MSDS 451 Term Project Checkpoint B

Project Report: Adaptive Global Income and Growth (AGIG) ETF

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1. Introduction

This research project proposes the development of a robust, quant-based investment framework—the Adaptive Global Income and Growth (AGIG) ETF—designed to manage portfolios dynamically over time, moving beyond simple, single-period decisions (Markowitz, 1952). The fundamental concept is to make cutting-edge quantitative research—typically reserved for large hedge funds—available to all personal investors in a low-cost ETF structure. The starting point of this research is the Modern Portfolio Theory (MPT), pioneered by Markowitz (1952), which established the principle of maximizing return for a given level of risk. However, MPT will need to be extended to adjust to changing market conditions and times.

The AGIG ETF overcomes these limitations by integrating Artificial Intelligence (AI) and Operations Research (OR). The fund's objective is to provide personalized financial planning for all age groups, optimizing for high Growth for younger investors and controlled Income (consistent withdrawals, e.g., the 4% rule) for retirees, via dynamic risk control. This research project proposes the development of a robust, adaptive investment framework—the Adaptive Global Income and Growth (AGIG) ETF—designed to manage portfolios dynamically over time, moving beyond simple, single-period decisions (Markowitz, 1952). The fundamental concept is to make cutting-edge quantitative research—typically reserved for large hedge funds—available to all personal investors in a low-cost ETF structure. The starting point of this research is the Modern Portfolio Theory (MPT), pioneered by Markowitz (1952), which established the principle of maximizing return for a given level of risk. However, MPT will need to be extended to adjust to changing market conditions and times.

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2. Literature Review

The AGIG ETF strategy will augment the MPT by leveraging machine learning and artificial intelligence.

2.1 The Need for Better Risk Control

The original idea established the core trade-off: more risk, more potential reward (Markowitz, 1952).

- Conditional Value at Risk (CVaR) - CVaR will be the primary risk measure. CVaR is much better than older methods because it measures the expected loss at the worst market downturns, protecting investors from "tail risk" (Chen 2025).

2.2 Dynamic Portfolio Management with AI and OR

To move from a static strategy to one that adapts daily, especially to handle assets with "fat tails", the ETF shall use two key computational techniques:

- Solving the Two-Goal Problem (OR): The fund has two conflicting goals: maximize growth and minimize CVaR risk. The proposal is to solve the "Multi-Objective Problem" using the intelligent optimization algorithm NSGA II (Kaucic, Moradi, and Mirzazadeh, 2019). This tool from Operations Research finds the perfect balance of investments to meet both Growth and Income targets.
- Achieving Long-Term Stability (AI): The ETF will use Reinforcement Learning (RL), specifically the Actor Critic algorithm, to manage the portfolio minute by minute. This technique is like a self-teaching game where the system learns the best long-term moves. Crucially, we use Performance-Based Regularization (PBR) to stabilize the input data, stopping the AI from making wild, erratic changes that ruined older models (Ban, El Karoui, & Lim, 2018).
- Experiments have been conducted using Financial Transformer Reinforcement Learning (FTRL) for Portfolio Management to uncover latent linkages between assets. FTRL outperformed other RL methods in terms of returns, Sharpe Ratio, and Sortino Ratio, and achieved cumulative returns that were more than 40% higher on average (Ren et al. 2025).

3. Methods

The AGIG ETF adopts a quantitative, algorithmic, and data-driven approach designed for automated implementation.

3.1. Asset Allocation and Diversification

The fund aims for a diversified portfolio encompassing US and foreign stocks, mutual funds, commodity ETFs (Gold, Silver), Bitcoin, US Treasuries, and Real Estate ETFs. This explicit leverage of the diversification principle is often noted as the "closest thing in investment to a free lunch", a quote attributed to Markowitz.

- Real Estate Integration: Real estate is incorporated through REIT-based ETFs, which provide the liquidity needed for this alternative asset class. Real estate serves as a crucial diversifier, historically showing extremely low correlations with traditional equity assets, thus offering substantial risk-reduction benefits. The downside is that REITs involve tax-related considerations; however, they tend to provide recession-proof portfolio investments (Waterworth 2025).
- Strategy Reconciliation: The fund proposes a combination of the desired buy-and-hold/SIP structure by implementing a Strategic Asset Allocation (SAA) for long-term targets, augmented by Tactical Asset Allocation (TAA) driven by AI/ML for dynamic risk mitigation and periodic rebalancing as proposed by Sharpe et. al in Managing Investment Portfolio: Asset Allocation.

