# Capital Funding Efficiency Margin and the Cross Section of Stock Returns

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**Abstract**

This paper studies the asset pricing implications of Capital Funding Efficiency Margin (CFEM), and its robustness in predicting returns in the cross-section of equities using the protocol proposed by Novy-Marx and Velikov (2023). A value-weighted long/short trading strategy based on CFEM achieves an annualized gross (net) Sharpe ratio of 0.52 (0.40), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 21 (18) bps/month with a t-statistic of 2.93 (2.50), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net debt financing, Change in financial liabilities, Net external financing, Asset growth, Inventory Growth, change in ppe and inv/assets) is 19 bps/month with a t-statistic of 2.76.

# 1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn excess returns. However, a growing body of literature documents numerous market anomalies that appear to contradict this notion (Harvey et al., 2016). While many of these anomalies are related to firms' investment and financing decisions (Hou et al., 2020), the mechanisms through which capital allocation efficiency affects expected returns remain incompletely understood. This paper introduces a novel measure, the Capital Funding Efficiency Margin (CFEM), that captures how effectively firms deploy external capital to generate operating profits.

Prior research has focused primarily on the quantity rather than the quality of firms' capital allocation decisions. While studies have examined the asset pricing implications of investment rates (Titman et al., 2004) and external financing (Bradshaw et al., 2006), less attention has been paid to how efficiently firms convert invested capital into operating performance. This gap is particularly notable given the theoretical importance of capital allocation efficiency in determining firms' cost of capital and expected returns.

We develop our hypothesis about CFEM's return predictability based on the q-theory of investment (Cochrane and Saa-Requejo, 2000). This framework suggests that firms invest more when their marginal q (the ratio of marginal investment benefits to costs) is high. Extending this logic, firms with higher capital funding efficiency should generate greater marginal benefits from each dollar of external capital, leading to higher q ratios and subsequently lower expected returns.

The relationship between CFEM and expected returns can also be understood through the investment-based asset pricing framework of (Zhang and Kogan, 2012). In their model, firms' investment decisions reveal managers' private information about future productivity. We argue that CFEM provides an observable signal of this private information - firms demonstrating higher efficiency in converting funding into operating profits likely have superior investment opportunities and management quality.

Moreover, the behavioral finance literature suggests that investors may systematically underreact to signals of operational efficiency (Hirshleifer et al., 2015). If market participants focus primarily on simple measures like total investment or external financing while overlooking the efficiency dimension, CFEM could capture mispricing that persists due to limited attention.

Our empirical analysis reveals that CFEM strongly predicts cross-sectional stock returns. A value-weighted long-short strategy that buys stocks with high CFEM and sells those with low CFEM generates significant abnormal returns of 21 basis points per month (t-statistic = 2.93) relative to the Fama-French five-factor model plus momentum. The strategy achieves an annualized gross Sharpe ratio of 0.52, placing it in the top 7% of documented anomalies.

Importantly, CFEM's predictive power remains robust after controlling for related anomalies. When we simultaneously control for six closely related predictors including net debt financing, asset growth, and inventory growth, CFEM continues to generate an alpha of 19 basis points monthly (t-statistic = 2.76). This indicates that CFEM captures a distinct dimension of cross-sectional return predictability.

The effect is particularly pronounced among large-cap stocks, where the long-short CFEM strategy earns 37 basis points monthly (t-statistic = 4.22). This finding is especially notable since many anomalies are concentrated in small, illiquid stocks. The robustness of CFEM among large caps suggests that the anomaly is more likely to survive transaction costs and be economically meaningful.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures an understudied dimension of firms' capital allocation decisions - the efficiency with which external funding translates into operating performance. While prior work by (Titman et al., 2004) and (Bradshaw et al., 2006) examined investment and financing quantities, CFEM provides new insights into the quality of these decisions.

Second, we contribute to the growing literature on investment-based asset pricing (Hou et al., 2020). Our findings suggest that the efficiency of capital deployment contains important information about expected returns beyond what is captured by traditional investment factors. This helps refine our understanding of how firms' investment decisions relate to their cost of capital.

Finally, our results have important implications for both academic research and investment practice. For researchers, CFEM provides a new lens for studying market efficiency and capital allocation. For practitioners, our findings suggest that incorporating measures of funding efficiency into investment strategies could improve portfolio performance, particularly given CFEM's robust predictive power among large, liquid stocks.

# 2 Data

Our study investigates the predictive power of Capital Funding Efficiency Margin, a financial signal derived from accounting data for cross-sectional returns. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item DLTIS for long-term debt issuance, and PPEGT for gross property, plant, and equipment. Long-term debt issuance (DLTIS) represents the cash proceeds from issuance of long-term debt, while gross property, plant, and equipment (PPEGT) captures the total cost of tangible fixed assets before accumulated depreciation. The construction of the signal follows a change-based approach, where we calculate the difference between current period DLTIS and its lagged value, and then scale this difference by lagged PPEGT. This scaled difference measures the year-over-year change in debt issuance relative to the firm's existing asset base, providing insight into the efficiency of capital funding decisions. By focusing on this relationship, the signal aims to capture the dynamics of capital structure decisions and their relative magnitude compared to the firm's existing capital investments. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

# 3 Signal diagnostics

Figure 1 plots descriptive statistics for the CFEM signal. Panel A plots the time-series of the mean, median, and interquartile range for CFEM. On average, the cross-sectional mean (median) CFEM is -0.49 (-0.00) over the 1974 to 2023 sample, where the starting date is determined by the availability of the input CFEM data. The signal's interquartile range spans -0.18 to 0.18. Panel B of Figure 1 plots the time-series of the coverage of the CFEM signal for the CRSP universe. On average, the CFEM signal is available for 5.88% of CRSP names, which on average make up 7.12% of total market capitalization.

# 4 Does CFEM predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on CFEM using NYSE breaks. The first two lines of Panel A report monthly average excess returns for each of the five portfolios and for the long/short portfolio that buys the high CFEM portfolio and sells the low CFEM portfolio. The rest of Panel A reports the portfolios' monthly abnormal returns relative to the five most common factor models: the CAPM, the Fama and French (1993) three-factor model (FF3) and its variation that adds momentum (FF4), the Fama and French

(2015) five-factor model (FF5), and its variation that adds momentum factor used in Fama and French (2018) (FF6). The table shows that the long/short CFEM strategy earns an average return of 0.26% per month with a t-statistic of 3.65. The annualized Sharpe ratio of the strategy is 0.52. The alphas range from 0.21% to 0.31% per month and have t-statistics exceeding 2.93 everywhere. The lowest alpha is with respect to the FF6 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is 0.29, with a t-statistic of 6.11 on the CMA factor. Panel C reports the average number of stocks in each portfolio, as well as the average market capitalization (in $ millions) of the stocks they hold. In an average month, the five portfolios have at least 481 stocks and an average market capitalization of at least $1,562 million.

