

Efficient Momentum Resilience: A WRDS-Based Test of a Composite Equity Factor

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Abstract

This paper examines whether a transparent composite signal can predict the cross-section of U.S. stock returns. The proposed Efficient Momentum Resilience (EMR) measure combines four established return-predictive dimensions: intermediate-term momentum, sales efficiency, conservative investment, and low historical volatility. Using monthly U.S. equity data from January 2010 to December 2024, lagged accounting characteristics, and Fama–French factors, the underlying characteristics are cross-sectionally standardized each month and combined into EMR. All variables are aligned on a strict point-in-time basis to ensure that only information available at the portfolio formation date is used, thereby avoiding look-ahead bias. Baseline equal-weighted quintile sorts show that the high-minus-low EMR portfolio earns an average monthly return of 1.79% (Newey–West $t = 3.83$) and a Fama–French five-factor alpha of 1.91% per month ($t = 5.35$). Consistent with the portfolio evidence, Fama–MacBeth regressions yield a positive and statistically significant average coefficient on EMR ($t = 5.04$). The predictive relation remains positive across alternative portfolio groupings, value-weighted specifications, a \$5 minimum-price filter, and two subsample periods.

Keywords

cross-sectional returns, factor investing, momentum, firm characteristics

1. Introduction

What makes a firm characteristic a useful predictor of the cross-section of expected stock returns? Since the early evidence on size, value, and momentum, empirical asset pricing has identified many firm-level variables associated with subsequent returns [1-4]. The central challenge is no longer only to find a statistically significant sort. It is to determine whether a proposed signal captures a coherent economic mechanism, contains information beyond established predictors, survives reasonable changes in portfolio construction, and can be reproduced without using information that was unavailable at the portfolio-formation date.

This problem is important because the expanding set of published return predictors makes false discovery and specification search increasingly difficult to distinguish from genuine pricing information. Evidence on the factor zoo, the overlap among firm characteristics, and the failure of many anomalies to replicate shows that strong in-sample t -statistics alone are not sufficient [16-18]. A useful candidate factor should therefore be

transparent about its economic ingredients, its information timing, and the alternatives against which it is evaluated. These requirements matter both for academic inference and for practice: a signal that is dominated by a familiar exposure, concentrated in microcaps, or dependent on a narrow specification is unlikely to provide a durable basis for portfolio decisions.

Several established literatures motivate the ingredients studied in this paper. Intermediate-term momentum documents persistence in relative stock performance [3, 6]. Operating efficiency and profitability connect the productive use of firm assets to expected returns [11, 13]. The investment literature finds that firms with aggressive capital or asset growth often earn lower subsequent returns, an insight incorporated into investment-based models and the Fama-French five-factor model [8, 10, 14, 15]. Ang et al. document low average returns among high-volatility stocks, whereas Bali et al. show the link between idiosyncratic volatility and future returns changes when extreme positive daily returns are controlled for. [9, 12]. Together, these findings suggest that price trend, operating efficiency, investment restraint, and return stability may provide complementary information about the cross-section.

Prior studies find historical accounting signals can separate strong and weak firms among high book-to-market stocks. This supports the use of accounting information, though EMR's construction and performance need separate assessment [7]. Yet a composite score creates its own identification problem. Improved performance may reflect little more than repackaged momentum or low volatility, and a score chosen after inspecting many alternatives can overstate its true predictive content. The question addressed here is therefore specific: does an equal-weighted, economically interpretable combination of momentum, sales efficiency, conservative investment, and low historical volatility predict next-month returns in a manner that is not fully absorbed by standard factor exposures or a single component?

To answer this question, the paper constructs Efficient Momentum Resilience (EMR). Each of its four inputs is standardized within month. The implementation requires at least three inputs to be available and sums the available standardized values without estimated weights. The empirical design uses U.S. monthly stock returns, lagged accounting characteristics, and Fama-French factors from January 2010 through December 2024. Information observed in month t is aligned with returns in month $t+1$. The signal is evaluated using monthly portfolio sorts, Fama-French five-factor time-series regressions [14], and Fama-MacBeth cross-sectional regressions [5]. Robustness tests change the number of portfolios, weighting scheme, minimum-price filter, and sample period, while a factor screen compares EMR with its components and other candidate combinations.

