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Regime-Based Predictive Modeling of Equity Factor Returns

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1. Introduction

Equity factors such as **Value**, **Momentum**, **Size**, and **Market** have long been recognized as systematic drivers of stock returns. However, the performance of these factors is **highly regime-dependent** — what performs well in one macroeconomic environment often underperforms in another. For instance, Value tends to outperform during economic recoveries, while Momentum thrives during sustained growth phases but suffers during sharp regime reversals. This cyclical behavior suggests that **understanding the prevailing market regime** can provide valuable insights into future factor performance.

This project aims to **systematically identify market regimes and leverage them to predict equity factor returns**. By constructing macroeconomic feature vectors and comparing the current environment with historically similar periods, we can infer how factors behaved under analogous conditions. The resulting model provides a framework for **regime-aware portfolio construction**, where positions in factors are dynamically adjusted based on predicted performance. Ultimately, this approach seeks to enhance **predictive accuracy and alpha generation** beyond traditional static factor models.

2. Research Objectives and Hypothesis

2.1 Objectives

The primary objective of this research is to develop a **data-driven, interpretable framework** that links macro-financial conditions to equity factor performance. Specifically, the project aims to:

1. **Identify macroeconomic variables** that exhibit meaningful influence on equity factor returns, while mitigating redundancy through correlation and multicollinearity checks.

2. **Construct dynamic features** — representing the level, trend, and volatility of key macro variables — to characterize the evolving economic environment.

3. **Define and detect market regimes** by measuring the similarity of the current macroeconomic state to historical periods, using distance-based or unsupervised learning approaches (e.g., Euclidean distance, PCA, or clustering).

4. **Predict next-period factor returns** by averaging historical outcomes from the most similar regimes, generating directional (long/short) signals for each factor.

5. **Construct and evaluate a market-neutral long–short factor portfolio** based on these regime-informed predictions.

6. **Assess the predictive and economic value** of the regime-based framework using metrics such as hit rate, information coefficient (IC), Sharpe ratio, and alpha.

Through these objectives, the study seeks to test whether **regime awareness improves factor timing ability** relative to static or naïve models.

2.2 Hypothesis

Market regimes, defined by macroeconomic, financial, and geopolitical conditions, systematically influence the performance of equity factors. By identifying the current regime and comparing it to historically similar periods, we can predict factor returns and construct a market-neutral portfolio that generates positive alpha.

3. Literature Review

Paper 1: Regime-Switching Factor Investing Using Hidden Markov Models — Wang, Lin & Mikhelson (2020)

Wang et al. (2020) propose a regime-switching approach to factor investing, where a Hidden Markov Model (HMM) identifies latent market states that guide dynamic portfolio allocation. The authors aim to classify bull and bear market regimes using purely quantitative techniques and to rotate among different factor strategies accordingly. Using historical data from the U.S. equity market (2007–2017) and the S&P 500 as the underlying reference index, the model estimates the probability that the market is currently in each regime and adjusts factor exposure based on the most probable state.

Their results show that switching between factor models depending on the detected market regime significantly improves out-of-sample performance. In the 2017–2020 test period, the HMM-based adaptive factor strategy achieved higher absolute and risk-adjusted returns than any static factor model used in isolation. The main finding is that timely recognition of regime changes—such as transitions from expansion to recession or from calm to volatile markets—allows the investor to rebalance exposures toward factors historically favored in similar regimes. The study's strength lies in its use of unsupervised machine learning for regime detection, which avoids subjective classification. Its limitation, however, is the relatively short time span and single-market focus. Nonetheless, the study offers crucial empirical evidence that quantitative regime detection can meaningfully enhance factor return prediction, aligning strongly with our project's methodological foundation.

Paper 2: Factor Timing: Keep It Simple — Aked (2021, Research Affiliates)

Michael Aked's (2021) Research Affiliates white paper takes a practitioner's view on the challenge of timing equity factors and tests whether macroeconomic or cyclical signals can meaningfully improve performance. The study evaluates three systematic timing strategies across eight equity style factors (Market, Value, Size, Investment, Profitability, Low Volatility, Momentum, and Liquidity) over six global regions (U.S., Europe, U.K., Japan, Australia, and Emerging Markets) from 1969 onward. The three timing rules are:

1. Performance momentum—tilting toward recently outperforming factors;
2. Economic cycle prediction—allocating based on the predicted macroeconomic phase (expansion, slowdown, recession, recovery); and
3. Factor valuation plus momentum—increasing weights for factors that are both undervalued and currently gaining momentum.