Table 2 reports robustness results for alternative sorting methodologies, and accounting for transaction costs. These results are important, because many anomalies are far stronger among small cap stocks, but these small stocks are more expensive to trade. Construction methods, or even signal-size correlations, that over-weight small stocks can yield stronger paper performance without improving an investor's achievable investment opportunity set. Panel A reports gross returns and alphas for the long/short strategies made using various different protfolio constructions. The first row reports the average returns and the alphas for the long/short strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios. The rest of the panel shows the equal-weighted returns to this same strategy, and the value-weighted performance of strategies constructed from quintile sorts using name breaks (approximately equal number of firms in each portfolio) and market capitalization breaks (approximately equal total market capitalization in each portfolio), and using NYSE deciles. The average return is lowest for the quintile sort using NYSE breakpoints and equal-weighted portfolios, and equals

19 bps/month with a t-statistics of 4.31. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-two exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from Chen and Velikov (2022). The net average returns reported in the first column range between -7-25bps/month. The lowest return, (-7 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.17. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the CFEM trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in nineteen cases.

Table 3 provides direct tests for the role size plays in the CFEM strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and CFEM, as well as average returns and alphas for long/short trading CFEM strategies within each size quintile. Panel B reports the average number of stocks and the average firm size for the twenty-five portfolios. Among the largest stocks (those with market capitalization greater than the $80^{\text{th}}$ NYSE percentile), the CFEM strategy achieves an average return of 37 bps/month with a t-statistic of 4.22. Among these large cap stocks, the alphas for the CFEM strategy relative to the five most common factor models range from 29 to 42 bps/month with t-statistics between 3.20 and 4.76.

# 5 How does CFEM perform relative to the zoo?

Figure 2 puts the performance of CFEM in context, showing the long/short strategy performance relative to other strategies in the "factor zoo." It shows Sharpe ratio histograms, both for gross and net returns (Panel A and B, respectively), for 212 documented anomalies in the zoo.[1] The vertical red line shows where the Sharpe ratio for the CFEM strategy falls in the distribution. The CFEM strategy's gross (net) Sharpe ratio of 0.52 (0.40) is greater than 93% (96%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a \$1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a \$1 invested in the CFEM strategy (red line).[2] Ignoring trading costs, a \$1 invested in the CFEM strategy would have yielded \$3.39 which ranks the CFEM strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the CFEM strategy would have yielded \$2.12 which ranks the CFEM strategy in the top 5% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the CFEM relative to those. Panel A shows that the CFEM strategy gross alphas fall between the 61 and 71 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 197406 to 202306 sample. For example, 45%

[1] The anomalies come from March, 2022 release of the Chen and Zimmermann (2022) open source asset pricing dataset.

[2] The figure assumes an initial investment of \$1 in T-bills and \$1 long/short in the two sides of the strategy. Returns are compounded each month, assuming, as in Detzel et al. (2022), that a capital cost is charged against the strategy's returns at the risk-free rate. This excess return corresponds more closely to the strategy's economic profitability.

(53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The CFEM strategy has a positive net generalized alpha for five out of the five factor models. In these cases CFEM ranks between the 79 and 87 percentiles in terms of how much it could have expanded the achievable investment frontier.

# 6 Does CFEM add relative to related anomalies?

With so many anomalies, it is possible that any proposed, new cross-sectional predictor is just capturing some combination of known predictors. It is consequently natural to investigate to what extent the proposed predictor adds additional predictive power beyond the most closely related anomalies. Closely related anomalies are more likely to be formed on the basis of signals with higher absolute correlations. Figure 5 plots a name histogram of the correlations of CFEM with 209 filtered anomaly signals.[3] Figure 6 also shows an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

A closely related anomaly is also more likely to price CFEM or at least to weaken the power CFEM has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of CFEM conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{CFEM}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CFEM} CFEM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ from spanning tests of the form: $r_{CFEM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile

[3]When performing tests at the underlying signal level (e.g., the correlations plotted in Figure 5), we filter the 212 anomalies to avoid small sample issues. For each anomaly, we calculate the common stock observations in an average month for which both the anomaly and the test signal are available. In the filtered anomaly set, we drop anomalies with fewer than 100 common stock observations in an average month.

sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on CFEM. Stocks are finally grouped into five CFEM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CFEM trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on CFEM and the six anomalies most closely-related to it. The six most-closely related anomalies are picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the $R^2$ from the spanning tests in Figure 7, Panel B. Controlling for each of these signals at a time, the t-statistics on the CFEM signal in these Fama-MacBeth regressions exceed 2.31, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on CFEM is 1.56.

Similarly, Table 5 reports results from spanning tests that regress returns to the CFEM strategy onto the returns of the six most closely-related anomalies and the six Fama-French factors. Controlling for the six most-closely related anomalies individually, the CFEM strategy earns alphas that range from 20-22bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.80, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the CFEM trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.76.

# 7 Does CFEM add relative to the whole zoo?

Finally, we can ask how much adding CFEM to the entire factor zoo could improve investment performance. Figure 8 plots the growth of $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). The combinations use either the 156 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 156 anomalies augmented with the CFEM signal.[4] We consider one different methods for combining signals.

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 156-anomaly combination strategy grows to $935.00, while $1 investment in the combination strategy that includes CFEM grows to $895.95.

# 8 Conclusion

This study provides compelling evidence for the effectiveness of Capital Funding Efficiency Margin (CFEM) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on CFEM generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.52 (0.40 net of transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for established factor models and related anomalies from the factor zoo.

[4] We filter the 207 Chen and Zimmermann (2022) anomalies and require for each anomaly the average month to have at least 40% of the cross-sectional observations available for market capitalization on CRSP in the period for which CFEM is available.

The persistence of CFEM's predictive power, evidenced by monthly abnormal returns of 21 basis points (gross) and 18 basis points (net) relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information about firm value that is not fully reflected in current market prices. Furthermore, the signal's ability to generate an alpha of 19 basis points per month even after controlling for six closely related strategies indicates that CFEM provides distinct incremental information beyond existing financial metrics.

However, several limitations should be noted. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, the study period may not fully capture the signal's behavior across different market regimes and economic cycles.

Future research could explore the application of CFEM in international markets, its interaction with other established anomalies, and its performance during specific market conditions or economic cycles. Additionally, investigating the underlying economic mechanisms driving the CFEM premium could provide valuable insights for both academics and practitioners. Despite these limitations, our findings suggest that CFEM represents a valuable addition to the investment practitioner's toolkit and contributes meaningfully to our understanding of cross-sectional return predictability.

