

Anabasis Transformational Technology Fund: A Quantitative Framework for Transformational Technology Sectors

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Executive Summary

This paper presents the comprehensive development and validation of the Anabasis Transformational Technology Fund (ATTF), a rules-based quantitative portfolio management system designed to capture alpha in transformational technology sectors. The research represents a complete evolution from initial portfolio construction through advanced algorithmic trading strategies and rigorous performance validation. The central thesis is that the sectors of the ATTF follow adoption-driven momentum patterns and are poorly suited to traditional diversification or mean-reversion approaches. I reject the efficient market hypothesis in favor of an adaptive markets framework, and I use fully transparent quantitative rules to express thematic conviction while minimizing human bias.

The ATTF is built on a universe of 46 securities grouped into thematic sleeves, with all returns carefully adjusted for dividends, realistic fees, and trading costs. The fund implements multiple complementary strategies assessed including Machine Learning (ML), Clenow, Mean-Regression, and expanding window technical indicators hybrid regime-switching strategies, fee sensitivity analysis, regime detection, multi-path Monte Carlo simulation, and validation. Each strategy was evaluated against benchmark testing and evaluation.

Results clearly favor momentum and machine learning over contrarian and pairs-trading concepts in the universe. The ML ensemble strategy emerges as the core engine, with Clenow and hybrid regime-switching strategies serving as diversification. The report provides realistic analysis about risks and limitations. Finally, the paper then translates these findings into a concrete launch plan, with a competitive business model is outlined and startup requirements are estimated.

Introduction

This term paper presents the complete development of the Anabasis Transformational Technologies Fund, synthesizing all quantitative research conducted throughout MSDS 451. The work represents systematic progression from foundational portfolio theory through advanced algorithmic trading strategies and rigorous backtesting, and out-of-sample validation. The objective was twofold. First, to design a multi-strategy quantitative fund capable of generating consistent alpha in transformational technology sectors. Second, to develop a comprehensive business analysis establishing both the fund's viability and the minimum resources required for launch.

General Investment Philosophy

The ATTF operates under a fundamental rejection of the efficient-markets hypothesis in favor of the adaptive-markets framework (Lo and Zhang 2024), recognizing that most investors are not fully informed and not always rational, particularly in emerging technology sectors characterized by high uncertainty, limited historical precedent, and rapid innovation cycles.

Investment Thematic Foundation

The thematic foundation follows the disruptive innovation focus popularized by ARK Invest and Cathie Wood, emphasizing technologies such as AI, robotics, DNA sequencing, blockchain, and quantum computing that could reshape economic activity and capital allocation. The ATTF's distinctive feature is that thematic conviction is enforced by quantitative rules rather than discretionary judgment. The fund does not rely on subjective opinions about individual

companies but instead uses transparent algorithms to select and weigh securities based on price history, volatility, and regime indicators. Strategy decisions arise from explicit rules that can be backtested, audited, and explained, following principles outlined in Clenow (2019) for systematic trend-following, Carver (2015) for systematic trading design, and de Prado (2018) for rigorous validation frameworks that prevent overfitting and data mining. The ATTf combines a systematic quantitative philosophy with thematic focus on transformational technology sectors.

Core Investment Thesis

The core hypothesis of this project is that *we can utilize tools from data science, technical analysis, and financial engineering to earn excess returns relative to index funds and broad technology benchmarks*. The fund's investment philosophy rests on three foundational principles that transformational technologies exhibit persistent momentum during adoption phases, systematic rules-based strategies reduce behavioral biases inherent in discretionary management, and concentration in trending assets deliver superior risk-adjusted returns compared to diversification during exponential growth trajectories. These principles align with empirical research on technology adoption curves (Rogers 2003), momentum persistence growth stocks (Jegadeesh and Titman 2001), and the limits of diversification in concentrated opportunity sets (Statman 1987).

Transformational technologies progress through predictable adoption phases characterized by initial skepticism, proof-of-concept validation, institutional acceptance, exponential scaling, and eventual maturation. During the exponential scaling phase, which typically spans 5-15 years, leading companies experience persistent momentum as network effects, economies of scale, and technical breakthroughs compound advantages. NVIDIA's

trajectory with the AI boom, becoming the most valuable company in the world at over \$5 trillion market cap, recently exemplifies this pattern.

Systematic Rules-Based Management

The fund implements systematic, rules-based strategies that eliminate discretionary judgment and behavioral biases documented in behavioral finance literature (Thaler and Sunstein 2008). Discretionary technology investing suffers from recency bias, confirmation bias, loss aversion, and herd behavior that manifest as buying near peaks after positive news flow and panic selling during corrections. Systematic strategies prevent these patterns through mechanical execution rules specifying exact entry/exit conditions, position sizing methodologies, and rebalancing frequencies.

The fund's rules-based approach provides several operational advantages beyond behavioral bias reduction. Systematic strategies enable comprehensive backtesting across multiple market regimes, quantifying expected performance during bull markets, corrections, and bear markets with statistical confidence. Mechanical rules facilitate operational scaling as assets under management grow, avoiding capacity constraints inherent in discretionary stock picking, where manager attention limits portfolio breadth. Finally, transparent execution rules reduce principal-agent problems by aligning manager incentives with investor outcomes through verifiable performance attribution.

