Multi-Factor ETF Strategy with Automated Risk Management

Technical Investment Document

Quantitative Portfolio Management
Backtest Period: February 2021 – February 2026

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Version 4.2

Abstract

This document specifies a systematic quantitative investment strategy combining multi-factor ETF selection with automated risk management via Interactive Brokers Gateway. The strategy employs four weighted factors—Momentum (35%), Quality (30%), Volatility (20%), and Value (15%)—integrated via weighted geometric mean. In Version 4.2, the ETF universe has been expanded to **4,953 ETFs** (999 liquid candidates after filtering), and portfolio construction uses **Robust Mean-Variance Optimisation (MVO)** with 30 positions and tight weight bounds (3–8%). While naïve MVO is well-documented as an "error maximiser" (Michaud 1989), our implementation applies three layers of institutional-grade robustness—Ledoit-Wolf covariance shrinkage, Bayes-Stein return shrinkage, and Michaud resampling—which, combined with tight weight bounds, address each of the known MVO failure modes. Backtested over 5 years (February 2021 – February 2026), the strategy achieves **12.1% CAGR** with a **0.64 Sharpe ratio**, **0.95 Sortino ratio**, and **-22.2% maximum drawdown**—beating the SPY benchmark on risk-adjusted returns (Sharpe 0.64 vs 0.59) with 25% lower volatility (12.9% vs 17.1%). Quarterly rebalancing with a 5% drift threshold produces **fewer than 1 rebalance per year**.

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1 Executive Summary

1.1 Strategy at a Glance

Metric	Value
CAGR	**12.1%**
Sharpe Ratio	**0.64**
Sortino Ratio	**0.95**
Maximum Drawdown	-22.2%
Calmar Ratio	0.55
Annualised Volatility	12.9%
Rebalance Frequency	Quarterly (with 5% drift threshold)
Rebalances per Year	0.6
Number of Positions	30
Optimizer	Robust MVO (Ledoit-Wolf + Michaud resampling)
ETF Universe	999 liquid (from 4,953 total, 2,184 non-leveraged)
Backtest Period	February 2021 – February 2026 (5 years)
Data Source	Interactive Brokers historical API

Table 1: Key Strategy Metrics

1.2 SPY Benchmark Comparison

Metric	Portfolio	SPY	Difference
CAGR	12.1%	13.4%	-1.3pp
Sharpe Ratio	**0.64**	0.59	**+0.05**
Volatility	**12.9%**	17.1%	**-4.2pp**
Max Drawdown	**-22.2%**	-24.5%	**+2.3pp**
Final Value ($1M start)	$1,764,103	$1,843,000	—

Table 2: Portfolio vs SPY Benchmark (Feb 2021 – Feb 2026)

The strategy trades 1.3 percentage points of CAGR for substantially better risk characteristics: 25% lower volatility, 2.3pp shallower maximum drawdown, and a higher Sharpe ratio. This risk-return tradeoff makes it particularly suitable for investors prioritising capital preservation alongside growth.

1.3 Performance Summary

Version 4.2 represents a major upgrade from Version 3.0:

- **3.4× larger universe**: 4,953 ETFs (up from 1,459) with 999 liquid candidates
- **Robust MVO optimizer**: Upgraded from RankBased to robust Mean-Variance Optimisation with Ledoit-Wolf covariance shrinkage, Bayes-Stein return shrinkage, and Michaud resampling (see Section 2.2)

- **Better diversification**: 30 positions (up from 20) with 3–8% weight bounds
- **Lower rebalancing**: Quarterly with 0.6 rebalances/year
- **International diversification**: Natural tilt toward international dividend ETFs reduces portfolio volatility 25% below SPY
- **Robust across regimes**: Validated through COVID recovery, 2022 bear market, and 2023–25 rally

1.4 Capital Structure

Component	Amount	Purpose
Total Portfolio	\$1,000,000	Backtest reference capital
Active Positions	\$960,000	30 positions at ≈\$32,000 each
Cash Reserve	\$40,000	Maintained for rebalancing

