Term Paper

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Course: Financial Engineering Term Project

Executive Summary

This term paper evaluates the commercial viability of launching an active ETF fund based on a machine learning directional timing strategy for NVIDIA (NVDA) stock. After rigorous testing through three research checkpoints baseline model development (Checkpoint A), feature enhancement and strategy implementation (Checkpoint B), and comprehensive validation (Checkpoint C) we conclude that **this fund should NOT be launched**.

The strategy consistently underperformed buy-and-hold across all validation methods:

- Historical test: Captured only 23% of benchmark returns
- Monte Carlo simulation (500 scenarios): 38.8% win rate
- Walk-forward validation (14 annual folds): 14.3% win rate, negative Sharpe ratio

Management Recommendation: Do not pursue this business opportunity. The strategy would destroy investor capital relative to passive alternatives. As a researcher, I would not work for this fund in its current form, nor would I invest personal capital in it.

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1. General Investment Philosophy

1.1 Market View and Theoretical Position

This project adopts the **adaptive markets hypothesis** (Lo 2019; Lo and Zhang 2024) rather than strict efficient market hypothesis. We acknowledge that:

1. **Markets are not perfectly efficient -** Behavioral biases and information asymmetries create temporary mispricings
2. **Patterns exist but are fragile -** Historical patterns may not persist, especially during regime changes
3. **Rigorous validation is essential -** Backtesting alone is insufficient; strategies must survive Monte Carlo and walk-forward testing

Our philosophy embraces data-driven investment using machine learning (Hilpisch 2020a, 2020b) while maintaining skepticism about market timing, particularly for high-growth assets.

1.2 Investment Thesis

Core Hypothesis: Systematic, machine learning-based signals can provide a reliable edge in short-horizon directional forecasting for NVIDIA (NVDA), enabling an active fund to beat buy-and-hold after fees.

Rationale for Testing:

- NVDA exhibits high volatility, creating potential timing opportunities
- Machine learning can process multiple signals (technical + macro context)
- Active ETFs represent growing institutional interest in systematic strategies

Critical Questions:

1. Can we consistently predict next-day direction?
2. Does timing create value, or does it destroy value by missing rallies?
3. Can any fee structure preserve alpha for investors?

1.3 Research Philosophy: Test Before Deploy

Our approach prioritizes **rigorous validation over optimistic backtesting**:

Stage 1 (Checkpoint A): Establish baseline, identify challenges (class imbalance)
Stage 2 (Checkpoint B): Enhance features, implement strategy, test on 2020-2024 period
Stage 3 (Checkpoint C): Stress test with Monte Carlo (500 scenarios) and walk-forward validation (14 folds)

This three-stage progression ensures we don't launch a fund based on spurious backtest results. As López de Prado (2018) emphasizes, most published trading strategies fail rigorous validation.

1.4 Philosophical Stance on Negative Results

We embrace **scientific integrity over commercial pressure**. If our strategy fails validation, we will:

- Transparently document the failure
- Explain why it doesn't work
- Recommend against launching the fund
- Prevent investor capital destruction

Negative results are valuable - they guide future research and prevent misallocation of resources.

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2. Investment Methods and Rules Employed

2.1 Model Architecture

Primary Model: XGBoost Gradient Boosting Classifier

Why XGBoost?

- Handles non-linear relationships effectively
- Built-in feature importance for interpretability
- Resistant to overfitting with proper regularization

- Industry standard for tabular financial data

Model Parameters:

- Estimators: 100 trees
- Max depth: 5 (prevents overfitting)
- Learning rate: 0.1
- Evaluation metric: Log loss

2.2 Feature Engineering

Price-Based Features (NVDA-specific):

- Log returns
- Volatility (5-day and 20-day rolling windows)
- Simple Moving Averages (SMA5, SMA20)
- Relative Strength Index (RSI-14)
- Relative strength vs. S&P 500

Macro Context Features:

- VIX level (market fear gauge)
- S&P 500 daily returns (market direction/beta)
- 10-Year Treasury yield (regime proxy)

Rationale: Combining single-asset technical indicators with macro context captures both NVDA-specific patterns and broader market regime information.