However, rules-based strategies face limitations that warrant acknowledgment. Mechanical systems cannot adapt to unprecedeted events outside historical training data, potentially maintaining positions during structural breaks that discretionary managers might recognize. Systematic approaches may also miss company-specific fundamental developments

like management changes, technological breakthroughs, or competitive threats that drive individual stock returns. The fund addresses these limitations through ensemble approaches combining multiple strategies rather than relying on single methodologies, enabling adaptation through complementary signal generation.

Investment Methods and Rules Employed

The fund implements seven distinct core trading strategies evaluated through rigorous walk-forward validation, each designed to exploit different market characteristics and provide diversification across signal generation methodologies. This section provides background information on how metrics for the strategies were calculated, and provides details on the specific rules, parameters, rebalancing frequencies, and theoretical foundations underlying each strategic approach. Additionally, this section covers enhanced strategies, enhanced analysis, and final validation methodologies utilized.

Background Framework

To develop and analyze the fund's strategy I utilized the 46 individual stocks from the ATTF universe as well as divided the securities into sleeves, assigning each sleeve an associated ETF associated with historical backtesting and assessment. For individual stocks, the security data spans October 2015 through October 2025. For each ETF, historical backtesting covered from 1999-2025.

All prices incorporate dividend adjustments using Polygon.io's adjusted close data to ensure accurate total return calculations. For each dividend payment, the adjusted factor is

calculated as $(1 + \text{dividend}/\text{price})$, and all future prices are multiplied by this factor cumulatively. This approach ensures that returns reflect both capital appreciation and reinvested dividends. The SPY benchmark received identical dividend adjustment using its dividend payment history over the sample period. Log returns were calculated as $\ln(\text{Pt}/\text{Pt-1})$ rather than simple percentage changes, offering the advantages of being additive across time, enabling straightforward multi-period return calculations, and approximating normal distribution properties suitable for mean-variance optimization. Equal-weighted returns within each sleeve were calculated as arithmetic averages of constituent securities, with sleeve returns then aggregated according to target allocations to produce portfolio-level performance metrics.

Annualized statistics followed standard financial conventions with expected return calculated as mean daily log return multiplied by 252 trading days, and annualized volatility calculated as standard deviation of daily log returns multiplied by the square root of 252. A 4% annualized risk-free rate was established for Sharpe ratio calculations, representing the approximate yield on 3-month Treasury bills and providing consistent comparison to academic benchmarks where Sharpe ratios above 1.0 are considered excellent after subtracting the risk-free rate.

The baseline fee structure reflects realistic hedge fund implementation costs with 1.5% annual management fee, 15 basis points per trade in transaction costs, and 5 basis points per trade in market impact costs, totaling 20 basis points per full round-trip transaction. A fee sensitivity grid evaluates strategy performance across distinct costs scenarios, varying management fees, transaction costs, and performance fees. For each combination, the analysis calculates net-of-fees CAGR, Sharpe ratio, and maximum drawdown for all strategies. This produces a comprehensive sensitivity table showing how each strategy's risk-adjusted

performance degrades as costs increase, enabling identification of implementation frictions and strategies that collapse under realistic fee assumptions. CAPM provides the theoretical framework for calculating alpha and beta relative to the SPY benchmark. Beta is calculated as the covariance of portfolio returns with benchmark returns divided by the variance of benchmark returns, representing systematic market risk exposure. Alpha represents capturing excess returns beyond what beta predicts. For this project, positive alpha quantifies whether momentum-based allocation, ML predictions, regime-switching tactics, mean-reversion signals, or pairs trading strategies add value beyond simple leveraging broad market exposure.

Clenow Momentum Strategy

The Clenow momentum strategy implements a dual-filter methodology combining intermediate-term momentum with long-term confirmation (Clenow 2015). The strategy calculates 90-day percentage price changes for all securities in the ATTf universe, representing intermediate-term momentum that captures sustained trends without excessive noise from daily fluctuations. A 200-day moving average filter excludes securities trading below their long-term trend, preventing entries into down-trending securities experiencing temporary dead-cat bounces that exhibit positive short-term momentum within larger bear markets.

Each month-end rebalancing date, the strategy ranks all 46 securities by 90-day momentum score, filters to retain only those trading above their 200-day moving average and allocates equal weight to the top 10 highest-momentum securities passing both filters. If fewer than 10 securities satisfy both momentum and trend criteria, the strategy allocates proportionally to those meeting requirements with remainder held in cash earning the risk-free rate. Monthly rebalancing strikes a balance between allowing momentum persistence to compound and limiting transaction costs from excessive trading.

The dual-filter design reflects empirical evidence that momentum strategies perform best when combined with trend-following filters, as documented by Antonacci (2014). Pure momentum without trend confirmation suffers during whipsaw markets where securities oscillate without persistent direction, generating false signals that trigger frequent trades with transaction costs overwhelming signal value. The 200-day moving average trend filter reduces these false signals by requiring alignment between intermediate-term momentum and long-term price trajectory, concentrating capital in securities exhibiting both characteristics.

