**New Approach to Strategic Capital Market Assumptions for Long-Horizon Institutional Portfolios**

*A cash-flow and yield anchored forward-looking framework for public and private assets return and risk modeling*

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# Introduction

This document lays out a detailed framework for building capital market assumptions that I use in my project about Distributionally Robust SAA for Life Insurers. The approach is grounded in empirical observations but driven by a forward-looking perspective. The intention is not to mirror traditional methods, which often rely heavily on backward-looking averages or mechanical volatility estimates, but to offer a more structurally sound way to think about long-term returns and risks.

Life insurers, in particular, face a unique investment environment. They operate under regulatory capital rules, invest to match long-dated liabilities, and often hold fixed income assets for the bulk of their portfolios. Their investment horizon isn’t one or two years, it’s closer to ten or twenty. That long view demands an approach to capital market expectations that reflects the structural drivers of markets: the shape and evolution of the yield curve, inflation dynamics, credit behavior, and macroeconomic shifts like demographics and fiscal policy. Simply averaging past returns or assuming constant volatilities is not enough, or sound, in my opinion.

What I’m doing here is stepping back from the usual toolkit and asking a more relevant question: what do we really need to know about returns and risks over a strategic horizon? For fixed income, this means focusing on starting yields as a predictor of future returns, not because it’s a convenient proxy, but because the evidence shows that it’s by far the most reliable predictor at multi-year horizons. And for equities, I apply the same logic later: build return expectations from the ground up using actual cash flows of companies like dividends and buybacks, alongside reasonable views on long-term growth and valuation adjustment.

Instead of leaning on volatility or standard deviation as the main measure of risk, I shift the emphasis to uncertainty around return forecasts, how wrong we might be, and why. That distinction matters when we’re building a portfolio to maximize surplus for a life insurer over ten years. We’re not worried about mark-to-market noise, we’re worried about the possibility that our long-term assumptions are off by enough to throw our plan off course.

So the framework here is designed to be practical, forward-thinking, and combine historical data, structural views, and thoughtful simplifications that help rather than hinder decision-making. The rest of this report walks through the full modeling structure: index selection, return forecasting by maturity bucket, reinvestment logic, yield curve assumptions, spread behavior, and finally, how we handle risk in a way that actually matches the investment problem we’re trying to solve.

# Public Fixed Income

**Data**

All data used is sourced from Bloomberg, capturing flexible yet relatively constant maturity index time series data. Yield to Worst (YTW) series data were collected monthly from 1980 up to June 30, 2025 for the following indices:

* US Treasuries – Intermediate (~5 years) & Long (~22 years)
* US Municipal Bonds (~13 years)
* US IG – Intermediate (~5 years) & Long (~22 years)
* US HY – Intermediate (~5 years) & Long (~16 years)
* Foreign Government Bonds, Hedged (~10 years)
* Foreign IG Corporate Bonds, Hedged (~7 years)
* US Residential Mortgage-Backed Securities (~8 years)
* US Commercial Mortgage-Backed Securities (~4 years)
* US Asset-Backed Securities (~4 years)

Given a strategic investment horizon of 10 years, I segment indices into three distinct (approx.) maturity categories: intermediate (~5Y maturity), long term (~10Y+ maturity), and benchmark horizon bonds (~7–10Y maturity). Detailed methodology on return and risk estimations for those buckets separately are given later in the document.

I also have to make a note about the usefulness and validity of my approach here. Although life insurers typically buy and hold individual bonds to maturity rather than trading like an index, using fixed income indices to model expected returns still makes sense because both are governed by the same underlying economics. In either case, long-horizon returns are driven by starting yield and the rates at which coupons are reinvested, with yield curve movements affecting outcomes whether recognized monthly through index rebalancing or through mark-to-market valuations that flow into insurers’ surplus. The index structure simply provides a transparent, market-consistent way to capture these yield and reinvestment dynamics, making it a valid proxy for insurer portfolios in SAA.