The empirical results reveal that strategy (3)—combining factor valuation and factor momentum—delivers the highest Sharpe ratio and most consistent alpha generation. By contrast, pure factor momentum (strategy 1) performs no better than random, and macroeconomic cycle-based timing (strategy 2) adds little predictive power. While Research Affiliates acknowledge that "upcoming economic phases influence factor performance," they emphasize that accurately forecasting these phases is extremely difficult with current data. Therefore, direct market-based signals (valuation and momentum) tend to capture much of the same information that macro predictors would provide. The key takeaway is pragmatic: economic awareness is valuable conceptually, but simplicity in signal design yields more robust out-of-sample performance. For our project, Aked's findings serve as a caution that regime identification must be statistically strong and economically interpretable—otherwise, macro-based factor timing may underperform simpler, data-driven approaches.

Paper 3: Regimes — Mulliner, Harvey, Xia, Fang & van Hemert (2025, Man Group & Duke)

Mulliner et al. (2025), in collaboration between Man Group and Professor Campbell Harvey, introduce a non-parametric regime identification framework that resonates strongly with our project design. Instead of assuming a fixed number or type of regimes (e.g., "expansion" or "recession"), their model constructs a macroeconomic feature vector for each month—consisting of GDP growth, inflation, interest rates, credit spreads, and volatility measures—and computes the similarity between current and historical macro conditions. The most similar historical periods form the “regime analogues,” while the least similar are designated as “anti-regimes.”

The authors then evaluate how factor portfolios historically performed in those similar regimes, using six long–short equity factors from 1985–2024. Their results show that factor allocation guided by regime analogues consistently outperforms static weighting and yields statistically significant positive alpha even after transaction costs. Intriguingly, the study finds that “anti-regimes” (historical conditions least similar to today) also contain predictive value, providing insights into which factors to avoid. The strength of this approach lies in its data-driven flexibility—it discovers meaningful macro patterns without imposing arbitrary regime labels. However, its interpretability is lower than traditional models, as the regimes are discovered algorithmically rather than defined by explicit economic categories. Still, this study provides powerful evidence that macro-regime similarity analysis—essentially what our project implements—can generate genuine predictive information about factor performance.

Paper 4: Dynamic Asset Allocation with Asset-Specific Regime Forecasts — Shu, Yu & Mulvey (2024)

Yu, Mulvey, and Nie (2025) (related work; Shu, Yu & Mulvey, 2024) present a rigorous academic framework that integrates regime identification and machine learning-based regime forecasting for dynamic factor allocation. Their central innovation is the notion of “allocation-focused regimes”—regimes defined not by macro variables per se, but by relative patterns of factor performance. The study first applies a jump model to detect structural breaks in the relative returns of different factor strategies, effectively segmenting history into distinct performance regimes. Then, using XGBoost, the authors forecast the probability of entering each identified regime based on macroeconomic and market indicators such as yield curve slope, volatility indices, and growth metrics.

Empirical tests using U.S. equity factor portfolios (1960–2024) demonstrate that portfolios dynamically tilted according to these regime forecasts significantly outperform both static equal-weighted allocations and naive momentum-based timing. Applications include multi-factor dynamic allocation and paired factor switching (e.g., Value vs. Growth, Momentum vs. Reversal). In both cases, regime-aware models achieve higher Sharpe ratios and positive information ratios even after transaction costs. Strengths include the blend of modern ML (XGBoost) with interpretable economic modeling; limitations include computational complexity and potential overfitting.

Paper 5: Time to Tilt: Harnessing Factor Cyclicality — BlackRock Systematic (2025)

The BlackRock Systematic Equities team (2025) presents a practitioner-focused framework for dynamic factor rotation implemented in the actively managed ETF DYNF. Their philosophy is that factor performance is inherently cyclical—each factor thrives under specific macroeconomic and market conditions—and investors can enhance returns by "tilting" toward those currently favored. The framework integrates four signal dimensions: (1) macroeconomic regime, (2) factor valuation, (3) factor momentum (sentiment), and (4) factor-specific fundamentals.

