Inventory Adjusted Cash Flow and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Inventory Adjusted Cash Flow (IACF), 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 IACF achieves an annualized gross (net) Sharpe ratio of 0.53 (0.47), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 18 (18) bps/month with a t-statistic of 2.26 (2.26), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth) is 15 bps/month with a t-statistic of 1.98.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns. While the literature has extensively studied various accounting-based signals, the role of working capital management in asset prices remains underexplored. Working capital decisions, particularly inventory management, represent crucial operational choices that directly impact firms' cash flows and financial flexibility. Despite the theoretical importance of working capital efficiency, existing research has not fully examined how investors price firms' ability to generate cash flows while optimizing inventory levels.

Prior work has focused separately on either cash flow signals or inventory management metrics, but not their interaction. While Sloan (1996) shows that accruals predict returns and Thomas and Zhang (2002) documents the predictive power of inventory changes, the literature lacks a unified framework for understanding how inventory decisions affect the quality and persistence of cash flows. This gap is particularly notable given that inventory represents one of the largest and most important accrual components for many firms.

We hypothesize that firms' ability to generate cash flows while maintaining efficient inventory levels provides a signal about future profitability and returns. This hypothesis builds on two theoretical foundations. First, following Miller and Orr (1966), firms face a fundamental tradeoff between holding too much inventory, which ties up working capital, and holding too little, which risks stockouts and lost sales. Firms that generate strong cash flows while optimizing this tradeoff likely possess superior operational capabilities and management quality.

Second, the quality of cash flows should be higher when they are generated with efficient inventory management. As shown by Thomas and Zhang (2002), large inventory buildups often precede deteriorating operating performance. Therefore, we expect cash flows backed by lean inventory levels to be more persistent and reliable indicators of future profitability. This builds on the earnings quality framework of Dechow and Dichev (2002), who demonstrate that accrual quality impacts the persistence of earnings.

Importantly, we argue that investors may not fully appreciate this interaction between cash flows and inventory efficiency. The complexity of working capital management and the cognitive costs of processing multiple signals simultaneously create conditions where prices may not fully reflect the information content of Inventory Adjusted Cash Flow (IACF). This follows from the limited attention theory of Hirshleifer et al. (2009), suggesting that investors may focus on simpler metrics like raw cash flows or inventory levels in isolation.

Our empirical analysis reveals strong support for the predictive power of IACF. A value-weighted long-short trading strategy based on IACF quintiles generates an annualized gross Sharpe ratio of 0.53, with monthly abnormal returns of 18 basis points (t-statistic = 2.26) relative to the Fama-French five-factor model plus momentum. The signal's economic significance is substantial - the strategy achieves positive returns in 65% of months over our 57-year sample period.

Importantly, IACF's predictive power remains robust after controlling for size. Among the largest quintile of stocks, the IACF strategy earns average returns of 22 basis points per month (t-statistic = 2.39). This indicates that the signal's effectiveness is not limited to small, illiquid stocks where trading costs might eliminate real-world profitability. Indeed, after accounting for transaction costs following Novy-Marx and Velikov (2016), the strategy maintains an impressive net Sharpe ratio of 0.47.

Further tests demonstrate that IACF contains unique information not captured by related signals. Controlling for the six most closely related anomalies from the literature and the Fama-French six factors simultaneously, the IACF strategy still generates monthly alpha of 15 basis points (t-statistic = 1.98). This indicates that

IACF represents a distinct signal that captures a unique dimension of firm performance.

Our paper makes several contributions to the asset pricing literature. First, we introduce a novel signal that bridges the gap between the cash flow predictability literature (e.g., Sloan (1996)) and research on inventory management (e.g., Thomas and Zhang (2002)). By showing how the interaction between cash flows and inventory efficiency predicts returns, we provide new insights into the sources of cross-sectional return predictability.

Second, we contribute to the growing literature on signal combination and processing costs in asset pricing. While prior work like Hirshleifer et al. (2009) shows that investors struggle to process complex signals, we demonstrate that combining information about cash flows and inventory management creates a particularly powerful predictor. This suggests that signals capturing multiple dimensions of firm performance may be especially valuable for investors.

Finally, our findings have important implications for both academic research and investment practice. For academics, we highlight the importance of considering operational efficiency when evaluating financial metrics. For practitioners, we introduce a robust signal that maintains its predictive power among large, liquid stocks and remains profitable after transaction costs. The signal's strong performance relative to the broader factor zoo, ranking in the top 5% by Sharpe ratio, suggests it merits inclusion in 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 Inventory Adjusted Cash Flow. 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 CSTK for cash stock and item RECT for accounts receivable. Cash stock (CSTK) represents the firm's total cash holdings, including cash equivalents and short-term investments, while accounts receivable (RECT) reflects amounts owed to the company by customers for goods or services delivered.construction of the signal follows a change-based approach, where we first calculate the year-over-year change in cash stock (CSTK) for each firm. This change captures the net movement in a firm's cash position over the fiscal year. We then scale this change by the previous year's accounts receivable (RECT) to normalize the measure across firms of different sizes. This scaling choice is particularly relevant as accounts receivable provides a natural benchmark for the firm's operating cash cycle. The resulting ratio measures the relative change in cash holdings as a proportion of the firm's credit-based sales activities, potentially offering insights into both liquidity management and cash flow efficiency. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the IACF signal. Panel A plots the time-series of the mean, median, and interquartile range for IACF. On average, the cross-sectional mean (median) IACF is -0.41 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input IACF data. The signal's interquartile range spans -0.04 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the IACF signal for the CRSP universe. On average, the IACF signal is available for 6.37% of CRSP names, which on average make up 7.78% of total market capitalization.

