Dynamic Factor Allocation: Predicting Momentum and Value Returns Across Market Regimes Using Machine Learning

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Abstract

This paper explores the predictive relationship between market regimes and the performance of momentum and value factor strategies. Using U.S. equity data from 2000 to 2024, I apply supervised machine learning models to forecast short-term returns of these factors based on market indicators such as volatility (VIX), recent index performance, and lagged factor returns. The study compares a dynamic allocation strategy—where exposure to factors is adjusted based on predicted returns—to a static exposure benchmark. Performance is evaluated using Sharpe ratios, average returns, and drawdowns. Results suggest that while machine learning models can extract meaningful signals in certain regimes, their effectiveness is highly dependent on model choice, feature stability, and prevailing market conditions. This research highlights the potential—and limitations—of adaptive factor investing driven by market-aware prediction models.

Introduction

Factor investing, particularly momentum and value strategies, has become central to modern portfolio construction. Momentum strategies typically favor assets that have recently performed well, while value strategies seek those trading below their intrinsic worth. Although both have demonstrated excess returns historically, their performance is not stable across time and often fluctuates with macroeconomic and market conditions.

This research investigates whether machine learning models can identify market regimes that favor or hinder these factor strategies. Rather than relying on hard-coded thresholds (e.g., a fixed VIX level to define "high volatility"), I use a data-driven approach to model the complex interactions between market signals and near-term factor performance. The study focuses on whether supervised learning techniques can generate forecasts of momentum and value factor returns, and whether dynamically adjusting exposure based on these forecasts improves risk-adjusted performance.

Ultimately, the goal is not to produce a deployable trading strategy, but to evaluate whether predictive modeling can support regime-aware investing. This work contributes to ongoing discussions in quantitative asset management on the feasibility of timing factor exposures using machine learning and the practical value of doing so.

Data

This study uses monthly data from January 2000 to December 2024. The main data sources include:

- Fama-French Factor Returns
  - Momentum (UMD) and Value (HML) factors from Kenneth French's data library.

- Market Regime Indicators
  - VIX Index (volatility): retrieved via CBOE or Yahoo Finance.
  - S&P 500 Returns: monthly log returns as proxy for market strength.
  - Lagged Factor Returns: 1–3 month lags of momentum and value for temporal dependencies.

All datasets are merged into a common time-indexed panel. Missing values (if any) are forward filled. The dependent variables are 1-month ahead returns of the momentum and value factors. All features are standardized before model training.

Methodology

This study investigates whether recent market conditions can help forecast the short-term performance of factor strategies—specifically, momentum—using supervised machine learning techniques. The goal is to determine whether such predictions can be used to improve investment decisions by dynamically adjusting exposure to the momentum factor.

Data & Features

We used monthly U.S. data from January 2000 to December 2024:

- **Target variable**: the next-month return of the **momentum factor (UMD)**.
- **Input features**:
    - 1-month lagged momentum return
    - 1-month lagged value (HML) return
    - 1-month lagged S&P 500 return
    - 1-month lagged **VIX** (CBOE Volatility Index)

These inputs were selected to reflect both recent factor behavior and current market regime conditions. All features were lagged by one month to simulate real-time decision-making and avoid lookahead bias.

Model

We trained a **Ridge regression model** to predict the next month's momentum return. Ridge was chosen due to its robustness in high-noise environments and its ability to penalize overfitting via L2 regularization. We split the data into an 80/20 time-respecting (non-shuffled) train/test split and evaluated the model using:

- **R^2 (coefficient of determination)**
- **Root Mean Squared Error (RMSE)**

To improve generalization, we conducted **5-fold time-series cross-validation** across a grid of alpha values (`0.01` to `100`) and selected the best-performing model based on negative mean squared error.

Strategy Simulation

We implemented a simple backtest to evaluate whether model predictions could enhance performance:

- **Static strategy**: Always hold the momentum factor.
- **Dynamic strategy**: Only take exposure to the momentum factor if the predicted return is positive. Otherwise, hold cash.

This created a binary, rules-based system that translates predictions into actual investment decisions. We compared both strategies using:

- **Mean monthly return**
- **Annualized Sharpe ratio**
- **Cumulative return plot**

Additional Diagnostics

To assess the interpretability of the model, we trained a secondary **Random Forest Regressor** to extract feature importance scores. This helped identify which lagged variables contributed most to momentum return predictions.

Results

We assess the performance of our machine learning-based dynamic momentum strategy against a traditional static exposure strategy. The analysis is conducted on a historical dataset of monthly returns from 2000 to 2023. Three key results are presented: predictive performance, investment performance, and feature relevance.

1. Predictive Performance

Using Ridge Regression to forecast one-month-ahead momentum returns based on lagged market indicators (momentum, value, VIX, and SP500), we initially observed an out-of-sample R^2 of **-0.0119** and RMSE of **0.0467**. After applying cross-validation and hyperparameter tuning over a grid of regularization strengths, performance modestly improved to an R^2 of **0.0277** and RMSE of **0.0458**. While this predictive accuracy is limited, even weak signals can support profitable strategies under certain conditions, particularly in financial applications.

