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

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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

Market efficiency remains a central question in financial economics, with researchers continually seeking to identify reliable signals that predict cross-sectional stock returns. While hundreds of potential predictors have been documented in the literature (Harvey et al., 2016), many fail to survive careful scrutiny or prove robust to transaction costs (Chen and Velikov, 2022). This creates an ongoing need to identify economically meaningful signals that maintain predictive power after accounting for both statistical biases and implementation costs.

One understudied area in the cross-sectional prediction literature is the relationship between firms' operational assets and their non-operating income streams. While extensive research has examined capital investment (Titman et al., 2004) and asset growth (Cooper et al., 2008) separately, the potential mismatch between property/machinery assets and non-operating income has received little attention despite its potential to reveal operational inefficiencies.

We hypothesize that the Property Machinery Non-operating Income Discrepancy (PMNID) captures operational inefficiencies that markets are slow to fully incorporate into prices. This builds on the Q-theory of investment (Cochrane and Saá-Requejo, 2000), which suggests that firms optimally adjust their capital stock to maintain marginal productivity. When non-operating income diverges significantly from property and machinery levels, it may indicate either poor asset utilization or earnings management attempts that eventually reverse.

The slow incorporation of this information into prices can be explained through several mechanisms established in the literature. First, limited attention theory (Hirshleifer and Teoh, 2003) suggests investors may struggle to process the complex relationship between operational assets and non-operating income streams. Second, the gradual diffusion of information about operational efficiency (Hong and Stein, 1999) implies that sophisticated investors who can assess asset utilization effectiveness will face limits to arbitrage.

Additionally, agency theory (Jensen and Meckling, 1976) predicts that managers may maintain inefficient levels of physical assets to extract private benefits or engage in empire-building. The PMNID measure could therefore identify firms where agency problems lead to systematic overinvestment relative to the income these assets generate, creating predictable underperformance as these inefficiencies are eventually recognized.

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

Crucially, the predictive power of PMNID remains robust after controlling for transaction costs. The strategy maintains a net Sharpe ratio of 0.38 and delivers a monthly net alpha of 23 basis points (t-statistic = 2.14) after accounting for trading frictions using the methodology of Novy-Marx and Velikov (2016). This indicates that the signal captures a genuine market inefficiency that sophisticated investors could potentially exploit.

The signal's predictive power persists across size groups and is particularly strong among large-cap stocks, where a long-short strategy generates monthly alphas of 25 basis points (t-statistic = 1.82). This finding is especially notable given that many anomalies are concentrated in small, illiquid stocks. The robustness among large caps suggests that PMNID captures a pervasive inefficiency in how markets process information about operational asset utilization.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures operational inefficiencies through the lens of asset-income relationships, extending the investment-based asset pricing literature pioneered by Titman et al. (2004) and Cooper et al. (2008). Unlike existing investment and asset growth measures, PMNID specifically identifies mismatches between physical capital and non-operating income streams.

Second, we demonstrate that PMNID's predictive power is distinct from existing anomalies. Controlling for the six most closely related predictors from the literature, including investment-to-assets and asset growth measures, the strategy still generates significant monthly alpha of 30 basis points (t-statistic = 2.73). This indicates that PMNID captures a unique dimension of mispricing not addressed by current factors.

Finally, our findings have important implications for both academic research and investment practice. For researchers, we provide new evidence that markets can systematically misprice complex operational relationships, even among large, liquid stocks. For practitioners, we identify a robust signal that maintains its efficacy after transaction costs and could potentially be integrated into quantitative investment strategies.

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 dynamic approach, where we calculate the difference between the current period's FATE and its lagged value, then scale this difference by the lagged value of NOPI. This construction method captures the relative change in fixed assets against the backdrop of non-operating income, potentially offering insights into asset utilization efficiency and the relationship between operational and non-operational aspects of the business. By focusing on this relationship, the signal aims to reflect aspects of asset management and income generation patterns 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^{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 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%

[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 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.

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

[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.

