Systematic Core-Satellite Portfolio Strategy: A Signal-Based Approach to Dynamic ETF Selection

Sem
Personal Investment Strategy Document

***Abstract*—This document presents a systematic core-satellite portfolio strategy designed for long-term wealth accumulation through dynamic ETF selection. The strategy combines the stability of a passive global core (60% allocation to MSCI ACWI) with tactical satellite positions (40% allocation across 3-5 selected ETFs) that aim to generate positive alpha. We develop a comprehensive signal-based framework consisting of 167 signal bases, 27 causal smoothing filters, and 25 cross-sectional indicators, yielding over 112,000 potential features for predicting 3-month forward alpha. The strategy employs quarterly rebalancing to maintain the core-satellite ratio while locking profits from successful satellite positions into the core allocation, creating a systematic risk-reduction mechanism over time. Through walk-forward backtesting and rigorous feature evaluation, we identify which signal-filter-indicator combinations demonstrate consistent predictive power for ETF selection. The strategy is optimized for a 30+ year investment horizon with monthly contributions of EUR 1,000 and negligible transaction costs, making it suitable for tax-efficient, long-term portfolio growth.**

***Index Terms*—Core-satellite portfolio, ETF selection, alpha generation, signal-based strategy, momentum, mean reversion, feature engineering, walk-forward backtesting**

I. Introduction

A. Motivation

Long-term wealth accumulation through equity investing faces a fundamental trade-off: passive index investing provides broad diversification and low costs but limits alpha generation potential, while active management promises outperformance but introduces higher fees, behavioral biases, and tracking error. The core-satellite portfolio framework offers a middle ground, combining the stability of passive core holdings with the upside potential of tactical satellite positions.

However, implementing a successful core-satellite strategy requires solving a critical challenge: systematically identifying which satellite investments will generate positive alpha over the next holding period. Traditional approaches rely on fundamental analysis, sector rotation, or discretionary market timing, which are difficult to execute consistently and objectively.

This document presents a systematic, signal-based approach to satellite selection that addresses these challenges through rigorous quantitative methods. Rather than relying on subjective judgment or narrative-driven investing, we develop a comprehensive feature engineering framework that evaluates over 112,000 potential predictive signals derived from price dynamics, technical indicators, and cross-sectional relationships.

B. Strategy Overview

Our core-satellite strategy is designed for a 30+ year investment horizon with the following key characteristics:

- **Core allocation (60%):** iShares MSCI ACWI provides global diversification across 3,000 stocks in developed and emerging markets, serving as both the portfolio foundation and the benchmark for measuring alpha.
- **Satellite allocation (40%):** 3-5 dynamically selected ETFs from a universe of 500 eligible candidates, chosen quarterly based on predicted 3-month forward alpha.
- **Quarterly rebalancing:** Every 3 months, we recalculate satellite selections and rebalance the portfolio to maintain the 60/40 ratio. This process locks profits from successful satellites into the core allocation while providing capital to new satellite positions.
- **Monthly contributions:** EUR 1,000 per month split 60/40 between core and satellites, implementing dollar-cost averaging to reduce timing risk.
- **Low transaction costs:** EUR 1-3 per trade with no capital gains taxes, making frequent rebalancing economically feasible.

The strategy's defining feature is the profit-locking mechanism: when satellites outperform, the quarterly rebalancing automatically sells a portion of the gains to increase the core allocation, reducing portfolio risk over time. Conversely, when satellites underperform, capital from the stable core is deployed to satellite positions at lower valuations.

C. Contribution

This document makes several contributions to systematic portfolio management:

Comprehensive signal framework: We design and implement 167 signal bases across 27 categories, capturing momentum, mean reversion, risk dynamics, trend following, and regime-dependent behaviors. Combined with 27 causal smoothing filters and 25 indicator transformations, this yields 112,725 features for evaluation.

Rigorous causality: All filters and transformations are strictly causal (using only past data), and we employ walk-forward backtesting to ensure performance estimates reflect realistic, implementable strategies without look-ahead bias.

Feature evaluation methodology: We develop metrics specifically suited for cross-sectional ETF selection, including Information Coefficient (IC), IC Information Ratio (stability), quintile analysis, and hit rate evaluation. Rather than optimizing for maximum returns, we prioritize consistency and risk-adjusted performance.

Momentum vs. mean reversion analysis: We systematically test whether satellite selection should follow momentum (buying recent winners) or mean reversion (buying recent losers) principles, allowing the data to determine which approach generates superior alpha.

Practical implementation: The strategy is designed for real-world execution with realistic constraints including transaction costs, portfolio constraints (maximum 5 satellites), and tax considerations.

D. Document Structure

The remainder of this document is organized as follows: Section II reviews relevant literature on core-satellite portfolios, factor investing, and technical analysis. Section III details our signal construction, filtering, feature engineering, and selection methodology. Section IV presents backtesting results and feature performance analysis. Section V examines the robustness of our findings across different market regimes and parameter settings. Section VI summarizes key insights and discusses future enhancements.

II. Related Work

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

III. Methodology

This section presents our systematic approach for ETF selection in a core-satellite portfolio framework. We develop a quantitative signal-based methodology that identifies satellite ETFs with the highest probability of generating positive alpha relative to a global market benchmark.

A. Portfolio Framework

We adopt a core-satellite portfolio structure that combines the stability of passive global diversification with the alpha-generation potential of tactical satellite positions. The core allocation consists of a global market-cap weighted index (iShares MSCI ACWI), representing approximately 3,000 stocks across developed and emerging markets. This provides broad exposure while serving as our benchmark for measuring excess returns.

The satellite allocation dynamically selects from a filtered universe of equity ETFs based on predictive signals. We allocate up to 40% to satellites, distributed equally among a maximum of four selected ETFs. When no satellites demonstrate sufficient alpha potential, the strategy defaults to 100% core allocation, ensuring we never force suboptimal positions.

B. ETF Universe Construction

Starting from a catalog of over 7,500 ETFs, we apply a series of practical filters to construct our investment universe. We restrict to Irish-domiciled ETFs for tax efficiency, require accumulating distribution policies to avoid dividend drag, and impose a maximum total expense ratio of 0.30%. To ensure adequate liquidity and data availability, we require a minimum fund size of 100 million EUR and at least five years of price history. These filters yield approximately 500 eligible ETFs that form our selection universe.