- Historical daily price data for a selected universe of assets (AAPL, GOOG, MSFT, NVDA, AMD, INTC, META, BIDU, TSM, COST, PG, KO, PEP, CME, AVGO, WMT, ABBV, HD, XOM, SCHD, VYM, PFF, VWO, VEA, GLD, FXY, FXE, VNQ, EQIX, TLT) and the benchmark (SPY) are downloaded using the yfinance library. A 25-year period is initially requested, but the effective period is limited by data availability for all assets, resulting in approximately 10 years of usable data.

3.2. Analysis Methods (Forecasting and Risk Modeling)

The methodology consists of two critical sub-domains -

1. Forecasting: The primary forecasting tool is the MBi-LSTM network for predicting asset prices, returns, and risks. Its superior accuracy (often exhibiting the lowest MAE and RMSE) over traditional models makes it ideal for generating the critical input parameters (expected return vector and covariance matrix) required for optimization (Gaurav, Baishnab, and Singh, 2025)..
2. Risk Modeling: The ETF fund shall prioritize measures reflecting downside risk and non-normality. As described earlier, CVaR will be calculated, as it addresses the issues inherent in mean-variance analysis, particularly concerning tail risk.
3. Estimation Error Mitigation: To stabilize input parameters, notably the covariance matrix, the ETF will employ techniques such as Performance-Based Regularization (PBR). This approach is designed to protect against estimation errors in the portfolio variance, thereby improving out-of-sample performance (Ban, El Karoui, & Lim, 2018).

3.3 Market Data

3.3.1. OHLCV Data

The market data for this research is primarily sourced from publicly available financial data from Yahoo Finance, accessed via the yfinance Python library. Daily historical data, including open, high, low, close, and adjusted close prices, as well as volume and dividend information, were downloaded for the following assets (AAPL, GOOG, MSFT, NVDA, AMD, INTC, META, BIDU, TSM, COST, PG, KO, PEP, CME, AVGO, WMT, ABBV, HD, XOM, SCHD, VYM, PFF, VWO, VEA, GLD, FXY, FXE, VNQ, EQIX, TLT) and the SPY benchmark.

While an initial aim was to acquire a more extended history, comprehensive data availability for all selected tickers through yfinance provides approximately 12 years of daily data, effectively covering the period from early 2013 to the present. This timeframe, while shorter than the initial target, is still significant, as it encompasses several major financial events and market cycles, enabling valuable analysis of portfolio performance under diverse conditions. Notable events covered within this period include:

- The latter part of the European sovereign debt crisis (post-2013): While the peak was earlier, the lingering effects and recovery phases are included.
- Periods of significant market volatility and corrections: Including various macroeconomic-driven fluctuations.
- The COVID-19 pandemic and subsequent market crash (early 2020): This marked a sharp, significant market downturn.

- The market recovery following the COVID-19 crash.
- Periods of increasing inflation and interest rate hikes (2022-2023)
- Ongoing geopolitical events and trade tensions: Including the impact of tariffs and other global uncertainties on markets.

The daily frequency of the data is sufficient for this research, which focuses on portfolio allocation and evaluation rather than high-frequency trading. A consistent time period across all assets is crucial for calculating portfolio-level metrics and for subsequent predictive modeling and optimization. Dividend data is specifically used to inform the portfolio optimization's income objective.

3.3.2. **Sentimental Analysis and Event Processing**

Beyond traditional historical price and volume data, market sentiment and specific economic or political events can significantly influence stock movements. Incorporating these factors into a predictive model, such as a Bi-LSTM, can enhance its accuracy and robustness.

Data Sources:

- News Articles: Sources such as NewsAPI, Kaggle, and scraping reputable financial news websites (Reuters, CME FedWatch) can provide a stream of textual data on individual companies, sectors, or the overall market.
- Social Media: Platforms such as X (formerly Twitter) and Reddit (particularly finance-related subreddits) are rich, albeit noisy, sources of public opinion and sentiment. APIs or scraping techniques can be used to collect this data.
- Economic and Government Policies: Data from the Federal Reserve Economic Data (FRED) database is invaluable for tracking macroeconomic indicators, interest rates, inflation, employment figures, and other government policy announcements that can impact market expectations. Official government websites and news releases are also key sources.
- Converting sentiment analysis into time-series features would be critical to implementing the data preparation module. The data processing would require the following modules to be implemented -
    - Extracting sentiment data from various sources - NewsAPI, FRED, Reddit etc.
    - Identify significant economic and policy events, such as interest rate decisions, job reports, tariff announcements.
    - Aggregating sentiment scores per day (e.g., averaging, summing).
    - Creating binary or categorical features for specific event types on the days they occur.
    - Implementing decaying effects for sentiment or events to model their diminishing influence over time. This involves assigning a value at the event timestamp and gradually reducing it over subsequent periods.

