ORIE 5260 - Quantitative Portfolio Strategies

Building a Managed Futures Strategy

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1 Data Description

The dataset comprises monthly returns for a diverse set of financial instruments spanning four major asset classes: foreign exchange (FX), equities (EQ), fixed income (FI), and commodities (COMM). Each column represents a unique instrument, identified by a ticker (ID), while each row corresponds to a month-end observation.

1.1 Instrument Mapping

The `AssetMapCsv` file provides the instrument ID, name, currency, and associated asset class (FX, EQ, COMM, and FI).

1.2 Returns Dataset

The `MonthlyReturns` file contains realized returns for each instrument in decimal form. Rows correspond to month-end dates, and columns correspond to instrument IDs. This structure allows for cross-sectional and time-series analyses across multiple instruments and asset classes.

1.3 Temporal Coverage

The dataset spans multiple decades, with the analysis focusing on data from 1969 to 2014. To ensure reliable cross-sectional calculations, months with fewer than 10 available instruments are excluded. Missing returns are handled by ignoring those instruments for that month's average return.

2 Data Exploration

2.1 Summary Statistics

Note: Different starting years are considered for each class to handle NaN values. We consider only years with minimum of 4 assets in each asset class

Asset Class	Mean Annual Return	Annual Volatility	Sharpe Ratio
FX	1.3%	7.1%	0.181
EQ	6.6%	16.1%	0.410
COMM	4.8%	14.4%	0.332
FI	2.6%	8.4%	0.306

Table 1: Summary statistics across asset classes.

2.2 Time Series Plots of Cumulative Returns

Cumulative return plots are generated for each asset class to visualize performance over time.

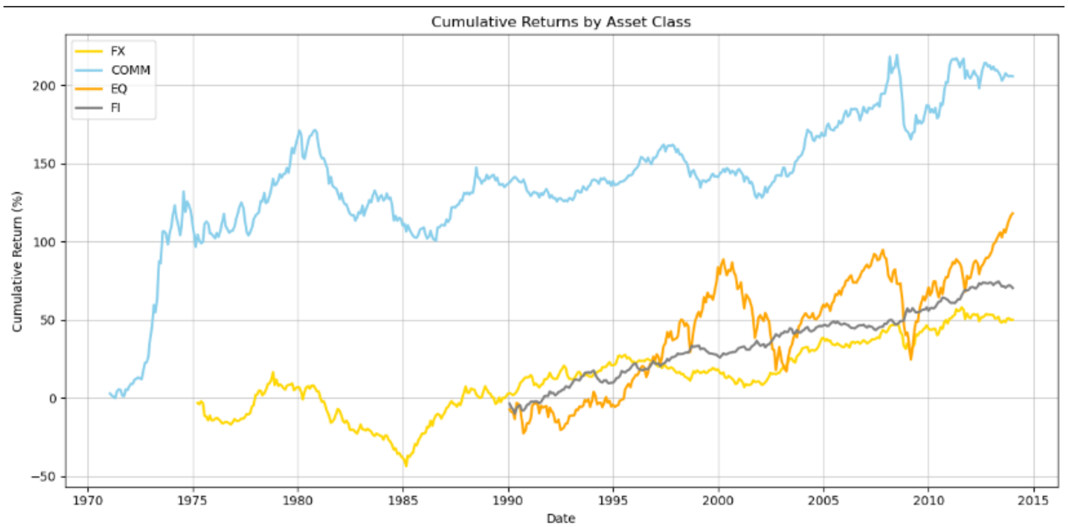
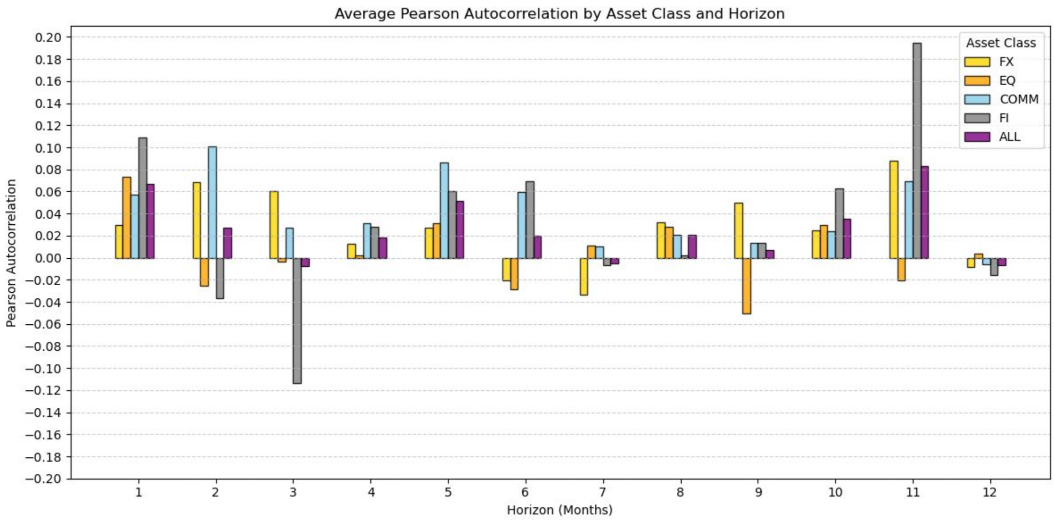
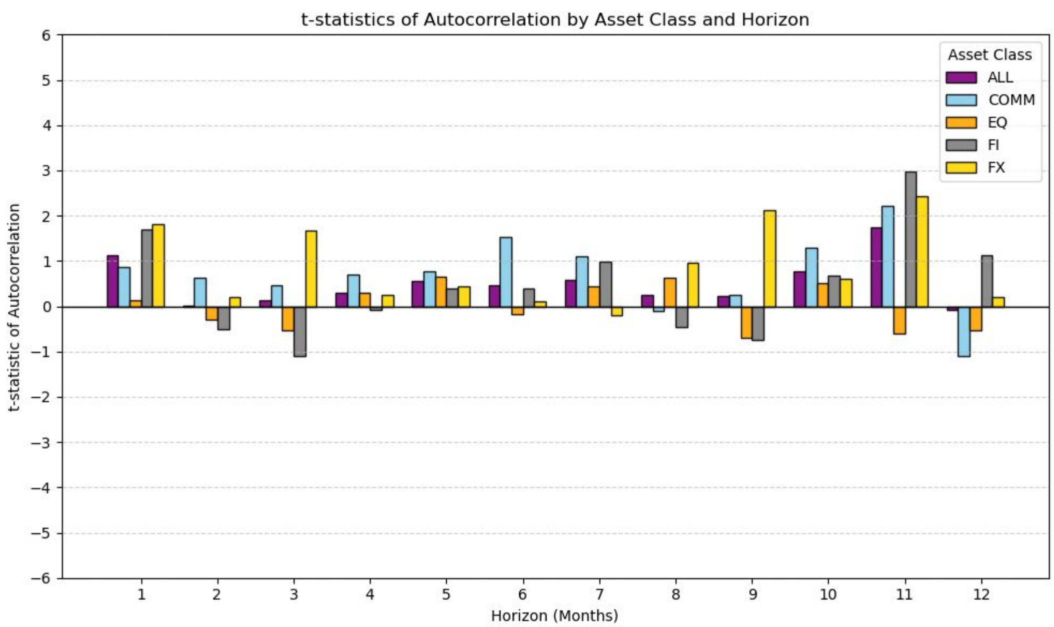


Figure 1: Cumulative returns across the four major asset classes (FX, EQ, COMM, FI).

The cumulative return plot reveals distinct performance patterns across the four asset classes. Commodities (blue) exhibit the strongest long-term growth, particularly after the mid-1980s, with significant appreciation during commodity booms such as the early 2000s, although they also display notable cyclical drawdowns. Equities (orange) show steady upward performance with pronounced cycles, peaking around 2007–2008 before a major decline during the financial crisis, and recovering strongly thereafter. Foreign Exchange (yellow) demonstrates high volatility and prolonged periods of negative cumulative returns, indicating that currency strategies offered limited long-term trend persistence. In contrast, Fixed Income (grey) shows the most stable and consistent growth path, reflecting its defensive nature and lower volatility profile. Overall, the figure highlights clear differences in both return potential and risk characteristics across asset classes, emphasizing the benefits of cross-asset diversification in a multi-strategy portfolio.

