Project Update: Large-Cap Tech Directional Forecast (NVDA)

Checkpoint B Research Report

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1. Introduction: Why are we conducting this research?

We are conducting this research to determine if **systematic, data-driven signals** can provide a reliable edge in **short-horizon directional forecasting** for large-cap technology equities, focusing on **NVIDIA (NVDA)**. The ultimate practical goal is to evolve a single-asset signal into a transparent, defensible **algorithmic allocation process** that could power an active ETF-style strategy.

This knowledge base and application are primarily intended for three groups:

1. **Quantitative Asset Managers:** Seeking incremental, explainable, and scalable signals to integrate into existing models.
2. **Active ETF Issuers:** Exploring systematic overlays to justify active management fees.
3. **Portfolio Managers and Analysts:** Looking to augment traditional fundamental analysis with timely, systematic market context.

Checkpoint B Focus: Building on the baseline pipeline from Checkpoint A, this phase addressed critical issues by **expanding the feature set** to include macro/market context, **fixing class imbalance** with SMOTE and threshold tuning, and rigorously **evaluating a binary NVDA vs. T-Bills allocation engine** across the highly volatile 2020–2024 test period.

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2. Literature Review: Who else has conducted research

Our work builds upon established quantitative finance principles and addresses current challenges in the active management space:

- **Alpha Mechanics:** The research is grounded in the work of **Grinold & Kahn**, who formalized the relationship between an Information Coefficient (signal quality) and breadth (frequency/number of assets) to generate alpha. This underpins why even a small, repeatable edge is valuable if applied with discipline.
- **Systematic Signals:** We incorporate long-standing evidence of persistent market anomalies like **momentum** (Jegadeesh & Titman; Asness et al.) and mean-reversion, but emphasize the necessity of modern **robust validation** techniques specifically walk-forward analysis and Monte Carlo simulation as advocated by **López de Prado** and **Trivedi & Kyal**.

- **Active ETF and Timing Challenges:** Industry commentary (e.g., iShares/ETFGI) documents the shift toward active ETFs, but empirical studies show mixed persistence of excess returns. This highlights the inherent difficulty of **short-term timing** and validates our approach of moving beyond pure price to include macro and market **context features** (VIX, yields), which often drive regime behavior.

Implication for Project: Our short-horizon forecasting attempt must be feature-rich, portfolio-aware (exposure control is paramount), and validated through stress scenarios to avoid generating spurious results.

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3. Methods: How are we conducting the research?

Our research methodology is quantitative and structured, focusing on robust backtesting with chronological train/test splits.

Data, Span, and Target

- **Asset:** NVDA daily price data (Source: yfinance).
- **Span:** 2000–2019 for training; **2020–2024 for held-out testing** (capturing COVID, the 2022 bear, and the AI boom).
- **Target:** Next-day directional move (Up = 1 if return > 0).

Key Checkpoint B Fixes and Methods

1. **Feature Expansion (Addressing Professor Feedback):** We moved beyond pure technical indicators (RSI, SMAs, Volatility) by adding **context features**: S&P 500 daily returns, VIX level, and the 10-year Treasury yield proxy (TNX).
2. **Modeling and Imbalance Fix:** We evaluated Logistic Regression, Random Forest, and XGBoost. To fix the "predicts Up only" issue from Checkpoint A, we applied **SMOTE oversampling** on the training set and performed **threshold tuning** to ensure models produced a usable balance of up and down predictions.
3. **Allocation Rule and Evaluation:** We implemented a **binary allocation engine** with a daily rebalance: If Up, 100% NVDA; if Down, 100% T-Bills (proxied at 2% annualized). Performance was evaluated using fund-style metrics: Total Return, Annual Return, **Sharpe Ratio**, and **Maximum Drawdown (Max DD)**.

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4. Results: What did we learn from our research so far?