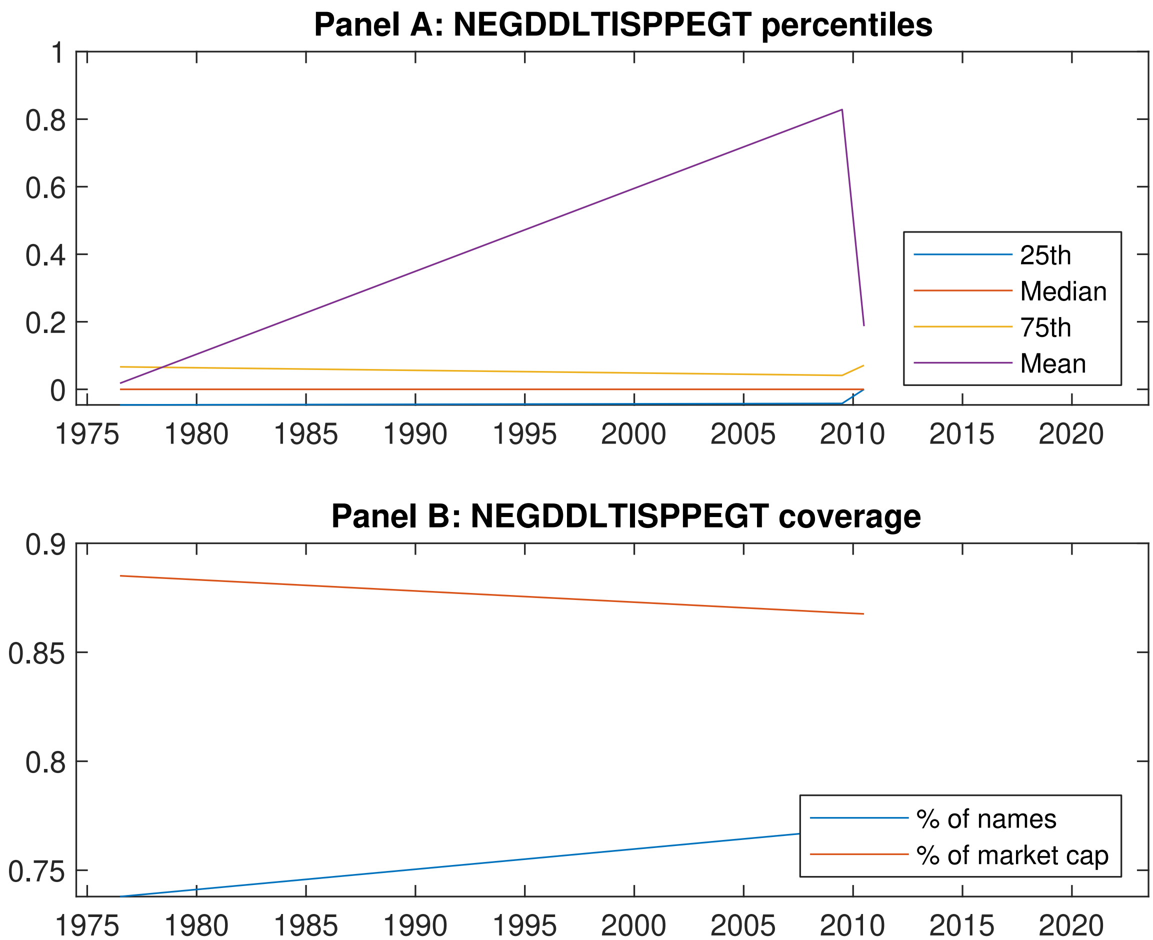


**Figure 1:** Times series of CFEM percentiles and coverage.
This figure plots descriptive statistics for CFEM. Panel A shows cross-sectional percentiles of CFEM over the sample. Panel B plots the monthly coverage of CFEM relative to the universe of CRSP stocks with available market capitalizations.

**Table 1:** Basic sort: VW, quintile, NYSE-breaks

This table reports average excess returns and alphas for portfolios sorted on CFEM. At the end of each month, we sort stocks into five portfolios based on their signal using NYSE breakpoints. Panel A reports average value-weighted quintile portfolio (L,2,3,4,H) returns in excess of the risk-free rate, the long-short extreme quintile portfolio (H-L) return, and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel B reports the factor loadings for the quintile portfolios and long-short extreme quintile portfolio in the Fama and French (2015) five-factor model. Panel C reports the average number of stocks and market capitalization of each portfolio. T-statistics are in brackets. The sample period is 197406 to 202306.

| Panel A: Excess returns and alphas on CFEM-sorted portfolios | | | | | | |
|---|---|---|---|---|---|---|
| | (L) | (2) | (3) | (4) | (H) | (H-L) |
| $r^e$ | 0.65 | 0.68 | 0.70 | 0.72 | 0.91 | 0.26 |
| | [2.92] | [3.80] | [3.55] | [4.06] | [4.36] | [3.65] |
| $\alpha_{CAPM}$ | -0.13 | 0.06 | 0.02 | 0.11 | 0.18 | 0.31 |
| | [-2.36] | [1.19] | [0.35] | [2.08] | [3.40] | [4.43] |
| $\alpha_{FF3}$ | -0.12 | 0.04 | 0.08 | 0.11 | 0.19 | 0.31 |
| | [-2.22] | [0.88] | [1.44] | [2.07] | [3.71] | [4.41] |
| $\alpha_{FF4}$ | -0.09 | 0.05 | 0.12 | 0.07 | 0.17 | 0.27 |
| | [-1.72] | [0.99] | [2.20] | [1.30] | [3.32] | [3.77] |
| $\alpha_{FF5}$ | -0.10 | -0.05 | 0.12 | 0.01 | 0.13 | 0.23 |
| | [-1.81] | [-1.08] | [2.02] | [0.23] | [2.54] | [3.26] |
| $\alpha_{FF6}$ | -0.08 | -0.04 | 0.15 | -0.01 | 0.13 | 0.21 |
| | [-1.52] | [-0.79] | [2.52] | [-0.16] | [2.39] | [2.93] |
| Panel B: Fama and French (2018) 6-factor model loadings for CFEM-sorted portfolios | | | | | | |
| $\beta_{\text{MKT}}$ | 1.10 | 0.97 | 0.96 | 0.95 | 1.05 | -0.05 |
| | [87.72] | [89.23] | [72.17] | [81.46] | [87.17] | [-2.88] |
| $\beta_{\text{SMB}}$ | 0.10 | -0.11 | -0.00 | -0.05 | 0.15 | 0.05 |
| | [5.30] | [-6.68] | [-0.23] | [-2.77] | [8.00] | [1.85] |
| $\beta_{\text{HML}}$ | 0.00 | 0.02 | -0.15 | -0.05 | -0.12 | -0.13 |
| | [0.15] | [1.00] | [-6.07] | [-2.46] | [-5.33] | [-4.06] |
| $\beta_{\text{RMW}}$ | 0.06 | 0.14 | -0.02 | 0.10 | 0.08 | 0.02 |
| | [2.52] | [6.43] | [-0.60] | [4.15] | [3.31] | [0.52] |
| $\beta_{\text{CMA}}$ | -0.17 | 0.17 | -0.08 | 0.21 | 0.12 | 0.29 |
| | [-4.67] | [5.33] | [-2.03] | [6.15] | [3.41] | [6.11] |
| $\beta_{\text{UMD}}$ | -0.03 | -0.02 | -0.05 | 0.03 | 0.01 | 0.04 |
| | [-2.12] | [-2.16] | [-3.73] | [2.89] | [0.94] | [2.33] |
| Panel C: Average number of firms ($n$) and market capitalization ($me$) | | | | | | |
| $n$ | 677 | 481 | 1007 | 524 | 653 | |
| me ($\$10^6$) | 1596 | 2468 | 2010 | 2411 | 1562 | |

