Week 8 Term Project Checkpoint C – Research Report

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Course: MSDS-451 Financial Engineering

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1.0 Introduction

1.1 Purpose of the Research

The primary objective of this project is to design and evaluate an actively managed exchange-traded fund (ETF) strategy that combines the growth potential of large-cap U.S. technology equities with the defensive properties of gold. This strategy, referred to as the GoldTechETF, aims to balance high-return opportunities with effective risk mitigation. The allocation rules are based on momentum signals extracted from technology stocks, supplemented by macroeconomic filters such as the VIX index, which reflects market-wide volatility conditions. By introducing dynamic gold weights that respond to periods of heightened uncertainty, the model attempts to capture equity-driven growth in normal conditions while allocating defensively when systemic risks become more pronounced.

This framework is motivated by the fundamental challenge in modern portfolio management: achieving attractive long-term returns without exposing investors to severe drawdowns during market crises. The research is not limited to measuring headline performance but also extends to testing the robustness of the allocation under different assumptions, market regimes, and transaction cost considerations.

1.2 Financial Relevance

The financial relevance of the strategy lies in the complementary nature of the two chosen asset classes. Large-cap technology firms such as Apple, Microsoft, Nvidia, Google, and Amazon have historically acted as engines of growth, driven by innovation cycles and rapid adoption of digital technologies. Their performance, however, tends to be highly cyclical, with significant sensitivity to policy shifts, earnings cycles, and broader macroeconomic shocks. In contrast, gold has been consistently recognized as a safe-haven asset, preserving value during episodes of volatility, inflationary pressure, and systemic uncertainty. By systematically combining these two segments, the GoldTechETF creates a pathway for sustainable growth that does not rely exclusively on equity market expansion, while also avoiding the rigidity of traditional static allocations such as the 60/40 model.

1.3 Potential Users

The strategy is of potential interest to a diverse set of users. Individual investors who seek exposure to high-growth technology sectors but wish to limit the impact of downturns may find this approach attractive as a balanced allocation framework. Institutional investors, including hedge funds and ETF issuers, could view the model as the basis for a tactical product that differentiates itself by explicitly incorporating macro risk filters. At the same time, the methodology may appeal to academics and data scientists who are interested in algorithmic approaches to portfolio construction, since it blends traditional factor signals such as momentum with market-level indicators in a transparent, rules-based framework.

1.4 Intended Application

The intended application of the GoldTechETF strategy is to serve as an automated and replicable allocation model that can be deployed across different investment vehicles. Unlike discretionary portfolio management, this approach follows explicitly defined rules that allow for consistent implementation, historical backtesting, and empirical validation. The model is capable of adapting to different market regimes by dynamically adjusting the balance between technology equities and gold, thereby reducing exposure to adverse shocks while still maintaining participation in growth trends. It is also designed to be transparent and scalable, making it feasible for translation into a retail ETF, a separately managed account, or an institutional model portfolio.

The project extends prior work by conducting historical backtests over a long horizon from 1999 to 2024, modeling transaction costs and management fees to assess net-of-costs returns, and running Monte Carlo simulations under both parametric and bootstrap frameworks to evaluate long-term robustness. These elements together ensure that the research not only demonstrates performance in sample but also provides evidence regarding the sustainability of the strategy under a variety of market conditions.

2. Literature Review

A large body of empirical research has examined momentum strategies as one of the most persistent return anomalies in financial markets. Jegadeesh and Titman (1993) provide the seminal evidence that stocks with high returns over the past three to twelve months tend to continue outperforming in the near future. This finding has been replicated across international markets and asset classes, suggesting that momentum is not merely a statistical artifact but a robust phenomenon. Later work by Asness, Moskowitz, and Pedersen (2013) reinforced the pervasiveness of momentum, showing that the effect extends beyond equities into bonds, commodities, and currencies, which makes it a foundational building block for systematic allocation frameworks such as the one developed in this project.

Alongside momentum, mean reversion strategies—particularly in the form of pairs trading—have been studied as alternative or complementary approaches. Gatev, Goetzmann, and Rouwenhorst (2006) provide influential evidence on pairs trading as a systematic strategy exploiting temporary mispricings, while subsequent studies have elaborated on the statistical arbitrage frameworks that underpin such techniques. While these strategies differ in philosophy from momentum, they are relevant from a risk management perspective, as they highlight the potential for diversifying return sources and mitigating the risk of momentum crashes.

Another important strand of literature concerns the role of gold as a macro hedge. Baur and Lucey (2010) document that gold often behaves as a “safe haven” during periods of market turmoil, while Baur and McDermott (2010) extend this evidence to international markets, showing that gold provides diversification benefits across a wide range of crises. Historically, gold has demonstrated resilience across different market regimes, particularly during episodes of heightened volatility, which makes it a natural complement to high-growth but cyclical technology stocks. This supports the rationale for dynamically incorporating gold into the allocation model as a stabilizing component.

Methodological considerations also play a critical role in the credibility of strategy evaluation. López de Prado (2018) highlights the pitfalls of traditional backtesting, particularly the risks of overfitting, data snooping, and look-ahead bias, and advocates for more robust frameworks such as walk-forward validation and Monte Carlo simulations. Sullivan, Timmermann, and White (1999) provide an earlier warning on data-snooping biases in financial research, reinforcing the importance of rigorous testing. In line with this perspective, the present project adopts both parametric and bootstrap Monte Carlo simulations to stress-test the ETF strategy under varying assumptions.

