MSDS 451 Term Project Checkpoint C

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.

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. The fund aims to combine income targeting with active risk management and return enhancement from disciplined forecasting and multi-objective optimization.

1.1. Fund Prospectus and Classification

1.1.1 Fund Classification: Growth and Income, Large Blend

The Adaptive Global Income and Growth (AGIG) ETF is classified as a "Growth and Income" fund with a "Large Blend" investment style under Morningstar's categorization standards. This classification reflects the fund's dual mandate: capital appreciation through growth-oriented equity positions combined with steady income generation through dividend-paying securities.

1.1.2. Investment Strategy

The AGIG ETF employs an active, quantitatively-driven investment strategy that dynamically allocates investor capital across multiple asset classes:

1.1.2.1. Equity Holdings (60-75% target allocation)

- Large-Cap Technology: High-growth companies (AAPL, MSFT, NVDA, GOOG, META, AMD, INTC, AVGO, BIDU, TSM)
- Consumer Staples: Defensive dividend-paying stocks (KO, PEP, PG, COST, WMT)
- Financial Services: Diversified financials and exchanges (CME)
- Healthcare: Large-cap pharmaceutical companies (ABBV)
- Energy: Integrated oil and gas (XOM)
- Retail: Home improvement and consumer discretionary (HD)

1.1.2.2. Fixed Income Securities (10-20% target allocation)

- Long-term U.S. Treasury Bonds (TLT): Provides stability and an interest rate hedge
- Investment-grade Corporate Bonds (SPLB): Enhances yield with moderate credit risk

1.1.2.3. Alternative Assets (10-20% target allocation)

- Precious Metals: Gold (GLD) and Silver (SLV) for inflation protection and portfolio diversification
- Real Estate: REITs and data center infrastructure (VNQ, EQIX) for income and low correlation to equities
- International Equities: Developed and emerging market exposure (VEA, VWO)
- Currency Hedges: Yen (FXY) and Euro (FXE) for currency diversification

1.1.2.4. Dividend-Focused ETFs (5-10% target allocation)

- High-Dividend Equity ETFs (SCHD, VYM): Enhances portfolio income stream
- Preferred Stock ETFs (PFF): Provides fixed-income-like stability with higher yields

1.1.3. How the Fund Invests Investor Money

The AGIG ETF utilizes a systematic, AI-driven process to allocate investor capital:

1.1.3.1. Predictive Forecasting

A deep learning Bidirectional LSTM (Bi-LSTM) neural network analyzes 25 years of historical market data, incorporating 150+ technical indicators, to forecast future asset returns and risks.

1.1.3.2. Multi-Objective Optimization

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) generates a Pareto-optimal frontier of portfolios that simultaneously optimize four objectives:

- Maximize expected returns (growth objective)
- Maximize dividend yield (income objective, targeting 4%+ annually)
- Minimize portfolio volatility (risk management)
- Minimize Conditional Value at Risk/CVaR (tail risk protection)

1.1.3.3. Dynamic Rebalancing

The portfolio is rebalanced monthly to maintain target allocations based on updated ML predictions and market conditions, with transaction costs and slippage factored into execution.

1.1.3.4. Fee Structure

- Management Fee: 1.0% annually (competitive with actively managed funds)
- Performance Fee: 20% on returns exceeding the S&P 500 (SPY) benchmark
- Transaction Costs: Minimized through efficient monthly rebalancing (estimated 10 basis points per trade)

1.1.3.5. Income Distribution

The fund targets a 4% annual dividend yield, distributed quarterly to investors, making it suitable for retirement income planning ("4% rule" compatibility).

1.1.3.6. Target Investor Profile

- Growth-oriented investors seeking above-market returns with controlled risk
- Income-focused investors (retirees) requiring 4%+ annual dividend yield
- Investors seeking diversification beyond traditional 60/40 stock/bond allocations
- Long-term investors are comfortable with active management and AI-driven strategies

1.1.3.7. Benchmark: S&P 500 (SPY)

The fund's performance is measured against the S&P 500 index, and risk-adjusted metrics (Sharpe ratio, alpha, beta) are calculated to assess the value-added from the active management strategy.

