# Net Property Plant and Equipment to Nonoperating Income Scale and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

**Abstract**

This paper studies the asset pricing implications of Net Property Plant and Equipment to Nonoperating Income Scale (NPPENI), 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 NPPENI achieves an annualized gross (net) Sharpe ratio of 0.52 (0.44), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 16 (14) bps/month with a t-statistic of 2.26 (1.93), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (change in ppe and inv/assets, change in net operating assets, Asset growth, Change in capex (two years), Change in capex (three years), Change in equity to assets) is 13 bps/month with a t-statistic of 2.04.

# 1 Introduction

The efficient market hypothesis suggests that asset prices should fully reflect all 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 well-documented, the relationship between firms' physical capital allocation and their non-operating income remains relatively unexplored. This gap is particularly notable given the importance of capital investment decisions in determining firm value and future profitability (Titman et al., 2004).

Prior research has established that corporate investment patterns can predict stock returns (**?**), but the existing literature has primarily focused on aggregate investment measures without considering the specific relationship between fixed assets and non-operating income. This distinction is crucial because non-operating income may provide important signals about the efficiency of capital allocation and management's ability to generate returns from peripheral activities.

We propose that the ratio of Net Property Plant and Equipment to Non-operating Income Scale (NPPENI) contains valuable information about future stock returns for several reasons. First, building on (Chen and Zhang, 2010)'s investment-based asset pricing framework, firms with high NPPENI may indicate suboptimal capital allocation, where substantial fixed assets fail to generate proportional peripheral income streams. This inefficiency should be reflected in future stock returns as the market gradually recognizes the misallocation.

Second, following (Cooper et al., 2008)'s arguments about investment-based return predictability, high NPPENI could signal agency problems where managers overinvest in fixed assets without developing complementary revenue sources. This overinvestment hypothesis suggests that firms with elevated NPPENI ratios should subsequently underperform (**?**).

Third, the NPPENI ratio may capture information about management's skill in deploying capital across both core and non-core activities. Drawing on (Fama and French, 2015)'s investment factor framework, firms that efficiently balance fixed asset investments with diverse income streams should deliver superior returns compared to those maintaining suboptimal capital allocations.

Our empirical analysis reveals strong evidence that NPPENI predicts cross-sectional stock returns. A value-weighted long-short trading strategy based on NPPENI quintiles generates a significant monthly alpha of 16 basis points (t-statistic = 2.26) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized gross Sharpe ratio of 0.52, placing it in the top 7% of documented market anomalies.

Importantly, the predictive power of NPPENI remains robust after controlling for transaction costs. The strategy delivers a net Sharpe ratio of 0.44 and maintains statistical significance with a monthly net alpha of 14 basis points (t-statistic = 1.93). This performance persists across different size segments, with the largest quintile of stocks producing a monthly alpha of 23 basis points (t-statistic = 2.57).

Further analysis demonstrates that NPPENI's predictive ability is distinct from related anomalies. Controlling for six closely related investment-based strategies, including changes in PPE, asset growth, and capital expenditures, NPPENI continues to generate a significant monthly alpha of 13 basis points (t-statistic = 2.04). This suggests that NPPENI captures unique information about future returns not contained in existing investment-based predictors.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that bridges the gap between physical capital allocation and non-operating performance, extending the investment-based asset pricing literature pioneered by (?) and (Cooper et al., 2008). Unlike existing measures that focus solely on investment levels, NPPENI provides insights into the efficiency of capital deployment across different revenue streams.

Second, we contribute to the growing literature on the role of corporate investment in asset pricing (Fama and French, 2015; Hou et al., 2015). Our findings suggest that the market does not fully incorporate information about the relationship between fixed assets and non-operating income, creating a persistent mispricing that survives common risk adjustments and transaction costs.

Third, our work has important implications for the efficient market hypothesis and the broader asset pricing literature. The robust performance of NPPENI, particularly among large stocks and after accounting for trading costs, challenges the notion that readily available accounting information is quickly incorporated into stock prices. These findings complement recent work on market efficiency and the limits of arbitrage (Stambaugh and Yuan, 2017).

# 2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the change in net property, plant and equipment scaled by nonoperating income. 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 PPENT for net property, plant and equipment and item NOPI for nonoperating income. Net property, plant and equipment (PPENT) represents the cost of tangible fixed property used in the production of revenue, less accumulated depreciation. Nonoperating income (NOPI), on the other hand, captures income or expenses not directly related to a company's core operations, including items such as interest income, dividend income, and gains or losses from non-core activities. The construction of the signal follows a change-based approach, where we calculate the difference between the current period's PPENT and its lagged value, then scale this change by the lagged value of NOPI for each firm in each year of our sample. This ratio captures the relative magnitude of changes in a firm's fixed asset base compared to its nonoperating income, potentially offering insight into how firms finance their capital expenditures and the relationship between operational and nonoperational aspects of the business. By focusing on this relationship, the signal aims to reflect aspects of capital investment decisions and their financing in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both PPENT and NOPI to ensure consistency and comparability across firms and over time.

# 3 Signal diagnostics

Figure 1 plots descriptive statistics for the NPPENI signal. Panel A plots the time-series of the mean, median, and interquartile range for NPPENI. On average, the cross-sectional mean (median) NPPENI is -9.83 (-0.97) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input NPPENI data. The signal's interquartile range spans -16.64 to 2.65. Panel B of Figure 1 plots the time-series of the coverage of the NPPENI signal for the CRSP universe. On average, the NPPENI signal is available for 6.09% of CRSP names, which on average make up 7.56% of total market capitalization.

# 4 Does NPPENI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on NPPENI 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 NPPENI portfolio and sells the low NPPENI 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 NPPENI strategy earns an average return of 0.29% per month with a t-statistic of 3.97. The annualized Sharpe ratio of the strategy is 0.52. The alphas range from 0.16% to 0.30% per month and have t-statistics exceeding 2.23 everywhere. The lowest alpha is with respect to the FF5 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 0.22, with a t-statistic of 4.67 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 527 stocks and an average market capitalization of at least $993 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 cap breakpoints and value-weighted portfolios, and equals 17 bps/month with a t-statistics of 2.50. Out of the twenty-five alphas reported in Panel A, the t-statistics for nineteen exceed two, and for seven 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 13-29bps/month. The lowest return, (13 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 1.96. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the NPPENI trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-five cases, and significantly expands the achievable frontier in eleven cases.

