Profitable Investment Flow and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Profitable Investment Flow (PIF), 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 PIF achieves an annualized gross (net) Sharpe ratio of 0.40 (0.32), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 20 (19) bps/month with a t-statistic of 2.51 (2.46), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Asset growth, Change in financial liabilities, Growth in book equity, change in net operating assets, change in ppe and inv/assets, Change in equity to assets) is 15 bps/month with a t-statistic of 2.03.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents various market anomalies that appear to contradict this notion (Harvey et al., 2016). While many of these anomalies are related to firms' investment activities (?Cooper et al., 2008), the mechanisms through which investment decisions affect expected returns remain debated.

One particularly puzzling aspect is how the interaction between firms' profitability and their investment decisions influences future stock returns. While high investment typically predicts lower returns (Cooper et al., 2008), and high profitability predicts higher returns (Novy-Marx, 2013), the joint signal from these characteristics has received limited attention. This gap is notable given that efficient investment theory suggests firms should invest more when their profitability is high (Cochrane and Saa-Requejo, 2021).

We propose that examining the flow of profitable investment - the degree to which firms' investment activities align with their profitability levels - can provide valuable insights into future stock returns. Building on q-theory (??), firms should optimally invest more when their marginal q is high, which occurs when profitability is high relative to the cost of capital. Deviations from this optimal investment behavior may signal agency problems or managerial mistakes (Jensen and Meckling, 1976).

Specifically, we construct a Profitable Investment Flow (PIF) measure that captures the alignment between a firm's investment activities and its profitability. When investment is high but profitability is low, PIF takes negative values, potentially indicating empire-building or overconfident managers (?). Conversely, positive PIF values occur when highly profitable firms make substantial investments, consistent with optimal capital allocation.

This framework suggests that firms with low PIF scores may be destroying shareholder value through suboptimal investment decisions, while those with high PIF scores are making value-enhancing investments. Consequently, we hypothesize that PIF should positively predict future stock returns as the market gradually recognizes the implications of firms' investment efficiency.

Our empirical analysis strongly supports the predictive power of PIF. A value-weighted long-short strategy that buys stocks with high PIF and shorts those with low PIF generates significant abnormal returns of 20 basis points per month (t-statistic = 2.51) after controlling for the Fama-French five factors plus momentum. The strategy achieves an annualized gross Sharpe ratio of 0.40, placing it in the top quintile of documented market anomalies.

Importantly, PIF's predictive power remains robust after controlling for related investment-based anomalies. When we simultaneously control for six closely related predictors including asset growth and changes in financial liabilities, PIF continues to generate an alpha of 15 basis points per month (t-statistic = 2.03). This suggests that PIF captures a distinct aspect of investment efficiency not reflected in existing measures.

The economic significance of PIF is substantial and persists across size groups. Among the largest quintile of stocks, a long-short PIF strategy earns average returns of 25 basis points per month (t-statistic = 2.49), indicating that the anomaly is not confined to small, illiquid stocks where trading costs might impede implementation.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel measure that integrates insights from investment-based asset pricing (Cochrane and Saa-Requejo, 2021) with the growing literature on investment anomalies (Cooper et al., 2008; **?**). Unlike existing measures that examine investment or profitability in isolation, PIF captures their interaction in a theoretically motivated way.

Second, we extend the literature on managerial decision-making and stock returns

(Baker and Wurgler, 2002) by showing how the alignment between investment and profitability provides a valuable signal about management quality and future returns. Our findings suggest that the market does not fully appreciate the implications of investment efficiency, creating opportunities for informed investors.

Third, our results contribute to the debate about market efficiency and the sustainability of anomaly returns (McLean and Pontiff, 2016). The fact that PIF generates significant abnormal returns even among large stocks, and remains robust to trading costs, suggests it captures a persistent inefficiency in how markets process information about corporate investment decisions. These findings have important implications for both asset pricing theory and investment practice.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Profitable Investment Flow measure. 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 ICAPT for capital investments and item NI for net income. Capital investments (ICAPT) represents the firm's capital expenditures and acquisitions, reflecting the total investment in long-term assets. Net income (NI) provides a comprehensive measure of a company's profitability after accounting for all operating and non-operating expenses, revenues, gains, and losses.construction of the signal follows a change-based approach, where we calculate the difference between the current period's ICAPT and its lagged value, then scale this difference by the previous period's net income. This scaled difference captures the relative change in investment activities relative to the firm's historical profitability, offering insight into how firms allocate capital in relation to their earnings capacity. By focusing on this relationship, the signal aims to reflect aspects of investment efficiency and capital allocation decisions in a manner that is both economically meaningful and comparable across firms. We construct this measure using end-of-fiscal-year values for both ICAPT and NI to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the PIF signal. Panel A plots the time-series of the mean, median, and interquartile range for PIF. On average, the cross-sectional mean (median) PIF is -2.25 (-0.73) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input PIF data. The signal's interquartile range spans -3.08 to 1.03. Panel B of Figure 1 plots the time-series of the coverage of the PIF signal for the CRSP universe. On average, the PIF signal is available for 6.55% of CRSP names, which on average make up 7.93% of total market capitalization.

4 Does PIF predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on PIF 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 PIF portfolio and sells the low PIF 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 PIF strategy earns an average return of 0.27% per month with a t-statistic of 3.05. The annualized Sharpe ratio of the strategy is 0.40. The alphas range from 0.20% to 0.34% per month and have t-statistics exceeding 2.51 everywhere. The lowest alpha is with respect to the FF6 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is 0.66, with a t-statistic of 12.59 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 662 stocks and an average market capitalization of at least $1,280 million.