2.3 Autocorrelation and T-Stat Plots





3 Methodology

3.1 Baseline Strategy Construction

The baseline strategy is a Time-Series Momentum (TSMOM) approach constructed using the cleaned monthly returns dataset. The data is sorted chronologically, and months with fewer than 10 available instruments are excluded to ensure robust cross-sectional averaging.

For each instrument, a 12-month rolling cumulative return is computed to serve as the momentum signal. This signal is shifted forward by one month to prevent look-ahead bias, ensuring that only information available at the time is used. Positions are assigned based on the sign of past returns:

- +1 for positive 12-month cumulative returns (long)
- -1 for negative 12-month cumulative returns (short)

To control for risk, the **full-sample volatility** of each instrument is calculated and annualized by multiplying the monthly standard deviation by $\sqrt{12}$. **A target annualized asset volatility of 40%** is set, and **each instrument's position is scaled inversely by its volatility**. This ensures high-volatility instruments receive smaller position sizes, equalizing risk contribution across the portfolio.

Monthly strategy returns are computed as the **equal-weighted average of risk-scaled positions** multiplied by realized returns across instruments. A static benchmark is constructed similarly but uses the absolute value of positions, representing a long-only exposure of equal magnitude.

Performance metrics, including annualized return, volatility, and Sharpe ratio, are computed from monthly returns. Cumulative returns are generated using the sum of monthly returns, which is a reasonable approximation given their small magnitudes.

4 Baseline Strategy Results

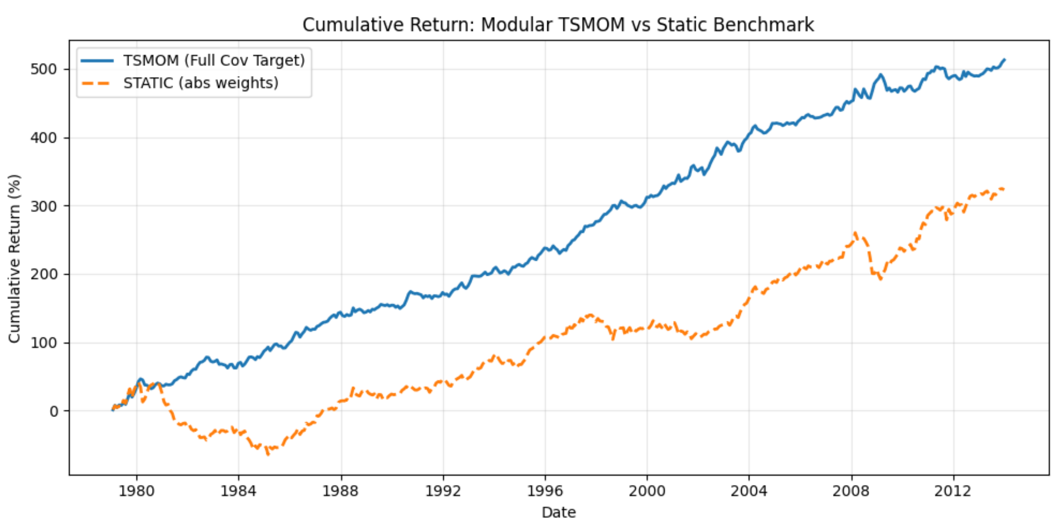


Figure 2: Cumulative returns across both strategies

The figure above shows that the TSMOM strategy consistently outperforms the static benchmark from 1976 to 2013. The TSMOM portfolio exhibits smoother growth and smaller drawdowns, particularly during crisis periods, reflecting its ability to adapt to changing market trends. The volatility-scaling mechanism further stabilizes returns by balancing risk across assets. Overall, the results highlight time-series momentum as a persistent and robust return source relative to a static long-only benchmark.

Strategy	**Annual Return**	**Annual Volatility**	**Sharpe Ratio**
TSMOM	14.65%	13.71%	1.07
STATIC	9.22%	18.30%	0.50

Table 2: Performance comparison between TSMOM and Static Benchmark strategies.

5 Finding Optimal Strategy (V1)

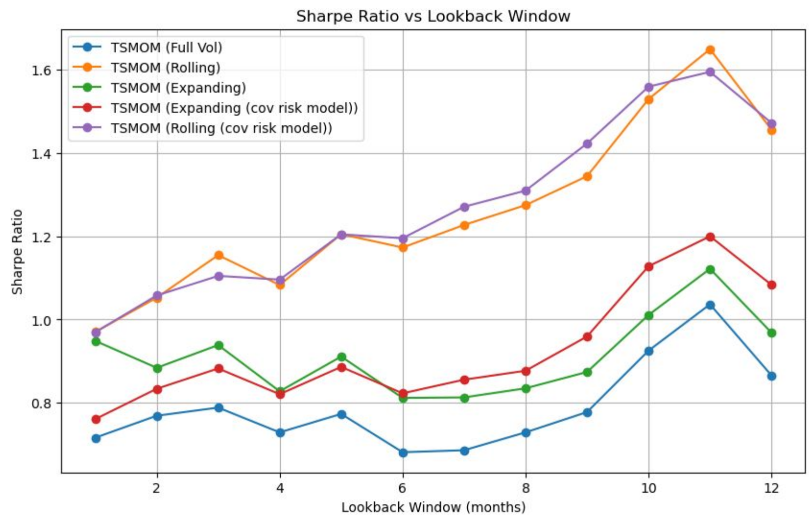
5.1 Sensitivity Analysis

We performed a comprehensive sensitivity analysis for a Time-Series Momentum (TSMOM) strategy, systematically testing its robustness across a three-dimensional parameter space. The analysis evaluates how performance metrics vary with:

- Target volatility levels (10% to 100%)
- Momentum lookback windows (1 to 12 months)
- Volatility estimation methods (full-sample, rolling, expanding)

The **full-sample method** uses the entire dataset's volatility (introducing look-ahead bias but serving as a benchmark). The **rolling method** uses a window matching the lookback for realistic out-of-sample estimates, while the **expanding method** incorporates all available data up to each point in time.

For each parameter combination, the strategy constructs a momentum signal, scales positions to target the specified volatility, and calculates performance for both the dynamic TSMOM and static long-only benchmark. This generates a comprehensive dataset enabling the identification of parameter combinations and volatility estimation techniques that yield the most robust and favorable performance outcomes.



6 Optimum Strategy (V1) - Mid-term submission

We did a sensitivity analysis to check how sharpe varies with the momemtum lookback and rolling window length for volatility computation. We decided to use a rolling 12-month window for volatility and 11-month returns for momentum to generate our signals based on the heatmaps. We are targeting a portfolio volatility of 14% which is close to the annual vol for SG Trend Index. This will also help us keep our results and comparisons fair.

Strategy	Annual Return	Annual Volatility	Sharpe Ratio
OPTIMAL	18.91%	11.60%	1.63
STATIC	6.23%	15.46%	0.40

Table 3: Performance comparison between optimized TSMOM and Static Benchmark strategies

6.1 Comparing the TSMOM Strategies

In the plots below, Strategy 1 (blue) refers to the baseline TSMOM strategy, whereas Strategy 2 (orange) refers to the optimized V1 TSMOM strategy. There is a clear improvement in returns and a reduction in annualized volatilities.

To put things in perspective, the plot above shows the wildly varying volatility breakdown across asset classes under the baseline TSMOM strategy.