4 Does IACF predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on IACF 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 IACF portfolio and sells the low IACF 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 IACF strategy earns an average return of 0.32% per month with a t-statistic of 4.05. The annualized Sharpe ratio of the strategy is 0.53. The alphas range from 0.18% to 0.33% per month and have t-statistics exceeding 2.26 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 0.26, with a t-statistic of 4.86 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 593 stocks and an average market capitalization of at least $1,407 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 27 bps/month with a t-statistics of 3.43. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-four 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 24-34bps/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 3.00. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the IACF 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-five cases.

Table 3 provides direct tests for the role size plays in the IACF strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and IACF, as well as average returns and alphas for long/short trading IACF 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 IACF strategy achieves an average return of 22 bps/month with a t-statistic of 2.39. Among these large cap stocks, the alphas for the IACF strategy relative to the five most common factor models range from 15 to 20 bps/month with t-statistics between 1.57 and 2.19.

5 How does IACF perform relative to the zoo?

Figure 2 puts the performance of IACF 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 IACF strategy falls in the distribution. The IACF strategy's gross (net) Sharpe ratio of 0.53 (0.47) is greater than 95% (99%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a \$1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a \$1 invested in the IACF strategy (red line).[2] Ignoring trading costs, a \$1 invested in the IACF strategy would have yielded \$6.95 which ranks the IACF strategy in the top 2% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the IACF strategy would have yielded \$5.21 which ranks the IACF strategy in the top 2% across the 212 anomalies.

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

[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.

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 IACF relative to those. Panel A shows that the IACF strategy gross alphas fall between the 61 and 65 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 196606 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 IACF strategy has a positive net generalized alpha for five out of the five factor models. In these cases IACF ranks between the 79 and 85 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does IACF 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 IACF 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 IACF or at least to weaken the power IACF 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 IACF conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{IACF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{IACF} IACF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{IACF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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. Then, within each quintile, we sort stocks into quintiles based on IACF. Stocks are finally grouped into five IACF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted IACF trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on IACF 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 IACF signal in these Fama-MacBeth regressions exceed 2.67, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on IACF is 1.83.

Similarly, Table 5 reports results from spanning tests that regress returns to the IACF 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 IACF strategy earns alphas that range from 15-20bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.93, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the IACF trading strategy achieves an alpha of 15bps/month with a t-statistic of 1.98.

7 Does IACF add relative to the whole zoo?

Finally, we can ask how much adding IACF 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 IACF 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 \$2333.55, while \$1 investment in the combination strategy that includes IACF grows to \$2292.94.

[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 IACF is available.