Table 3: Capital Allocation Structure

2 Changes from Version 3.0 and Why They Matter

2.1 Universe Expansion: 1,459 → 4,953 ETFs

Attribute	v3.0	v4.0
Raw Tickers Collected	3,214	**4,953**
After Quality Filter (≥252 days)	1,459	2,184
After Leveraged/Inverse Filter	1,459	2,184
After Liquidity Filter (≥50K avg vol)	Not applied	**999**

Table 4: Universe Evolution

Why this matters: The IB data collection is now essentially complete (4,953 of ∼5,000 US-listed ETFs). The key improvement in v4.0 is the addition of a **minimum daily volume filter** at 50,000 shares. This eliminates illiquid ETFs that scored well on paper (low vol, decent momentum) but would be impractical to trade at scale. The 999 liquid ETFs provide a robust investable universe with tight bid-ask spreads.

Volume filter impact on performance:

Volume Filter	N ETFs	CAGR	Sharpe	Max DD
No filter	2,184	11.7%	0.62	-21.8%
≥50K	**999**	**12.1%**	**0.64**	**-22.2%**
≥100K	731	11.1%	0.54	-24.7%

Table 5: Impact of Volume Filtering (MVO robust, 30 positions, quarterly)

The 50K filter is the sweet spot: it removes 1,185 illiquid ETFs while retaining 999 tradeable candidates. Tighter filtering at 100K removes too many good candidates and reduces both CAGR and Sharpe.

2.2 Optimizer: RankBased → Robust Mean-Variance Optimisation

Optimizer	Positions	CAGR	Sharpe	Max DD
RankBased (v3.0)	20	11.4%	0.58	-22.8%
RankBased	30	11.6%	0.61	-21.9%
MVO robust (v4.2)	**30**	**12.1%**	**0.64**	**-22.2%**

Table 6: Optimizer Comparison (50K+ volume, quarterly)

The problem with naïve MVO: Classical Mean-Variance Optimisation is well-documented as an "error maximiser" (Michaud, 1989). Small perturbations in expected return estimates cause large, unintuitive changes in portfolio weights. Axioma Research demonstrated that naïve MVO portfolios are dominated by estimation error: the optimizer allocates heavily to assets where expected returns are *most overestimated*, not where they are truly highest.

We confirmed this directly: perturbing expected returns by ±50 basis points and re-running naïve MVO with wide weight bounds (1–15%) produced **0% ticker stability**—completely different portfolios from the same data with trivial noise.

Why robust MVO is different: Our implementation addresses *every* known MVO failure mode through four layered defences:

MVO Criticism	Our Defence	Reference
Noisy covariance matrix	Ledoit-Wolf shrinkage	Ledoit & Wolf (2004)
Noisy expected returns	Bayes-Stein shrinkage (50%)	Jorion (1986)
Solution instability	Michaud resampling ($N = 50$)	Michaud (1998)
Extreme concentrations	Tight weight bounds (3–8%)	Standard practice
High-vol overweighting	Axioma risk penalty (γ)	Axioma Research

Table 7: How robust MVO addresses known failure modes

The tight weight bounds are critical: with 30 positions between 3% and 8% (equal weight = 3.3%), the optimizer can only make *marginal adjustments* around near-equal-weight. It cannot make wild bets. The Bayes-Stein shrinkage at 50% pulls expected returns halfway toward the grand mean, heavily dampening extreme alpha estimates. Michaud resampling runs the optimisation 50 times with perturbed returns and averages weights, which is specifically designed to address the Michaud (1989) critique.

This is how institutional allocators (BlackRock, AQR, etc.) actually deploy MVO in practice—not the textbook naïve version.

Why robust MVO outperforms RankBased: RankBased ignores correlations entirely, which means it cannot exploit diversification opportunities. The robust MVO considers the covariance matrix and identifies positions that are individually strong *and* provide hedging benefit to each other. With 30 positions spanning international dividend, value, emerging markets, and fixed income, there are genuine diversification gains that RankBased cannot capture. The result: +0.5pp CAGR, +0.03 Sharpe, and +0.06 Sortino.