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 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

This study provides compelling evidence for the predictive power of Property Machinery Nonop Income Discrepancy (PMNID) in forecasting cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short strategy based on PMNID generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.42 (0.38 after transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for traditional risk factors 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 PMNID is available.

The persistence of PMNID's predictive power, evidenced by monthly abnormal returns of 22-23 basis points relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information not fully reflected in existing factor models. Moreover, the signal's ability to generate a significant alpha of 30 basis points per month when controlling for six closely related strategies indicates its distinctive contribution to the understanding of asset pricing dynamics.

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

Future research could extend this work in several directions. Investigating the signal's performance in international markets, examining its interaction with other established anomalies, and exploring the underlying economic mechanisms driving the PMNID effect would be valuable contributions. Additionally, research into the signal's stability across different market conditions and its potential applications in portfolio management could enhance our understanding of its practical utility.

In conclusion, PMNID represents a promising addition to the arsenal of return predictors available to investors and researchers, though careful consideration of implementation costs and market conditions remains essential for practical applications.

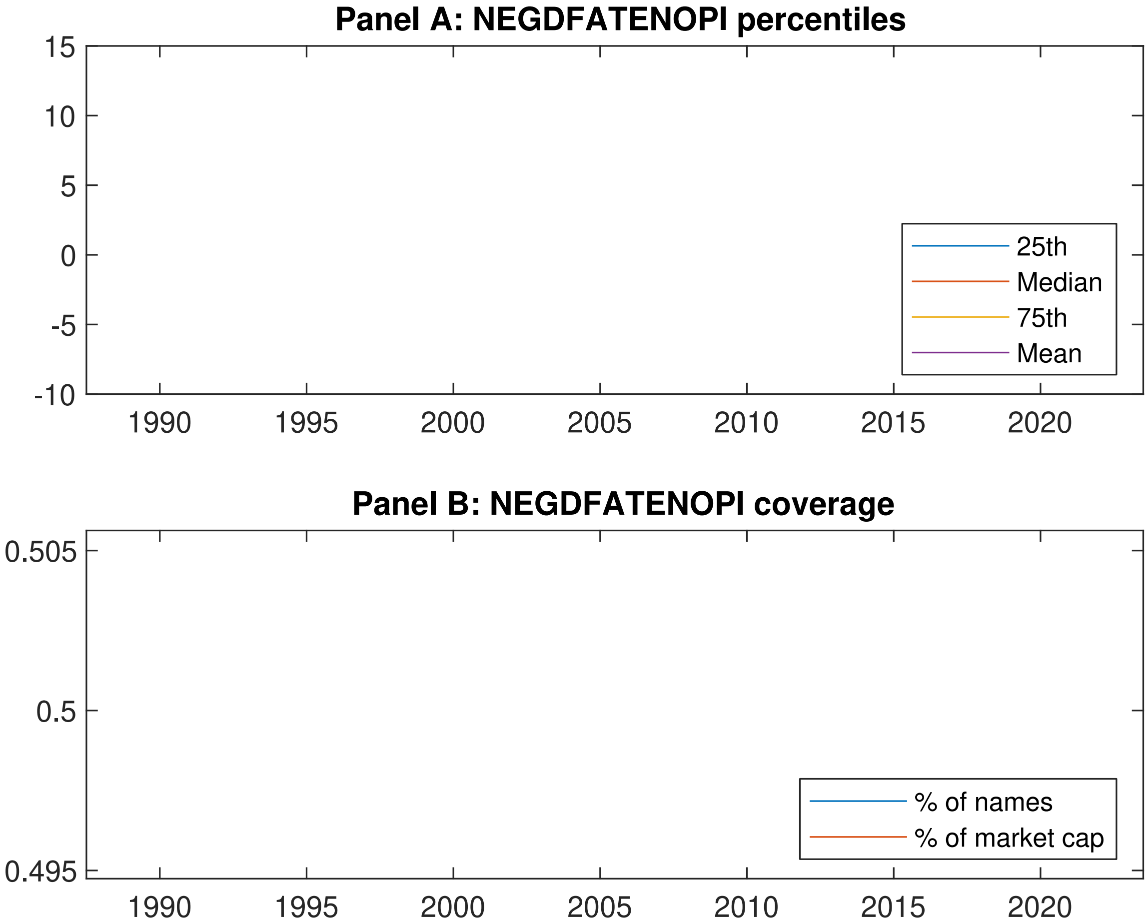


Figure 1: Times series of PMNID percentiles and coverage.
This figure plots descriptive statistics for PMNID. Panel A shows cross-sectional percentiles of PMNID over the sample. Panel B plots the monthly coverage of PMNID relative to the universe of CRSP stocks with available market capitalizations.

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

Size quintiles	PMNID Quintiles					PMNID Strategies					
	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(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

Size quintiles	PMNID Quintiles Average n					PMNID Quintiles Average market capitalization ($\$10^6$)				
	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(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