**Table 2:** Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the CFEM strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, and the choices are specified in the first three columns. For each strategy construction methodology, the table reports average excess returns and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel A reports average returns and alphas with no adjustment for trading costs. Panel B reports net average returns and Novy-Marx and Velikov (2016) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 197406 to 202306.

| Panel A: Gross Returns and Alphas | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Portfolios | Breaks | Weights | $r^e$ | $\alpha_{\text{CAPM}}$ | $\alpha_{\text{FF3}}$ | $\alpha_{\text{FF4}}$ | $\alpha_{\text{FF5}}$ | $\alpha_{\text{FF6}}$ |
| Quintile | NYSE | VW | 0.26 | 0.31 | 0.31 | 0.27 | 0.23 | 0.21 |
| | | | [3.65] | [4.43] | [4.41] | [3.77] | [3.26] | [2.93] |
| Quintile | NYSE | EW | 0.19 | 0.21 | 0.20 | 0.20 | 0.20 | 0.19 |
| | | | [4.31] | [4.90] | [4.60] | [4.37] | [4.44] | [4.34] |
| Quintile | Name | VW | 0.28 | 0.32 | 0.33 | 0.30 | 0.26 | 0.25 |
| | | | [3.90] | [4.54] | [4.59] | [4.11] | [3.67] | [3.46] |
| Quintile | Cap | VW | 0.27 | 0.33 | 0.33 | 0.29 | 0.24 | 0.22 |
| | | | [4.23] | [5.08] | [5.12] | [4.46] | [3.72] | [3.41] |
| Decile | NYSE | VW | 0.32 | 0.38 | 0.37 | 0.32 | 0.23 | 0.21 |
| | | | [3.40] | [4.13] | [3.90] | [3.33] | [2.45] | [2.22] |
| **Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas** | | | | | | | | |
| Portfolios | Breaks | Weights | $r^e_{net}$ | $\alpha^*_{\text{CAPM}}$ | $\alpha^*_{\text{FF3}}$ | $\alpha^*_{\text{FF4}}$ | $\alpha^*_{\text{FF5}}$ | $\alpha^*_{\text{FF6}}$ |
| Quintile | NYSE | VW | 0.20 | 0.26 | 0.26 | 0.24 | 0.20 | 0.18 |
| | | | [2.80] | [3.70] | [3.70] | [3.38] | [2.74] | [2.50] |
| Quintile | NYSE | EW | -0.07 | | | | | |
| | | | [-1.17] | | | | | |
| Quintile | Name | VW | 0.22 | 0.27 | 0.27 | 0.26 | 0.22 | 0.21 |
| | | | [3.03] | [3.77] | [3.83] | [3.60] | [3.08] | [2.90] |
| Quintile | Cap | VW | 0.22 | 0.29 | 0.29 | 0.27 | 0.22 | 0.20 |
| | | | [3.41] | [4.45] | [4.46] | [4.15] | [3.29] | [3.07] |
| Decile | NYSE | VW | 0.25 | 0.32 | 0.30 | 0.27 | 0.18 | 0.17 |
| | | | [2.63] | [3.35] | [3.17] | [2.87] | [1.98] | [1.79] |

**Table 3:** Conditional sort on size and CFEM

This table presents results for conditional double sorts on size and CFEM. In each month, stocks are first sorted into quintiles based on size using NYSE breakpoints. Then, within each size quintile, stocks are further sorted based on CFEM. Finally, they are grouped into twenty-five portfolios based on the intersection of the two sorts. Panel A presents the average returns to the 25 portfolios, as well as strategies that go long stocks with high CFEM and short stocks with low CFEM .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 197406 to 202306.

Panel A: portfolio average returns and time-series regression results

| Size quintiles | CFEM Quintiles (L) | (2) | (3) | (4) | (H) | CFEM Strategies $r^e$ | $\alpha_{CAPM}$ | $\alpha_{FF3}$ | $\alpha_{FF4}$ | $\alpha_{FF5}$ | $\alpha_{FF6}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 0.73 | 0.91 | 0.98 | 0.97 | 0.87 | 0.13 | 0.17 | 0.14 | 0.11 | 0.10 | 0.08 |
| | [2.47] | [3.41] | [3.50] | [3.48] | [2.86] | [1.29] | [1.64] | [1.36] | [1.02] | [0.96] | [0.78] |
| (2) | 0.78 | 0.96 | 0.82 | 0.99 | 0.90 | 0.12 | 0.15 | 0.13 | 0.14 | 0.09 | 0.11 |
| | [2.83] | [3.81] | [3.20] | [4.01] | [3.45] | [1.41] | [1.87] | [1.64] | [1.75] | [1.17] | [1.31] |
| (3) | 0.87 | 0.84 | 0.85 | 0.86 | 0.98 | 0.11 | 0.16 | 0.15 | 0.11 | 0.16 | 0.13 |
| | [3.36] | [3.82] | [3.49] | [3.95] | [4.02] | [1.34] | [1.96] | [1.90] | [1.40] | [2.01] | [1.65] |
| (4) | 0.78 | 0.83 | 0.85 | 0.83 | 0.91 | 0.13 | 0.16 | 0.14 | 0.11 | 0.12 | 0.10 |
| | [3.31] | [3.95] | [3.80] | [4.01] | [4.03] | [1.66] | [2.06] | [1.81] | [1.39] | [1.44] | [1.19] |
| (5) | 0.56 | 0.64 | 0.62 | 0.62 | 0.93 | 0.37 | 0.42 | 0.42 | 0.35 | 0.33 | 0.29 |
| | [2.65] | [3.58] | [3.25] | [3.41] | [4.67] | [4.22] | [4.71] | [4.76] | [3.94] | [3.67] | [3.20] |

Panel B: Portfolio average number of firms and market capitalization

| Size quintiles | CFEM Quintiles Average $n$ (L) | (2) | (3) | (4) | (H) | CFEM Quintiles Average market capitalization ($\$10^6$) (L) | (2) | (3) | (4) | (H) |
|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 374 | 375 | 375 | 375 | 371 | 33 | 30 | 29 | 30 | 32 |
| (2) | 103 | 103 | 103 | 103 | 102 | 55 | 55 | 53 | 56 | 55 |
| (3) | 73 | 73 | 73 | 73 | 73 | 97 | 97 | 94 | 96 | 97 |
| (4) | 62 | 62 | 62 | 62 | 61 | 213 | 218 | 209 | 218 | 211 |
| (5) | 57 | 57 | 57 | 57 | 57 | 1315 | 1877 | 1637 | 1885 | 1356 |

