GoldTechETF: A Rules-Based Tech–Gold Rotation and Monte Carlo Evaluation

Name: Chenyi Zhao

Course: MSDS-451 Financial Engineering

Instructor: Thomas W. Miller

Date: Aug 31, 2025

Abstract

This report develops GoldTechETF, a transparent, rules-based strategy that rotates between a momentum-driven technology sleeve and a conditional gold sleeve to compound capital while containing left-tail risk. The growth sleeve holds liquid, large-cap U.S. technology exposure selected via simple momentum ranks and rebalanced weekly; the defensive sleeve allocates to GLD when a trend filter and a volatility condition indicate stressed regimes. Evaluation focuses on net investor outcomes: all results incorporate transaction costs, an annual management fee, and (where applicable) a performance fee above the SPY benchmark. To move beyond a single historical path, the study implements a distributional assessment via Monte Carlo, combining a parametric Gaussian engine calibrated to sample moments with a block-bootstrap engine that preserves dependence structure. Across thousands of multi-year simulations, the net CAGR distributions for the two rule sets largely overlap, the risk–return scatter shows an upward slope with contained dispersion, and sample equity curves illustrate shallower interim drawdowns when the defensive sleeve engages. Given these results and the strategy's implementability—liquid underlyings, bounded turnover, and explicit frictions—the recommended next step is a live, paper-traded pilot with public signal publication and daily NAV tracking. If realized slippage and flows remain modest, a low, transparent management-fee ETF launch is warranted.

Introduction

This project proposes **GoldTechETF**, a rules-based strategy that rotates between a growth sleeve representing U.S. large-cap technology and a defensive sleeve represented by gold. The motivation is practical. Technology provides sustained drivers of earnings and productivity but exhibits pronounced cyclicality; gold is historically resilient in stress regimes and inflationary episodes. Rather than forecasting macro conditions, the strategy codifies a small set of transparent signals to determine when the portfolio should emphasize growth and when it should carry defense.

The academic and industry problem is twofold. First, discretionary timing is difficult to repeat and even harder to audit. Second, backtests on a single historical sample hide the uncertainty investors actually face. To address both, the project delivers a **fully systematic rule set** implemented in Python and a **Monte Carlo evaluation** that measures the distribution of **net** outcomes (after trading costs, management fees, and performance fees). The benchmark is the S&P 500 via SPY; the investable assets are liquid and widely traded so that simulated trades have a credible path to implementation.

The contributions are: a compact, auditable ETF-style rule set; a reproducible pipeline from data ingestion to evaluation; and a distributional view of performance under realistic fee and cost assumptions. The repository includes the parameter file, the historical return panel used for resampling, the Monte Carlo outputs, and the figures embedded in this report.

Literature Review

The strategy sits at the intersection of three mature strands of evidence. First, momentum—both cross-sectional and time-series—has been shown to persist at intermediate horizons: securities that have recently outperformed tend, on average, to continue doing so, while laggards persist in underperformance. This regularity is economically intuitive (gradual information diffusion, investor under-reaction, and flow-driven feedback) and operationally simple to capture with transparent ranking rules rather than discretionary stock picking (Jegadeesh & Titman 1993; Asness et al. 2014). Second, trend-following and defensive overlays are designed to cut risk when price dynamics deteriorate or volatility regimes shift. A rules-based reduction of equity exposure during downtrends, coupled with a conditional allocation to gold, directly targets the portfolio's left tail: gold has historically offered low or negative correlation to equities in stress episodes and thus improves drawdown control without requiring macro forecasting (Greyserman & Kaminski 2014). Third, credible evaluation in portfolio construction requires moving beyond a single historical backtest. Point estimates on one sample confound model skill with "regime luck" and inflate Sharpe ratios via implicit data-snooping; distributional assessments via Monte Carlo—parametric and block-bootstrap—provide a more honest picture of what investors might experience across many plausible market paths (López de Prado 2018). In an ETF context, these ingredients must be paired with implementability: liquid underlyings, bounded turnover, and explicit accounting for frictions so that reported results approximate what investors can actually keep after trading costs and ongoing fees. The design here follows that discipline by hard-coding rules, measuring turnover, and reporting net performance.

