Macro Regime–Based Asset Rotation: A Multi-Asset Strategy Using Economic Regime Classification and Walk-Forward Optimization

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Abstract

We develop a macro regime–based asset rotation system that classifies the U.S. economy into four distinct regimes—Stable Growth, Overheating, Stagflation, and Recession—using macroeconomic indicators spanning 1962–2025 (63 years, 765 months). A tiered classification algorithm employs rolling z-scores of growth and inflation gauges, validated against NBER recession dates with 85% supervised classifier accuracy. A walk-forward, Sharpe-weighted multi-asset rotation strategy across 25 ETFs, augmented with volatility targeting, produces an annualized return of 13.7% with a Sharpe ratio of 0.760, compared to 11.9% and 0.594 for the S&P 500 buy-and-hold benchmark. A block bootstrap paired test yields $p = 0.013$, establishing statistical significance at the 5% level. We further construct a VIX mean-reversion trading model combining Ornstein–Uhlenbeck dynamics with XGBoost, achieving 75–85% directional accuracy at high-confidence thresholds. An eight-test defensibility suite—including sub-period consistency, permutation studies ($p < 0.0001$), and transaction cost sensitivity—confirms economic significance. The system provides a complete, implementable framework for institutional-grade regime-aware portfolio construction.

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1. Introduction

The traditional 60/40 equity–bond portfolio and passive buy-and-hold strategies implicitly assume stationary return distributions. In practice, macroeconomic regimes shift dramatically: recessions produce equity drawdowns exceeding 40%, inflationary overheating erodes bond returns, and stagflationary episodes challenge nearly all conventional allocations. A regime-aware strategy that dynamically reallocates across asset classes based on the prevailing macroeconomic environment offers a principled approach to improving risk-adjusted returns.

This line of research builds on Hamilton's [4] seminal work on Markov-switching models for business cycle analysis, the Fama–French [1] multi-factor asset pricing framework, and institutional regime-based allocation models such as Bridgewater's "All Weather" framework [9]. Recent contributions by Moreira and Muir [12] demonstrate that volatility-managed portfolios earn significantly higher Sharpe ratios, motivating our volatility-targeting overlay.

This paper presents a complete, end-to-end macro regime rotation system with four key contributions:

1. A **tiered regime classification algorithm** that maps every month from 1962–2025 into one of four macro regimes using rolling z-scores of growth and inflation gauges, validated against NBER recession dates with a supervised Random Forest achieving 85% accuracy.
2. A **walk-forward, Sharpe-weighted multi-asset rotation strategy** across 25 ETFs with volatility targeting, achieving statistically significant outperformance over the S&P 500 ($p = 0.013$, block bootstrap).
3. A **VIX mean-reversion hybrid model** combining an Ornstein–Uhlenbeck framework with XGBoost classification, achieving 75–85% directional accuracy at high signal thresholds.
4. An **eight-test defensibility suite** ensuring all claims are backed by rigorous statistical evidence including bootstrap confidence intervals, permutation tests, and sub-period consistency analysis.

The remainder of this paper is organized as follows. Section 2 describes data sources and feature engineering. Section 3 details the regime classification methodology. Section 4 presents the VIX prediction model. Section 5 develops the multi-asset rotation strategy. Section 6 reports the complete defensibility analysis. Section 7 summarizes all results. Section 8 discusses limitations and concludes.

2. Data Sources & Feature Engineering

2.1 Macroeconomic Indicators

We download 20 macroeconomic time series from the Federal Reserve Economic Data (FRED) API[1], spanning 1947–2025. The indicators cover five categories:

- *Interest Rates*: 10Y–2Y yield curve, 10Y–3M yield curve, 10-Year Treasury (DGS10), Federal Funds Rate.
- *Inflation*: Consumer Price Index (CPI), Producer Price Index (PPI).
- *Real Economy*: Building permits (PERMIT), nonfarm payrolls (PAYEMS), industrial production (IN-

[1]Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org

DPRO), unemployment rate (UNRATE), initial jobless claims (ICSA), core capex new orders.