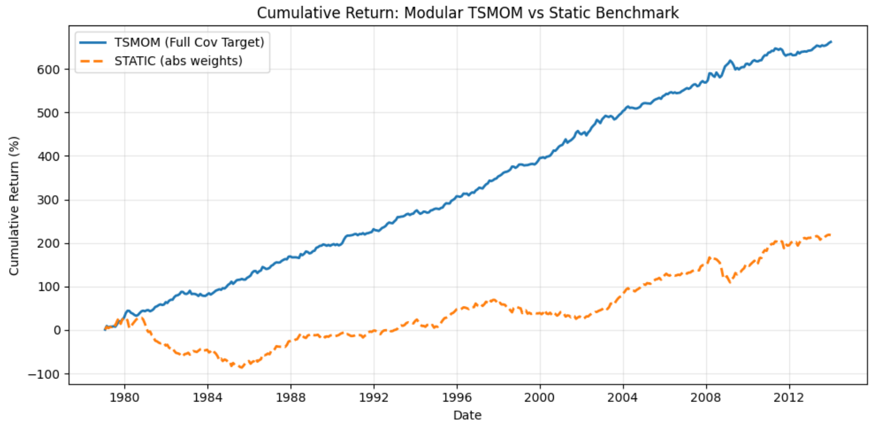


Figure 3: Comparing the returns of the optimal V1 strategy and the Static Benchmark

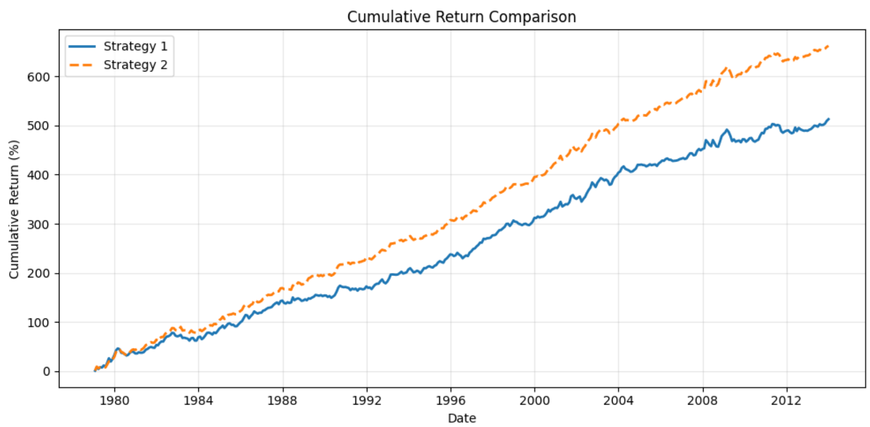


Figure 4: Comparing the returns of two TSMOM strategies

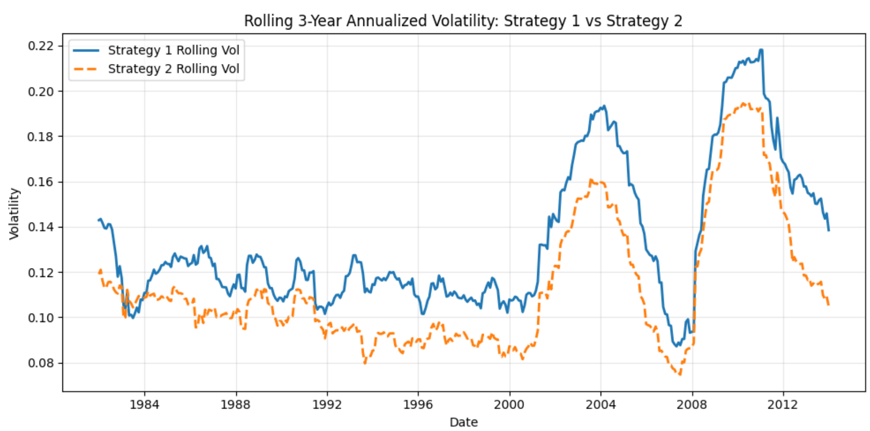
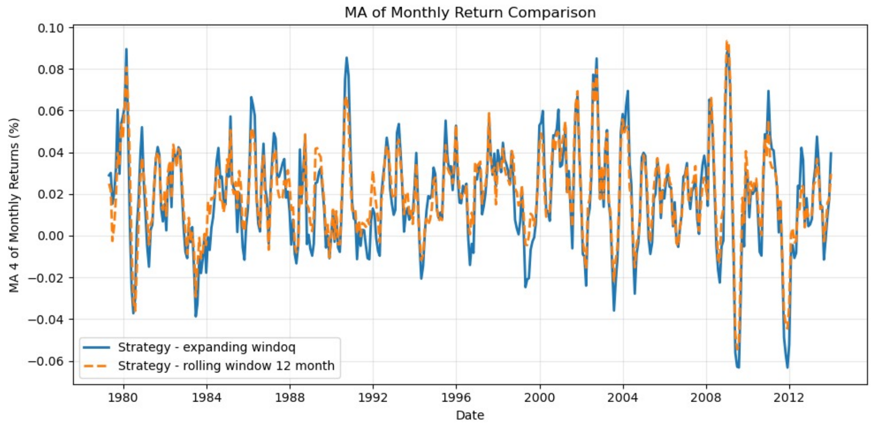
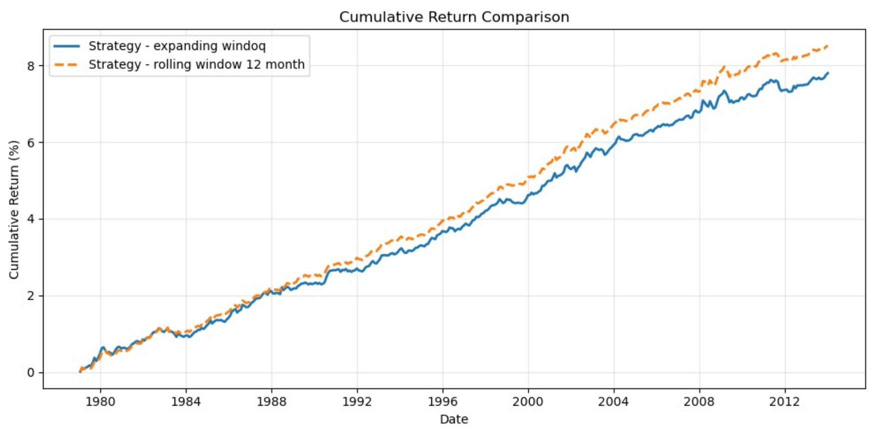


Figure 5: Comparing the Realized Volatilities of the two TSMOM Strategies

7 Further





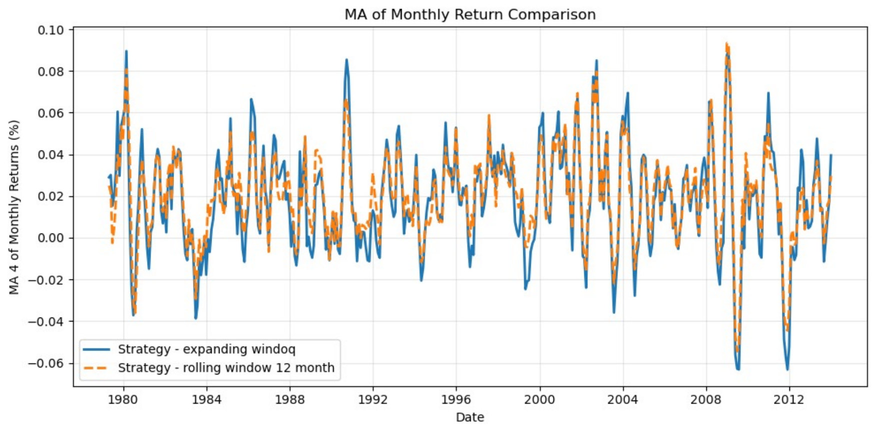
Strategy	Annual Return	Annual Volatility	Sharpe Ratio	Correlation w/Static
strat_ret	14.65%	13.72%	1.07	0.15
static_ret	9.22%	18.30%	0.50	1.00
strat_optimal_v1	18.91%	11.59%	1.63	0.07

Table 4: Performance metrics (annualized, assuming RF = 0)

Strategy	Alpha (Monthly)	Beta (Mkt–RF)	Correlation with Mkt–RF
strat_ret	0.0126	-0.0603	-0.0690
static_ret	0.0037	0.6009	0.5158
strat_optimal_v1	0.0169	-0.0801	-0.1086

Table 5: CAPM regression results using the Fama–French Market factor

8 But, are we cherry-picking?



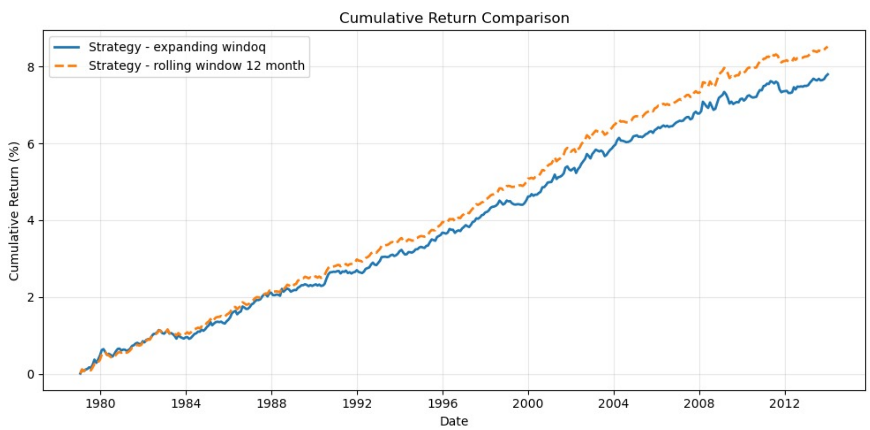


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Table 6: Performance metrics (annualized, assuming RF = 0)

Note: Correlation in the above table refers to correlation with the static benchmark.

