NORTHERN TRUST
ASSET MANAGEMENT

RESEARCH REPORT

FACTOR MOMENTUM WITHIN FACTORS

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KEY FINDINGS

- We leverage two popular machine learning (ML) techniques in conjunction with linear regression to create a novel dynamically-weighted composite factor. We then construct a set of equity portfolios from the new ML-based composite factor and evaluate the portfolio's long-term risk and return performance.
- An empirical analysis of the stocks in the MSCI World Index shows that our ML-enhanced dynamically-weighted composite factor outperforms a naïve equally-weighted composite by 190 bps on an annualized basis in the most recent 22 year period.

SUMMARY

In this paper, we evaluate the long-term performance of quantile portfolios constructed from an ML-enhanced composite factor. The composite factor is based on a dynamic weighting scheme informed by the linear and nonlinear contributions of each underlying factor (signal) to the cross-section of stock returns. We leverage the beta estimates of a linear regression model on a moving average basis to construct an initial set of weights, giving incrementally higher weight to signals with higher beta estimates. To arrive at the ML-enhanced composite factor, we adjust the initial weighting scheme based on the degree of correlation between the signal contributions from the linear model and those from the nonlinear model. Signal contributions from the linear model are derived by multiplying the signal exposures of each stock by the corresponding beta estimates. There are two steps to quantify the contribution of a signal in a nonlinear model. First, we estimate an ensemble of weak models using a supervised machine learning technique called Extreme Gradient Boosting method (XGBoost). Second, we utlize a unified framework for explaining machine learning model results called Shapley Additive Explanations (SHAP). Signals with higher correlation between the linear and nonlinear contributions receive higher weight than those with lower correlation. By introducing this dynamic aspect to the signal weightings commensurate with recent performance, we demonstrate how composite factor performance may be improved relative to a naïve equally-weighted counterpart.

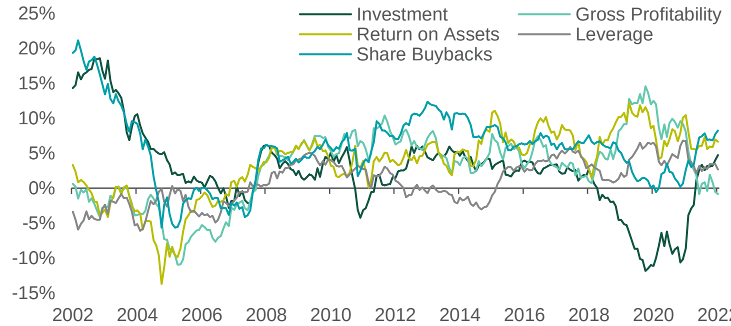
Style factor investing remains popular among investors seeking to beat a market cap-weighted benchmark. While style factors have historically outperformed over the long run, recent performance serves as a reminder that they are not entirely without drawbacks. Unfortunately, style factors are susceptible to prolonged periods of underperformance. Diversification represents the most popular method of mitigating factor cyclicality, applied both *across* factors (investing in more than one factor) and *within* factors (using more than one signal to define a factor). Another way of dealing with cyclicality is to introduce market timing – i.e. placing more (or less) emphasis on certain factors over time to increase return, reduce risk, or both. While factor timing is notoriously difficult, a growing body of literature[1] documents factor performance persistence. Factor momentum has thus been gaining popularity as a market timing tool. While most of the research has analyzed momentum at the factor level, the focus of this research report is whether momentum may be applied within a factor to accentuate the diversification benefits of multi-dimensional factors.

To illustrate the potential of combining diversification and momentum within factors, we plot the performance of five representative quality factors[2,3,4] (signals) in **Exhibit 1**. While the cumulative performance[5] of each signal is positive over the reported time period, the dispersion of returns over time clearly motivates diversification. The persistence of returns is

[1] See Zaremba and Shemer (2018), Gupta and Kelly (2019), Falck et al (2020), Arnott et al (2021), Ehsani and Linnainmaa (2022), Flögel et al (2022), and Ma et al (2023).
[2] See Exhibit A in the Appendix for the list of all variables used in this report and the category to which each belongs.
[3] We exclude financial and real estate stocks as some of the factors included in the analysis are not applicable to these sectors.
[4] All factors have been standardized within each region of the MSCI World Index.
[5] We present equally-weighted returns as we find them to be most relevant to the cross-sectional analysis of stock returns.

also obvious, as each signal has come in and out of favor over the past two decades. For example, the rolling three-year return of "Share Buybacks" has been positive almost entirely since June 2008, while "Investment" suffered negative returns for most of the period following 2018. This suggests that the performance of a composite quality factor can be enhanced by overweighting recent winners and underweighting recent losers.