Table 3 provides direct tests for the role size plays in the NPPENI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and NPPENI, as well as average returns and alphas for long/short trading NPPENI 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 NPPENI strategy achieves an average return of 23 bps/month with a t-statistic of 2.57. Among these large cap stocks, the alphas for the NPPENI strategy relative to the five most common factor models range from 9 to 26 bps/month with t-statistics between 1.08 and 2.90.

# 5 How does NPPENI perform relative to the zoo?

Figure 2 puts the performance of NPPENI 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 NPPENI strategy falls in the distribution. The NPPENI strategy's gross (net) Sharpe ratio of 0.52 (0.44) is greater than 93% (99%) 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 NPPENI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the NPPENI strategy would have yielded \$6.24 which ranks the NPPENI strategy in the top 4% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the NPPENI strategy would have yielded \$4.36 which ranks the NPPENI strategy in the top 3% 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 NPPENI relative to those. Panel A shows that the NPPENI strategy gross alphas fall between the 53 and 63 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 196506 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 NPPENI strategy has a positive net generalized alpha for five out of the five factor models. In these cases NPPENI ranks between the 72 and 79 percentiles in terms of how much it could have expanded the achievable investment frontier.

# 6 Does NPPENI 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 NPPENI with 210 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 NPPENI or at least to weaken the power NPPENI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of NPPENI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{NPPENI}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{NPPENI} NPPENI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ from spanning tests of the form: $r_{NPPENI,t} = \alpha +$

[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.

$\beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 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 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on NPPENI. Stocks are finally grouped into five NPPENI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted NPPENI trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on NPPENI 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 NPPENI signal in these Fama-MacBeth regressions exceed 2.25, with the minimum t-statistic occurring when controlling for change in ppe and inv/assets. Controlling for all six closely related anomalies, the t-statistic on NPPENI is 1.74.

Similarly, Table 5 reports results from spanning tests that regress returns to the NPPENI 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 NPPENI strategy earns alphas that range from 13-18bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.93, which is achieved when controlling for change in ppe and inv/assets. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the NPPENI trading strategy achieves an alpha of 13bps/month with a t-statistic of

2.04.

## 7 Does NPPENI add relative to the whole zoo?

Finally, we can ask how much adding NPPENI 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 155 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 155 anomalies augmented with the NPPENI 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 155-anomaly combination strategy grows to $3027.42, while $1 investment in the combination strategy that includes NPPENI grows to $2661.51.

## 8 Conclusion

This study provides compelling evidence for the predictive power of Net Property Plant and Equipment to Nonoperating Income Scale (NPPENI) in forecasting stock returns. Our findings demonstrate that NPPENI generates economically and statistically significant returns, with a value-weighted long/short strategy achieving an impressive annualized Sharpe ratio of 0.52 (0.44) on a gross (net) basis. The strategy's robustness is further validated by its ability to generate significant abnormal

[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 NPPENI is available.

returns even after controlling for well-established risk factors and related investment strategies.

Particularly noteworthy is the signal's persistence in generating alpha of 13 basis points per month (t-statistic = 2.04) even after controlling for six common factors and the six most closely related strategies from the factor zoo. This suggests that NPPENI captures unique information about future stock returns that is not fully explained by existing investment factors.

However, several limitations should be considered. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, transaction costs and market impact could affect the strategy's real-world implementation, particularly for smaller stocks or during periods of market stress.

Future research could explore several promising directions. First, investigating the economic mechanisms underlying the NPPENI signal's predictive power could provide valuable insights into market efficiency and asset pricing. Second, examining the signal's interaction with other established anomalies could reveal potential complementarities or substitution effects. Finally, testing the signal's robustness across different market regimes and international markets would help establish its broader applicability.

In conclusion, our findings suggest that NPPENI represents a valuable addition to the quantitative investor's toolkit, offering meaningful predictive power that persists even after controlling for related factors. This research contributes to our understanding of the cross-section of stock returns and highlights the ongoing potential for discovering novel signals in financial markets.

