Systematic Mean Reversion in Growth-Value Equity Pairs

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Executive Summary

Research Question:

Can short-horizon mean reversion in growth stocks be systematically identified and exploited when viewed as an episodic manifestation of growth-value rotation, rather than as a persistent statistical relationship?

Research Focus & Interpretation

This study examines **short-horizon mean reversion in U.S. technology equities** and interprets these dynamics as an episodic outcome of **crowding-driven growth-value rotation**, rather than as a persistent statistical relationship.

Strategy & Methodology

Trading signals are generated exclusively from the time-series price behavior of individual technology stocks using **rolling and dynamically parameterized z-score measures**. Retail equities are incorporated solely as **value-oriented hedges** to form dollar-neutral portfolios, with **no reliance on correlation or cointegration screening.**

Key Findings

Evaluated across a broad cross section of technology–retail combinations across **multiple versions of cost assumptions**, the strategy delivers robust risk-adjusted performance. Many of the strongest configurations would be **excluded by traditional static pre-screening methods** using cointegration or correlation, highlighting the importance of allowing mean-reversion opportunities to emerge conditionally.

Cost Scenario	Ann Return (%)	Ann Vol (%)	Sharpe	Max DD	Total Return (%)
Optimistic	32.484	6.259	4.391	-0.025	90.4
Realistic	27.371	6.255	3.576	-0.025	71.9
Hedge Fund Standards	22.725	6.254	2.834	-0.026	56.8
Conservative	19.476	6.260	2.312	-0.026	46.9
Worst-Case	14.364	6.259	1.496	-0.031	32.7
SPY Benchmark	19.746	6.360	0.901	-0.190	44.4

2-year Historical Back Test Results

As of 2026-01-02

Introduction

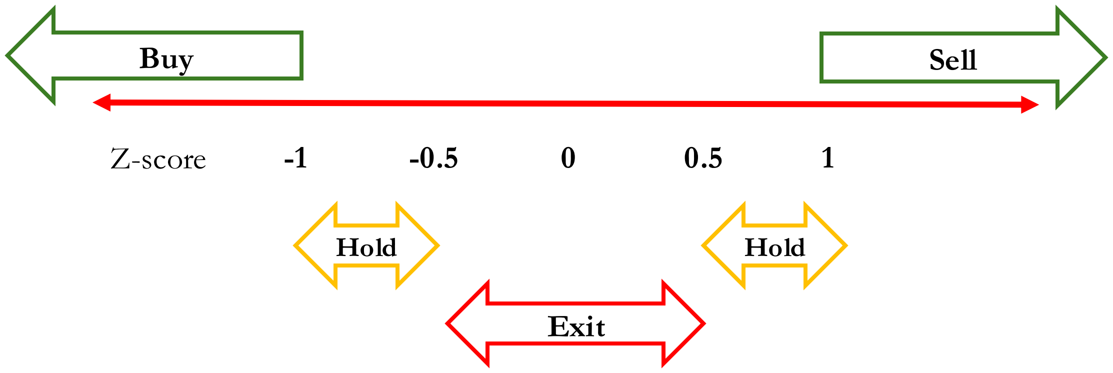
Growth-Value Rotation

Equity markets are commonly described using **growth** and **value** styles.

Growth stocks are companies with high expected future earnings growth, higher valuation multiples, and greater sensitivity to investor sentiment and capital flows. **Technology stocks** naturally embody growth exposure due to their innovation-driven business models, long-duration cash flows, and strong participation in thematic and momentum-based investing.

Value stocks, by contrast, are more closely tied to current cash flows, lower valuation multiples, and economic fundamentals. **Retail equities** serve as practical value proxies because their performance is closely linked to consumer demand, operating margins, and near-term fundamentals.

