[Working paper] Cross-Asset Momentum: Design, Performance, and Robustness

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Abstract

We investigate a cross-asset momentum strategy applied to a diversified portfolio of five liquid instruments spanning commodities, foreign exchange, and energy markets. Building on established evidence that momentum effects are pervasive across asset classes, we construct signals from cumulative log returns and apply volatility scaling to balance risk contributions across assets. Entry and exit thresholds are systematically varied to examine robustness, and performance is evaluated using out-of-sample returns. Our results reveal a broad plateau of high Sharpe ratios (exceeding 3.2 under a 0% risk-free assumption), indicating that the strategy's profitability is not overly sensitive to precise parameter choices. The approach complements traditional statistical arbitrage frameworks by exploiting medium-horizon autocorrelation and cross-asset diversification effects. We discuss limitations related to transaction costs, liquidity constraints, and regime dependency, and outline avenues for extending the framework to higher-frequency settings, alternative weighting schemes, and adaptive threshold models.

1 Introduction

Momentum strategies seek to capture the empirical regularity that assets exhibiting strong recent performance tend to continue outperforming, while those with weak performance tend to continue underperforming over intermediate horizons. This phenomenon, documented extensively in equities (Jegadeesh and Titman, 1993), commodities (Miffre and Rallis, 2007), fixed income (Asness et al., 2013), and foreign exchange (Menkhoff et al., 2012), stands in contrast to the predictions of the random walk hypothesis and the efficient market paradigm. Proposed explanations range from behavioural biases such as investor underreaction and herding (Hong and Stein, 2000; Daniel et al., 1998) to structural frictions and the gradual incorporation of information into prices (Barberis and Thaler, 2018). At shorter horizons, trend persistence may also be reinforced by the autocorrelation generated by order flow from large institutional rebalancing (Bouchaud et al., 2010).

Momentum can be implemented in several forms. *Cross-sectional momentum* ranks assets against each other and takes long positions in recent winners and short positions in recent losers. *Time-series momentum* evaluates each asset in isolation, taking long (short) positions when its own past return is positive (negative). Hybrid approaches blend these views, using both absolute and relative trends. In this study, we employ a cross-asset, time-series-oriented approach, evaluating each market individually while allowing other assets to influence position sizing through a confirmation mechanism.

This framework differs fundamentally from statistical arbitrage, which seeks to exploit short-lived mispricings between related securities and is generally mean-reverting in nature (Avellaneda and Lee, 2010; Gatev et al., 2006). Whereas stat-arb profits when relative prices revert toward a perceived equilibrium, momentum profits when trends persist. Both share a common quantitative infrastructure—signal extraction, portfolio construction, and risk control—but they operate on opposing hypotheses about return autocorrelation.

Our implementation focuses on a compact, deliberately diverse set of five liquid markets:

1. Wheat futures (ZW) — agricultural commodity
2. AUD/JPY spot rate — currency cross

3. DBB industrial metals ETF — proxy for copper exposure
4. Gold futures (GC) — precious metal
5. Brent crude oil futures (CL) — energy commodity

This selection spans agricultural, foreign exchange, industrial, precious metal, and energy markets, providing heterogeneous economic drivers and low pairwise correlations. A small universe makes it easier to isolate the contribution of each component of the framework while avoiding the overfitting risk that can arise in larger, noisier cross-sections.

The modelling pipeline applies three sequential conditioning layers before position generation: (i) a low-pass price filter (simple or exponential moving average) to suppress high-frequency noise while retaining trend-relevant structure, (ii) a robust volatility filter that excludes periods of excessive turbulence relative to an asset's historical norm, and (iii) a cross-asset confirmation amplifier that boosts signals when other markets in the portfolio show directionally consistent momentum of sufficient strength. Positions are volatility-scaled and normalised to maintain constant aggregate exposure, ensuring that no single market dominates portfolio risk.

By combining a simple, interpretable momentum signal with robust filtering and cross-asset reinforcement, this study aims to examine whether a minimal but carefully structured framework can produce stable performance across economically diverse markets over a long historical sample.