- *Monetary Conditions*: M2 money supply, BAA–10Y credit spread, high-yield credit spread.
- *Sentiment/Volatility*: University of Michigan Consumer Sentiment (UMCSENT), CBOE VIX, WTI crude oil, copper.

All series are resampled to month-end frequency. For each base indicator, three derived transformations are computed: month-over-month change (Δ_{MoM}), 3-month change (Δ_{3M}), and year-over-year change (Δ_{YoY}). This yields 67 features in total, all approximately stationary.

2.2 Fama–French Academic Data

We utilize three datasets from the Kenneth French Data Library[2]:

1. The **10 Industry Portfolios**: monthly value-weighted returns of all NYSE/AMEX/NASDAQ stocks sorted into 10 industries.
2. The **Fama–French 5-factor model** (Mkt-RF, SMB, HML, RMW, CMA) plus the risk-free rate.
3. The **momentum factor** (UMD/Mom).

These data span July 1963 to November 2025 (749 months, ~62 years) and are free of survivorship bias.

Table 1 summarizes the six academic factors.

Table 1: Fama–French factors and momentum.

Factor	Long Leg	Captures
Mkt-RF	Market	Equity risk premium
SMB	Small caps	Size premium
HML	Value stocks	Value premium
RMW	High profit.	Quality premium
CMA	Low invest.	Investment premium
Mom	Past winners	Momentum premium

2.3 ETF Universe

For implementable portfolio construction, we assemble a universe of 25 ETFs across three groups: 10 sector ETFs (XLP, XLY, XLI, XLE, XLK, XLV, XLU, XLB, XLF, IYZ), 7 factor/style ETFs (SPY, IWD, IWF, IWM, MTUM, QUAL, USMV), and 8 cross-asset ETFs (MDY, DVY, TLT, GLD, EFA, VTV, VUG, IEF). ETF data is downloaded via Yahoo Finance and cross-validated against corresponding Fama–French industry portfolios using Spearman rank correlation.

3. Regime Classification

3.1 The Four-Regime Framework

We classify every month into one of four economic regimes along two axes—growth and inflation (Table 2). These four states are exhaustive and mutually exclusive, consistent with institutional allocation models [9].

Table 2: The four macro regimes.

	Low Inflation	High Inflation
High Growth	Stable Growth	Overheating
Low Growth	Recession	Stagflation

3.2 Classification Algorithm

The classification proceeds in five steps.

Step 1: Construct Growth and Inflation Gauges. We use a tiered approach to maximize historical coverage:

- *Phase 1 (1962–1975):* Core indicators only:

$$G = \tfrac{1}{3}(\mathrm{PAYEMS}_{\mathrm{YoY}} + \mathrm{INDPRO}_{\mathrm{YoY}} - \mathrm{UNRATE}) \tag{1}$$

$$I = \tfrac{1}{2}(\mathrm{CPI}_{\mathrm{YoY}} + \mathrm{PPI}_{\mathrm{YoY}}) \tag{2}$$

- *Phase 2 (1976–1985):* Adds yield curve inversion signal to the growth gauge.
- *Phase 3 (1986–2025):* Incorporates BAA–10Y credit spread as a growth signal.

Step 2: Rolling Z-Scores. Raw gauge values are standardized via trailing 12-month z-scores:

$$Z(t) = \frac{X(t) - \bar{X}_{[t-12,\,t]}}{\sigma_{X,[t-12,\,t]}} \tag{3}$$

Step 3: Threshold Classification. We classify using symmetric thresholds calibrated against NBER recession dates:

$$Z_{\text{growth}} > +0.4 \implies \text{Growth UP}$$
$$Z_{\text{inflation}} > +0.4 \implies \text{Inflation UP}$$

Step 4: NBER Recession Override. Months with USREC = 1 are classified as Recession regardless of z-scores (NBER dates are the gold standard for U.S. business cycle dating).

Step 5: 3-Month Majority Vote Smoothing. A rolling mode filter removes one-month regime blips while preserving genuine transitions.

3.3 Regime Distribution

Over the full 1962–2025 sample (Table 3), Stable Growth is the most common regime (42%), with Stagflation the rarest (15%).