1.1.3.8. Risk Considerations

- Model Risk: AI/ML predictions may degrade during unprecedented market regimes
- Concentration Risk: Technology sector holdings may exceed 30% during growth phases
- Fee Impact: Active management fees reduce net returns vs. passive index funds
- Liquidity Risk: Some alternative assets (SLV, EQIX) have lower trading volumes
- Market Risk: Portfolio remains exposed to systematic market downturns despite CVaR optimization

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. 25 years 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 yielding the lowest MAE and RMSE) over traditional models makes it ideal for generating the critical input parameters (the 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 because it addresses the issues inherent in mean-variance analysis, particularly regarding 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 sourced from publicly available financial data via Yahoo Finance, accessed through the yfinance Python library. To overcome the initial data availability limitations, a custom Zipline data bundle was created, providing 25 years of comprehensive daily historical data (1999-2024) for rigorous backtesting and validation.

3.3.2. Data Bundle Specifications

- Time Period: 25 years (January 1999 - October 2024)
- Frequency: Daily OHLCV (Open, High, Low, Close, Volume) data
- Additional Data: Adjusted close prices, dividend distributions, stock splits
- Total Trading Days: Approximately 6,300 trading days per asset
- Benchmark: S&P 500 (SPY) for performance comparison

3.3.3. Asset Universe (30 assets across 7 categories)

3.3.3.1. Large-Cap Technology (10 assets)

- U.S. Tech Giants: AAPL (Apple), MSFT (Microsoft), GOOG (Alphabet), META (Facebook/Meta)
- Semiconductors: NVDA (NVIDIA), AMD (Advanced Micro Devices), INTC (Intel), AVGO (Broadcom)

3.3.3.2. Consumer Staples & Retail (6 assets)

- Beverages: KO (Coca-Cola), PEP (PepsiCo)
- Consumer Products: PG (Procter & Gamble)
- Retail: COST (Costco), WMT (Walmart), HD (Home Depot)

3.3.3.3. Financial Services (1 asset)

- Exchanges: CME (Chicago Mercantile Exchange)

3.3.3.4. Healthcare & Energy (2 assets)

- Pharmaceuticals: ABBV (AbbVie)
- Energy: XOM (ExxonMobil)

3.3.3.5. Fixed Income ETFs (2 assets)

- Government Bonds: TLT (iShares 20+ Year Treasury Bond ETF)
- Corporate Bonds: SPLB (SPDR Portfolio Long Term Corporate Bond ETF) [Note: Limited history, supplemented where needed]

3.3.3.6. Dividend & Income ETFs (3 assets)

- High-Dividend Equity: SCHD (Schwab U.S. Dividend Equity ETF), VYM (Vanguard High Dividend Yield ETF)
- Preferred Stock: PFF (iShares Preferred and Income Securities ETF)

3.3.3.7.. Alternative Assets & International Exposure (6 assets)

- Precious Metals: GLD (SPDR Gold Shares), SLV (iShares Silver Trust) [Note: GLD inception 2004, backfilled where necessary]

- Real Estate: VNQ (Vanguard Real Estate ETF), EQIX (Equinix - Data Center REIT)
- International Equity: VWO (Vanguard Emerging Markets ETF), VEA (Vanguard Developed Markets ETF)
- Currency: FXY (Invesco CurrencyShares Japanese Yen Trust), FXE (Invesco CurrencyShares Euro Trust)

3.3.4. Custom Bundle Creation Process

To address data availability constraints for assets with shorter histories (e.g., GLD inception 2004, SPLB limited data):

1. Primary Data Source: yfinance API for maximum available history per ticker
2. Data Alignment: All assets aligned to a common 25-year period (1999-2024)
3. Missing Data Handling: For assets with shorter histories, either:
    a. Backfilled using correlated proxies (e.g., gold spot prices for GLD pre-2004)
    b. Excluded from the portfolio during unavailable periods in backtesting
    c. Forward-filled conservatively for analysis purposes
4. Zipline Bundle Format: Converted to Zipline-compatible format with OHLCV + dividends + splits
5. Quality Assurance: Verified data integrity, removed outliers, adjusted for corporate actions

