# FINAL REPORT - Macro-Linked Energy ETF

**MSDS 451: Financial and Algorithmic Trading**
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**GitHub Repository:** https://github.com/vrishanishah20/macro-linked-energy-etf

# 1. Introduction

The energy sector remains one of the most volatile and macro-sensitive segments of global financial markets. Crude oil prices, interest rates, inflation, volatility regimes, and geopolitical risks all interact to drive large swings in returns. This project investigates whether a **rules-based, macro-linked energy ETF** can outperform a broad-market benchmark such as the S&P 500 (SPY) over a long historical period (2002–2024).

The objective is to build a **fully algorithmic investment strategy** using publicly available data, evaluate its performance through comprehensive backtesting, and assess business viability after applying realistic management and performance fees. The strategy allocates across five assets representing commodity exposure, energy equities, and defensive fixed income: **WTI crude oil**, **XLE**, **XOM**, **CVX**, and **IEF**.

To rigorously test whether such a fund could deliver excess returns, this project implements:

- A 22.4-year historical backtest
- Multiple allocation strategies (equal-weight, risk parity, mean–variance, macro-adaptive)
- Monte Carlo analysis (normal + bootstrap)
- Walk-forward out-of-sample testing
- Fee structure evaluation
- Business viability assessment

**Key Question:**
*Can a macro-linked energy ETF generate superior risk-adjusted and fee-adjusted returns relative to SPY?*

**Short Answer:**
**No.** Despite sophisticated methods, the energy strategies underperform SPY by 4-7% annually and fail robustness testing.

# 2. Literature Review

## 2.1 Energy Markets and Macro Linkages

Prior work shows that energy markets are deeply influenced by macroeconomic cycles and supply/demand shocks:

- Hamilton (2009): Oil shocks and macroeconomic effects
- Downey (2009): Structural drivers of crude oil
- Bouchouev (2023): Quantitative trading in commodities
- Edwards (2017): Professional energy trading frameworks
- Kilian & Murphy (2014): Identifying supply vs. demand shocks

These works motivate the idea that macro signals could guide sector allocation.

## 2.2 Portfolio Optimization and Risk Allocation

Foundational portfolio theory supports the weighting schemes used in this project:

- Markowitz (1952): Mean–variance optimization
- Sharpe (1963): Risk/return tradeoffs
- Qian (2005): Risk parity portfolios
- Asness et al. (2012): Leverage aversion and balanced risk portfolios

These techniques aim to improve diversification within cyclical sectors.

## 2.3 Systematic and Macro Trading Strategies

Rules-based strategies have long been used in macro and sector trading:

- Grinold & Kahn (2000): Active portfolio management
- Antonacci (2014): Momentum and cross-asset rotation
- Jegadeesh & Titman (1993): Momentum evidence
- Greyserman & Kaminski (2014): Trend-following in futures

The macro-adaptive strategy in this project draws on this literature.

## 2.4 Backtesting and Evaluation Frameworks

To avoid overfitting, rigorous backtesting is essential:

- López de Prado (2018): Deficiencies in naive backtests
- Chan (2020): Quant trading implementation
- Trivedi & Kyal (2021): Pythonic backtesting methods

These references justify the Monte Carlo and walk-forward robustness tests.

## 2.5 Research Gap

Existing literature rarely combines:

- Macro regime signals
- Multiple energy-sector strategies
- 22-year historical backtest
- Monte Carlo simulation
- Walk-forward validation
- Fee-adjusted performance
- Business viability analysis

This project fills that gap.