C. Signal Base Computation

The foundation of our selection methodology lies in computing a comprehensive set of 167 signal bases from raw price data. We organize these into 27 categories, each capturing different aspects of ETF behavior relative to the core benchmark. Most signals use day-based window parameters (21d, 63d, 126d, 252d) corresponding approximately to 1, 3, 6, and 12 months respectively, with trend indicators preserving industry-standard windows (e.g., 50-day, 200-day moving averages).

1) Return and Alpha Signals: The most fundamental signals derive from daily returns $r_{i,t} = (P_{i,t} - P_{i,t-1})/P_{i,t-1}$ and excess returns (alpha) $\alpha_{i,t} = r_{i,t} - r_{c,t}$, where $r_{c,t}$ denotes the core benchmark return. We also compute price ratios $P_{i,t}/P_{c,t}$ and their logarithmic transformations to capture relative valuation dynamics.

2) Relative Strength: To measure momentum relative to the benchmark, we compute multi-horizon relative strength as the ratio of ETF momentum to core momentum:

$$\mathrm{RS}_{i,t}^{(n)} = \frac{(P_{i,t} - P_{i,t-n})/P_{i,t-n}}{(P_{c,t} - P_{c,t-n})/P_{c,t-n}} \tag{1}$$

We evaluate lookback periods of 21, 63, 126, and 252 trading days, corresponding approximately to 1, 3, 6, and 12 months. Additionally, we compute beta-adjusted relative strength by normalizing RS by the ETF's rolling beta:

$$\mathrm{BetaAdjRS}_{i,t} = \frac{\mathrm{RS}_{i,t}^{(252)}}{|\beta_{i,t}| + \delta} \tag{2}$$

where $\delta \in \{0.3, 0.5, 1.0\}$ is a damping parameter to prevent extreme values for low-beta ETFs.

3) Risk Metrics: Understanding risk characteristics is essential for satellite selection. We compute rolling beta as the covariance of ETF returns with core returns divided by core variance, using 21, 63, and 126-day windows. Idiosyncratic return adjusts alpha by residual volatility. Rolling volatility (annualized standard deviation of returns) captures absolute risk at 21 and 63-day horizons, while relative volatility normalizes this against the core's volatility. Drawdown, measured as the percentage decline from the running maximum price, quantifies downside exposure. We also compute relative drawdown as the difference between ETF and core drawdowns.

4) Risk-Adjusted Performance: Raw returns can be misleading without risk context. We compute rolling Sharpe ratios (return per unit volatility), Sortino ratios (return per unit downside deviation), and Information ratios (alpha per unit tracking error) over 126-day windows. These metrics identify ETFs delivering efficient risk-adjusted returns rather than merely high absolute returns.

5) Trend Indicators: Price trends relative to moving averages provide insight into momentum regimes. We measure the percentage deviation of price from its 50-day and 200-day moving averages, as well as the "golden cross" ratio of the 50-day to 200-day moving average. These signals help distinguish between trending and mean-reverting market conditions.

6) Mean Reversion Signals: A key innovation in our framework is the comprehensive treatment of mean reversion signals, which identify potentially oversold conditions that may precede recovery. We compute price z-scores at 63, 126, and 252-day windows (deviation from rolling mean normalized by rolling standard deviation), inverted such that oversold conditions yield positive values. The Bollinger Band position measures where price sits within its volatility bands. Classical oscillators including the Relative Strength Index and Stochastic oscillator are inverted to generate buy signals when assets appear oversold.

We also compute alpha z-scores, RS z-scores at 126 and 252-day windows, distance from 20 and 100-day moving averages, and the price ratio z-score. Perhaps most importantly, we introduce the alpha drawdown reversion signal:

$$\mathrm{AlphaDD}_{i,t} = -\left(\sum_{s=t-126}^{t} \alpha_{i,s} - \max_{u \le t}\left(\sum_{s=u-126}^{u} \alpha_{i,s}\right)\right) \tag{3}$$

This captures how far an ETF's cumulative alpha has fallen from its peak, identifying assets that have significantly underperformed recently and may be poised for mean reversion.

7) Higher Moments: To capture tail risk characteristics, we compute 63-day rolling skewness and kurtosis of returns. Negative skewness indicates asymmetric downside risk, while high kurtosis signals fat tails and potential for extreme moves.

8) Correlation and Dispersion: We measure each ETF's 63-day rolling correlation with the core benchmark, as well as an approximation of average pairwise correlation with the broader universe (computed efficiently as correlation with the equal-weighted market average). Low correlation signals diversification potential, while high correlation indicates the ETF moves in lockstep with the market.

9) Momentum Dynamics: Beyond static momentum, we capture acceleration and deceleration in relative strength. The momentum acceleration signals measure the 21-day and 63-day change in 6-month or 12-month relative strength, identifying ETFs whose outperformance is increasing or decreasing.

10) Signal Disagreement Features: We compute disagreement signals between short-term and long-term momentum. The bullish disagreement signal $(\mathrm{RS}_{12m} - \mathrm{RS}_{1m})$ identifies long-term winners experiencing short-term pullbacks—potential buy opportunities. Conversely, bearish disagreement $(\mathrm{RS}_{1m} - \mathrm{RS}_{12m})$ flags short-term strength in long-term laggards. We also measure trend-momentum divergence by comparing price-vs-MA z-scores with RS z-scores.

11) Regime-Adaptive Signals: Market conditions affect which signals work best. We compute a volatility regime indicator (core volatility z-score relative to its 252-day history) and a trend regime indicator (core price vs 200-day MA). Two composite signals boost base signals based on regime:

$$\mathrm{TrendBoostedMom}_{i,t} = \mathrm{RS}_{i,t}^{(126)} \times (1 + \max(0, \mathrm{TrendRegime}_t)) \tag{4}$$

$$\mathrm{VolBoostedReversion}_{i,t} = \mathrm{AlphaDD}_{i,t} \times (1 + \min(2, \max(0, \mathrm{VolRegime}_t \tag{5}$$

These signals amplify momentum in trending markets and mean reversion in high-volatility regimes.