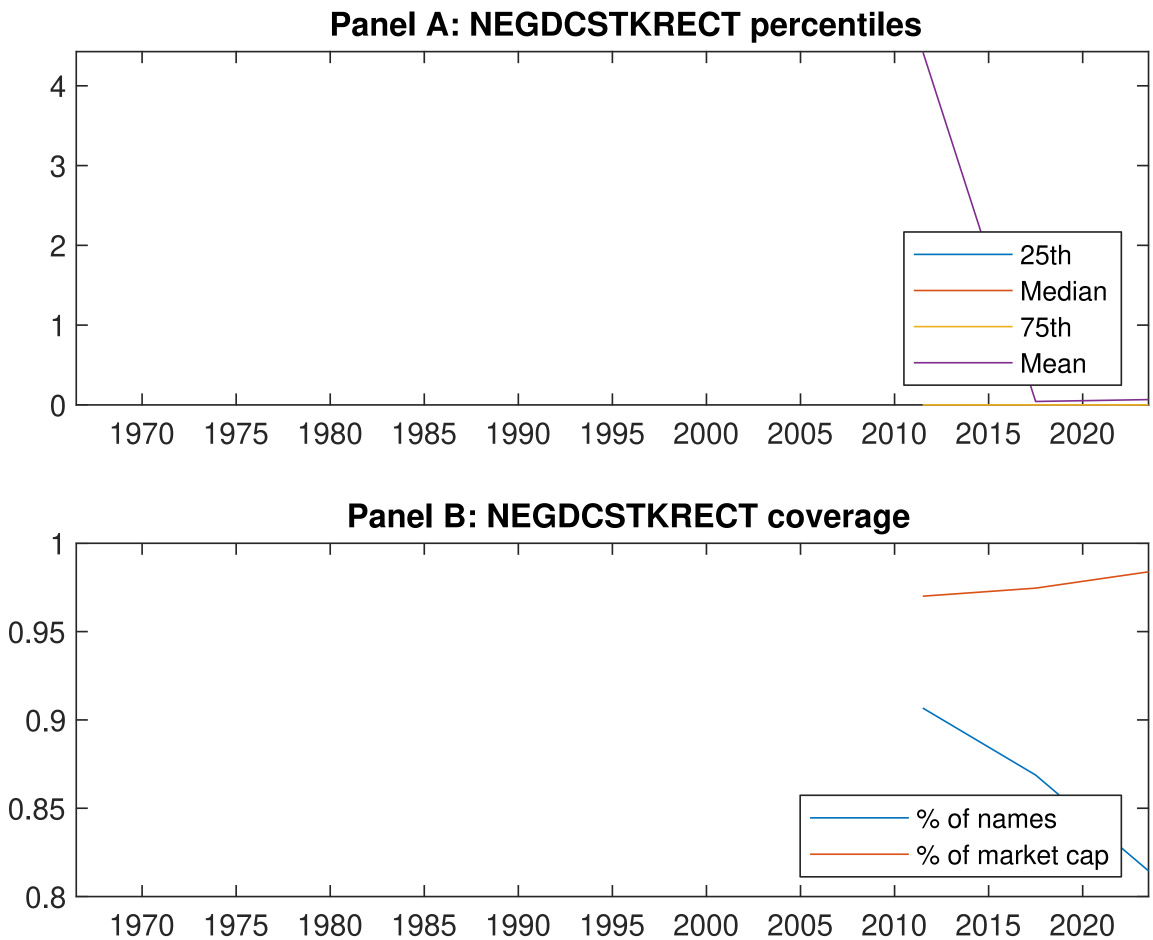


Figure 1: Times series of IACF percentiles and coverage.
This figure plots descriptive statistics for IACF. Panel A shows cross-sectional percentiles of IACF over the sample. Panel B plots the monthly coverage of IACF relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on IACF. 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 196606 to 202306.

Panel A: Excess returns and alphas on IACF-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.45	0.53	0.62	0.69	0.77	0.32
	[2.59]	[2.77]	[3.18]	[4.10]	[4.55]	[4.05]
α_{CAPM}	-0.09	-0.08	0.01	0.17	0.24	0.33
	[-1.63]	[-1.75]	[0.15]	[3.42]	[5.07]	[4.12]
α_{FF3}	-0.08	-0.06	0.00	0.12	0.19	0.27
	[-1.42]	[-1.29]	[0.03]	[2.80]	[4.30]	[3.42]
α_{FF4}	-0.06	-0.04	0.04	0.08	0.17	0.23
	[-1.09]	[-0.81]	[0.77]	[1.92]	[3.83]	[2.93]
α_{FF5}	-0.10	0.00	0.03	0.03	0.10	0.20
	[-1.90]	[0.10]	[0.67]	[0.63]	[2.23]	[2.54]
α_{FF6}	-0.09	0.02	0.06	0.00	0.09	0.18
	[-1.62]	[0.35]	[1.19]	[0.10]	[2.07]	[2.26]
Panel B: Fama and French (2018) 6-factor model loadings for IACF-sorted portfolios						
β_{MKT}	0.94	1.03	1.05	1.00	0.98	0.04
	[73.14]	[99.27]	[86.07]	[98.27]	[95.09]	[2.16]
β_{SMB}	-0.02	0.04	0.02	-0.07	-0.01	0.02
	[-1.29]	[2.51]	[1.04]	[-4.53]	[-0.40]	[0.67]
β_{HML}	-0.00	-0.03	0.06	0.07	0.06	0.06
	[-0.02]	[-1.46]	[2.51]	[3.32]	[3.06]	[1.70]
β_{RMW}	0.12	-0.08	0.01	0.13	0.13	0.01
	[4.83]	[-4.11]	[0.60]	[6.37]	[6.56]	[0.30]
β_{CMA}	-0.06	-0.12	-0.14	0.19	0.20	0.26
	[-1.71]	[-3.91]	[-4.08]	[6.65]	[6.67]	[4.86]
β_{UMD}	-0.02	-0.02	-0.04	0.04	0.01	0.03
	[-1.73]	[-1.73]	[-3.48]	[3.58]	[0.94]	[1.71]
Panel C: Average number of firms (n) and market capitalization (me)						
n	733	696	593	686	750	
me ($\$10^6$)	1699	1407	2055	2241	2414	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the IACF 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 196606 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	0.32	0.33	0.27	0.23	0.20	0.18
			[4.05]	[4.12]	[3.42]	[2.93]	[2.54]	[2.26]
Quintile	NYSE	EW	0.54	0.62	0.53	0.44	0.38	0.32
			[7.42]	[9.06]	[8.54]	[7.29]	[6.40]	[5.50]
Quintile	Name	VW	0.31	0.32	0.27	0.25	0.22	0.21
			[4.01]	[4.07]	[3.43]	[3.20]	[2.74]	[2.66]
Quintile	Cap	VW	0.27	0.27	0.23	0.19	0.19	0.16
			[3.43]	[3.42]	[2.89]	[2.37]	[2.32]	[1.99]
Decile	NYSE	VW	0.35	0.34	0.28	0.23	0.25	0.21
			[3.46]	[3.36]	[2.78]	[2.21]	[2.45]	[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	0.28	0.30	0.24	0.22	0.18	0.18
			[3.60]	[3.70]	[3.10]	[2.86]	[2.36]	[2.26]
Quintile	NYSE	EW	0.34	0.41	0.33	0.28	0.16	0.15
			[4.29]	[5.48]	[4.81]	[4.25]	[2.54]	[2.26]
Quintile	Name	VW	0.28	0.29	0.24	0.24	0.20	0.20
			[3.55]	[3.67]	[3.12]	[3.02]	[2.56]	[2.56]
Quintile	Cap	VW	0.24	0.25	0.20	0.18	0.17	0.16
			[3.00]	[3.05]	[2.58]	[2.32]	[2.19]	[2.03]
Decile	NYSE	VW	0.31	0.30	0.25	0.22	0.23	0.21
			[3.07]	[2.98]	[2.47]	[2.17]	[2.24]	[2.06]

Table 3: Conditional sort on size and IACF

This table presents results for conditional double sorts on size and IACF. 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 IACF. 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 IACF and short stocks with low IACF .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196606 to 202306.