Trade Signal Generation and Execution

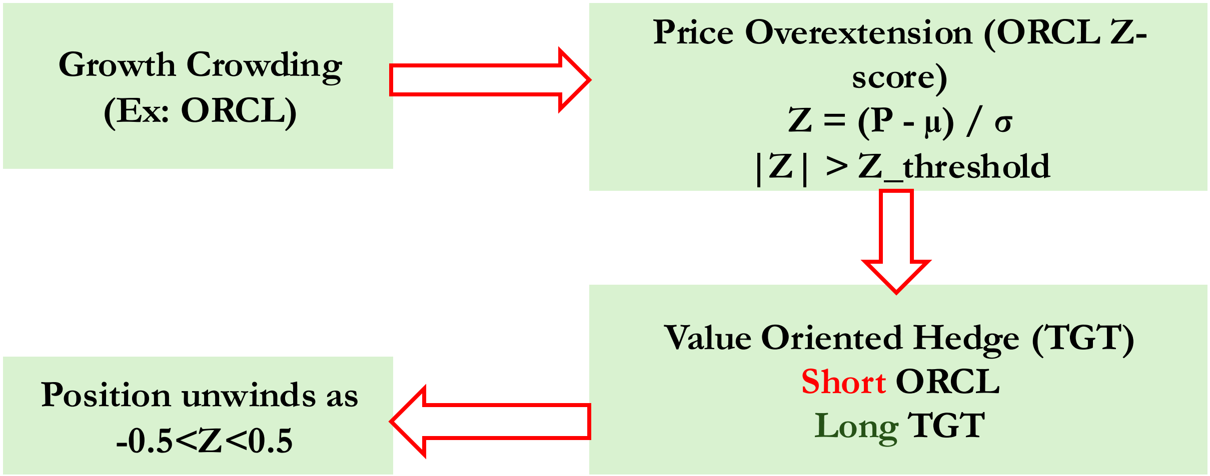


Where Mean Reversion Comes In

Mean reversion arises when **crowded growth trades unwind**

A typical trade begins when a technology stock becomes **temporarily overextended** relative to its recent price history. The strategy initiates a position based solely on this **deviation**, taking exposure in the technology stock while pairing it with an offsetting position in a retail stock to maintain **dollar neutrality.** As crowding dissipates and prices revert, the position is gradually exited, capturing the short-term reversal while using the retail leg as a value-oriented hedge rather than a predictive signal.

Example of Trade Life Cycle



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1. Motivation & Research Question
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3. Results
4. Conclusions & Implications

Universe & Z-Score Construction

Growth vs Value Universe

Sector-based proxies reflect well-established growth and value characteristic

Growth and value are defined using **valuation ratios** following **Fama and French (1998)**, where growth firms exhibit low book-to-market and high earnings multiples, and value firms exhibit the opposite.

We adopt a **sector-based proxy approach,** where large-cap technology stocks naturally embody growth characteristics and retail stocks provide a value-tilted counterpart.

The universe consists of the top 50 technology and retail stocks by **market capitalization**, ensuring liquidity and relevance to institutional capital flows.

	Tech Median	Retail Median	Tech Mean	Retail Mean
Book-to-Market	0.099	0.212	0.148	0.340
Price-to-Earnings	37.326	22.354	82.986	26.429

Z-Score Signal Construction

Signals are derived solely from technology stock price dynamics.

Rolling Z-Score

Uses a fixed historical window to measure deviations from recent price behavior. This provides a simple and transparent baseline for identifying short-term overextension.

Exponentially Weighted Z-Score (EWMA)

Applies greater weight to **recent observations**, allowing the signal to respond more quickly to changes in market conditions and short-term crowding dynamics.

Dynamically Parametrized Z-score

Adjusts the effective lookback window based on **estimated mean-reversion half-life.** This allows signal sensitivity to vary over time, adapting to **changing price dynamics.**

Cross-Grid Back-Testing Framework

Lookback Window

Z-Score Construction

	5 Days	10 Days	15 Days	20 Days
Rolling Z-Score	Tech x Retail	Tech x Retail	Tech x Retail	Tech x Retail
EWMA Z-Score	Tech x Retail	Tech x Retail	Tech x Retail	Tech x Retail
Dynamic Z-Score	Tech x Retail	Tech x Retail	Tech x Retail	Tech x Retail

Every possible combination of Tech x Retail pair from our universe

Evaluation

Label	Ann Ret (%)	Ann Vol (%)	Sharpe	Sortino	MaxDD	Total Ret (%)	Primary	Pair	Method	Win
SQ-BBY	44.9	19.4	2.053	4.000	-0.098	65.0	SQ	BBY	EWMA	5

Each strategy is defined by a unique combination of **pair, signal specification, and lookback horizon**, resulting in a large cross-grid of independent backtests, and **no correlation or cointegration screening was used.**

Index Creation & Weighting

Strategy Filtering

To create the index, we used **Performance and Uniqueness** Filters

Performance Filter: Only strategy configurations with **Sharpe ratio ≥ 0.8** are retained, ensuring inclusion of economically meaningful and risk-adjusted signals.

