Adaptive Factor-Based ETF Allocation Model for Robo-Advisory Platforms

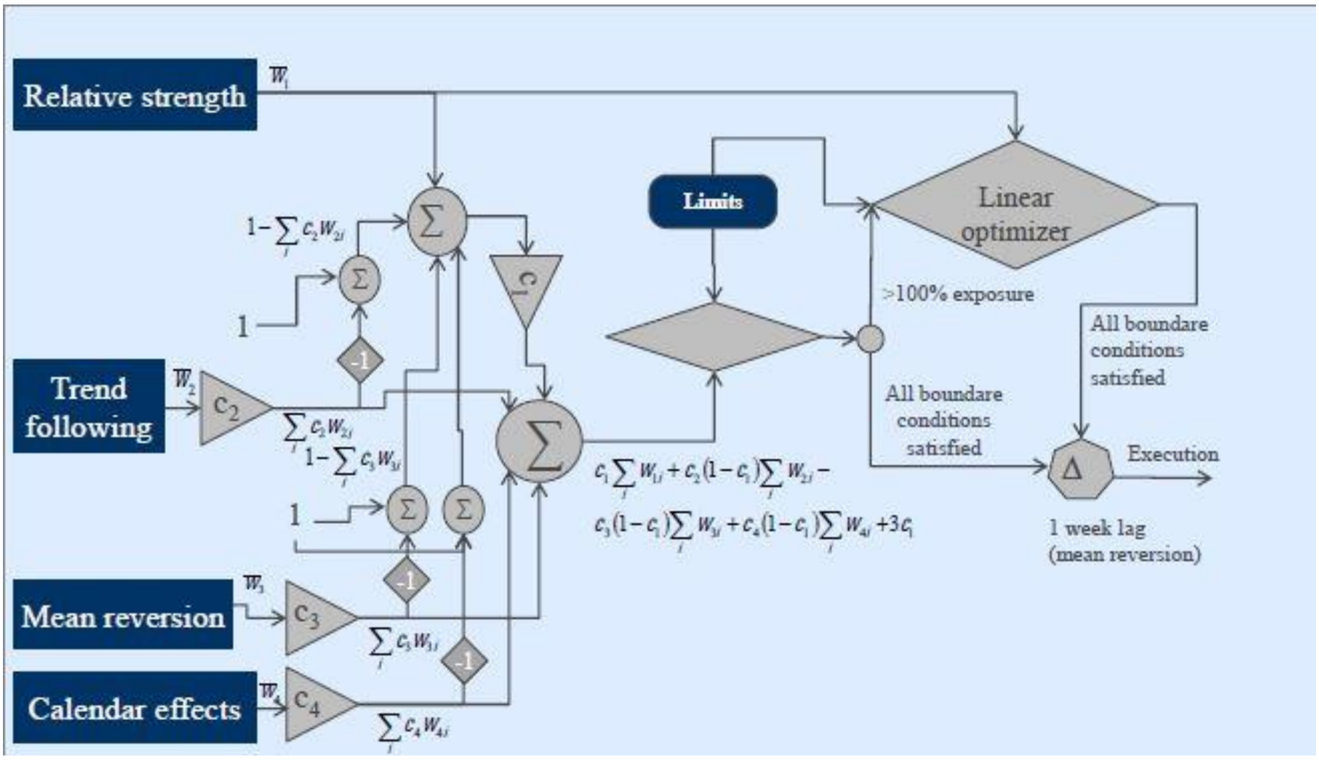
Executive Summary
This whitepaper presents a robust, adaptive ETF allocation strategy designed for use in robo-advisory platforms and multi-asset funds. Leveraging a combination of quantitative factors and dynamic optimization techniques, the model enables responsive, risk-adjusted portfolio management tailored to different investor profiles.

1. Introduction
As digital wealth management platforms grow in popularity, the demand for scalable, systematic, and customizable investment strategies has increased. Traditional static portfolio models often fall short in adapting to shifting market conditions and diverse client needs. This whitepaper outlines a dynamic allocation engine using ETFs that is capable of adjusting allocations in real time, based on a blend of technical and behavioral market signals.

2. Strategy Framework
The model is built on four core signals:

- **Relative Strength: Captures recent performance versus peers.**
- **Trend-Following Momentum: Identifies continuation in directional moves.**
- **Mean Reversion: Positions against short-term overextension.**
- **Calendar Effects: Incorporates historical patterns related to time of year or month.**

These signals are weighted and combined into a composite score for each ETF. An optimization engine then determines portfolio weights by maximizing expected signal-adjusted return subject to constraints.