3.3.5. Historical Period Coverage - Major Market Events (1999-2024)

This 25-year period provides comprehensive exposure to diverse market regimes, including:

- Dot-Com Bubble Burst (2000-2002): Tech sector crash, >75% NASDAQ decline
- 9/11 Terrorist Attacks (2001): Market closure and subsequent recovery
- Housing Bubble and Subprime Crisis (2006-2007): Pre-cursor to financial crisis
- Global Financial Crisis (2008-2009): Lehman Brothers collapse, SPY -56.8% drawdown
- European Sovereign Debt Crisis (2010-2012): Greece, Spain, Italy debt concerns
- Fed Taper Tantrum (2013): Market volatility from QE withdrawal signals
- Oil Price Collapse (2014-2016): Crude oil from $100+ to $30 per barrel
- Brexit Referendum (2016): UK vote to leave EU, global market uncertainty
- Trade War Volatility (2018-2019): U.S.-China tariff disputes

- ❖ COVID-19 Pandemic Crash (February-March 2020): Fastest bear market in history, 34% decline in weeks
- ❖ Zero Interest Rate Policy & Quantitative Easing (2009-2021): Unprecedented monetary stimulus
- ❖ Inflation Surge & Rate Hikes (2022-2023): Fed raising rates from 0% to 5.25% in 18 months
- ❖ Banking Crisis (2023): Silicon Valley Bank, Signature Bank failures
- ❖ AI-Driven Bull Market (2023-2024): Tech sector surge led by AI/ML adoption

This comprehensive 25-year dataset enables robust evaluation of the AGIG ETF strategy across multiple economic cycles, market regimes, and crisis scenarios, providing statistically significant validation of the Bi-LSTM + NSGA-II methodology.

3.3.5.1. Data Quality and Consistency

The daily frequency of the data is optimal for this research, which focuses on portfolio allocation and monthly rebalancing rather than high-frequency trading. A consistent 25-year time period across all assets (with appropriate handling of limited-history assets) is crucial for:

- Calculating reliable portfolio-level metrics (Sharpe ratio, alpha, beta)
- Training the Bi-LSTM model with sufficient historical patterns (6,300+ days)
- Validating NSGA-II optimization across diverse market conditions
- Performing Monte Carlo simulations with historically calibrated parameters

Dividend data is specifically tracked and incorporated into:

1. NSGA-II optimization (dividend yield objective targeting 4%+ annually)
2. Zipline backtesting (quarterly 1% withdrawals simulating retirement income)
3. Historical performance evaluation (total return including dividends reinvested)

3.3.6. 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 is critical for 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, and 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

Historical closing price data for the portfolio assets (excluding SPY) are prepared as input to 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.

3.5. 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).

3.6. Backtesting and Strategy Evaluation

Three distinct backtesting and validation methodologies have been implemented to evaluate the AGIG ETF strategy's effectiveness rigorously:

3.6.1. Historical Backtesting with Zipline (Primary Method)

The primary backtesting framework utilizes the Zipline library, a professional-grade event-driven backtesting engine. This implementation provides the most realistic evaluation of the strategy by:

3.6.1.1. Implementation Details:

- Custom Data Bundle: A Zipline data bundle was created containing 25 years of daily OHLCV data (1999-2024) for 30 portfolio assets plus SPY benchmark, sourced from Yahoo Finance.
- Realistic Fee Structure:
  - Management Fee: 1% annually (deducted daily as 0.01/252)
  - Performance Fee: 20% on excess returns above SPY benchmark (charged annually)
  - Transaction Costs: 10 basis points (0.001) per trade using Zipline's PerDollar commission model
  - Slippage: Volume-based slippage model (2.5% volume limit, 0.1 price impact)
  - Dividend Simulation: 1% quarterly dividend withdrawals to simulate the 4% annual withdrawal rule
  - Rebalancing Strategy: Monthly rebalancing (first day of each month) to maintain target weights from NSGA-II optimization
  - Benchmark Tracking: SPY set as benchmark with alpha/beta calculations vs. the market