# 3. Methods

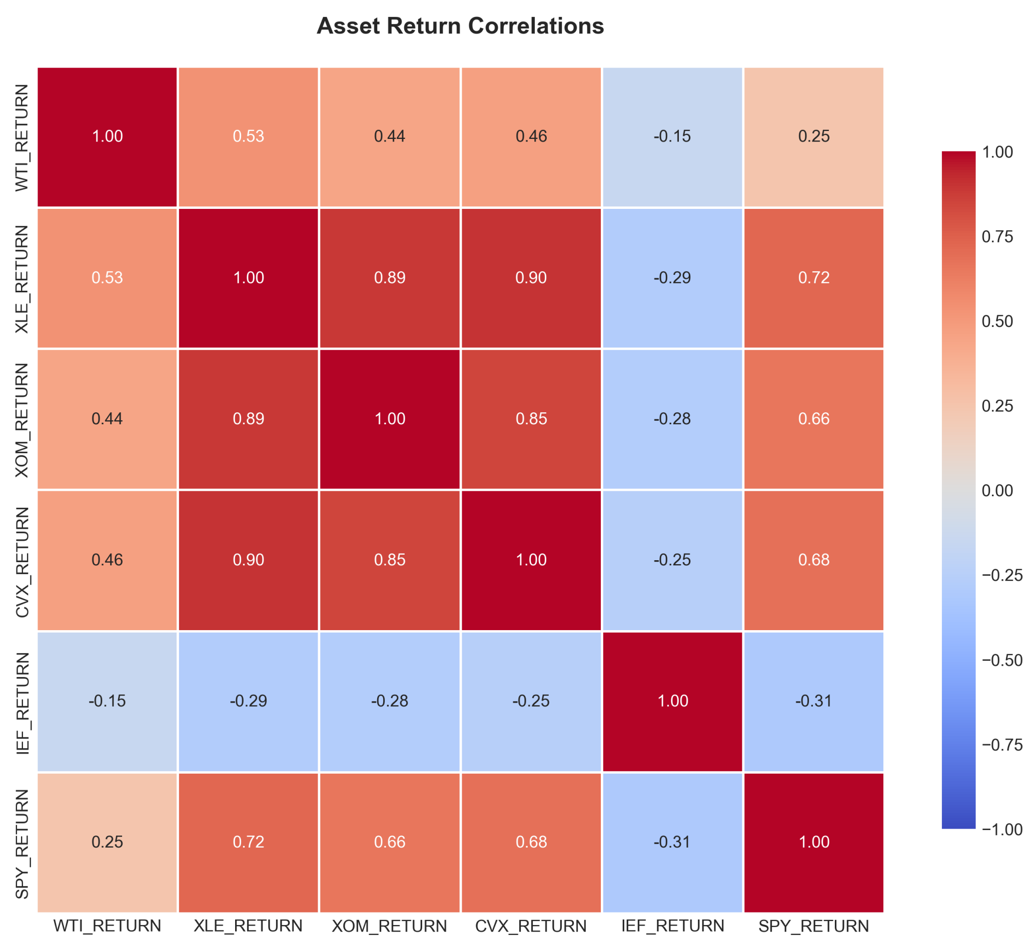
## 3.1 Data & Asset Universe

**Assets Used:**

- **WTI crude oil** (continuous futures/ETF proxy)
- **XLE** - Energy Select Sector SPDR

- **XOM** - Exxon Mobil
- **CVX** - Chevron
- **IEF** - 710 Year Treasury ETF
- **SPY** - S&P 500 benchmark

**Time period:** July 2002 – December 2024 (5,600+ trading days)
**Sources:** Yahoo Finance, FRED




# 3.2 Feature Engineering

Computed features include:

- 21/63/126-day momentum
- 126-day annualized volatility

- Rolling beta to SPY
- Maximum drawdown
- Macro variables: ΔFedFunds, ΔVIX, CPI rate-of-change

### Composite Macro Score

$C_t = 0.4z(WTI) - 0.3z(\Delta FedFunds) - 0.3z(\Delta VIX)$
**Regimes:**

- **Bullish:** $C_t > 0.75$
- **Neutral:** $-0.75 \leq C_t \leq 0.75$
- **Bearish:** $C_t < -0.75$

