Cross-Asset Trend Following Strategy

Data as of 06/30/2024

A combination of a top-down approach across asset classes, while aiming to capture trends within each asset class.

This fully rule-based strategy is designed for investors with a medium-to-high risk appetite, seeking global exposure across both geographies and asset classes, and who believe in the weak form of the efficient market hypothesis.

Key Benefits

1. Diversification across asset classes and geographies
2. Leveraging machine learning techniques to profit from asset momentum
3. Fundamentals-driven, top-down asset allocation approach

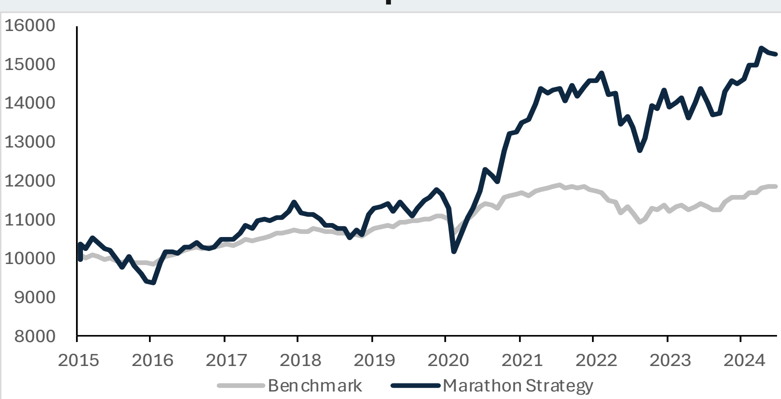
Key Performance Metrics

	Marathon	Benchmark
Mean Return	4,84%	1,85%
Cummulative Return	52,88%	18,72%
Mean Volatility	0,0855	0,0296
Sharp Ratio	0,1633	0,1802
Max Drawdown	-13,62%	-8,04%

Investment Universe

Equity	15 assets
Bonds	9 assets
Currencies	10 assets
Commodities	13 assets

Growth of Hypothetical $10,000 CAD Since Inception



Beginning value : 10 000$ as of 01/01/2015**, End value**: 15 288,75$ as of 06/30/2024

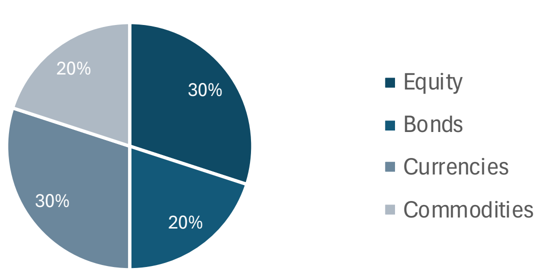
Machine Learning

Techniques:	Ridge Regression, Random Forest, K-means clustering
Training set:	Daily data from 2001 to end of 2012
Validation set:	2013 to end of 2014
Cross-Validation :	K-folds
Explanatory variables:	Returns, EMA, MACD, Bollinger Bands, Breakout Signals

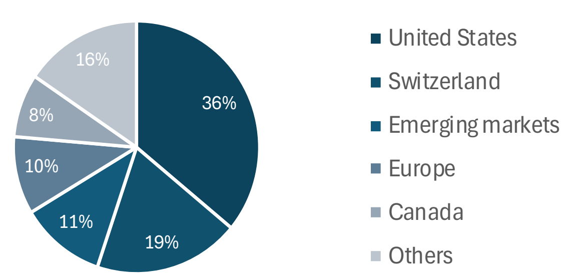
Performance

	Cumulative					Annuazied			Calendar Year				
	1 month	3 month	6 month	YTD	1 Y	3Y	5Y	S.I.*	2024	2023	2022	2021	2020
Marathon Fund	-0,26%	1,86%	5,25%	5,25%	6,13%	2,05%	6,22%	4,57%	5,24%	0,98%	-1,58%	10,15%	13,62%
Benchmark	0,05%	1,33%	2,48%	2,48%	3,94%	0,01%	1,60%	1,82%	2,47%	1,56%	-3,40%	1,06%	5,21%

Asset Class Diversification



Geography Diversification**



All presented results are from the past and it should not be taken for granted that those are reflective of future performance. Investing involves risks, including the possible loss of principal. *Since Inception: 01/01/2015, **: Include only Bonds and Equity

Overall, our strategy performs strongly in the long run, with some volatility during market downturns but a clear recovery and outperformance relative to the portfolio without a macroeconomic overlay (here as a reference) and the equally-weighted benchmark portfolio. It is clear that including macroeconomic conditions into the investment strategy pays off in the long run by enhancing the portfolio's resilience to economic fluctuations and ability to dynamically adjust asset allocation which align with prevailing market conditions.