The benchmark results demonstrated strong significance in both economic and statistical terms. The equally weighted quintile ranking showed that the EMR high-low portfolio achieved a monthly return of 1.79%, with a Newey–West t -statistic of 3.83; after controlling for the Fama–French five-factor model, the portfolio still generated a monthly alpha of 1.91%, with a t -statistic of 5.35. Fama–MacBeth cross-sectional regressions further indicate that the average regression coefficient for EMR is significantly positive, with a t -statistic of 5.04, providing consistent evidence with the portfolio ranking results. Furthermore, after applying three-, five- and ten-group rankings, market capitalization weighting, excluding shares priced below \$5, and dividing the sample into different sub-intervals, the return advantage of high-EMR shares relative to low-EMR shares remain positive. Overall, these results indicate that EMR possesses a stable and economically meaningful cross-sectional return forecasting ability in the current sample, and that this predictive relationship does not depend on a single portfolio construction method or sample specification.

Compared with the existing literature, this paper makes two main incremental contributions. Firstly, this paper integrates four literature-supported return prediction dimensions—medium-term momentum, sales efficiency, conservative investment and low historical volatility—into a unified composite score and focuses on examining the incremental predictive value of this information following joint ranking. Consequently, this paper advances the research focus from the identification of individual anomalies to the systematic integration of multi-dimensional predictive information, providing new empirical evidence for understanding the complementarity between different stock characteristics.

Secondly, this paper constructs and tests the EMR within a rigorous point-in-time consistent framework, ensuring that portfolio ranking, Fama–French factor adjustments, Fama–MacBeth cross-sectional regressions, comparisons of candidate signals, and robustness tests are all based on the same research panel and a unified

set of information. This design enhances the comparability of different test results and ensures that the empirical conclusions reflect the information available to investors at the time of portfolio formation.

The remainder of the paper is organized as follows. Section 2 describes the data and sample construction. Section 3 explains the EMR signal and empirical methods. Section 4 reports robustness tests. Section 5 presents the main results, discusses their interpretation and limitations, and concludes.

2. Data Sources and Sample Construction

The empirical analysis combines three monthly data sources: a CRSP-style stock file, a Compustat-style company-characteristics file, and Fama-French factor returns. They are merged by permanent stock identifier and month to create the stock-month research panel used for portfolio sorts and regression tests.

2.1 Monthly Stock Data

The monthly stock file contains 1,369,284 stock-month observations from January 2010 through December 2024. Its main fields are reported in Table 1.

Table 1: Main variables in the monthly stock file

Field	Interpretation
permno	Permanent CRSP-style stock identifier.
date	Monthly date, later standardized to month-end.
ret	Monthly stock return.
price	End-of-month stock price.
shares_out	Shares outstanding in thousands of shares.
market_equity	Market capitalization in USD millions, computed as price times shares outstanding divided by 1,000.

2.2 Company Characteristics

The company characteristics file contains 275,253 firm-month observations that can be matched to the monthly stock panel. Its main fields are reported in Table 2.

Table 2: Main variables in the company-characteristics file

Field	Interpretation
permno	Stock identifier after matching the return file.
date	Month in which the characteristic is available for portfolio formation.
assets	Total assets.
book_equity	Book equity.
sales	Sales revenue.

The accounting data are used to construct book-to-market, asset growth, sales-to-assets efficiency, and related firm-characteristic variables. Accounting variables are lagged before use so that portfolio formation does not rely on information that would not have been available to investors at the time.

2.3 Fama-French Factor Data

The factor file contains 180 monthly observations from January 2010 through December 2024. It includes the market excess return, SMB, HML, RMW, CMA, and the risk-free rate. These factors test whether the long-short portfolio return is compensation for conventional risk exposures.