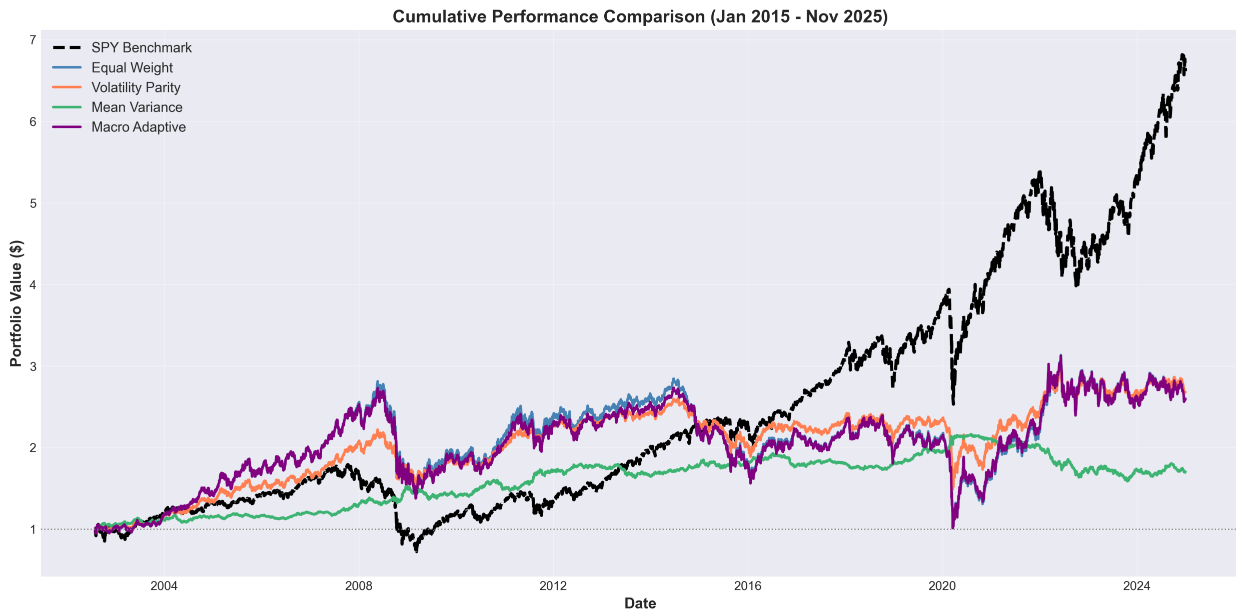
## 3.3 Portfolio Strategies

1. **SPY Benchmark** - Buy-and-hold
2. **Equal-Weight**
3. **Volatility Parity**
4. **Risk Parity** (equal risk contribution)
5. **Mean-Variance (Markowitz)**
6. **Macro-Adaptive** (tilts based on C_t)

Monthly rebalancing; 10 bps transaction cost per rebalance.

## 3.4 Historical Backtest

- 126-day lookback
- Long-only
- Fully invested
- Includes transaction costs
- No leverage

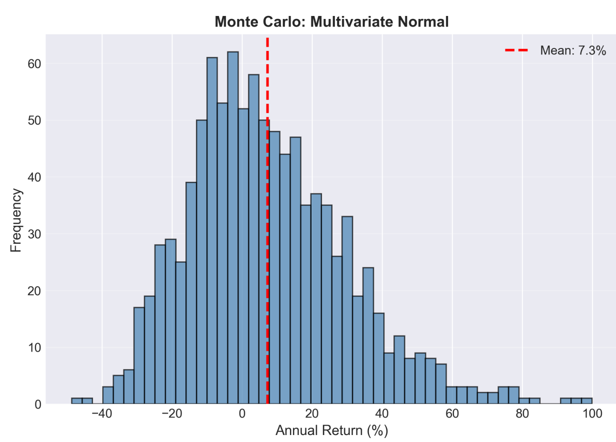


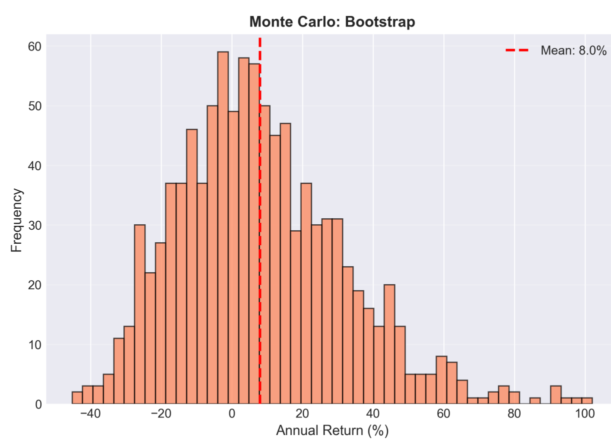

# 3.5 Monte Carlo Simulations

Two models:

1. **Multivariate normal draws** using historical covariance
2. **Bootstrap resampling** preserving return patterns

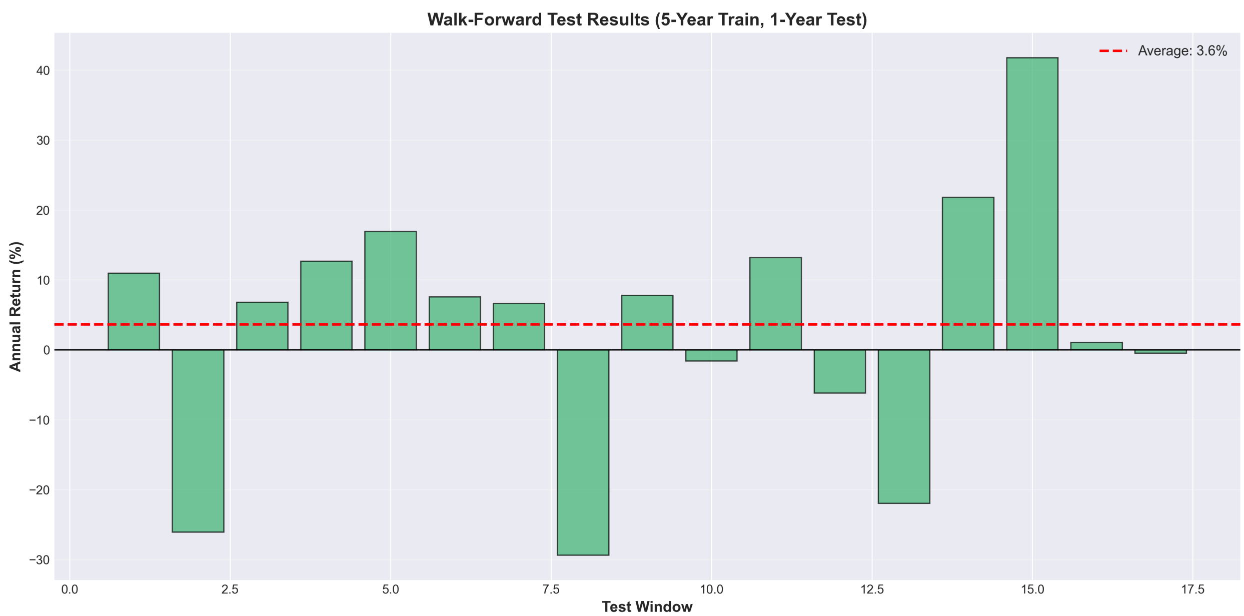
1,000 scenarios each.



