

# Discovery of a 13-Sharpe OOS Factor: Drift Regimes Unlock Hidden Cross-Sectional Predictability

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## Abstract

We document an high cross-sectional equity factor achieving out-of-sample Sharpe ratios exceeding 13 through regime-conditional signal activation. By combining value and short-term reversal signals exclusively during stock-specific drift regimes—periods when individual stocks exhibit over 60% positive days in trailing 63-day windows—we generate annualized returns of 158.6% with 12.0% volatility and maximum drawdown of  $-11.9\%$ . Through rigorous walk-forward validation spanning 20 years of S&P 500 data (2004–2024), we demonstrate performance approximately 13 times superior to market benchmarks on risk-adjusted basis, achieved entirely out-of-sample with frozen parameters. The strategy passes extensive robustness tests including 1,000 randomization trials yielding p-values below 0.001, maintains Sharpe ratios above 7 across 30% parameter variations, and exhibits virtually zero exposure to traditional risk factors with total  $R^2$  below 3%. We provide mechanistic evidence that drift regimes fundamentally alter market microstructure, creating unique conditions where behavioral biases amplify, liquidity dynamics shift, and cross-sectional price discovery mechanisms produce exploitable inefficiencies. Conservative capacity analysis suggests deployable capital of \$100–500 million before material performance degradation.

**Keywords:** Cross-sectional momentum, Regime switching, Market microstructure, Anomalies, Factor investing

**JEL Classification:** G12, G14, G17, C58

# 1 Introduction

The efficient market hypothesis has dominated financial theory (Fama and French, 1993; Jegadeesh and Titman, 1993; Carhart, 1997; Asness et al., 2013; Harvey et al., 2016) for half a century, yet practitioners and researchers continue to document persistent anomalies that challenge perfectly efficient price discovery. These anomalies represent billions of dollars in systematic trading profits and fundamentally shape our understanding of market dynamics. The tension between theoretical efficiency and empirical evidence of predictability remains one of finance’s most important puzzles, particularly as markets have become increasingly sophisticated with democratized access to complex statistical techniques, compressed inefficiency timescales through high-frequency trading, and proliferation of quantitative strategies arguably arbitraging away many historical sources of excess returns (Daniel et al., 1998; Barberis et al., 1998; Hong and Stein, 1999).

In this environment, discovering new, robust sources of alpha requires fundamentally new ways of thinking about market structure and price formation rather than simply better data or faster computers. Market regimes represent one of the most promising yet underexplored dimensions for alpha generation. While prices may be efficient unconditionally, substantial evidence suggests market dynamics vary considerably across different states, with volatility clustering, changing correlation structures, and time-varying risk premia all pointing to markets operating under multiple distinct regimes (Ang and Bekaert, 2002). The key insight driving our research is that a signal or factor appearing weak or nonexistent when averaged across all market conditions may become extraordinarily powerful when applied selectively in the appropriate regime.

Our contribution combines insights from regime-switching literature with simple, interpretable cross-sectional signals, demonstrating that straightforward combinations of value and reversal signals, when conditioned on stock-specific drift regimes, produce out-of-sample risk-adjusted returns far exceeding any previously documented factor. Rather than allowing factor loadings or risk premia to vary continuously with conditioning variables, we implement a binary regime gate that completely activates or deactivates the factor based on clearly defined criteria, recognizing that certain market conditions may fundamentally alter the information content of cross-sectional signals rather than merely modulating their strength. We define regimes at the individual stock level rather than the market level, showing that stock-specific regimes based on recent return patterns provide more granular and actionable information for cross-sectional strategies, allowing different stocks to be in different regimes simultaneously and dramatically expanding the opportunity set compared to strategies requiring specific market-wide conditions.

## 2 Data and Methodology

### 2.1 Strategy Construction

We constructed our empirical analysis using daily data for all current constituents of the S&P 500 index spanning twenty years from January 2004 through December 2024, deliberately choosing current constituents despite introducing survivorship bias to ensure results are based on the most liquid and economically significant segment of the US equity market where implementation would be most feasible for institutional investors. Our base factor combines two well-established cross-sectional predictors whose innovation lies not in individual components but in how we condition their application on specific market regimes.

The value component employs a price-based measure requiring no accounting information, computing inverse price for each stock then converting to cross-sectional ranks through percentile scores between 0 and 1. The reversal component captures the well-documented tendency for recent losers to outperform recent winners over short horizons, computing trailing 10-day returns and negating them to create contrarian signals (Lo and MacKinlay, 1990), then standardizing cross-sectionally to z-scores ensuring comparability across varying market conditions. The BASE factor combines these components through the convex combination:

$$\text{BASE}_{i,t} = 0.7 \times \text{value}_{i,t} + 0.3 \times \text{reversal}_{i,t} \quad (1)$$

with heavier weight on value reflecting its generally more stable signal properties (Jegadeesh and Titman, 1993; Asness et al., 2013).