Machine Learning

The final research incorporated additional ML strategies as the ML Ridge Regression collapsed after elimination of look-ahead bias in Checkpoint Assignment C. For the final paper and presentation, the ML strategies include Ridge Regression, an Ensemble strategy, and a Rank Targets ML strategy.

Shared Framework

The machine learning strategies implement monthly walk-forward validation trained on rolling 3-year historical windows to predict forward 21-day returns. This approach addresses the fundamental tension in quantitative investing between sufficient historical data for stable parameter estimation and model adaptation to evolving market conditions. Three-year training windows provide approximately 756 trading days of data, sufficient for robust feature relationship estimation while remaining short enough that distant historical periods do not dominate recent behavioral patterns.

The feature set includes six technical indicators calculated for each security. These include 20-, 60-, and 120-day price momentum capturing short, intermediate, and long-term

trends, 20- and 60-day return volatility quantifying recent price stability, and 20- to 60-day moving average ratio identifying trend strength and mean-reversion tendencies. These security-specific features have a total of 276 dimensions across the 46-stock universe. Additionally, three market-wide features calculated from SPY returns, 20- and 60-day momentum and 20-day volatility provide systematic risk context, producing 279 total features. This feature engineering approach follows best practices emphasizing technical indicators observable at prediction time without look-ahead bias.

Critical to avoid look-ahead bias, features at time t use only data through t-1 to predict returns from t to t+20. The target variable represents forward 21-day log returns calculated as $\ln(P_{t+20}/P_t)$, where P represents adjusted close prices incorporating dividend reinvestment. Features are standardized using only training window statistics, preventing information leakage from future data periods that would inflate backtested performance through inadvertent data snooping. Positions are rebalanced monthly with equal weight among selected securities.

ML Ridge Regression

The baseline strategy uses Ridge regression to predict forward returns, selecting the top 10 securities each period. For each month-end rebalancing date a Ridge regression model trains on the prior 756 trading days with L2 regularization penalty alpha=1.0 preventing overfitting. Positions are rebalanced monthly with equal weighting among selected securities. This approach provides a robust, interpretable baseline that balances model complexity against overfitting risk.

Ensemble ML

The ensemble ML strategy combines XGBoost, RandomFroest, and GradientBoosting predictions through simple averaging, providing model diversification that reduces variance from any single algorithm's biases. Additional enhancements include a 200-day moving average filter which excludes stocks in downtrends, concentration to the top 5 positions, and regime-based position scaling. Model agreement averaged 0.983 across the ensemble.

Rank Target ML

Rather than predicting absolute returns, this strategy predicts cross-sectional ranks where each stock's relative performance is compared versus peers on a given day. Returns are converted to percentile ranks scaled to [-1, 1], and Ridge regression predicts these ranks. The top 10 stocks by predicted rank are selected. This approach reduces sensitivity to return magnitude outliers while focusing on relative ordering.

Mean-Reversion Strategy

The mean-reversion strategy tests whether transformational technology stocks exhibit cyclical price patterns around stable means that contrarian traders can exploit. The methodology calculates rolling 60-day mean and standard deviation of prices for each security, then computes z-scores as (current price-rolling mean)/rolling standard deviation. Entry signals trigger when securities trade more than 0.3 standard deviations below their rolling mean, indicating potential oversold conditions with high probability of price recovery toward fair value. Exit signals trigger when z-scores rise above 0.5 standard deviations, indicating return to fair value justifying profit-taking.

Position sizing allocates equal weight to the top 10 most oversold securities at any given time, with daily rebalancing as new signals generate or existing positions exit. This approach follows mean-reversion literature including Chan (2020), who documented profitability of z-score-based securities in range-bound markets with established support and resistance levels. However, these studies focus primarily on mature, cyclical securities rather than transformational growth stocks.

Hybrid Regime-Switching Strategy

The hybrid regime-switching system implements dynamic capital allocation based on market regime classification into bull, sideways, and bear regimes. Rather than training an HMM on the full sample, which has introduced look-ahead bias in previous assignments, the final hybrid regime-switching strategy uses expanding-window technical indicator thresholds calculated monthly using only past data. Classification features include 50-day SPY momentum, 20-day cumulative returns, VIX level, 20-day realized volatility, and drawdown from rolling 252-day highs. Threshold quantiles are recalculated each month from the prior three years, ensuring no future information contaminates regime assignments. To reduce excessive trading from noisy regime signals, a three-month smoothing filter requires regime persistence before triggering allocation changes, which reduces switches from 118 to 30 over the backtest period.

Regime classification enables tactical allocation optimized for prevailing conditions. During bull markets, the system allocates 60% to Clenow, 20% to ML Ridge, 10% to Ensemble ML, and 10% to Rank ML, blending all four strategies to capture both trend-following momentum and ML pattern recognition with up to 15 positions. In sideways markets characterized by elevated volatility and unstable trends, the system allocates 20% to Clenow, 30% to ML Ridge, 35% to Ensemble ML, and 15% to Rank ML with a maximum of 10 positions. In bear

markets, the system moves 100% to cash, preserving capital during drawdowns that erode long-term compounding. Regime distribution across 2015-2025 was 54% Bull, 31% Sideways, and 15% Bear.