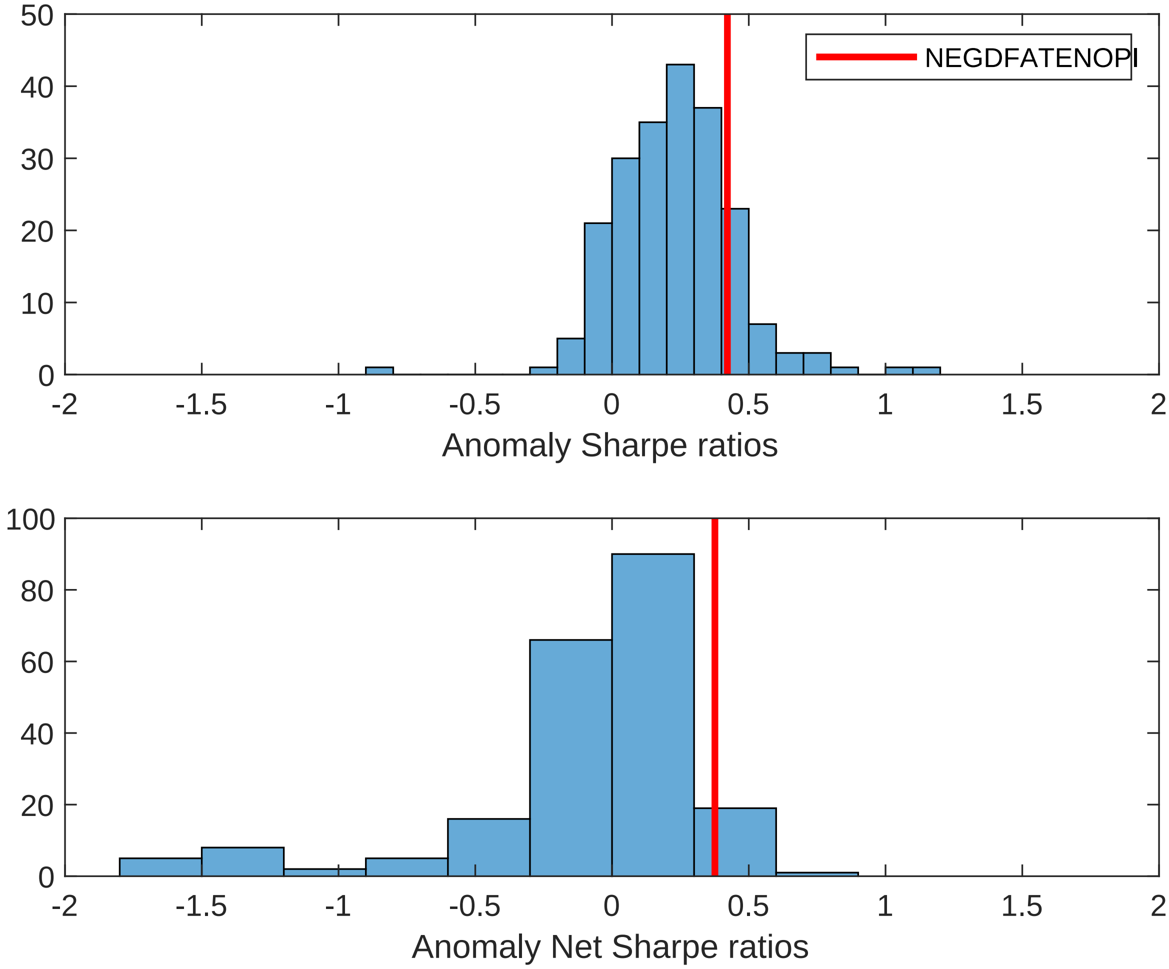


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the PMNID with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