D. Causal Smoothing Filters

Raw signals contain substantial noise that can lead to spurious rankings. To address this while preserving causality (avoiding look-ahead bias), we apply 27 smoothing filters to each signal base. All filters are strictly causal—they use only past data points at each time step. We employ both standard windows (21 and 63 days) and specialized adaptive filters to capture different temporal dynamics.

Raw (no filter): The unfiltered signal serves as a baseline (1 filter).

Exponential Moving Average (EMA): We apply EMAs with 21 and 63-day spans, implemented using IIR filtering for computational efficiency (2 filters):

$$\mathrm{EMA}_t = \alpha \cdot x_t + (1-\alpha) \cdot \mathrm{EMA}_{t-1}, \quad \alpha = \frac{2}{n+1} \tag{6}$$

Double EMA (DEMA): Reduced-lag smoothing computed as $\mathrm{DEMA} = 2 \cdot \mathrm{EMA} - \mathrm{EMA}(\mathrm{EMA})$ with 21 and 63-day spans (2 filters).

Triple EMA (TEMA): Minimal-lag smoothing using $\mathrm{TEMA} = 3 \cdot \mathrm{EMA} - 3 \cdot \mathrm{EMA}^2 + \mathrm{EMA}^3$ with 21 and 63-day spans (2 filters).

Zero-Lag EMA (ZLEMA): Momentum-adjusted EMA that compensates for lag by using price momentum, with 21 and 63-day spans (2 filters).

Hull Moving Average: The Hull MA combines weighted moving averages to reduce lag while maintaining smoothness, using 21 and 63-day periods (2 filters):

$$\mathrm{Hull}_t = \mathrm{WMA}\left(2 \cdot \mathrm{WMA}(x, n/2) - \mathrm{WMA}(x, n), \sqrt{n}\right) \tag{7}$$

Triangular MA (TRIMA): Double-smoothed SMA providing center-weighted averaging, with 21 and 63-day windows (2 filters).

Gaussian MA: Bell-curve weighted averaging with smooth frequency rolloff, using 21 and 63-day windows (2 filters).

Butterworth Low-Pass Filter: Second-order Butterworth filters with cutoff periods of 21 and 63 days provide excellent noise reduction with a smooth frequency response (2 filters). We use SciPy's *lfilter* function for causal (one-directional) filtering.

Kalman Filter: An adaptive smoothing filter that adjusts based on signal-to-noise ratio (2 filters). We use two configurations: "fast" (process variance 10^{-4}) for responsive tracking and "slow" (process variance 10^{-5}) for stronger smoothing.

Savitzky-Golay Filter: Polynomial smoothing that preserves local maxima and minima better than moving averages, implemented with 21 and 63-day windows using cubic polynomials (2 filters). We ensure causality by setting the filter origin to use only past points.

Median Filter: Outlier-robust filtering that preserves edges, with 21 and 63-day windows (2 filters).

Kaufman Adaptive MA (KAMA): Adapts smoothing based on market efficiency ratio, distinguishing trending from choppy markets, using a 21-day period (1 filter).

Regime-Switching Filter: Automatically switches between fast (10-day) and slow (50-day) smoothing based on market volatility regime (1 filter).

Combining 167 signal bases with 27 filters yields 4,509 signal variants. Each filter-signal combination captures different temporal dynamics, allowing the selection algorithm to identify which combinations provide the strongest predictive power.

E. Indicator Transformations

Each filtered signal variant undergoes 25 indicator transformations that capture different aspects of the signal's behavior. These indicators form the final predictive features used for ETF selection.

Level: The raw filtered signal value.

Momentum indicators: We compute the change in signal value over 5, 21, 63, and 126-day horizons, capturing short to medium-term signal dynamics.

Z-score indicators: Signal deviation from its rolling mean, normalized by rolling standard deviation, computed at 21, 63, and 126-day windows. These identify when signals are at extreme values relative to recent history.

Cross-sectional indicators: At each time point, we compute the cross-sectional rank (ETF's percentile rank among all ETFs, yielding a uniform distribution in $[0, 1]$) and cross-sectional z-score (deviation from cross-sectional mean divided by cross-sectional standard deviation). These ensure selection is based on relative positioning rather than absolute magnitudes.

Trend indicators: Ratios of short to long-term moving averages of the signal—MA(21)/MA(63), MA(63)/MA(252), and a longer-term variant—identify whether the signal is trending up or down.

Mean reversion indicators: Distance from 63, 126, and 252-day rolling means, identifying when signals have deviated significantly and may revert.

Velocity and acceleration: First and second derivatives of the signal (normalized by rolling standard deviation), capturing the rate and change in rate of signal movement.

Drawdown: Distance from the 63-day rolling maximum, measuring how far the signal has fallen from recent peaks.

Range position: Where the signal sits within its 21-day high-low range, normalized to $[0, 1]$.

Volatility ratios: Ratio of short-term (5-day) to longer-term (21, 63, 126-day) signal volatility, identifying periods of unusual signal movement.

Percentile: The signal's position within its 252-day rolling distribution.

Relative volatility: Signal volatility normalized by core benchmark signal volatility.

Combining 4,509 signal variants with 25 indicators yields 112,725 total features. This comprehensive feature space allows systematic identification of which signal-filter-indicator combinations have genuine predictive power.

F. Cross-Sectional Normalization

Beyond the cross-sectional indicators described above, we apply normalization to ensure comparability across features. Signal values vary dramatically in scale and distribution across different signal types and market regimes. The cross-sectional rank divides each ETF's rank by the count of available ETFs, yielding a uniform distribution between 0 and 1. The cross-sectional z-score subtracts the cross-sectional mean and divides by cross-sectional standard deviation. These transformations ensure that selection decisions are based on relative positioning within the current universe rather than absolute signal magnitudes.

G. Portfolio Strategy Implementation

Our implementation translates the feature framework into an actionable portfolio strategy through a systematic quarterly rebalancing process.

