Regime-Aware Asset Allocation using HMM and CVaR: An Analysis of Retirement Portfolio Withdrawal Strategies

Sehee Jung[1]

[1]Department of Statistics and Data Science, Yonsei University, Seoul, South Korea.
*Address correspondence to: sh.jung9128@gmail.com

Abstract

This study proposes a dynamic retirement portfolio strategy that combines regime-aware inference via Hidden Markov Models (HMM) with Conditional Value-at-Risk (CVaR)-based portfolio optimization. Using daily log returns of SPY and VIX to infer latent market states, the HMM framework classifies regimes into Bull, Neutral, and Bear phases. Based on the prevailing regime, portfolio weights are recalibrated through a Mean-CVaR optimization model with ℓ_2 regularization to balance expected return, tail risk, and diversification.

The proposed HMM + Mean-CVaR strategy is evaluated against two benchmarks: a static Mean-CVaR strategy and a conventional 60:40 allocation. Simulation results under a fixed monthly withdrawal setting reveal that the regime-aware strategy consistently outperforms alternatives in both total return and withdrawal-adjusted sustainability. It achieves superior risk-adjusted performance (sharpe ratio), reduced drawdowns, and more adaptive asset allocation.

In particular, the strategy demonstrates resilience during macroeconomic shocks by adjusting exposure away from volatile assets and toward income-generating instruments when necessary. It also provides stable dividend income tailored to market conditions. Further analysis shows that rebalancing frequency significantly impacts outcomes: while the 60:40 strategy prefers annual rebalancing, the HMM-based approach benefits from monthly or semiannual adjustments.

Overall, the findings highlight the potential of combining probabilistic state inference with risk-sensitive portfolio optimization for long-term retirement planning under uncertainty.

Keywords: Retirement Portfolio, Hidden Markov Model, Regime-Switching, Conditional Value-at-Risk (CVaR), Portfolio Optimization, Rebalancing Frequency

1 Introduction

The primary goal of retirement financial planning is to ensure a stable stream of income that lasts throughout an individual's lifetime. In this context, managing the decumulation phase—when assets are no longer being accumulated but gradually withdrawn—becomes a critical task. While much of traditional financial planning focuses on growing wealth during the working years, the real challenge lies in converting accumulated assets into a sustainable income flow in retirement. The failure to do so can lead to a distressing phenomenon often termed "retirement bankruptcy," where retirees outlive their savings.

A key issue in this domain is that higher wealth does not necessarily translate into higher income. In particular, retirees require consistent and predictable cash flows to meet their living expenses. To address this, a variety of strategies have been proposed—most notably, the so-called "4% rule," which recommends withdrawing 4% of one's portfolio in the first year of retirement and adjusting the amount annually for inflation[1]. Although this rule has received widespread attention, it remains highly sensitive to market conditions and does not account for sequence risk or longevity risk[2].

In recent years, covered call ETFs and other income-generating financial products have gained popularity among retirees seeking monthly distributions. These products provide relatively high payout ratios by sacrificing some upside potential, making them attractive for generating retirement income. However, their performance is highly dependent on the state of the market. For instance, in bullish markets, covered call ETFs may underperform due to capped upside, while in flat or slightly bearish markets, they may outperform traditional growth assets due to their premium income.

Motivated by this observation, this study explores a regime-dependent asset allocation framework for fixed withdrawal retirement portfolios, using Hidden Markov Models (HMM) to estimate market regimes and Conditional Value at Risk (CVaR)-based optimization for asset allocation. By combining market regime identification with risk-sensitive optimization, we aim to construct a portfolio that is robust to early-retirement sequence risk and capable of sustaining long-term withdrawals.

The remainder of this paper is structured as follows. Section 2 presents background on retirement income risks and the structure of covered call ETFs. Section 3 describes the dataset and assets used in the empirical analysis. Section 4 introduces the methodology, including market regime classification using HMM and CVaR-based portfolio optimization. Section 5 presents the simulation results and comparative performance analysis. Finally, Section 6 concludes with practical implications and future research directions.

2 Background

In the context of retirement planning, ensuring a stable and sustainable income stream after retirement is one of the primary goals. Unlike the accumulation phase during one's working years, where maximizing expected returns is often prioritized, the decumulation phase emphasizes consistency and downside protection. With increasing life expectancy and inflation risks, retirees face the challenge of maintaining their standard of living over decades of retirement. This has driven interest in income-generating strategies that can support regular withdrawals without significantly eroding the principal value of the portfolio.

Among various income-oriented strategies, covered call ETFs have garnered attention for their ability to generate consistent cash flows through option premiums. A covered call strategy involves owning a stock (or an ETF) and simultaneously writing (selling) a call option on that asset. This provides the investor with an upfront premium, which can be viewed as an income source. However, the trade-off is that the upside potential of the asset is capped at the strike price plus the premium received[3]. The payoff structure is illustrated in Figure 1.

While covered call strategies may underperform in strongly bullish markets due to the limited upside, they tend to outperform in flat or moderately bearish markets where the premium income offsets price stagnation or mild declines. This characteristic makes covered call ETFs potentially suitable for retirees seeking steady income rather than high capital appreciation. To illustrate how the strategy behaves under different market regimes, we simulated portfolio values under three scenarios: bull market, neutral market, and bear market. Each simulation compares a buy-and-hold strategy with a covered call strategy that includes both price and dividend effects.

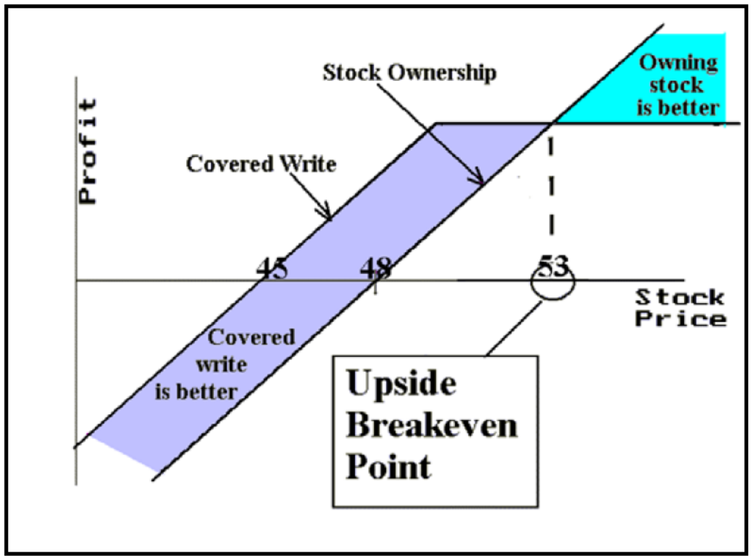


Figure 1: Payoff diagram of a covered call strategy versus outright stock ownership.

As seen in Figure 2, in a bullish environment, covered call strategies significantly underperform due to forfeited upside gains (Figure 2a). In contrast, during a neutral market phase, the consistent income from option premiums allows the covered call strategy to outperform buy-and-hold (Figure 2b). Most notably, in a bear market, while both strategies incur losses, the covered call strategy mitigates the decline more effectively by cushioning the drop with earned premiums (Figure 2c).

(a) Bull Market (b) Neutral Market (c) Bear Market

Figure 2: Performance comparison of covered call vs. buy-and-hold strategy under different market conditions.

These contrasting outcomes highlight the sensitivity of the covered call strategy to the prevailing market regime. Given that retirees are less able to tolerate large drawdowns or volatility shocks, adopting a static asset allocation may be suboptimal. Instead, adapting asset exposure based on the market environment—particularly identifying bull, bear, and neutral phases—can improve portfolio resilience. This motivates the application of regime-switching models such as Hidden Markov Models (HMMs), which allow for probabilistic estimation of latent market states based on observable indicators. In this study, we explore whether integrating HMM-based market regime detection with a mean-CVaR optimization framework can enhance retirement portfolio outcomes by allocating more conservatively in drawdown-prone regimes and taking measured risk when market conditions are favorable.

3 Data and Asset Universe

In this study, we construct a retirement portfolio composed of a diverse set of exchange-traded funds (ETFs) spanning both risky and safe assets. The risky asset group is further divided into growth-oriented and income-generating ETFs, while the safe asset group consists of short-term government bond ETFs. This classification allows us to flexibly design an asset allocation strategy that balances capital preservation with income generation under varying market regimes.

Daily historical data for all ETFs were sourced from Yahoo Finance, covering the period from January 2014 to May 31, 2025. This time frame was selected to align with the availability of covered call ETFs such as XYLD and QYLD, which began trading during this interval. For regime identification and portfolio optimization, we utilized adjusted closing prices to reflect splits and dividends. However, for backtesting retirement withdrawals, we used raw closing prices in combination with separately retrieved dividend distributions to simulate real-world cash flows more accurately.

The ETF universe selected for the portfolio is summarized in Table 1. It includes two growth ETFs (QQQ and SPY), two covered call ETFs (QYLD and XYLD), and one safe bond ETF (SHY). Covered call ETFs are especially important in this study due to their potential to deliver high dividend yields, albeit at the cost of limited capital gains. These instruments are central to the portfolio's income-generating capabilities.

