Property Machinery Nonop Income Discrepancy and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Property Machinery Nonop Income Discrepancy (PMNID), 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 PMNID achieves an annualized gross (net) Sharpe ratio of 0.42 (0.38), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 22 (23) bps/month with a t-statistic of 2.01 (2.14), 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, Employment growth, Change in equity to assets, Growth in book equity, change in net operating assets, Asset growth) is 30 bps/month with a t-statistic of 2.73.

1 Introduction

The efficient market hypothesis suggests that asset prices should fully reflect all available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents numerous market anomalies that appear to contradict this notion McLean and Pontiff (2016). While many of these anomalies are related to firms' investment activities and asset growth Cooper et al. (2008), the relationship between non-operating activities and future stock returns remains relatively unexplored. This gap is particularly notable given the increasing importance of non-operating income in modern corporate finance Lev and Gu (2016).

The discrepancy between property and machinery-related non-operating income (PMNID) represents a potentially important signal that may reveal information about future firm performance. This disconnect could indicate either managerial manipulation of financial statements or underlying economic changes that are not fully appreciated by market participants Sloan (1996).

We propose three potential mechanisms through which PMNID may predict future returns. First, following Hirshleifer et al. (2004), investors may have limited attention and fail to fully process the implications of complex non-operating activities, leading to systematic mispricing. The cognitive load required to analyze the relationship between property, machinery, and non-operating income may exceed investors' information processing capacity.

Second, building on Titman et al. (2004)'s investment-based explanation, PMNID may capture managers' empire-building tendencies or overconfidence in their ability to generate returns from non-core activities. When managers overinvest in property and machinery relative to their non-operating income generation capability, it may signal future underperformance.

Third, drawing from the accounting literature Dechow et al. (2010), large discrepancies between property, machinery, and non-operating income could indicate potential earnings management or poor accounting quality. Such discrepancies may predict future returns as the true economic performance is eventually revealed.

Our empirical analysis reveals that PMNID is a robust predictor of cross-sectional stock returns. A value-weighted long-short portfolio strategy based on PMNID quintiles generates a significant monthly alpha of 22 basis points (t-statistic = 2.01) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.42, placing it in the top 15% of documented market anomalies.

Importantly, the predictive power of PMNID persists after controlling for size. Among the largest quintile of stocks, the PMNID strategy earns a monthly alpha of 25 basis points (t-statistic = 1.82), suggesting that the effect is not confined to small, illiquid stocks. The signal's robustness is further demonstrated by its performance after accounting for transaction costs, with a net Sharpe ratio of 0.38.

Most notably, PMNID maintains its predictive power even after controlling for six closely related anomalies, including changes in PPE, investment-to-assets, and asset growth. The strategy generates a monthly alpha of 30 basis points (t-statistic = 2.73) in spanning tests that include these related factors, indicating that PMNID captures a distinct aspect of mispricing.

Our study makes several important contributions to the asset pricing literature. First, we extend the work of Titman et al. (2004) and Cooper et al. (2008) on investment-based anomalies by identifying a novel signal based on the relationship between physical assets and non-operating activities. While prior research has focused primarily on total investment or operating activities, we show that the disconnect between property, machinery, and non-operating income contains valuable information about future returns.

Second, we contribute to the growing literature on accounting-based anomalies Dechow et al. (2010) by demonstrating how complex financial statement relationships can reveal mispricing. Our findings suggest that investors may not fully process the implications of non-operating activities, particularly when they diverge from patterns in physical assets.

Finally, our results have important implications for both academic research and investment practice. For researchers, we provide new evidence on the limits of market efficiency and the importance of considering non-operating activities in asset pricing. For practitioners, we document a novel signal that can be implemented in large, liquid stocks and remains profitable after transaction costs.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Property Machinery Nonop Income Discrepancy. 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 FATE for property, plant, and equipment, and item NOPI for non-operating income. Property, plant, and equipment (FATE) represents the firm's tangible fixed assets used in business operations, while non-operating income (NOPI) captures income from sources outside the company's core business activities. The construction of the signal follows a change-based approach, where we calculate the difference between the current period's FATE and its lagged value, then scale this difference by the previous period's non-operating income (NOPI). This scaled difference captures the relative change in fixed assets against the backdrop of non-core income generation, potentially offering insight into firms' capital investment decisions and their relationship to peripheral business activities. By focusing on this relationship, the signal aims to reflect aspects of asset management and non-operational income dynamics in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both

FATE and NOPI to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the PMNID signal. Panel A plots the time-series of the mean, median, and interquartile range for PMNID. On average, the cross-sectional mean (median) PMNID is -11.36 (-1.49) over the 1987 to 2023 sample, where the starting date is determined by the availability of the input PMNID data. The signal's interquartile range spans -14.69 to 2.60. Panel B of Figure 1 plots the time-series of the coverage of the PMNID signal for the CRSP universe. On average, the PMNID signal is available for 3.78% of CRSP names, which on average make up 4.00% of total market capitalization.

4 Does PMNID predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on PMNID 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 PMNID portfolio and sells the low PMNID 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 PMNID strategy earns an average return of 0.28% per month with a t-statistic of 2.55. The annualized Sharpe ratio of the strategy is 0.42. The alphas range from 0.22% to 0.31% per month and have t-statistics exceeding 2.01 everywhere. The lowest alpha is with respect to the FF4 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 -0.12, with a t-statistic of -3.09 on the SMB 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 373 stocks and an average market capitalization of at least $889 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 1.70. Out of the twenty-five alphas reported in Panel A, the t-statistics for nineteen exceed two, and for five 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 4-25bps/month. The lowest return, (4 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.47. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the PMNID 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 ten cases.