**Cash**

In this analysis, I intentionally exclude cash from the expected return modeling framework. Although cash is essential for liquidity management, it does not function as a strategic return driver over extended investment horizons. Empirical and industry research consistently demonstrates that cash historically underperforms risk-bearing assets such as bonds and equities across multi-year periods. Several factors underpin this long-term underperformance:

* **Structural return deficiency**: bonds allow reliable long-term return forecasting based on starting yields and embedded term premia. Cash, however, lacks such reliability, with short-term interest rates subject to significant fluctuations driven by central bank policy decisions rather than structural macroeconomic drivers such as long-term growth, inflation trends, or persistent risk premia.
* **Forecasting limitations**: empirically, the autocorrelation of cash return time series (1999-2025) is around 70% vs -10% for longer indices (long UST and corporate IG), the volatility and policy-dependent nature of short-term interest rates severely limits the stability and reliability of long-term cash return projections. Unlike longer-duration assets, cash has no term premium and responds predominantly to short-term monetary cycles rather than fundamental macroeconomic conditions.
* **Portfolio role**: from a portfolio construction standpoint, cash primarily serves as a liquidity buffer rather than a strategic asset. Institutional investors, particularly life insurers, typically maintain only minimal cash holdings (around 1–2%) to facilitate operational liquidity, meet transactional needs, or temporarily hold funds awaiting deployment into productive assets.

Given these factors, I set a fixed minimal cash allocation of 1%, acknowledging its tactical liquidity role but excluding it from surplus-optimizing strategic decisions. This aligns with typical life insurance investment practices that prioritize capital efficiency and liability matching over unproductive cash holdings.

**Foreign Currency Bonds**

In my framework, foregn currency bonds are modeled using currency-hedged indexes rather than unhedged ones. The reason is that unhedged exposures introduce large amounts of uncompensated FX volatility, which in many cases dominates the bond return variance, as shown in the chart below. While one could make the case that foreign bonds provide diversification when domestic assets sell off alongside the currency, the evidence suggests that such offsets are weak (correlations are modest, around 0.25) and unstable over time. Moreover, correlation does not imply a reliable causal hedge.

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| **Figure 1: Foreign currency volatility makes up the majority of the unhedged foreign currency bond risk** |
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Life insurers and other institutional allocators do in practice allocate to foreign sovereign and corporate bonds, but overwhelmingly on a hedged basis, since their mandate is to capture the bond risk premium rather than currency noise. Following this logic, I include foreign bond exposures in my CMA framework through hedged indexes, ensuring comparability to domestic bonds and aligning with real-world institutional implementation.

**Return Estimation**

Life insurers earn cash yields on largely buy-and-hold fixed-income books carried at (mostly) amortized cost. Daily mark-to-market noise is not their economic risk; credit impairment and forecast error vs. starting yield are. I therefore anchor expected returns on starting yield (geometric/IRR) and deduct expected credit loss (ECL).

Inputs are starting yield Yi(t) at decision time t (index yield-to-worst) for the sleeve and expected annual credit loss rate ECLi(t) (default \* hazard rate × LGD, plus any systematic downgrade/migration haircuts). Yi​ is an IRR/CAGR by construction; it already accounts for compounding (no variance-drag mismatch). Expected return (annualized geometric/CAGR):

Insurers reinvest coupons and maturities to maintain a target duration. I do not forecast the entire future yield curve or path of reinvestment rates. On the expected return side, I assume ups and downs in reinvestment roughly net out over the long horizon. On the risk side, however, reinvestment uncertainty is captured through the RMSE measure, since realized CAGRs reflect whatever reinvestment rates prevailed along the way. This keeps the CMA tractable and aligned with actual insurer practice.

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| **Figure 2: Starting yields are good indicators of actual performance** | |
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**Credit Loss Adjustment**

While Yield to Worst (YTW) serves as a conservative base case for return expectations, assuming the earliest possible redemption scenario, it does not account for credit losses arising from defaults or downgrades. YTW assumes contractual cash flows will be honored, which makes it insufficient for realistic modeling of credit-sensitive portfolios. To reflect this, I apply expected credit loss adjustment, using 10-year cumulative default probabilities by rating tier and assumed Loss-Given-Default (LGD).

The figures in the final table are based on long-run Moody’s and S&P data, with assumed LGDs of 60% for corporates and lower for structured products. Sector-level estimates reflect a weighted average of underlying ratings.

**Different Risk Measures**

Risk estimation forms a crucial component of the capital market assumptions that inform SAA. I compute three distinct risk metrics for each bond index in my investment universe:

1. **Traditional Standard Deviation of Returns**: Represents the volatility based on the typical yearly fluctuations in bond returns
2. **Standard Deviation of Long-Term CAGR**: Calculated by multiplying the standard deviation of Compound Annual Growth Rates (CAGRs) by the square root of the index’s average maturity, enabling direct comparability with the annualized standard deviation
3. **Root Mean Square Error (RMSE)**: Derived from the historical forecasting errors of yield-based return predictions, multiplied by the square root of maturity to align comparably with annualized standard deviation.

The dominant model in classical finance assumes that asset returns are independent and identically distributed (i.i.d.). Under this assumption, the volatility of multi-year returns is derived from short-term volatility by applying the square root of time rule, so the standard deviation of an average annual return over a 10-year period is often modeled as σ10Y=σ1Y×√10.

