greater model complexity, higher uncertainty of inputs and assumptions, and more extensive use of the model for making important pension plan decisions.

Efforts to effectively manage model risks include identifying, measuring, monitoring, and mitigating risks throughout the stages of model development and implementation. Identifying the sources of model risk

[4] Bégin cites a weather forecasting example. An older but extensive review covering many domains concluded that "Combining forecasts is especially useful when you are uncertain about the situation, uncertain about which method is most accurate, and when you want to avoid large errors." See "Combining Forecasts" in *Principles of Forecasting: A Handbook for Researchers and Practitioners*, edited by J. Scott Armstrong. International Series in Operations Research & Management Science 30. New York: Springer, 2007.

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and measuring these risks are crucial for model risk management because model outputs are used to make critical decisions regarding policies pertaining to asset allocation and funding.

Best practices for model risk management—discussed in depth in *Supervisory Guidance on Model Risk Management* (Federal Reserve SR Letter 11-7, 2011); the *Comptroller's Handbook: Model Risk Management* (Office of the Comptroller of the Currency, 2021); and *Actuarial Standard of Practice No. 56: Modeling* (Actuarial Standards Board, 2019)—are summarized here. Model users should refer to these sources directly for a deeper understanding of best practices.

During model development, the model should go through rigorous quality control to ensure alignment with its intended use, robust theoretical support, consistency with industry practices, and accurate coding. Data inputs should be verified to ensure the dataset's quality and the underlying data sources' reliability. The computer coding process should be logged and reviewed. Benchmarking should be conducted to compare the inputs and outputs of the model with those of alternative models used in industry. Differences between the current model and alternative models identified in the benchmarking process should be analyzed. Back-testing compares model outputs to historical data to assess validity, but it requires out-of-sample testing and stress scenarios to avoid false confidence. Users should be wary of overfitting—adjusting models to fit noise rather than signal. This can be mitigated by cross-validation (dividing the data into separate subsets to test the model), parsimony (keeping the model as simple as possible while retaining predictive power), and theoretical discipline.

Model testing and validation continue from the model development stage to the implementation and use stages. Model testing assesses whether the model produces accurate outputs across a wide range of input values and assumptions. This should be done in and out of sample, although it is not possible to examine potential model performance in periods that have no analog in history.

Testing also helps illustrate the potential impact of changes in inputs and assumptions. Sensitivity analysis can be conducted to demonstrate how the outputs of a model change across a wide range of inputs and assumptions. Extreme values could be used in the model to show the boundaries of the model's applicability.

Appropriate testing and validation help ensure that a model performs as expected before its use in decision-making. If the model does not perform as anticipated, adjustments should be made. Testing, validation, and adjustments should continue during model implementation and be used to ensure the model continues to perform well as conditions change.

Documentation should show how the model was developed, including the underlying financial and statistical models, model design and formulas, data sources, key inputs, and assumptions. It should also detail the model's intended use and limitations. This transparency allows users to apply the model for decision-making while being aware of the potential model risk. Documents should be provided with the model for the users, with updates as necessary.

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Illustrating the Impact of ESG Model Selection and Parameter Risk

How ESG model selection and parameter estimates can affect a user's assessment of pension fund asset-related risks is now illustrated. Stylized investment-return models are used to generate annual returns for a simple pension model, allowing observation of how alternative assumptions alter key risk metrics. First, the methodology is described, followed by the results.

METHODOLOGY

AN ILLUSTRATION OF ESG MODEL-SELECTION RISK

Choosing among different return-generating models can substantially alter asset-return dynamics and, by extension, pension risk assessments.

Example: Stochastic Volatility with Leverage vs. Without

Stochastic volatility (SV) models are often used in modeling investment returns within an ESG framework. They assume that not only are asset returns stochastic, but the volatility of asset returns is itself driven by a stochastic process.[5] They capture the phenomenon of long-memory effects, where volatility can persist for long periods.

- A leverage SV model explicitly models a correlation ρ ("rho") between return innovations and innovations to the latent volatility process. In equity markets, ρ is often negative, meaning volatility shocks tend to occur alongside negative return shocks—consistent with the empirical tendency for volatility to rise during or after negative returns.
- A non-leverage SV model omits this correlation, constraining return and volatility innovations to be independent. Such a model may be chosen for simplicity, or because empirical evidence for leverage effects is weak at the chosen sampling frequency (e.g., if leverage effects are present, they are often clearer in daily data than in annual data).

If real-market data exhibits strong leverage effects, yet the chosen model omits them, it will likely underestimate volatility in market downturns and thus mischaracterize tail risk.

Another example of model choice relates to how volatility in returns is modeled. One alternative to a stochastic volatility model is a generalized autoregressive conditional heteroskedasticity (GARCH) model. Like a stochastic volatility model, a GARCH model allows the volatility of investment returns to vary over time. However, the volatility estimate is predictable for GARCH models, whereas it is latent for stochastic volatility models.

ESG MODEL PARAMETER RISK

Even when a plausible model form is chosen, parameter uncertainty can significantly skew simulated outcomes. Small errors in parameter estimates—whether due to limited data, changing market conditions, or miscalibration—may amplify through the model and lead to substantially different risk profiles.

[5] Another popular approach—not implemented in this report—is the generalized autoregressive conditional heteroskedasticity (GARCH) model, which ties current volatility to past values of returns and past volatility. It would be a straightforward extension, illustrating another dimension of model-selection risk.

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Example: Inaccurate Leverage Parameter in a Stochastic Volatility Model
Consider an SV model with a leverage effect, where the true but unobserved correlation parameter ρ between returns and volatility innovations is −0.8. If estimation finds ρ = −0.3, the model will underestimate the spike in volatility during market downturns. This can produce overly optimistic risk assessments and possibly inadequate hedging or funding strategies.

IMPLEMENTATION APPROACH

This section describes how alternative sets of investment returns were generated and, in turn, the use of these returns to drive a simple model of pension fund assets and contributions. The model does not examine how alternative returns would affect liability valuation.

GENERATING INVESTMENT RETURN SCENARIOS

Examining Model Selection: Stochastic Volatility and a Detailed ESG
To examine the impact of model selection, four different return-generation approaches were used:

1. **Three variants of a stochastic volatility model** (Gaussian SV, Skew-normal SV, and Leverage SV) estimated for two portfolios: (1) high-equity: 70% equity / 30% fixed income, and (2) high-fixed-income: 30% equity / 70% fixed income.[6]
2. **A "detailed ESG"** based on models in the public domain previously used to inform industry and regulatory analysis.[7] Results by asset class are combined into two portfolios: (1) high-equity: 70% equity / 30% fixed income, and (2) high-fixed-income: 30% equity / 70% fixed income.

Stochastic Volatility Framework

The stochastic volatility framework is:[8]

$$y_t = \sigma_t e^{h_t/2} \epsilon_t$$

$$h_{t+1} = \phi h_t + \sigma_h \eta_t$$

where y_t is the observed log returns and h_t is the logarithm of the variance. The distribution of the innovations ϵ_t differs across variants of the model. Parameters include σ_h (volatility of volatility) and ϕ (persistence of volatility). The higher σ_h is, the more volatility varies. If ϕ is near 1, volatility exhibits high persistence. If ϕ is closer to 0, volatility quickly reverts to its long-term mean.