Table 3 provides direct tests for the role size plays in the PMNID strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and PMNID, as well as average returns and alphas for long/short trading PMNID 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 PMNID strategy achieves an average return of 25 bps/month with a t-statistic of 1.82. Among these large cap stocks, the alphas for the PMNID strategy relative to the five most common factor models range from 17 to 29 bps/month with t-statistics between 1.27 and 2.09.

5 How does PMNID perform relative to the zoo?

Figure 2 puts the performance of PMNID 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

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

ratio for the PMNID strategy falls in the distribution. The PMNID strategy's gross (net) Sharpe ratio of 0.42 (0.38) is greater than 85% (95%) 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 PMNID strategy (red line).[2] Ignoring trading costs, a $1 invested in the PMNID strategy would have yielded $2.24 which ranks the PMNID strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a $1 invested in the PMNID strategy would have yielded $1.85 which ranks the PMNID strategy in the top 4% 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 PMNID relative to those. Panel A shows that the PMNID 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 198706 to 202306 sample. For example, 45% (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 PMNID strategy has a positive net generalized alpha for five out of the five factor models. In these cases PMNID ranks between the 82 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

6 Does PMNID 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 PMNID with 208 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 PMNID or at least to weaken the power PMNID has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of PMNID conditioning on each of the 208 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{PMNID} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{PMNID} PMNID_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 208 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{PMNID,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 208 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 208 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on PMNID. Stocks are finally grouped into five PMNID portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns

[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.

of these conditional double-sorted PMNID trading strategies conditioned on each of the 208 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on PMNID 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 PMNID signal in these Fama-MacBeth regressions exceed -0.43, 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 PMNID is -0.69.

Similarly, Table 5 reports results from spanning tests that regress returns to the PMNID 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 PMNID strategy earns alphas that range from 24-31bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.17, 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 PMNID trading strategy achieves an alpha of 30bps/month with a t-statistic of 2.73.

7 Does PMNID add relative to the whole zoo?

Finally, we can ask how much adding PMNID 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 159 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 159 anomalies augmented with the PMNID 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 159-anomaly combination strategy grows to \$57.58, while \$1 investment in the combination strategy that includes PMNID grows to \$55.75.

8 Conclusion

Our analysis demonstrates that Property Machinery Nonop Income Discrepancy (PMNID) serves as a significant predictor of cross-sectional stock returns, exhibiting both statistical and economic significance. The signal generates impressive risk-adjusted returns, with a value-weighted long/short strategy achieving an annualized Sharpe ratio of 0.42 (0.38) on a gross (net) basis. The strategy's robustness is evidenced by its ability to generate significant abnormal returns even after controlling for well-established risk factors and related investment strategies.

Particularly noteworthy is the signal's persistence in generating alpha when compared against the Fama-French five-factor model plus momentum, as well as its maintained significance when controlling for six closely related strategies from the factor zoo. The monthly alpha of 30 basis points (t-statistic = 2.73) in the presence of these controls suggests that PMNID captures unique information about future stock returns that is not subsumed by existing factors.

However, several limitations should be noted. First, our analysis focuses on U.S.

[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 PMNID is available.

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 signal's performance in international markets, its interaction with other accounting-based anomalies, and its underlying economic mechanisms. Additionally, investigating the signal's stability across different market conditions and its potential variation across different industry sectors could provide valuable insights. Finally, examining the impact of changing accounting standards and reporting practices on the signal's effectiveness could enhance our understanding of its long-term viability as a return predictor.