Table 1: ETF Asset Universe and Characteristics

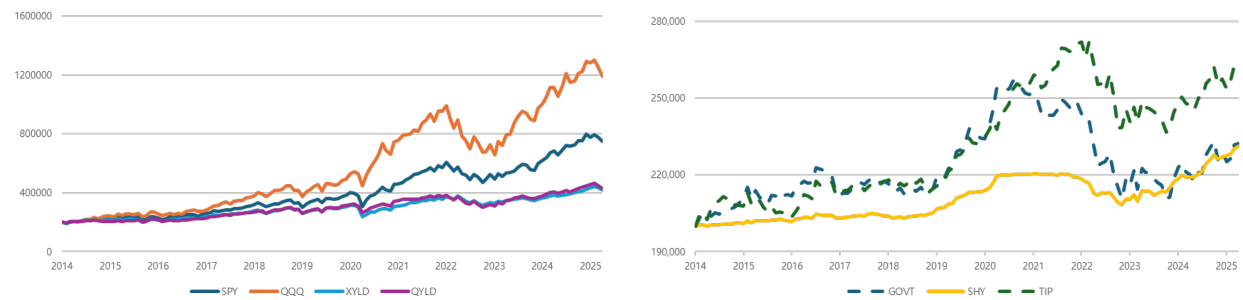
Category	ETF	Dividend Yield	Expense Ratio
Risky - Growth	QQQ	0.5%	0.20%
	SPY	1.6%	0.09%
Risky - Income	QYLD	11%	0.60%
	XYLD	10%	0.60%
Safe	SHY	1%	0.15%

Growth-oriented ETFs such as QQQ and SPY track large-cap equity indices—the NASDAQ 100 and S&P 500, respectively. QQQ is heavily tilted toward technology companies, thus offering high growth potential but also increased volatility. SPY provides broader market exposure with relatively lower volatility and a modest dividend yield, making it a balanced growth option.

In contrast, covered call ETFs like QYLD and XYLD generate income by writing monthly at-the-money call options on QQQ and SPY, respectively. These strategies sacrifice upside potential in exchange for option premium income, making them attractive in flat or range-bound markets. Their consistent distributions serve as a substitute for fixed income in retirement portfolios, especially in environments where traditional bond yields are low.

On the conservative end of the spectrum, we considered multiple short-duration government bond ETFs. While GOVT and TIP were initially evaluated, they were ultimately excluded due to significant drawdowns observed during the 2022 interest rate shock—a period of rapid rate hikes by the U.S. Federal Reserve in response to inflationary pressures. These assets experienced large capital losses, which undermine their role as stable anchors in retirement portfolios. In contrast, SHY (iShares 1–3 Year Treasury Bond ETF) maintained capital stability and demonstrated resilience, thus it was selected as the primary safe asset.

Figures 3 visualize the historical price performance of the selected ETFs over the full sample period.



(a) Risky assets: QQQ, SPY, QYLD, XYLD

(b) Safe assets: SHY, GOVT, TIP

Figure 3: Cumulative price performance of risky and safe ETFs (2014–2025)

4 Methodology

In this section, we detail the methodology used to identify market regimes and optimize the retirement portfolio. Our approach employs a Hidden Markov Model (HMM) for probabilistic state estimation based on financial time series data, followed by a Mean-CVaR portfolio optimization with ℓ_2 regularization. These models together enable dynamic adaptation of asset allocation under uncertain and regime-varying market conditions.

4.1 Hidden Markov Model (HMM)

The Hidden Markov Model (HMM) is a doubly stochastic process introduced by Baum and Petrie (1966), designed to model time-series data with unobserved latent states[4]. In an HMM, the observation at time t is generated by an unobservable (hidden) state, and the sequence of hidden states satisfies the first-order Markov property. The key assumptions are:

- Hidden states are finite and transition based on a stationary transition matrix.
- Each observation depends solely on the current hidden state.
- The emission distribution is Gaussian, parameterized by state-dependent means and variances.

We define the model parameters as $\lambda = (A, \mu, \sigma, \pi)$, where A is the transition matrix, μ and σ are the emission means and standard deviations, and π is the initial state distribution. Parameter estimation is performed via the Baum-Welch algorithm[5, 6], and state inference is conducted using the Viterbi algorithm[7].

We use daily log returns of SPY and VIX, extracted from Yahoo Finance from January 2014 to May 2025. Each observation vector comprises $r_t^{(\mathrm{SPY})}$ and $r_t^{(\mathrm{VIX})}$, defined as $r_t = \log(P_t/P_{t-1})$. Multiple models are trained with different state counts, and the optimal number of hidden states is chosen using the Bayesian Information Criterion (BIC).

This probabilistic framework allows us to infer the latent market regime from observable price dynamics. Once the model parameters are estimated, the hidden state sequence can be decoded using the Viterbi algorithm, which computes the most likely sequence of regimes over the observation period.

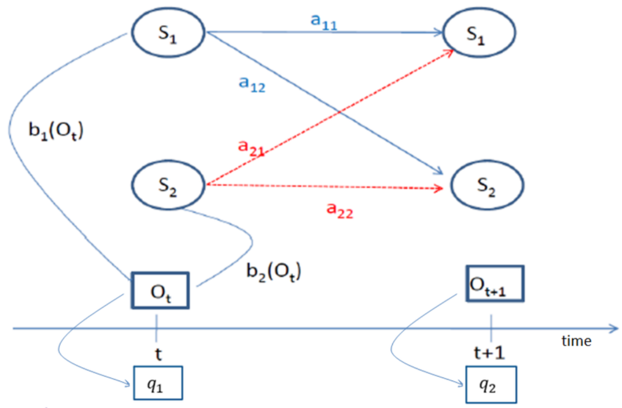


Figure 4: Structure of a Hidden Markov Model with two hidden states. Transitions are governed by matrix A, while emissions follow Gaussian distributions parameterized by μ and σ.

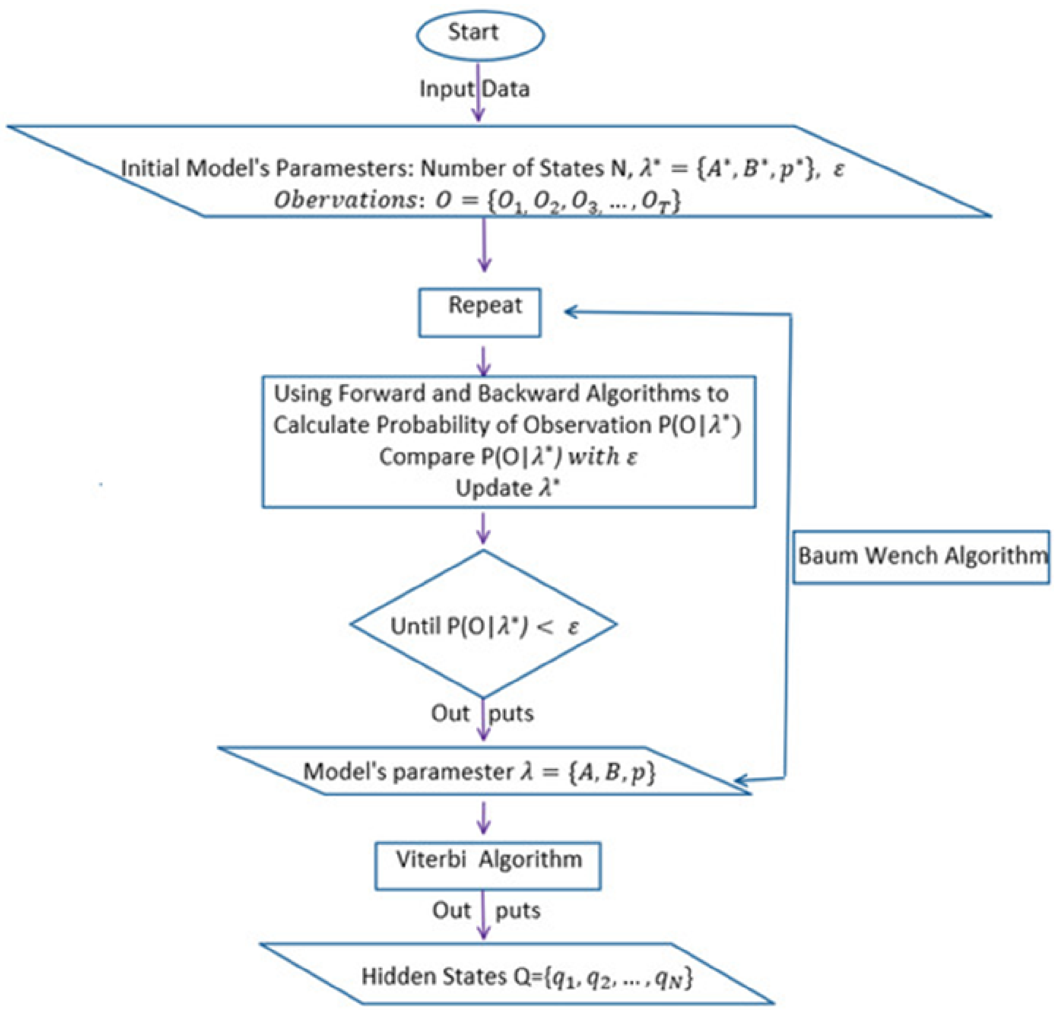


Figure 5: HMM training and decoding workflow. The model parameters are initialized and refined iteratively using the Baum-Welch algorithm until convergence. The Viterbi algorithm is then applied to infer the most likely hidden state sequence.