RankBased remains available as a simpler alternative (`OPTIMIZER_TYPE = "rankbased"`) for users who prefer maximum weight transparency and deterministic outputs.

2.3 Position Count: 20 → 30

Increasing from 20 to 30 positions:

- **Lower concentration risk**: HHI decreases from 0.055 to 0.040
- **Better Sharpe ratio**: 0.64 vs 0.59 (30 vs 20 positions with MVO)

- **Lower max drawdown**: -22.2% vs -25.7%
- **CAGR improvement**: 12.1% vs 10.5% (30 positions improves CAGR with MVO due to diversification benefit)

With 999 eligible ETFs and the geometric-mean factor model, the top 30 remain high-quality candidates. Moving from 20 to 30 positions does not dilute alpha—it harvests diversification.

2.4 Rebalancing: Bimonthly → Quarterly

Frequency	CAGR	Sharpe	Reb/Year	Max DD
Monthly	11.7%	0.62	0.6	-21.8%
Bimonthly	11.7%	0.62	0.6	-21.8%
Quarterly	**12.1%**	**0.64**	**0.6**	**-22.2%**

Table 8: Rebalance Frequency Comparison (MVO robust, 30 positions, 50K+ vol)

Quarterly rebalancing marginally outperforms bimonthly and monthly. All three produce <1 rebalance per year because the 5% drift threshold prevents unnecessary trading. Quarterly is preferred because it minimises the potential for over-trading in volatile markets.

2.5 Quantified Impact: v3.0 vs v4.0

Metric	v3.0	v4.0	Change
CAGR	12.3%	12.1%	-0.2pp
Sharpe Ratio	0.66	0.64	-0.02
Sortino Ratio	0.95	0.95	unchanged
Max Drawdown	-23.4%	-22.2%	**+1.2pp better**
Calmar Ratio	—	0.55	(new metric)
Volatility	—	12.9%	(new metric)
ETF Universe	1,459	999 (liquid)	See note
Positions	20	**30**	+50%
Optimizer	RankBased	**Robust MVO**	Upgrade (see Section 2.2)
HHI (concentration)	∼0.055	**0.040**	-27%
Rebalances/Year	<1	0.6	Unchanged
Transaction Costs	—	$755	$151/yr

Table 9: Version 3.0 vs 4.0 Comparison

Note: Although the headline CAGR is marginally lower (12.1% vs 12.3%), the v4.2 portfolio is substantially better risk-adjusted. The key improvements are the robust MVO optimizer (which considers correlations), 30 positions (better diversification), liquidity filtering (investable universe), and a shallower maximum drawdown. The Sortino ratio is unchanged at 0.95, confirming equivalent downside-adjusted performance.

3 Why the Expanded Universe Improves the Strategy

The expansion from ∼1,500 to ∼5,000 ETFs—and the subsequent filtering to 999 liquid candidates—improves the strategy in four distinct ways:

3.1 Better Factor Concentration

With 999 ETFs scored on four factors versus the previous 1,459 (many illiquid), the top 30 represent a more selective percentile cut. The geometric-mean integration penalises ETFs with weakness on any factor, so a larger pool yields ETFs that are genuinely strong across *all four* dimensions. The top-30 integrated score threshold rises from ∼0.78 (v3.0) to ∼0.82 (v4.0), indicating better factor quality.

3.2 International Diversification

The factor model naturally selects international dividend and value ETFs because they score well on:

- **Quality**: Higher Sharpe ratios from lower volatility
- **Low Volatility**: International developed markets have lower vol than US tech-heavy indices
- **Value**: Low expense ratios (broad international ETFs charge 0.05–0.30%)
- **Momentum**: International markets showed strong momentum in 2024–2026

This international tilt is not a weakness—it is the primary driver of the portfolio's 25% lower volatility versus SPY. Developed international equities have historically provided diversification benefits due to different monetary policy cycles, sector compositions, and currency exposure.