Our trading strategy employs a multi-step approach that integrates technical analysis signals, machine learning models, and macroeconomic data to optimize asset allocation. Firstly, we compute eight key technical indicators to inform our two models, using Ridge regression to forecast monthly returns and Random Forest to predict upward movement probabilities. These predictions are converted into z-scores used to rank individual assets, whose final weights are adjusted based on the prevailing macroeconomic regime identified through K-means clustering (*see the flowchart in Figure 1.*) The following paragraphs detail each step of our strategy.

Description of the Strategy

To begin, we compute eight trading signals based on technical analysis indicators. More specifically, we work with the 22-days return, the 65-days return, the exponential moving average (EMA), the 65-days moving average convergence/divergence (MACD), the 260-days MACD, the 22-day Bollinger bands and the 65-days breakout signal (*see Appendices, Table 4.*). They serve as the features in our machine learning models, and we respectively define them as $X = \{X_1, X_2, ..., X_8\}$, and Y as the asset returns per month.

We then train two distinct machine learning models using these signals: Ridge regression and Random Forest. On the one hand, the Ridge regression provides us with an expected return for each asset per month,

$$\hat{y}_{i,t}^{\text{ridge}} = X_{i,t-1} \cdot \beta$$

where $\hat{y}_i^{\text{ridge}}$ represents the i-th asset's forecasted returns per month, $X_{i,t-1}$ are the technical indicator signals at the previous month, and β is the coefficient vector. The hyperparameter α controlling the strength of the regularization is found by performing a grid search using 5-fold cross-validation, and by selecting the value with the best cross-validated R^2 score in the following objective function,

$$\min_{\beta} \left(\sum_{i=1}^{n} (y_{i,t} - \mathbf{X}_{i,t-1}\beta)^2 + \alpha \sum_{j=1}^{p} \beta_j^2 \right)$$

On the other hand, the Random Forest model is used in a classification framework, and generates the probability of an upward movement for each asset per month.

$$\hat{p}_i^{\text{rf}} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}\{y_i = 1|X\}$$

where, N is the number of trees, 1 is an indicator function returning 1 if the prediction is upwards and 0 otherwise. The hyperparameters (i.e. the number of estimators, the depth of the tree, the number of samples required to split an internal node, the number of sample required to be at a leaf node, and the class weight) are found by performing a grid search using 5-fold cross-validation and by selecting the value with the best accuracy.

Next, we convert our predictions into z-scores, cross-sectionally within each asset class. In other words, for each asset, we subtract the mean predicted value of all assets in the class during that month from the asset's prediction and divide by the standard deviation of those values for the same month. This process is repeated for each asset, across all months, and for both the Ridge regression and Random Forest models. We then sum the z-scores from both models to produce one final z-score per asset per month.

$$z_i^{\text{ridge}} = \frac{\hat{y}_i^{\text{ridge}} - u^{\text{ridge}}}{\sigma^{\text{ridge}}} \quad , \quad z_i^{\text{rf}} = \frac{\hat{p}_i^{\text{rf}} - u^{\text{rf}}}{\sigma^{\text{rf}}}$$

$$z_i^{\text{final}} = z_i^{\text{ridge}} + z_i^{\text{rf}}$$

After calculating the z-scores, we rank the assets within each asset class based on their respective z-scores, with higher values indicating better prospects. We determine the asset weights to be the inverse of these rankings, which is central to our strategy, ensuring that more capital is allocated to assets with the best predicted performance.

The final layer of our strategy involves a macroeconomic overlay. Based on key macroeconomic criteria, we compute the weights allocated to each asset class for every month. To do so, we work with the Real GDP (YoY), the CPI (YoY), the unemployment rate and the yield curve as our features. We proceed firstly by identify different macroeconomic environments by assuming the existence of 4 macroeconomic regimes and by applying K-means clustering on quarterly data starting in 1954. Hereon, we define an adjustment rule in asset class weights for each cluster or regime. For instance, cluster 0 corresponds to a regime with strong growth (high GDP, moderate inflation and unemployment, and positive yield curve), for which the asset class allocation will overweight equities. The final weights for each asset are obtained by multiplying the asset-specific weights by the corresponding asset class weights.

To summarize our strategy and backtest methodology, at the end of each month, we calculate signals for each asset across all asset classes. We then use these signals in our Ridge and Random Forest models to predict the next month returns and the probability of up movement respectively. Hereon, we rank the assets and construct a portfolio within each asset class. Finally, we use the latest macroeconomic data to estimate the economic regime we are in and apply the asset class deviations accordingly to obtain our portfolio to hold for the next month.