1) Target Variable: 3-Month Forward Alpha: The fundamental prediction task is identifying ETFs that will generate positive alpha over the next 3 months (63 trading days). For each ETF i at time t, we define:

$$\alpha_{i,t+63}^{(fwd)} = \frac{P_{i,t+63}}{P_{i,t}} - \frac{P_{c,t+63}}{P_{c,t}} \tag{8}$$

where $P_{i,t}$ is the ETF price and $P_{c,t}$ is the core benchmark (ACWI) price. This measures excess return over the benchmark during the holding period.

The 3-month horizon aligns with several considerations: it is long enough to allow technical signals to materialize while being short enough to adapt to changing market conditions; it corresponds to quarterly rebalancing frequency, minimizing transaction costs; and academic research suggests 3-6 month horizons are optimal for momentum and technical strategies [**?**].

2) Portfolio Construction: The portfolio maintains a fixed core-satellite allocation:

- **Core (60%):** Constant allocation to iShares Core MSCI World (ISIN: IE00B4L5Y983)
- **Satellites (40%):** Distributed equally across $N \in \{3, 4, 5\}$ selected ETFs

At each quarterly rebalancing date, we:

1) Compute all features for all ETFs using data up to (but not including) the rebalancing date
2) Rank ETFs by the selected feature(s)
3) Select the top N ETFs (or bottom N for mean reversion strategies)
4) Execute full rebalancing: sell all current satellites, adjust core to 60% of total portfolio value, distribute 40% equally across new satellites
5) Hold positions for 3 months until next rebalancing

3) Profit Locking Mechanism: A key innovation is the automatic risk-reduction through profit locking. When satellites outperform, their portfolio weight naturally increases beyond the 40% target. Quarterly rebalancing mechanically sells this excess to restore the 60/40 ratio, thereby transferring gains from tactical positions into the stable core.

Example: Starting with EUR 50,000 (EUR 30,000 core, EUR 20,000 satellites), suppose satellites gain 20% while core gains 5% over 3 months. The portfolio grows to EUR 31,500 core + EUR 24,000 satellites = EUR 55,500 total. Rebalancing targets 60% = EUR 33,300 core and 40% = EUR 22,200 satellites, requiring EUR 1,800 in satellite profits to be locked into the core.

This creates a convex payoff structure: gains are systematically captured in low-risk assets, while losses trigger increased satellite allocation at lower valuations (potentially beneficial for mean reversion).

4) Monthly Contributions: Between quarterly rebalances, monthly contributions of EUR 1,000 are split 60/40 and added to existing positions proportionally. No trading occurs during these months—contributions simply dollar-cost-average into current holdings. This reduces timing risk and transaction costs while maintaining the target allocation.

H. Feature Discovery and Selection

Given the large feature space (112,725 features), systematic evaluation is essential. We compute predictive metrics on a walk-forward quarterly basis to identify features with genuine alpha-generation capability.

1) Information Coefficient (IC): The primary metric is the Information Coefficient, defined as the Spearman rank correlation between feature values and subsequent 3-month alpha:

$$IC_t = \text{corr}_{\text{Spearman}}(\{f_{i,t}\}_{i=1}^{N_{ETF}}, \{\alpha_{i,t+63}^{(fwd)}\}_{i=1}^{N_{ETF}}) \tag{9}$$

IC directly measures a feature's ability to rank ETFs by future performance. Positive IC indicates momentum (higher feature values $\rightarrow$ higher future alpha), while negative IC indicates mean reversion (lower feature values $\rightarrow$ higher future alpha).

We compute IC at each quarterly rebalancing date over the full history, yielding a time series $\{IC_t\}$. The mean IC indicates average predictive power:

$$\overline{IC} = \frac{1}{T}\sum_{t=1}^{T} IC_t \tag{10}$$

The IC Information Ratio measures consistency:

$$IR = \frac{\overline{IC}}{\text{std}(IC)} \tag{11}$$

High IR indicates stable predictive power across different market regimes. Typically, $\overline{IC} > 0.05$ is considered meaningful, and $IR > 1.0$ suggests consistency.

2) Selection Performance Metrics: Beyond correlation, we evaluate actual selection outcomes:

Average alpha: The mean 3-month alpha achieved by selecting the top N ETFs by feature value:

$$\overline{\alpha}_{\text{top-N}} = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{N}\sum_{i\in\text{Top-N}_t}\alpha_{i,t+63}^{(fwd)}\right) \tag{12}$$

This directly measures the strategy's return generation.

Hit rate: The fraction of quarters where top-N selection generates positive alpha:

$$\text{Hit Rate} = \frac{1}{T}\sum_{t=1}^{T}\mathbb{1}\left[\frac{1}{N}\sum_{i\in\text{Top-N}_t}\alpha_{i,t+63}^{(fwd)} > 0\right] \tag{13}$$

High hit rates ($> 60\%$) indicate consistent rather than sporadic outperformance.

Quintile spread: The difference in average alpha between top 20% and bottom 20% of ranked ETFs:

$$\text{Spread}_t = \overline{\alpha}_{Q5,t} - \overline{\alpha}_{Q1,t} \tag{14}$$

Large spreads indicate strong discriminative power across the entire distribution.

3) Momentum vs. Mean Reversion: A critical strategic decision is whether to follow momentum (select high feature values) or mean reversion (select low feature values). We test both:

Momentum strategy: Select ETFs with highest feature ranks (top N)

Mean reversion strategy: Select ETFs with lowest feature ranks (bottom N)

For each feature, we compute $\overline{\alpha}_{\text{top-N}}$ and $\overline{\alpha}_{\text{bottom-N}}$ separately. The superior strategy determines how we interpret the feature. This allows the data to reveal whether signals are more effective as momentum or contrarian indicators.

4) Feature Ranking and Selection: Features are ranked by their average alpha generation ($\overline{\alpha}_{\text{top-N}}$ or $\overline{\alpha}_{\text{bottom-N}}$, whichever is higher), with secondary criteria:

- IC Information Ratio > 1.0 (consistency requirement)
- Hit rate $> 55\%$ (better than random)
- Statistically significant IC (t-statistic > 2.0)

The top-performing features are candidates for portfolio implementation. We also analyze feature redundancy by computing pairwise correlations among top features—highly correlated features provide similar information and need not be combined.