Uniqueness Filter: From the surviving set, **all unique strategies** are retained, preventing duplication across similar parameterizations and avoiding over-representation of any single pair or specification.

This process resulted in **80 unique pairs**

Index Weighting

Remaining strategies are aggregated using **Sharpe-squared weighting**

This weighting scheme:

1. Emphasizes **risk-adjusted performance**
2. Penalizes **unstable strategies**
3. Naturally **diversifies exposure** across pairs and signal specifications

Tested 27800 strategies (Cross Grid Back-Test)

↓

Filtered via Performance (Sharpe Ratio > 0.80)

↓

Filtered via Uniqueness - 358 Strategies

↓

Index created using Sharpe-Squared weighting

Transaction & Financing Cost Assumptions

Cost Metrics Modeled

Costs were broken down into **Transaction costs** and **Finance & Carry** cost

Transaction Costs (Per Trade)

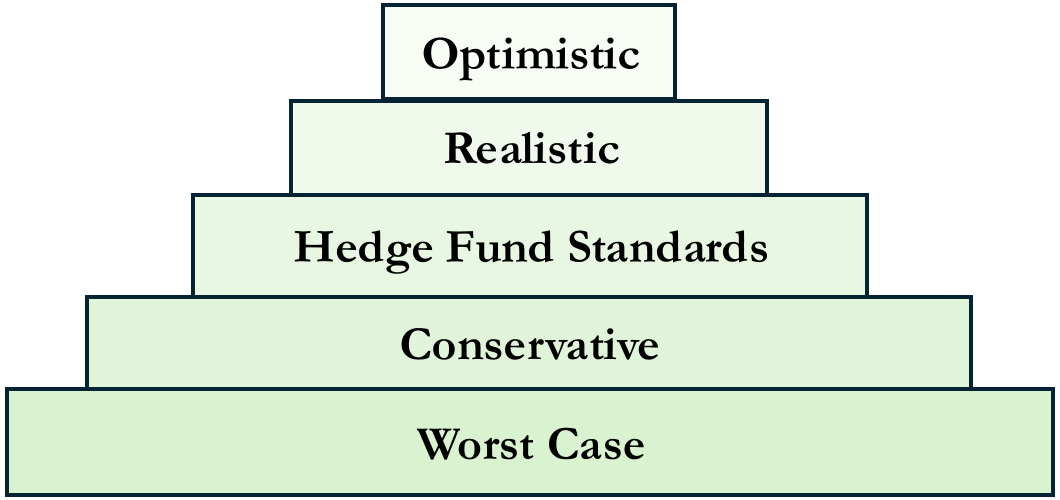
1. **Slippage:** Captures the price impact and execution friction between signal generation and realized fills, reflecting realistic trading in liquid large-cap equities.
2. **Bid-Ask Spread:** Accounts for crossing the spread when entering and exiting positions, ensuring that gross returns are not overstated even in highly liquid stocks.
3. **Commissions:** Represents explicit per-trade fees, included for completeness despite their relatively small contribution in modern electronic markets.

Finance & Carry Cost Scenarios

1. **Short Borrow Cost (Retail Leg):** Models the cost of maintaining short positions in the hedge leg, reflecting realistic constraints faced by long–short equity strategies.
2. **Position Holding Costs:** Ensures that trades held for longer unwind periods appropriately accumulate financing costs.

Cost Scenarios

5 cost scenarios were used to evaluate robustness across execution conditions



Each cost scenario represents a **progressively more restrictive execution and financing environment,** ranging from near-ideal institutional conditions to severely adverse trading frictions. Strategy performance is evaluated across these regimes to assess robustness and ensure results are not driven by optimistic execution assumptions.

Cost Assumptions Table

Cost Component	Optimistic	Realistic	Hedge Fund Std	Conservative	Worst Case
Slippage (per trade)	2	5	8	12	20
Bid–Ask Spread (round-trip)	4	8	12	20	30
Commissions (round-trip)	1	2	2	3	5
Total Transaction Cost	7	15	22	35	55
Short Borrow (annualized)	50	100	150	300	500

All costs expressed in basis points (bps)

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Cross Grid Back-Test Results