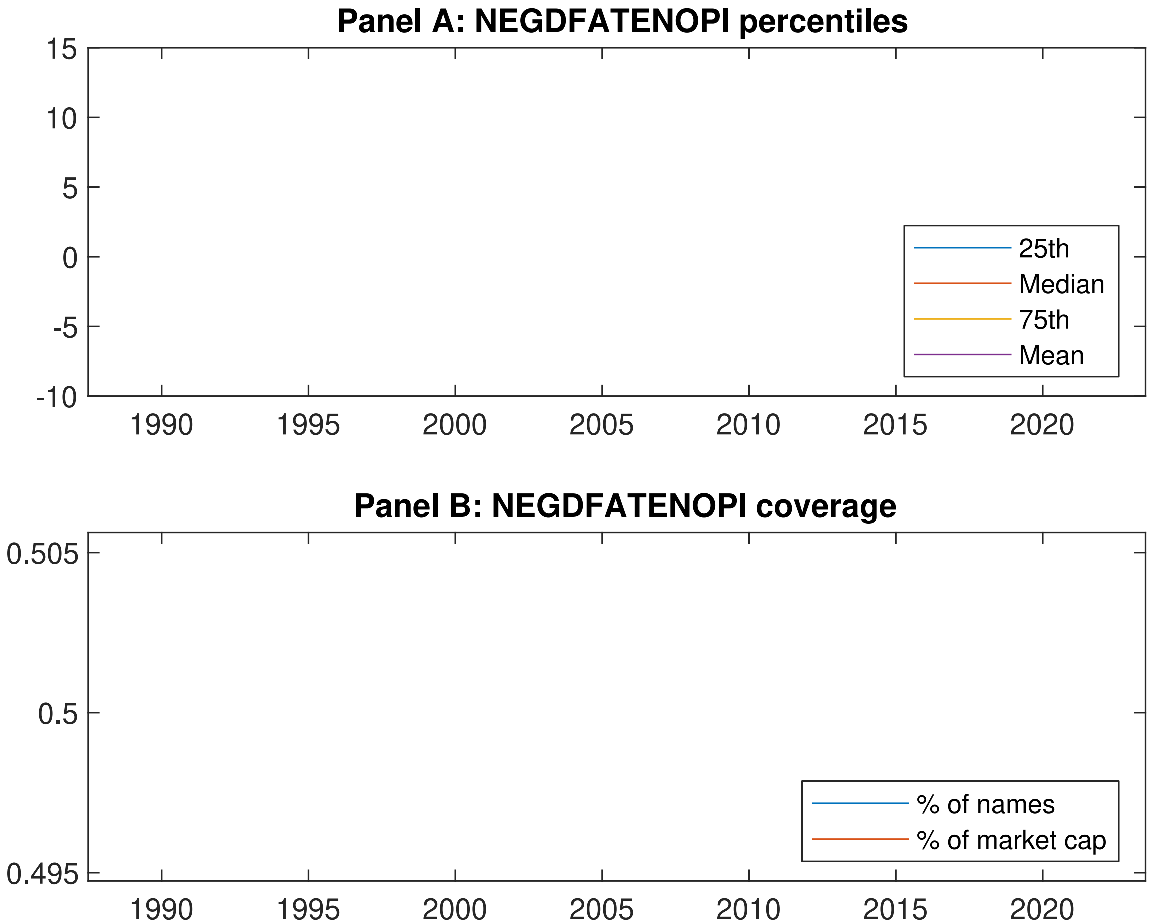


Figure 1: Times series of PMNID percentiles and coverage.
This figure plots descriptive statistics for PMNID. Panel A shows cross-sectional percentiles of PMNID over the sample. Panel B plots the monthly coverage of PMNID relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on PMNID. 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 198706 to 202306.

Panel A: Excess returns and alphas on PMNID-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.53	0.71	0.71	0.73	0.81	0.28
	[2.17]	[3.11]	[3.15]	[3.27]	[3.50]	[2.55]
α_{CAPM}	-0.18	0.03	0.05	0.07	0.13	0.31
	[-1.98]	[0.46]	[0.62]	[1.00]	[1.64]	[2.81]
α_{FF3}	-0.14	0.05	0.08	0.09	0.13	0.27
	[-1.68]	[0.77]	[1.07]	[1.24]	[1.63]	[2.54]
α_{FF4}	-0.08	0.04	0.06	0.09	0.14	0.22
	[-0.95]	[0.58]	[0.82]	[1.19]	[1.71]	[2.03]
α_{FF5}	-0.20	-0.02	0.04	0.04	0.06	0.26
	[-2.32]	[-0.25]	[0.59]	[0.54]	[0.77]	[2.34]
α_{FF6}	-0.15	-0.02	0.03	0.04	0.07	0.22
	[-1.80]	[-0.33]	[0.46]	[0.57]	[0.89]	[2.01]
Panel B: Fama and French (2018) 6-factor model loadings for PMNID-sorted portfolios						
β_{MKT}	0.99	1.01	0.99	0.99	1.01	0.02
	[50.17]	[60.10]	[54.10]	[54.32]	[50.58]	[0.61]
β_{SMB}	0.24	0.08	-0.05	-0.03	0.11	-0.12
	[8.02]	[3.39]	[-2.00]	[-1.02]	[3.84]	[-3.09]
β_{HML}	-0.20	-0.13	-0.18	-0.15	-0.06	0.14
	[-5.51]	[-4.17]	[-5.40]	[-4.52]	[-1.64]	[2.88]
β_{RMW}	0.21	0.15	0.02	0.04	0.13	-0.08
	[5.66]	[4.65]	[0.49]	[1.12]	[3.36]	[-1.70]
β_{CMA}	-0.08	0.02	0.09	0.15	0.08	0.15
	[-1.44]	[0.54]	[1.95]	[3.02]	[1.51]	[2.22]
β_{UMD}	-0.09	0.01	0.02	-0.01	-0.02	0.07
	[-5.08]	[0.75]	[1.15]	[-0.33]	[-1.09]	[2.97]
Panel C: Average number of firms (n) and market capitalization (me)						
n	384	373	446	539	375	
me ($\$10^6$)	1211	1514	2063	1511	889	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the PMNID 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 198706 to 202306.

Panel A: Gross Returns and Alphas

Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.28	0.31	0.27	0.22	0.26	0.22
			[2.55]	[2.81]	[2.54]	[2.03]	[2.34]	[2.01]
Quintile	NYSE	EW	0.25	0.25	0.25	0.23	0.31	0.30
			[3.10]	[3.09]	[3.23]	[3.01]	[4.16]	[4.00]
Quintile	Name	VW	0.21	0.23	0.20	0.16	0.23	0.20
			[1.99]	[2.12]	[1.89]	[1.47]	[2.11]	[1.82]
Quintile	Cap	VW	0.17	0.20	0.17	0.13	0.20	0.17
			[1.70]	[2.04]	[1.78]	[1.32]	[2.01]	[1.68]
Decile	NYSE	VW	0.28	0.30	0.28	0.28	0.27	0.27
			[2.16]	[2.31]	[2.17]	[2.12]	[2.07]	[2.06]

Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas

Portfolios	Breaks	Weights	r^e_{net}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{FF6}
Quintile	NYSE	VW	0.25	0.30	0.27	0.23	0.25	0.23
			[2.27]	[2.64]	[2.46]	[2.17]	[2.32]	[2.14]
Quintile	NYSE	EW	0.04	0.05	0.04	0.04	0.07	0.07
			[0.47]	[0.55]	[0.50]	[0.47]	[0.83]	[0.86]
Quintile	Name	VW	0.18	0.21	0.19	0.16	0.21	0.20
			[1.72]	[1.94]	[1.77]	[1.53]	[2.01]	[1.85]
Quintile	Cap	VW	0.14	0.19	0.17	0.14	0.20	0.18
			[1.44]	[1.91]	[1.72]	[1.46]	[1.99]	[1.81]
Decile	NYSE	VW	0.24	0.27	0.26	0.26	0.25	0.25
			[1.86]	[2.08]	[1.97]	[1.96]	[1.89]	[1.90]

Table 3: Conditional sort on size and PMNID

This table presents results for conditional double sorts on size and PMNID. 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 PMNID. 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 PMNID and short stocks with low PMNID .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 198706 to 202306.