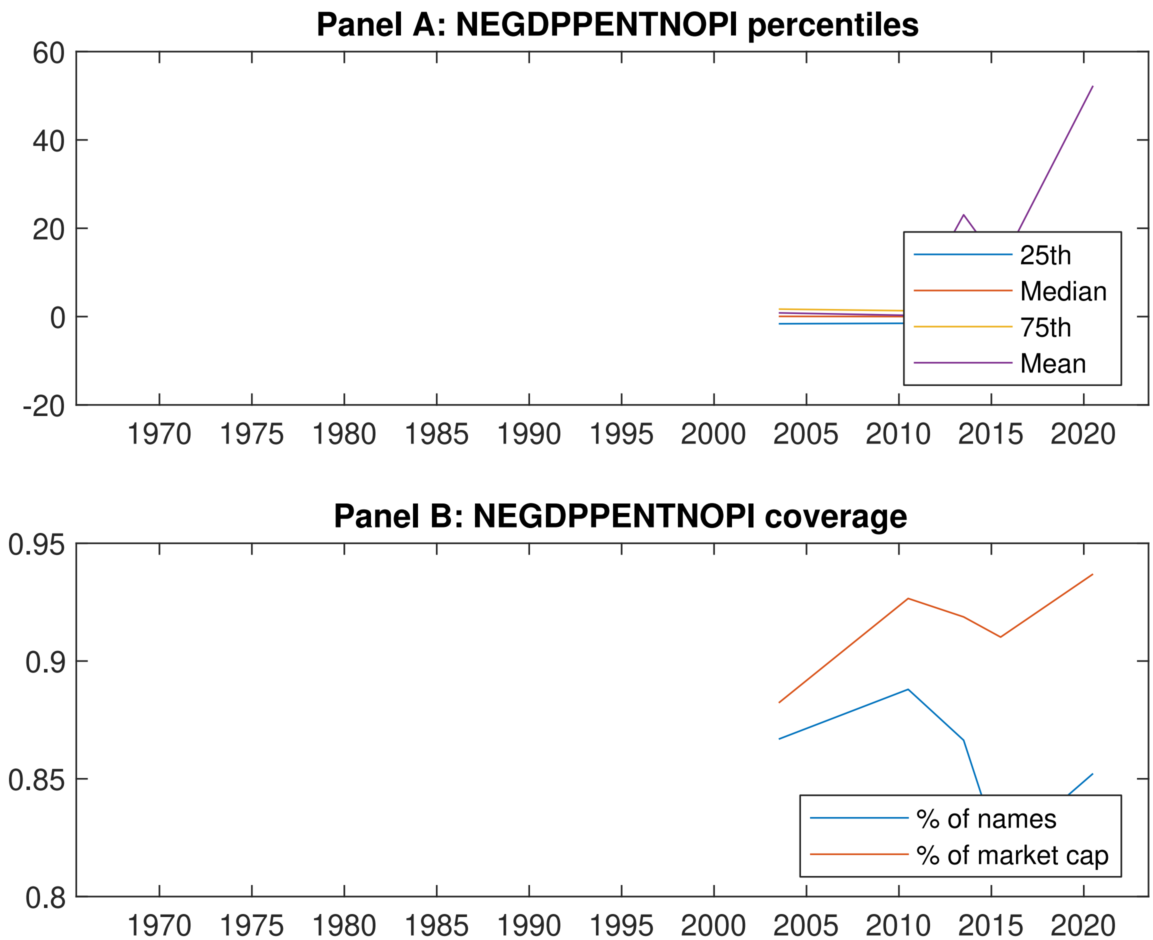


**Figure 1:** Times series of NPPENI percentiles and coverage.
This figure plots descriptive statistics for NPPENI. Panel A shows cross-sectional percentiles of NPPENI over the sample. Panel B plots the monthly coverage of NPPENI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on NPPENI. 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 196506 to 202306.

| Panel A: Excess returns and alphas on NPPENI-sorted portfolios | | | | | | |
|---|---|---|---|---|---|---|
| | (L) | (2) | (3) | (4) | (H) | (H-L) |
| $r^e$ | 0.42 | 0.60 | 0.60 | 0.55 | 0.71 | 0.29 |
| | [2.26] | [3.58] | [3.50] | [3.14] | [3.83] | [3.97] |
| $\alpha_{CAPM}$ | -0.16 | 0.07 | 0.05 | 0.00 | 0.13 | 0.30 |
| | [-3.14] | [1.63] | [1.34] | [0.06] | [2.27] | [3.96] |
| $\alpha_{FF3}$ | -0.13 | 0.11 | 0.07 | -0.06 | 0.07 | 0.20 |
| | [-2.52] | [2.66] | [1.67] | [-1.34] | [1.20] | [2.84] |
| $\alpha_{FF4}$ | -0.10 | 0.11 | 0.06 | -0.06 | 0.09 | 0.19 |
| | [-2.00] | [2.71] | [1.40] | [-1.25] | [1.58] | [2.75] |
| $\alpha_{FF5}$ | -0.15 | 0.14 | 0.06 | -0.11 | 0.01 | 0.16 |
| | [-2.91] | [3.30] | [1.45] | [-2.29] | [0.14] | [2.23] |
| $\alpha_{FF6}$ | -0.13 | 0.14 | 0.05 | -0.10 | 0.03 | 0.16 |
| | [-2.49] | [3.28] | [1.26] | [-2.11] | [0.57] | [2.26] |
| Panel B: Fama and French (2018) 6-factor model loadings for NPPENI-sorted portfolios | | | | | | |
| $\beta_{\text{MKT}}$ | 1.01 | 0.94 | 0.99 | 1.02 | 1.04 | 0.03 |
| | [82.65] | [93.13] | [100.97] | [87.76] | [76.45] | [1.81] |
| $\beta_{\text{SMB}}$ | 0.02 | -0.09 | -0.08 | -0.00 | 0.12 | 0.11 |
| | [0.94] | [-6.39] | [-5.80] | [-0.17] | [6.25] | [4.35] |
| $\beta_{\text{HML}}$ | -0.05 | -0.06 | -0.03 | 0.13 | 0.09 | 0.14 |
| | [-2.02] | [-3.01] | [-1.82] | [5.87] | [3.48] | [4.26] |
| $\beta_{\text{RMW}}$ | 0.13 | -0.05 | -0.02 | 0.06 | 0.12 | -0.01 |
| | [5.60] | [-2.76] | [-1.17] | [2.63] | [4.55] | [-0.38] |
| $\beta_{\text{CMA}}$ | -0.12 | -0.05 | 0.07 | 0.13 | 0.10 | 0.22 |
| | [-3.44] | [-1.74] | [2.41] | [3.89] | [2.71] | [4.67] |
| $\beta_{\text{UMD}}$ | -0.03 | -0.00 | 0.01 | -0.01 | -0.04 | -0.01 |
| | [-2.49] | [-0.13] | [1.06] | [-0.96] | [-2.70] | [-0.38] |
| Panel C: Average number of firms ($n$) and market capitalization ($me$) | | | | | | |
| $n$ | 563 | 527 | 677 | 820 | 645 | |
| me ($\$10^6$) | 1477 | 2203 | 2688 | 1789 | 993 | |

**Table 2:** Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the NPPENI 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 196506 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 | 0.29 | 0.30 | 0.20 | 0.19 | 0.16 | 0.16 |
| | | | [3.97] | [3.96] | [2.84] | [2.75] | [2.23] | [2.26] |
| Quintile | NYSE | EW | 0.50 | 0.50 | 0.43 | 0.41 | 0.42 | 0.40 |
| | | | [7.69] | [7.66] | [7.54] | [6.98] | [7.32] | [6.96] |
| Quintile | Name | VW | 0.25 | 0.26 | 0.15 | 0.15 | 0.10 | 0.10 |
| | | | [3.56] | [3.56] | [2.31] | [2.22] | [1.51] | [1.55] |
| Quintile | Cap | VW | 0.17 | 0.19 | 0.09 | 0.09 | 0.03 | 0.03 |
| | | | [2.50] | [2.78] | [1.47] | [1.36] | [0.44] | [0.50] |
| Decile | NYSE | VW | 0.27 | 0.26 | 0.22 | 0.21 | 0.22 | 0.22 |
| | | | [2.97] | [2.91] | [2.39] | [2.32] | [2.40] | [2.36] |
| 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 | 0.25 | 0.26 | 0.17 | 0.17 | 0.13 | 0.14 |
| | | | [3.37] | [3.44] | [2.48] | [2.45] | [1.79] | [1.93] |
| Quintile | NYSE | EW | 0.29 | 0.29 | 0.23 | 0.22 | 0.18 | 0.18 |
| | | | [4.04] | [3.97] | [3.40] | [3.27] | [2.87] | [2.84] |
| Quintile | Name | VW | 0.21 | 0.22 | 0.12 | 0.12 | 0.07 | 0.08 |
| | | | [2.91] | [3.00] | [1.92] | [1.88] | [1.02] | [1.20] |
| Quintile | Cap | VW | 0.13 | 0.16 | 0.07 | 0.07 | 0.01 | 0.02 |
| | | | [1.96] | [2.28] | [1.12] | [1.06] | [0.13] | [0.28] |
| Decile | NYSE | VW | 0.21 | 0.22 | 0.18 | 0.18 | 0.17 | 0.18 |
| | | | [2.37] | [2.39] | [1.93] | [1.92] | [1.85] | [1.91] |

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

This table presents results for conditional double sorts on size and NPPENI. 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 NPPENI. 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 NPPENI and short stocks with low NPPENI .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196506 to 202306.