Gaussian SV Model

- Volatility follows a latent stochastic process with normal (Gaussian) errors.

[6] To keep the models simple, the S&P 500 index (^GSPC) was used as the measure of equities and the iShares Core U.S. Aggregate Bond ETF (AGG) index as the measure of bonds. The S&P 500 index measures the stock performance of 500 large companies listed on U.S. stock exchanges, and the iShares Core U.S. Aggregate Bond ETF serves as a proxy for the total U.S. investment-grade bond market. The returns were combined by asset classes into the two portfolios and estimated and simulated returns for each portfolio for each model in R using stochvolTMB.
[7] It bears similarities to the AIRG model developed by the Society of Actuaries and the American Academy of Actuaries, and to the ACLI model developed by the LATF.
[8] See Jens Christian Wahl, *stochvolTMB: Likelihood estimation of stochastic volatility*, n.d., https://cran.r-project.org/web/packages/stochvolTMB/vignettes/stochvolTMB_vignette.html.

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Skew-Normal SV Model

- Extends Gaussian SV by allowing the returns to be **skewed**, (ϵ_t is skew normal) often capturing heavier downside tails.
- Introduces an **α (alpha) parameter** to quantify skewness.

Leverage SV Model

- Adds a correlation parameter ρ between returns and volatility shocks, capturing the leverage effect. When ρ < 0, negative returns raise future volatility more than positive returns of similar magnitude.

For each of these SV models, 360 months (30 years) of monthly log returns × 10,000 simulations for each portfolio were generated, then the monthly returns for each portfolio were collapsed into annual returns for use in the pension model.[9] [10]

Detailed ESG

- Has four equity classes each driven by a stochastic volatility process. It also has multiple interest rates.
- Equity returns incorporate a stochastic volatility component.
- The model is well-documented, and users can modify most parameters.[11]

Figure 1 shows the equity asset equations in the detailed ESG model. The model used for this report is based on a publicly available model. The figure below is copied from the documentation developed for that model.

[9] Bégin and Boudreault (2021) showed that the underlying frequency of the data used in estimation—daily, weekly, monthly, etc.—can influence results. Monthly data were used for estimation because this approach has been employed by many researchers. The analysis did not examine whether this choice has a material impact on parameter estimates, but the data frequency selected for estimation represents a potential additional source of parameter uncertainty.
[10] The monthly returns are for portfolios, not individual assets. In essence, portfolios are rebalanced monthly.
[11] Although the model has a parameter, rho, that should control leverage effects, altering the parameter value does not change results.

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Figure 1
STRUCTURE OF THE DETAILED ESG MODEL

$$\tilde{v}(t) = Min\left[v^{+}, (1-\phi)\times v(t-1) + \phi \times \ln(\tau)\right] + \sigma_v \times {}_vZ_t$$

$$v(t) = Max\left\{v^{-}, Min\left[v^{*}, \tilde{v}(t)\right]\right\}$$

$$\mu(t) = A + B\times\sigma(t) + C\times\sigma^2(t)$$

$$\ln\left[\frac{S(t)}{S(t-1)}\right] = \frac{\mu(t)}{12} + \frac{\sigma(t)}{\sqrt{12}} \times {}_sZ_t$$

$S(t)$ = stock index level at time t

$v(t)$ = natural logarithm of annualized volatility in month t

$\sigma(t)$ = annualized volatility of stock return process in month $t = \exp\left[v(t)\right]$

$\mu(t)$ = mean annualized log return ("drift") in month t

v^{-} = lower bound for log volatility = $\ln\sigma^{-}$

v^{+} = upper bound for log volatility (before random component) = $\ln\sigma^{+}$

v^{*} = absolute upper bound for log volatility = $\ln\sigma^{*}$

Source: American Academy of Actuaries (2005)

Examining Model Parameters—Varying Values of Key Parameters in the Detailed ESG
To demonstrate **parameter estimation risk**, important equity-return parameters within the detailed ESG mode are varied. The model's documentation does not provide information on parameter uncertainty so approximate 90% confidence intervals were constructed by:

1. Gathering data for assets similar to those used in the detailed ESG over the longest possible time period (converted to monthly log returns).[12]
2. Estimating a stochastic volatility model for each asset, capturing parameter estimates and standard errors.
3. Applying these standard errors to build upper and lower 90% confidence bounds for the detailed ESG's parameters.

For each of the four equity classes, 10,000 simulations for each "upper-bound" and "lower-bound" parameter estimate were generated. This approach **varies one parameter at a time** to highlight which individual parameters most strongly affect portfolio outcomes—albeit without capturing correlations between parameters (e.g., equity and bond returns).

Ignoring potential correlations among parameters could understate or overstate risk, particularly if parameters move together in certain market environments. More sophisticated methods—such as Bayesian posterior sampling, bootstrap-based covariance estimation, or Monte Carlo resampling of a multivariate parameter distribution—can capture potential interactions among parameters. These approaches require additional data, computational resources, and expertise. For many practical

[12] The S&P 500 index (^GSPC) was used as the measure of equities, and the iShares Core U.S. Aggregate Bond ETF (AGG) was used as the measure of bonds.

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applications, analysts still choose a one-at-a-time approach for clarity and tractability, while remaining aware that truly robust risk assessments may benefit from examining correlated parameter shifts.

CONSTRUCTING COMPARISON RETURN SETS

Alternative models or parameter values can change not just the mean return but also the standard deviation, skewness, and autocorrelation of returns. To facilitate comparisons **each scenario** is paired with two simpler "benchmark" sets:

1. **Deterministic** returns: Same mean log return as the modeled scenario but zero volatility.
2. **Random Normal** returns: Same mean and standard deviation as the modeled scenario but normally distributed with no other higher-moment or autocorrelation features.

By including these two benchmarks, the distributional nuances of each scenario can be compared to a baseline where the mean, or mean and standard deviation, are matched.

SIMPLE PENSION FUND ASSET MODEL AND RISK MEASURES

THE MODEL

A simplified defined-benefit pension fund model without explicit demographic changes is employed. The stochastic driver for this pension plan is the investment returns from an ESG model. These returns drive assets and in turn affect employer contributions but do not, in this simplified model, affect liabilities. Many public pension plans also have COLAs that are driven by inflation, which is an output of some ESG models (but not the models used here). Readers should keep in mind that this simple model helps illustrate the impacts of investment returns on plan assets and contributions but does not examine additional risks that pension plans face in the real world. For each simulation path of 30 years:

- Assets (A) evolve by

$$A_{t+1} = A_t (1 + r_t) + c_t - c^p W_t \quad (1)$$

where r_t is the investment return in year t, c_t is the sponsor contribution, and benefit payments $c^p W_t$ are a fixed percent (c^p) of payroll (W).

- Liabilities (L) evolve by

$$L_{t+1} = L_t (1 + d) + c^n W_t - c^p W_t \quad (2)$$

where d is the discount rate (rolling the present value of benefits forward), $c^n W_t$ is the normal cost (a fixed percent of payroll), and benefit payments are $c^p W_t$.

- Contributions use 30-year open amortization:

$$c_t = c^n W_t + \frac{(L_{t-1} - A_{t-1})}{\ddot{a}_{30}} \quad (3)$$

where $\ddot{a}_{30}$ is the present value factor for a 30-year level-percent amortization.