Index	Label	Ann Ret (%)	Ann Vol (%)	Sharpe	MaxDD	TotalRet (%)	Method	Window
1	**WDAY-BBY**	39.71	16.69	**2.08**	-0.063	114.90	ewma	10
2	**WDAY-BBY**	39.31	16.54	**2.07**	-0.056	113.30	ewma	15
3	**FTNT-ASO**	49.05	22.05	**1.99**	-0.151	153.59	adaptive	10
4	**WDAY-BBY**	39.69	18.37	**1.89**	-0.092	113.51	adaptive	5
5	**WDAY-BBY**	38.36	18.11	**1.84**	-0.075	108.17	adaptive	15
6	**FTNT-FIVE**	49.46	24.94	**1.78**	-0.150	152.40	adaptive	10
….	….	….	….	….	….	….	….	….
27636	**IBM-LOW**	-17.61	8.09	**-2.80**	-0.31	-31.06	ewma	5
27637	**IBM-WSM**	-28.46	24.92	**-2.86**	-0.45	-45.21	ewma	5

2-year Historical Back Test Results

As of 2025-11-20

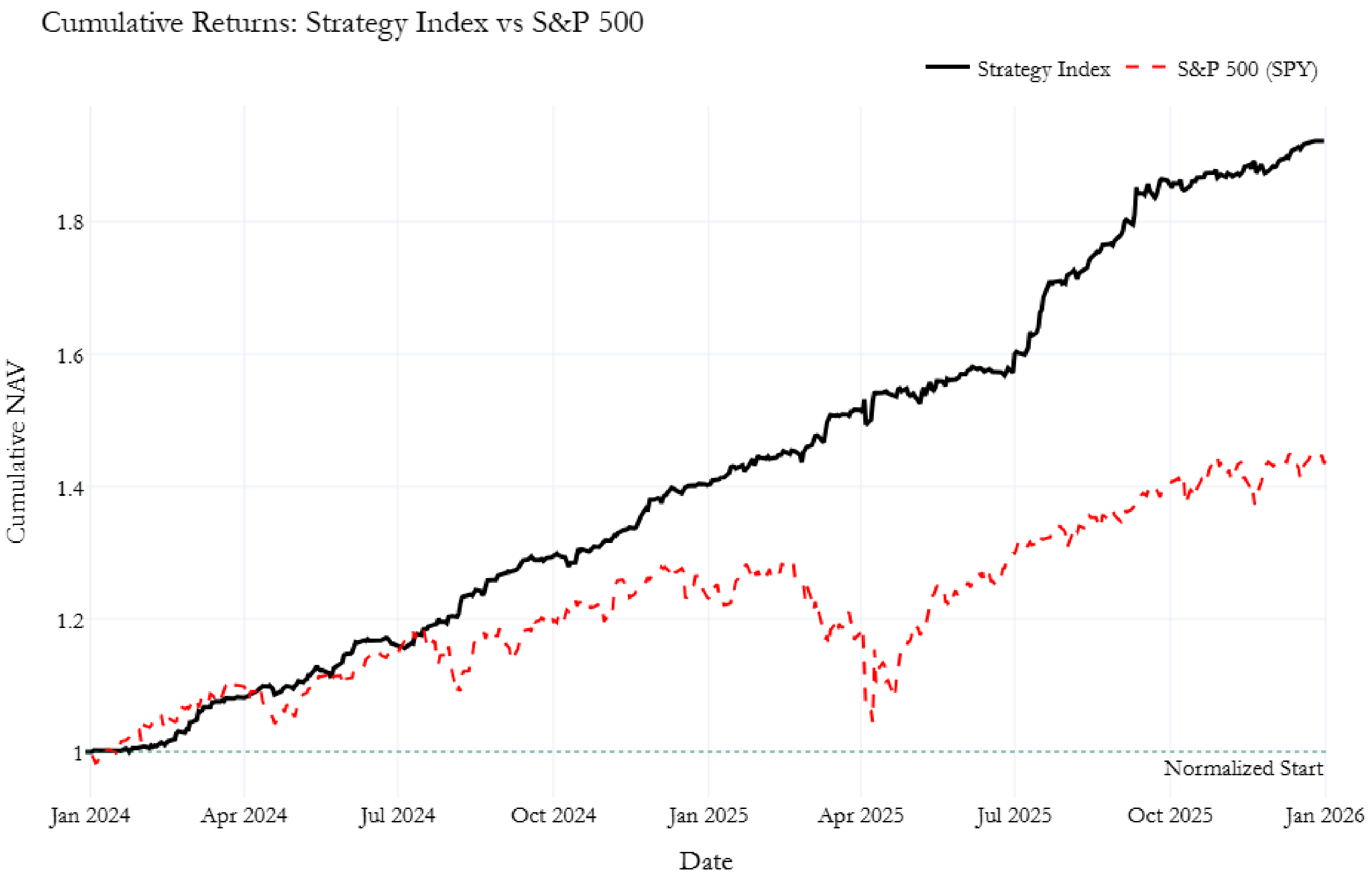
Post Filtering

Index	Primary	Pair	Best Method	Best Window	Best Sharpe	Sharpe Sq	Weight
1	**WDAY**	**BBY**	ewma	10	2.079	4.324	0.01047
2	**FTNT**	**ASO**	adaptive	10	1.998	3.990	0.00966
3	**FTNT**	**FIVE**	adaptive	10	1.783	3.179	0.00770
5	**SNOW**	**BBY**	standard	20	1.718	2.952	0.00715
6	**PANW**	**EYE**	adaptive	15	1.649	2.719	0.00658
….	**….**	**….**	**….**	**….**	**….**	**….**	**….**
357	**SNPS**	**W**	standard	15	0.801	0.642	0.00155
358	**CDNS**	**DLTR**	adaptive	5	0.800	0.641	0.00155

