

Volatility-Adjusted Momentum Strategy

Overview

Core Principles **Introduction**

The Importance of Volatility in Momentum Strategy and the Concept of Volatility-Adjusted Momentum

Mechanics of our Risk-Adjustment Approaches

Strategy

Methodology
Implementation Details

Strategy Performance

Backtest

Results Walk-Through and Various Strategy Versions Comparison

Key Insights, Implementation Review and Potential Improvements

Summary

Review & Future Outlook

Introduction

- In traditional momentum strategies: investors follow the simple principle of buying assets with strong recent performance, expecting the trend to continue
- However, this approach overlooks a critical factor: **Volatility**
- Without considering volatility, investors may inadvertently expose themselves to assets with large, unpredictable price swings, leading to significant drawdowns, especially in turbulent markets.

Ranking: Long/Short top/bottom 20%

Price Momentum
Winner Minus Loser (WML)
Portfolio

Momentum Factor

Rolling 12-1 / 6-1 (over the past 12/6 months, excluding the most recent month), adding vol-considerations

Scaling Position

Adjust position sizes of the strategy portfolio inversely to the volatility of the momentum returns.

**Enhanced Volatility
Adjusted Momentum**

Strategy

❖ Enhancement 1. Vol-adjusted Momentum Factor

Reference: Fan, M., Kearney, F., Li, Y., & Liu, J. (2022). Momentum and the Cross-Section of Stock Volatility.

- Traditional Momentum Strategy: Involves ranking assets based on past returns, leading to potential clustering in high-volatility stocks, which can increase portfolio risk.
- Stocks with high volatility during the formation period tend to exhibit weaker momentum effects.
- Generalized Approach: Ranks assets by adjusting past returns with their realized volatility raised to the power of N.

Benefits:

- Reduces concentration in high-volatility stocks, thereby lowering portfolio risk.
- Enhances risk-adjusted returns

$$\hat{R}_{t-12,t-1}^k = \frac{R_{t-12,t-1}^k}{(\sigma_t^k)^N}.$$

- $\hat{R}_{t-12,t-1}^k$: Risk-adjusted return for asset k at time t
- $R_{t-12,t-1}^k$: Return over the past 12 months skip the recent month
- σ_t^k : Realized volatility over the same period
- N : Volatility adjustment parameter

Our construction :

$$\hat{R}_{k,t} = \frac{Z(R_{k,t-12,t-1})}{Z(\sigma_{k,t})}$$

❖ Enhancement 2. Volatility-Scaled Position Sizes

Reference: Momentum Has Its Moments (Barroso & Santa-Clara, 2014)

$$\hat{\sigma}_{WML,t}^2 = 21 \sum_{j=0}^{125} r_{WML,d_{t-1-j}}^2 / 126.$$

- $\hat{\sigma}_{WML,t}^2$: Estimated variance of momentum returns at time t .
- $r_{WML,d_{t-1-j}}$: Daily returns of the momentum strategy on the j -th trading day before $t - 1$.

$$r_{WML^*,t} = \frac{\sigma_{\text{target}}}{\hat{\sigma}_t} r_{WML,t},$$

- $r_{WML,t}$: the unscaled or plain momentum
- $r_{WML^*,t}$: the scaled or risk-managed momentum
- σ_{target} : a constant corresponding to the target level of volatility

Assumed 21 days in 1 month, and 126 is the average trading days over 6 months.

Increase positions in stable markets (low volatility) to capture momentum, and reduce them in down markets (high volatility) to control risk.

AR(1) using our Dataset:

Statistically Significance suggests that Past Realized Variance can be used as a Predictor of Future Volatility.

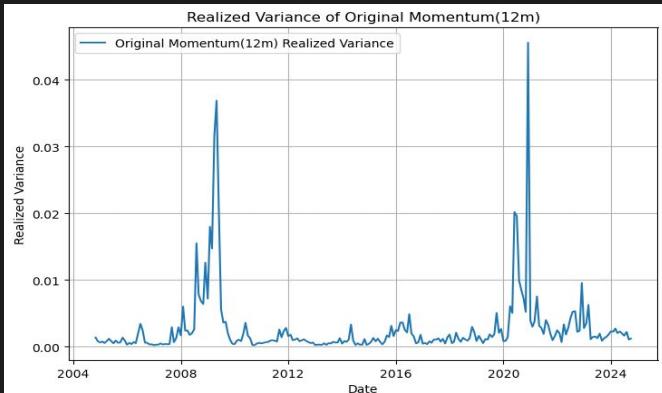


Table 1: Regression Results of Different Momentum Portfolios

Portfolio	α	t-stat(α)	ρ	t-stat(ρ)	R ²
Original Momentum(12m)	0.00	3.68	0.58	10.94	33.54
Original Momentum(6m)	0.00	2.92	0.71	15.61	50.08
Enhanced Momentum(12m)	0.00	5.45	0.60	11.40	35.41
Enhanced Momentum(6m)	0.00	6.43	0.51	9.29	26.20

