Inventory Payment Pressure Margin and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Inventory Payment Pressure Margin (IPPM), 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 IPPM achieves an annualized gross (net) Sharpe ratio of 0.44 (0.39), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 25 (25) bps/month with a t-statistic of 2.51 (2.52), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Inventory Growth, Inventory Growth, change in ppe and inv/assets, Change in current operating assets, change in net operating assets, Employment growth) is 20 bps/month with a t-statistic of 2.17.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to understand how information is incorporated into security prices. While traditional asset pricing theory suggests that systematic risk should be the primary driver of expected returns, a growing body of evidence documents various firm characteristics that predict future stock returns (Harvey et al., 2016). Among these predictive signals, those related to firms' operating activities and working capital management have emerged as particularly important (Thomas and Zhang, 2002). Despite extensive research on individual components of working capital, the literature has paid limited attention to the joint dynamics of inventory management and supplier payment terms.

This gap is particularly notable given that inventory and accounts payable represent major components of firms' balance sheets and are fundamentally linked through firms' operating cycles. While prior work has examined inventory growth (Belo et al., 2019) and supplier relationships (Cohen et al., 2008) separately, the interaction between inventory financing pressure and payment terms to suppliers may contain important information about firms' financial health and future performance that is not fully reflected in current prices.

We develop our hypothesis about the predictive power of Inventory Payment Pressure Margin (IPPM) by drawing on theories of working capital management and financial constraints. When firms face pressure to finance growing inventory levels while simultaneously managing supplier payment obligations, they must either access external capital markets or adjust their operations. Following (Whited and Wu, 2006), firms with limited financial flexibility may be forced to make suboptimal operational decisions that impact future profitability.

The relationship between IPPM and expected returns can be understood through two primary channels. First, high IPPM may signal financial distress risk, as firms struggling to manage working capital cycles face higher probability of default (?). Second, building on (Thomas and Zhang, 2002), inventory buildup combined with stretched supplier payments may indicate demand uncertainty or operational inefficiencies that the market does not fully appreciate.

Importantly, IPPM differs from simple measures of inventory growth or accounts payable turnover because it captures the joint pressure from both components. This interaction is crucial because firms can temporarily mask operational difficulties by extending supplier payment terms, but this strategy becomes unsustainable when combined with growing inventory levels. Following (Hirshleifer and Teoh, 2003), we expect such complex interactions to be particularly prone to investor underreaction.

Our empirical analysis reveals that IPPM strongly predicts future stock returns. A value-weighted long-short portfolio strategy that buys stocks with high IPPM and sells stocks with low IPPM generates significant abnormal returns of 25 basis points per month (t-statistic = 2.51) after controlling for the Fama-French five factors plus momentum. The strategy achieves an annualized gross (net) Sharpe ratio of 0.44 (0.39), placing it in the top 13% of documented return predictors.

The predictive power of IPPM remains robust across various methodological specifications. The signal maintains significant predictability when using different portfolio construction approaches, with net returns ranging from 24-43 basis points per month. Importantly, IPPM's predictive ability persists among large-cap stocks, generating monthly returns of 37 basis points (t-statistic = 3.20) in the largest size quintile.

Most notably, IPPM continues to generate significant abnormal returns even after controlling for six closely related anomalies, including inventory growth and changes in operating assets. In spanning tests that control for these related signals and the Fama-French six factors simultaneously, IPPM produces an alpha of 20 basis points per month (t-statistic = 2.17), indicating it captures unique information not contained in existing predictors.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures the interaction between inventory management and supplier financing, extending the literature on operating efficiency and stock returns (Thomas and Zhang, 2002). While prior work has examined these components separately, we show that their interaction contains important predictive information.

Second, we contribute to the growing literature on the role of working capital management in asset pricing (Belo et al., 2019). Our findings suggest that markets do not fully incorporate the complex interactions between different components of working capital, consistent with theories of limited investor attention (Hirshleifer and Teoh, 2003). The robust predictive power of IPPM, even among large stocks and after controlling for transaction costs, challenges the efficient market hypothesis.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the value of examining interactions between related firm characteristics rather than studying them in isolation. For practitioners, our findings suggest profitable trading strategies that remain robust after accounting for transaction costs and are implementable even among large-cap stocks.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Inventory Payment Pressure Margin. 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 INVT for inventory and item NP for net profit.

Inventory (INVT) represents the value of goods held by the firm for sale or production, including raw materials, work in progress, and finished goods. Net profit (NP) provides a comprehensive measure of a firm's profitability after accounting for all operating and non-operating expenses, taxes, and other charges. The construction of the signal follows a change-based approach, where we calculate the difference between current period inventory and its lagged value, then scale this change by the previous period's net profit. This scaled difference captures the relative pressure that inventory changes place on a firm's financial resources, offering insight into working capital management efficiency and potential cash flow implications. By focusing on this relationship, the signal aims to reflect aspects of inventory management and financial strain in a manner that is both economically meaningful and comparable across firms. We construct this measure using end-of-fiscal-year values for both INVT and NP to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the IPPM signal. Panel A plots the time-series of the mean, median, and interquartile range for IPPM. On average, the cross-sectional mean (median) IPPM is -6.14 (-0.14) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input IPPM data. The signal's interquartile range spans -3.56 to 0.55. Panel B of Figure 1 plots the time-series of the coverage of the IPPM signal for the CRSP universe. On average, the IPPM signal is available for 2.83% of CRSP names, which on average make up 5.27% of total market capitalization.

