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

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

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Introduction

This document lays out a detailed framework for building capital market assumptions that I use in my project about Strategic Asset Allocation 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 and practical 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:

	Asset
Government	US Treasuries, Short/Intermediate
	US Treasuries, Long
	US Taxable Munis
	Global ex-US Government, hedged
Public Corporates	US Public Corporates IG AAA
	US Public Corporates IG AA
	US Public Corporates IG A
	US Public Corporates IG BBB
	US Public Corporates, HY Intermediate
	US Public Corporates, HY Long
	Global ex-US Corporates, hedged
Structured	Residential Mortgage-Backed Securities
	Commercial Mortgage-Backed Securities
	Asset-Backed Securities
Private Credit	Corporate IG Private Placement A
	Corporate IG Private Placement BBB
	Corporate HY Private (Leveraged Loans)
	Residential Mortgage Whole Loans
	Commercial Mortgage Whole Loans

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.

Figure 1: Foreign currency volatility makes up the majority of the unhedged foreign currency bond risk
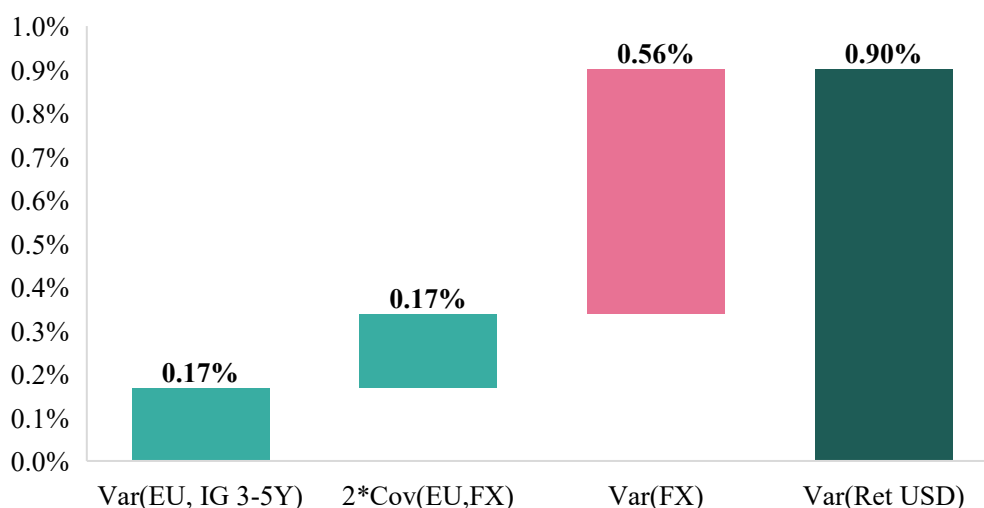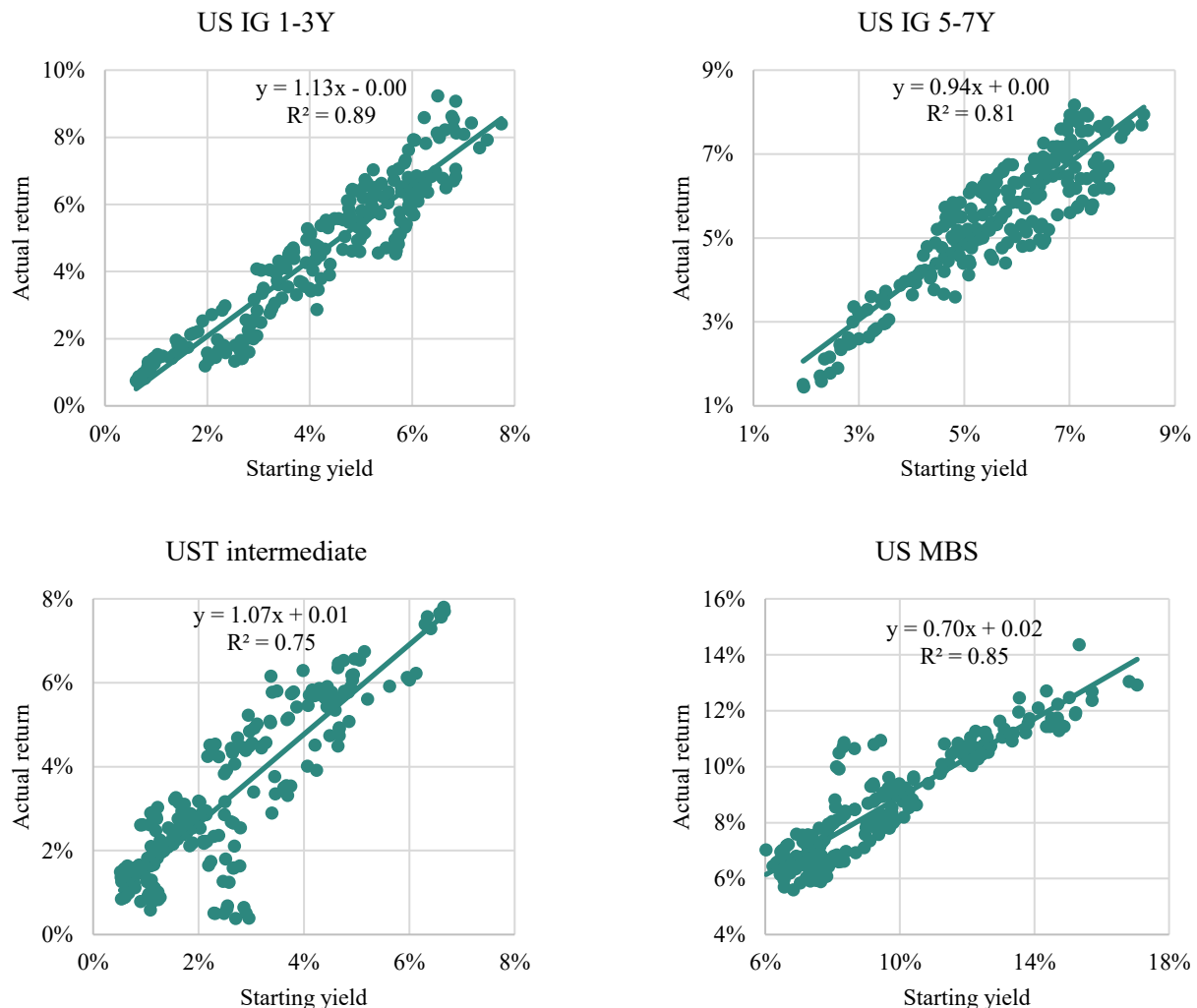

Life insurers and other institutional allocators do in practice allocate to foreign sovereign and corporate bonds, but on a hedged basis, since their mandate is to capture the bond risk premium rather than currency noise. Following this logic, I include foreign bond exposures in my CMA framework through 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 $Y_i(t)$ at decision time t (index yield-to-worst) for the sleeve and expected annual credit loss rate $ECL_i(t)$ (default * hazard rate × LGD, plus any systematic downgrade/migration haircuts). Y_i is an IRR/CAGR by construction; it already accounts for compounding (no variance-drag mismatch). 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.