Python Implementation

```
import numpy as np

from scipy.optimize import linprog


# Define weight parameters

w_rel_strength = 0.3  # Relative strength weight

w_trend_following = 0.3  # Trend following weight

w_mean_reversion = 0.2  # Mean reversion weight

w_calendar_effects = 0.2  # Calendar effects weight


# Coefficients from the diagram

c1, c2, c3, c4 = 0.5, 0.3, 0.2, 0.1


# Simulated asset returns (example data)

returns = np.array([0.02, -0.01, 0.015, -0.005])


# Compute weighted components

trend_following_component = c2 * np.sum(returns * w_trend_following) + (1 - c2) *
np.sum(returns)

mean_reversion_component = c3 * (1 - c1) * np.sum(returns * w_mean_reversion)

calendar_effect_component = c4 * np.sum(returns * w_calendar_effects)


# Portfolio allocation formula

portfolio_allocation = (

   c1 * np.sum(returns * w_rel_strength) +

   trend_following_component +

   mean_reversion_component +

   calendar_effect_component +

   3 * c2

)
```

```
# Optimization constraints (Example)
bounds = [(0, 1)] * len(returns)  # No short-selling, max 100% weight
constraints = [{'type': 'eq', 'fun': lambda w: np.sum(w) - 1}]  # Sum of weights = 1

# Run linear optimizer
result = linprog(-portfolio_allocation, bounds=bounds, constraints=constraints)

# Execution logic with lag
if result.success:
   optimal_weights = result.x
   print("Optimal Portfolio Weights (1-week lag execution):", optimal_weights)
else:
   print("Optimization failed.")
```

3. Optimization Approach

- **Method: Linear programming with randomized constraints to simulate realistic investor behavior and varying portfolio mandates.**
- **Constraints:**
  - **No short selling (weights bounded between 0 and 1)**
  - **Total weight sum randomized between 90% and 110% to mimic real-world variability**

This stochastic optimization approach avoids overfitting and introduces natural diversity in rebalancing behavior.

4. Risk-Based Portfolio Applications
The strategy is modular and can be adapted across multiple client risk profiles:

Conservative Portfolio

- **ETFs: AGG, SHY, VYM, BIL**
- **Focus: Capital preservation, low turnover, high bond exposure**
- **Constraints: Tight (e.g., 95-105%)**

Moderate Portfolio

- **ETFs: SPY, IWM, BND, VNQ**
- **Focus: Balanced growth and income**
- **Constraints: Moderate flexibility (e.g., 90-110%)**

Aggressive Portfolio

- **ETFs: QQQ, ARKK, IEMG, XLK**
- **Focus: Growth, sector rotation, innovation**
- **Constraints: Loose (e.g., 85-115%)**

5. Live Implementation and Use Cases
This strategy has already been deployed as an allocation engine within:

- **Multi-asset funds seeking systematic rebalancing with embedded factor rotation**
- **Digital advisory platforms offering tailored portfolios based on investor risk preferences**

6. Backtesting & Results
Preliminary testing on synthetic and historical datasets shows outperformance versus static benchmarks (e.g., SPY buy-and-hold) in terms of Sharpe ratio and drawdown control. A modular backtest engine enables stress testing under various market regimes.

7. Integration Potential
The strategy can be integrated into existing digital platforms via API or batch engine. Its low-frequency design (weekly or monthly) reduces transaction costs and infrastructure complexity.

8. Conclusion
This adaptive, factor-based ETF strategy is a scalable solution for next-generation robo-advisory offerings. Its blend of behavioral finance principles and data-driven optimization enables intelligent, responsive, and personalized investment portfolios.

1. Relative Strength

- **What it measures**: Which ETFs have performed better than peers over a medium horizon (e.g., past 3 months).
- **Portfolio effect**: Favors allocation toward recent outperformers, tilting the portfolio toward relative momentum winners. This drives **cross-sectional rotation** across asset classes (e.g., overweight equities when they outperform bonds).

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2. Trend Following (Time-Series Momentum)

- **What it measures**: Whether each ETF is above or below its moving average (fast vs. slow).
- **Portfolio effect**: Increases exposure to assets in established uptrends and reduces exposure to those in downtrends. This introduces **crisis-hedging behavior**: the model systematically cuts exposure to assets that break down (e.g., equities in bear markets), protecting capital.