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

		IACF Quintiles					IACF Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.39	0.68	0.92	0.96	0.97	0.59	0.67	0.58	0.52	0.40	0.36
		[1.42]	[2.61]	[3.67]	[3.74]	[4.13]	[6.18]	[7.33]	[7.04]	[6.31]	[5.17]	[4.73]
	(2)	0.54	0.72	0.84	0.89	0.94	0.40	0.48	0.36	0.33	0.26	0.24
		[2.19]	[2.95]	[3.51]	[3.92]	[4.22]	[4.30]	[5.31]	[4.40]	[3.98]	[3.11]	[2.90]
	(3)	0.60	0.60	0.81	0.80	0.96	0.36	0.39	0.30	0.28	0.25	0.23
		[2.80]	[2.66]	[3.54]	[3.74]	[4.68]	[4.27]	[4.62]	[3.76]	[3.45]	[3.03]	[2.84]
	(4)	0.46	0.63	0.81	0.81	0.82	0.35	0.38	0.29	0.26	0.13	0.12
		[2.31]	[2.96]	[3.78]	[4.02]	[4.26]	[4.24]	[4.57]	[3.76]	[3.27]	[1.70]	[1.50]
	(5)	0.50	0.42	0.52	0.58	0.72	0.22	0.20	0.17	0.15	0.17	0.15
		[2.98]	[2.19]	[2.77]	[3.34]	[4.28]	[2.39]	[2.19]	[1.83]	[1.57]	[1.81]	[1.64]

Panel B: Portfolio average number of firms and market capitalization

		IACF Quintiles					IACF Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	380	380	380	378	379	31	34	38	28	29
	(2)	109	108	108	108	108	55	56	56	55	56
	(3)	79	78	78	78	78	95	95	96	98	98
	(4)	66	66	66	66	66	203	204	209	211	215
	(5)	61	60	60	60	60	1359	1443	1722	1583	1749

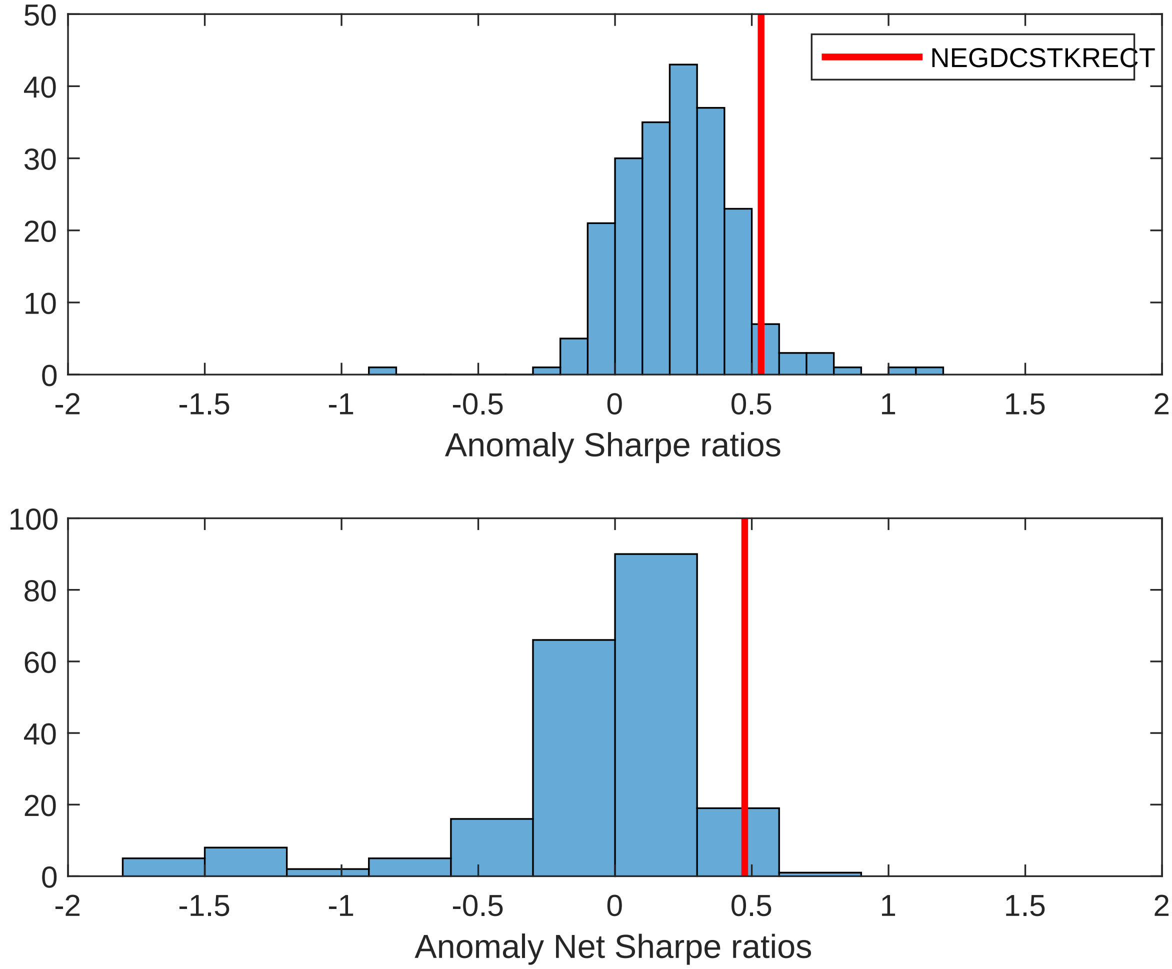


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the IACF with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