The decoded state sequence is subsequently used to adapt asset allocation models dynamically, enabling regime-aware portfolio construction tailored to prevailing market conditions.

4.2 Mean-CVaR Portfolio Optimization with ℓ_2 Regularization

To optimize retirement portfolio weights under uncertainty, we apply a Mean-CVaR optimization framework enhanced with ℓ_2 regularization. Conditional Value-at-Risk (CVaR) at confidence level β is defined as the expected portfolio loss given that the loss exceeds the Value-at-Risk (VaR) threshold:

$$\mathrm{CVaR}_\beta(w) = \alpha + \frac{1}{1-\beta} \cdot E[u], \tag{1}$$

where $u_i = \max(0, -w^\top r_i - \alpha)$ is a slack variable representing excess loss.

Following the formulation of Rockafellar and Uryasev (2000, 2002)[8, 9], we extend the classical Mean-CVaR optimization by incorporating an ℓ_2 regularization term $\gamma w^\top w$ to control concentration and promote diversification. The full optimization problem is:

$$\begin{aligned}
\max_{w,\alpha} \quad & E[r^\top w] - \gamma w^\top w \\
\text{s.t.} \quad & u_i \geq 0, \\
& u_i \geq -w^\top r_i - \alpha, \quad i = 1, \ldots, T \\
& \alpha + \frac{1}{(1-\beta)T} \sum_{i=1}^{T} u_i \leq \text{target_CVaR}, \\
& \sum_j w_j = 1, \quad w_j \in [0, 1].
\end{aligned}$$

Here, w is the vector of portfolio weights, r_i is the return vector at time i, α is the VaR threshold, $\beta = 0.95$ is the CVaR confidence level, and γ controls the strength of regularization.

To identify the optimal risk constraint, we tested multiple values of target_CVaR $\in \{0.02, 0.03, 0.04, 0.05\}$ across fixed monthly withdrawals of \$800, \$1600, and \$2400. The results are shown in Figure **??**, where we compare Compound Annual Growth Rate (CAGR), Sharpe ratio, and Maximum Drawdown (MDD) across target CVaR values.

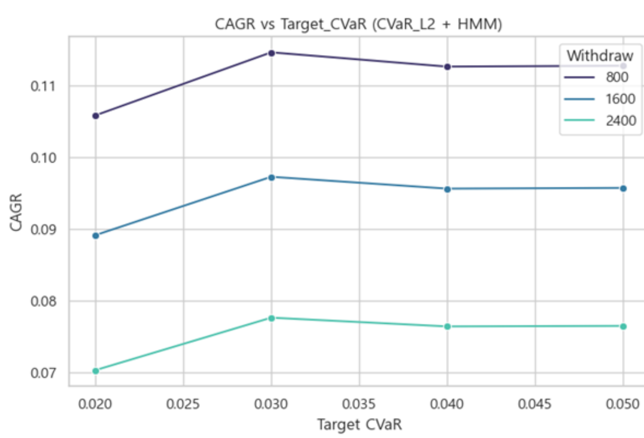


Figure 6: CAGR by target CVaR under different withdrawal levels

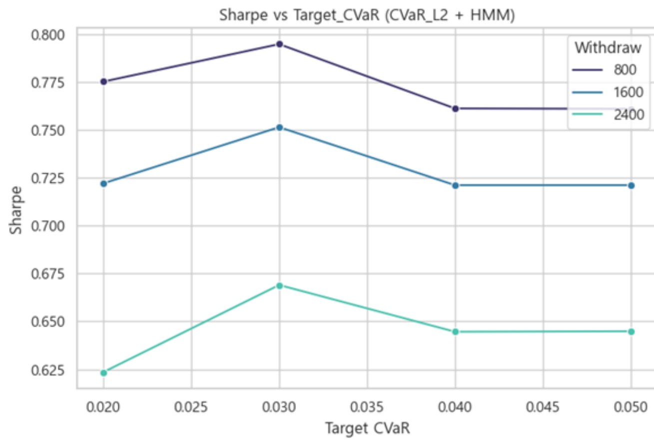


Figure 7: Sharpe Ratio by target CVaR under different withdrawal levels

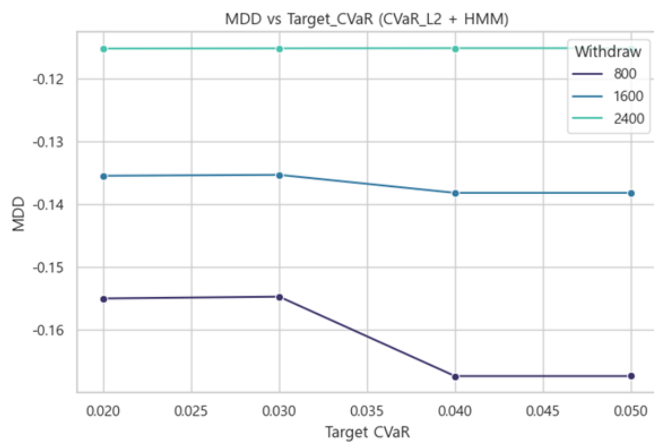


Figure 8: Maximum Drawdown (MDD) by target CVaR under different withdrawal levels

Empirically, the setting target_CVaR = 0.03 yielded the best tradeoff between risk and return. At a 95% confidence level, this constraint ensures that the expected loss in the worst 5% of cases does not exceed 3% of the portfolio value. As Figures 6, 7, and 8 show, this level consistently achieves the highest CAGR and Sharpe ratio while maintaining drawdown at manageable levels. This threshold is therefore used in all subsequent backtests and comparative evaluations.

4.3 Withdrawal Simulation Framework

To evaluate the sustainability and robustness of portfolio strategies in a retirement context, we simulate monthly withdrawals under dynamic asset allocation. The simulation pipeline integrates regime identification via HMM and CVaR-based portfolio optimization, aligned with the structure illustrated in Figure 10.

Initial Setup and Parameters

We begin with an initial capital of $200,000 and perform fixed monthly withdrawals (e.g., $1,600). ETF-specific transaction costs are applied, consisting of trading fees (0.1%) and asset-level slippage and expense ratios.

At time $T = 0$ and $T = 1$, the portfolio is constructed using CVaR optimization under the HMM-inferred market regime. Portfolio weights are computed based on historical returns within the prior three years (window size), and the portfolio is initially invested at the beginning of $T = 1$.

Monthly Simulation Loop ($T \geq 2$)

Each month, we simulate the following steps:

1. **Dividend Collection:** For each ETF, we compute monthly cash dividends based on shareholdings and declared dividend rates. Dividend income is taxed and added to the cash balance.

2. **Withdrawal and Rebalancing:** The target withdrawal amount (e.g., $1,600) is deducted. If the cash reserve is insufficient, assets are liquidated proportionally based on descending value contribution. Rebalancing is triggered based on a user-defined frequency (monthly by default) to realign the portfolio to the HMM-regime-optimized weights.

3. **Portfolio Update:** The post-withdrawal portfolio value is computed, and all performance metrics (portfolio value, cash, dividends, cumulative withdrawal, total value, etc.) are recorded.

Rebalancing uses asset prices, trading costs, slippage, and updated target weights from the optimizer. If insufficient funds remain after liquidation, the withdrawal is capped at the available amount.

Sliding Window Regime Estimation

A key methodological element is the *sliding window HMM*. Rather than using the full data sample, which risks information leakage or distorted regime classification, we estimate HMM parameters based only on recent data — a rolling window of three years, updated monthly. This approach mimics real-world usage where only past data is available.

As illustrated in Figure 9, each month t uses the prior 36 months of daily SPY and VIX log-returns to train an HMM. The current regime is predicted from this model and used to select the regime-specific return distribution and associated optimized weights. Thus, dynamic state transitions are captured without peeking into future data.

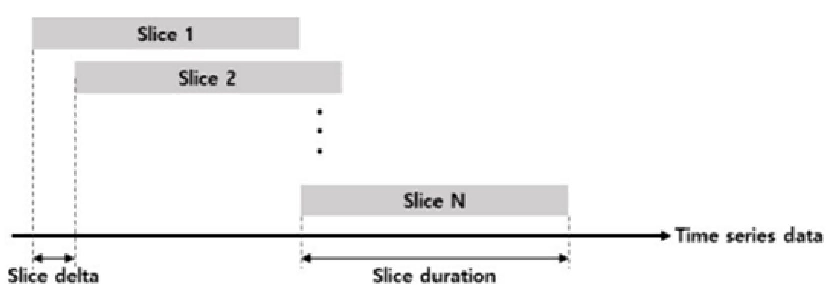


Figure 9: Sliding window HMM with 3-year window and 1-month stride. Each slice uses past 36 months of data for HMM calibration and regime prediction. Testing begins in Jan 2017.