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

| | | NPPENI Quintiles | | | | | NPPENI Strategies | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (L) | (2) | (3) | (4) | (H) | $r^e$ | $\alpha_{CAPM}$ | $\alpha_{FF3}$ | $\alpha_{FF4}$ | $\alpha_{FF5}$ | $\alpha_{FF6}$ |
| Size quintiles | (1) | 0.57 | 0.77 | 0.86 | 0.88 | 0.91 | 0.34 | 0.32 | 0.29 | 0.21 | 0.24 | 0.19 |
| | | [2.26] | [3.04] | [3.49] | [3.56] | [3.36] | [3.92] | [3.72] | [3.33] | [2.47] | [2.75] | [2.13] |
| | (2) | 0.67 | 0.74 | 0.77 | 0.89 | 0.85 | 0.18 | 0.21 | 0.17 | 0.15 | 0.17 | 0.16 |
| | | [2.81] | [3.14] | [3.23] | [3.99] | [3.69] | [2.34] | [2.73] | [2.24] | [1.94] | [2.21] | [2.01] |
| | (3) | 0.66 | 0.71 | 0.74 | 0.78 | 0.87 | 0.21 | 0.21 | 0.15 | 0.16 | 0.16 | 0.18 |
| | | [3.13] | [3.30] | [3.35] | [3.79] | [4.09] | [2.56] | [2.54] | [1.78] | [1.97] | [1.97] | [2.13] |
| | (4) | 0.60 | 0.67 | 0.74 | 0.77 | 0.75 | 0.16 | 0.15 | 0.07 | 0.08 | 0.06 | 0.07 |
| | | [2.98] | [3.45] | [3.63] | [3.86] | [3.73] | [1.97] | [1.87] | [0.95] | [1.03] | [0.81] | [0.92] |
| | (5) | 0.33 | 0.68 | 0.57 | 0.45 | 0.56 | 0.23 | 0.26 | 0.16 | 0.14 | 0.10 | 0.09 |
| | | [1.83] | [4.14] | [3.32] | [2.62] | [3.27] | [2.57] | [2.90] | [1.84] | [1.67] | [1.12] | [1.08] |

Panel B: Portfolio average number of firms and market capitalization

| | | NPPENI Quintiles | | | | | NPPENI Quintiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Average $n$ | | | | | Average market capitalization ($\$10^6$) | | | | |
| | | (L) | (2) | (3) | (4) | (H) | (L) | (2) | (3) | (4) | (H) |
| Size quintiles | (1) | 351 | 352 | 351 | 349 | 345 | 34 | 32 | 29 | 29 | 28 |
| | (2) | 101 | 101 | 101 | 101 | 101 | 52 | 52 | 51 | 52 | 52 |
| | (3) | 75 | 75 | 74 | 74 | 74 | 91 | 91 | 90 | 89 | 91 |
| | (4) | 63 | 63 | 64 | 63 | 63 | 193 | 191 | 199 | 194 | 195 |
| | (5) | 58 | 58 | 58 | 58 | 58 | 1219 | 1448 | 1985 | 1539 | 1126 |