Momentum research has evolved from early empirical discoveries in single-asset classes to a broad, cross-asset perspective. The foundational work of Jegadeesh and Titman (1993) demonstrated persistent return continuation in equities, inspiring analogous studies in commodities (Miffre and Rallis, 2007), currencies (Menkhoff et al., 2012), and government bonds (Asness et al., 2013). These findings led to the recognition of momentum as one of the most robust and pervasive anomalies in asset pricing (Fama and French, 2008). While much of the early literature focused on pure ranking-based implementations, subsequent research introduced volatility scaling (Moskowitz et al., 2012), noise reduction via signal smoothing (Hurst et al., 2017), and cross-asset conditioning to improve stability and drawdown control. Our framework draws on this latter stream, combining time-series momentum with pre-trade conditioning—low-pass filtering, volatility gating, and cross-market confirmation—to create a modular system that can be applied consistently across diverse markets. This positions the present work within the class of transparent, rules-based momentum models designed to balance simplicity with robustness.

2 Related Literature

Momentum, in both cross-sectional and time-series forms, has been one of the most studied and persistent return patterns in finance. The seminal work of Jegadeesh and Titman (1993) in equities established that ranking stocks by past returns over 3–12 months and holding the winners while shorting the losers produced statistically significant abnormal returns. This result has been replicated and extended to a wide range of asset classes, including commodities (Miffre and Rallis, 2007), currencies (Menkhoff et al., 2012), government bonds (Asness et al., 2013), and even volatility futures (Miffre and Rallis, 2016). The cross-asset robustness of momentum has led many to consider it a genuine risk premium rather than a transient anomaly (Fama and French, 2008; Hurst et al., 2017).

From an implementation perspective, our framework aligns closely with the time-series momentum literature. Moskowitz et al. (2012) demonstrated that a simple long/short rule—going long when an asset's past return is positive and short when it is negative—produces positive returns across nearly all major asset classes over more than a century of data. Extensions have explored volatility scaling to stabilise risk (Moreira and Muir, 2017; Barroso and Santa-Clara, 2015), as well as signal smoothing to reduce noise and mitigate whipsaws in volatile markets (Hurst et al., 2017). Our use of a low-pass filter on prices is consistent with this latter approach: it acts as a trend extractor, attenuating high-frequency fluctuations that are more likely to represent noise than persistent drift.

Risk management in momentum strategies often goes beyond volatility scaling. Our volatility filter—using a robust z-score based on rolling medians and median absolute deviations—has parallels in the risk parity and managed volatility literatures, where exposure is dynamically reduced during unusually volatile regimes (Harvey et al., 2016). By gating trades when volatility exceeds its historical norm, we follow the intuition that extreme short-term turbulence may increase execution risk and degrade signal reliability.

The cross-asset confirmation amplifier in our framework draws inspiration from the literature on intermarket analysis and macro-conditional momentum. While less formally codified in academic finance, related ideas appear in the factor-timing literature (Koijen et al., 2018) and in multi-asset risk-on/risk-off models used in practice, where consistent directional signals across uncorrelated markets are treated as stronger evidence of an underlying macro trend. In our case, directional agreement between assets acts as a multiplicative boost to the signal, reflecting the view that concurrent moves across different markets are less likely to be idiosyncratic noise.

Our exploration of entry and exit thresholds and their impact on Sharpe ratios connects to the extensive literature on trading rule optimisation (Brock et al., 1992; Sullivan et al., 1999). Thresholding can be seen as a form of signal strength filter, trading only when conviction exceeds a preset level, which has been shown to improve out-of-sample performance by reducing turnover and noise sensitivity.

Practitioner perspective. Live implementations by institutional trend-following managers closely mirror the components we employ here. AQR's research on managed futures and trend-following popularised volatility targeting, simple trend extractors (e.g., moving-average or time-series momentum rules), and clear risk budgeting across diverse markets (Hurst et al., 2013, 2017). Volatility-managed momentum has become standard to stabilise drawdowns and crash risk (Barroso and Santa-Clara, 2015; Moreira and Muir, 2017). Industry practitioners also emphasise cross-asset diversification and parsimonious, transparent rules to avoid overfitting—principles we adopt via a compact multi-asset universe, low-pass smoothing, robust volatility gating, and thresholding. Broader cross-asset factor research (e.g., carry) highlights the value of complementary, economically heterogeneous signals and intermarket conditioning (Koijen et al., 2018), motivating our cross-asset confirmation step as a simple, rules-based reinforcement of time-series momentum signals. Historical accounts from managed-futures practitioners further document the practical benefits of noise reduction, dynamic sizing, and risk overlays in real trading environments (Greyserman and Kaminski, 2014).