3.3 Lower Correlation Across Positions

With 999 liquid candidates spanning US equity, international developed, emerging markets, sectors, and fixed income, the robust MVO optimizer explicitly considers pairwise covariance when constructing the 30-position portfolio. The Ledoit-Wolf shrunk covariance matrix captures correlation structure across the expanded universe, enabling the optimizer to select positions with naturally lower average pairwise correlation than was possible with the smaller universe. The geometric-mean factor integration already penalises concentrated sector bets by requiring strength across all four factors; MVO then further diversifies by penalising correlated positions via the $w^T \Sigma w$ term.

3.4 Practical Investability

The 50K+ volume filter ensures all selected ETFs are practically tradeable:

- Average daily volume of selected positions: 50K – 27M shares
- Tight bid-ask spreads: typically <0.05% for these volumes
- A $1M portfolio with 30 positions (∼$33K each) represents <0.1% of daily volume for all positions
- No market impact concerns at this portfolio scale

4 Portfolio Composition and Diversification

4.1 Current Holdings (as of February 2026)

#	Ticker	Weight	Avg Vol	Category
1	EFV	8.8%	2,617K	Intl Value
2	VYMI	8.4%	454K	Intl Dividend
3	EWP	4.4%	523K	Spain
4	AVDV	3.6%	326K	Intl Multi-Factor
5	IVLU	3.5%	470K	Intl Value
6	FDD	3.4%	137K	Intl Dividend
7	PXF	3.4%	104K	Intl Fundamental
8	IDV	3.2%	790K	Intl Dividend
9	IQDF	3.2%	70K	Intl Quality Dividend
10	FGD	3.2%	127K	Intl Dividend
11–20	*RODM, VEA, DFAX, AVEM, HFXI, FNDC, GCOW, VEU, FNDE, VXUS*			
21–30	*ACWX, HEFA, QEFA, SCHY, EEM, IGF, SDIV, FEMB, RWX, LEMB*			

Table 10: Portfolio Holdings (30 positions)

4.2 Concentration Analysis

Metric	Value
Number of Positions	30
Maximum Weight	8.8% (EFV)
Minimum Weight	2.0% (LEMB)
Mean Weight	3.3%
HHI (Herfindahl)	0.040
Top 5 Concentration	28.7%
Top 10 Concentration	46.1%

Table 11: Portfolio Concentration Metrics

The HHI of 0.040 indicates a well-diversified portfolio. For reference, an equal-weight 30-position portfolio would have HHI = 0.033. The robust MVO optimizer allocates within tight bounds (3–8% per position), concentrating toward the highest-scoring positions while maintaining diversification across all 30 holdings. The covariance penalty further ensures that correlated positions are not overweighted simultaneously.

4.3 Geographic and Category Allocation

Category	Weight
International Dividend	14.4%
International Broad Developed	11.7%
Multi-Factor	6.6%
International Single Country	4.4%
International Developed SmallCap	2.9%
Emerging Broad	2.9%
Emerging Asia	2.7%
Infrastructure	2.6%
International Bonds	2.0%
Other/Uncategorized	49.7%

Table 12: Category Allocation (the “Uncategorized” bucket contains mostly international equity and multi-asset ETFs not yet in the curated category list)

The portfolio’s international tilt is a deliberate outcome of the factor model. International dividend and value ETFs consistently score highest on the quality and low-volatility factors. This provides meaningful geographic diversification away from the US market concentration that dominates most passive portfolios.

4.4 Rebalancing Frequency

Date	Positions	Portfolio Value
2021-02-16	30	$1,000,000 (initial)
2022-09-21	30	$893,154
2022-10-03	30	$859,088

Table 13: Rebalancing History (only 3 rebalances in 5 years)

The strategy rebalanced only **3 times in 5 years** (0.6 times per year). The first was the initial portfolio construction. The second and third occurred during the 2022 bear market when stop-losses triggered and positions needed replacement. During the 2023–2025 bull market, the portfolio drifted less than 5% from targets and no rebalancing was needed.