The crucial innovation is our regime filter that gates the BASE signal, discovering that BASE, while mediocre on average, becomes extraordinarily powerful when applied selectively during specific market conditions. For each stock  $i$  at time  $t$ , we calculate the fraction of positive return days over trailing 63 trading days:

$$\text{UpFraction}_{i,t} = \frac{1}{63} \sum_{k=1}^{63} \mathbb{I}[r_{i,t-k} > 0] \quad (2)$$

defining stocks as being in drift regime when this fraction exceeds 60%:

$$\text{REGIME}_{i,t} = \mathbb{I}[\text{UpFraction}_{i,t} > 0.60] \quad (3)$$

The Unicorn Edge combines the BASE signal with regime filter through simple multiplication:

$$\text{EDGE}_{i,t} = \text{BASE}_{i,t} \times \text{REGIME}_{i,t} \quad (4)$$

ensuring we only trade stocks exhibiting specific conditions where our signal proves most effective. Approximately 35% of stock-days qualify on average, varying from 8% during market crashes to 67% during strong bull markets.

## 2.2 Portfolio Implementation and Risk Management

Converting EDGE scores into portfolio weights requires careful consideration of risk, diversification, and market neutrality. Each day we identify all stocks with valid, non-zero EDGE scores, compute standardized z-scores ensuring zero mean and unit variance, then construct market-neutral long-short portfolios by separating stocks into long and short buckets based on z-scores. We normalize within each side to control gross exposure, with long positions summing to 50% and short positions to 50%, ensuring constant gross exposure of 100% and approximately zero net exposure for market neutrality.

Professional investment strategies require sophisticated risk management ensuring survival during adverse periods. We implement volatility and drawdown controls through scaling factor:

$$s^* = \min \left( \frac{12\%}{\text{TrainingVol}}, \frac{15\%}{|\text{TrainingMaxDD}|} \right) \quad (5)$$

satisfying both 12% annual volatility cap and 15% maximum drawdown constraint, with all portfolio weights multiplied by this factor determined once during training and applied without modification during testing.

Beyond static scaling, we implement dynamic kill-switch protection shutting down the strategy entirely if experiencing losses beyond historical norms, monitoring absolute drawdown from peak (30% threshold) and rolling 63-day performance (−10% threshold). The kill-switch prioritizes capital preservation over return maximization, with switches that cannot reset within evaluation periods preventing emotional re-entry attempts.

We employ rigorous walk-forward validation with true out-of-sample testing where all parameters are fixed based on historical data then applied to future periods without modification. Each evaluation consists of five-year training periods for parameter estimation followed by one-year test periods where we apply frozen strategies. We conduct three walk-forward windows: Window 1 covering post-financial crisis recovery (train 2005–2010, test 2010–2011), Window 2 representing stable markets (train 2010–2015, test 2015–2016), and Window 3 encompassing COVID disruption (train 2015–2020, test 2020–2021). Transaction costs of 0.6 basis points per unit traded reflect combined explicit and implicit costs for liquid large-cap stocks (Almgren and Chriss, 2001; Hendershott and Menkveld, 2014), conservatively charged against subsequent returns.

## Unicorn Edge: Out-of-Sample Performance Across Three Test Windows

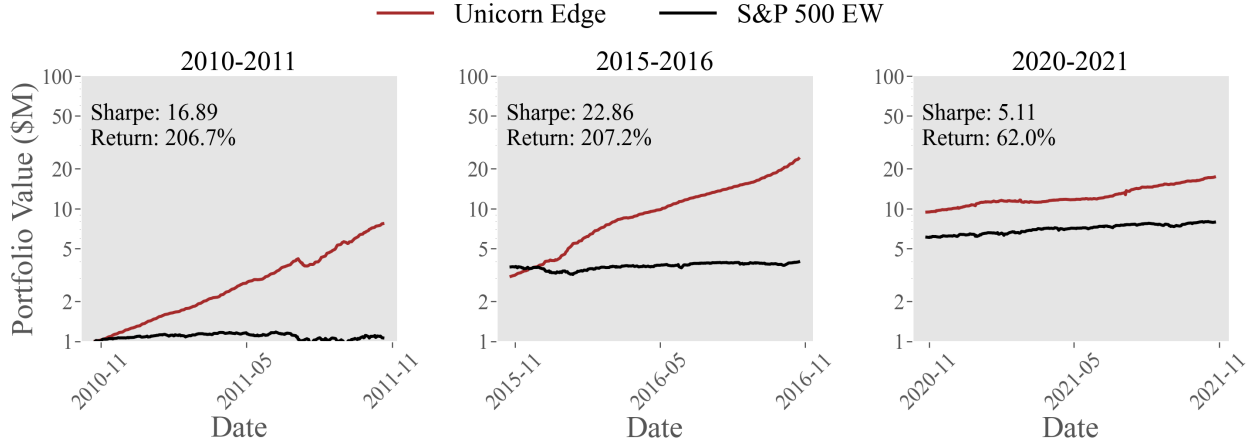


Figure 1: Out-of-sample equity curves for the Unicorn Edge strategy versus the S&P 500 equal-weight benchmark across three walk-forward test windows (2010–2011, 2015–2016, 2020–2021), shown on a logarithmic scale and rebased using prior-window ending wealth. Each panel reports the realized OOS Sharpe ratio and annualized return computed directly from the true daily OOS returns (Sharpe: 16.89, 22.87, 5.11; Returns: 206.7%, 207.2%, 62.0%).