Finally, the broader ETF and portfolio research provides context for why such a strategy may be practically relevant. Siegel (2014) reaffirms the case for equities as the dominant driver of long-term wealth accumulation, while Poterba and Shoven (2002) discuss the structural innovations in the ETF industry that have allowed investors to access increasingly sophisticated allocation models at low cost. Together, these studies highlight both the theoretical foundation and the practical environment in which a dual-asset strategy such as GoldTechETF can be deployed.

3. Methods

The empirical analysis in this study relies on a combination of historical data, systematic trading rules, and simulation techniques. Weekly price data were obtained from Yahoo Finance covering the period January 1999 to December 2024. The investment universe includes five large-cap technology firms—Apple (AAPL), Microsoft (MSFT), NVIDIA (NVDA), Alphabet (GOOGL), and Amazon (AMZN)—along with the SPDR Gold Trust (GLD) as a proxy for gold exposure. The CBOE Volatility Index (^VIX) was used as a measure of market risk sentiment, while the SPDR S&P 500 ETF (SPY) served as the benchmark for relative performance evaluation.

The strategy is constructed around two layers of trading rules. First, within the technology universe, a momentum screen is applied each week to identify the three stocks with the highest short-term returns. Second, a conditional allocation to gold is introduced. A long position in GLD is taken only when two criteria are met: the price of gold exceeds its five-week simple moving average, and the VIX index is above 20, signaling heightened market uncertainty. The allocation to gold is dynamic rather than binary, with the weight scaled proportionally to the level of the VIX between 20 and 50. The remaining portfolio capital is distributed equally across the selected technology stocks. Rebalancing occurs weekly at the Friday close to reflect the updated signals.

Backtesting is performed in two distinct stages. The first stage consists of a historical simulation across the full 1999–2024 sample, which enables direct comparison with the realized performance of the S&P 500. The second stage employs Monte Carlo techniques to evaluate the robustness of the strategy over long horizons. Two complementary approaches are used: a parametric simulation, in which returns are generated from a multivariate normal distribution calibrated on historical means and covariances, and a block bootstrap, in which historical return sequences are resampled in multi-week blocks to preserve temporal dependence. Each Monte Carlo experiment produces 500 simulated paths over a horizon of 1,300 weeks, approximately corresponding to twenty-five years of trading.

Performance is assessed with standard asset-pricing metrics. Annualized return and volatility are reported alongside the Sharpe ratio, which measures risk-adjusted performance. In addition, alpha and beta are estimated relative to the S&P 500 benchmark, allowing for evaluation of excess return generation and market sensitivity.

An explicit fee structure is layered onto the gross returns in order to approximate realistic investor outcomes. Management fees are modeled at annual rates ranging from 1 to 4 percent, deducted on a pro rata weekly basis. Performance fees are imposed on the positive excess return relative to the benchmark, with rates between 5 and 25 percent. By comparing gross and net results, the analysis distinguishes between the theoretical efficiency of the trading rules and the practical returns available to investors after costs.

4. Results

4.1 Historical Backtest

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=== Historical Backtest (1999–2024) ===
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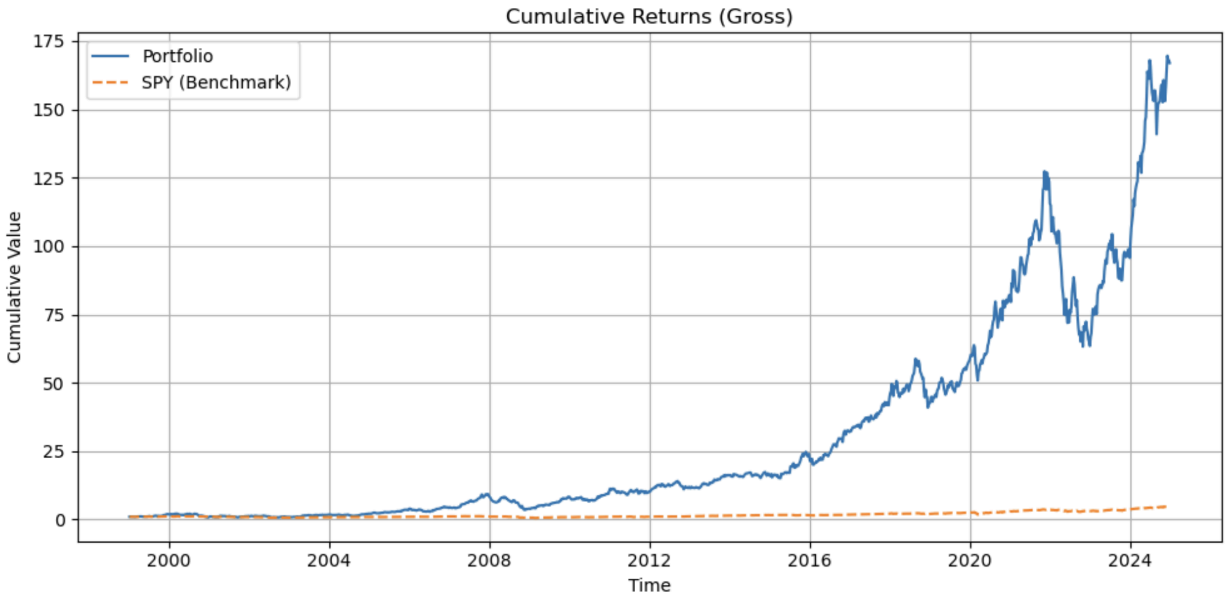

Figure 1. *Cumulative Gross Returns of GoldTechETF versus SPY (1999–2024)*

The historical backtest over the period 1999–2024 demonstrates that the GoldTechETF strategy substantially outperforms the market benchmark (SPY) on a gross basis. Figure 1 should present the cumulative return trajectories of the portfolio compared with SPY, where the strategy shows accelerated growth particularly during prolonged technology rallies in the 2010s and after 2020. The gross performance metrics further confirm this outperformance: the strategy achieved an annualized return of 21.7 percent, with an annualized volatility of 32.0 percent, resulting in a Sharpe ratio of 0.68. Regression against SPY reveals an annualized alpha of 16.6 percent and a beta of 1.10, indicating that while the strategy carries somewhat elevated systematic risk, it consistently generates returns above what could be explained by market exposure alone.