Strategy	Alpha (Monthly)	Beta (Mkt–RF)	Correlation with Mkt–RF
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static_ret	0.0037	0.6009	0.5158
strat_optimal_v1	0.0169	-0.0801	-0.1086

Table 7: CAPM regression results using the Fama–French Market factor

PART- II Further enhancements

8.1 Cross-sectional strategy

We looked at why the momentum signal works and is profitable. We first checked how good it is at predicting the sign of the returns of a particular asset and found that it had only a 41.8% accuracy in predicting sign of the returns of asset, i.e. our signal and the sign of the monthly returns match for only 41.8% instances.

So then we divided the assets cross-sectionally using momentum and looked at the performance across different fractiles of momentum scores. That shows a strong pattern and shows that momentum signal works because assets with larger momentum than other assets have higher returns.

This inspired us to add a cross-sectional part to our strategy where along with looking at the sign of the returns in the past lookback window, we also look at the magnitude of the signal and rank assets based on the magnitude within each asset class.

So the rule now is:

1. **signal** $= +1$ for asset a if sign(past_11_month_ret_for_a) $= +1$ and the percentile of the magnitude of past_11_month_ret_for_a within its asset class is ≥ 60.
2. **signal** $= -1$ for asset a if sign(past_11_month_ret_for_a) $= -1$ and the percentile of the magnitude of past_11_month_ret_for_a within its asset class is ≤ 40.

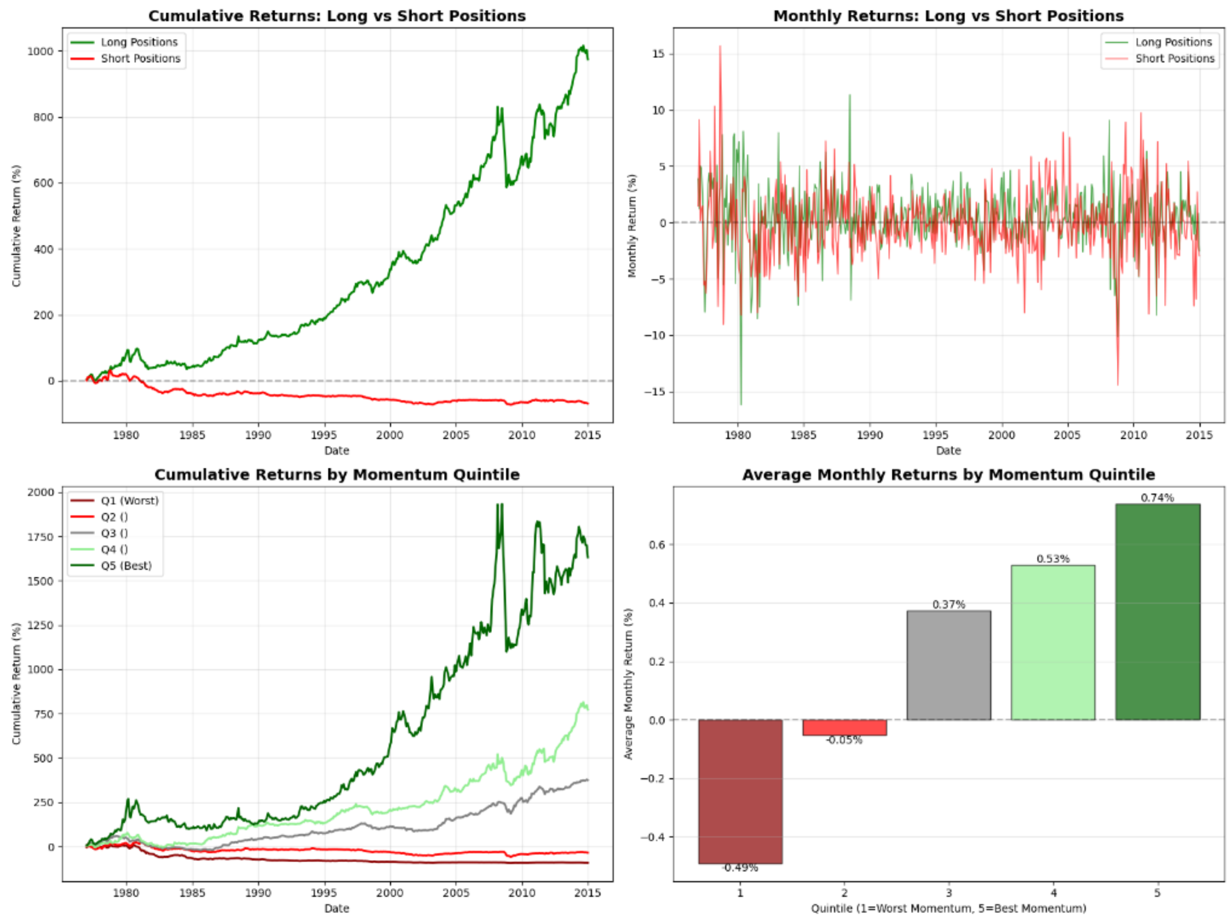


Table 8: Summary Statistics for Long, Short, and Long–Short Portfolios

Portfolio	Avg. Monthly Return	Ann. Ret.	Ann. Vol.	SR
Long Positions	0.561%	6.73%	9.75%	0.690
Short Positions	-0.202%	-2.43%	11.18%	-0.217
Long–Short Spread	0.763%	9.16%	—	—

Table 9: Summary Statistics by Momentum Quintile

Quintile	Description	Avg. Monthly Return	Ann. Ret.	Ann. Vol.	SR
Q1	Worst Momentum	-0.491%	-5.89%	14.66%	-0.402
Q2	—	-0.053%	-0.63%	9.93%	-0.064
Q3	—	0.374%	4.49%	8.85%	0.507
Q4	—	0.529%	6.35%	11.42%	0.556
Q5	Best Momentum	0.738%	8.86%	16.38%	0.541

The results indicate that the 11-month momentum specification performs well because it creates a clean separation between past winners and losers, producing a monotonic return pattern across momentum quintiles. Securities in the worst-momentum quintile continue to underperform, generating strongly negative annualized returns, while those in the best-momentum quintile deliver the highest returns, resulting in a smooth and intuitive cross-sectional gradient. This structure supports the idea that 11-month lookback horizons successfully capture medium-term trend persistence while avoiding the short-term reversal effects that typically contaminate 1–3-month momentum signals.

The long–short portfolio further reinforces this: the long leg produces solid positive returns, while the short leg remains consistently negative, leading to a meaningful +9.16% annualized spread. Importantly, the long side appears to carry most of the performance, suggesting that the lookback window effectively identifies sustained upward-trending assets rather than relying on noisy short-term behavior. Across the summary statistics and plots, the 11-month window thus strikes the right balance, long enough to filter out transient reversals, but short enough to avoid including stale information thereby explaining why it emerges as the strongest performer.

We also see that including cross-sectional part to our strategy shows better performance in returns and volatility.