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

		PMNID Quintiles					PMNID Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.67	0.93	0.64	0.65	0.98	0.31	0.30	0.32	0.27	0.31	0.28
		[2.07]	[2.71]	[1.81]	[1.71]	[2.60]	[1.72]	[1.68]	[1.80]	[1.48]	[1.69]	[1.50]
	(2)	0.72	0.82	0.72	0.63	0.78	0.06	0.07	0.08	0.10	0.20	0.22
		[2.27]	[2.75]	[2.28]	[1.89]	[2.48]	[0.54]	[0.61]	[0.74]	[0.88]	[1.91]	[2.01]
	(3)	0.84	0.92	0.69	0.80	0.90	0.06	0.04	0.05	0.05	0.14	0.14
		[2.90]	[3.22]	[2.28]	[2.65]	[3.04]	[0.53]	[0.34]	[0.45]	[0.41]	[1.14]	[1.10]
	(4)	0.69	0.77	0.83	0.85	0.77	0.08	0.09	0.08	0.10	0.10	0.12
		[2.50]	[2.91]	[3.02]	[3.17]	[2.84]	[0.81]	[0.84]	[0.81]	[0.95]	[0.95]	[1.06]
	(5)	0.49	0.72	0.70	0.73	0.74	0.25	0.29	0.25	0.17	0.26	0.20
		[2.04]	[3.13]	[3.06]	[3.38]	[3.36]	[1.82]	[2.09]	[1.88]	[1.27]	[1.87]	[1.45]

Panel B: Portfolio average number of firms and market capitalization

		PMNID Quintiles Average n					PMNID Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	236	236	236	234	231	28	27	26	23	25
	(2)	69	69	69	69	69	47	47	47	46	47
	(3)	47	47	47	47	47	78	79	76	77	78
	(4)	40	40	40	40	40	169	174	174	173	171
	(5)	33	34	33	34	33	967	1059	1303	1350	898

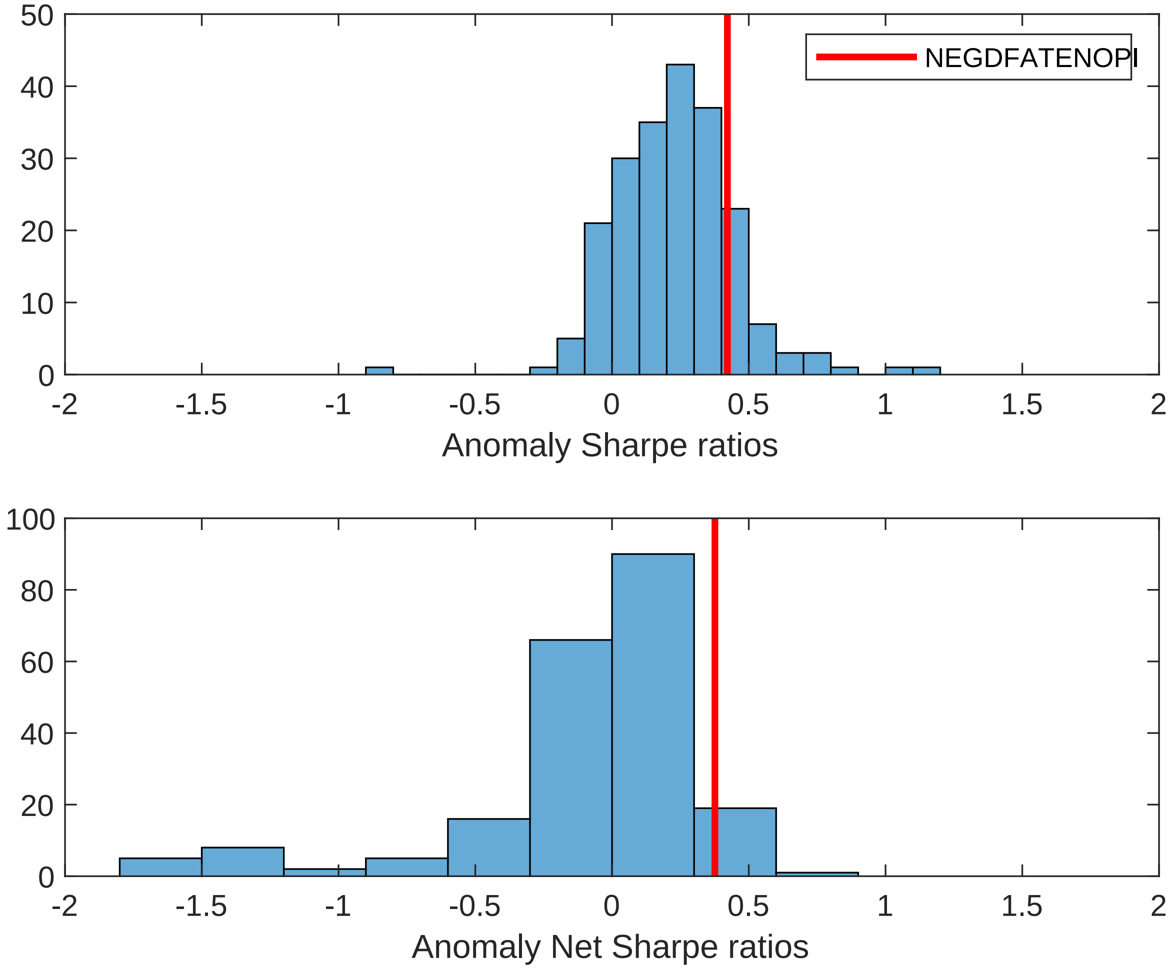


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the PMNID with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