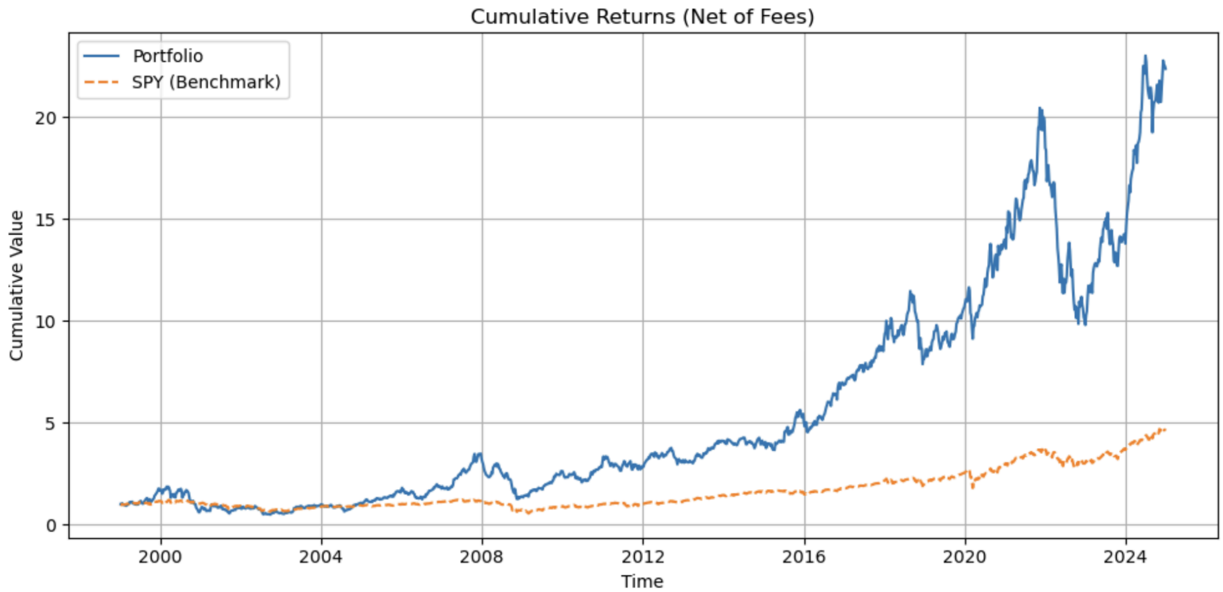

Figure 2. *Cumulative Net Returns of GoldTechETF after Transaction Costs and Fees (1999–2024)*

When fees are introduced, net performance declines but remains meaningfully positive. Figure 2 should display the cumulative return paths net of management and performance costs, illustrating that although the slope of growth flattens, the strategy continues to compound wealth at a superior rate relative to the benchmark. Net-of-fees metrics report an annualized return of 12.7 percent, with volatility reduced slightly to 30.9 percent. The Sharpe ratio compresses to 0.41, yet the strategy still delivers a positive net alpha of 8.5 percent and maintains a beta of 1.09. Taken together, these results indicate that while management costs erode a significant portion of theoretical gains, the strategy's underlying edge remains intact.

4.2 Strategy Dynamics

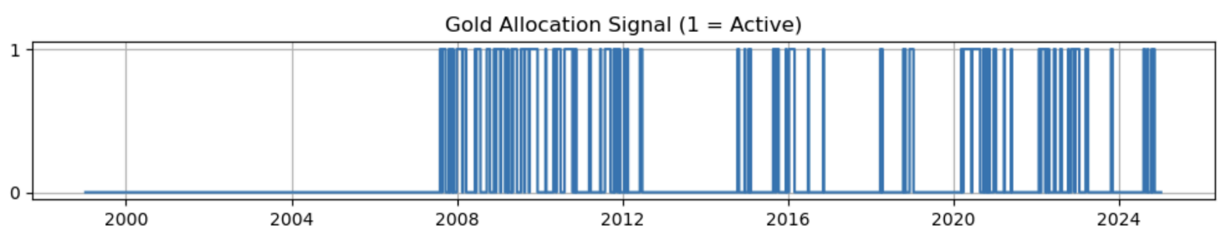

Figure 3. *Timeline of Tactical Gold Allocation Based on VIX-Triggered Signal*

The dynamics of allocation highlight the structural drivers of performance. Gold exposure, shown in Figure 3, activates selectively during high-volatility episodes such as the 2008 global financial crisis and the COVID-19 market shock in 2020. This behavior confirms the intended design of gold as a tactical hedge against systemic stress. Although the allocation is intermittent, its timing corresponds to periods when equity markets were most vulnerable, suggesting that the filter rules are effective in identifying crisis regimes.