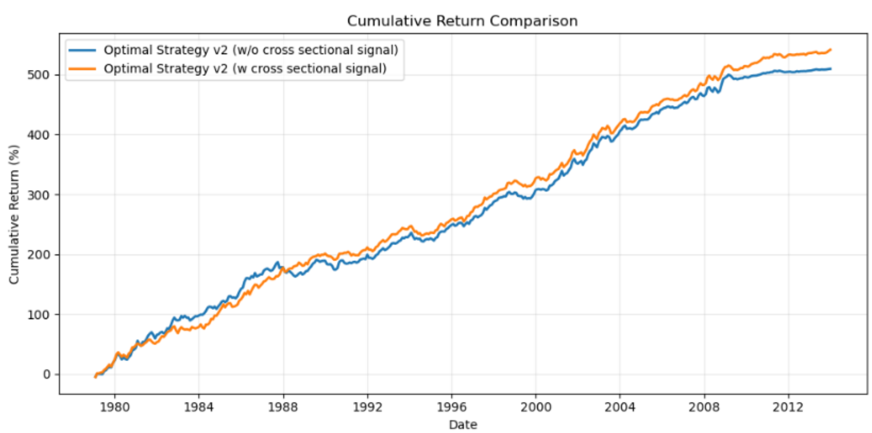


Figure 6: Comparing Cumulative Returns of Optimal Strategies

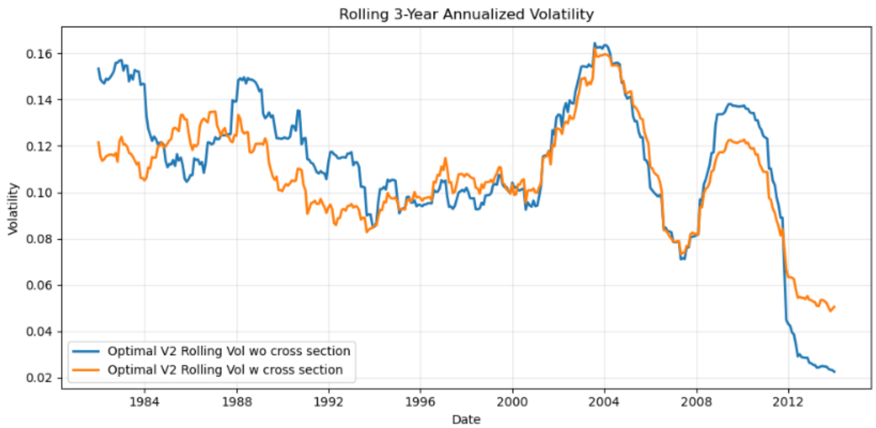


Figure 7: Comparing Rolling Annualized 3-Year Volatility of Optimal Strategies

9 Volatility Forecasting and Risk Estimation

9.1 How Well Do Rolling Windows Predict Future Volatility?

This section evaluates how accurately different rolling-window estimators forecast future volatility. The objective is to determine which historical lookback window provides the most reliable predictor of next-month realized volatility, and whether shorter windows (more reactive) or longer windows (more stable) carry stronger predictive content.

First, for each asset and for each rolling window (ranging from 1 to 36 months), a predicted volatility measure is computed using the rolling standard deviation of historical returns, annualised. Second, these predictions are compared to realized volatility one month ahead. For a one-month forecast horizon, realized volatility is proxied by next-month absolute returns (annualised). Third, for each window, a cross-sectional regression is run where realized volatility is regressed on predicted volatility, yielding slope coefficients, t-statistics, correlations, and R^2 values.

The performance measures are then aggregated across assets to assess which rolling window delivers the most reliable forecasts. The accompanying plots present (i) predicted versus actual volatility for a set of representative assets, and (ii) the average t-statistics, correlations, R^2 values, and slope estimates for each rolling window.

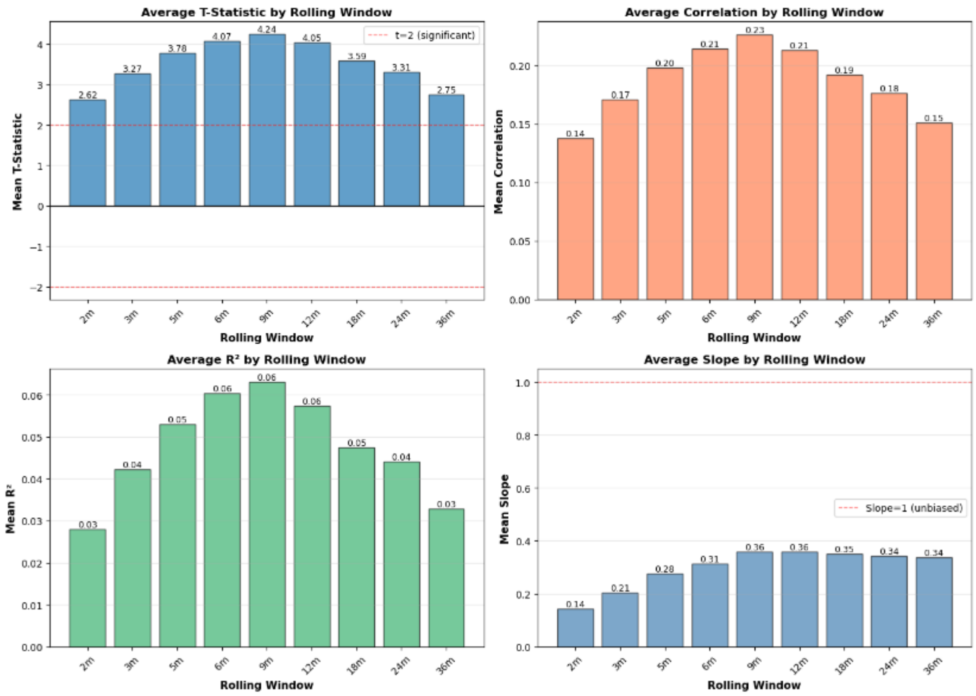


Table 10: Summary: Volatility Prediction by Rolling Window

R.Wind	mean_t_stat	med_t_stat	mean_correlation	mean_r_sqrd	mean_slope	n_assets
2	2.619	2.329	0.138	0.028	0.144	58
3	3.273	2.810	0.171	0.042	0.205	58
5	3.777	3.504	0.198	0.053	0.277	58
6	4.070	3.885	0.214	0.060	0.313	58
9	4.242	4.042	0.226	0.063	0.359	58
12	4.045	3.635	0.213	0.057	0.358	58
18	3.591	3.418	0.192	0.047	0.351	58
24	3.314	2.859	0.176	0.044	0.342	58
36	2.747	2.433	0.151	0.033	0.338	58

9.2 EWMA Volatility Prediction Analysis

To complement the rolling-window approach, we conducted an Exponentially Weighted Moving Average (EWMA) volatility analysis. The objective was to assess which EWMA half-life provides the most accurate forecast of next-month realized volatility. EWMA allows for more weight on recent observations, potentially improving responsiveness to market changes compared to simple rolling windows.