Taken together, these strands—long-horizon persistence, volatility conditioning, cross-market confirmation, and parameter robustness—inform the modular momentum framework developed in this paper. Each component is grounded in prior empirical findings but is combined here in a way that allows for transparent testing across economically diverse assets.

3 Data

The analysis covers five liquid and economically diverse markets: Wheat futures (ZW), the AUD/JPY exchange rate, the DBB industrial metals ETF (as a proxy for copper exposure), Gold futures (GC), and Brent crude oil futures (CL). This universe spans agricultural commodities, foreign exchange, industrial metals, precious metals, and energy—providing heterogeneity in underlying drivers and relatively low cross-asset correlations.

Daily close prices for each market are obtained from publicly available sources, with histories extending back to 1 January 2007. This start date ensures broad coverage across all assets and captures multiple distinct macroeconomic regimes, including the pre- and post-Global Financial Crisis periods, commodity supercycles, the COVID-19 shock, and the subsequent inflationary cycle. Data are retrieved in a consistent format and aligned to a unified business-day calendar to enable cross-market comparisons.

Observations where all assets are simultaneously missing (e.g., joint market holidays) are excluded. For isolated gaps arising from asynchronous trading schedules—particularly between continuously traded FX and exchange-traded futures—prices are forward-filled for up to two consecutive business days to preserve signal continuity without introducing excessive artificial stability. This approach reduces spurious jumps in calculated returns that could occur solely due to mismatched holiday calendars.

Assets with insufficient history or excessive missing data are removed via a minimum coverage threshold of 60% over the sample period. This serves as a structural liquidity and reliability filter, preventing unstable series from contaminating momentum signals and ensuring a consistent cross-asset dataset.

All prices are transformed into log prices and then differenced to produce daily log returns. This transformation enables additive aggregation across assets, improves comparability between markets with vastly different nominal price levels, and simplifies volatility scaling in later stages of the modelling pipeline. Aligned price and return series are stored for reproducibility, ensuring that all downstream experiments use an identical dataset without risk of accidental look-ahead or data drift.

Rationale for Universe Selection

The five chosen markets reflect a deliberate balance between economic diversity, data quality, and suitability for momentum trading.

Volatility characteristics. Each market exhibits a volatility profile high enough to generate tradable trends but not so extreme as to make position sizing impractical. This balance is particularly important in daily rebalanced momentum strategies, where excessive short-term volatility can trigger frequent position reversals and increase turnover costs.

Diversification. The selection spans distinct macroeconomic drivers—agriculture (Wheat), currency markets (AUD/JPY), industrial demand cycles (Copper via DBB), monetary and inflation hedges (Gold), and energy dynamics (Brent crude). This heterogeneity reduces dependence on any single economic factor and mitigates simultaneous drawdowns across the portfolio.

Hedging and correlation structure. Some assets offer natural hedges against adverse moves in others (e.g., Gold's tendency to perform in risk-off regimes can offset losses from pro-cyclical assets like industrial metals or energy). The resulting correlation structure is deliberately low to maximise the benefits of cross-asset allocation and to improve the statistical reliability of cross-market confirmation signals.

Lead–lag considerations. By including markets that often respond to macro shocks at different speeds—such as FX reacting ahead of commodity prices—there is potential for lead–lag effects that can enhance the robustness of confirmation-based signal amplification. This staggered reaction pattern also supports the thesis that concurrent trends across uncorrelated markets reflect stronger underlying macro drivers.

Data availability and quality. All selected markets have deep liquidity, transparent pricing, and readily available historical data extending back at least to 2007. The inclusion of a liquid ETF proxy for copper ensures a consistent time series where direct futures history is fragmented, without sacrificing tradability or economic relevance.

