ACMIO Quantitative Technologies Limited

Market-Neutral Long-Short Strategy

Seeking consistent returns in cryptocurrency markets
through disciplined, research-driven quantitative investing.

Strategy: Market-Neutral Long-Short Strategy
Asset Class: Liquid Digital Assets (Top 100)
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Contents

1 Executive Summary

This white paper describes the investment strategy of **ACMIO Quantitative Technologies Limited**, a systematic, market-neutral fund that seeks consistent risk-adjusted returns from cryptocurrency perpetual-futures markets. The strategy ranks the top-100 coins by market capitalisation at each rebalance, constructs a beta-neutral long–short portfolio, and targets performance that is uncorrelated with the broad crypto market.

The core thesis rests on a simple observation: cryptocurrency markets exhibit persistent pricing inefficiencies driven by behavioural dispersion, informational fragmentation, and structural frictions. Because the strategy profits from *relative* performance rather than market direction, it can generate returns in both bull and bear regimes.

The fund combines research-driven signals with machine-learning ensembles to produce a composite forecast. Rigorous signal evaluation, realistic transaction-cost modelling, and disciplined risk management form the backbone of the investment process.

Strategy at a Glance

Style	Systematic, quantitative
Structure	Market-neutral long–short
Universe	Multi-tier: large-cap, mid-cap, full top-100
Rebalance	Daily
Signals	Technical, fundamental, positioning
Combination	Plain alpha + ML ensemble
Risk	β-neutral, market-neutral, drawdown control

How It Works — In Three Steps

Step 1 | Rank. Every day, the system scores each coin in the universe using hundreds of research-driven signals spanning price momentum, volatility, funding rates, and market sentiment.

Step 2 | Build. The highest-ranked coins form the *long basket* (expected outperformers); the lowest-ranked coins form the *short basket* (expected underperformers). The portfolio is constructed to be beta-neutral — its sensitivity to broad market moves is targeted at zero — so returns depend on coin selection, not market direction.

Step 3 | Protect. Real-time drawdown monitors, intraday stop-losses, and concentration limits safeguard capital at every level.

2 Introduction

2.1 Market Opportunity

The cryptocurrency derivatives market represents hundreds of billions of dollars in daily trading volume. Unlike traditional stock or bond markets, crypto markets operate 24 hours a day, 7 days a week. They exhibit wider dispersion of returns across different coins and attract a broad mix of participants—from individual traders to large institutions. These structural features create fertile ground for systematic, research-driven strategies.

Perpetual contracts—futures without an expiry date—are the dominant derivative instrument in crypto. They offer deep liquidity, tight bid–ask spreads for the largest coins, and the ability to go both long and short. A built-in *funding-rate* mechanism keeps the perpetual price anchored to the spot price and provides an additional data signal for the strategy.

Key Insight

Cryptocurrency markets operate 24/7, creating continuous pricing inefficiencies across time zones and trading sessions. Systematic strategies can exploit these dislocations around the clock.

2.2 Why Top-100 Market Capitalisation

The investment universe is restricted to the top 100 coins by market capitalisation that have active perpetual-futures contracts on major exchanges. This filter serves several purposes.

First, it ensures adequate **liquidity**: top-100 coins represent the vast majority of futures trading volume, reducing slippage and execution risk. Second, it mitigates **delisting risk**: coins that fall outside the top 100 tend to suffer from declining liquidity and heightened blow-up risk. Third, a universe of approximately 100 instruments provides sufficient **breadth** to build well-diversified long–short portfolios.

The universe is reconstituted periodically based on trailing average market capitalisation to avoid whipsaw from short-lived capitalisation spikes.

2.3 Multi-Tier Universe

Within the broad top-100 universe, the strategy operates across several capitalisation tiers. A **large-cap tier** focuses on the most liquid, highest-capitalisation assets where capacity is deepest and execution costs are lowest. A **mid-cap tier** broadens the opportunity set and benefits from wider cross-sectional dispersion. The **full universe** encompasses the entire top-100 to maximise diversification.

Each tier is run as a self-contained sub-strategy with its own portfolio-construction and risk parameters. This tiered design allows the fund to allocate capital across the liquidity spectrum and to blend the tiers in a way that balances capacity, alpha potential, and risk.