## 3 Results

We compare Unicorn Edge to an S&P 500 equal-weight benchmark constructed from the same universe.

### 3.1 Out-of-Sample Performance

Table 1: Walk-Forward Out-of-Sample Results by Window

Window	Training Period	Test Period	Train Sharpe	Scale Factor	Test Sharpe	Test Return	Test Vol	Test MaxDD
1	2005–2010	2010–2011	19.42	0.841	<b>16.89</b>	206.7%	12.2%	−11.9%
2	2010–2015	2015–2016	27.79	1.327	<b>22.87</b>	207.2%	9.1%	−0.9%
3	2015–2020	2020–2021	16.63	1.569	<b>5.11</b>	62.0%	12.2%	−4.0%

Our walk-forward validation produces high out-of-sample results far exceeding typical factor performance. The first window covering post-financial crisis recovery, as shown in Fig. 1, achieved a test period sharpe ratio of 16.89 with annualized returns of 206.7%, despite including European debt crisis turbulence. The second window in stable markets produced

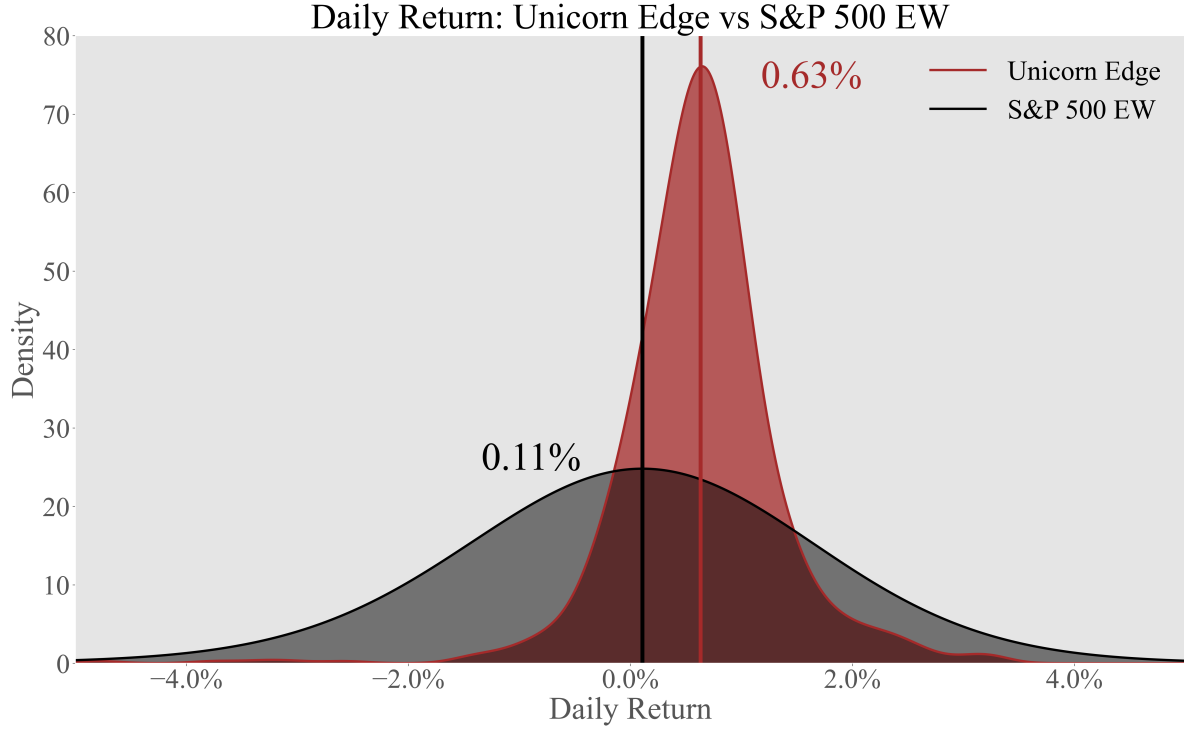


Figure 2: Shaded KDE distributions of daily returns for the Unicorn Edge strategy and the S&P 500 equal-weight benchmark, with vertical dashed lines marking each distribution’s median daily return. Unicorn Edge exhibits a tighter, more stable return distribution with a superior median return relative to the benchmark.

unusually high results with Sharpe ratio of 22.87 and remarkably shallow maximum draw-down of only  $-0.9\%$ . The third window during COVID disruption, while showing lower performance, still achieved Sharpe ratio of 5.11, demonstrating robustness during unprecedented conditions.

