Risk-Adjusted Momentum (RAM)

A Quantitative Framework for Conditional Crypto Exposure

Michael Hyland February 2026

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1. Introduction

Bitcoin (BTC) has delivered strong long-term returns but with substantial volatility and deep drawdowns, making passive buy-and-hold exposure difficult for many investors to maintain as a core allocation.

This paper presents a systematic alternative: the **Risk-Adjusted Momentum (RAM)** strategy. The objective of RAM is to seek to improve the risk efficiency of crypto exposure while reducing volatility and drawdown through conditional exposure.

Rather than maintaining constant market exposure, the strategy allocates capital dynamically across major cryptocurrencies based on recent risk-adjusted performance. Capital is deployed only when market conditions are favorable and reduced when signals deteriorate.

The central research question is:

Can conditional exposure based on risk-adjusted momentum improve the risk efficiency of crypto investing relative to passive BTC buy-and-hold (BTC BAH)?

The analysis focuses on liquid large-capitalization assets to reduce implementation risk and is evaluated using daily data from January 2021 through December 2025.

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2. Research Framework

This study follows a standard quantitative research process:

1. Define an economic objective
2. Formulate testable hypotheses
3. Construct a systematic signal using observable data
4. Select model parameters using a defined training period
5. Evaluate robustness across multiple performance metrics
6. Validate results using an independent out-of-sample period

All parameter selection decisions were made prior to out-of-sample evaluation to mitigate overfitting risk.

The objective is not to maximize in-sample returns, but to identify a stable framework that generalizes across market regimes.

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3. Hypotheses

The RAM framework is designed to test two primary hypotheses.

H1: Risk-Adjusted Momentum Persistence

Cryptocurrencies exhibiting high recent risk-adjusted returns (as measured by RAM) will, on average, generate superior near-term performance relative to assets with weaker signals.

This hypothesis evaluates whether momentum persists when measured on a return-per-unit-of-risk basis rather than by absolute returns.

H2: Diversification Improves Risk Efficiency

Allocating capital across multiple large cryptocurrencies, rather than concentrating solely in BTC, will reduce portfolio volatility and drawdown due to imperfect cross-asset correlation.

Together, these hypotheses suggest that a dynamically allocated, multi-asset framework may deliver superior risk-adjusted performance relative to passive BTC exposure.

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4. Strategy Overview

Investment Universe

The five largest non-stable cryptocurrencies by market capitalization:

- BTC
- ETH
- XRP
- SOL
- BNB

Signal Definition

For each asset:

$$Signal\ Ratio\ (SR) = \frac{Average\ daily\ return\ over\ n\ days}{Standard\ deviation\ of\ daily\ returns\ over\ n\ days}$$

This represents recent **return per unit of risk**.

Trading Logic

- Long if the absolute value of SR exceeds its threshold
- Neutral otherwise
- No short positions

Capital is allocated equally across each asset. If the SR for a certain asset does not indicate a long position then its capital remains in cash (no yield assumed).

Rebalancing occurs daily using only information available at the close.

All performance stats in the paper are based on the total capital allocated to the strategy (the gross amount) and not the amount actually invested each day.

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5. Execution Assumptions

The model's signals are generated using closing prices and are therefore not ready until after the end of the day. Trades dictated by the signals are executed at the following day's open.

Because of data limitations, it is assumed that the following day's opening price is the same as the previous day's closing price. This is assumed to be a reasonable choice because of the continuous 24-hour trading in crypto and the fact that the signal calculations should be ready within seconds of the previous day's close/next day's open. This assumption should be further investigated as part of any next steps prior to model implementation.

Transaction costs of 0.16 bps per trade are applied. No additional slippage is assumed.

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6. Data and Implementation Assumptions

- Assets are selected based on current market capitalization
- Data source: Binance daily closing prices
- Training period: Jan 2021 – Dec 2023
- Testing period: Jan 2024 – Dec 2025
- Signals use only prior data (no look-ahead bias)
- Parameters selected using training data only
- No tuning performed using out-of-sample results

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7. Surprising Signal Behavior

During parameter exploration, **extreme negative RAM values were associated with short-term return reversals**, consistent with volatility-induced mean reversion.