2.3 Target Variable and Training

Target: Binary classification

- 1 if next-day return > 0 (UP)
- 0 if next-day return ≤ 0 (DOWN)

Training Period: 2000-2019 (80% of data, ~5,000 days)
Test Period: 2020-2024 (20% of data, ~1,250 days)

Class Imbalance Handling:

- Applied SMOTE (Synthetic Minority Over-sampling) to training data
- Balanced training set to 50/50 UP/DOWN distribution
- Test set unchanged to reflect real market conditions

Threshold Tuning:

- Searched 0.35-0.55 range to ensure balanced predictions
- Optimal threshold: 0.45-0.50 (varies by validation method)

2.4 Trading Rules: Binary Allocation Strategy

Allocation Rule:

If model predicts UP (probability ≥ threshold):
  Allocate 100% to NVDA
Else (model predicts DOWN):

Allocate 100% to risk-free asset (T-Bills at 2% annual)

Rebalancing Frequency: Daily

Position Sizing: Binary (0% or 100%) - all-in or all-out

Risk Management: None explicitly modeled beyond binary switching

2.5 Benchmarks

Primary Benchmark: Buy-and-hold NVDA (100% invested throughout period)
Secondary Benchmark: S&P 500 (SPY) for market comparison

Performance Metrics:

- Total return and annualized return
- Sharpe ratio (risk-adjusted returns)
- Maximum drawdown
- Win rate (% of periods strategy beats benchmark)

2.6 Evolution Through Checkpoints

Checkpoint A → B Improvements:

- Expanded features to include macro context (VIX, SPY, TNX)
- Applied SMOTE to fix "always predicts up" problem
- Upgraded from Logistic Regression to XGBoost/Random Forest
- Implemented binary allocation strategy

Checkpoint B → C Improvements:

- Added Monte Carlo simulation (500 synthetic price paths)
- Implemented walk-forward validation (14 annual folds)
- Analyzed fee structure impact (15 scenarios)
- Established viability criteria (5 requirements)

Full methodological details: See Checkpoint B and C reports in the repository.

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3. Description of Securities

3.1 Primary Security: NVIDIA Corporation (NVDA)

Asset Class: Large-cap U.S. equity, Technology sector

Why NVDA?

1. **Strong secular trend** - AI/GPU computing megatrend provides structural growth
2. **High volatility** - Amplifies both opportunities and risks for timing strategies
3. **Institutional quality** - Large-cap liquidity enables realistic fund implementation ($800B+ market cap)
4. **Data availability** - 25 years of historical data (2000-2025) for robust testing
5. **Represents tech sector** - Exposure to innovation and growth

Historical Performance:

- 2000-2019 training period: Highly volatile with multiple boom-bust cycles
- 2020-2024 test period: Explosive growth (+999% buy-and-hold return)
- Key events captured: Dot-com crash, financial crisis, COVID recovery, AI boom

3.2 Cash Alternative: U.S. Treasury Bills

Asset Class: Risk-free government securities

Proxy Used: 2% annual return (conservative estimate)

Purpose: Defensive position when model predicts DOWN

Rationale: T-Bills provide:

- Capital preservation during predicted downturns
- Positive carry (vs. holding cash at 0%)
- Liquidity for rapid redeployment

3.3 Fund Structure

Proposed Fund Type: Active ETF (daily liquidity, transparent holdings)

Investment Universe: Single-stock timing (NVDA) vs. risk-free (T-Bills)

Allocation Strategy: Binary switching

- Aggressive: 100% equity exposure when bullish
- Defensive: 100% cash when bearish

Target Clients:

- Sophisticated investors seeking tactical NVDA exposure
- Clients who believe in market timing for high-volatility stocks
- Investors willing to pay active management fees

3.4 Comparison to Alternatives

Strategy	Allocation	Fees	Complexity
Our Fund	0-100% NVDA	2% + 20% performance	High (ML model)
Buy-Hold NVDA	100% NVDA	0% (or ~0.2% ETF)	None
Tech Sector ETF	Diversified tech	~0.5%	Low
S&P 500 Index	Broad market	~0.03%	None

Key Question: Can our fund's active management justify the fee differential vs. passive alternatives?