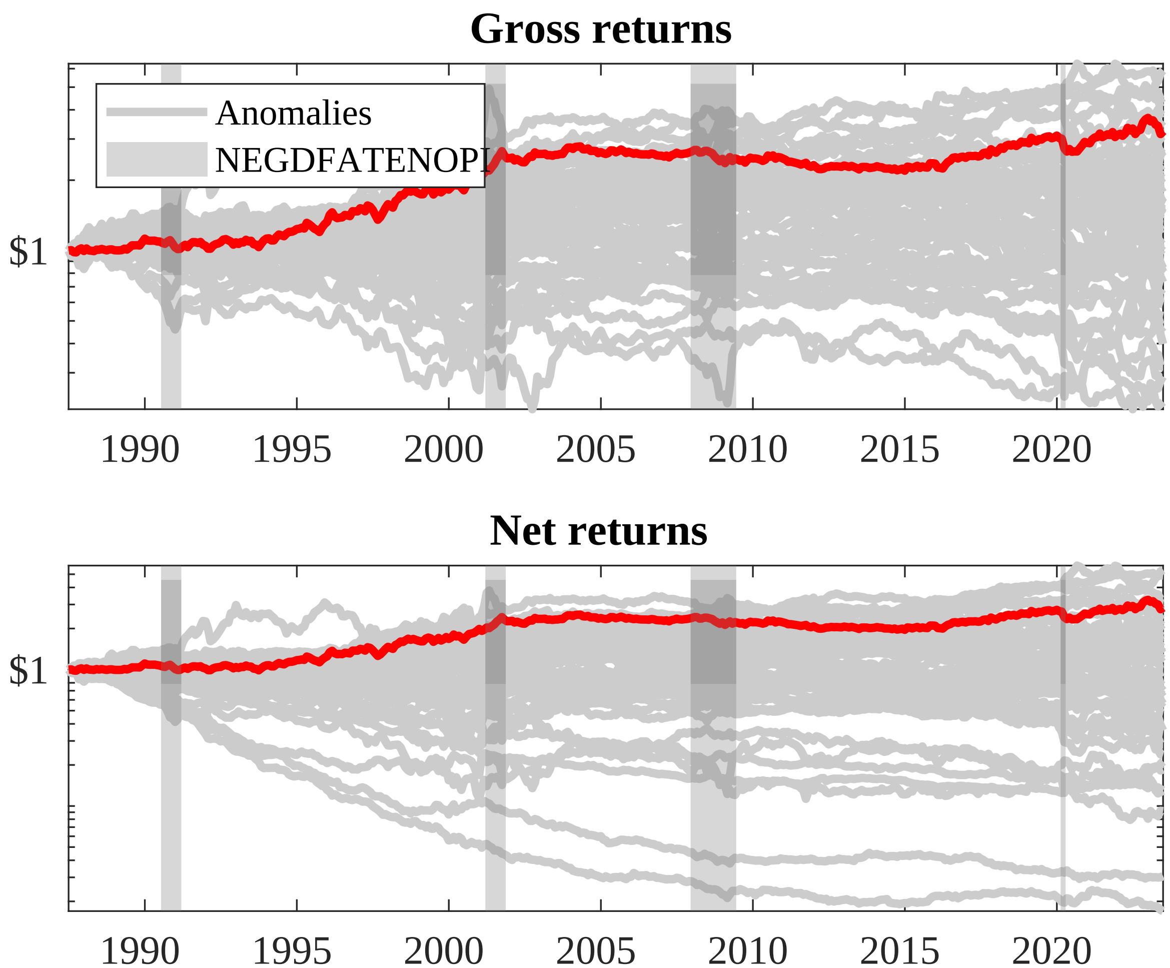


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the PMNID trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