3.6.1.2. Key Results from Zipline Backtesting

- Dual Performance Reporting: Both unadjusted (as reported) and adjusted (after dividend withdrawals) portfolio values are tracked to show accurate investor returns
- Alpha Calculation: Using CAPM formula: $\alpha = Rp - [Rf + \beta(Rm - Rf)]$
- Beta Measurement: Calculated via the covariance method using aligned daily returns
- Fee Impact: Cumulative tracking of management fees, performance fees, and dividends paid over the 25 years
- Drawdown Analysis: Portfolio drawdown compared directly with SPY drawdown to assess downside protection

This Zipline-based backtesting provides the most accurate assessment of real-world performance, accounting for market microstructure, transaction costs, and realistic fee deductions that would occur in an actual ETF.

3.6.2. Monte Carlo Performance Evaluation (Implemented)

To address the limitation of evaluating on a single historical path, a comprehensive Monte Carlo simulation was implemented to generate 10,000 synthetic 25-year market scenarios:

3.6.2.1. Implementation

- Historical Parameter Estimation: Mean returns and covariance matrix calculated from 1999-2024 actual data

- Correlated Return Generation: Using Cholesky decomposition to maintain asset correlation structure
- Day-by-Day Simulation: Each of 10,000 trials simulates 252 × 25 = 6,300 trading days
- Fee Deduction: Management fees, performance fees, and transaction costs are deducted in real-time during simulation
- Rebalancing Costs: Monthly rebalancing with 10% turnover and 10 bps transaction costs
- Dividend Withdrawals: Quarterly 1% withdrawals tracked and removed from portfolio value

3.6.2.2. Monte Carlo Outputs

- Distribution Analysis: Final portfolio values, ROI, and annualized returns across 10,000 scenarios
- Risk Metrics: Sharpe ratio, maximum drawdown, CVaR for each simulation
- Confidence Intervals: 95% CI for ROI, annualized return, and final value
- Probability Calculations: P(positive ROI), P(beat benchmark), percentile distributions
- Visualization Dashboard: 9-chart comprehensive display including histograms, box plots, scatter plots, CDF curves, and a summary statistics table

This Monte Carlo approach provides statistical confidence in the strategy's performance across a wide range of potential market conditions, rather than relying on a single historical path.

3.6.3. Walk-Forward Analysis (Theoretical Framework - Not Implemented)

While walk-forward backtesting was initially considered and documented in the methodology, it was ultimately not implemented due to:

3.6.3.1. Theoretical Concept

- Walk-forward analysis would involve:
- Dividing historical data into consecutive training/testing windows
- Training the Bi-LSTM model on each in-sample period
- Testing performance on the immediately following out-of-sample period
- Rolling the window forward through time to simulate real-world deployment

3.6.3.2. Reason for Exclusion

- Time Constraints: Training Bi-LSTM models repeatedly (20-30 times for proper walk-forward) requires significant computational resources
- Diminishing Returns: The combination of Zipline historical backtesting (single path, realistic execution) and Monte Carlo simulation (10,000 synthetic paths) already provides robust validation
- Complexity vs. Value: Walk-forward would add 2-3 weeks of development time with marginal additional insight, given the other two methods
- Current Focus: Emphasis placed on perfecting the Bi-LSTM → NSGA-II → portfolio selection pipeline rather than re-training validation

The decision to use Zipline backtesting (historical realism) combined with Monte Carlo simulation (scenario diversity) provides a more practical and comprehensive evaluation framework than walk-forward analysis alone, which primarily guards against look-ahead bias—a concern already addressed by temporal train/test/validation splits in the Bi-LSTM model development.

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 a portfolio's systematic risk, or its 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.

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