Key Insight

Operating across multiple capitalisation tiers reduces reliance on any single market segment. Large-cap tiers provide execution efficiency; mid-cap tiers offer wider cross-sectional dispersion; the full universe maximises diversification.

3 Investment Philosophy

We believe that fundamentals, market structure, and behavioural dynamics ultimately drive cryptocurrency prices over time. We look for opportunities where a coin's futures price has moved away from our estimate of its fair value relative to peers. We combine traditional finance insights with crypto-native data and advanced quantitative techniques to keep our process adaptive and evolving.

3.1 Long-Term Sustainable Factors

Academic research [10, 12] shows that well-known return drivers—momentum, value, carry, and sentiment—also work in cryptocurrency markets. We build on these findings by constructing factors specifically tuned to the crypto perpetual-futures setting, grounded in both economic theory and behavioural finance.

3.2 Efficient Targeting of Factor Exposures

Our adaptive framework dynamically weights each factor to reflect its current strength and the prevailing market regime. This combination of top-down systematic views and bottom-up coin-by-coin analysis produces a well-rounded portfolio.

3.3 Pursuit of Consistent Alpha

Disciplined risk management keeps factor exposures pure, while portfolio construction is calibrated to balance expected return against risk. Transaction-cost controls—including funding-rate awareness and slippage modelling—help maximise the returns that actually reach investors.

3.4 Wide Coverage

Our strategies span the entire top-100 perpetual-futures universe, with design principles built to navigate bull, bear, and range-bound market cycles.

3.5 Beta Neutrality and Market Neutrality

The strategy's primary hedging constraint is **beta neutrality**. Because individual coins have heterogeneous sensitivities to the broad market, equal dollar exposure on the long and short sides does not, by itself, eliminate directional risk. Beta neutrality addresses this directly:

$$\sum_i w_i \, \beta_i \;=\; 0 \tag{1}$$

where β_i is the rolling beta of coin i to a cap-weighted crypto index and w_i is the signed portfolio weight. This constraint targets zero sensitivity to broad market moves, even when individual coins respond to those moves with different magnitudes.

In addition, the portfolio maintains **dollar neutrality** as a structural baseline:

$$\sum_{i \in \mathcal{L}} w_i \;=\; -\sum_{j \in \mathcal{S}} w_j \tag{2}$$

where $\mathcal{L}$ and $\mathcal{S}$ denote the long and short baskets. Together, the two constraints provide a robust hedge against both uniform and beta-weighted market movements.

Key Insight

Because the portfolio targets zero beta to the broad crypto market, returns are driven by coin-selection skill rather than market direction. This is why the strategy can target positive returns in both rising and falling markets.

3.6 Sources of Edge

Three structural features create persistent cross-sectional inefficiencies.

Behavioural dispersion. Retail-dominated flow exhibits herd behaviour, attention cascades [3], and sentiment extremes that manifest differently across coins.

Informational fragmentation. Data is scattered across exchanges, on-chain explorers, and social platforms. Systematic aggregation provides an edge over discretionary participants.

Structural friction. Funding rates, margining rules, and exchange-specific events create temporary dislocations in relative pricing.

4 Data Infrastructure

All data is stored in a normalised, point-in-time database to prevent look-ahead bias. Three categories are ingested, sourced from major cryptocurrency exchanges and data providers.

4.1 Price and Volume Data

Perpetual-futures price data (open, high, low, close, volume, turnover) is captured at multiple time-scales—from minute-level to daily—along with volume-weighted average price (VWAP) and order-flow metrics such as taker buy/sell decomposition.

4.2 Fundamental and Supply Data

Daily market capitalisation and circulating-supply data are obtained from leading aggregators. Funding rates are collected at their native frequency and aggregated to daily.

4.3 Positioning and Sentiment Data

Global long/short ratios, top-trader positioning data, and open-interest time series are sourced from multiple exchanges. Premium-index and mark-price data provide additional insight into market sentiment and basis dynamics.

4.4 Data Inventory

Table 1 summarises the data categories used by the strategy.

Table 1: Data categories used by the strategy.

Category	Examples
Price / Volume	OHLCV, turnover, VWAP, order-flow metrics
Funding	Funding rates (multi-frequency)
Derivatives	Premium index, mark price, basis
Positioning	Long/short ratios, open interest
Fundamental	Market cap, circulating supply

5 Alpha Research

5.1 Research Philosophy

Alpha research follows a structured, **theory-first** approach. Every candidate signal must have an economic or behavioural rationale *before* it is tested empirically. This discipline guards against data mining, which is an acute risk given many potential features and limited cross-sectional history.