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Initial values are:[13]

- Liabilities: $100
- Assets: $78 (funded ratio of 78%)
- Starting payroll: $19 (19% of actuarial liabilities)
- Salary growth rate: 4%
- Benefit payout: $5.13 (27% of payroll)
- Benefit growth rate: 4%
- Amortization: 30-year open level percent
- Discount rate: 7%
- Normal cost rate: $2.28 (12% of payroll)

RISK MEASURES

After running the model for both portfolios for each scenario, the focus is on Year 10 outcomes to illustrate intermediate-term risks. Two VaR-based metrics are highlighted:

1. Asset-loss risk: The 5th percentile of the percentage change in assets relative to initial assets at Year 10. More-negative indicates larger asset drawdowns.
2. Contribution-increase risk: The 95th percentile of the percentage change in employer contributions relative to the initial contribution at Year 10. Higher values reflect worse contribution spikes.

Together, these measures gauge the downside exposures to asset values and employer cost escalation.

METHODOLOGY SUMMARY

This methodology generates a suite of alternative return scenarios through multiple model choices (stochastic volatility variants vs. a detailed ESG) and parameter-value variations, then runs each scenario's returns through a simplified pension fund model. By examining Year 10 risk measures it can be seen how changing models or parameters affects the distribution of outcomes.

The next section explores the results of these simulations. The conclusions pertain to these specific models, not ESG models generally—but they illustrate the important impacts these choices can have.

RESULTS

MODEL SELECTION RISK

Key Results From Alternative Models

This section begins by examining how different return-generating models can affect pension fund risk measures. Table and Table present results for high-equity and high-fixed-income portfolios, respectively. For this analysis mean and standard deviation log returns from alternative models were desired to be approximately the same, allowing to isolate the impact of return characteristics such as skewness and

[13] These are consistent with the median values for U.S. state pension plans, based on analysis of the Public Plans Database housed at the Center for Retirement Research at Boston College. https://publicplansdata.org/public-plans-database/download-full-data-set/

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leverage.[14] For a given portfolio, all scenarios are calibrated to have a mean log return of approximately 6.1% for the high-equity portfolio and 4.2% for the high-fixed-income portfolios.[15] Standard deviations were calibrated to be approximately the same across models within a portfolio, where possible.[16]

This calibration approach has the benefit of isolating the impact of skewness, leverage, and other model characteristics. However, it can understate risk because mean returns and standard deviations generally will vary across models. If model returns are used without adjustment, this is an additional risk to consider.

The results for Table , the high-equity portfolio, are described below:

- Row 1 (Deterministic): Constant 6.1% log return every year. Volatility is 0 so all simulations have the same result. By Year 10 assets grow 40.3% and the contribution increases 43.2%.[17]
- Row 2 (Random Normal): Investment return variability leads to some bad simulations. Year 10 assets at the 5th percentile are 17.3% below their Year 1 value (compared to +40.3% in the deterministic scenario). Year 10 contributions at the 95th percentile more than double from Year 1 (+107.6%).
- Row 3 (Gaussian SV): Variability in volatility makes bad outcomes slightly worse: Year 10 5th percentile assets are 17.6% below Year 1, and 95th percentile contributions are 108.2% above Year 1.
- Row 4 (Skew-Normal SV): Allowing a "skew" in returns, with heavier downside tails than upside worsens the tail metrics: 5th percentile Year 10 assets are down 20.8% from Year 1 vs. −17.3% in the purely Gaussian version. Similarly, contribution increases at the 95th percentile are worse.
- Row 5 (Leverage SV): Negative correlation (ρ) between returns and changes in volatility means big market drops can produce further volatility spikes. Even with a somewhat lower standard deviation overall, tail risks deepen. Assets at the 5th percentile are now −21.9% and 95th percentile contributions hit +112.2%.
- Row 6 (Detailed ESG): The detailed ESG has a higher standard deviation and introduces greater downside risk and contribution spikes than the other models. Year 10 5th percentile assets are 25.3% below Year 1, and 95th percentile contributions are 116% above Year 1.

All the stochastic volatility models indicate greater risk than a random-normal model with the same or similar standard deviation, with the leverage model indicating the greatest risk. The detailed ESG model, which has stochastic volatility equity-asset models at its core, shows even greater risk than the simpler models.

Table for the high-fixed-income portfolio shows similar relationships among the models, but with lower risk levels than the high-equity portfolio.

[14] Another approach would be to generate returns from models without attempting to attain comparability in means and standard deviations. This approach has value, too, but it would be hard to know whether differences across models were simply attributable to different mean returns or to other characteristics.
[15] The detailed ESG was used as the base model, and mean log returns from other models were calibrated to it. This approach was found to be the simplest way to achieve approximately equal mean returns.
[16] The standard deviation from the Gaussian, skew, and leverage models was calculated from the respective mean-adjusted returns and reflects the characteristics of each model. The random normal standard deviation was matched to the simplest of these models, the Gaussian model. It was not possible to calibrate the mean *and* standard deviation exactly for the leverage model or the detailed ESG.
[17] Assets grow because investment income plus contributions, including amortization of unfunded liability, exceed benefit payouts. Contribution increases reflect payroll growth.

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Table 1

RISK MEASURES FOR ALTERNATIVE MODELS *(HIGH EQUITY PORTFOLIO)*

Row number	Deterministic, Radom normal, or modeled returns	Mean annual log return	Standard deviation	VaR % asset loss Year 10 vs. Year 1 (5th percentile)	VaR % contribution increase Year 10 vs. Year 1 (95th percentile)
1	Deterministic	6.1%	0.0%	40.3%	43.2%
2	Random normal	6.1%	11.3%	-17.3%	107.6%
3	Gaussian SV	6.1%	11.3%	-17.6%	108.2%
4	Skewed SV	6.2%	11.4%	-20.8%	109.5%
5	Leverage SV	6.2%	10.8%	-21.9%	112.2%
6	Detailed ESG	6.2%	12.6%	-25.3%	116.0%

Source: Authors' analysis

Table 2

RISK MEASURES FOR ALTERNATIVE MODELS *(high fixed-income portfolio)*

Row number	Deterministic, Radom normal, or modeled returns	Mean annual log return	Standard deviation	VaR % asset loss Year 10 vs. Year 1 (5th percentile)	VaR % contribution increase Year 10 vs. Year 1 (95th percentile)
1	Deterministic	4.2%	0.0%	20.5%	63.9%
2	Random normal	4.2%	6.3%	-9.4%	97.6%
3	Gaussian SV	4.2%	6.3%	-9.1%	97.0%
4	Skewed SV	4.2%	6.4%	-9.6%	97.7%
5	Leverage SV	4.2%	6.0%	-11.3%	99.0%
6	Detailed ESG	4.2%	7.0%	-13.2%	102.0%

Source: Authors' analysis

Visualizing Results for Alternative Models

To complement these tables, Figure 2 and Figure 3 illustrate the asset-loss risk measure and contribution-increase risk measure, respectively, for both portfolios.[18] The numbers are drawn from Table and Table .

[18] The bar charts here and in the next section include the deterministic results. This makes it easy to see that any stochastic model has substantial risk of negative outcomes that differ greatly from the deterministic scenario, and that differences from one stochastic model to the next are much smaller than this difference. But including the deterministic scenario also makes it hard to see differences from one stochastic model to the next. To see details of these differences, readers can refer to the tables.