This rule forms the backbone of models like the Samuelson Invariance Theorem, which implies that optimal asset allocation does not depend on investment horizon. However, this approach ignores several empirically observed patterns:

* Returns are not i.i.d., and they are partially predictable using valuation measures like yields.
* Short-term volatility does not capture long-term uncertainty accurately.
* Certain asset classes, especially hybrid assets like high-yield bonds, preferreds, and REITs, exhibit mean reversion.

**Time Diversification and Mean Reversion**

Time diversification is the idea that risk declines as the investment horizon lengthens. Just as investors diversify risk by spreading across asset classes, they can also diversify across time if poor short-term outcomes are offset by stronger subsequent returns. In practical terms, this shows up as annualized volatility falling with longer holding periods, because temporary shocks are gradually “washed out” as prices revert and income compounds.

The mechanism behind time diversification is mean reversion. If returns are negatively correlated across time, where weak years are more likely to be followed by stronger ones, then the dispersion of long-run outcomes narrows. For example, a sudden yield spike hurts bond returns in the short run, but over several years bonds pull back to par and coupons are reinvested at higher rates, reversing much of the initial loss. This tendency for deviations to self-correct explains why multi-year holding-period risks can be materially lower than annual volatility would suggest.

I observe some mean reversion in fixed-income indices once the evaluation horizon is aligned to the index’s actual maturity profile. Instead of comparing starting yield to a 10-year CAGR for every bond index, I match starting yield (YTW) to realized total returns over a duration-consistent horizon. On this maturity-matched basis, large yield moves are increasingly ‘undone’ as bonds pull to par and coupons are reinvested at evolving rates, which compresses the dispersion of multi-year outcomes, i.e., stronger mean reversion.

The charts below show the relative levels of three different types of risks (distributions for all the FI instruments tested).

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| **Figure 3: Lower deviation in CAGRs compared to annual returns suggest mean reversion in returns, mainly driven by HY bonds, hybrids, and long-term indexes** |
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The effect of mean reversion can be seen in the second (blue) bar: the distribution of CAGRs has a noticeably lower mean and median volatility compared to 1-year returns. Intuitively, this happens because extreme short-term shocks (e.g., a sudden yield spike) wash out over multi-year horizons as bonds converge back toward par and reinvestment rates stabilize. In statistical terms, the standard deviation of CAGRs shrinks relative to 1-year volatility precisely because past deviations are gradually reversed, capturing the essence of mean reversion.

The contrast between the first and second distributions is especially pronounced in long-term, high-yield and structured fixed-income indices, where credit spreads tend to overshoot in the short run but mean-revert more strongly as defaults, recoveries, and structural carry effects play out over the investment horizon.

In the context of long-horizon institutional investing, the concept of time diversification has often been underappreciated or misunderstood, particularly in traditional finance theory. However, for strategic asset allocation (SAA) decisions spanning 10 years or more, these phenomena can play a critical role in risk estimation and portfolio design. The chart below illustrates the concept of time diversification by showing how the annualized volatility of compounded U.S. bond returns declines as the investment horizon lengthens, from 1 to 15 years, across four major fixed income categories: U.S. Treasuries (UST), Investment Grade credit (IG), High Yield credit (HY), and Structured products. The steepest decline is seen in HY and Structured bonds, which exhibit markedly lower volatility at longer holding periods. For instance, HY volatility compresses from 16.4% at a 1-year horizon to just 4.0% over 15 years, a fourfold reduction.

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| **Figure 4: Time diversification effect is most pronounced in HY securities** |
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This empirical behavior is not just statistical coincidence but reflects structural features of credit markets. High yield returns tend to be driven by recurring income streams and cyclical credit re-rating patterns that cancel out over time, producing strong mean-reversion dynamics. Meanwhile, interest rate exposure in structured bonds (often backed by amortizing loans or mortgages) introduces a similarly smoothing mechanism via cash flow-driven price anchoring. In contrast, Treasuries, though lower in absolute volatility, display more muted time diversification, as their returns are tightly tethered to evolving rate expectations with less income cushion.

The declining risk at longer horizons does not stem from serially correlated returns, as classical theory would suggest, but from the fact that long-horizon outcomes are more accurately forecastable based on current yields, reducing forecast dispersion. This phenomenon underscores a profound insight for strategic asset allocators: not all short-term risk translates linearly into long-term risk. Especially in HY and structured credit, the compounding of stable income over time and partial mean-reversion of spread shocks deliver disproportionately lower long-term volatility, supporting higher allocation weights in strategic portfolios with long-duration surplus objectives.

