QMIT's Enhanced Smart Betas

QMIT Enhanced Smart Beta Overview

Comprehensive Factor Research Framework

- 18 Enhanced Smart Betas (ESBs) developed from 25 years of extensive factor research.

- BFOM Strategy prevents look-ahead bias by selecting best flavor based on T-1 performance .

- Composite signals constructed from ESB BFOMs for advanced strategy deployment .

- Covers approximately 2,500 US names with robust data preprocessing and factor ranking .

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ESBs and Composite Signals

Enhanced Smart Betas (ESBs)

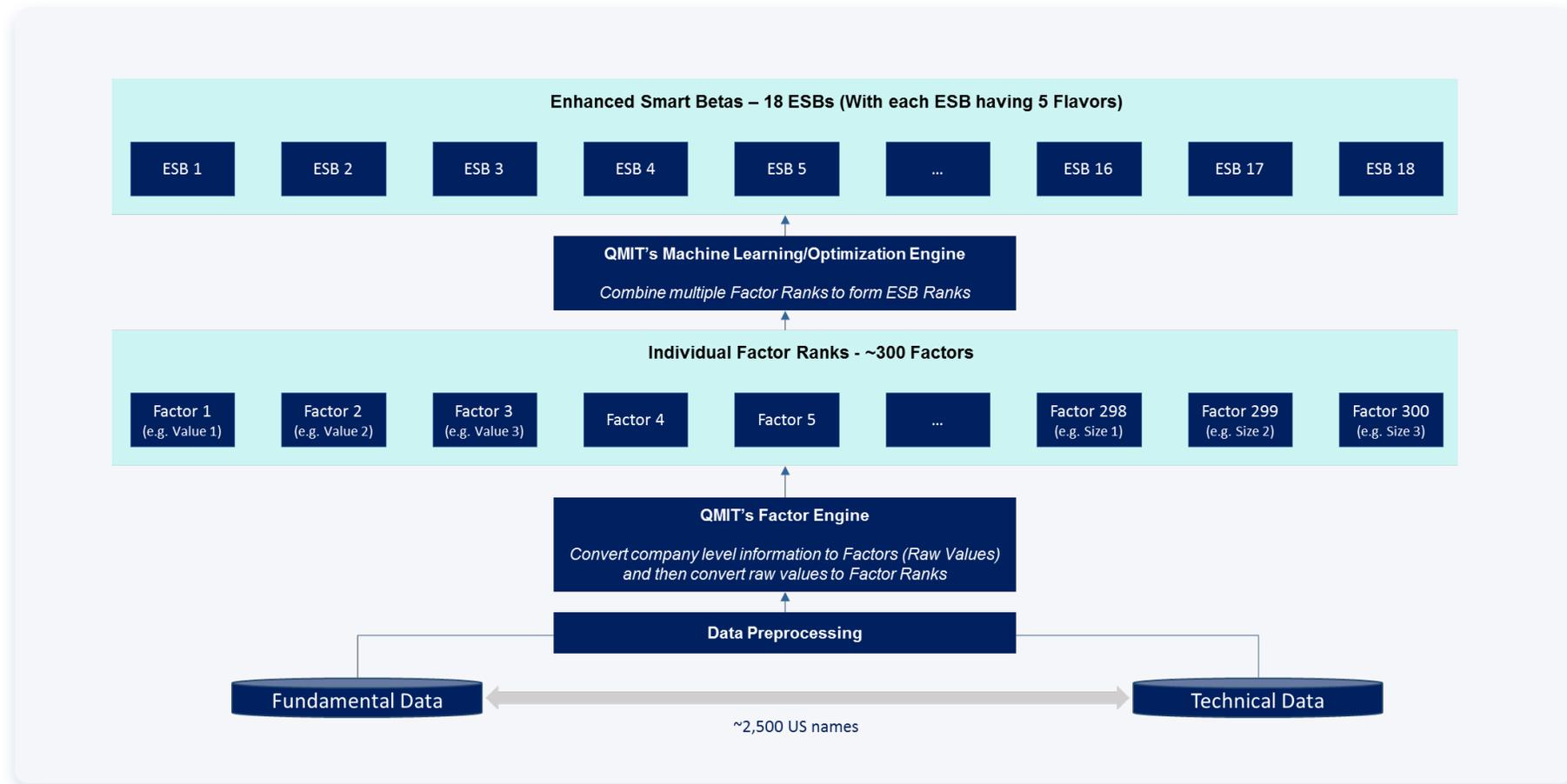| #	ESB Name
1	Deep Value (DV)
2	Relative Value (RV)
3	Dividends (DIVS)
4	Reversals (REVS)
5	Price Momentum (PMOM)
6	Enhanced Momentum (EnMom)
7	Analyst Revisions (ARS)
8	Analyst Ratings (ART)
9	Growth Historical (GROH)
10	Quality Earnings (EQ)
11	Quality Leverage (LEV)
12	Quality Profitability (PROF)
13	Quality Capital (CSU)
14	Quality Stability (STAB)
15-18	Efficiency, Size, SIRF, Risk

Composite Signals

Composite Signal Name
Famous Five
Sizzling Seven
Fabulous 14
Enterprise 18
Value Composite
Growth Momentum Composite
Quality Composite
Value Momentum Composite
Quality Momentum Composite
Quality Value Composite

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Data Mining Prevention

Robust Factor Selection Methodology

⚠️ Data mining concern: Factor formulations tweaked for best in-sample performance .