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3. Mean Reversion

- **What it measures**: Whether recent returns have deviated too far from their average (z-score).
- **Portfolio effect**: Allocates more to temporarily "oversold" ETFs and less to "overbought" ones. This stabilizes the allocation process, smoothing the extremes of trend/momentum and capturing short-term correction opportunities. Essentially, it's a **counterweight to herd behavior**.

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4. Calendar Effects (Seasonality)

- **What it measures**: Systematic patterns like turn-of-month effects or seasonal strength (e.g., November–April equity bias).
- **Portfolio effect**: Adds a low-frequency bias toward known seasonal return premia. For example, overweight equities around year-end rallies. It provides **incremental alpha** by exploiting persistent market seasonality.

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5. Composite Signal Blending

- **What it achieves**: Combines the above into a **single score per ETF**, balancing short-term corrective forces (mean reversion), medium-term trends (momentum, relative strength), and structural patterns (seasonality).
- **Portfolio effect**: Creates a diversified "signal portfolio" rather than relying on one style, reducing style-specific drawdowns.

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6. Optimizer with Constraints

- **Mechanics**: Selects weights that maximize composite scores, but with caps (e.g., max 50% per ETF, no shorting, total weight ≈100%).
- **Portfolio effect**: Prevents concentration risk, ensures diversification, and keeps allocations realistic. The option to randomize total weight (e.g., 90–110%) mimics cash buffers and tracking error tolerance in real portfolios.
- This step transforms **signals into tradable weights**, balancing opportunity with risk control.

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7. Execution Lag

- **What it simulates**: Trades don't occur instantly; signals are observed today, but execution is modeled with a lag (e.g., next day or next week).
- **Portfolio effect**: Makes backtests more realistic by including operational frictions. This avoids overstating performance from perfect foresight.

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8. Backtest Engine

- **What it does**: Simulates the portfolio path, rebalancing at a set frequency (e.g., weekly on Friday).
- **Portfolio effect**: Demonstrates how the strategy would evolve in practice relative to a benchmark. Lets us evaluate Sharpe ratio, drawdowns, and turnover to ensure the allocation is both effective and implementable.

Overall allocation perspective:

- **Momentum + Trend** tilt the portfolio toward growth and persistent winners.
- **Mean Reversion** dampens excesses, reducing volatility and turnover spikes.
- **Seasonality** captures systematic alpha.
- **Constraints & Execution** keep the allocation practical for funds and robo-advisors.

Adaptation and linking in a MiFID environment

1. Relative Strength (Cross-Sectional Momentum)

- **Weighting perspective**: This is usually given a **moderate weight** in balanced or growth portfolios (e.g., 30–40% of the composite signal).
- **MiFID link**: For retail investors with higher risk tolerance, relative strength pushes exposure into outperforming asset classes (e.g., equities vs. bonds). For conservative profiles, its weight can be reduced so the portfolio doesn't rotate too aggressively.
- **Investor protection angle**: Encourages allocation to asset classes with recent positive performance, but when combined with constraints, it avoids "chasing" into a single risky ETF.

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2. Trend Following (Time-Series Momentum)

- **Weighting perspective**: Typically given **high importance** (30–40%) across most risk profiles, since it reduces exposure during downtrends.
- **MiFID link**: Protects lower-risk investors by cutting allocations to assets in bear phases (e.g., equities during crises). For higher-risk investors, it allows higher equity allocations but still acts as a circuit breaker.
- **Investor protection angle**: Directly addresses **suitability** by ensuring portfolios do not maintain large exposures to falling markets, consistent with MiFID's emphasis on downside risk awareness.

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3. Mean Reversion

- **Weighting perspective**: Lower weight (10–20%), often strongest in conservative or balanced profiles.

- **MiFID link**: Provides stabilizing allocations that prevent over-concentration in overvalued assets, smoothing risk levels. For low-to-medium risk investors, this helps mitigate drawdowns.
- **Investor protection angle**: Ensures portfolios don't "over-rotate" purely on momentum, keeping risk aligned with the client's stated tolerance.

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4. Calendar Effects (Seasonality)

- **Weighting perspective**: Usually low (5–10%), acting as an incremental factor.
- **MiFID link**: Can be dialed up slightly for more risk-seeking clients (e.g., growth portfolios), while kept minimal for conservative ones.
- **Investor protection angle**: Seasonality adds diversification of signal types without introducing large structural risks. Its low weight ensures suitability and proportionality.