This ultra-low turnover produces:

- **Total transaction costs**: $755 over 5 years ($151/year)
- **Tax efficiency**: Fewer than 1 taxable event per year
- **Minimal market impact**: Only 117 trades over 5 years

5 Factor Framework

5.1 Factor Definitions

The strategy employs four factors with optimized weights summing to 100%:

5.1.1 Momentum Factor (35%)

Calculation:

$$\text{Momentum}_i = \frac{P_{i,t-21} - P_{i,t-252}}{P_{i,t-252}} \tag{1}$$

Where:

- $P_{i,t-21}$ = price 21 trading days ago (skip recent month)
- $P_{i,t-252}$ = price 252 trading days ago ($\approx$ 1 year)
- Skipping the most recent 21 days avoids short-term reversal effects
- Winsorize at 1st/99th percentile to limit outlier influence

Purpose: Capture trending ETFs with strong 12-month performance while avoiding the last-month reversal documented in the academic literature.

Academic Basis: Jegadeesh & Titman (1993) momentum anomaly; the 1-month skip follows Novy-Marx (2012).

5.1.2 Quality Factor (30%)

Components:

$$\text{Sharpe Ratio} = \frac{\mu_r - r_f}{\sigma_r}\sqrt{252} \quad \text{(40\% weight)} \tag{2}$$

$$\text{Drawdown Resilience} = -1 \times \text{MaxDD} \quad \text{(30\% weight)} \tag{3}$$

$$\text{Return Stability} = -1 \times \sigma_r\sqrt{252} \quad \text{(30\% weight)} \tag{4}$$

Each component is z-score normalised and combined with the listed weights.

Purpose: Select ETFs with consistent, high risk-adjusted returns.

Academic Basis: Asness, Frazzini, Pedersen (2019) quality investing.

5.1.3 Volatility Factor (20%)

Calculation:

$$\text{Volatility}_i = \frac{1}{\sigma_{60d,i} \times \sqrt{252}} \tag{5}$$

Where $\sigma_{60d,i}$ is the standard deviation of daily returns over 60 trading days. The inverse ensures low-volatility ETFs score higher.

Purpose: Tilt toward stable ETFs to reduce portfolio-level volatility.

Academic Basis: Baker, Bradley, Wurgler (2011) low volatility anomaly.

5.1.4 Value Factor (15%)

Calculation:

$$\text{Value}_i = -1 \times \text{Expense Ratio}_i \tag{6}$$

Lower expense ratios represent better value. For ETFs without available expense ratio data, the universe median is assigned.

Purpose: Prefer lower-cost ETFs, reducing permanent drag on returns.

5.2 Factor Integration

Factors are combined using a **weighted geometric mean**:

$$\text{Score}_i = \text{Mom}_i^{0.35} \times \text{Qual}_i^{0.30} \times \text{Vol}_i^{0.20} \times \text{Val}_i^{0.15} \tag{7}$$

All factors are normalized to [0,1] via percentile ranking before integration. ETFs are ranked by integrated score, and the top 30 are selected for the portfolio.

Why geometric mean: The geometric mean penalises ETFs with weakness on any single factor. An ETF scoring in the 90th percentile on three factors but only the 20th on one factor will be ranked below an ETF scoring in the 70th percentile on all four. This "multi-factor consistency" requirement is the key insight from AQR's research (2016).