Figure 2: Starting yields are good indicators of actual performance

US IG 1-3Y

y = 1.13x - 0.00
R² = 0.89

US IG 5-7Y

y = 0.94x + 0.00
R² = 0.81

UST intermediate

y = 1.07x + 0.01
R² = 0.75

US MBS

y = 0.70x + 0.02
R² = 0.85

Credit Loss and Capital Efficiency Adjustments

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.

Since the analysis is aimed at life insurers' portfolios, which face probably the highest number of regulations among large institutional asset allocators, I am also adjusting the yields by how much capital drag each asset has, which in public fixed income space is dependent on the credit ratings. The table below shows the list of assets along with their assigned schedule NAIC papers, ratings, NAIC designations, and capital charges (times portfolio adjustment factor which accounts for the number of issuers in a given index, and which I assume to be around 500 for each index I take, with PAF of ~1).

Asset	Schedule	Rating	NAIC Designation	Capital Charge X PAF
US Treasuries, Short/Intermediate	D-1	AAA	1A	0.00%
US Treasuries, Long	D-1	AAA	1A	0.00%
US Taxable Munis	D-1	AA	1C	0.00%
Global ex-US Government, hedged	D-1	AA	1C	0.42%
US Public Corporates IG AAA	D-1	AAA	1A	0.16%
US Public Corporates IG AA	D-1	AA	1C	0.42%
US Public Corporates IG A	D-1	A	1F	0.82%
US Public Corporates IG BBB	D-1	BBB	2B	1.52%
US Public Corporates, HY Intermediate	D-1	BB–	3C	6.02%
US Public Corporates, HY Long	D-1	BB–	3C	6.02%
Global ex-US Corporates, hedged	D-1	A	1F	0.82%
Residential Mortgage-Backed Securities	D-1	AA	1C	0.00%
Commercial Mortgage-Backed Securities	D-1	AA	1C	0.00%
Asset-Backed Securities	D-1	AA	1C	0.42%

The capital charge drags the expected return as it ties up the capital that could be invested at the hurdle rate for the given company, which is also its cost of capital and I assume to be 10%. The typical RBC ratio (how much capital above the required charge they typically hold for a given asset) for life insurers is 4. The final credit-loss- and capital-adjusted return estimation formula looks like this:

$$\mu_i = y_i - ECL_i - Cap_{Charge_i} * RBC\ ratio * Cost\ of\ Capital$$

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 $\sigma_{10Y} = \sigma_{1Y} \times \sqrt{10}$.

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 public fixed income instruments tested).

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
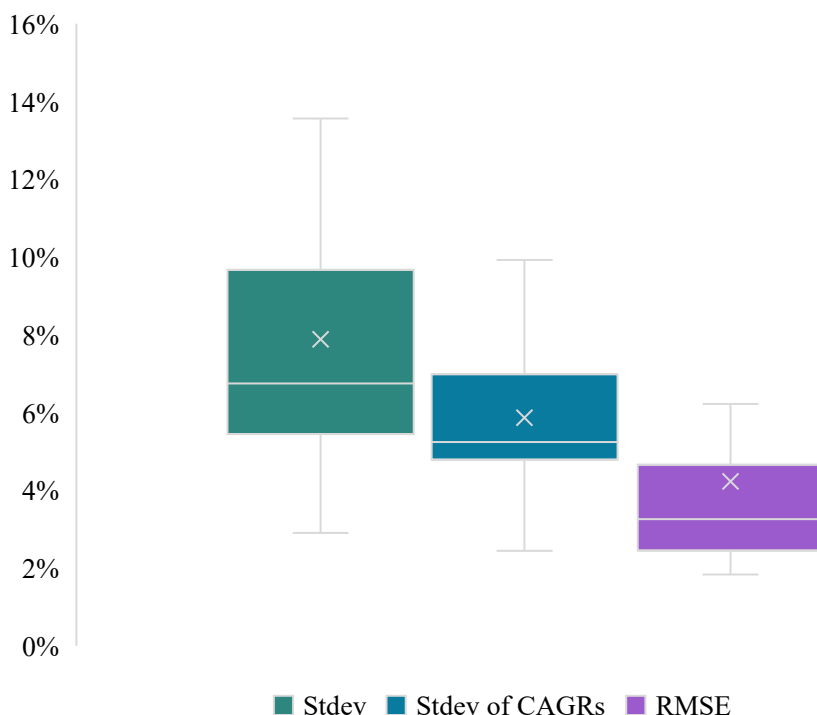

The effect of mean reversion can be seen in the second (blue) bar: the distribution of CAGRs has a noticeably lower mean and median volatility compared to 1-year returns. Intuitively, this happens because extreme short-term shocks (e.g., a sudden yield spike) wash out over multi-year horizons as bonds 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.