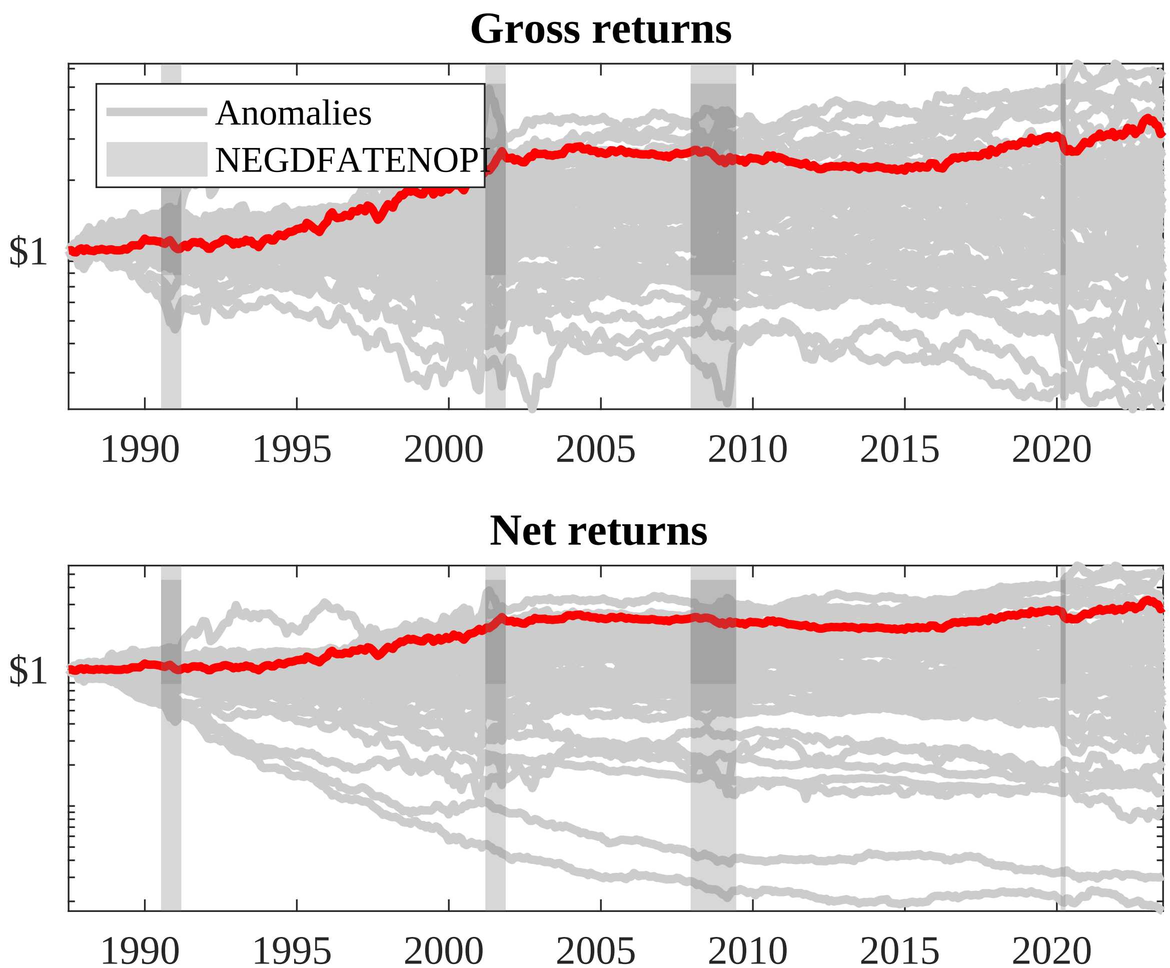


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the PMNID trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