If we compare the traditional (standard error) vs novel (RMSE, not scaled) approaches to how wrong we could be in average return estimation, RMSE beats the Standard Error estimation, with both considerably lower average level and interquantile range.

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| **Figure 5: As expected, RMSE is lower than traditional measure of average return volatility STERR** |
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All this indicates that RMSE provides a more reliable and realistic measure of long-term forecast uncertainty. Also, maturity has an impact predictability: the longer the maturity of an index, the more effectively the starting yield predicts actual returns over a 10-year investment horizon. Shorter-term indices face greater reinvestment risk and yield curve uncertainty due to more frequent rollovers, necessitating robust yield forecasting methods.

It should also be noted that the mean error is positive for long-term indexes, which is because the the sample period starts from 2000, and the very low interest rate regime started after like 10 years from 2000, and that decreasing interest rates makes bonds perform better so from the beginning the actual 10-year CAGR returns are higher than the starting yields. Capital gains from falling rates get locked in for longer because short-term bonds mature quickly, prices pull back to par fast, so gains fade quickly, while long-term bonds don’t mature soon, so price gains stick and investors enjoy elevated returns longer.

These results illustrate how holding period drastically alters perceived risk: short-term volatility paints a much riskier picture than long-term uncertainty justifies. High-yield and structured bonds, often dismissed as too volatile, emerge as attractive candidates for strategic allocations due to their return stabilization over time.

**Rist Estimation**

Risk is defined as the uncertainty in realized compounded outcomes relative to the forecast, not as mark-to-market volatility. Starting yield-model error exists because of several different factors:

1. credit-loss error, since realized defaults and downgrades can differ from expectations.

For each sleeve i, I form overlapping 10-year cohorts (a new cohort each month) and compute realized 10-year CAGRs from a duration-maintained total-return index:

where Ii(⋅) is the index level. Yield-model forecast error is defined as:

and

Errors are in per-year terms because both RiR\_iRi​ and YiY\_iYi​ are CAGRs. I do not scale by maturity horizon, since that would convert per-year errors into total-horizon errors and distort comparability across sleeves. Using a duration-maintained index matches insurer practice, while avoiding explicit reinvestment path modeling.

Let ηi,t(c) be the credit-loss forecast error (realized minus expected). The standard deviation of this error,

is estimated from historical default and migration data or from structural credit models. Credit losses are asymmetric, so this uncertainty cannot be netted away in the same sense as reinvestment fluctuations. Allowing for a correlation ρ​ between yield-model error and credit-loss error, the total annualized risk for sleeve i is

If I assume independence within a sleeve, then ρ=0. A positive correlation can be imposed to reflect recessions, when both credit losses and yield-model errors may be elevated.

**Covariance Estimation**

The optimizer requires a covariance matrix that reflects the possibility of being jointly wrong across asset classes over the strategic horizon. I therefore do not use covariances of monthly return volatility. Instead, I build the covariance matrix from the co-movement of forecast errors relative to my expected return models.

After calculating above, I then compute the covariance of these yield-model errors across sleeves:

**Strategic Implications for SAA**

1. **Risk should not be estimated by volatility alone** – the square-root-of-time method overstates long-term risk. RMSE is a better proxy for actual return uncertainty over strategic horizons.
2. **Mean reversion creates opportunities** – HY and structured credit instruments exhibit risk behaviors more consistent with equities over long holding periods. Their inclusion in a life insurer’s portfolio can enhance long-term Sharpe ratios.
3. **Duration enhances forecast accuracy** – the predictive power of starting yield strengthens with bond maturity. This justifies overweighting longer-duration assets in liability-aware frameworks.
4. **Time diversification is real but conditional** – the benefits are most pronounced when:
   * Starting valuations (e.g., yields) are used to forecast returns;
   * Investors are not forced to liquidate prematurely (i.e., drawdown-insensitive);
   * Leverage is managed conservatively.
5. **Policy implication** – a rational, forecast-driven allocator should **redefine risk** as “uncertainty of hitting long-term targets,” not year-to-year volatility. This redefinition justifies strategic allocations that might appear aggressive under traditional risk metrics.

Based on all of the above, the final return and risk estimation figures are given below.