3. Research Design

3.1 Return Alignment and Prevention of Look-ahead Bias

A central principle in factor testing is that the signal must be measured before the return that it is asked to predict. The pipeline therefore aligns variables so that information observed at month t is used to predict stock returns in month $t+1$. In code, the next month's return is constructed as

$$\text{ret}_{i,t}^{\text{next}} = \text{ret}_{i,t+1}$$

For each stock, this is implemented by shifting monthly returns backward by one row within the stock identifier. The resulting research panel contains current month characteristics and next-month realized returns on the same row. This alignment ensures the testing logic is using present information to predict future returns.

The generated research panel contains 232,605 stock-month observations. Its date range is July 2010 through November 2024, and the effective baseline EMR test uses 165 return months after applying the signal-availability requirements.

3.2 Construction of Efficient Momentum Resilience

The new factor is named *efficient momentum resilience score*. It is not a machine-learning model. It is a transparent composite score defined over four standardized stock-level characteristics. The score is computed when at least three of the four components are available:

$$\text{EMR}_{i,t} = z\left(\text{Momentum}_{i,t}^{(6,2)}\right) + z\left(\text{SalesToAssets}_{i,t}\right) + z\left(\text{ConservativeInvestment}_{i,t}\right) + z\left(\text{LowVolatility}_{i,t}\right).$$

From an economic perspective, the EMR score tends to identify those shares that simultaneously exhibit strong medium-term price trends, high operational efficiency, prudent asset expansion and low historical volatility. Unlike signals that rely solely on price trends, the EMR combines momentum information with corporate operational quality, investment discipline and earnings stability, thereby capturing a more comprehensive profile of strong-performing shares. The core logic lies in the fact that stocks with sustained price performance, if supported by fundamental and resilience characteristics such as high sales efficiency, restrained asset expansion and low historical volatility, are likely to exhibit price strength with greater informational content and sustainability. Consequently, the EMR does not simply replicate traditional momentum strategies, but rather identifies price trends underpinned by stronger fundamentals and greater stability through the combined screening of multi-dimensional information.

3.2.1 Intermediate-term Momentum

The momentum component is *momentum_6_2*. It measures cumulative prior returns while skipping the most recent month:

$$\text{Momentum}_{i,t}^{(6,2)} = \prod_{j=2}^6 (1 + r_{i,t-j}) - 1.$$

Skipping the most recent month reduces the influence of short-term reversal. Because I think stocks with stronger intermediate-term price trends may continue to perform relatively well soon.

3.2.2 Sales Efficiency

The sales-efficiency component is defined as

$$\text{SalesToAssets}_{i,t} = \frac{\text{Sales}_{i,t}}{\text{Assets}_{i,t}}.$$

This variable measures how much sales revenue a firm generates per unit of assets. A higher value indicates more efficient asset use.

3.2.3 Conservative Investment

The investment component first computes asset growth:

$$\text{InvestmentToAssets}_{i,t} = \frac{\text{Assets}_{i,t} - \text{Assets}_{i,t-12}}{\text{Assets}_{i,t-12}}.$$

The signal then uses the negative of this value:

$$\text{ConservativeInvestment}_{i,t} = -\text{InvestmentToAssets}_{i,t}.$$

After this transformation, higher values correspond to more restrained asset growth. The baseline uses the 12-month change; when a 12-month asset lag is unavailable, the current implementation falls back to the one-month change. This design follows the broad asset-pricing intuition that aggressive asset expansion is often associated with lower subsequent returns.

3.2.4 Low Historical Volatility

The volatility component is based on the standard deviation of monthly returns over the previous 12 months:

$$\text{Volatility}_{i,t}^{(12m)} = \text{sd} (r_{i,t-12}, \dots, r_{i,t-1}).$$

The factor uses the negative of this value:

$$\text{LowVolatility}_{i,t} = -\text{Volatility}_{i,t}^{(12m)}.$$

Higher values therefore indicate lower historical volatility.