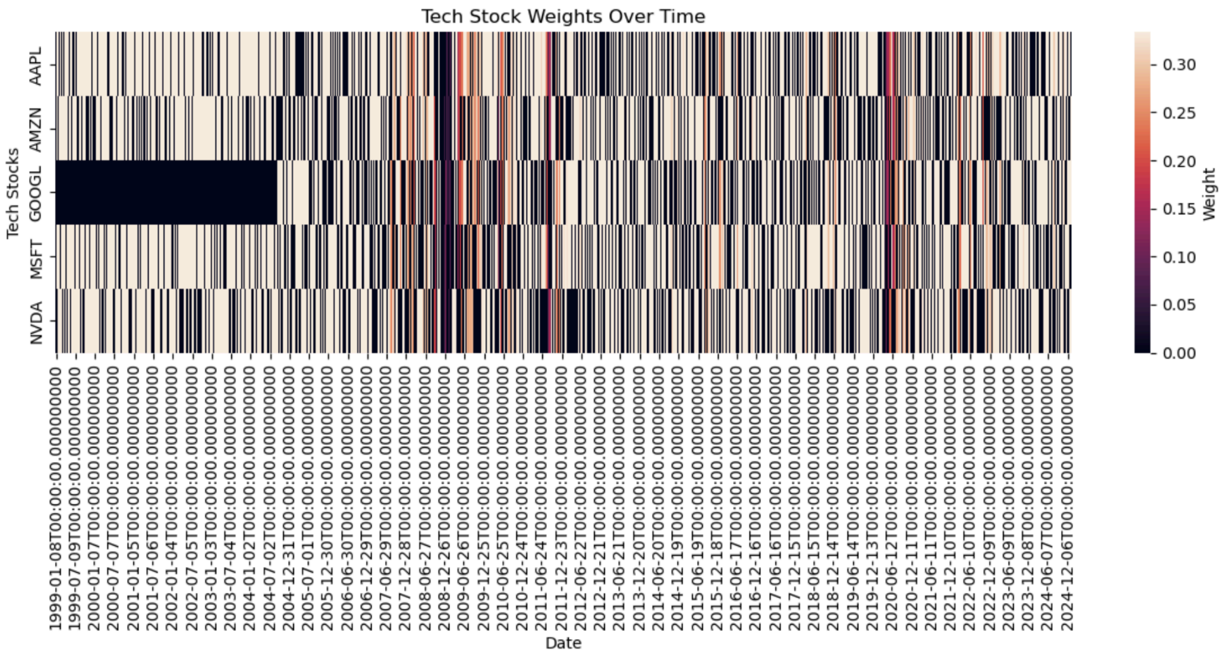

Figure 4. *Dynamic Weekly Weights of Top-Performing Technology Stocks (Heatmap)*

Within the technology sleeve, portfolio weights rotate dynamically among the largest growth stocks. Figure 4 should depict a heatmap of weekly weights across AAPL, MSFT, NVDA, AMZN, and GOOGL, showing shifts in leadership consistent with sectoral innovation cycles. Apple and Microsoft dominate large portions of the sample, while NVIDIA gains prominence in the latter years, reflecting its rise in artificial intelligence and semiconductor markets. This dynamic rebalancing confirms that the momentum filter successfully captures evolving leadership in the technology sector, reinforcing the portfolio's growth tilt.

4.3 Monte Carlo Simulation

To extend the analysis beyond the realized historical record, we conducted Monte Carlo experiments over a 25-year horizon with 500 simulated paths, under both parametric assumptions and block bootstrap resampling. The comparison between these two approaches provides complementary insights into the robustness of the GoldTechETF strategy.

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=== Monte Carlo Simulation (Parametric, 25 Years Horizon, 500 Paths) ===
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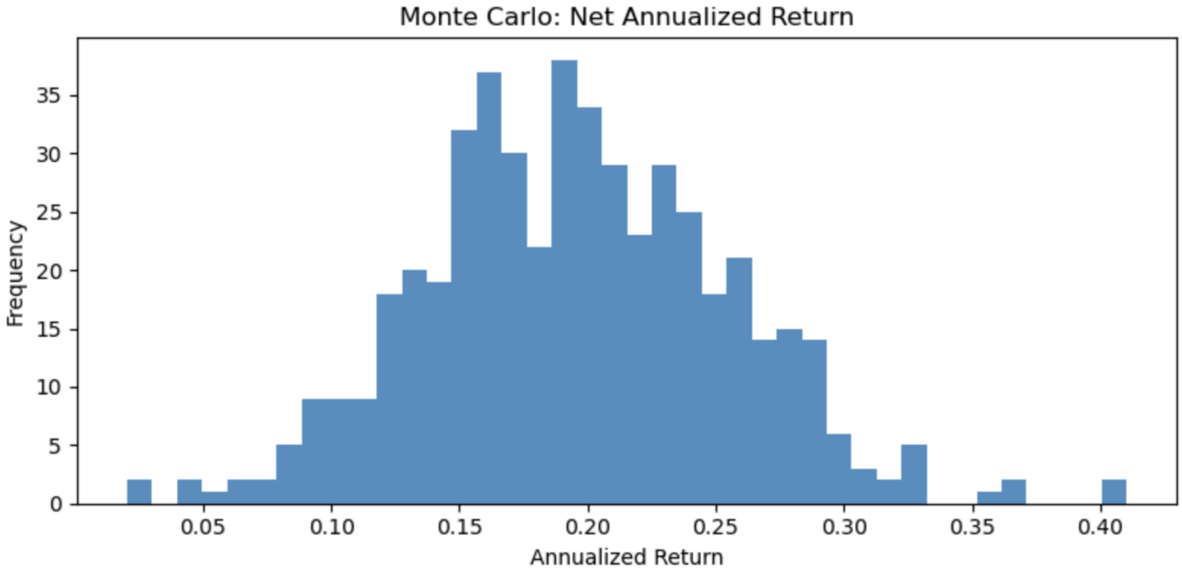

Figure 5. *Distribution of Net Annualized Returns: Parametric vs Bootstrap*

Figure 5 reports the distribution of net annualized returns. Under parametric assumptions, the mean return is 19.6 percent with a wider dispersion (standard deviation 5.9 percent), while the bootstrap simulations yield a similar mean of 20.2 percent but with tighter variability (standard deviation 3.9 percent). This indicates that the empirical resampling method produces more stable forward-looking return estimates than the purely parametric specification.