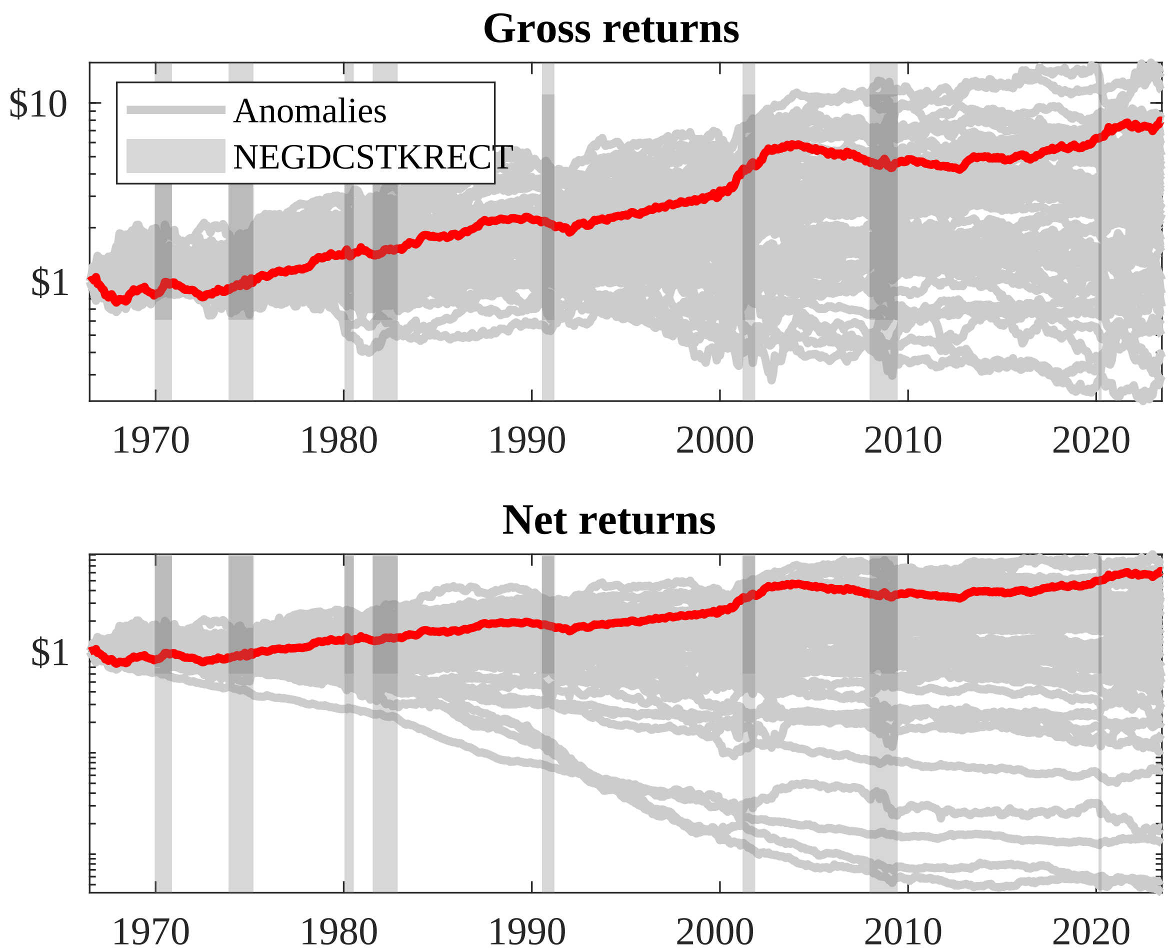


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the IACF trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