Full Simulation Pipeline

Figure 10 summarizes the overall simulation pipeline. Starting with historical asset returns, we classify monthly regimes using a rolling HMM, apply regime-specific Mean-CVaR optimization to determine optimal portfolio weights, simulate monthly withdrawals and rebalancing, and finally evaluate performance metrics such as CAGR, MDD, Sharpe ratio, and income stability.

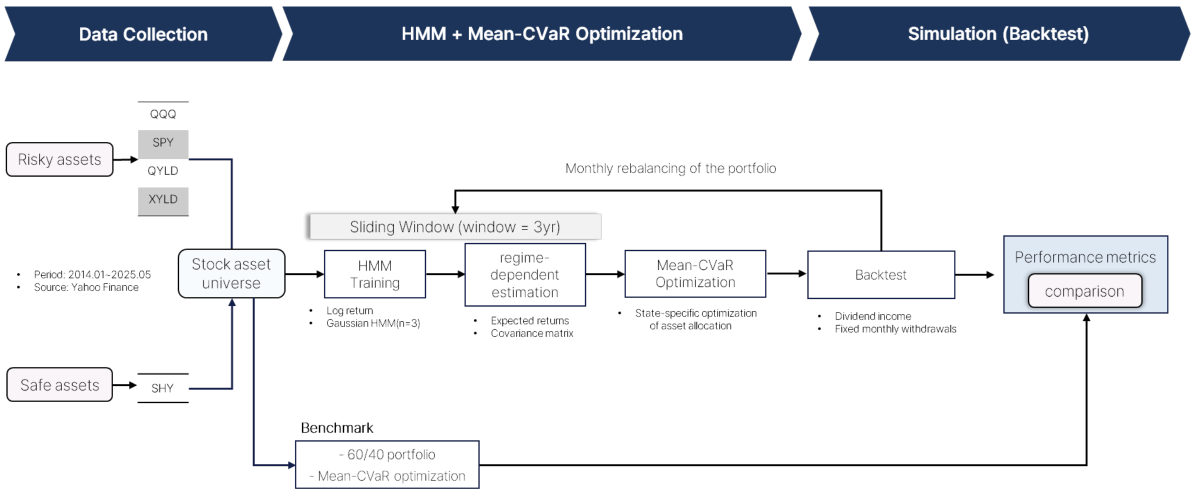


Figure 10: Overall backtesting simulation pipeline. Regime-aware optimization and withdrawal simulation are integrated for performance evaluation.

4.4 Benchmark Strategies and Evaluation Metrics

To evaluate the performance of the proposed retirement portfolio strategy, we compare it against several benchmark strategies using standard financial evaluation metrics. This section outlines the structure and rationale of the benchmarks and metrics used.

4.4.1 Benchmark Strategies

Table 2: Benchmark Investment Strategies

Strategy	**Description**
HMM + Mean-CVaR	CVaR optimization using regime-specific parameters predicted by HMM
Mean-CVaR	CVaR optimization using average returns over the full period
60:40 Portfolio	Fixed allocation: 60% to risky assets, 40% to safe assets

These benchmarks are constructed as follows:

- **HMM + Mean-CVaR**: Incorporates probabilistic market regime estimation using a Hidden Markov Model (HMM). For each estimated state, we compute state-specific expected returns and apply Mean-CVaR optimization.
- **Mean-CVaR**: Applies Mean-CVaR optimization on the entire historical dataset, without considering market regime dynamics. This serves as a static allocation benchmark.

- **60:40 Portfolio**: A commonly used heuristic portfolio composed of 60% in risky assets (e.g., equities) and 40% in safe assets (e.g., bonds). This allocation remains fixed throughout the investment horizon.

4.4.2 Evaluation Metrics

Table 3: Performance Evaluation Metrics

Category	Metric	Description
Return Metrics	Total Return	Cumulative return over the entire backtest period
	CAGR (Compound Annual Growth Rate)	Annualized geometric return
Risk Metrics	Annualized Volatility	Standard deviation of monthly returns, annualized
	Sharpe Ratio	Return-to-risk ratio (CAGR divided by volatility)
	Maximum Drawdown (MDD)	Largest peak-to-trough decline during the backtest period

These metrics allow for a holistic evaluation of each strategy:

- **Total Return** indicates overall growth of the portfolio.
- **CAGR** reflects the compounded growth rate on an annual basis, enabling long-term comparison.
- **Volatility** captures the variability of returns and hence investment risk.
- **Sharpe Ratio** assesses risk-adjusted performance. Higher values indicate better returns per unit of risk.
- **MDD** is crucial in retirement planning, as it quantifies the worst-case loss from a historical peak.

Strategic Expectation. Among the benchmarked methods, we anticipate that the proposed **HMM + Mean-CVaR** approach will outperform others in key aspects of retirement asset management. Specifically, we expect:

- Lower volatility and maximum drawdown, enhancing psychological comfort for retirees.
- Higher Sharpe ratio, indicating better risk-adjusted returns.
- More consistent cash withdrawal performance, ensuring sustainability.

Overall, this method aims to reduce risk and psycological distress while enhancing return efficiency through adaptive, regime-aware optimization.

5 Empirical Results and Interpretation

5.1 Market Regime Estimation and Interpretation

To evaluate the effectiveness of our regime-aware strategy, we begin by inspecting the inferred market states from the Hidden Markov Model (HMM). Figure 11 overlays the estimated market regimes on the SPY and

VIX price series. The regime classification is based on three states: **Bull**, **Neutral**, and **Bear**, which are derived from the relative ranking of expected returns in each hidden state.

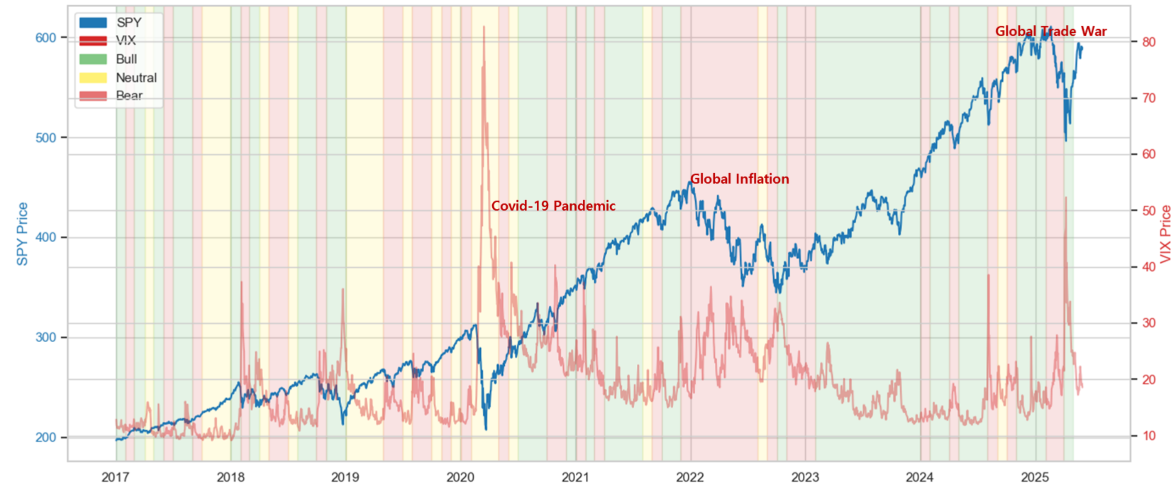


Figure 11: SPY and VIX with regime overlay (2017–2025). Colored backgrounds indicate inferred regimes from HMM: green for Bull, yellow for Neutral, and red for Bear. Key macroeconomic events are annotated.

The model accurately captures extended periods of market stress, such as the *Global Inflation Shock* and the *U.S.–China Trade War*, labeling them as Bear markets. However, it fails to fully recognize sharp, transient crises such as the *COVID-19 crash* in early 2020. This limitation is primarily due to the monthly granularity of regime labeling, despite the model being trained on daily log-returns.

Such episodic events — often categorized as *systemic shocks* — induce rapid, short-term volatility but may be followed by equally swift recoveries. Incorporating them into regime switching models may introduce undesired lag or result in suboptimal portfolio reallocation. In fact, avoiding reactionary responses to sudden spikes can be beneficial. Since the HMM framework is diagnostic rather than predictive, it identifies the prevailing regime based on historical context rather than anticipating future reversals.

In retirement portfolio management, this characteristic can act as a natural buffer against overfitting to noise. Adjusting asset allocation based on transient dips could lead to unnecessary liquidation of risky assets during imminent rebounds, missing out on recovery gains. Thus, filtering out short-term volatility while adapting to sustained trends enhances the robustness of regime-based strategies.