This effect was validated in out-of-sample testing.

Including both positive and negative thresholds as entry signals materially improved overall performance.

More details about the separate analysis of positive and negative thresholds can be found in Appendix I.

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8. Model Selection and Robustness

The two main evaluation metrics used to determine optimal RAM parameters are the:

- Sharpe ratio
- Maximum drawdown amount

Both are measured using rolling 365-day windows (defined as 365 trading days, advanced one day at a time) and for each 365-day window a “winner” is chosen between RAM and BTC BAH. The percentage of RAM “wins” is then used in the evaluation. This method emphasizes continuous outperformance rather than just outperformance over a single static period.

The two main RAM parameters that need to be optimized are the:

- Observation window expressed in days (n)
- Signal threshold ($\pm ST$)

Parameter ranges were intentionally limited to reduce multiple-testing bias. Optimal parameters were required to lie within a broad region of stable performance rather than a single peak.

Because the strategy is invested only intermittently, effective sample size is lower than the full daily observation count.

Two comments should also be made with respect to avenues of further investigation:

1. There is no reason why each of the five cryptocurrencies must use the same parameters. This model is assuming that they should be the same across each cryptocurrency for the sake of simplicity and computational brevity.

2. There is also no reason why the positive and negative thresholds must be symmetric. Again, this assumption was made to keep the myriad permutations in check for computational purposes.

To the extent that the model demonstrates potential, both assumptions should be relaxed during future inquiries.

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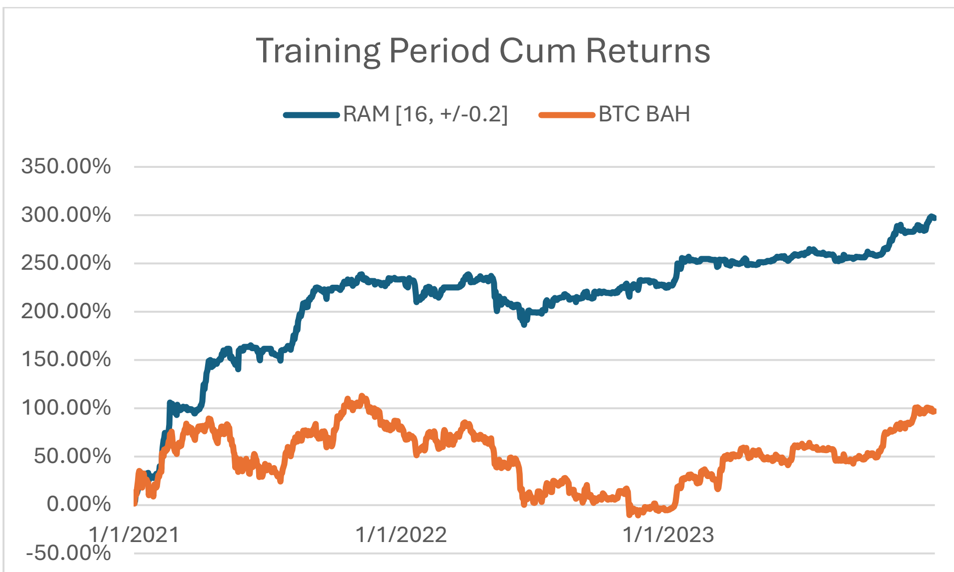
9. In-Sample Results (2021–2023)

Appendix I contains a more comprehensive recap of the process followed during the analysis of the training period data.

Using the evaluation metrics above, the optimal training parameters were:

[*n* = 16, *st* = ±0.2]



Key additional findings using the optimal training parameters:

- Sharpe ratio: 1.98 (vs. 0.52 for BTC)
- Max drawdown: -53% (vs. XX for BTC)
- Beta to BTC: 0.50
- Correlation to BTC: 0.65
- Annual alpha[1]: 67%
- Alpha t-stat: 2.30

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[1] Alpha is estimated from a daily regression versus BTC returns and annualized using 252 trading days.