🛡️ Prevention strategy: Only factors with extensive research validation and economic rationale .

🚫 Exclusion criteria: Clearly contrived formulations rejected in favor of proven factors .

📈 Out-of-sample focus: Ensuring comparable performance beyond historical data .

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ESB Construction Process

Enhanced Smart Betas – 18 ESBs (With each ESB having 5 Flavors)

| ESB 1 | ESB 2 | ESB 3 | ESB 4 | ESB 5 | ... | ESB 16 | ESB 17 | ESB 18 |

QMIT's Machine Learning/Optimization Engine

Combine multiple Factor Ranks to form ESB Ranks

Individual Factor Ranks - ~300 Factors

| Factor 1 (e.g. Value 1) | Factor 2 (e.g. Value 2) | Factor 3 (e.g. Value 3) | Factor 4 | Factor 5 | ... | Factor 298 (e.g. Size 1) | Factor 299 (e.g. Size 2) | Factor 300 (e.g. Size 3) |

QMIT's Factor Engine

Convert company level information to Factors (Raw Values) and then convert raw values to Factor Ranks

Data Preprocessing

Fundamental Data ⟷ Technical Data

~2,500 US names

Comprehensive data pipeline transforming ~2,500 US names through factor engine and machine learning optimization to produce 18 Enhanced Smart Betas, each with 5 distinct flavors

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ESB Flavors and Weighting Schemas

Multiple Proprietary Weighting Methodologies

⚖️ Intra-cohort weighting: Monthly optimization using expanding window LTD data.

📈 Performance measurement: Top 5% vs bottom 5% spread returns.

🔻 Perverse factor exclusion: Negative LTD returns AND IC excluded.

Maximum weight: 1/3 limitper factor within ESB cohort.

> **Key Advantage:** *Ensemble learners adapt to market conditions while maintaining factor diversification.*

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Portfolio Construction Rules

Top 5% vs Bottom 5% Portfolio Construction

📊 Standard Rule: If total stocks ≥ 500, take top/bottom 5% for long-short portfolio construction.

📚 Medium Universe: If 100 ≤ stocks < 500, take top/bottom 25 stocks each for portfolio formation.

⚠️ Small Universe: If stocks < 100, set fractile differential return to 0% due to insufficient universe size.

⚖️ Tie-breaker Logic: Include all stocks at threshold rank to handle situations with identical factor scores.

Rebalancing Discipline

📅 Monthly Rebalancing: Recommended for investors concerned about transaction costs and excessive turnover.

🕐 Daily Rebalancing: Available from January 2019 onwards with live daily data; historical data on month-end basis.

$ Dollar-Neutral Basis: All portfolios tracked on dollar-neutral basis with optional beta-neutral performance reporting.

Practical Focus: The 5%-tile approach corresponds to approximately 150 stocks, aligning with typical quantamental manager attention bandwidth and operational capacity.

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Bias Mitigation Strategies

Comprehensive Bias Prevention Framework

☠ **Survivorship Bias** eliminated by including both live and dead companies at each historical point in time.

🚫 **Look-ahead Bias** prevented through conservatively lagged fundamentals and T-1 data availability constraints.

🔍 **Data Mining** minimized by focusing only on factors with extensive academic validation and clear economic rationale.

$ **Liquidity Bias** addressed by including only stocks with minimum $250 million market cap for institutional tradability.

🕘 **Hindsight Bias** avoided through BFOM strategy using only ex-ante information through T-1.

Additional Safeguards

🛡 Reject purely statistical approaches that result in compelling but contrived back-tests failing out-of-sample.

🧠 Focus on factors supported by research and trader intuition rather than data-mined accounting ratios.

Critical Foundation: Rigorous bias mitigation ensures factor performance represents genuine alpha generation rather than statistical artifacts or data quality issues.

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BFOM Investable Strategies

Best Flavor of the Month Framework

⇄ 18 BFOM strategies systematically switch between alternate ESB flavors to prevent look-ahead bias.

🧠 Ensemble learners operate on expanding windows, re-optimizing monthly using only T-1 data.

📈 Selection criteria based on cumulative risk and return profile through T-1, ex ante.

🛡 Bias prevention ensures no hindsight advantage in factor weight optimization process.

Implementation: BFOM represents the investable equivalent from ensemble learners, avoiding hindsight bias in ESB performance representation.

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Cross-Sectional Rank Correlations

ESB Rank Relationships (12-31-24)

🔗 Strong correlations between EnMOM-PMOM (0.86) and momentum factors.

⚖️ Quality factors show moderate interconnections across metrics.

📊 Cross-sectional analysis based on latest ranks across universe.

✛ Orthogonal factors like SIRF and REV show low correlation.

Key Insight: Matrix reveals diversification opportunities and multicollinearity concerns.

Return Correlations Analysis

3-Year Return Correlations (12-31- 24)

Recent correlation patterns with notable relationships like EnMOM-PMOM (0.86) and quality factor interconnections.

20-Year Return Correlations (12- 31-24)

Long-term stability with consistent factor relationships and structural persistence across market cycles.