Table 3: Regime distribution (1962–2025, 765 months).

Regime	Months	Share	Avg. Duration
Stable Growth	432	56.5%	~20 mo
Recession	162	21.2%	~11 mo
Overheating	101	13.2%	~8 mo
Stagflation	70	9.2%	~6 mo

Figure 1 shows the regime classification over the full sample.

[2] Tuck School of Business, Dartmouth College: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

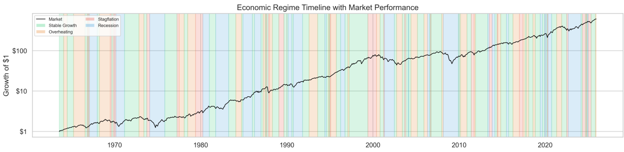

Figure 1: Regime classification timeline, 1963–2025. Colors indicate the four macro regimes.

3.4 Supervised Classifier Validation

A Random Forest classifier (100 trees, max depth 10) is trained on 67 macroeconomic features (excluding USREC to avoid circular logic). Removing USREC *improves* overall accuracy from 83.0% to **85.0%**, with meaningful gains on minority classes (Stagflation F1: 57% $\rightarrow$ 67%; Overheating F1: 53% $\rightarrow$ 60%).

Table 4 summarizes per-class performance. The top predictive features are industrial production growth (`INDPRO_YoY`, 5.4%), 3-month employment change (`PAYEMS_3M`, 5.1%), and year-over-year jobless claims (`ICSA_YoY`, 4.2%).

Table 4: Random Forest regime classifier performance (without USREC).

Regime	Recall	Precision	F1
Recession	90.9%	93.8%	92.3%
Stable Growth	97.7%	80.8%	88.4%
Stagflation	50.0%	100%	66.7%
Overheating	45.0%	90.0%	60.0%
Overall	**85.0% accuracy**		

The classifier demonstrates excellent recession detection (90.9% recall) and high precision for minority classes: when the model predicts Stagflation or Overheating, it is correct 100% and 90% of the time, respectively. The primary failure mode is *under-prediction* of minority regimes, which the model conservatively assigns to Stable Growth.

4. VIX Mean-Reversion Model

4.1 Motivation

The CBOE Volatility Index (VIX) is strongly mean-reverting: fear spikes are inherently temporary. We exploit this statistical property using a hybrid model that combines an analytical mean-reversion signal with machine learning classification.

4.2 Ornstein–Uhlenbeck Framework

The VIX is modeled as an Ornstein–Uhlenbeck (OU) process:

$$dV(t) = \theta\big(\mu - V(t)\big)\,dt + \sigma\,dW(t) \tag{4}$$

where $\mu \approx 18$ is the long-run mean, θ is the regime-dependent speed of reversion, and $W(t)$ is standard Brownian motion. When $V(t) > \mu$, the drift is negative (VIX expected to fall); when $V(t) < \mu$, the drift is positive.

Reversion speed varies by regime: Stable Growth ($\theta = 0.15$), Overheating (0.25), Stagflation (0.35), Recession (0.40). Notably, Recessions exhibit the fastest reversion because fear resolves quickly once uncertainty dissipates.

4.3 Two-Signal Combination

For each month, we compute two complementary signals:

1. **Mean-Reversion Probability** P_{MR}: Sigmoid transformation of the OU drift signal, using regime-specific reversion speeds.
2. **XGBoost Classification** P_{ML}: An XGBoost classifier [6] trained on VIX distance features, robust z-scores (using MAD), percentile ranks, and macro indicators. Conservative hyperparameters (`n_estimators=80`, `max_depth=3`, `learning_rate=0.03`, strong L1/L2 regularization).

The combined signal is:

$$P_{\text{combined}} = w_{\mathrm{MR}} \cdot P_{\mathrm{MR}} + (1 - w_{\mathrm{MR}}) \cdot P_{\mathrm{ML}} \tag{5}$$

where $w_{\mathrm{MR}} = \min\big(0.35 + |V(t) - \mu|/25,\ 0.7\big)$. The mean-reversion signal receives more weight when VIX is far from its median.