**Figure 4: Time diversification effect is most pronounced in HY securities**
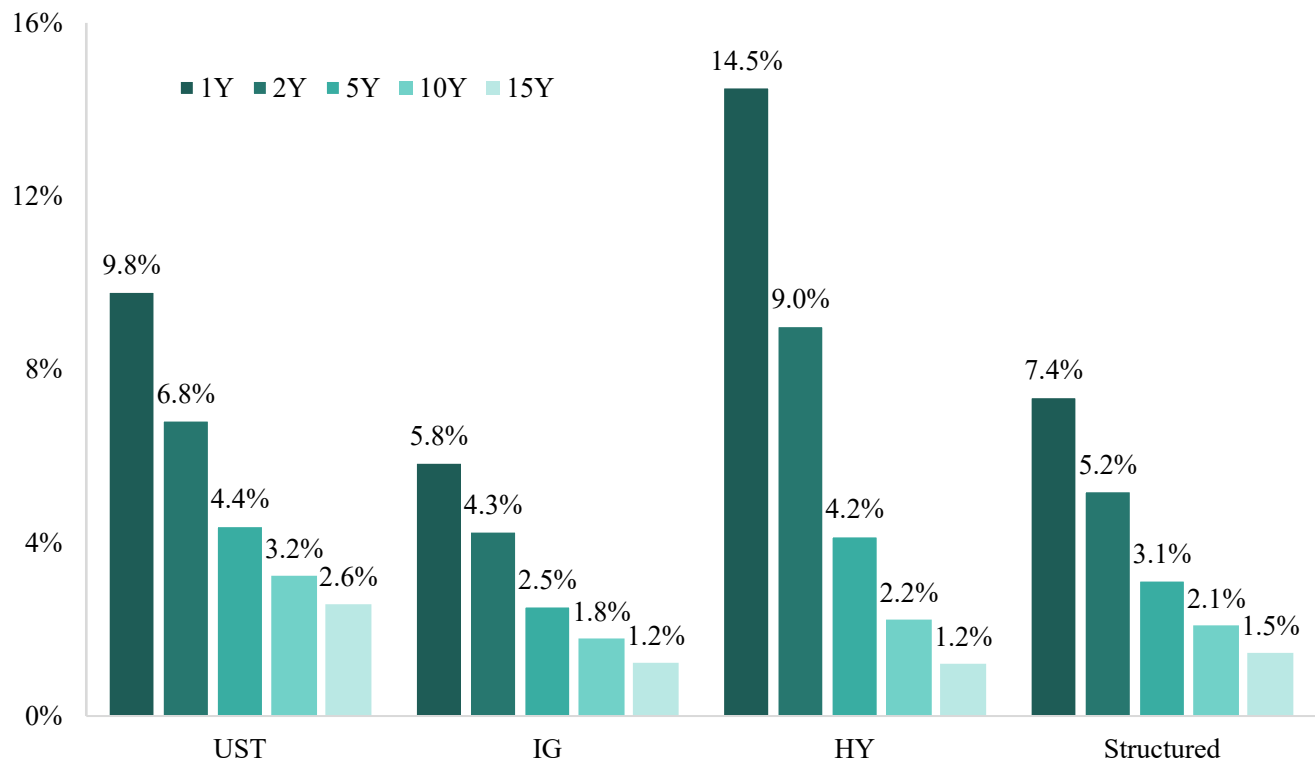
This empirical behavior is not just statistical coincidence but reflects structural features of credit markets. High yield returns tend to be driven by recurring income streams and cyclical credit re-rating patterns that cancel out over time, producing strong mean-reversion dynamics. Meanwhile, interest 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.

Figure 5: As expected, RMSE is lower than traditional measure of average return volatility STERR
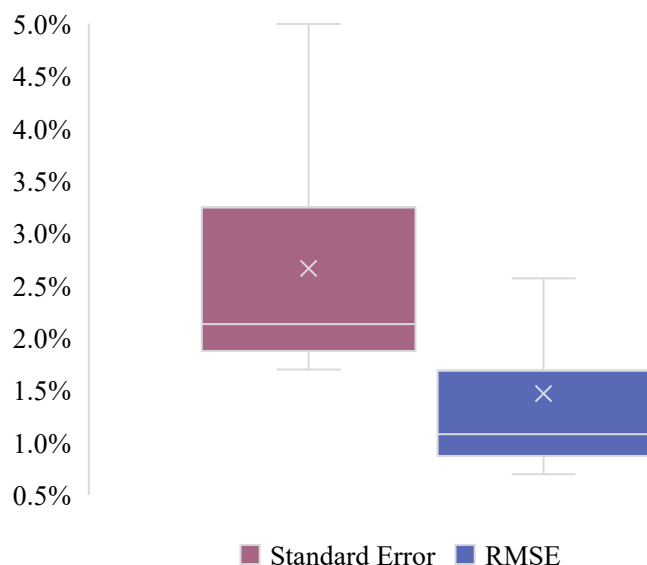
All this indicates that RMSE provides a more reliable and realistic measure of long-term forecast uncertainty. Also, maturity has an impact predictability: the longer the maturity of an index, the more effectively the starting yield predicts actual returns over a 10-year investment horizon. Shorter-term 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.

Risk 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 1) coupon reinvestment risk and 2) 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:

$$Ri(t \to t + 10) = (\frac{I_i(t + 120)}{I_i(t)})^{1/10} - 1$$

where $I_i(\cdot)$ is the index level. Yield-model forecast error is defined as:

$$\epsilon_{i,t}^{(y)} = R_{i(t \to t+10)} - Y_i(t) \quad \text{and} \quad RMSE_i = \sqrt{\frac{1}{N_i}\Sigma_t(\epsilon_{i,t}^{(y)^2})}$$

RMSE of bond returns, which is basically the measure of "wrongness" in compunded average return of an index (along with all its mean reversion and time diversification) is an appropriate risk measure because of holding to maturity practice and book accouning instead of mark to market. It does not take into account the market swings in interest rates that would introduce the volatility, but it combines two important measure of risk: reinvestment risk and credit risk.

To be comparable to the traditional risk measure of standard deviation, I scale this RMSE by square root of 10. The intuition behing this scaling is that the RMSE number corresponds to the "wrongness" in the average 10-year CAGR, which is comparable to standard error (not standard deviation), and that "smoothed-out" measure should be multiplied by the square root of time horizon. In addition, using a duration-maintained index matches insurer practice, while avoiding explicit reinvestment path modeling.

In this analysis, I assume that this risk measure includes both types of errors mentioned above (reinvestment & credit loss). However, as a final risk measure which I give to my optimizer is the weighted average of long-term uncertainty (scaled RMSE) and short-term risk (historical standard deviation, which more or less stays within the reasonable bounds over time and so is a good proxy for expected volatility). I give former 0.7 and latter 0.3 weight. The reason for this weights are somewhat subjective but dependent on the idea that while life insurance and retirement products liabilities are fairly long-term and can withstand substantial drawdowns, the short-term volatility is still relevant because of regulations (rbc requirements) and liquidity constraints along the way. If it was endowment asset allocation problem, for example, I would give even less weight to short-term volatility, because they have the longest investment horizons and fewest regulatory/board restrictions among institutional asset allocators (pensions, insurance, SWFs), so for them larger drawdowns are tolerable, although maximizing wealth growth also requires high risk-adjusted returns, which itself depends on maximizing compounded returns and relatively moderate drawdowns.