3.5 Trading Activity

Historical Trading Frequency:

- Checkpoint B test (2020-2024): 150-180 trades (30-36 per year)

- Walk-forward validation: Similar frequency across folds
- Rebalancing: Daily, based on model predictions

Transaction Costs (Not Modeled):

- Bid-ask spread: ~0.05-0.10% per trade
- Commissions: Minimal for institutional traders
- Market impact: Negligible for liquid stock like NVDA
- **Estimated drag:** ~1.5-2% annually (30 trades × 0.05-0.07%)

Note: Transaction costs were not explicitly modeled in our analysis. Real-world performance would be worse than reported results.

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4. Performance Evaluation

This section summarizes results from **Checkpoint C: Monte Carlo Simulation & Walk-Forward Validation**. Full details, figures, and statistical tables are available in the Checkpoint C folder.

4.1 Historical Test Results (2020-2024)

Test Period: February 2020 - October 2024 (~1,250 trading days)

Metric	Strategy	Buy-and-Hold NVDA	Verdict
Total Return	+230.73%	+998.51%	Strategy Lost
Annualized Return	~27.8%	~66.2%	Strategy Lost
Value Captured	23.1%	100.0%	Strategy Lost
Time in Market	~52%	100%	Strategy missed ~48% of days

Key Findings:

1. Strategy captured only **23% of benchmark returns** despite being "active"
2. Sat in cash ~48% of the time, missing the 2023-2024 AI boom (+238% rally)
3. The cost of missing critical up days completely dominated any defensive benefits

Interpretation: The binary switching strategy proved too extreme. Missing NVDA's massive 2023-2024 surge due to volatility-based signals was catastrophic. The model, trained on 2000-2019 data (dot-com crash, financial crisis), interpreted high volatility as bearish and stayed in cash during the most profitable period.

4.2 Monte Carlo Simulation Results (500 Scenarios)

Objective: Test strategy robustness across diverse market conditions using synthetic price paths

Methodology:

- Generated 500 synthetic NVDA return paths using Geometric Brownian Motion
- Matched historical statistics: mean return, volatility, autocorrelation
- Applied same trained model predictions to each synthetic path

- Calculated strategy vs. buy-and-hold performance for each scenario

Results:

Metric	Strategy	Buy-and-Hold	Interpretation
Mean Return	+106.98%	+292.00%	Strategy captured 37% of benchmark
Median Return	+34.55%	+292.00%	High variance; median << mean
Win Rate	38.8%	N/A	Beats buy-hold in only 39% of scenarios
Mean Sharpe Ratio	0.309	N/A	Poor risk-adjusted returns
Mean Max Drawdown	-60.90%	N/A	Catastrophic losses possible

Distribution Analysis:

- Strategy returns highly skewed: Some scenarios +1,200%, others near 0%
- Median (34.55%) well below mean (106.98%) indicates inconsistency
- Buy-and-hold outperformed in **61.2% of simulations**

Interpretation: The strategy does NOT robustly outperform buy-and-hold. In the majority of plausible market scenarios, sitting in cash during predicted "down" days causes underperformance. High variance suggests the strategy occasionally gets lucky but lacks consistent edge.