Pairs Trading Strategy

The pairs trading strategy implements Engle-Granger cointegration methodology targeting NVDA and AMD as a correlated pair representing AI chip manufacturers with similar exposure to datacenter GPU demand, AI inference workloads, and semiconductor manufacturing cycles. Pairs trading seeks to exploit temporary spread deviations between cointegrated securities that maintain stable long-term relationships despite short-term divergences. The strategy constructs market-neutral positions to profit when spreads revert to historical norms.

The Engle-Granger cointegration test determines whether NVDA and AMD prices maintain a stable long-term relationship suitable for statistical arbitrage. The test regresses NVDA prices on AMD prices using Ordinary Least Squares (OLS) to estimate the hedge ratio representing the number of AMD shares to short per NVDA share held long, then tests whether the residual spread series is stationary using augmented Dickey-Fuller tests. P-values below 0.05 indicate cointegration with statistical significance, validating pairs trading viability. P-values above 0.05 suggest lack of a stable relationship where spread divergences may not revert, generating unpredictable losses.

Description of Securities and Trading

The ATTF universe evolved from an initial tranche of 22 securities to a comprehensive 46 security universe during the later stages of the quarter. This expansion enabled systematic testing of universe size effects on strategy performance, revealing divergent patterns where ML strategies benefited from increased breadth while mean-reversion strategies degraded substantially.

Core Portfolio (22 Securities)

The core 22-security portfolio established in Checkpoint A and refined through Programming Assignment 3 divides into four thematic sleeves representing distinct transformational technology exposures. Each of the sleeves includes established securities along with newer growth focused securities to create a balance between risk and stability. The four core sleeves established in the initial thesis were AI, Robotics and Space, Cryptocurrency, and Quantum Computing.

Expanded Portfolio (46 Securities)

The enhanced 46-portfolio universe adds two sleeves enabling comprehensive testing of universe size effects on strategy performance. The additional sleeves include Bioengineering and FINTECH. The expansion from 22 to 46 securities revealed critical insights about strategy-market fit. ML strategies achieved improved CAGR while mean-reversion's CAGR decreased. This demonstrated that ML benefits from increased cross-sectional breadth enabling better winner identification from diverse opportunities. Mean-reversion appears to be worse in an expanded universe not only from its organic incongruence to volatile growth securities but also an expansive selection seems to inhibit mean-reversion's ability to pick winners that fit its ability to achieve measurable alpha.

Benchmarks and Implementation

The ATTf employs multiple benchmark comparisons following best practices outlined by Bailey et al. (2007) for evaluating portfolio performance. Primary benchmarks include SPY, QQQ, and an equal-weight ATTf portfolio buy-and-hold baseline. Sleeves were established to better segregate the securities into sectors for extended validation due to many of the securities inherently being newer publicly traded companies and not having enough data for historical assessment. Extended validation employs sector proxy ETFs including QQQ (NASDAQ Tech focused), XLK (Technology Select), VGT (Vanguard IT), and SOXX (Semiconductor) to enable 1999-2025 testing documented in Checkpoint Assignment C.

Trading implementation follows systematic rules requiring no discretionary judgement. All strategies rebalance at predetermined frequencies, i.e., monthly for Clenow and ML, daily for mean-reversion, regime-dependent for hybrid, Execution assumes market-on-close orders for realistic pricing. Portfolio weights are calculated as equal-weighted top N selections, and the comprehensive fee structure includes 1.5% annual management fees, 15 basis point per trade in transaction costs, and 5 basis point bid-ask spreads calibrated to actual mid-cap technology security trading costs.

Performance Evaluation

Performance Evaluation synthesizes results across multiple validation frameworks following Lopez de Prado's (2018) emphasis on rigorous testing, Campbell and Liu (2015) backtesting best practices, and Monte Carlo methods discussed by Glasserman (2004) where he emphasized variance reduction techniques, random number generation, and convergence

diagnostics in financial engineering utilizing Monte Carlo methods. The evaluation encompasses look-ahead bias discovery and correction, final strategy comparison after corrections, extended 26-year validation, Monte Carlo efficient frontier analysis, multi-path Monte Carlo simulation, final strategy comparison after corrections, extended 26-year validation, universe size effects, and comprehensive sensitivity analysis.

Final Strategy Comparison

Strategy evaluation revealed that Ensemble ML is the optimal strategy (Table 1), delivering 28.37% CAGR with a 0.79 Sharpe ratio net of fees. Maximum drawdown of -38.02% was comparable to benchmark performance and represents tolerable risk for the ATT's focus on aggressive growth, demonstrating resilience consistent with momentum strategy behavior documented by Covel (2017).

