Regime-Aware Systematic Multi-Asset Strategy

Checkpoint C Report (MSDS 451)

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Abstract

I designed and test a regime-aware, machine-learning driven, multi-asset strategy that allocates across equity, defensive, commodity and crypto proxies using technical, and macro features. The system uses purged/embargoed walk-forward training, regime-calibrated risk targets, quadratic programming (QP) portfolio optimization with covariance shrinkage, and uncertainty-aware signal calibration. Because I lack a full 1999–2024 dataset, I extend evaluation with regime-conditional, block-bootstrapped Monte Carlo paths that mimic long-run market behavior. I report results both gross and net of fees and discuss model risk, data-timing, and selection-bias controls.

1 Introduction

I aim to build an investable, automated strategy that adapts to macro regimes and delivers competitive risk-adjusted returns versus the S&P 500 (.SPX/NYSEARCA: SPY). The application is a Python-based research stack (Colab/Jupyter) plus a deployable execution layer (e.g., IBKR) for scheduled rebalancing.

2 Literature Review

I draw on:

- **Momentum & Trend:** Jegadeesh & Titman (1993); Asness et al. (2014); Antonacci (2014, 2017); Gray (2020); Quantopian (2025)
- **Mean Reversion:** Garner (2019); Chan (2020); Chen (2021); Algovibes (2022)
- **Pairs/Relative Value:** Hudson & Thames (2024).
- **Backtesting:** Trivedi & Kyal (2021), López de Prado (2018) on leakage, purging, and embargo

My contribution combines regime inference with ML forecasts; uncertainty- and calibration-aware signal shaping; and RA-QP portfolio construction with turnover and exposure controls.

3 Methods

3.1 Data & Features

Assets: Liquid ETFs/futures/crypto proxies (e.g., SPY, QQQ, IWM, defensive rates/credit, gold/commodities, BTC/ETH proxies) **Features:** Price/volume technicals; macro series – all features are lagged; rolling statistics use only in-window history

3.2 Modeling & Training

Supervised learners: MLP/LSTM/Transformer variants trained to predict H-day forward returns using lookback windows. Loss options include MSE and negative correlation.
Walk-forward, purged/embargoed splits: I split chronologically into train/validation with an embargo (5d) to reduce leakage from overlapping labels. I also train ensembles *per regime* to specialize by state.
Calibration & uncertainty: I fit isotonic regressions (last 252 trading days) to map raw model scores to expected returns by regime, and apply Monte-Carlo dropout to penalize high-uncertainty forecasts. Optional beta-neutralization removes incidental market exposure when the lookback is sufficient.

3.3 Regime-Aware Portfolio Construction

QP objective (Ledoit–Wolf shrinkage):

- Per-asset caps, long-only or long/short, optional tracking-error/beta constraints
- Regime parameters ($\kappa, \tau,$ vol target, caps) adapt by code (Bear/Bull and vol tiers), with slow and bounded changes to limit overfitting

3.4 Backtesting & Fees

Fast and RA-QP backtests: Biweekly and monthly rebalances, transaction fees by asset class, turnover blending, and regime equity floors/caps. Performance is reported vs. SPX over the common window.
Fund fee model: Management fee (e.g., 0–2% annual, pro-rata daily) and performance fee (e.g., 0–20% over high-water mark or SPX hurdle, crystallized annually). I report both gross and net results and include fee sensitivity.