BlackRock combines these signals into a composite factor outlook to overweight "tailwind" factors and underweight "headwind" ones. Evidence from DYNF's real-world implementation (2021–2024) shows that this multi-signal, regime-aware approach generated positive alpha, improved multi-year Sharpe ratios, and reduced drawdowns relative to static multifactor portfolios. While model details remain proprietary, the approach exemplifies a multi-dimensional predictive framework that blends macro, behavioral, and structural insights—precisely the philosophy our project seeks to emulate.

4. Data Description

3.1 Overview

This study integrates two datasets to examine how macroeconomic conditions affect equity factor performance:

1. **Macroeconomic Dataset** — monthly indicators representing the state of the economy and financial markets from 1962 onward.

2. **Equity Factor Dataset** — Fama–French 5-Factor data capturing systematic sources of equity returns.

Both datasets are structured at **monthly frequency**, allowing consistent temporal alignment and facilitating regime-based analysis over multiple economic cycles (1962–present).

3.2 Equity Factor Dataset

The equity factor data are sourced from the **Fama–French Research Data 5 Factors (2×3)** file.
This dataset provides **monthly factor returns (in percentages)** for five key systematic styles that explain cross-sectional stock performance:

Factor	Description
MKT (Market Risk Premium)	Return on the market portfolio minus the risk-free rate. Captures overall market risk exposure.
SMB (Small Minus Big)	Size factor — return spread between small-cap and large-cap stocks.
HML (High Minus Low)	Value factor — return spread between high book-to-market (value) and low book-to-market (growth) firms.
RMW (Robust Minus Weak)	Profitability factor — return spread between firms with robust vs. weak operating profitability.
CMA (Conservative Minus Aggressive)	Investment factor — return spread between firms with conservative vs. aggressive investment behavior.

The data originate from **Kenneth R. French's online data library**, a standard academic source for empirical asset pricing research.
All returns are expressed in **percent per month**. Factors are used both individually and as part of a **long–short factor portfolio** when assessing predictive relationships.

3.3 Macroeconomic Dataset

The macroeconomic dataset contains **monthly observations** from **January 1962 onward**, capturing a concise but powerful set of indicators that describe the broad macro-financial environment. These variables span market performance, yield curve dynamics, commodity prices, monetary conditions, volatility, and cross-asset relationships.

Variable	Description

market	Aggregate equity market index level (e.g., S&P 500 or equivalent).
yield_curve	Term spread (difference between long-term and short-term yields).
oil ($/bbl)	Spot price of crude oil per barrel (USD).
copper ($/metric ton)	Spot price of copper (USD per metric ton).
monetary_policy	Policy rate or short-term interest rate (likely Fed Funds Rate).
volatility	Equity market volatility measure (e.g., realized or implied volatility).
stock_bond_corr	Rolling correlation between stock and bond returns.

5. Methodology

5.1. Macroeconomic Variable Selection

To capture the underlying drivers of market regimes, seven macro-financial indicators were selected based on their theoretical and empirical relevance to equity factor performance. These include the aggregate market index, yield curve slope, oil and copper prices, monetary policy rate, equity market volatility, and stock–bond correlation. Together, they represent key dimensions of economic growth, inflation pressure, policy stance, and risk sentiment. Variables were filtered for reliability and interpretability, with redundant series removed through correlation and multicollinearity checks. This selection balances parsimony and coverage, ensuring that the resulting regime model captures distinct macroeconomic environments without overfitting.

5.2. Feature Engineering

1. To ensure comparability across variables and over time, each economic state variable undergoes a multi-step transformation process.
2. First, for each variable, we compute the **12-month change**, capturing medium-term economic dynamics rather than short-term noise. This transformation aligns with the investment horizon typically relevant for asset pricing and factor allocation decisions.