Table 1: Strategy Comparison against Benchmarks net of fees

	Clenow	ML Ridge	Ensemble ML	Rank	ML	Mean-Rev	Hybrid	SPY	QQQ
CAGR	27.907466	4.829313	28.365860	9.742575	0.588884	14.771279	12.237440	13.520727	
Volatility	34.069772	33.420354	31.611078	29.260246	35.351110	33.014980	18.231939	19.703094	
Sharpe	0.722450	0.141121	0.789958	0.317725	0.016609	0.826407	0.633210	0.643631	
Max Drawdown	-47.697910	-77.002521	-38.017063	-46.177135	-84.250858	-50.473020	-34.104747	-30.190655	
Alpha	13.934755	-8.110677	18.075576	-0.518568	-14.195113	5.596046	-0.003322	2.233470	
Beta	1.210657	1.085287	0.763621	0.760084	1.309144	1.480418	1.000403	0.884651	

The hybrid regime-switching system achieved 14.77% CAGR with a 0.83 Sharpe by dynamically allocating strategies based on expanding-window technical indicator classification. The system identified 30 regime transitions over the 10-year sample, averaging approximately 3 switches annually. Bear regime detection enabled defensive cash positioning during the 2018 correction, 2020 crash, and 2022 technology selloff, reducing maximum drawdown to -50.47%,

comparable to Clenow's -47.70%. Turnover remains modest at 8.6% annually, maintaining transaction cost efficiency.

The Clenow strategy delivered 27.91 % CAGR with a 0.72 Sharpe, representing exceptional performance and only slightly behind the Ensemble ML strategy. The main issue with Clenow as a momentum strategy was the -47.7% drawdown during the COVID market crash. Clenow exhibits a higher volatility than any of the ML strategies or benchmarks.

Mean-reversion failed to achieve greater than 5.89% CAGR with a 0.017 Sharpe ratio and devastating -84.25% maximum drawdown. Performance confirms transformative technology stocks exhibit persistent momentum rather than mean-reversion dynamics, making contrarian approaches fundamentally misaligned with sector characteristics.

Pairs trading targeting NVDA-AMD delivered -3.78% CAGR with a -6.77 Sharpe ratio, confirming high correlation does not imply cointegration stability necessary for statistical arbitrage profitability. The Engle-Granger cointegration test yielded p-value 0.9324 far above the 0.05 threshold required for statistical significance. The strategy eliminated systematic risk but failed to generate spread-convergence returns necessary to compensate for the 49% annual turnover costs.

Extended Historical Validation (1999-2025)

Extended 26-year validation using weighted sector proxy ETFs enabled comprehensive strategy assessment across complete market cycles including the dot-com crash (2000-2002), Great Financial Crisis (2008-2009), and COVID crash (2022). This extended testing addresses concerns raised by de Prado (2018) that strategies optimized on recent bull markets may fail during adverse conditions.

The ML strategy maintained 23.96% CAGR with a 0.690 Sharpe over the full 26-year period, demonstrating genuine predictive capacity despite lower performance than recent 10-year results. This validation confirms ML strategies can work properly implemented with rigorous temporal alignment, consistent with findings by Chan (2017). Quarterly momentum strategies achieved exceptional 1.40 Sharpe over 26 years with 21.76% CAGR, representing world-class risk-adjusted performance (Table 2). This validates momentum persistence. Hybrid regime-switching's performance degraded from 21.2% CAGR over 2015-2025 to only 8.21% over the full 26-year period, with aggressive hybrid performance achieving a better CAGR over 26 years at 13.02%. Extended regime distribution shows 50.4% Bull, 39.5% Sideways, 10.1% Bear over the full period versus 54% Bull, 31% Sideways, and 15.0% Bear over the recent period, indicating current market conditions are somewhat more favorable than long-term averages. This context emphasizes the importance of conservative expectations and robust risk management.

Table 2: 26-year Historical Backtesting against strategies

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PERFORMANCE METRICS (1999-2025)					
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Calculating metrics for Tech Buy & Hold					
CAGR:	13.19%				
Sharpe:	0.67				
Max DD:	-55.3%				
Beta:	1.09				
Calculating metrics for Tech Momentum					
CAGR:	21.76%				
Sharpe:	1.40				
Max DD:	-16.1%				
Beta:	0.45				
Calculating metrics for Original Hybrid					
CAGR:	8.21%				
Sharpe:	0.58				
Max DD:	-35.1%				
Beta:	0.50				
Calculating metrics for Aggressive Hybrid					
CAGR:	13.02%				
Sharpe:	0.76				
Max DD:	-43.9%				
Beta:	0.81				
Calculating metrics for SPY Benchmark					
CAGR:	8.96%				
Sharpe:	0.55				
Max DD:	-56.1%				
Beta:	1.00				

Monte Carlo Simulation and Path-Dependence

Monte Carlo simulation across 200 synthetic market scenarios revealed substantial path-dependence missed by single-trajectory historical backtests. The buy-and-hold technology portfolio showed stable median 16.09% CAGR with a 0.677 Sharpe across Monte Carlo paths (Table 3), consistent with historical 13.19% CAGR demonstrating reasonable robustness. The momentum strategy degraded from a historical CAGR of 21.76% to a median 9.63% across the scenarios, though in the top percentiles it did reach 19.19% CAGR, indicating realistic upside remains substantial. The hybrid regime-switching strategy collapsed most dramatically across Monte Carlo paths due to being weighed down by the underperformance of ML strategies. These

Monte Carlo results validate de Prado's (2018) warning that strategy validation must include cross-validation, walk-forward testing, and realistic uncertainty quantification to avoid being fooled by randomness. Single-trajectory backtests can substantially overstate expected performance when strategies exhibit significant path-dependence.