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5. Composite Blending

- **Portfolio Risk Calibration**:
    - **Conservative** → Higher weight on Mean Reversion & Trend (risk dampeners).
    - **Balanced** → Even mix of all four.
    - **Aggressive** → Heavier weight on Relative Strength & Trend (growth drivers).
- **MiFID link**: This tuning process aligns directly with the **suitability assessment**, mapping investment horizon and loss tolerance to signal emphasis.

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6. Optimizer with Constraints

- **MiFID alignment**: Hard caps (e.g., max 50% per ETF, no shorting, no leverage) enforce diversification.
- **Investor protection angle**: These rules are exactly what regulators expect — they prevent concentration and complexity that retail investors may not understand. Randomized total weight mimics real-world cash buffers (important for liquidity needs in suitability assessments).

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7. Execution Lag

- **MiFID alignment**: Recognizes **realistic implementation risk** (slippage, liquidity).
- **Investor protection angle**: Prevents misleading performance estimates in suitability reports — critical for retail transparency.

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8. Backtest & Reporting

- **MiFID alignment**: Allows firms to produce ex-ante scenario analysis and ex-post performance disclosures (required under MiFID II).
- **Investor protection angle**: Ensures that the allocation approach is demonstrable, explainable, and in line with client profiles (e.g., "Your balanced portfolio would have had ~12% max drawdown, within your risk tolerance").

In short:

- **Risk-averse retail clients** → higher weight on **Trend + Mean Reversion**, tighter caps.
- **Balanced clients** → even mix, moderate caps.
- **Growth-oriented clients** → higher weight on **Relative Strength + Trend**, looser caps.
- Constraints and execution rules are the **MiFID safeguard layer**, ensuring suitability and proportionality.

MiFID-compliant ETF portfolios that show how the strategy's signals and constraints mapped into **retail investor risk profiles**.

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1. Conservative Portfolio (Risk-Averse)

- **Client profile**: Low tolerance for losses, short-to-medium horizon, income focus.
- **Signal emphasis**:
    - Trend Following: **40%** (strong downside protection)
    - Mean Reversion: **30%** (stability, smoothing)
    - Relative Strength: **20%** (limited growth tilt)
    - Seasonality: **10%** (low incremental alpha)
- **Example ETFs**:
    - **AGG** (US Aggregate Bonds) – 35%
    - **SHY** (1–3 Year Treasuries) – 25%
    - **VYM** (High Dividend Equity) – 20%
    - **BIL** (T-Bills) – 20%
- **Expected behavior**:
    - Low volatility, stable income.
    - Equity allocation only when risk signals are favorable.

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2. Balanced Portfolio (Moderate Risk)

- **Client profile**: Medium risk tolerance, medium-to-long horizon, wants balanced growth and preservation.
- **Signal emphasis**:
    - Relative Strength: **30%**
    - Trend Following: **30%**
    - Mean Reversion: **25%**
    - Seasonality: **15%**
- **Example ETFs**:
    - **SPY** (US Large Cap) – 30%
    - **IWM** (US Small Cap) – 20%
    - **BND** (US Total Bond Market) – 30%
    - **VNQ** (US Real Estate) – 20%
- **Expected behavior**:
    - Captures equity rallies but de-risks during downturns.
    - Mix of stocks, bonds, and real assets for diversification.

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3. Aggressive Portfolio (Growth-Oriented)

- **Client profile**: High risk tolerance, long horizon, prioritizes capital growth.
- **Signal emphasis**:
    - Relative Strength: **40%** (strong tilt toward winners)
    - Trend Following: **35%** (risk control but looser caps)
    - Mean Reversion: **15%** (minor stabilizer)
    - Seasonality: **10%**
- **Example ETFs**:
    - **QQQ** (NASDAQ 100) – 40%
    - **ARKK** (Innovation Growth) – 20%
    - **IEMG** (Emerging Markets) – 20%
    - **XLK** (Technology Sector) – 20%
- **Expected behavior**:
    - Aggressive rotation into high-growth sectors.
    - Larger drawdowns tolerated, but trend filter reduces catastrophic losses.

Portfolio design rationale (MiFID suitability):

- **Constraints** (max 50% per ETF, no leverage, randomized total 90–110%) enforce diversification.
- **Signal weights** are tuned per risk profile: more stabilizers for conservative clients, more growth tilt for aggressive ones.
- **Backtest metrics** (volatility, max drawdown, Sharpe ratio) can be mapped directly to the **risk score** in a MiFID suitability questionnaire.