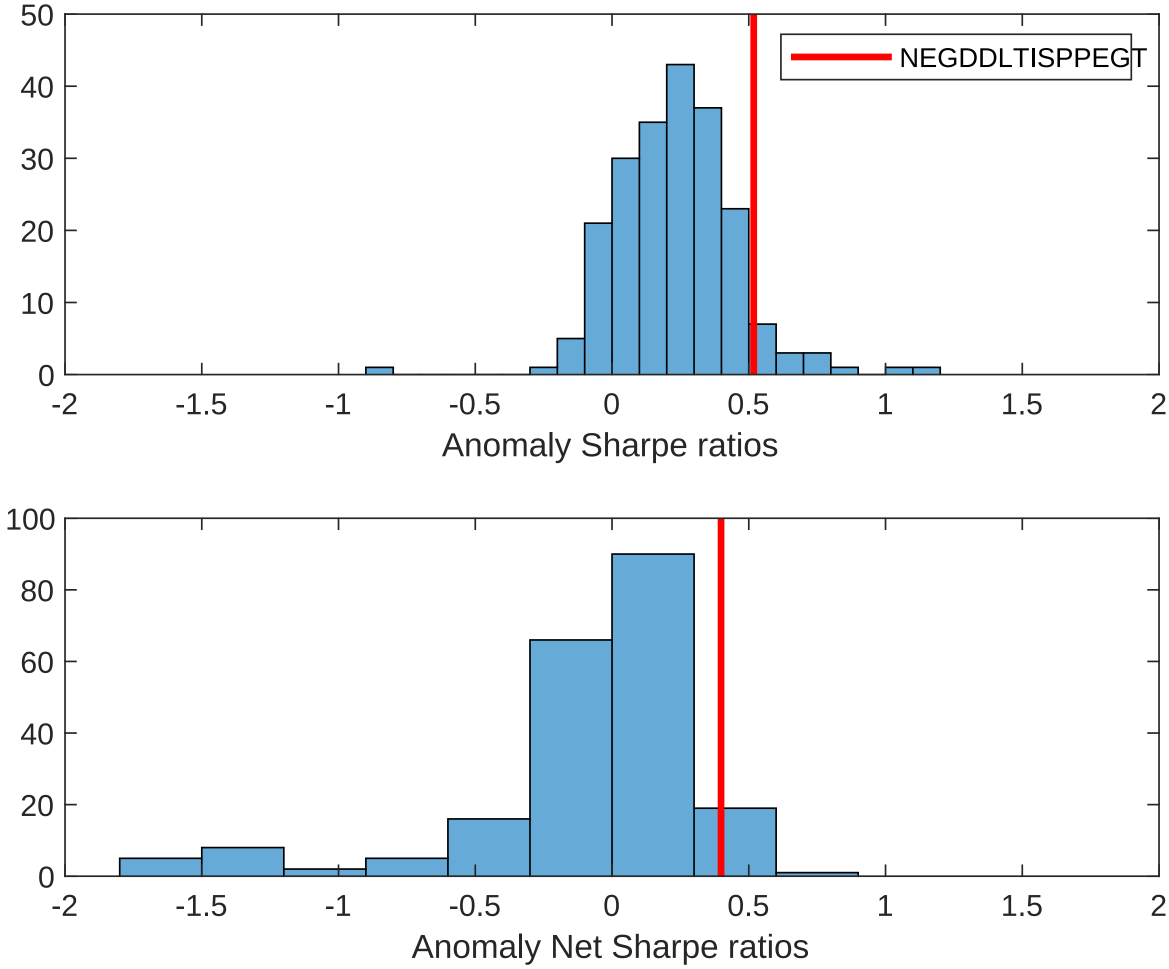


**Figure 2:** Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CFEM with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

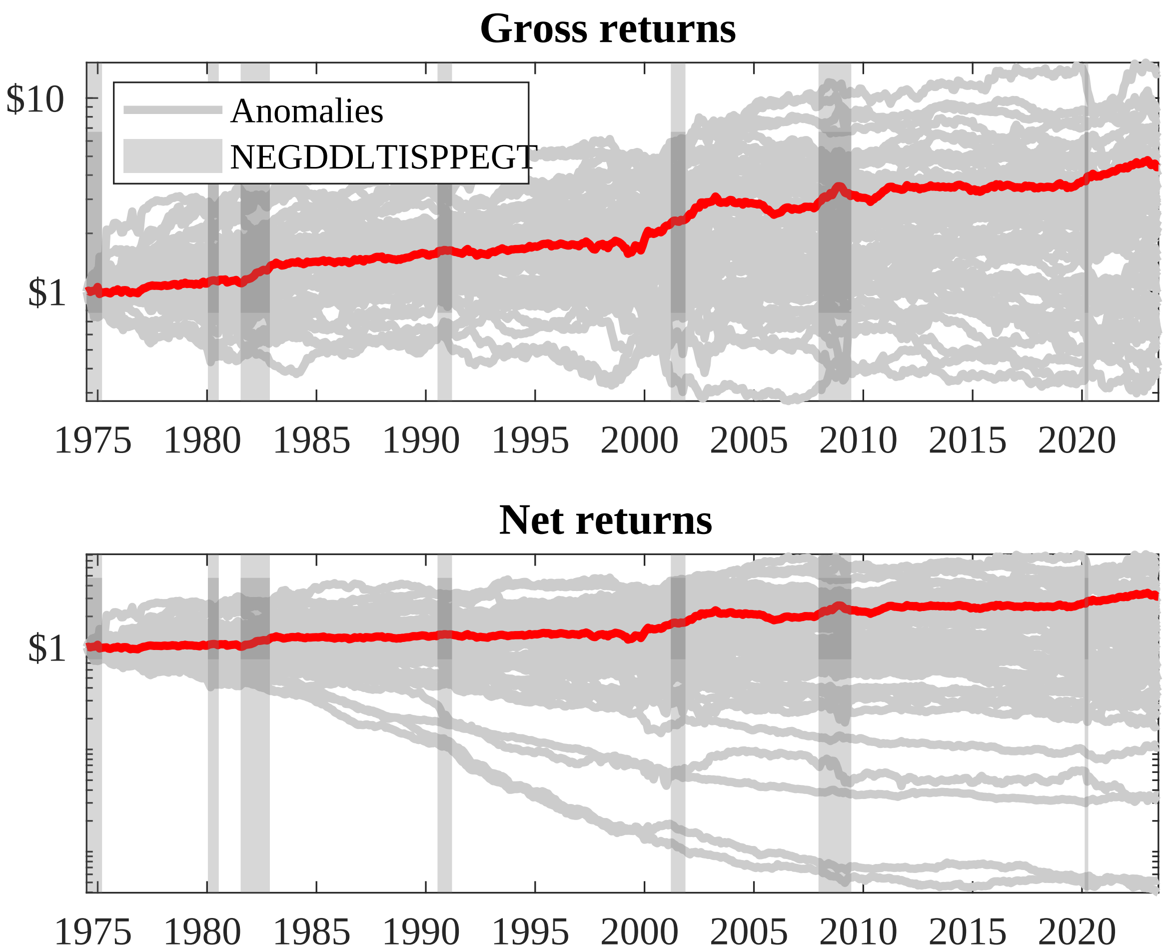


**Figure 3:** Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CFEM trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross strategy returns. Panel B plots results for net strtaegy returns.