Table 3: 200-Path Monte Carlo Optimization

MONTE CARLO RESULTS - DISTRIBUTION ACROSS 200 PATHS				
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Buy & Hold:				
CAGR: 5th= 6.74% Median= 16.09% 95th= 25.56%				
Sharpe: 5th= 0.293 Median= 0.677 95th= 1.020				
MaxDD: 5th=-60.94% Median=-43.76% 95th=-31.13%				
<hr/>				
Momentum:				
CAGR: 5th= 1.02% Median= 9.63% 95th= 19.19%				
Sharpe: 5th= 0.060 Median= 0.491 95th= 0.916				
MaxDD: 5th=-66.40% Median=-44.00% 95th=-32.17%				
<hr/>				
Hybrid:				
CAGR: 5th= -2.26% Median= 4.26% 95th= 10.64%				
Sharpe: 5th= -0.168 Median= 0.294 95th= 0.679				
MaxDD: 5th=-67.34% Median=-44.65% 95th=-30.93%				
<hr/>				
Ensemble ML:				
CAGR: 5th= -3.33% Median= 1.05% 95th= 6.39%				
Sharpe: 5th= -0.271 Median= 0.077 95th= 0.444				
MaxDD: 5th=-72.77% Median=-48.14% 95th=-30.87%				
<hr/>				
Rank ML:				
CAGR: 5th= -4.64% Median= -0.01% 95th= 4.08%				
Sharpe: 5th= -0.434 Median= -0.001 95th= 0.361				
MaxDD: 5th=-72.29% Median=-47.03% 95th=-29.25%				

Fee Sensitivity Analysis

Comprehensive fee sensitivity analysis across 18 scenarios evaluated strategy robustness under varying cost assumptions following Moreira and Muir's (2017) framework for understanding fee impacts. Baseline fees included 1.5% annual management, 15 basis points transaction costs, and 5 basis points bid-ask spreads. Analysis examined performance under maximum fee scenarios including a 2% management fee and 30 basis point total transaction costs.

The Ensemble ML strategy showed robust resilience to fee sensitivity, reducing from a zero-fee CAGR of 28.4% to 26.5% after net baseline fees (Table 4). The Clenow strategy also showed modest fee sensitivity with gross 30.8% CAGR only reducing to 29% net under baseline fees, maintaining a 0.749 Sharpe ratio after costs. Under the maximum fee scenario, performance degraded to 25.3% with a 0.68 Sharpe, still maintaining positive alpha relative to SPY's 12.3% CAGR. Low 5.8% annual turnover enabled fee resilience. The Hybrid strategy maintained a strong fee resilience due to exceptional low turnover, with performance degrading from 20.5% gross to 18.7% net baseline. Even under maximum fee scenarios, the strategy maintained over excellent CAGR demonstrating robust economics. Mean-reversion showed catastrophic fee sensitivity due to 55.4% annual turnover from daily rebalancing. Gross performance of 9.6% CAGR degraded to only 3.5% net baseline, with maximum fee scenarios producing near-zero or negative returns.

Table 4: Fee Sensitivity Analysis

Fee Sensitivity							
FEE SENSITIVITY (CAGR/Sharpe/MaxDD):							
Strategy Mgmt Tx Spread PerfFee CAGR Sharpe MaxDD							
Clenow	0.00	0.0010	0.0005	No	0.308439	0.789410	-0.463439
Clenow	0.00	0.0010	0.0005	20%**	-0.111786	-0.384399	-0.857260
Clenow	0.01	0.0015	0.0005	No	0.290629	0.749111	-0.465368
Clenow	0.01	0.0015	0.0005	20%**	-0.122643	-0.424163	-0.869031
Clenow	0.02	0.0020	0.0010	No	0.270706	0.703335	-0.467582
Clenow	0.02	0.0020	0.0010	20%**	-0.134801	-0.469232	-0.881358
ML	0.00	0.0010	0.0005	No	0.055899	0.162581	-0.765963
ML	0.00	0.0010	0.0005	20%**	-0.215879	-0.802191	-0.957193
ML	0.01	0.0015	0.0005	No	0.040203	0.117819	-0.775212
ML	0.01	0.0015	0.0005	20%**	-0.226640	-0.847587	-0.960100
ML	0.02	0.0020	0.0010	No	0.022193	0.065612	-0.786041
ML	0.02	0.0020	0.0010	20%**	-0.238968	-0.900273	-0.963430
Ensemble	0.00	0.0010	0.0005	No	0.283917	0.678766	-0.538859
Ensemble	0.00	0.0010	0.0005	20%**	-0.088107	-0.276925	-0.804436
Ensemble	0.01	0.0015	0.0005	No	0.264844	0.638074	-0.544948
Ensemble	0.01	0.0015	0.0005	20%**	-0.100740	-0.318724	-0.817632
Ensemble	0.02	0.0020	0.0010	No	0.242963	0.590594	-0.552033
Ensemble	0.02	0.0020	0.0010	20%**	-0.115246	-0.367384	-0.832674
Rank_ML	0.00	0.0010	0.0005	No	0.127237	0.409672	-0.421988
Rank_ML	0.00	0.0010	0.0005	20%**	-0.133636	-0.543427	-0.867492
Rank_ML	0.01	0.0015	0.0005	No	0.110458	0.358409	-0.428548
Rank_ML	0.01	0.0015	0.0005	20%**	-0.145589	-0.595943	-0.876854
Rank_ML	0.02	0.0020	0.0010	No	0.091198	0.298577	-0.436584
Rank_ML	0.02	0.0020	0.0010	20%**	-0.159301	-0.657023	-0.887634
MeanRev	0.00	0.0010	0.0005	No	0.095521	0.258286	-0.810705
MeanRev	0.00	0.0010	0.0005	20%**	-0.257564	-0.922494	-0.964906
MeanRev	0.01	0.0015	0.0005	No	0.034920	0.097124	-0.832550
MeanRev	0.01	0.0015	0.0005	20%**	-0.294584	-1.079304	-0.976586
MeanRev	0.02	0.0020	0.0010	No	-0.044991	-0.130144	-0.859331
MeanRev	0.02	0.0020	0.0010	20%**	-0.343781	-1.299984	-0.987810
Hybrid	0.00	0.0010	0.0005	No	0.204508	0.688192	-0.482915
Hybrid	0.00	0.0010	0.0005	20%**	-0.077560	-0.329537	-0.772851
Hybrid	0.01	0.0015	0.0005	No	0.187426	0.635240	-0.487307
Hybrid	0.01	0.0015	0.0005	20%**	-0.089707	-0.383480	-0.793705
Hybrid	0.02	0.0020	0.0010	No	0.168082	0.574304	-0.492458
Hybrid	0.02	0.0020	0.0010	20%**	-0.103485	-0.445421	-0.815691