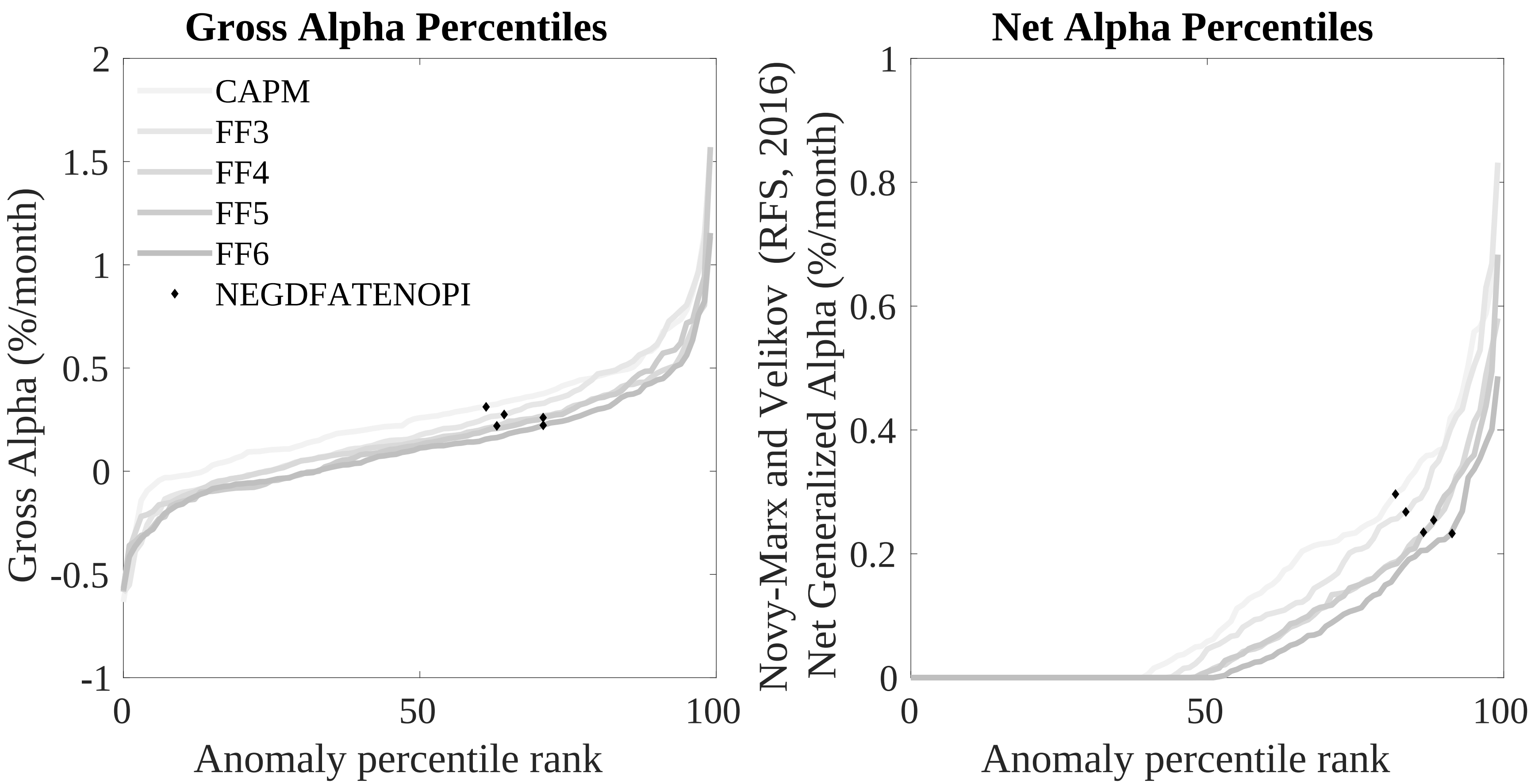
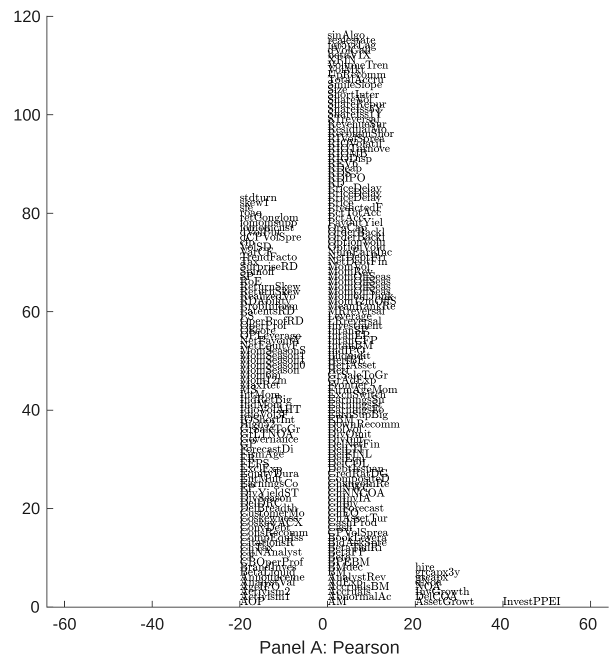


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the PMNID trading strategy alphas (diamonds). The strategies are constructed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



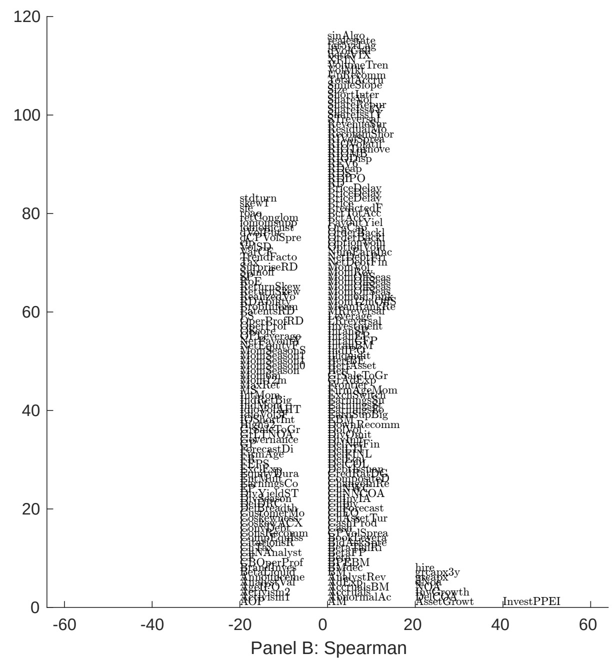


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 208 filtered anomaly signals with PMNID. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