Viability Check: FAIL (requires win rate > 50%)

4.3 Walk-Forward Validation Results (14 Annual Folds, 2010-2024)

Objective: Test if strategy adapts to changing market regimes through periodic retraining

Methodology:

- Rolling 10-year training window, 1-year test period
- Retrain XGBoost model with SMOTE at start of each fold
- Test on next 1-year period, then advance window by 1 year
- 14 total folds covering 2010-2024

Results:

Metric	Strategy	Buy-and-Hold	Interpretation
Mean Annual Return	+5.09%	+48.55%	Strategy captured 10% of benchmark
Median Annual Return	+3.72%	+29.43%	Consistently poor
Win Rate	14.3%	N/A	Beat buy-hold in only 2 of 14 years
Mean Sharpe Ratio	-0.058	N/A	**NEGATIVE** risk-adjusted returns

Annual Performance Breakdown (Selected Years):

Year	Strategy Return	Buy-Hold Return	Winner	Notes
2010	+14.2%	+19.2%	Buy-Hold	Strategy lagged
2011	-49.3%	-38.6%	Both Lost	Strategy worse in crash
2016	+15.9%	+161.9%	Buy-Hold	**Missed massive rally**
2020	**+116.5%**	+64.5%	**Strategy Won**	Only win during COVID volatility
2023	+15.5%	+241.9%	Buy-Hold	**Missed AI boom**

Key Observations:

1. **Catastrophic failure -** Won only 2 out of 14 years (14.3% win rate)
2. **Negative Sharpe ratio** - Investors lose money on risk-adjusted basis
3. **2016 and 2023 disasters -** Sat in cash during structural regime shifts
4. **2020 exception -** Strategy worked during COVID crash/recovery, but this was the outlier

Interpretation: The strategy **cannot adapt to regime changes**. Periodic retraining didn't help because the model learned from historical data that "high volatility = bearish." This heuristic broke down when high volatility accompanied explosive growth (2016 post-election rally, 2023-2024 AI boom).

Viability Check: FAIL (requires win rate > 50% and positive Sharpe)

4.4 Fee Structure Analysis

Objective: Determine net investor returns after realistic management and performance fees

Fee Scenarios Tested:

- Management fees: 0%, 1%, 2%, 3%, 4% (annual)
- Performance fees: 0%, 10%, 20% (on excess returns vs. benchmark)
- Total: 15 combinations

Results:

Scenario	Management Fee	Performance Fee	Mean Net Return	Success Rate
Best Case	0%	0%	+106.98%	62.0%
Typical Hedge Fund	2%	20%	+97.15%	60.0%
High Fee	4%	20%	+95.30%	59.4%

Comparison to Benchmark:

- Strategy with 0% fees: +107% mean return
- Strategy with 2%/20% fees: +97% mean return
- Buy-and-hold NVDA: **+292% mean return** (3× better)
- Low-cost NVDA ETF (~0.5% fees): ~285% return

Interpretation: Fees further erode already-poor performance. Even in the **best-case scenario with zero fees**, the strategy underperforms buy-and-hold by ~185 percentage points. With realistic fees (2% + 20%), the value proposition to investors disappears entirely.

Key Insight: There is **no fee structure that makes this strategy attractive to investors.**

Viability Check: FAIL (strategy underperforms even at 0% fees)

4.5 Viability Assessment Summary

A strategy is considered commercially viable if it meets **ALL** of the following criteria:

Criterion	Required	Achieved	Status
1. Historical test success	Strategy > Buy-Hold	231% < 999%	FAIL
2. Monte Carlo win rate	> 50%	38.8%	FAIL
3. Walk-forward win rate	> 50%	14.3%	FAIL
4. Positive Sharpe ratio	> 0	-0.058 (WF)	FAIL
5. Reasonable drawdowns	< 50%	-60.9%	FAIL

Result: 0 out of 5 criteria met

Overall Assessment: The strategy fails ALL viability criteria and should NOT be commercialized.

4.6 Why Did the Strategy Fail?

Root Cause: Regime Adaptation Failure

The model was trained on 2000-2019 data, learning that "high volatility = bearish" from:

- Dot-com crash (2000-2002): high vol → crash
- Financial crisis (2008-2009): high vol → crash

When tested on 2020-2024, this heuristic failed during:

- **2023-2024 AI boom:** High volatility accompanied explosive growth
- The model interpreted the surge as a bubble and stayed in cash

Key Insight: Financial markets are non-stationary. Patterns from one regime (crises) don't generalize to new regimes (structural growth drivers like AI adoption).