Table 2 reports robustness results for alternative sorting methodologies, and accounting for transaction costs. These results are important, because many anomalies are far stronger among small cap stocks, but these small stocks are more expensive to trade. Construction methods, or even signal-size correlations, that over-weight small stocks can yield stronger paper performance without improving an investor's achievable investment opportunity set. Panel A reports gross returns and alphas for the long/short strategies made using various different protfolio constructions. The first row reports the average returns and the alphas for the long/short strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios. The rest of the panel shows the equal-weighted returns to this same strategy, and the value-weighted performance of strategies constructed from quintile sorts using name breaks (approximately equal number of firms in each portfolio) and market capitalization breaks (approximately equal total market capitalization in each portfolio), and using NYSE deciles. The average return is lowest for the quintile sort using NYSE breakpoints and equal-weighted portfolios, and equals 21 bps/month with a t-statistics of 3.19. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for thirteen 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 -3-22bps/month. The lowest return, (-3 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -0.36. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the PIF trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-two cases, and significantly expands the achievable frontier in fifteen cases.

Table 3 provides direct tests for the role size plays in the PIF strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and PIF, as well as average returns and alphas for long/short trading PIF 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 PIF strategy achieves an average return of 25 bps/month with a t-statistic of 2.49. Among these large cap stocks, the alphas for the PIF strategy relative to the five most common factor models range from 14 to 32 bps/month with t-statistics between 1.57 and 3.23.

5 How does PIF perform relative to the zoo?

Figure 2 puts the performance of PIF 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 PIF strategy falls in the distribution. The PIF strategy's gross (net) Sharpe ratio of 0.40 (0.32) is greater than 81% (93%) 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 PIF strategy (red line).[2] Ignoring trading costs, a $1 invested in the PIF strategy would have yielded $4.79 which ranks the PIF strategy in the top 6% across the 212 anomalies. Accounting for trading costs, a $1 invested in the PIF strategy would have yielded $3.05 which ranks the PIF strategy in the top 5% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the PIF relative to those. Panel A shows that the PIF strategy gross alphas fall between the 64 and 69 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% (53%) of the 212 anomalies would not have improved the investment opportunity

[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.

set for an investor having access to the Fama-French three-factor (six-factor) model. The PIF strategy has a positive net generalized alpha for five out of the five factor models. In these cases PIF ranks between the 81 and 86 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[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.

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 PIF. Stocks are finally grouped into five PIF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted PIF trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on PIF 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 PIF signal in these Fama-MacBeth regressions exceed -0.89, 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 PIF is -1.41.

Similarly, Table 5 reports results from spanning tests that regress returns to the PIF 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 PIF strategy earns alphas that range from 15-20bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.04, 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 PIF trading strategy achieves an alpha of 15bps/month with a t-statistic of 2.03.

7 Does PIF add relative to the whole zoo?

Finally, we can ask how much adding PIF 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 PIF 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 PIF grows to $3732.45.

8 Conclusion

This study provides compelling evidence for the predictive power of Profitable Investment Flow (PIF) in forecasting cross-sectional stock returns. Our findings demonstrate that PIF generates economically and statistically significant returns, with a value-weighted long/short strategy achieving impressive Sharpe ratios of 0.40 (gross) and 0.32 (net). The signal's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for established factors and related investment-based signals.

The persistence of PIF's predictive ability, evidenced by monthly abnormal re-

[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 PIF is available.

turns of 20 basis points (gross) and 19 basis points (net) relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information about future stock returns. Furthermore, the signal's alpha remains significant at 15 basis points monthly even when controlling for six closely related investment strategies, indicating that PIF provides incremental information beyond existing investment-based measures.

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 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 the signal's performance in different market regimes, its interaction with other established anomalies, and its effectiveness across different asset classes. Additionally, investigating the underlying economic mechanisms driving PIF's predictive power could provide valuable insights into investment-based asset pricing theories. Researchers might also consider examining how the signal's effectiveness varies with firm characteristics and market conditions to better understand its practical applications for investment management.