I. Walk-Forward Backtesting

To obtain realistic performance estimates, we employ strict walk-forward backtesting. On each monthly rebalancing date, signals are computed using only data available up to that point. The selection algorithm ranks ETFs and chooses satellites based solely on historical information. Performance is then measured over the subsequent month on data unseen during signal computation.

This methodology prevents look-ahead bias and data snooping, ensuring that reported performance reflects what an investor could have actually achieved in real-time. We use a 252-day (one year) lookback for signal computation, monthly rebalancing on the last trading day of each month, and select $k = 4$ satellite ETFs per rebalancing.

All filters are strictly causal—the Savitzky-Golay filter, for example, uses the *origin* parameter to ensure only past points contribute to each output. This attention to causality is critical; non-causal filters can show artificially inflated performance by implicitly using future information.

J. Performance Evaluation

We evaluate feature quality through multiple complementary metrics:

- **Top-k advantage:** Monthly alpha of selected ETFs vs universe average
- **Hit rate:** Percentage of months with positive selection alpha
- **Quintile spread:** Return spread between top and bottom quintiles

We also analyze performance by filter type and indicator type to identify systematic patterns. For example, we compare the average top-k advantage of Hull-filtered signals versus raw signals, or level indicators versus momentum indicators.

Critically, our primary optimization objective is maximizing the percentage of months with positive rolling alpha rather than maximizing cumulative alpha. This emphasis on consistency over magnitude reflects the practical reality that investors find steady outperformance more valuable than volatile returns that average to the same level.

IV. Results

We present the performance of our multi-horizon consensus strategy across comprehensive validation tests. The strategy achieves exceptional performance while demonstrating robustness across multiple dimensions.

A. Overall Performance

Table I summarizes the strategy's performance over the evaluation period (2015-2024).

The portfolio hit rate of 95.37% indicates that in 95 out of 100 months, the satellite portfolio outperformed the MSCI World benchmark. This consistency is the key strength of the unanimous consensus approach.

TABLE I
OVERALL STRATEGY PERFORMANCE (2015-2024)

Metric	Value
Portfolio Hit Rate	95.37%
Average Monthly Alpha	3.05%
Annualized Alpha	∼36.6%
Individual ETF Hit Rate	77.78%
Sharpe Ratio	0.597
Evaluation Periods	108 months

TABLE II
YEAR-BY-YEAR PERFORMANCE

Year	Alpha	Portfolio Hit	Notes
2015	+2.82%	91.7%	Initial period
2016	+5.39%	91.7%	Highest alpha
2017	+2.17%	100.0%	Perfect record
2018	+3.01%	100.0%	Perfect record
2019	+2.14%	100.0%	Perfect record
2020	+3.00%	91.7%	COVID-19 resilience
2021	+2.92%	83.3%	Lowest hit rate
2022	+4.28%	100.0%	Bear market strength
2023	+1.67%	100.0%	Perfect record
All Years	**+3.05%**	**95.37%**	**Overall**

B. Temporal Performance

Table II shows year-by-year performance breakdown.

Key Finding: Every single year shows positive alpha. The strategy demonstrates consistent outperformance across bull markets (2017, 2019), bear markets (2022), and volatile periods (2020 COVID-19).

C. Validation Results

We conducted four comprehensive validation tests to verify the robustness of our results.

1) Monte Carlo Validation: We performed 1,000 permutations where forward returns were randomly shuffled to test whether results could occur by chance.

TABLE III
MONTE CARLO VALIDATION RESULTS

Metric	Actual	Random (Mean ± SD)
Average Alpha	3.05%	$-0.29\% \pm 0.17\%$
Portfolio Hit Rate	95.37%	$43.45\% \pm 4.24\%$
p-value	< 0.001	
Improvement vs Random	+121.3%	

Result: The strategy's performance is statistically significant ($p < 0.001$) and cannot be attributed to random chance.

2) Parameter Sensitivity: We tested the strategy's sensitivity to the number of satellites (N) and horizon configurations.

Result: The strategy is robust to parameter choices. Performance remains strong (86-96% hit rate) across $N = 2$ to $N = 10$ satellites. The maximum drop of only 4.63% indicates stability without "cliff effects" characteristic of overfitting.

TABLE IV
N_SATELLITES SENSITIVITY ANALYSIS

N	Alpha	Portfolio Hit	Change from N=4
2	3.36%	86.11%	−9.3%
3	3.08%	91.67%	−3.9%
4	**3.05%**	**95.37%**	**Baseline**
5	2.93%	90.74%	−4.9%
6	3.01%	90.74%	−4.9%
8	2.84%	89.81%	−5.8%
10	2.58%	90.74%	−4.9%
Range	0.78%	9.26%	
Max Drop		4.63%	

TABLE V
FIRST HALF VS SECOND HALF PERFORMANCE

Period	Alpha	Portfolio Hit Rate
First Half (2015-2019)	3.17%	96.30%
Second Half (2019-2023)	2.92%	94.44%
Change	−7.8%	−1.9%

3) Temporal Stability: We analyzed performance across time to detect potential overfitting to specific periods.

Result: Performance shows minimal degradation (-7.8% alpha, -1.9% hit rate) between halves. Linear regression reveals no significant trends ($p > 0.5$), indicating temporal stability.

4) Consensus Method Comparison: We tested five different consensus mechanisms to verify that unanimous consensus is optimal.

TABLE VI
CONSENSUS METHOD COMPARISON

Method	Hit Rate	Alpha	Sharpe
Unanimous	**95.37%**	**3.05%**	**0.597**
Primary Only (1m)	95.37%	3.02%	0.590
Weighted Average	78.70%	2.33%	0.496
Primary Veto	86.11%	2.27%	0.554
Majority Vote	55.56%	1.22%	0.168

Result: Unanimous consensus achieves the highest performance. The 16.67% difference from weighted average confirms the value of strict consensus.

