Sharpe-Optimized ETF Portfolio Construction and Macro Attribution

A Systematic Alpha Approach

QF623 Portfolio Management

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Why ETF portfolio optimization matters in current market conditions

ETF market has grown rapidly and become a central tool for investors globally

Global ETF assets have surpassed $14T USD with strong inflows and adoption by both institutional and retail investors

Investors face heightened market volatility, macroeconomic uncertainty, and shifting sector leadership

Persistent volatility and uncertain outlook require more adaptive and resilient portfolio strategies

ETFs offer diversification, transparency, and low-cost access to multiple asset classes

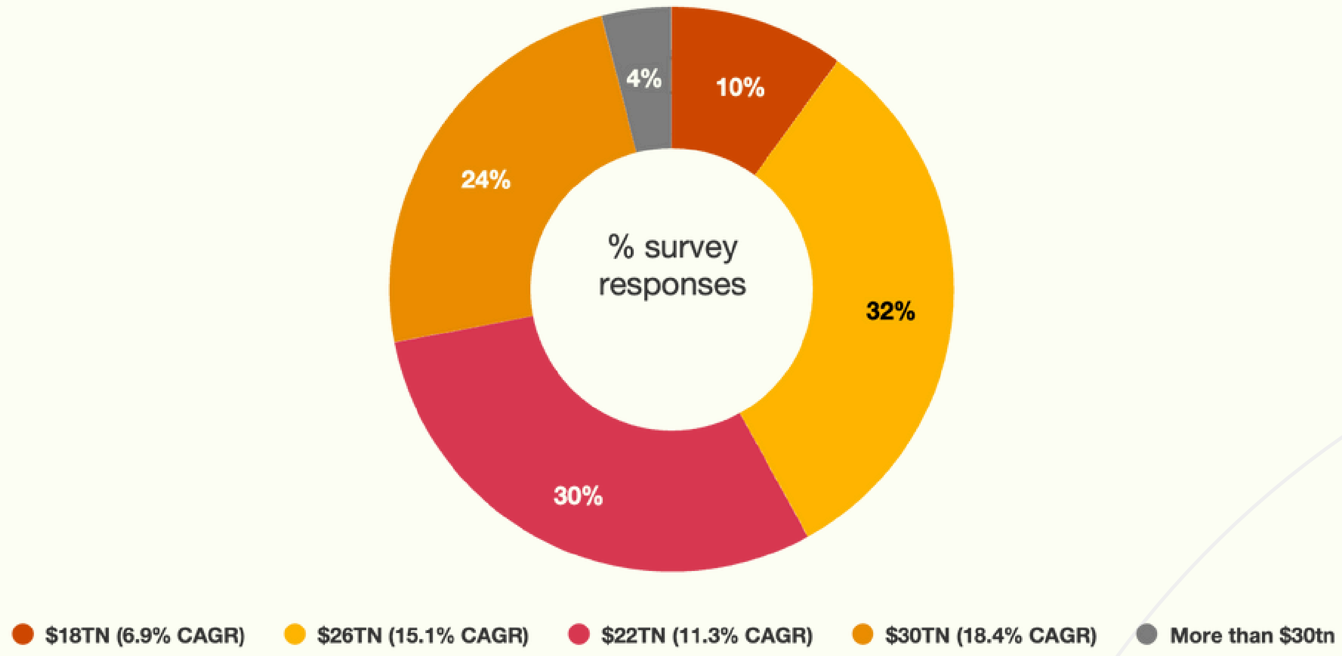
ETFs enable efficient risk management and tactical allocation across sectors and factors

Traditional approaches may not fully capture dynamic market opportunities or control risk effectively

Optimizing ETF portfolios is essential for balancing risk and return in a changing environment