Exhibit 1: Rolling Three-Year Long/Short Returns in the MSCI World Index (12/31/1999 – 12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data from 12/31/1999 to 12/31/2022. Long/Short returns represent the top quintile minus the bottom quintile. Quintile portfolios were equally-weighted and rebalanced monthly.

While the data in Exhibit 1 presents a case for signal diversification and momentum, there are some important issues to consider. Primarily, how can we effectively separate the contributions of individual signals within the context of the composite? This is particularly challenging given the similarities of some signals (e.g. earnings yield and cash flow yield both commonly appear in value composites). To complicate things further, asymmetries and interaction effects are increasingly important aspects of factor research, where the limitations of linear models are becoming more apparent.[6] While machine learning (ML) models offer the ability to account for these dynamics, they do so at the cost of transparency, interpretability, and an increased risk of overfitting. In light of these considerations, this research report utilizes both traditional linear regressions and nonlinear ML models to quantify each signal's contribution to the cross-section of stock returns. Our empirical analysis shows that adapting a factor composite based on the time-varying contributions of the underlying signals can improve performance vis-à-vis a naïve, equally-weighted counterpart. We continue our analysis of the quality factor to demonstrate our approach.

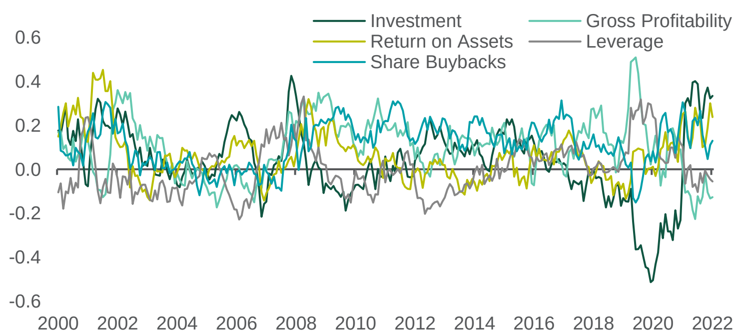
LINEAR REGRESSION FRAMEWORK

We begin our analysis by utilizing the traditional OLS framework to estimate monthly cross-sectional models using data from December 1999 to December 2022 within the MSCI World Index, and obtain the betas to each quality signal at every month end. The linear model takes the form:

$$r_{i,t+1} = \alpha + \beta_0 MarketBeta_{i,t} + \beta_1 x_{i,t}^{(1)} + \cdots + \beta_5 x_{i,t}^{(5)} + \beta_6 Value_{i,t} + \beta_7 Size_{i,t} + \beta_8 Mom_{i,t} + \varepsilon_{i,t+1} \quad \text{Eq. [1]}$$

where the dependent variable $r_{i,t+1}$ is the forward one-month active[7] return of security i relative to the MSCI World Index, and $x_{i,t}^{(1)},\ldots, x_{i,t}^{(5)}$ are the five popular quality signals[8] (Investment, Gross Profitability, Return on Assets, Leverage, and Share Buybacks). In addition to the quality variables of interest, we also include four control variables: sensitivity to market returns (Market Beta), Value, Size, and Momentum. The regression coefficients β_1 to β_5 measure the forward one-month active return's sensitivity to each quality signal in month t as described by Eq. [1]. In order to transform the estimated betas into a measure of momentum, we adopt a technique called Exponentially Weighted Moving Average (EWMA) to smooth the time series of our estimated betas using a 6 month[9] half-life. **Exhibit 2** plots the time series of smoothed betas for each of the five quality signals, which reflect the average cross-sectional return contribution per unit of each signal, with more weight assigned to recent performance. Compared to the signal returns shown in Exhibit 1, the beta coefficients are more volatile, even after applying the EWMA technique. Despite the differences, we do observe some similarity between the two charts which serves as a sanity check for our linear results. For example, the plunge of Investment and the peak of Gross Profitability in beta coefficients around 2020 synchronize with their respective individual signal's performance in Exhibit 1.