4 Does IPPM predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on IPPM 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 IPPM portfolio and sells the low IPPM 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 IPPM strategy earns an average return of 0.36% per month with a t-statistic of 3.39. The annualized Sharpe ratio of the strategy is 0.44. The alphas range from 0.25% to 0.40% per month and have t-statistics exceeding 2.35 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 0.53, with a t-statistic of 7.96 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 281 stocks and an average market capitalization of at least $722 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 28 bps/month with a t-statistics of 2.94. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for twelve 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 24-43bps/month. The lowest return, (24 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.54. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the IPPM 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 twenty-four cases.

Table 3 provides direct tests for the role size plays in the IPPM strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and IPPM, as well as average returns and alphas for long/short trading IPPM 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 IPPM strategy achieves an average return of 37 bps/month with a t-statistic of 3.20. Among these large cap stocks, the alphas for the IPPM strategy relative to the five most common factor models range from 25 to 40 bps/month with t-statistics between 2.15 and 3.42.

5 How does IPPM perform relative to the zoo?

Figure 2 puts the performance of IPPM 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 IPPM strategy falls in the distribution. The IPPM strategy's gross (net) Sharpe ratio of 0.44 (0.39) is greater than 87% (96%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a $1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a $1 invested in the IPPM strategy (red line).[2] Ignoring trading costs, a $1 invested in the IPPM strategy would have yielded $8.22 which ranks the IPPM strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a $1 invested in the IPPM strategy would have yielded $5.80 which ranks the IPPM strategy in the top 2% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of

[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.

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 IPPM relative to those. Panel A shows that the IPPM strategy gross alphas fall between the 67 and 75 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 set for an investor having access to the Fama-French three-factor (six-factor) model. The IPPM strategy has a positive net generalized alpha for five out of the five factor models. In these cases IPPM ranks between the 85 and 92 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does IPPM 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 IPPM with 202 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 IPPM or at least to weaken the power IPPM has predicting the cross-section of returns. Figure 7 plots histograms

[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 t-statistics for predictability tests of IPPM conditioning on each of the 202 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{IPPM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{IPPM} IPPM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 202 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{IPPM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 202 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 202 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on IPPM. Stocks are finally grouped into five IPPM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted IPPM trading strategies conditioned on each of the 202 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on IPPM 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 IPPM signal in these Fama-MacBeth regressions exceed 2.41, with the minimum t-statistic occurring when controlling for Inventory Growth. Controlling for all six closely related anomalies, the t-statistic on IPPM is 1.15.

Similarly, Table 5 reports results from spanning tests that regress returns to the IPPM 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 IPPM strategy earns alphas that range from 14-33bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.54, which is achieved when controlling for Inventory Growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the IPPM trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.17.

7 Does IPPM add relative to the whole zoo?

Finally, we can ask how much adding IPPM 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 IPPM 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 IPPM grows to $3175.77.

8 Conclusion

This study provides compelling evidence for the effectiveness of Inventory Payment Pressure Margin (IPPM) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on IPPM generates economically and statistically significant returns, with

[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 IPPM is available.

an impressive annualized Sharpe ratio of 0.44 (0.39) on a gross (net) basis. The strategy's robustness is further validated by its persistent performance even after controlling for well-known risk factors and related investment strategies.

Particularly noteworthy is the strategy's ability to generate significant abnormal returns of 25 basis points per month relative to the Fama-French five-factor model plus momentum, with strong statistical significance (t-statistic ¿ 2.5). Even more compelling is the signal's maintained significance when controlling for six closely related strategies from the factor zoo, yielding a monthly alpha of 20 basis points with a t-statistic of 2.17. These results strongly suggest that IPPM captures unique information about future stock returns that is not explained by existing factors.

However, several limitations should be noted. Our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Additionally, while we demonstrate robust performance after transaction costs, implementation challenges may vary across different market environments and investor circumstances.

Future research could explore the application of IPPM in international markets, its interaction with other established signals, and its performance during different economic cycles. Additionally, investigating the underlying economic mechanisms driving the IPPM premium could provide valuable insights for both academics and practitioners. These findings contribute significantly to the literature on return prediction and offer practical implications for investment professionals seeking to enhance their portfolio management strategies.