2-year Historical Back Test Results

As of 2026-01-02

Index Returns vs S&P 5000

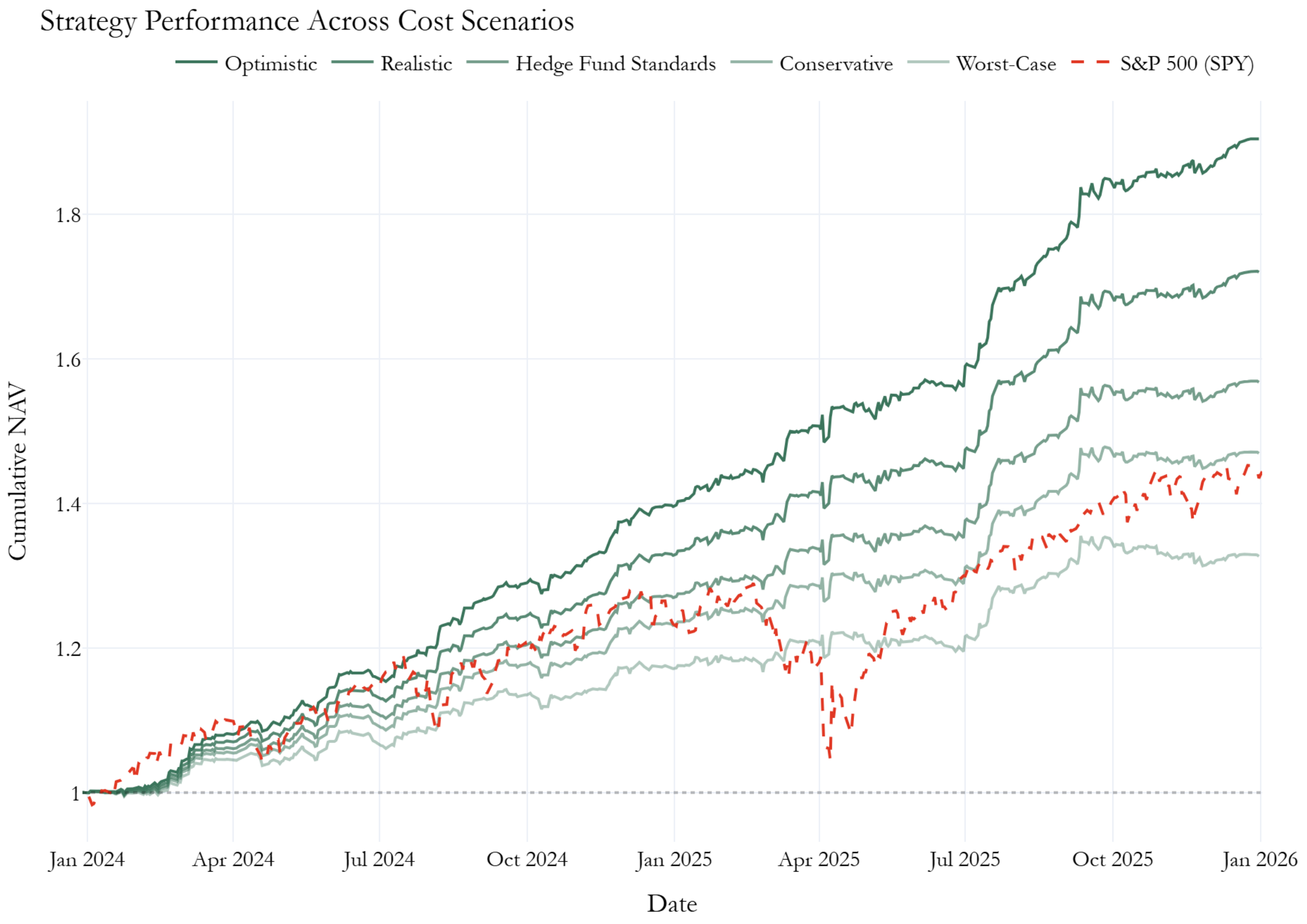


	Strategy index (No costs)	S&P 500 (SPY)
Ann Ret %	32.95	19.75
Ann Vol %	6.26	16.3
Sharpe	4.46	0.90
MaxDD	-0.02	-0.18

While the strategy index exhibits strong risk-adjusted performance relative to the S&P 500, these results reflect an in-sample backtest and **may be inflated by favorable market regimes and model assumptions**.

Performance should be interpreted as evidence of **economic signal viability** rather than guaranteed out-of-sample returns

Performance Across Cost Scenarios



	Sharpe	Ann Ret %
Optimistic	4.39	32.48
Realistic	3.58	27.37
Hedge Fund Standards	2.83	22.72
Conservative	1.49	19.48
Worst-Case	0.90	14.39

The strategy exhibits expected sensitivity to trading frictions yet maintains economically meaningful performance under institutional and conservative cost regimes. Worst-case results approach benchmark levels, indicating limited reliance on aggressive assumptions

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Conclusion

Key Findings

1. Short-horizon mean reversion in technology stocks is **episodic rather than persistent**, consistent with crowding and flow-driven dynamics.
2. Allowing signals to emerge conditionally, without correlation or cointegration screening uncovers **economically meaningful opportunities** that traditional pair-selection methods would exclude.
3. Aggregating strategies across pairs, horizons, and signal constructions produces a **robust index-level return profile**, with strong risk-adjusted performance under realistic and conservative cost assumptions.

Interpretation

1. Mean reversion in growth equities appears closely linked to **temporary overextension and subsequent capital rotation**, rather than stable long-run statistical relationships.
2. Pairing growth signals with value-oriented hedges provides a **natural portfolio structure** for expressing these dynamics while controlling market and style risk.