Pros and Cons

Overall, the main advantages of the strategy are the following :

- Combining two complementary machine learning models enhances the model's predictive power by addressing different aspects of prediction and reducing variance, leading to better generalization. On the one hand, Ridge Regression provides continuous return estimates, quantifies the linear relationship between the technical indicators and the returns, and handles well multicollinearity in these indicators. On the other hand, Random Forest provides the probability of an upward movement and handles the nonlinear relationships between features and the target. In short, Ridge Regression adds interpretability and precision in expected returns, while Random Forest enhances directional accuracy and captures non-linear patterns.
- Implementing regularization, robust hyperparameter tuning and z-score normalization ensures that the trading model is not over-fitted, that the hyperparameters are optimally selected and that the decision-making process is cross-sectionally adjusted, preventing biases in asset selection. These steps help ensure that the model is robust and performs consistently.
- Including a macroeconomic overlay for asset class allocation makes the strategy adaptable to changing economic conditions, enhancing its overall resilience by allowing for more responsive adjustments to market shifts. Figure 1 clearly illustrates the benefits of this approach, showcasing how the macro clustering portfolio outperforms strategies that do not consider macroeconomic factors.

However, we note the following disadvantages :

- Summing the Z-scores from both models could potentially dilute the signal if one model significantly outperforms the other, leading to sub-optimal rankings.
- The success of the strategy depends heavily on the assumption that technical indicators can reliably predict asset price movements. In volatile or low-liquidity markets, these indicators may provide false signals.
- Some assets (e.g., currencies) may be more reactive over a shorter time horizon. Therefore, using an investment horizon of a month may not be ideal. The fact that we standardize the signals for certain periods across all asset classes is likely not optimal. Ideally, we should parameterize each signal to the dynamics of the asset.
- Our signals mainly focus on asset returns, and little attention is given to volatility. Knowing that volatility can cause false signals, it would be interesting to account for shifts in an asset's volatility.
- Some arbitrary choices were made when building the strategy. For the macro clustering, we assume only four regimes and select variables that we believe could help define those clusters. Also, it is difficult to convincingly interpret the different regimes coming from the clusters. This decision is based on a fundamental approach but may introduce significant bias. Furthermore, the deviation rule for each cluster is based on a fundamental approach but is arbitrary.
- Although our strategy over performs the benchmark, when we adjust for volatility, we under perform the benchmark. This means our over performance on a return basis comes from higher risk-taking.

Disclaimer

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Appendices

Table 1: Assets traded

Commodity*	Equity	Currencies**	Bonds
Crude Oil	SPY	USDJPY	LBUSTRUU Index
Natural Gas	EWU	EURUSD	XBB
Cooper	FEZ	GBPUSD	LP06TREU Index
Wheat	EWJ	USDCAD	EMUSTRUU Index
Aluminium	EWH	NZDUSD	LUACTRUU Index
Nickel	EWQ	USDMXN	LECPTREU Index
Steel	EWG	EURCHF	CA IG
Gold	EWC	NOKSEK	LF98TRUU Index
Silver	IWM	EURGBP	LP01TREU Index
Corn	QQQ	USDAUD	
Cocoa	EZU		
Soybean	EWT		
Cattle	EWI		
	EWL		
	EZA		

*Front month future contract

**Spot rate

All data was pulled from Bloomberg on 9/12/2024 and 9/19/2024

Table 2: Cluster Overview and Weight Adjustments

Cluster	Characteristics	EQUITY	BONDS	FX	COMMOD
0	High Growth, Upward Sloping Yield Curve	+0.10	-0.10	0.00	0.00
1	Decent Growth, Flat Yield Curve	+0.05	-0.05	+0.05	-0.05
2	Recession	-0.10	+0.10	-0.05	+0.05
3	High Inflation, Inverted Yield Curve	+0.05	-0.10	-0.05	+0.10

Table 3: Average Feature Importances

BONDS (Random Forest)

Feature	Mean Importance
Signal Return 22D	0.196206
Signal Return 65D	0.178719
Signal EMA 22D	0.168660
Signal EMA 65D	0.154543
Signal MACD 22D 65D	0.139060
Signal MACD 65D 260D	0.133240
Signal Bollinger 22D	0.027489
Signal Breakout 65D	0.002082

FX (Random Forest)

Feature	Mean Importance
Signal Return 22D	0.184533
Signal Return 65D	0.171569
Signal EMA 22D	0.164732
Signal EMA 65D	0.149149
Signal MACD 22D 65D	0.141456
Signal MACD 65D 260D	0.129974
Signal Bollinger 22D	0.041758
Signal Breakout 65D	0.016831