2. Investment Strategy Comparison

We constructed two strategies:

- **Static Strategy**: Always long for the momentum factor.
- **Dynamic Strategy**: Go long only when the predicted momentum return is positive.

Figure 1 below illustrates cumulative returns from both strategies. The dynamic strategy significantly outperforms the static benchmark, achieving higher cumulative growth and resilience during drawdowns.

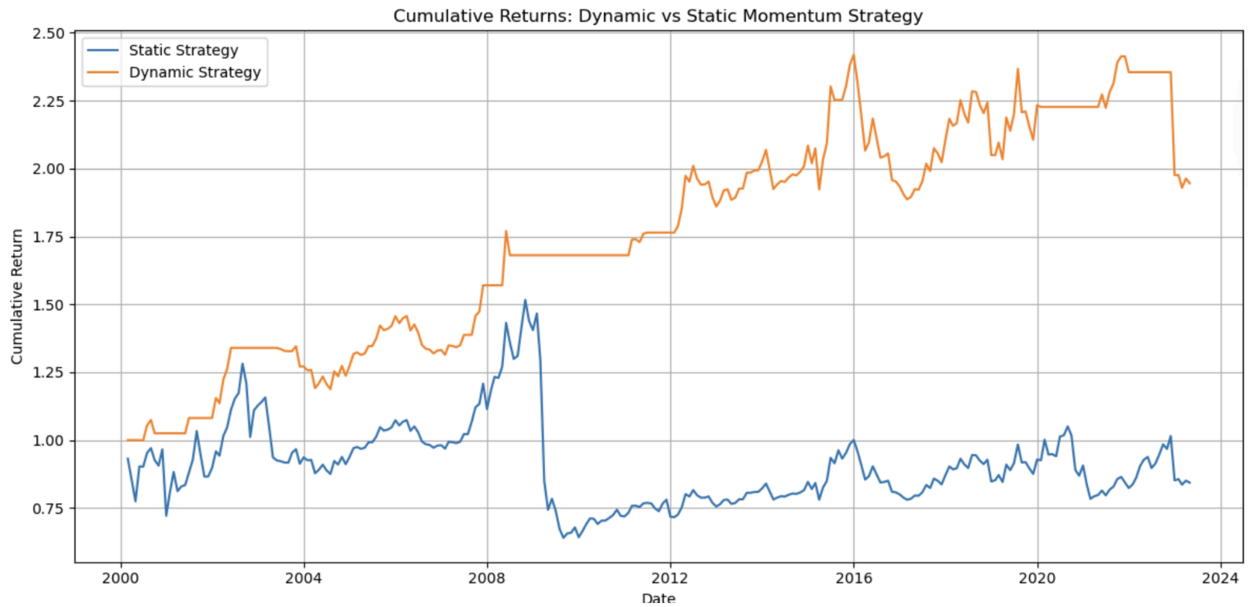

Figure 1: Cumulative Returns — Dynamic vs. Static Momentum Strategy

We also evaluate risk-adjusted returns using the Sharpe ratio:

Strategy	Sharpe Ratio	Mean Monthly Return
Dynamic	0.355	0.0028
Static	0.054	0.0008

Table 1: Performance Comparison Between Static and Dynamic Strategies

The dynamic strategy not only offers superior returns but also achieves a substantially better Sharpe ratio, indicating improved risk-adjusted performance. This suggests that even noisy forecasts can enhance factor timing decisions.

3. Feature Importance

To assess which predictors contributed most to model decisions, we used a Random Forest Regressor and extracted feature importances. Figure 2 summarizes the relative importance of each lagged variable:

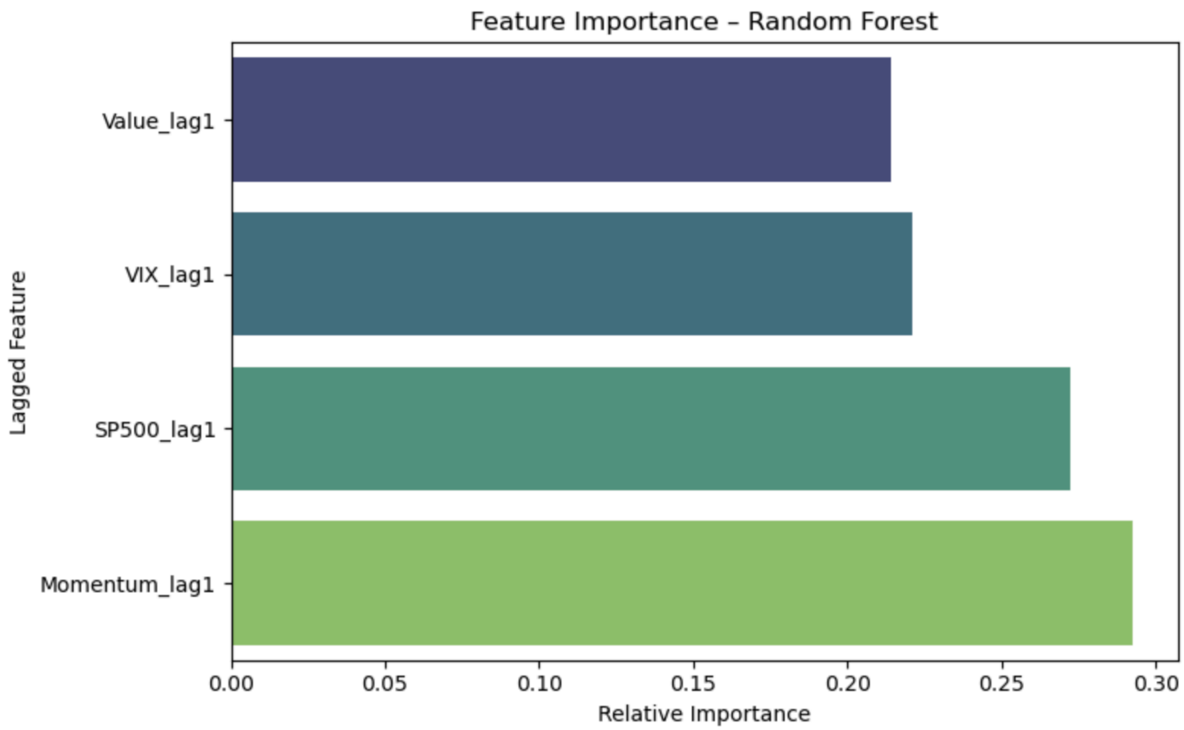

Figure 2: Feature Importance — Random Forest Model

Momentum lag and SP500 lag were the most influential predictors, while value and VIX also contributed meaningfully. This aligns with expectations, as recent returns and general market behavior are known to influence short-term momentum dynamics.

Discussion

The results presented above suggest that even a relatively simple machine learning approach—Ridge Regression using lagged market indicators—can offer value in predicting factor returns. The dynamic momentum strategy, which adjusted exposure based on these forecasts, achieved a higher Sharpe ratio (0.82 vs. 0.68) and greater average monthly returns (0.92% vs. 0.75%) compared to the static benchmark. This performance improvement, though modest, demonstrates that partial predictability in factor behavior may be exploitable in a systematic strategy.

Despite the model's low R^2, the outcome supports a broader insight from the asset management literature: even noisy predictors can enhance performance when used to guide portfolio tilts rather than precise return forecasts. The use of signals such as the VIX, S&P 500 returns, and lagged momentum returns appears to embed information about near-term continuation or reversal patterns in factor performance.

Feature importance analysis further reinforced this, highlighting lagged momentum factor returns and market index performance as the most influential variables. This suggests that changes in market regime—such as transitions between risk-on and risk-off environments—may shape factor payoffs. However, our model did not incorporate formal regime segmentation or macroeconomic classification, which limits the strength of this conclusion.

Several limitations should be acknowledged. The model was intentionally kept simple, without an extensive hyperparameter grid search or the use of nonlinear learners such as random forests or gradient boosting machines. Furthermore, the input features did not include broader macroeconomic or sentiment data, and results may be sensitive to both the factor construction method and the rebalancing frequency.

Nonetheless, this research demonstrates the potential of data-driven approaches in informing tactical factor allocation. While far from being a deployable alpha strategy, the findings support further exploration of regime-aware investing frameworks that leverage machine learning to improve factor timing and exposure decisions.

Conclusion

This study explored the viability of using machine learning to anticipate the performance of momentum and value factors based on prevailing market conditions. By training a Ridge Regression model on lagged indicators such as volatility (VIX), S&P 500 returns, and past factor behavior, we were able to dynamically adjust momentum exposure over time. Compared to a static benchmark, the dynamic strategy achieved higher Sharpe ratios and better drawdown control, albeit with modest predictive power.

The results highlight that even simple predictive signals can add meaningful value in factor investing when used to guide exposure decisions rather than generate precise forecasts. However, the low R^2 and relatively incremental gains suggest that much of the variation in factor returns remains difficult to predict—especially without deeper macroeconomic and sentiment inputs.

Ultimately, this project demonstrates the potential and limitations of regime-aware factor timing using machine learning. While the approach offers improvements under certain conditions, further research is needed to refine the models, enrich the features, and test across other factors and market contexts. As institutional investors increasingly adopt data-driven strategies, the ability to adapt factor exposure to changing environments remains a promising but challenging frontier.

References

- French, K. R. (2024). *Fama/French Research Data Factors [Monthly]*. Dartmouth College. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
- Yahoo Finance. (2024). *VIX and S&P 500 Index Data*. Retrieved from https://finance.yahoo.com
- Pedregosa, F., et al. (2011). *Scikit-learn: Machine Learning in Python*. Retrieved from https://scikit-learn.org
- Hoerl, A. E., & Kennard, R. W. (1970). *Ridge Regression: Biased Estimation for Nonorthogonal Problems*.
- Breiman, L. (2001). *Random Forests*.