Secondary Factors:

1. **Binary switching too extreme** - 100% in or 100% out amplifies errors
2. **Feature limitations** - Couldn't anticipate structural changes (ChatGPT launch, AI adoption)
3. **Overfitting to historical patterns** - Past relationships broke down
4. **Transaction costs not modeled** - Real performance would be worse by ~1.5-2% annually

The Fundamental Asymmetry:

For high-growth assets like NVDA:

- **Cost of missing a rally:** -98% (miss +100% gain, earn 2% in T-Bills)
- **Benefit of avoiding a crash:** +32% (avoid -30% loss, earn 2% in T-Bills)

Missing rallies is ~3× more costly than failing to avoid crashes. The risk/reward asymmetry overwhelmingly favors buy-and-hold.

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5. Management Recommendation

This section addresses the critical business question: **Should we launch this fund?**

5.1 Business Decision: Do Not Launch

Recommendation: NO. Do not pursue this business opportunity.

Rationale:

The strategy fails on every dimension required for commercial viability:

1. **Destroys investor value** - Captures only 23% of buy-and-hold returns
2. **No competitive advantage** - Underperforms in 61-86% of test scenarios
3. **Negative risk-adjusted returns** - Walk-forward Sharpe ratio of -0.058
4. **No viable fee structure** - Even at 0% fees, massively underperforms
5. **Ethical concerns** - Launching would knowingly harm investors

Business Reality Check:

Aspect	Assessment
Market demand?	Low - why pay 2%+20% to underperform?
Competitive moat?	None - passive beats active here
Regulatory viability?	Difficult - how to justify fees in prospectus?
Investor retention?	Impossible - after 2-3 years of underperformance, clients flee
Reputational risk?	High - launching a broken product damages future opportunities

The 2% + 20% Fee Reality:

To cover startup costs (50-100K) and annual maintenance:

- Need ~$10M AUM to generate $200K revenue (2% × $10M)
- Performance fees require outperformance (we have none)
- **Problem:** No investor should give us $10M based on these results

Alternative Perspective:

Some might argue: "The mean return is positive (+107%), so it's not a total failure."

Counter-argument:

- Mean return is irrelevant when benchmark is 3× higher (+292%)
- Investors compare to alternatives: Why not just buy NVDA directly?
- Win rate (38.8% MC, 14.3% WF) shows systematic underperformance

- Negative Sharpe in walk-forward means losing money on risk-adjusted basis

Bottom Line: Launching this fund would be **value-destructive and potentially fraudulent** given our knowledge of its poor performance.

5.2 Personal Investment Decision: Would I Invest My Own Money?

Answer: Absolutely not.

Personal Capital Allocation Strategy:

If I had $100,000 to invest in NVDA exposure, here's what I would do:

Option	Allocation	Rationale
Our ML Fund	$0 (0%)	Proven underperformer
Buy-and-Hold NVDA	$60,000 (60%)	Simple, effective, low-cost
Low-Cost Tech ETF	$30,000 (30%)	Diversification (NVDA + AAPL, MSFT, etc.)
S&P 500 Index	$10,000 (10%)	Broad market exposure

Why Not Our Fund?

1. **Expected value is negative** - Strategy captured 10-37% of benchmark depending on test
2. **Fees worsen outcomes** - 2% + 20% turns bad into terrible
3. **Opportunity cost** - Missing 2023 AI boom cost 240% return
4. **Better alternatives exist** - Passive NVDA exposure costs ~0.2% in fees

Personal Risk Tolerance:

Even as a risk-tolerant investor, I would not gamble on a strategy that:

- Lost 12 out of 14 years in walk-forward testing
- Has negative Sharpe ratio
- Systematically misses major rallies

The Math:

- Our fund (2%/20% fees): Expected ~97% return over test period
- Buy-hold NVDA: Expected ~292% return
- **Difference:** -195 percentage points = **$195,000 opportunity cost on $100K investment**

Verdict: I would invest $0 in this fund and recommend friends/family do the same.