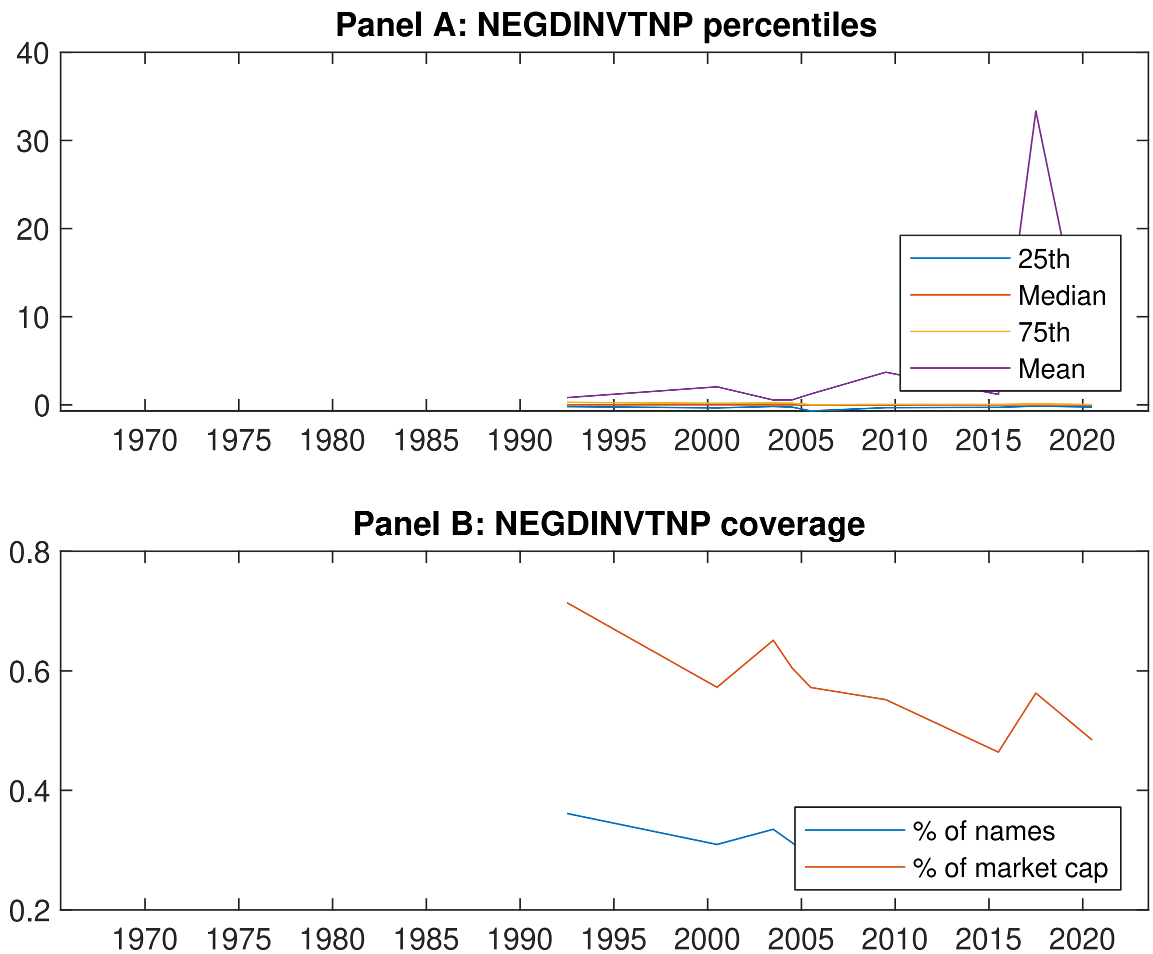

Figure 1: Times series of IPPM percentiles and coverage.
This figure plots descriptive statistics for IPPM. Panel A shows cross-sectional percentiles of IPPM over the sample. Panel B plots the monthly coverage of IPPM relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on IPPM. 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 IPPM-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.41	0.48	0.58	0.55	0.77	0.36
	[2.18]	[2.97]	[3.51]	[3.19]	[4.29]	[3.39]
α_{CAPM}	-0.17	-0.01	0.08	0.03	0.24	0.40
	[-2.54]	[-0.09]	[1.26]	[0.41]	[3.16]	[3.77]
α_{FF3}	-0.14	-0.01	0.04	-0.06	0.17	0.31
	[-2.07]	[-0.19]	[0.68]	[-1.21]	[2.39]	[2.98]
α_{FF4}	-0.09	-0.03	0.02	-0.03	0.16	0.25
	[-1.30]	[-0.42]	[0.30]	[-0.54]	[2.17]	[2.35]
α_{FF5}	-0.16	-0.18	-0.05	-0.09	0.13	0.29
	[-2.52]	[-3.10]	[-0.93]	[-1.75]	[1.84]	[2.97]
α_{FF6}	-0.12	-0.18	-0.06	-0.06	0.13	0.25
	[-1.89]	[-3.03]	[-1.12]	[-1.15]	[1.76]	[2.51]
Panel B: Fama and French (2018) 6-factor model loadings for IPPM-sorted portfolios						
β_{MKT}	0.98	0.95	0.98	1.02	1.00	0.02
	[65.07]	[68.68]	[74.44]	[80.32]	[57.52]	[0.67]
β_{SMB}	0.07	-0.09	-0.12	-0.17	0.01	-0.05
	[3.00]	[-4.71]	[-6.39]	[-9.44]	[0.56]	[-1.51]
β_{HML}	-0.03	-0.03	0.15	0.26	0.02	0.05
	[-0.92]	[-1.29]	[5.94]	[10.71]	[0.57]	[1.01]
β_{RMW}	0.21	0.32	0.21	0.04	-0.08	-0.29
	[7.16]	[11.81]	[8.19]	[1.66]	[-2.24]	[-6.25]
β_{CMA}	-0.20	0.24	0.04	0.09	0.32	0.53
	[-4.79]	[6.03]	[1.15]	[2.49]	[6.62]	[7.96]
β_{UMD}	-0.06	-0.00	0.02	-0.05	0.01	0.06
	[-3.96]	[-0.18]	[1.28]	[-3.73]	[0.30]	[2.77]
Panel C: Average number of firms (n) and market capitalization (me)						
n	282	281	308	325	310	
me ($\$10^6$)	833	1198	1492	1220	722	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the IPPM 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	0.36	0.40	0.31	0.25	0.29	0.25
			[3.39]	[3.77]	[2.98]	[2.35]	[2.97]	[2.51]
Quintile	NYSE	EW	0.55	0.58	0.50	0.46	0.52	0.49
			[6.90]	[7.17]	[6.55]	[5.95]	[6.82]	[6.37]
Quintile	Name	VW	0.36	0.38	0.28	0.20	0.27	0.20
			[3.58]	[3.70]	[2.84]	[1.98]	[2.79]	[2.13]
Quintile	Cap	VW	0.28	0.32	0.24	0.18	0.27	0.23
			[2.94]	[3.31]	[2.54]	[1.94]	[3.07]	[2.59]
Decile	NYSE	VW	0.48	0.52	0.44	0.29	0.45	0.33
			[3.82]	[4.12]	[3.54]	[2.37]	[3.72]	[2.79]
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	0.32	0.36	0.28	0.25	0.27	0.25
			[2.98]	[3.36]	[2.70]	[2.36]	[2.74]	[2.52]
Quintile	NYSE	EW	0.33	0.32	0.26	0.24	0.23	0.22
			[3.76]	[3.74]	[3.13]	[2.92]	[2.89]	[2.78]
Quintile	Name	VW	0.32	0.33	0.25	0.21	0.24	0.21
			[3.14]	[3.27]	[2.55]	[2.10]	[2.53]	[2.23]
Quintile	Cap	VW	0.24	0.28	0.21	0.18	0.24	0.22
			[2.54]	[2.92]	[2.27]	[1.96]	[2.74]	[2.54]
Decile	NYSE	VW	0.43	0.45	0.39	0.31	0.39	0.33
			[3.39]	[3.61]	[3.15]	[2.52]	[3.28]	[2.80]