5.2 Idea Origination

Signal ideas are sourced from multiple channels:

Academic literature. Leading finance journals are systematically screened for new cross-sectional return predictors.

Preprints and conferences. Working papers and quantitative-finance conferences provide early access to emerging research.

Industry research. Sell-side quantitative strategy notes and asset-manager publications.

Open-source. Community platforms for prototyping and novel data transformations.

Insights from traditional equity markets (momentum, reversal, volume, volatility, liquidity) are carefully adapted to the crypto setting, accounting for 24/7 trading and the funding-rate mechanism.

5.3 Signal Taxonomy

The alpha signals are organised into six families.

5.3.1 Technical / Price–Volume

Derived from price and volume data: cross-sectional momentum [7] (trailing returns over multiple look-back windows), short-term reversal, trend-strength indicators, and volume-weighted price deviations. Order-flow imbalance and volume surprise signals round out this category.

5.3.2 Volatility

Realised volatility at multiple horizons, range-based volatility, downside risk measures, and tail-risk indicators. Assets exhibiting elevated downside risk relative to the cross-section tend to underperform on a risk-adjusted basis, consistent with the low-volatility anomaly [5].

5.3.3 Microstructure

Features that exploit high-frequency price and volume data: liquidity measures [1], informed-trading proxies [9], and trade-arrival patterns. These signals capture short-lived liquidity dynamics that are invisible at daily frequency.

5.3.4 Fundamental / On-Chain

Market-capitalisation rank, changes in circulating supply, and funding-rate carry [8]. A persistently positive funding rate signals crowded long positioning and tends to predict underperformance relative to peers.

5.3.5 Positioning and Sentiment

Long/short ratios, open-interest changes, and the premium-index basis capture speculative positioning. Rising long exposure combined with rising open interest may indicate speculative excess, predicting subsequent underperformance.

5.3.6 Behavioural

Signals motivated by documented behavioural biases: herding, salience, and lottery-demand effects [2]. These signals exploit systematic mispricings rooted in investor psychology.

6 Signal Evaluation Framework

Every candidate signal passes through a rigorous, multi-step evaluation before it is admitted into the live portfolio. The metrics below measure how well a signal predicts which coins will outperform or underperform in the next period.

6.1 Information Coefficient (IC)

The primary metric is the **rank IC**, defined as the Spearman rank correlation between signal values and subsequent forward returns, computed cross-sectionally at each rebalance date t:

$$\mathrm{IC}_t = \rho_{\mathrm{Sp}}\big(\mathbf{s}_t,\ \mathbf{r}_{t\to t+1}\big) \tag{3}$$

where $\mathbf{s}_t \in \mathbb{R}^{N_t}$ is the signal vector and $\mathbf{r}_{t\to t+1}$ is the forward-return vector. The **Pearson IC** is computed in parallel:

$$\mathrm{IC}_t^P = \frac{\mathrm{Cov}(\mathbf{s}_t, \mathbf{r}_{t\to t+1})}{\sigma_{\mathbf{s}_t}\ \sigma_{\mathbf{r}_{t\to t+1}}} \tag{4}$$

6.2 IC Distribution Analysis

A single average IC is insufficient. The full distribution $\{\mathrm{IC}_t\}_{t=1}^T$ is examined via mean ($\overline{\mathrm{IC}}$), standard deviation (σ_{IC}), the **IC information ratio** ($\mathrm{ICIR} = \overline{\mathrm{IC}} / \sigma_{\mathrm{IC}}$), and skewness. A signal with a modestly positive mean but low dispersion and positive skew is preferred to one with a higher mean but a fat left tail.

Signal Admission Criteria	
Mean Rank IC	Positive and statistically significant
ICIR	Sufficiently high for consistent predictive value
Quintile monotonicity	Near-monotonic Q1→Q5

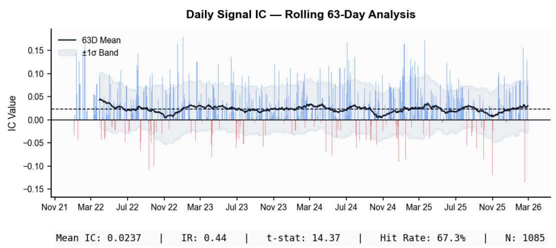

Figure 1: Daily Signal IC — rolling 63-day mean $\pm 1\sigma$ band.

