**Regime-Adaptive 50-Stock S&P 500 Fund**

**Introduction**

This research explores a regime-adaptive long/short strategy limited to a universe of 50 large-cap U.S. equities selected from the S&P 500. Each stock has at least 10 years of price history since IPO, ensuring robust data for analysis. The aim is to exploit market inefficiencies using Hidden Markov Models (HMMs) to identify regimes and technical signals (momentum and mean reversion) for allocation. Potential users include quantitative investors, ETF managers, and clients seeking equity-only strategies with superior risk-adjusted returns.

**Literature Review**

Prior work supports the value of regime-switching models, technical indicators, and systematic portfolio management. Hamilton (1989) and Wang et al. (2020) showed Hidden Markov Models effectively capture bull and bear regimes. Brock et al. (1992) and Park & Irwin (2007) provided evidence of profitable technical trading rules. Greyserman and Kaminski (2014) demonstrated the crisis-alpha potential of long/short strategies. Markowitz (1952) and Sharpe (1994) laid the groundwork for portfolio optimization and risk-adjusted performance, further extended by volatility-timed allocation models (Moreira & Muir, 2017). These insights inform our 50-stock equity-only approach.

**Methods**

We fixed a 50-stock universe from the S&P 500 using screens for liquidity, volatility, sector balance, and 10+ years of price history. Within this universe, an HMM identifies market regimes (bull, bear, neutral). Momentum rules overweight the top quintile of stocks by 6–12 month returns, while mean reversion strategies exploit short-term deviations (RSI, Bollinger Bands, and sector pairs). Monte Carlo simulations tested performance under synthetic regimes, while backtests from 2010–2023 validated results.

**Results**

From the readings and literature, several clear takeaways emerge for our 50-stock S&P 500 strategy. First, regime-awareness is consistently shown to improve risk-adjusted returns. Hamilton (1989) established that Hidden Markov Models can successfully classify latent market states, and later studies such as Wang et al. (2020) confirmed that regime-based allocation tends to outperform static strategies. This validates our use of HMMs to scale exposure up in favorable regimes and down in high-risk conditions.  
  
Second, momentum strategies remain one of the most reliable sources of excess returns. Jegadeesh & Titman (1993) and Brock et al. (1992) provided strong evidence that past winners tend to keep outperforming, and more recent reviews reaffirm their value in systematic trading. This supports our approach of overweighting the top quintile of momentum names within our 50-stock universe. However, Park & Irwin (2007) cautioned about the impact of data-snooping and costs, reminding us to keep implementation practical and turnover controlled.  
  
Third, mean reversion adds a complementary edge in range-bound markets. Literature highlights that many equities revert after extreme moves (e.g., RSI or Bollinger Band signals), but such strategies struggle during persistent trends. This aligns with our plan to apply them selectively when volatility is high but directional trends are weak.  
  
Finally, risk management is central. Markowitz (1952) emphasized diversification, and Sharpe (1994) introduced the Sharpe ratio as a standard of performance evaluation. More recent work by Moreira & Muir (2017) demonstrated the benefits of volatility targeting, which resonates with our intent to manage risk through regime-based scaling. Taken together, the readings reinforce that our equity-only, regime-adaptive strategy has strong theoretical support: momentum drives returns in trends, mean reversion provides balance in sideways markets, and HMM-based regime detection underpins smarter risk control.

**Conclusions**

Restricting to a 50-stock S&P 500 universe creates a focused, realistic equity-only strategy. Literature and empirical evidence confirm that HMM-based regime adaptation, technical overlays, and diversification across sectors yield robust risk-adjusted returns. The strategy is economically viable and attractive to investors seeking an alternative to passive index exposure.

**References**

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**Update — 2025-08-17 Results**

This section summarizes the latest backtest results using strategy version v4.4. Key changes since the 2025-08-03 report include:

* Regime-specific stock selection (bull: long momentum winners only; neutral: blended; bear: short momentum losers with small contrarian longs).
* SMA-200 upgrade/degrade override on top of HMM regimes to avoid staying bearish into recoveries.
* Macro safety valve: when SPY is above the 200-day and 1‑month momentum is positive, shorts are reduced/disabled and beta floors applied.
* Tilt‑aware beta targeting (preserves L1 exposure), weekly rebalance with smoothing, EWMA vol targeting.
* ETF‑like trading costs on turnover, optional management fee (set to 0 bps here), and borrow costs on shorts.

Performance Summary (net):

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Series | CAGR | AnnVol | Sharpe | MaxDD | TotalReturn |
| Strategy (net) | 10.27% | 15.75% | 0.70 | -54.93% | 360.09% |
| SPY (net ER) | 13.70% | 17.33% | 0.83 | -33.72% | 641.95% |

Figure A: Equity Curve — Strategy (net) vs SPY (net ER)

**A graph of a chart

AI-generated content may be incorrect.**Figure B: Rolling Drawdowns**A graph of a graph with numbers and lines

AI-generated content may be incorrect.**

Figure C: Strategy Equity (net fees)

**A line graph with numbers and a line

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