EQUITY (Random Forest)

Feature	Mean Importance
Signal Return 22D	0.193892
Signal Return 65D	0.173885
Signal EMA 22D	0.161568
Signal EMA 65D	0.148859
Signal MACD 22D 65D	0.137387
Signal MACD 65D 260D	0.128937
Signal Bollinger 22D	0.037072
Signal Breakout 65D	0.018400

COMMOD (Random Forest)

Feature	Mean Importance
Signal Return 22D	0.195511
Signal Return 65D	0.177832
Signal EMA 22D	0.157884
Signal EMA 65D	0.149158
Signal MACD 22D 65D	0.141671
Signal MACD 65D 260D	0.132829
Signal Bollinger 22D	0.043005
Signal Breakout 65D	0.002110

Table 4: Trading Signals with Descriptions and Formulas

Signal	Short Description	Formula
Return (22d)	Percentage return over the last 22 trading days.	$R_{22} = \frac{P_{22}-P_0}{P_0} \times 100$
Return (65d)	Percentage return over the last 260 trading days.	$R_{65} = \frac{P_{65}-P_0}{P_0} \times 100$
EMA(22d)	Moving average giving more weight to recent prices.	$\text{EMA}_t = \alpha P_t + (1-\alpha)\text{EMA}_{t-1}$(22d)
EMA(65d)	Moving average giving more weight to recent prices.	$\text{EMA}_t = \alpha P_t + (1-\alpha)\text{EMA}_{t-1}$(65d)
MACD (65d)	Average price over the last 65 days, used to smooth price data.	$\text{MACD}_{65} = \text{EMA}_{22} - \text{EMA}_{65}$
MACD (260d)	Indicates momentum.	$\text{MACD}_{260} = \text{EMA}_{65} - \text{EMA}_{260}$
Bollinger Bands (22d)	Volatility measure and provides upper and lower price levels.	Upper Band $= \text{SMA}_{65} + (2 \times \text{STD}_{65})$ Lower Band $= \text{SMA}_{65} - (2 \times \text{STD}_{65})$
Breakout Signal (65d)	Indicates a breakout when price exceeds the 65-day high/low.	Signal $= 1$ if $P_t > \text{High}_{65}$ (Breakout) Signal $= -1$ if $P_t < \text{Low}_{65}$ (Breakdown)