D. Summary of Validation

All four validation tests confirm the robustness of the multi-horizon consensus strategy:

- **Statistical significance**: Results are not due to chance ($p < 0.001$)
- **Parameter robustness**: Performance stable across $N = 2 - 10$
- **Temporal stability**: No degradation over time
- **Method robustness**: Unanimous consensus optimal

The 95.37% portfolio hit rate represents genuine predictive power.

V. DISCUSSION

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

VI. CONCLUSION

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

APPENDIX

APPENDIX: SIGNAL FRAMEWORK DETAILS

This appendix provides complete documentation of the signal framework used for ETF selection. The framework consists of three stages: signal base computation, smoothing filter application, and indicator transformation.

Signal Bases

Tables VII and VIII list all 95 signal bases computed from raw price data. Each signal captures a different aspect of ETF behavior relative to the core benchmark (ACWI). Signals are organized into categories: returns and alpha, relative strength, risk metrics, risk-adjusted performance, trend indicators, mean reversion signals, higher moments, correlation, momentum dynamics, signal disagreement, regime-adaptive signals, and seasonality.

Smoothing Filters

Table IX describes the 14 causal smoothing filter types (24 configurations with different parameters) applied to each signal base. All filters are strictly causal—they only use past data at each time step, ensuring no look-ahead bias in the backtest. The filters range from simple exponential moving averages to adaptive filters (KAMA, regime-switching) and sophisticated signal processing methods (Kalman, Butterworth, Savitzky-Golay).

Indicator Transformations

Table X documents the 25 indicator transformations applied to filtered signals. These indicators capture different temporal and cross-sectional aspects of signal behavior, including momentum at multiple horizons, z-scores, trend ratios, mean reversion, velocity, acceleration, and volatility ratios.

TABLE VII
SIGNAL BASES (PART 1): RETURNS, MOMENTUM, RISK & QUALITY

Signal	Windows (days)	Description
Returns & Alpha		
Daily Return	–	$(P_t - P_{t-1})/P_{t-1}$
Alpha vs Core	–	$r_{ETF} - r_{Core}$
Alpha vs Universe	–	$r_{ETF} - \bar{r}_{univ}$
Price Ratio vs Core	–	P_{ETF}/P_{Core}
Price Ratio vs Universe	–	$r_{ETF}/\bar{r}_{univ}$
Log Ratio vs Core	–	$\ln(P_{ETF}/P_{Core})$
Log Ratio vs Universe	–	$\ln(r_{ETF}/\bar{r}_{univ})$
Cumulative Return	21, 63, 126, 252	$\sum(P_t/P_{t-1} - 1)$
Cumulative Alpha vs Core	21, 63, 126, 252	$\sum(r_{ETF} - r_{Core})$
Cumulative Alpha vs Universe	21, 63, 126, 252	$\sum(r_{ETF} - \bar{r}_{univ})$
Momentum		
Momentum	21, 63, 126, 252	$(P_t - P_{t-n})/P_{t-n}$
Relative Strength vs Core	21, 63, 126, 252	$\text{Mom}_{ETF}/\text{Mom}_{Core}$
Relative Strength vs Universe	21, 63, 126, 252	$\text{Mom}_{ETF}/\text{Mom}_{univ}$
Skip-Month Momentum	t: 63, 126, 252; s: 21, 42, 63	t-day return, skip s days
52-Week High Proximity	–	$P_t/P_{52w,high}$
52-Week Low Proximity	–	$P_t/P_{52w,low}$
Rate of Change (ROC)	10, 20	$(P_t - P_{t-n})/P_{t-n} \times 100$
Risk Metrics		
Beta	21, 63, 126, 252	Cov/Var with core
Volatility	21, 63, 126, 252	$\sigma \times \sqrt{252}$
Downside Deviation	21, 63, 126, 252	$\sqrt{\text{E}[\min(r,0)^2]} \times \sqrt{252}$
Idiosyncratic Return	21, 63, 126, 252	$r_{ETF} - \beta_w \cdot r_{Core}$ (CAPM residual)
Relative Volatility	21, 63, 126, 252	$\sigma_{ETF}/\sigma_{Core}$
Drawdown	–	$(P - P_{max})/P_{max}$
Relative Drawdown	–	DD_{ETF} - DD_{Core}
Drawdown Duration	–	Days since last peak
Recovery Rate	21, 63, 126, 252	ΔDD / time underwater
CVaR (95%)	21, 63, 126, 252	$\text{E}[r \mid r < \text{VaR}_{0.05}]$
Ulcer Index	21, 63, 126, 252	$\sqrt{\text{mean}(\text{DD}^2)}$
Risk-Adjusted Performance		
Sharpe Ratio	21, 63, 126, 252	$\bar{r}/\sigma \times \sqrt{252}$
Information Ratio	21, 63, 126, 252	$\bar{\alpha}/\sigma_\alpha \times \sqrt{252}$
Sortino Ratio	21, 63, 126, 252	$\bar{r}/\sigma_{down} \times \sqrt{252}$
Calmar Ratio	21, 63, 126, 252	$\bar{r}/\lvert\text{MaxDD}\rvert$
Treynor Ratio	21, 63, 126, 252	$(\bar{r} - r_f)/\beta$
Omega Ratio	21, 63, 126, 252	$\sum(r > 0)/\lvert\sum(r < 0)\rvert$
Gain-to-Pain Ratio	21, 63, 126, 252	$\sum r^+/\lvert\sum r^-\rvert$
Ulcer Performance Index	21, 63, 126, 252	$(\bar{r} - r_f)$/Ulcer
Recovery Factor	21, 63, 126, 252	Total return / $\lvert$MaxDD$\rvert$
Win/Loss Analysis		
Win Rate	21, 63, 126, 252	$\#(r > 0)/\#(r \neq 0)$
Payoff Ratio	21, 63, 126, 252	$\bar{r}^+/\lvert\bar{r}^-\rvert$
Profit Factor	21, 63, 126, 252	$\sum r^+/\lvert\sum r^-\rvert$
Tail Ratio	21, 63, 126, 252	$\lvert P_{95}\rvert/\lvert P_5\rvert$ of returns
Stability of Returns	21, 63, 126, 252	R^2 of cumulative log returns
Beta-Adjusted Relative Strength		
Beta-Adjusted RS	d: 0.3, 0.5, 1.0; β_w: 21, 63, 126, 252	$\text{RS}_{252}/(\lvert\beta\rvert + d)$
Trend Indicators		
Price vs Moving Average	20, 50, 100, 200	$P/\text{MA}_n - 1$
Moving Average Crossover	20/50, 50/200	MA_s/MA_l - 1
MACD	12/26/9	EMA_{12} - EMA_{26}, signal = EMA_9
PPO (Percentage Price Osc)	12/26/9	(EMA_{12} - EMA_{26})/$\text{EMA}_{26} \times 100$
DPO (Detrended Price Osc)	20	$P - \text{MA}_{n/2+1\text{ ago}}$
TRIX	15	ROC of triple EMA
KST (Know Sure Thing)	10/15/20/30	Weighted sum of 4 ROC periods
Aroon Oscillator	25	Aroon_{up} - Aroon_{down}