$$\sigma = 0.7 * RMSE + 0.3 * Vol$$

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:
   o Starting valuations (e.g., yields) are used to forecast returns;
   o Investors are not forced to liquidate prematurely (i.e., drawdown-insensitive);
   o 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
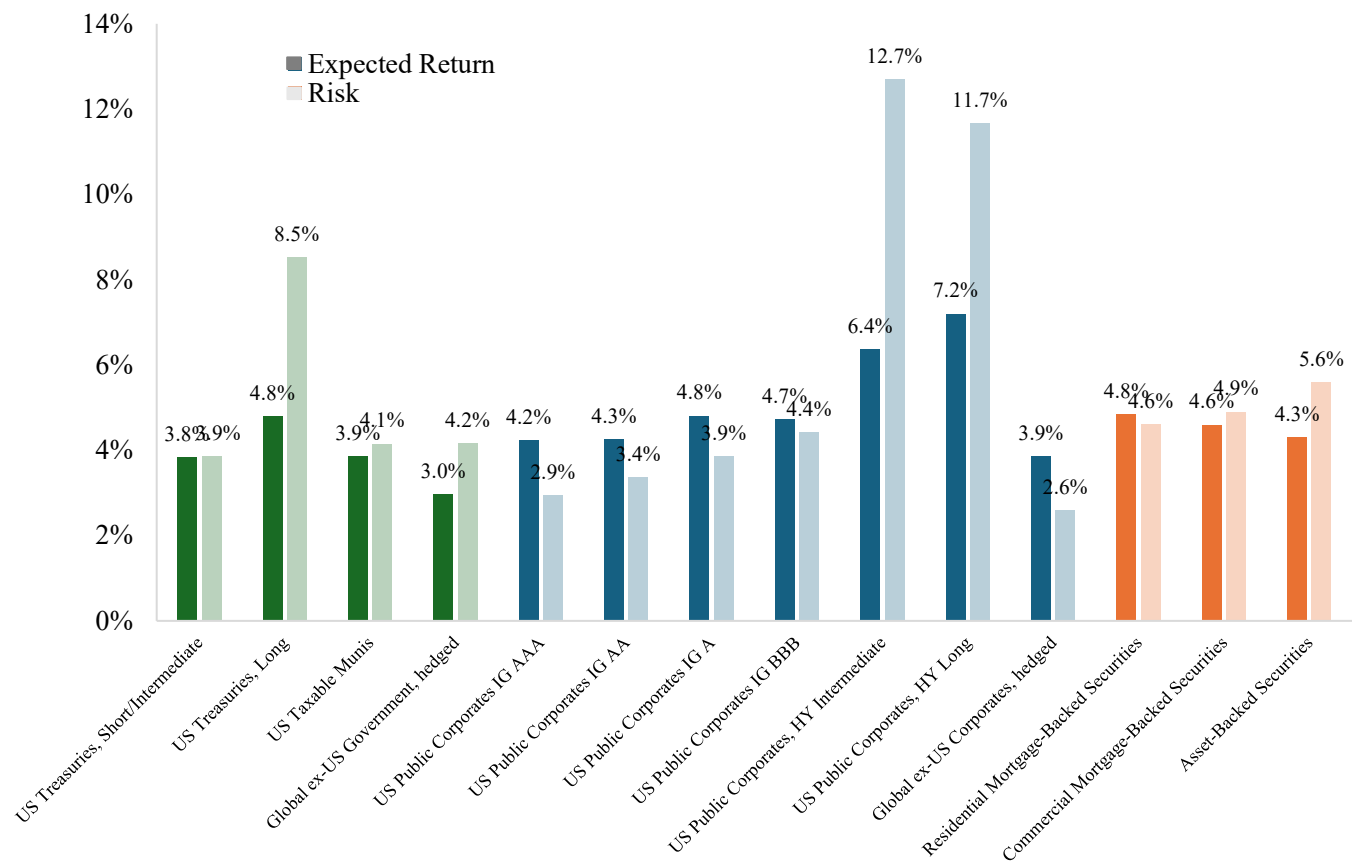
Public Equity

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.

Figure 7: Buyback yields have considerably increased since 2012
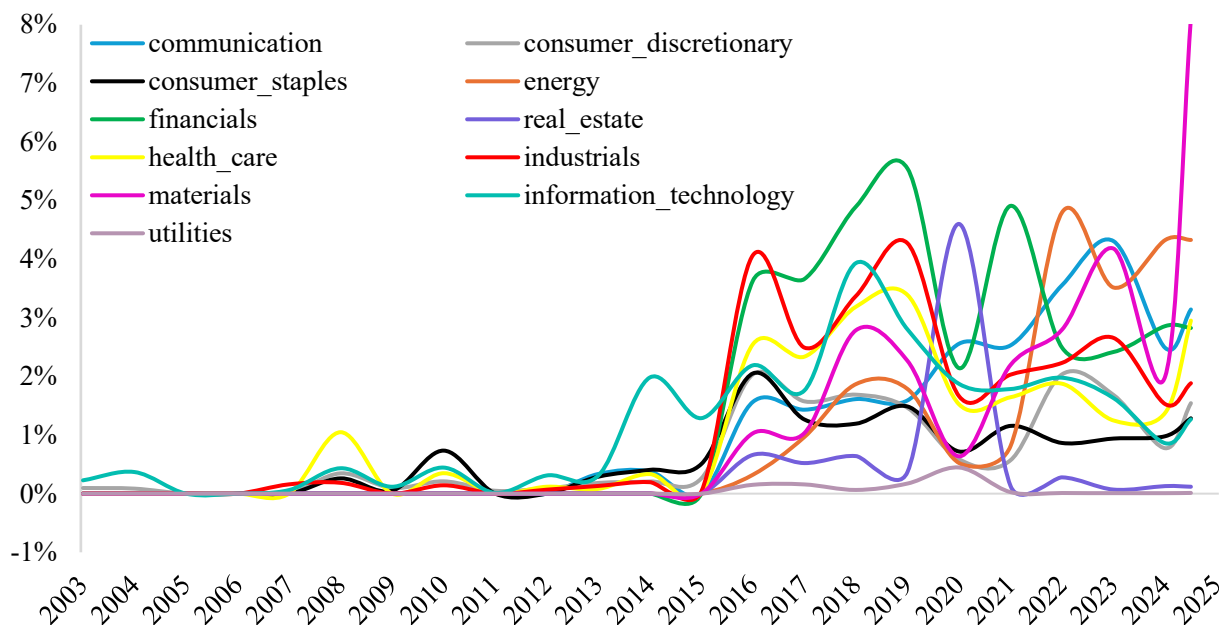
Over the past two decades, share buybacks have become a structurally important component of shareholder return policy across nearly all U.S. equity sectors. As illustrated in the chart, buyback yields were negligible or even negative during the early 2000s but began rising meaningfully post-2010, with 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:

$$P = \sum_{(t=1)}^{5} \llbracket D\_0\,(1+g) \rrbracket\,{}^t/(1+r)^t + (D\_0\,(1+g)^5\,(1+g\_term))/((r - g\_term)\,(1+r)^5)$$

- P is the index level at year-end
- D_0 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.