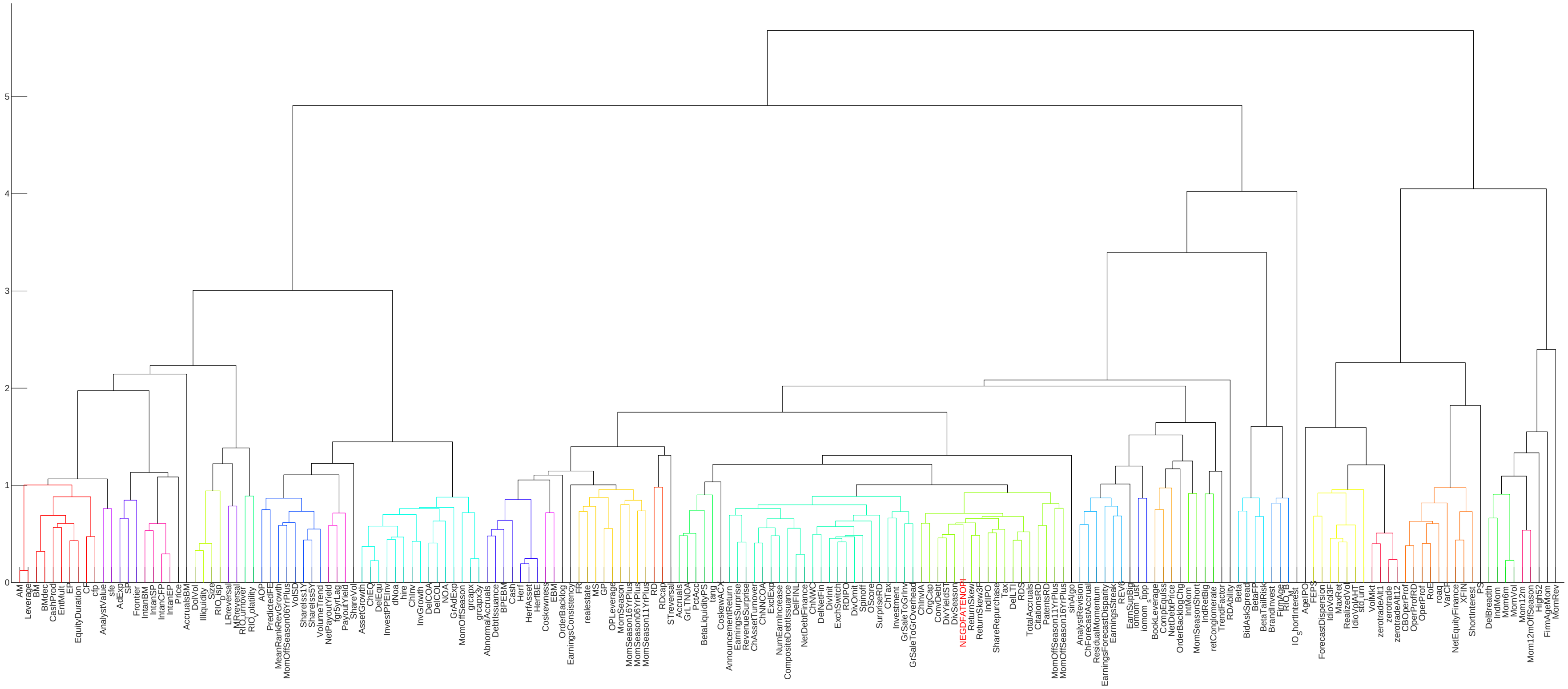


Figure 6: Agglomerative hierarchical cluster plot

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

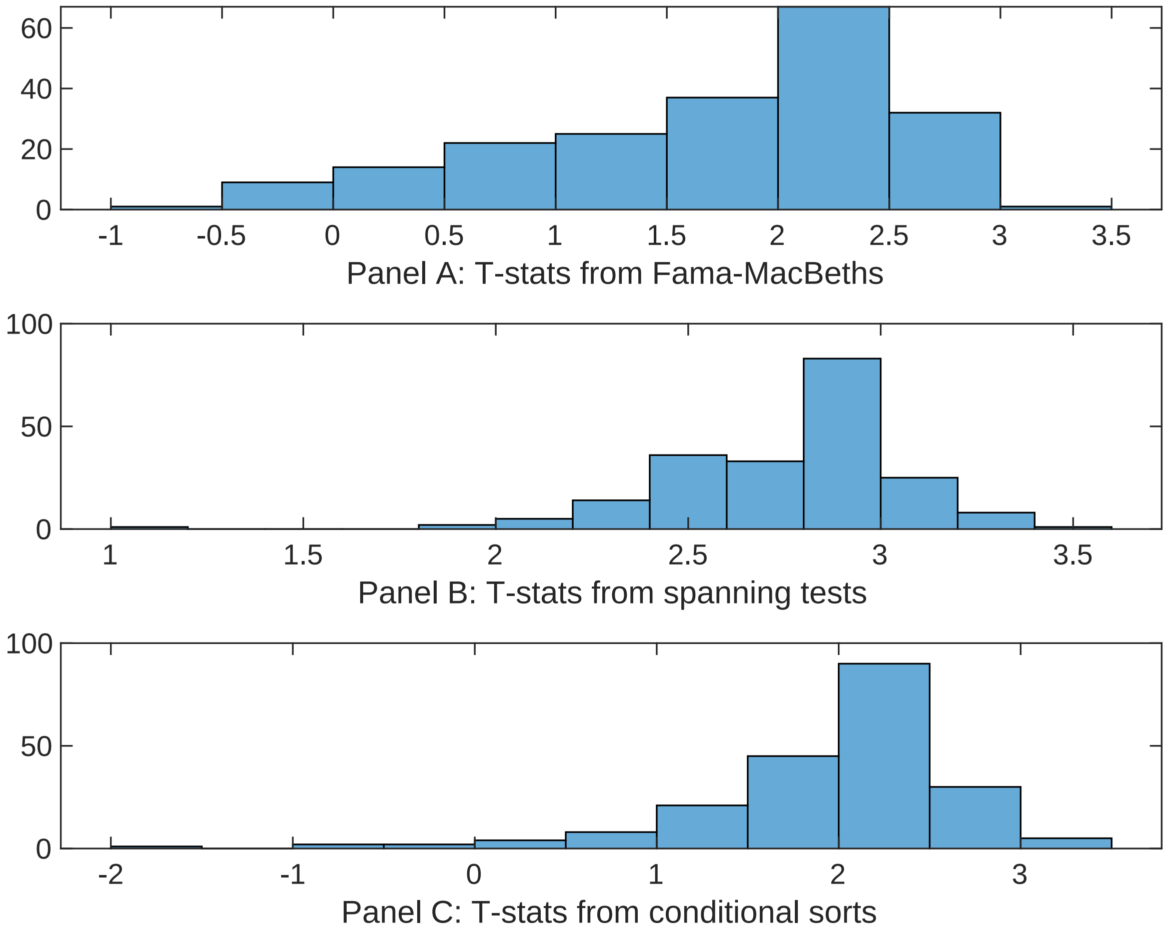


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of PMNID conditioning on each of the 208 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{PMNID} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{PMNID}PMNID_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 208 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{PMNID,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 208 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 208 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on PMNID. Stocks are finally grouped into five PMNID portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted PMNID trading strategies conditioned on each of the 208 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies

This table presents Fama-MacBeth results of returns on PMNID. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{PMNID} PMNID_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are change in ppe and inv/assets, Employment growth, Change in equity to assets, Growth in book equity, change in net operating assets, Asset growth. 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 198706 to 202306.