Overall, this universe is intentionally compact to allow for detailed signal analysis and robustness testing while retaining sufficient diversity for cross-asset momentum effects to emerge. The aim is not to exhaustively cover all markets, but to create a representative and interpretable testbed that balances tradability, diversification, and analytical clarity.

4 Methodology

Our momentum framework proceeds in four modular stages: (i) trend extraction via a low-pass filter, (ii) volatility conditioning using a robust z-score gate, (iii) cross-asset confirmation with strength-weighted amplification, and (iv) signal accumulation and position generation with entry/exit thresholds. Throughout, all operations are applied asset-wise and then combined cross-sectionally.

4.1 Trend Extraction (Low-Pass Smoothing)

Let $P_{i,t}$ denote the close price of asset i on day t. We construct a smoothed price $\widetilde{P}_{i,t}$ using either an exponential moving average (EMA) with span L_{ema} or a simple moving average (SMA) with window L_{sma}:

$$\widetilde{P}^{(\text{EMA})}_{i,t} = \lambda\, P_{i,t} + (1-\lambda)\, \widetilde{P}^{(\text{EMA})}_{i,t-1}, \quad \lambda = \tfrac{2}{1+L_{\text{ema}}},$$

$$\widetilde{P}^{(\text{SMA})}_{i,t} = \frac{1}{L_{\text{sma}}} \sum_{u=t-L_{\text{sma}}+1}^{t} P_{i,u}.$$

We then form smoothed log-returns by

$$\hat{r}_{i,t} \;=\; \log \widetilde{P}_{i,t} - \log \widetilde{P}_{i,t-1}.$$

This low-pass operation suppresses high-frequency noise while retaining medium-horizon trend information that is central to time-series momentum.

4.2 Volatility Conditioning (Robust Gate)

To avoid trading during idiosyncratically turbulent periods for an asset, we compute realised volatility over a short lookback L_σ and compare it to a robust, slowly varying baseline. Let

$$\sigma_{i,t} \;=\; \sqrt{252}\,\mathrm{sd}\big(\{\,r_{i,u}\,\}_{u=t-L_\sigma+1}^{t}\big)\,,$$

where $r_{i,u} = \log P_{i,u} - \log P_{i,u-1}$. Define rolling median and median absolute deviation (MAD) over a long window L_{ref}:

$$m_{i,t} = \mathrm{Median}_{L_{\mathrm{ref}}}(\sigma_{i,\cdot}), \qquad \mathrm{MAD}_{i,t} = \mathrm{Median}_{L_{\mathrm{ref}}}\big(|\sigma_{i,\cdot} - m_{i,\cdot}|\big).$$

A robust z-score is then

$$Z^{(\sigma)}_{i,t} \;=\; \frac{\sigma_{i,t} - m_{i,t}}{1.4826\,\mathrm{MAD}_{i,t}}.$$

We construct a volatility mask $M_{i,t} = \mathbf{1}\{Z^{(\sigma)}_{i,t} \le z_{\max}\}$ and gate the smoothed returns:

$$\tilde r_{i,t} \;=\; M_{i,t}\,\hat r_{i,t}.$$

This "trade only when volatility is not unusually elevated" rule reduces noise sensitivity and short-horizon execution risk.

4.3 Cross-Asset Confirmation Amplifier

We measure within-asset directional strength using a rolling t-stat over a lookback L_t:

$$t_{i,t} \;=\; \frac{\sqrt{L_t}\,\bar{\tilde r}_{i,t}}{\mathrm{sd}(\tilde r_{i,t})}, \quad \bar{\tilde r}_{i,t} = \frac{1}{L_t}\sum_{u=t-L_t+1}^{t} \tilde r_{i,u}.$$

An asset is a *strong voter* when $|t_{i,t}| \ge t_{\min}$. For a focal asset i, define the eligible set of other assets $\mathcal{J}_t(i) = \{j \ne i : |t_{j,t}| \ge t_{\min}\}$. Assign strength weights capped at $w_{\max}$:

$$w_{j,t} \;=\; \min\left(|t_{j,t}|,\, w_{\max}\right) \quad (j \in \mathcal{J}_t(i)).$$