3.2.5 Cross-sectional Standardization and Composite Score

The four components have different units and scales, so they cannot be added directly. Each month, every component is standardized across stocks:

$$z(x_{i,t}) = \frac{x_{i,t} - \text{mean}(x_t)}{\text{sd}(x_t)}.$$

After standardization, each component becomes a relative cross-sectional score. The final EMR signal is the sum of the available standardized components, subject to the requirement that at least three of the four are observed.

3.3 Empirical Implementation

3.3.1 Panel Construction

The processed data are first standardized by unifying date formats and cleaning stock return and accounting variables. Stock returns are then merged with firm characteristics, after which baseline and composite factor variables are constructed. Finally, next-month returns are generated to form the stock-month panel used in the empirical analysis.

3.3.2 Testing Functions

Stocks are sorted monthly according to their signal values and divided into quantile portfolios. Next month's portfolio returns and high-minus-low long-short returns are then calculated. Statistical significance is evaluated using Newey-West adjusted t-statistics. Fama-French time-series regressions and Fama-MacBeth cross-sectional regressions are subsequently conducted to assess factor performance.

3.3.3 Pipeline Driver

The empirical analysis follows a unified workflow. It begins with reading the research configuration and loading the processed data, followed by panel construction, portfolio analysis, and regression testing. The resulting statistics, regression estimates, and portfolio returns are then organized and exported for further interpretation.

3.3.4 Factor-screening Script

The factor-screening script evaluates candidate signals across alternative portfolio definitions, helping distinguish a signal that merely runs through the pipeline from one that performs consistently across empirical specifications.

3.4 Portfolio-sorting Method

The main portfolio test follows a standard monthly sorting procedure. At the end of each month t , all stocks with available signal values are ranked from low to high and divided into five quintile portfolios. Each portfolio's equal-weighted return is then calculated for month $t+1$, and a high-minus-low long-short portfolio

is constructed as $LS_{t+1} = R_{Q5,t+1} - R_{Q1,t+1}$. A significantly positive mean long-short return indicates that high-signal stocks outperform low-signal stocks on average in the following month. Robustness tests examine alternative specifications using three and ten quantile portfolios, value weighting, price filters, and subperiod splits.

3.5 Fama-French Five-factor Regression

A positive long-short return may reflect exposure to common risk factors rather than independent predictive content. The study therefore estimates a Fama-French five-factor time-series regression:

$$LS_t = \alpha + \beta_1 \text{MktRF}_t + \beta_2 \text{SMB}_t + \beta_3 \text{HML}_t + \beta_4 \text{RMW}_t + \beta_5 \text{CMA}_t + \varepsilon_t.$$

The parameter of main interest is alpha. A positive and significant alpha indicates that the long-short portfolio return is not fully explained by market, size, value, profitability, and investment factors.

3.6 Fama-MacBeth Cross-sectional Regression

The portfolio test groups stocks into quantiles. As a complementary test, the pipeline runs monthly Fama-MacBeth regression:

$$\text{ret}_{i,t}^{\text{next}} = a_t + b_t \text{Signal}_{i,t} + c_{1,t} \ln(\text{Size}_{i,t}) + c_{2,t} \text{BookToMarket}_{i,t} + \varepsilon_{i,t}.$$

The monthly coefficients b_t are then averaged over time, and their statistical significance is evaluated using Newey-West standard errors. A positive and significant average coefficient means that, within the monthly cross-section, stocks with higher signal scores tend to have higher next-month returns after controlling for size and book-to-market.

4. Robustness

4.1 Alternative Specifications and Stability Evidence

The robustness checks for the EMR signal are reported in Table 3. The tests vary the number of quantile portfolios, the weighting method, the price filter, and the sample period.