Consequently, our HMM-based regime estimation provides a conservative and stable foundation for strategic allocation. Although it may underreact to abrupt crises, it effectively aligns long-term allocations with broader market dynamics — the ultimate objective of regime-aware portfolio construction.

5.2 Summary of Portfolio Performance

We now compare the empirical results of our strategy against benchmark approaches using comprehensive performance metrics. Table 4 presents key indicators such as total return, annualized return (CAGR), risk-adjusted returns, and drawdown levels.

The HMM + Mean-CVaR strategy stands out with a CAGR of 9.58% and Sharpe ratio of 73.76%, outperforming both baseline strategies. In contrast, the traditional 60:40 portfolio eventually depletes principal due to monthly withdrawals, ending the period with a -23.83% loss. This confirms that a static allocation is

Table 4: Performance Comparison across Strategies (2017–2025)

Value	Method	Total Return	CAGR	Volatility	Sharpe	MDD
Total value	**HMM + Mean-CVaR**	114.29%	**9.58%**	10.15%	**73.76%**	**-13.31%**
	Mean-CVaR	84.35%	7.62%	9.74%	57.75%	-15.25%
	60:40 Strategy	56.17%	5.50%	6.53%	51.37%	-10.37%
Value after withdrawal	**HMM + Mean-CVaR**	34.29%	3.60%	13.43%	16.83%	-24.12%
	Mean-CVaR	4.35%	0.51%	12.99%	-6.38%	-27.47%
	60:40 Strategy	-23.83%	-3.21%	9.07%	-55.51%	-26.71%

insufficient for sustained drawdowns during adverse market phases.

To better understand these differences, Figure 12 illustrates the evolution of portfolio value after withdrawal, highlighting the sensitivity of each strategy to both return and drawdown.

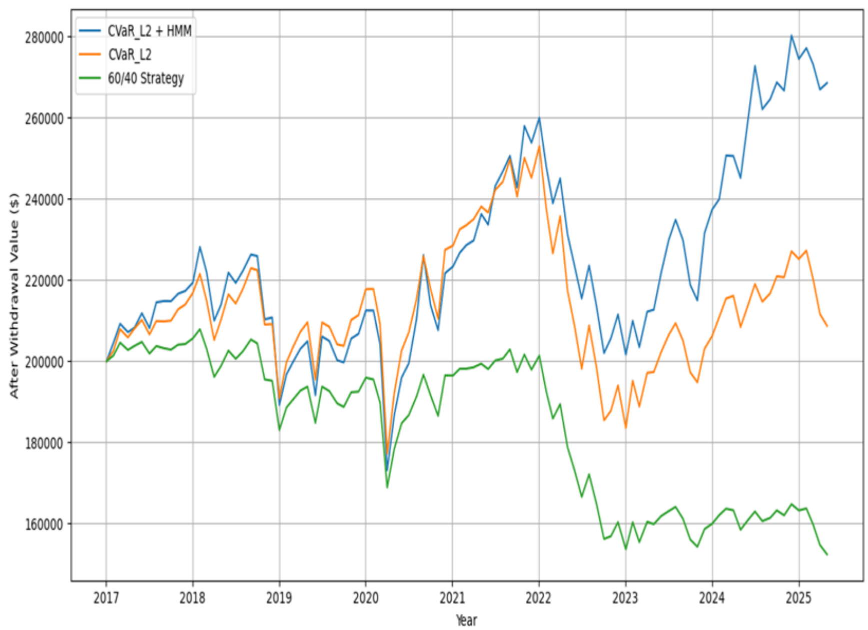


Figure 12: After-withdrawal value trajectory of each strategy (2017–2025). The HMM+CVaR strategy maintains capital more effectively during downturns and rebounds more quickly in recovery. Total value includes reinvested dividends.

The result also reflects in asset allocation behavior. Figure 13 and Figure 14 compare the time-varying asset weights under each strategy. The HMM-based approach exhibits dynamic responsiveness to market regimes, adjusting exposure across assets such as QQQ, XYLD, and SHY. For instance, it reduces QQQ allocation during volatile periods (e.g., 2019–2020 trade conflict, 2022 inflation shock) and increases hedged or defensive positions.

In summary, regime-awareness contributes significantly to portfolio resilience. By adjusting risk exposure ahead of drawdowns and restoring growth allocation during recoveries, the HMM + Mean-CVaR strategy not only enhances long-term performance but also ensures greater sustainability under withdrawal pressure — a key goal in retirement financial planning.

Figure 13: Asset allocation over time (HMM+Mean-CVaR). Dynamic reallocation aligns with market regimes.

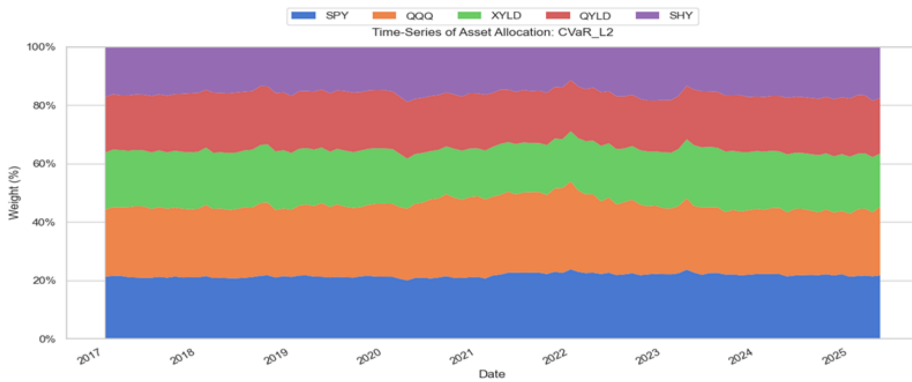


Figure 14: Asset allocation over time (Mean-CVaR). Portfolio weights remain relatively static.

5.3 Dividend Yield Analysis

Dividend income is a crucial component of retirement portfolios, providing a steady stream of cash flow to support periodic withdrawals. To evaluate the income-generating efficiency of each strategy, we analyze the **annual dividend yield**, calculated from an investor's perspective as:

$$\text{Annual Dividend Yield} = \frac{\text{Total Dividends Received in a Year}}{\text{Initial Investment}} \times 100 \tag{2}$$

This formulation reflects the effective yield relative to the original capital commitment, which is particularly meaningful in assessing the portfolio's long-term sustainability and liquidity support for regular withdrawals.

Figures 15, 16, and 17 compare the annual dividend yield trends of each strategy from 2017 to 2024. Each bar represents total dividends received in a year, while the line graph tracks the corresponding dividend yield percentage.

The HMM + Mean-CVaR strategy demonstrates pronounced variability in dividend yield across years. The yield peaks in 2022 at 5.63%, coinciding with increased allocation to high-income assets such as QYLD and XYLD during the global inflation regime. Conversely, during bull phases, the strategy deliberately reduces exposure to these high-dividend instruments in favor of growth-oriented assets (e.g., QQQ), leading to lower yields (e.g., 2.92% in 2021).

This reflects the regime-aware nature of the HMM-based approach: rather than consistently holding

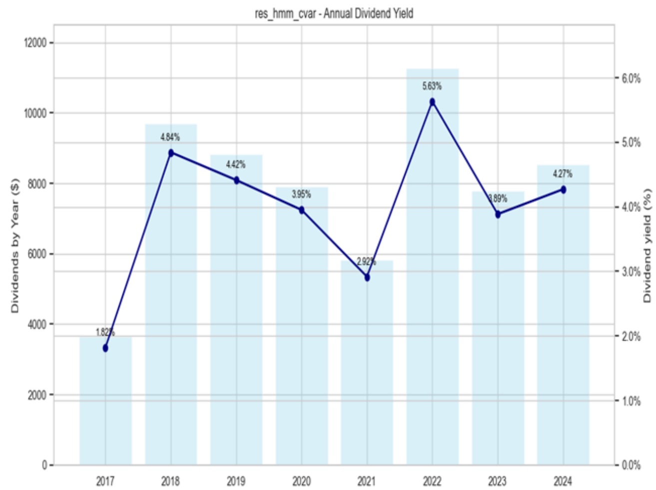


Figure 15: Annual Dividend Yield – HMM + Mean-CVaR (Avg: 4.07%)

high-income assets, it reallocates capital in response to inferred market states, prioritizing income in volatile markets and capital growth during expansions.

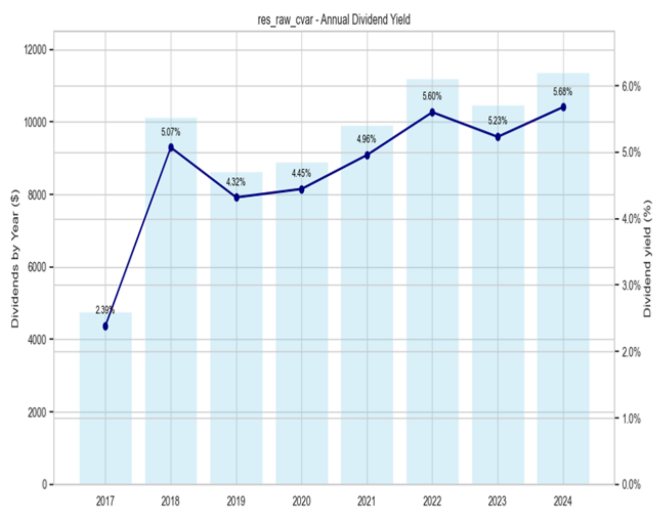


Figure 16: Annual Dividend Yield – Mean-CVaR (Avg: 4.71%)

The Mean-CVaR strategy, by contrast, maintains a relatively stable yield pattern around 4.5–5.6%. Since asset weights are fixed irrespective of market regime, the strategy consistently retains high-dividend holdings, ensuring predictable income but lacking flexibility to optimize risk-adjusted returns.

