Current Affairs **November 5, 2026**

PUTTING THE ALPHA IN ALPHAROC

Consumer Surveys and Sentiment in Macro Models

- **AlphaROC.** In this research, we introduce and analyze AlphaROC's proprietary survey database, which covers more than 270 million US consumer profiles and includes more than 5,000 surveys across a broad range of economic and demographic categories. Through its Occam platform, AlphaROC provides timely macroeconomic nowcasts and granular survey responses segmented by demographic, socioeconomic, and geographic characteristics, allowing us to examine relationships that traditional aggregate indicators may overlook.
- **Surveys, Forecasts, and the Real Economy.** By examining survey responses across demographic and socioeconomic groups, we find meaningful relationships with labor market conditions, inflation, GDP growth, and consumer spending, with correlations generally stronger than those observed in our previous research. Comparing AlphaROC data with our proprietary QES indicators, we find that HDI exhibits stronger relationships with measures of current and historical financial conditions, while COMPASS captures more forward-looking consumer expectations, particularly among higher-income and older households. Evaluating the forecasting ability of AlphaROC data, we find that combining AlphaROC and QES forecasts improves overall predictive performance, suggesting that AlphaROC's survey-based information provides complementary signals that can enhance existing macroeconomic forecasting models.
- **Asset Return Implications.** We investigate whether granular AlphaROC consumer sentiment data can improve systematic asset allocation and style factor rotation by incorporating survey data into our existing forecasting framework. To evaluate the incremental predictive value of these signals, we compare five modeling approaches—OLS, xRFM, CatBoost, RealMLP, and Kumo-Tabular. Incorporating AlphaROC data produces substantial improvements for nonlinear models, particularly CatBoost, which achieves a 41% increase in average rank IC to 17.9% for asset allocation. Overall, our findings suggest that granular consumer sentiment provides incremental predictive information for investment strategies
- **Current Strategic Outlook.** In the near term, our GTAA models favor commodities, US small-cap equity, and international DM equity; and are cautious on crude oil, US Treasury bonds, and EM credit. Sector-wise, we currently overweight information technology, energy, and industrials. Among style factors in the US, we prefer EBITDA/TEV, earnings yield, ROE, dividend yield, and earnings quality. In Europe, we expect EBITDA/TEV, ROE, dividend yield, short-term growth, and earnings yield to outperform.



Source: ChatGPT

Jesse Neumann, PhD
JNeumann@wolferesearch.com

Yin Luo, CFA, CPA
YLuo@wolferesearch.com

Gaurav Rohal, CFA
GRohal@wolferesearch.com

Shu Liu
SLiu@wolferesearch.com

Xiaohui (Victor) Li
XLi@wolferesearch.com

Larry Chen
LChen@wolferesearch.com

Jenny Huang
JHuang@wolferesearch.com

Max Gao, CFA
MGao@wolferesearch.com

Javed Jussa
JJussa@wolferesearch.com

Sheng Wang
SWang@wolferesearch.com

Hallie Martin
HMartin@wolferesearch.com

Kai Wu
KWu@wolferesearch.com

David Elledge, CFA
DElledge@wolferesearch.com

QES Desk: 1.646.582.9230
Luo.QES@wolferesearch.com

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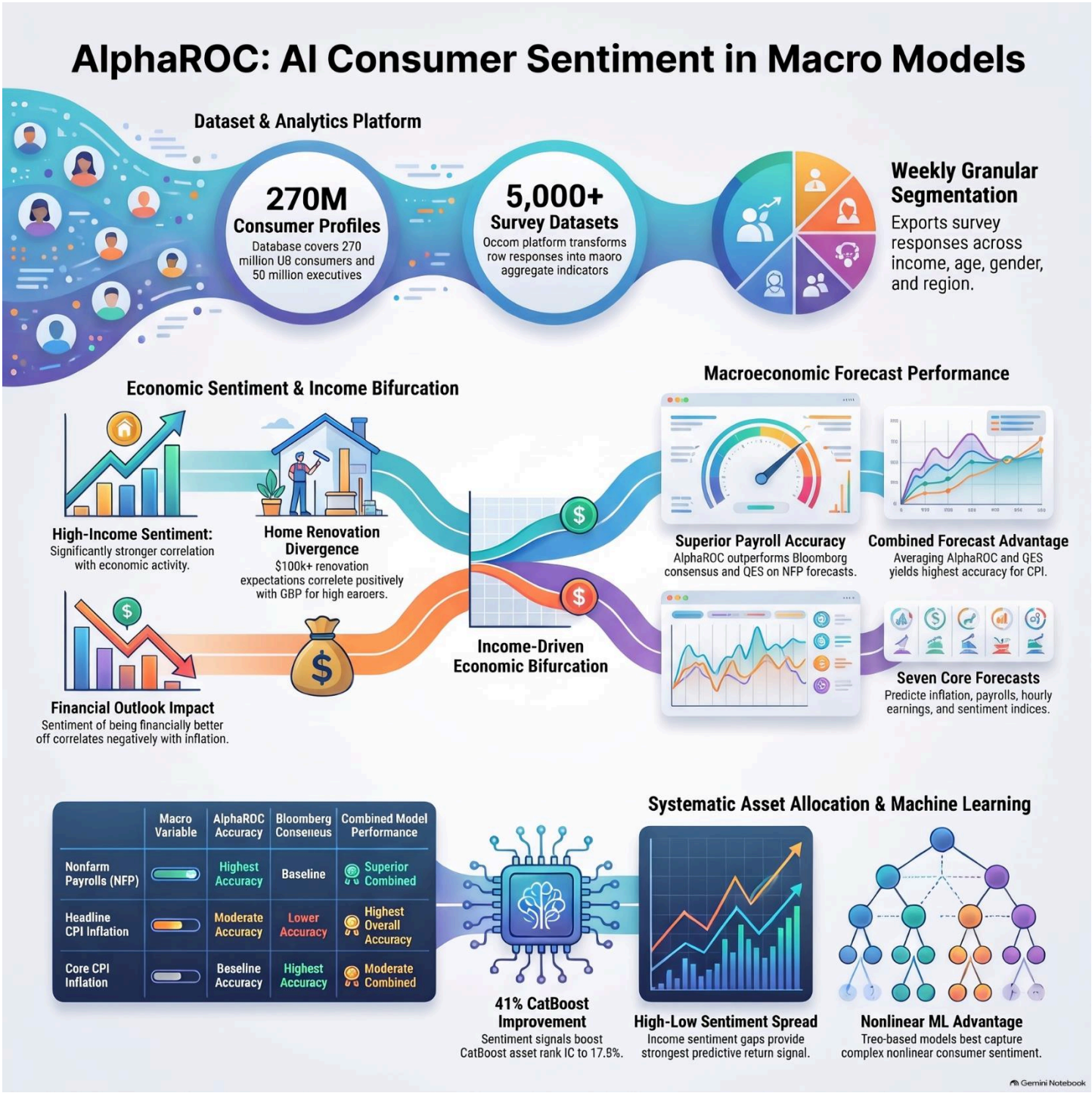
A High-Level Infographic Overview

Before we dive into the details, Figure 1 provides a high-level overview.

Figure 1 A High-Level Infographic Overview



Sources: NotebookLM, Wolfe Research Luo's QES

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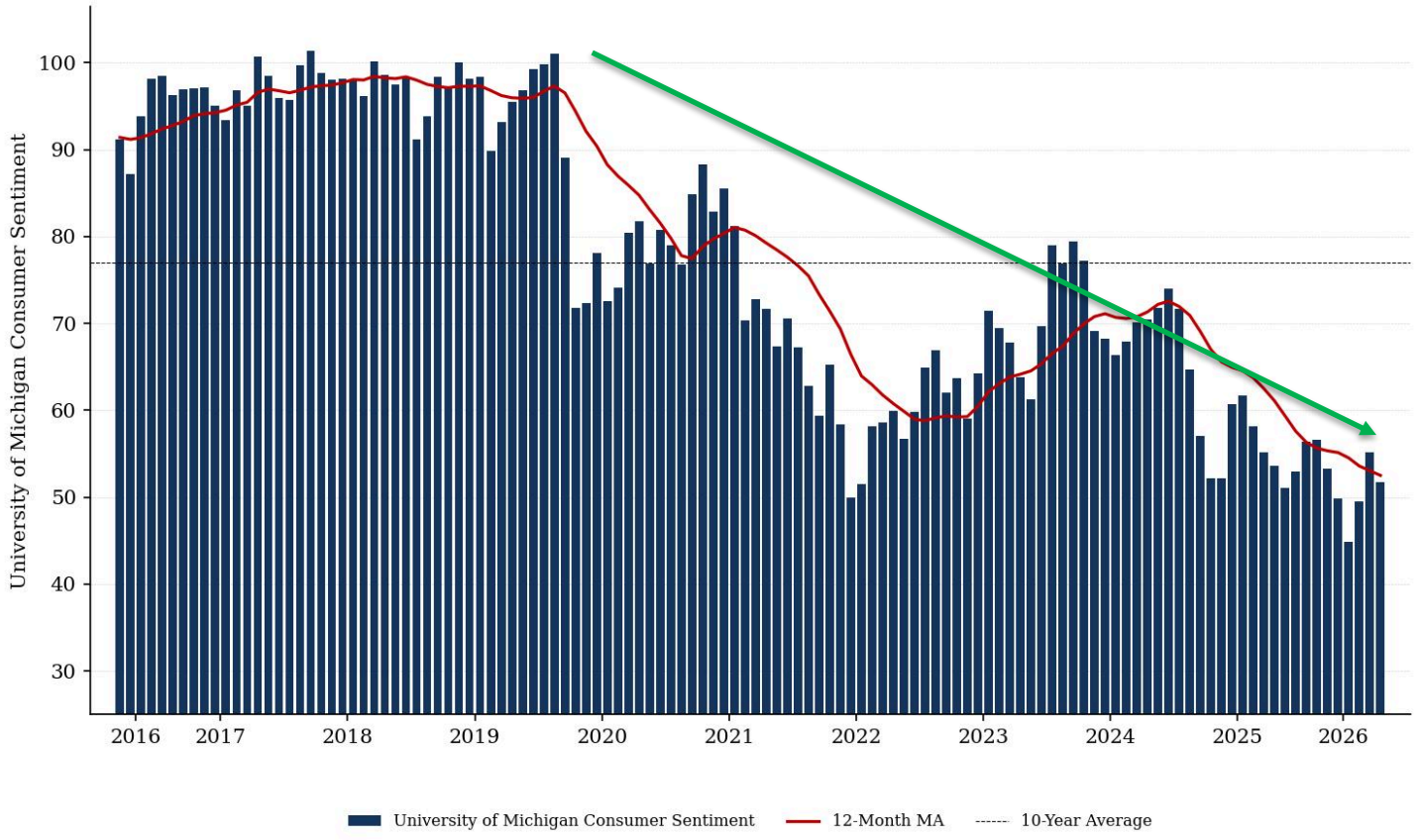
ALPHAROC: A NEW CONSUMER SENTIMENT DATASET

Consumer sentiment sits at the intersection of the real economy and financial markets. It captures how households assess their personal finances, spending expectations, inflation, labor market conditions, and the broader economic outlook, while also reflecting the reinforcing relationship between asset prices and consumer confidence. Recent academic research has shown that this relationship operates in both directions: stronger equity markets can boost confidence through wealth effects, while changes in consumer sentiment can influence future asset returns by shaping spending expectations, risk appetite, and investor positioning (see Gaspar and Jiaming [2025]). However, there is also evidence that these relationships are state-dependent, with stronger effects during periods of heightened uncertainty (see Chung, et al. [2012] and Ginn and Saadaoui [2026]). Given the elevated economic and geopolitical uncertainty in the current environment, these findings are particularly relevant.

For investors, the key takeaway is that consumer sentiment is more than a survey-based measure of household confidence. It can provide early indications of the sustainability of consumer spending, financial markets' resilience to macroeconomic shocks, and the extent to which asset prices are supported by economic fundamentals rather than investor psychology. With aggregate consumer sentiment hovering near historical lows (see Figure 2), we believe this is an appropriate time to revisit the empirical relationships between consumer confidence, economic activity, and asset performance.

Figure 2 University of Michigan Consumer Sentiment



Sources: International Monetary Fund, Yahoo! Finance

However, our previous research also suggests that headline consumer sentiment indicators rarely capture the full picture. In *AI-Powered Consumer Sentiment* (see Neumann, et al [2025b]), we demonstrate that sentiment among

high-income consumers is more important for economic activity than aggregate consumer confidence, while the spread between high- and low-income consumer sentiment provides the strongest predictive information for asset returns. In *The Unsolicited Economic Outlook Survey* (see Neumann, et al [2026]), we examine sentiment from a corporate perspective, extending traditional Purchasing Managers' Index (PMI) measures by extracting macroeconomic insights from management commentary during earnings calls. Building on this framework, in *An LLM-Based Measure of Interest Rate Uncertainty* (see Luo, et al [2026]), we further demonstrate that disagreement in management sentiment can provide valuable information about monetary policy expectations and interest rate uncertainty.

In this research, we extend our investigation of granular consumer sentiment by examining proprietary survey data from AlphaROC. AlphaROC specializes in AI-driven market research, offering integrated data collection, analysis, and analytics platforms. The company conducts surveys across more than 50 countries, with its proprietary US database covering more than 270 million individual consumer profiles and over 50 million business executives, allowing for highly targeted consumer and business-to-business (B2B) research. One advantage of this survey-based data is its intuitive interpretation, as respondents provide straightforward answers to economically relevant questions. For example, responses to the question, "Do you expect you and your family to be better off financially in a year?" include "Better off," "About the same," and "Worse off." Similarly, responses to "How would you rate employment conditions today?" include "Jobs are plentiful," "Jobs are not so plentiful," and "Jobs are hard to get." Importantly, once AlphaROC initiates a particular survey, it generally continues collecting responses at regular intervals, creating substantial historical datasets, in some cases extending back to 2019. Certain surveys are available at a weekly frequency, with responses further segmented across demographic and socioeconomic groups.

AlphaROC's flagship platform, Occam, is an AI-native analytics platform that transforms raw survey responses into aggregate indicators across more than 5,000 individual surveys (see Figure 3). Data from Occam can be exported for further quantitative analysis or integrated directly into internal large language model (LLM) workflows through an application programming interface (API).

Figure 3 Occam Platform



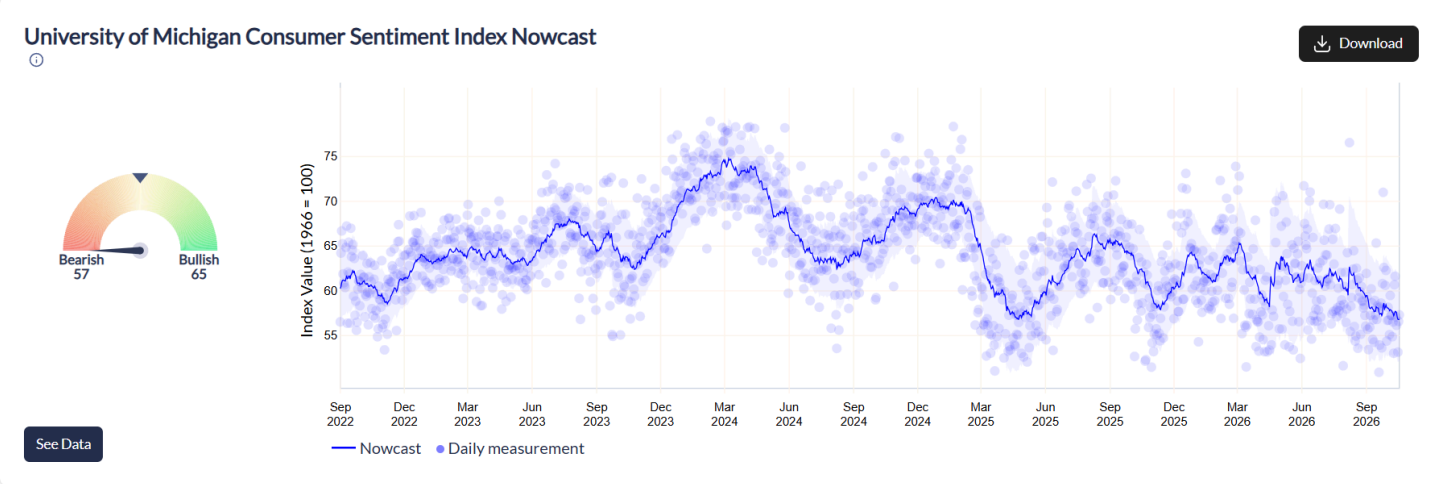
Sources: AlphaROC Occam

Consistent with our previous research on extracting more timely and granular economic information than traditional aggregate surveys can provide (e.g. Neumann, et al [2026]), AlphaROC leverages its extensive survey database to produce timely estimates of widely followed sentiment indicators while providing additional insights

into their underlying drivers. As shown in Figure 4(A) AlphaROC produces a nowcast of the University of Michigan Consumer Sentiment Index, while Figure 4(B) presents the underlying survey series used to construct the estimate.

Figure 4 Consumer Sentiment Nowcast and Underlying Data Series

A) AlphaROC Consumer Sentiment Nowcast



B) Nowcast Underlying Survey Series

Topic	Question	Show details	Participants	Data since
Financial Condition vs 1 Year Ago	Are you and your family better off financially than you were a year ago?		957,065	May 2020
Good Time for Major Purchase	Is now a good time to buy major household items?		962,536	April 2020
Financial Condition in 1 Year	Do you expect you and your family to be better off financially in a year?		869,797	April 2020
Economic Conditions Next Five Years	Will we have good times or bad times financially over the next 5 years?		911,861	April 2020
Business Conditions Next 12 Months	Do you think businesses will have good times or bad times over the next 12 months?		920,738	April 2020

Sources: AlphaROC Occam

For each survey included in AlphaROC's macroeconomic forecasts and nowcasts, individual responses can be exported across a range of demographic, socioeconomic, and geographic categories. The same level of detail is also available for surveys not incorporated into AlphaROC's proprietary forecasting models. As we demonstrated in *AI-Powered Consumer Sentiment* (see Neumann, et al [2025b]), these granular distinctions can be just as important, if not more important, than the underlying survey questions themselves. Accordingly, Figure 5 summarizes the available response categories within Occam, including major demographic characteristics (e.g., age, gender, and race), socioeconomic attributes (e.g., household income and education), and geographic classifications (e.g., region).

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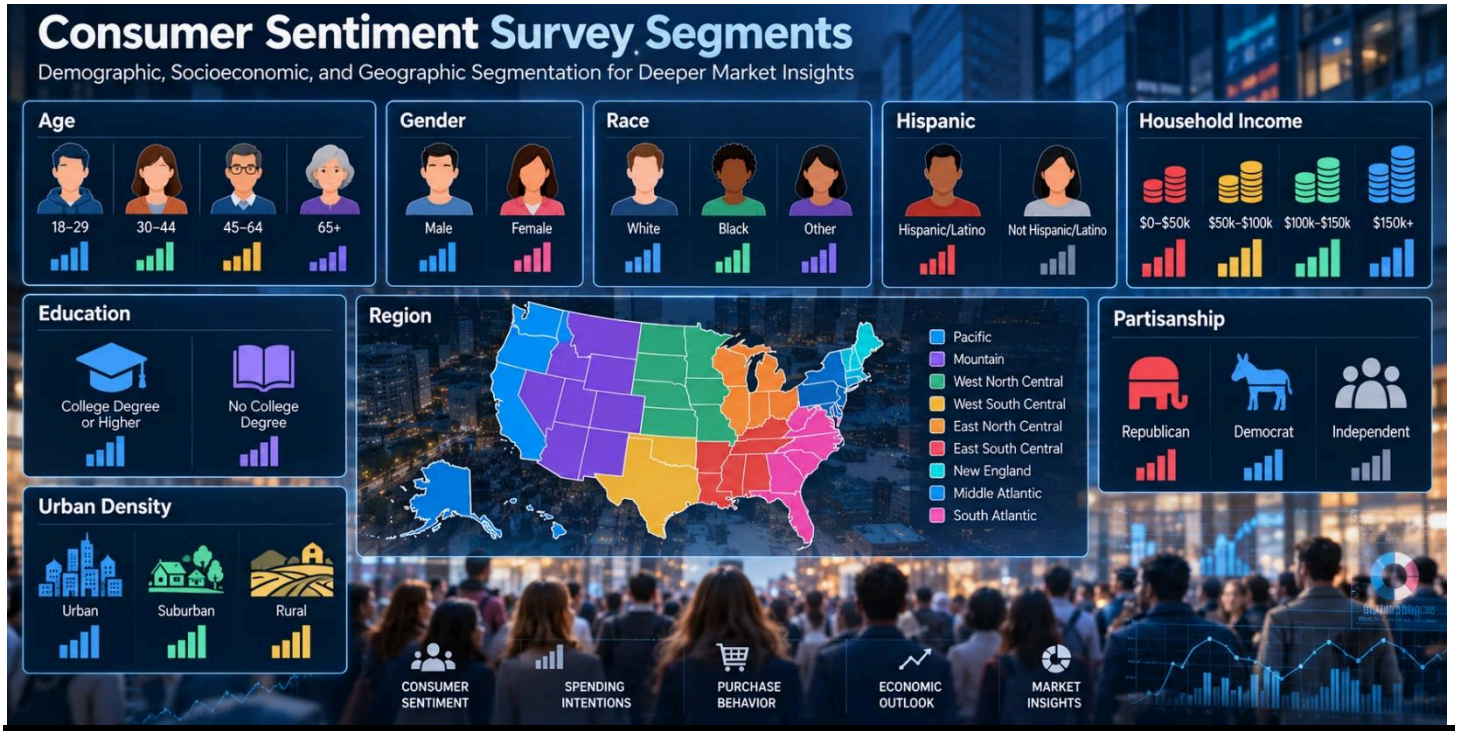
Figure 5 Demographic, Socioeconomic and Geographic Categories



Sources: ChatGPT

Although AlphaROC maintains a database of more than 5,000 surveys, our analysis focuses specifically on macroeconomic indicators. More importantly, we seek to identify surveys with the strongest potential relationships to the economic activity and financial asset returns we aim to predict. We therefore concentrate on the surveys summarized in Figure 6. Most of the selected indicators are available at a weekly frequency, although certain series, including voting preferences, stock market sentiment, and home renovation expectations, are collected monthly. A key consideration in selecting these indicators is the availability of sufficient historical observations to support robust backtesting. Consequently, we restrict our analysis to surveys and questions with histories beginning in 2022 or earlier.

