

Enhancing Kairos: A Quantitative Strategy Enhancement Blueprint

From a ~1.0 Active Sharpe baseline, systematic enhancements across six dimensions can reasonably target **1.5-2.0 Active Sharpe** within 12-18 months. The highest-impact opportunities are transitioning to long-short (20-50% Sharpe improvement), adding gross profitability and protected momentum factors (+0.15-0.3 Sharpe each), implementing ML-based factor combination (potentially doubling Sharpe vs. linear methods per Gu-Kelly-Xiu 2020), and applying volatility targeting (+0.1-0.2 Sharpe). This report provides specific academic evidence, implementation guidance, and data source recommendations for each enhancement area.

Long-short construction unlocks full alpha expression

The 130/30 structure represents the optimal balance of alpha expression and implementation complexity for benchmark-aware strategies. Academic research from Clarke, de Silva, Thorley, and Sapra establishes 130/30 as mathematically optimal, ([Meketa Investment Group](#)) while Lo & Patel (2008) in the *Journal of Portfolio Management* demonstrated significant advantages over long-only with manageable complexity. Regulation T caps the short side at 50%, making 150/50 the practical maximum.

Expected improvements are substantial but require realistic expectations. Picton Mahoney's 130/30 backtest showed **570 bps annual outperformance** with Sharpe improvement from 0.38 to 0.72. However, the short side is structurally harder—Alpha Theory estimates a **~9% annual disadvantage** from market headwind (~5%), borrowing costs (~2%), management intensity (~1%), and return asymmetry (~1%). Stambaugh, Yu & Yuan (2015) in the *Journal of Finance* documented "arbitrage asymmetry"—the relation between idiosyncratic volatility and alpha is positive among underpriced stocks but negative and stronger among overpriced stocks.

([Alpha Architect](#))

For short book construction, focus on larger-cap liquid stocks (83-84% of institutional short interest is in General Collateral stocks with 17-30 bps annual cost). Hard-to-borrow stocks underperform by **12-19% annually** per Henderson, Jostova & Philipov, but high borrow fees largely offset profits. The best use of borrow fee data may be avoiding high-fee stocks in the long book rather than shorting them.

Configuration	Long	Short	Net	Expected Sharpe Improvement
Conservative Start	115%	15%	100%	+10-20%
Standard 130/30	130%	30%	100%	+20-40%
Aggressive	150%	50%	100%	+30-50%

Implementation complexity: High. Requires prime brokerage setup, borrow cost monitoring (assume 0.75% annually for GC stocks in backtests), margin management, and compliance with Rule 201 (alternative uptick

rule) and new Rule 13f-2 (monthly Form SHO filing for positions $\geq \$10M$ or $\geq 2.5\%$ of shares outstanding, effective January 2, 2025). **(ACA Group)** Position sizes should be asymmetric: **1.5-2% maximum for shorts** versus 3-4% for longs due to unlimited loss potential.

High-value alternative factors complement existing quality and value

Gross profitability: The single most valuable addition

Novy-Marx (2013) in the *Journal of Financial Economics* demonstrated that gross profitability (Revenue minus COGS divided by Total Assets) has "as much power as book-to-market predicting cross-sectional returns." Critically, it provides **value-like returns with growth characteristics**, offering an excellent hedge for value positions. A March 2025 Novy-Marx & Medhat paper confirms profitability explains "multiple widely-studied, seemingly disparate anomalies."

Expected contribution: +0.15-0.2 Sharpe, IC of 0.04-0.06. Implementation is easy—standard financial statement data, already available in Sharadar SF1. This factor distinguishes "bargain stocks" from "value traps" and combining with value increases returns while reducing volatility and drawdowns.

Days-to-cover outperforms simple short interest

Hong, Li, Ni, Scheinkman & Yan (2016) showed days-to-cover generates **1.2% monthly return** (14.4% annualized) on long-short strategies, outperforming simple short interest ratio in 20 of 25 years tested. The signal maintains predictive power internationally and works best in less liquid stocks.

Expected contribution: +0.1-0.15 Sharpe (short side primarily). Implementation complexity is medium—requires bi-monthly FINRA data with 11-day delay, or ORTEX (\$39/month) for daily updates. Calculate as Short Interest Ratio divided by Average Daily Turnover.