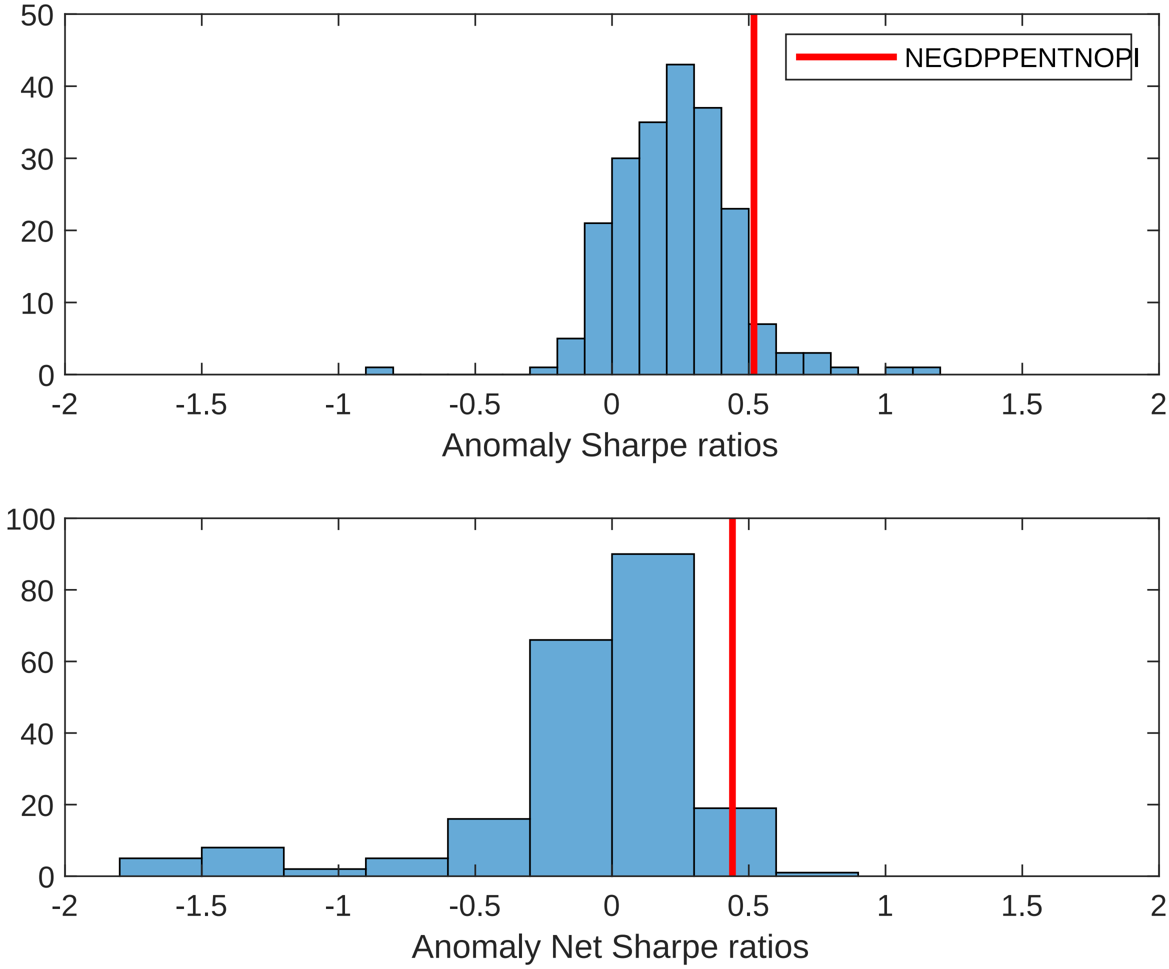


**Figure 2:** Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the NPPENI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

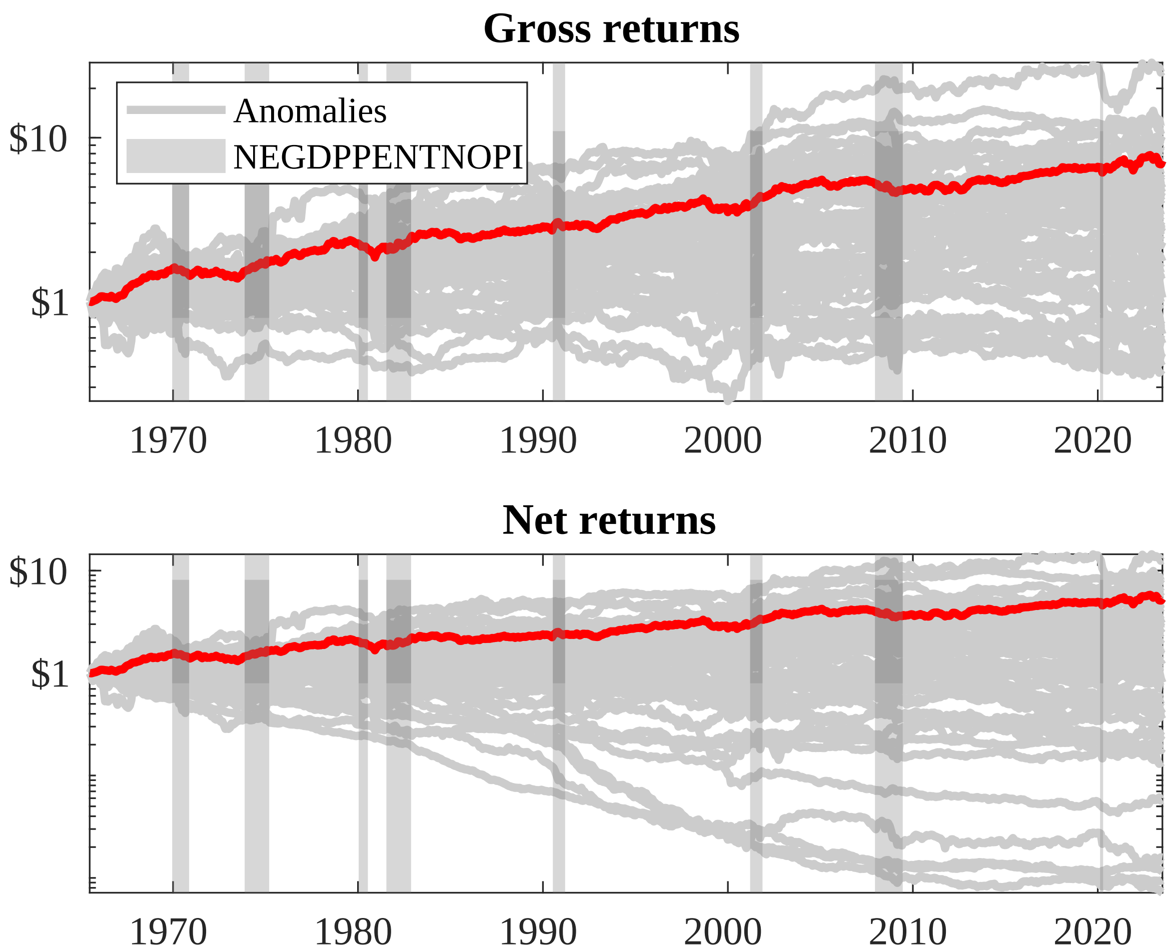


**Figure 3:** Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the NPPENI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results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