Figure 8: Implied ERP levels have been more volatile in the last decade
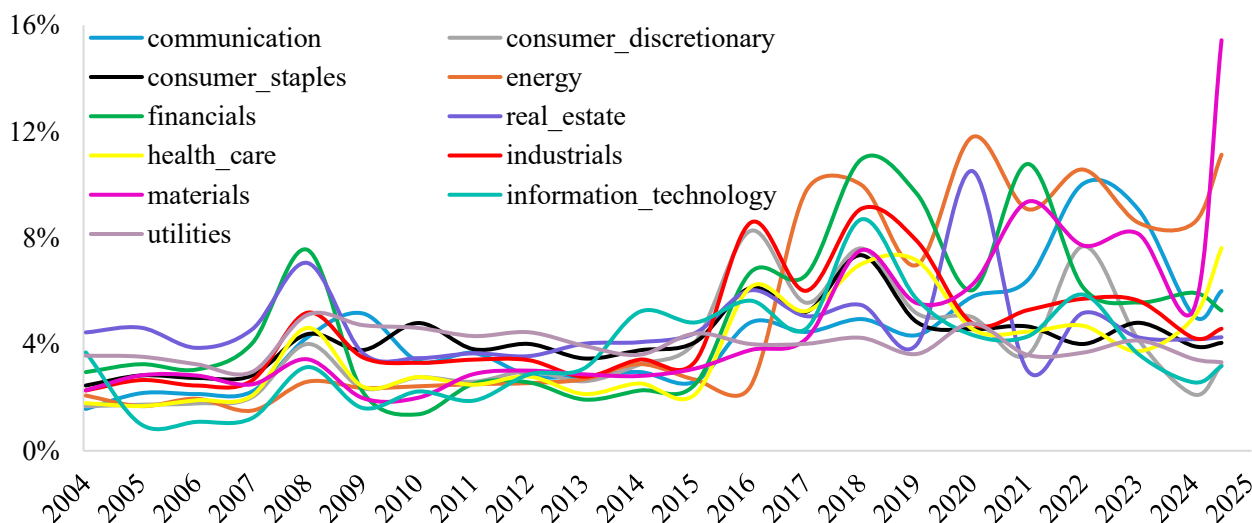
The chart below plots the evolution of implied ERP by sector over the 2004–2025 period. The series are highly dynamic, influenced by fluctuations in valuation, payout behavior, and forward growth expectations. Notably, a pronounced upward shift in implied ERP levels is visible post-2015 across most sectors, 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.
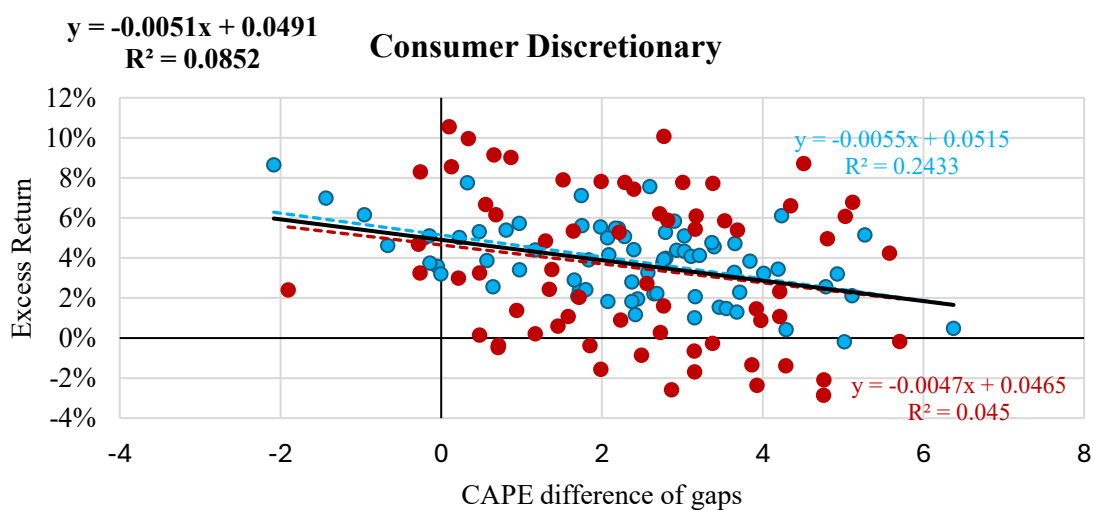
Having established base return expectations using implied cost of equity (implied ERP + long-term riskfree rate), the next step introduces a valuation-sensitive overlay via sector-specific CAPE adjustments. The cyclically adjusted P/E ratio (CAPE) serves as a signal of valuation deviation from historical 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).

Communication

$y = -0.0054x + 0.0435$
$R^2 = 0.2763$

$y = -0.0049x + 0.067$
$R^2 = 0.8166$

$y = 0.0022x - 0.0041$
$R^2 = 0.0417$

Excess Return

CAPE difference of gaps

Consumer Discretionary

$y = -0.0051x + 0.0491$
$R^2 = 0.0852$

$y = -0.0055x + 0.0515$
$R^2 = 0.2433$

$y = -0.0047x + 0.0465$
$R^2 = 0.045$

Excess Return

CAPE difference of gaps

Consumer Staples

y = -0.0085x - 0.0494
R² = 0.2869

y = -0.0067x - 0.0373
R² = 0.119

y = -0.0061x - 0.0544
R² = 0.2097

Excess Return

CAPE difference of gaps

Energy

y = 0.0015x - 0.1066
R² = 0.003

y = -0.0194x - 0.1651
R² = 0.5977

y = 0.0107x - 0.102
R² = 0.1156

Excess Return

CAPE difference of gaps

Financials

y = -0.0013x - 0.0197
R² = 0.008

y = 0.0004x - 0.0053
R² = 0.0011

y = -0.0106x - 0.047
R² = 0.4736

Excess Return

CAPE difference of gaps

Real Estate

y = -0.0028x - 0.0483
R² = 0.0435

y = -0.009x - 0.0171
R² = 0.5321

y = 0.0006x - 0.0767
R² = 0.0044

Health Care

y = -0.0059x + 0.0018
R² = 0.1871

y = -0.0099x + 0.0177
R² = 0.6187

y = -0.0009x - 0.0201
R² = 0.0132

Industrials

y = -0.0078x + 0.0052
R² = 0.5166

y = -0.0065x + 0.019
R² = 0.6974

y = -0.0063x - 0.0106
R² = 0.4289

Materials

y = -0.006x - 0.0698
R² = 0.2994

y = -0.0085x - 0.0762
R² = 0.7238

y = -0.0012x - 0.0573
R² = 0.0091

Excess Return

CAPE difference of gaps

Information Technology

y = 0.0002x + 0.0685
R² = 0.0002

y = -0.0096x + 0.1033
R² = 0.6828

y = -0.0113x - 0.0033
R² = 0.3723

Excess Return

CAPE difference of gaps

Utilities

y = -0.0036x - 0.0094
R² = 0.2853

y = 0.0013x - 0.0022
R² = 0.0338

y = -0.0098x + 0.0306
R² = 0.399

Excess Return

CAPE difference of gaps

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:

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%**

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%**

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.