6.3 Quintile Analysis

At each rebalance date, coins are sorted into quintiles (Q1 = lowest signal, Q5 = highest signal). The mean forward return of each quintile is computed and averaged across all dates. A predictive signal exhibits a **monotonic** spread: Q5 should consistently outperform Q1 (or vice versa, depending on direction).

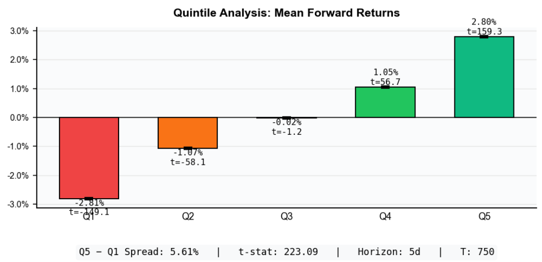

Figure 2: Quintile bar chart — Q1→Q5 mean forward returns.

6.4 Cross-Sectional Correlation

To ensure diversification within the alpha pool, the pairwise cross-sectional correlation matrix of all candidate signals is monitored. Highly correlated signal pairs are flagged as redundant; only the stronger signal is retained. This pruning process ensures that every component of the ensemble contributes unique information.

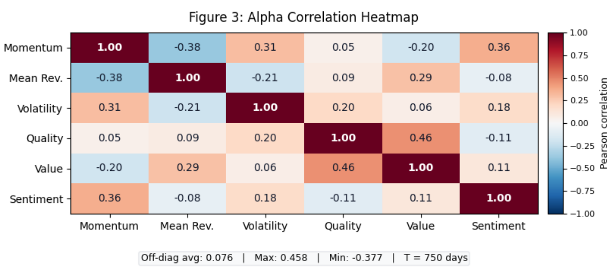

Figure 3: Illustrative alpha correlation heatmap

7 Portfolio Construction

Portfolio construction translates the composite alpha forecast into tradable positions. It proceeds in two parallel tracks that are subsequently blended.

7.1 Track 1: Plain Alpha Overlay

Signals with individually strong Sharpe ratios and low mutual correlation are combined via simple equal-weighted or IC-weighted rank averaging.

Selection Methodology. To ensure concentration in our highest-conviction ideas, the strategy utilises a **ranking-based selection approach**. At each rebalance:

- **Long Basket:** The coins with the highest composite scores.
- **Short Basket:** The coins with the lowest composite scores.

Weights within each basket are normalised to satisfy both dollar neutrality (Eq. 2) and beta neutrality (Eq. 1).

This track is intentionally transparent and robust. Its simplicity provides a stable baseline and makes attribution straightforward.

7.2 Track 2: Machine-Learning Ensemble

Following the empirical asset pricing via machine learning framework of Gu, Kelly, and Xiu [6], the full set of alpha signals—together with their pairwise interactions and lagged values —is fed into two complementary model families:

Penalised linear model performs automatic feature selection over the expanded feature space, distilling raw signals and their derived terms into a sparse, interpretable linear combination.

Gradient-boosted tree model captures non-linear interactions and threshold effects that a linear model cannot exploit. Hyperparameters are selected via time-series-aware cross-validation (expanding window or purged k-fold [11]) to prevent look-ahead bias.

The outputs of both models are rank-normalised and blended with the plain alpha composite. The blending weight is calibrated on out-of-sample performance and may be tilted toward the model track when signal density is high and toward the plain track during thin data regimes.

7.3 Position Sizing and Constraints

The final portfolio satisfies the following constraints: beta neutrality (Eq. 1), dollar neutrality (Eq. 2), maximum single-name weight, maximum gross exposure, and a turnover penalty that regularises trading costs. These constraints are encoded in a portfolio optimiser that balances tracking the target portfolio as closely as possible against the full set of risk and cost constraints.