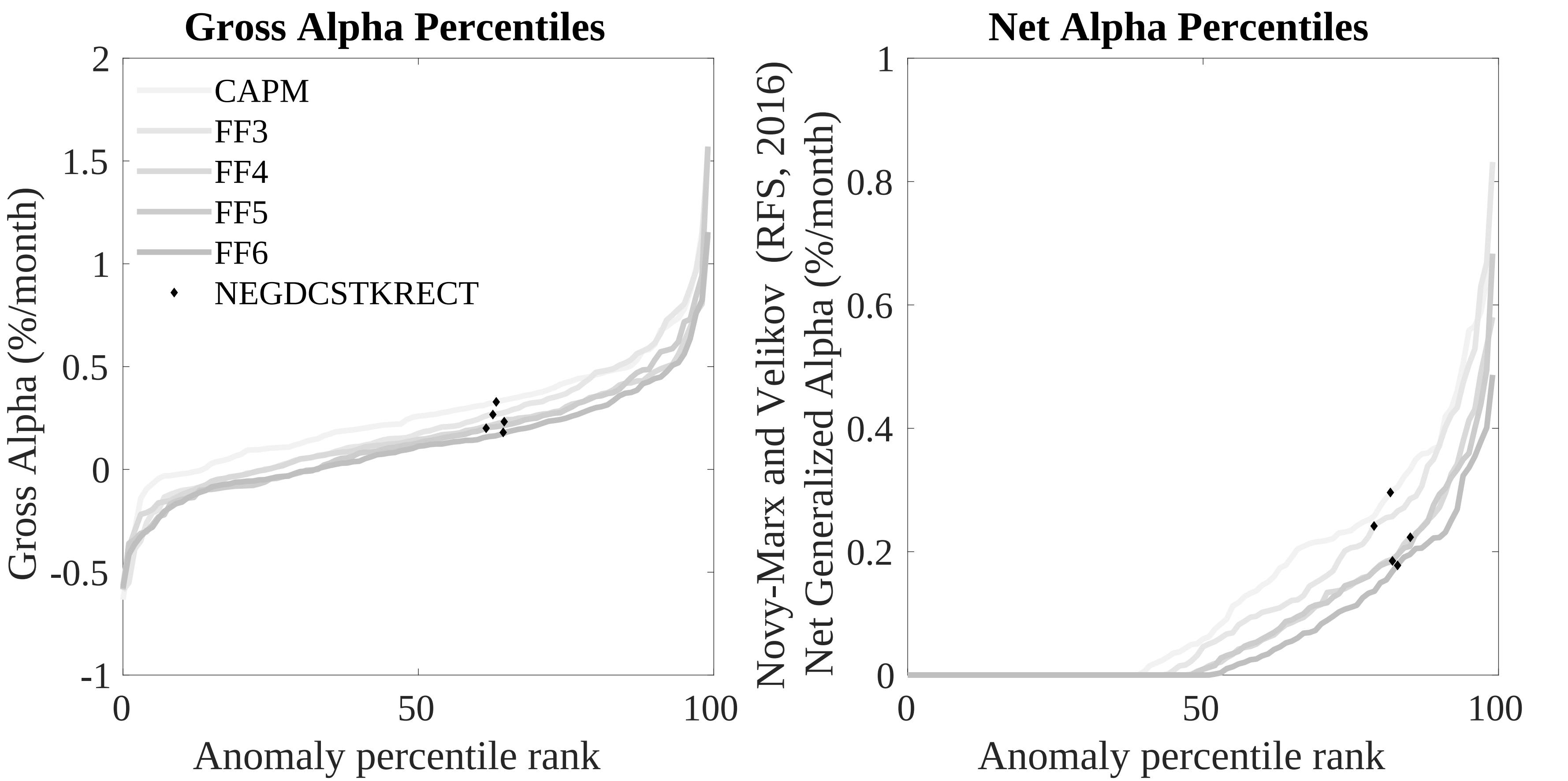
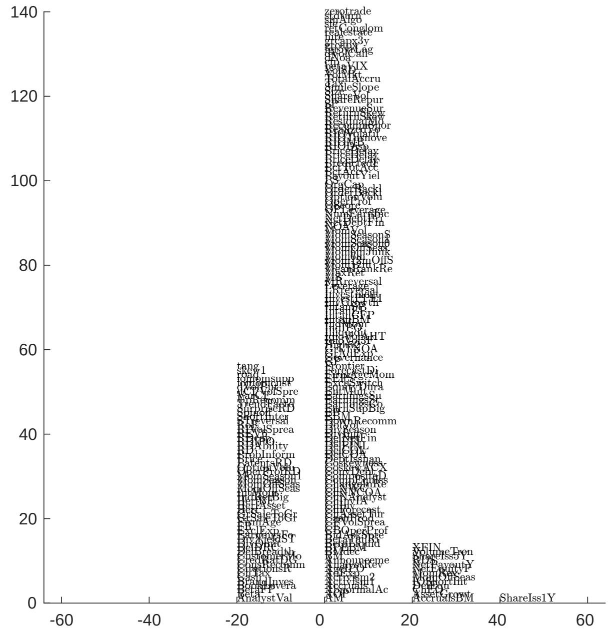
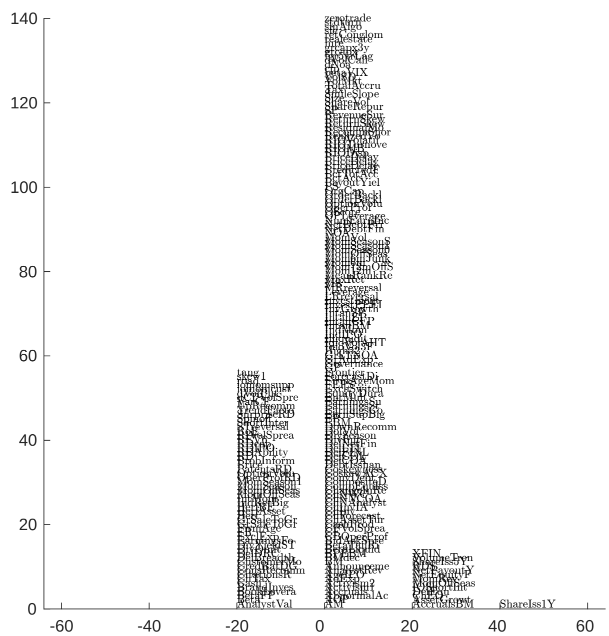


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the IACF trading strategy alphas (diamonds). The strategies are constructed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



Panel A: Pearson



Panel B: Spearman

Figure 5: Distribution of correlations.