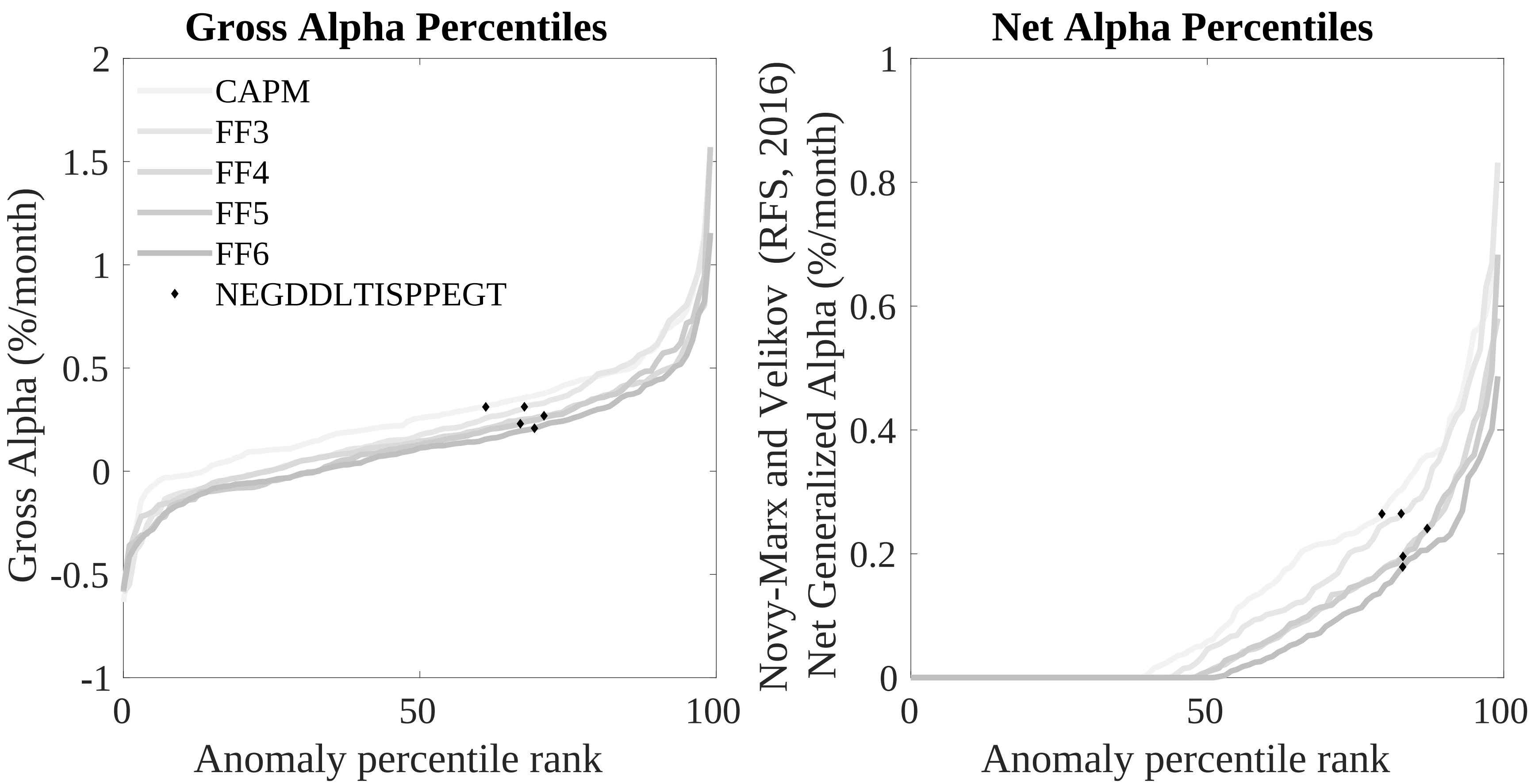


**Figure 4:** Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CFEM trading strategy alphas (diamonds). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. The alphas include those with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). The left panel plots alphas with no adjustment for trading costs. The right panel plots Novy-Marx and Velikov (2016) net generalized alphas.

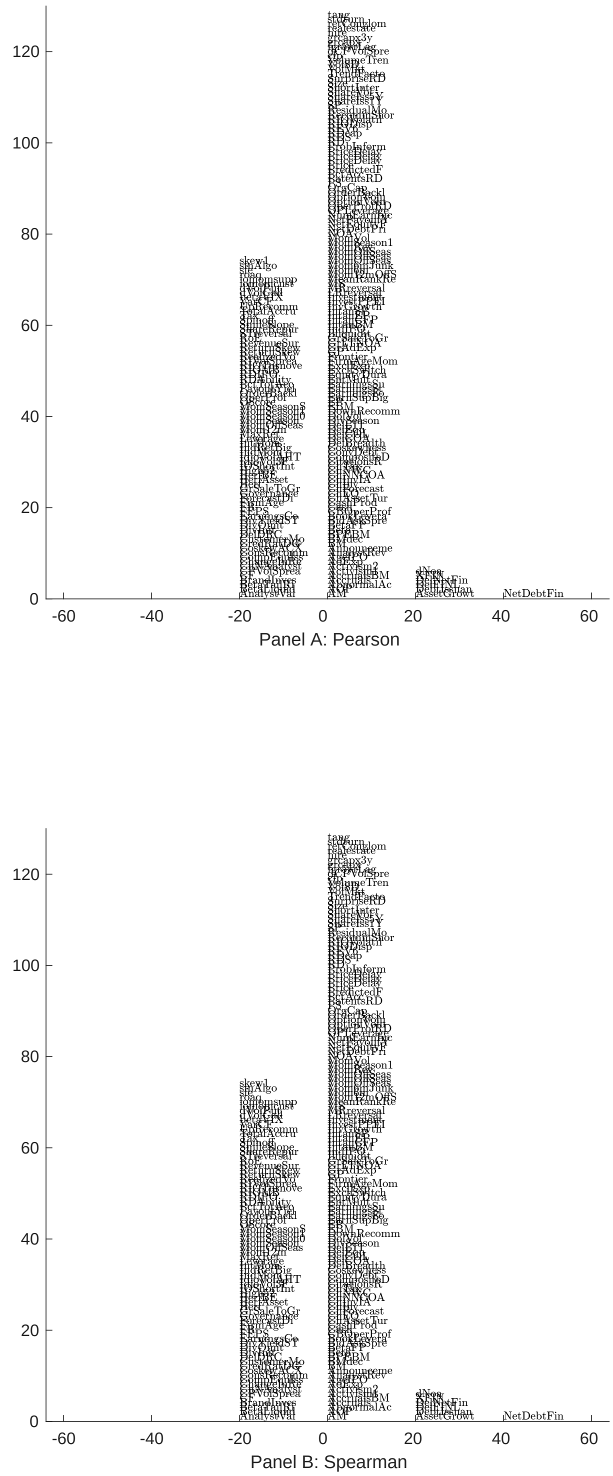


**Figure 5:** Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with CFEM. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