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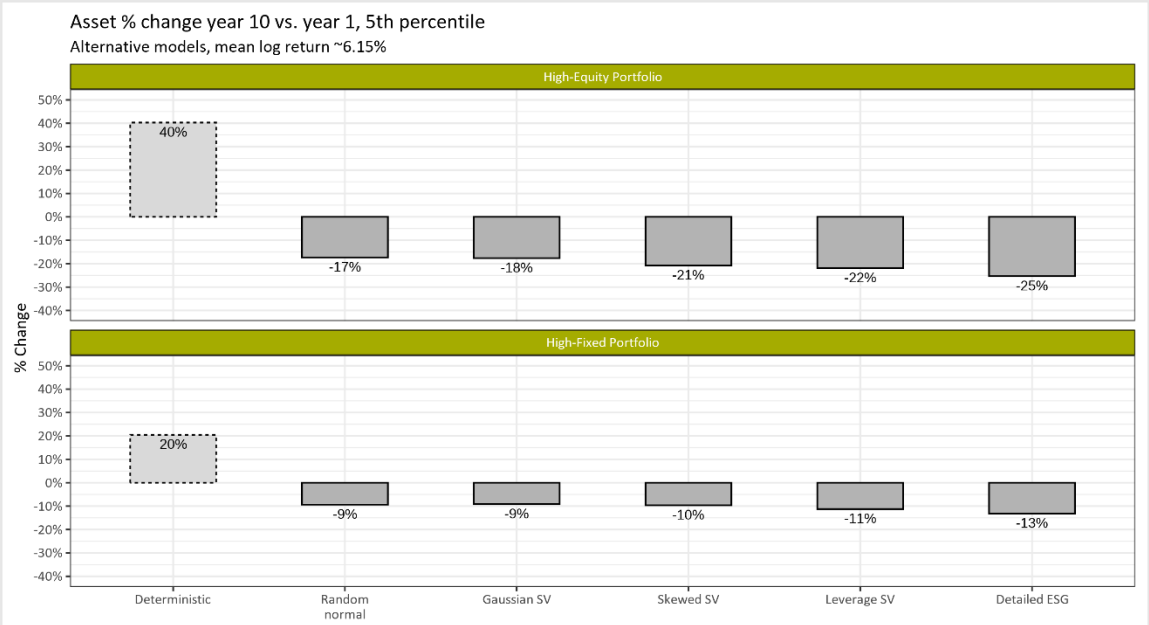
Figure 2

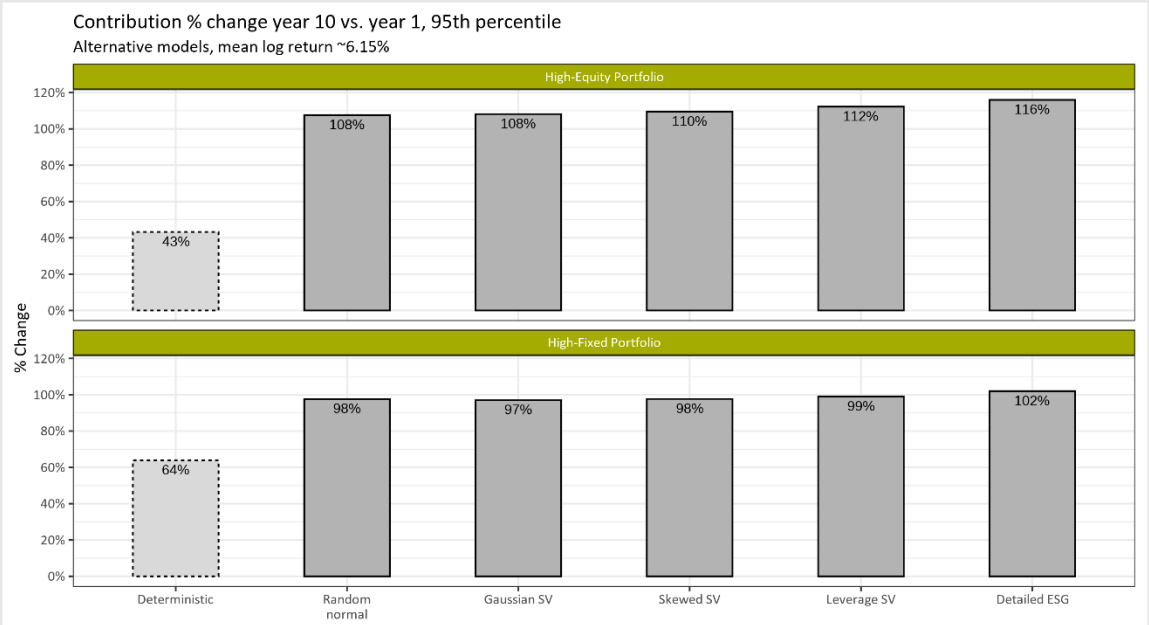
MODEL CHOICE AND THE ASSET-LOSS RISK MEASURE



Source: Authors' analysis

Figure 3

MODEL CHOICE AND THE CONTRIBUTION-INCREASE RISK MEASURE



Source: Authors' analysis

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Lessons About Model Selection Risk

The results highlight several key takeaways:

1. Random Normal vs. Deterministic: Simply introducing randomness into returns introduces substantial risk for assets and contributions.
2. Comparisons Among Stochastic Volatility Models: Accounting for skewness or leverage can meaningfully increase the estimated severity of adverse outcomes compared to purely normal volatility.
3. Leverage Effects: Markets often exhibit greater volatility after negative shocks, so models that capture this effect tend to produce more pessimistic tail outcomes.
4. Detailed ESG Model: Because it exhibits even higher volatility (and other complexities), it yields greater risk in both asset loss and employer cost.
5. Practical Implication: Model selection might shift a pension manager's perception of risk sufficiently to change policy decisions such as funding strategy or asset allocation. A shift from a naive random normal model to a leverage SV or a robust ESG may reveal a substantially higher chance of severe asset drawdowns and large contribution spikes.

In short, model selection risk is nontrivial. Failing to choose a suitably realistic return-generation process can materially understate or overstate pension-plan vulnerability.

MODEL PARAMETER ESTIMATE RISK

This section focuses on model parameter risk, examining how uncertain or misestimated parameters within the same structural model can alter projections. The detailed ESG for this demonstration was chosen because it has multiple parameters and has been used in real-world risk analysis settings. Its equity returns use a stochastic volatility framework. In this exercise, only the equity parameters are varied and model defaults for the interest-rate parameters are used.

Key Equity Parameters[19]

- tau (τ): The model's long-run volatility level.
- phi (ϕ): The speed at which volatility reverts toward the long-run level.
- sigmaV (σ_v): The "volatility of volatility," i.e., how strongly volatility itself fluctuates.

Impact of Alternative Parameter Values on Investment Returns

Unlike the simpler SV models, the detailed ESG cannot easily be calibrated to hold both mean and standard deviation constant when parameters change. Consequently, parameter variations can shift both the mean and volatility of returns. Figure 4 shows the mean and standard deviation for a baseline run with default parameters and for six scenarios: each of the three main parameters set, individually, to upper and lower 90% bounds for the high-equity and high-fixed-income portfolios.[20]

[19] In addition, the model has a leverage parameter, but the spreadsheet model is not configured to implement changes in the parameter.
[20] When a parameter was adjusted, it was adjusted for all four equity funds.