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

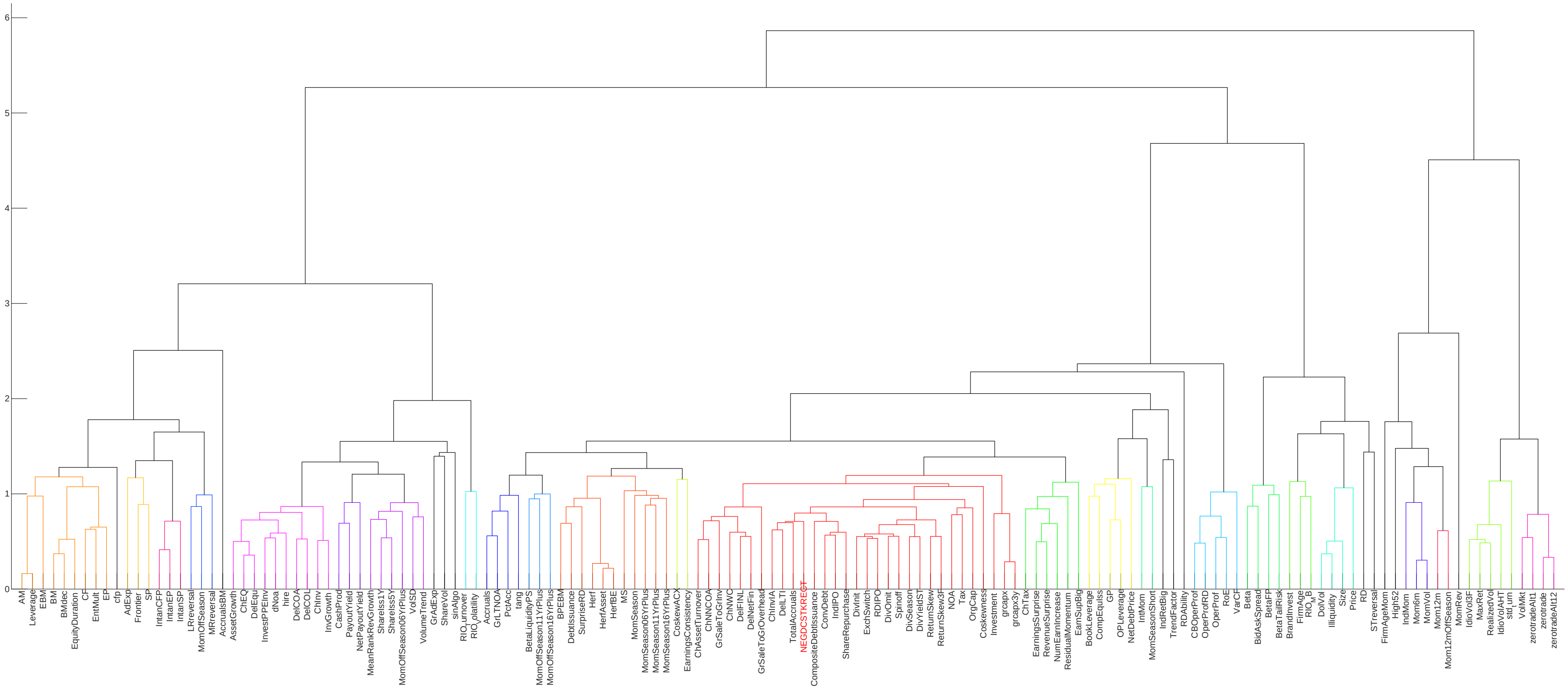


Figure 6: Agglomerative hierarchical cluster plot

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

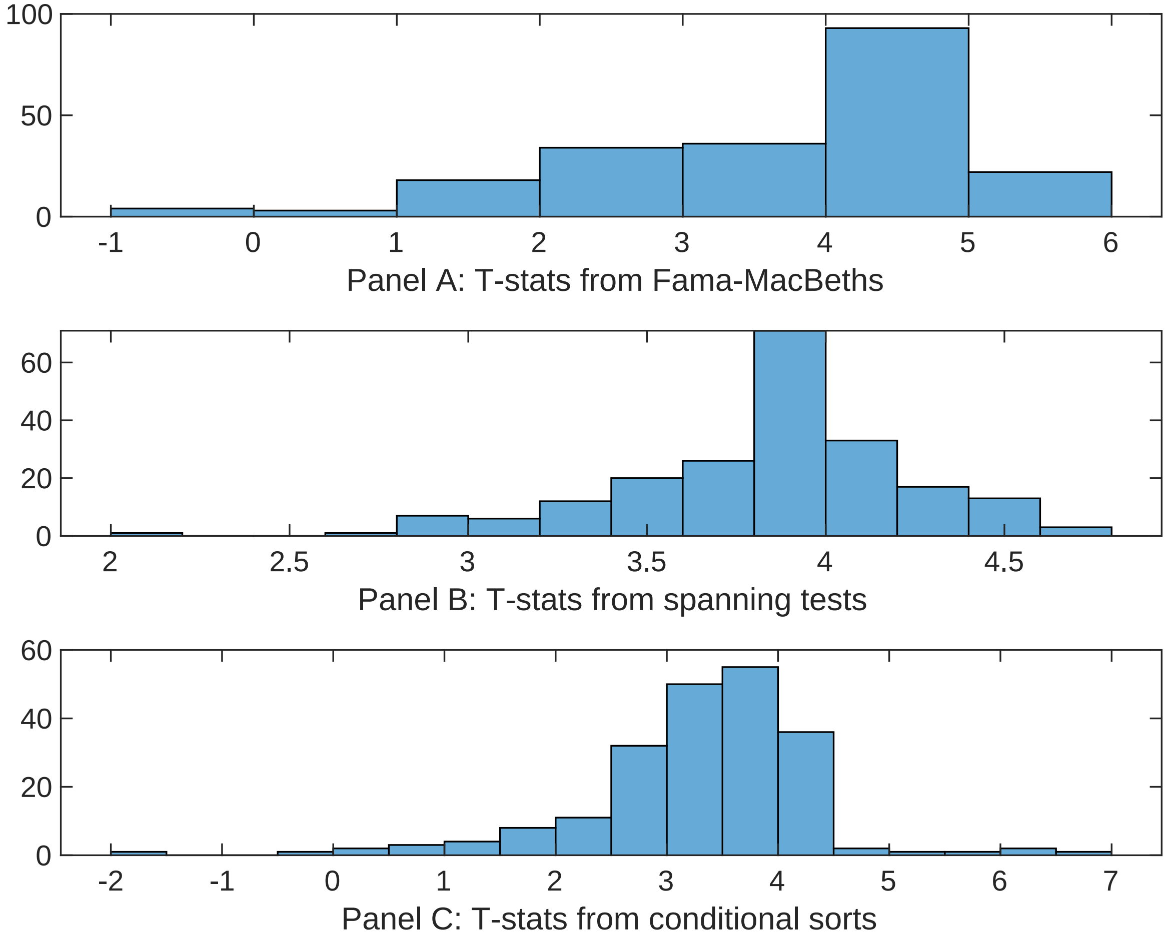


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of IACF conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{IACF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{IACF} IACF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{IACF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 IACF. Stocks are finally grouped into five IACF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted IACF 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 IACF. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{IACF} IACF_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to 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 196606 to 202306.

Intercept	0.13	0.18	0.12	0.13	0.13	0.14	0.12
	[5.71]	[7.48]	[5.24]	[6.06]	[5.65]	[6.11]	[5.15]
IACF	0.57	0.45	0.35	0.50	0.51	0.41	0.25
	[4.44]	[3.55]	[2.67]	[3.65]	[3.92]	[3.19]	[1.83]
Anomaly 1	0.25						0.85
	[5.53]						[2.02]
Anomaly 2		0.51					-0.12
		[4.80]					[-0.77]
Anomaly 3			0.30				0.23
			[3.01]				[2.28]
Anomaly 4				0.38			0.54
				[4.55]			[0.62]
Anomaly 5					0.16		0.17
					[4.55]		[0.30]
Anomaly 6						0.11	0.74
						[9.20]	[7.41]