Exhibit 2: EWMA Linear Regression Coefficients in the MSCI World Index (12/31/1999 – 12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data from 12/31/1999 to 12/31/2022.

[6] See Koenker (2005), and Allen and Singh (2011).

[7] Active return is computed as the stock return minus the equally-weighted average of the index, and scaled for readability.

[8] All independent variables (including control variables) have been winsorized by date and standardized within each region.

[9] While implementation is not the focus of this research report, a 6 month half-life was chosen with turnover considerations in mind.

Next, we use the smoothed time series to inform our dynamic weighting scheme of the composite quality factor. Specifically, at each month end, we rank the five signals by their smoothed betas from the smallest to the largest. Then we assign weights of 0.10, 0.15, 0.20, 0.25, and 0.30 to the signals from the lowest rank (1) to the highest rank (5). In contrast to a static, equally-weighted definition (which serves as our baseline[10]), this linear-model-informed scheme is time-varying and tilted towards the best performing contributors and away from the worst ones. The linear-model-informed composite factor ("linear" composite factor henceforth) is then defined as the weighted sum of all five standardized signals. We will compare the performance of the baseline and "linear" composite factor after introducing the ML framework in the next section.

MACHINE LEARNING AND SHAPLEY VALUE FRAMEWORK

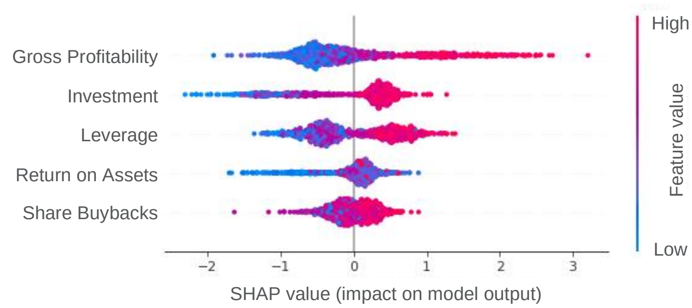
Machine learning models have gained popularity in quantitative finance in recent years for several advantages compared to traditional linear models. First, ML models excel at identifying hidden trends and patterns, which could prove useful in the detection and measurement of factor momentum. Second, ML models allow for more flexible functional forms and are therefore capable of capturing nonlinearities and interaction effects which are material to a signal's behavior. Third, ML models are adept at handling high-dimensional feature sets which traditional statistical models often struggle with (e.g. the notorious multicollinearity issue[11]). This paper leverages Extreme Gradient Boosting method (XGBoost), a decision-tree-based ensemble ML algorithm. XGBoost has been shown to outperform other machine learning algorithms in a variety of tasks, including regression and ranking, and is well-suited to capture the aforementioned elements which are missing in linear models.

To effectively explain the cross-sectional variation in forward active returns, we look for a function which takes the general form described in Eq. [2], and does not assume any specific relationship between or among the features and the target variable.[12] The XGBoost algorithm determines a function $f(\cdot)$ that minimizes the error term $\varepsilon_{i,t+1}$ (refer to Exhibit B in the Appendix for an example of an XGBoost regression tree).

$$r_{i,t+1} = f(x_{i,t}^{(1)}, \dots, x_{i,t}^{(5)}, MarketBeta_{i,t}, Value_{i,t}, Size_{i,t}, Mom_{i,t}) + \varepsilon_{i,t+1} \qquad \text{Eq. [2]}$$

Given the form of the XGBoost function, there are no directly observable model outputs analogous to OLS regression coefficients to quantify the effect of each feature on the target variable. To solve this problem, we borrow a concept in game theory called Shapley Value to derive each signal's marginal contribution to a stock's active return in the ML model. The theoretical framework of Shapley Value assigns a "fair" distribution among the players of a total surplus generated by the coalition of all players, and measures the average marginal contribution of each player to the total coalition payoff.[13] This framework fits well within our research question: individual signals are players who together contribute to the active returns of each stock, taking interaction effects among signals into account. As an added benefit, the Shapley Value framework assists in the interpretation of nonlinear model results, thereby making them more intuitive.[14] For these reasons Shapley values have become ubiquitous in ML.