Figure 6 AlphaROC Surveys Included in this Report

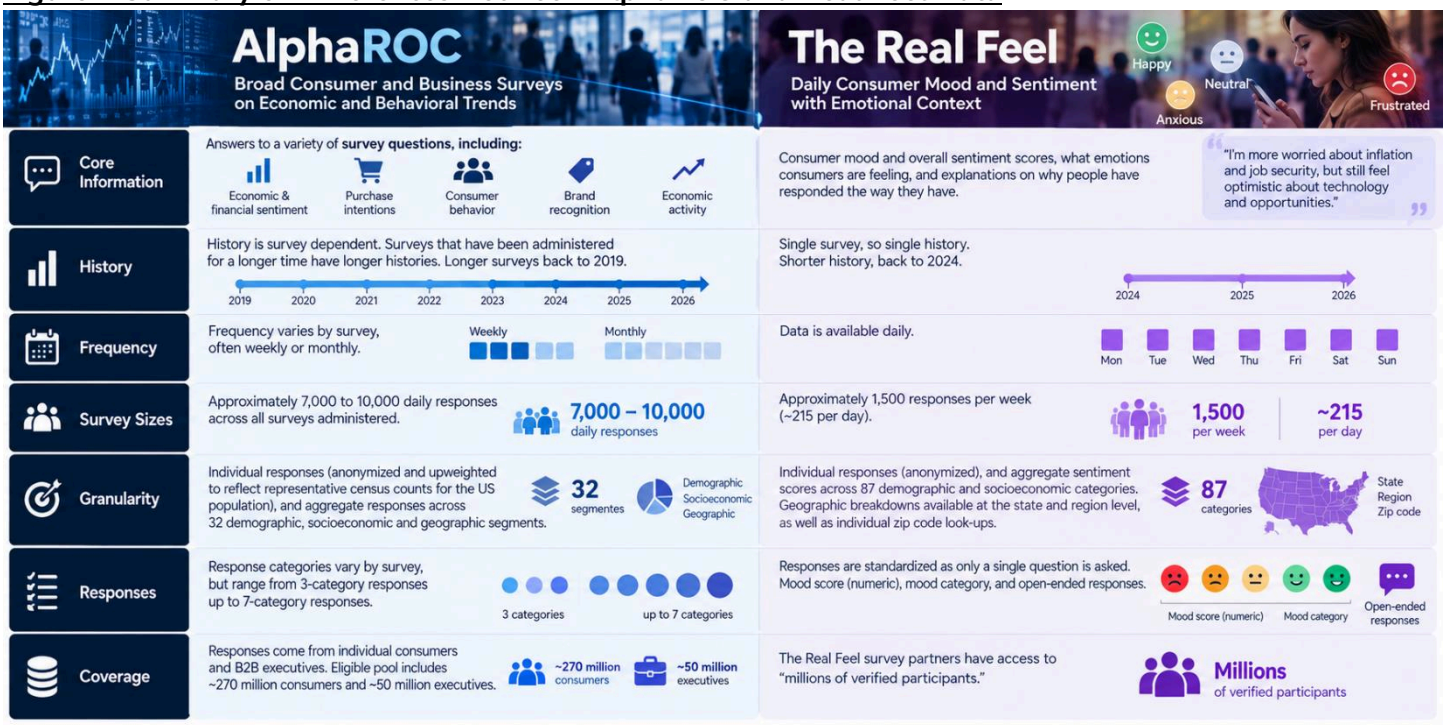
Type	Topic	Question	Start Date	Frequency
Consumer Sentiment	Housing Spending Expectation	Over the next year, do you expect to spend more or less on Rent/Mortgage?	Jul-19	Weekly
Consumer Sentiment	Standard of Living Satisfaction	How satisfied do you feel about your standard of living?	Jul-19	Weekly
Consumer Sentiment	Financial Conditions vs 1 Year Ago	Are you and your family better off financially than you were a year ago?	Apr-20	Weekly
Consumer Sentiment	Financial Conditions in 1 Year	Do you expect you and your family to be better off financiall in a year?	Apr-20	Weekly
Consumer Sentiment	Home Value 5 Years	What do you expect to happen to the price of your home in the next 5 years? (Homeowners)	Apr-20	Weekly
Consumer Sentiment	Employment Conditions	How would you rate employment conditions today?	May-20	Weekly
Consumer Sentiment	Employment Conditions in 6 Months	How do you think employment conditions will be in six months?	May-20	Weekly
Consumer Sentiment	Household Income in 6 Months	How do you think your household income will be in six months?	May-20	Weekly
Consumer Sentiment	Home Value in 12 Months	What do you expect to happen to the price of your home in the next 12 month?	May-20	Weekly
Consumer Sentiment	Anticipated Home Renovation Spend	How much do you anticipate spending on renovations to your home over the next 12 months?	Jan-21	Monthly
Financial	Cryptocurrency Familiarity	How familiar are you with cryptocurrency, such as Bitcoin ro Ethereum?	Dec-21	Monthly
Financial	Cryptocurrency Investment	Which best describes your investment level in cryptocurrency?	Dec-21	Weekly
Financial	Interest Rate Expectation	Where will interest rates be in six months?	Jun-22	Weekly
Financial	Recession Expectation	Will we enter an economic recession over the next six months?	Jun-22	Weekly
Financial	Bitcoin Expectation	Where will the price of Bitcoin be in six months?	Jun-22	Weekly
Financial	Gold Expectation	Where will the price of gold be in six months?	Jun-22	Weekly
Financial	Stock Market Expectation	Where will the stock market be in six months?	Aug-22	Weekly
Financial	Stock Market Sentiment	Are you bullish or bearish on the stock market? (Non-Retirement Retail Investors)	Oct-22	Monthly
Macro	Household Credit Card Debt	How much credit card debt does your household currently owe?	Jul-19	Weekly
Macro	Household Goods Spend Expectation	Over the next year, do you expect to spend more or less on Household Goods?	Apr-20	Weekly
Macro	Gasoline Spending Expectation	Over the next year, do you expect to spend more or less on Gasoline/Fuel?	Apr-20	Weekly
Macro	Retirement Savings Expectation	Over the next year, do you expect to save more or less on Savings for Retirement?	May-20	Weekly
Macro	Grocery Spend Expectation	Over the next year, do you expect to spend more or less on Groceries?	May-20	Weekly
Macro	Employment Status	Which best describes your current employment status?	Jan-21	Weekly
Macro	Labor Participation Hesitancy	Why are you currently not looking for work? (Full-time Homemakers and Unemployed)	Jan-22	Weekly
Macro	Inflation Concern	How often are you thinking about inflation or rising prices?	May-22	Weekly
Political	Country Direction Satisfaction	Are you satisfied with the way things are going in the United States at this time?	Jan-21	Weekly
Political	Congressional Ballot Party	In the next election for Congress, which political party candidate will you vote for?	Jan-21	Monthly

Sources: AlphaROC, Wolfe Research Luo's QES

AlphaROC vs. The Real Feel

Clients may recall that last year we evaluated another novel, AI-native dataset focused on consumer sentiment from a company called The Real Feel (see *AI-Powered Consumer Sentiment*, Neumann, et al [2025b]). While the datasets provided by AlphaROC and The Real Feel share several similarities, there are also important distinctions. Importantly, we view these differences as complementary strengths rather than evidence of direct competition between the two providers. The primary distinctions include the length of historical coverage, the granularity of demographic, socioeconomic, and geographic classifications, and the breadth of topics covered. We summarize the key differences between the two datasets across several dimensions in Figure 7.

Figure 7 Summary of Differences Between AlphaROC and Real Feel Data



Sources: AlphaROC, The Real Feel, ChatGPT

Overall, both datasets offer distinct advantages in understanding consumer sentiment and its implications for economic activity and financial markets. AlphaROC covers a broader range of survey topics, potentially providing insights into a wider set of economic and financial questions. Its historical coverage is also longer, with aggregate responses constructed from larger sample sizes. In contrast, The Real Feel provides higher-frequency observations and more granular demographic, socioeconomic, and geographic classifications. Additionally, its use of open-ended survey questions allows for greater flexibility in extracting information beyond the predefined responses typically associated with traditional consumer surveys. Taken together, we believe these complementary characteristics provide different perspectives on consumer sentiment, with each dataset offering distinct advantages depending on the research objective.

SURVEYS, SENTIMENT, AND THE REAL ECONOMY

In addition to its importance for financial markets, consumer sentiment is also widely recognized as an important driver of real economic activity (see, e.g., Lagerborg, et al [2023]). Under normal economic conditions, negative shocks to consumer confidence are associated with contractions in industrial production, private consumption, and labor market activity. However, in 2025, we began to observe a divergence from this historical relationship, as consumer sentiment deteriorated sharply while realized economic activity remained resilient. This divergence contributed to the emergence of the "K-shaped economy" narrative, in which economic growth was increasingly supported by higher-income households, while many lower-income consumers continued to struggle, contributing to declining aggregate consumer confidence.

In *AI-Powered Consumer Sentiment* (see Neumann, et al [2025b]) we provided empirical support for this previously unconfirmed hypothesis by examining differences in sentiment across income, age, and other demographic and socioeconomic characteristics relevant to economic outcomes. However, our analysis remained constrained by several limitations, most notably the relatively short history of available observations (approximately one year at the time of publication) and the narrow focus on aggregate mood and sentiment rather

than specific dimensions of economic activity. Using AlphaROC data, we can now conduct a more comprehensive investigation of the relationships between consumer sentiment, household behavior, and the broader economy.

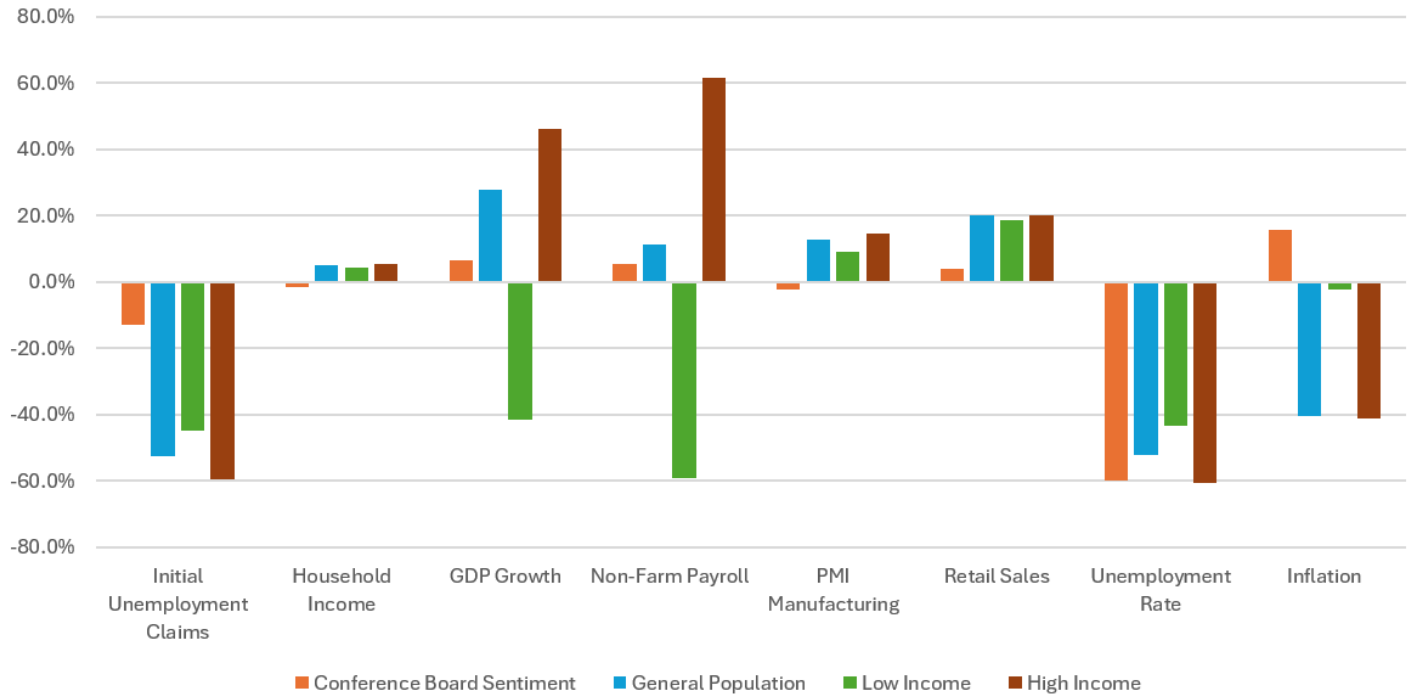
By "more comprehensive," we mean that AlphaROC provides a much broader collection of surveys addressing specific aspects of economic activity, rather than relying on a single aggregate measure of consumer confidence. For example, the information most relevant to labor market conditions may differ substantially from the sentiment measures associated with inflation or GDP growth. Figure 8 presents the correlations between positive AlphaROC survey responses (i.e., the percentage of respondents selecting the most favorable response category) and selected economic indicators. For each economic variable, we identify survey questions with particularly relevant economic interpretations. The questions, response categories, and corresponding relationships are summarized below.

- **How would you rate employment conditions today?** The most positive response is "Jobs are plentiful," so we use the percentage of consumers selecting this response. We examine its correlation with initial unemployment claims, household income, and the unemployment rate. The results are intuitive, with relationships consistently stronger among high-income consumers than among low-income respondents or the overall population. The correlations between perceptions of plentiful job opportunities and labor market measures are strongly negative, while the relationship with household income is positive, albeit weaker. This distinction is reasonable, as the availability of employment opportunities does not necessarily translate into higher-paying positions.
- **How much do you anticipate spending on renovations to your home over the next 12 months?** The most positive response is "$100,000 or more," so we use the percentage of consumers selecting this category over time. We examine its correlation with GDP growth and nonfarm payroll (NFP) growth, as substantial discretionary expenditures, such as home renovations, are generally more likely during periods of sustained economic expansion. We believe the relationship with NFP growth may reflect the greater stability of payroll employment relative to self-employment and gig-based work. Interestingly, the relationship between anticipated renovation spending and both GDP and NFP growth varies considerably across consumer segments. While correlations are relatively weak for the overall population, they are strongly negative among low-income consumers and strongly positive among high-income households, consistent with the hypothesis that higher-income consumers are disproportionately supporting economic activity.
- **How do you think employment conditions will be in six months?** The most positive response is "More jobs available than there are now," so we use the percentage of consumers selecting this answer. We examine its correlation with the manufacturing Purchasing Managers' Index (PMI) and retail sales. Intuitively, consumers expecting stronger future labor market conditions may be more willing to increase spending, supporting retail sales and potentially encouraging greater manufacturing activity. Consistent with this interpretation, correlations are positive across all AlphaROC consumer segments, although the relationships are strongest among high-income households.
- **Are you and your family better off financially than you were a year ago?** The most positive response is "Better off," so we use the percentage of respondents selecting this category. We examine its correlation with inflation. Intuitively, higher inflation erodes the purchasing power of wages and investment returns, potentially limiting improvements in household financial conditions. This relationship is reflected in the AlphaROC data, where correlations with inflation are negative across all consumer segments, despite the positive correlation observed between inflation and Conference Board consumer sentiment.

Two broader observations emerge from this analysis. First, the correlations are generally stronger than those documented in Neumann, et al [2025]. We believe this improvement reflects two important differences: the ability

to select survey questions more closely aligned with specific economic indicators and the availability of longer historical time series for estimating these relationships. Second, correlations between economic variables and responses from high-income consumers are consistently stronger than those observed among low-income households. These findings provide additional support for the increasingly bifurcated nature of economic outcomes, particularly as AI-related investment and financial market performance continue to play an important role in the broader economy.

Figure 8 Correlation Between AlphaROC Positive Survey Responses and Economic Data



Sources: Bloomberg Finance LLP, FactSet, FTSE Russell, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

We can also investigate the relationships between AlphaROC survey responses and our proprietary QES indicators. This analysis allows us to examine how different demographic and socioeconomic segments respond to changes in monetary policy expectations and economic growth prospects. We begin by evaluating the correlations between AlphaROC survey responses, segmented by income and age, and our Hawk-Dove Index (HDI), which provides a real-time measure of the US monetary policy stance (see *Flight Patterns: Hawk-Dove Sentiment in Fedspeak*, Neumann, et al [2025a]). For this analysis, we focus on three surveys with particularly strong economic connections: current employment status, whether consumers are financially better off than one year ago, and whether they expect their financial circumstances to improve over the coming year.

The correlation between the percentage of respondents reporting full-time employment and our HDI index increases substantially with income, including a particularly pronounced increase between the lowest and second-lowest income categories (see Figure 9A). Since our HDI index leads changes in the federal funds rate, this relationship is consistent with monetary policy becoming more hawkish in response to an overheating economy. One potential explanation is that lower-paying, less-skilled positions, which may be more susceptible to automation and economic disruptions, face greater employment pressure, while higher-skilled and better-compensated jobs remain relatively resilient as economic activity expands. The relationship across age groups is similarly intuitive (see Figure 9B), highlighting differences in employment sensitivity to broader economic

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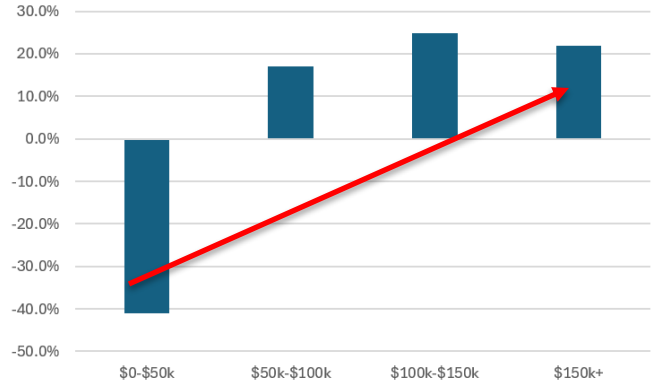
conditions. During periods of economic strength, younger and older workers may find it easier to obtain full-time employment, while prime-age workers (those aged 30–64) appear less sensitive to changes in the overall economic environment.

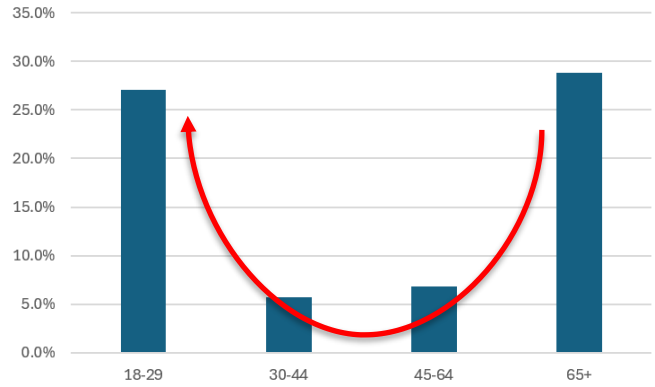
Figure 9(C) and Figure 9(D) examine the correlations between our HDI and the percentage of consumers reporting that they are financially better off than one year ago, segmented by income and age. Once again, correlations increase substantially with income, consistent with the hypothesis that higher-income households, which generally have greater equity market exposure, benefit disproportionately from stronger financial market performance. Conversely, correlations decline considerably with age. One possible explanation is that older consumers approaching retirement may be more sensitive to the potential consequences of increasingly hawkish monetary policy, including its implications for future equity market performance and retirement wealth.

Figure 9 Correlation Between HDI and AlphaROC Surveys

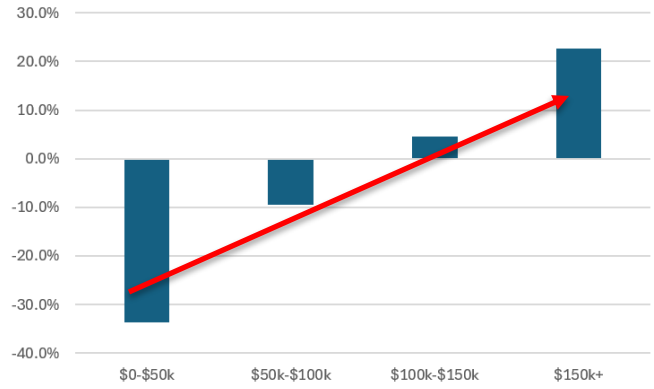
A) Current Employment — Income



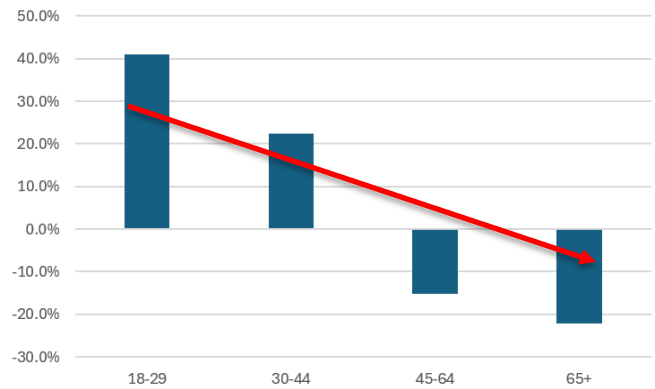
B) Current Employment -—Age



C) Better Off Financially This Year — Income



D) Better Off Financially This Year — Age



Sources: Bloomberg Finance LLP, FactSet, FTSE Russell, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

We can extend this framework by examining the correlations between AlphaROC survey responses, segmented by income and age, and our proprietary broad-market COMPASS index. COMPASS is constructed using macroeconomic information extracted from corporate management commentary during earnings calls and other investor events (see *The Unsolicited Economic Outlook Survey*, Neumann, et al [2026]).

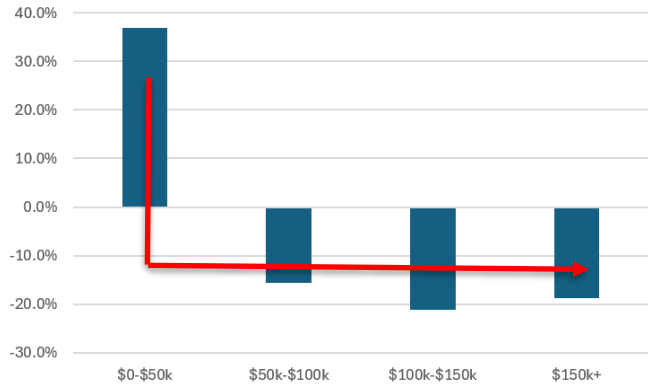
As shown in Figure 10(A), the correlation between the percentage of respondents reporting full-time employment and our COMPASS index exhibits an L-shaped relationship across income groups. Correlations are strongly positive among lower-income consumers, who appear to benefit disproportionately from improvements in

economic conditions. Although correlations become slightly negative among higher-income households, two important considerations warrant attention. First, COMPASS is a diffusion index, meaning that declining index values can still be consistent with continued economic expansion. Second, the correlations among higher-income consumers are considerably closer to zero, suggesting a relatively weak relationship rather than a meaningful negative association. Figure 10(B) presents a similar parabolic pattern across age groups to that observed with our HDI index. Given the diffusion-based construction of COMPASS, we interpret this pattern as evidence that younger and older workers are more sensitive to changes in economic conditions than prime-age workers, rather than emphasizing the direction of the correlations alone.

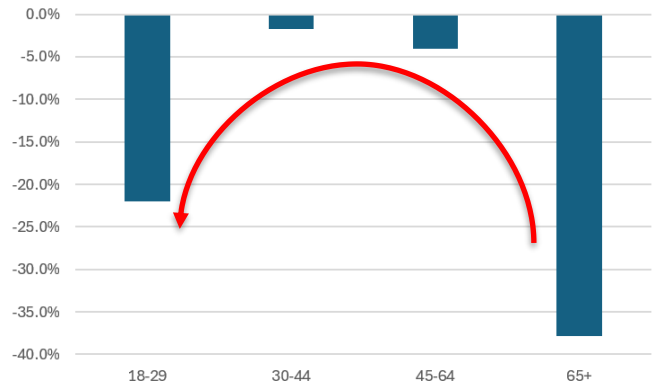
The relationship between expectations for future household financial conditions and our broad-market COMPASS index is particularly strong and economically intuitive. Correlations increase with both income (see Figure 10C) and age (see Figure 10D). Across income groups, this suggests that higher-income consumers expect to benefit more from improving economic conditions over the coming year. This interpretation is plausible, as these households may benefit from both stronger labor market conditions and greater financial market gains. Similarly, older consumers generally hold more financial assets than younger households and may therefore expect to benefit disproportionately from improvements in economic and financial market performance.