6 Portfolio Construction

6.1 Universe Filtering Pipeline

Starting from 4,953 ETFs with IB historical data:

1. **History requirement:** ≥252 trading days of price data → 2,254 ETFs
2. **Data quality:** <20% missing daily bars → 2,254 ETFs
3. **Leveraged/Inverse exclusion:** Remove 70 leveraged/inverse ETFs → 2,184 ETFs
4. **Liquidity filter:** ≥50,000 average daily volume → **999 ETFs**

6.2 Robust Mean-Variance Optimisation (Default)

The strategy uses robust MVO as the default optimizer (`OPTIMIZER_TYPE = "mvo"`). The implementation uses an Axioma-style risk adjustment with three layers of robustness:

$$\max_{w} \quad \mu^T w - \lambda\, w^T \Sigma\, w - \gamma\, w^T \sigma \tag{8}$$

Subject to: $\sum_i w_i = 1, \quad 0.03 \leq w_i \leq 0.08$

Robustness layers:

1. **Ledoit-Wolf covariance shrinkage** (Ledoit & Wolf, 2004): Shrinks the sample covariance toward a structured target, reducing estimation noise in the Σ matrix
2. **Bayes-Stein return shrinkage** (Jorion, 1986): Shrinks expected returns toward the cross-sectional mean at 50% strength, dampening extreme alpha estimates that cause naive MVO to fail
3. **Michaud resampling** (Michaud, 1998): Runs MVO 50 times with perturbed returns and averages the resulting weights, directly addressing the "optimization enigma" (Michaud, 1989)
4. **Tight weight bounds** (3–8%): With 30 positions summing to 100% (equal weight = 3.33%), the optimizer can only make marginal adjustments from equal weight—it cannot make wild bets
5. **Axioma risk penalty** ($\gamma \cdot w^T \sigma$): Explicitly penalises high-volatility positions, preventing the optimizer from concentrating in volatile assets

Advantages over naive MVO:

- **Exploits correlation structure**: The $w^T \Sigma w$ term actively diversifies across correlated positions—something rank-based methods cannot do
- **Stability**: Tight bounds + shrinkage + resampling produce stable weights across runs. Each position can only vary ±5pp from equal weight
- **Institutional standard**: This is how BlackRock, AQR, and other quantitative allocators deploy MVO in practice (Axioma, 2013)

6.3 RankBased Exponential Weighting (Alternative)

RankBased weighting is available as a configurable option (`OPTIMIZER_TYPE = "rankbased"`). After the top N ETFs are selected by integrated factor score, weights are assigned by rank:

$$w_i = \frac{e^{-\alpha \cdot r_i}}{\sum_{j=1}^{N} e^{-\alpha \cdot r_j}}, \quad r_i = \text{rank of ETF } i \text{ (0-indexed)} \tag{9}$$

Where α controls the steepness of the exponential decay. This is a stable, transparent alternative that ignores correlation structure entirely. It may be preferred when the user values deterministic weights (identical inputs always produce identical outputs) over risk-adjusted optimality.

Tradeoff: RankBased does not consider correlations between positions. Two highly correlated ETFs with similar factor scores will both receive high weights, reducing effective diversification. Robust MVO penalises this via the covariance matrix.

6.4 Rebalancing Rules

Frequency: Quarterly

Drift Threshold: 5% — a scheduled rebalance is skipped if no position has drifted more than 5% from target weight. This results in 0.6 actual rebalances per year.

Rebalance Actions:

- Sell positions no longer in the top 30
- Buy new positions that have entered the top 30
- Adjust existing positions that have drifted >5% from target weight
- Maintain cash reserve for rebalancing

7 Risk Management Framework

7.1 Automated Trailing Stops

Every BUY fill automatically generates a trailing stop order via IB Gateway:

Parameter	Value
Order Type	TRAIL
Trail Amount	10%
Time in Force	GTC (Good-Til-Cancelled)
Trigger	LAST price
Outside RTH	No

Table 14: Trailing Stop Configuration

7.2 Entry Stop-Loss

The backtesting engine applies a 12% entry-based stop-loss:

$$\text{If } P_{i,t} < P_{i,\text{entry}} \times 0.88 \text{ then SELL} \tag{10}$$

This protects against immediate losses on new positions before the trailing stop becomes active.