Finally, the 60:40 strategy exhibits the lowest average yield at 3.58%. Its conservative tilt toward broad-market equity and short-duration bonds results in limited income generation. This outcome underscores the limitations of static allocation models in income-focused retirement scenarios.

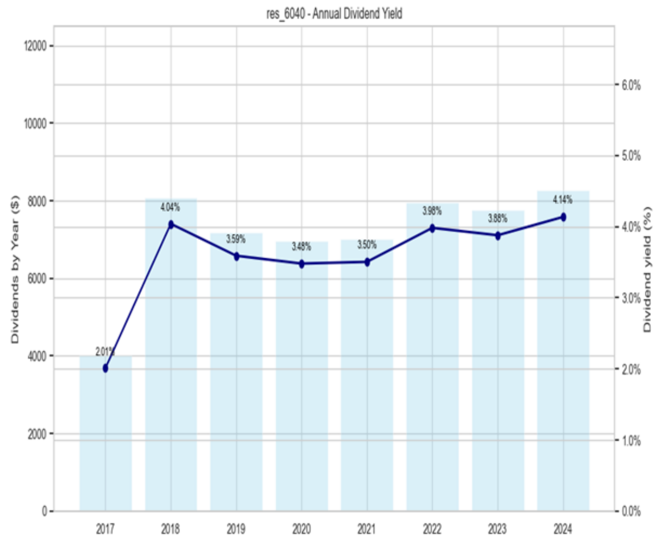


Figure 17: Annual Dividend Yield – 60:40 Strategy (Avg: 3.58%)

5.4 Rebalancing Frequency Analysis

Rebalancing frequency plays a critical role in the long-term performance and risk profile of retirement portfolios. In practice, retirement accounts such as IRPs or 401(k)s often lack API access, meaning that automatic trading is not feasible and rebalancing must be done manually. This constraint makes it essential to understand how different rebalancing intervals affect portfolio sustainability and volatility.

Typical retirement portfolios are rebalanced **annually or semiannually** due to operational and cost considerations. Less frequent rebalancing reduces transaction costs and aligns better with a long-term investment horizon. However, strategies that depend on high-frequency regime signals — such as those using Hidden Markov Models — may benefit from **monthly rebalancing**, which enables more responsive adjustments in dynamic market environments.

Figures 18 and 19 compare the after-withdrawal portfolio values of different rebalancing frequencies under the **HMM + Mean-CVaR** strategy and the traditional **60:40 allocation**. The key findings are as follows:

- In the **60:40 strategy**, annual rebalancing yielded the best results, while monthly rebalancing resulted in the lowest portfolio value. This aligns with the expectation that low-turnover strategies perform better with less frequent rebalancing, as they avoid overtrading and stay aligned with broad market trends.

- In the **HMM + Mean-CVaR strategy**, **monthly rebalancing** consistently outperformed quarterly and annual frequencies, with **semiannual rebalancing** being a competitive alternative. This suggests that dynamic, regime-aware models benefit from more frequent re-optimization, enabling better alignment with shifting market states.

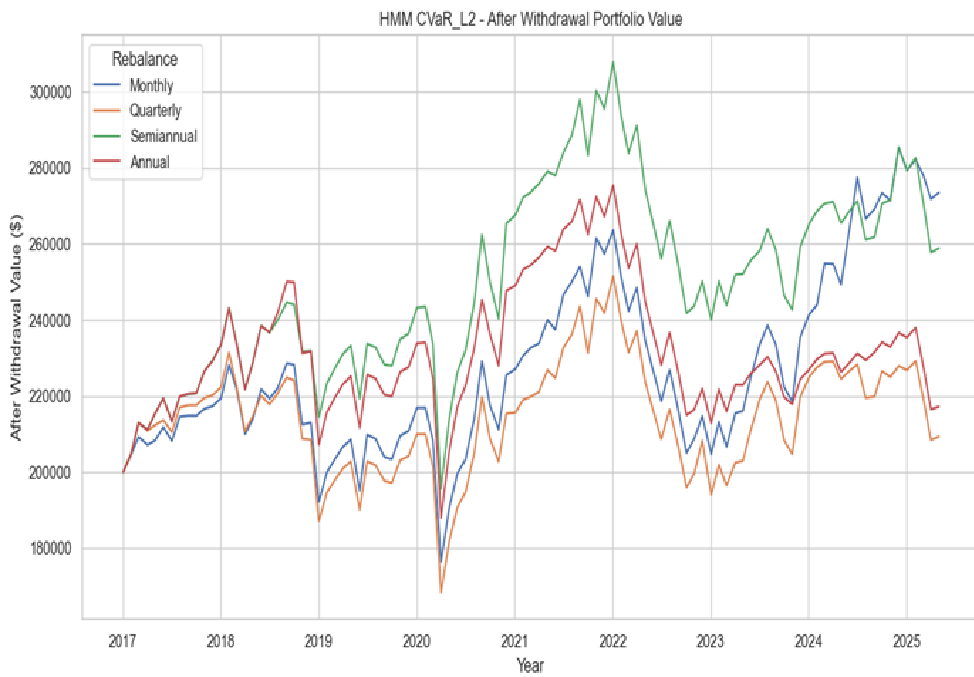


Figure 18: After Withdrawal Portfolio Value under HMM + Mean-CVaR by Rebalancing Frequency

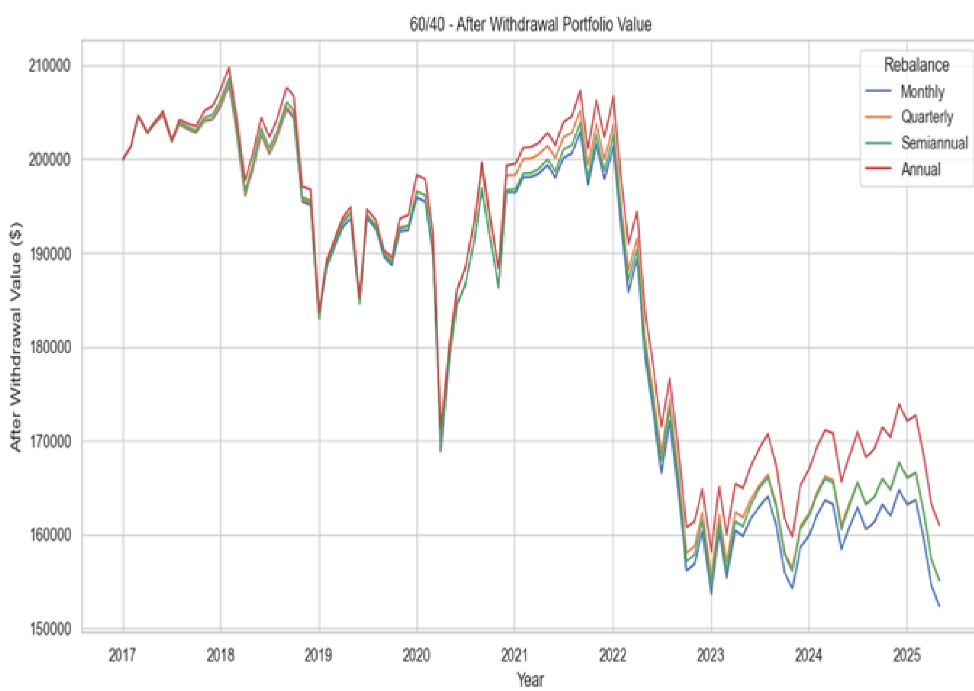


Figure 19: After Withdrawal Portfolio Value under 60:40 Strategy by Rebalancing Frequency

To further understand the performance gaps, Figure 20 presents the time-series asset allocations under each rebalancing frequency for the HMM + Mean-CVaR strategy. Monthly rebalancing (top-left) shows fine-grained responsiveness to market regimes, frequently rotating between growth and income-generating ETFs. In contrast, annual rebalancing (bottom-right) results in long-held positions with infrequent changes, often missing short-term regime shifts.