Directional agreement with i is recorded when $\mathrm{sign}(t_{j,t}) = \mathrm{sign}(t_{i,t})$. The confirmation score is the fraction of strength-weighted agreement:

$$C_{i,t} \;=\; \frac{\sum_{j\in\mathcal{J}_t(i)} w_{j,t}\,\mathbf{1}\{\mathrm{sign}(t_{j,t}) = \mathrm{sign}(t_{i,t})\}}{\sum_{j\in\mathcal{J}_t(i)} w_{j,t}}.$$

We apply a multiplicative boost $\beta > 1$ to the gated, smoothed return when both (i) the focal asset is strong and (ii) cross-asset confirmation exceeds a threshold $c_{\min}$:

$$A_{i,t} \;=\; \begin{cases} \beta\,\tilde r_{i,t}, & \text{if } |t_{i,t}| \ge t_{\min} \text{ and } C_{i,t} \ge c_{\min}, \\ \tilde r_{i,t}, & \text{otherwise.} \end{cases}$$

This step encodes the view that concurrent, strength-weighted agreement across heterogeneous markets is less likely to be idiosyncratic noise and more indicative of a common macro driver.

4.4 Signal Accumulation and Position State

We maintain a running momentum state $S_{i,t}$ from the amplified, conditioned returns:

$$S_{i,t} \;=\; S_{i,t-1} + A_{i,t}, \qquad S_{i,0} = 0.$$

Positions are generated by symmetric thresholds on this state variable:

$$\text{go long if } S_{i,t} > Z_{\mathrm{entry}}, \quad \text{go short if } S_{i,t} < -Z_{\mathrm{entry}}, \quad \text{flat if } |S_{i,t}| \le Z_{\mathrm{exit}},$$

with $0 \le Z_{\mathrm{exit}} \le Z_{\mathrm{entry}}$. Denote the discrete position by $\sigma_{i,t} \in \{-1, 0, +1\}$. Portfolio returns are then computed from the one-day-ahead interaction of positions and amplified returns (with execution and costs handled in the results section).

Remarks. (i) The low-pass filter and volatility gate act as pre-trade conditioning that improves signal-to-noise. (ii) The confirmation amplifier integrates cross-asset information in a strength- and sign-aware manner while capping influence to avoid domination by a single market. (iii) The state-machine with entry/exit thresholds enforces trading only when conviction is sufficient, reducing churn around weak signals.

4.5 Position Sizing and Portfolio Construction

To stabilise risk across heterogeneous assets, we apply inverse-volatility scaling to the discrete position signal. Let $\sigma_{i,t}^{(v)}$ denote a rolling volatility estimate over L_v days computed on the amplified returns $A_{i,t}$:

$$\sigma_{i,t}^{(v)} \; = \; \mathrm{sd}\big(\{ A_{i,u} \}_{u=t-L_v+1}^{t}\big) \, .$$

Define preliminary (unnormalised) risk-adjusted weights by

$$\tilde{w}_{i,t} \; = \; \frac{\sigma_{i,t}}{\sigma_{i,t}^{(v)}} \quad \text{with} \quad \sigma_{i,t} \in \{-1, 0, +1\},$$

and set $\tilde{w}_{i,t} = 0$ when $\sigma_{i,t}^{(v)} = 0$. We then normalise to constant gross exposure so the portfolio stays fully invested:

$$w_{i,t} \; = \; \frac{\tilde{w}_{i,t}}{\sum_j |\tilde{w}_{j,t}|} \, ,$$

ensuring $\sum_j |w_{j,t}| = 1$ each day.