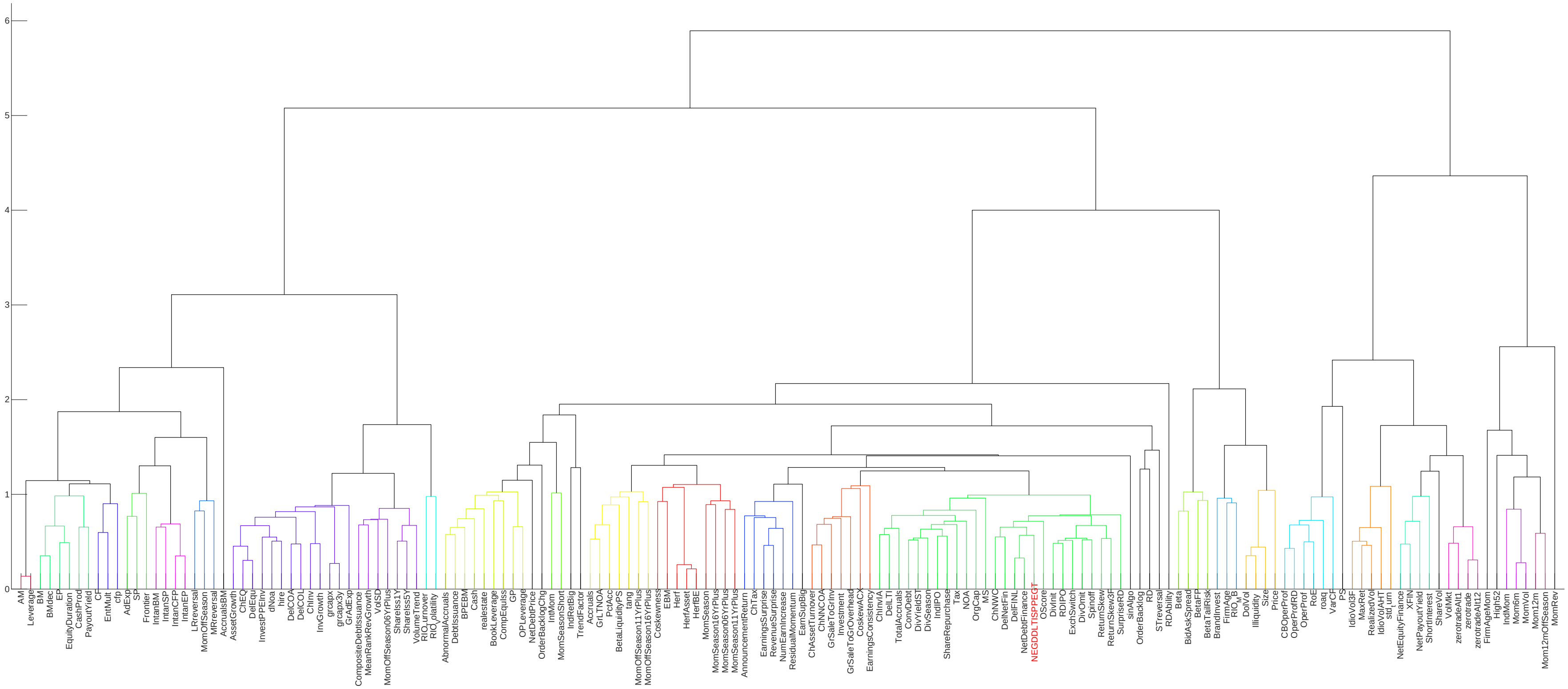

**Figure 6:** Agglomerative hierarchical cluster plot

This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

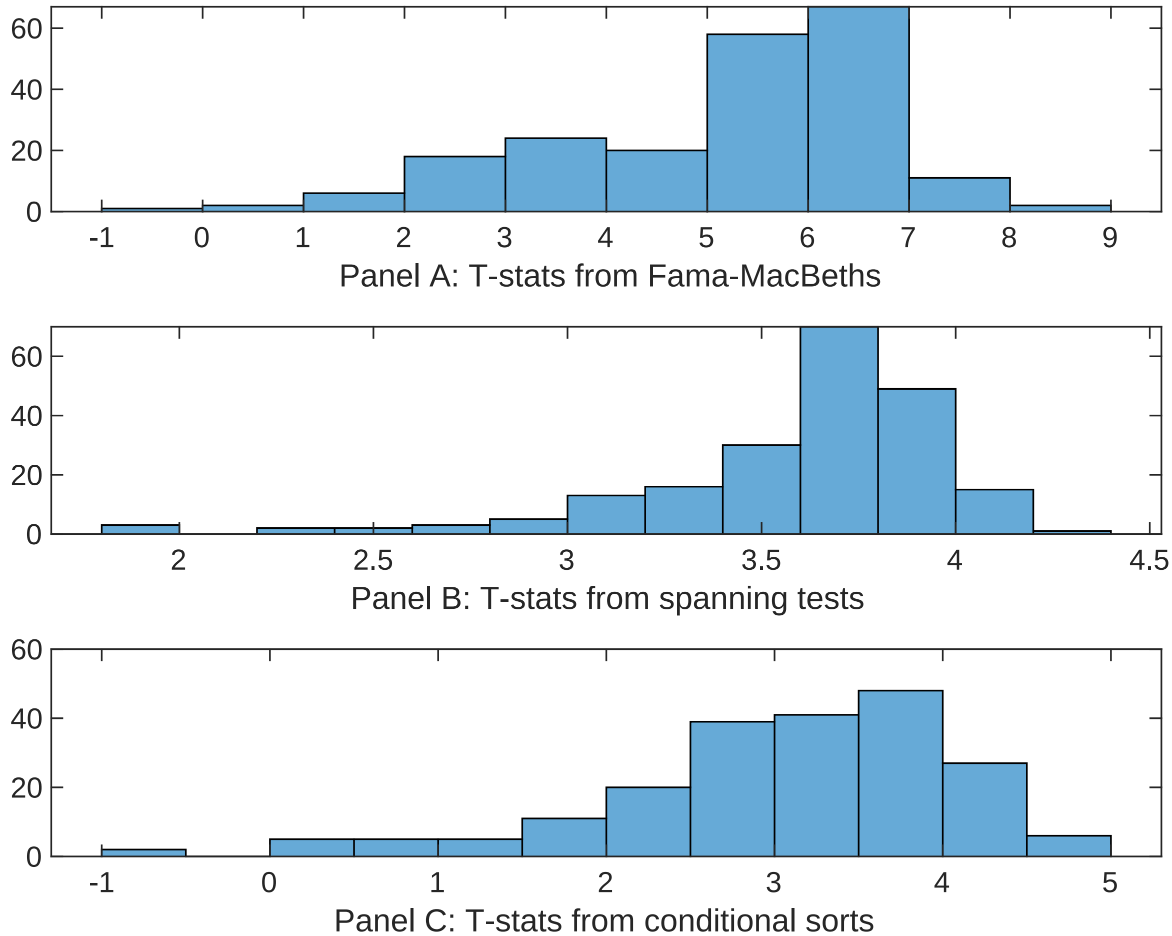


**Figure 7:** Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CFEM conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{CFEM}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CFEM} CFEM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ from spanning tests of the form: $r_{CFEM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 209 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on CFEM. Stocks are finally grouped into five CFEM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CFEM trading strategies conditioned on each of the 209 filtered anomalies.