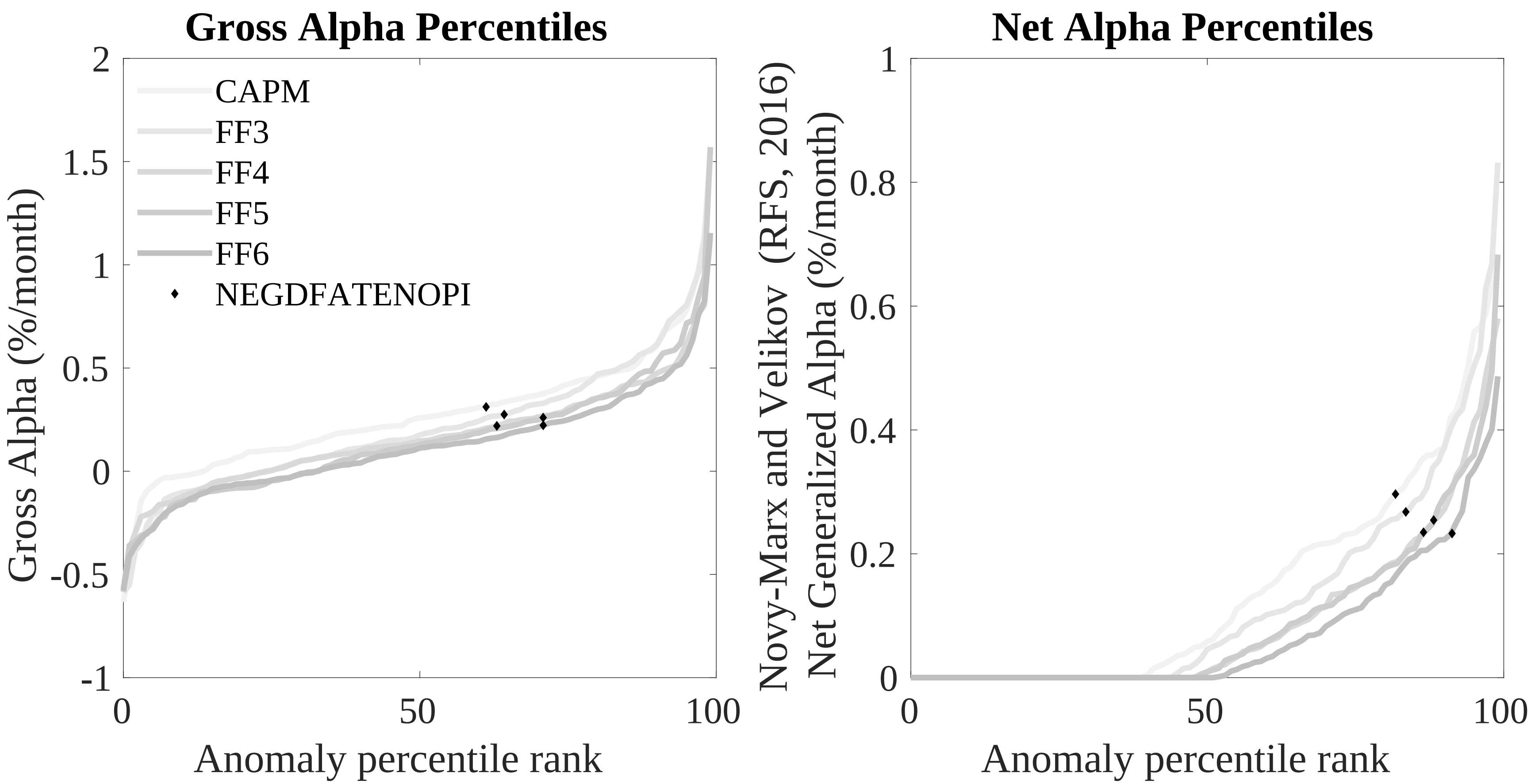
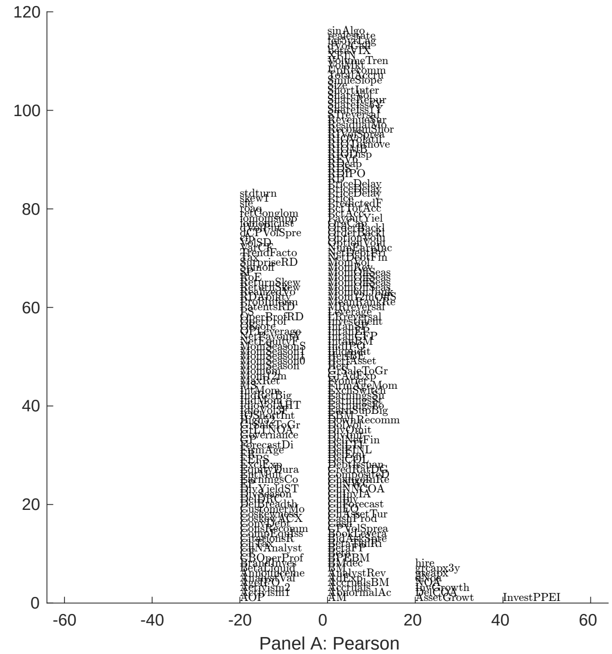