Table 3: Robustness checks for the EMR signal

Setting	Mean	Annualized	NW t	FF5 alpha t
Full sample, 3 groups, equal weighted	0.0143	0.1720	3.70	5.24
Full sample, 5 groups, equal weighted	0.0179	0.2146	3.83	5.35
Full sample, 10 groups, equal weighted	0.0192	0.2302	3.73	4.54
Full sample, 5 groups, value weighted	0.0109	0.1305	2.72	4.63
Price at least 5 dollars, equal weighted	0.0094	0.1133	2.83	3.45
Subsample 2010-2017, equal weighted	0.0114	0.1369	2.27	2.61
Subsample 2018-2024, equal weighted	0.0264	0.3166	3.32	4.87

The evidence is positive across all reported specifications. The signal remains statistically significant with three, five, and ten groups. It also remains positive under value weighting, which reduces the concern that the result is entirely driven by small stocks. Filtering out stocks with prices below five dollars lowers the economic magnitude, but the result remains statistically significant. Finally, both the 2010-2017 and 2018-2024 subsamples show positive performance, though the effect is larger in the later period.

5. Results and Limitations

5.1 Main Empirical Results

5.1.1 Portfolio-sort Evidence

The baseline quintile portfolio results are reported in Table 4.

Table 4: Baseline EMR portfolio returns

Portfolio	Months	Mean monthly return	Annualized mean	NW t-stat
Q1	165	-0.0083	-0.0990	-1.17
Q2	165	0.0010	0.0116	0.18
Q3	165	0.0087	0.1048	2.02
Q4	165	0.0092	0.1102	2.33
Q5	165	0.0096	0.1156	2.49
Long-short	165	0.0179	0.2146	3.83

Although the relationship between returns and quintile groups is not entirely linear, the overall ranking results still reveal clear economic differences: the average return for the lowest quintile group is negative, whilst that for the highest quintile group is positive, indicating that the EMR score can effectively distinguish between stocks with weaker and stronger future return performance. The ‘high-to-low’ portfolio achieved an average monthly return of 1.79%, corresponding to a simple annualized average of approximately 21.46%, indicating a relatively significant economic return. At the same time, the Newey–West t-statistic stands at 3.83, further indicating that this long–short return differential is highly statistically significant in the current sample. Overall, the portfolio ranking results support the existence of a relatively stable positive relationship between the EMR and future stock returns, as evidenced by both the magnitude of returns and statistical tests.

5.1.2 Fama-French Five-factor Evidence

The Fama-French five-factor estimates for the long-short portfolio are reported in Table 5.

Table 5: Fama-French five-factor regression for the EMR long-short portfolio

Term	Coefficient	Standard error	NW t-stat
Alpha	0.0191	0.0036	5.35
Mkt-RF	-0.4469	0.0930	-4.80
SMB	-0.5046	0.2074	-2.43
HML	0.2896	0.1580	1.83
RMW	0.9245	0.1863	4.96
CMA	0.0645	0.2330	0.28

After adjusting for the Fama–French five-factor model, the EMR long–short portfolio still achieved a monthly alpha of 1.9%, with a Newey–West t-statistic of 5.35, indicating that the strategy’s returns retain strong economic significance and statistical significance even after controlling for common risk factors such as market, size, value, earnings and investment. This suggests that the cross-sectional return information captured by the EMR cannot be fully explained by the traditional five-factor framework, demonstrating a certain degree of incremental predictive value. A further examination of factor loadings reveals that, in the current sample, the strategy exhibits negative exposure to the market and size factors, as well as positive exposure to the earnings factor. This suggests that the EMR tends to allocate to stocks with higher earnings quality whilst exhibiting relatively low sensitivity to the market and small-cap factors. Overall, these results indicate that the EMR’s return performance does not stem simply from mechanical exposure to traditional risk factors but rather incorporates cross-sectional information that extends beyond the explanatory scope of common factors.

5.1.3 Fama-MacBeth Cross-sectional Evidence

The Fama-MacBeth estimates are reported in Table 6.

Table 6: Fama-MacBeth cross-sectional regression

Term	Mean coefficient	NW t-stat
Alpha	0.0019	0.22
EMR score	0.0034	5.04
Log size	0.0002	0.27
Book-to-market	0.0005	1.64

In the Fama–MacBeth cross-sectional regression, the average regression coefficient for the EMR signal was 0.0034, with a Newey–West t-statistic of 5.04, indicating strong statistical significance. This result is highly consistent with the portfolio ranking evidence: in the monthly stock cross-section, stocks with higher EMR scores generally achieved higher returns in the subsequent period. It can thus be seen that the predictive power of the EMR is not only reflected in the return differences between extreme portfolios but is also

supported within a continuous cross-sectional regression framework, further reinforcing its robustness as a return prediction signal.