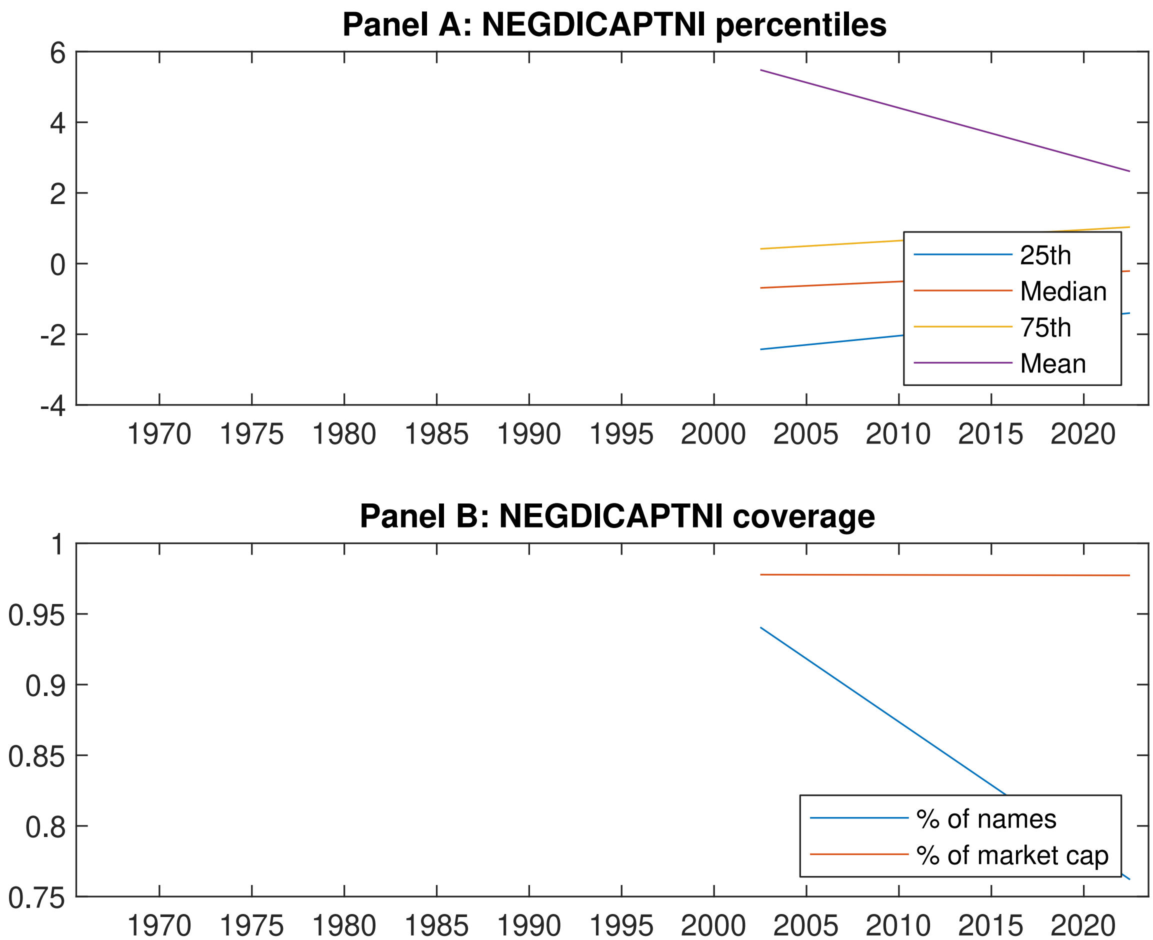

Figure 1: Times series of PIF percentiles and coverage.
This figure plots descriptive statistics for PIF. Panel A shows cross-sectional percentiles of PIF over the sample. Panel B plots the monthly coverage of PIF relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on PIF. 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 PIF-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.38	0.56	0.65	0.62	0.65	0.27
	[1.83]	[3.13]	[3.93]	[3.89]	[3.46]	[3.05]
α_{CAPM}	-0.27	-0.01	0.12	0.12	0.07	0.34
	[-4.56]	[-0.21]	[3.27]	[2.54]	[1.14]	[3.81]
α_{FF3}	-0.28	-0.01	0.13	0.10	0.02	0.30
	[-4.75]	[-0.12]	[3.72]	[2.27]	[0.42]	[3.47]
α_{FF4}	-0.21	-0.00	0.13	0.08	0.02	0.23
	[-3.49]	[-0.03]	[3.43]	[1.82]	[0.40]	[2.57]
α_{FF5}	-0.19	0.02	0.09	-0.05	0.06	0.25
	[-3.36]	[0.58]	[2.55]	[-1.41]	[1.16]	[3.17]
α_{FF6}	-0.14	0.02	0.09	-0.05	0.06	0.20
	[-2.45]	[0.54]	[2.39]	[-1.39]	[1.18]	[2.51]
Panel B: Fama and French (2018) 6-factor model loadings for PIF-sorted portfolios						
β_{MKT}	1.09	1.01	0.96	0.98	1.04	-0.05
	[81.83]	[100.69]	[111.13]	[105.35]	[89.67]	[-2.60]
β_{SMB}	0.06	-0.05	-0.07	-0.08	0.09	0.03
	[3.24]	[-3.21]	[-5.97]	[-6.19]	[5.67]	[1.23]
β_{HML}	0.15	0.09	0.01	-0.07	-0.06	-0.21
	[5.78]	[4.46]	[0.63]	[-3.94]	[-2.67]	[-5.84]
β_{RMW}	-0.01	0.02	0.12	0.20	-0.25	-0.25
	[-0.21]	[0.93]	[6.98]	[10.99]	[-11.14]	[-6.84]
β_{CMA}	-0.37	-0.18	-0.01	0.39	0.29	0.66
	[-9.85]	[-6.19]	[-0.47]	[14.90]	[8.77]	[12.59]
β_{UMD}	-0.08	0.00	0.01	-0.00	-0.00	0.08
	[-5.95]	[0.21]	[0.79]	[-0.02]	[-0.23]	[4.13]
Panel C: Average number of firms (n) and market capitalization (me)						
n	736	662	666	666	808	
me ($\$10^6$)	1572	1976	2617	2334	1280	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the PIF 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	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.27	0.34	0.30	0.23	0.25	0.20
			[3.05]	[3.81]	[3.47]	[2.57]	[3.17]	[2.51]
Quintile	NYSE	EW	0.21	0.22	0.22	0.23	0.32	0.33
			[3.19]	[3.36]	[3.50]	[3.57]	[5.80]	[5.78]
Quintile	Name	VW	0.27	0.31	0.30	0.23	0.29	0.24
			[3.06]	[3.52]	[3.38]	[2.56]	[3.54]	[2.92]
Quintile	Cap	VW	0.24	0.30	0.28	0.21	0.17	0.13
			[3.06]	[3.95]	[3.63]	[2.71]	[2.46]	[1.86]
Decile	NYSE	VW	0.26	0.27	0.27	0.19	0.28	0.22
			[2.32]	[2.39]	[2.42]	[1.66]	[2.64]	[2.05]
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	0.22	0.29	0.26	0.22	0.22	0.19
			[2.48]	[3.27]	[2.97]	[2.47]	[2.85]	[2.46]
Quintile	NYSE	EW	-0.03				0.03	0.04
			[-0.36]				[0.49]	[0.56]
Quintile	Name	VW	0.22	0.26	0.25	0.21	0.24	0.21
			[2.43]	[2.92]	[2.78]	[2.34]	[2.99]	[2.63]
Quintile	Cap	VW	0.20	0.26	0.24	0.20	0.16	0.13
			[2.52]	[3.39]	[3.12]	[2.63]	[2.26]	[1.87]
Decile	NYSE	VW	0.19	0.21	0.21	0.16	0.23	0.18
			[1.71]	[1.84]	[1.86]	[1.44]	[2.10]	[1.73]