Figure 10 Correlation Between COMPASS and AlphaROC Surveys

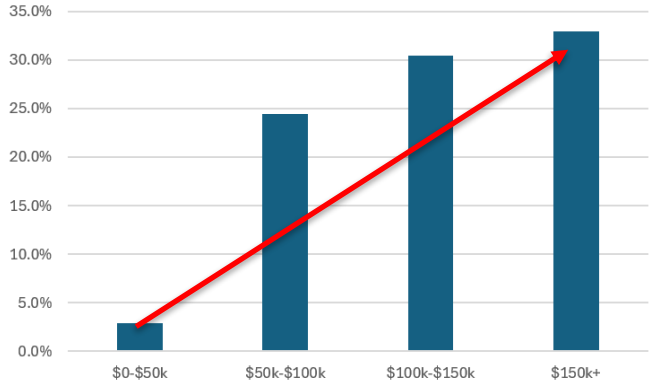
A) Current Employment — Income



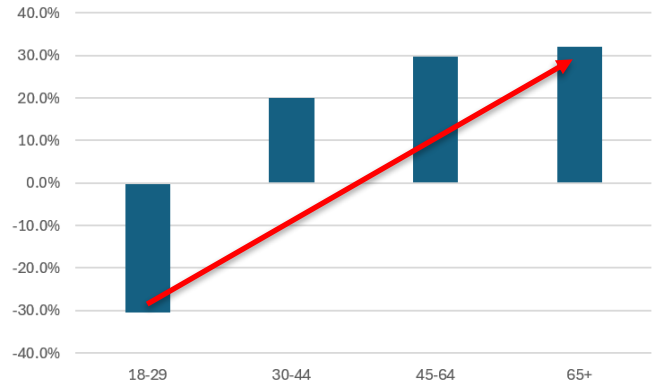
B) Current Employment — Age



C) Better Off Financially Next Year — Income



D) Better Off Financially Next Year — Age



Sources: Bloomberg Finance LLP, FactSet, FTSE Russell, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

One important takeaway from this analysis is the ability of our COMPASS index to capture forward-looking economic information, as demonstrated by its strong correlations with surveys measuring expectations for future

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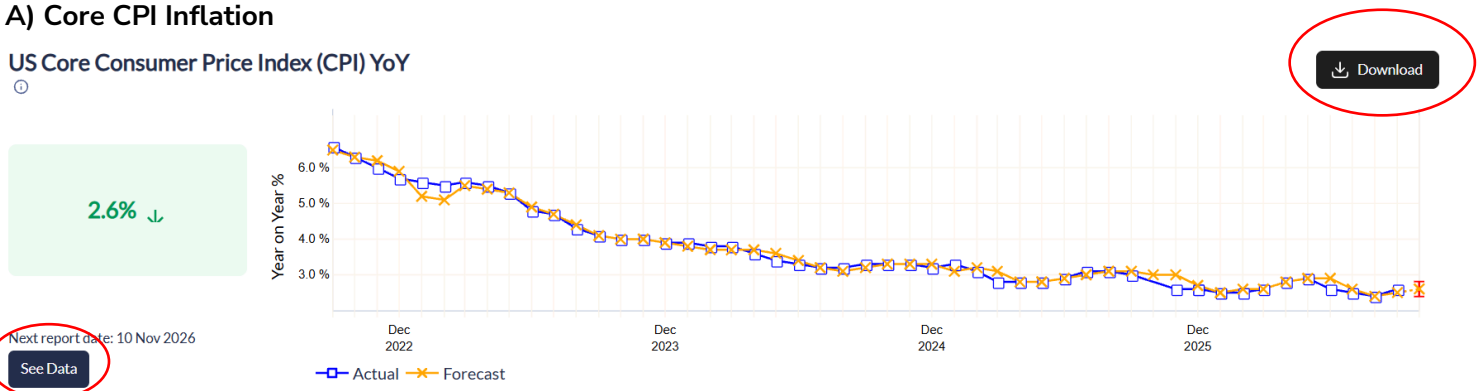
financial conditions. While our HDI index also contains forward-looking information, its relationship with consumer expectations appears more limited, as Federal Open Market Committee (FOMC) members formulate monetary policy decisions partly in response to previously reported economic data. This distinction is reflected in the stronger relationships between HDI and surveys assessing current or historical financial conditions, compared with the more pronounced correlations between COMPASS and forward-looking sentiment measures (see Figure 9 and Figure 10).

AlphaROC Forecast Accuracy

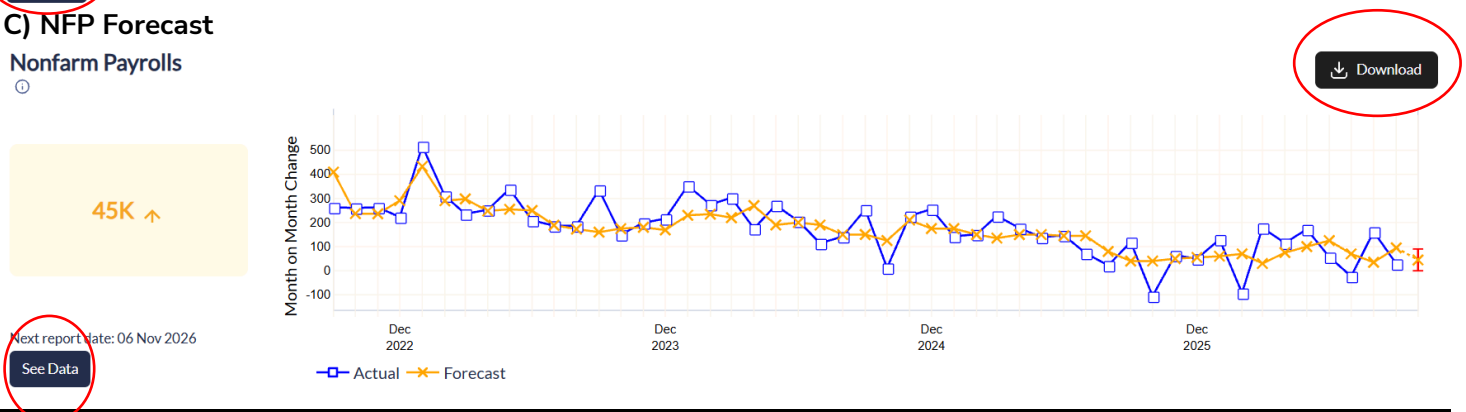
As discussed in the previous sections, one of the principal advantages of AlphaROC is the breadth of topics covered by its survey database, ranging from brand awareness and political participation to macroeconomic expectations. This extensive coverage allows AlphaROC to identify numerous signals with meaningful relationships to realized economic activity, potentially providing timely information about important economic and financial market indicators. Figure 11 compares AlphaROC forecasts with realized values for core Consumer Price Index (CPI) inflation (see Figure 11A) and NFP (see Figure 11B). Through the Occam platform, users can examine the underlying survey data used to construct these estimates and export the resulting forecasts for further analysis (circled in red). In total, AlphaROC produces forecasts for seven macroeconomic indicators: year-over-year (YoY) headline CPI inflation, YoY core CPI inflation, NFP, average hourly earnings, one-year inflation expectations, University of Michigan consumer sentiment, and Conference Board consumer confidence.

Figure 11 Select AlphaROC Economic Forecasts

A) Core CPI Inflation



C) NFP Forecast



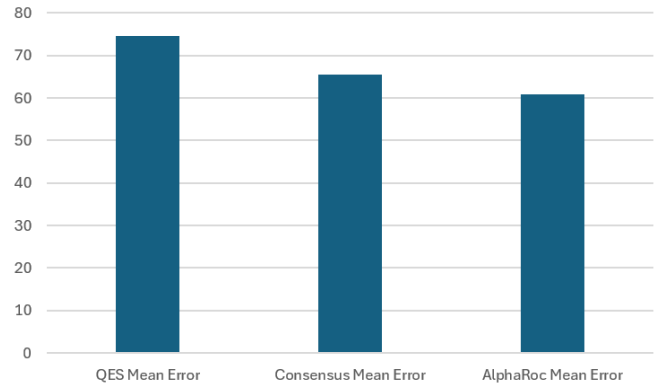
Sources: AlphaROC, Wolfe Research Luo's QES

Given the extensive availability of forecasts for major macroeconomic indicators, an important question is how AlphaROC's estimates compare with existing alternatives. We evaluate this by examining three indicators for which QES also produces forecasts: NFP, YoY headline CPI inflation, and YoY core CPI inflation. Overall, AlphaROC

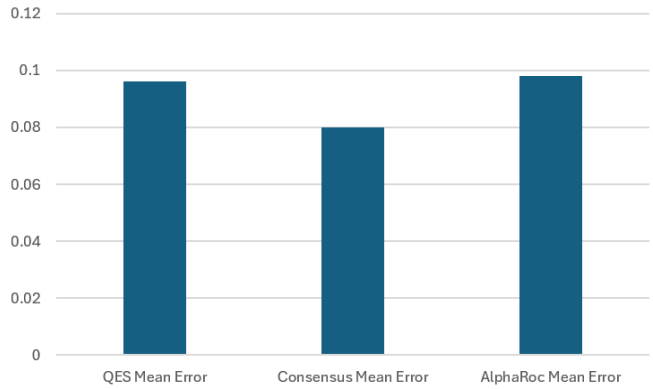
performs well, achieving greater forecast accuracy than both Bloomberg consensus and QES for NFP (see Figure 12A) while also outperforming QES for headline CPI inflation (see Figure 12C). For core CPI, however, Bloomberg consensus remains more accurate than either individual forecast, while QES performs slightly better than AlphaROC for this more persistent inflation measure (see Figure 12B). Importantly, QES maintains stronger directional accuracy, defined as the percentage of months in which the forecast correctly predicts whether the realized value will be above or below consensus (see Figure 12D). This distinction suggests that the somewhat larger absolute forecast errors observed for QES could be driven by a relatively small number of substantial misses rather than a persistent directional bias.

Figure 12 AlphaROC, QES, and Consensus Forecast Comparison

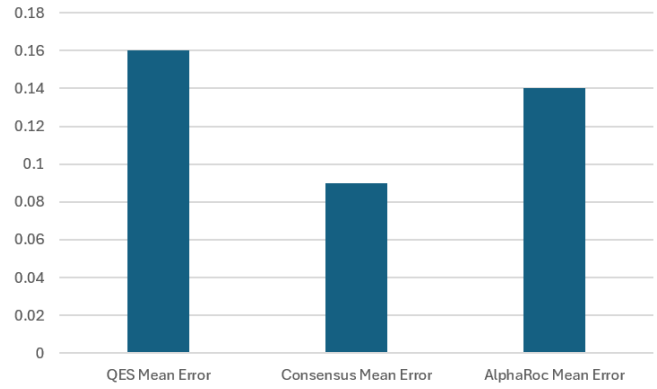
A) NFP Forecast Comparison



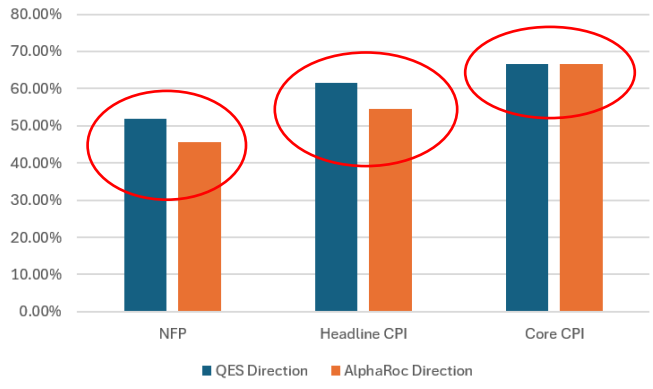
B) Core CPI Forecast Comparison



C) Headline CPI Forecast Comparison



D) Directional Accuracy Comparison



Sources: Bloomberg Finance LLP, FactSet, FTSE Russell, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

Given the differences in absolute and directional forecast accuracy between QES and AlphaROC, a natural extension is to investigate whether combining their predictions can improve overall performance. More broadly, we want to determine whether incorporating AlphaROC forecasts into an existing forecasting framework can generate incremental predictive value. At a high level, our proprietary QES models generally belong to the autoregressive (AR) family of forecasting methods (see e.g. *Inflation Forecasts Everywhere*, Neumann, et al [2024], and *Non-Farm Payroll Prediction*, Neumann, et al [2023]) and rely on historical data extending considerably further back than the available AlphaROC surveys and forecasts. Consequently, the most straightforward approach is to combine the final forecast outputs rather than reconstruct the underlying models using a common estimation sample. We conduct this experiment using headline CPI inflation, for which both QES and AlphaROC exhibit lower forecast

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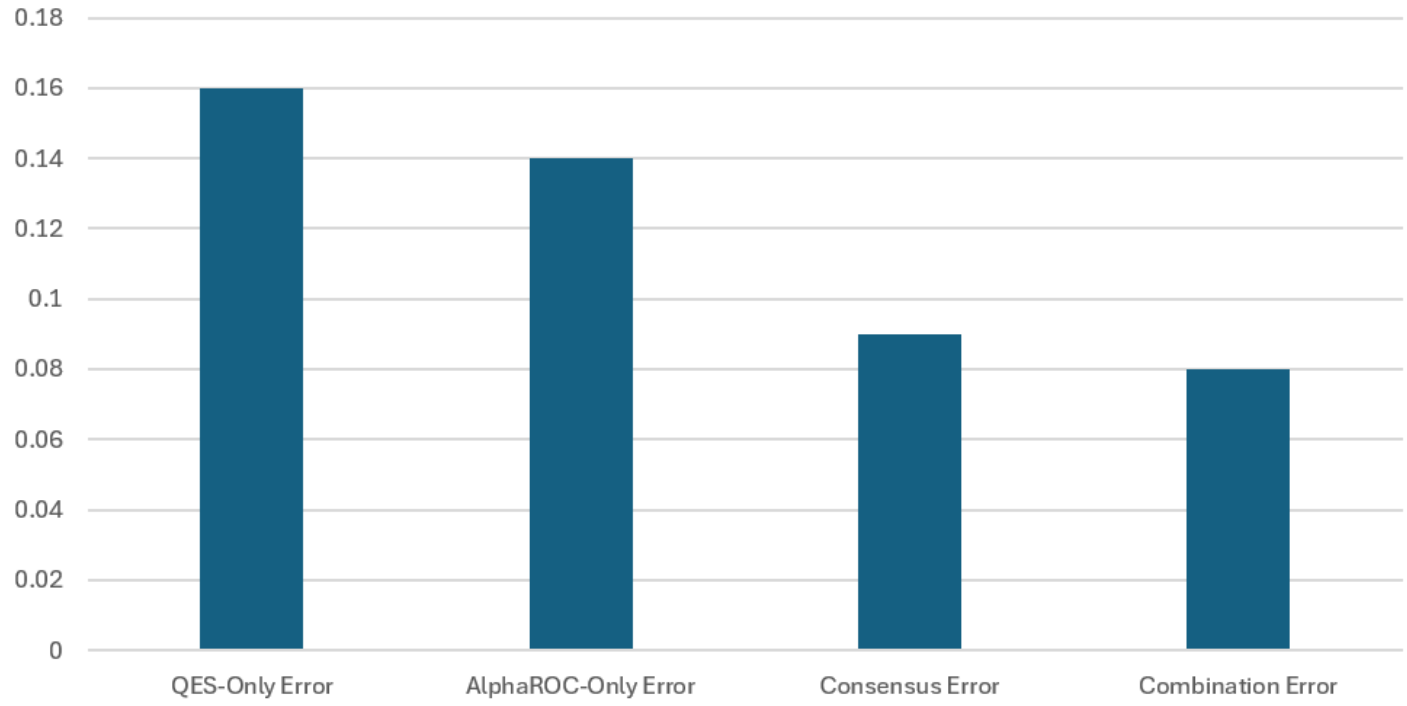
accuracy than consensus (see Figure 13). Specifically, we construct an equally weighted average of the QES and AlphaROC forecasts, providing a simple benchmark for evaluating the potential benefits of forecast combination. The results are very positive, with the combined forecast more accurate than both individual forecasts, as well as the Bloomberg consensus.

Figure 13 Combination QES and AlphaROC Headline CPI Inflation Forecast Accuracy



Sources: Bloomberg Finance LLP, FactSet, FTSE Russell, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

Overall, the periods during which AlphaROC forecasts perform most accurately do not necessarily coincide with those in which alternative forecasts achieve their strongest results, creating opportunities to improve accuracy through forecast combination. This finding is economically intuitive, as AlphaROC relies on survey-based information that differs meaningfully from the inputs used in many traditional forecasting models. We believe additional improvements may be possible through more sophisticated statistical methods for combining forecasts or by incorporating individual AlphaROC survey indicators directly into existing models rather than relying exclusively on their final predictions. Nevertheless, our results demonstrate that AlphaROC forecasts can provide incremental information that improves the performance of established macroeconomic forecasting processes.

Asset Predictions with AlphaROC Data

Finally, and perhaps most importantly, we seek to determine whether AlphaROC survey data can predict asset returns and improve investment decisions. To evaluate this, we incorporate signals constructed from AlphaROC surveys into the inputs of our existing tactical asset allocation (TAA) and style factor rotation models. Given the relatively limited history of AlphaROC data, directly incorporating these indicators into our existing LMacro rotation models (see *Systematic Global Macro Investing*, Luo et al [2017]) would be impractical. Instead, we construct a common baseline feature set using the union of variables from our three component rotation models that have fixed inputs. These variables include our proprietary nowcasting indices, macroeconomic indicators, capital market variables, and aggregate factors.

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Following our findings in *AI-Powered Consumer Sentiment* (see Neumann, et al [2025b]), we construct additional signals using the spread between high- and low-income consumer responses across 13 AlphaROC surveys with the longest available histories. Specifically, for each survey, we calculate the difference between the percentage of high-income respondents selecting the most positive response category and the corresponding percentage of low-income respondents. The intuition is that a widening sentiment gap may reveal important economic information obscured by aggregate survey and macroeconomic indicators. This distinction is particularly relevant given the increasingly important role of higher-income households in supporting overall economic activity and financial market performance.

To ensure our findings are applicable across a broad range of investment strategies, we evaluate the incremental predictive value of AlphaROC data using several modeling approaches, including ordinary least squares (OLS), traditional machine learning, tree-based methods, neural networks, and pretrained foundation models for tabular data. We select one representative model from each category, informed by the current rankings on the TabArena leaderboard[1], allowing us to compare the benefits of AlphaROC data across different model architectures. The five models included in our analysis are summarized below.

- **Ordinary Least Squares (OLS):** The simplest linear econometric model, which retains the Best Linear Unbiased Estimator (BLUE) properties under the classical regression assumptions. Widely used and straightforward to interpret, OLS remains a foundational econometric approach despite decades of advances in nonlinear modeling and machine learning.
- **xRFM:** A machine learning model that measures similarity between observations while accounting for the relative importance of individual features and their interactions. To accommodate large datasets and capture local relationships, xRFM partitions predictors into disjoint subsets, each associated with a separate model. It then repeatedly fits kernel-based predictors within these local regions, allowing the model to identify complex relationships that may not be captured by traditional global estimation methods (see Beaglehole et al [2026] for more information).
- **CatBoost:** A tree-based machine learning model that uses gradient boosting to sequentially construct decision trees, with each iteration seeking to correct errors from the preceding ensemble. Unlike alternative boosting methods such as XGBoost, CatBoost employs symmetric decision trees and enhanced regularization to reduce overfitting. Its ordered boosting framework further limits estimation bias by calculating each observation's residual using a model that has not previously been trained on that observation (see Prokhorenkova et al [2019] for more information).
- **RealMLP:** A neural network model based on the traditional multilayer perceptron (MLP) and feedforward architecture. Although its underlying structure is conventional, RealMLP distinguishes itself through carefully calibrated default hyperparameters that allow the model to perform effectively across a broad range of tabular prediction tasks without extensive application-specific tuning (see Hozmuller et al [2025] for more information).
- **Kumo-Tabular:** A pretrained foundation model containing 215 million parameters and employing a transformer architecture specifically designed for tabular data rather than natural language processing. The model uses in-context learning, allowing it to adapt to new prediction tasks using the information provided at inference time without updating its pretrained parameters. In other words, Kumo-Tabular is trained to recognize and learn relationships within tabular datasets rather than estimate a single predetermined relationship between inputs and outputs (see NVIDIA [2026]).

[1] See: https://huggingface.co/spaces/TabArena/leaderboard, with leadership as of 10/25/2026.

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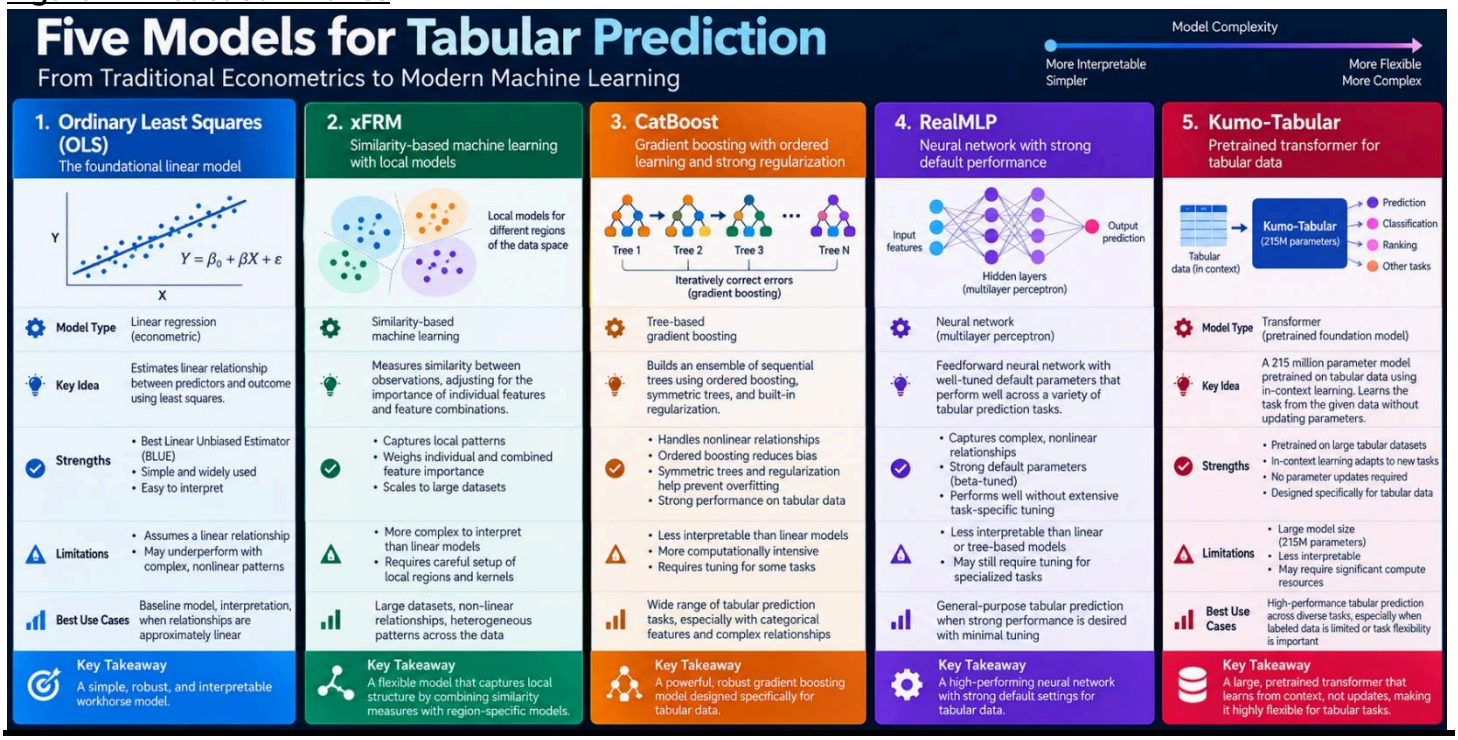
We summarize the principal characteristics of these models in Figure 14.