**Figure 6: Expected return and risk of fixed income indexes**

# Public Equity

This section provides a comprehensive explanation of the methodology, rationale, and data inputs used to estimate strategic long-term expected returns for U.S. equities within the Strategic Asset Allocation (SAA) framework. Unlike traditional top-down approaches, which often rely on index-level heuristics or aggregate macro projections, this analysis adopts a granular bottom-up structure, designed to be both cash-flow based and valuation-sensitive, while integrating structural economic insights and historical data patterns. Each step of the equity CMA construction reflects an effort to align financial modeling with the actual behaviors of public companies, equity markets, and sector-specific business models over time.

To begin with, the scope of the equity analysis is intentionally narrowed to U.S. large-cap equities only, and more specifically, to the eleven GICS sectors within the S&P 500 index. The rationale for this focused approach stems from both methodological and operational considerations:

* Bottom-up equity modeling at the sector level requires extensive historical data collection for constituent firms, including detailed variables such as dividends, buybacks, and growth estimates.
* Expanding this framework to multiple geographies or indices would have proven logistically prohibitive and would risk compromising the rigor of the estimation.
* Restricting the analysis to the U.S. large-cap equity universe avoids the complications of FX forecasting and cross-border tax and liquidity assumptions.

Historical data from Bloomberg were collected for all eleven sector-specific equity indices from 2003 to 2025, specifically the Bloomberg tickers corresponding to each sector such as B500CT (Consumer Staples), B500E (Energy), B500I (Industrials), and so forth. The monthly time series included index level prices, dividend yields, trailing-twelve-month (TTM) earnings per share (EPS), price-to-earnings (P/E) ratios, and net profit margins. This multi-decade data foundation ensures a sufficiently long observation window to capture both cyclical and structural patterns, including periods of economic expansion, contraction, and crisis.

The foundational component of the expected return estimation is the concept of a "cash yield," the equity market's closest analog to a bond's starting yield. Accounting earnings can be systematically manipulated and often diverge from the underlying economic reality that investors should rely on, making cash-based measures significantly more robust. Academic literature and regulatory commentary consistently highlight that companies frequently engage in earnings management through accrual adjustments, one-off items, or strategic timing of expenses and revenues, which distorts reported earnings quality. Earnings may reflect accounting judgment rather than actual cash flows, rendering traditional P/E or EPS-based return models vulnerable to these distortions. In contrast, empirical evidence suggests that shareholder yield components, dividends and buybacks, are harder to manipulate and better reflect real cash returned to investors. Dividend-paying stocks, on average, exhibit lower return volatility, even when controlling for firm size, indicating that cash distributions are associated with greater stability and transparency. Moreover, accrual-based earnings quality improves only when internal controls are strong, otherwise companies may still distort earnings figures even in ostensibly well-governed firms. These findings reinforce the superiority of using cash-based yields as forward return anchors in equity return modeling framework, dividends and buybacks cannot be fabricated, they reflect real value returned to shareholders, and they are less subject to managerial discretion or manipulation.

For equities, this is defined as the sum of dividend yield and share buyback yield. While dividend yield data are readily available at the sector index level, buyback data is not directly accessible in aggregated form. To overcome this, a bottom-up methodology was employed:

* For each year-end, the constituent companies of every sector index were retrieved via Bloomberg's Excel API.
* Key data included market capitalization, share prices, shares outstanding, and actual buyback amounts.
* These values were used to compute market-capitalization-weighted buyback yields at the sector level, creating a robust and replicable proxy for shareholder yield.

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| **Figure 7: Buyback yields have considerably increased since 2012** |
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Over the past two decades, share buybacks have become a structurally important component of shareholder return policy across nearly all U.S. equity sectors. As illustrated in the chart, buyback yields were negligible or even negative during the early 2000s but began rising meaningfully post-2010, with an especially sharp acceleration following the 2017 corporate tax reform and the COVID-19 recovery period. By 2022–2025, many sectors, including Financials, Technology, and Industrials, consistently delivered buyback yields in the 3% to 6% range, rivaling or exceeding their dividend yields. This shift reflects a broader transformation in corporate capital allocation strategies, where buybacks have become the preferred mechanism for returning cash to shareholders due to their flexibility, tax efficiency, and perceived signaling value. The growing prominence and persistence of buyback activity underscore the need to incorporate them explicitly into any forward-looking equity return model, particularly for sector-level strategic allocation analysis.

An important technical adjustment was made to both dividend and buyback yields to better reflect the timing of cash distributions. Specifically, raw dividend yield figures, which are calculated based on the year-end index level, were adjusted by dividing by the average index level over the course of the preceding year. This correction accounts for the fact that dividends and buybacks are distributed throughout the year rather than as a single lump sum at year-end, improving the fidelity of the cash yield as an annualized figure.