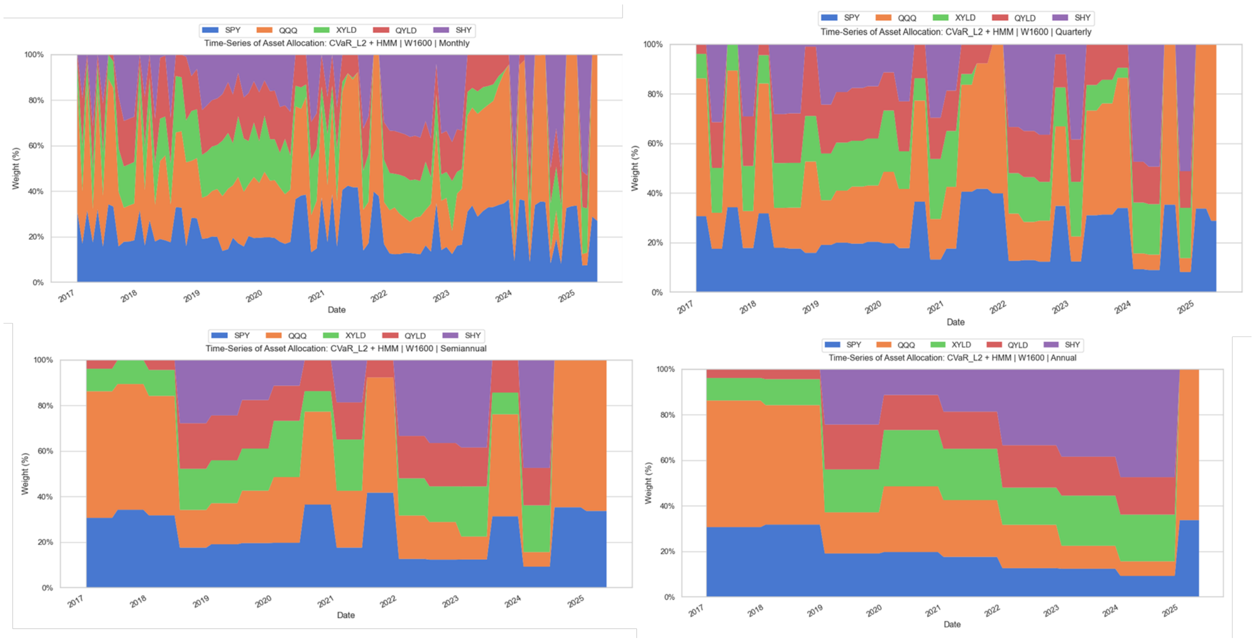


Figure 20: Asset Allocation under Different Rebalancing Frequencies (HMM + Mean-CVaR)

The analysis confirms the importance of matching rebalancing frequency to portfolio strategy:

- **Static allocation models** (e.g., 60:40) benefit from lower turnover and thus prefer annual rebalancing.
- **Regime-sensitive models** (e.g., HMM + Mean-CVaR) perform better with higher-frequency rebalancing, which allows them to exploit short-term signals and mitigate losses during transitions.
- **Semiannual rebalancing** offers a balanced trade-off, delivering strong performance with moderate transaction effort — a compelling option for human-managed accounts.

These findings have practical implications for implementation. Investors using HMM-based dynamic strategies in discretionary or semi-automated accounts should consider rebalancing at least semiannually or monthly for optimal outcomes.

Interpretation and Implications

The HMM + Mean-CVaR strategy offers a compelling balance between adaptability and income efficiency. While its dividend yield fluctuates more than the fixed-weight benchmarks, this is a direct result of tactical reallocations designed to optimize overall portfolio performance under different regimes.

Notably, the ability to lean into high-income assets during turbulent periods provides additional liquidity to support withdrawals without excessive asset sales. Conversely, shifting away from income-producing assets during bull markets allows the portfolio to fully participate in equity upswings.

In retirement financial planning, such flexibility is valuable: it enables a smoother balance between income needs and capital growth, helping retirees preserve purchasing power while mitigating drawdown risks.

Thus, from an income sustainability perspective, the HMM-enhanced approach proves not only viable but strategically superior under varying market conditions.

6 Conclusion and Practical Implications

This study explored a regime-aware retirement portfolio strategy that combines Hidden Markov Models (HMM) for market state inference with a Mean-CVaR optimization framework tailored for downside risk control. Through extensive withdrawal simulations, the proposed method was benchmarked against traditional approaches such as static 60:40 allocation and regime-agnostic Mean-CVaR optimization.

The results highlight several key findings:

- **Superior performance of HMM + Mean-CVaR**: The regime-sensitive approach consistently achieved higher compound annual growth rate (CAGR), lower drawdowns, and more stable withdrawals. Notably, it demonstrated enhanced resilience during market crises (e.g., 2022 inflation shock), dynamically reducing exposure to volatile assets and increasing allocation to income-generating ETFs.

- **Dynamic income and risk adjustment**: By adapting asset weights to inferred market conditions, the strategy delivered variable but well-timed dividend yields. This contrasts with regime-agnostic strategies that emphasize constant income but are slower to adjust risk exposure.

- **Practical rebalancing insights**: The rebalancing frequency played a significant role. While annual rebalancing was more effective for passive strategies like 60:40, monthly or quarterly rebalancing yielded better outcomes under HMM-guided dynamic strategies, especially when using high-turnover instruments like covered call ETFs.

- **Real-world applicability**: The use of high-yield ETFs such as QYLD and XYLD is particularly relevant in retirement planning. Despite their volatility, when integrated with regime-based allocation, they support sustainable withdrawals and buffer portfolio value during adverse regimes. However, such strategies are better suited to taxable brokerage accounts with sufficient flexibility, as Korea's tax-advantaged pension accounts (e.g., IRP) restrict ETF trading and automatic execution.

- **Insights from single-asset simulations**: Supplementary experiments with single-asset withdrawal strategies revealed a counterintuitive but important insight: focusing solely on income-generating assets such as covered call ETFs may actually shorten portfolio longevity. Although products like XYLD and LYB offer attractive headline yields, their low capital appreciation leads to faster asset depletion, especially under fixed withdrawal plans. Conversely, high-growth assets like MSFT, despite offering minimal dividends, preserved capital over the full simulation horizon. This suggests that neither extreme—pure income nor pure growth—is optimal for retirement. Rather, a prudent combination is required: adjusting exposure to high-yield assets based on one's initial capital and target withdrawal rate, while anchoring the rest of the portfolio in stable or growth-oriented assets. Such balance helps mitigate drawdown risk and supports long-term sustainability without relying excessively on volatile or overly conservative instruments.

Limitations and Future Directions

Several limitations must be acknowledged. First, the simulation assumes ideal trading conditions, omitting practical factors such as taxation on dividends, and institutional restrictions in tax-advantaged accounts such as Korea's IRP (Individual Retirement Pension). Additionally, the HMM assumes stationary regime transitions and does not incorporate exogenous macroeconomic signals that might improve regime inference.

Another important limitation is the relatively short analysis window. Due to the recent inception of covered call ETFs such as QYLD and XYLD, the dataset spans just over a decade. This limits the ability to evaluate the long-term sustainability of strategies under multiple full market cycles. Future work could address this by employing bootstrap resampling or synthetic return simulations to construct extended 30-year horizons. Such simulation-based studies would offer deeper insight into portfolio durability and withdrawal stability over a full retirement period.

In addition, methods such as reinforcement learning could be explored to jointly optimize asset allocation and withdrawal policies under realistic constraints. This would open the door to more adaptive, autonomous retirement solutions that evolve with market conditions and investor needs.

In sum, this research supports the notion that intelligent regime detection combined with risk-aware optimization offers a promising pathway for retirement asset management. By balancing return potential, drawdown mitigation, and withdrawal sustainability—and avoiding the pitfalls of overly concentrated high-dividend strategies—the proposed approach provides a practical foundation for building resilient retirement portfolios in an uncertain market environment.

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Appendix. Withdrawal Performance of Single-Asset Strategies

To complement the multi-asset portfolio analysis, we conduct a single-asset withdrawal simulation. This experiment evaluates whether individual assets with high capital gains or dividend yields can sustain retirement withdrawals on their own.

Setup

- **Initial capital:** $100,000
- **Monthly withdrawal:** $1,600
- **Transaction cost:** 0.1% per trade
- **Slippage:** 0.01%
- **Assets:** SPY, XYLD, MSFT, JPM, KO, LYB

Each simulation assumes full initial investment in a single asset, held passively until portfolio depletion or May 2025, the simulation endpoint.

Selected Asset Profiles

Table 5: Selected Single-Asset Candidates

Type	Ticker	Sector	Risk	Return Potential	Dividend Yield
ETF	SPY	Market Index	Moderate	Moderate	Low (1.86%)
ETF	XYLD	Covered Call	Moderate	Low	Very High (11.92%)
Stock	MSFT	Technology	High	High	Low (0.71%)
Stock	JPM	Financials	Moderate	Moderate	Medium (2.11%)
Stock	KO	Consumer Staples	Low	Low	Medium (2.68%)
Stock	LYB	Materials	Moderate	Low	Very High (9.69%)

Normalized Price

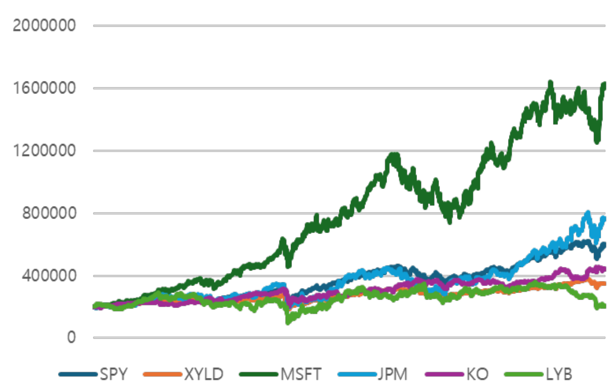

Figure 21: Normalized price (2017–2025). MSFT exhibits dominant growth, while high-yield assets underperform in price.