Figure 14 Model Summaries



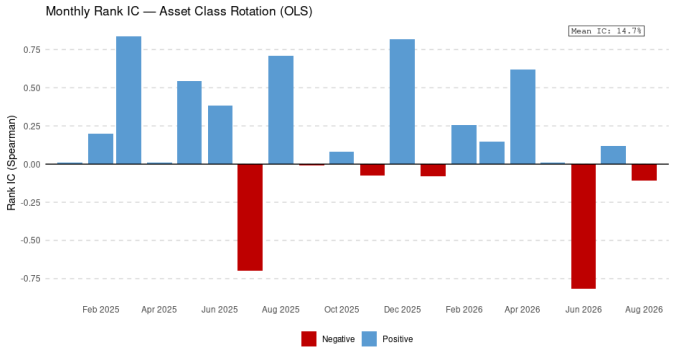
Sources: ChatGPT, Wolfe Research Luo's QES

Each model is initially trained using five years of monthly observations to forecast asset and factor returns one month ahead. We subsequently expand the training window each month, incorporating newly available observations before generating the next forecast. Given the relatively short training histories and out-of-sample evaluation periods available for this analysis, we primarily rely on default model configurations and limit hyperparameter optimization (HPO). Consequently, we view the results as a conservative benchmark for potential model performance and the incremental benefits of incorporating AlphaROC data, rather than a definitive assessment of each model's predictive capabilities.

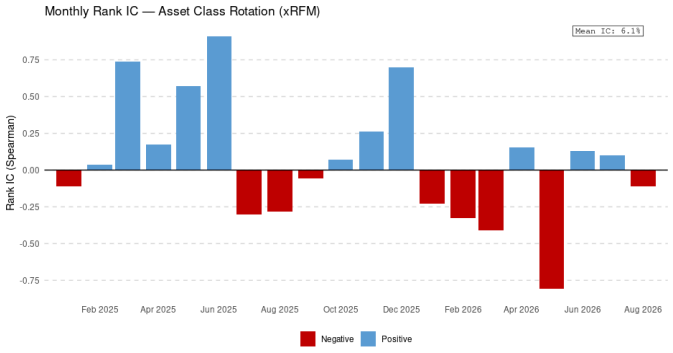
We begin by examining baseline performance for our 11-asset TAA model in Figure 15. Despite the limited historical sample, all five models perform reasonably well at the monthly forecasting horizon. We believe this is partly attributable to the underlying feature set, which was originally selected for its ability to predict macro asset returns within our existing LMacro rotation framework. OLS delivers the strongest performance, achieving an average IC of 14.7% (see Figure 15A). This result is intuitive, as the relatively simple linear specification is less susceptible to overfitting in a small sample, particularly when the baseline predictors have already demonstrated strong relationships with asset returns in a predominantly linear setting such as our LMacro framework. Nevertheless, Kumo-Tabular (see Figure 15E), CatBoost (see Figure 15C) and RealMLP (see Figure 15D also produce competitive results.

Figure 15 Baseline Model Performance — Assets

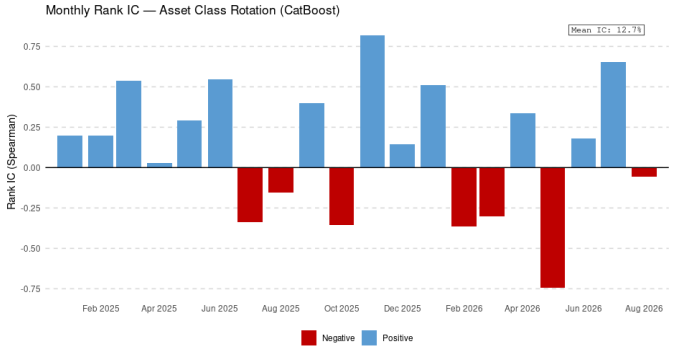
A) OLS



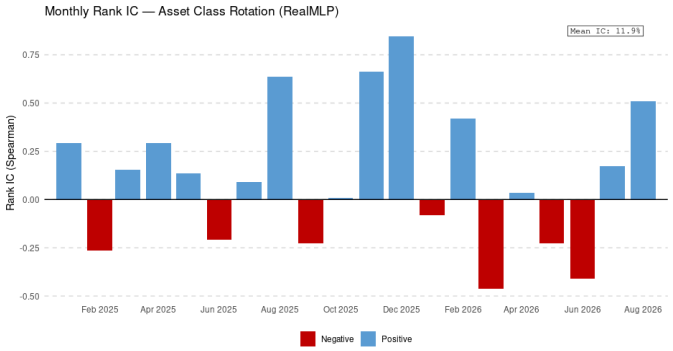
B) xRFM



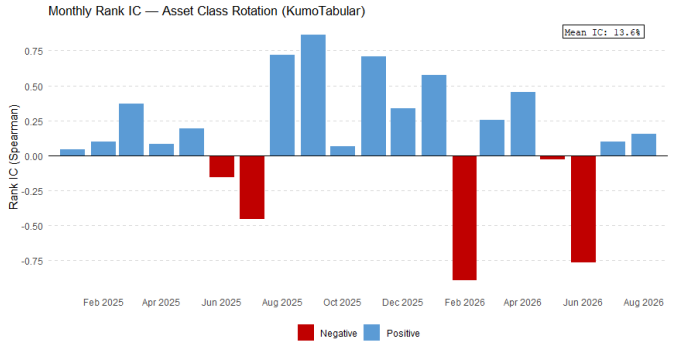
C) CatBoost



D) RealMLP



E) Kumo-Tabular



Sources: Bloomberg Finance LLP, FactSet, FTSE Russell, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

Baseline performance for style factor rotation is considerably more varied. The more interpretable models, including OLS (see Figure 16A), xRFM (see Figure 16B) and CatBoost (see Figure 16C), generally perform well, with OLS again producing the highest average rank IC. In contrast, the more complex RealMLP (see Figure 16D) and Kumo-Tabular (see Figure 16E) exhibit weaker predictive performance. One potential explanation is that the relationships between equity style factors and the broader macroeconomic environment are more nuanced, while the limited historical sample may prevent Kumo-Tabular's in-context learning framework or RealMLP's default hyperparameters from adequately capturing these dynamics.

The performance of xRFM is particularly noteworthy. Its periods of negative performance are largely concentrated toward the end of 2025 and the beginning of 2026, coinciding with the US government shutdown and the conflict

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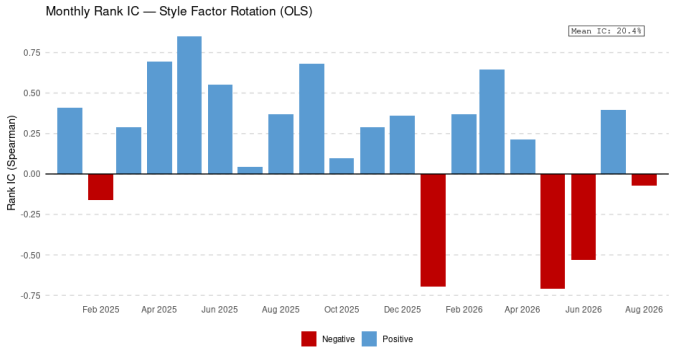
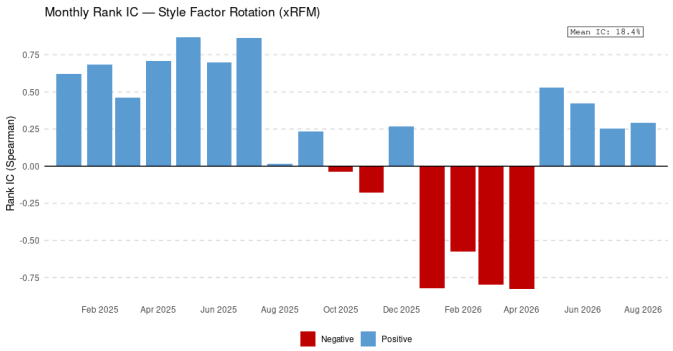
with Iran, both of which both introduced substantial uncertainty into financial markets, and resulted in a strong deterioration of signal input quality. Outside these periods, the model delivers almost uniformly positive results, suggesting that its relatively weaker overall performance may be concentrated around a small number of unusual macroeconomic events.

Figure 16 Baseline Model Performance —ß Factors

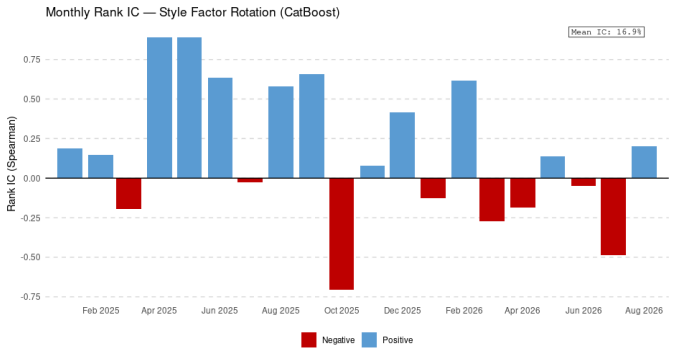
A) OLS



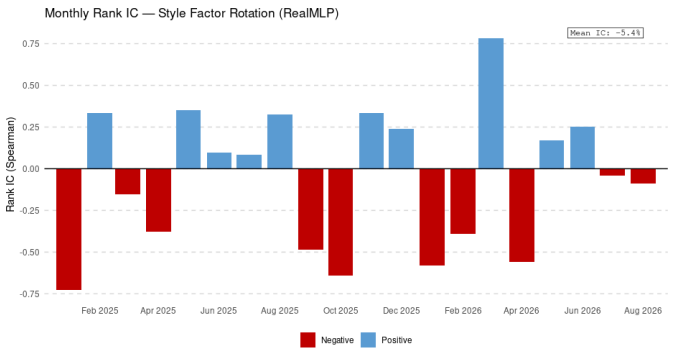
B) xRFM



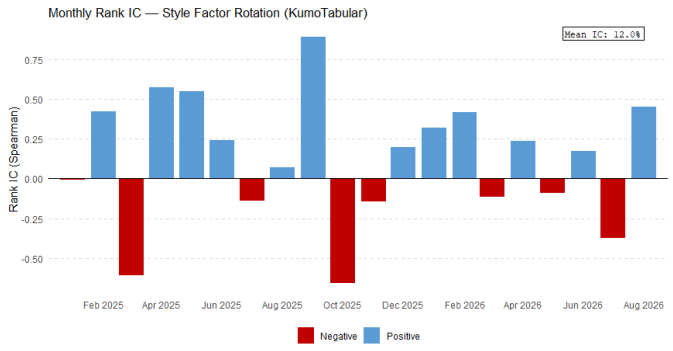
C) CatBoost



D) RealMLP



E) Kumo-Tabular



Sources: Bloomberg Finance LLP, FactSet, FTSE Russell, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

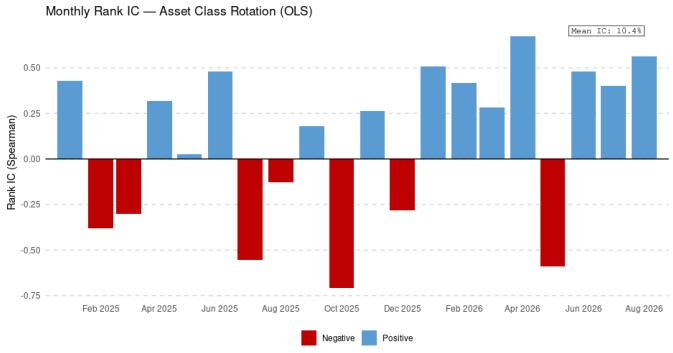
We next incorporate the AlphaROC survey signals into our baseline asset rotation models. Interestingly, the addition of consumer sentiment data reduces the predictive performance of OLS (see Figure 17A). This finding suggests that the relationship between granular consumer sentiment and asset returns may be predominantly nonlinear, consistent with our previous findings in *AI-Powered Consumer Sentiment* (see Neumann, et al [2025b]). RealMLP also experiences a deterioration in performance (see Figure 17D), potentially reflecting an increased risk

of overfitting as the number of explanatory variables expands while the available training sample remains relatively small.

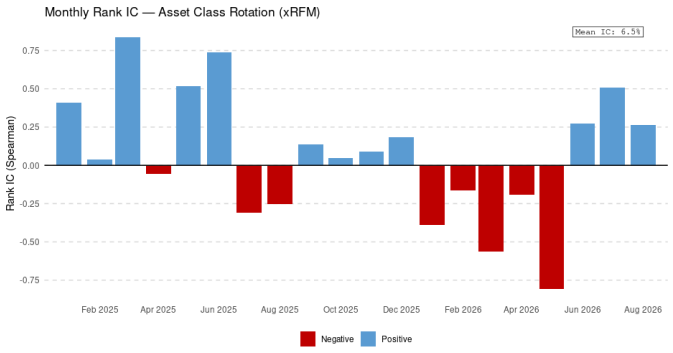
In contrast, Kumo-Tabular benefits from the additional survey information (see Figure 17DE), suggesting that its in-context learning framework may be better equipped to incorporate new predictors without the same degree of overfitting, at least under certain conditions. However, CatBoost is the primary beneficiary of the AlphaROC signals, with its average rank IC increasing by 41% to 17.9% (see Figure 17C). This substantial improvement suggests that tree-based methods may be particularly effective at extracting nonlinear relationships between consumer sentiment and future asset returns.

Figure 17 AlphaROC Augmented Model Performance — Assets

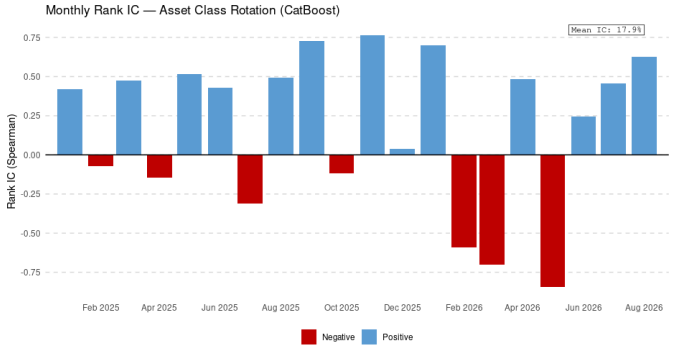
A) OLS



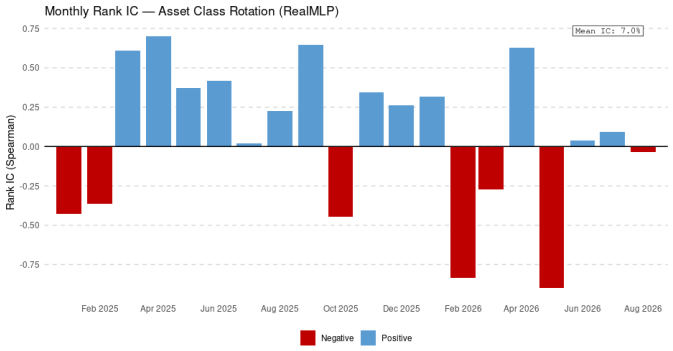
B) xRFM



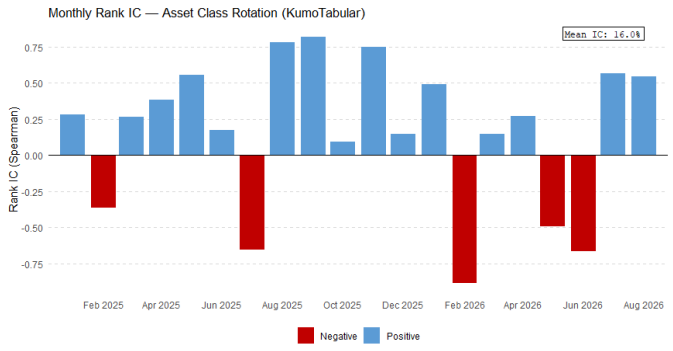
C) CatBoost



D) RealMLP



E) Kumo-Tabular



Sources: Bloomberg Finance LLP, FactSet, FTSE Russell, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

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The results for style factor rotation differ somewhat from those observed across asset classes. Unlike the asset allocation models, incorporating AlphaROC survey data improves the predictive performance of OLS for style factors (see Figure 18A). This suggests that at least some of the relationships between granular consumer sentiment and equity style factor returns can be captured using a linear specification. However, nonlinear relationships also appear important, as both CatBoost (see Figure 18C) and RealMLP (see Figure 18D) benefit from the additional sentiment indicators.

The performance of xRFM remains particularly interesting (see Figure 18B). As observed in the baseline results, its periods of underperformance are largely concentrated around the US government shutdown and the initial stages of the conflict with Iran. The persistence of this pattern after incorporating AlphaROC data suggests that the model's sensitivity to these unusual macroeconomic conditions is not fully addressed by the additional consumer sentiment information.

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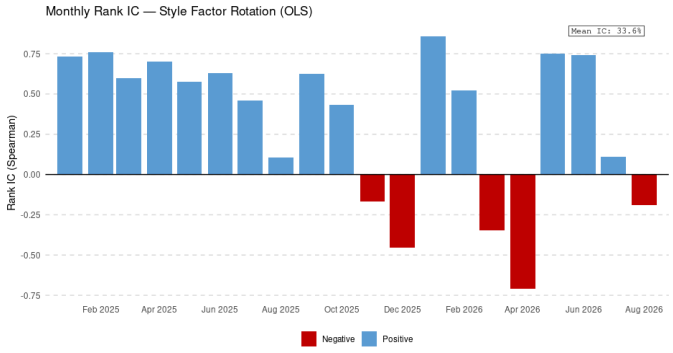
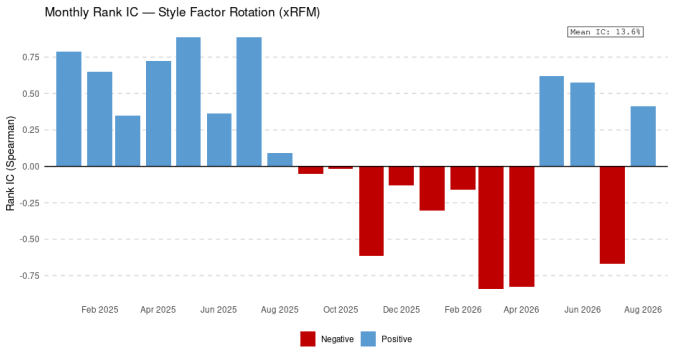
Figure 18 AlphaROC Augmented Model Performance — Factors

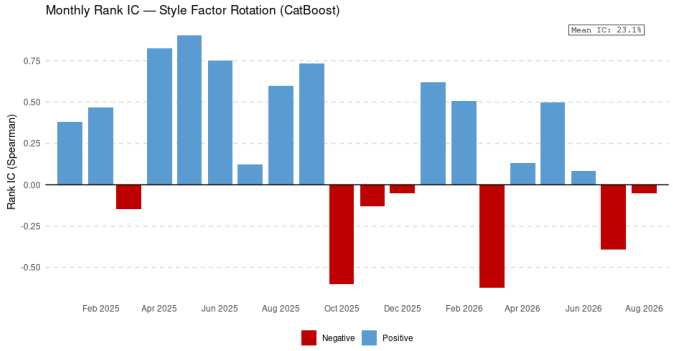
A) OLS



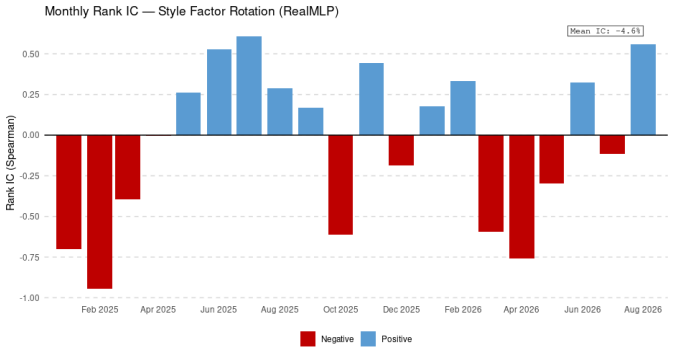
B) xRFM



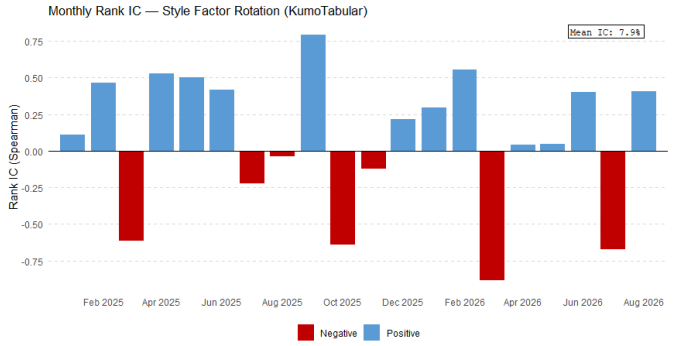
C) CatBoost



D) RealMLP



E) Kumo-Tabular



Sources: Bloomberg Finance LLP, FactSet, FTSE Russell, S&P Capital IQ, Refinitiv, Wolfe Research Luo's QES

Overall, CatBoost exhibits the largest and most consistent improvement in predictive performance following the inclusion of AlphaROC survey data. This finding suggests that tree-based models may be particularly well suited to incorporating granular consumer sentiment into asset and factor rotation strategies. Their ability to identify localized relationships across different regions of the feature space may help isolate the effects of substantial changes in sentiment and differences in survey responses that would otherwise be obscured by aggregate indicators or linear specifications.

However, our conclusions remain constrained by the relatively limited in-sample and out-of-sample evaluation periods. As additional observations become available, we expect the relative performance of more complex neural network-based approaches, including RealMLP and Kumo-Tabular, to improve. Longer training histories should

allow these models to estimate more complex relationships with a lower risk of overfitting, while providing additional information for Kumo-Tabular's in-context learning framework. Nevertheless, our initial findings indicate that granular AlphaROC survey data contains incremental predictive information that can improve systematic asset allocation and style factor rotation, particularly when incorporated through models capable of capturing nonlinear relationships.

GLOBAL ECONOMIC FORECAST

This section provides a brief economic outlook for the US and other major economies (Europe, UK, China, Japan, Canada, and Australia), based on our macroeconomic forecasting models explained in in *Multi-Dimensional Alpha: From Nowcasting to Forecasting*.