3. Next, we normalise the 12-month changes by computing a **rolling z-score over a 10-year window**. Specifically, each observation is standardised relative to its historical mean and standard deviation calculated using the preceding 10 years of data. To mitigate the influence of extreme observations, the resulting z-scores are capped within the range of −3 to +3.
4. In addition to this standardisation, we compute an alternative volatility-adjusted measure. For each variable, the 12-month change is divided by the **rolling standard deviation of 12-month changes**, again estimated over a 10-year window. This adjustment captures the magnitude of economic shifts relative to their historical variability, allowing for more stable comparisons across periods with differing levels of volatility.
5. Finally, the transformed variables are **winsorized at ±3** to further reduce the impact of outliers. This step improves robustness and prevents extreme macro-financial shocks from disproportionately influencing downstream model estimation.
6. The resulting series constitute the **transformed economic state variables** used as inputs in our analysis.

5.3. Regime Identification

5.3.1. Statistical Models

- Test autocorrelation of features (should vanish)
- Test cross-correlation (generally low and indicates diverse parameters)
- KNN models with Euclidean Distance (Kaya *et al.*, 2010)
- Improve Euclidean distance by using Mahalanobis distance, which scales differences by the variables' covariance matrix and accounts for correlations among factors (Kaya *et al.*, 2010)

Correlation distance

- It computes the shape similarity. It is suitable for two periods with different magnitudes in their observed data, but have similar patterns

Cosine Similarity

- Compute the geometric angle between the vectors, which is independent of the magnitude

5.3.2. Clustering Models

- K-means clustering (Crone, 2005)
- Gaussian Mixture Model (GMM) (Bott & Bao, 2021)
    - Use various Gaussian distributions to model different parts of the data
    - Data-driven unsupervised model

5.3.3. Econometric Models

- Hidden Markov Models (Wang, et al. 2020)

- Use HMM models to identify different market regimes in the US stock market
  - Assume that latent states, such as market regimes, follow a Markov chain, and that the observation data are generated conditionally on these states.

- Regime-Switching Models (Zhu, 2022)
  - Capture cyclical/latent state-driven patterns
  - Identify which state the current stage would potentially switch to

5.4. Factor Return Prediction

The objective of this step is to forecast next-month returns for each factor based on the **current market regime**, inferred from the macroeconomic feature set constructed earlier. The core idea is that i**f the current macro state resembles a subset of historical periods, then factor returns observed in those periods contain predictive information for the next month.**

5.4.1 Prediction Procedure

1. **Identify the current regime**
- At time t, construct the macro feature vector F_t, consisting of Level / Trend / Volatility features of the selected macro variables.
- Compare F_t, with historical feature vectors F_s, for all $s < t$ using a distance metric such as:
  - Euclidean distance
  - Mahalanobis distance
  - Cosine distance
  - Correlation distance
2. **Select similar historical periods (analogues)**
- Select the K historical months with the smallest distance to F_t (K-nearest neighbors).
- Optional: also identify **anti-regime** periods (months with the largest distances) for contrast and robustness checks.
3. **Forecast next-month factor returns**
- For each factor i, collect realized returns in the first quintile months (most similar): $r_i(s+1)$
- Compute the forecast as the simple average:

$$\hat{r}(t+1) = \sum_{s \in N_T} w_s \bullet r_i(s+1)$$

where the weights w_s are typically inversely proportional to the distance:

$$(w_s = \frac{1}{Nt})$$

4. **Generate long/short signals**

- If $\hat{r}(t + 1) > 0$: generate a **long** signal for factor ii.
- If $\hat{r}(t + 1) < 0$: generate a **short** signal.
- If $\hat{r}(t + 1)$ is small, reduce exposure or discard the signal to mitigate noise.

5.4.2 Look-Ahead Bias Control and Stability

- All features at time tt are constructed using data available up to $t - 1$ only (shifted, expanding or rolling windows).
- Regime similarity is computed strictly against historical observations ($s < t$).
- Forecasting and backtesting are conducted in a rolling-window framework to mimic real-time implementation.

5.4.3 Variants and Forecast Robustness

- **Similarity-weighted forecasts**: closer analogues receive higher weights.
- **Probabilistic regimes** (e.g., HMM/GMM): use probability-weighted expected returns.
- **Anti-regime validation**: if forecasts derived from anti-regimes imply opposite returns, position sizes can be reduced.
- **Signal normalization**: z-score $\hat{r}_i$ using historical distributions to improve cross-factor comparability.