In terms of the two evaluation statistics, the optimized parameters produced:

- Sharpe outperformance: 94% of rolling periods
- Drawdown outperformance: XX% of rolling periods

The tables below show heatmaps of Sharpe and drawdown outperformance for the different combinations of parameters that were tested. Note that the optimal parameters were part of an overperformance region.

[heatmaps]

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10. Out-of-Sample Validation (2024–2025)

All model parameters, signal definitions, and allocation rules were fixed at the end of the training phase. No adjustments were made after observing out-of-sample performance. This separation ensures that the testing results represent a true out-of-sample evaluation and reduces the risk of overfitting to historical data.

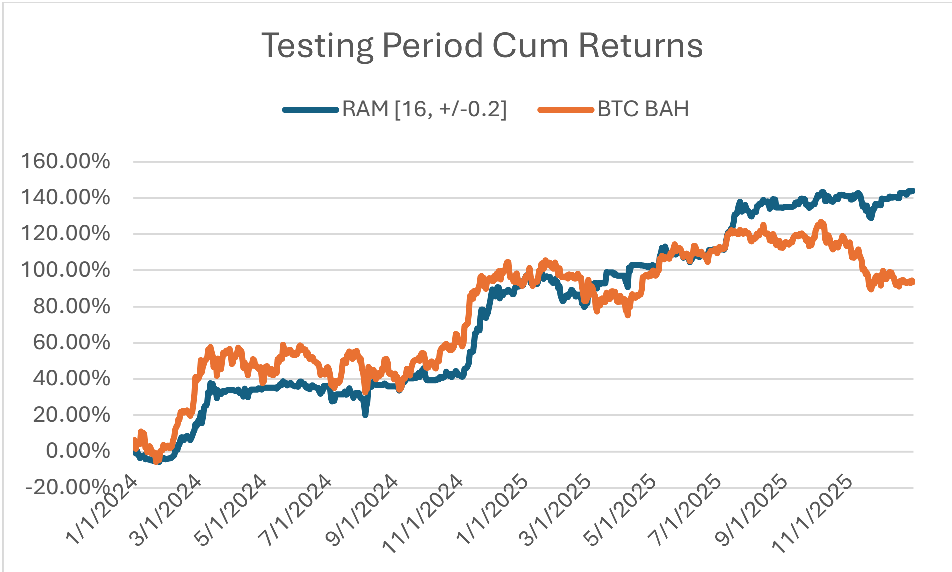
Using the optimal RAM parameters of [n = 16, st = ±0.2] from the training period produced the following results during the testing period:

- Sharpe ratio: 2.26 (vs. 0.98 for BTC)
- Max drawdown: -19% (vs. -37% for BTC)
- Beta to BTC: 0.45
- Correlation to BTC: 0.68
- Annual alpha: 25%
- Alpha t-stat: 1.01

Out-of-sample alpha is positive but not statistically significant, though risk-adjusted performance remains strong.

In terms of the two evaluation statistics, the optimized parameters produced:

- Sharpe outperformance: 100% of rolling periods
- Drawdown outperformance: XX% of rolling periods



The tables below show that out-of-sample performance was consistent with training results, supporting the robustness of the framework.

[heatmaps]

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11. Economic Interpretation

The results are consistent with structural characteristics of crypto markets:

- Momentum persistence driven by trend-following and leveraged positioning
- Periodic volatility shocks that make unconditional exposure inefficient
- Imperfect correlation among major crypto assets

Conditional exposure reduces participation during high-volatility regime transitions, which historically account for a disproportionate share of drawdowns. The RAM framework increases exposure during stable trending environments and reduces exposure during unstable or transition periods.