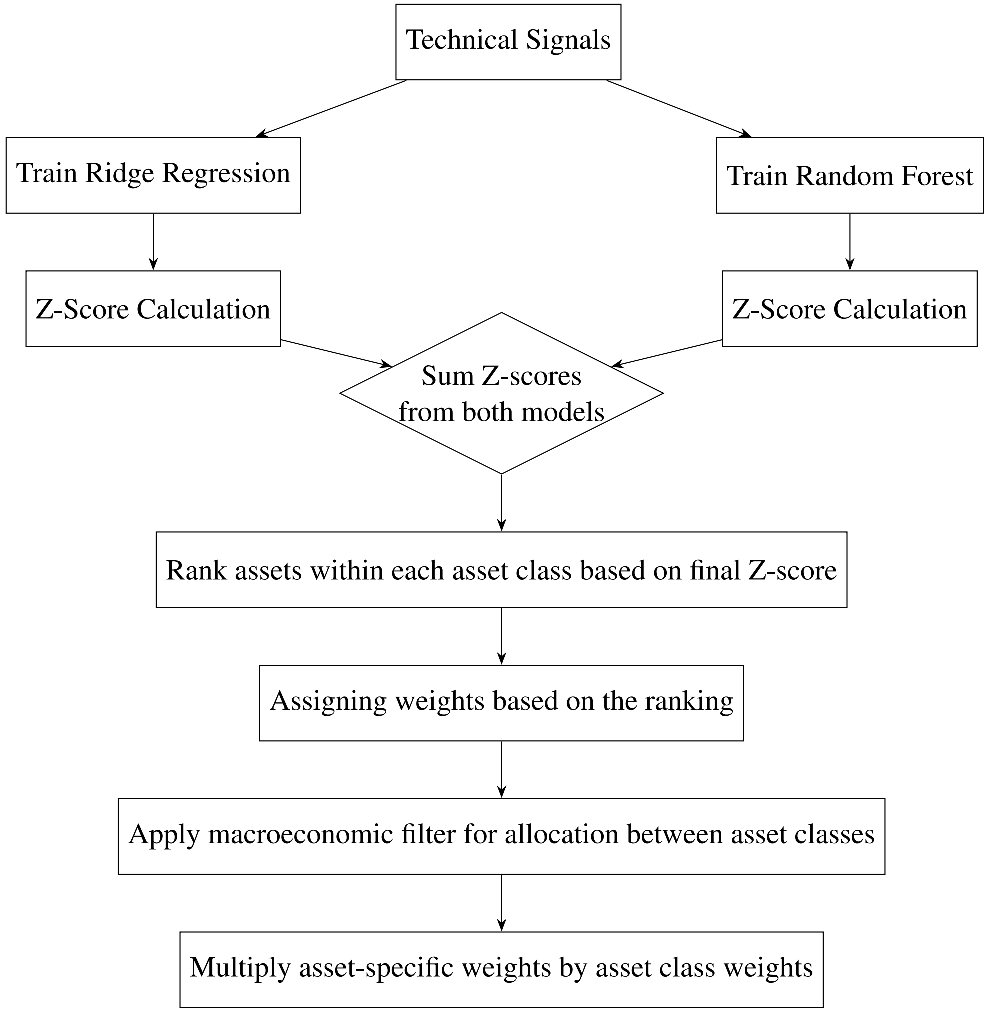

Figure 1: Flowchart of the strategy

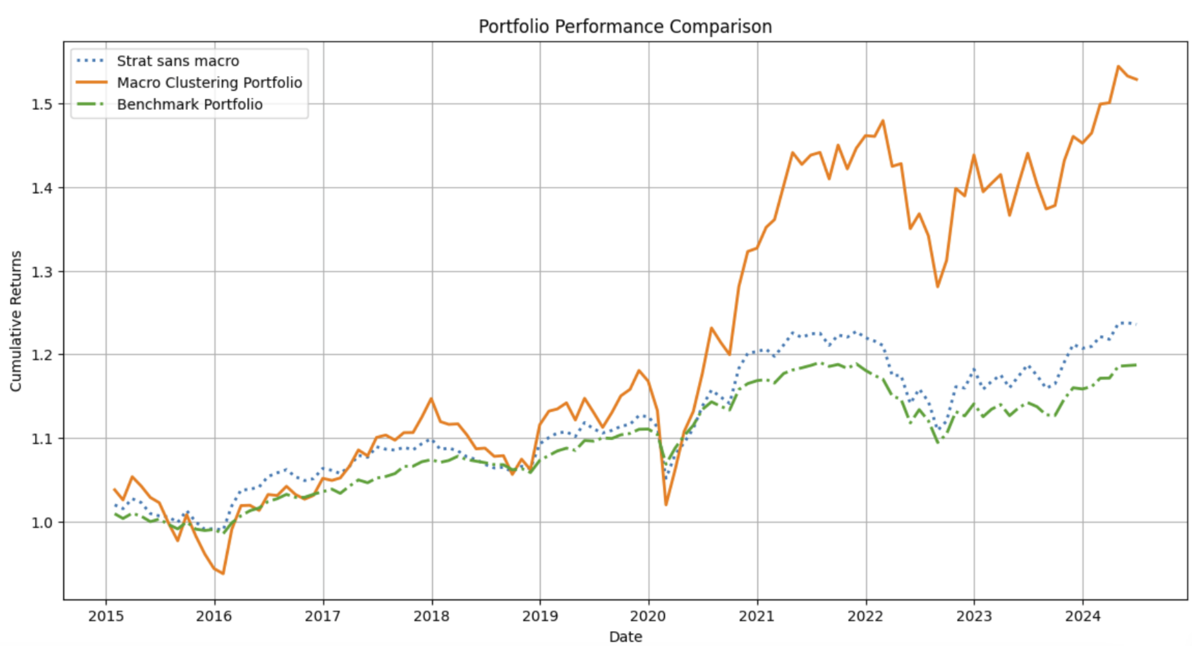

Figure 2: Cumulative Strategy Performance vs. Benchmark

Sources

Generative AI:

- AI was used for debugging, validating syntax, generating docstrings, producing the LaTeX document and the marathon logo.

Financial Data:

- All financial data mentioned above was retrieved from Bloomberg L.P. (2006). Historical price function {HP}. Retrieved from Bloomberg database on two dates, 9/12/2024 and 9/19/2024.

Machine Learning:

- David Ardia (2024), *MATH 60610A-Machine Learning Applied to Financial Data*, class notes, chapters 4 to 8. [PDF], HEC Montréal.

Signals:

- Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen. "Time Series Momentum." *Journal of Financial Economics*, vol. 104, no. 2, 2012, pp. 228-250. https://doi.org/10.1016/j.jfineco.2011.11.003.