Table 3: Conditional sort on size and PIF

This table presents results for conditional double sorts on size and PIF. 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 PIF. 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 PIF and short stocks with low PIF .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

		PIF Quintiles					PIF Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.66	0.85	0.96	0.78	0.71	0.05	0.05	0.07	0.01	0.20	0.15
		[2.60]	[3.49]	[3.90]	[3.09]	[2.57]	[0.44]	[0.42]	[0.62]	[0.12]	[1.85]	[1.36]
	(2)	0.66	0.83	0.96	0.72	0.82	0.16	0.18	0.18	0.17	0.30	0.29
		[2.64]	[3.62]	[4.43]	[3.32]	[3.29]	[1.70]	[1.91]	[1.91]	[1.78]	[3.36]	[3.18]
	(3)	0.52	0.85	0.80	0.82	0.78	0.26	0.31	0.31	0.30	0.43	0.41
		[2.21]	[4.05]	[3.98]	[4.23]	[3.51]	[2.65]	[3.18]	[3.10]	[2.90]	[4.58]	[4.36]
	(4)	0.64	0.64	0.79	0.70	0.72	0.08	0.12	0.07	0.11	0.07	0.11
		[2.93]	[3.34]	[4.15]	[3.79]	[3.47]	[0.99]	[1.40]	[0.89]	[1.35]	[0.88]	[1.36]
	(5)	0.31	0.55	0.56	0.60	0.56	0.25	0.32	0.30	0.20	0.20	0.14
		[1.58]	[3.04]	[3.33]	[3.74]	[3.19]	[2.49]	[3.23]	[3.01]	[2.05]	[2.26]	[1.57]

Panel B: Portfolio average number of firms and market capitalization

		PIF Quintiles					PIF Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	389	389	389	390	387	35	35	31	32	31
	(2)	110	110	110	110	109	56	57	57	56	55
	(3)	80	80	80	80	79	97	99	97	97	96
	(4)	67	67	67	67	67	207	209	213	208	204
	(5)	62	62	62	62	62	1473	1440	1808	1799	1286

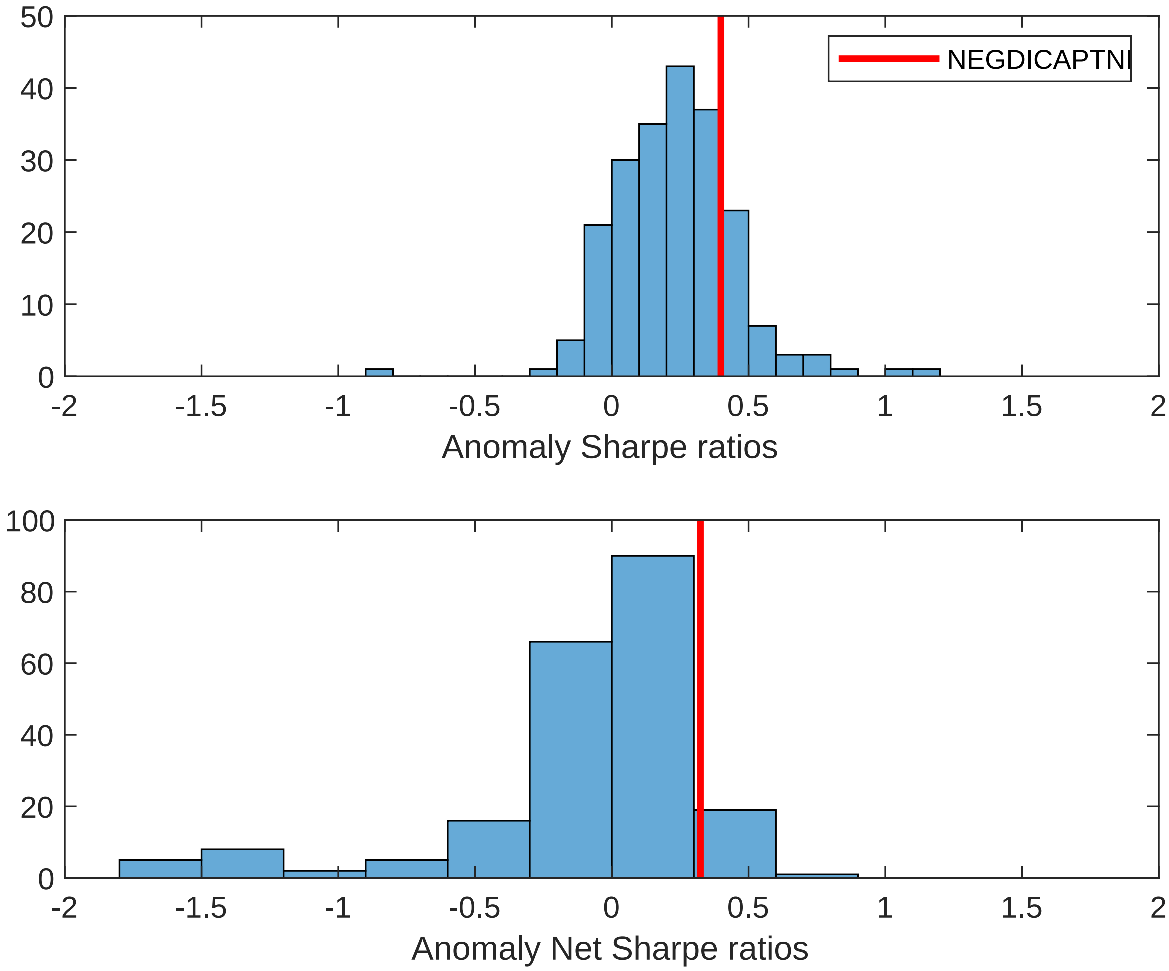

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the PIF with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