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12. Limitations and Risks

- Performance is driven by episodic exposure rather than continuous trading, increasing outcome variability.
- Momentum effects in crypto may weaken as market structure evolves.
- Strategy remains exposed to crypto market risk
- Execution assumptions may be optimistic

- Parameter stability should be monitored over time
- Capacity constraints may arise at larger scale

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13. Conclusion

This paper demonstrates a systematic research process for developing and validating a quantitative trading framework.

Starting from an economic objective—improving risk efficiency relative to BTC buy-and-hold—a risk-adjusted momentum signal was constructed, evaluated across a multi-year training period, and validated on an independent out-of-sample dataset.

The RAM strategy delivered comparable returns to BTC with materially lower volatility, reduced market exposure, and statistically significant in-sample alpha and positive but weaker out-of-sample evidence.

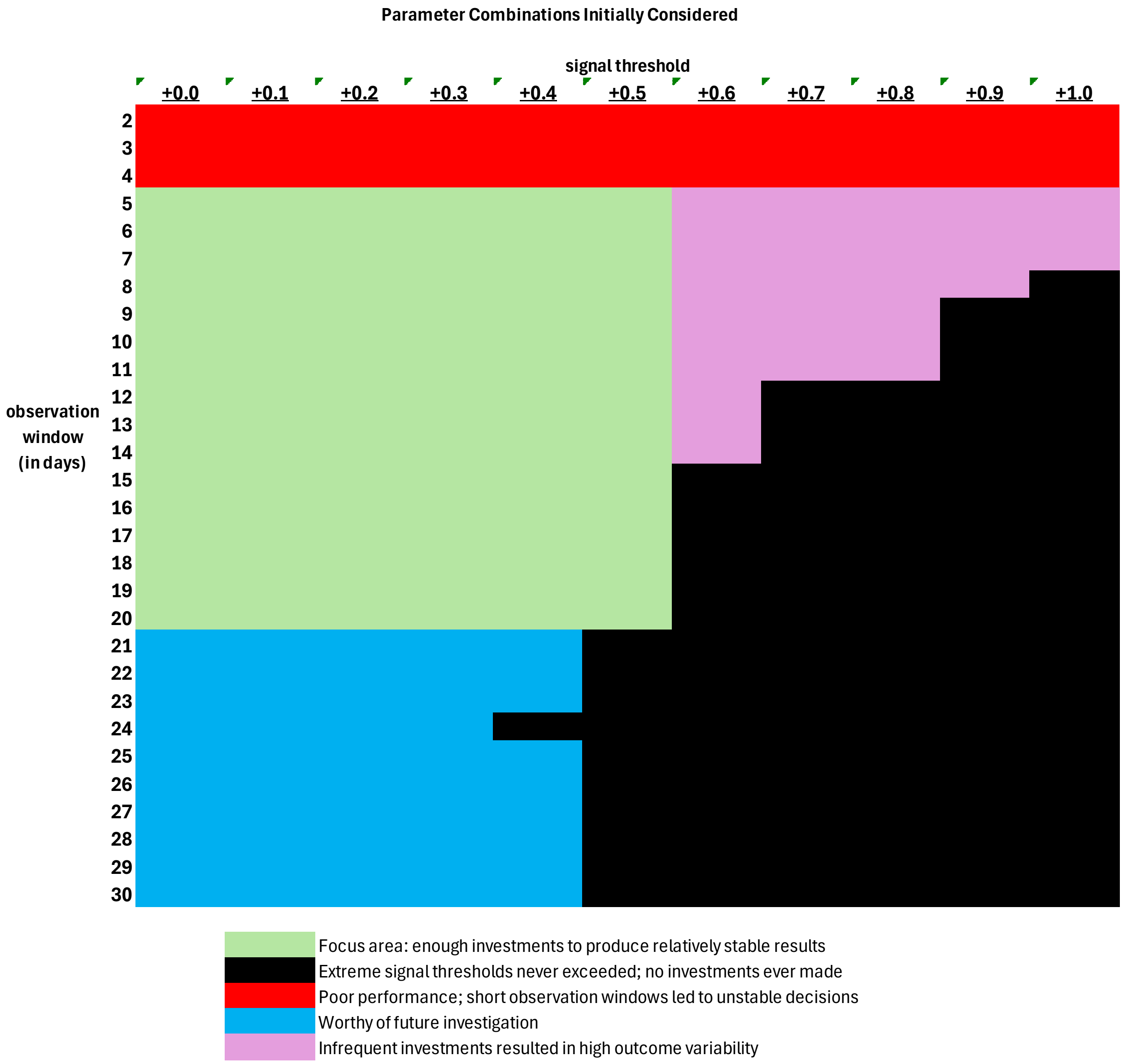
More broadly, the results illustrate the importance of disciplined hypothesis testing, robustness analysis, and out-of-sample validation when developing quantitative strategies for highly volatile markets.