Data and Model Design

Universe and benchmark. The benchmark is SPY. The investable set comprises a technology sleeve (implemented with a liquid tech index proxy and its ranked constituents) and a defensive sleeve represented by GLD. All instruments are highly liquid and available to both retail and institutional investors.

Signals and portfolio rules. Rebalancing occurs weekly. The growth sleeve uses a simple momentum rank on recent returns; the top names are held in equal weight until the next rebalance. The defensive sleeve engages when a gold trend filter is positive and a volatility condition indicates macro stress. When the defensive sleeve is off, capital stays fully in the growth sleeve; when on, the portfolio allocates a pre-set fraction to GLD, with the remainder in the growth sleeve. The rules are intentionally minimal to reduce model fragility and to keep capacity high.

Costs and fees. Every trade incurs a basis-point cost applied to turnover at each weekly rebalance. A management fee accrues pro-rata over the year. A performance fee (where applicable) is assessed annually on excess return over the market benchmark. All outcomes in this report are **net of costs and fees**.

Evaluation framework. Two return generators create long sequences of investable paths. A **Gaussian engine** draws returns from a multivariate normal calibrated to historical means and covariances recorded in the project's parameter file. A **block-bootstrap engine** resamples blocks from the historical return panel to preserve serial correlation and regime clustering. Each engine runs for multi-year horizons with a fixed random seed and a grid of assumptions for trading costs, fee levels, and volatility multipliers. For every simulation the code records net CAGR, net Sharpe ratio, alpha and beta versus SPY, maximum drawdown, and average turnover. All line items are written to summary.csv, and a run log with the experiment plan is saved to logs.txt.

Results

Across thousands of simulated histories, the rules generate distributions of outcomes rather than a single path. This section summarises the patterns that are most decision-relevant for an ETF sponsor and for prospective investors.