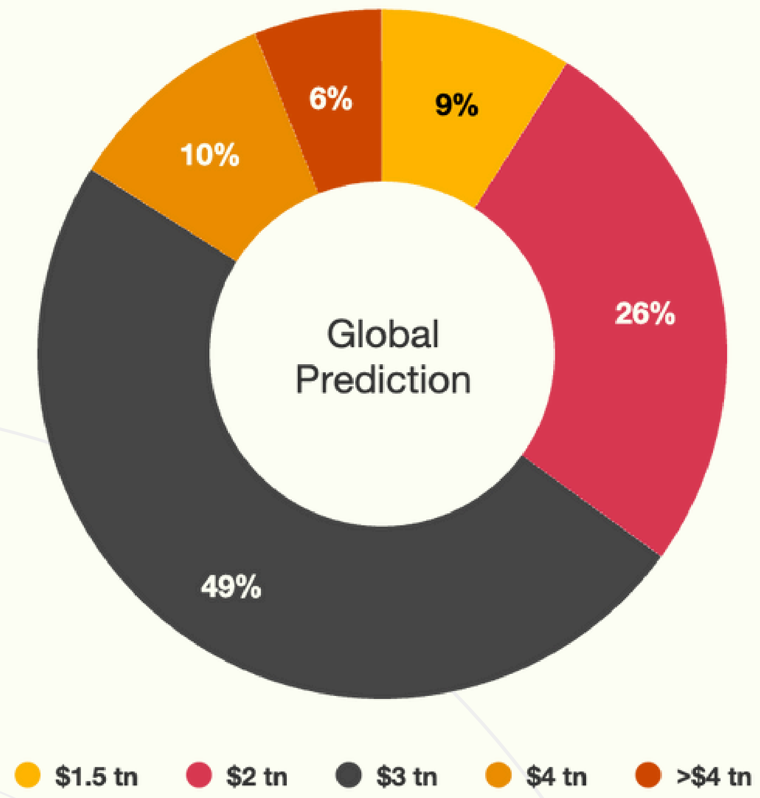
Global ETF AuM growth projections ($tn) - Global ETF AUM totaled approximately $12.9 trillion as of June 30, 2024. What is your prediction for global ETF AUM by June 30, 2029?