Future improvements may be made with relaxed assumptions about model parameters and threshold symmetry.

The primary contribution of this study is the demonstration of a disciplined quantitative research process rather than the optimization of a specific trading rule.

Appendix I – Training Period Lessons Learned

Initial efforts around RAM focused on finding a combination of parameters to test for the "go long after positive threshold breach" portion of the strategy. Some quick analysis yielded the following:



After establishing the structure for the analysis of the positive scenario, it was a simple and natural progression to test the negative scenario (i.e., go <u>short</u> after a breach of the negative threshold). Surprisingly, the expected negative strategy performed poorly. Instead, it became quickly apparent that the piercing of the negative threshold suggested a “go long” strategy was warranted as shown by the table below:

[heatmap]

The complimentary nature of both "go long" strategies suggested they could be combined into one larger approach. At that point, arbitrary but well-guided decisions had to be made to keep the number of parameter combinations tractable (see table below). Each of these choices should be relaxed in future investigations of this strategy.

In theory:	**Arbitrary decisions made:**
• Any number of cryptocurrencies could be used as part of RAM	• Limit to top five by market cap
• Each cryptocurrency could have independent thresholds for their positive and negative signals	• Require same symmetric thresholds for each cryptocurrency
• Each cryptocurrency could have an independent observation window in days for their positive and negative signals	• Require consistent observation window for each cryptocurrency

Another outcome from combining strategies was the elimination of 0 as a threshold. Keeping zero as a threshold would have resulted in 100% investment throughout the period and would have defeated the dynamic allocation hypothesis being tested.

Finally, the complimentary nature of the two strategies needed to be evaluated to see if they performed better as a combination than either performed on their own.

[heatmap]

Appendix II - Investment Frequencies Based on Optimal Parameters

One interesting aspect of the RAM strategy is that the investment of each cryptocurrency is made independently. This means that on any given day, anywhere between zero and one hundred percent of allocated capital can be invested. The tables below show the frequency of investments based on the optimal parameters [16, +/-0.2] identified during the training period.

In terms of the frequency of investment:

	Training		Testing	
# of Investments	**# Days**	**% of Days**	**# Days**	**% of Days**
0	194	18%	166	23%
1	220	20%	153	21%
2	226	21%	154	21%
3	155	14%	78	11%

4	153	14%	105	14%
5	147	13%	75	10%
sum	1095	100%	731	100%

While there is a slight decline associated with the percentage of time that either four or all five of the cryptocurrencies are invested simultaneously, the number of simultaneous investments is spread out relatively evenly.

In terms of how frequently each cryptocurrency was invested (percentage refers to percentage of days invested relative to total days in period):

	Training		Testing	
Crypto	**# Days**	**% of Days**	**# Days**	**% of Days**
BTC	477	44%	293	40%
ETH	494	45%	324	44%
BNB	472	43%	291	40%
XRP	493	45%	261	36%
SOL	548	50%	321	44%

It is interesting to observe that each of the cryptocurrencies are invested roughly the same percentage of the time (43%-50% in training and 36%-44% in testing).