3.4. **Data Preparation for Bi-LSTM**: The historical closing price data for the portfolio assets (excluding SPY) is prepared as input for the Bi-LSTM model. This involves:

1. Calculating additional features such as log daily returns, High-Low difference, Open-Close difference, Simple Moving Averages (SMA), Exponential Moving Averages (EMA), and lagged closing prices.
2. Structuring the data into sequences using a defined look-back period (60 days). Each sequence consists of the past look-back days of features for all assets, and the corresponding label is the scaled closing price vector for the next day.
3. Applying Min-Max scaling to the feature data to normalize the input for the neural network. A separate scaler is used for the target (closing prices) to enable inverse transformation of predictions back to the original price scale.
4. Data Splitting: The prepared sequences and labels are split into training, validation, and test sets to train and evaluate the Bi-LSTM model and prevent overfitting effectively.
5. Bi-LSTM Model Development: A multivariate Bidirectional LSTM model is built using TensorFlow/Keras. The architecture includes a Bidirectional LSTM layer followed by a Dense output layer with the same number of units as assets, predicting the scaled closing price for each asset. The model is compiled with the Adam optimizer and Mean Squared Error loss, using Mean Absolute Error as an additional metric.
6. Bi-LSTM Model Training and Evaluation: The model is trained on the training data, with validation performed on the validation set. The training history (loss and MAE) is monitored. The trained model's performance is evaluated on the unseen test set using the specified metrics. Predictions are made on the test data and inverse-transformed to the original price scale to compare with actual prices.
7. Data Preparation for NSGA-II: The Bi-LSTM model's predicted future stock prices are used to calculate daily returns for each asset. Historical dividend data is obtained using yfinance and processed to calculate an average annual dividend yield for each asset, which serves as an input for the NSGA-II's dividend objective.

3.4. Decision-Making (Buying/Selling/Rebalancing via AI)

A multi-period, dynamic control approach governs investment decisions.

1. NSGA-II Algorithm Implementation: The NSGA-II algorithm from the pymoo library is implemented to solve the multi-objective portfolio optimization problem. A custom Problem class is defined to encapsulate the objectives and constraints:
2. Objectives: Maximize predicted portfolio return, maximize predicted portfolio dividend yield, and minimize predicted portfolio volatility. These are formulated as minimization problems for the algorithm (-Return, -Dividend Yield, +Volatility).
3. Constraints: The portfolio weights must sum to 1 (with a small tolerance for feasibility during optimization). Lower and upper bounds are set for the weights (0 to 1 for long-only, or -1 to 1 allowing shorts, with dividend-paying assets restricted to non-negative weights). An optional constraint targeting a specific dividend yield is also included.
4. The algorithm is configured with parameters such as population size and number of generations.

5. NSGA-II Optimization: The NSGA-II algorithm is executed to find the Pareto front, representing a set of non-dominated portfolios that offer the best trade-offs among the three objectives. The optimization is run for both a "long only" scenario and a "shorts allowed" scenario (with dividend payers still long-only).
6. Portfolio Selection and Evaluation: Portfolios are selected from the resulting Pareto fronts based on specific criteria (e.g., the portfolio with the lowest predicted volatility or the portfolio with the highest predicted Sharpe Ratio). The historical performance of the selected portfolio(s) is evaluated using actual historical daily returns. Key historical performance metrics (Annualized Volatility, Sharpe Ratio, Value at Risk (VaR), and Conditional Value at Risk (CVaR) are calculated and compared with those of the SPY benchmark and an equal-weighted portfolio. The historical cumulative returns and dividend payments of the selected portfolio(s) are also calculated and visualized.
7. Performance Comparison and Analysis: Historical performance metrics and cumulative return plots are used to compare the selected portfolio(s) against the benchmarks, assessing their effectiveness in achieving the desired balance of growth, income, and risk. The impact of allowing short selling on the Pareto front and selected portfolio performance is also examined.
8. Dynamic Rebalancing (Optimal Control): The rebalancing policy is defined as an optimal control problem. We deploy the Actor-Critic Reinforcement Learning (RL) algorithm for dynamic rebalancing. The RL agent's reward function will be explicitly tied to maximizing long-term wealth while adhering to the fund’s investment philosophy (Growth and Income) and dynamically managing cash flows from investor contributions (SIP) and redemptions (4% withdrawal rule). This enables the system to adaptively adjust compositions in response to evolving market conditions (Ban, El Karoui, & Lim, 2018).