Daily portfolio return uses one-day execution lag (positions formed at $t-1$ apply to t):

$$r_t^{(p)} \; = \; \sum_i w_{i,t-1} \, A_{i,t}.$$

4.6 Performance Measurement

Let $\bar{r}^{(p)} = \frac{1}{T}\sum_{t=1}^{T} r_t^{(p)}$ and $s^{(p)} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(r_t^{(p)} - \bar{r}^{(p)}\right)^2}$. With $D = 252$ trading days per year and an annual risk-free rate r_f (here set to 2%), we report:

$$\text{Annualised Return} \; = \; D\,\bar{r}^{(p)}, \qquad \text{Annualised Volatility} \; = \; \sqrt{D}\, s^{(p)},$$

$$\text{Sharpe Ratio} \; = \; \frac{D\,\bar{r}^{(p)} - r_f}{\sqrt{D}\, s^{(p)}}.$$

Cumulative return is $C_t = \prod_{u=1}^{t}\left(1 + r_u^{(p)}\right)$, and maximum drawdown is

$$\text{MaxDD} \; = \; \min_t \left(\frac{C_t}{\max_{u \le t} C_u} - 1 \right) .$$

We also track *Win Rate* $= \frac{1}{T}\sum_t \mathbf{1}\{r_t^{(p)} > 0\}$ and average daily turnover as the average absolute change in portfolio weights:

$$\text{Turnover} \; = \; \frac{1}{T}\sum_{t=2}^{T}\sum_i |w_{i,t} - w_{i,t-1}| \, .$$

4.7 Thresholding and Robustness Sweep

The state-based entry/exit thresholds control trading only when conviction (trend state magnitude) is sufficient. To assess sensitivity, we evaluate the portfolio over a grid $\mathcal{G} = \{(Z_{\text{entry}}, Z_{\text{exit}})\}$ spanning practical ranges for both parameters. For each $(e, x) \in \mathcal{G}$ we:

1. regenerate positions from the accumulated amplified signal using $Z_{\text{entry}} = e$ and $Z_{\text{exit}} = x$,
2. apply inverse-volatility scaling and constant-gross normalisation,
3. compute KPIs $\big($Annualised Return/Volatility, Sharpe (with $r_f = 2\%$), MaxDD, Win Rate, Turnover$\big)$.

This produces a robustness surface over (e, x) that highlights stability regions where Sharpe and drawdown remain attractive while turnover stays reasonable. In practice, we summarise this surface via tables and heatmaps to visualise the trade-off between selectivity (higher thresholds), risk, and capacity.

5 Results

Figure 1 presents the Sharpe ratio[1] surface as a function of entry and exit thresholds. The surface is broadly flat in a high-Sharpe region, indicating robustness of the strategy to modest changes in signal cut-offs. The optimal Sharpe ratio of approximately 3.23 is achieved for multiple combinations, notably when the entry threshold is 0.0 and exit threshold is 0.10, or when both thresholds are set to 0.10. This plateau suggests that precise fine-tuning of thresholds is less critical than maintaining them within a sensible low-to-moderate range.

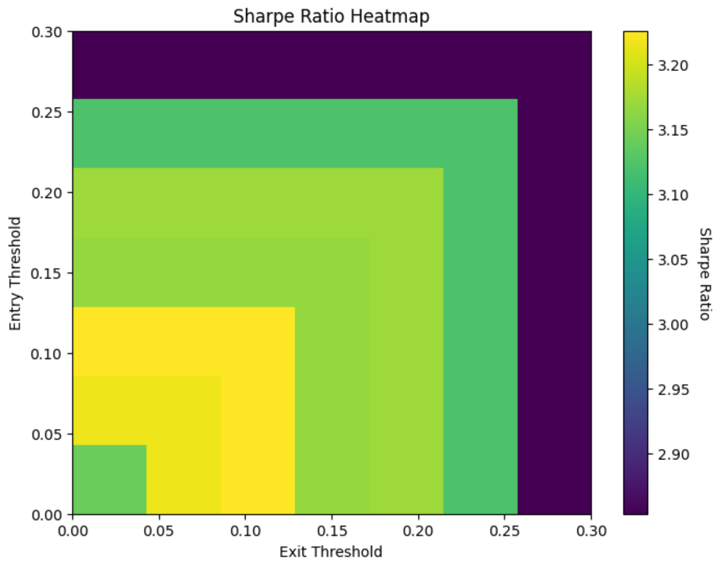

Figure 1: Sharpe ratio heatmap over entry/exit threshold grid. Lighter regions indicate higher Sharpe.