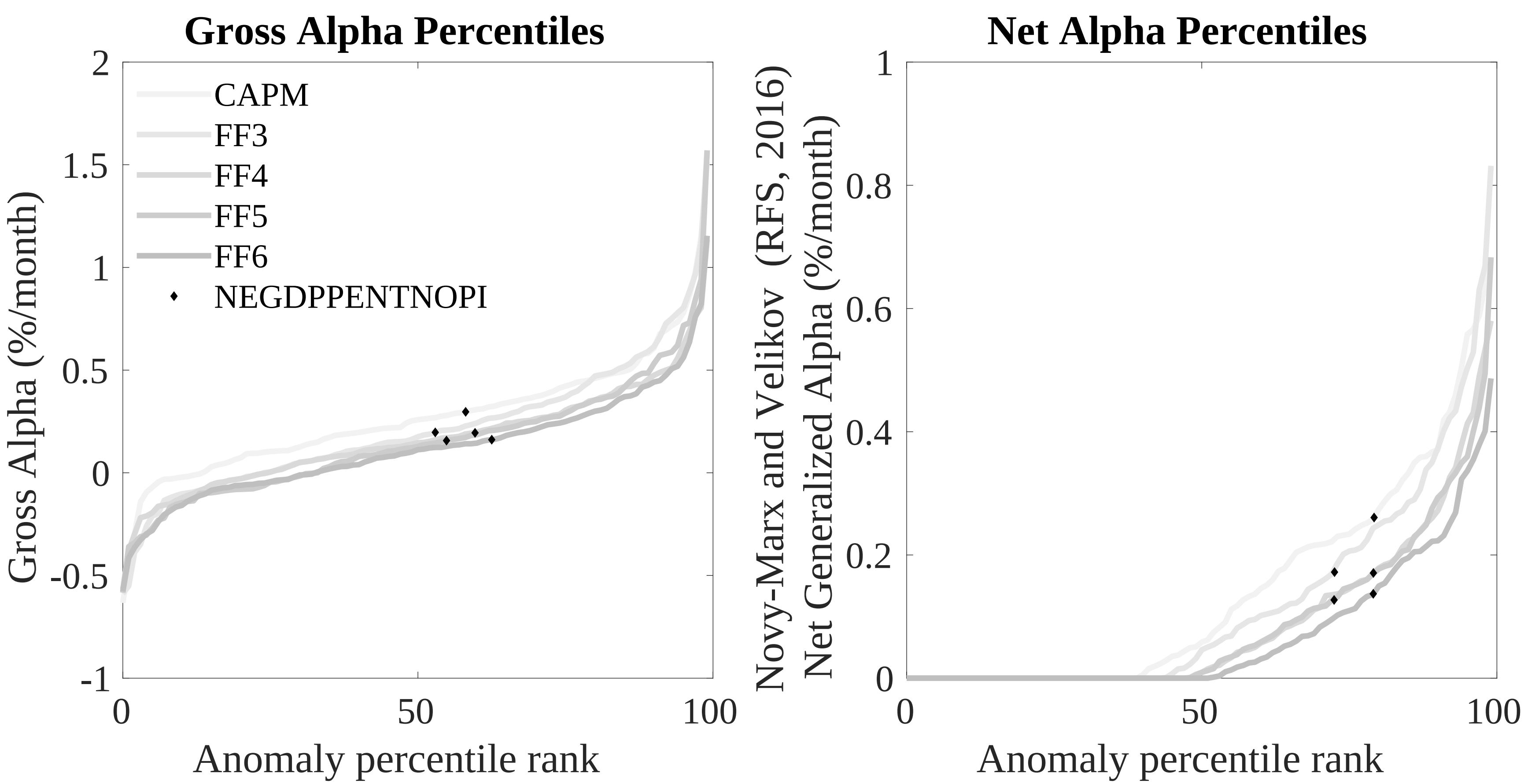


**Figure 4:** Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the NPPENI trading strategy alphas (diamonds). The strategies are constructed 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.

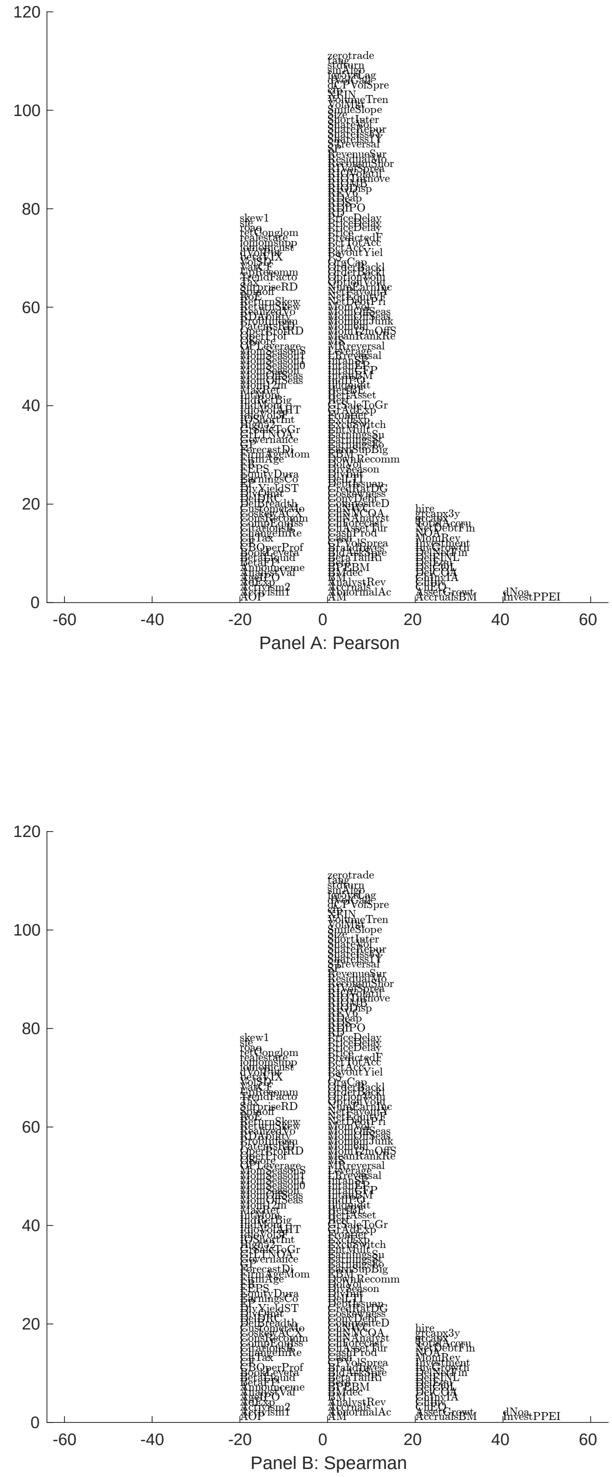


**Figure 5:** Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with NPPENI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