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the PMNID trading strategy alphas (diamonds). The strategies are constructed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



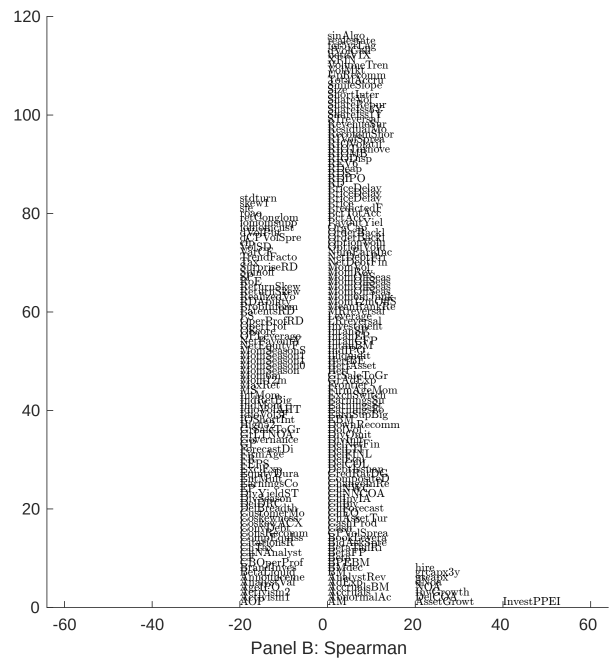


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 208 filtered anomaly signals with PMNID. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