**Table 4:** Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on CFEM. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{CFEM} CFEM_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, $X$, are Net debt financing, Change in financial liabilities, Net external financing, Asset growth, Inventory Growth, change in ppe and inv/assets. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the $R^2$ from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.14 | 0.14 | 0.14 | 0.15 | 0.14 | 0.15 | 0.15 |
| | [5.51] | [5.54] | [5.89] | [5.95] | [5.47] | [5.91] | [5.88] |
| CFEM | 0.81 | 0.69 | 0.94 | 0.63 | 0.15 | 0.93 | 0.48 |
| | [3.15] | [2.85] | [3.92] | [2.31] | [5.34] | [3.65] | [1.56] |
| Anomaly 1 | 0.19 | | | | | | 0.11 |
| | [8.48] | | | | | | [1.60] |
| Anomaly 2 | | 0.17 | | | | | -0.86 |
| | | [9.07] | | | | | [-1.82] |
| Anomaly 3 | | | 0.18 | | | | 0.10 |
| | | | [6.13] | | | | [1.84] |
| Anomaly 4 | | | | 0.10 | | | 0.55 |
| | | | | [8.82] | | | [2.61] |
| Anomaly 5 | | | | | 0.39 | | 0.81 |
| | | | | | [6.76] | | [0.13] |
| Anomaly 6 | | | | | | 0.16 | 0.77 |
| | | | | | | [7.49] | [2.79] |
| # months | 588 | 588 | 588 | 588 | 588 | 588 | 588 |
| $\bar{R}^2(\%)$ | 0 | 0 | 1 | 0 | 0 | 0 | 0 |

**Table 5:** Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the CFEM trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{CFEM} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where $X_k$ indicates each of the six most-closely related anomalies and $f_j$ indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, $X$, are Net debt financing, Change in financial liabilities, Net external financing, Asset growth, Inventory Growth, change in ppe and inv/assets. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the $R^2$ from the spanning tests in Figure 7, Panel B. The sample period is 197406 to 202306.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.20 | 0.20 | 0.20 | 0.22 | 0.21 | 0.21 | 0.19 |
| | [2.85] | [2.87] | [2.80] | [3.05] | [3.01] | [2.99] | [2.76] |
| Anomaly 1 | 17.30 | | | | | | 11.25 |
| | [4.36] | | | | | | [2.04] |
| Anomaly 2 | | 12.76 | | | | | 2.14 |
| | | [3.06] | | | | | [0.38] |
| Anomaly 3 | | | 16.91 | | | | 12.16 |
| | | | [4.73] | | | | [3.07] |
| Anomaly 4 | | | | 13.21 | | | 6.80 |
| | | | | [2.87] | | | [1.39] |
| Anomaly 5 | | | | | 5.37 | | 3.26 |
| | | | | | [1.91] | | [1.11] |
| Anomaly 6 | | | | | | 6.27 | -0.41 |
| | | | | | | [1.91] | [-0.12] |
| mkt | -5.05 | -4.90 | -2.77 | -5.00 | -5.20 | -5.20 | -3.44 |
| | [-3.13] | [-3.01] | [-1.65] | [-3.07] | [-3.17] | [-3.18] | [-2.03] |
| smb | 3.19 | 3.21 | 9.79 | 3.02 | 4.90 | 4.46 | 6.96 |
| | [1.27] | [1.26] | [3.57] | [1.18] | [1.92] | [1.76] | [2.37] |
| hml | -12.62 | -12.21 | -10.99 | -13.38 | -13.04 | -13.60 | -11.64 |
| | [-4.07] | [-3.90] | [-3.53] | [-4.27] | [-4.15] | [-4.29] | [-3.69] |
| rmw | 0.92 | 1.35 | -7.79 | 2.41 | 3.07 | 2.55 | -5.52 |
| | [0.28] | [0.41] | [-2.02] | [0.74] | [0.94] | [0.78] | [-1.40] |
| cma | 23.89 | 24.07 | 17.00 | 11.85 | 23.53 | 23.42 | 5.54 |
| | [4.98] | [4.88] | [3.24] | [1.59] | [4.38] | [4.34] | [0.74] |
| umd | 2.51 | 2.69 | 3.87 | 4.46 | 3.43 | 3.86 | 2.75 |
| | [1.51] | [1.59] | [2.38] | [2.69] | [2.05] | [2.33] | [1.61] |
| # months | 588 | 588 | 588 | 588 | 588 | 588 | 588 |
| $\bar{R}^2(\%)$ | 14 | 13 | 15 | 13 | 12 | 12 | 16 |

## Panel A: Average rank

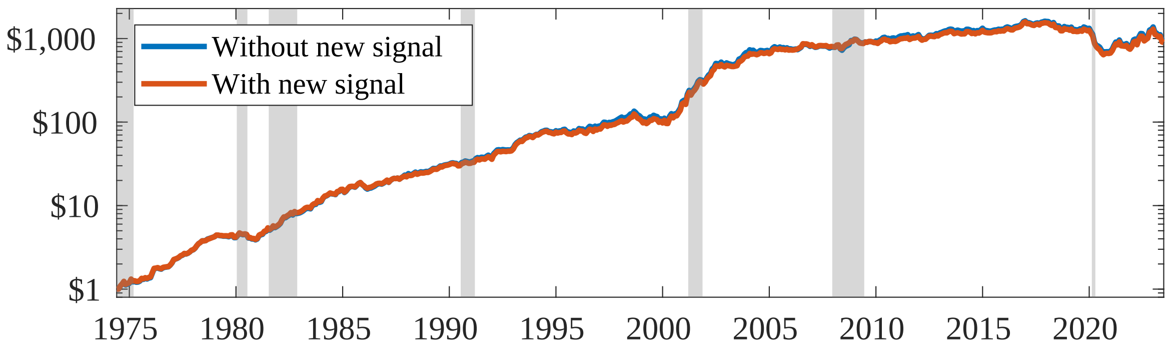


**Figure 8:** Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines indicate combination trading strategies that utilize the 156 anomalies as well as CFEM. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

# References


Bradshaw, M. T., Richardson, S. A., and Sloan, R. G. (2006). The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics*, 42(1-2):53–85.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.

Cochrane, J. H. and Saa-Requejo, J. (2000). Beyond arbitrage: Good-deal asset price bounds in incomplete markets. *Journal of Political Economy*, 108(1):79–119.

Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance, Forthcoming.*

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Harvey, C. R., Liu, Y., and Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.

Hirshleifer, D., Li, J., and Yu, J. (2015). Asset pricing in production economies with extrapolative expectations. *Journal of Monetary Economics*, 76:87–106.

Hou, K., Xue, C., and Zhang, L. (2020). Replicating anomalies. *Review of Financial Studies*, 33(5):2019–2133.

Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper.*

Titman, S., Wei, K. J., and Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39(4):677–700.

Zhang, X. F. and Kogan, L. (2012). Information revelation and expected stock returns. *Journal of Finance*, 67(4):1437–1466.