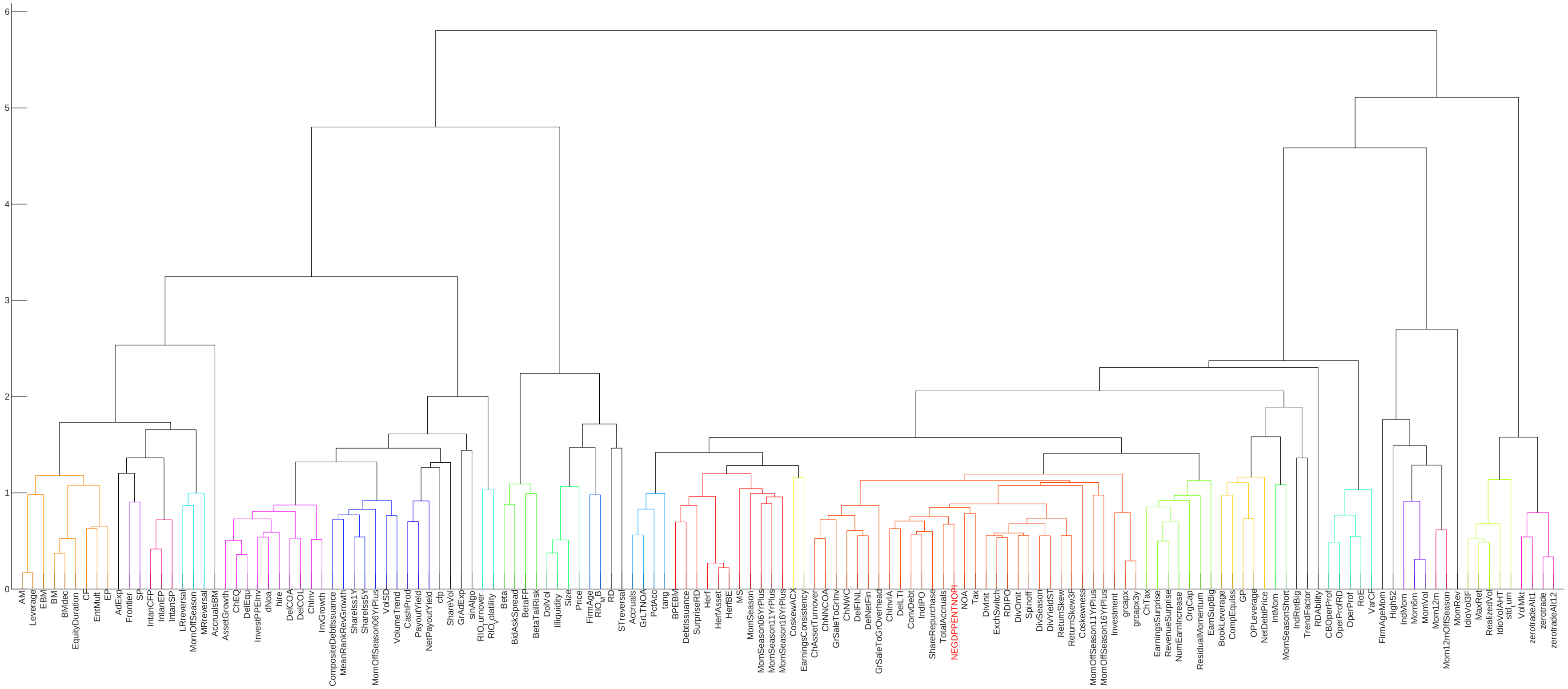

**Figure 6:** Agglomerative hierarchical cluster plot

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

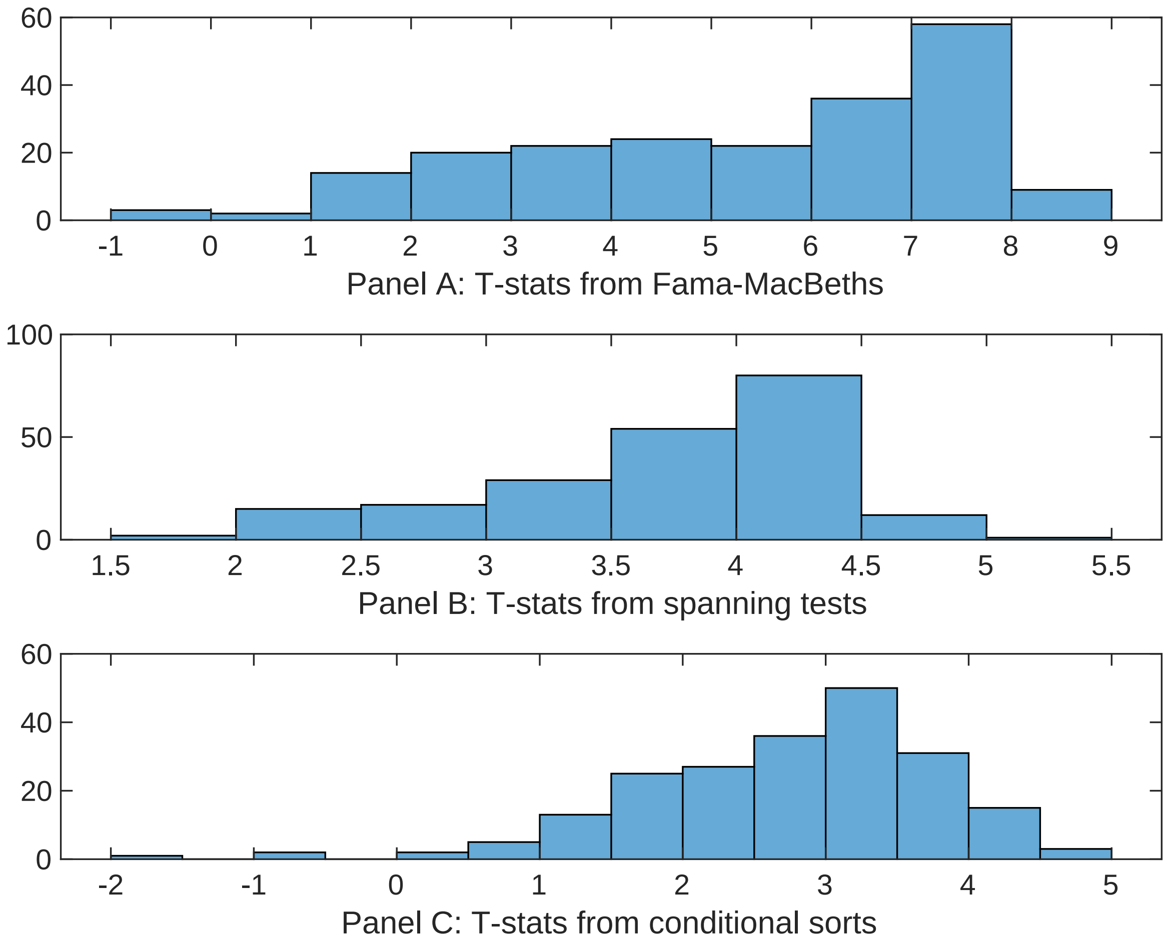


**Figure 7:** Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of NPPENI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{NPPENI}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{NPPENI} NPPENI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ from spanning tests of the form: $r_{NPPENI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 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 210 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on NPPENI. Stocks are finally grouped into five NPPENI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted NPPENI trading strategies conditioned on each of the 210 filtered anomalies.