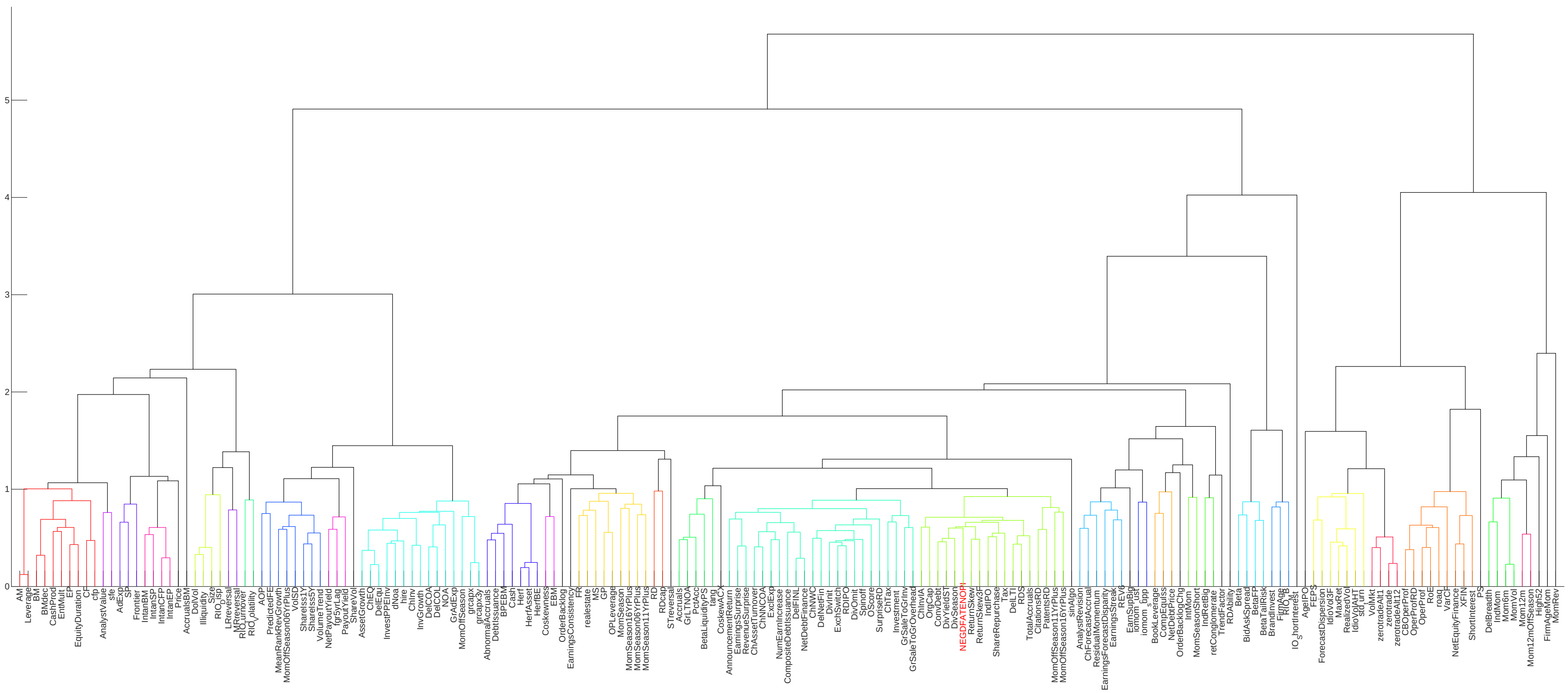


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

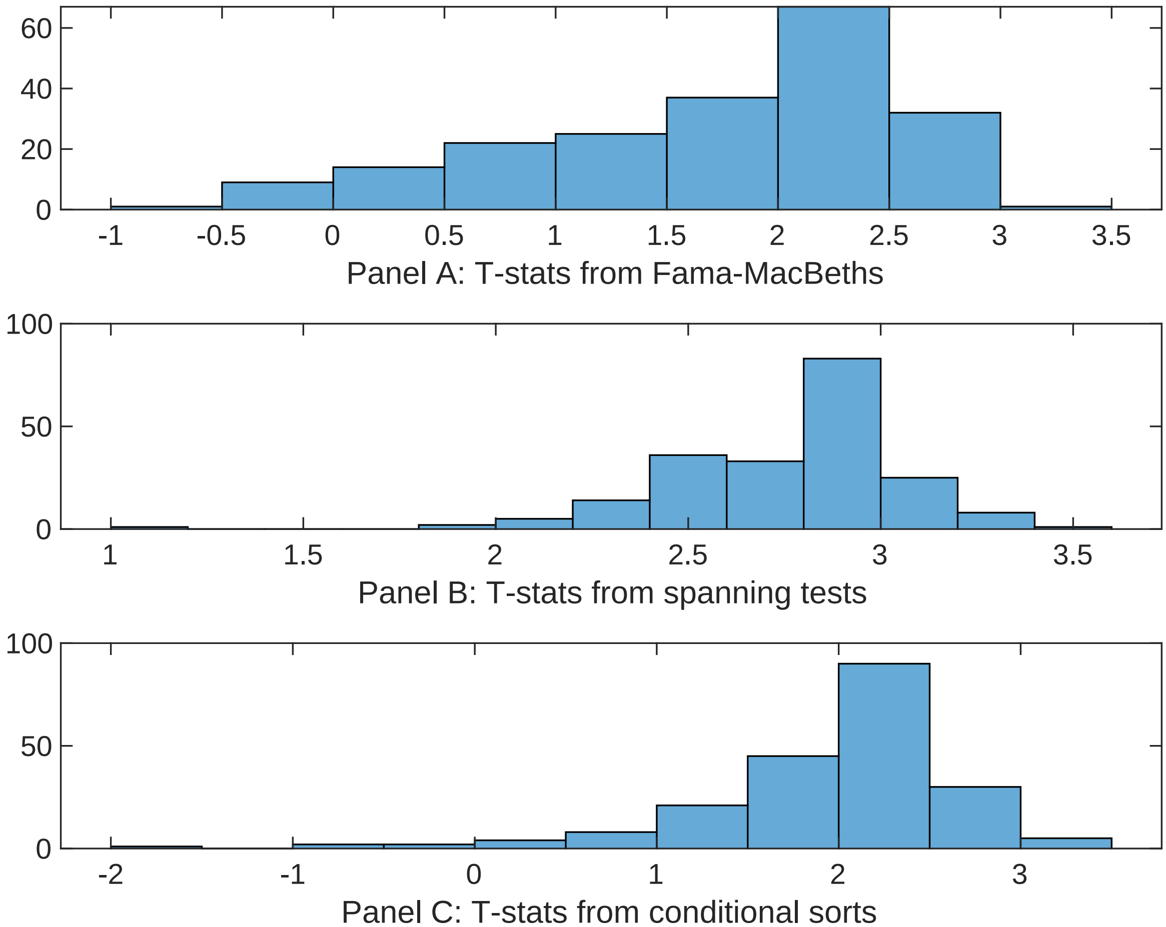


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of PMNID conditioning on each of the 208 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{PMNID} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{PMNID} PMNID_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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