Exhibit 3: XGBoost Shapley Value Distributions of Quality Signals in the MSCI World Index (8/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data as of 8/31/2022.

To obtain the Shapley values for each signal at the security level, we first estimate a series of XGBoost models at each month end using the same sample as the linear model. The technical details of model estimation (including hyperparameter tuning) and Shapley Value computation are described in the Appendix. For a given month, we can plot the Shapley Value distribution of each signal as shown in **Exhibit 3**. The signals are ranked from top to bottom in terms of importance. For the given month shown (8/31/2022), Gross Profitability was the biggest positive contributor to stock performance, as indicated by it having the largest spread in SHAP values, and higher SHAP values associated with higher signal values. More interestingly, the plot visualizes the asymmetric property of the signal contributions among stocks in the MSCI World universe – an insight which is missing in linear models. High values for Gross Profitability (the red dots) were associated with large forward active returns, as evidenced by the positive skew of the distribution. On the other hand, low values for Gross Profitability had smaller impacts on active returns, as indicated by the concentration of blue dots plotting between zero and -1. In

[10] The equally-weighted composite factor contains the same five quality signals, with each one assigned a constant weight of 0.2.

[11] The variance inflation factor (VIF) of each quality signal used in our analysis falls well below generally accepted thresholds for multicollinearity (4 or above). However, multicollinearity is an important consideration for general applications of OLS.

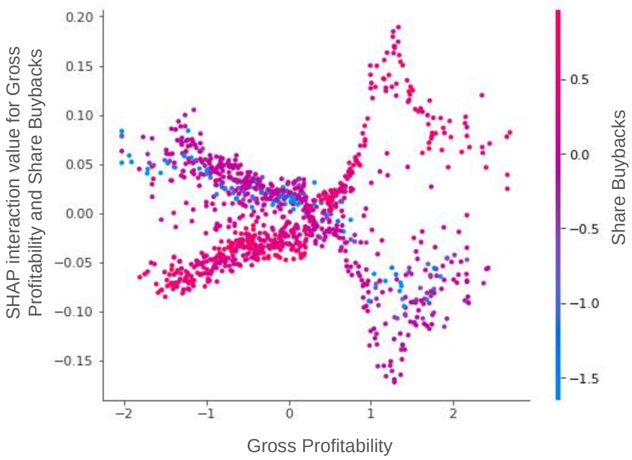
[12] The definitions of the target variable and features are the same as those in the linear model.

[13] The technical notes in the Appendix provide mathematical details of Shapley Value.

[14] See Lundberg and Lee (2017).

contrast, Investment had the largest negative impact on stock returns among all signals, with its SHAP values plotting furthest to the left, while the positive impact of the signal was limited. Note that unlike linear models, there need not be a direct relationship between signal values and Shapley values. In other words, while it is usually the case that higher (lower) signal values have larger Shapley values (posititve or negative), it is not strictly enforced by the model – blue dots may be found among red dots, and vice-versa.

Exhibit 4: Example of Interaction Effect between Quality Signals in the MSCI World Index (12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data as of 12/31/2022.

In addition to the signal contributions reported in Exhibit 3, the Shapley Value framework provides us with insights into the interactions among signals. To demonstrate this, we plot a dependence plot with SHAP interaction values between Gross Profitability and Share Buybacks in **Exhibit 4**. The dispersion of dots to the right indicates that the interaction effect increased as Gross Profitability increased, where Share Buybacks effectively separated winners from losers. High values for Share Buybacks (denoted by red dots) were associated with positive interaction values, whereas low values (denoted by purple and blue dots) were negative. This example shows that the strength of the interaction effect may jointly depend on both signals, and the relationship may be nonlinear.

The asymmetry and interaction effects revealed by ML models represent important dynamics that are not accounted for by linear models, and could therefore enhance our measure of signal momentum. In the next section, we will explore a method of combining both models to refine our weighting scheme.