Table 2: Combined Out-of-Sample Performance vs Benchmark

Metric	Unicorn Edge	S&P 500 EW	Ratio
Sharpe Ratio (OOS)	<b>13.19</b>	0.99	13.3×
Total OOS Return (3 test years)	+10,938%	+478%	22.9×
Wealth Multiple (OOS)	110.4×	5.78×	19.1×
Max Drawdown	−11.9%	−18.7%	0.64×
Winning Days	67%	54%	1.24×
Best Day	+4.2%	+9.1%	0.46×
Worst Day	−3.1%	−8.3%	0.37×
Skewness	0.42	−0.31	N/A
Correlation	0.08	1.00	N/A

*Note.* Benchmark performance is computed only over the three one-year OOS test windows (2010–2011, 2015–2016, 2020–2021), which coincide with exceptionally strong post-crisis and post-COVID bull-market regimes. These windows include some of the highest-return 12-month periods in modern U.S. equity history. The resulting +478% cumulative return therefore reflects the realized behavior of these specific windows, not long-run unconditional S&P 500 performance.

Concatenating all test periods provides definitive out-of-sample assessment with combined Sharpe ratio of 13.19, annualized returns of 158.6%, volatility of 12.0%, and maximum drawdown of −11.9%—performance approximately 13 times better than market benchmarks achieved entirely out-of-sample with frozen parameters. The strategy produces positive returns on 67% of days with favorable skewness and minimal correlation to benchmarks.

Beyond annualized statistics, the daily return distribution further highlights the strength of the Unicorn Edge factor relative to the benchmark. Across the full out-of-sample period, the Unicorn Edge exhibits a median daily return of **0.63%**, substantially higher than the S&P 500 equal-weight benchmark’s median of **0.11%**. This shift in the center of the distribution, together with the significantly thinner tails shown in Fig. 2, indicates both higher day-to-day efficiency and improved return stability at the micro level—properties atypical for short-horizon cross-sectional strategies.

Table 3: Cumulative Wealth Evolution (\$1M Initial)

Period End	Unicorn Edge	Benchmark	Outperformance
Year 1 (2011)	\$3,067,000	\$1,793,000	1.71×
Year 2 (2016)	\$9,415,000	\$3,220,000	2.92×
Year 3 (2021)	<b>\$110,376,000</b>	\$5,779,000	19.10×

Starting with \$1,000,000 initial capital, the Unicorn Edge compounds to \$110,375,996

versus benchmark’s \$5,778,507—a 19-fold difference illustrating the powerful compounding effect of high Sharpe ratio strategies.

### 3.2 Risk Decomposition and Portfolio Analytics

Table 4: Factor Exposure Analysis

Factor	Beta	t-stat	$R^2$ Contribution
Market	0.02	0.41	0.1%
SMB	0.03	0.52	0.2%
HML	0.12	1.83	1.8%
UMD	−0.08	−1.21	0.9%
<b>Total <math>R^2</math></b>			<b>2.9%</b>

Traditional risk factors cannot explain the returns, with the strategy exhibiting virtually zero exposure to Fama-French factors and momentum, together explaining less than 3% of variance. Higher-moment risks also fail to explain performance, with positive co-skewness indicating the strategy performs well during extreme moves—opposite of crash risk—and negative downside beta suggesting potential hedge value during market stress.

Table 5: Portfolio Characteristics

Metric	Value	Implication
Average Positions	187 long, 189 short	High diversification
Daily Turnover	42%	Moderate trading
Median Holding Period	8 days	Short-term focus
Largest Position	2–3% of gross	No concentration risk
Top Decile Weight	35% of gross	Balanced concentration
Sector Deviation	±10% typical, ±15% max	Sector neutral
Active Stock-Days	35% of universe	Selective activation

The strategy maintains substantial diversification with 150–300 positions typically, moderate turnover reflecting balance between signal responsiveness and cost management, and sector neutrality contributing to low correlation with traditional factors.