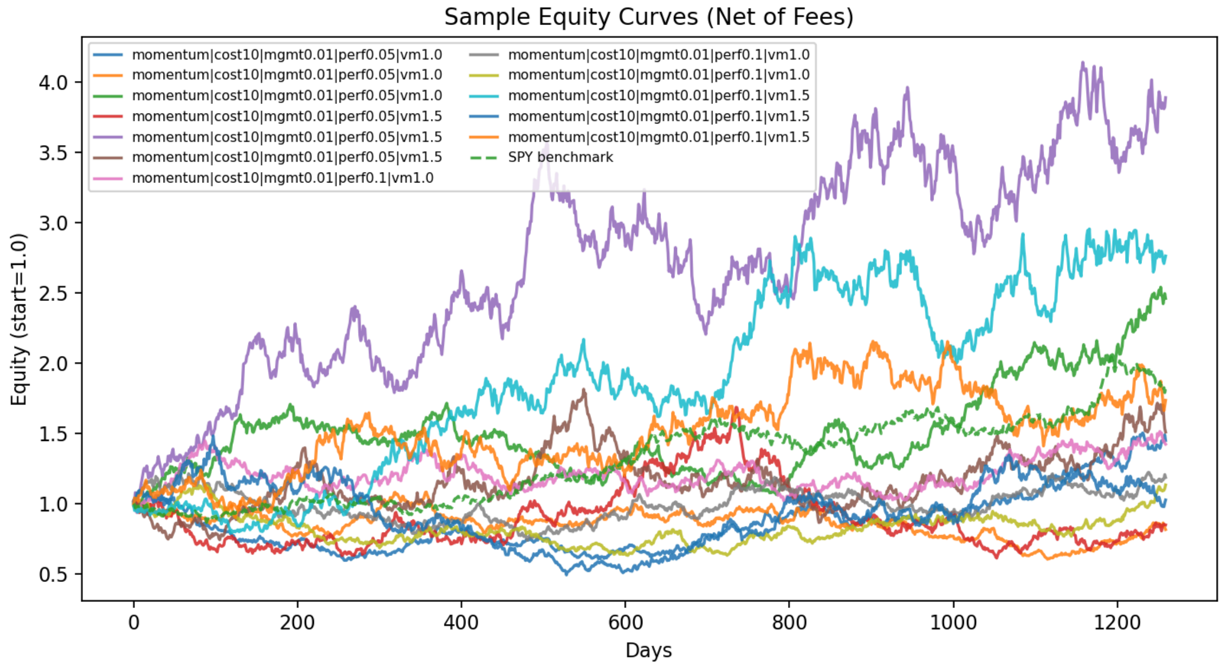

Figure 1. Sample equity curves (net of fees) versus SPY

The sample paths illustrate the intended behaviour. Periods with persistent technology leadership produce strong compounding in the momentum sleeve; when volatility rises and the gold filter activates, equity curves exhibit visibly shallower interim drawdowns, particularly in sequences with clustered down-moves in equities. The benchmark line provides context for market-level risk.

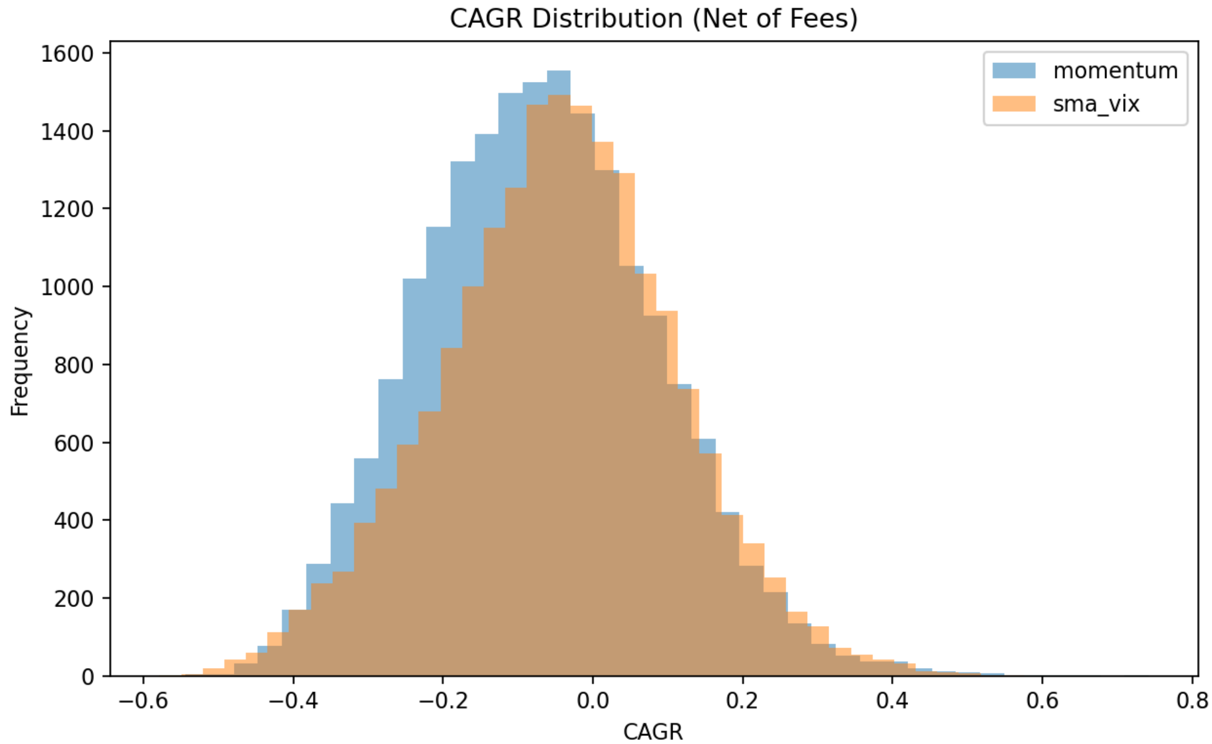

Figure 2. Distribution of net CAGR across simulations for momentum and SMA-VIX rules

The two rule sets produce highly overlapping net CAGR distributions, a useful sign of robustness. The left tail is present but relatively contained; the right tail captures scenarios in which extended growth regimes coincide with limited time in defense. Fee drag compresses both tails as expected but does not eliminate the central tendency of positive compounding under a broad range of assumptions.