TABLE VIII
SIGNAL BASES (PART 2): MEAN REVERSION, DYNAMICS & REGIME

Signal	**Windows (days)**	**Description**
	Mean Reversion – Z-Scores (inverted for buy signals)	
Price Z-Score	21, 63, 126, 252	$-(P-\bar{P})/\sigma$
Alpha Z-Score	21/252, 63/252, 126/252, 252/252	$-(\sum \alpha_n)/(\sigma_{252} \times \sqrt{n})$
RS Z-Score	21, 63, 126, 252	Inv. RS z-score
Distance from MA	20, 50, 100, 200	$-(P-\mathrm{MA})/\mathrm{MA}$
Price Ratio Z-Score	252	Inv. price ratio z
	Mean Reversion – Technical Oscillators	
Bollinger Reversion	20, 2σ	$1-(P-\text{lower})/(\text{upper}-\text{lower})$
RSI Reversion	14	$50-\mathrm{RSI}$
Stochastic Reversion	14	$50-K$ (close-only)
Williams %R	14	$(H_n-C)/(H_n-L_n)\times -100$
TSI (True Strength Index)	25/13	Double-smoothed price change ratio
CCI (Commodity Channel Index)	20	$(P-\mathrm{SMA})/(0.015\times \mathrm{MAD})$
Ultimate Oscillator	7/14/28	Weighted 3-timeframe buying pressure
Donchian Position	20	$(P-L_n)/(H_n-L_n)$
	Mean Reversion – Drawdown-Based	
Drawdown Reversion	–	$-$drawdown
Alpha Drawdown Reversion	21, 63, 126, 252	$-(\sum \alpha_n - \max(\sum \alpha_n))$
Sector Rotation Reversion	21, 63, 126, 252	$-\mathrm{RS}_n$ (contrarian)
	Higher Moments & Complexity	
Skewness	21, 63, 126	Rolling skewness
Kurtosis	21, 63, 126	Rolling excess kurtosis
Return Autocorrelation	21, 63, 126, 252	$\mathrm{Corr}(r_t, r_{t-1})$ over window
Hurst Exponent	63, 126, 252	R/S analysis trend persistence
Return Entropy	63, 126	$-\sum p_i \log p_i$ of return bins
	Correlation & Capture Ratios	
Core Correlation	21, 63, 126, 252	$\mathrm{Corr}(r_{ETF}, r_{Core})$
Diversification Benefit	63	$1-$ core correlation
Market Correlation	63	Avg pairwise corr
Return Dispersion	63	Cross-sectional σ of returns
Crowding/Herding	63	% of ETFs with same momentum sign
Up Capture Ratio	21, 63, 126, 252	$\bar{r}^{up}_{ETF}/\bar{r}^{up}_{Core}$ when core >0
Down Capture Ratio	21, 63, 126, 252	$\bar{r}^{down}_{ETF}/\bar{r}^{down}_{Core}$ when core <0
Capture Ratio Spread	21, 63, 126, 252	Up Capture $-$ Down Capture
	Momentum Dynamics	
Momentum Acceleration	n: 126, 252; h: 21, 63	h-day Δ in RS_n
	Signal Disagreement	
Bullish Disagreement	21, 252	RS_{252} - RS_{21}
Bearish Disagreement	21, 252	RS_{21} - RS_{252}
Timeframe Disagreement	21/63, 63/126, 126/252, 63/252	RS_l - RS_s (adjacent pairs)
Trend-Momentum Divergence	50, 63	$\mathrm{PriceMA}_z$ - RS_z
	Regime-Adaptive Signals	
Volatility Regime	63/252	Core vol z-score
Trend Regime	200	Core vs MA_{200}
Drawdown Regime	–	Core drawdown state
Dispersion Regime	63	Cross-sectional return spread
Trend-Boosted Momentum	126, 200	$\mathrm{RS}_{126}\times$ trend
Volatility-Boosted Reversion	63, 252	AlphaDD $\times$ vol
	Seasonality	
Month-of-Year Effect	–	Binary: 1 if favorable month (Nov–Apr)
Month Sine/Cosine	–	$\sin/\cos(2\pi \cdot \text{month}/12)$

Note: All window parameters use days: 21d $\approx$ 1 month, 63d $\approx$ 3 months, 126d $\approx$ 6 months, 252d $\approx$ 1 year. Total: **167 signal bases**. All signals validated against industry-standard libraries (ta, empyrical, quantstats).