First, to measure current economic activities, we apply our suite of Nowcasting indices, which aggregate thousands of macroeconomic and alternative Big Data time series globally, in real-time. Once we have an accurate reading on current economic cycles, we further apply our econometric models to forecast future economic growth, anticipated growth, inflation, and employment for more than 40 countries of the world. Please contact us for details on other countries/regions not covered in this section.

US

The U.S. economy remains resilient, supported by consumer spending and business investment, while the labor market continues to cool gradually. Inflation remains sticky, keeping the Fed cautious and policy restrictive, with the main risks coming from persistent price pressures and a sharper slowdown in household demand.

Real GDP exceeded expectations and grew at an annual rate of 3.4% in Q3/2026 (i.e. compared to 2.2% in Q2/2026) according to the latest estimate released by the BEA, reflecting continued strength in consumer spending, investment, and government spending (see Figure 19A). Anticipated growth ticks up slightly (see Figure 19B). Headline inflation reaccelerated to 3.7% in September, amid a sharp jump in energy prices and persistent increases in shelter, autos, airfares and other core categories (see Figure 19C). Unemployment rate ticked up to 4.2% in September (see Figure 19D). The Fed raised rates by 25 bp in September to 3.75%–4.00%, responding to persistent inflation despite signs of a softer labor market (see Figure 19E). The yield curve (slope) has steepened in the recent quarters (see Figure 19F).

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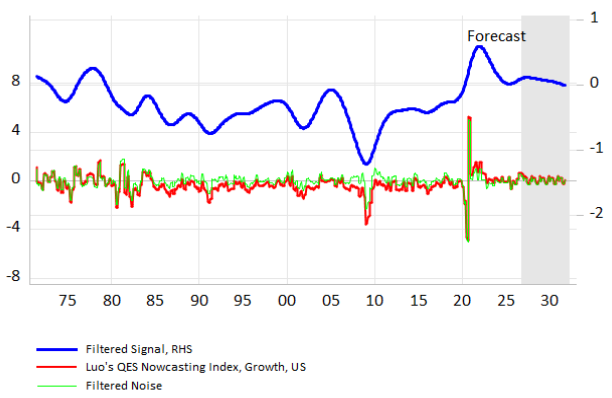
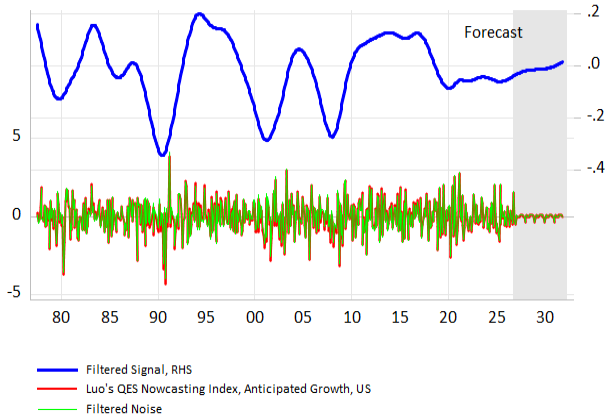
Figure 19 US Economic Forecast

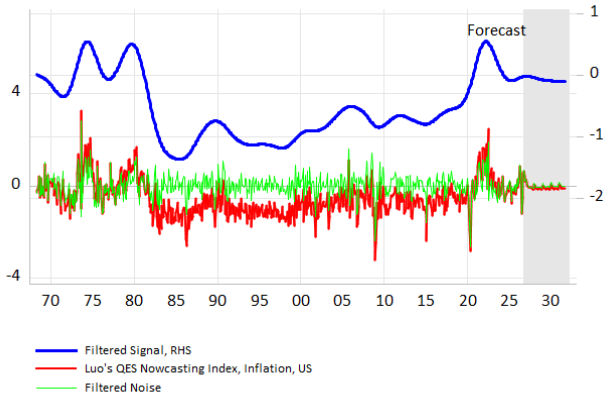
A) Economic Growth



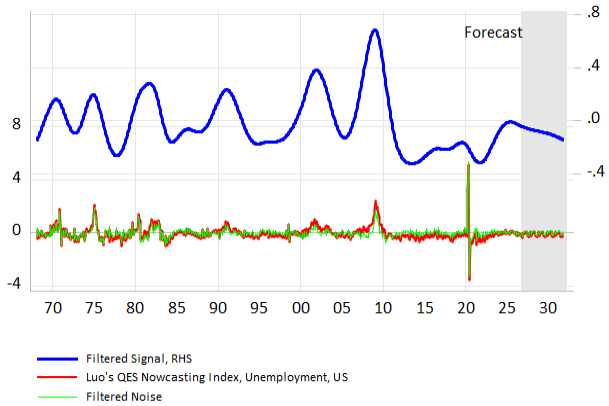
B) Anticipated Growth



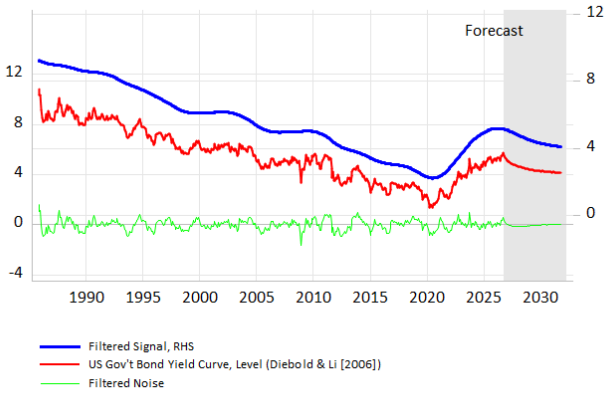
C) Inflation



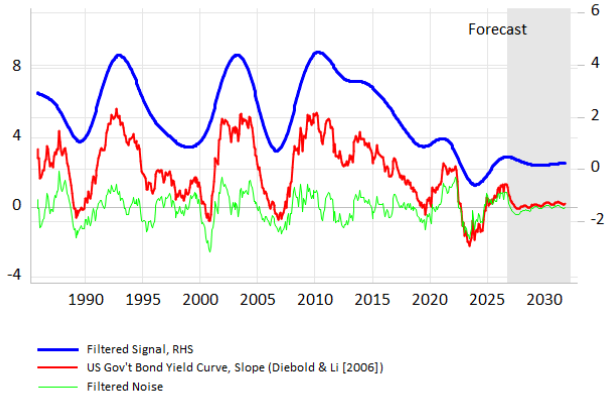
D) Unemployment & Wages



E) Yield Curve, Level



F) Yield Curve, Slope



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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GLOBAL ECONOMIC GROWTH OUTLOOK

Figure 20 shows the next 12-month forecast of economic growth for six of the largest economies – Eurozone, UK, China, Japan, Canada, and Australia:

- Global growth remains positive but uneven, supported by resilient emerging markets and technology-related investment. Inflation, geopolitical tensions, energy risks, fiscal pressures and restrictive monetary policy remain key downside risks, while AI-driven investment and productivity gains continue to provide an important upside support.
- European economies slowed down and grew by 0.4% in Q3/2026 (compared to 0.6% in Q2/2026). Annual inflation in the Euro area further increased to 4% in October on soaring energy prices. The ECB raised rates in September 2026 by 25bps in response to inflation pressure from the recent energy shock.
- UK's economy slowed down and grew 0.5% in Q2/2026 (compared to 0.6% growth in Q1/2026), with services sector being the largest contributor. Headline inflation rose to 3.5% in September. The Bank of England last cut its benchmark rate from 4% to 3.75% in December 2025.
- China's economy grew by 4.5% YOY in Q3/2026, reaccelerating from 4.3% in Q2/2026. China's economy is supported by exports and policy stimulus, but weak property and domestic demand continue to weigh on growth.

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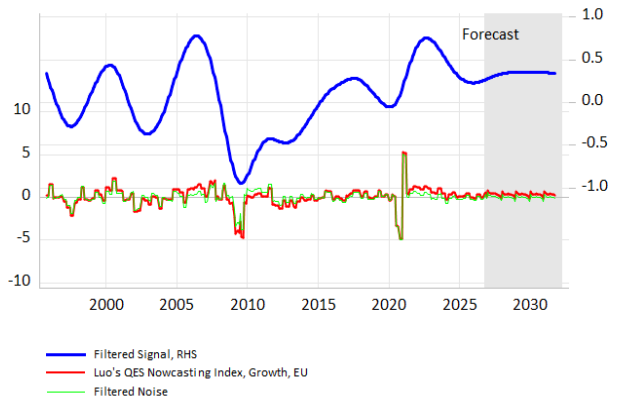
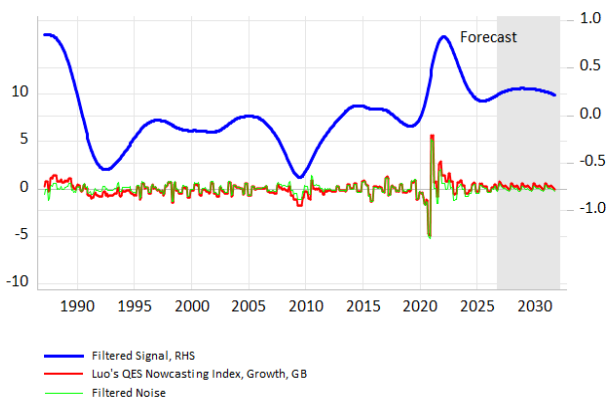
Figure 20 Global Economic Growth Forecast

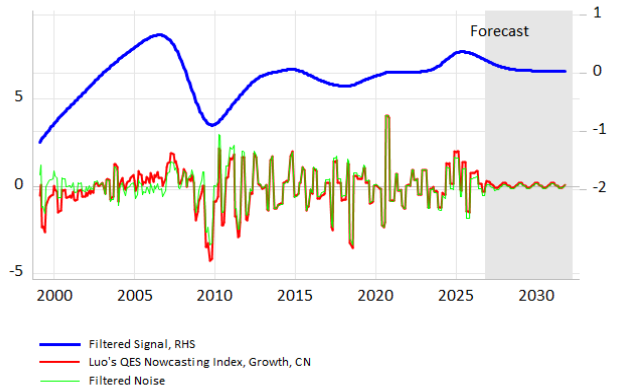
A) Europe



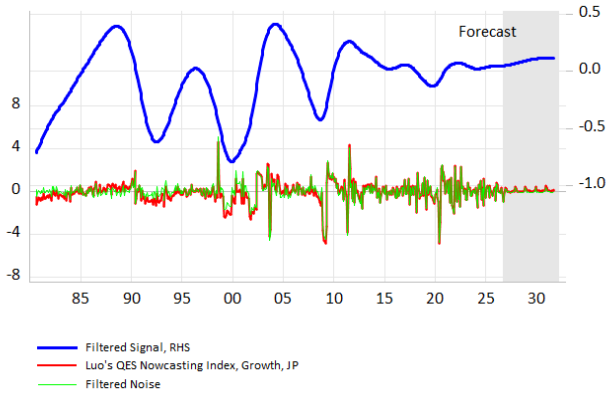
B) UK



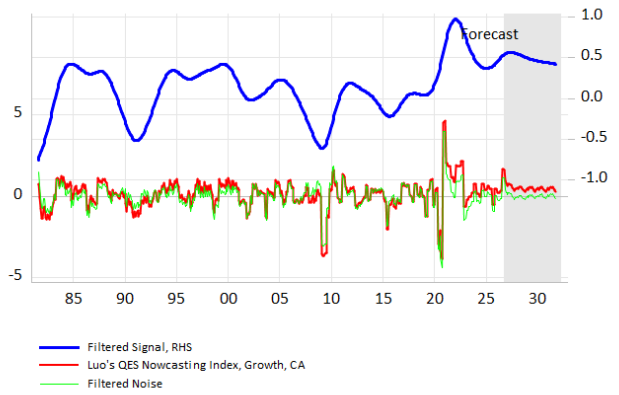
C) China



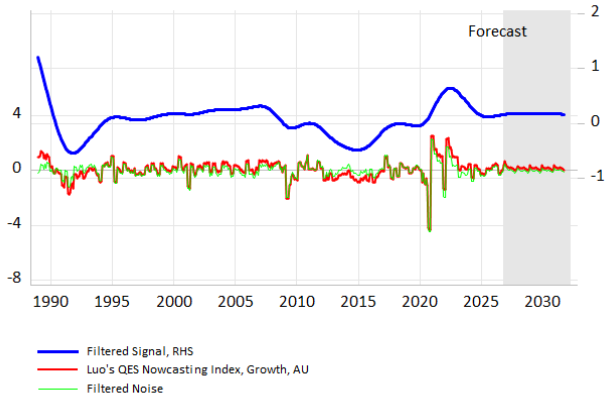
D) Japan



E) Canada



F) Australia



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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TACTICAL ASSET ALLOCATION

Our TAA model covers 11 major global asset classes:

- US Large Cap Equity (S&P 500)
- US Small Cap Equity (Russell 2000)
- Developed Markets Equity (MSCI EAFE)
- Emerging Markets Equity (MSCI EM)
- Global Real Estate (S&P Global REIT)
- US Treasuries (Bloomberg BarCap US Treasury Bond Total Return Index)
- US High Yield Bonds (Bloomberg BarCap US Corporate High Yield Total Return Index)
- EM Credit (Bloomberg BarCap EM Debt Total Return Index)
- Commodities (S&P GSCI Total Return Index)
- Gold (Gold Spot)
- Crude Oil (NYMEX Front Month Futures)

Recent Performance

Global financial markets continued to face heightened uncertainties amid geopolitical risks and trade tensions. Most major asset classes recorded gains in October, led by crude oil and commodities, while emerging markets equity and gold posted losses (see Figure 21A).

Using a minimum spanning tree[2] graph (see Figure 21C), it is clear that US high yield bonds stay at the center in the recent period.

[2] Minimum spanning tree (MST) is a powerful algorithm used for network analysis. Mantegna [1999] first introduces the MST in finance. In a network of multiple assets, the MST graph helps to distinguish between the assets playing a central role versus the peripheral assets having limited power to influence the overall market.

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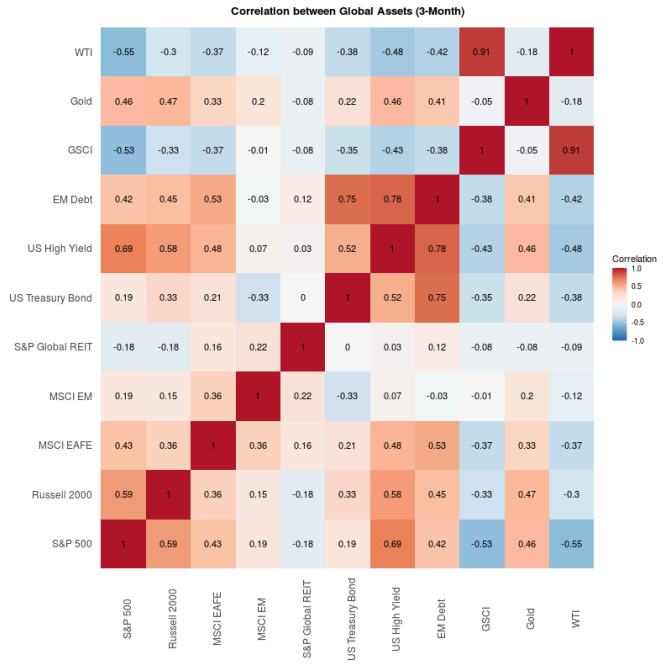
Figure 21 Recent Performance – TAA

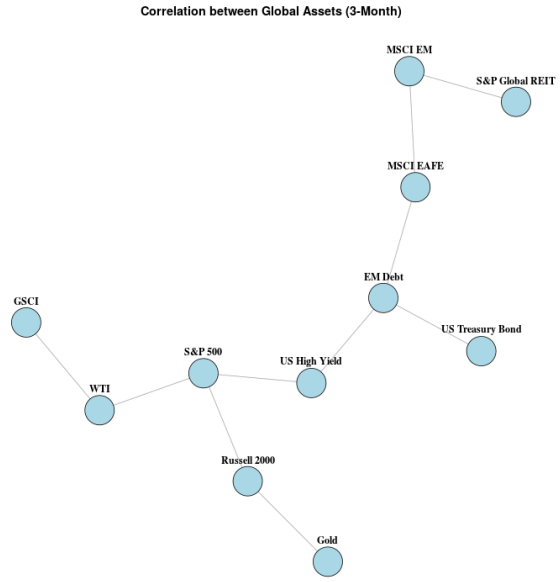
A) Summary Statistics

Major Asset Class	Cumulative Return			All History			
	Last Month (%)	3 Month (%)	12 Month (%)	Annual Return (%)	Annual Vol (%)	Sharpe Ratio	Max Drawdown (%)
S&P 500 TR	-0.87	+1.48	+12.41	+11.00	+17.55	+0.63	-55.25
Russell 2000 TR	+0.58	-4.25	+15.43	+10.73	+19.74	+0.54	-58.89
MSCI EAFE TR, USD	-0.72	-1.78	+13.81	+5.74	+16.72	+0.34	-60.15
MSCI EM TR, USD	-8.04	-5.39	+13.61	+8.68	+18.32	+0.47	-65.14
S&P Global REIT TR, USD	+1.89	-6.42	+9.25	+7.71	+16.13	+0.48	-72.54
US Treasury Bond TR	+2.36	+0.37	-0.19	+5.92	+5.38	+1.10	-18.88
US High Yield Bond TR (Unhedged)	+0.30	-1.28	+1.56	+6.08	+4.83	+1.26	-35.34
EM Debt (USD Unhedged) TR	+1.26	-0.96	+0.40	+7.77	+7.82	+0.99	-31.46
S&P GSCI TR	+4.80	+16.49	+62.08	+6.82	+17.96	+0.38	-88.54
Gold Spot	-6.74	-4.24	-3.21	+5.84	+18.90	+0.31	-70.29
Crude Oil WTI Futures TR	+15.91	+30.70	+81.88	+5.39	+45.23	+0.12	-109.02

B) Correlation Heatmap, Past 3M



C) Minimum Spanning Tree, Past 3M



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

Investment Outlook

In the near term, our macro models favor commodities, US small-cap equity, and international developed markets equity. At the same time, we are cautious on crude oil, US Treasury bonds, and emerging markets credit (see Figure 22A).

Our mid-term views are overweighting commodities, gold, and US large-cap equity, and underweighting US Treasury bonds, US high yield bonds, and crude oil (see Figure 22B).

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Figure 22 Return Forecast

A) Short-Term (1M) Outlook

Major Asset Class	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Asset Rank (1=Best)	Model Uncertainty
S&P 500 TR	Neutral	Positive	Positive	Neutral	Neutral	4	Medium
Russell 2000 TR	Positive	Neutral	Neutral	Positive	Positive	2	Medium
MSCI EAFE TR, USD	Neutral	Neutral	Neutral	Neutral	Positive	3	Low
MSCI EM TR, USD	Neutral	Positive	Negative	Neutral	Neutral	6	Medium
S&P Global REIT TR, USD	Neutral	Neutral	Positive	Neutral	Neutral	7	High
US Treasury Bond TR	Negative	Negative	Neutral	Negative	Negative	10	Low
US High Yield Bond TR (Unhedged)	Neutral	Neutral	Negative	Neutral	Neutral	8	Medium
EM Debt (USD Unhedged) TR	Negative	Negative	Neutral	Negative	Negative	9	Medium
S&P GSCI TR	Positive	Positive	Positive	Positive	Positive	1	Low
Gold Spot	Negative	Neutral	Neutral	Positive	Neutral	5	High
Crude Oil WTI Futures TR	Positive	Negative	Negative	Negative	Negative	11	High

B) Mid-Term Outlook

Major Asset Class	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Asset Rank (1=Best)	Model Uncertainty
S&P 500 TR	Neutral	Positive	Neutral	Positive	Positive	3	Medium
Russell 2000 TR	Positive	Neutral	Negative	Neutral	Neutral	6	Medium
MSCI EAFE TR, USD	Neutral	Neutral	Neutral	Neutral	Neutral	5	Low
MSCI EM TR, USD	Neutral	Neutral	Neutral	Neutral	Neutral	4	Medium
S&P Global REIT TR, USD	Neutral	Neutral	Positive	Neutral	Neutral	7	Medium
US Treasury Bond TR	Negative	Negative	Neutral	Negative	Negative	11	Medium
US High Yield Bond TR (Unhedged)	Neutral	Negative	Negative	Negative	Negative	10	Low
EM Debt (USD Unhedged) TR	Negative	Negative	Neutral	Neutral	Neutral	8	High
S&P GSCI TR	Positive	Positive	Positive	Positive	Positive	1	Low
Gold Spot	Negative	Neutral	Positive	Positive	Positive	2	High
Crude Oil WTI Futures TR	Positive	Positive	Negative	Negative	Negative	9	High

Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

GTAA Model Performance

All four models behind our TAA strategy have shown decent predictive power in the long run (see Figure 23).

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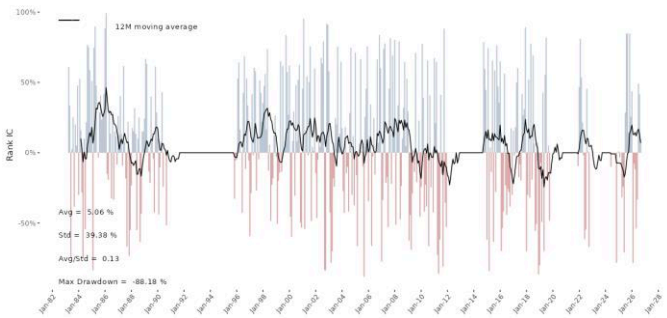
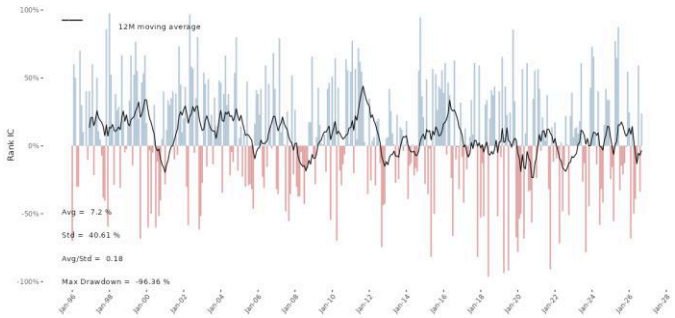
Figure 23 GTAA Model Performance

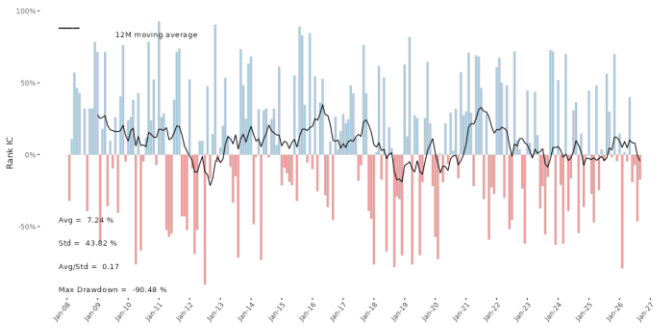
A) Cross Sectional Model (CSM)



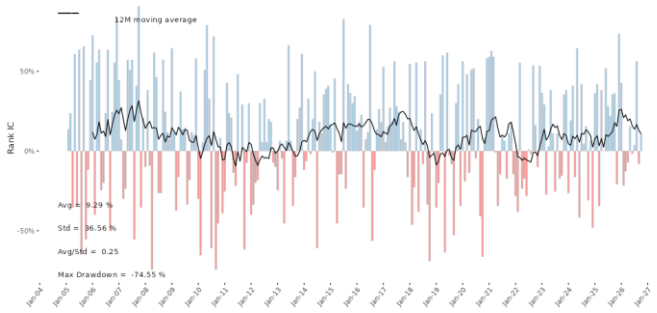
B) Tactical Regression Model (TRM)



C) Economic Cycle Model (ECM)



D) Machine Learning Model (MLM)



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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US Sector and Industry Rotation

In this section, we first provide a review of the performance of the 11 GICS sectors in all major countries/regions. Then we shift our focus to sector rotation in the US, along with our industry views on the 24 GICS industry groups.