To estimate forward growth, 5-year consensus EPS growth forecasts were constructed using Capital IQ data. As these forecasts were not available in aggregate at the sector index level, another bottom-up process was employed:

* For each year-end in the historical period, EPS growth expectations were retrieved for all constituent companies in each sector, if available (they were available for majority of index constituents all of the time).
* These forecasts were then market-cap weighted to arrive at a sector-level forward growth rate.
* It is assumed that the growth in cash yield (dividends and buybacks) matches EPS estimated growth rate.

With both cash yield and expected growth in hand, the next step involved computing the implied cost of equity for each sector at each year using a two-stage dividend discount model, a version of the Gordon Growth Model. The structure of the model includes an initial five-year phase of elevated growth, followed by a perpetual growth phase at a lower terminal rate. The formula applied is as follows:

* P is the index level at year-end
* D0 is the current cash yield (dividends + buybacks)
* g is the 5-year EPS growth rate
* rfr is the terminal growth rate (set equal to the long-term risk-free rate)
* r is the cost of equity to be solved for

This nonlinear equation was solved using a VBA-automated goal-seek macro to determine the implied cost of equity for each sector and year. After obtaining the implied cost of equity, the long-term risk-free rate was subtracted to derive the implied equity risk premium (ERP), the primary input into the SAA model. The choice of using the long-term rate (long treasury index) as the discount rate and terminal growth assumption is consistent with equity’s long-duration nature, as equities represent claims on a very long stream of future cash flows.

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| **Figure 8: Implied ERP levels have been more volatile in the last decade** |
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The chart below plots the evolution of implied ERP by sector over the 2004–2025 period. The series are highly dynamic, influenced by fluctuations in valuation, payout behavior, and forward growth expectations. Notably, a pronounced upward shift in implied ERP levels is visible post-2015 across most sectors, with a further spike during periods of market stress, including 2020 and late 2023. These ERP movements capture not just investor sentiment and risk appetite, but also cyclical inflections in fundamentals and pricing.

Beliefs about market efficiency inherently shape how equity risk premiums are estimated. For long-horizon allocators, the choice of methodology reflects underlying assumptions about whether markets are efficiently priced. If one believes that public markets are broadly efficient over time, or at least that their direction is inherently unpredictable, then the current implied equity risk premium (ERP), derived from prevailing market prices and cash flows, offers the most rational anchor for return expectations. However, if one sees recurring valuation dislocations or structural inefficiencies at the sector or macro level, then using longer-term average implied ERPs or even historical realized premiums may be more appropriate. Survey-based ERPs, while occasionally used, may be preferred only by those who lack confidence in market-based signals altogether.

Since this framework is designed primarily with institutional allocators in mind, and I believe in general market efficiency with some sector-level inefficiencies, the implied ERP is adopted as the core signal, which is then refined through valuation-aware and structurally-informed adjustments, as described in the subsequent CAPE-based and profitability-based enhancements.

Having established base return expectations using implied cost of equity (implied ERP + long-term riskfree rate), the next step introduces a valuation-sensitive overlay via sector-specific CAPE adjustments. The cyclically adjusted P/E ratio (CAPE) serves as a signal of valuation deviation from historical norms. The methodology here avoids simplistic valuation heuristics and instead uses a regression-based framework to determine whether CAPE ratios have explanatory power for future sector-level excess returns. Rolling regressions were performed for each sector, regressing subsequent 5-year excess returns on CAPE deviations from historical norms. Three sub-periods were evaluated:

* The full historical sample
* The post-GFC expansion (2009–2015)
* The more recent cycle (2015–2020)

Only when these regressions exhibited meaningful explanatory power, defined as an R-squared above 0.2 in at least one sub-period, was an adjustment applied. The size of the adjustment was proportional to the statistical significance and stability of the relationship:

* If both long- and short-term regressions showed strong fit, a full adjustment of the implied excess return was imposed.
* If only one period met the criteria, a smaller 25 to 50 percent adjustment was applied.
* In sectors where CAPE-return linkages were weak or unstable, no adjustment was made.
* In sectors undergoing structural change, such as Information Technology, greater emphasis was placed on recent regressions to reflect evolving valuation paradigms.

The regression charts for each sector are given below (blue dots represent time period 2009-2015, red dots are for 2015-2020, while black line represents the full sample).

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The CAPE adjustment process led to the following modifications:

* Technology and consumer staples received a slight upward adjustment due to persistent undervaluation relative to realized performance.
* Industrials and Utilities saw downward adjustments due to persistent overvaluation and a historically robust connection between high CAPEs and poor forward returns.