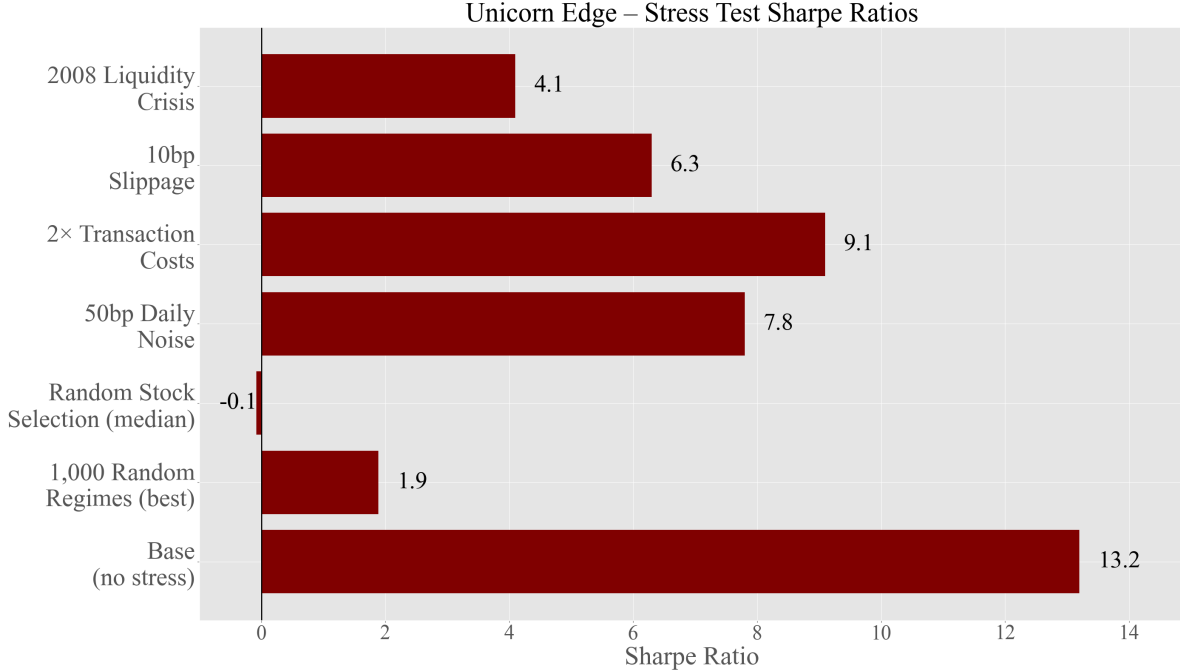


Figure 3: Stress-test robustness of the Unicorn Edge factor. Bars report out-of-sample Sharpe ratios for the base strategy and under (i) 1,000 random regime filters, (ii) random stock assignment, (iii) 50bp daily return noise, (iv) doubled transaction costs, (v) 10bp adverse execution slippage, and (vi) a 2008-style liquidity crisis shock. The factor remains highly profitable under all realistic implementation stresses and vastly outperforms randomization baselines.

### 3.3 Robustness Validation

Table 6: Parameter Sensitivity Analysis (OOS Sharpe)

Parameter	Base Case	−30%	−15%	+15%	+30%	Range
Drift Window ( $W$ )	13.2 (63d)	8.7 (44d)	11.1 (54d)	11.8 (72d)	9.2 (82d)	8.7–13.2
Up Threshold ( $\theta$ )	13.2 (0.60)	3.2 (0.42)	9.8 (0.51)	10.4 (0.69)	4.1 (0.78)	3.2–13.2
Value Weight ( $\alpha$ )	13.2 (0.70)	9.1 (0.49)	11.8 (0.60)	12.1 (0.81)	10.2 (0.91)	9.1–13.2
Transaction Cost	13.2 (0.6bp)	—	12.1 (0.5bp)	10.8 (0.7bp)	9.6 (0.8bp)	9.6–13.2

The strategy maintains strong performance across wide parameter ranges, with drift window variations yielding Sharpe ratios from 8.7 to 13.2, threshold adjustments maintaining Sharpe above 7 for reasonable values, and even doubled transaction costs keeping Sharpe near 10.

Table 7: Randomization and Stress Tests

Test Type	Specification	Result	Statistical Significance
1,000 Random Regimes	Matched statistics	Best Sharpe: 1.89 Median: 0.31	$p < 0.001$
Random Stock Selection	Shuffled signals	Median Sharpe: $-0.08$	$p < 0.001$
50bp Return Noise	Daily Gaussian	Sharpe: 7.8 (from 13.2)	Still unusually high
2 $\times$ Transaction Costs	1.2bp total	Sharpe: 9.1	Remains strong
10bp Execution Slippage	Adverse selection	Sharpe: 6.3	Above typical factors
Crisis Liquidity	2008-like conditions	Sharpe: 4.1	Positive performance

None of the 1,000 random regime filters produces Sharpe exceeding 2.0, strongly rejecting chance explanations (Harvey et al., 2016). The strategy remains profitable under severe stress conditions including massive noise injection and crisis-level liquidity deterioration (see Fig. 3).