# months	679	684	679	679	684	684	679
$\bar{R}^2$(%)	0	0	1	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 IACF trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{IACF} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to 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 196606 to 202306.

Intercept	0.16	0.18	0.18	0.15	0.20	0.19	0.15
	[2.04]	[2.33]	[2.28]	[1.93]	[2.55]	[2.33]	[1.98]
Anomaly 1	27.54						17.32
	[6.96]						[3.78]
Anomaly 2		35.06					32.45
		[8.25]					[5.23]
Anomaly 3			17.10				4.90
			[5.63]				[1.41]
Anomaly 4				15.60			1.43
				[3.78]			[0.33]
Anomaly 5					22.95		-3.59
					[5.53]		[-0.62]
Anomaly 6						6.15	-15.35
						[1.17]	[-2.80]
mkt	6.43	5.43	7.09	6.47	3.91	4.30	7.70
	[3.53]	[3.01]	[3.78]	[3.38]	[2.12]	[2.28]	[4.14]
smb	3.55	0.97	5.65	1.56	1.78	1.58	4.29
	[1.35]	[0.37]	[2.09]	[0.58]	[0.67]	[0.57]	[1.59]
hml	3.35	2.50	0.30	2.62	3.70	6.40	-0.64
	[0.94]	[0.71]	[0.08]	[0.69]	[1.03]	[1.76]	[-0.17]
rmw	-8.19	2.55	-8.77	-2.05	3.00	0.61	-6.30
	[-2.17]	[0.73]	[-2.20]	[-0.55]	[0.83]	[0.17]	[-1.52]
cma	12.67	-9.12	13.45	21.38	1.79	18.21	3.95
	[2.27]	[-1.38]	[2.32]	[3.87]	[0.26]	[2.19]	[0.49]
umd	2.98	2.83	4.75	3.44	3.90	3.37	2.47
	[1.66]	[1.58]	[2.60]	[1.87]	[2.12]	[1.79]	[1.38]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	17	17	15	13	13	9	22

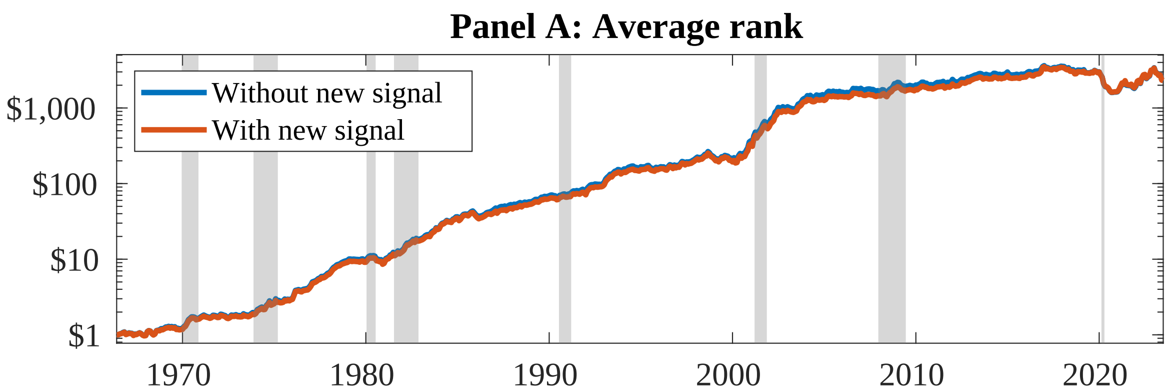


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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