8 Backtesting Methodology

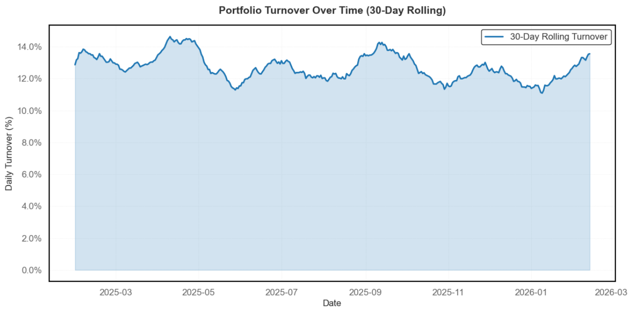

Figure 4: Portfolio turnover over time

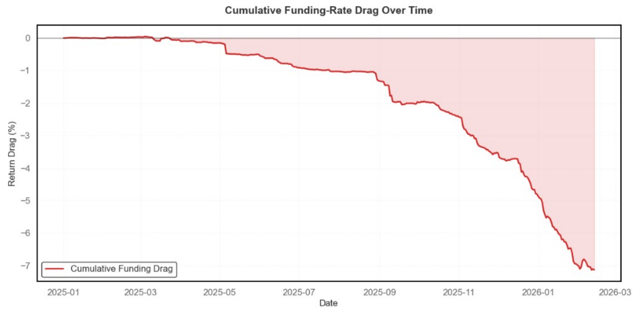

Figure 5: Cumulative funding-rate drag over time.

Backtests are the primary tool for out-of-sample validation. The fund employs a strict protocol to prevent overfitting and ensure that reported performance is realistic.

8.1 Temporal Separation

The sample is divided into **in-sample** (IS), **validation** (VAL), and **out-of-sample** (OOS) periods. All signal research and model tuning use IS and VAL only. OOS is touched at most once for final reporting.

8.2 Transaction-Cost Model

Three cost components are modelled explicitly.

Funding rate. Perpetual contracts charge or pay a funding rate at fixed intervals — typically every 8 hours, though some exchanges and contract types use 4-hour or 1-hour cycles. The cumulative funding-rate drag is computed position-by-position using the realised funding-rate time series. Because the portfolio is long–short, funding received on one leg partially offsets funding paid on the other, but the net effect is non-zero and must be accounted for.

$$\text{FR drag}_t = \sum_i w_{i,t} \cdot \text{fr}_{i,t} \tag{5}$$

Slippage. Market-impact slippage is estimated using a square-root model [4] (the “square root law” of volatility × participation rate), calibrated to historical order-book depth:

$$\text{Slippage}_i = \eta_i \cdot \sigma_i \cdot \sqrt{\frac{Q_i}{\text{ADV}_i}} \tag{6}$$

where η_i is a coin-specific calibration constant, σ_i is intraday volatility, Q_i is trade size, and ADV_i is average daily volume.

Commission. Exchange taker/maker fees are applied to every fill.

8.3 Performance Metrics

Table 2 lists the key performance statistics reported for every backtest.

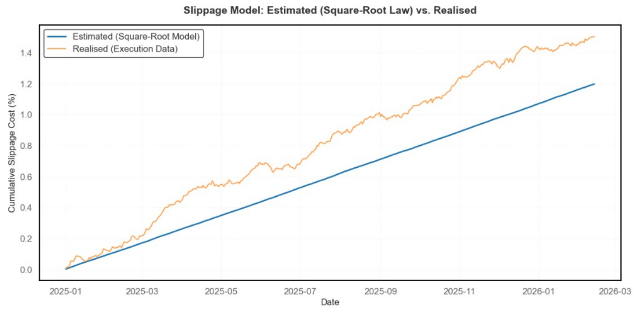

Figure 6: Slippage model: estimated (square-root law) vs. realised.

Table 2: Performance metrics.

Metric	Definition
Annualised Return	Geometric mean of daily returns × 365
Annualised Vol	Std of daily returns × $\sqrt{365}$
Sharpe Ratio	Ann. return / Ann. vol
Sortino Ratio	Ann. return / downside vol
Max Drawdown	Largest peak-to-trough decline
Calmar Ratio	Ann. return / |Max DD|
Win Rate	% of positive-return days
Profit Factor	Gross profit / gross loss
Avg. Turnover	Daily two-sided turnover

9 Backtest Results (Illustrative)

This section presents the standard suite of charts and summary statistics produced for every backtest run. All figures and statistics shown are illustrative and based on simulated performance. Table 3 summarises the key metrics.

Table 3: Backtest summary statistics (illustrative).