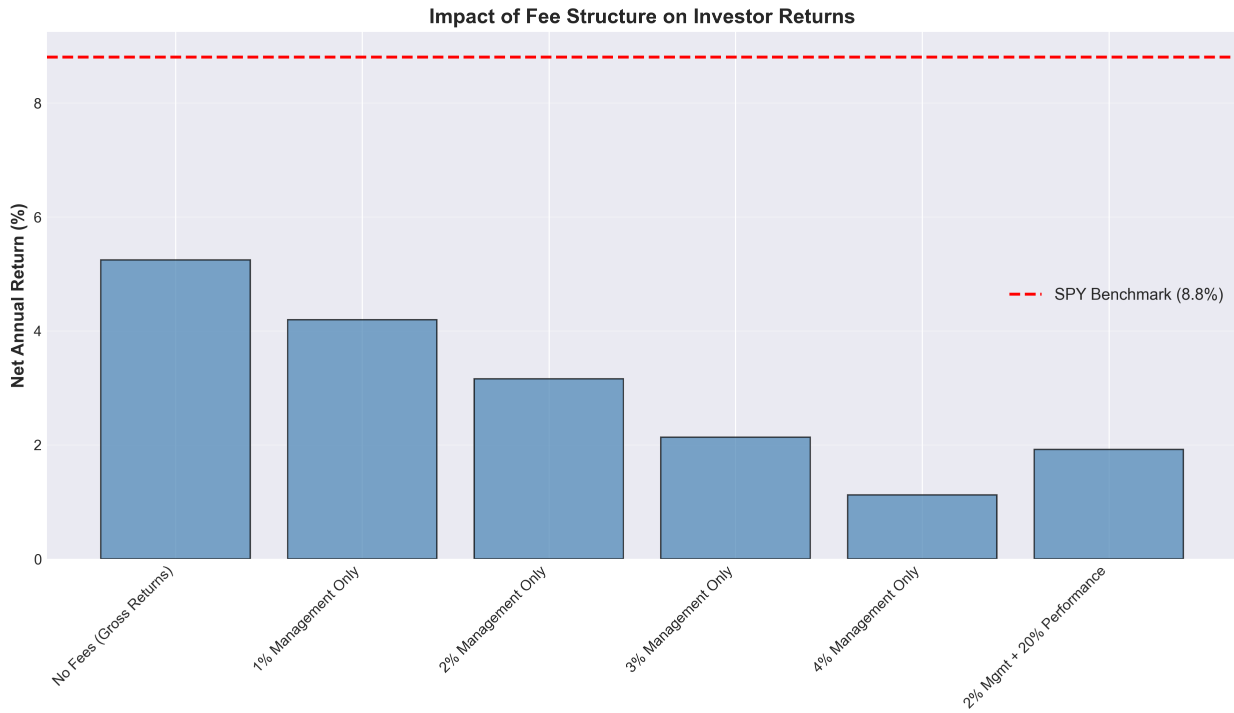
## 3.6 Walk-Forward Validation

- 17 windows
- Train: 5 years
- Test: 1 year
- Rolling window




## 3.7 Fee Structure Analysis

- Management fees: 0–4%
- Performance fees: 0–25%
- High-water mark accounting




# 4. Results

## 4.1 Full-Period Performance (2002–2024)

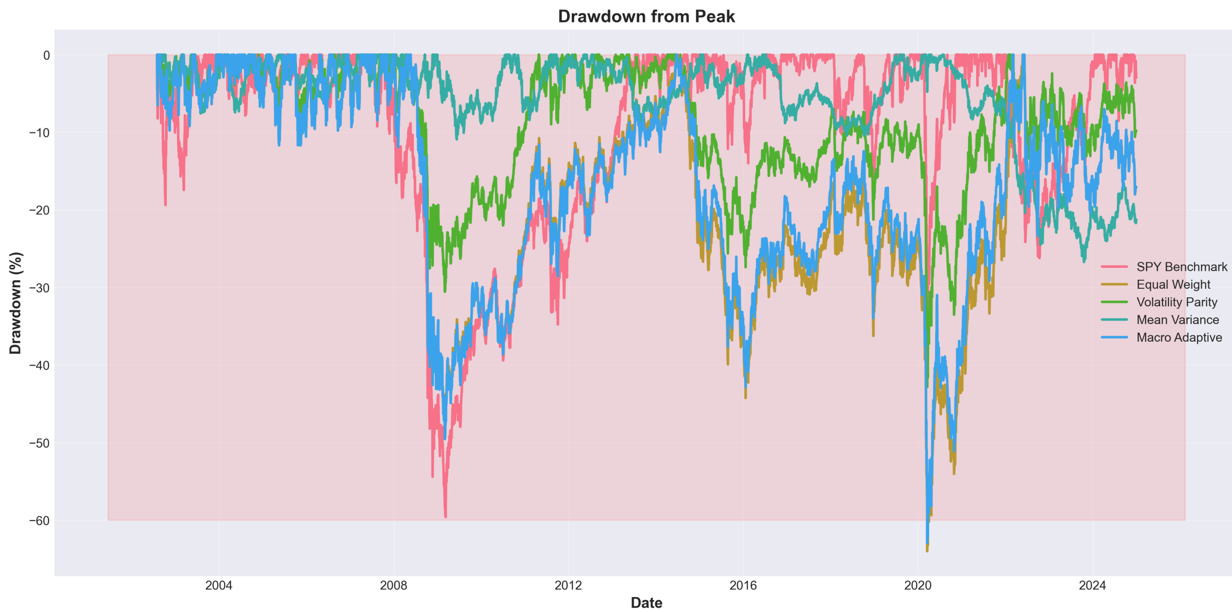
full_period_metrics

| | Total Return (%) | Annual Return (%) | Annual Volatility (%) | Sharpe Ratio | Sortino Ratio | Max Drawdown (%) | Calmar Ratio |
|---|---|---|---|---|---|---|---|
| **SPY_Benchmark** | 559.9112801723910 | 8.806366051451670 | 18.92449382812550( | 0.43586768851163700 | 0.4346230045930700 | -59.57597704092440 | 0.1478174003827470 |
| **Equal_Weight** | 156.49507833485500 | 4.303159696534850 | 20.99124065281650 | 0.2540332766582150 | 0.1406110234237710 | -63.980162020373500 | 0.06725771802773150 |
| **Volatility_Parity** | 164.3865157081790 | 4.444626924809960 | 13.52419594167060 | 0.308108033234217 | 0.23345224263528900 | -42.820775118284500 | 0.10379604088278400 |
| **Mean_Variance** | 69.02389025616940 | 2.375435292146520( | 6.894054996002250 | 0.21219776557219500 | 0.08235182784770930 | -26.71819499855930 | 0.08890702730010800 |
| **Macro_Adaptive** | 155.4978576734830 | 4.284987761637590 | 21.3765106269318 | 0.2524710245200920 | 0.13612803012401200 | -62.92817599367430 | 0.06809330945915750 |

**Key Findings:**

- SPY returns: **559.91% total**, **8.81% annualized**
- Best energy strategy: **Volatility Parity - 4.44% annualized**