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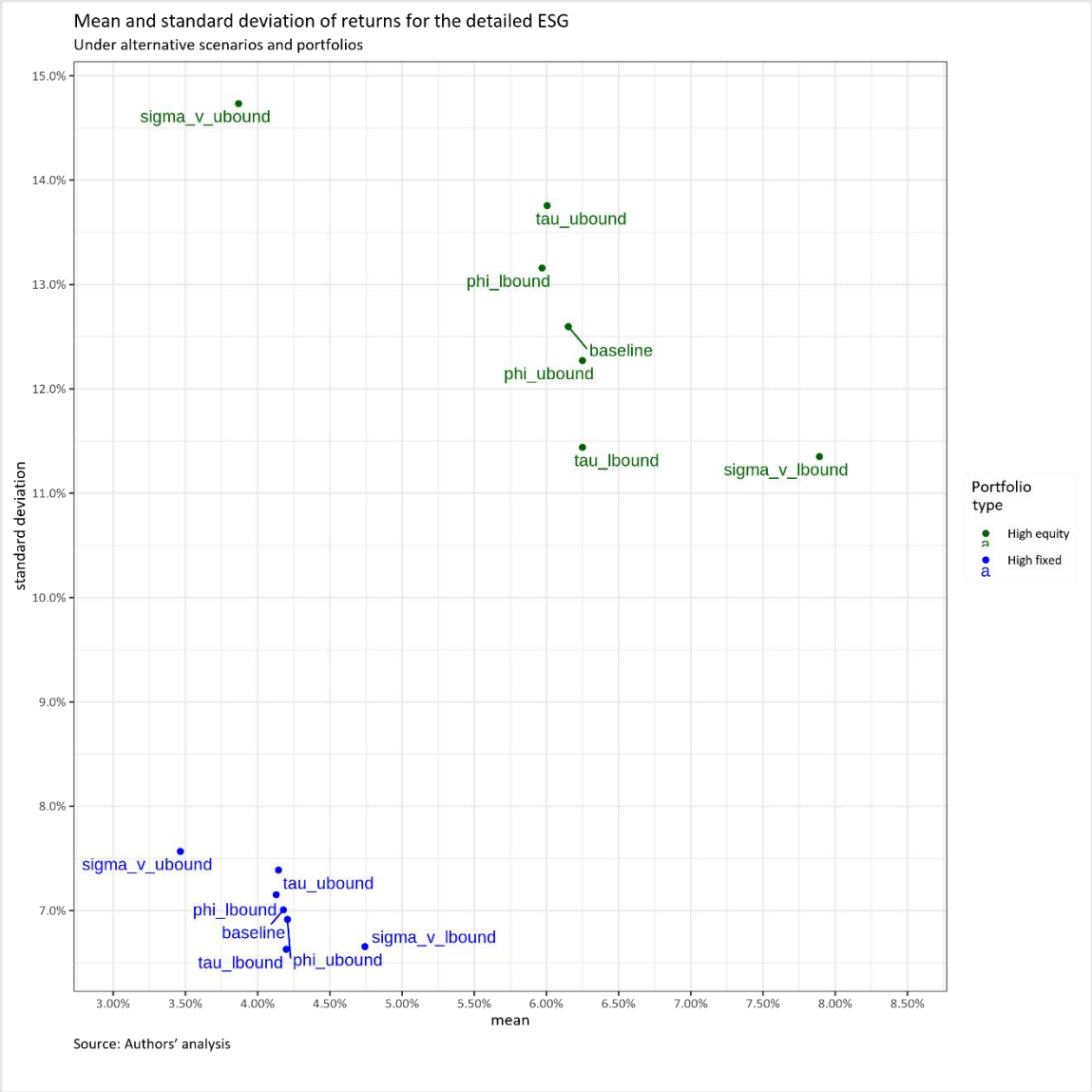
Figure 4

THE VOLATILITY OF VOLATILITY (Σ_v) HAS THE GREATEST IMPACT ON INVESTMENT RETURNS



From these simulations:

- **High-equity portfolio** consistently has higher volatility and generally higher average returns.
- **tau (τ) and phi (ϕ)** strongly affect volatility, though in different ways (e.g., a higher τ directly raises the volatility level, whereas a higher ϕ lowers *overall* variance but can intensify persistence).
- **sigmaV (σ_v)** emerges as a major driver: raising or lowering σ_v can dramatically expand the possible range of market outcomes.

Key Results From Alternative Parameter Values

Table 3 (high equity) and Table 4 (high fixed income) parallel Table 1 and Table 2 but now vary parameter assumptions within the detailed ESG model. For a given parameter adjustment, each row shows mean and standard deviation of log returns plus the two pension fund risk measures.

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Table 3

RISK MEASURES FOR ALTERNATIVE PARAMETER VALUES *(HIGH EQUITY PORTFOLIO)*

Row number	Deterministic, Radom normal, or modeled returns	Mean annual log return	Standard deviation	VaR % asset loss Year 10 vs. Year 1 (5th percentile)	VaR % contribution increase Year 10 vs. Year 1 (95th percentile)
1	Deterministic	6.2%	0.0%	40.5%	43.0%
2	Random normal	6.2%	12.6%	-22.7%	113.7%
3	Baseline	6.2%	12.6%	-25.3%	116.0%
4	Speed of mean reversion in volatility (phi): reduced to lower bound of 90% CI	6.0%	13.2%	-29.1%	120.8%
5	Speed of mean reversion in volatility (phi): increased to upper bound of 90% CI	6.2%	12.3%	-22.5%	113.2%
6	Monthly sd of the log volatility process (sigma(v)): reduced to lower bound of 90% CI	7.9%	11.4%	-7.0%	96.6%
7	Monthly sd of the log volatility process (sigma(v)): increased to upper bound of 90% CI	3.9%	14.7%	-46.2%	139.6%
8	Target volatility (tau): reduced to lower bound of 90% CI	6.2%	11.4%	-19.5%	109.6%
9	Target volatility (tau): increased to upper bound of 90% CI	6.0%	13.8%	-30.8%	122.4%

Source: Authors' analysis

Table 4

RISK MEASURES FOR ALTERNATIVE PARAMETER VALUES *(HIGH FIXED-INCOME PORTFOLIO)*

Row number	Deterministic, Radom normal, or modeled returns	Mean annual log return	Standard deviation	VaR % asset loss Year 10 vs. Year 1 (5th percentile)	VaR % contribution increase Year 10 vs. Year 1 (95th percentile)
1	Deterministic	4.2%	0.0%	20.6%	63.8%
2	Random normal	4.2%	7.0%	-12.2%	100.9%
3	Baseline	4.2%	7.0%	-13.2%	102.0%
4	Speed of mean reversion in volatility (phi): reduced to lower bound of 90% CI	4.1%	7.2%	-14.3%	103.4%
5	Speed of mean reversion in volatility (phi): increased to upper bound of 90% CI	4.2%	6.9%	-12.6%	101.2%
6	Monthly sd of the log volatility process (sigma(v)): reduced to lower bound of 90% CI	4.7%	6.7%	-7.3%	95.6%
7	Monthly sd of the log volatility process (sigma(v)): increased to upper bound of 90% CI	3.5%	7.6%	-20.6%	110.2%
8	Target volatility (tau): reduced to lower bound of 90% CI	4.2%	6.6%	-11.4%	100.1%
9	Target volatility (tau): increased to upper bound of 90% CI	4.1%	7.4%	-15.0%	104.1%

Source: Authors' analysis

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The sigmaV (σ_v) volatility-of-volatility adjustments produce much larger differences in pension risk outcomes for the high-equity portfolio than do the tau (τ) volatility and phi (ϕ) persistence adjustments. This is true but less pronounced for the high-fixed-income portfolio as well.