Recent Performance

As shown in Figure 24 (A), the energy, consumer staples, health care, and utilities sectors recorded great gains across multiple regions in October, while the information technology and materials sectors posted losses in most regions.

In the US, 19 of the 24 GICS industries recorded gains in October, led by food & staples retailing and energy, while media & entertainment and semiconductors retreat significantly (see Figure 25A).

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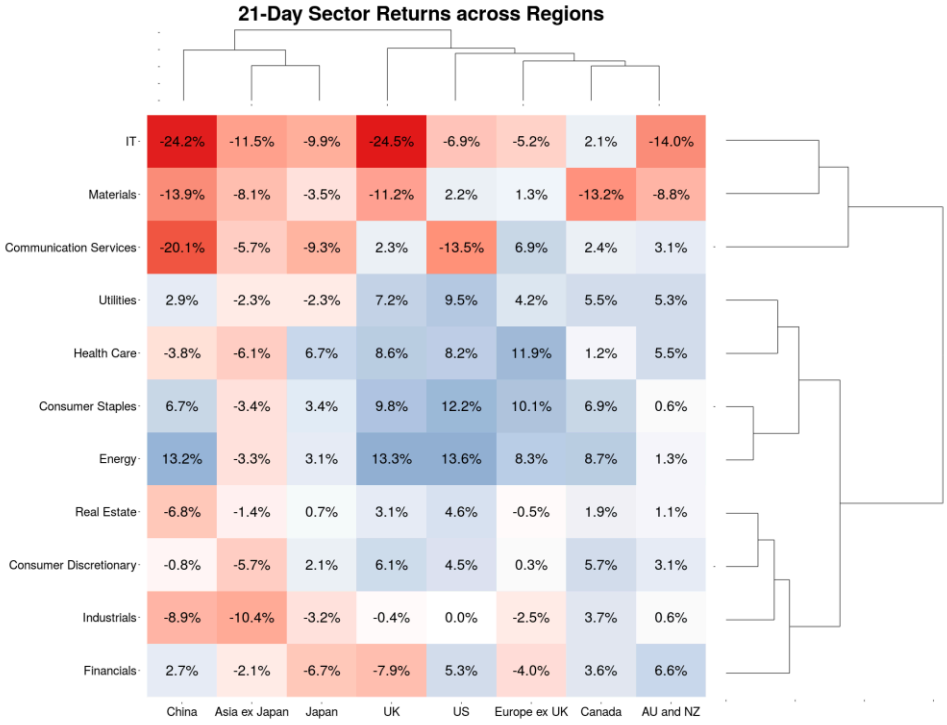
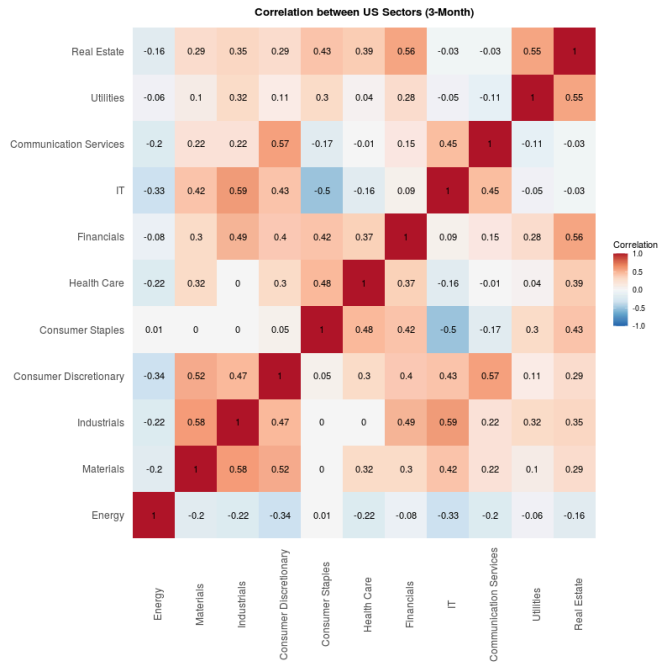
Figure 24 Recent Performance – Global Sectors

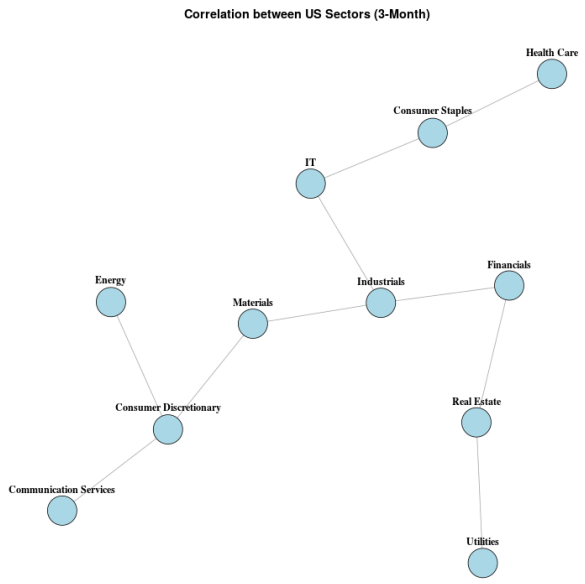
A) Global Sector Performance



B) Correlation Heatmap, US, Past 3M



C) Minimum Spanning Tree, US, Past 3M



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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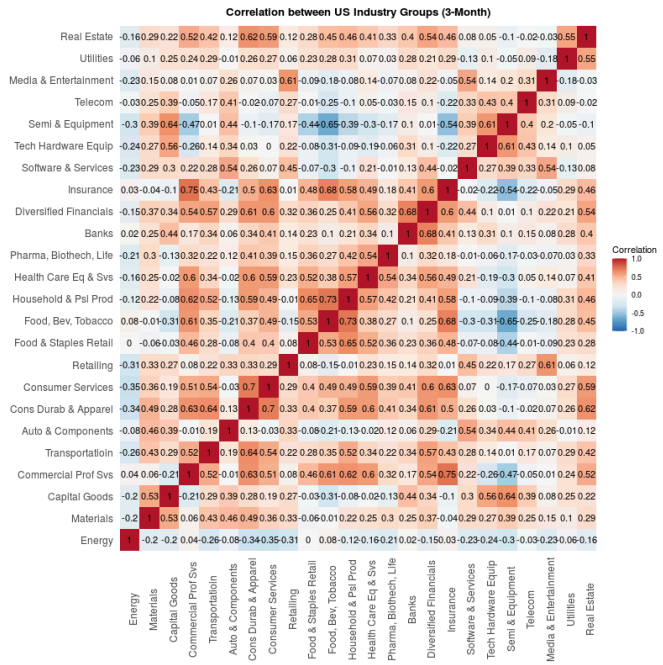
Figure 25 Recent Performance – US Industry Groups

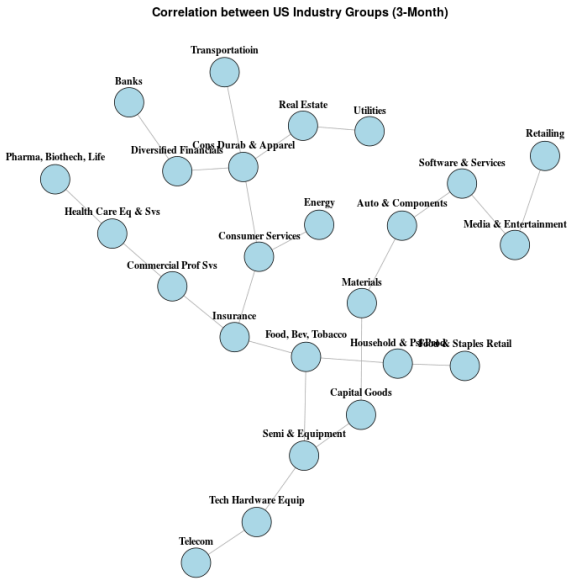
A) Summary Statistics

US Equity Industry Groups (R3K)	Cumulative Return			All History			
	Last Month (%)	3 Month (%)	12 Month (%)	Annual Return (%)	Annual Vol (%)	Sharpe Ratio	Max Drawdown (%)
Energy, TR	+13.56	+17.11	+60.52	+8.81	+22.95	+0.38	-75.27
Materials, TR	+2.15	+2.52	+20.29	+7.21	+20.51	+0.35	-63.39
Capital Goods, TR	-2.83	-9.48	+6.81	+8.99	+20.14	+0.45	-65.47
Commercial Prof Svs, TR	+13.29	+6.79	+4.99	+9.17	+20.80	+0.44	-67.56
Transportation, TR	+4.75	-3.06	+14.76	+8.32	+21.70	+0.38	-58.39
Auto & Components, TR	+11.17	+21.81	-11.10	+7.15	+27.61	+0.26	-87.00
Cons Durab & Apparel, TR	+7.18	-2.35	+0.60	+6.67	+21.39	+0.31	-70.96
Consumer Services, TR	+7.05	-4.95	+0.71	+9.05	+23.24	+0.39	-75.45
Retailing, TR	+0.45	-8.26	-1.89	+10.58	+22.39	+0.47	-61.99
Food & Staples Retail, TR	+14.69	+8.03	+20.88	+9.03	+17.73	+0.51	-54.45
Food, Bev, Tobacco, TR	+9.73	+4.78	+23.96	+9.96	+15.67	+0.64	-50.73
Household & Psl Prod, TR	+11.91	+9.82	+12.24	+8.64	+17.63	+0.49	-48.84
Health Care Eq & Svs, TR	+8.03	+5.06	+5.70	+8.88	+20.07	+0.44	-62.52
Pharma, Biotech, Life, TR	+8.31	+15.86	+43.20	+11.01	+18.92	+0.58	-48.65
Banks, TR	+0.88	-6.77	+11.61	+7.41	+23.98	+0.31	-81.42
Diversified Financials, TR	+6.25	+0.90	+5.62	+8.51	+26.30	+0.32	-80.89
Insurance, TR	+11.11	+1.76	+18.13	+7.71	+21.54	+0.36	-74.37
Software & Services, TR	+0.27	+12.26	-6.67	+13.28	+30.61	+0.43	-90.24
Tech Hardware Equip, TR	-2.28	+5.44	+32.56	+10.35	+25.21	+0.41	-85.33
Semi & Equipment, TR	-14.13	-3.68	+19.93	+17.25	+30.76	+0.56	-65.77
Telecom Services, TR	-8.50	+10.28	-19.74	+4.96	+17.88	+0.28	-78.19
Media & Entertainment, TR	-14.98	-12.26	-6.87	+10.33	+21.76	+0.47	-76.88
Utilities, TR	+9.48	-1.28	-0.72	+6.08	+15.72	+0.39	-61.67
Real Estate, TR	+4.62	-4.42	+9.21	+6.91	+22.53	+0.31	-78.33

B) Correlation Heatmap, Past 3M



C) Minimum Spanning Tree, Past 3M



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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MODEL RECOMMENDATIONS

In the short-term, our models overweight the information technology, energy, and industrials sectors, and underweight the utilities, materials, and financials sectors (see Figure 26A).

In the medium horizon (i.e., 12 months), we prefer the information technology, energy, and health care sectors, while maintaining a bearish view on the materials, real estate, and utilities sectors (see Figure 26B).

Figure 26 US Sector Return Forecast

A) Short-Term (1M) Outlook

US Equity Sectors (R3K)	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Sector Rank (1=Best)	Model Uncertainty
Energy, TR	Positive	Positive	Neutral	Positive	Positive	2	Medium
Materials, TR	Neutral	Negative	Neutral	Negative	Negative	10	Medium
Industrials, TR	Neutral	Neutral	Neutral	Positive	Positive	3	Medium
Consumer Discretionary, TR	Neutral	Negative	Positive	Neutral	Neutral	6	Medium
Consumer Staples, TR	Positive	Positive	Positive	Neutral	Neutral	4	Low
Health Care, TR	Neutral	Positive	Negative	Neutral	Neutral	5	High
Financials, TR	Negative	Neutral	Positive	Negative	Negative	9	High
Info Tech, TR	Positive	Neutral	Neutral	Positive	Positive	1	Low
Communication Services, TR	Neutral	Negative	Negative	Neutral	Neutral	8	Medium
Utilities, TR	Negative	Neutral	Neutral	Negative	Negative	11	Low
Real Estate, TR	Negative	Neutral	Negative	Neutral	Neutral	7	High

B) Mid-Term (12M) Outlook

US Equity Sectors (R3K)	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Sector Rank (1=Best)	Model Uncertainty
Energy, TR	Positive	Positive	Positive	Positive	Positive	2	Low
Materials, TR	Neutral	Negative	Negative	Negative	Negative	11	Medium
Industrials, TR	Neutral	Neutral	Neutral	Neutral	Neutral	6	Low
Consumer Discretionary, TR	Neutral	Negative	Neutral	Neutral	Neutral	5	High
Consumer Staples, TR	Positive	Positive	Negative	Neutral	Neutral	4	High
Health Care, TR	Neutral	Positive	Positive	Positive	Positive	3	Low
Financials, TR	Negative	Neutral	Negative	Neutral	Neutral	8	High
Info Tech, TR	Positive	Neutral	Positive	Positive	Positive	1	Medium
Communication Services, TR	Neutral	Negative	Neutral	Neutral	Neutral	7	Medium
Utilities, TR	Negative	Neutral	Neutral	Negative	Negative	9	Medium
Real Estate, TR	Negative	Neutral	Neutral	Negative	Negative	10	Medium

Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

As shown in Figure 27(A), in the near term, the top three industry groups favored by our models are food, beverages & tobacco, semiconductors, and auto & components, while the bottom three are telecommunication services, health care equipment & services, and materials. In the longer term, semiconductors, energy, and pharmaceuticals, biotech & life sciences are ranked at the top; meanwhile, telecommunication services, materials, and consumer durables & apparel receive the most negative ratings (see Figure 27B).

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Figure 27 US Industry Return Forecast

A) Short-Term (1M) Outlook

US Equity Industry Groups (R3K)	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Industry Rank (1=Best)	Model Uncertainty
Energy, TR	Positive	Positive	Negative	Positive	Neutral	9	High
Materials, TR	Negative	Neutral	Neutral	Negative	Negative	22	Low
Capital Goods, TR	Negative	Negative	Positive	Negative	Negative	18	High
Commercial Prof Svs, TR	Positive	Neutral	Negative	Neutral	Negative	21	Medium
Transportation, TR	Positive	Positive	Positive	Negative	Neutral	14	Medium
Auto & Components, TR	Negative	Negative	Positive	Positive	Positive	3	High
Cons Durab & Apparel, TR	Neutral	Negative	Positive	Negative	Neutral	15	High
Consumer Services, TR	Positive	Positive	Neutral	Neutral	Neutral	16	Medium
Retailing, TR	Positive	Neutral	Neutral	Neutral	Neutral	11	Low
Food & Staples Retail, TR	Positive	Positive	Neutral	Neutral	Neutral	10	Low
Food, Bev, Tobacco, TR	Neutral	Neutral	Positive	Positive	Positive	1	Low
Household & Psl Prod, TR	Positive	Positive	Neutral	Positive	Positive	5	Medium
Health Care Eq & Svs, TR	Neutral	Positive	Negative	Negative	Negative	23	High
Pharma, Biotech, Life, TR	Negative	Positive	Negative	Positive	Neutral	13	High
Banks, TR	Neutral	Negative	Positive	Neutral	Positive	6	Medium
Diversified Financials, TR	Neutral	Neutral	Positive	Neutral	Positive	4	Low
Insurance, TR	Positive	Neutral	Neutral	Neutral	Neutral	12	Medium
Software & Services, TR	Neutral	Negative	Negative	Positive	Negative	17	High
Tech Hardware Equip, TR	Neutral	Positive	Negative	Positive	Positive	8	Medium
Semi & Equipment, TR	Negative	Negative	Positive	Positive	Positive	2	High
Telecom Services, TR	Negative	Negative	Negative	Negative	Negative	24	Low
Media & Entertainment, TR	Neutral	Negative	Neutral	Negative	Negative	19	Low
Utilities, TR	Negative	Neutral	Negative	Negative	Negative	20	Low
Real Estate, TR	Negative	Neutral	Neutral	Neutral	Positive	7	Medium

B) Mid-Term (12M) Outlook

US Equity Industry Groups (R3K)	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Industry Rank (1=Best)	Model Uncertainty
Energy, TR	Positive	Positive	Positive	Positive	Positive	2	Low
Materials, TR	Negative	Neutral	Negative	Negative	Negative	23	Low
Capital Goods, TR	Negative	Negative	Neutral	Negative	Negative	18	Low
Commercial Prof Svs, TR	Positive	Neutral	Negative	Neutral	Negative	20	High
Transportation, TR	Positive	Neutral	Neutral	Neutral	Neutral	15	Low
Auto & Components, TR	Negative	Negative	Positive	Positive	Positive	4	High
Cons Durab & Apparel, TR	Neutral	Negative	Negative	Negative	Negative	22	Medium
Consumer Services, TR	Positive	Positive	Neutral	Neutral	Positive	8	Medium
Retailing, TR	Positive	Negative	Positive	Positive	Positive	7	Medium
Food & Staples Retail, TR	Positive	Positive	Positive	Neutral	Positive	5	Low
Food, Bev, Tobacco, TR	Neutral	Positive	Negative	Positive	Neutral	11	Medium
Household & Psl Prod, TR	Positive	Positive	Neutral	Neutral	Neutral	10	Medium
Health Care Eq & Svs, TR	Neutral	Positive	Negative	Negative	Negative	21	High
Pharma, Biotech, Life, TR	Negative	Neutral	Positive	Positive	Positive	3	High
Banks, TR	Neutral	Negative	Neutral	Negative	Negative	19	Low
Diversified Financials, TR	Neutral	Positive	Neutral	Neutral	Neutral	12	Low
Insurance, TR	Positive	Positive	Negative	Neutral	Negative	17	High
Software & Services, TR	Neutral	Negative	Negative	Positive	Neutral	13	High
Tech Hardware Equip, TR	Neutral	Neutral	Neutral	Positive	Positive	6	Medium
Semi & Equipment, TR	Negative	Negative	Positive	Positive	Positive	1	High
Telecom Services, TR	Negative	Neutral	Negative	Negative	Negative	24	Low
Media & Entertainment, TR	Neutral	Negative	Positive	Negative	Neutral	14	High
Utilities, TR	Negative	Neutral	Neutral	Neutral	Neutral	9	Medium
Real Estate, TR	Negative	Neutral	Positive	Negative	Neutral	16	Medium

Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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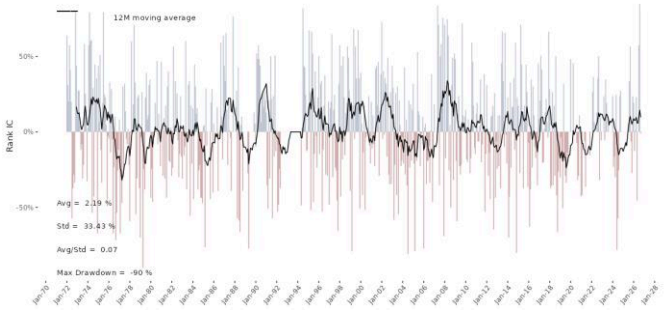
Sector and Industry Rotation Model Performance

For both sector and industrial rotation, most of our models have delivered strong performance in the long run (see Figure 28 and Figure 29).

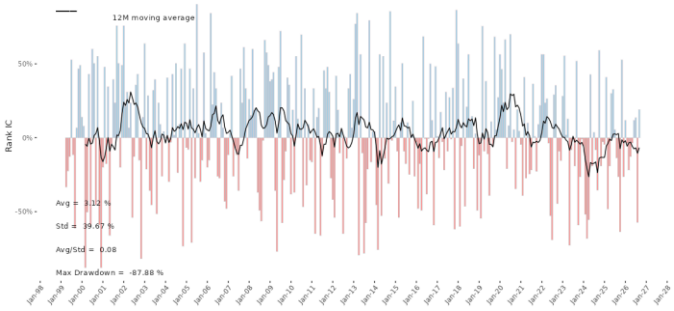
Given the larger universe at the industry level (24 industries), the CSM model performs much better for industry selection (see Figure 29A) than in sector rotation (see Figure 28A). The MLM model shows strong performance in recent years (see Figure 28D).