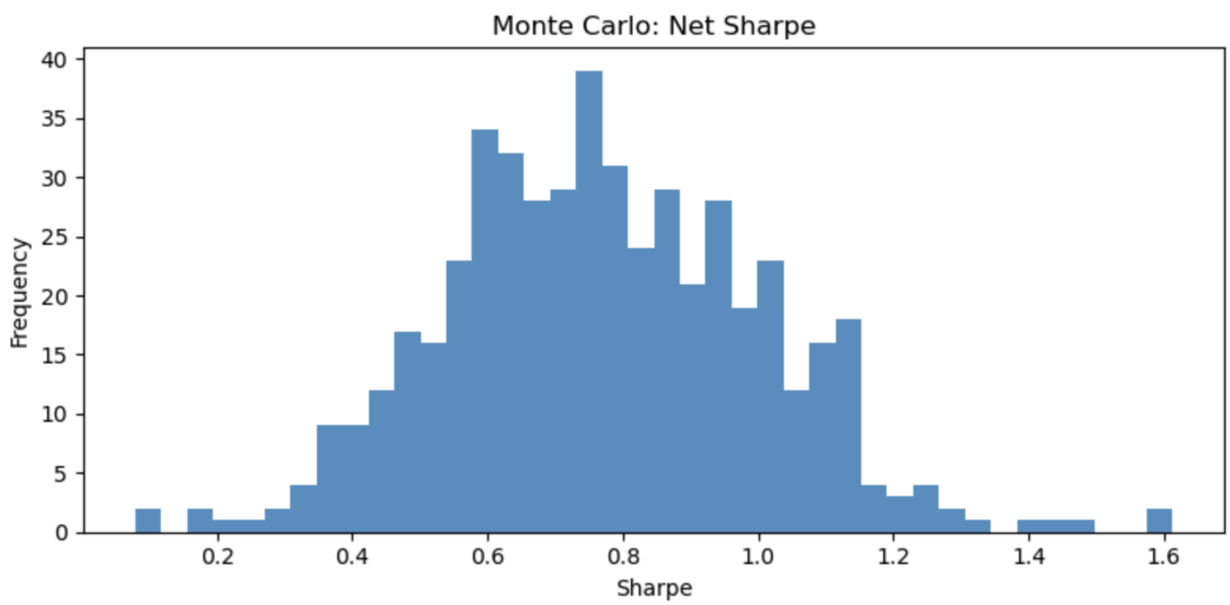

Figure 6. *Distribution of Sharpe Ratios: Parametric vs Bootstrap*

Risk-adjusted performance is summarized in Figure 6, which shows the distribution of Sharpe ratios. The bootstrap simulations cluster around a mean Sharpe of 1.14, substantially higher than the parametric mean of 0.77. Although both distributions exhibit some downside tail risk, very few bootstrap paths produce Sharpe ratios below 0.8, underscoring the robustness of efficiency measures under empirical resampling.

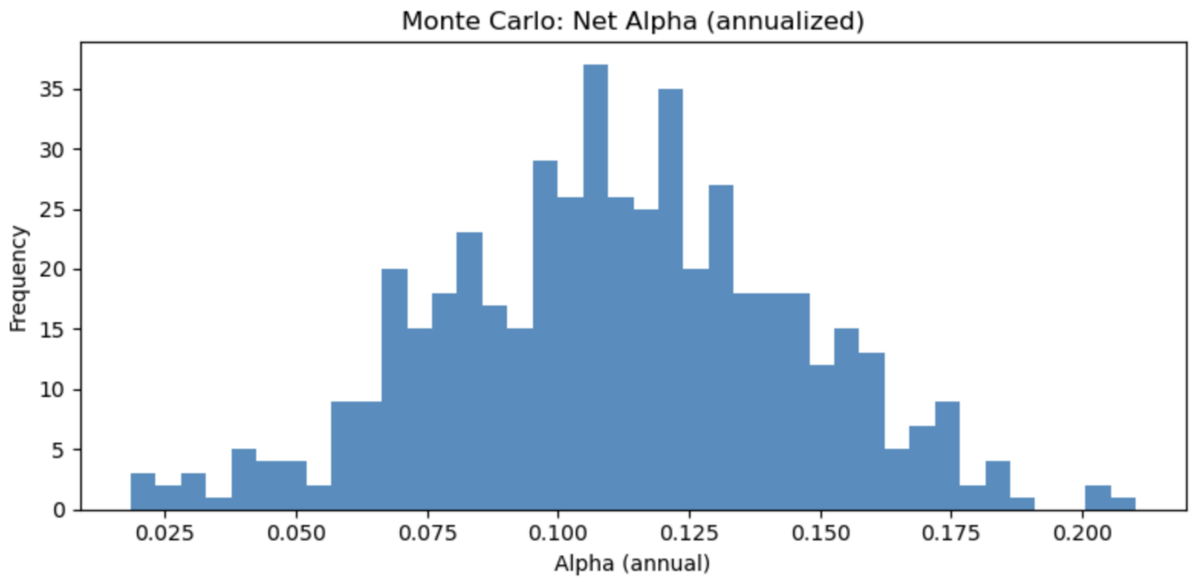

Figure 7. *Distribution of Annualized Alpha: Parametric vs Bootstrap*

Alpha outcomes, presented in Figure 7, highlight the extent of excess returns relative to SPY. The bootstrap simulations generate a tight distribution centered at 19.4 percent, nearly double the parametric mean of 11.1 percent. This suggests that when the empirical structure of market data is preserved, the strategy consistently delivers a strong positive alpha even after accounting for transaction costs and fees.