Figure 9: Net profit margins by sector
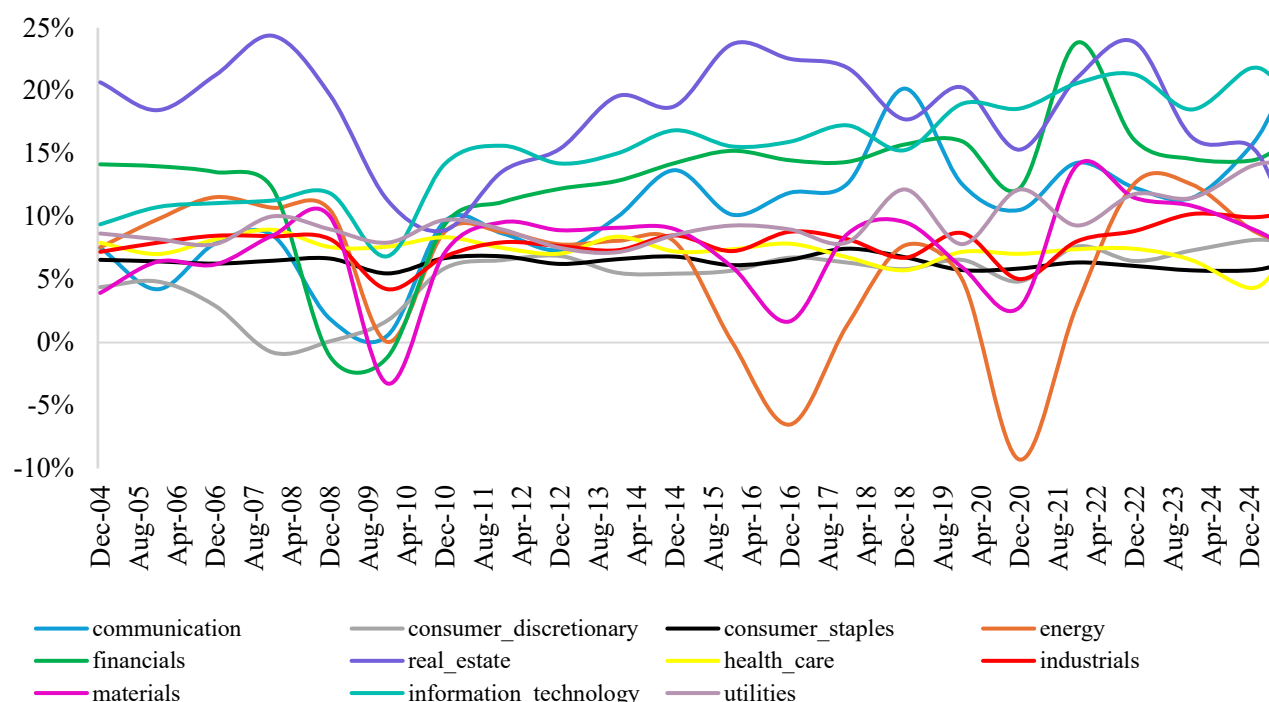
Together, the methodology outlined above represents a rigorous, data-intensive, and forward-looking approach to equity return forecasting. By anchoring expectations in actual cash flows, layering in valuation and structural considerations, and avoiding reliance on simplistic heuristics or backward-looking 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.

Figure 10: RMSE vs Standard Deviation

	RMSE	Stdev
utilities	8.79%	13.92%
information_technology	33.15%	24.61%
materials	5.54%	19.12%
industrials	14.88%	16.83%
health_care	20.58%	13.17%
real_estate	6.86%	20.28%
financials	14.22%	22.09%
energy	18.68%	24.64%
consumer_staples	9.40%	9.65%
consumer_discretionary	25.89%	22.96%
communication	27.27%	23.89%
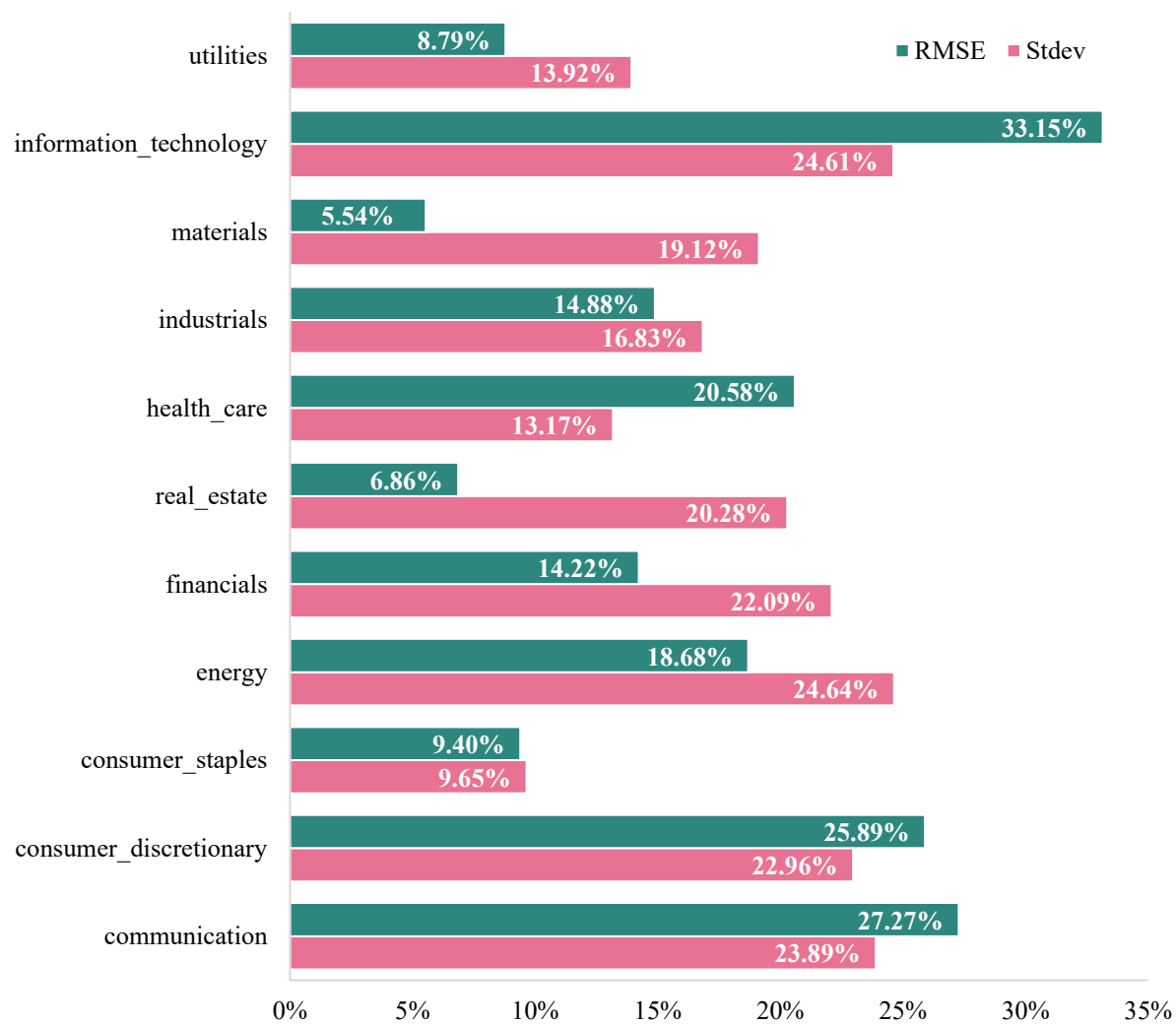
Notably, in some sectors, specifically Communication Services, Consumer Discretionary, Health Care, and Information Technology, the RMSE actually exceeds the observed standard deviation of returns. This counterintuitive outcome suggests that for these sectors, return forecasts have historically exhibited 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
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%