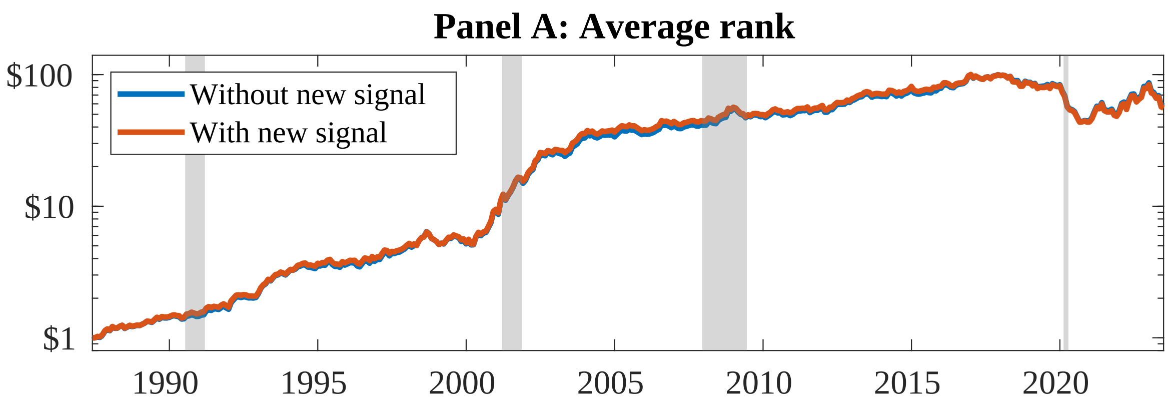


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines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

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

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.

Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3):337–386.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, 54(6):2143–2184.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

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.