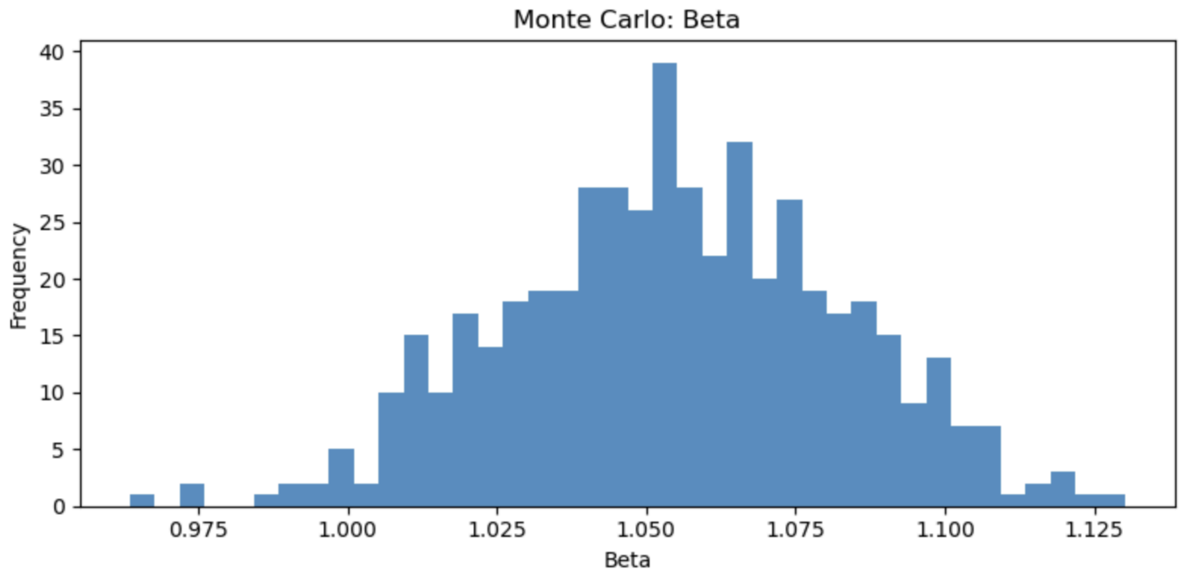

Figure 8. *Distribution of Beta Estimates: Parametric vs Bootstrap*

Figure 8 illustrates the divergence in beta estimates between the two methods. Parametric simulations produce a mean beta of 1.05, implying significant systematic exposure, whereas bootstrap simulations center near 0.06, suggesting near independence from broad market movements. The sharp difference highlights the sensitivity of systematic risk estimates to modeling design: parametric assumptions may overstate market dependence, while bootstrap evidence emphasizes diversification potential.