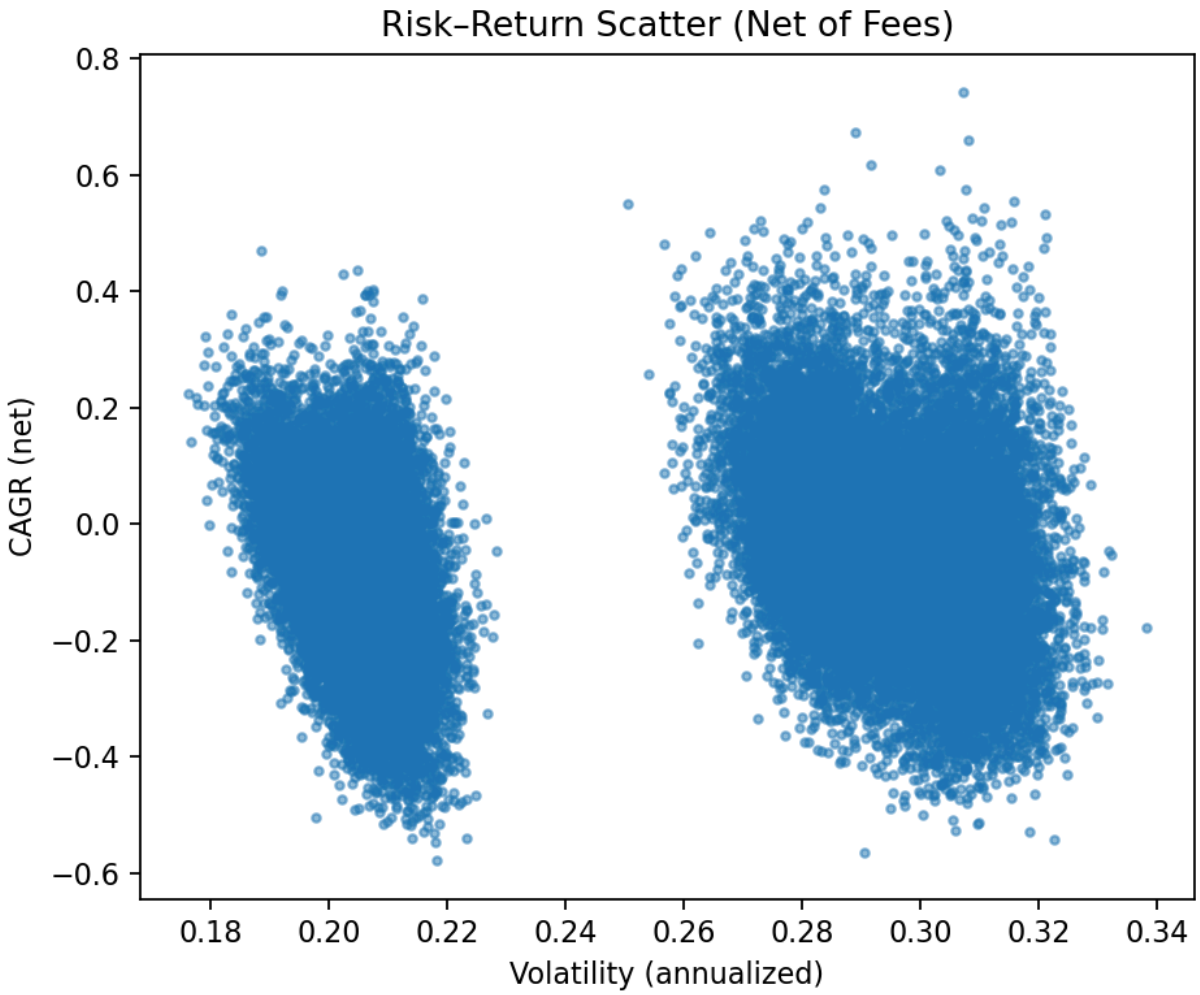

Figure 3. Net Risk–Return Scatter (annualized volatility vs. net CAGR)

The cloud separates into clusters corresponding to distinct turnover and fee settings. Lower-volatility clusters reflect more frequent engagement of the defensive sleeve; higher-volatility clusters correspond to extended exposure to growth. The upward slope of the main mass indicates that incremental volatility is, on average, compensated by higher net CAGR, while the dispersion shows the cost of being wrong-footed by regime transitions.