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.

y_u	g_u	$r_u = y_u + g_u$	D/E	k_d	$r_l = r_u + (D/E)*(r_u - k_d)$	m	$r_g = r_l + m$	f	$r_r = r_g - f$	i	$r = r_r + i$
Income Yield	Real Growth Rate	Real Unlevered Return	Debt to Equity	Real Cost of Debt	Real levered Return	Multiple Expansion	Gross Real Expected Return	Fees	Net Expected Real Return	Expected Inflation	Net Expected Return
3.6%	+ 3.0%	= 6.6%	52.0%	3.1%	8.4%	+ 0.3%	= 8.7%	-4.0%	= 4.7%	+ 2.3%	= 7.0%

Income Yield – I collected data on recent private equity transactions from Bloomberg and focused on last-twelve-month deal multiples. Since direct earnings yields weren't available, I used transaction value to EBIT (TV/EBIT) ratios as a proxy. For most deals, these figures weren't automatically downloadable, so I retrieved them manually for around 200 companies. I then averaged the inverse of these ratios to estimate an income yield for PE, which came out to about 3.6%.

Growth Rate – To capture the real growth potential of PE portfolios, I assumed an unlevered real growth rate of 3.0%, which is about twice as high as the same metric for public markets (Russell 2000 estimated EPS growth rate). The reasoning is that private equity managers can add value through operational improvements, margin expansion, and concentration in higher-growth sectors.

Leverage – I applied a debt-to-equity ratio of 52%, interpolated from post-2008 LBO data and reflecting today's more conservative financing because of high cost of debt. Leveraging the unlevered return (6.6%) with this D/E and a real cost of debt of 3.1% raises the real levered equity return to about 8.4%. The logic is standard corporate finance: equity holders benefit from borrowing so long as operating returns exceed the interest cost.

Real Cost of Debt – I estimate the real cost of debt as real cash rate (nominal SOFR-expected inflation) + one-third of the HY OAS, averaged over the last year to match how I average purchase multiples. The logic is: most LBO debt is floating-rate secured bank debt; a practical proxy for its spread is about two-thirds of the HY OAS, but issuers don't effectively pay the full stated spread once you account for default losses borne by lenders. So I haircut the spread by half, which leaves ~one-third of HY OAS added to real LIBOR. I also ignore the interest tax shield (jurisdictions vary), which biases k_d slightly up, but that's offset by the conservative haircut I already apply to the spread.

Multiple Expansion – I added a conservative adjustment of +0.3% for multiple expansion. This reflects the possibility that PE managers, through active ownership and timing of exits, can sell companies at somewhat higher valuation multiples than entry. I floor this component at zero, consistent with AQR's skeptical stance, and only allow for a small partial convergence toward public market multiples.

Fees – I subtracted 4.0% to reflect management and performance fees. This haircut is somewhat below AQR's 5.7% historical average, since I expect net performance fees to be lower going forward as returns compress. Even so, the fee drag remains the single largest deduction in the framework.

Inflation Adjustment – Finally, I added back expected inflation of 2.3% to convert from real to nominal returns, yielding a net nominal expected return of roughly **7.0%.**

Real Estate

NOI yield	CapEx (~NOI/3)		Cashflow yield		Real growth		Unlevered real ER		Expected inflation		Unlevered nominal ER
4.7%	-	1.6%	=	3.1%	+	0.0%	=	3.1%	+	2.3%	=	5.4%

NOI Yield – I begin with the net operating income yield, which reflects rental income as a percentage of property market value. This is the steady income stream that properties generate before accounting for maintenance costs. It is analogous to a gross yield, similar in spirit to a dividend yield in equities but based on property-level cashflows.

CapEx Deduction – From NOI, I subtract recurring capital expenditures. These are the costs required to maintain and preserve the property's income-generating capacity. Empirical work (e.g., Pagliari 2017) shows that these expenditures typically average about one-third of NOI. In my case, that adjustment reduces the yield by 1.56%.

Cashflow Yield – The result is the free cashflow yield, representing the actual income available to investors after maintaining the property. This measure is more relevant than raw NOI because it accounts for the fact that real estate is capital-intensive and requires continual upkeep. At this stage, my unlevered real cashflow yield is 3.13%.

Real Growth – For growth assumptions, I use a conservative real growth rate of zero. While rents may rise with GDP or demographics, long-term evidence suggests that real estate income growth has often barely kept up with inflation, or, in some cases, underperformed it. This assumption is consistent with AQR's treatment of private real estate, where the long-run real growth contribution is taken as negligible.

Unlevered Real Expected Return – By combining the free cashflow yield and the real growth assumption, I arrive at an unlevered real expected return of 3.13%. This reflects the baseline compensation investors can expect before inflation and leverage, directly from property-level economics.

Inflation – To convert to nominal terms, I add expected inflation. Here, I assume 2.28%, which captures the anticipated erosion of purchasing power over time. This step aligns real estate projections with nominal return frameworks used in portfolio construction.

Unlevered Nominal Expected Return – Finally, adding inflation to the unlevered real expected return yields a nominal expected return of 5.41%. This is the figure I use for strategic asset allocation purposes, providing a consistent basis of comparison with public equities and fixed income.

Correlations and Variance/Covariance

In building the variance–covariance matrix for my optimizer, I take a different path from the usual volatility-driven framework. Rather than starting with historical standard deviations, I first define risk measures that reflect the long-term economic properties of each asset class. For public fixed income indices, this comes from excess return distributions.

For private equity, I rely on two complementary approaches: a yield-based build that stacks up income yield, growth, leverage, and fees; and a public proxy that scales Russell 2000 excess returns by a leverage factor to capture the higher beta of buyouts. For private real estate, I combine a cashflow-based expected return (NOI less CapEx plus inflation) with a listed REIT proxy that reflects the true volatility and market co-movement of the asset class, as appraisal-based indices are too smooth. In each case, the "σ" I use is my own forward-looking risk measure, not simply a sample standard deviation.