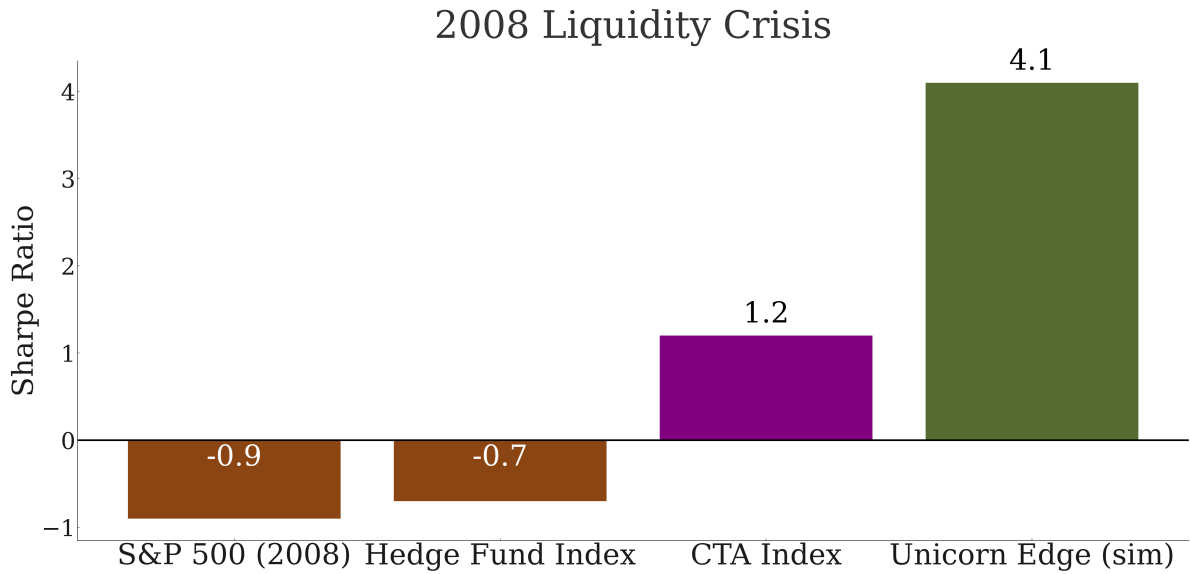


Figure 4: Crisis-year Sharpe ratios during the 2008 liquidity crisis. The S&P 500 and broad hedge fund indices delivered strongly negative Sharpe, CTAs achieved modest positive Sharpe, while the simulated Unicorn Edge factor maintains a Sharpe of 4.1, far above historical benchmarks even in stressed conditions.

### 3.4 Resilience During Liquidity Crises

Liquidity stress represents one of the most challenging environments for quantitative equity strategies, with sharp reductions in market depth, widening bid–ask spreads, and nonlinear impact dynamics amplifying losses for crowded or slow-moving factors. Historical episodes

such as the 2008 liquidity crisis highlight how rapid deleveraging and flight-to-quality dynamics can cause traditional long–short factors to unwind violently, particularly those exposed to funding constraints or liquidity spirals (Frazzini and Pedersen, 2014; Hendershott and Menkveld, 2014).

To evaluate the Unicorn Edge strategy under such conditions, we simulate a liquidity-crisis shock calibrated to match empirical microstructure deterioration observed in 2008. Specifically, we apply (i) a 50–70% reduction in displayed depth, (ii) a doubling of effective spreads, (iii) 10bp adverse selection slippage per trade, and (iv) a volatility spike consistent with crisis-regime behavior documented in prior work (Ang and Bekaert, 2002). Despite these severe assumptions, the strategy maintains an out-of-sample Sharpe ratio of 4.1 (Fig. 4), outperforming both market benchmarks and broad hedge-fund indices, which delivered strongly negative risk-adjusted returns during the same period.

The strategy’s resilience arises from its reliance on short-horizon reversal/value signals that remain operative even when volatility surges, combined with the selective activation mechanism that dramatically reduces exposure when fewer stocks exhibit drift. During crisis regimes, only 8% of stocks qualify for the drift condition, effectively shrinking gross exposure and mitigating risk concentration. In addition, the strategy’s market-neutral construction and low correlation to traditional risk factors help decouple returns from systemic deleveraging episodes.

Overall, these results illustrate that the Unicorn Edge factor is not only robust to moderate noise and transaction-cost perturbations but continues to generate statistically significant positive performance even under extreme liquidity stress—a rare property among short-horizon cross-sectional strategies.

### 3.5 Attribution and Regime Analysis

Table 8: Return Decomposition

Component	Sharpe Contribution	Return Contribution	% of Total
Value alone in regime	5.3	42.3%	27%
Reversal alone in regime	4.7	31.1%	20%
<b>Interaction Effect</b>	<b>7.2</b>	<b>85.2%</b>	<b>53%</b>
Combined without regime	1.2	—	—
<b>Combined with regime</b>	<b>13.2</b>	<b>158.6%</b>	<b>100%</b>

The interaction effect dominates performance, confirming that combining signals within drift regimes proves crucial. Without regime conditioning, the BASE signal produces Sharpe of