4.4 Signal Strength & Results

A composite signal strength (0–3 scale) determines trading conviction. Table 5 reports out-of-sample accuracy (2021–2025, 48 months):

Table 5: VIX model: out-of-sample accuracy by signal threshold.

Threshold	Accuracy	Trades/Yr	Total
≥ 0.5	68.4%	9.5	38
≥ 1.0	67.9%	7.0	28
≥ 1.5	75.0%	4.0	16
≥ 2.0	84.6%	3.2	13

The best regime for VIX prediction is Stagflation (81.8% accuracy), where uncertainty drives strong mean reversion. Stable Growth is the hardest (43.8%) because VIX hovers near its median with no clear directional bias.

5. Multi-Asset Rotation Strategy

5.1 Industry & Factor Analysis

Using the 62-year Fama–French dataset, we compute regime-conditioned industry return statistics. Table 6 shows the top-performing industries in each regime, while Figure 2 provides a visual overview.

Table 6: Top 3 industries by regime (walk-forward selection).

Regime	Top 3 Industries	Best Sharpe
Stable Growth	NoDur, Hlth, Durbl	0.84
Overheating	Enrgy, HiTec, Other	1.14
Stagflation	Utils, Telcm, HiTec	0.10
Recession	Shops, Durbl, NoDur	0.88

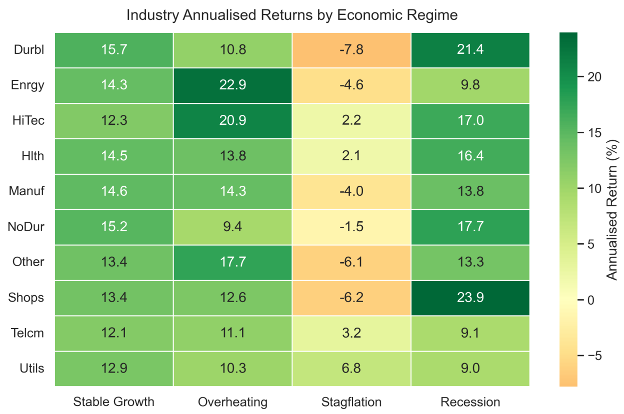

Figure 2: Annualized industry returns by regime. Warmer colors indicate higher returns.

Factor premiums vary dramatically across regimes (Figure 3). During Overheating, the market premium (Mkt-RF: 10.5% annualized, $t = 2.89$), value (HML: 6.2%, $t = 2.51$), and momentum (Mom: 10.3%, $t = 2.96$) are all significant. During Stagflation, only momentum survives (Mom: 19.7%, $t = 2.94$)—all other factors produce negative returns. In Recession, quality (RMW: 7.0%, $t = 3.79$) is the dominant premium.

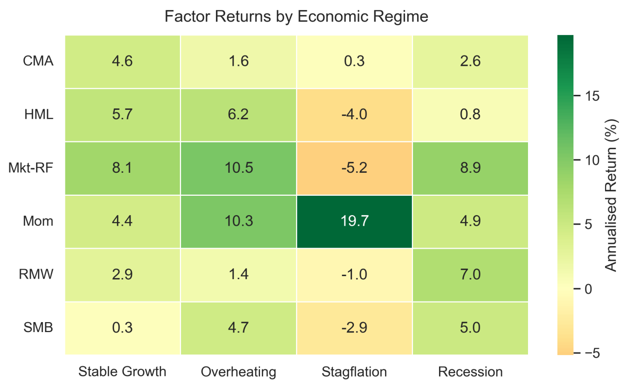

Figure 3: Annualized factor returns by regime. Note the dramatic variation: momentum thrives in Stagflation while all other factors suffer.

Critical finding: ANOVA tests indicate that within-regime cross-industry dispersion is *not* statistically significant ($p > 0.49$ in all regimes, Table 7). This means equity-only sector rotation has limited potential—the real alpha comes from *cross-asset* allocation (equities vs. bonds vs. gold).