To capture how these asset classes move together, I calculate correlations directly from the proxy return series. All returns are expressed in excess form to ensure comparability across equities, bonds, and alternatives. For private equity, that means excess returns from a levered Russell 2000 series; for private real estate, excess returns from REITs; and for other public asset classes, excess returns from their respective indices. With these monthly series, I estimate the correlation matrix empirically. Finally, I combine these correlations with my custom risk measures using the standard covariance identity:

$$Cov_{i,j} = \rho_{i,j} * \sigma_i * \sigma_j$$

This way, the covariance matrix preserves the realistic cross-asset co-movement that emerges from market data, while its diagonal elements reflect the non-standard, horizon-matched risks that I believe are more appropriate for long-term allocators. The result is a covariance structure that ties together consistent forward-looking returns, risks, and correlations for public markets, private equity, and private real estate in a unified framework.

The final variance/covariance matrix is given below:

	US Treasuries, Short/Intermediate	US Treasuries, Long	US Taxable Munis	Global ex-US Government, hedged	US Public Corporates IG AAA	US Public Corporates IG AA	US Public Corporates IG A	US Public Corporates IG BBB	US Public Corporates, HY Intermediate	US Public Corporates, HY Long	Global ex-US Corporates, hedged	Residential Mortgage-Backed Securities	Commercial Mortgage-Backed Securities	Asset-Backed Securities	Corporate IG Private Placement A	Corporate IG Private Placement BBB	Corporate HY Private (Leveraged Loans)	Residential Mortgage Whole Loans	Commercial Mortgage Whole Loans	Private Equity	Real Estate (via partnerships, equity)
US Treasuries, Short/Intermediate	1.0	0.9	0.5	0.8	0.9	0.7	0.6	0.5	0.0	0.1	0.7	0.8	0.2	0.3	0.2	0.1	-0.4	0.2	0.2	0.0	0.0
US Treasuries, Long	0.9	1.0	0.6	0.8	0.9	0.8	0.6	0.5	0.0	0.1	0.7	0.8	0.2	0.3	0.2	0.2	0.3	0.2	0.2	0.0	0.0
US Taxable Munis	0.5	0.6	1.0	0.7	0.7	0.7	0.7	0.7	0.5	0.5	0.6	0.7	0.4	0.6	0.3	0.3	0.2	0.5	0.4	0.0	0.0
Global ex-US Government, hedged	0.8	0.8	0.7	1.0	0.8	0.8	0.7	0.6	0.2	0.3	1.0	0.8	0.3	0.3	0.3	0.2	-0.1	0.4	0.3	0.0	0.0
US Public Corporates IG AAA	0.9	0.9	0.7	0.8	1.0	0.9	0.7	0.6	0.2	0.3	0.6	0.9	0.4	0.4	0.3	0.2	0.4	0.5	0.4	0.0	0.0
US Public Corporates IG AA	0.7	0.8	0.7	0.8	0.9	1.0	1.0	0.9	0.5	0.6	0.6	0.8	0.5	0.5	0.4	0.4	0.4	0.5	0.5	0.0	0.1
US Public Corporates IG A	0.6	0.6	0.7	0.7	0.7	1.0	1.0	0.9	0.6	0.7	0.6	0.7	0.6	0.6	0.4	0.4	0.4	0.5	0.6	0.1	0.1
US Public Corporates IG BBB	0.5	0.5	0.7	0.6	0.6	0.9	0.9	1.0	0.8	0.8	0.6	0.6	0.6	0.7	0.5	0.5	0.4	0.5	0.6	0.0	0.0
US Public Corporates, HY Intermediate	0.0	0.0	0.5	0.2	0.2	0.5	0.6	0.8	1.0	0.9	0.2	0.3	0.7	0.6	0.5	0.5	0.8	0.5	0.7	0.0	0.1
US Public Corporates, HY Long	0.1	0.1	0.5	0.3	0.3	0.6	0.7	0.8	0.9	1.0	0.2	0.4	0.7	0.6	0.5	0.5	0.8	0.5	0.7	0.0	0.1
Global ex-US Corporates, hedged	0.7	0.7	0.6	1.0	0.6	0.6	0.6	0.6	0.2	0.2	1.0	0.7	0.7	0.7	-0.1	-0.1	-0.1	0.4	0.4	-0.2	-0.2
Residential Mortgage-Backed Securities	0.8	0.8	0.7	0.8	0.9	0.8	0.7	0.6	0.3	0.4	0.7	1.0	0.3	0.4	0.2	0.2	0.0	0.5	0.3	0.0	0.0
Commercial Mortgage-Backed Securities	0.2	0.2	0.4	0.3	0.4	0.5	0.6	0.6	0.7	0.7	0.7	0.3	1.0	0.4	0.5	0.4	0.0	0.5	1.0	0.0	0.2
Asset-Backed Securities	0.3	0.3	0.6	0.3	0.4	0.5	0.6	0.7	0.6	0.6	0.7	0.4	0.4	1.0	0.5	0.4	0.0	0.5	0.5	0.0	0.1
Corporate IG Private Placement A	0.2	0.2	0.3	0.3	0.3	0.4	0.4	0.5	0.5	0.5	-0.1	0.2	0.5	0.5	1.0	1.0	0.7	0.5	0.5	0.2	0.2
Corporate IG Private Placement BBB	0.1	0.2	0.3	0.2	0.2	0.4	0.4	0.5	0.5	0.5	-0.1	0.2	0.4	0.4	1.0	1.0	0.7	0.5	0.4	0.1	0.2
Corporate HY Private	-0.4	0.3	0.2	-0.1	0.4	0.4	0.4	0.4	0.8	0.8	-0.1	0.0	0.0	0.0	0.7	0.7	1.0	0.4	0.4	0.7	0.4
Residential Mortgage Whole Loans	0.2	0.2	0.5	0.4	0.5	0.5	0.5	0.5	0.5	0.5	0.4	0.5	0.5	0.5	0.5	0.5	0.4	1.0	1.0	0.4	0.3
Commercial Mortgage Whole Loans	0.2	0.2	0.4	0.3	0.4	0.5	0.6	0.6	0.7	0.7	0.4	0.3	1.0	0.5	0.5	0.4	0.4	1.0	1.0	0.0	0.2
Private Equity	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	-0.2	0.0	0.0	0.0	0.2	0.1	0.7	0.4	0.0	1.0	0.7
Real Estate (via partnerships, equity)	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.1	-0.2	0.0	0.2	0.1	0.2	0.2	0.4	0.3	0.2	0.7	1.0