3.5. Backtesting and Strategy Evaluation

Backtesting is a critical step in evaluating the potential effectiveness of an investment strategy. It involves simulating how a strategy would have performed using historical market data. However, simple backtesting on a single historical path has limitations, as market conditions are constantly evolving, and past performance is not a guarantee of future results.

To address these limitations and gain greater confidence in the investment strategies and trading rules, more sophisticated backtesting methodologies are employed. One such approach is walk-forward backtesting with Monte Carlo-generated data.

3.5.1. Walk-Forward Backtesting with Monte Carlo Simulation:

This method combines two powerful techniques:

1. **Walk-Forward Analysis**: Instead of training a model or defining rules on the entire historical dataset and testing on a separate, later period (in-sample vs. out-of-sample), walk-forward analysis involves a rolling process. The data is divided into consecutive segments. The strategy is developed or parameters are optimized using data from an "in-sample" training period. Then its performance is evaluated on the immediately following "out-of-sample" testing period. This process is then "walked forward" by

shifting both the training and testing windows through the historical data. This simulates the real-world scenario in which decisions are made based on data available up to a given point in time.

2. **Monte Carlo Generated Data**: To move beyond evaluating the strategy on a single historical path, Monte Carlo simulation generates numerous synthetic market data scenarios. These simulated datasets are designed to have statistical characteristics (mean, volatility, correlation, and potentially higher-order moments such as skewness and kurtosis) drawn from historical data. Still, they represent different plausible sequences of market movements. This allows for testing the strategy across a wide range of potential future market environments, including those that may differ significantly from the single historical path.

4. Results

Research on integrating advanced quantitative techniques provides strong evidence in support of the AGIG ETF's methodological approach.

4.1 **Superior Predictive Performance with Deep Learning**: Research consistently shows that deep learning models achieve high predictive accuracy. Specifically, models like MBi-LSTM exhibit the lowest error metrics (MAE, RMSE) when forecasting stock returns, outperforming statistical methods such as ARIMA and SVR, as well as sophisticated ensemble models.

4.2 **Enhanced Optimization Efficiency**: Using multi-objective optimization techniques, such as NSGA, has proven highly effective. Studies comparing NSGA-enabled portfolio methods to the Mean-Variance Markowitz (MVM) model show significantly higher similarity to actual returns (Ban, El Karoui, and Lim, 2018). These multi-objective models consistently achieve high portfolio returns with risk levels comparable to, or better than, conventional strategies.

4.3 **Benchmarking and Backtesting**: The portfolio will be benchmarked against the S&P 500 index to measure performance and backtested using as much data as possible. The proposal to use MBi-LSTM networks will require a large amount of data for training and testing. The performance evaluation will be conducted using a Monte Carlo walk-forward simulation that accounts for the various fee structures in a typical ETF or Mutual Fund. The fund's net performance, measured by dividends, yields, and growth relative to the S&P 500 index benchmark, aligns with. The data will be published alongside performance metrics, including volatility, Sharpe Ratio, VaR, and CVaR, to compare the fund's performance against industry benchmarks.

4.4 Performance Evaluation

Evaluating the performance of an investment portfolio goes beyond simply looking at its total return. It's crucial to assess risk-adjusted returns, understand the portfolio's sensitivity to market movements, and account for costs, such as management and performance fees. This section presents the performance evaluation of the designed portfolio prototype, comparing it with the S&P 500 (SPY) benchmark and a simple equal-weighted portfolio of the selected assets, using key financial metrics and accounting for fees.

4.4.1. Key Performance Metrics:

Based on the historical backtesting period (approximately the last 10-12 years), the following metrics were calculated:

- Cumulative Return: The total percentage change in portfolio value over the evaluation period.
- Annualized Volatility: A measure of the dispersion of returns, indicating the portfolio's price fluctuations and risk.
- Sharpe Ratio: A widely used metric for risk-adjusted return, calculated as the excess return (portfolio return minus the risk-free rate, assumed to be 0 for simplicity in this analysis) divided by the portfolio's volatility. A higher Sharpe Ratio indicates better risk-adjusted performance.
- Alpha: Represents the portfolio's excess return relative to the returns predicted by its beta (market sensitivity). A positive alpha suggests the portfolio has outperformed its benchmark on a risk-adjusted basis. Alpha can be calculated on a daily or annualized basis.
- Beta: Measures the portfolio's systematic risk or sensitivity to market movements. A beta of 1 indicates the portfolio's price will move with the market (SPY in this case). A beta greater than 1 suggests higher volatility than the market, while a beta less than 1 suggests lower volatility.
- Value at Risk (VaR): An estimate of the maximum potential loss in portfolio value over a specific time horizon at a given confidence level (e.g., 95% or 99%).
- Conditional Value at Risk (CVaR): Also known as Expected Shortfall, CVaR is the expected loss given that the loss exceeds the VaR. It provides a more conservative measure of tail risk.
- Dividend Yield: The income generated by the portfolio through dividends, typically expressed as a percentage of the portfolio's value.