Table 3: Conditional sort on size and IPPM

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

	IPPM Quintiles					IPPM Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.52	0.65	0.46	0.80	1.05	0.53	0.56	0.50	0.41	0.51	0.44
	[1.99]	[2.69]	[1.97]	[3.39]	[3.89]	[4.67]	[4.90]	[4.43]	[3.59]	[4.55]	[3.91]
(2)	0.66	0.65	0.88	0.80	0.95	0.30	0.36	0.31	0.21	0.30	0.22
	[2.53]	[2.77]	[3.98]	[3.61]	[3.99]	[2.46]	[2.97]	[2.55]	[1.71]	[2.42]	[1.76]
(3)	0.67	0.79	0.80	0.81	0.87	0.20	0.27	0.21	0.21	0.21	0.21
	[2.80]	[3.66]	[3.99]	[3.92]	[3.94]	[1.75]	[2.42]	[1.87]	[1.87]	[1.88]	[1.93]
(4)	0.59	0.79	0.68	0.76	0.79	0.20	0.25	0.19	0.14	0.18	0.15
	[2.75]	[3.88]	[3.53]	[3.89]	[3.92]	[2.04]	[2.60]	[1.96]	[1.49]	[1.87]	[1.52]
(5)	0.36	0.47	0.59	0.47	0.73	0.37	0.40	0.30	0.25	0.33	0.30
	[2.02]	[2.84]	[3.49]	[2.66]	[4.27]	[3.20]	[3.42]	[2.64]	[2.15]	[3.11]	[2.72]

Panel B: Portfolio average number of firms and market capitalization

	IPPM Quintiles Average n					IPPM Quintiles Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	155	154	153	153	151	11	10	10	10	9
(2)	42	42	42	42	42	16	16	17	17	17
(3)	34	35	34	34	34	32	33	33	33	32
(4)	33	33	33	33	33	84	85	86	84	83
(5)	38	38	38	38	38	785	1112	981	995	876

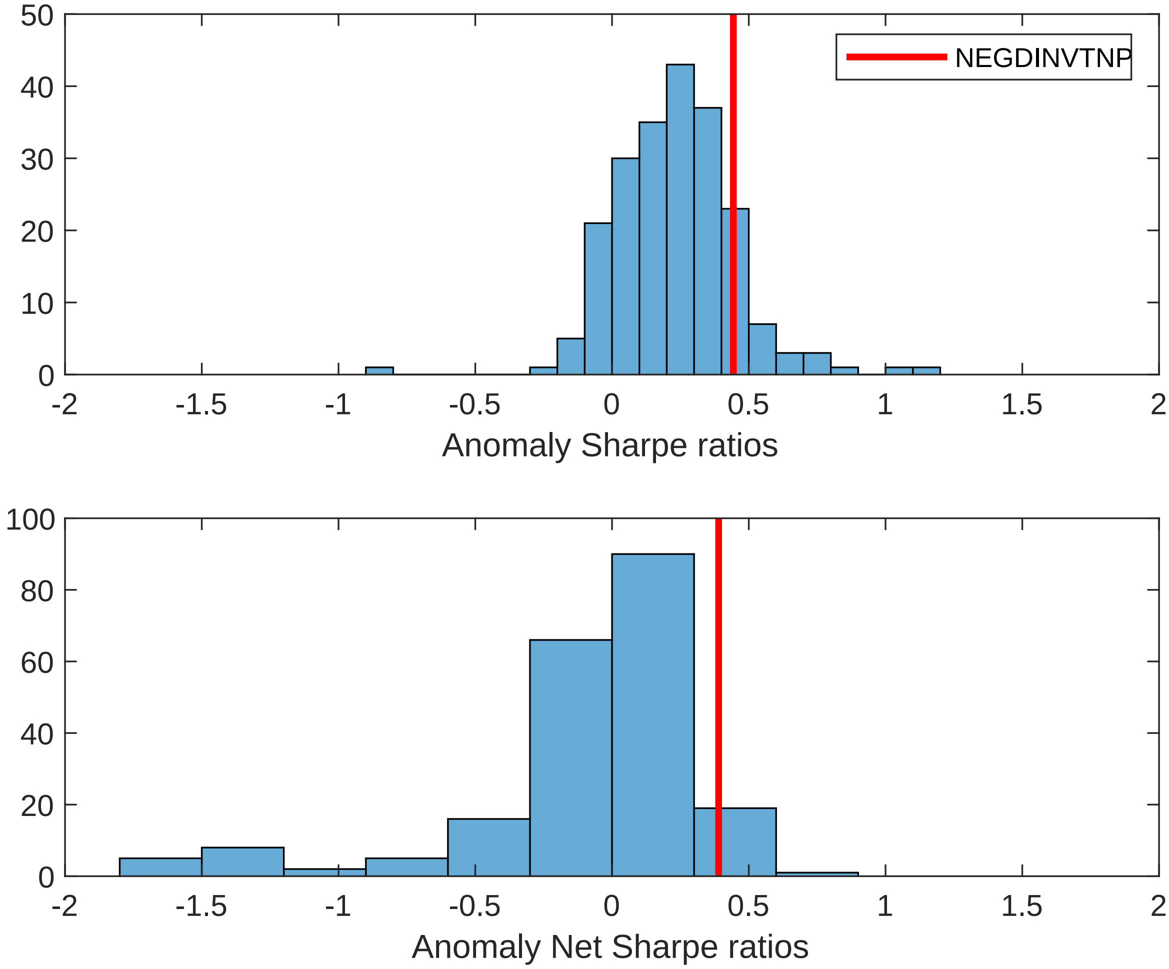

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the IPPM with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