❖ Enhancement 2. Volatility-Scaled Position Sizes

Our Construction and Modifications

1. Original Position Scaling

$$r_{WML^*,t} = \frac{\sigma_{\text{target}}}{\hat{\sigma}_t} r_{WML,t}$$

In the reference, the author suggested to use 12% annual volatility as target

2. Amplified Position Scaling

$$r_{WML^*,t} = \left(\frac{\bar{\sigma}_{\text{forecasted}}}{\hat{\sigma}_t} \right)^n r_{WML,t}$$

3. Fama-French Position Scaling

- Adjust volatility based on Fama-French-Carhart UMD factor
- Use UMD Factor as a representation of market volatility

$$\text{Mom} = 1/2 (\text{Small High} + \text{Big High}) - 1/2(\text{Small Low} + \text{Big Low}).$$

$$r_{WML^*,t} = \frac{1}{\hat{\sigma}_{\text{UMD},t}} r_{WML,t}$$

Our Modifications:

- Replace target vol with the mean of forecasted vol
- Add a power factor n for the coefficients
- Add leverage constraints for extreme scenarios

Backtest

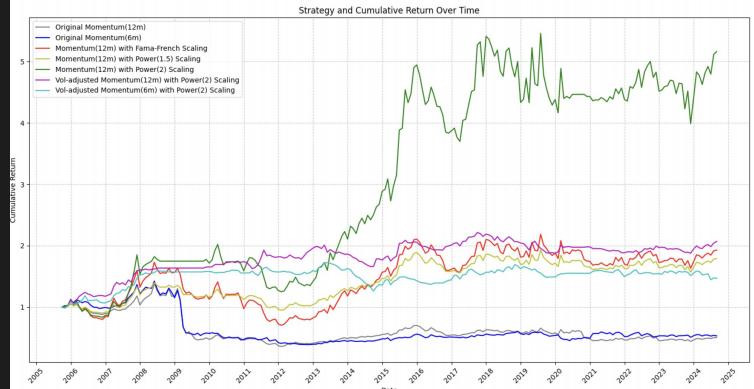
❑ Universe, Data Usage and Source

- **Universe : S&P 500 : * Real-time tickers are Used**
(Daily Holdings Found: https://github.com/fja05680/sp500/blob/master/sp500_by_date.ipynb)
- **Data**
 - **Daily Price of the Stocks ('adjust close' from yfinance)**
 - **Famma French Scaling Factor: Kenneth R. French Data Library**
(https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html)
 - **Daily Trading Volume of the Stocks ('volume' from yfinance) → Liquility Criteria**

□ Results Comparison

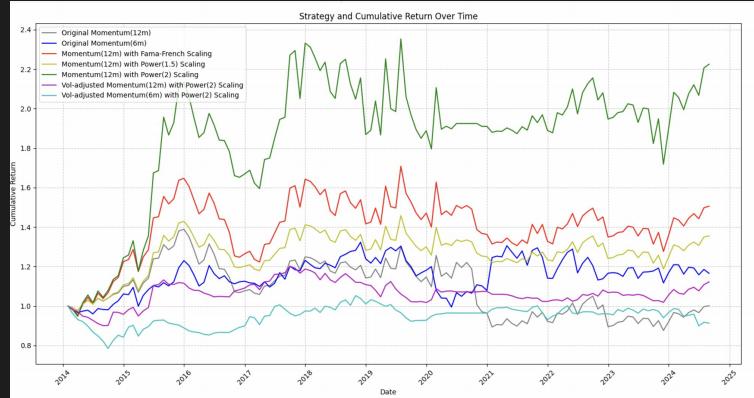
Strategy Performance (2005-2024)

	Annualized Return	Annualized Volatility	Sharpe Ratio	Max Drawdown	Mean Monthly Return	Monthly Volatility	Skewness	Kurtosis
Original Momentum(12m)	-0.035101	0.181807	-0.193065	-0.739280	-0.001647	0.052483	-2.005040	12.996391
Original Momentum(6m)	-0.025069	0.160505	-0.156191	-0.726047	-0.000922	0.046334	-2.567056	20.047919
Momentum(12m) with Fama-French Scaling	0.036083	0.196615	0.183522	-0.592090	0.004554	0.056758	0.143717	0.553241
Momentum(12m) with Power(1.5) Scaling	0.031144	0.117305	0.265495	-0.319786	0.002927	0.033863	0.216554	0.535644
Momentum(12m) with Power(2) Scaling	0.094972	0.214213	0.443356	-0.381128	0.009442	0.061838	0.607490	1.430967
Vol-adjusted Momentum(12m) with Power(2) Scaling	0.039027	0.083691	0.466322	-0.174011	0.003317	0.024160	1.417746	4.443344
Vol-adjusted Momentum(6m) with Power(2) Scaling	0.024763	0.077773	0.318401	-0.267768	0.002290	0.022451	0.442450	1.220786