5.4.4 Expected Outcomes

- Directional return forecasts for individual factors.
- Improved hit rate and Information Coefficient (IC) relative to baselines such as random allocation or simple momentum strategies.

5.5 Portfolio Construction

After generating long/short signals for each factor, a **market-neutral portfolio** is constructed to exploit return differentials between winning and losing factors within each regime.

5.5.1 Portfolio Structure

- **Market-neutral long–short** factor portfolio (zero market beta).
- **Net exposure = 0**, **gross exposure = 1** (or 100%).
- Long factors with $\hat{r}_i > 0$; short factors with $\hat{r}_i < 0$;.

5.5.2 Weight Allocation Methods

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PERFORMANCE COMPARISON: TIMED vs UNTIMED, EQUAL-WEIGHTED vs OPTIMIZED
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--- TRAINING SET (In-Sample) ---

	Ann. Return	Ann. Vol	Sharpe	Max DD	Hit Rate
Untimed EW FF5+Mom	7.1%	6.1%	1.16	-12.8%	72.3%
Q1 Timed EW	5.9%	5.9%	1.00	-10.6%	69.6%
Q1 Timed Optimal L/S	6.4%	5.6%	1.14	-7.7%	69.4%
Q1 Timed Optimal L-Only	6.4%	5.6%	1.14	-7.8%	69.2%

--- TEST SET (Out-of-Sample) ---

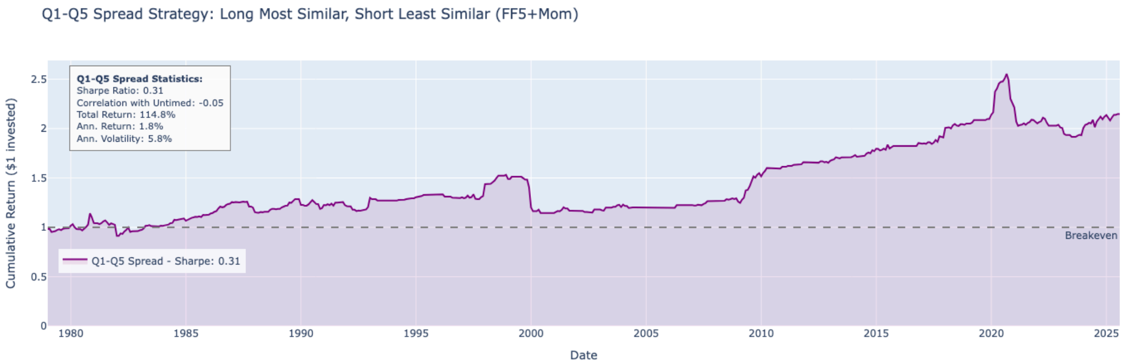
	Ann. Return	Ann. Vol	Sharpe	Max DD	Hit Rate
Untimed EW FF5+Mom	3.0%	5.1%	0.59	-13.5%	61.3%
Q1 Timed EW	2.8%	4.9%	0.58	-8.8%	54.9%
Q1 Timed Optimal L/S	2.9%	4.1%	0.70	-6.8%	55.8%
Q1 Timed Optimal L-Only	2.9%	4.1%	0.70	-6.9%	55.8%

The portfolio employs a Sharpe ratio maximization approach to determine optimal factor weights, using a chronological train/test split (80/20) to avoid look-ahead bias. On the training set (1978–2016), the optimizer uses Sequential Least Squares Programming (SLSQP) to find weights that maximize the annualized Sharpe ratio of the Q1-timed factor portfolio, subject to a full-investment constraint (weights sum to 1). Two optimization variants are tested: a long-short specification allowing weights between −100% and +200%, and a long-only version restricting weights to [0, 1].

The optimized weights are then applied out-of-sample to the test set (2016–2025) to evaluate generalization. The long-short optimization revealed a significant tilt away from equal-weighting, overweighting defensive quality factors (RMW: 24.7%, CMA: 25.2%)

while nearly eliminating value exposure (HML: −1%), reflecting the historical Sharpe-optimal factor mix during the training period. Out-of-sample, the optimized portfolio achieved a Sharpe of 0.70 versus 0.58 for equal-weighted, demonstrating that the weight optimization adds value beyond the timing signal alone, though some in-sample overfitting is evident given the larger performance gap in training (Sharpe 1.14 vs 1.00).