5.3 Employment Decision: Would I Work for This Fund?

Short Answer: Not as a fund manager, but possibly as a researcher to improve it.

Role Analysis:

WOULD NOT accept these roles:

Role	Reason for Declining
Fund Manager	Cannot ethically sell a product I know underperforms
CEO	Would not start a company around a flawed product
Marketing/Sales	Morally cannot pitch this to investors
Compliance Officer	Risk of regulatory issues with poor performance

MIGHT consider these roles:

Role	Conditions
Researcher/Quant	Only if tasked with fixing strategy (not deploying current version)
Data Scientist	If working on fundamental improvements (see Section 5.5)
Advisor/Consultant	To help team realize this shouldn't launch

What Role Would I Take? Researcher with Mandate to Improve

Job Description:

- **Title:** Quantitative Researcher
- **Mission:** Redesign strategy to achieve commercial viability
- **Success Criteria:** Achieve >50% win rate in walk-forward validation
- **Timeline:** 6-12 months of R&D before any investor capital at risk
- **Compensation:** Salary-based (not tied to flawed fund performance)

What I Would Work On:

1. Dynamic position sizing (0-100% vs. binary)
2. Explicit regime detection (Markov switching models)
3. Multi-asset diversification (NVDA + AMD + peers)
4. Risk management overlays (stop-losses, volatility targeting)
5. Alternative strategies (mean reversion, pairs trading)

Red Lines:

- Would NOT work on marketing/launching current strategy
- Would NOT accept fund management role unless strategy passes all viability tests
- Would resign if pressured to launch despite negative results

Honest Self-Assessment:

Given my skillset (ML, data analysis, financial engineering), the **Researcher** role makes sense. However, I would only join if:

1. Management accepts current strategy is not viable
2. There's genuine commitment to R&D (not just window dressing)
3. No investor capital deployed until strategy passes rigorous validation
4. I have authority to recommend "do not launch" if improvements fail

5.4 Wealth-Building Assessment: Is This a Good Way to Build Personal Wealth?

Answer: No. This fund is a poor vehicle for wealth accumulation.

Wealth-Building Comparison (20-Year Horizon):

Assume $10,000 initial investment, compared over 20 years:

Strategy	Expected Annual Return	20-Year Value	Notes
Our ML Fund	~5-10%*	~$26,500	Based on walk-forward results
Buy-Hold NVDA	~35%**	~$1,900,000	Historical returns
S&P 500 Index	~10%	~$67,300	Historical average
Tech Sector ETF	~15%	~$163,700	Tech outperformance

*Conservative estimate from walk-forward mean (5.09%) + optimistic scenario
**Not sustainable long-term, but illustrates opportunity cost

Wealth-Building Failure Modes:

1. **Underperformance compounds** - Missing 2023 (+242%) is nearly impossible to recover from
2. **Fees erode wealth** - 2% + 20% turns $100K → $97K in gross returns, while benchmark → $292K
3. **Psychological cost** - Watching buy-and-hold soar while your fund flatlines damages investor discipline
4. **Opportunity cost** - Capital locked in underperforming fund instead of simple, effective alternatives

Better Wealth-Building Strategies:

For NVDA Exposure:

1. **Buy and hold** - Simplest, most effective based on our testing
2. **Dollar-cost averaging** - Systematic purchases reduce timing risk
3. **Low-cost ETF** - NVDA-focused or tech sector diversification

For General Wealth:

1. **Diversified index funds** - S&P 500 or total market
2. **Target-date funds** - Automatic rebalancing
3. **Employer 401(k) match** - Free money before fancy strategies

The Paradox:

Our research proves that **doing nothing (buy-and-hold) is superior to active management** for NVDA. This aligns with decades of research showing passive strategies beat active funds after fees (S&P SPIVA reports).

Verdict: This fund would destroy personal wealth, not build it. Investors should use passive strategies.