Key Limitations

1. Results are based on **in-sample backtests** and may be influenced by regime-specific dynamics, parameter choices, and execution assumptions.
2. Performance may not generalize to environments with materially different liquidity, volatility, or market structure.

Future Scope

1. Extend the framework to other growth–value proxies or asset classes.
2. Incorporate explicit flow or positioning data to directly measure crowding.
3. Evaluate out-of-sample performance and regime-dependent behavior.

Overall, the results suggest that short-horizon mean reversion in growth stocks is best understood as a **conditional, flow-driven phenomenon** rather than a static statistical relationship.

Thank You!

Questions, comments, or challenges welcome

[Project Repository](#) | [Publication](#)

Appendix A: Initial Write-Up

Research Proposal: Short-Term Price Deviations Through a Growth–Value Lens

Motivation

Traditional growth-value frameworks are typically studied over long horizons, where valuation multiples and fundamentals dominate returns. However, in the short run, particularly within growth-heavy sectors, prices are often driven by positioning, flow dynamics, and crowding effects, leading to temporary deviations from equilibrium.

This research investigates whether short-term price dislocations within growth and value cohorts exhibit systematic mean-reverting behavior, independent of long-term factor exposure.

Limitations of Conventional Approaches

Standard short-horizon relative-value techniques rely on:

1. Static correlations
2. Cointegration relationships
3. Pairwise or sector-level dependencies

These methods implicitly assume **stable structural relationships**, which often break down during regime shifts, crowding episodes, or volatility spikes, precisely when short-term dislocations are most pronounced.