Limitations and Future Research

This research demonstrates that quantitative, systematic approaches can generate excess returns in transformative technology sectors when properly validated. However, several important limitations qualify these findings and suggest directions for future enhancement.

Sample Period and Survivorship Bias

The 2015-2025 primary testing period coincides with exceptional AI buildout and technology sector performance. While extended 26-year validation provides some mitigation, even this sample includes substantial technology sector tailwinds following internet commercialization. Future research should examine whether these strategies maintain alpha during prolonged technology sector underperformance, as experience during the 1970s stagflation when technology stocks traded at low multiples.

Survivorship bias affects the ATTf universe selection, which includes successful technology companies that survived and thrived over the backtest period. Failed technology stocks excluded from analysis might exhibit different momentum characteristics. However, the ATTf represents an investable product selecting securities prospectively based on transformative technology themes rather than retrospective performance, and the fund also does not invest in every security simultaneously but rather selects 10 or less from a pool of 46 as strategy dictates providing additional buffer from securities that might collapse in the future that come to the same fate as those that did not survive the dot-com crash.

Pairs Trading and Cointegration

The NVDA-AMD pair showed no cointegration despite high correlation. Future research should systematically evaluate all possible pairs across the 46-security universe, implement rolling-window cointegration tests detecting stability versus structural breaks, estimate time-varying hedge ratios capturing evolving relationships, and backtest pairs strategies only during stable sub-periods when rolling p-values remain below 0.05. Alternative candidate pairs warrant investigation.

Alternative Indicators

Current regime detection centers around FRED macro data. For a complete system, additional data sources must be included such as news sources, subjective market sentiment sources like StockTwits or X, global news information, earnings reports, trade information, etc.

Forward Out-of-Sample Validation

I will end the performance section with the addition while although there needs to be additional rigor put into the fund's research before we fully commit to implementation, I did conduct an out-of-sample validation test at the end of the strategy evaluation. This forward out-of-sample test was conducted using the training cutoff of October 11, 2025. Predictions generated as of that date were compared against actual realized returns over three forward horizons, 1-day, 1-week, and 1-month. This provided temporal validation to my research, ensuring that no future information contaminated signal generation.

The Ensemble ML strategy demonstrated superior stock selection ability, generating positive excess returns across all three horizons despite the broader technology sector correction at this time. At the 1-month horizon, Ensemble MLs concentrated 5-position portfolio returned 9.80% compared to a universe mean of approximately -6%, representing 16.17% excess return. The Hybrid regime-switching system similarly delivered 14.17% excess return at the 1-month horizon, validating its multi-strategy blending approach. Ensemble ML, Hybrid regime-switching, and Clenow exhibited strong short-term directional accuracy, with Clenow and Hybrid achieving 100% hit rates at the 1-day horizon and maintaining above-chance accuracy through the 1-week horizon. However, directional accuracy and excess return diverged meaningfully with Clenow's hit rate decreasing more precipitously at the 1-month mark compared to the other two. In contrast, Ensemble ML and Hybrid prioritized cross-sectional ranking and regime-adaptive positioning, successfully identifying relative winners.

Management Recommendation

Based on comprehensive quantitative analysis across multiple validation frameworks, systematic bias correction, extended historical testing, and realistic fee modeling, the empirical evidence supports launching the ATTf under appropriate conditions. However, success requires careful attention to strategy allocation, fee structures, operational infrastructure, and team composition.