Protected momentum addresses crash risk

Daniel & Moskowitz (2016) documented momentum crashes of **-49.79%** in the worst month, occurring during market reversals from bear to bull markets. Multiple protection strategies exist:

- **Constant Volatility Scaling (Barroso & Santa-Clara 2015):** 15.3% annual return, Jensen's alpha of 1.93%, reduces drawdowns by ~50%
- **Idiosyncratic Momentum (Hanauer & Windmueller):** Best performer in multi-model tests, Sharpe improvement $>2x$ versus standard momentum
- **Stop-Loss Strategy (Han et al. 2016):** Reduces worst monthly return from -49.79% to -11.36%, doubles Sharpe for small caps

Expected contribution: +0.2-0.3 Sharpe with protection. Volatility scaling is now widely adopted by quant managers and essential for any momentum implementation.

Classic factors show varied decay status

Factor	Expected Alpha	Current Status	Complexity	Key Academic Source
Days-to-Cover	14.4% ann.	Moderate decay	Medium	Hong et al. (2016)
SUE/PEAD	2-9% quarterly	Significant decay in US large caps	Easy	Bernard & Thomas (1990)
Analyst Revisions	Similar to momentum	Resilient (MSCI 2025 confirms)	Medium	MSCI (2025)
Cluster Insider Buying	2.1% monthly	Still effective	Medium-Hard	Alldredge & Blank (2019)
Options Signals	40bps-11% ann.	Moderate, requires sophistication	Hard	Pan & Potoshman (2006)

PEAD has declined substantially from Bernard & Thomas's original 18% to near insignificance in US large caps, per Chordia et al. (2014). It still exists in small caps, international markets, and less-covered stocks. **Analyst revisions remain resilient**—MSCI's 2025 study confirms sentiment "remained a valuable and resilient factor" through 2022-2025 market turbulence. **Cluster insider buying** (3+ insiders buying within 2-14 days) generates 0.9% premium over solitary purchases, with C-suite purchases most informative. [\(2iqresearch\)](#)

Machine learning doubles Sharpe versus linear methods in academic tests

Gu, Kelly, and Xiu's 2020 *Review of Financial Studies* paper "Empirical Asset Pricing via Machine Learning" provides the foundational evidence: trees and neural networks are best-performing methods, with **out-of-sample R² unprecedented** compared to traditional approaches. [\(Oxford Academic\)](#) In some cases, ML methods doubled the Sharpe ratio of leading regression strategies. [\(Semantic Scholar\)](#)

Gradient boosting is most practical for production

XGBoost and LightGBM offer mature, interpretable, production-ready solutions with excellent SHAP integration. Key hyperparameters for financial data:

- **Learning rate:** Start low (0.01-0.1) with early stopping
- **Max depth:** Keep shallow (3-6 leaves)—financial data has low signal-to-noise ratio
- **Subsample:** 50-80% aggressive subsampling is beneficial
- **L2 regularization:** Set high (~1)

Expected IC improvement: 0.02-0.05 over linear methods. Implementation complexity is low-medium. Neural networks (3 hidden layers optimal per Kelly/Xiu research) offer additional nonlinear interaction capture but require more data and tuning.

Validation requires rigorous anti-bias measures

Harvey, Liu, and Zhu (2016) in the *Review of Financial Studies* ("...and the Cross-Section of Expected Returns") established that t-ratio thresholds should exceed **3.0** (not 2.0) for newly discovered factors. (SSRN) (NBER) Of 316 documented factors, most claimed findings are "likely false." (Oxford Academic) Harvey & Liu (2020) propose a **50% haircut to reported Sharpe ratios** as a rule of thumb for multiple testing adjustment. (Duke University)

López de Prado's *Advances in Financial Machine Learning* (2018) provides essential validation techniques:

- **Purging:** Remove training samples whose label horizon overlaps test period
- **Embargoing:** Remove samples after test fold end (typically 5% of observations)
- **Combinatorial Purged Cross-Validation (CPCV):** Generates multiple backtest paths for distribution of performance estimates

Libraries: (`timeseriescv`), (`mlfinlab`), (`shap`) for interpretability, (`evidently`) for drift detection.