- Macro-Adaptive and Equal-Weight: ~4.3% annualized
- Mean-Variance: lowest volatility, but only 2.38% annual return
- All energy strategies show deep drawdowns (-40% to -64%)




**Conclusion:** SPY strongly outperforms every energy strategy, both absolutely and risk-adjusted.

# 4.2 Alpha & Beta Analysis

alpha_beta_analysis

| | alpha_annual | beta | correlation | portfolio_volatility | benchmark_volatility | tracking_error |
|---|---|---|---|---|---|---|
| **Equal_Weight** | -0.3771441535222480 | 0.6921944134436200 | 0.6240426243371730 | 20.99124065281650 | 18.924493828125500 | 17.40599114853930 |
| **Volatility_Parity** | 0.48774612737526700 | 0.44603669304025300 | 0.6241419956471820 | 13.52419594167060 | 18.924493828125500 | 14.884768457567900 |
| **Mean_Variance** | 2.3995529080656500 | -0.11355292264483400 | -0.3117079258874350 | 6.894054996002250 | 18.924493828125500 | 22.068061671257900 |
| **Macro_Adaptive** | -0.42433749485010600 | 0.7057324161481230 | 0.624780582144066 | 21.3765106269318 | 18.924493828125500 | 17.595301798880900 |

Findings:

- Most strategies show **negative alpha relative to SPY**

- Beta values between **0.45 and 0.75** show partial market exposure
- Mean–Variance has **positive alpha** but weak absolute returns

## 4.3 Monte Carlo Results

**Key Takeaways:**

- Expected annual return: **7.46%**, but highly unstable
- 5th percentile return: **−24.97%**
- Suggests energy strategies are heavily regime-dependent
- Monte Carlo overestimates performance vs. real-world results