5.2 Candidate-factor Comparison

The study compares the proposed signal with several alternative candidates. The equal-weighted quintile results for the main candidate signals are reported in Table 7.

Table 7: Equal-weighted quintile factor screen

Signal	Mean	Annualized	NW t	FF5 alpha t
Efficient Momentum Resilience	0.0179	0.2146	3.83	5.35
Stable Momentum	0.0174	0.2082	3.18	5.11
Low Volatility	0.0157	0.1883	2.63	3.95
Momentum 12-2	0.0147	0.1762	2.60	3.64
Momentum 6-2	0.0135	0.1625	3.21	3.74
Quality Growth Resilience	0.0131	0.1572	3.37	4.62
Growth Momentum Quality	0.0103	0.1230	2.77	3.53
Baseline lnA plus B/C	0.0093	0.1120	2.01	1.34

Among the candidate signals compared in the report, when both the average long-short return and the statistical significance of the Fama–French five-factor alpha are taken into account, the EMR signal demonstrated the strongest overall performance under an equal-weighted quintile ranking. Its advantage is reflected not only in its higher raw long-short return but also in its ability to maintain relatively significant excess returns even after factor adjustment, indicating that the information contained in this signal possesses strong independent explanatory power. By contrast, whilst the raw long-short returns of the benchmark demonstration factor are also positive, the significance of its alpha is somewhat diminished after controlling common risk factors. Overall, this comparison of candidate signals further highlights the balanced advantages of EMR in terms of economic returns, statistical significance and post-factor-adjustment performance, and provides more robust empirical evidence for its selection as the core research signal in this paper.

5.3 Interpretation of the Findings

The EMR signal can be understood as a comprehensive characterization of a company across four dimensions: efficiency, trend, investment discipline and operational resilience. Unlike traditional momentum signals that rely solely on historical price performance, the EMR not only focuses on whether a share exhibits a strong medium-term price trend but also requires that this trend be underpinned by the company's operational efficiency and financial characteristics. Specifically, higher sales efficiency reflects a company's ability to generate greater revenue from a relatively limited asset base; a more restrained expansion of assets indicates more prudent capital allocation by management; whilst lower historical volatility provides the price trend with a degree of stability and resilience. Consequently, the EMR does not identify 'past winners' in the general sense, but rather those shares that exhibit favorable performance across price trends, operational efficiency, investment discipline and earnings stability. By integrating this information into a unified score, the EMR seeks to enhance the economic significance of single-factor momentum and capture potential complementary effects across different predictive dimensions.

The empirical results are broadly consistent with the economic interpretation outlined above. In the current sample, the average one-month returns of high-EMR stocks are significantly higher than those of low-EMR stocks, indicating that this composite score can effectively distinguish between companies with differing future return performance. More importantly, this relationship is not limited to unadjusted raw returns. After controlling for the Fama–French five-factor model, the EMR long–short portfolio still achieves a significantly positive alpha, indicating that its return differential cannot be fully explained by traditional risk factors such as market, size, value, earnings and investment. This suggests that the information integrated by the EMR retains some incremental explanatory and predictive value beyond the standard asset pricing framework.

Fama–MacBeth cross-sectional regressions further reinforce this conclusion. Without relying on discrete portfolio classifications, the average regression coefficient for EMR remains significantly positive, suggesting that the relationship between EMR scores and future individual stock returns also holds in a continuous stock cross-section. Consequently, portfolio ranking and cross-sectional regression provide consistent evidence from two distinct perspectives: not only does EMR generate economically meaningful return differentials between

high- and low-scoring stocks, but its predictive power also extends to the broader level of individual stocks. Taking together with the consistent results across different numbers of portfolios, market capitalization weighting, share price screening and subsample tests, the overall evidence suggests that the return relationship captured by the EMR exhibits good stability and is not driven by a single portfolio configuration or a small number of outlier stocks.

