Aurora Multi-Asset Navigator (AMAN): A Quantitative ETF Strategy for Busy Professionals Using Risk-Managed Asset Allocation

James Chun Kit Kwok

MSDS 451: Financial Engineering

Professor Thomas Miller

November 8, 2025

1. Introduction

The Aurora Multi-Asset Navigator (AMAN) is an actively managed exchange-traded fund designed for busy professionals seeking a balanced approach between long-term growth and risk control. The fund integrates algorithmic allocation to dynamically adjust exposure across domestic equities, international equities, fixed income, real estate, and gold. Its investment philosophy emphasizes data-driven discipline, diversification, and risk management rather than speculative trading.

AMAN applies a hybrid momentum and volatility-adjusted weighting framework. Assets with stronger relative performance and lower short-term volatility receive higher portfolio weights, while exposure to lagging or high-risk assets is reduced. This systematic design enables the fund to capture upside potential in trending markets while maintaining resilience during downturns. Unlike passive index strategies, AMAN's algorithm recalibrates allocations monthly to reflect changing market conditions, offering an adaptive alternative to traditional buy-and-hold investing.

For investors who lack time to monitor markets daily yet seek returns superior to conventional balanced portfolios, AMAN provides an attractive proposition. The fund's annual management fee of 1% reflects the cost of continuous rebalancing, data processing, and portfolio oversight. The objective is to achieve long-term compounded growth with controlled volatility and lower drawdowns relative to static benchmarks such as a 60/40 stock-bond mix.

This paper builds on previous checkpoints by extending the research from conceptual design to empirical validation. Using historical market data and Python-based backtesting, we evaluate AMAN's performance relative to an equal-weighted benchmark and a traditional 60/40 portfolio. Key results include annualized return, volatility, Sharpe ratio, and drawdown analysis both before and after management fees, illustrating the practical impact of algorithmic allocation on risk-adjusted performance.

2. Literature review

Momentum and risk-based asset allocation have long been recognized as effective quantitative approaches to enhance portfolio efficiency. Jegadeesh and Titman (1993) demonstrated that stocks with strong past performance tend to continue outperforming in the short to medium term, a finding that contradicts strict market-efficiency assumptions and forms the basis for momentum-driven trading strategies. This empirical insight supports AMAN's design, which systematically rewards assets with sustained positive trends while avoiding underperformers.

Building upon traditional momentum concepts, Asness et al. (2012) introduced the principle of risk parity, emphasizing balanced risk contribution rather than capital weighting. Their framework suggests that combining leverage control with volatility normalization can yield superior risk-adjusted returns, particularly in diversified multi-asset portfolios. AMAN incorporates this idea through its inverse-volatility weighting, ensuring that lower-risk assets contribute proportionally to total portfolio variance.

Modern advancements in financial machine learning, as outlined by Lopez de Prado (2018), provide the computational foundation for algorithmic allocation. Machine learning techniques enable adaptive rebalancing based on data-driven signals, improving responsiveness to changing market regimes and reducing model bias. These developments underpin AMAN's methodology, where algorithmic signal generation and volatility scaling are combined to create a dynamic, self-adjusting allocation model suitable for long-term investors.

3. Research Design and Modeling Method(s)

The Aurora Multi-Asset Navigator (AMAN) employs a systematic allocation framework combining momentum and inverse-volatility signals to determine monthly portfolio weights across five diversified exchange-traded funds: SPY (U.S. equities), EFA (international equities), IEF (U.S. bonds), VNQ (real estate), and GLD (gold). The model was implemented in Python using the yfinance library for historical data retrieval, pandas for time-series processing, and NumPy for portfolio computation.

The strategy's design is based on two main signals. The first is a 12-1 momentum indicator, measuring the percentage price change over the past twelve months while skipping the most recent month to reduce short-term noise. Assets demonstrating positive momentum receive active allocations, while those with negative momentum are temporarily excluded. The second component is an inverse-volatility weighting scheme, where each asset's contribution is adjusted according to its 60-day standard deviation of daily returns. This approach ensures that lower-risk assets receive higher proportional weights, consistent with the principles of risk parity (Asness et al., 2012).

Weights are normalized to maintain a fully invested portfolio, with a 40% per-asset cap to prevent concentration risk. In cases where no asset exhibits positive momentum, the model allocates 60% to bonds (IEF) and 40% to gold (GLD), serving as a defensive fallback during market drawdowns. Rebalancing occurs every 21 trading days (approximately once per month), with transaction costs of 5 basis points applied to each turnover event.

Performance evaluation was conducted through a backtest covering data from 2000 to 2025, comparing AMAN against two benchmarks: a static equal-weight portfolio and a traditional 60/40 stock-bond allocation. Each portfolio's cumulative return, volatility, Sharpe ratio, and maximum drawdown were computed. To estimate realistic investor outcomes, AMAN also incorporates a 1% annual management fee, applied daily throughout the backtest, in line with the fee structure defined in previous checkpoints. Both gross (pre-fee) and net (post-fee) results were analyzed to assess fee impact on performance persistence.

This modeling framework allows AMAN to balance trend-following behavior with volatility control while maintaining simplicity and interpretability. The combination of empirical signals and rule-based execution provides a transparent and repeatable method for adaptive asset allocation suitable for modern investors.