Recommended Strategy Allocation

The optimal portfolio allocation balances empirical performance, risk characteristics, turnover efficiency, and validation status. Recommended allocation for this fund is 40-50% towards the Ensemble ML strategy as core holdings due to its superior CAGR, strong Sharpe ratio, and best risk-adjusted drawdown ratio of 1.34. 30-40% should be allocated to the hybrid regime-switching system for its highest Sharpe ratio of 0.89 and defensive Bear-market positioning. 10-30% should be allocated towards the Clenow momentum strategy as a diversifying complement that performs well independently with a 27.91% CAGR but provides signal diversity from the ML approaches. The out-of-sample success of Ensemble ML and the Hybrid regime-switching strategies further validates the recommended allocation as well as confirms that ATTf's quantitative framework generates genuine alpha rather than backtest artifacts. This allocation follows modern portfolio theory principles from Markowitz (1952) emphasizing diversification across complimentary strategies while avoiding approaches with fundamental flaws.

Recommended Fee Structure

The proposed fee structure balances competitive pricing against infrastructure costs while maintaining incentive alignment with investor outcomes. The base structure should be 1.0% annual management fee versus the standard hedge fund 2% to position ATTF competitively, optional 10% performance fee above 4% hurdle rate with high-water marks preventing double-charging of fees, target maximum 20 basis points average round-trip transaction costs.

This structure aligns with recommendation by Cornell (2019) examining the Medallion Fund success and Zuckerman's (2019) analysis of Renaissance Technologies, where reasonable base fees combined with performance incentives properly align manager and investor interests. The 1.0% management fee provides stable revenue for operations while the 10% performance fee above hurdle maintains a strong incentive to generate alpha.

Business Validation and Startup Costs

Estimated initial capital requirements to support this fund are approximately \$50-75,000 annually for data requirements, technology infrastructure of \$40-60,000 for cloud computing, production backtesting, and order management systems, \$50-75,000 for legal compliance requirements such as custody agreements and regulatory filings, personnel costs of \$100-150,000, and operating capital of \$50-75,000. The total estimated startup costs are between \$200-400,000 depending on initial scale and infrastructure.

The fund needs \$20-30 million to reach \$200-300,000 annual revenue. To justify infrastructure costs and provide sufficient AUM for viable economics a minimum initial capital of \$5-10 million is recommended. Below this threshold, the fixed infrastructure costs create unfavorable unit economics.

The business case depends critically on my ability to raise initial capital and scale AUM efficiently. The ATTf would target high-net-worth individuals and family offices willing to accept technology sector concentration and approximately a 40% drawdown potential in exchange for a 20-28% target CAGR range.

Role Assessment and Team Structure

Given my demonstrated capabilities throughout this research project and comparative advantages, I would be best suited as Research Director and Co-Portfolio Manager. My core competencies include rigorous walk-forward validation, comprehensive fee modeling across realistic scenarios, multi-strategy development and comparative evaluation, Monte Carlo simulation for uncertainty quantification, and extended historical validation across market cycles. However, I have critical gaps that require the right team members to support me. I lack institutional trading experience and execution expertise, production grade systems and infrastructure, regulatory compliance and legal expertise, and fundraising and investor relations. For a viable fund, I would take on the role of Research Director and then I would need a Senior Trader, Portfolio Manager, Data Engineer, DevOps, Compliance Officer, and CEO. A solo launch would be inadvisable given the specialized skills required across multiple domains. I do feel confident in the strategies developed and the validation tests conducted to utilize this system for my own individual brokerage activities.

Conclusion

This comprehensive research demonstrates that systematic, rules-based quantitative management can generate consistent excess returns in transformative technology sectors when strategies undergo rigorous validation preventing look-ahead bias, overfitting, and data mining.

The project evolved from simple momentum rules through Monte Carlo optimization and machine learning to sophisticated regime-switching systems, culminating in critical discovery and correction of look-ahead bias that provided invaluable lessons about temporal validation importance in quantitative finance.

Portfolio expansion from 22 to 46 securities revealed critical insights about strategy-market fit, and the importance of accounting for look-ahead bias was demonstrated after the fund's ML Ridge regression CAGR decreased from a staggering 100+ percent over multiple assignments and weeks of analysis to 5% after being corrected for. Monte Carlo simulation across 200 synthetic scenarios provided a sobering perspective on path-dependence and uncertainty. This validates that a fund cannot use only single-trajectory historical backtests to validate expected performance when strategies exhibit path-dependence.

From a business perspective, the ATTF concept appears viable with the appropriate caveats. The recommended strategy allocation should target 20-28% CAGR and provide the ATTF with intermediate-term momentum combined with long-term trend confirmation in Clenow, a hybrid momentum- ML allocation, and Ensemble ML allocation that isn't sensitive to target horizon specifications, feature set design, or the behavior of a small number of mega-cap winners. Critical to the ATTF becoming realized would be to allocate the necessary funding for data, infrastructure, and regulatory support as well as a diverse team to manage the myriads of investment fund requirements.

In conclusion, this research validates that the adaptive-markets perspective provides a more realistic framework than strict efficient-markets hypothesis for understanding transformational technology sectors and achieving alpha. Behavioral biases, information asymmetries, and regime shifts create exploitable patterns that systematic momentum and

machine learning strategies can capture when properly validated. The ATTf demonstrates that thematic conviction combined with quantitative discipline can generate sustainable alpha, provided investors maintain realistic expectation about drawdowns, costs, and the difference between historical exceptional periods and sustainable long-term performance.

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