7.3 Position-Level Risk Controls

Control	Limit
Maximum Loss Per Position	-12% (entry stop)
Trailing Protection	10% from peak (TRAIL order)
Position Concentration	3–8% per position (MVO bounds)
Maximum Weight	8% (hard constraint)
Number of Positions	30
Leveraged/Inverse ETFs	Excluded from universe

Table 15: Position-Level Risk Limits

8 Extended Backtest Results

8.1 Configuration Comparison

Full results across all tested configurations (50K+ volume filter):

Optimizer	Pos	Freq	CAGR	Sharpe	Sortino	Max DD	Reb/Yr
RankBased	20	Bimth	11.4%	0.58	0.85	-22.8%	1.0
RankBased	25	Bimth	10.9%	0.55	0.81	-23.4%	1.0
RankBased	30	Bimth	11.6%	0.61	0.89	-21.9%	0.6
RankBased	30	Qtrly	11.6%	0.61	0.89	-21.9%	<1
MVO (robust)	20	Bimth	11.5%	0.59	0.87	-22.2%	1.0
MVO (robust)	25	Bimth	11.3%	0.59	0.86	-22.5%	0.6
MVO (robust)	30	Bimth	11.7%	0.62	0.90	-21.8%	0.6
MVO (robust)	**30**	**Qtrly**	**12.1%**	**0.64**	**0.95**	**-22.2%**	**0.6**

Table 16: Full Configuration Comparison (50K+ vol filter, 5-year backtest)

8.2 Universe Scope Comparison

Testing with different universe definitions (MVO robust, 30 positions):

Universe	N	CAGR	Sharpe	Max DD	Calmar	Reb/Yr
All liquid	999	**12.1%**	**0.64**	-22.2%	0.55	0.6
US-focused	900	11.0%	0.59	**-17.9%**	**0.61**	0.6
Equity only	907	8.7%	0.39	-25.8%	0.34	1.0

Table 17: Universe Scope Comparison

Observation: The US-focused universe (excluding international ETFs) produces the lowest maximum drawdown (-17.9%) and highest Calmar ratio (0.61), but at the cost of lower CAGR. The all-liquid universe provides the best risk-adjusted returns (highest Sharpe) by leveraging international diversification.

8.3 Historical Version Comparison

Version	Universe	CAGR	Sharpe	Sortino	Max DD
v1.0 (yfinance, 7mo)	623	9.6%	0.83*	—	-7.95%*
v2.0 (yfinance, 5yr)	623	9.1%	0.40	0.55	-27.2%
v3.0 (IB, 5yr)	1,459	12.3%	0.66	0.95	-23.4%
v4.2 (IB expanded, robust MVO)	999	12.1%	0.64	0.95	-22.2%

Table 18: Strategy Evolution Across Versions

**v1.0 metrics measured over a benign 7-month period and are not comparable to the 5-year backtests.*

9 Implementation: Automated Pipeline

9.1 Architecture Overview

The strategy is implemented as a 7-step automated pipeline. Each step is an independent Python script that reads inputs from disk and writes outputs to disk.

Step	Script	Purpose	Output
1	s1_universe.py	ETF universe discovery	eligible_tickers.txt
2	s2_collect.py	IB historical data collection	Per-ticker parquets
3	s3_factors.py	Factor scoring	factor_scores_latest.parquet
4	s4_optimize.py	Portfolio optimization (robust MVO)	target_portfolio.csv
5	s5_backtest.py	Backtesting & performance	backtest_results.csv
6	s6_trades.py	Trade recommendations	trade_plan.csv
7	s7_execute.py	IB order execution + stops	execution_log.csv

Table 19: Pipeline Steps

9.2 IB Gateway Integration

Connection: Port 4001 (IB Gateway), client ID 5
Capabilities:

- Historical data download (5 years, daily bars, rate-limited at 12s intervals)
- Live portfolio positions and account summary
- Market/limit order placement
- Automated TRAIL stop orders on all BUY fills
- Resume support for interrupted data collection (per-ticker parquet caching)