Visualizing the Parameter-Value Scenarios

Figure illustrates the asset-loss risk measure for each parameter scenario and portfolio, using values from Table 3 and Table 4. The further left a bar extends, the larger the asset drawdown. The outsized effect of volatility-of-volatility (σ_v) is clear.

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Figure displays the contribution risk measure; again, σ_v produces the largest swings, although adjustments to tau (τ) and phi (ϕ) create substantial contribution risk.

Figure 5

MODEL PARAMETER ASSUMPTIONS AND THE ASSET-LOSS RISK MEASURE

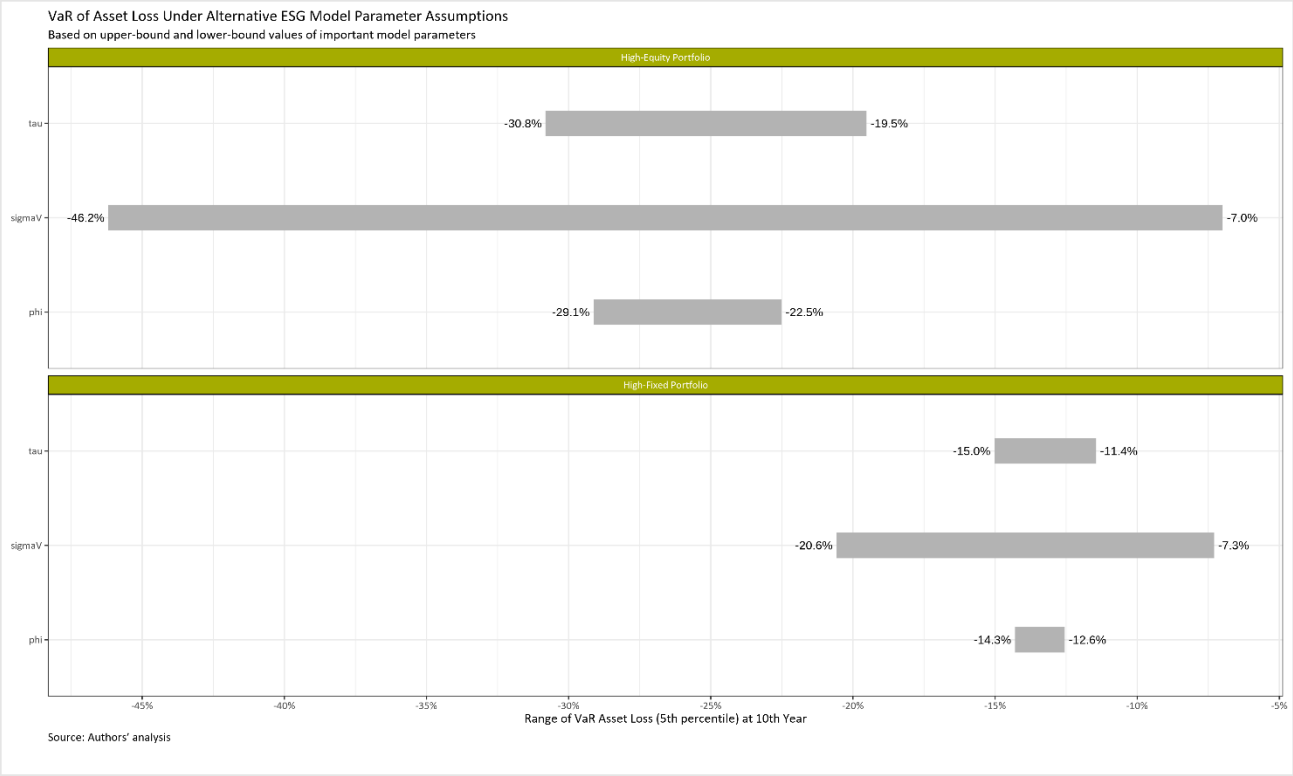

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Figure shows the contribution-risk measure for each portfolio. As in Figure the risk measures are sensitive to all three parameters, with volatility-of-volatility (σ_v) having the greatest impact. The high-fixed-income portfolio is less affected than the high-equity portfolio due to its lower overall investment risk.

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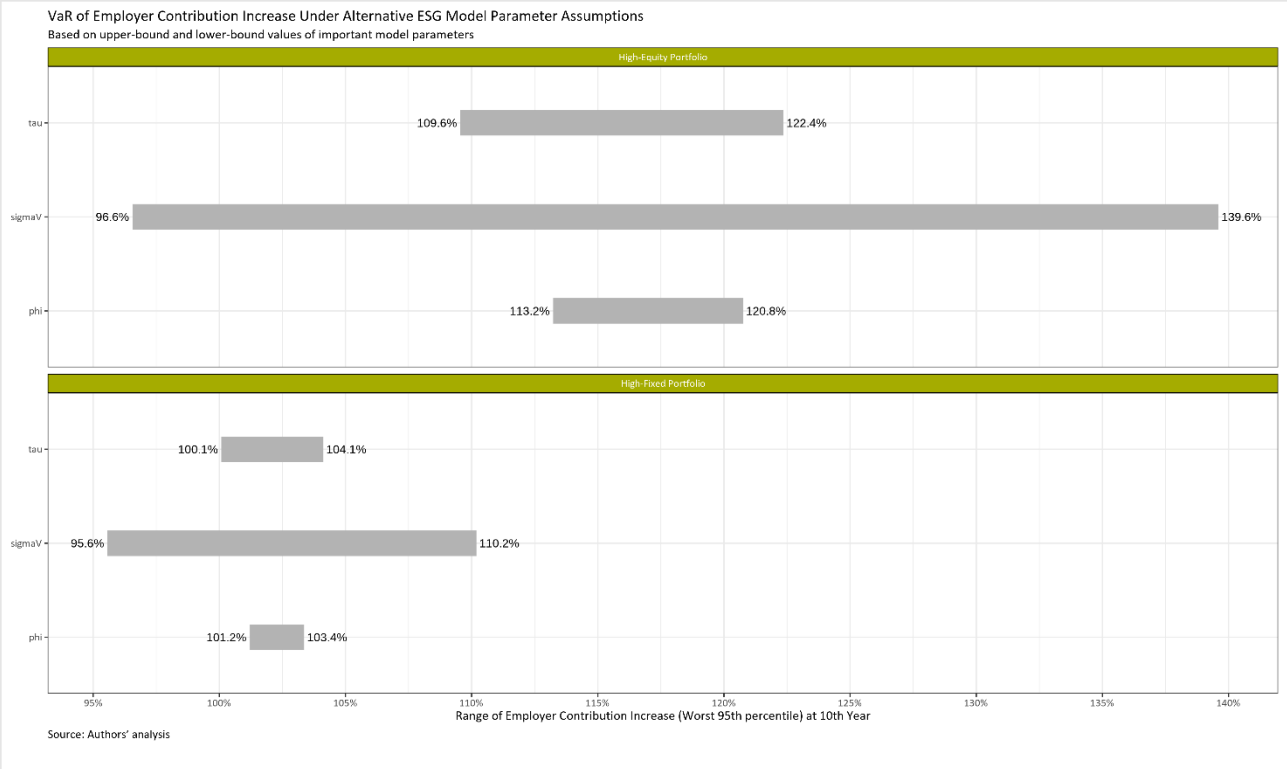
Figure 6