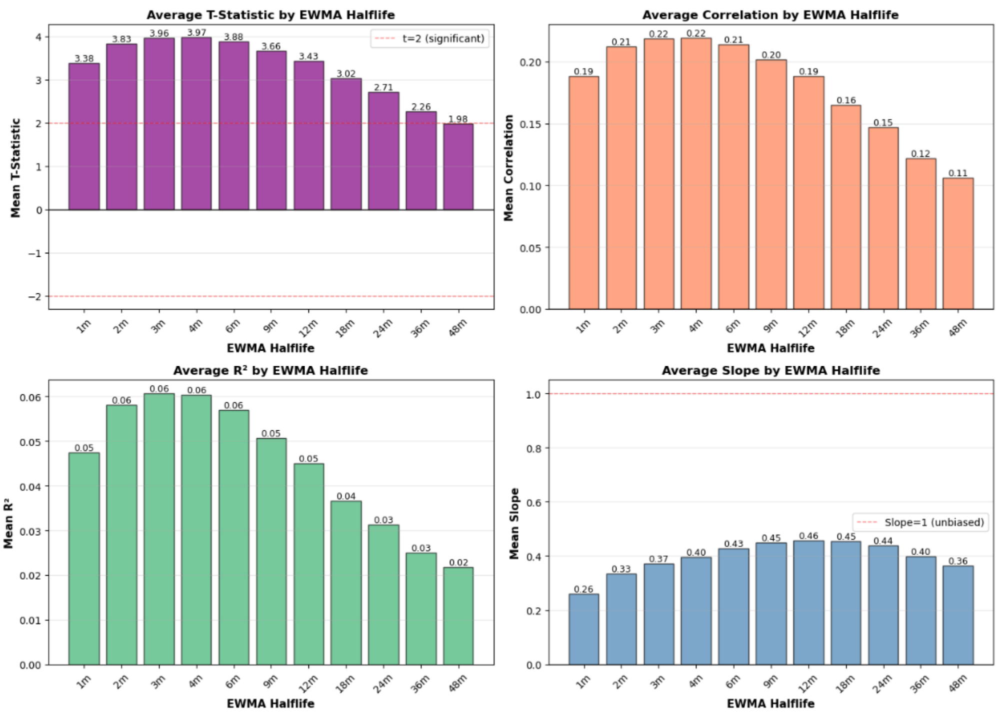
For each asset, we computed EWMA volatility for a range of halflife values (1, 2, 3, 4, 6, 9, 12, 18, 24, 36 months). Realized volatility was proxied by the absolute returns over the forecast horizon. For each halflife, we ran a cross-sectional regression of actual on predicted volatility to obtain slope, t-statistic, correlation, and R^2 for each asset. Results were then averaged across all assets to identify the most effective halflife.

9.2.1 Average Metrics Across Halflife Values

Table 10 presents the average t-statistics, correlations, R^2, slopes, and number of assets for each EWMA halflife. These metrics help identify which halflife provides the most accurate next-month volatility forecasts.

Table 11: Summary: EWMA Volatility Prediction by Halflife

Halflife (mths)	mean t-stat	med. t-stat	mean corr.	mean R^2	mean slope	n assets
1	3.376	3.207	0.188	0.048	0.260	58
2	3.828	3.733	0.212	0.058	0.334	58
3	3.956	3.728	0.219	0.061	0.373	58
4	3.972	3.675	0.219	0.060	0.397	58
6	3.884	3.586	0.214	0.057	0.427	58
9	3.662	3.250	0.202	0.051	0.450	58
12	3.427	2.908	0.188	0.045	0.458	58
18	3.021	2.465	0.165	0.037	0.454	58
24	2.706	2.092	0.147	0.031	0.438	58
36	2.264	1.805	0.122	0.025	0.399	58
48	1.975	1.644	0.106	0.022	0.364	58



9.3 Optimal Parameters for Volatility Prediction

Based on analyses of rolling-window and EWMA volatility predictors, the table below summarizes the half-life/window that produced the strongest predictive performance across different metrics.

Table 12: Best Performing Parameters for Volatility Forecasting

Method	Best by T-statistic	Best by Correlation	Best by R^2
Rolling Window	9 months	9 months	9 months
EWMA	4 months	4 months	3 months

Observations:

- For **rolling windows**, a 9-month lookback provides the most statistically significant and highly correlated predictions, with the highest explanatory power.
- For **EWMA**, shorter halflives (3 - 4 months) tend to give the best predictive performance, capturing recent trends effectively.
- Comparing both approaches, EWMA with 3 - 4 months is more responsive to recent volatility changes, while the rolling 9-month window offers a more stable, longer-term estimate.

10 Effect of Shrinkage

We then examined the effect of disabling shrinkage in the covariance estimation step of the modular TSMOM framework. Shrinkage is typically applied to stabilize the covariance matrix, especially in expanding-window estimation where sampling noise can accumulate over time. By setting `use_shrinkage=False`, the strategy relies entirely on the raw expanding-window covariance matrix without any regularization. All other components remain unchanged, including the EWMA volatility model, the 11-month momentum lookback, a 9-month volatility window, and the use of the cross-sectional momentum signal.

Even without shrinkage, the strategy exhibits strong performance. The annualized net return increases to 15.95%, with a net Sharpe ratio of 1.39 and a portfolio volatility of 11.51%. However, the absence of shrinkage leads to slightly higher leverage (4.16 vs. 3.67 in the baseline) and elevated turnover (24.10 vs. 21.00), which in turn raises total transaction costs (0.51% vs. 0.44%). The cross-sectional signal remains active, producing balanced long and short exposures across asset classes (e.g., in commodities: 8.9 long, 8.1 short on average).

Overall, removing shrinkage produces a modest increase in raw returns but at the cost of higher leverage, higher turnover, and increased estimation instability. This highlights the role of shrinkage as a stabilizing force that moderates risk-taking without materially degrading performance.

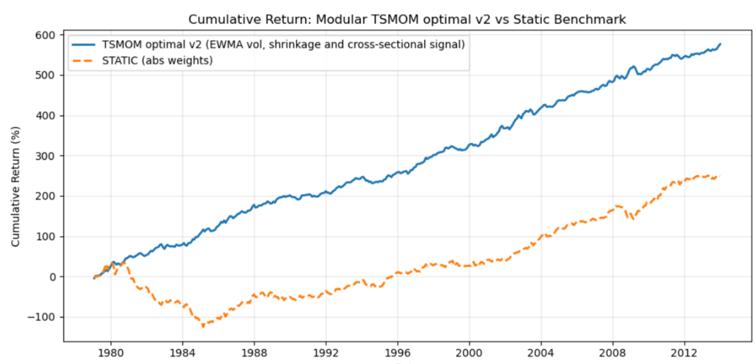


Figure 8: Comparing the Effect of Shrinkage on Cumulative Returns of Optimal Strategy V2 with the Static Benchmark Strategy

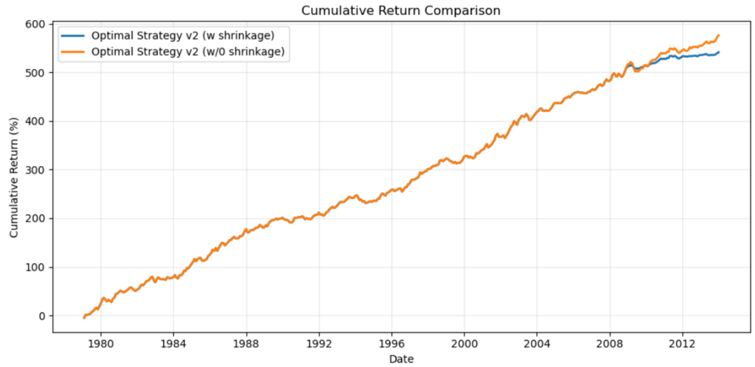


Figure 9: Comparing the Optimal Strategy with and without Shrinkage

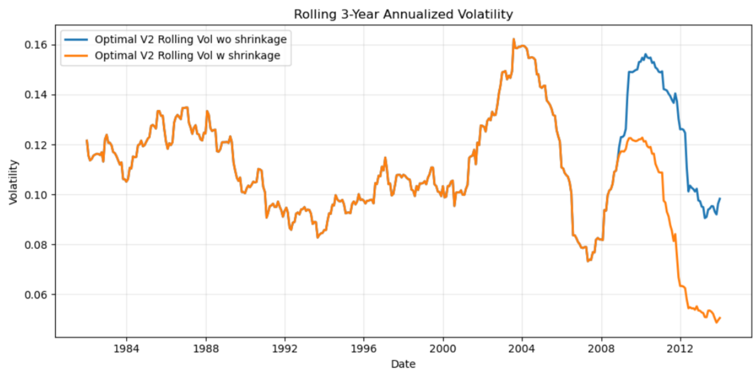
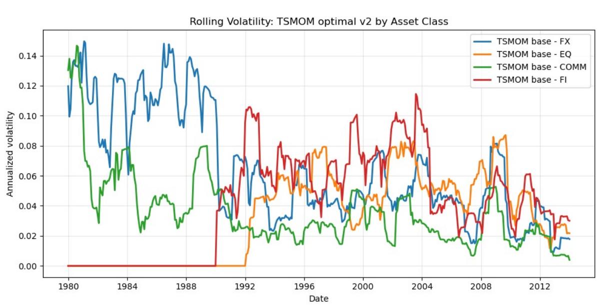
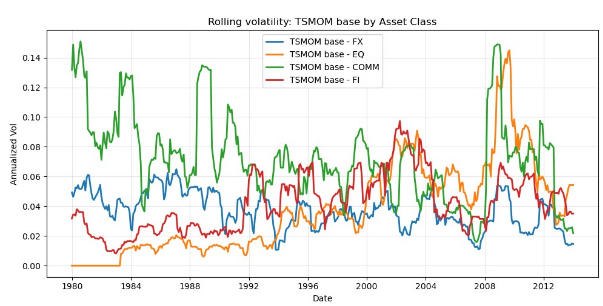


Figure 10: Comparing Rolling 3-Year Annualized Volatilities of Both Optimal Strategies

11 Risk Asset Control

The aim was to scale the weights based on a risk-budget, to ensure equal risk was assigned to asset classes.