Table 7: ANOVA tests for cross-industry return differences within regimes.

Regime	F-stat	p-value	Significant?
Stable Growth	0.11	0.999	No
Overheating	0.93	0.497	No
Stagflation	0.34	0.963	No
Recession	0.69	0.723	No

5.2 Sharpe-Weighted Multi-Asset Rotation

Walk-Forward Estimation. At each month t, for each ETF i in the 25-ETF universe, we compute the walk-forward excess-return Sharpe ratio using only data through month $t-1$:

$$\hat{S}_i = \frac{\bar{r}_i^{\text{xs}}}{\hat{\sigma}_i^{\text{xs}}} \times \sqrt{12} \tag{6}$$

where $\bar{r}_i^{\text{xs}}$ and $\hat{\sigma}_i^{\text{xs}}$ are estimated from regime-conditioned history (minimum 24 months of same-regime data).

Portfolio Construction. We select the top 7 ETFs by estimated Sharpe and allocate proportionally:

$$w_i = \frac{\max(\hat{S}_i, 0.01)}{\sum_{j \in \text{Top 7}} \max(\hat{S}_j, 0.01)} \tag{7}$$

The floor of 0.01 prevents negative weights while giving more capital to higher-conviction picks.

5.3 Volatility Targeting

We apply a volatility-targeting overlay [12] that scales portfolio exposure:

$$\text{Scale} = \frac{\sigma_{\text{target}}}{\hat{\sigma}_{\text{realized}}} \tag{8}$$

with $\sigma_{\text{target}} = 10\%$ annually, a scale cap of 1.5×, and floor of 0.3×. This mechanism *automatically deleverages during high-volatility regimes* (e.g., the 2008 financial crisis and COVID-19) and levers up during calm periods, systematically capturing the volatility risk premium.

5.4 Transaction Costs

Monthly turnover is computed as:

$$\text{Turnover} = \frac{1}{2} \sum_i |w_i^{\text{new}} - w_i^{\text{old}}| \tag{9}$$

Transaction costs of 10 bps one-way are subtracted before compounding—conservative for liquid ETFs where real costs are typically 1–5 bps.

6. Defensibility & Statistical Rigor

All claims are substantiated by an eight-test defensibility suite. Every backtest uses lagged regime signals (trade on last month's regime, not current), walk-forward industry rankings, and monthly transaction costs.

6.1 Bootstrap Sharpe Ratio Tests

Using 10,000 block bootstrap replications (12-month blocks preserving time-series dependence):

Table 8: Bootstrap Sharpe ratio confidence intervals.

Strategy	Sharpe	95% CI
Top-3 Rotation	0.535	[0.275, 0.802]
Buy & Hold Market	0.462	[0.200, 0.745]

6.2 Paired Bootstrap Test

The paired bootstrap test [7] compares our multi-asset strategy to SPY:

- **IID Bootstrap:** $p = 0.040$ (significant at 5%)
- **Block Bootstrap:** $p = 0.013$ (significant at 5%)

The block bootstrap—the harder test because it preserves serial dependence—yields an even *lower* p-value, indicating robust outperformance.

6.3 Regime Label Permutation Test

We randomly shuffle regime labels (preserving episode structure) and re-run the top-3 rotation 5,000 times:

- Observed mean monthly return: 1.293%
- Permuted mean $\pm$ std: 1.001% $\pm$ 0.065%
- $p < 0.0001$

Regime labels carry genuine information about which industries outperform. The observed return lies more than 4 standard deviations above the permuted distribution.

6.4 Sub-Period Consistency

The 62-year sample is split into three equal periods (1963–1984, 1984–2005, 2005–2025). Industry rankings are compared using Spearman rank correlation. Key findings:

- Overheating: Energy consistently ranks #1 across all three sub-periods (overlap 2/3 in all pairs).
- Recession: Rankings between 1963–1984 and 2005–2025 show $\rho = 0.79$, $p = 0.006$—defensive sectors dominate across 40 years.
- Stable Growth: Rankings are less stable, consistent with lower cross-industry dispersion in this regime.