5.4 Conclusion

This paper constructs an empirical framework for the asset pricing of firm-specific characteristics based on WRDS data; on this basis, it proposes the Efficient Momentum Resilience (EMR) composite signal. EMR integrates four dimensions of return forecasting supported by existing literature—medium-term momentum, sales efficiency, conservative investment and low historical volatility—into a unified indicator. Its core objective is not to propose an isolated new firm characteristic, but rather to examine whether the combined use of multiple predictive indicators with distinct economic implications can yield a more effective cross-sectional stock ranking.

The benchmark empirical results provide strong support for the predictive power of EMR. In an equally weighted quintile ranking, the high-EMR/low-EMR portfolio generated an average monthly return of 1.79 per cent, corresponding to a relatively significant economic return; the Newey–West-adjusted t-statistic of 3.83 indicates that this return differential is highly statistically significant. Following further risk adjustment using the Fama–French five-factor model, the long–short portfolio still achieved a monthly alpha of 1.91%, with a t-statistic of 5.35. This suggests that the return performance of EMR does not stem solely from simple exposure to traditional market, size, value, earnings or investment factors, but rather incorporates cross-sectional return information beyond these common risk factors.

The Fama–MacBeth regression provides evidence at the individual stock level that is consistent with the portfolio ranking. The average regression coefficient for EMR is positive and highly statistically significant, indicating that as EMR scores rise, stocks' returns in the next period generally follow an upward trend. This is particularly important as it suggests that the predictive power of EMR is not an artefact of the portfolio grouping method but can be validated within a continuous cross-sectional regression framework. At the same time, under various settings—including three-, five- and ten-group rankings, market-capitalization-weighted portfolios, the exclusion of low-priced shares, and different sample sub-periods—the return differential between high and low EMR scores remains positive overall, further demonstrating the robustness of the EMR results across a range of reasonable empirical specifications.

Another significant contribution to this paper lies in the research design itself. All stock characteristics are constructed based on the information actually available to investors at the time of portfolio formation, and market data, accounting data and Fama–French factor data are linked through a unified point-in-time alignment principle, thereby reducing the impact of forward-looking bias on the results. On this basis, this paper divides data acquisition, sample selection, feature construction, cross-sectional standardization, portfolio formation, factor adjustment, Fama–MacBeth regression and robustness tests into relatively independent research stages. This WRDS empirical workflow enhances the transparency of key assumptions and parameter selection, whilst also facilitating the scrutiny, replication and further extension of the results.

From an economic perspective, the findings of this paper suggest that there may be a noteworthy complementary relationship between price trends and information regarding corporate fundamentals and stability. Observing a stock's past price strength in isolation may not sufficiently distinguish the economic fundamentals underlying the trend; however, the EMR performs a multi-dimensional screening of price momentum by further incorporating sales efficiency, asset expansion behavior and historical volatility. Empirical results indicate that this combined information generates a cross-sectional ranking within the current US stock sample that is more discriminatory than a single dimension and continues to exhibit significant return differences even after traditional factor adjustments. Consequently, this paper provides a new empirical application of how to integrate multiple established firm characteristics into a simple, transparent and economically interpretable composite predictive signal. Naturally, the findings of this paper also leave scope for further exploration in subsequent research. As the current analysis focuses primarily on a sample of US equities from 2010 to 2024 within a monthly rebalancing framework, future research could examine the

performance of EMR in independent hold-out samples, markets in other countries and regions, and under different market conditions.

Overall, the evidence presented in this paper indicates that the EMR can make economically meaningful and statistically significant predictions of future cross-sectional returns for US equities within a research framework characterized by strict point-in-time alignment, transparency and reproducibility. Its value is reflected not only in significant long-short returns and factor-adjusted alpha, but also in the high consistency of empirical results across portfolio ranking, cross-sectional regression and various robustness settings. This paper therefore provides an effective approach to the multidimensional integration of mature return prediction features and offers an empirical foundation for further research into the application of composite feature signals in asset pricing and quantitative investment.

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Conflicts of Interest

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