4.4.2. Dividend Yield and Income

A key objective of this portfolio is to provide income through dividends. While the NSGA-II optimization aimed for a target dividend yield based on predicted future dividends, the historical evaluation offers insight into the actual revenue generated.

4.4.3. Impact of Fees

It is crucial to acknowledge that the performance metrics presented above do not account for potential fees that would be charged in a real-world ETF. These fees would reduce investors' net returns. Typical fees include:

1. Management Fees: An annual percentage charged on the total assets under management (e.g., 0.5% to 2%).

2. Performance Fees: A percentage of the profits earned above a particular benchmark or high-water mark (e.g., 10% to 20%).
3. Trading Fees/Costs: Brokerage commissions and market impact costs incurred when buying and selling assets.

5. Conclusion

The Adaptive Global Income and Growth (AGIG) ETF is uniquely positioned to address the needs of the modern investor by merging robust portfolio theory with cutting-edge AI/ML and Operations Research methodologies. The fund successfully leverages the "free lunch" of diversification by incorporating low-correlation assets, such as Real Estate ETFs. It employs dynamic AI to manage risk and cash flows associated with the SIP and 4% withdrawal goals. The shift from static MPT to a multi-period optimal risk control framework (utilizing MBi-LSTM for forecasting and NSGA-II/RL or FTRL for optimization) provides the essential algorithmic foundation for a sophisticated, modern investment vehicle.

Concerns and Next Steps

The primary challenges moving forward are rooted in the computational complexity and theoretical rigor of the methodology:

1. Lack of expertise: With a limited Finance background, this will be an experimental approach.
2. Complexity: Given the time constraints, implementing the various modules is too complex.

References

Ban, Gah-Yi, Noureddine El Karoui, and Andrew Lim. 2018. "Machine Learning and Portfolio Optimization." *Management Science* 64, no. 3 (March): 1136-54. https://www.jstor.org/stable/48748004.

Chen, James. 2025. "Conditional Value at Risk (CVaR): Expert Guide, Uses, and Formula." Investopedia. https://www.investopedia.com/terms/c/conditional_value_at_risk.asp.

Gaurav, Apurv, Kripamay Baishnab, and Piyush Kumar Singh. 2025. "Intelligent ESG portfolio optimization: A multi-objective AI-driven framework for sustainable investments in the Indian stock market." *Sustainable futures* 9 (June). https://doi.org/10.1016/j.sftr.2025.100832.

Kaucic, Massimiliano, Mojtaba Moradi, and Mohammad Mirzazadeh. 2019. "Portfolio optimization by improved NSGA-II and SPEA 2 based on different risk measures." *Financial Innovation* 5, no. 1 (June): 1-28. https://doi.org/10.1186/s40854-019-0140-6.

Liu, Yong-Jun, Wei-Guo Zhang, and Wei-Jun Xu. 2012. "Fuzzy multi-period portfolio selection optimization models using multiple criteria." *Automatica* 48, no. 12 (12): 3042-3053. https://doi-org.turing.library.northwestern.edu/10.1016/j.automatica.2012.08.036.

Markowitz, Harry. 1952. "Portfolio Selection." *The Journal of Finance* 7, no. 1 (March): 77-91. https://doi.org/10.2307/2975974.

Markowitz, Hary. 1991. “Foundations of Portfolio Theory.” *The Journal of Finance* 46, no. 2 (June): 466-477. https://doi.org/10.2307/2328831.

Ren, Xiaotian, Ruoyu Sun, Zhengyong Jiang, Angelos Stefanidis, Hongbin Liu, and Jionglong Su. 2025. “Time series is not enough: Financial Transformer Reinforcement Learning for portfolio management.” *Neurocomputing* 647 (September). https://doi-org.turing.library.northwestern.edu/10.1016/j.neucom.2025.130451.

Waterworth, Kristi. 2025. “2 Data Center REITs to Consider in 2025.” The Motley Fool. https://www.fool.com/investing/stock-market/market-sectors/real-estate-investing/reit/data-center-reit/.