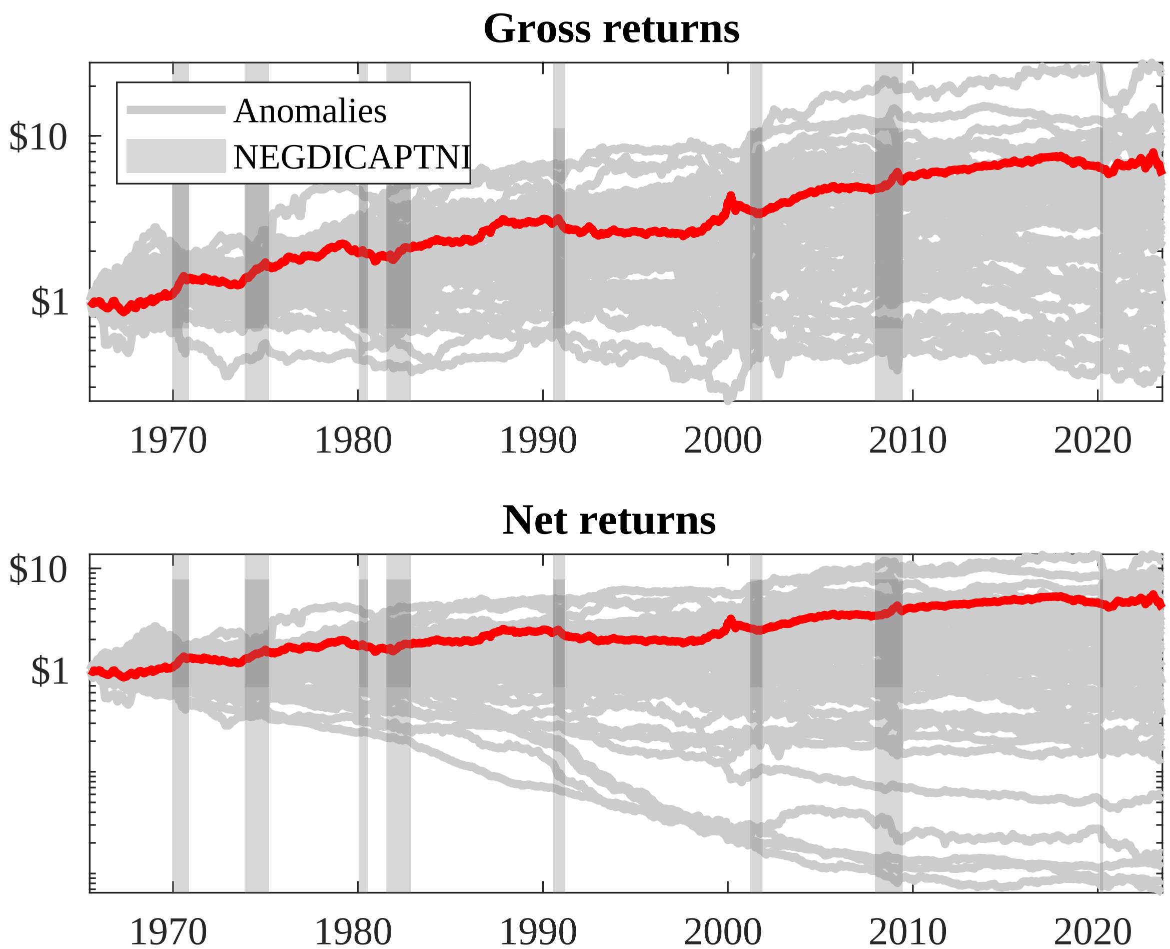

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the PIF trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