Intercept	0.12	0.12	0.12	0.17	0.12	0.13	0.13
	[4.08]	[3.91]	[3.85]	[5.54]	[4.02]	[4.18]	[4.94]
PMNID	-0.20	0.50	0.65	0.61	-0.70	-0.12	-0.31
	[-0.43]	[1.07]	[1.42]	[1.31]	[-0.15]	[-0.26]	[-0.69]
Anomaly 1	0.16						-0.52
	[5.53]						[-0.16]
Anomaly 2		0.11					0.34
		[5.98]					[1.84]
Anomaly 3			0.13				0.24
			[4.52]				[0.49]
Anomaly 4				0.48			0.55
				[6.23]			[0.52]
Anomaly 5					0.12		0.32
					[7.67]		[1.67]
Anomaly 6						0.95	0.51
						[7.89]	[3.56]
# months	432	432	432	432	432	432	432
$\bar{R}^2(\%)$	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 PMNID trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{PMNID} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Employment growth, Change in equity to assets, Growth in book equity, change in net operating assets, Asset growth. 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 198706 to 202306.

Intercept	0.25	0.31	0.25	0.24	0.24	0.25	0.30
	[2.32]	[2.85]	[2.24]	[2.17]	[2.17]	[2.21]	[2.73]
Anomaly 1	22.22						18.22
	[4.54]						[3.27]
Anomaly 2		25.10					20.91
		[4.15]					[3.19]
Anomaly 3			15.95				-5.79
			[2.48]				[-0.53]
Anomaly 4				17.28			23.42
				[2.79]			[2.30]
Anomaly 5					3.61		-8.95
					[0.56]		[-1.26]
Anomaly 6						2.66	-14.05
						[0.39]	[-1.66]
mkt	1.82	3.12	2.70	2.95	2.08	2.18	3.51
	[0.70]	[1.19]	[1.02]	[1.11]	[0.78]	[0.82]	[1.35]
smb	-11.75	-12.35	-12.94	-14.10	-12.97	-13.24	-12.12
	[-3.03]	[-3.18]	[-3.29]	[-3.57]	[-3.27]	[-3.32]	[-3.10]
hml	11.68	9.06	13.67	13.92	14.89	15.06	7.92
	[2.44]	[1.83]	[2.83]	[2.90]	[3.06]	[3.10]	[1.62]
rmw	-8.78	-8.36	-8.96	-10.54	-9.81	-9.89	-9.51
	[-1.80]	[-1.70]	[-1.80]	[-2.13]	[-1.96]	[-1.98]	[-1.94]
cma	-2.62	-8.33	-2.28	-2.23	11.35	10.87	-10.55
	[-0.34]	[-0.95]	[-0.24]	[-0.24]	[1.33]	[1.00]	[-0.93]
umd	7.80	7.09	8.07	7.62	7.82	8.00	6.34
	[3.24]	[2.93]	[3.30]	[3.12]	[3.17]	[3.23]	[2.61]
# months	432	432	432	432	432	432	432
$\bar{R}^2$(%)	14	13	11	12	10	10	17

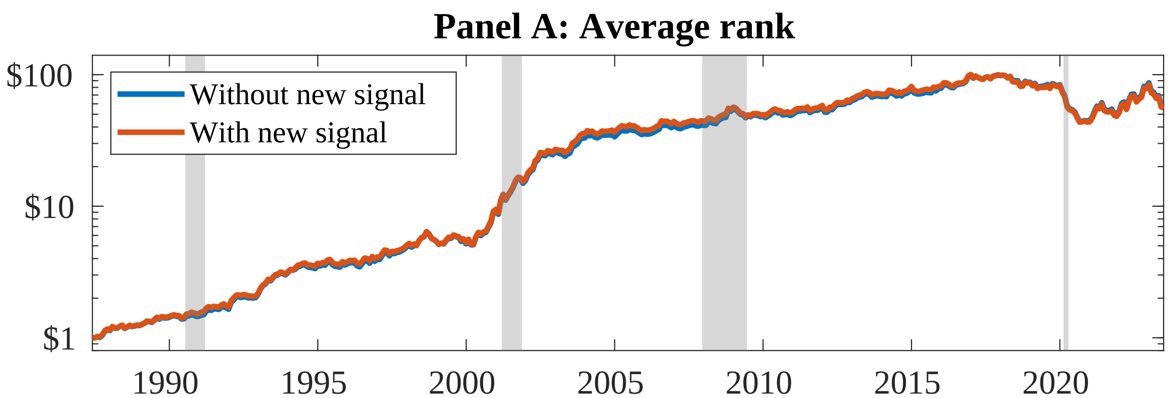


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines indicate combination trading strategies that utilize the 159 anomalies as well as PMNID. 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.

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.

Dechow, P., Ge, W., and Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics*, 50(2-3):344–401.

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.

Hirshleifer, D., Hou, K., Teoh, S. H., and Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, 38:297–331.

Lev, B. and Gu, F. (2016). The end of accounting and the path forward for investors and managers. *Journal of Applied Corporate Finance*, 28(2):47–55.

McLean, R. D. and Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, 71(1):5–32.

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.*

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3):289–315.

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