Metric	Value
CAGR	20.34%
Annualised Volatility	11.69%
Sharpe Ratio	1.74
Sortino Ratio	2.21
Max Drawdown	−9.54%
Calmar Ratio	2.13
Win Rate (daily)	51.7%
Profit Factor	1.12
Avg. Daily Turnover	18.3%
Beta to BTC	−0.003

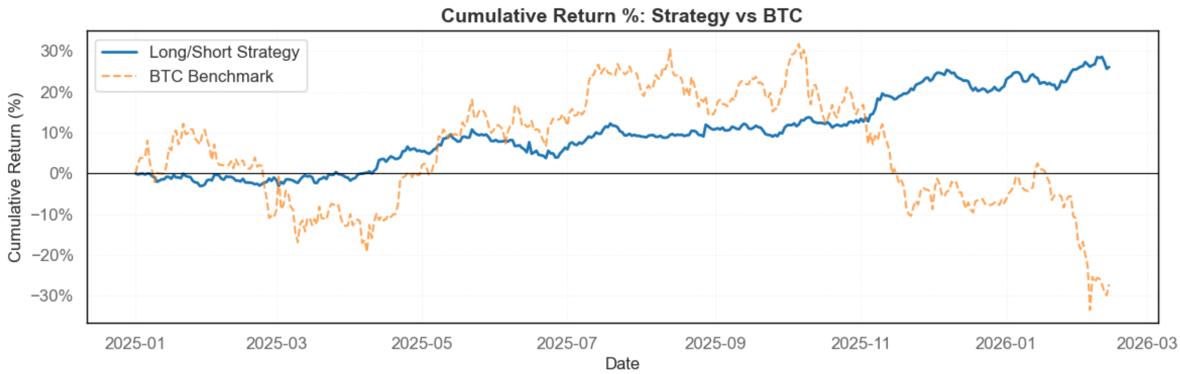

Figure 7: Cumulative return: L/S combined and BTC benchmark

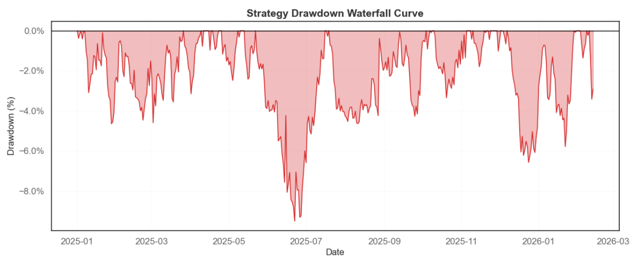

Figure 8: Strategy drawdown waterfall curve

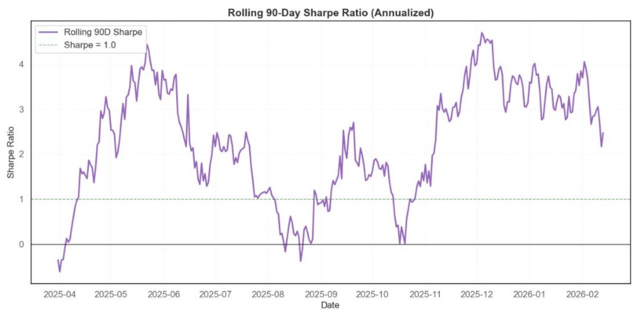

Figure 9: Rolling 90-day Sharpe ratio (annualized)

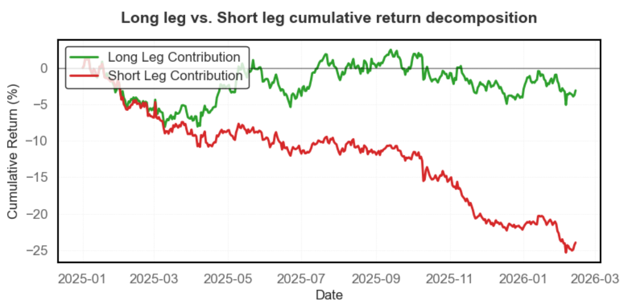

Figure 10: Long leg vs. Short leg return decomposition

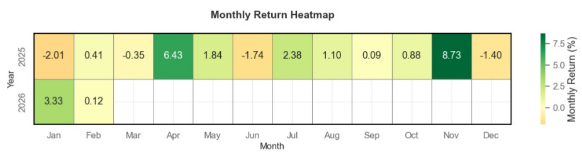

Figure 11: Monthly return heatmap.