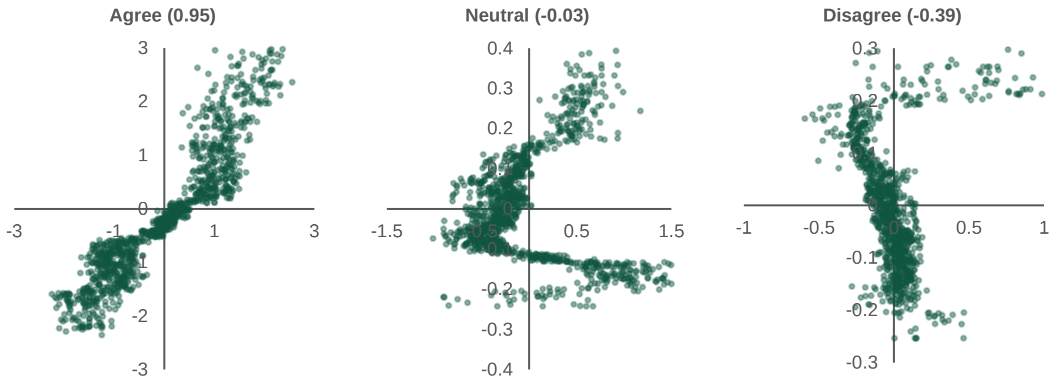
USING MACHINE LEARNING TO STRENGTHEN FACTOR PERFORMANCE

When determining how to combine the results of both models into a single weighting scheme our considerations were both philosophical and practical. We generally favor simpler models over more complex ones, given the transparency and interpretability they provide. From a practical standpoint transaction costs must be taken into account, and momentum is a fast-moving signal relative to other style factors. Holding all else equal, models with higher degrees of freedom have greater potential to fit to noise and induce higher levels of turnover. For these reasons, our approach to combining models anchors first to the results of the linear model and then incorporates the ML model as a signal strength indicator. To integrate the ML model, we evaluate the degree of similarity between the linear and nonliner model results for each signal. Specifically, we compute the spearman rank correlation between the signal contributions from the OLS model and those from the XBGoost model at every month end. For the linear model, the signal contribution may be derived by multiplying the regression coefficient (β_i) by the security's signal exposure (x_i). This product ($\beta_i x_i$) is directly equivalent to the corresponding Shapley Value[15] of the nonliner model. The correlation across all stocks in the index represents the degree to which linear and nonlinear models agree on each signal's contribution to the cross-section of active returns.

To illustrate how the agreement can vary over time, we plot the active return contributions for Gross Profitability in the MSCI World Index for three distinct months in **Exhibit 5**. While the right-most panel (August 2022) shows that it is possible for the two models to disagree, negative correlations are not common. For example, the correlation for Gross Profitability was negative in only 34 out of the 276 months in our analysis period.

[15] Shapley values are not relevant to linear models since the signal contributions may be computed directly as described here.

Exhibit 5: Scatterplots of Gross Profitability Active Return Contributions in the MSCI World Index November 30, 2018 (Agree), December 31, 2011 (Neutral), and August 31, 2022 (Disagree)



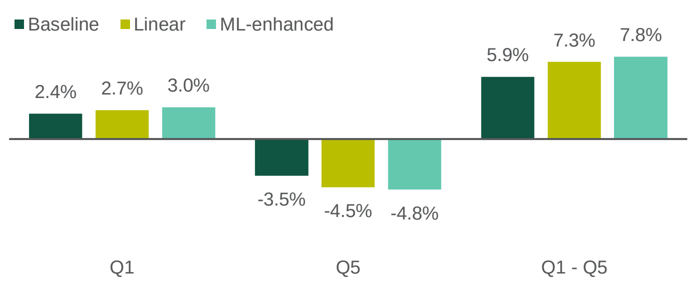
Source: Northern Trust Quantitative Research, MSCI, FactSet. XGBoost contributions (Shapley values) plotted on the x-axis. OLS contributions ($\beta_i x_i$) plotted on the y-axis. Spearmen rank correlations reported in parenthesis at the top of each scatterplot.

In order to transform the monthly correlations into a measure of signal strength, we apply the same EWMA methodology as before using a 6 month half-life (for the time series of each quality signal refer to Exhibit C in the Appendix). We then define a threshold to "boost" the weighting scheme of the linear model described previously, rescaling the weights as required. To illustrate this methodology and evaluate the impact of both the linear and ML-enhanced dynamic weighting schemes, we extend our analysis of the quality factor by way of a case study.