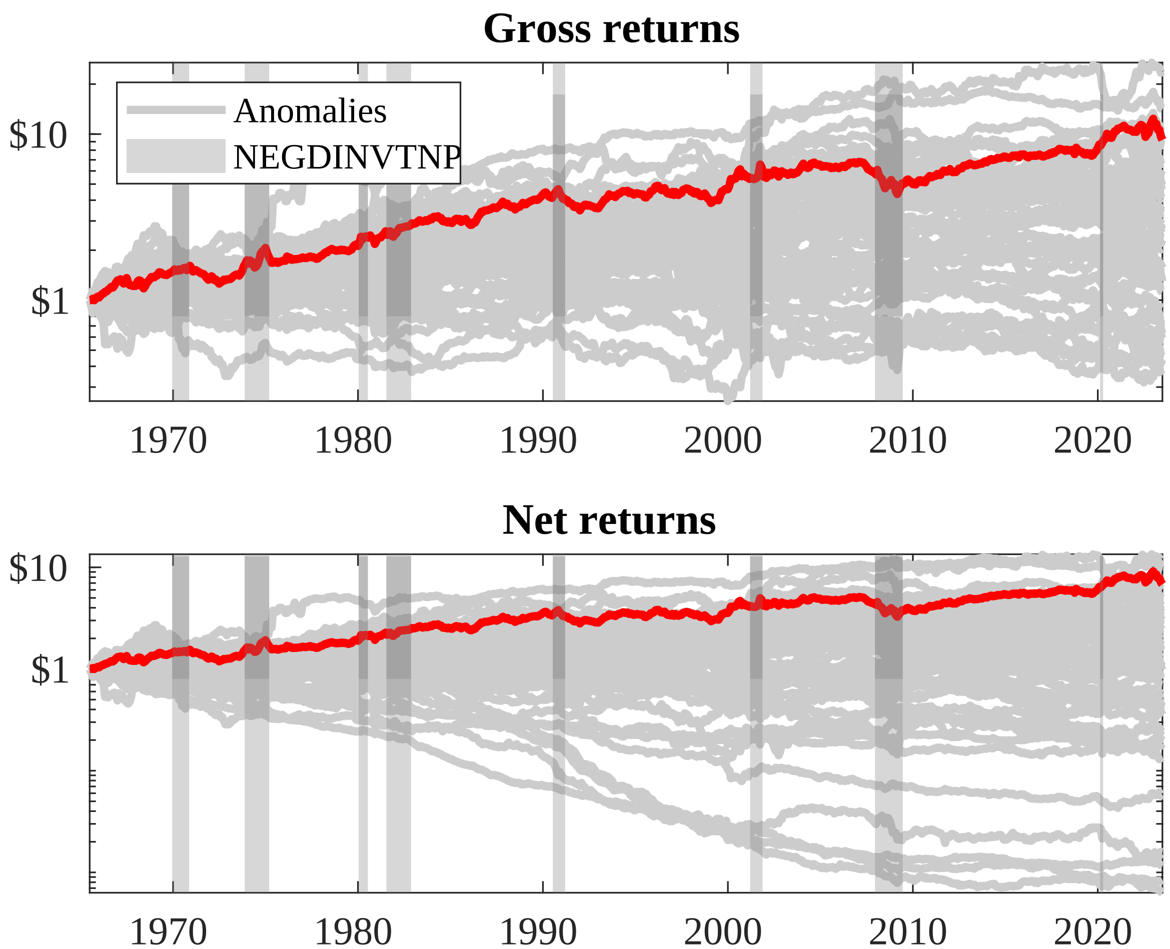

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the IPPM trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