MODEL PARAMETER ASSUMPTIONS AND THE CONTRIBUTION-INCREASE RISK MEASURE



Lessons About ESG Model Parameter Risk

These parameter-risk experiments confirm several points:

1. **sigmaV (Volatility of Volatility):** Even modest uncertainty in sigmaV can widen the range of outcomes dramatically, especially in equity-heavy portfolios.
2. **tau (Long-Run Volatility):** Although overshadowed by sigmaV, it still exerts a significant influence on risk.
3. **phi (Persistence):** Changes to persistence can matter, but not as forcefully as variability in volatility levels.
4. **Alignment with Prior Research:** These results echo findings by **Bégin (2019)**, showing that once parameter uncertainty enters the picture, risk measures (like VaR) often increase significantly compared to a single "best-estimate" parameter set.
5. **Real-World Implication:** Practitioners who rely on point estimates for parameters risk underestimating the true downside potential, thereby making underinformed decisions about funding or asset allocation.

IMPLICATIONS OF THE ANALYSIS

These results underscore that both **model selection** and **parameter specification** can alter the outcome of asset simulations for the simplified pension plan substantially. Portfolios with heavier equity exposure are especially susceptible to volatility misestimations or omitted effects (like leverage). Adopting multiple scenario analyses, robust parameter estimation techniques, or ensemble models can help mitigate these risks—ensuring pension funds have a more comprehensive view of potential downside events and contribution spikes.

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Considerations for Pension Model Users

Pension models are indispensable tools for managing plan funding and guiding investment strategies. By projecting future liabilities, determining contributions, and assessing potential outcomes under various market conditions, these models inform critical decisions that affect plan sponsors, beneficiaries, and other stakeholders. The risk of incorrect risk assessment and adverse outcomes due to inaccurate data, inappropriate models, inaccurate parameters, or misunderstood or poorly communicated results is a crucial concern. Goals of pension model users include understanding, managing, and disclosing these risks effectively.

Key insights from the review of research are summarized below:

- Risks arise in any stage of pension model development or use: model selection, data preparation, model coding and implementation, model execution, analysis of results, and communication of results. Risks arise whether the models are used for defined benefit pension plans, defined contribution plans, cash balance plans, or hybrid plans.
- Economic scenario generators provide critical investment-return inputs to pension funding models.
    - The choice of ESG model—how it assumes the economy and financial assets behave—influences assessments of pension fund risk.
    - The parameter values of the ESG model—how large the movements in the economy and financial assets are, when they occur, and how they interact—also influence risk assessments.
- No single ESG model is correct or even "best." No model captures all important features of the economy or financial assets correctly. A model may perform well and rank high in some time periods and circumstances but do poorly and rank low in others. It is important to have useful models that are fit for their purposes.
- Ensemble approaches—combining the results of multiple models—can reduce the risk of large errors and can reduce risk when applied to asset allocation. Simple methods of combining models can yield benefits. Research on optimal approaches to combining models is ongoing.
- Complex models may reproduce nuances in history more accurately than simpler models but may not do as well in forecasting or in producing the range of possible outcomes.
- Every model has its intended applications and inherent limitations, and users should be aware of what the model can and cannot do. ESGs for life insurance liabilities may focus on interest rates and policyholder behaviors, whereas ESGs for property and casualty insurance might emphasize the impact of inflation and other economic factors, such as GDP growth and unemployment rates. ESGs designed for pension plans may prioritize equity return forecasts due to their direct impact on pension funding adequacy and their influence on the interest rate used to calculate pension liabilities.
- Models vary in their applicable time horizon. Longer time periods must consider economic cycle characteristics. It is essential to recognize the scenarios in which the model's predictions are less reliable and the contexts in which the model might fail.
- Data, the economy, and financial markets change frequently. Monitoring and managing model risks are ongoing challenges not a onetime effort.

The discussion begins with an overview of model risk mitigation and then presents questions that ESG users might consider before committing to the use of ESG in pension fund asset modeling.

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OVERVIEW OF MODEL RISK MITIGATION

For a more-detailed discussion of risk mitigation see the section, *Model Risk Management for Pension Funds*. For a deeper understanding, refer to the sources cited there (Federal Reserve SR 11-7, 2011; ASOP No. 51, 2017; ASOP No. 56, 2019; Office of the Comptroller of the Currency, 2021).

1. Model Validation

- Compare the model's outputs against real-world data, external models, or expert judgments.
- Perform regular back-testing and stress tests reflecting severe market dislocations.
- Document any discrepancies, refine parameters, and re-test frequently.

2. Sensitivity Analysis

- Systematically vary key parameters (volatility, correlation, discount rate, etc.) to see which ones produce the largest impact on outcomes.
- *If minimal changes in a single parameter drastically alter funded status, highlight that parameter as high priority for more precise estimation.*

3. Model Calibration and Parameter Values

- Recalibrate models for specific applications. A general ESG may need adjustments for multi-decade pension horizons vs. shorter horizons in insurance.
- Periodically re-estimate parameters as market conditions evolve (e.g., regime changes, structural shifts).

4. Documentation and Transparency

- Thoroughly log model development steps, assumptions, data sources, and known limitations.
- Ensure stakeholders (plan sponsors, boards, regulators) can understand the rationale behind the model and any limitations in its outputs.

5. Continuous Monitoring and Updating

- Economic conditions shift—interest rates, market volatility, and demographics do not remain static.
- *Schedule recurring reviews* to verify whether model assumptions (e.g., mean reversion speed, equity-bond correlations) still hold.

6. Diversification of Models

- Use multiple models or an ensemble approach to mitigate the "single-model bias."
- Weigh different methodologies (e.g., a GARCH-based model alongside a leverage SV model) and compare outputs for a more robust view of tail risk.
- As research by Bégin (2023) shows, *combining* predictions can often outperform any single model by offsetting individual biases.

7. Expert Oversight

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- Involve independent experts (actuaries, quantitative analysts, academic researchers) in development, validation, and interpretation.
- Solicit feedback from external audits or second opinions to catch hidden flaws and validate assumptions from fresh perspectives.

KEY QUESTIONS MODEL USERS CAN ASK REGARDING ESGS

1. What assumptions underlie the model?

- Does it incorporate regime-switching for bull/bear markets? Are extreme events (financial crises) modeled?
- Assess whether economic, demographic, and market assumptions are grounded in current realities and whether they match the plan's long-term horizon.

2. How are parameters estimated and from which data sources?

- Are estimates derived from sufficiently long, relevant time periods to capture shocks and recoveries?
- Investigate robustness, potential biases, and how missing or outlier data were handled.

3. What are the intended applications and limitations?

- For example, models designed for life insurance might emphasize short-term yield curve movements, the negative correlation often observed between interest rates and equity returns during financial crises, and disintermediation risk—the risk that policyholders might seek higher yields in other financial instruments. Pension-focused ESGs often prioritize equity-return modeling and very long-run relationships between interest rates and equities. An ESG model that is appropriate for life insurers may be inappropriate for pension funds.
- Recognize the context in which the model thrives—and where it may falter.