Portfolio optimization gains come from shrinkage and volatility targeting

Shrinkage estimators are essential with 75 positions

Raw sample covariance with 75 positions is severely ill-conditioned. (PubMed Central) Ledoit-Wolf (2004) shrinkage toward a single-factor model is the minimum standard; (HAL) Ledoit-Wolf (2017) nonlinear shrinkage provides better eigenvalue correction for larger portfolios. **Expected improvement: +0.10-0.15 Sharpe, 10-50 bps out-of-sample.**

Implementation is trivial—available in scikit-learn and PyPortfolioOpt. This should be implemented immediately.

Black-Litterman integrates alpha signals naturally

Express your alpha signals as views in the Black-Litterman framework: (arXiv) absolute views ("AAPL will return 10%") or relative views ("GOOG outperforms FB by 3%"). (Readthedocs) Research shows Sharpe improvements of **~2.4x versus market index** when combining ML-generated views with Black-Litterman. (ResearchGate) The framework produces more stable portfolios with 30-50% reduction in turnover versus raw mean-variance optimization.

Implementation complexity: Medium-high. Use factor model residuals as views, set $\tau = 1/T$ where T = estimation period, and consider sector-relative views to avoid extreme bets.

Volatility targeting provides reliable improvement

Moreira & Muir (2017) in the *Journal of Finance* documented significant Sharpe improvement of **0.1-0.2** for risk assets through volatility targeting. The mechanism works via the leverage effect—volatility is negatively correlated with returns—and reduces left-tail events by scaling down when volatility is high.

For a 1.0 Active Sharpe strategy, target ~10-12% annualized tracking error. Implementation: Scale exposure by $\text{target_vol} / \text{realized_vol}$ (Research Affiliates) using trailing 20-30 day exponential-weighted volatility. Set reasonable leverage bounds (0.5x to 1.5x) and rebalance weekly or when volatility changes >20%.

Position sizing via fractional Kelly

The Kelly criterion suggests $f^* = (\mu - r) / \sigma^2$ for continuous investment. (Bsic) With ~1.0 Active Sharpe and 16% volatility, full Kelly implies ~156% leverage—far too aggressive for real-world application. **Fractional Kelly (0.25-0.5x) is standard practice:**

Fraction	Growth vs Full Kelly	Volatility vs Full Kelly
Full Kelly	100%	100%
Half Kelly	~75%	~50%
Quarter Kelly	~44%	~25%

Size positions by: $\text{position_size} = (\alpha_i / \sigma_i^2) \times \text{conviction} \times \text{scaling_factor}$, with maximum single position of 3-5%.

Risk management priorities for strategy resilience

Correlation breakdown during stress is the critical risk

Sandoval & Franca (2012) in *Nature Scientific Reports* documented that average correlation among DJIA stocks **increases linearly with market stress**—a universal pattern across 72 years of data. Page & Panariello (2018) in the *Financial Analysts Journal* confirmed "diversification fails when needed most," with left-tail correlations jumping 0.2-0.4 above normal levels.

Never use full-sample correlations alone in risk models. Build correlation regimes (normal using trailing 1-year, stress using crisis periods) and stress test monthly with crisis correlations. For a 75-position equity portfolio, assume intra-equity correlation $\rightarrow 0.6-0.8$ in stress.

Drawdown control via tiered deleveraging

Implement tiered deleveraging rather than binary stop-losses:

- **5% drawdown:** Monitor closely
- **10% drawdown:** Reduce gross exposure 25%
- **15% drawdown:** Reduce exposure 50%, review strategy

Use Conditional Drawdown-at-Risk (CDaR)—the average of worst $\alpha\%$ drawdowns—in optimization. Research shows 5-15% reduction in maximum drawdown versus variance-only optimization.

Factor hedging for long-short transition

When transitioning to long-short, always hedge market beta using E-mini S&P 500 futures (liquid, capital efficient). Rebalance hedge monthly or when beta drifts >0.1 . For factor neutralization, use factor ETFs (MTUM, QUAL, VLUE) to manage unwanted exposures.