5.5 Path Forward: What Would Make This Viable?

If we insist on pursuing active management for NVDA, these changes are REQUIRED:

1. Dynamic Position Sizing (Critical)

- Replace binary (0% or 100%) with continuous exposure (0-100%)
- Use model confidence scores: 70% confidence → 70% allocation
- Reduces catastrophic impact of being 100% out during rallies

2. Explicit Regime Detection (Critical)

- Implement Markov switching models or Hidden Markov Models
- Identify bull/bear/sideways regimes before making allocation decisions
- Different strategies for different market conditions

3. Risk Management Overlays

- Stop-loss rules (exit if drawdown exceeds threshold)
- Volatility targeting (reduce exposure when VIX spikes above historical norms)
- Maximum drawdown constraints (protect against catastrophic losses)

4. Multi-Asset Diversification

- Expand from single-stock (NVDA) to tech portfolio (NVDA, AMD, INTC, ARM)
- Sector rotation based on relative strength
- Increases breadth (more independent bets → better alpha potential)

5. Alternative Strategies

- Test mean reversion (buy dips, sell spikes)
- Pairs trading (long NVDA / short AMD when spread diverges)
- Momentum with trend filters (only trade in direction of 200-day MA)

6. Realistic Cost Modeling

- Include transaction costs (bid-ask, slippage)
- Model tax drag (short-term capital gains)
- Weekly or monthly rebalancing to reduce costs

Estimated Timeline:

- 6-12 months of R&D and testing
- Requires passing same validation: Monte Carlo + walk-forward
- Must achieve >50% win rate and positive Sharpe ratio
- **Only then** consider launching with investor capital

Success Probability: Low to moderate (~20-30% chance of achieving viability)

Alternative Recommendation: Focus on longer-horizon strategies (weekly/monthly rebalancing), mean-reversion for broad tech sector, or factor-based quant strategies (value/momentum/quality).

5.6 Final Management Recommendation

For Immediate Decision (Next 30 Days):

DO:

1. Publish this research as educational content (blog, GitHub)
2. Share negative results with academic community (valuable contribution)
3. Use findings to guide future strategy development
4. Thank team for rigorous, honest work

DO NOT:

1. Launch fund with investor capital
2. Market this strategy to potential clients

3. File for ETF regulatory approval
4. Raise seed funding for this specific strategy

For 6-12 Month Horizon:

IF the team wants to pursue active NVDA management:

1. Assign researcher to implement improvements (Section 5.5)
2. Re-test with same validation standards (Monte Carlo + walk-forward)
3. Establish clear success criteria: >50% win rate, positive Sharpe, beats buy-hold after 2%+20% fees
4. **Only if improved strategy passes all tests:** Consider commercial launch

IF improved strategy still fails:

1. Pivot to passive NVDA products (e.g., smart-beta NVDA ETF)
2. Pivot to broader tech sector strategies
3. Pivot to different asset classes (currencies, commodities, volatility)

Personal Stance:

As a researcher, I **strongly recommend DO NOT LAUNCH**. The evidence is overwhelming:

- 0 out of 5 viability criteria met
- Systematic underperformance across all validation methods
- No path to investor value with current design

If forced to choose: I would resign rather than participate in launching a fund I know will destroy investor capital.

However: I'm willing to work as a researcher to improve the strategy, with no guarantee of success and full transparency about negative results.

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6. Conclusion

6.1 Summary of Findings

This term project rigorously evaluated a machine learning-based directional timing strategy for NVIDIA (NVDA) through three research phases:

Checkpoint A: Established baseline pipeline, identified class imbalance challenge
Checkpoint B: Enhanced features with macro context, implemented binary allocation strategy, tested on 2020-2024
Checkpoint C: Validated with Monte Carlo (500 scenarios) and walk-forward (14 folds), analyzed fee structures

Verdict: The strategy is **NOT commercially viable** and should NOT be launched as an active fund.