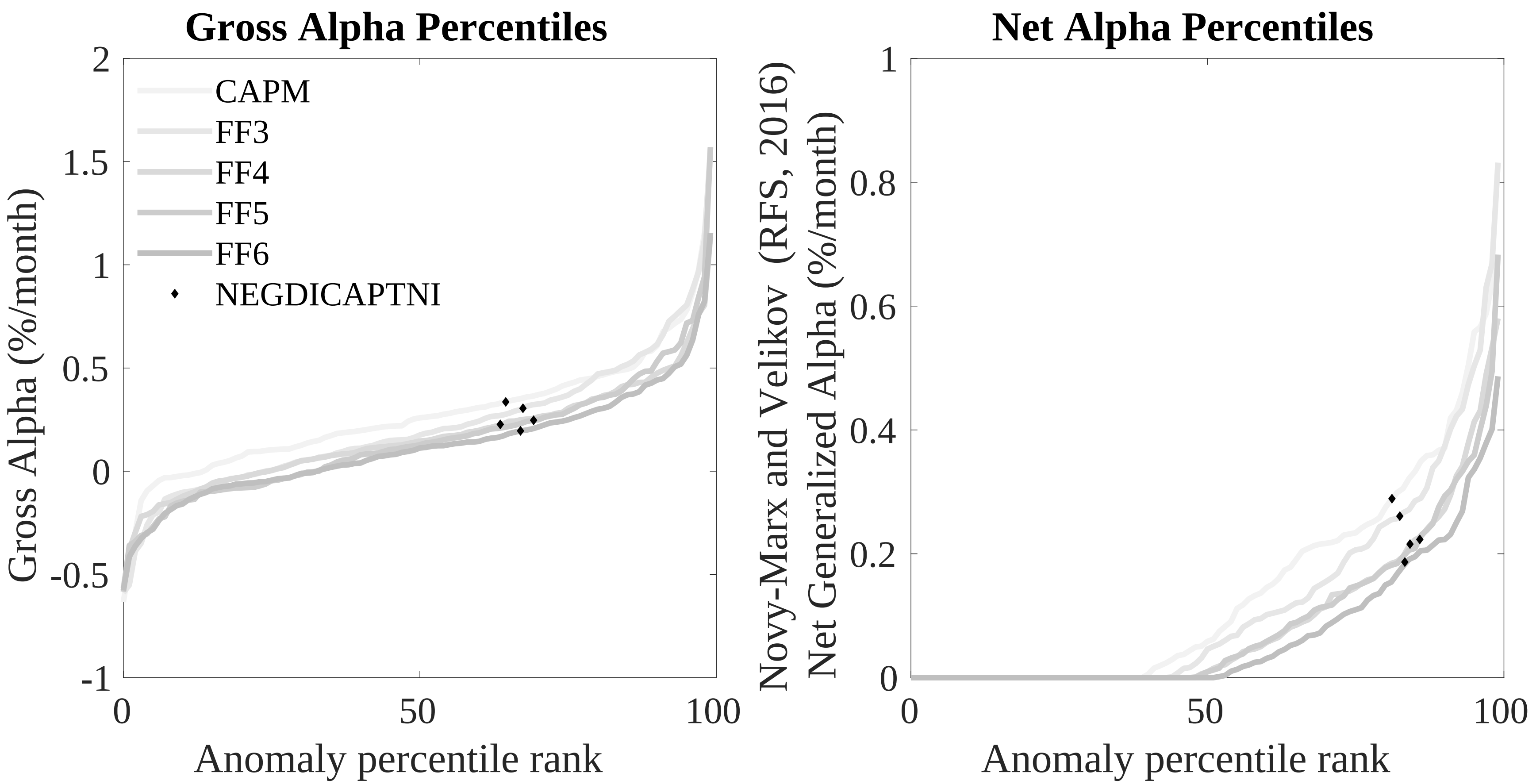

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the PIF trading strategy alphas (diamonds). The strategies are constructed using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

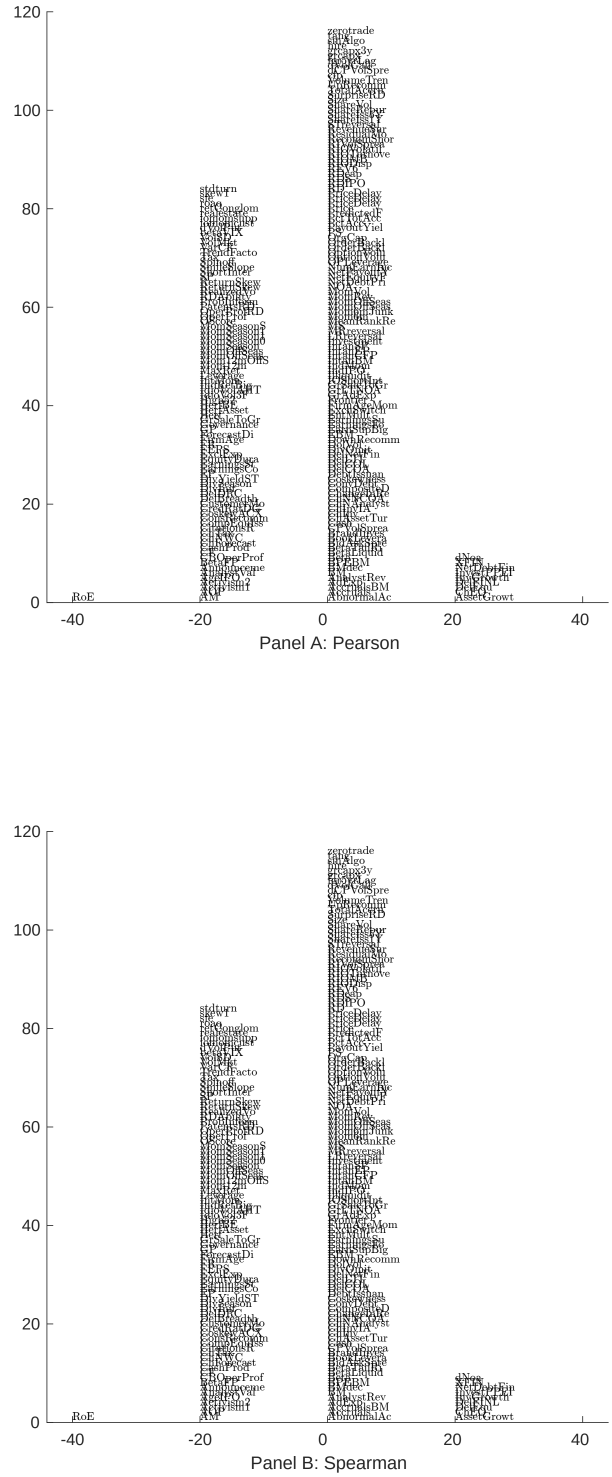

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with PIF. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