We begin our case study by choosing 0.45 as the threshold[16] for signal boosting, and 0.05 as the incremental weight to assign boosted signals. At every month end we examine two things for each signal: (1) whether the threshold is breached, and (2) whether that signal is over-weighted (rank 4 or 5) or under-weighted (rank 1 or 2) in the linear framework. If both conditions are met, we add (subtract) an extra 0.05 to the signal weight if it is over-weighted (under-weighted) by the linear framework. We do this procedure for each signal and then proportionally adjust the weights across all five signals so they sum to 1. We then construct the ML-enhanced composite factor as the weighted sum of all five standardized signals (as we have done for the linear factor).

To evaluate the relative performance of our baseline, linear, and ML-enhanced quality factors, we rank and sort all constituents in the MSCI World Index by each respective composite factor score and bucket all stocks into five equal groups (quintiles) by count (20% of index constituents). Quintile portfolios were equally-weighted and rebalanced monthly. **Exhibit 6** compares the active return[17] of all three composite factors using this methodology from 12/31/2000[18] through 12/31/2022. The annualized returns show the general efficacy of the quality factor as well as the incremental benefits of the two dynamic weighting schemes. Over the 22-year period ending 12/31/2022, the top portfolio (Q1) outperformed the bottom portfolio (Q5) by 5.9% (2.4% vs. -3.5%) in the baseline, whereas the performance spread increased to 7.3% in the linear factor and 7.8% in the ML-enhanced version, respectively.

Exhibit 6: Active Return Comparison of Composite Quality Factor Portfolios in the MSCI World Index (12/31/2000 – 12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data from 12/31/2000 to 12/31/2022. Quintile portfolios were formed by composite factor scores, equally weighted, and rebalanced monthly.

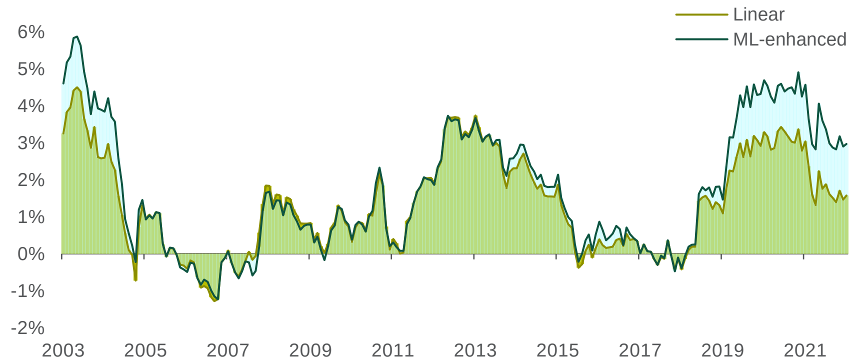
[16] 0.45 corresponds approximately to the 75th percentile of EWMA correlations across all quality signals. Each EWMA time series exhibits evidence of stationarity.

[17] Active return is computed as the portfolio return minus the equally-weighted index return to ensure a like-for-like comparison.

[18] Though our dataset begins in 12/31/1999 the linear and nonlinear models require a 12 month warm-up period.

To demonstrate the consistency of our dymanically-weighted factors, we plot the rolling three-year long/short return difference between the dynamically-weighted composites and the baseline composite in **Exhibit 7**. The performance improvement for both the linear and ML-enhanced composites is robust across the time period analyzed – the trailing three-year return difference of each method was positive 84% of the time (both lines plot above zero in 193 of the 229 months reported). Exhibit 7 also reveals that the most notable periods of incremental ML-enhanced performance (the blue shaded regions) occur at the start and end of our analysis period. This is intuitive as it aligns with the large and protracted periods of signal dispersion reported in Exhibit 1. From this perspective, the ML-enhanced model is working as desired, detecting periods where signals are strongly in favor (out of favor) and steepening the tilt accordingly. This encouraging result suggests that our approach of complementing traditional methods with machine learning could generalize effectively as a fusion of classic modeling and modern data science.