Strategy Performance (2014-2024)

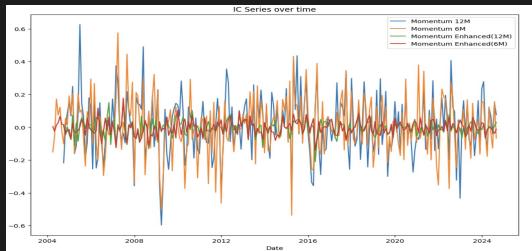
	Annualized Return	Annualized Volatility	Sharpe Ratio	Max Drawdown	Mean Monthly Return	Monthly Volatility	Skewness	Kurtosis
Original Momentum(12m)	0.000131	0.144142	0.000906	-0.369140	0.001190	0.041610	-0.120823	1.578560
Original Momentum(6m)	0.014485	0.126409	0.114587	-0.248383	0.002115	0.036491	0.123774	1.992088
Momentum(12m) with Fama-French Scaling	0.039125	0.168713	0.231905	-0.257524	0.004981	0.048703	0.538392	0.678051
Momentum(12m) with Power(1.5) Scaling	0.028915	0.115890	0.249506	-0.185780	0.003272	0.033454	0.541338	0.813573
Momentum(12m) with Power(2) Scaling	0.077868	0.222384	0.350151	-0.269696	0.008996	0.064197	0.746003	1.596221
Vol-adjusted Momentum(12m) with Power(2) Scaling	0.010902	0.071989	0.151438	-0.152973	0.001024	0.020782	1.782473	6.540916
Vol-adjusted Momentum(6m) with Power(2) Scaling	-0.008441	0.077045	-0.109558	-0.214891	-0.000555	0.022241	0.132784	0.560820



- Vol-adjusted Momentum Factors improved performance of all time, but did not perform well in recent years
- Power scaling boosted performance significantly

□ Results Comparison

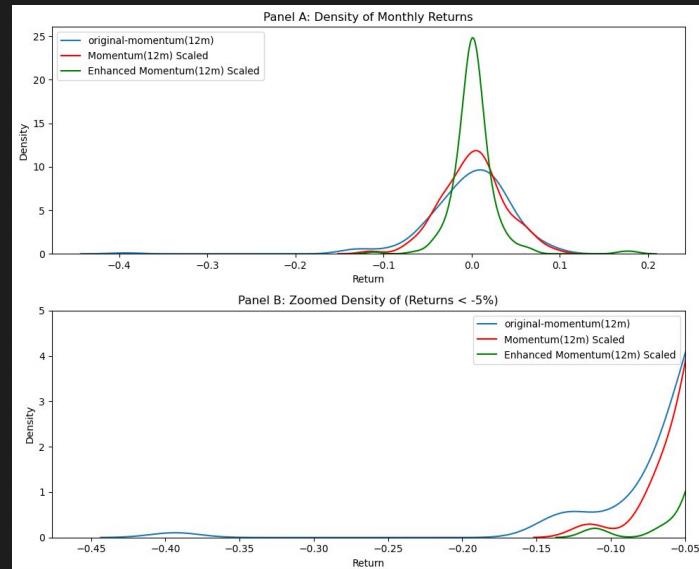
IC Series



Turnover

	Turnover_Before_Scaling	Turnover_After_Scaling
12m	0.227323	0.351660
6m	0.339349	0.500940
Vol_adj 12m	0.558102	0.794224
Vol_adj 6m	0.585917	0.832431

Skewness and Fat tail



Lower the excess kurtosis from 13.00 to 0.53.
Reduce the skewness from -2.01 to 0.21.

Summary

Review & Future Outlook

Both adjusting the Momentum Factor and scaling portfolio position sizes are effective in mitigating large drawdowns and smoothing performance. However, their significance can vary depending on the time horizon and real-time market conditions

- ❖ Something else we tried but not seeing significance

- Liquidity Filterings
- Change in quantile of group returns
- Change from equally-weighted to rank-weighted

- ❖ Limitations & Future Improvements:

- Historical data missing
- Using optimizer functions to find the best parameters (MA time window, power of the scaling, etc)
- Developing adaptive strategies to maximize risk-adjusted returns across different market environments

The End

Thank You !