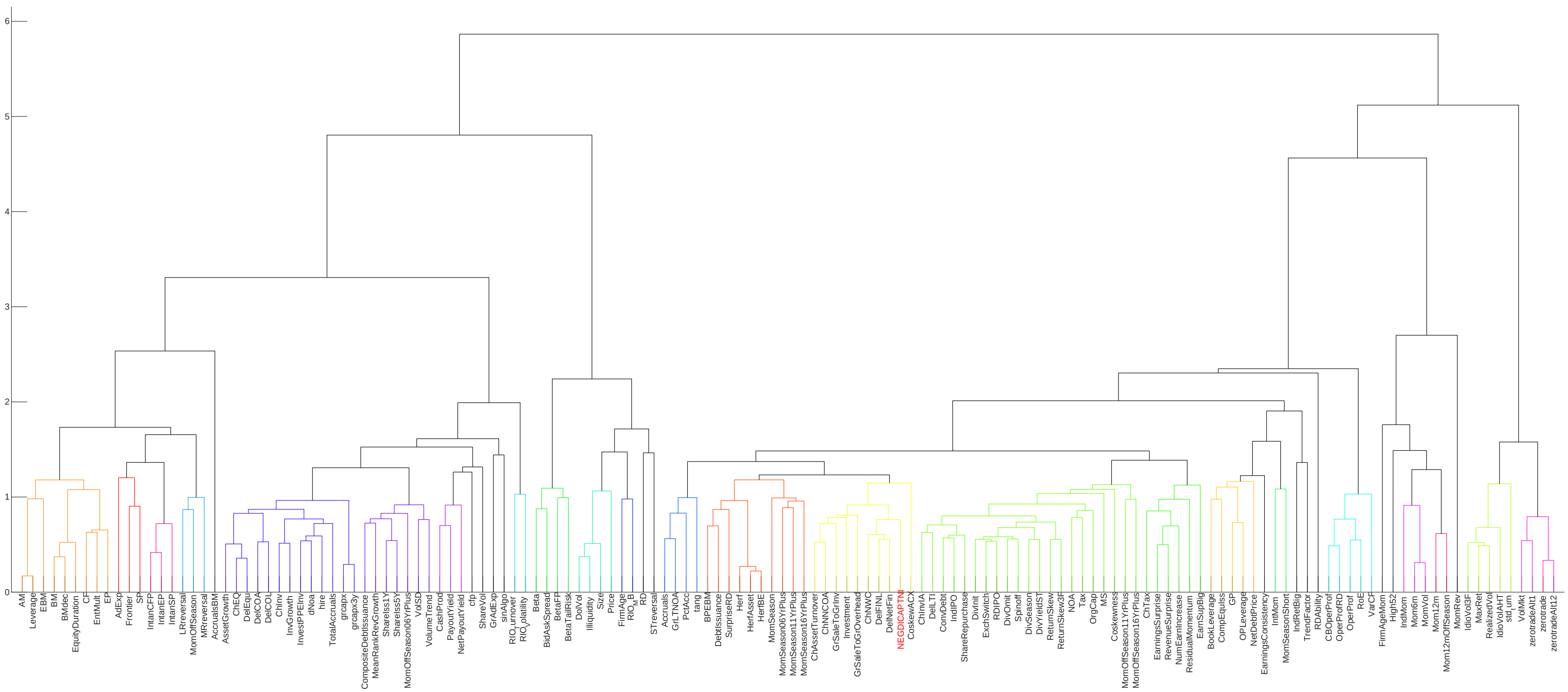

Figure 6: Agglomerative hierarchical cluster plot

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

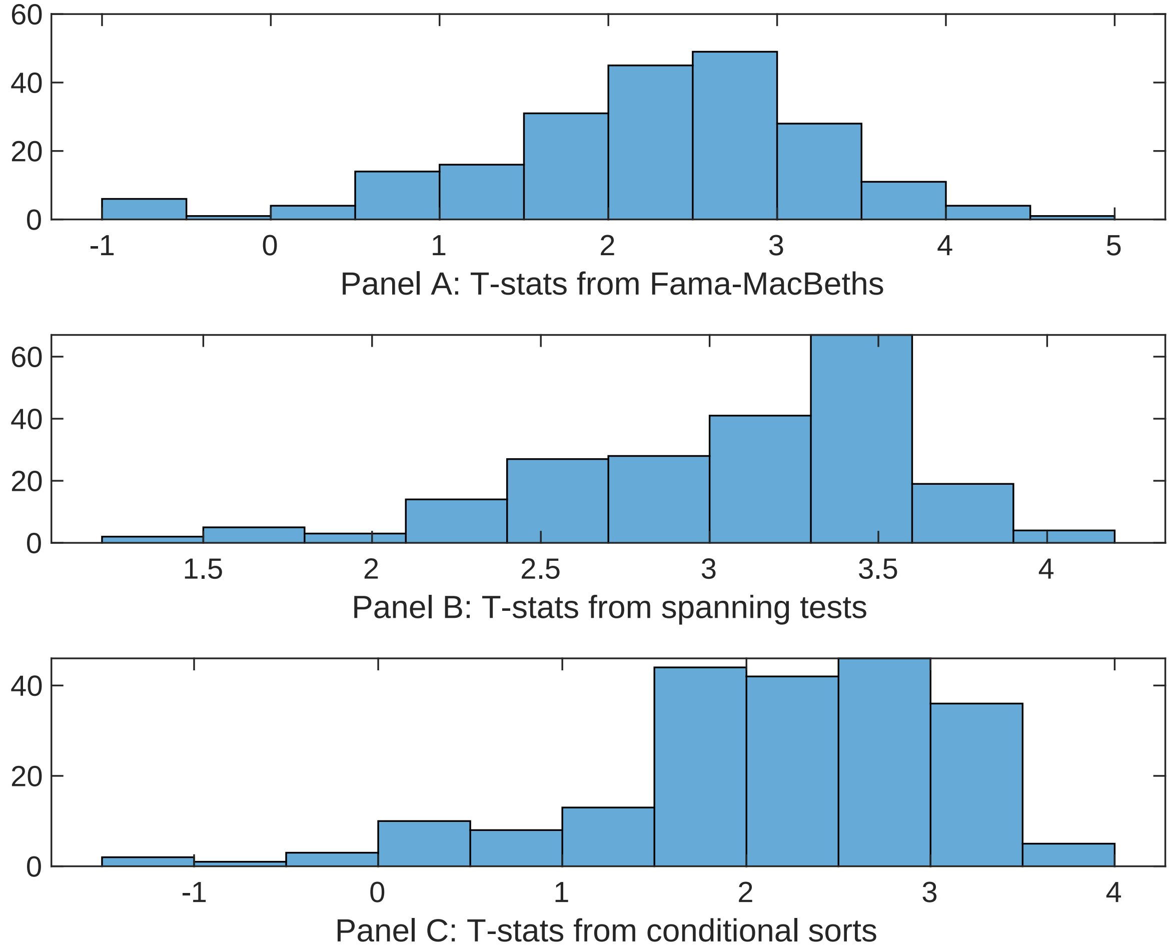

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of PIF conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{PIF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{PIF} PIF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{PIF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 PIF. Stocks are finally grouped into five PIF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted PIF 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 PIF. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{PIF} PIF_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Asset growth, Change in financial liabilities, Growth in book equity, change in net operating assets, change in ppe and inv/assets, 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	0.13	0.12	0.18	0.13	0.13	0.12	0.15
	[6.09]	[5.62]	[7.39]	[5.92]	[5.90]	[5.64]	[6.84]
PIF	-0.14	0.38	0.49	-0.15	-0.28	0.56	-0.44
	[-0.51]	[0.11]	[1.70]	[-0.51]	[-0.89]	[1.89]	[-1.41]
Anomaly 1	0.10						0.27
	[9.06]						[1.49]
Anomaly 2		0.18					0.62
		[10.08]					[1.77]
Anomaly 3			0.49				0.12
			[4.66]				[0.99]
Anomaly 4				0.14			0.28
				[9.97]			[1.31]
Anomaly 5					0.17		0.56
					[8.75]		[2.45]
Anomaly 6						0.14	0.34
						[4.22]	[0.58]