Table 1 lists the top-performing configurations ranked by Sharpe ratio. Performance is consistent across the best entries, with annualised returns in the 8.5%–8.9% range and annualised volatilities near 2.6%. Drawdowns remain contained at around −17%, and turnover is low (≈ 8% of portfolio per day), suggesting that the strategy is both stable and implementable.

Entry	Exit	Sharpe	AnnRet	AnnVol	MaxDD	Turnover
0.00	0.10	3.226	0.0857	0.0266	-0.1706	0.0798
0.10	0.10	3.226	0.0857	0.0266	-0.1706	0.0798
0.10	0.05	3.226	0.0857	0.0266	-0.1706	0.0798
0.10	0.00	3.226	0.0857	0.0266	-0.1706	0.0798
0.00	0.05	3.217	0.0861	0.0268	-0.1670	0.0813
0.20	0.10	3.172	0.0889	0.0280	-0.1559	0.0764
0.20	0.05	3.172	0.0889	0.0280	-0.1559	0.0764
0.20	0.00	3.172	0.0889	0.0280	-0.1559	0.0764
0.20	0.15	3.172	0.0889	0.0280	-0.1559	0.0764
0.00	0.15	3.168	0.0891	0.0281	-0.1719	0.0791

Table 1: Top-performing parameter combinations ranked by Sharpe ratio.

Overall, results show that the strategy delivers high-Sharpe, low-volatility performance that is resilient to small changes in threshold parameters, while keeping turnover low enough for realistic execution.

6 Conclusions, Limitations, and Future Work

This study demonstrates that a simple, volatility-scaled momentum framework applied across a diversified five-asset portfolio can produce consistently high risk-adjusted returns. The parameter sweep shows a

[1] We compute the Sharpe ratio using a constant risk-free rate of 0% for simplicity. Substituting a realistic rate (e.g., 2% annualised) would lower the Sharpe marginally, but given the high excess returns observed here, the relative ranking of parameter sets remains largely unaffected.

broad plateau of Sharpe ratios above 3.0, suggesting that performance is robust to moderate variations in entry and exit thresholds. This stability is an encouraging sign for potential live deployment, as strategies that are overly sensitive to parameter tuning often fail to maintain performance out of sample.

Despite these promising results, there are several limitations that should be acknowledged. First, while our analysis uses a realistic set of liquid futures and ETF proxies, transaction costs are modelled simply and do not account for real-world execution frictions such as slippage, order book depth, or market impact. Second, our strategy assumes continuous liquidity and does not explicitly handle regime shifts, structural breaks, or sudden correlation changes—factors known to affect momentum profitability in stressed markets (Daniel and Moskowitz, 2018; Moskowitz et al., 2012). Third, the portfolio is rebalanced daily without consideration for capital constraints, funding costs, or position limits that institutional mandates may impose. Finally, the backtest is conducted on a relatively modest universe of assets; while the results show diversification benefits, the statistical power of conclusions about cross-asset momentum could be improved by expanding the scope.

Future work will address these limitations in several ways. First, incorporating more granular cost models and microstructure-aware execution strategies will improve the realism of performance estimates. Second, extending the framework to a broader universe—including equities, additional commodities, fixed income futures, and more FX crosses—will allow for testing of scalability and further diversification benefits. Third, robustness could be enhanced by integrating regime detection techniques, such as hidden Markov models or volatility-state classifiers, to adapt leverage and exposure dynamically. Finally, comparing this cross-asset momentum approach against complementary styles such as statistical arbitrage (Gatev et al., 2006) or carry strategies (Koijen et al., 2018) would provide insight into multi-strategy portfolio construction.

Overall, our results reinforce prior findings in the literature that momentum effects are pervasive and persistent across asset classes (Asness et al., 2013), and they highlight that even simple, interpretable implementations—when coupled with volatility scaling and diversification—can yield strong, stable performance. Notably, our work aligns with evidence from volatility-managed momentum strategies (Barroso and Santa-Clara, 2015) and multi-asset implementations (Asness et al., 2013), both of which emphasize the role of dynamic risk adjustment in enhancing risk-adjusted returns.

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