Exhibit 7: Rolling Three-Year Long/Short Return Difference between Dynamically-Weighted Quality Composites vs. Baseline Quality Composite in the MSCI World Index (12/31/2000 – 12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data from 12/31/2000 to 12/31/2022. Long/Short returns represent the top quintile minus the bottom quintile. Quintile portfolios were formed by composite factor score, equally weighted, and rebalanced monthly.

CONCLUSION

Multi-dimensional factor definitions are essential to capturing factor premia efficiently. Effective factor design requires evaluating the contribution of individual signals to the broader composite. In this research report, we utilize both traditional linear regressions and nonlinear ML models, in conjunction with Shapley values, to quantify each signal's marginal contribution to the cross-section of stock returns. We then develop a framework to enhance a composite factor's definition by introducing a dynamic weighting scheme to capture the momentum effect among the underlying signals. Our linear and ML-enhanced dynamically-weighted factors demonstrate materially better long-term performance than a naïve equally-weighted counterpart. We believe the integration of machine learning as a complement to traditional models is an effective method of harnessing the potential of data science in finance.

APPENDIX

Methodology Notes

Shapley Value

Shapley Value is a concept originally developed in cooperative game theory and named after Lloyd Shapley in his seminal paper *A Value for n-Person Games (1953).* His research question is: what is a “fair” way for a coalition to divide its payoff? In the paper, he derives a unique solution to evaluate members’ marginal contributions from three basic axioms: symmetry, dummy players, and additivity. The mathematical definitions of Shapley Value for each player $\emptyset_i$ is described below:

$$\emptyset_i(N, v) = \frac{1}{N!} \sum_{S \subseteq N \setminus \{i\}} |S|!\,(|N| - |S| - 1)!\,[v(S \cup \{i\}) - v(S)] \qquad \text{Eq. [3]}$$

Where i = each player;
N = entire set of players;
v = coalition’s payoff;
S = certain coalition;

Machine Learning Model Estimation

To adjust the various hyperparameters of the XGBoost algorithm to optimize the model's performance, we use a Bayesian optimization method together with K-fold cross-validation. We select eight parameters important in controlling the model’s behavior (listed in the table below).

Hyperparameter	Function
eta/learning_rate	Step size shrinkage used in update to prevent overfitting
max_depth	Maximum depth of a tree; used to control model complexity and prevent overfitting
subsample	Subsample ratio of the training instances; used to prevent overfitting
min_child_weight	Minimum sum of instance weight needed in a child. The tree building process will stop further partitioning if the tree partition step results in a leaf node with the sum of instance weight less than min_child_weight.
colsample_bytree	Subsample ratio of columns when constructing each tree
gamma/ min_split_loss	Minimum loss reduction required to make a further partition on a leaf node of the tree
reg_alpha	L1 regularization term on weights
reg_lambda	L2 regularization term on weights

The Bayesian optimization method builds a probability model of the objective function (in our case to minimize the squared errors in regressions) and use it to select the most promising hyperparameters to evaluate in the true objective function. Compared to other popular hyperparameter tuning methods, such as grid search and randomized search, Bayesian optimization significantly reduces the time spent to arrive at an optimal set of parameters, and is documented to bring better generalization performance on the test set.

To effectively evaluate models in the hyperparameter tuning process, we utilize K-fold cross-validation where we divide the input dataset into 5 groups of samples of equal sizes (K=5). For each group, the function uses four folds (K-1) for the training purpose and the rest (one fold) is used for the test set. The K-fold cross-validation approach allows us to use more data for training and helps us avoid overfitting.

Both hyperparameter tuning and Shaley Value computing[19] are computationally intensive. With the help of our cloud platform, we gain access to virtual machines with large computation capacity to fully harness Ray, an open-source distributed computing application. The use of these advanced technologies enables us to run multiple iterations in parallel, thereby significantly reducing the total runtime relative to local desktop execution.

[19] We use a measure called SHapley Additive exPlanations (SHAP) value for Shapley values in ML models. The measure was first introduced by Lundberg and Lee (2017). The computing time for Shapley values grows exponentially as the number of features increases. Four features mean 64 total coalitions to consider; 32 features increases the number of coalitions to 17.1 billion.