# months	696	696	696	696	696	696	696
$\bar{R}^2$(%)	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 PIF trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{PIF} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Asset growth, Change in financial liabilities, Growth in book equity, change in net operating assets, change in ppe and inv/assets, 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	0.20	0.15	0.19	0.18	0.19	0.19	0.15
	[2.59]	[2.04]	[2.46]	[2.33]	[2.49]	[2.47]	[2.03]
Anomaly 1	12.02						-1.29
	[2.37]						[-0.22]
Anomaly 2		34.47					40.17
		[7.89]					[8.24]
Anomaly 3			11.54				25.45
			[2.68]				[4.24]
Anomaly 4				8.35			-12.82
				[1.85]			[-2.47]
Anomaly 5					10.11		9.98
					[2.75]		[2.59]
Anomaly 6						0.28	-8.92
						[0.07]	[-1.54]
mkt	-4.13	-3.54	-3.80	-4.16	-4.42	-4.18	-2.74
	[-2.25]	[-2.00]	[-2.07]	[-2.27]	[-2.41]	[-2.27]	[-1.56]
smb	2.16	-0.10	2.86	3.47	2.99	3.28	-1.88
	[0.80]	[-0.04]	[1.08]	[1.31]	[1.13]	[1.23]	[-0.72]
hml	-20.65	-17.32	-21.56	-20.78	-21.25	-20.17	-18.89
	[-5.86]	[-5.10]	[-6.07]	[-5.87]	[-6.01]	[-5.65]	[-5.56]
rmw	-25.72	-28.35	-24.99	-25.40	-25.53	-25.61	-28.53
	[-7.19]	[-8.20]	[-6.98]	[-7.09]	[-7.15]	[-7.08]	[-8.34]
cma	51.04	52.28	54.30	59.34	57.94	65.41	37.87
	[6.32]	[9.92]	[8.10]	[9.53]	[9.82]	[9.69]	[4.69]
umd	8.23	5.01	7.63	7.56	7.73	7.75	4.21
	[4.52]	[2.83]	[4.22]	[4.17]	[4.28]	[4.26]	[2.37]
# months	696	696	696	696	696	696	696
$\bar{R}^2(\%)$	33	38	33	33	33	33	40

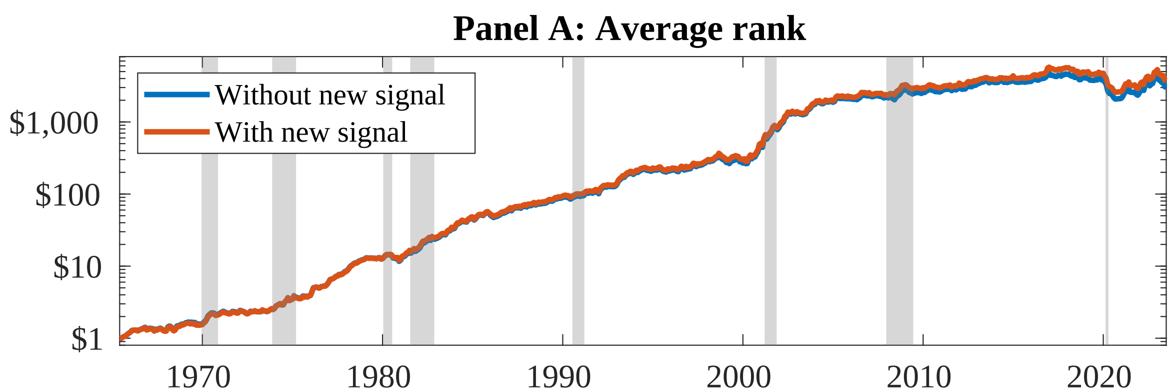

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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