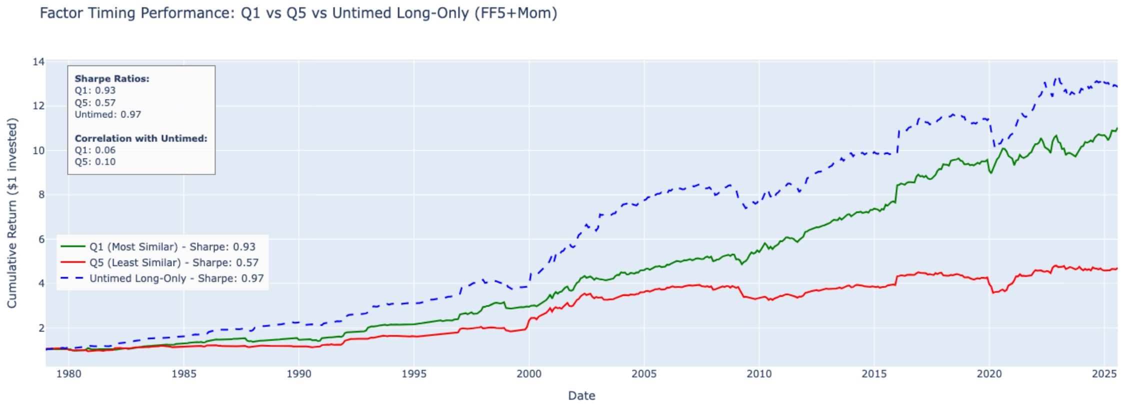
5.5.2 Predictive Power Assessment



The Q1-Q5 spread strategy—which goes long the quintile of dates most similar to the current regime and short the least similar—provides a direct test of the regime model's predictive power. The spread achieved a Sharpe ratio of 0.31 over the 47-year sample period (1978–2025), which is statistically meaningful but economically modest.

While the strategy generated a cumulative return of 114.8% (1.81% annualized), this is considerably weaker than simply holding the factors untimed (Sharpe 0.97, 1187% total return). Notably, the spread exhibits near-zero correlation (−0.05) with the untimed portfolio, suggesting the regime signal captures timing information orthogonal to passive factor exposure.
However, the relatively low Sharpe and high volatility (5.84% annualized) indicate that the similarity-based quintile ranking provides only weak discriminatory power between favorable and unfavorable factor environments. The positive Q1 performance (Sharpe 0.93) combined with the weaker Q5 performance (Sharpe 0.57) confirms some predictive value in the regime model, but the narrow spread suggests the signal is better suited for enhancing a long-only factor strategy rather than constructing a standalone long-short timing portfolio.

5.5.3 Performance Evaluation



The cumulative return chart reveals that the Q1 timed strategy closely tracks the untimed long-only benchmark over the 47-year period, with both generating substantial wealth accumulation—1003.6% for Q1 versus 1187.1% for untimed.

The Q1 strategy achieves a Sharpe ratio of 0.93, marginally below the untimed baseline's 0.97, indicating that the regime-based timing does not meaningfully enhance risk-adjusted returns on an aggregate basis. However, the remarkably low correlation of 0.06 between the two portfolios suggests the timing mechanism produces a fundamentally different return stream despite similar cumulative outcomes. Visually, the Q1 strategy exhibits periods of both outperformance and underperformance relative to the baseline, with notable divergences during market stress episodes. This pattern implies the regime model successfully identifies distinct macroeconomic environments, but the timing signals do not consistently translate into superior factor selection. The near-parity in Sharpe ratios, combined with the low correlation, suggests the regime model may be more valuable as a diversification tool or regime-aware overlay rather than a pure alpha-generating timing strategy.

5.5.5 Implementation Notes

- Transaction costs are not included in the initial scope but turnover is monitored to assess cost sensitivity.
- Weight caps may be imposed to prevent over-concentration in individual factors.

6. References

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