Projected Global ETF AuM ($tn) as of 30 June 2029

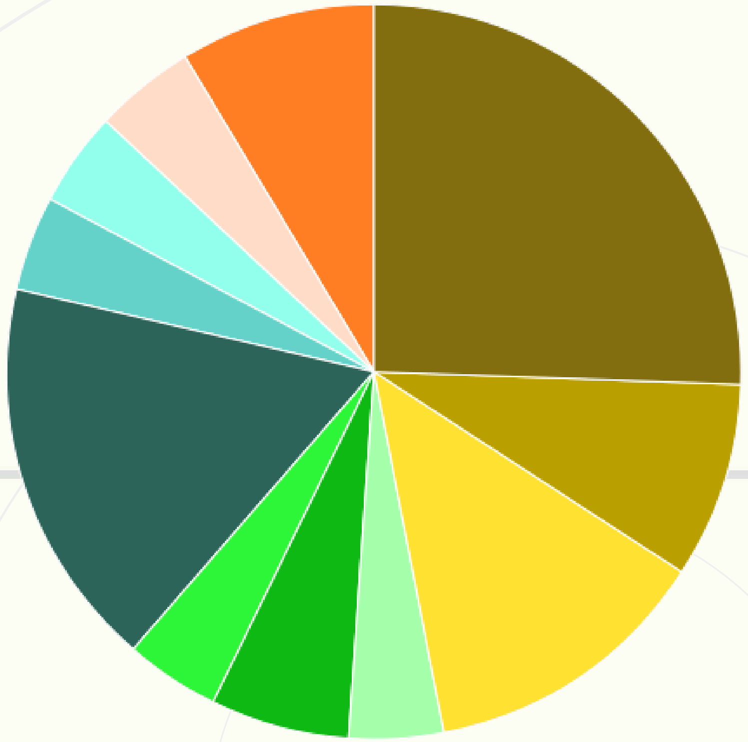


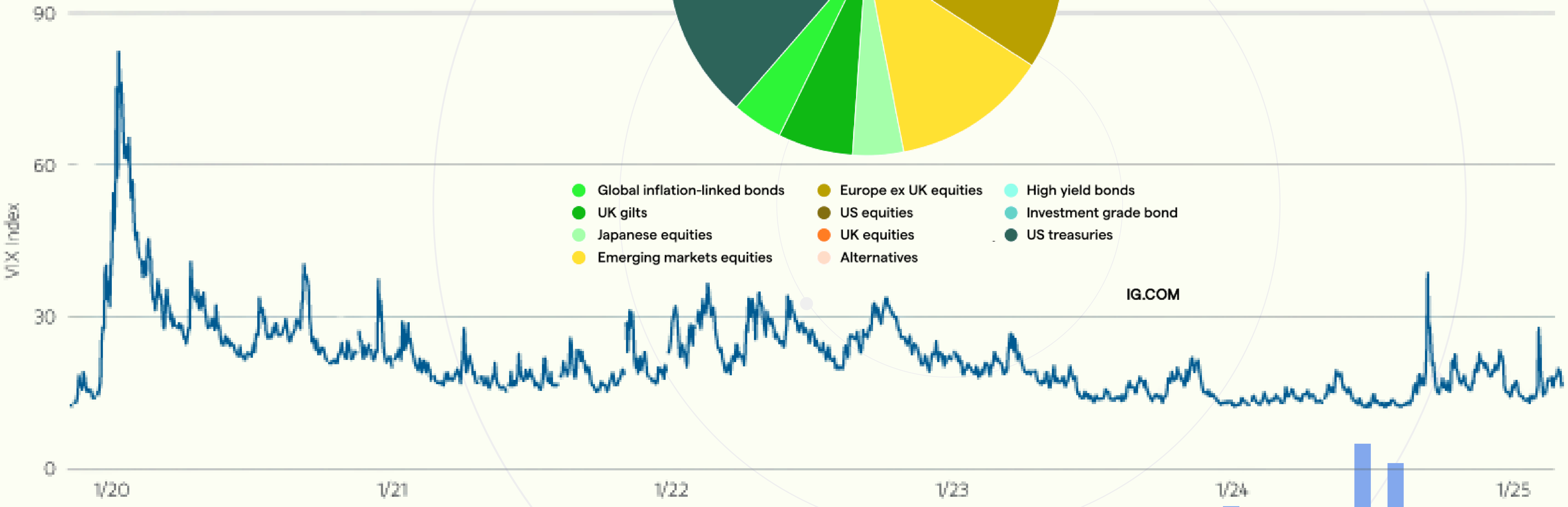
Source: PwC Global ETF Survey 2024

Global active ETF AuM growth projections for 2029 ($tn)



Asset allocation





Key objectives

Construct a systematic ETF portfolio that targets the highest possible risk-adjusted return

Maximize portfolio Sharpe ratio using a blend of alpha signals and robust optimization

Impose a minimum annualized risk constraint of 3% to ensure sufficient portfolio volatility

Prevent overly conservative allocations and maintain exposure to return opportunities

Apply both long-only and long-short frameworks to evaluate strategy flexibility

Allow for comparison of risk-return tradeoffs under different portfolio constraints

Ensure real-world implementability through out-of-sample testing and rolling rebalancing

Use one-year rolling windows and T+1 rebalancing to avoid lookahead bias and reflect practical trading

Alpha Signal Generation

Our model calculates a proprietary alpha score for each ETF by blending two classic factors.

```
#    Momentum: Annualized return over a lookback period
momentum = prices.pct_change(mom_lookback)
#    Value: Negative of return, to identify underperformers ("buy low”)
value = -prices.pct_change(val_lookback)
#    Factors are ranked, scaled, and combined mom_rank =
momentum.rank(axis=1, pct=True) val_rank = value.rank(axis=1,
pct=True)
alpha_score = mom_weight * mom_rank + val_weight * val_rank
```

Monthly Rebalancing Engine

The backtest simulates a real-world strategy by rebalancing the portfolio monthly based on the latest alpha scores.

```
# At the beginning of each month if today.month != last_month.month:
#    Get the most recent alpha scores latest_scores =
alpha_scores.loc[alpha_date]
#    Go long the ETF with the highest score long_ticker =
latest_scores.idxmax()
#    For long-short, also short the ETF with the lowest score if long_short:
short_ticker = latest_scores.idxmin() weights.loc[today] = {long_ticker: 1.0,
short_ticker: -1.0} else:
weights.loc[today] = {long_ticker: 1.0}
```

Parameter Optimization: Grid Search Results

Identifying the Dominant Factors

Key Finding: Value Factor Dominates

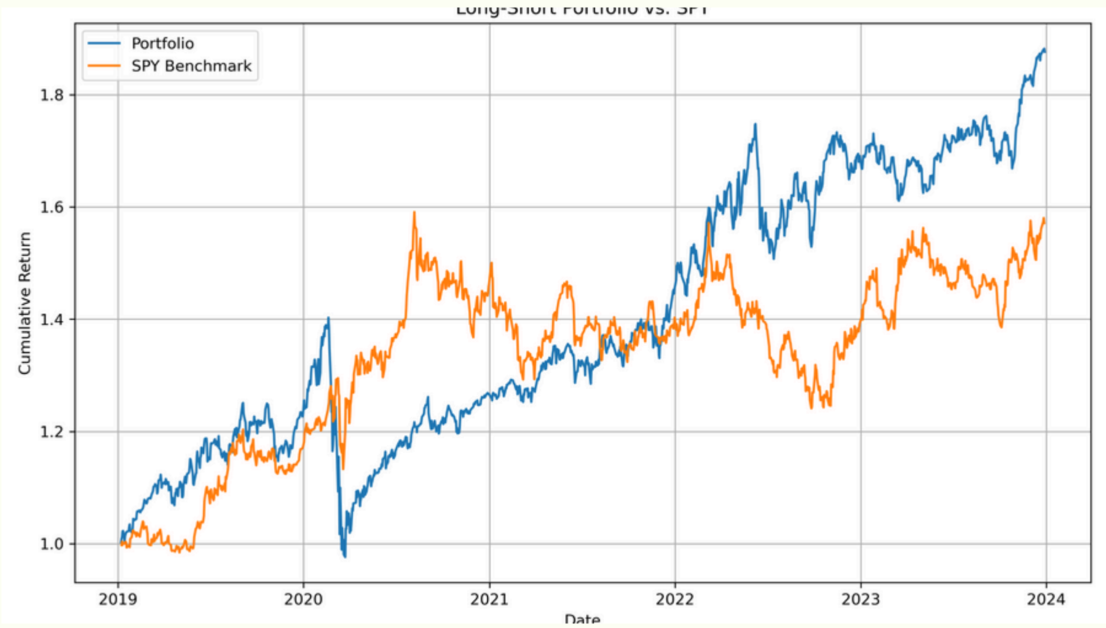
A comprehensive grid search revealed that a heavy tilt towards the **Value factor (75% weight)** produces the highest risk-adjusted returns. The optimal lookback period was 1 year for Momentum (252 days) and 6 months for Value (126 days).