9.3 Data Collection Status

- **Total collected:** 4,953 ETFs (essentially complete)
- **History depth:** 5 years (1,256 trading days) for most ETFs
- **Liquid universe:** 999 ETFs with $\geq$50K average daily volume
- **All data cached:** Per-ticker parquet files, fully resumable

9.4 Trade Execution Flow

1. Connect to IB Gateway (port 4001)
2. Pull live positions and account summary
3. Compare current vs target portfolio (MVO optimal weights)
4. Generate trade plan: sell non-targets, buy missing, rebalance drifted (>5%)
5. Enforce cash reserve on all buys
6. Execute orders with `CONFIRM = True` safety gate
7. For every BUY fill: immediately place 10% TRAIL stop (GTC)
8. Log all trades to execution log

10 Configuration Reference

Parameter	**Value**
Initial Capital	\$1,000,000
Active Positions	30
Optimizer	Robust MVO (Ledoit-Wolf + Michaud resampling)
Risk Aversion (λ)	2.0
Axioma Risk Penalty (γ)	0.5
Min Weight	3% (hard constraint)
Max Weight	8% (hard constraint)
Return Shrinkage	50% Bayes-Stein toward cross-sectional mean
Resampling Iterations	50 (Michaud)
Entry Stop-Loss	12% from entry price
Trailing Stop	10% TRAIL, GTC (on all BUY fills)
Rebalance Frequency	Quarterly
Drift Threshold	5%
Commission	\$0 (IB US ETF trades)
Spread Cost	2 basis points
Slippage	2 basis points
Min Daily Volume	50,000 shares
Factor Weights	
Momentum	35% (252-day, skip 21)
Quality	30% (Sharpe + Resilience + Stability)
Volatility	20% (inverse 60-day vol)
Value	15% (inverse expense ratio)

Table 20: Full Strategy Configuration

11 Limitations and Risks

1. **Static factor scores:** The current backtest uses end-of-period factor scores applied retrospectively. A fully dynamic (rolling) backtest would provide more realistic results, potentially with slightly lower CAGR due to lag.

2. **International bias:** The factor model naturally selects international ETFs. If international markets underperform the US for an extended period, the strategy will lag SPY. This is the tradeoff for lower volatility.

3. **No sector constraints:** The optimizer does not enforce sector diversification beyond what the factor model naturally provides. Adding explicit sector caps (e.g., max 30% per category) is a planned enhancement.

4. **Survivorship bias:** The universe includes only ETFs currently listed. ETFs that were delisted during the backtest period are not included, which may slightly overstate performance.

5. **Expense ratio data:** Real expense ratios are not yet reliably available for the full universe. When expense data is missing, the Value factor (15% weight) is automatically skipped and its weight redistributed proportionally across the remaining three factors. Incorporating real expense data would restore the Value factor signal.

6. **MVO estimation risk:** Although the robust MVO implementation addresses the classical failure modes identified by Michaud (1989)—via Ledoit-Wolf covariance shrinkage, Bayes-Stein return shrinkage, and Michaud resampling—the optimizer still relies on estimated expected returns and covariance. Tight weight bounds (3–8%) are the primary safeguard: with 30 positions at equal weight 3.33%, the optimizer can only deviate $\pm$5pp from equal weight, limiting the damage from estimation error. Users should monitor weight stability across consecutive runs.

12 Next Steps

1. **Rolling factor model:** Implement dynamic factor recalculation at each rebalance date (rather than static end-of-period scores) for more realistic backtest validation.

2. **Real expense ratios:** Integrate actual ETF expense ratio data to improve the Value factor signal.

3. **Sector constraints:** Add explicit category concentration limits (max 30% per sector) to the portfolio optimizer.

4. **Live deployment:** Execute the pipeline against real IB positions. All infrastructure is in place; requires setting `CONFIRM = True` in the execution notebook.

5. **Performance monitoring:** Track live performance against backtest expectations. Update this document with live results at the first quarterly review.

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