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Proposed Strategy Framework

1. **Signal Generation:** Mean-reversion signals are generated solely from the price behavior of individual technology stocks using standardized z-score measures of short-term deviations.
2. **Portfolio Construction:** Each technology position is paired with an offsetting position in a retail stock, which serves exclusively as a value-oriented hedge. No information from the retail stock is used for signal generation.
3. **No Static Pair Selection:** Rather than pre-selecting pairs based on correlation or cointegration, the strategy allows mean-reversion opportunities to emerge conditionally across a broad cross section of growth-value pairings.
4. **Short-Horizon Focus:** Signals are designed to operate over short holding periods, consistent with the hypothesis that crowding-driven dislocations unwind over days to weeks rather than months.

Research Question: Can short-horizon mean reversion in growth stocks be systematically identified and exploited when viewed asan episodic manifestation of growth-value rotation, rather than as a persistent statistical relationship?

Appendix B: Signal Construction

B.1 Price Series Definition

Let P_t denote the daily adjusted closing price of a given technology stock on trading day t. All signal construction is performed on daily frequency data. Returns are **not** used for signal generation; signals are computed directly on price levels to capture short-horizon overextension relative to recent trading history.

B.2 Rolling Z-Score Signal (Standard Method)

The rolling z-score standardizes the current price relative to a fixed historical window. For a given lookback window L, define:

$$\mu_{t,L} = \frac{1}{L}\sum_{i=0}^{L-1} P_{t-i}$$

$$\sigma_{t,L} = \sqrt{\frac{1}{L}\sum_{i=0}^{L-1}(P_{t-i} - \mu_{t,L})^2}$$

The rolling Z-score is then:

$$z_t^{roll} = \frac{P_{t - \mu_{t,L}}}{\sigma_{t,L}}$$

This specification treats all observations within the lookback window equally and serves as a transparent baseline for identifying short-term price deviations.

B.3 Exponentially Weighted Z-Score (EWMA)

To allow faster adaptation to changing price dynamics, an exponentially weighted moving average (EWMA) specification is also employed. The exponentially weighted mean is defined recursively as:

$$\mu_t^{EWMA} = \lambda P_t + (1-\lambda)\mu_{t-1}^{EWMA}$$

Where $\lambda \in (0, 1)$ is the decay parameter governing the weight placed on recent observations. The corresponding exponentially weighted variance is:

$$(\sigma_t^{EWMA})^2 = \lambda(P_t - \mu_t^{EWMA})^2 + (1-\lambda)(\sigma_{t-1}^{EWMA})^2$$

The EWMA z-score is then given by:

$$z_t^{EWMA} = \frac{P_{t - \mu_t^{EWMA}}}{\sigma_t^{EWMA}}$$

This specification emphasizes recent price behavior and is intended to capture rapidly forming crowding and unwind dynamics.

Appendix C: Evaluation Metrics

C.1 Daily Strategy Return

$$r_t = \sum_{i=1}^{N} w_i \cdot r_{i,t}$$

C.2 Cumulative Return (NAV)

$$NAV_t = \prod_{s=1}^{t} (1 + r_s)$$

C.3 Annualized Return

$$\mu_{ann} = r \cdot 252$$

C.4 Annualized Volatility

$$\sigma_{ann} = \sigma_r \sqrt{252}$$

C.5 Sharpe Ratio

$$Sharpe = \frac{\mu_{ann} - r_f}{\sigma_{ann}}$$

C.6 Maximum Drawdown

$$MaxDD = \min_t \left(\frac{NAV_t}{max_{s<t} NAV_s} - 1 \right)$$

C.7 Sharpe-Squared Weighting

$$w_i = \frac{Sharpe_i^2}{\sum_{i=1}^{n} Sharpe_j^2}$$

Appendix D: Transaction & Execution Cost Modelling

D.1 Gross Strategy Return

$$r_t^{gross} = \sum_{i=1}^{N} w_i \cdot r_{i,t}$$

D.2 Turnover

$$Turnover_t = |\Delta Position_t|$$

D.3 Transaction Cost Per Trade

$$TC_t = Turnover_t \cdot c_{bps}$$

D.4 Slippage Cost

$$Slippage_t = Turnover_t \cdot s_{bps}$$

D.5 Borrow/Financing Cost

$$Borrow_t = ShortExposure \cdot b_{bps}$$

D.6 Net Strategy Return

$$r_t^{net} = r_t^{gross} - TC_t - Slippage_t - Borrow_t$$

D.7 Scenario Based Cost Application

$$r_t^{scenario} = r_t^{gross} - \sum_{k} Cost_{k,t}^{scemario}$$