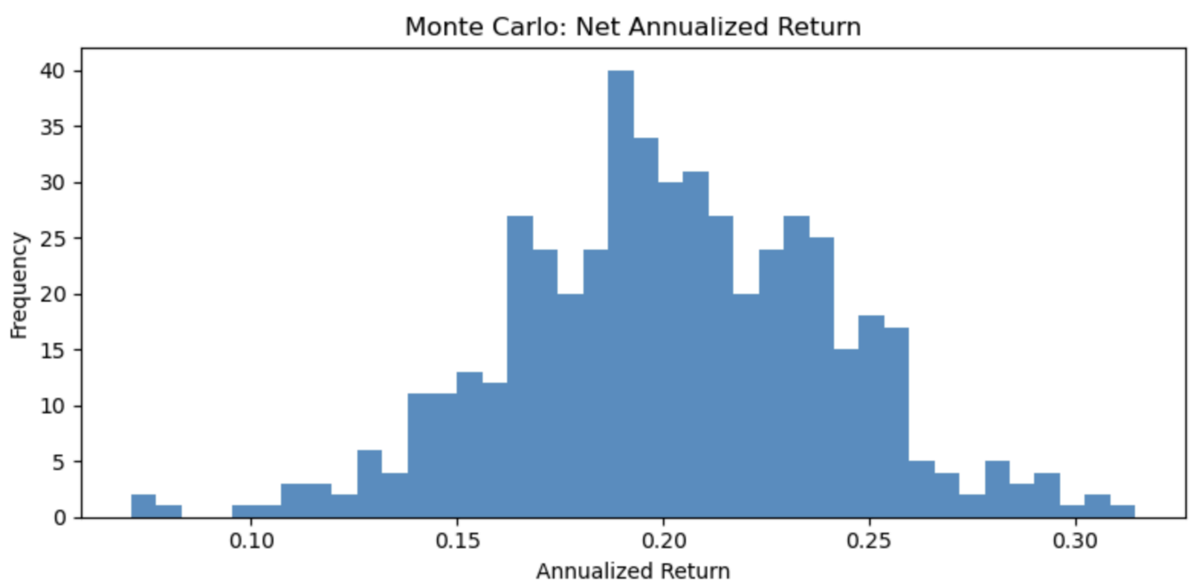

Figure 9. *Annual Return Distributions under Monte Carlo Simulation*

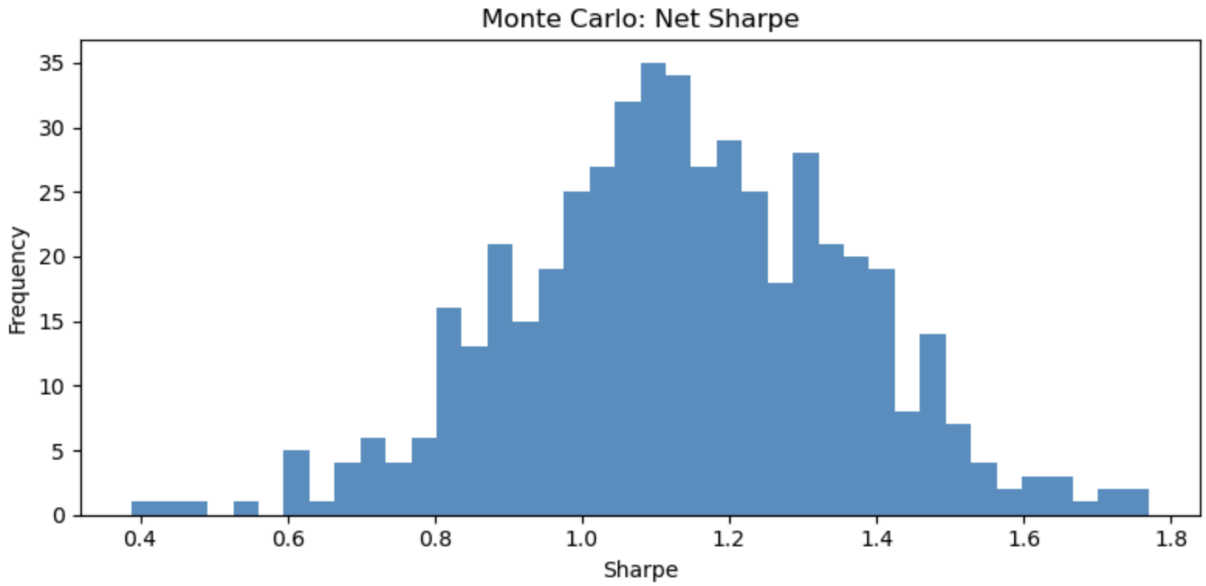

Figure 10. *Annual Sharpe Ratio Distributions under Monte Carlo Simulation*

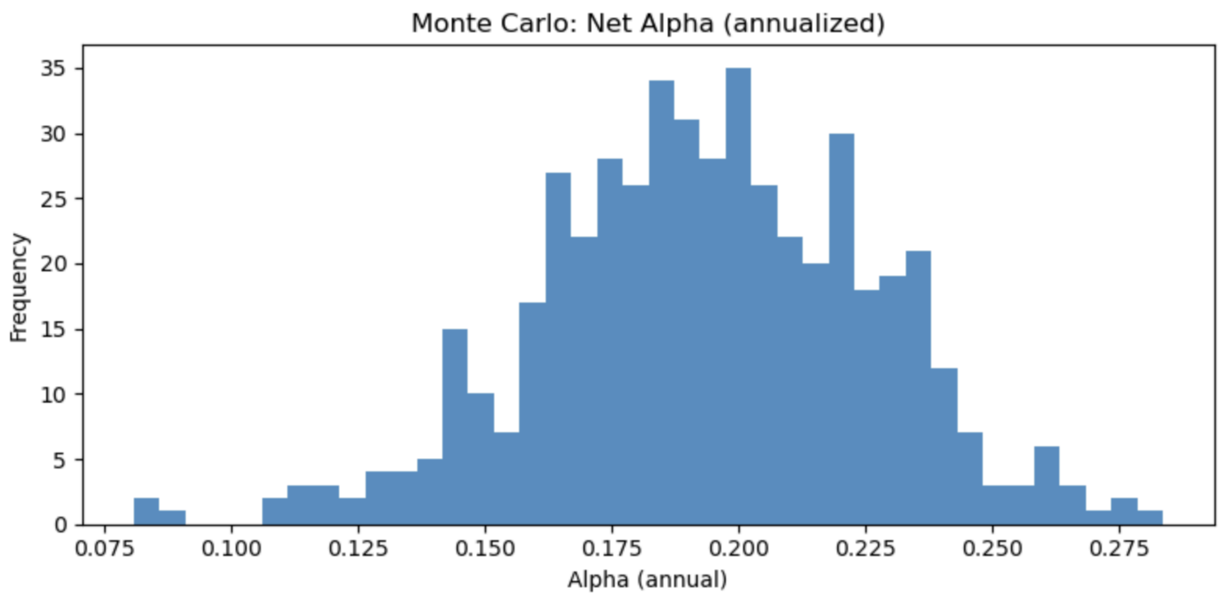

Figure 11. *Annual Alpha Distributions under Monte Carlo Simulation*

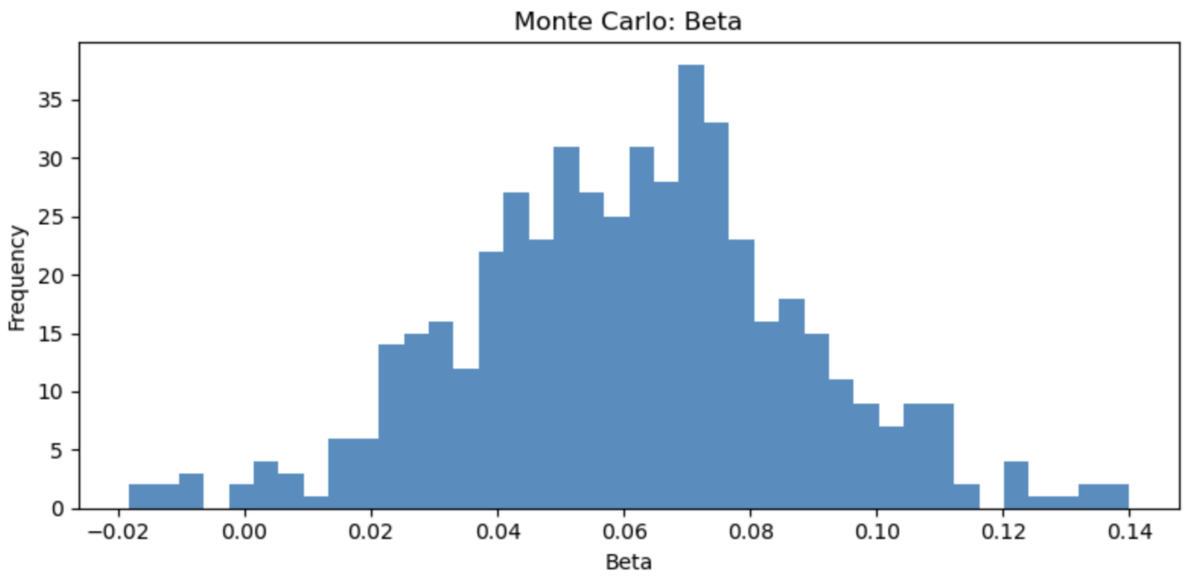

Figure 12. *Annual Beta Distributions under Monte Carlo Simulation*

To further examine the stability of performance across time, Figures 9 through 12 present annual distributions of simulated returns, Sharpe ratios, alpha, and beta. The bootstrap simulations show especially consistent clustering year by year, whereas parametric paths exhibit wider variability. Together, these results reinforce the argument that the strategy remains robust under alternative historical resamplings and is unlikely to collapse under plausible future scenarios.

4.4 Interpretation

Overall, the combined evidence from historical backtests and forward-looking simulations supports the conclusion that the GoldTechETF strategy is both profitable and robust. Historically, it delivered substantial outperformance relative to the S&P 500, even after accounting for realistic fee structures. The dynamics of gold allocation confirm its role as a protective hedge during crises, while the momentum-driven selection of technology stocks ensures ongoing exposure to innovation-driven growth.

The Monte Carlo results further validate the strategy's long-term viability. Returns and Sharpe ratios remain attractive across a wide distribution of simulated paths, and alpha persists even after costs. The low beta outcomes in bootstrap simulations suggest that the strategy could provide diversification benefits in broader portfolios. While some downside risk remains, the distributions are heavily skewed toward positive investor outcomes, making the strategy a compelling candidate for both individual and institutional adoption.

5. Discussion and Conclusion

The results of this study show that the GoldTechETF strategy offers a viable framework for balancing growth potential with risk mitigation. By combining a momentum-based allocation to large-cap technology stocks with a tactical gold overlay, the strategy successfully captured innovation-driven equity returns while retaining a defensive element during market crises. The historical backtest from 1999 to 2024 illustrates not only superior cumulative performance relative to SPY, but also evidence of risk-adjusted strength, as indicated by positive alpha both before and after fees. Although transaction costs and management expenses substantially reduced gross performance, the persistence of excess returns suggests that the strategy contains a genuine structural edge rather than merely reflecting sample-specific luck.