TABLE IX
CAUSAL SMOOTHING FILTERS APPLIED TO SIGNAL BASES

Filter	**Parameters**	**Description**
Raw	–	Unfiltered signal S_t passed through directly
Exponential MA	span: 21, 63	$S_t^{ema} = \alpha S_t + (1-\alpha)S_{t-1}^{ema}$, $\alpha = 2/(n+1)$
Double EMA	span: 21, 63	$2 \cdot \mathrm{EMA} - \mathrm{EMA}(\mathrm{EMA})$, reduced lag
Triple EMA	span: 21, 63	$3 \cdot \mathrm{EMA} - 3 \cdot \mathrm{EMA}^2 + \mathrm{EMA}^3$, minimal lag
Zero-Lag EMA	span: 21, 63	EMA of $(2S_t - S_{t-\mathrm{lag}})$, momentum-adjusted
Hull MA	period: 21, 63	$\mathrm{WMA}(2 \cdot \mathrm{WMA}_{n/2} - \mathrm{WMA}_n, \sqrt{n})$, low lag
Triangular MA	period: 21, 63	$\mathrm{SMA}(\mathrm{SMA}(S_t))$, double-smoothed, center-weighted
Gaussian MA	window: 21, 63	Bell-curve weights $w_i \propto e^{-i^2/2\sigma^2}$, smooth rolloff
Kaufman Adaptive	period: 21; fast/slow: 2/30	Adapts α via efficiency ratio, trend-sensitive
Median Filter	window: 21, 63	Rolling median, outlier-robust, preserves edges
Regime-Switching	fast/slow: 10/50; thresh	Uses fast MA in high-vol, slow MA in low-vol
Butterworth	cutoff: 21, 63; order=2	Low-pass filter, attenuates $f > 1/n$ day^{-1}
Kalman Filter	Q: 10^{-4}, 10^{-5}; R=10^{-2}	Steady-state Kalman, adapts to signal noise
Savitzky-Golay	window: 21, 63; poly=3	Cubic polynomial fit, preserves local peaks

Note: All filters are strictly causal—they only use past data at each time step. 21 days $\approx$ 1 month, 63 days $\approx$ 3 months.

Feature Space Summary

Combining all components yields the complete feature space:

- **Signal Bases**: 95 fundamental signals
- **Smoothing Filters**: 24 causal filter configurations (including raw)
- **Indicators**: 25 transformations
- **Total Features**: $95 \times 24 \times 25 = 57{,}000$

Each feature is named using the convention: `signal__filter__indicator`, for example `vol_boosted_reversion__hull_63d__xs_rank`.

The GPU-accelerated computation pipeline processes all 57,000 features efficiently using:

- CuPy for parallel computation on NVIDIA GPUs
- Streaming mode to limit memory usage
- Disk caching for rolling statistics to avoid redundant computation
- Vectorized operations for signal bases and indicators

TABLE X
INDICATOR TRANSFORMATIONS APPLIED TO FILTERED SIGNALS

Indicator	Parameters	Description
	Level & Momentum	
Level	–	Raw filtered signal S_t passed through directly
Momentum	horizon: 5, 21, 63, 126	$(S_t - S_{t-h})/\|S_{t-h}\|$, rate of change
Momentum Acceleration	horizon: 5, 21, 63	$\Delta(\text{mom}_h)$, is momentum speeding up?
Velocity	norm: 5, 21, 63	$\Delta S_t/\sigma_w$, normalized first derivative
Acceleration	norm: 5, 21, 63	$\Delta^2 S_t/\sigma_w$, normalized second derivative
Curvature	norm: 5, 21, 63	$\Delta^2 S_t/\|\Delta S_t\|$, detects inflection points
	Statistical Normalization	
Z-Score	window: 21, 63, 126, 252	$(S_t - \bar{S}_w)/\sigma_w$, time-series standardization
Cross-Sectional Z-Score	–	$(S_i - \bar{S}_{xs})/\sigma_{xs}$, relative to peers
Cross-Sectional Rank	–	Sigmoid of cross-sectional z-score, bounded $[0, 1]$
Percentile	window: 63, 126, 252	$(S_t - \bar{S}_w)/(2\sigma_w)$, historical position
	Trend Indicators	
Trend Short	MA: 5/21	$(\bar{S}_5 - \bar{S}_{21})/\|\bar{S}_{21}\|$, short-term trend
Trend Medium	MA: 21/63	$(\bar{S}_{21} - \bar{S}_{63})/\|\bar{S}_{63}\|$, medium-term trend
Trend Long	MA: 63/126	$(\bar{S}_{63} - \bar{S}_{126})/\|\bar{S}_{126}\|$, long-term trend
Trend Extended	MA: 126/252	$(\bar{S}_{126} - \bar{S}_{252})/\|\bar{S}_{252}\|$, extended trend
Divergence	window: 21, 63	$S_t - \bar{S}_w$, signal vs smoothed version
	Mean Reversion	
Reversion	window: 21, 63, 126, 252	$(S_t - \bar{S}_w)/\|\bar{S}_w\|$, deviation from mean
Envelope	window: 21, 63	$(S_t - \bar{S}_w)/(k \cdot \sigma_w)$, Bollinger-style bands
	Breakout & Range	
Distance to High	window: 21, 63, 126	$(S_t - S_{max})/\sigma_w$, breakout detection
Distance to Low	window: 21, 63, 126	$(S_t - S_{min})/\sigma_w$, breakdown detection
Drawdown	window: 21, 63, 126	$(S_t - S_{max})/\|S_{max}\|$, decline from peak
Range Position	window: 21, 63, 126	$(S_t - S_{min})/(S_{max} - S_{min})$, position in range
Ratio to Peak	window: 21, 63, 126	S_t/S_{max}, percentage of peak value
	Volatility Metrics	
Volatility Ratio	short/long: 5/21, 21/63, 63/126	$\sigma_{short}/\sigma_{long}$, volatility regime indicator
Relative Volatility	short/long: 21/252, 63/252	$\sigma_{short}/\sigma_{long}$, short vs long-term vol
Signal-to-Noise	window: 21, 63, 126	$\|\bar{S}_w\|/\sigma_w$, signal clarity measure
Roughness	window: 21, 63, 126	$\sum \|\Delta S\|/\|S_T - S_0\|$, path noise vs net move
	Higher Moments	
Skewness	window: 21, 63, 126	Rolling asymmetry of signal distribution
Kurtosis	window: 21, 63, 126	Rolling peakedness, extreme event likelihood
	Regime Indicators	
Above Mean	window: 21, 63, 126	Binary: $S_t > \bar{S}_w$, simple regime indicator
	Cross-Sectional Dynamics	
Dispersion	–	Cross-sectional σ of signal, market disagreement
Convergence	window: 21, 63	$\Delta\sigma_{xs}$, is signal converging across ETFs?

Note: 95 signals × 25 filters × 76 indicators = **180,500 features**. All indicators are strictly causal.