12 Final Optimal Strategy and Results

12.1 Momentum Signal

The strategy uses **simple time-series momentum**:

$$\text{signal}_{i,t} = \text{sign}\left(\sum_{k=1}^{12} r_{i,t-k}\right).$$

12.2 Volatility Estimation

Per-asset volatility uses an expanding-window standard deviation, annualized by $\sqrt{12}$. Weight scaling:

$$w_{i,t} = \frac{\text{signal}_{i,t} \cdot \sigma_{\text{target,asset}}}{\sigma_{i,t}},$$

with $\sigma_{\text{target,asset}} = 40\%$ annualized.

12.3 Covariance Matrix

Portfolio-level volatility uses:

- Expanding covariance matrices
- Ledoit–Wolf optimal shrinkage

12.4 Portfolio Volatility Targeting

The portfolio is scaled to achieve 14% annualized volatility:

$$w_t^* = w_t \cdot \frac{\sigma_{\text{target}}}{\hat{\sigma}_{\text{ex-ante},t}}.$$

12.5 Transaction Costs

- Trading cost: 2 bps per unit turnover
- Rolling cost: 2 bps per roll
- Rolling frequency: 4 months per year

13 TSMOM Optimal: Rolling Volatility, Shrinkage, Cross-Sectional Signal, and AC Risk Control

This section evaluates an enhanced version of the strategy, denoted **TSMOM Optimal v2**. Relative to the previous specification (v1), this version incorporates:

- **Rolling Volatility** (rolling window = 9 months),
- **Cross-sectional rank-based momentum** within asset classes,
- **Ledoit–Wolf optimal covariance shrinkage**,
- **Asset-class risk control** to equalize risk contribution,
- **Higher portfolio volatility target**: $\sigma_{\text{target}} = 14\%$.

13.1 High-Level Performance

Metric	**TSMOM V2**	**Static**
Annualized Return (Gross)	16.17%	6.12%
Annualized Return (Net)	15.66%	5.63%
Annualized Volatility	11.85%	15.59%
Sharpe Ratio (Gross)	1.36	0.39
Sharpe Ratio (Net)	1.32	0.36

Table 13: Performance Summary

The TSMOM strategy outperforms the static benchmark on both an absolute and risk-adjusted basis.

13.2 Transaction Costs

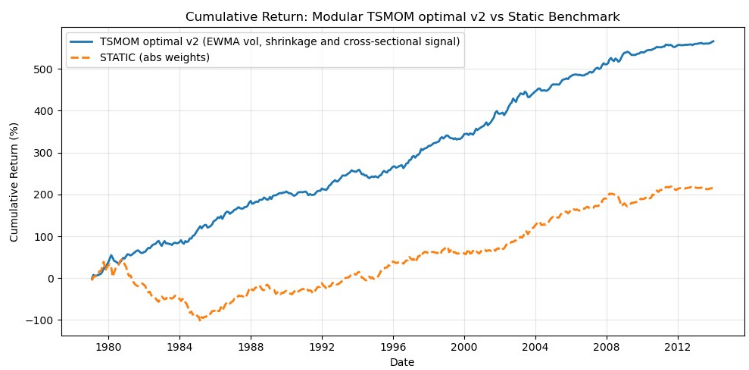
Cost Component	**TSMOM V2**	**Static**
Annual Turnover	23.71	22.92
Trading Cost (Annual)	0.47%	0.46%
Rolling Cost (Annual)	0.02%	0.02%
Total Cost	0.50%	0.48%

Table 14: Transaction Costs

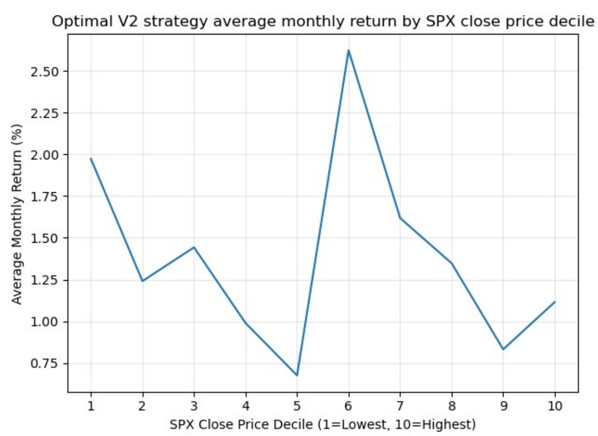
13.3 Portfolio Structure

Statistic	TSMOM V2	Static
Average Leverage	3.12	3.12
Average Long Positions	20.33	36.21
Average Short Positions	15.88	0.00
Net Imbalance	0.74	3.12

Table 15: Portfolio Diagnostics



(a) Cumulative returns of TSMOM optimal v2 vs static benchmark



(b) Rolling 3 year volatility of TSMOM optimal v2 strategy

Figure 12: Results of TSMOM v2 Strategy

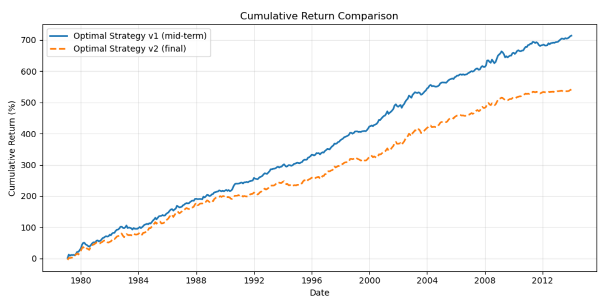
13.4 Observations

The upgraded specification introduces several improvements:

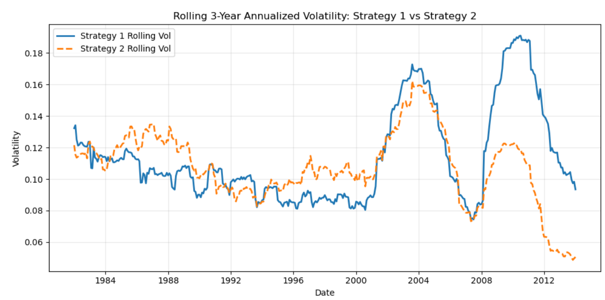
- **Rolling volatility** responds faster to regime shifts, stabilizing position sizing.
- **Cross-sectional momentum** enhances selection within asset classes, improving signal quality.
- **Ledoit–Wolf shrinkage** produces more stable ex-ante risk estimates and smoother scaling, especially for out of sample data.
- **Asset-class risk control** reduces concentration in historically volatile sectors such as commodities.

The resulting cumulative return curve is smoother and shows improved robustness compared to the static benchmark.

14 TSMOM v1 vs v2 Performance



(a) Returns Comparison



(b) Volatility Comparison

Figure 13: TSMOM v1 v/s v2

15 Additional Results: SG Trend Comparison and Static Benchmark Correlation

To benchmark the performance of our strategies against a well-known industry trend-following proxy, we incorporated the SG Trend Index into our analysis.

SG Trend refers to the Société Générale Trend Index, a widely followed benchmark that tracks the performance of major trend-following (managed futures / CTA) strategies. It represents a composite of professional systematic managers who utilize time-series momentum (TSMOM) across multiple asset classes, typically including equities, fixed income, commodities, and FX. Essentially, it captures the "industry average" behavior of trend-following funds.

All strategy return series were first standardized to a monthly frequency to ensure consistent temporal alignment. The SG Trend Index price data was then loaded, converted to monthly observations, and transformed into percentage returns.