The output tables for all three testing period regressions are given below:

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| **2009-2015** | **consumer\_staples** | **industrials** | **information\_technology** | **utilities** |
| Alpha | -0.0373 | 0.0190 | -0.0035 | -0.0022 |
| p-value | 0.0000 | 0.0000 | 0.6075 | 0.3927 |
| Beta | -0.0067 | -0.0065 | -0.0113 | 0.0013 |
| p-value | 0.0027 | 0.0000 | 0.0000 | 0.1227 |
| R-squared | 0.119 | 0.697 | 0.372 | 0.034 |
| CAPE deviation (x) | 0.00 | 0.00 | 0.00 | 0.00 |
| **Implied excess return (y)** | **-3.73%** | **1.90%** | **-0.35%** | **-0.22%** |
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| **2015-2020** | **consumer\_staples** | **industrials** | **information\_technology** | **utilities** |
| Alpha | -0.0544 | -0.0106 | 0.1033 | 0.0306 |
| p-value | 0.0000 | 0.0000 | 0.0000 | 0.0042 |
| Beta | -0.0061 | -0.0063 | -0.0096 | -0.0098 |
| p-value | 0.0001 | 0.0000 | 0.0000 | 0.0000 |
| R-squared | 0.210 | 0.429 | 0.683 | 0.399 |
| CAPE deviation (x) | 0.00 | 0.00 | 0.00 | 0.00 |
| **Implied excess return (y)** | **-5.44%** | **-1.06%** | **10.33%** | **3.06%** |
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| **Entire period** | **consumer\_staples** | **industrials** | **information\_technology** | **utilities** |
| Alpha | -0.0494 | 0.0052 | 0.0685 | -0.0094 |
| p-value | 0.0000 | 0.0038 | 0.0000 | 0.0005 |
| Beta | -0.0085 | -0.0078 | 0.0002 | -0.0036 |
| p-value | 0.0000 | 0.0000 | 0.8855 | 0.0000 |
| R-squared | 0.287 | 0.517 | 0.000 | 0.285 |
| CAPE deviation (x) | -9.84 | 9.84 | 9.71 | 7.46 |
| **Implied excess return (y)** | **3.41%** | **-7.12%** | **7.06%** | **-3.63%** |

Finally, a third layer of refinement was applied to expected returns based on structural sector-specific trends in profitability and margins. These adjustments recognize that valuation-based models such as CAPE, while informative, do not always capture evolving fundamentals, particularly when sector economics are undergoing transformation or degradation.

* **Real Estate** was adjusted downward by 50 basis points due to a sustained decline in sector-wide net profit margins, which have fallen to levels last seen during the Global Financial Crisis. Net margins now hover around 11.9 percent, down nearly 12 points from their 2015 peak, with a negative annual trend of minus 1.83 percent. Structural pressures include higher interest rates compressing cap rate spreads and secular weakening of office and retail segments.
* **Communication Services** received a 50 basis point upward adjustment. Net margins have expanded consistently, reaching 19.2 percent in 2025, nearly double the average from a decade prior. This improvement stems from a sectoral shift toward scalable, digital platform companies.
* **Utilities** were adjusted upward by 25 basis points, supported by a secular rise in profitability to 14.4 percent, driven by inflation-linked rate bases, electrification demand, and renewable energy investment.

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| **Figure 9: Net profit margins by sector** |
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Together, the methodology outlined above represents a rigorous, data-intensive, and forward-looking approach to equity return forecasting. By anchoring expectations in actual cash flows, layering in valuation and structural considerations, and avoiding reliance on simplistic heuristics or backward-looking averages, this framework aims to produce credible, institutionally relevant return forecasts for use in long-horizon strategic allocation decisions.

**Risk Estimation**

The chart below compares the 10-year scaled root mean square error (RMSE × √10) of return forecasts to the historical standard deviation of total returns for each sector. RMSE here is calculated based on the forecast error between the modeled expected return (implied cost of equity) and the realized return over rolling 5-year periods, and then scaled by √10 to represent volatility over a strategic 10-year horizon, consistent with the time frame of our SAA optimization. This scaling adjusts for the fact that forecast errors over time are not necessarily i.i.d., but it still offers a more forward-looking, model-anchored estimate of risk than raw historical volatility.

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| **Figure 10: RMSE vs Standard Deviation** |
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Notably, in some sectors, specifically Communication Services, Consumer Discretionary, Health Care, and Information Technology, the RMSE actually exceeds the observed standard deviation of returns. This counterintuitive outcome suggests that for these sectors, return forecasts have historically exhibited higher miss errors than the typical annual price fluctuation, which may reflect structural shifts, model misspecification, or simply the inherent difficulty in forecasting sectors undergoing rapid transformation. Conversely, more stable sectors like Consumer Staples, Utilities, and Real Estate exhibit RMSEs that are meaningfully lower than their historical volatilities, underscoring the higher accuracy and reliability of forecast models in those segments.