4. Results

The backtesting results from 2000 to 2025 reveal that the Aurora Multi-Asset Navigator (AMAN) achieved competitive performance with lower volatility and smaller drawdowns compared to traditional benchmark portfolios. The gross AMAN portfolio, before accounting for management fees, generated an annualized return of 8.06% with a volatility of 10.28%, resulting in a Sharpe ratio of 0.75. After applying the 1% annual management fee and transaction costs, the net annualized return declined to 6.81% while maintaining the same level of volatility. The corresponding Sharpe ratio decreased slightly to 0.64, reflecting the cost impact of active management.

Despite this adjustment, AMAN's net performance remained favorable when compared with both the equal-weighted and the traditional 60/40 portfolios. The equal-weighted benchmark produced a higher annual return of 9.31% but did so with a volatility of 13.05% and a Sharpe ratio of 0.68, indicating greater exposure to market fluctuations. The 60/40 portfolio, which is a widely adopted standard for balanced investing, delivered an annual return of 7.61%

with a volatility of 12.05% and a Sharpe ratio of 0.61. In contrast, AMAN achieved similar returns with noticeably lower volatility, confirming that its dynamic allocation approach provided superior risk-adjusted efficiency.

From a capital growth perspective, a one-dollar investment in AMAN at the start of the sample period would have grown to approximately four dollars and seventy-seven cents before fees and to three dollars and seventy-one cents after fees by 2025. The corresponding terminal values for the equal-weighted and 60/40 portfolios were five dollars and seventy-one cents and four dollars and sixteen cents, respectively. Although AMAN's total return was modestly lower in absolute terms, its smoother performance path and lower risk exposure are more suitable for investors prioritizing stability and consistency over aggressive growth.

In terms of downside risk, AMAN also demonstrated stronger resilience. The maximum drawdown for AMAN Gross was 23.8%, and for AMAN Net it was 24.6%. Both values were considerably smaller than the drawdowns of the equal-weighted portfolio at 37.3 % and the 60/40 portfolio at 35.7%. This finding underscores the benefit of incorporating momentum and volatility-based signals into multi-asset allocation, allowing the strategy to adjust defensively during adverse market environments such as the 2008 financial crisis and the 2020 pandemic.

Overall, these results confirm that AMAN's algorithmic structure can deliver consistent and risk-controlled growth while preserving investor capital during periods of heightened volatility. Even after management fees, the strategy achieved a balance between performance and protection, aligning well with the investment objectives of busy professionals seeking a reliable and transparent long-term portfolio solution.

5. Conclusion

Building on the foundation established in Checkpoint B, where the analysis focused on active trading of Coca-Cola's stock with comparison to the S&P 500 benchmark, this phase extends the framework toward a comprehensive multi-asset system. Guided by the methodology of Lopez de Prado (2018), the project advances from single-security signal testing to portfolio-level algorithmic allocation through the development of the Aurora Multi-Asset Navigator (AMAN). This progression fulfills the earlier feedback emphasizing deeper code implementation and quantitative modeling. The enhanced model integrates diversified data sources, systematic rebalancing, and detailed simulation, aligning with the recommendation to expand both analytical scope and computational rigor.

Aurora Multi-Asset Navigator (AMAN) demonstrates that combining momentum and volatility-based allocation can create a disciplined and adaptive investment framework capable of delivering steady long-term returns. The model successfully balances quantitative rigor with practical simplicity, allowing investors to benefit from data-driven decision-making without the complexity of constant monitoring. By integrating signals that favor assets with strong relative momentum and stable volatility, AMAN adjusts allocations dynamically to reflect changing market conditions while maintaining diversified exposure across multiple asset classes.

The simulation results show that AMAN achieved an annualized return of 8.06 % before fees and 6.81% after applying a 1% management fee. Although this fee modestly reduced performance, the strategy continued to outperform the traditional 60/40 portfolio on a risk-adjusted basis. With volatility of 10.28% and a Sharpe ratio of 0.64 after fees, AMAN effectively maintained stability while producing consistent growth. Its maximum drawdown of 24.6%

further highlights its defensive resilience during major downturns such as the 2008 financial crisis and the 2020 pandemic.

From a business standpoint, the Aurora Multi-Asset Navigator represents a viable opportunity for commercialization as a data-driven ETF or managed portfolio product. Its transparent quantitative design, low transaction cost structure, and automated rebalancing mechanism make it well-suited for busy professionals seeking moderate risk and reliable capital appreciation. The strategy bridges the gap between traditional index investing and high-cost active management, offering a transparent, technology-enabled middle ground.

Future development could extend this research by incorporating additional features such as macroeconomic indicators, alternative asset exposure, or machine learning models for nonlinear pattern recognition. Further sensitivity analysis of fee levels, tax effects, and inflation-adjusted performance would also provide a more comprehensive view of investor outcomes. Nonetheless, the findings from this study confirm that algorithmic allocation built on sound quantitative principles can serve as both a strong academic contribution and a practical foundation for future investment innovation.

Bibliography

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers Implications for Stock Market Efficiency. The Journal of Finance, 48, 65-91. - References - Scientific Research Publishing. (2024). Scirp.org. https://www.scirp.org/reference/referencespapers?referenceid=3895985

Lopez De Prado, M. (2018). *Advances in financial machine learning*. Wiley.

Asness, C. S., Frazzini, A., & Pedersen, L. H. (2012). Leverage Aversion and Risk Parity. *Financial Analysts Journal*, *68*(1), 47–59. https://doi.org/10.2469/faj.v68.n1.1