Data architecture for factor expansion

Sharadar provides strong foundation with specific gaps

Sharadar via Nasdaq Data Link (~\$50-150/month) provides fundamentals (SF1, 16,000+ companies since 1990), prices (SEP, 20,000+ tickers since 1998), insiders (SF2, Form 4 since 2005), and institutional ownership (SF3, 13F since 2013). Critical gaps require supplementation:

Data Type	Recommended Source	Monthly Cost	Priority
Short Interest	ORTEX Basic	\$39	High
Earnings Estimates	Zacks via Nasdaq Data Link	~\$20-40	High
Alternative/Sentiment	Quiver Quant	\$25	Medium
Options Data	Cboe DataShop	Pay-per-use	Medium
ESG	Free web lookups	\$0	Low

Estimated total: \$150-300/month for comprehensive factor coverage.

ORTEX for short interest signals

ORTEX Basic (\$39/month) provides daily short interest updates versus FINRA's twice-monthly with 11-day

delay. Data includes shares on loan, utilization rate, days-to-cover, and cost-to-borrow metrics essential for both long-short construction and days-to-cover factor calculation.

Zacks for earnings estimates

Zacks via Nasdaq Data Link (~\$200-500/year) provides professional-grade earnings estimates with history since 1979, covering 4,500 US/Canadian companies. Includes consensus EPS estimates, revenue estimates, analyst ratings, and earnings surprises—sufficient for SUE construction and analyst revision momentum.

Quiver Quant for unique alternative data

Quiver Quant (\$25/month) provides uniquely valuable datasets: congressional trading (highly accurate versus SEC records), WallStreetBets sentiment, government contracts, and insider trading with predictive scores. The congressional trading dataset in particular offers **alpha unavailable from institutional data vendors**.

Implementation roadmap and priority matrix

Phase 1 (Months 1-3): Foundation enhancements

Enhancement	Expected Improvement	Complexity	Priority
Ledoit-Wolf shrinkage for covariance	+0.10-0.15 Sharpe	Low	Immediate
Gross profitability factor	+0.15-0.2 Sharpe	Easy	Immediate
Volatility targeting	+0.10-0.20 Sharpe	Low	Week 1
Asset growth factor	+0.10-0.15 Sharpe	Easy	Week 2
ORTEX + Zacks data integration	Enables new factors	Medium	Week 2

Phase 2 (Months 4-6): Factor expansion

Enhancement	Expected Improvement	Complexity	Priority
Protected momentum (vol-scaled)	+0.2-0.3 Sharpe	Medium	High
Days-to-cover factor	+0.1-0.15 Sharpe	Medium	High
Analyst revision momentum	Similar to momentum	Medium	Medium
XGBoost factor combination	+0.1-0.2 Sharpe vs linear	Medium	Medium

Enhancement	Expected Improvement	Complexity	Priority
Black-Litterman integration	+0.1-0.2 Sharpe	Medium-High	Medium

Phase 3 (Months 7-12): Long-short transition

Enhancement	Expected Improvement	Complexity	Priority
115/15 conservative long-short	+10-20% Sharpe	High	Phased
130/30 full implementation	+20-40% Sharpe	High	After validation
Beta hedging via futures	Risk reduction	Medium	Required
Drawdown control system	Risk reduction	Medium	Required

Critical warnings

- **Short-side alpha is lower:** Expect shorts to generate 50-70% of long-side alpha due to structural disadvantages
- **ML Sharpe degradation:** Apply 50% haircut to backtested Sharpe (Harvey & Liu 2020) Duke University
- **Factor decay:** PEAD has declined substantially; focus on resilient factors (profitability, analyst revisions)
- **Correlation breakdown:** Stress test with 0.6-0.8 intra-equity correlation assumptions
- **Borrowing costs:** 75 bps baseline for GC stocks can erode 50%+ of theoretical short alpha
- **Multiple testing:** Require t-statistic >3.0 for new factor significance NBER

Conclusion

The path from 1.0 to 1.5-2.0 Active Sharpe is achievable through systematic enhancement across portfolio construction, factor expansion, and risk management. **Immediate priorities** are implementing shrinkage estimators and volatility targeting (low complexity, reliable improvement), adding gross profitability (easy implementation, robust evidence), and integrating ORTEX/Zacks data to enable new factors. The long-short transition offers the largest potential improvement (+20-50% Sharpe) but requires significant infrastructure and realistic expectations about short-side alpha generation. Machine learning factor combination can potentially double Sharpe versus linear methods, but requires rigorous validation with purging, embargoing, and $t>3.0$ thresholds. Throughout implementation, maintain stress correlation assumptions and tiered drawdown controls —diversification fails precisely when needed most.