**Table 4:** Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on NPPENI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{NPPENI} NPPENI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, $X$, are change in ppe and inv/assets, change in net operating assets, Asset growth, Change in capex (two years), Change in capex (three years), Change in equity to 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 196506 to 202306.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.14 | 0.13 | 0.13 | 0.13 | 0.14 | 0.12 | 0.14 |
| | [5.90] | [5.91] | [6.12] | [5.84] | [6.40] | [5.64] | [6.12] |
| NPPENI | 0.75 | 0.88 | 0.11 | 0.22 | 0.18 | 0.25 | 0.63 |
| | [2.25] | [2.48] | [3.08] | [5.58] | [4.64] | [6.54] | [1.74] |
| Anomaly 1 | 0.16 | | | | | | 0.20 |
| | [8.33] | | | | | | [0.74] |
| Anomaly 2 | | 0.13 | | | | | 0.34 |
| | | [8.67] | | | | | [1.75] |
| Anomaly 3 | | | 0.10 | | | | 0.27 |
| | | | [8.84] | | | | [1.62] |
| Anomaly 4 | | | | 0.56 | | | 0.19 |
| | | | | [7.31] | | | [1.53] |
| Anomaly 5 | | | | | 0.11 | | 0.27 |
| | | | | | [7.47] | | [1.14] |
| Anomaly 6 | | | | | | 0.14 | 0.48 |
| | | | | | | [3.95] | [1.28] |
| # months | 696 | 696 | 696 | 691 | 691 | 696 | 691 |
| $\bar{R}^2(\%)$ | 0 | 0 | 0 | 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 NPPENI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{NPPENI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 change in ppe and inv/assets, change in net operating assets, Asset growth, Change in capex (two years), Change in capex (three years), Change in equity to 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 196506 to 202306.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.17 | 0.13 | 0.18 | 0.17 | 0.18 | 0.18 | 0.13 |
| | [2.53] | [1.93] | [2.55] | [2.46] | [2.50] | [2.51] | [2.04] |
| Anomaly 1 | 30.24 | | | | | | 26.99 |
| | [9.50] | | | | | | [7.61] |
| Anomaly 2 | | 28.18 | | | | | 15.46 |
| | | [7.05] | | | | | [3.52] |
| Anomaly 3 | | | 15.57 | | | | -2.39 |
| | | | [3.36] | | | | [-0.49] |
| Anomaly 4 | | | | 13.91 | | | 9.90 |
| | | | | [3.97] | | | [1.64] |
| Anomaly 5 | | | | | 11.07 | | -8.67 |
| | | | | | [3.22] | | [-1.46] |
| Anomaly 6 | | | | | | 12.04 | 1.24 |
| | | | | | | [3.21] | [0.33] |
| mkt | 2.75 | 3.54 | 3.55 | 3.41 | 3.34 | 3.31 | 3.10 |
| | [1.74] | [2.18] | [2.13] | [2.07] | [2.01] | [1.98] | [2.01] |
| smb | 9.74 | 11.25 | 9.17 | 8.52 | 8.14 | 10.40 | 10.52 |
| | [4.26] | [4.79] | [3.74] | [3.52] | [3.29] | [4.31] | [4.43] |
| hml | 11.27 | 12.42 | 13.95 | 11.01 | 11.43 | 13.03 | 9.27 |
| | [3.69] | [3.96] | [4.35] | [3.40] | [3.51] | [4.02] | [3.03] |
| rmw | -1.80 | -1.32 | -2.22 | -3.00 | -2.46 | -0.89 | -1.21 |
| | [-0.58] | [-0.42] | [-0.68] | [-0.93] | [-0.76] | [-0.27] | [-0.39] |
| cma | -1.55 | 0.19 | 2.66 | 16.45 | 17.98 | 9.14 | -7.20 |
| | [-0.30] | [0.03] | [0.36] | [3.25] | [3.55] | [1.49] | [-1.01] |
| umd | -0.57 | -1.12 | 0.12 | -1.45 | -1.19 | -0.12 | -1.02 |
| | [-0.36] | [-0.70] | [0.07] | [-0.89] | [-0.73] | [-0.07] | [-0.65] |
| # months | 696 | 696 | 696 | 692 | 692 | 696 | 692 |
| $\bar{R}^2$(%) | 28 | 24 | 20 | 20 | 20 | 20 | 30 |

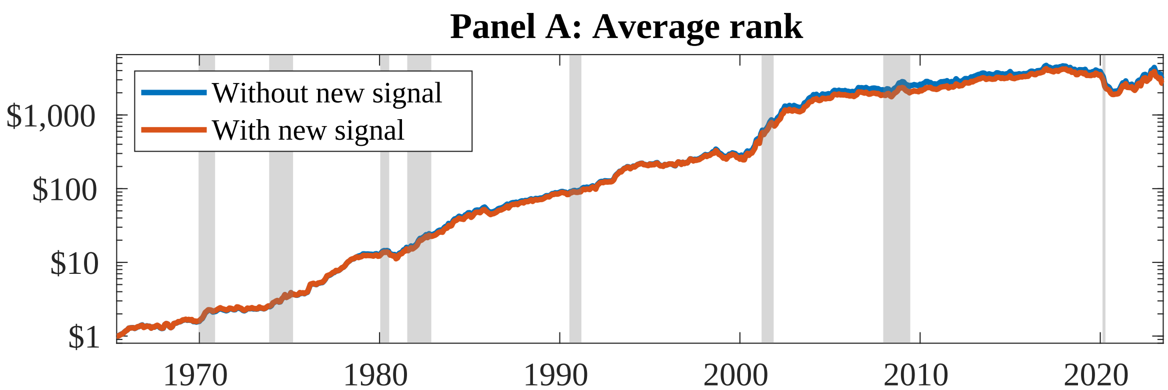


**Figure 8:** Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines indicate combination trading strategies that utilize the 155 anomalies as well as NPPENI. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

# References

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.

Chen, L. and Zhang, L. (2010). Risk and return in equilibrium. *Journal of Financial Economics*, 95(2):174–187.

Cooper, M. J., Gulen, H., and Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *Journal of Finance*, 63(4):1609–1651.

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.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, 28(3):650–705.

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*.

Stambaugh, R. F. and Yuan, Y. (2017). Mispricing factors. *Review of Financial Studies*, 30(4):1270–1315.

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