Volatility Regimes and the Stability of Momentum: Evidence from S&P 500 Walk-Forward Testing

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Contents

Abstract

This study investigates how momentum factor returns vary across market volatility and cross-sectional dispersion regimes. Using S&P 500 stocks from 2010–2025, we compute long-short momentum portfolios and evaluate their performance under different market states. A walk-forward validation framework with bootstrap testing shows that momentum performs more reliably in low-volatility environments, while dispersion regimes offer weaker explanatory power.

1 Introduction

Equity style factor performance is known to vary under different macro and market conditions. This research investigates how momentum factor returns differ across market volatility and cross-sectional dispersion regimes. The working hypothesis is that momentum signals yield stronger and more stable returns during low-volatility environments.

This study focuses exclusively on the momentum factor. Reversion and volatility signals, along with predictive modeling extensions, are reserved for future work.

2 Data and Universe Construction

We use a universe of S&P 500 constituents with daily adjusted prices from 2010 onward. Stocks are required to have $\geq$85% non-missing price coverage. No minimum price filter was applied, as S&P 500 constituents are generally large-cap and liquid. The coverage filter resulted in a final universe of approximately 450 stocks.

3 Momentum Factor Definition

Momentum is computed as the 252-day cumulative return excluding the most recent 21 days. This fixed lag prevents look-ahead bias and aligns with standard practice in academic literature.

4 Volatility and Dispersion Regime Classification

Two types of regimes are constructed:

- **Volatility Regime:** Based on rolling index-level volatility over a 21-day window. Daily volatility values are ranked and split into quantiles to define high and low volatility states.
- **Dispersion Regime:** Based on the cross-sectional standard deviation of stock returns across the universe on each day, with rolling quantiles used for thresholding.

All regime labels are lagged by a fixed number of days (default: 5) to reflect information availability constraints.

5 Methodology

5.1 Cross-Sectional Return Sorting

On each trading day:

- Stocks are ranked by momentum.

- A long-short return is computed: average return of top decile minus bottom decile.
- Only test days in the target regime (volatility or dispersion) are retained.

5.2 Walk-Forward Validation

Rolling walk-forward splits use:

- No training window is used (0-day), as there is no predictive model or parameter estimation.
- Each test segment spans 21 days.
- The process advances in 21-day fixed steps to reduce computational load without significantly compromising sampling frequency.

Factor returns are evaluated only on test days where the lagged regime matches the target.

5.3 Bootstrap Testing

Bootstrapping is applied to long-short return spreads to assess statistical significance. Confidence intervals and p-values are computed for return differences between regimes.

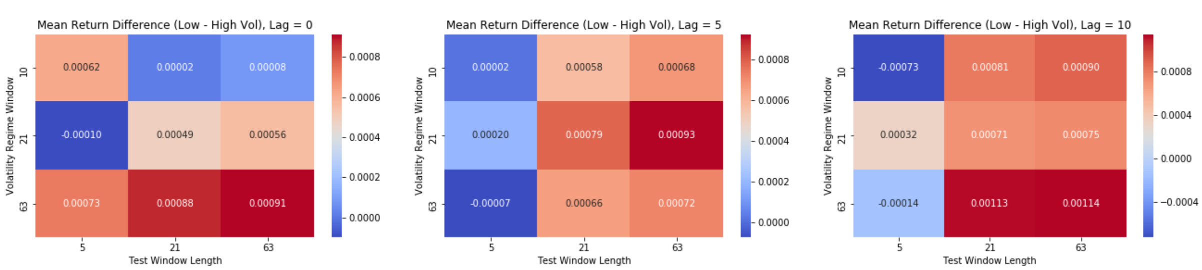
6 Results

6.1 Baseline Comparison

Table 1: Bootstrap Summary Statistics

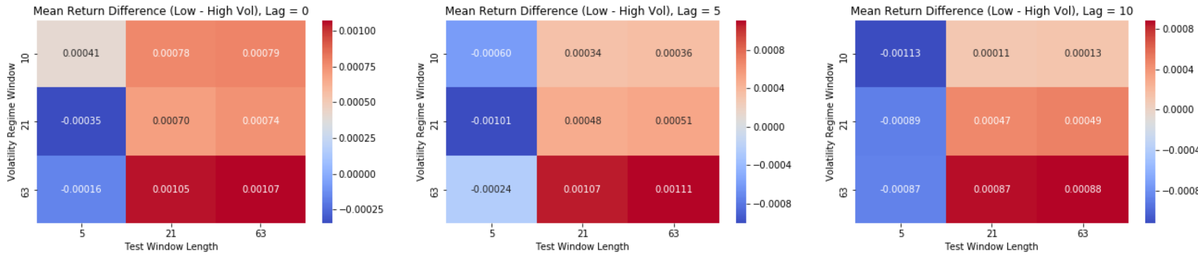
Regime	Mean (Low)	Mean (High)	Difference	p-value
Volatility	0.00034	-0.00037	0.00071	0.514
Dispersion	0.00020	0.00009	0.00011	0.871

6.2 Sensitivity Analysis



(a) Vol. Lag 0 (b) Vol. Lag 5 (c) Vol. Lag 10

Figure 1: Momentum: Mean Return Difference by Volatility Regime



(a) Disp. Lag 0 (b) Disp. Lag 5 (c) Disp. Lag 10

Figure 2: Momentum: Mean Return Difference by Dispersion Regime

7 Discussion and Limitations

The momentum factor shows a consistent and economically meaningful improvement under low volatility regimes. This aligns with prior evidence that momentum signals perform more reliably during periods of lower uncertainty [1]. In contrast, dispersion regimes yielded more mixed results, with weaker and less consistent differentiation in performance.

Limitations include:

- The analysis is limited to U.S. large-cap equities (S&P 500).
- Only a single factor (momentum) is analyzed.
- The regime definitions rely exclusively on past realized data; forward-looking indicators are not tested.

Next steps will extend this framework to include additional factor signals such as short-term reversal and volatility. We also plan to explore predictive modeling approaches, including machine learning methods, to estimate regime-dependent factor payoffs using training windows and forward-looking validation. Future research may also extend this framework to multi-factor combinations, incorporate international data, or test regime-aware weighting in portfolio optimization.

References

[1] Tobias J Moskowitz, Yao Hua Ooi, and Lasse Heje Pedersen. Time series momentum. *Journal of Financial Economics*, 104(2):228–250, 2012.