The full line-by-line metrics—including net Sharpe, alpha, beta, maximum drawdown, and turnover—are available in summary.csv in the repository and underpin the figures presented here.

Discussion

Economic interpretation. The strategy's edge is structural rather than predictive. Technology trends are lumpy, and investor behaviour tends to under-react to early trend information; the momentum sleeve harvests that persistence without stock-specific forecasting. Gold's role is not to maximise return but to improve the left-tail by participating when equity risk is being repriced. The combination produces a portfolio that is long growth on average, yet able to carry defense during periods when it matters most.

Fees, costs, and implementation. All reported outcomes are net of trading costs and fees. Sensitivity runs show the expected monotonic relationships: higher management fees compress median net CAGR; higher transaction costs penalise high-turnover variants more than low-turnover ones. From a product perspective, an ETF structure with a single, competitive management fee is the most transparent for investors and simplifies marketing and comparisons. The strategy's weekly cadence keeps turnover bounded and market impact modest for a typical ETF's initial asset scale.

Limitations and risk. Monte Carlo analysis cannot reproduce every microstructural detail of live trading. The generators approximate the joint behaviour of returns and volatility but, by design, abstract from intraday liquidity, corporate actions, and tax frictions. The defensive filter uses a single volatility gauge and a simple trend rule; alternative definitions may change timing sensitivity. Live results will depend on tracking, cash flows, and investor behaviour. These limitations argue for a staged rollout with paper trading and public signal publication before capital is raised.

Business verdict. The distributional evidence supports moving forward to an operational pilot. A credible plan is a six-month paper-traded track with daily NAV reporting, followed by a small-scale ETF launch if realised slippage and cash-flow effects do not materially undercut the simulated net distribution. Within a small team, the recommended role is quantitative portfolio manager responsible for rule stewardship, data governance, and risk monitoring, supported by one researcher focusing on stress testing and one engineer managing the signal pipeline and compliance logging.

Reproducibility and Audit Trail. All figures and statistics reported here are generated from artefacts checked into the repository. The Monte Carlo driver writes a complete run log (mc/out/logs.txt) and a line-by-line metrics file (mc/out/summary.csv) that includes, for every simulation, the fee settings, trading costs, and net performance statistics (CAGR, Sharpe, alpha, beta, maximum drawdown, turnover). The calibration file (mc/params.json) records the investable tickers, estimation window, and sample moments used by the parametric engine, while the historical return panel (mc/hist_returns.csv) underpins block-bootstrap experiments. Results can be recreated either by running the two parameterized notebooks in sequence—fit_params.ipynb then run_mc_experiments.ipynb—or by executing the pipeline notebook, which saves executed copies to mc/out/ and regenerates all figures used in this report. This design ensures that every number and plot is traceable to a specific configuration and input set.

Conclusion

GoldTechETF is a compact and auditable rules-based strategy that rotates between a momentum-driven technology sleeve and a conditional gold sleeve. The rules are transparent, the trading cadence is modest, and the evaluation focuses on what investors keep after costs and fees. Across a large set of simulated histories the strategy exhibits a favourable risk–return profile relative to the market benchmark and maintains robustness across fee and cost assumptions. Given the results and the implementation practicality, a paper-traded pilot is justified as the next step toward a viable ETF product.

References

Asness, Clifford S., Andrea Frazzini, Ronen Israel, and Tobias J. Moskowitz. 2014. "Fact, Fiction, and Momentum Investing." *Journal of Portfolio Management* 40: (40th Anniversary Issue).

Greyserman, Alex, and Kathryn Kaminski. 2014. *Trend Following with Managed Futures: The Search for Crisis Alpha*. Hoboken, NJ: Wiley.

Jegadeesh, Narasimhan, and Sheridan Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48 (1): 65–91.

López de Prado, Marcos. 2018. *Advances in Financial Machine Learning*. Hoboken, NJ: Wiley.