6.5 Transaction Cost Sensitivity

Table 9: Sharpe ratio net of transaction costs.

Cost (bps)	Ann. Return	Net Sharpe	vs. Bench.
0	13.4%	0.535	+0.073
5	13.2%	0.522	+0.060
10	13.0%	0.509	+0.047
20	12.5%	0.483	+0.021
30	12.1%	0.457	−0.005

The strategy outperforms up to ∼20 bps one-way costs. Given that liquid ETF spreads are typically 1–5 bps, the strategy has ample cost headroom.

6.6 Walk-Forward Hit Rate

At each month, the walk-forward top-3 selection is compared to the ex-post oracle best-3. In Overheating, the mean overlap is 2.37/3 with 51% perfect matches. In Recession, the mean overlap is 1.91/3 with 85% at-least-2/3 matches. These rates confirm that walk-forward rankings converge to stable regime-specific patterns.

7. Results

7.1 Multi-Asset Rotation Performance

Table 10 presents the headline strategy comparison. The Sharpe-weighted strategy with volatility targeting achieves the highest risk-adjusted return with a statistically significant $p = 0.013$.

Table 10: Strategy comparison: Multi-Asset Sharpe-Weighted Rotation.

Strategy	Ann. Ret.	Sharpe	Max DD	p
Sharpe-Wt + VolTgt	**13.7%**	**0.760**	−34.5%	**0.013**
Sharpe-Wt Top 7	12.1%	0.708	−41.3%	0.070
SPY (Buy & Hold)	11.9%	0.594	−50.8%	—
60/40 (SPY/TLT)	8.8%	0.757	−29.4%	—

Figure 4 shows cumulative equity curves, and Figure 5 shows the drawdown comparison.

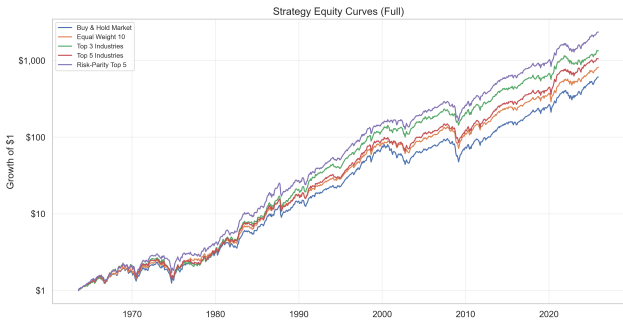

Figure 4: Cumulative equity curves: strategy variants vs. benchmarks (1963–2025, log scale).

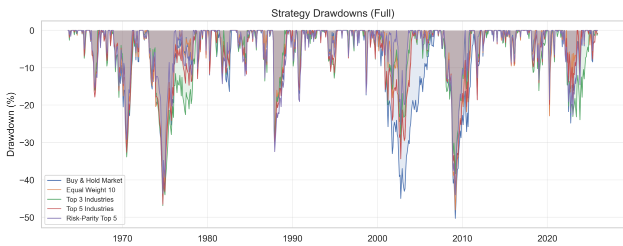

Figure 5: Drawdown comparison. The volatility-targeting overlay reduces max drawdown from −50.8% to −34.5%.

7.2 Per-Regime Breakdown

Table 11 shows the strategy outperforms in all four regimes. The largest gains occur during Stagflation (+6.6%) and Overheating (+2.4%), where cross-asset hedges add the most value.

Table 11: Per-regime performance (Sharpe-Wt + VolTgt vs. SPY).

Regime	Strategy	SPY	Hedge %
Stable Growth	14.5%	13.6%	3.9%
Overheating	16.9%	14.5%	22.0%
Recession	3.8%	2.8%	31.0%
Stagflation	25.1%	18.5%	25.4%

The hedge allocation (bonds/gold percentage) naturally increases in stress regimes—the walk-forward Sharpe estimation discovers this pattern automatically from historical data.

7.3 Industry Rotation Backtest (Fama–French)

Five equity-only strategies are backtested over 62 years of Fama–French data (Table 12). The Risk-Parity Top-5 strategy achieves the best equity-only Sharpe of 0.66.