Evidence:

- Historical test: Captured 23% of buy-and-hold returns
- Monte Carlo: 38.8% win rate, Sharpe 0.31
- Walk-forward: 14.3% win rate, Sharpe -0.058
- Fee analysis: Underperforms even at 0% fees

Failures: 0 out of 5 viability criteria met

6.2 Root Cause Analysis

Why did the strategy fail?

1. **Regime adaptation failure** - Model trained on crises (2000-2019) couldn't anticipate AI boom (2023-2024)
2. **Binary switching too extreme** - Missing rallies more costly than avoiding crashes for growth stocks
3. **Fundamental asymmetry** - For NVDA, cost of being out (-98%) >> benefit of being defensive (+32%)

Key Insight: Market timing of high-growth technology stocks with strong secular trends is extremely difficult, even with sophisticated ML models. The opportunity cost of missing rallies dominates any defensive benefits.

6.3 Management Decision

Business Recommendation: DO NOT launch this fund.

Personal Investment: Would invest $0 in this fund; would buy-and-hold NVDA instead

Employment: Would not work as fund manager; might work as researcher to improve strategy

Wealth Building: This fund would destroy personal wealth, not build it

6.4 Scientific Contribution

Despite commercial failure, this project makes valuable contributions:

1. **Methodological rigor** - Three-stage validation (historical → Monte Carlo → walk-forward)
2. **Negative results are valuable** - Prevents capital misallocation, guides future research
3. **Transparent documentation** - All code, data, and results available in public repository
4. **Honest assessment** - Resisted temptation to overfit or cherry-pick results

Academic Value: This research demonstrates the importance of skepticism toward backtested trading strategies. By applying rigorous validation, we avoided the trap of launching a spuriously profitable strategy.

6.5 Lessons Learned

Technical Lessons:

1. Backtesting alone is insufficient - must validate with Monte Carlo and walk-forward
2. Regime changes break static models - need explicit regime detection
3. Binary strategies amplify errors - continuous position sizing more forgiving
4. Transaction costs matter - even small costs compound over many trades

Business Lessons:

1. Negative results require integrity - don't launch products you know will fail
2. Simple strategies often best - buy-and-hold hard to beat for growth stocks
3. Fee structures can't fix fundamental underperformance
4. Ethical responsibility to investors outweighs commercial pressure

Personal Lessons:

1. Complexity doesn't guarantee performance - XGBoost with 9 features lost to simple buy-and-hold
2. Markets are (mostly) efficient - exploitable patterns are rare and fragile

3. Domain knowledge matters - understanding market dynamics as important as ML sophistication
4. Embrace failure - negative results teach more than lucky successes

6.6 Future Directions

If pursuing active NVDA management, implement:

1. Dynamic position sizing (0-100% continuous)
2. Explicit regime detection (Markov switching)
3. Multi-asset diversification (tech portfolio)
4. Risk management overlays (stops, vol targeting)
5. Alternative strategies (mean reversion, pairs trading)
6. Longer holding periods (weekly/monthly rebalancing)

Estimated success probability: 20-30%

More promising research directions:

- Broader tech sector strategies (10-20 stocks)
- Factor-based quant strategies (value/momentum/quality)
- Volatility trading (VIX options)
- Alternative asset classes (currencies, commodities)

6.7 Final Word

This research journey from initial concept through rigorous validation demonstrates that **creating profitable trading strategies is extraordinarily difficult**. Even with sophisticated machine learning models, comprehensive feature engineering, and state-of-the-art validation techniques, we could not overcome the fundamental challenges of market timing for high-growth assets.

The negative result is not a failure it's a valuable contribution. By transparently documenting what doesn't work, we help prevent capital misallocation and guide future researchers toward more promising approaches.

For NVIDIA investors, the evidence is clear: buy and hold.

For aspiring fund managers: Test rigorously before deploying capital. If your strategy fails validation, have the integrity to walk away.

For the financial industry: Negative results should be published and celebrated, not hidden. They advance our collective understanding and protect investors from flawed products.

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Data Sources

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