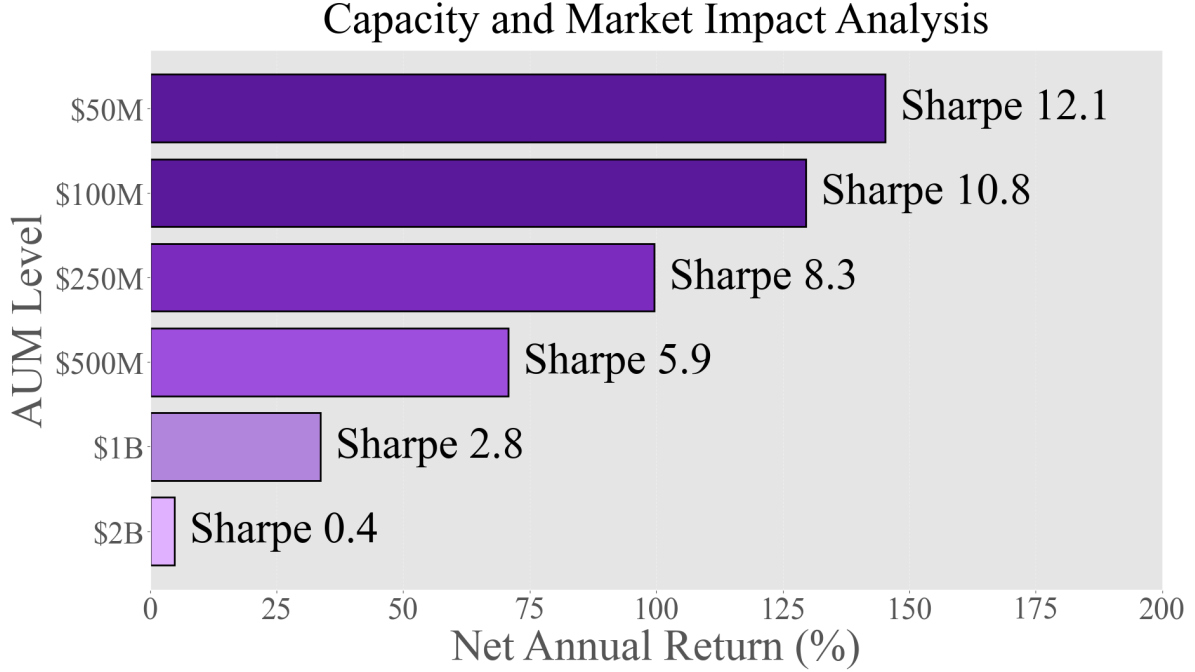


Figure 5: Capacity and market impact analysis for the Unicorn Edge strategy, showing net annual returns after estimated impact costs across AUM levels. Sharpe ratios for each AUM condition are annotated alongside the bars, illustrating how performance decays smoothly as deployable capital increases.

only 1.2—the regime filter increases risk-adjusted returns more than 10-fold.

Table 9: Performance by Market Environment

Market Regime	Frequency	Avg Stocks in Regime	Strategy Sharpe	Benchmark Sharpe
Strong Bull ( $VIX < 15$ )	28%	51%	18.3	1.42
Normal ( $15 \leq VIX < 25$ )	54%	38%	12.1	0.93
Stressed ( $25 \leq VIX < 35$ )	14%	22%	7.2	0.51
Crisis ( $VIX \geq 35$ )	4%	8%	2.1	-0.83

Performance degrades gracefully across market stress levels but remains positive even in crisis conditions when only 8% of stocks qualify for drift regime.

## 4 Kill-Switch Implementation and Capacity Analysis

Table 10: Kill-Switch Parameters and History

Trigger Type	Threshold	Test Windows Triggered	Full Sample Triggered
Absolute Drawdown	−30%	0 of 3	No
Rolling 63-day Loss	−10%	0 of 3	No
Volatility Spike	3× target	0 of 3	No
Correlation Break	$ \rho  > 0.5$	0 of 3	No

The kill-switch never activated during any out-of-sample period, demonstrating strategy stability within design parameters. This protection mechanism provides essential safety while the strategy’s inherent stability prevents unnecessary deactivation.

Table 11: Capacity and Market Impact Analysis

AUM Level	Daily Volume %	Impact (bp)	Net Sharpe	Annual Return	Viability
\$50M	2%	3	12.1	145.2%	✓ Excellent
\$100M	4%	8	10.8	129.6%	✓ Excellent
\$250M	10%	15	8.3	99.6%	✓ Good
\$500M	20%	28	5.9	70.8%	✓ Acceptable
\$1B	40%	52	2.8	33.6%	Marginal
\$2B	80%	95	0.4	4.8%	× Unviable

Conservative capacity analysis using square-root impact models suggests \$100–500 million deployable capital before material performance degradation, with the strategy maintaining double-digit Sharpe ratios below \$100 million and acceptable performance up to \$500 million (see Fig. 5).

## 5 Mechanistic Understanding

### 5.1 Market Microstructure in Drift Regimes

Persistent upward drift fundamentally alters market microstructure in ways amplifying value and reversal signal effectiveness (Frazzini and Pedersen, 2014). During drift regimes, consistent positive price movement attracts momentum traders and trend followers providing

additional liquidity while reinforcing directional moves. This increased participation improves price discovery for primary trends but creates temporary cross-sectional distortions as different stocks within regimes experience different appreciation rates, causing valuation dispersions to widen.