Figure 28 US Sector Rotation Model Performance

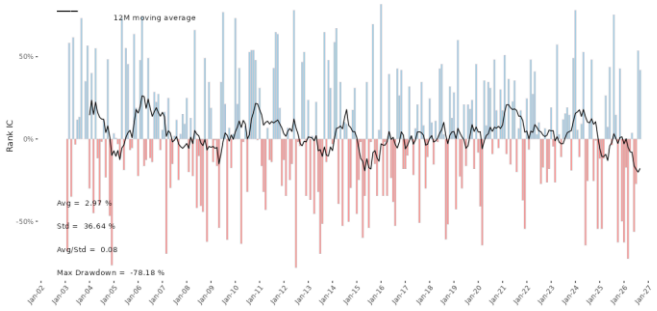
A) Cross Sectional Model (CSM)



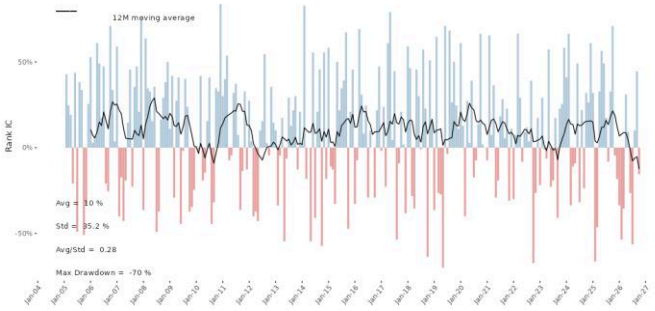
B) Tactical Regression Model (TRM)



C) Economic Cycle Model (ECM)



D) Machine Learning Model (MLM)



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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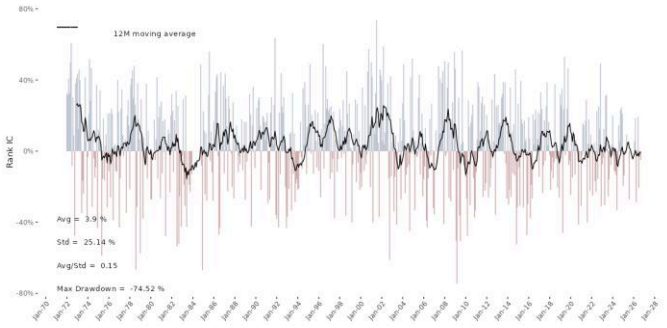
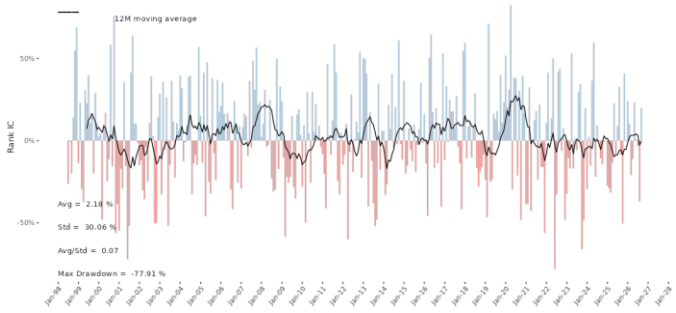
Figure 29 US Industry Rotation Model Performance

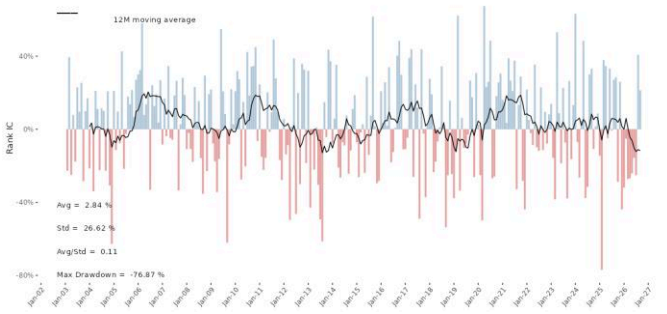
A) Cross Sectional Model (CSM)



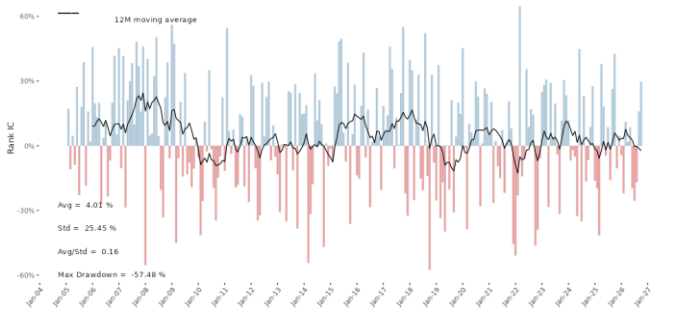
B) Tactical Regression Model (TRM)



C) Economic Cycle Model (ECM)



D) Machine Learning Model (MLM)



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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US AND GLOBAL EQUITY STYLE FACTOR ROTATION

In this section, we discuss our global equity style rotation models. We pick 15 common factors that represent six major investment styles – value, growth, momentum and reversal, analyst sentiment, quality, and risk. For active quantitative equity managers, these factors represent the most commonly used signals for stock selection[3]. For asset allocation and global macro investing, these factors compose the majority of the equity alternative beta (or risk premia) products.

The factor portfolios are constructed as long/short quintile portfolios[4]. All stocks[5] in each of the ten regions (US, Canada, LATAM, Europe ex UK, UK, Emerging EMEA, Asia ex Japan, Japan, Australia and New Zealand, and China A) are sorted every month, based on the factor of interest. The top 20% stocks are selected for the long portfolio and the bottom 20% fall into the short basket. Stocks in the long (and short) bucket are equally weighted. Factor portfolios are rebalanced monthly and returns are tracked daily without transaction cost. To capture pure factor performance, we adjust for sector effect within single countries (i.e., US, Canada, UK, Japan, and China A). For multi-country regions (i.e., LATAM, Europe ex UK, Emerging EMEA, and AxJ), we neutralize country effect. We normalize factors based on sectors for ANZ. All factor returns are computed using local currency.

From this issue onwards, we also summarize factor crowdedness status for global regions except China, in the end of this chapter.

Please note that we have over 400 global stock-selection factors in our factor library. We can backtest any factor for any specific investment universe and provide a data feed on daily factor performance. Please contact us at Luo.QES@wolferesearch.com for details.

RECENT PERFORMANCE

In October, low beta, ROE, short-term reversal, and value factors (EBITDA/TEV, earnings yield, dividend yield) recorded gains in most regions, while size (small-cap), momentum, earnings revision, and long-term growth factors fell in multiple regions (see Figure 30).

[3] For active investors, we strongly recommend managers to go beyond these conventional factors. The focus of our quantitative research has always been on alternative Big Data. Even when we work with traditional fundamental/market data, we always search for different and more sophisticated ways to construct factors. The performance of unconventional factors is more likely to be consistent over time.

[4] The portfolio construction process is relatively naïve by the standard of quantitative equity investing. However, it is easier to implement, fully transparent, and consistent with standard finance literature.

[5] We use a fairly broad investment universe in all countries, i.e., the Russell 3000 for the US, S&P/TSX Composite Index for Canada, and S&P/BMI index for other countries.

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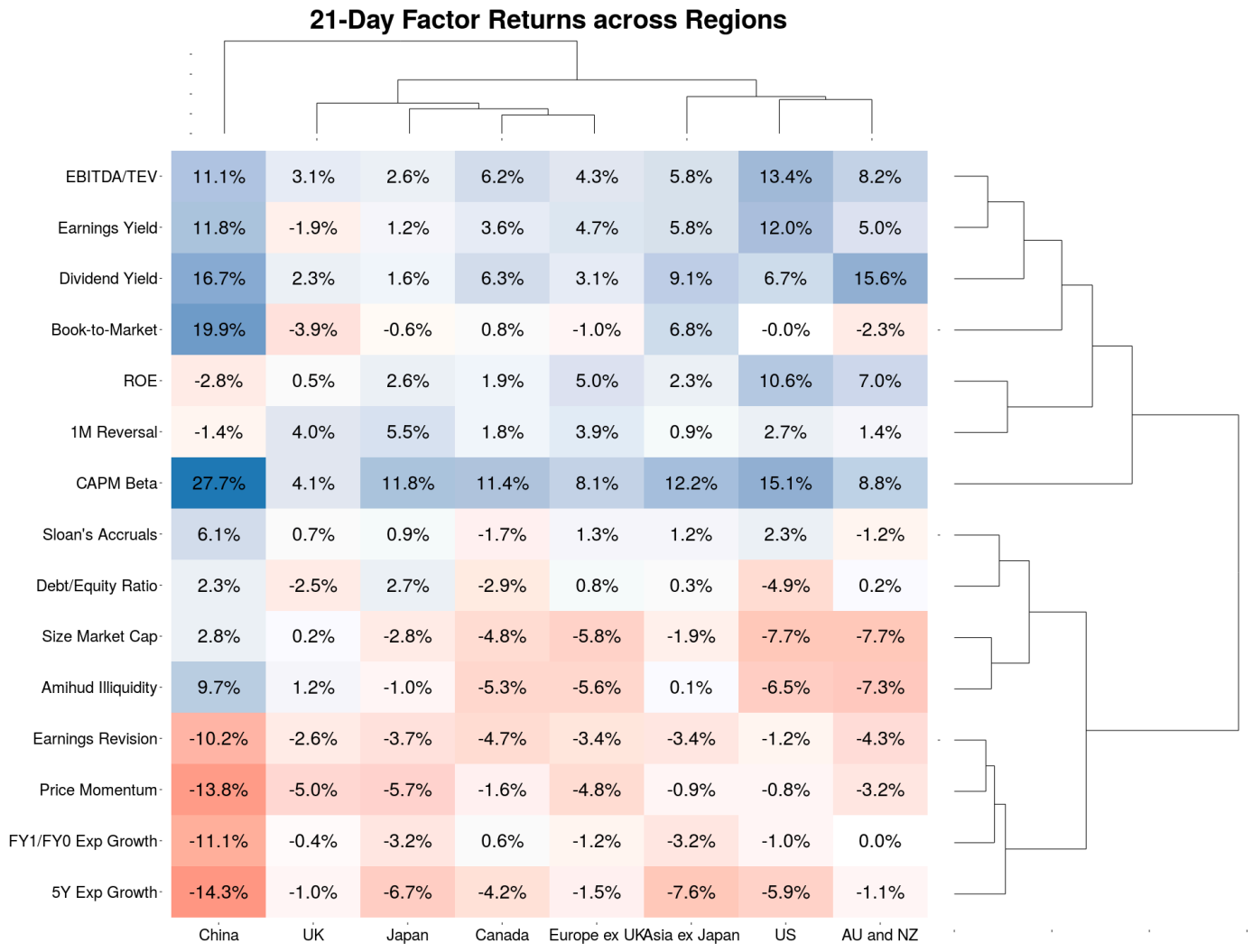
Figure 30 Recent Global Style Factor Performance



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

US Equity Style Rotation

In the US, low beta, EBITDA/TEV, earnings yield, and ROE factors recorded great gains in the last month; meanwhile, size (small-cap), illiquidity, and long-term growth factors retreated (see Figure 31A).

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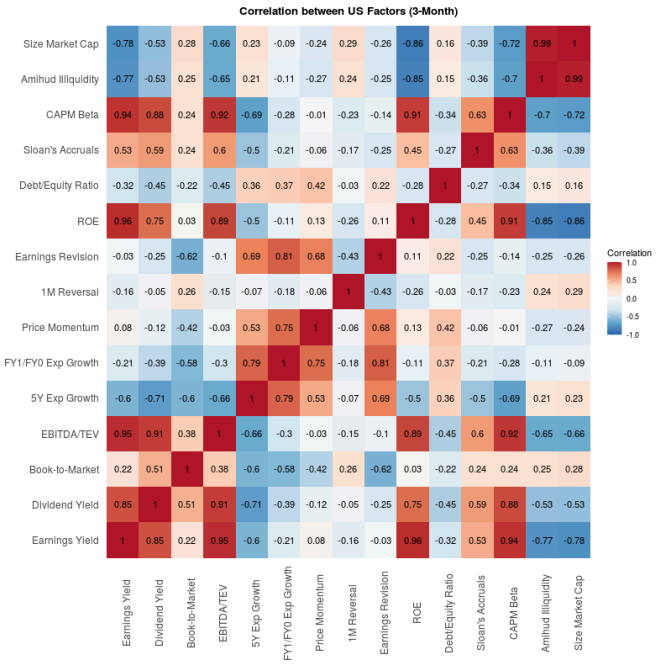
Figure 31 US Factor Recent Performance

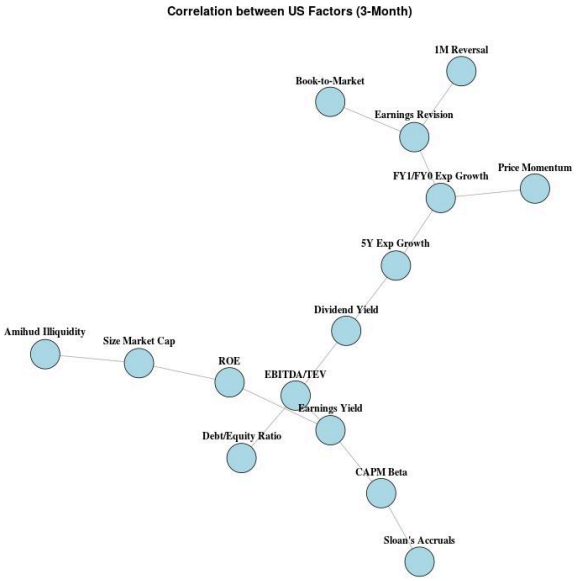
A) US Factor Summary Statistics

US Equity Style Factors	Cumulative Return			All History			
	Last Month (%)	3 Month (%)	12 Month (%)	Annual Return (%)	Annual Vol (%)	Sharpe Ratio	Max Drawdown (%)
Earnings Yield (Cheap-Expensive)	+12.03	+13.12	+30.74	+9.38	+9.42	+1.00	-41.09
Dividend Yield (High-Low)	+6.67	+3.15	+10.95	+2.90	+11.06	+0.26	-56.82
Book-to-Market (Cheap-Expensive)	-0.00	+1.14	+22.49	+3.74	+10.12	+0.37	-38.49
EBITDA/TEV (Cheap-Expensive)	+13.37	+12.19	+40.48	+10.79	+9.07	+1.19	-39.80
Consensus 5Y Exp Growth (High-Low)	-5.94	-5.50	-7.96	-2.52	+8.23	-0.31	-71.07
FY1/FY0 Exp Growth (High-Low)	-1.02	+0.81	-0.60	+1.32	+6.44	+0.20	-40.78
Price Momentum, 12M TR (High-Low)	-0.83	-0.45	+1.66	+11.77	+12.67	+0.93	-59.60
1M Reversal (Low-High)	+2.75	+6.79	+6.51	+15.01	+11.29	+1.33	-37.02
Earnings Revision, 3M (High-Low)	-1.25	+0.49	-1.33	+8.73	+6.63	+1.32	-27.55
ROE (High-Low)	+10.57	+11.20	+19.75	+6.50	+9.44	+0.69	-49.00
Debt/Equity Ratio (Low-High)	-4.92	-0.29	+2.15	+1.41	+6.61	+0.21	-48.21
Sloan's Accruals (Low-High)	+2.31	+2.63	+15.18	+5.05	+4.11	+1.23	-9.79
CAPM Beta (Low-High)	+15.14	+9.99	+6.02	-1.55	+16.58	-0.09	-77.31
Amihud Illiquidity (High-Low)	-6.51	-6.52	-6.04	-3.47	+12.10	-0.29	-93.59
Size Market Cap (Small-Big)	-7.70	-6.41	-6.19	-0.82	+13.34	-0.06	-91.74

B) Correlation Heatmap, Past 3M



C) Minimum Spanning Tree, Past 3M



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

Our style timing models favor EBITDA/TEV, earnings yield, ROE, dividend yield, and earnings quality in the near term (see Figure 32A). Meanwhile, size (small-cap), illiquidity, long-term growth, low leverage, and low beta are likely to struggle.

In the medium horizon, we recommend overweighting EBITDA/TEV, earnings yield, ROE, momentum, and short-term reversal; while underweighting illiquidity, size (small-cap), long-term growth, book-to-market, and low leverage (see Figure 32B).

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Figure 32 US Factor Return Forecast

A) Short-Term (1M) Outlook

US Equity Style Factors	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Style Rank (1=Best)	Model Uncertainty
Earnings Yield (Cheap-Expensive)	Positive	Positive	Positive	Positive	Positive	2	Low
Dividend Yield (High-Low)	Negative	Positive	Positive	Positive	Positive	4	High
Book-to-Market (Cheap-Expensive)	Negative	Positive	Neutral	Neutral	Neutral	7	High
EBITDA/TEV (Cheap-Expensive)	Positive	Positive	Positive	Positive	Positive	1	Low
Consensus 5Y Exp Growth (High-Low)	Neutral	Negative	Negative	Negative	Negative	13	Medium
FY1/FY0 Exp Growth (High-Low)	Positive	Neutral	Neutral	Neutral	Neutral	6	Medium
Price Momentum, 12M TR (High-Low)	Neutral	Negative	Positive	Positive	Neutral	8	High
1M Reversal (Low-High)	Neutral	Neutral	Neutral	Negative	Neutral	9	High
Earnings Revision, 3M (High-Low)	Positive	Negative	Neutral	Neutral	Neutral	10	High
ROE (High-Low)	Positive	Positive	Positive	Positive	Positive	3	Medium
Debt/Equity Ratio (Low-High)	Neutral	Neutral	Negative	Negative	Negative	12	Low
Sloan's Accruals (Low-High)	Neutral	Neutral	Neutral	Neutral	Positive	5	Low
CAPM Beta (Low-High)	Negative	Neutral	Negative	Neutral	Negative	11	Medium
Amihud Illiquidity (High-Low)	Negative	Negative	Negative	Negative	Negative	14	Low
Size Market Cap (Small-Big)	Negative	Negative	Negative	Negative	Negative	15	Medium

B) Mid-Term (12M) Outlook

US Equity Style Factors	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Style Rank (1=Best)	Model Uncertainty
Earnings Yield (Cheap-Expensive)	Positive	Positive	Positive	Positive	Positive	2	Low
Dividend Yield (High-Low)	Negative	Neutral	Positive	Positive	Neutral	8	High
Book-to-Market (Cheap-Expensive)	Negative	Neutral	Negative	Neutral	Negative	12	Medium
EBITDA/TEV (Cheap-Expensive)	Positive	Positive	Positive	Positive	Positive	1	Low
Consensus 5Y Exp Growth (High-Low)	Neutral	Negative	Neutral	Negative	Negative	13	Medium
FY1/FY0 Exp Growth (High-Low)	Positive	Negative	Neutral	Negative	Neutral	9	High
Price Momentum, 12M TR (High-Low)	Neutral	Negative	Positive	Neutral	Positive	4	High
1M Reversal (Low-High)	Neutral	Positive	Neutral	Negative	Positive	5	High
Earnings Revision, 3M (High-Low)	Positive	Neutral	Neutral	Neutral	Neutral	7	Medium
ROE (High-Low)	Positive	Positive	Positive	Positive	Positive	3	Medium
Debt/Equity Ratio (Low-High)	Neutral	Neutral	Negative	Neutral	Negative	11	Low
Sloan's Accruals (Low-High)	Neutral	Neutral	Neutral	Positive	Neutral	6	Medium
CAPM Beta (Low-High)	Negative	Positive	Negative	Neutral	Neutral	10	High
Amihud Illiquidity (High-Low)	Negative	Negative	Negative	Negative	Negative	15	Low
Size Market Cap (Small-Big)	Negative	Negative	Negative	Negative	Negative	14	Low

Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

Cross Sectional Analysis

As shown in Figure 33(A), cross-sectionally, ROE and earnings yield are top ranked. On the other hand, illiquidity and size (small-cap) are ranked at the bottom.

The variables with the best ability to rank style factors cross sectionally are earnings revision and trend following (see Figure 33B and C).

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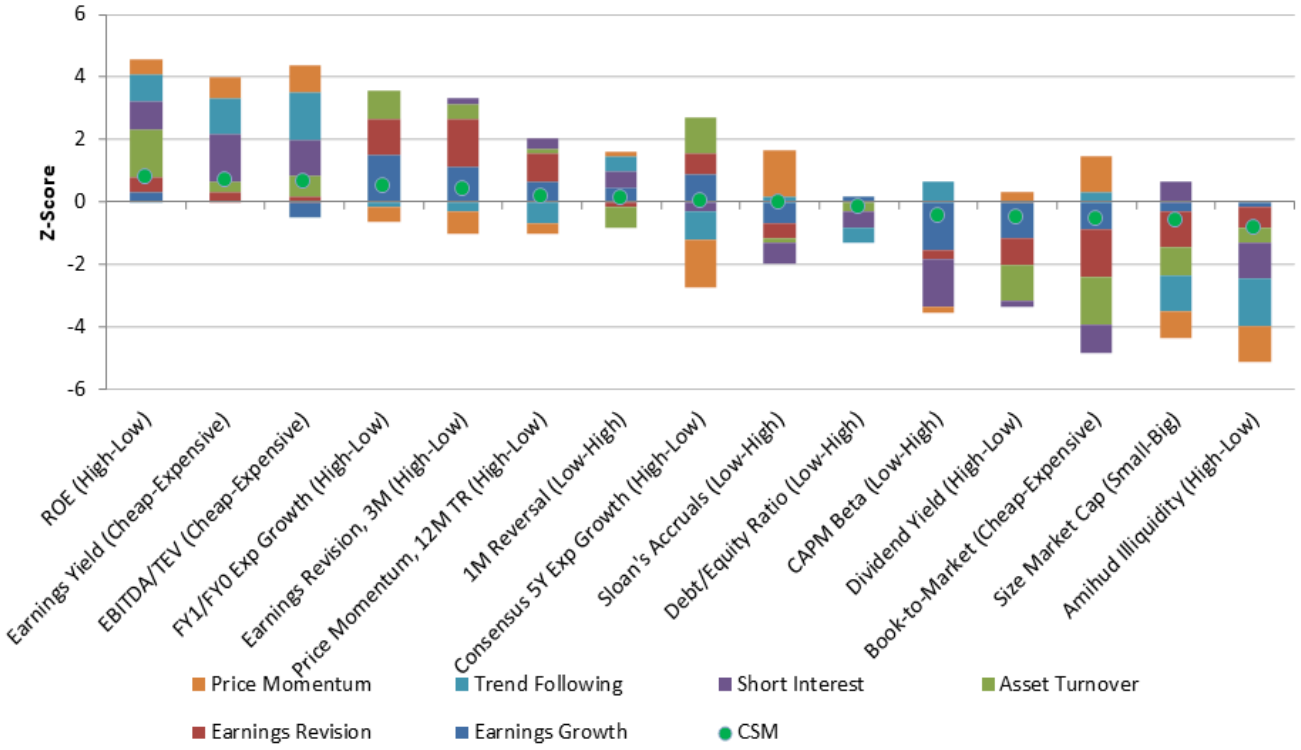
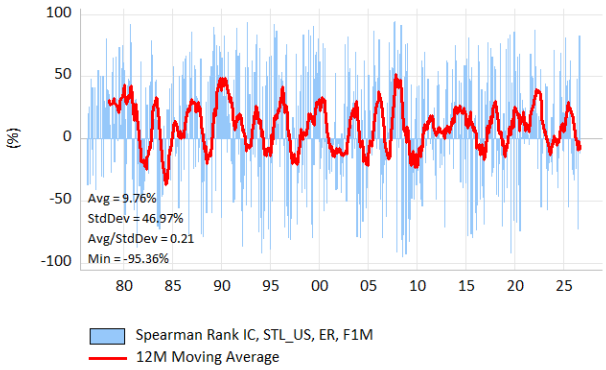
Figure 33 Cross Sectional Analysis

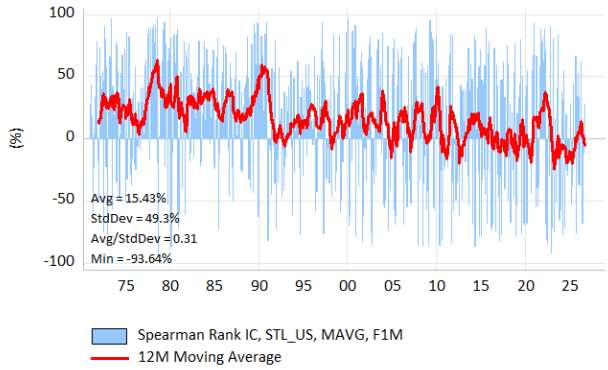
A) Current Cross Sectional Alpha



B) Performance, Earnings Revision



C) Performance, Trend Following



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

Model Performance

Over the long term, the MLM and ECM models have better performance relative to the other two models.