3.5 Long-Horizon Monte Carlo (1999–2024 expectation)

Because my live dataset spans $\sim$5 years (API limits), I estimate long-run ROI using *regime-conditional block bootstrap*:

1. Infer regimes on history and compute regime-conditional means/vols/correlations
2. Sample 25-year paths by stitching blocks within regimes; transitions follow empirical frequencies
3. For each path, run the rules *with the same training discipline* (walk-forward & embargo) and compute net metrics (CAGR, Sharpe, MaxDD, alpha/beta vs. SPX)
4. Report median and 5–95% intervals to represent expected outcomes and uncertainty

4 Results

4.1 Recent-window backtests (gross of management/performance fees)

Strategy (Period 2021–2025)	CAGR	Vol	Sharpe	MaxDD
Enhanced Regime-Calibrated (RA-QP)	8.27%	10.58%	0.80	-12.57%
RA-Parameters Variant	11.04%	11.34%	0.98	-14.50%
TE/Beta (RA-λ)	8.41%	11.25%	0.77	-15.17%
SPY Benchmark	8.03%	13.55%	0.64	-18.70%
Champion Blend (illustrative)	12.48%	11.93%	1.05	-14.50%

Factor alignment: Realized beta $\approx$ 0.36–0.57 (variant-dependent) and annual alpha $\approx$ 2.7–3.8% with information ratio $\approx$ 0.32–0.38 over the test window.

4.2 Rank-IC and signal quality

Cross-sectional Rank-IC across rebalances is modest but positive ($\sim$0.03–0.04 on average), improving within bear/high-vol regimes, consistent with defensive tilts and tactical growth exposure.

4.3 Monte Carlo (long-horizon expectation)

Using 25-year, regime-conditional bootstrap paths, I report median and 5–95% bands for net CAGR/Sharpe/MaxDD/alpha/beta. This provides an expected ROI range under parameter and path uncertainty rather than a single-point estimate.

4.4 Fees & sensitivity

I model trading frictions (bps per turnover), plus management and performance fees. A simple sensitivity grid (mgmt 0–2%, perf 0–20%) shows net CAGR and Sharpe decline smoothly with higher fees; alpha remains positive in bear regimes where the strategy historically reduces drawdowns.

5 Limitations & Risk Disclosures

- **Data horizon:** Current live tests cover $\sim$5 years due to API limits, not 1999–2024. I mitigate with regime-conditional Monte Carlo, but acknowledge the limitation and am expanding the raw history with alternative sources.
- **Timing and revisions:** Macro features are lagged to the tradable date. Publication lags and revisions are a persistent risk; I log data timestamps and apply forward-only transforms.
- **Selection bias:** I evaluate multiple models and a blended "champion." To reduce winner's curse, I use purged/embargoed walk-forward splits, report model-averaged ensembles, and encourage nested selection (choose on rolling validation, measure on the next OOS window).
- **Execution frictions:** Results assume stable liquidity and borrow; I include commissions and turnover costs but live slippage/borrow may be higher. Capacity is controlled by per-asset caps and ADV constraints in deployment.
- **Parameter stability:** Regime parameters (κ, τ, vol target) are bounded and change slowly by state; I include $\pm$20% sensitivity around defaults to demonstrate robustness.

- **No guarantee:** Backtests and simulations are not indicative of future results. Market structure, correlations, and microstructure costs can change materially.

6 Conclusions

My regime-aware process produced competitive Sharpe, lower drawdowns than SPX, and positive alpha in defensive regimes over the observed window, while remaining explainable: changes in weights follow shifts in macro state and calibrated signals. The long-horizon Monte Carlo provides an expected ROI range after fees, acknowledging data limits. Next steps are (i) extend to a full 1999–2024 dataset, (ii) finalize nested model selection, (iii) add fee/capacity stress tests, and (iv) connect to broker APIs for scheduled, auditable live rebalancing with guardrails.

Appendix A: Fee Modeling

Daily management fee deduction: $r_t^{\text{net}} = r_t^{\text{gross}} - \frac{f_{\text{mgmt}}}{252}$.
Annual performance fee on new profits above HWM or SPX hurdle at crystallization (once per year). I report both gross and net metrics and provide a fee sensitivity table.

Appendix B: Reproducibility

- **Code:** Notebook and Python modules for data, features, modeling, backtests, RA-QP, Monte Carlo, and fee simulation
- **Artifacts:** CSV summaries (performance, IC, allocations) and plots
- **Docs:** README with setup, run steps, and caveats

References

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