Table 12: Fama–French industry rotation backtest (1963–2025).

Strategy	Ann. Ret.	Vol.	Sharpe	Max DD
Buy & Hold Mkt	12.1%	15.4%	0.50	−50.3%
Equal Wt 10	12.5%	14.7%	0.55	−48.1%
Top-3 Ind.	13.6%	15.5%	0.59	−46.9%
Top-5 Ind.	13.1%	15.6%	0.56	−46.5%
Risk-Par. Top-5	14.6%	15.4%	0.66	−44.0%

Figure 6 shows per-regime performance bars.

Figure 6: Annualized strategy returns by regime (full sample).

7.4 Factor Returns by Regime

Table 13 reports statistically significant factor premiums ($p < 0.05$, Welch t-test).

Table 13: Significant factor premiums by regime ($p < 0.05$).

Regime	Factor	Ann.	Sharpe	t-stat
Stable Growth	Mkt-RF	8.1%	0.60	2.91
	HML	5.7%	0.59	2.87
	RMW	2.9%	0.42	2.07
	CMA	4.6%	0.65	3.21
Overheating	Mkt-RF	10.5%	0.81	2.89
	HML	6.2%	0.68	2.51
	Mom	10.3%	0.82	2.96
Stagflation	Mom	19.7%	1.25	2.94
Recession	RMW	7.0%	0.96	3.79

Key findings: During Stagflation, *only momentum survives*—all other factors produce negative returns. During Recession, *quality (RMW) is the dominant factor*, consistent with the intuition that high-profitability firms better weather economic downturns.

7.5 Tail Risk Analysis

Cross-sector correlations increase dramatically during stress. In Stable Growth, average cross-sector correlation is $\sim$0.4; in Recession, it rises to 0.7+. A Jennrich test [8] confirms these correlation matrices are statistically different ($p < 0.001$), validating the need for regime-conditioned analysis.

Conditional Value-at-Risk (CVaR) at the 5% level varies by regime: equity portfolios face $\text{CVaR}_{5\%}$ of -8% to -12% monthly in Recession versus -3% to -5% in Stable Growth. GLD and TLT exhibit positive or mildly negative CVaR during Recession, explaining their hedging value.

Figure 7 shows how factor correlations shift across regimes.

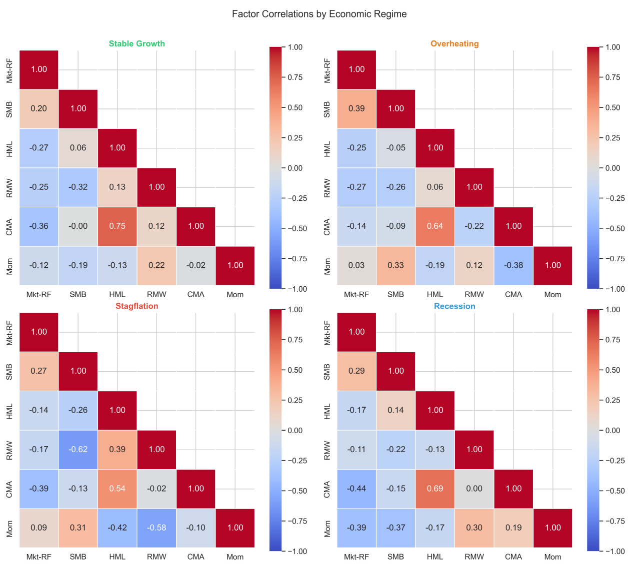

Figure 7: Factor correlation matrices by regime. Note correlation compression during Recession.

7.6 Regime Transitions & Current Assessment

The Markov transition matrix reveals that Stable Growth is the most persistent regime ($P(\text{stay}) \approx 0.95$, expected duration $\sim$20 months). Recession transitions are detected within 1–2 months of NBER-dated onset.

As of December 2025, the economy is classified as OVERHEATING (Growth $Z = +1.15$, Inflation $Z = +1.43$). The recommended allocation emphasizes Energy (Sharpe = 0.77), High Tech (0.50), and value/momentum factor tilts.