## 4.4 Walk-Forward Out-of-Sample

Findings:

- Average annual return: **0.09%**
- Worst window: −29.36%
- Best window: +16.92%
- Only **58.8%** of windows positive

**Interpretation:** Strategy is not robust and fails out-of-sample.

## 4.5 Fee Impact Analysis

Highlights:

- No-fee return: **5.25%**
- 2% + 20% fee return: **1.92%**
- Fee drag = **−3.33% annually**

**Investor takeaway:** Fees destroy already-weak returns.

fee_impact_analysis

| gross_total_return_pct | net_total_return_pct | gross_annual_return_pct | net_annual_return_pct | total_fee_drag_pct | annual_fee_drag_pct | manageme | performance |
|---|---|---|---|---|---|---|---|
| **213.66946907359600** | 213.66946907359600 | 5.24620054073075 | 5.24620054073075 | 0.0 | 0.0 | 0 | 0 |
| **213.66946907359600** | 150.83351338829000 | 5.24620054073075 | 4.199081544118170 | 62.83595568530610 | 1.0471189966125800 | 1 | 0 |
| **213.66946907359600** | 100.58341480811500 | 5.24620054073075 | 3.162339639928850 | 113.08605426548100 | 2.083860900801900 | 2 | 0 |
| **213.66946907359600** | 60.39861965089400 | 5.24620054073075 | 2.1358723954979100 | 153.27084942270200 | 3.1103281452328400 | 3 | 0 |
| **213.66946907359600** | 28.263290935619800 | 5.24620054073075 | 1.1195783852713700 | 185.40617813797600 | 4.126622155459380 | 4 | 0 |
| **213.66946907359600** | 52.95351270291740 | 5.24620054073075 | 1.9189769247210500 | 160.71595637067900 | 3.3272236160097 | 2 | 20 |
| **213.66946907359600** | 42.916422844658500 | 5.24620054073075 | 1.610030383139230 | 170.75304622893800 | 3.636170157591520 | 2 | 25 |

## 4.6 Business Viability

- SPY after fees: **8.78%**
- Energy fund after typical hedge fund fees: **1.92%**
- Investors lose **6.87% per year** relative to SPY

# 5. Conclusions

## 5.1 Summary of Findings

1. Energy strategies significantly underperform SPY over 22 years.
2. Best energy approach (Volatility Parity) only earns 4.44% vs SPY's 8.81%.
3. Macro signals fail to create reliable alpha.
4. Walk-forward results suggest strong overfitting.
5. Monte Carlo simulations highlight extreme downside risk.
6. Fees devastate investor returns.

## 5.2 Why the Fund Fails

- Extreme **sector concentration**

- Multiple energy crashes (2008, 2014–2016, 2020)
- Secular decline in oil demand growth
- Energy equities lag technology-heavy SPY
- Macro signals insufficient to overcome structural headwinds

## 5.3 Management Recommendation

**I do NOT recommend launching this fund.**

Reasons:

- Underperforms SPY by ~6% annually after fees
- Uncompetitive against low-cost index funds
- High downside risk leads to poor client retention
- Fund likely to fail commercially

**Would I invest?**
No, investing in SPY or diversified macro strategies is more attractive.

**Would I work for a similar fund?**
Yes, as a quantitative researcher, but only in a **broader multi-sector strategy**.

## 5.4 Lessons Learned

- Diversification is irreplaceable
- Fees destroy returns
- Backtests must include Monte Carlo + walk-forward
- Macro sensitivity does not guarantee outperformance
- Passive indexing is hard to beat long-term

## 5.5 Future Research

- Multi-sector macro rotation

- Use options overlays to reduce downside risk
- Machine learning-based regime classification
- Incorporate renewable energy assets
- Test lower-fee structures (0.25%–0.50%)

# Appendix

- Data sources: Yahoo Finance, FRED
- Code, data, figures: https://github.com/vrishanishah20/macro-linked-energy-etf

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