Backtest Results (2017–2025)

Table 6: Performance Summary Under Withdrawal Strategy

Ticker	Value After Withdrawal	Total Return	CAGR	Volatility	Sharpe	MDD	Depletion Date
MSFT	$318,160	218.16%	14.90%	21.11%	66.14%	-35.60%	None
SPY	-$91,310	-91.31%	-25.41%	19.39%	-149.16%	-91.62%	–
XYLD	-$100,000	-100.00%	-100.00%	52.47%	-151.41%	-100.00%	2023-09
JPM	-$100,000	-100.00%	-100.00%	47.56%	-119.10%	-100.00%	2025-05
KO	-$100,000	-100.00%	-100.00%	57.57%	-136.46%	-100.00%	2024-04
LYB	-$100,000	-100.00%	-100.00%	58.37%	-129.32%	-100.00%	2023-02

Sustainability and Income Insights

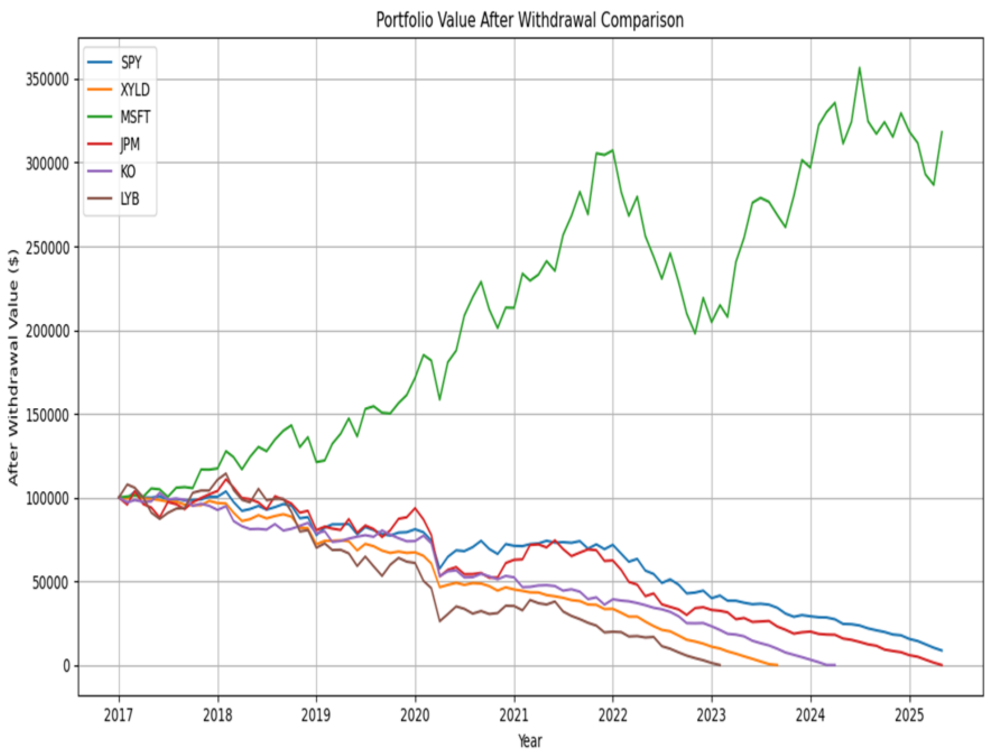

Figure 22: Portfolio Value After Withdrawal. MSFT alone maintains growth; all others deplete within the retirement horizon.

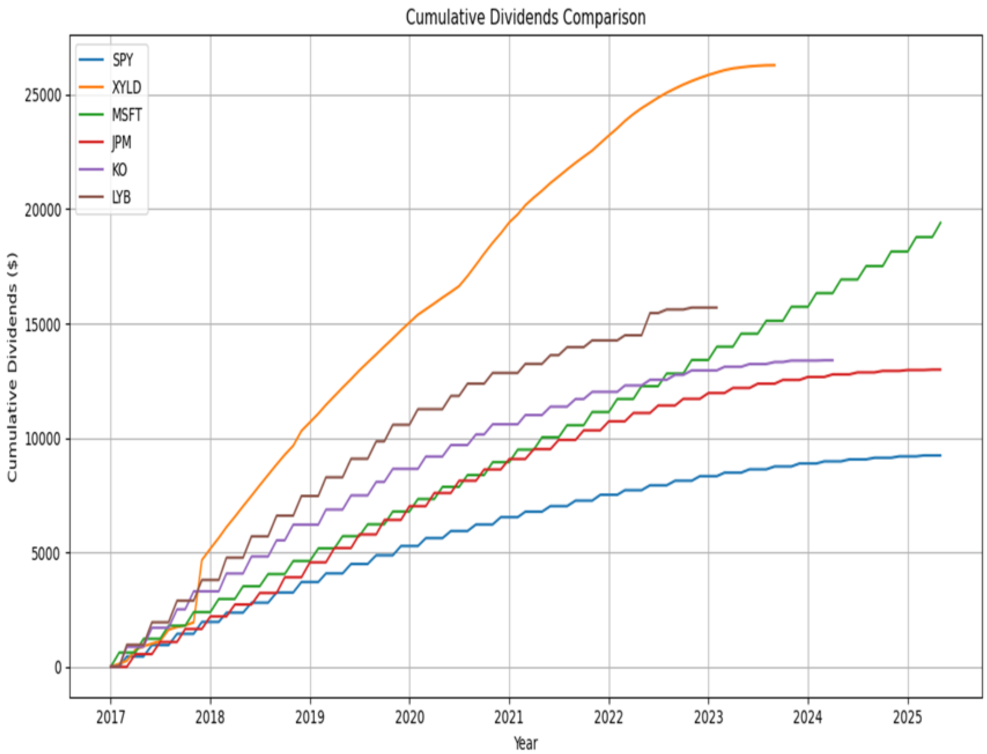

Figure 23: Cumulative Dividend Income. XYLD and LYB generate high cash income early on, but sustainability fails due to capital erosion.

Dividend Yield Dynamics

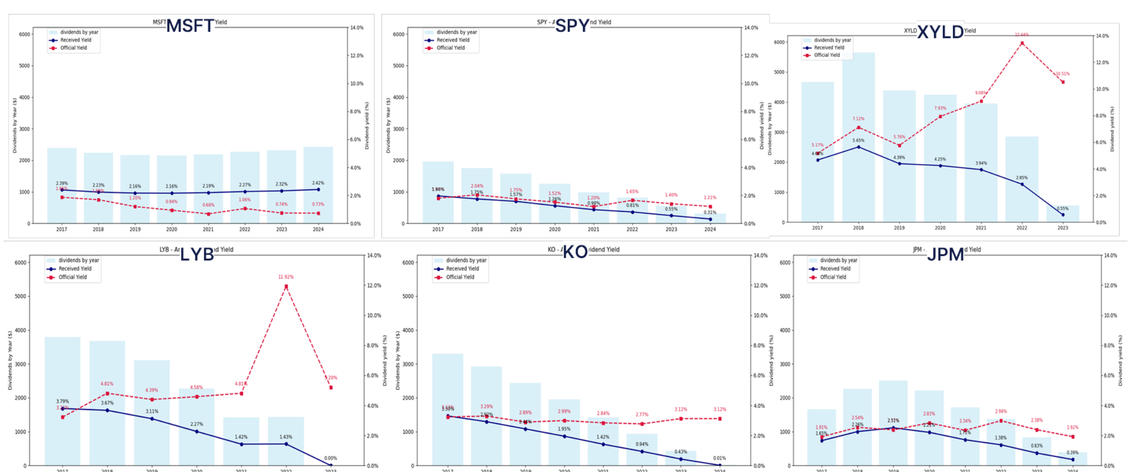

Figure 24: Received vs Official Yield (2017–2024). Official yields remain stable, but received yields decline as holdings are sold.

Key Takeaways

- Only MSFT exhibited sustainable growth sufficient to support fixed withdrawals, despite low dividend yield.
- High-yield assets (e.g., XYLD, LYB) failed to sustain withdrawals past 2023, despite large cumulative dividend payouts.
- Dividend income is proportional to the number of shares held at payout; as holdings are sold to fund withdrawals, future dividends decrease.
- Promotional (official) dividend yields assume full holdings, and overstate income for investors undergoing withdrawals.

This analysis highlights that capital appreciation is critical for single-asset sustainability, even when dividend yields appear attractive. The findings motivate a diversified, multi-asset portfolio design rather than relying solely on income-centric stocks.