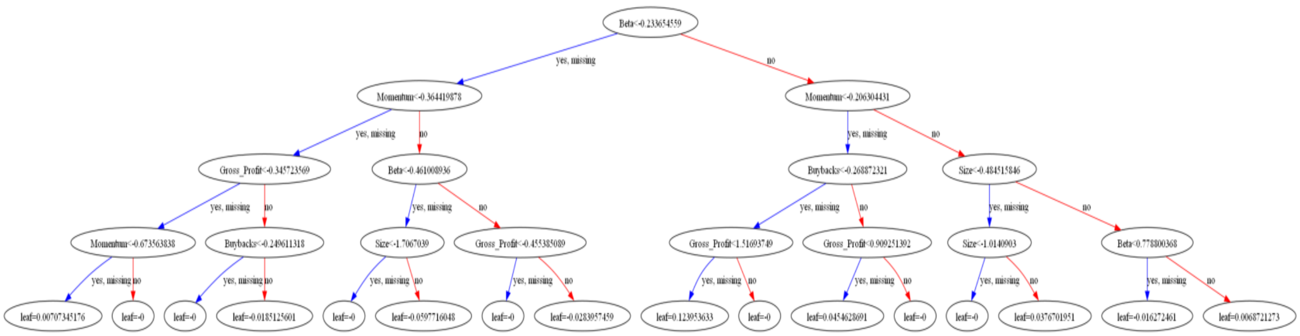
Supplemental Exhibits

Exhibit A: Definition of Stock Characteristics as Model Features

Features	Category	Definition
Investment	Quality	Year-on-year percentage change in total assets
Gross Profitability	Quality	Sales net of Cost of Goods Sold divided by assets
Return on Assets	Quality	Net income divided by net operating assets
Leverage	Quality	Total debt divided by total assets
Share Buybacks	Quality	Changes in shares over the last three years
Market Beta	Market	Sensitivity to the market returns, derived from GEMLT risk model
Size	Size	Log of market capitalization
Book to Price	Value	Book value of equity divided by market capitalization
Momentum	Momentum	Stock performance over the last 12 months excluding the most recent month

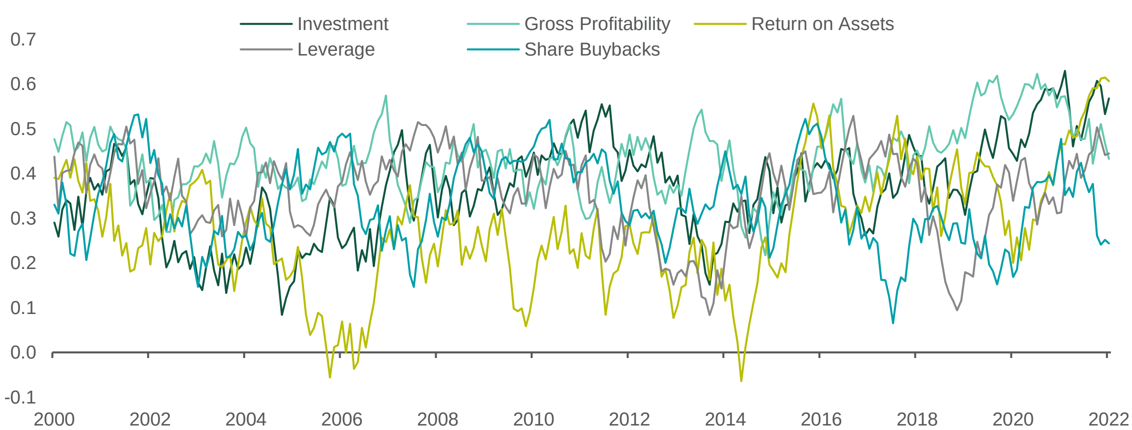
Note: The values of Investment, Leverage, and Share Buybacks are negated so that signal scores are directionally aligned with factor premia.

Exhibit B: Illustrative Example of an XGBoost Regression Tree in the MSCI World Index (12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet.

Exhibit C: EWMA Shapley Value Spearman Rank Correlations Between Linear (OLS) and Nonlinear (XGBoost) models in the MSCI World Index (12/31/1999 – 12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data from 12/31/1999 to 12/31/2022. Exponentially weighted moving average (EWMA) coefficients computed with a 6 month half-life.

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Important Information

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