Swiss Equity Portfolio Strategy

1 High-Level Strategy Overview

To build a robust and investable portfolio for the Swiss equity market, we apply a set of carefully designed selection filters based on financial quality, market behavior, and liquidity. Our investment philosophy is grounded in three pillars:

1. **Quality & Momentum tilts:** Academic evidence shows that profitability, earnings quality, and price momentum command positive premia worldwide. We tilt the portfolio towards high-quality and high-momentum stocks by filtering the universe with the `jkp_data` factor scores (`qmj`, `ret_12_1`, `resff3_6_1`).
2. **Machine-Learning alpha-signal:** We train an XGBoost learning-to-rank model that predicts the cross-sectional ordering of next-month returns using the rich firm-level features in `jkp_data`. The model produces a *score* for every stock-date, which is fed into the optimizer as Black–Litterman views.
3. **Risk-aware portfolio construction:** A Black–Litterman (BL) optimizer with a full empirical covariance matrix balances expected return against risk while respecting diversification and turnover constraints.

2 Data & Pre-Processing

- **Market data:** Daily OHLCV and corporate-actions for SPI constituents (`market_data.parquet`).
- **Fundamental factors:** Monthly firm-level characteristics from Jensen, Kelly & Pedersen (`jkp_data.parquet`).
- **Benchmark:** Swiss Performance Index total-return series (`spi_index.csv`).

All datasets are mapped to a common security identifier (`id`) and aligned on a monthly grid. For each `jkp_data` date t, we forward-shift to the next available trading day in `market_data` to avoid look-ahead bias. Missing values are forward-filled for ≤ 1 month; securities with longer gaps are excluded.

3 Detailed Strategy and Backtesting Framework

We establish a quantitative investment strategy combining traditional factor investing with machine learning. The framework is structured around security selection filters and portfolio optimization components. The selection process begins with three key factors from the JKP dataset: quality-minus-junk (`qmj`), 12-1 month momentum (`ret_12_1`), and residual momentum from a Fama-French 3-factor model (`resff3_6_1`). These factors serve as inputs for both security screening and expected return generation.

3.1 Selection Pipeline

The following filters are configured:

- A liquidity filter that excludes stocks with insufficient trading volume (median daily volume below 100,000).
- A data quality check that excludes securities with excessive missing data points.
- A trading continuity filter that removes stocks with significant trading gaps.
- A factor-based filter utilizing the JKP factors.
- A machine learning filter using a learning-to-rank approach.

3.2 Portfolio Optimization

The portfolio optimization framework incorporates the following components that generate the necessary inputs for the Black-Litterman model:

- A historical return series for covariance estimation.
- Benchmark return data aligned with the trading dates.
- A budget constraint ensuring full investment.
- Box constraints implementing long-only positions with maximum 20% allocation per security.
- Size-tiered position limits that enforce stricter constraints for smaller companies.
- Market capitalization weights for benchmark comparison.
- A turnover constraint limiting portfolio changes to 20% per rebalancing.
- Machine learning-generated scores using XGBoost with pairwise ranking objective.

3.3 Learning-to-Rank Task

We frame the problem as a monthly *learning-to-rank* task:

- **Feature matrix X:** The full set of JKP characteristics (≈ 153 variables) plus technical indicators (e.g., 1-, 5-, and 20-day realized volatilities, 63-day residual momentum) computed from `market_data`.
- **Label y:** Within-month rank of next-period ($t \to t+1$) total return (scaled to 0–100).
- **Model:** XGBoost with objective `rank:pairwise`, tuned via time-series cross-validation on a rolling 60-month window.

The optimization method uses a Black-Litterman approach with Pearson correlation-based covariance estimation and calibrated uncertainty parameters (`tau_psi` and `tau_omega`). All these components are assembled into a `BacktestService` instance that executes the strategy across the previously defined monthly rebalancing dates.

4 Results

4.1 Cumulative Performance

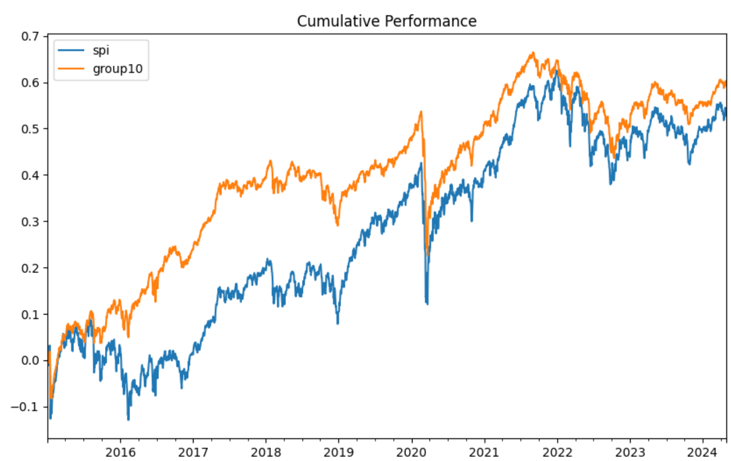

Figure 1: Log-scaled cumulative gross-of-fees performance (Jan 2015 – Mar 2024).

4.2 Descriptive Statistics

	Strategy	**SPI**
Annualised Return	6.40%	5.66%
Cumulative Return	82.06%	70.11%
Annualised Volatility	10.08%	14.57%
Sharpe Ratio	0.67	0.45
Max Drawdown	–26.7%	–26.3%

Table 1: Descriptive statistics for the strategy and benchmark.

5 Future Works

For further improvement, we could try the following:

1. **Factor Enhancements**
   - **Expand Factor Set:** Currently, we use `qmj`, `ret_12_1`, and `resff3_6_1`. Consider adding:
     - Value (e.g., book-to-market, earnings yield).
     - Low Volatility (past 12M realized vol).
     - Size (market-cap).
     - Dividend Yield.
     - Quality (profitability, leverage, earnings stability).
     - Growth (sales/earnings growth).
   - Non-linear factor combinations: Use interaction terms or polynomial features to capture nonlinearities.
2. **Machine Learning Improvements**
   - **Feature Engineering:**
     - Add technical indicators (momentum, RSI, moving averages).
     - Use rolling-window statistics (mean, std, skewness, kurtosis).
     - Include macroeconomic variables (rates, FX) if available.
   - **Modeling:** Try LightGBM, CatBoost, neural nets; use ensembles; cross-validate hyper-parameters.
   - **Target Engineering:** Predict probability of outperformance or expected drawdown; use classification or regression targets.
3. **Bear Market Preparation (Long-Only)**
   - Dynamic risk control – volatility targeting, drawdown triggers.

- Defensive factor tilt – favour low-vol, quality, dividend yield under negative signals.
- Market-regime detection via ML or regime-switching models.
- Allow a cash buffer (relax fully-invested constraint) during high-risk episodes.
- Sector rotation into utilities, healthcare, staples in bear markets.