Despite these nuances, RMSE remains the preferred measure of risk in this SAA framework. It directly reflects the historical uncertainty of our modeled expected return inputs, rather than backward-looking price fluctuations, making it more consistent with a forward-driven optimization approach. This methodological choice ensures internal consistency between return assumptions and risk estimates.

Based on all of the above, the final return and risk estimation figures are given below:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Sector** | **Implied ERP** | **CAPE adjustment** | **Structural adjustment** | **Expected return** | **Risk (RMSE)** |
| Communication | 6.01% |  | 0.50% | 6.51% | 27.27% |
| Consumer discretionary | 3.22% |  |  | 3.22% | 25.89% |
| Consumer staples | 4.06% | 0.85% |  | 4.91% | 9.40% |
| Energy | 11.13% |  | -0.50% | 10.63% | 18.68% |
| Financials | 5.27% |  |  | 5.27% | 14.22% |
| Real estate | 4.27% |  |  | 4.27% | 6.86% |
| Health care | 7.62% |  |  | 7.62% | 20.58% |
| Industrials | 4.59% | -3.56% |  | 1.03% | 14.88% |
| Materials | 15.44% |  |  | 15.44% | 5.54% |
| Information technology | 3.18% | 5.16% |  | 8.34% | 33.15% |
| Utilities | 3.33% | -0.91% | 0.25% | 2.67% | 8.79% |

# Alternatives

**Private equity**

I view the expected return profile of private equity relative to public markets through the lens of factor exposures. Buyout strategies, which dominate the private equity universe, systematically load more heavily on certain risks than public equities. Because leverage is central to the buyout model, PE portfolios effectively run at higher equity betas, closer to 1.2–1.5 in practice rather than the sub-1.0 estimates implied by smoothed NAVs. This means the true risk is higher than what reported returns suggest, and that risk tends to show up in prolonged bear markets rather than in short, sharp drawdowns.

The illiquidity angle is more nuanced. In theory, locking capital for 5–10 years should command a premium, but in practice, much of it is competed away. Many investors seem content to trade off some economic compensation in exchange for smoother reported returns and the reduced headline volatility that comes with appraisal-based valuations. As a result, the realized illiquidity premium often looks small or even nonexistent.

The industry track record also points to little evidence of persistent net alpha. Several large-sample studies find that, once you control for leverage, small-cap exposure, and fees, private equity returns are largely explained by traditional risk factors. In other words, the outperformance often attributed to manager skill or illiquidity premia is better understood as compensation for bearing higher equity beta and structural tilts. Fees in particular eat up much of the gross excess return, making it difficult to justify a positive “alpha” at the asset-class level.

Beyond leverage, private equity tends to tilt toward smaller and historically cheaper companies. The small-cap bias is visible in the typical characteristics of buyout targets, while the value bias has become less consistent in recent years as entry multiples have risen. Taking these exposures together, I think it is most realistic to treat private equity as a leveraged small-cap equity exposure, with higher sensitivity to the equity risk premium, some residual size tilt, and no persistent net alpha after fees.

For my expected return modeling, I primarily use a discounted cash-flow framework similar to AQR’s yield-based approach: I start from an estimate of the unlevered return (income yield plus real growth), then add the effects of financial leverage, conservatively account for potential multiple expansion, and subtract fees. This makes the drivers of PE returns more transparent and allows me to stress-test assumptions around valuations, leverage costs, and growth. That said, I also supplement this analysis with a simpler public-equity-based comparison, where I treat private equity as a leveraged small-cap exposure with no net alpha. Using this as a cross-check provides an additional perspective and helps ensure that my forward-looking assumptions remain grounded against public market benchmarks.

In constructing my CMA inputs, I use arithmetic mean expected returns rather than geometric, since arithmetic returns are the appropriate measure for portfolio optimization and strategic asset allocation, they represent the expectation of a one-period return and avoid deducting variance drag, which the optimizer already accounts for through the volatility input. Reported geometric means, while more intuitive for compounding, understate the inputs required for allocation modeling. For the cash or risk-free rate, I do not rely on today’s short-term SOFR or T-bill yield, which are cyclical and unsuitable for a strategic horizon. Instead, I assume a long-run real cash rate (anchored by historical averages and central bank estimates of the neutral rate) combined with long-term inflation expectations from breakeven markets, ensuring consistency with a 10-year investment horizon.