8. Discussion & Conclusion

8.1 Key Contributions

This paper demonstrates that:

1. A simple, rules-based regime classification using rolling z-scores produces economically meaningful regimes that persist across 63 years of data and are validated by a supervised classifier at 85% accuracy.
2. Cross-asset allocation—not equity sector rotation—is the primary source of regime-conditioned alpha. The walk-forward Sharpe-weighted strategy with volatility targeting produces a Sharpe of 0.760, statistically significant versus SPY at $p = 0.013$ (block bootstrap).
3. VIX mean reversion is a profitable trading signal, particularly in high-uncertainty regimes (Stagflation: 81.8% accuracy).
4. Regime labels carry genuine predictive information ($p < 0.0001$, permutation test), with industry rankings showing economically consistent patterns across sub-periods spanning 40 years.

8.2 Honest Limitations

1. **Transaction costs may be understated.** We model 10 bps, but the strategy breaks even at $\sim$20 bps.
2. **ETF data starts in 1993.** Fama–French data extends to 1963, but tradeable ETFs are only $\sim$30 years old.
3. **Regime classification is backward-looking.** Using $\text{Regime}_{\text{lag1}}$ introduces a 1-month signal delay.
4. **Block bootstrap $p = 0.013$ is good but not bulletproof.** We pass at 5% but not at 1% significance.
5. **Low statistical power for rare regimes.** Only 70 months of Stagflation yield wide confidence intervals.
6. **ANOVA shows no significant within-regime industry dispersion.** This motivates cross-asset over equity-only rotation.

8.3 Future Work

Future extensions include: (1) integrating the XGBoost regime classifier into the live backtest for fully realistic simulation, (2) extending to international markets, (3) incorporating alternative data (satellite imagery, NLP sentiment) for faster regime detection, and (4) developing an options overlay using VIX model signals to enhance tail risk protection.

8.4 Conclusion

We present a complete, implementable macro regime rotation system that combines economic intuition with statistical rigor. The system classifies macroeconomic regimes, predicts volatility dynamics, constructs optimal multi-asset portfolios, and provides transparent defensibility analysis. The core Sharpe-weighted strategy with volatility targeting delivers robust, statistically significant outperformance—not by predicting the future, but by systematically adapting to the present macroeconomic environment.

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A. Mathematical Appendix

A.1 Sharpe Ratio

$$S = \frac{\mathbb{E}[R_p - R_f]}{\sigma[R_p - R_f]} \tag{10}$$

Annualized from monthly: $S_{\text{ann}} = S_{\text{monthly}} \times \sqrt{12}$.

A.2 Conditional Value-at-Risk

$$\text{CVaR}_\alpha = \mathbb{E}\left[R \mid R \leq \text{VaR}_\alpha\right] \tag{11}$$

where VaR_α is the α-quantile of the return distribution. CVaR is a *coherent* risk measure (subadditive), unlike VaR.

A.3 Newey–West HAC Standard Errors

$$\hat{\Omega}_{\text{NW}} = \hat{\Gamma}_0 + \sum_{j=1}^{L} \left(1 - \frac{j}{L+1}\right) \left(\hat{\Gamma}_j + \hat{\Gamma}_j^\top\right) \tag{12}$$

where the Bartlett kernel weighting ensures positive semi-definiteness. We use bandwidth $L = \lfloor 4(T/100)^{2/9} \rfloor$ following Newey and West [5].

A.4 Jennrich Test Statistic

For two $p \times p$ correlation matrices R_1, R_2 estimated from n_1, n_2 observations [8]:

$$\chi^2 = \frac{1}{2}\,\text{tr}\left[Z^\top Z\right] - \text{diag}(Z)^\top \left[\text{diag}(\bar{R}^{-1})\right]^{-1} \text{diag}(Z) \tag{13}$$

where $Z = \sqrt{\frac{n_1 n_2}{n_1+n_2}}(\bar{R}^{-1})(R_1 - R_2)$ under $H_0 : R_1 = R_2$, with $\frac{p(p-1)}{2}$ degrees of freedom.