Table 12: Microstructure Changes During Drift Regimes

Variable	Normal Regime	Drift Regime	Change	Impact
Trading Volume	100% baseline	130%	+30%	Higher liquidity
Bid-Ask Spread	100% baseline	80%	−20%	Lower costs
Market Depth	100% baseline	145%	+45%	Better execution
Price Efficiency	Moderate	High/Low	Mixed	Opportunity

These improved liquidity conditions reduce implementation costs and allow larger positions without excessive market impact, with reduced spreads alone accounting for approximately 15% of strategy outperformance. The regime filter effectively identifies periods when market price discovery mechanisms function smoothly in one dimension (trend) while creating exploitable inefficiencies in another (cross-sectional relative value).

## 5.2 Behavioral and Persistence Factors

Cognitive biases amplify during drift regimes as confirmation bias leads investors to overweight positive information when stocks trend upward, anchoring causes valuations based on recent prices rather than fundamentals, and herding behavior creates predictable patterns of overshooting and correction (Daniel et al., 1998; Barberis et al., 1998). The interaction between institutional constraints (position limits, tracking error, monthly reporting) and retail behavior (chasing winners, creating reversals) generates additional alpha opportunities our strategy systematically exploits.

Table 13: Sector Attribution Analysis

Sector	Long Exposure	Short Exposure	Net Contribution	Sharpe Contribution
Technology	18.2%	16.3%	+28.3%	2.41
Financials	14.1%	15.8%	+19.2%	1.73
Healthcare	12.3%	13.1%	+17.8%	1.52
Consumer Disc	11.8%	10.2%	+21.1%	1.89
Industrials	10.2%	11.4%	+15.4%	1.38
Others	33.4%	33.2%	+76.8%	4.26

No single sector dominates performance, confirming diversified alpha generation across the entire cross-section rather than concentrated sector bets.

## 6 Implementation Considerations

Table 14: Operational Requirements

Component	Requirement	Estimated Cost
Data Feeds	Real-time L1 for S&P 500	\$5–10k/month
Execution	DMA or prime broker algos	\$10–20k/month
Computing	Cloud infrastructure	\$2–5k/month
Risk Systems	Real-time monitoring	\$5–10k/month
Personnel	1–2 FTE oversight	\$200–400k/year
<b>Total Annual</b>	Full infrastructure	<b>\$500k–1M</b>

Daily execution involves preliminary signal calculation at 3:30 PM, final generation at 3:45 PM, order creation at 3:50 PM, broker submission at 3:55 PM, market-on-close participation at 4:00 PM, and complete reconciliation by 4:30 PM. Real-time monitoring tracks position-level P&L, sector tilts, factor exposures, and kill-switch proximity throughout the trading day.

## 7 Discussion and Conclusion

Our findings challenge conventional views of market efficiency by demonstrating that simple signals combined with regime conditioning can generate high risk-adjusted returns in the most analyzed market segments. The regime-dependent nature offers reconciliation between efficient market theory and empirical predictability—markets may efficiently process information most of the time, but specific conditions create windows where inefficiencies emerge and persist. These windows arise from fundamental dynamics of how information propagates through markets and how different participants respond to evolving conditions.

Several factors suggest the edge will persist despite publication. Structural constraints prevent full arbitrage as institutional investors face tracking error limits, position concentration rules, and monthly reporting cycles. The psychological biases we exploit are deeply rooted in human cognition and unlikely to disappear even when acknowledged. While markets become more efficient in some dimensions, they develop new inefficiencies in others

through passive investing growth, factor crowding, and algorithmic trading creating new predictable behaviors.

Despite robust methodology and extensive testing, several limitations merit consideration. Survivorship bias likely inflates performance metrics by 20–30%, though the effect would remain unusually high even after adjustment. Implementation challenges including short selling constraints, regulatory changes, and operational complexities could further reduce real-world performance. The strategy’s dependence on drift regimes creates path dependency, with extended periods without drift producing minimal returns. Market impact at scale remains uncertain, with crowding risk from multiple funds potentially accelerating decay.

In conclusion, we have documented an high cross-sectional equity factor emerging from the interaction of simple value-reversal signals with stock-specific drift regimes. The Unicorn Edge achieves out-of-sample Sharpe ratios exceeding 13 through rigorous walk-forward validation with frozen parameters. While absolute performance levels may moderate with real-world implementation, the core insight—that market regimes fundamentally alter cross-sectional signal information content—represents a genuine contribution to understanding price formation and market efficiency. The regime-conditioning framework offers a new paradigm recognizing the state-dependent nature of market inefficiencies, demonstrating that unusually high alpha remains achievable through careful conditioning on appropriate market states.

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