The strategy returns and the SG Trend series were merged into a unified dataset, retaining only overlapping periods to enable a fair comparison. Cumulative (non-compounded) returns were computed and visualized on a single plot to illustrate the relative growth trajectories and co-movement patterns among the strategies.

Finally, annualized performance metrics - including mean return, volatility, and Sharpe ratio were calculated for each series, alongside their correlation with the SG Trend Index. This provided a high-level view of how closely each strategy's performance aligns with broader trend-following dynamics observed in institutional benchmarks.

Here, strat-ret is for Strategy 1 (baseline), strat-ret2 is for Strategy 2 (proposed optimum) and static-ret is for Static strategy:

15.1 Comparison with SG Trend Index (Full Sample)

Table 16: Annualized Performance vs. SG Trend Benchmark

Strategy	**AnnRet**	**AnnVol**	**Sharpe**	**Corr with SGTrend**
strat_ret	0.194879	0.214669	0.907811	0.632790
static_ret	0.187606	0.258151	0.726729	0.168913
strat_ret_optimal_v1	0.207763	0.136341	1.523843	0.636378
strat_ret_optimal_v2	0.153297	0.107765	1.422521	0.670662
SGTrend	0.069650	0.148214	0.469927	1.000000

The SG Trend benchmark exhibits significantly lower returns and Sharpe relative to all model-based trend strategies, while correlations around 0.6 indicate the expected directional similarity with institutional trend followers.

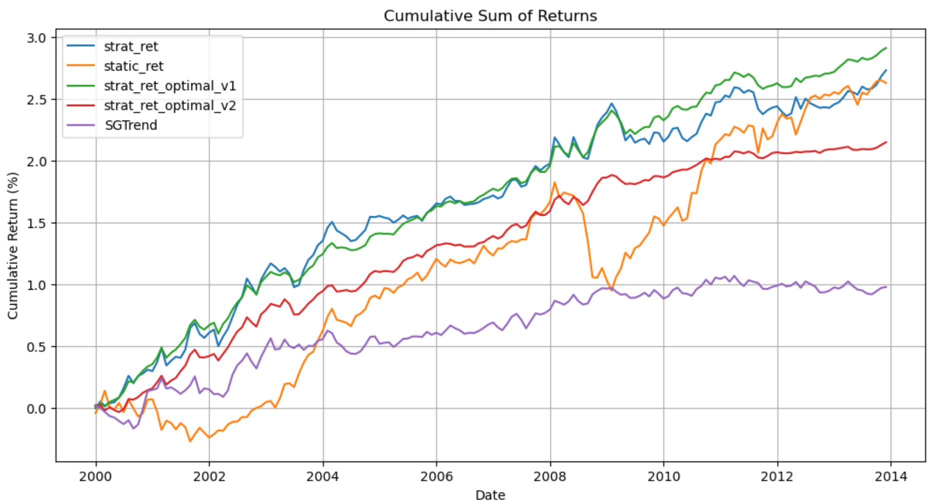


Figure 14: Cumulative Return Comparison with SG Trend

15.2 Performance and Correlation with Static Benchmark

Strategy	AnnRet (%)	AnnVol (%)	Sharpe	Corr_with_Static
strat_ret_base	15.59	14.59	1.068222	0.148514
static_ret	9.55	19.45	0.490994	1.000000
strat_ret_optimal_v1	20.01	12.22	1.637722	0.070072
strat_ret_optimal_v2	16.17	11.85	1.364745	0.104900

Table 17: Performance (annualized, RF = 0)

The correlations remain very low (< 0.15), confirming that TSMOM returns are structurally different from static long-only behavior and deliver diversification benefits.

16 Fama-French Decomposition

To evaluate the risk-adjusted performance of our trading strategies, we conducted a Fama–French style decomposition using the market factor data.

The analysis begins by loading and standardizing the Fama–French (Mkt–RF) series, converting it into a consistent monthly format for alignment with the strategy return data. Each strategy's monthly return series is normalized to the same frequency and merged with the market factor, creating a unified dataset suitable for cross-sectional comparison.

Annualized performance metrics - mean return, volatility, and Sharpe ratio are then computed to quantify each strategy's efficiency and stability. The correlation with the static benchmark provides insight into the similarity of performance dynamics across strategies.

Finally, a single-factor CAPM regression is applied to each strategy to estimate its alpha (excess return unexplained by the market) and beta (market exposure), allowing us to decompose overall returns into market-driven and strategy-specific components.

Here, strat-ret is for Strategy 1 (baseline), strat-retoptimal_vi is for Optimum Strategies 1 and 2, and static-ret is for Static strategy:

Strategy	**Alpha (Monthly)**	**Beta (Mkt–RF)**	**Correlation with Mkt–RF**
strat_ret_base	0.013	-0.06	-0.069
static_ret	0.03	0.64	0.52
strat_ret_optimal_v1	0.017	-0.08	-0.11
strat_ret_optimal_v2	0.014	-0.05	-0.06

Table 18: CAPM regression results using the Fama–French Market factor

16.1 Observations

The CAPM decomposition highlights several key differences between the time-series momentum (TSMOM) strategies and the static benchmark.

Positive and economically meaningful alphas. All TSMOM variants exhibit strong positive monthly alphas ranging from 1.33% to 1.75%. These values are substantially higher than the static portfolio's 0.49% alpha, indicating that the momentum-based strategies generate excess returns that cannot be explained by traditional market exposure alone.

Near-zero or mildly negative market betas. The TSMOM strategies have betas between –0.057 and –0.083, suggesting that their returns are effectively uncorrelated with, or slightly hedged against, broad market movements. In contrast, the static portfolio has a high beta of 0.82, reinforcing that its performance is predominantly driven by the market factor.

Low correlation with the market factor. The correlation of TSMOM strategies with the market factor is weak and negative (from –0.07 to –0.11), further confirming their limited market dependence. The static benchmark, however, shows a strong positive correlation of 0.52, consistent with its high beta.

16.2 Out Of Sample Performance

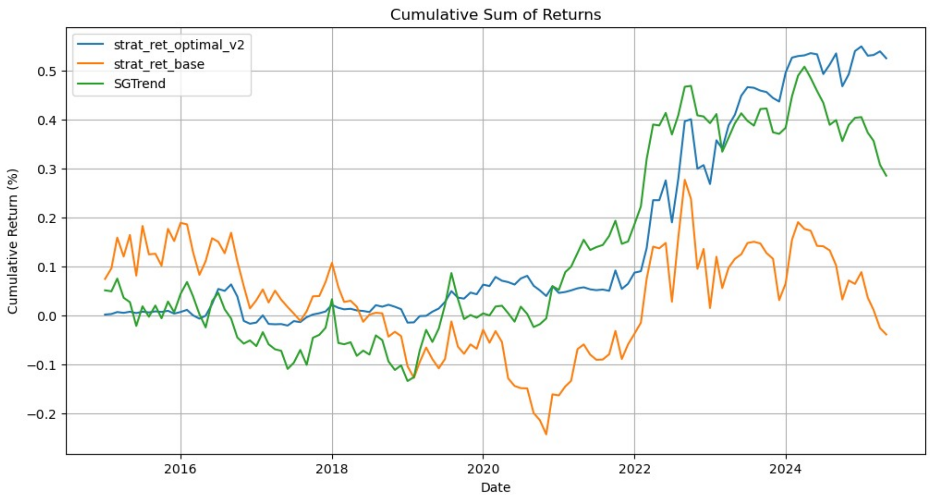


Figure 15: Out of Sample Performance

Strategy	AnnRet (%)	AnnVol (%)	Sharpe	Corr_with_SGTrend
strat_ret_optimal_v2	5.05	9.59	0.526344	0.570611
strat_ret_base	-0.37	16.17	-0.023143	0.718552
SGTrend	2.74	11.57	0.236982	1.000000

Table 19: Performance (annualized, RF=0)

17 Conclusion

Together, these results show that the TSMOM strategies deliver superior risk-adjusted performance that is largely independent of market direction. Their persistent positive alpha and low factor exposure highlight strong diversification benefits and suggest that the excess returns arise from genuine momentum effects rather than broad market co-movements.