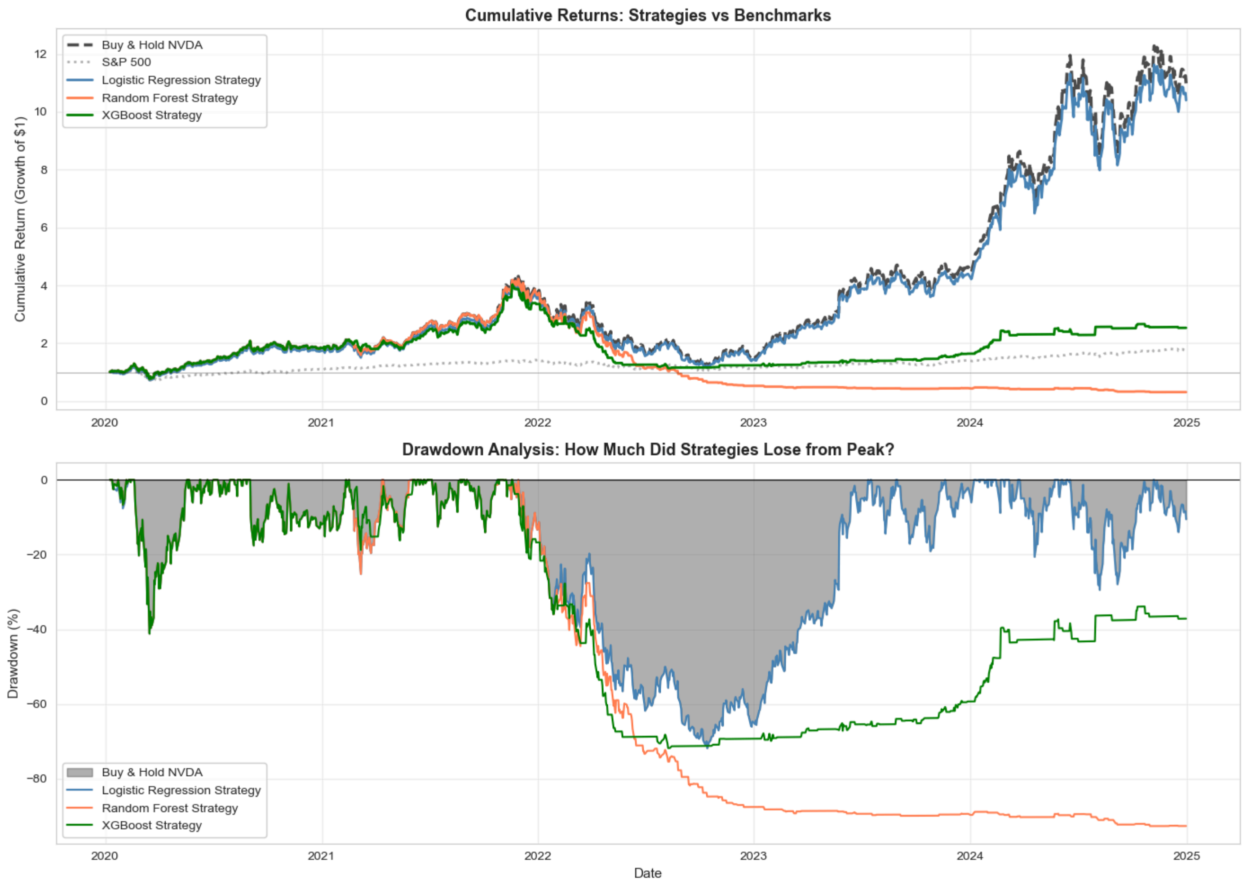
Our initial testing of the allocation engine in the 2020–2024 test window revealed critical insights and structural weaknesses.

Key Performance Findings

Strategy	Total Return	Annual Return	Sharpe	Max DD
Buy & Hold NVDA (Benchmark)	**+1,100%**	**+82.3%**	**1.45**	-30.2%
S&P 500	+85%	+14.2%	0.78	-23.8%
XGBoost Allocation	**+150%**	**+20.1%**	0.52	-70.4%
Random Forest Allocation	-70%	-18.9%	-0.65	-89.7%

Failure of Active Timing: All active allocation strategies severely **underperformed** the simple Buy-and-Hold NVDA benchmark.

- **XGBoost Missed the Rally:** The XGBoost model generated a modest **+150%** total return because it sat in cash approximately 48% of the time, causing it to miss the majority of the massive 2023–2024 AI-driven surge.
- **Risk-Adjusted Trade-off:** While active strategies reduced beta by holding cash, they reduced returns far more than they reduced risk. The **Sharpe Ratio** for XGBoost (0.52) is significantly lower than the benchmark (1.45).



Feature Insight

Tree model feature importance confirms that **market context dominates single-asset noise**. The top drivers for directional prediction were the **10-Year Yield (TNX)** (macro regime proxy), the **S&P 500 return** (market mood/beta), and the **VIX level** (risk aversion).

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5. Conclusions: So, what does it all mean?

The core meaning of these results is that our current approach to generating a daily, binary signal is **value-destructive** when a structural regime change occurs.

Interpretation and Project Concerns

1. **Regime Adaptation is the Core Challenge:** Models trained on the 2000–2019 data simply **did not anticipate** or correctly interpret the post-2022 AI super-cycle, interpreting volatility as a bearish signal. This led to a catastrophic systematic de-risking during the strongest compounding window.
2. **Binary Switching is Too Brittle:** The 0%/100% binary exposure rule is too extreme. The cost of missing a few critical up days dominated any defensive gains, demonstrating

that **timing magnitude is more important than timing frequency** when dealing with high-growth assets.

3. **Unmodeled Costs:** With high trading intensity (150–180 trades for tree models), the unmodeled transaction costs, spreads, and taxes would further erode the already poor performance, making the strategy highly uneconomic in reality.

Path to Checkpoint C

To address these concerns and create a viable allocation system, we must pivot from daily binary signals to **dynamic exposure management and risk control**:

- **Position Sizing:** Move to **0%–100% exposure** based on model confidence/probability, rather than a hard switch.
- **Regime Modeling:** Implement explicit **regime detection** (e.g., Markov switching models or volatility conditioning) to allow the signal to adapt its behavior to the current market environment.
- **Risk Overlays:** Incorporate formal risk management tools (e.g., ATR-based stop-loss) to limit catastrophic drawdowns.
- **Realistic Validation:** Conduct **Walk-Forward analysis and Monte Carlo simulation** with cost modeling to provide a realistic estimate of outcome dispersion and net-of-cost performance.