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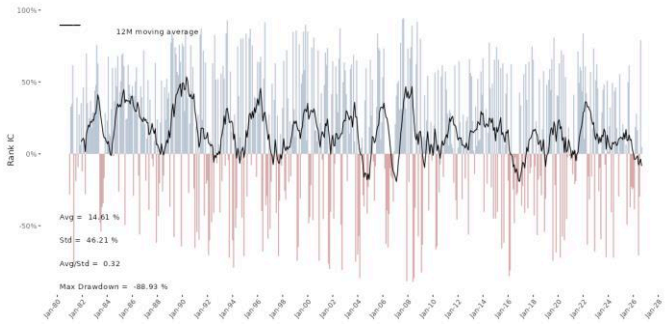
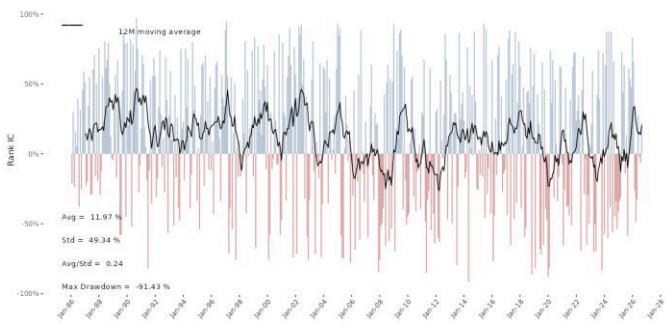
Figure 34 US Equity Style Factor Rotation Model Performance

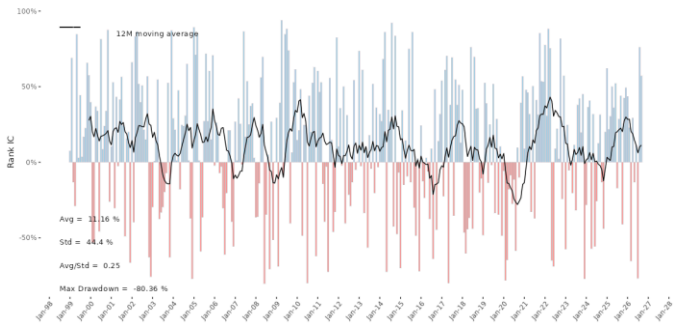
A) Cross Sectional Model (CSM)



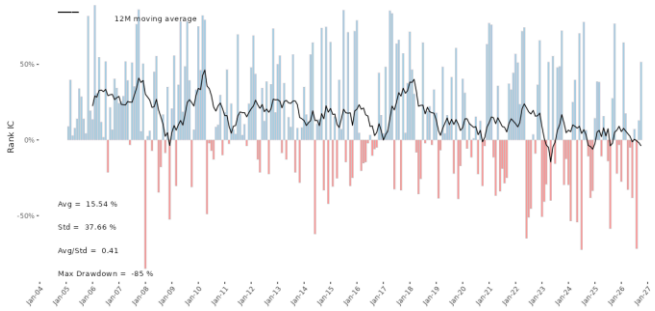
B) Tactical Regression Model (TRM)



C) Economic Cycle Model (ECM)



D) Machine Learning Model (MLM)



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

EUROPEAN EQUITY STYLE ROTATION

As seen in Figure 35(A), low beta, ROE, short-term reversal, and value factors (earnings yield, EBITDA/TEV, dividend yield) posted gains in Europe, while size (small-cap), illiquidity, and momentum factors fell.

Based on the minimum spanning tree, low beta is at the center of factor network during the past three months (see Figure 35C).

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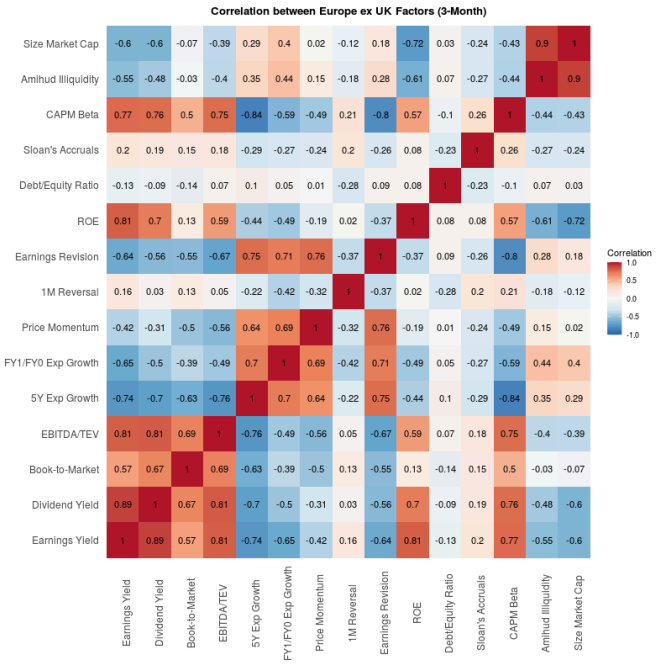
Figure 35 European Factor Recent Performance

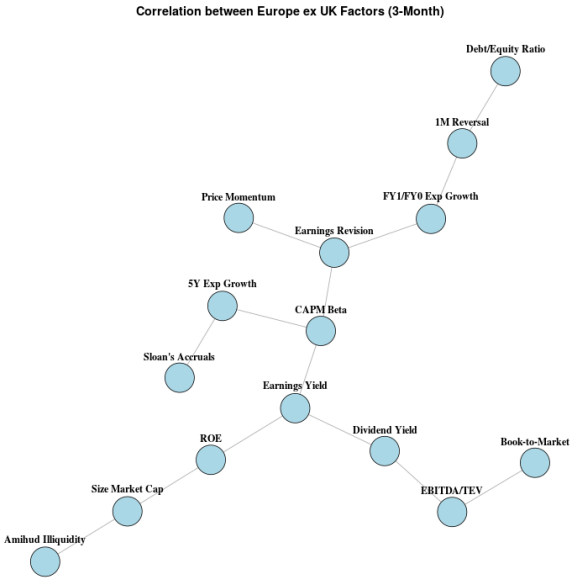
A) European Factor Summary Statistics

Europe Equity Style Factors	Cumulative Return			All History			
	Last Month (%)	3 Month (%)	12 Month (%)	Annual Return (%)	Annual Vol (%)	Sharpe Ratio	Max Drawdown (%)
Earnings Yield (Cheap-Expensive)	+4.74	+5.22	+18.90	+7.39	+7.51	+0.98	-31.14
Dividend Yield (High-Low)	+3.09	+4.07	+19.85	+6.70	+7.63	+0.88	-37.14
Book-to-Market (Cheap-Expensive)	-1.04	-2.69	-0.75	+0.94	+8.32	+0.11	-65.13
EBITDA/TEV (Cheap-Expensive)	+4.35	+8.02	+22.29	+9.39	+8.29	+1.13	-37.87
Consensus 5Y Exp Growth (High-Low)	-1.48	+0.34	-5.73	-1.89	+6.69	-0.28	-67.70
FY1/FY0 Exp Growth (High-Low)	-1.23	+0.81	-5.35	-0.40	+6.23	-0.06	-36.37
Price Momentum, 12M TR (High-Low)	-4.77	+0.12	+7.97	+14.24	+10.77	+1.32	-42.50
1M Reversal (Low-High)	+3.87	-2.06	-8.81	+0.40	+9.28	+0.04	-53.56
Earnings Revision, 3M (High-Low)	-3.44	+0.02	-5.12	+7.68	+6.19	+1.24	-23.55
ROE (High-Low)	+4.96	+7.77	+14.42	+8.02	+7.26	+1.11	-27.70
Debt/Equity Ratio (Low-High)	+0.81	+4.44	-2.10	+1.72	+6.37	+0.27	-40.95
Sloan's Accruals (Low-High)	+1.31	+1.16	+0.27	+2.15	+11.04	+0.19	-55.94
CAPM Beta (Low-High)	+8.12	+6.59	-2.66	+1.96	+17.14	+0.11	-61.19
Amihud Illiquidity (High-Low)	-5.61	-5.03	-14.45	-5.22	+10.07	-0.52	-88.30
Size Market Cap (Small-Big)	-5.78	-5.57	-12.23	-4.31	+8.90	-0.48	-84.73

B) Correlation Heatmap, Past 3M



C) Minimum Spanning Tree, Past 3M



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

In the near term, we expect EBITDA/TEV, ROE, dividend yield, short-term growth, and earnings yield to outperform, while short-term reversal, illiquidity, size (small-cap), long-term growth, and momentum are likely to struggle (see Figure 36A).

In the medium horizon (12 months), our models favor EBITDA/TEV, ROE, momentum, earnings yield, and dividend yield. On the other hand, we are negative on illiquidity, size (small-cap), short-term reversal, book-to-market, and long-term growth (see Figure 36B).

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Figure 36 European Factor Return Forecast

A) Short-Term (1M) Outlook

Europe Equity Style Factors	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Style Rank (1=Best)	Model Uncertainty
Earnings Yield (Cheap-Expensive)	Neutral	Negative	Positive	Positive	Positive	5	High
Dividend Yield (High-Low)	Negative	Neutral	Positive	Positive	Positive	3	High
Book-to-Market (Cheap-Expensive)	Negative	Neutral	Positive	Neutral	Neutral	10	Medium
EBITDA/TEV (Cheap-Expensive)	Neutral	Positive	Positive	Positive	Positive	1	Low
Consensus 5Y Exp Growth (High-Low)	Neutral	Neutral	Negative	Neutral	Negative	12	Low
FY1/FY0 Exp Growth (High-Low)	Positive	Positive	Neutral	Neutral	Positive	4	Low
Price Momentum, 12M TR (High-Low)	Positive	Negative	Neutral	Negative	Negative	11	High
1M Reversal (Low-High)	Negative	Negative	Negative	Negative	Negative	15	Low
Earnings Revision, 3M (High-Low)	Positive	Negative	Neutral	Neutral	Neutral	8	Medium
ROE (High-Low)	Positive	Neutral	Positive	Positive	Positive	2	Medium
Debt/Equity Ratio (Low-High)	Positive	Positive	Negative	Negative	Neutral	7	Medium
Sloan's Accruals (Low-High)	Neutral	Neutral	Neutral	Neutral	Neutral	6	Low
CAPM Beta (Low-High)	Neutral	Negative	Neutral	Positive	Neutral	9	Medium
Amihud Illiquidity (High-Low)	Negative	Positive	Negative	Negative	Negative	14	High
Size Market Cap (Small-Big)	Negative	Positive	Negative	Negative	Negative	13	High

B) Mid-Term (12M) Outlook

Europe Equity Style Factors	Cross Sectional CSM	Tactical Regression TRM	Economic Cycle ECM	Machine Learning MLM	Combined L-Macro	Style Rank (1=Best)	Model Uncertainty
Earnings Yield (Cheap-Expensive)	Neutral	Positive	Positive	Positive	Positive	4	High
Dividend Yield (High-Low)	Negative	Positive	Neutral	Positive	Positive	5	High
Book-to-Market (Cheap-Expensive)	Negative	Negative	Neutral	Negative	Negative	12	Medium
EBITDA/TEV (Cheap-Expensive)	Neutral	Positive	Positive	Positive	Positive	1	High
Consensus 5Y Exp Growth (High-Low)	Neutral	Neutral	Negative	Negative	Negative	11	Medium
FY1/FY0 Exp Growth (High-Low)	Positive	Neutral	Neutral	Neutral	Neutral	8	High
Price Momentum, 12M TR (High-Low)	Positive	Positive	Positive	Positive	Positive	3	Medium
1M Reversal (Low-High)	Negative	Negative	Negative	Negative	Negative	13	Low
Earnings Revision, 3M (High-Low)	Positive	Negative	Positive	Neutral	Neutral	6	High
ROE (High-Low)	Positive	Positive	Positive	Positive	Positive	2	Medium
Debt/Equity Ratio (Low-High)	Positive	Neutral	Negative	Neutral	Neutral	9	High
Sloan's Accruals (Low-High)	Neutral	Neutral	Neutral	Neutral	Neutral	10	Low
CAPM Beta (Low-High)	Neutral	Neutral	Neutral	Neutral	Neutral	7	Low
Amihud Illiquidity (High-Low)	Negative	Negative	Negative	Negative	Negative	15	Low
Size Market Cap (Small-Big)	Negative	Negative	Negative	Negative	Negative	14	Low

Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

Cross Sectional Analysis

Our cross-sectional analysis ranks ROE and momentum at the top; and illiquidity and book-to-market at the bottom (see Figure 37A).

Between value (see Figure 37B) and momentum (see Figure 37C), momentum has had higher efficacy at ranking styles in Europe both in the long term and in the recent years.

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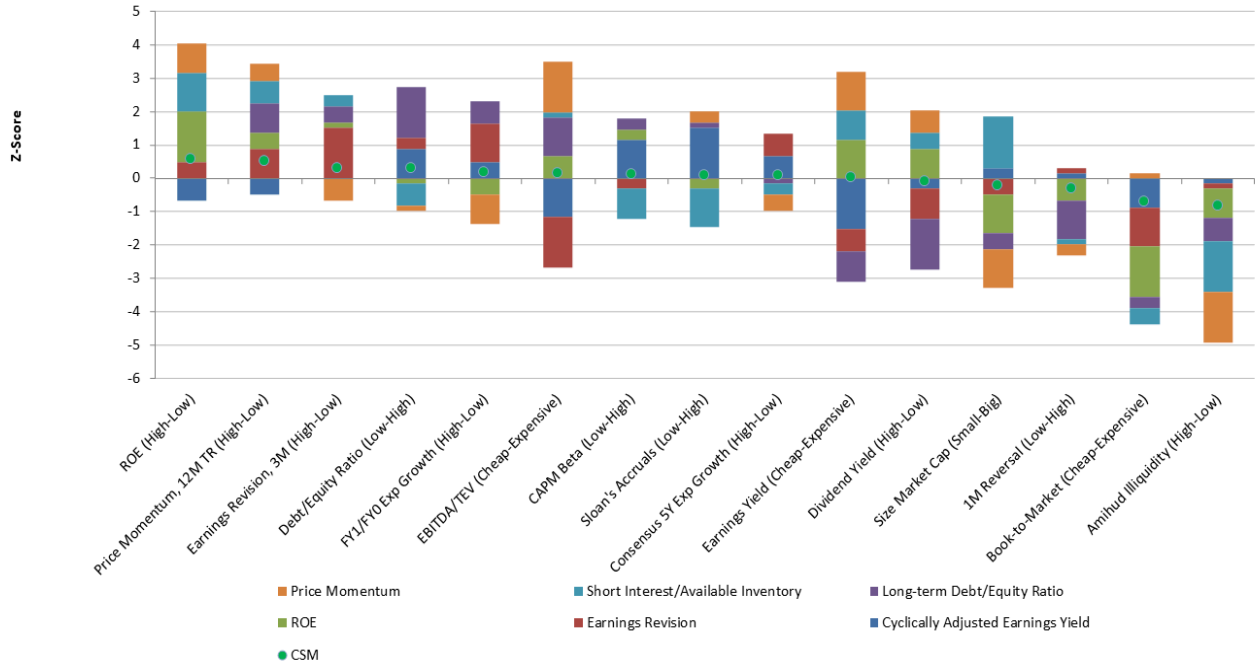
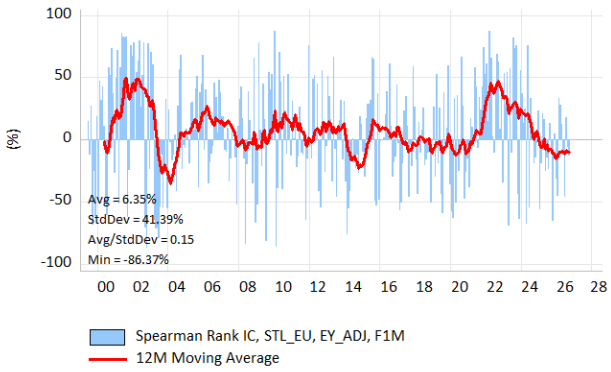
Figure 37 Cross Sectional Analysis

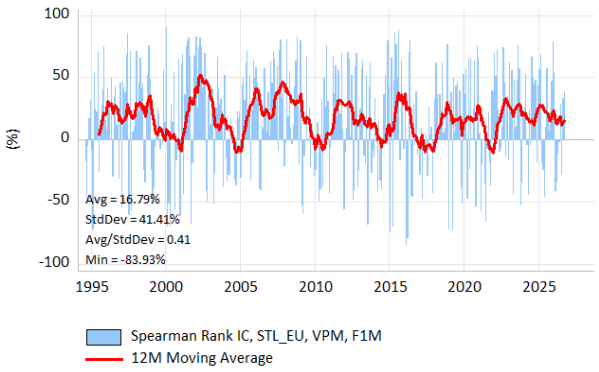
A) Current Cross Sectional Alpha



B) Performance, Earnings Yield



C) Performance, Price Momentum



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

Model Performance

In the long term, all models have delivered exceptional performance (see Figure 38D).

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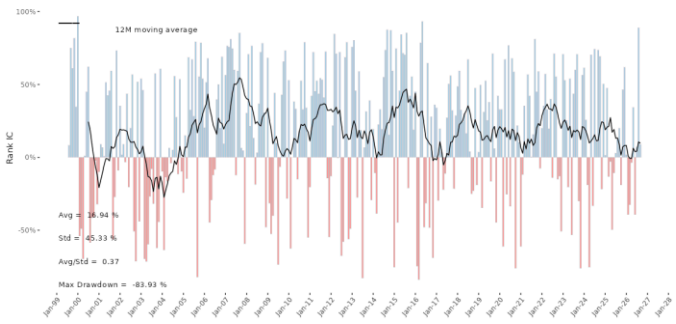
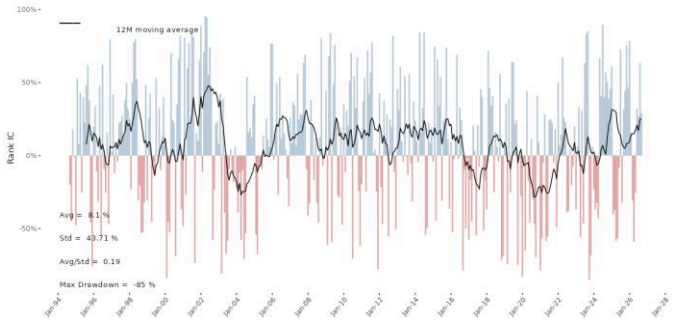
Figure 38 European Equity Style Factor Rotation Model Performance

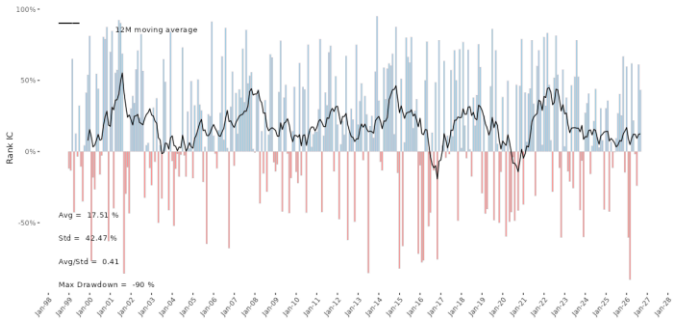
A) Cross Sectional Model (CSM)



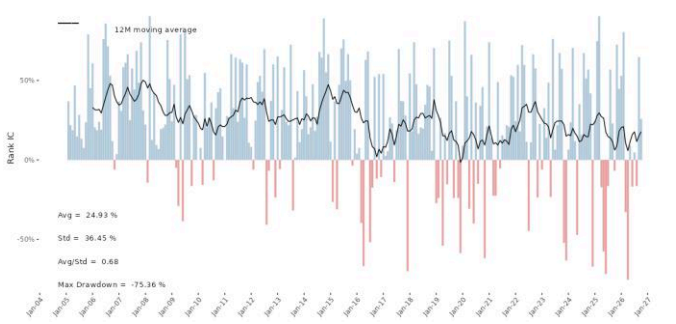
B) Tactical Regression Model (TRM)



C) Economic Cycle Model (ECM)



D) Machine Learning Model (MLM)



Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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GLOBAL EQUITY STYLE CROWDING

In *Factor Crowding, Tail Dependence, and Dynamic Allocation*, we use real-time securities lending data to measure the crowding risk of style factors. Our measure covers nine geographic regions globally. Since single stock shorting in China A Shares Market is largely restricted, we exclude China Onshore market from the analysis. We argue that the trend of crowding is typically more informative than the absolute level. In Figure 39, we summarize the current crowdedness of 15 style factors, using z-scores computed with rolling five-year data. A factor is identified as being "crowded" (or "uncrowded") if its crowding z-score is above $+1$ (or below -1).

Globally, signs of factor crowding are pronounced in the US, UK, Asia, and Japan. In the US, investors are gravitating toward stocks with strong short-term growth, price momentum, earnings revisions, profitability, and low market beta, whereas the UK market gets a similar factor crowding profile. All four value factors appear crowded in Japan. In Asia ex Japan, crowding is concentrated in earnings growth and revisions, profitability, low leverage, and low beta.

Empirically, our analysis suggests that extreme level of crowding may lead to future downside risk. Additionally, when a pair of factors are both crowded, it is more likely to result in a surge in their tail dependence, i.e., both factors are more likely to collapse at the same time than what is implied by correlation.

Figure 39 Global Factor Crowdedness

Equity Style Factors	US	Canada	Europe ex UK	UK	Japan	AU and NZ	Asia ex Japan	EMEA	LATAM
Earnings Yield (Cheap-Expensive)	Crowded	Modest	Modest	Crowded	Crowded	Modest	Crowded	Crowded	Uncrowded
Dividend Yield (High-Low)	Uncrowded	Modest	Modest	Uncrowded	Crowded	Crowded	Crowded	Modest	Crowded
Book-to-Market (Cheap-Expensive)	Uncrowded	Modest	Modest	Modest	Crowded	Modest	Modest	Modest	Modest
EBITDA/TEV (Cheap-Expensive)	Crowded	Modest	Modest	Crowded	Crowded	Modest	Modest	Modest	Modest
Consensus 5Y Exp Growth (High-Low)	Modest	Uncrowded	Uncrowded	Crowded	Modest	Modest	Modest	Uncrowded	Modest
FY1/FY0 Exp Growth (High-Low)	Crowded	Modest	Modest	Modest	Modest	Modest	Crowded	Uncrowded	Modest
Price Momentum, 12M TR (High-Low)	Crowded	Modest	Crowded	Crowded	Modest	Modest	Crowded	Crowded	Modest
1M Reversal (Low-High)	Uncrowded	Uncrowded	Uncrowded	Modest	Modest	Modest	Modest	Crowded	Modest
Earnings Revision, 3M (High-Low)	Crowded	Modest	Crowded	Crowded	Uncrowded	Modest	Crowded	Modest	Modest
ROE (High-Low)	Crowded	Modest	Modest	Crowded	Uncrowded	Crowded	Crowded	Modest	Uncrowded
Debt/Equity Ratio (Low-High)	Modest	Crowded	Crowded	Crowded	Modest	Modest	Crowded	Crowded	Modest
Sloan's Accruals (Low-High)	Modest	Crowded	Modest	Modest	Modest	Modest	Modest	Uncrowded	Modest
CAPM Beta (Low-High)	Crowded	Modest	Modest	Crowded	Modest	Uncrowded	Crowded	Uncrowded	Modest
Amihud Illiquidity (High-Low)	Uncrowded	Uncrowded	Modest	Modest	Uncrowded	Modest	Uncrowded	Modest	Modest
Size Market Cap (Small-Big)	Uncrowded	Uncrowded	Uncrowded	Uncrowded	Uncrowded	Modest	Modest	Modest	Uncrowded

Sources: Bloomberg Finance LLP, FTSE Russell, Haver, S&P Capital IQ, Refinitiv, EquiLend, Wolfe Research Luo's QES

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