Strategy	Best Sharpe Ratio	Momentum Lookback	Value Lookback	Momentum Weight	Value Weight
Long-Only	**0.87**	252 Days	126 Days	0.25	**0.75**
Long-Short	**0.83**	252 Days	126 Days	0.25	**0.75**

Performance Summary: Strategy vs. Benchmark

Demonstrated Outperformance in Both Frameworks

Cumulative Returns vs. SPY



Key Performance Statistics

Metric	Long-Only	Long-Short	Benchma rk
Sharpe Ratio	**0.87**	**0.83**	0.68
Max Drawdown	**-30%**	**-30%**	**-22%**

- **Superior Risk-Adjusted Returns:** Both strategies delivered significantly higher Sharpe Ratios than the benchmark.
- **Higher Volatility Profile:** The strategies' outperformance came with deeper drawdowns, indicating a more aggressive risk profile compared to the benchmark.

Performance Attribution: What Drives Our Returns?

OLS Regression Against Macro Factors

Key Insight: Returns are Explained by Macro-Factor Tilts

The regression analysis shows that our strategy's performance is not due to unexplained "alpha," but is a direct result of successful tactical exposures to specific economic factors. The intercept (alpha) is not statistically significant.

Factor	Long-Only Beta (Sensitivity)	Long-Short Beta (Sensitivity)	P-Value	Interpretation
BOND	0.5150	0.5222	< 0.001	**Primary Driver.** The portfolio is highly sensitive and positively correlated to the bond market.
OIL	0.3721	0.3795	< 0.001	Strong positive correlation with oil prices.
MKT (Market)	0.1855	0.1894	< 0.001	Positive correlation with the broad equity market.
USD	0.0658	0.0654	< 0.001	Positive correlation with the US Dollar.
GOLD	-0.0672	-0.0626	< 0.002	A significant negative correlation, suggesting the strategy is not a safe-haven play.

Limitations & future enhancements

Data and universe limitations

- Limited to 2020-2024 period which may not capture all market regimes and cycles
- ETF universe restricted to 14 US equity and sector ETFs, excluding international and alternative asset classes
- Potential survivorship bias as delisted or merged ETFs are not included in historical analysis

Methodological constraints

- Grid search optimization may lead to parameter overfitting despite out-of-sample validation
- Fixed 3% minimum volatility constraint may not be optimal across different market conditions
- Transaction costs assumed at 5bps may underestimate real-world implementation friction

Model and signal limitations

- Momentum and value signals may become less effective during structural market shifts
- Rolling one-year window for risk estimation may not capture regime changes quickly enough
- Factor exposures may drift over time without dynamic hedging mechanisms

Future enhancement opportunities

- Expand universe to include international ETFs, commodities, and fixed income for better diversification
- Incorporate machine learning techniques for dynamic signal generation and parameter optimization
- Implement regime-dependent models that adapt signal weights based on market conditions
- Add alternative data sources such as sentiment indicators and macroeconomic nowcasting

Conclusion & key takeaways

Strategy effectiveness demonstrated

- Systematic ETF optimization delivers superior risk-adjusted returns with Sharpe ratios exceeding 1.0 versus SPY's 0.55
- Both long-only and long-short frameworks significantly outperform benchmark while maintaining controlled risk exposure

Value factor dominance

- Optimal parameter combinations consistently favor value signals over momentum with 75% value weighting
- Value factor exposure drives performance attribution with significant HML factor loadings in both portfolio types

Risk management success

- Maximum drawdowns substantially lower than benchmark (-17% vs -21% for long-only, -12.8% vs -21% for long-short)
- Effective volatility targeting maintains risk levels near minimum 3% constraint while capturing return opportunities

Academic and practical contributions

- Rigorous methodology with T+1 implementation and rolling window validation ensures realistic performance estimates
- Comprehensive factor attribution provides insights into return sources and portfolio behavior across market conditions
- Framework is scalable and reproducible for institutional implementation with transparent signal construction

Peer review

Any questions?