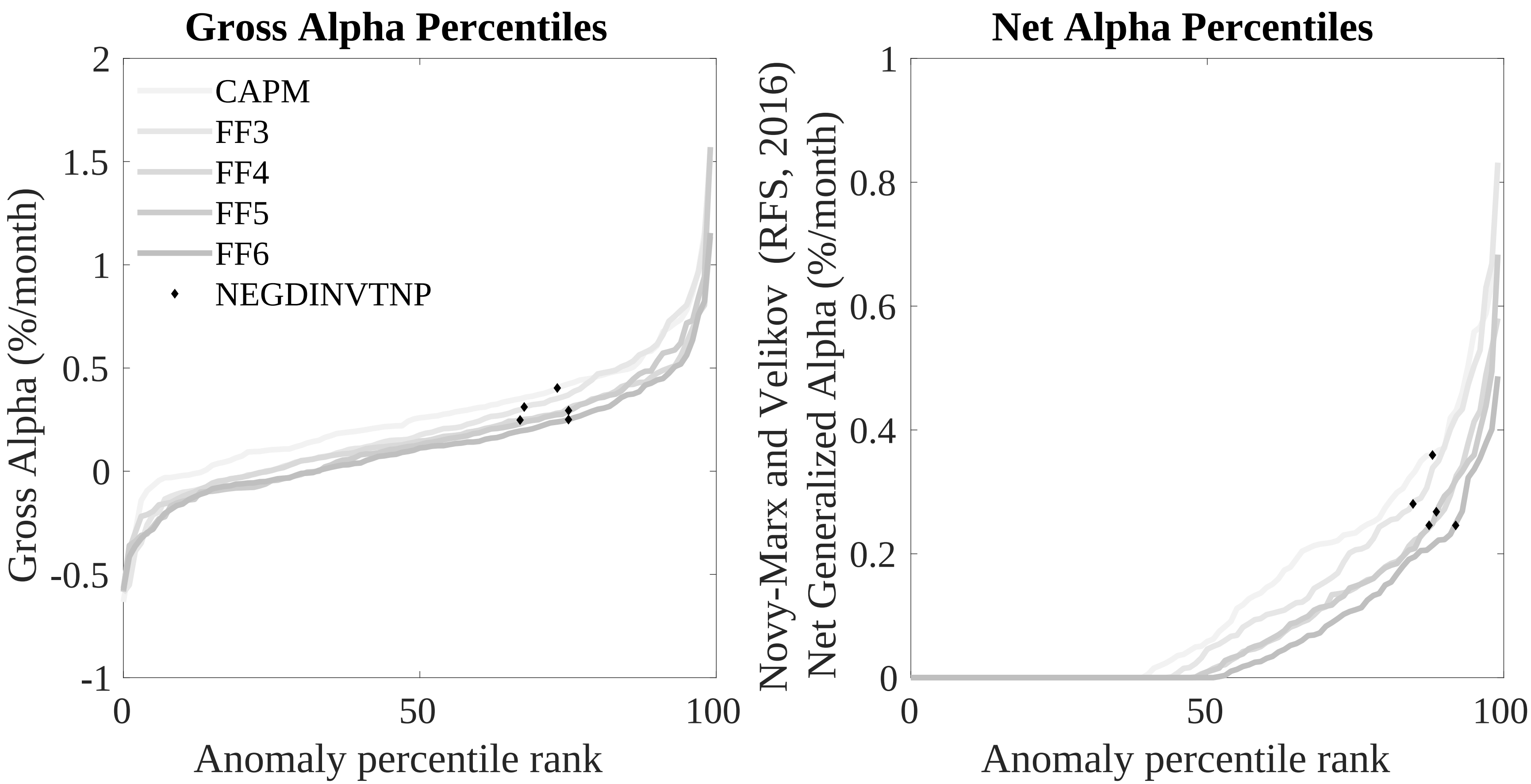

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the IPPM trading strategy alphas (diamonds). The strategies are constructed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

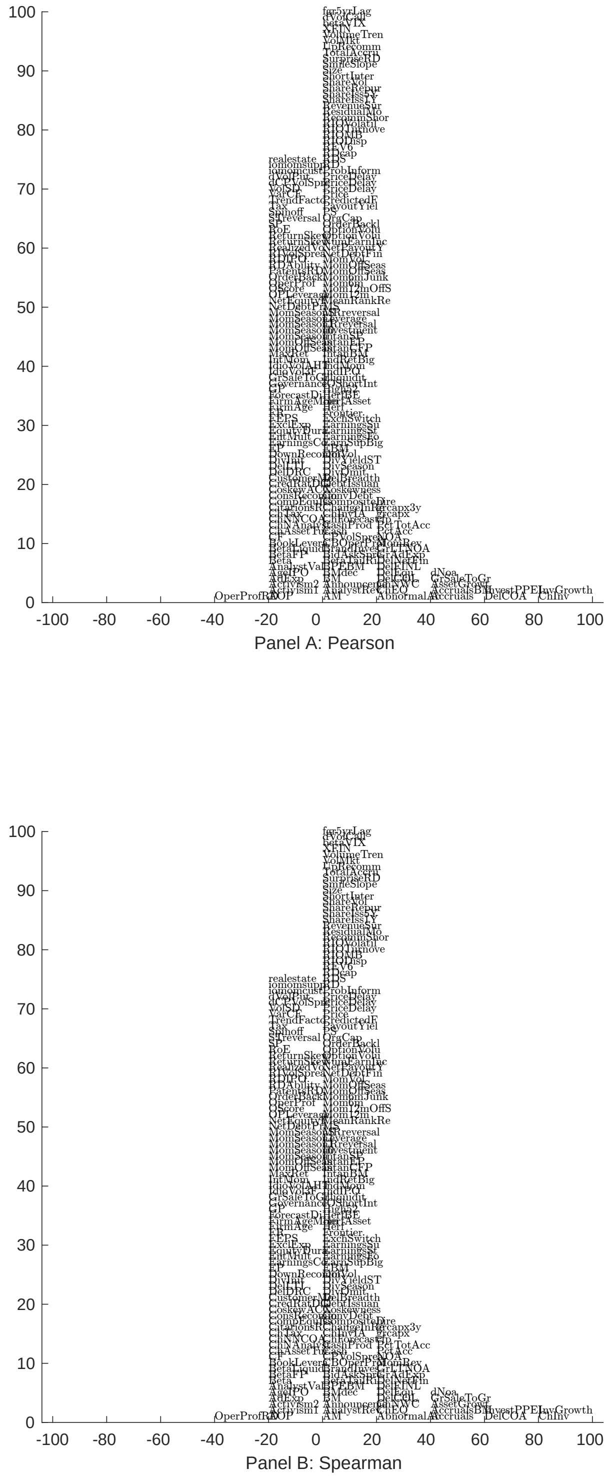

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 202 filtered anomaly signals with IPPM. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