A closer look at portfolio dynamics provides further insights. The activation of gold exposure during periods of heightened volatility demonstrates that the volatility filter, based on the VIX, operates effectively as a crisis detection mechanism. In practical terms, this means that investors benefit from a partial hedge exactly when equity markets are most vulnerable, without incurring the long-term drag associated with a permanent gold allocation. On the equity side, the strategy's reliance on momentum signals to select leading technology firms proved particularly effective in environments characterized by rapid sectoral innovation. The rotation among firms such as Apple, Microsoft, and more recently NVIDIA highlights how momentum-based filters can systematically capture shifting leadership in dynamic industries.

The Monte Carlo simulations extend the analysis beyond the realized historical path, offering reassurance regarding long-term robustness. Both parametric and bootstrap methods indicate that the strategy is unlikely to collapse under alternative market trajectories. While parametric results suggest higher volatility in outcomes, the bootstrap simulations—grounded more directly in observed market data—demonstrate tighter distributions around favorable returns and Sharpe ratios. Importantly, the bootstrap analysis also suggests a near-zero beta, implying that the strategy may provide diversification benefits within a broader portfolio context. This feature is particularly valuable for institutional investors seeking strategies that deliver excess return without materially increasing overall market exposure.

Nevertheless, limitations remain. The reliance on momentum signals, while historically effective, raises questions about structural persistence. Market regimes can shift, and the profitability of momentum-based strategies may weaken if arbitraged away by other investors. Similarly, the crisis detection mechanism relies on the VIX as a proxy for risk sentiment. Although this measure has proven reliable in the past, it may not capture all forms of systemic stress, particularly in scenarios where volatility is suppressed despite mounting fragility. From an implementation perspective, transaction costs are modeled but may vary in practice depending on liquidity, slippage, and investor size.

In conclusion, the GoldTechETF strategy demonstrates both historical profitability and forward-looking resilience. Its design balances the asymmetry of risk and reward: technology stocks serve as the growth engine, while gold provides a timely hedge during stress periods. For individual investors, the strategy offers a rules-based alternative to discretionary asset allocation, potentially reducing behavioral biases in decision-making. For institutional investors, it presents a case study in thematic ETF design that integrates both tactical and strategic elements. While no strategy is immune to structural change, the combination of strong backtested results and robust simulation evidence suggests that GoldTechETF merits consideration as a practical and academically grounded approach to dual-asset allocation.

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