4. How does the model address uncertainty and variability?

- Is it purely deterministic, or does it produce a distribution of outcomes (stochastic processes)?
- Understand whether it captures tail risk adequately or mainly centers on mean outcomes.

5. What validation and back-testing have been done?

- Did the model outputs align with historical data? What benchmarks were used to evaluate accuracy?
- Seek models with documented validation procedures, including stress tests for crisis periods.

6. What are the potential consequences of model risk on decision-making?

- Could underestimating downside risk lead to severe underfunding or contribution spikes?
- Materiality matters: The higher the stakes, the more rigorous the model risk management should be.

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CONCLUDING THOUGHTS

In a field as high-stakes and long-term as pension finance, it is beneficial to approach **model risk** with discipline, transparency, and ongoing vigilance. Effective model governance—through **regular calibration**, **robust validation**, **parameter-sensitivity checks**, and **communication of limitations**—is important. By **diversifying models** and relying on **expert oversight**, it can lead to pension plan policymakers making better-informed decisions that reflect both typical and tail-risk scenarios, ultimately helping to safeguard the financial security of plan participants.

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Project Oversight Group members:

David Cantor, ASA, Chairperson

Jean-Francois Begin

Gavin Benjamin, FSA, FCIA

Douglas Chandler, FCIA

Jason Kehrberg, FSA, MAAA

James Sharpe

Andrew Smith

Scott Steadman, FSA, MAAA, FCA, EA

At the Society of Actuaries Research Institute:

Barbara Scott, Sr. Research Administrator

Steve Siegel, ASA, MAAA. Sr. Practice Research Actuary

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References

Ahlgrim, K. C., D'Arcy, S., & Gorvett, R. W. "A Comparison of Actuarial Financial Scenario Generators". *Variance*, *2*(1), 0111–0134 (2008). https://variancejournal.org/article/141995

American Academy of Actuaries. *C3 Phase II Risk-Based Capital for Variable Annuities: Pre-Packaged Scenarios.* Presented by the American Academy of Actuaries' Life Capital Adequacy Subcommittees' C-3 Phase 2 Work Group to the National Association of Insurance Commissioners' Capital Adequacy Task Force. American Academy of Actuaries, March 2005. https://www.actuary.org/sites/default/files/pdf/life/c3supp_march05.pdf.

Andrews, Douglas, Stephen Bonnar, Lori J. Curtis, Jaideep S. Oberoi, Aniketh Pittea, and Pradip Tapadar. "Impact of the Choice of Risk Assessment Time Horizons on Defined Benefit Pension Schemes." *Annals of Actuarial Science* 16, no. 2 (July 2022): 214–242. https://doi.org/10.1017/S1748499521000178.

Armstrong, J. Scott, ed. *Principles of Forecasting: A Handbook for Researchers and Practitioners.* International Series in Operations Research & Management Science 30. New York: Springer, 2007.

Bégin, J.-F. "Economic Scenario Generator and Parameter Uncertainty: A Bayesian Approach." *ASTIN Bulletin* 49, no. 2 (2019): 335–372. https://doi.org/10.1017/asb.2019.6.

Bégin, J.-F. "On Complex Economic Scenario Generators: Is Less More?" *ASTIN Bulletin* 51, no. 3 (2021): 779–812. https://doi.org/10.1017/asb.2021.21.

Bégin, J.-F. "Ensemble Economic Scenario Generators: Unity Makes Strength." *North American Actuarial Journal* 27, no. 3 (2023): 444–471. https://doi.org/10.1080/10920277.2022.2100425.

Blake, D., Cairns, A. J. G., & Dowd, K. "Pensionmetrics: Stochastic pension plan design and value-at-risk during the accumulation phase." Insurance: Mathematics and Economics, 29(2), 187–215 (2001). https://doi.org/10.1016/S0167-6687(01)00082-8.

Blome, Sandra, Kai Fachinger, Dorothee Franzen, Gerhard Scheuenstuhl, and Juan Yermo. "Pension Fund Regulation and Risk Management: Results from an ALM Optimisation Exercise." *OECD Working Papers on Insurance and Private Pensions* 8 (May 1, 2007). https://doi.org/10.1787/171755452623.

Board of Governors of the Federal Reserve System. *Supervisory Guidance on Model Risk Management (SR Letter 11-7).* Board of Governors of the Federal Reserve System, April 4, 2011. https://www.federalreserve.gov/supervisionreg/srletters/sr1107.htm.

California Public Employees' Retirement System. *2024 Annual Review of Funding Levels and Risks.* California Public Employees' Retirement System, November 2024.

Collins, Patrick J., Huy Lam, and Josh Stampfli. "How Risky is Your Retirement Income Risk mModel?" SSRN Scholarly Paper. Rochester, N.Y.: Social Science Research Network, May 13, 2015. https://doi.org/10.2139/ssrn.2548651.

Cont, Rama. "Model uncertainty and its impact on the pricing of derivative instruments." Mathematical Finance, 16: 519-547 (2006). https://doi-org.libproxy.albany.edu/10.1111/j.1467-9965.2006.00281.x

Derman, E. "Model risk." Quantitative Strategies Research Notes. (1996). Goldman Sachs, New York, NY.

Gelman, Andrew, John B. Carlin, Hal S. Stern, David B. Dunson, Aki Vehtari, and Donald B. Rubin. *Bayesian Data Analysis.* 0 ed. Chapman and Hall/CRC, 2013. https://doi.org/10.1201/b16018.

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Hartman, Brian, Robert Richardson, and Rylan Bateman. “Parameter Uncertainty.” *Society of Actuaries,* April 2017. https://www.casact.org/sites/default/files/2021-02/parameter-uncertainty-report.pdf.

Lee, Marlena. “Stress Testing Monte Carlo Assumptions.” *Wharton Pension Research Council Working Papers,* October 1, 2013. https://repository.upenn.edu/cgi/viewcontent.cgi?article=1131&context=prc_papers.

Modeling Task Force of the General Committee of the Actuarial Standards Board. *Modeling (ASOP 56).* Actuarial Standards Board, December 2019. https://www.actuarialstandardsboard.org/wp-content/uploads/2020/01/asop056_195-1.pdf.

Office of the Comptroller of the Currency. *Comptroller’s Handbook: Model Risk Management.* Office of the Comptroller of the Currency, August 2021. https://www.occ.treas.gov/publications-and-resources/publications/comptrollers-handbook/files/model-risk-management/pub-ch-model-risk.pdf.

Pension Committee of the Actuarial Standards Board. *Assessment and Disclosure of Risk Associated with Measuring Pension Obligations and Determining Pension Plan Contributions (ASOP 51).* Actuarial Standards Board, September 2017. https://www.actuarialstandardsboard.org/wp-content/uploads/2017/10/asop051_188.pdf.

Rebonato, R. "Theory and Practice of Model Risk Management.” Quantitative Research Centre (QUARC) of the Royal Bank of Scotland. (2003). Oxford Financial Research Centre – Oxford University.

Taleb, N. N. "Statistical consequences of fat tails: Real World preasymptotics, epistemology, and applications." (2020). STEM Academic Press.

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8770 W Bryn Mawr Ave, Suite 1000
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