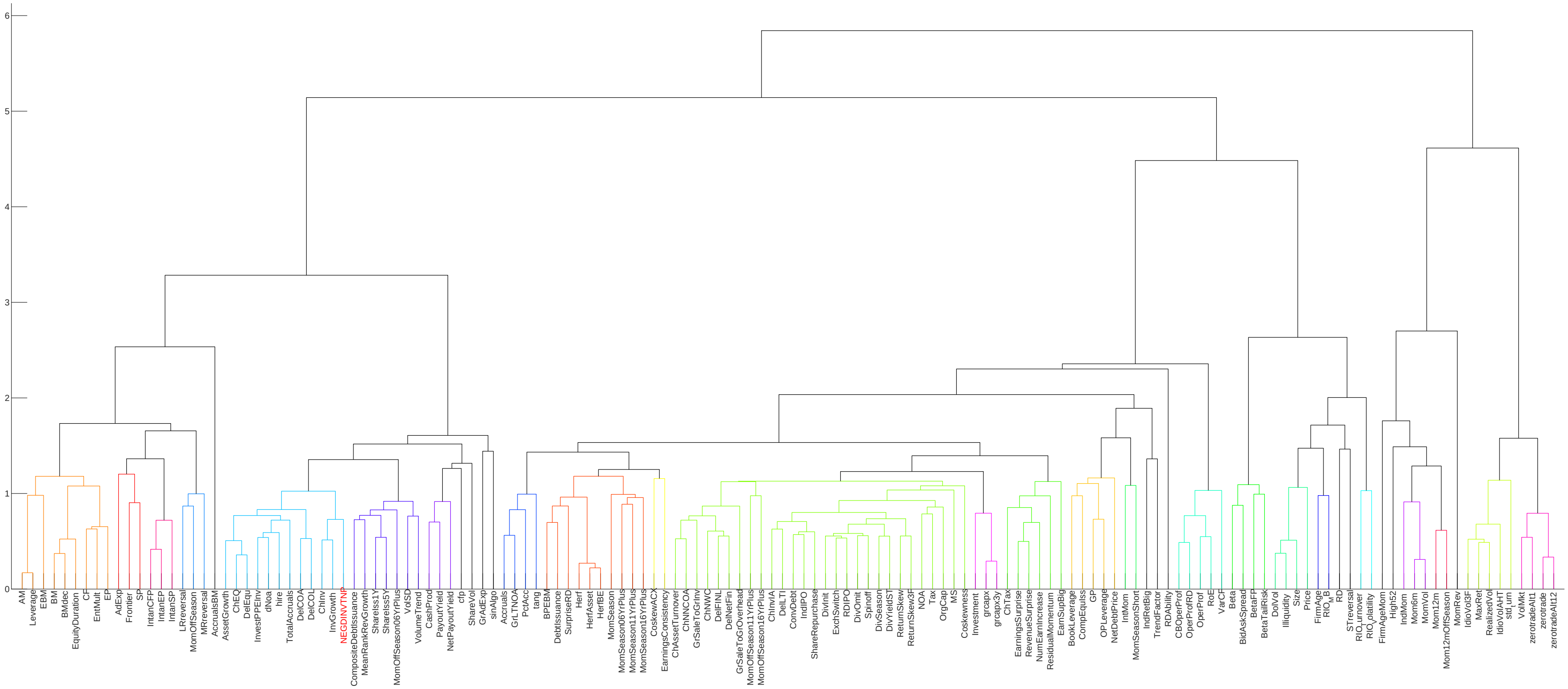

Figure 6: Agglomerative hierarchical cluster plot

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

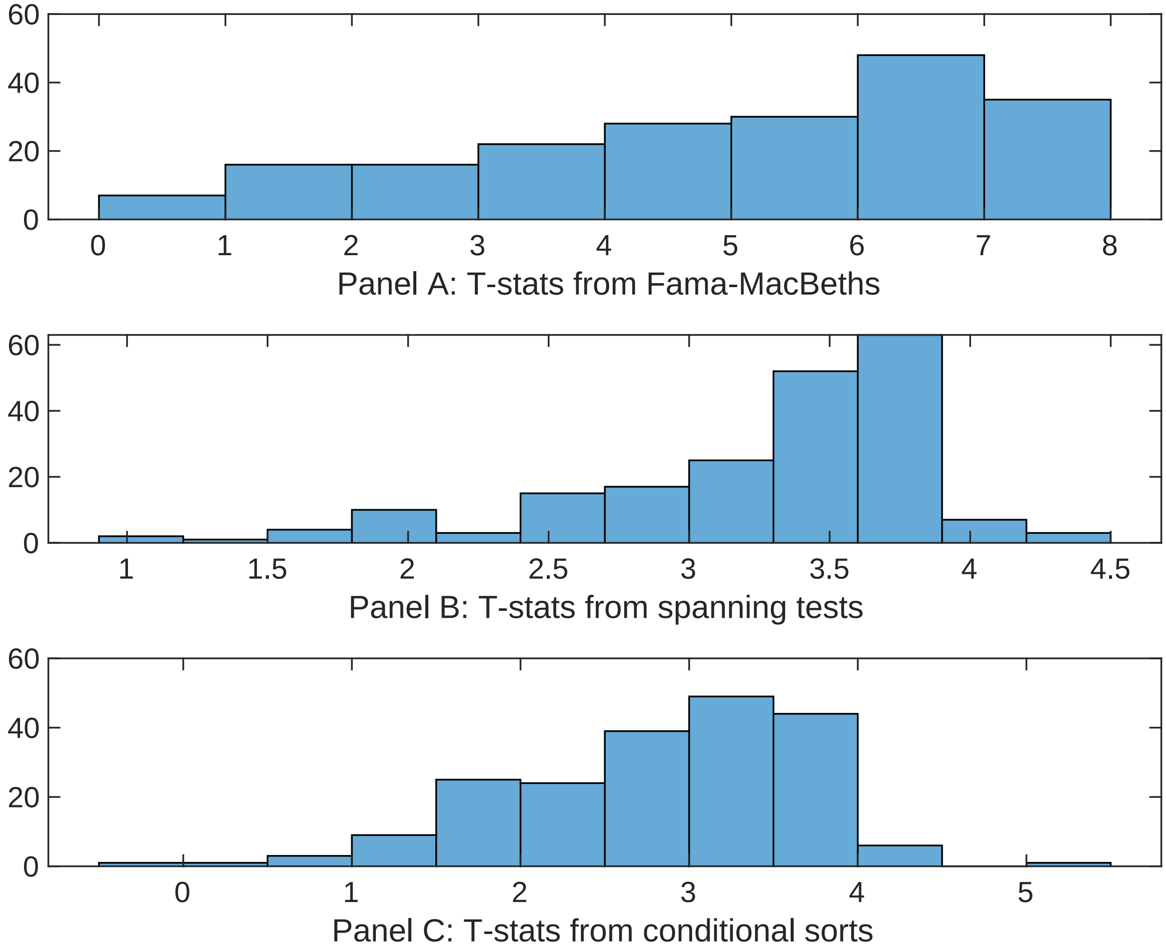

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of IPPM conditioning on each of the 202 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{IPPM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{IPPM} IPPM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 202 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{IPPM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 202 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 202 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on IPPM. Stocks are finally grouped into five IPPM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted IPPM trading strategies conditioned on each of the 202 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on IPPM. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{IPPM} IPPM_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Inventory Growth, Inventory Growth, change in ppe and inv/assets, Change in current operating assets, change in net operating assets, Employment 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 196506 to 202306.

Intercept	0.12	0.13	0.13	0.12	0.12	0.12	0.13
	[5.59]	[5.43]	[5.86]	[5.62]	[5.87]	[5.55]	[5.62]
IPPM	0.74	0.57	0.55	0.88	0.57	0.12	0.28
	[3.16]	[2.41]	[2.48]	[3.82]	[2.48]	[5.35]	[1.15]
Anomaly 1	0.37						-0.18
	[6.06]						[-1.57]
Anomaly 2		0.76					0.27
		[8.38]					[2.03]
Anomaly 3			0.20				0.39
			[8.70]				[0.86]
Anomaly 4				0.22			0.70
				[6.47]			[0.13]
Anomaly 5					0.18		0.14