10 Risk Management

Portfolios that employ leverage, shorting, or derivatives can face heightened challenges during a crisis. While a manager may intend to hold positions through turbulent periods, strategies that use leverage may not realistically have that option — the actual choice becomes whether risk-management decisions are planned in advance or forced upon the manager by margin calls and liquidity shocks.

ACMIO Quantitative Technologies Limited addresses this reality through a layered risk framework that operates at the portfolio, position, and intraday levels.

10.1 Drawdown Control System

A pre-defined **Drawdown Control System** is the strategy's primary circuit breaker. Although individual parameters are proprietary, the mechanism follows a tiered structure:

1. **Monitoring.** The system continuously tracks the strategy's peak-to-trough drawdown in real time.
2. **Alert.** When the trailing drawdown exceeds an initial threshold, the portfolio's target risk level is reduced by scaling down gross exposure.
3. **De-leverage.** If losses deepen further past a second threshold, exposure is reduced more aggressively, potentially to a minimal "capital preservation" posture.
4. **Recovery.** As performance recovers and drawdown narrows, risk targets are gradually restored to normal levels.

Key Insight

When performance is meaningfully negative and market risks are elevated, it is prudent to reduce a strategy's risk targets. These decisions are best made through a pre-defined, tested process rather than ad-hoc judgments made under stress.

10.2 Portfolio-Level Controls

Beta neutrality (Eq. 1) and dollar neutrality (Eq. 2) are enforced at every rebalance. Gross exposure is capped at a predefined multiple of NAV.

10.3 Single-Name Concentration Limits

Position-size limits are tiered by market capitalisation to reflect the different liquidity and risk profiles across the universe:

- **Large-cap coins** (e.g. the largest assets by market capitalisation) may receive a higher allocation given their superior liquidity and lower idiosyncratic risk.
- **Smaller altcoins** are subject to tighter concentration limits to guard against blow-up risk and thinner order books.

Coins whose trailing average daily volume falls below a minimum threshold are excluded from the tradeable universe for that rebalance.

10.4 Intraday Stop-Loss Protection

In addition to daily rebalancing, the strategy employs **intraday stop-loss** orders on individual positions. These are specifically designed to protect against sudden adverse moves such as short squeezes, flash crashes, or exchange-specific dislocations. If a position's unrealised loss breaches a predefined intraday limit, the position is automatically reduced or closed, preventing the drawdown from compounding before the next scheduled rebalance.

Key Insight

The strategy employs multiple independent risk controls—portfolio-wide circuit breakers, tiered concentration limits, and position-level stop-losses—operating continuously to limit drawdowns.

10.5 Factor Exposure Monitoring

Rolling betas to BTC, ETH, and a cap-weighted altcoin index are monitored daily. If the net portfolio beta breaches a tolerance band, a hedging overlay is applied.

10.6 Model Risk

The two-track design (plain alpha + ML) provides a natural hedge against model risk. The plain-alpha track is robust and interpretable; the ML track captures nonlinearities but is more prone to overfitting. Blending weights are adjusted based on rolling out-of-sample performance comparisons.

11 Execution and Operations

11.1 Execution Infrastructure

Orders are executed on major exchanges via low-latency API connections using proprietary algorithms designed to minimise market impact by scaling into positions passively. Every trade is measured against the pre-trade cost model, and the results feed back into continuous calibration.

11.2 Technology Stack

The research and execution platform uses a modern, modular architecture with automated data pipelines, built-in redundancy, and failover mechanisms across all production-critical paths.

12 Conclusion

The market-neutral long-short approach to cryptocurrency perpetual-futures markets offers a compelling risk–return profile. By focusing on relative performance rather than absolute price prediction, the strategy targets idiosyncratic returns and constructs a portfolio that is structurally hedged against market direction.

The fund's edge derives from disciplined, research-driven signal development; a rich, multi-source data infrastructure; a hybrid signal-combination framework that balances transparency with non-linear expressiveness; and a realistic cost model that bridges the gap between backtest and live performance.

The top-100 market-cap universe — structured across multiple capitalisation tiers — provides the liquidity depth and breadth necessary to sustain the strategy at meaningful capacity. Ongoing research into new data sources, higher-frequency signals, and adaptive portfolio-construction techniques will continue to evolve the strategy and maintain its edge.

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