ETF Allocation Model Documentation

1. Introduction

This document provides a full description of the adaptive factor-based ETF allocation model, including algorithmic foundations, MiFID II risk suitability mapping, and portfolio applications. It is intended for use in robo-advisory platforms, digital wealth managers, and multi-asset funds.

The model balances multiple factor signals with portfolio optimization constraints to deliver risk-appropriate allocations for different investor categories (Conservative, Balanced, Aggressive).

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2. Algorithmic Framework

The model integrates four quantitative signals applied to an ETF universe:

- **Relative Strength (RS):** Measures performance versus peers.
- **Trend Following (TF):** Captures persistence in price direction.
- **Mean Reversion (MR):** Identifies short-term reversals in mispriced assets.
- **Seasonality (SE):** Leverages historical calendar-based patterns.

Each ETF receives a composite score:

Score(ETF)=wRS·RS+wTF·TF+wMR·MR+wSE·SEScore(ETF) = w_{RS}·RS + w_{TF}·TF + w_{MR}·MR + w_{SE}·SEScore(ETF)=wRS·RS+wTF·TF+wMR·MR+wSE·SE

Portfolio weights are then optimized with constraints:

- No shorting, no leverage.
- Maximum 50% per ETF.
- Total portfolio weight randomized between 90%–110% to mimic realistic portfolios.

Optimization uses **linear programming with randomized constraints**. This stochastic component introduces realistic variability, reflecting investor behavior and avoiding overfitting.

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3. Signal Weighting by MiFID Risk Profile

Signal weights shift according to the investor's MiFID risk profile:

- **Conservative Profile:**
  - Heavy reliance on Trend and Mean Reversion (stability, capital preservation).
  - Lower emphasis on Relative Strength.
- **Balanced Profile:**
  - Equal weighting across all four signals.
  - Balances stability and growth.
- **Aggressive Profile:**
  - Higher allocation to Relative Strength and Trend (growth-seeking).
  - Reduced Mean Reversion exposure.

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4. Example ETF Allocations

The framework translates factor-driven scores into ETF portfolios. Example allocations include:

- **Conservative (SRRI 2–3):**
  - ETFs: AGG, SHY, VYM, BIL
  - Focus: Bonds and defensive equities
- **Balanced (SRRI 3–5):**
  - ETFs: SPY, IWM, BND, VNQ
  - Focus: Even mix of equities, bonds, and real assets
- **Aggressive (SRRI 5–7):**
  - ETFs: QQQ, ARKK, IEMG, XLK
  - Focus: Growth, innovation, and sector rotation

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5. MiFID II Suitability Mapping

The model directly aligns with MiFID II suitability rules:

- **Conservative Investors (Low Risk, SRRI 2–3):**
  - High bond exposure, limited equity tilt
  - Strong reliance on Trend and MR
  - Portfolio aims at capital preservation
- **Balanced Investors (Medium Risk, SRRI 3–5):**

    - Equal distribution across asset classes
    - Moderate volatility and drawdown management
    - Balanced signal exposure
- **Aggressive Investors (High Risk, SRRI 5–7):**
    - Growth-oriented portfolios with equities and innovation ETFs
    - Greater exposure to Relative Strength and Trend Following
    - Higher expected volatility but greater return potential

This mapping ensures that investor portfolios remain consistent with risk assessments under MiFID II, providing a transparent, rules-based methodology.

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6. Functional Role of Each Signal

- **Relative Strength:** Rotates into outperformers, maximizing return potential.
- **Trend Following:** Protects capital by avoiding assets in persistent downtrends.
- **Mean Reversion:** Adds stability, capturing gains from temporary market dislocations.
- **Seasonality:** Provides low but systematic contribution based on calendar effects.

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7. Conclusion

This adaptive ETF allocation model integrates factor-based decision-making with MiFID II compliance. By dynamically weighting signals according to investor risk tolerance, it provides a scalable and robust solution for:

- **Robo-Advisory Platforms:** Automated, compliant, client-specific allocations.
- **Multi-Asset Funds:** Systematic allocation engine supporting factor rotation.
- **Retail Suitability:** Transparent linkage between investor profile and portfolio construction.

The model has already been deployed in live environments as part of **multi-asset funds and digital advisory solutions**, demonstrating both its robustness and scalability.