					[10.74]		[5.32]
Anomaly 6						0.11	0.32
						[6.77]	[1.38]
# 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 IPPM trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{IPPM} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Inventory Growth, Inventory Growth, change in ppe and inv/assets, Change in current operating assets, change in net operating assets, Employment 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 196506 to 202306.

Intercept	0.14	0.24	0.25	0.27	0.22	0.33	0.20
	[1.54]	[2.67]	[2.57]	[2.73]	[2.23]	[3.31]	[2.17]
Anomaly 1	57.04						37.89
	[12.52]						[6.62]
Anomaly 2		41.56					19.14
		[11.28]					[4.26]
Anomaly 3			36.04				21.52
			[7.94]				[4.60]
Anomaly 4				29.66			3.79
				[6.16]			[0.76]
Anomaly 5					18.35		-12.86
					[3.19]		[-2.22]
Anomaly 6						26.53	0.79
						[4.98]	[0.15]
mkt	2.46	0.02	0.17	0.73	1.08	1.34	0.93
	[1.16]	[0.01]	[0.07]	[0.32]	[0.46]	[0.58]	[0.45]
smb	2.67	-1.14	-5.48	1.51	-4.02	-3.09	1.68
	[0.85]	[-0.36]	[-1.68]	[0.44]	[-1.19]	[-0.92]	[0.54]
hml	0.17	1.51	0.04	-7.35	2.60	-0.79	-2.67
	[0.04]	[0.36]	[0.01]	[-1.54]	[0.58]	[-0.17]	[-0.62]
rmw	-17.36	-22.54	-27.35	-23.69	-27.21	-27.05	-18.04
	[-4.10]	[-5.30]	[-6.21]	[-5.23]	[-5.95]	[-5.98]	[-4.38]
cma	16.14	19.62	25.81	37.00	39.48	30.14	3.58
	[2.40]	[2.88]	[3.55]	[5.27]	[4.97]	[3.74]	[0.46]
umd	2.61	1.71	5.99	7.38	5.65	4.64	2.13
	[1.23]	[0.79]	[2.69]	[3.24]	[2.44]	[2.01]	[1.01]
# months	696	696	696	696	696	696	696
$\bar{R}^2(\%)$	37	34	29	26	23	25	41

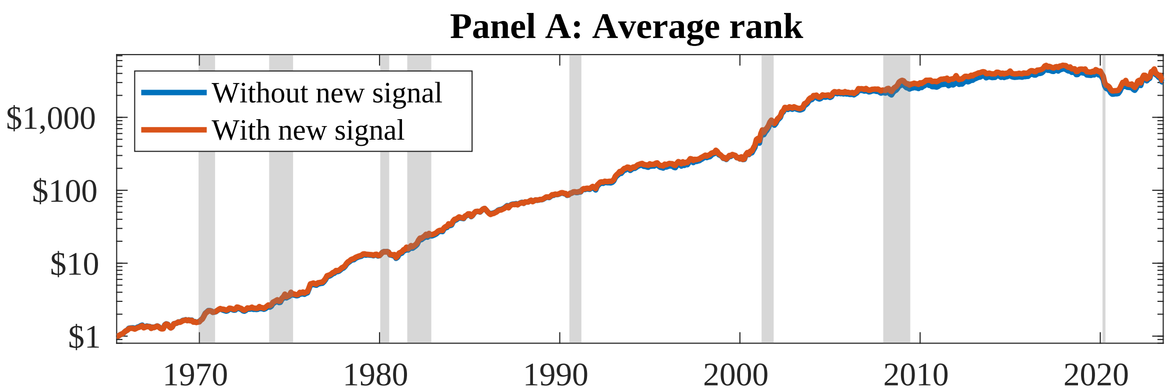

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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