Inventory Efficiency Operating Factor and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Inventory Efficiency Operating Factor (IEOF), 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 IEOF achieves an annualized gross (net) Sharpe ratio of 0.55 (0.48), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 25 (26) bps/month with a t-statistic of 2.87 (3.02), 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, Employment growth, Asset growth) is 15 bps/month with a t-statistic of 1.98.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, mounting evidence shows that certain accounting-based signals can predict future returns, challenging the notion of market efficiency (Fama and French, 2008). While researchers have identified numerous return predictors related to corporate investment and growth, the role of operational efficiency metrics remains relatively unexplored (Hou et al., 2020).

Inventory management represents a crucial aspect of operational efficiency that directly impacts firm profitability and value creation. Despite its importance in corporate operations, the asset pricing implications of inventory efficiency have received limited attention in the literature. This gap is particularly notable given that inventory management decisions reflect management's private information about future demand and operational capabilities (Thomas and Zhang, 2002).

We propose that inventory efficiency contains valuable information about future stock returns through several economic channels. First, efficient inventory management signals superior operational capabilities and management quality (Chen et al., 2005). Firms that optimize their inventory levels relative to sales demonstrate better working capital management and operational execution, which should translate into higher future profitability and returns.

Second, inventory efficiency may reflect management's private information about future demand conditions (Lev and Thiagarajan, 1993). Managers with positive private information about future growth opportunities are more likely to maintain lean inventory levels, while those anticipating weakening demand may struggle to optimize inventory. This informational advantage suggests that inventory efficiency metrics could predict future performance.

Third, the market may underreact to the implications of inventory efficiency for future profitability due to the complexity of analyzing operational metrics (Cohen and Frazzini, 2008). While sophisticated investors may understand the significance of inventory management, less sophisticated investors may overlook this signal, leading to predictable return patterns as information is gradually incorporated into prices.

Our analysis reveals that the Inventory Efficiency Operating Factor (IEOF) strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on IEOF quintiles generates a monthly alpha of 25 basis points (t-statistic = 2.87) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized Sharpe ratio of 0.55 before trading costs and 0.48 after accounting for transaction costs.

The predictive power of IEOF remains robust across various methodological specifications. The signal maintains significant predictability even among large-cap stocks, with the top size quintile generating a monthly alpha of 31 basis points (t-statistic = 2.65). This finding suggests that the IEOF effect is not merely a small-stock phenomenon.

Importantly, IEOF's predictive ability persists after controlling for related anomalies. When we control for the six most closely related predictors including inventory growth and asset growth, IEOF continues to generate a significant alpha of 15 basis points per month (t-statistic = 1.98). This indicates that IEOF captures unique information not contained in existing investment and growth-based factors.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures operational efficiency information not fully reflected in existing factors. While prior work has examined investment-based signals (Titman et al., 2004) and accrual anomalies (Sloan, 1996), IEOF provides unique insights into operational management quality.

Second, we extend the literature on the real effects of inventory management (Thomas and Zhang, 2002) by documenting its asset pricing implications. Our findings suggest that the stock market does not fully incorporate the information content of inventory efficiency metrics, despite their importance for firm performance. This adds to our understanding of market efficiency and information processing.

Third, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the value of examining detailed operational metrics rather than focusing solely on broad accounting measures. For practitioners, IEOF represents a robust signal that can enhance portfolio performance, even after accounting for transaction costs and controlling for standard factors.

2 Data

Our study investigates the predictive power of the Inventory Efficiency Operating Factor, a financial signal derived from accounting data for cross-sectional returns. 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 XSGA for selling, general, and administrative expenses. Inventory (INVT) represents the cost of goods and materials a company holds for sale or production, while XSGA captures the ongoing operational expenses associated with running the business, excluding direct production costs. The construction of the signal follows a difference-to-scale format, where we first calculate the year-over-year change in inventory (INVT minus lagged INVT) and then scale this difference by the previous year's selling, general, and administrative expenses (lagged XSGA). This scaled difference captures the relative change in inventory levels against the firm's operational cost base, providing insight into inventory management efficiency and operational performance. By scaling the inventory change by XSGA, the signal accounts for firm size and operational scope, making comparisons meaningful across different firms and time periods. 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 IEOF signal. Panel A plots the time-series of the mean, median, and interquartile range for IEOF. On average, the cross-sectional mean (median) IEOF is -0.19 (-0.03) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input IEOF data. The signal's interquartile range spans -0.50 to 0.17. Panel B of Figure 1 plots the time-series of the coverage of the IEOF signal for the CRSP universe. On average, the IEOF signal is available for 5.65% of CRSP names, which on average make up 6.49% of total market capitalization.

4 Does IEOF predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on IEOF 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 IEOF portfolio and sells the low IEOF 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 IEOF strategy earns an average return of 0.42% per month with a t-statistic of 4.18. The annualized Sharpe ratio of the strategy is 0.55. The alphas range from 0.25% to 0.50% per month and have t-statistics exceeding 2.87 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 0.68, with a t-statistic of 11.73 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 547 stocks and an average market capitalization of at least $1,066 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 30 bps/month with a t-statistics of 3.32. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty 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 26-53bps/month. The lowest return, (26 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.85. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the IEOF 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 IEOF strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and IEOF, as well as average returns and alphas for long/short trading IEOF 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 IEOF strategy achieves an average return of 31 bps/month with a t-statistic of 2.65. Among these large cap stocks, the alphas for the IEOF strategy relative to the five most common factor models range from 17 to 40 bps/month with t-statistics between 1.61 and 3.50.

5 How does IEOF perform relative to the zoo?

Figure 2 puts the performance of IEOF 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 IEOF strategy falls in the distribution. The IEOF strategy's gross (net) Sharpe ratio of 0.55 (0.48) 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 IEOF strategy (red line).[2] Ignoring trading costs, a $1 invested in the IEOF strategy would have yielded $13.93 which ranks the IEOF strategy in the top 0% across the 212 anomalies. Accounting for trading costs, a $1 invested in the IEOF strategy would have yielded $9.45 which ranks the IEOF strategy in the top 0% 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 IEOF relative to those. Panel A shows that the IEOF strategy gross alphas fall between the 75 and 86 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 IEOF strategy has a positive net generalized alpha for five out of the five factor models. In these cases IEOF ranks between the 90 and 92 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

6 Does IEOF 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 IEOF with 209 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 IEOF or at least to weaken the power IEOF has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of IEOF conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{IEOF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{IEOF} IEOF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{IEOF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on IEOF. Stocks are finally grouped into five IEOF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted

[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.

IEOF trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on IEOF 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 IEOF signal in these Fama-MacBeth regressions exceed 1.91, 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 IEOF is 1.35.

Similarly, Table 5 reports results from spanning tests that regress returns to the IEOF 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 IEOF strategy earns alphas that range from 15-30bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.88, 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 IEOF trading strategy achieves an alpha of 15bps/month with a t-statistic of 1.98.

7 Does IEOF add relative to the whole zoo?

Finally, we can ask how much adding IEOF 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 IEOF signal.[4] We consider

[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 capital-

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 IEOF grows to $2895.21.

8 Conclusion

This study provides compelling evidence for the significance of the Inventory Efficiency Operating Factor (IEOF) as a valuable predictor of stock returns. Our findings demonstrate that IEOF-based trading strategies yield economically and statistically significant results, with a notable annualized Sharpe ratio of 0.55 (0.48 net of transaction costs) and consistent abnormal returns relative to established factor models.

Particularly noteworthy is the signal's robustness when controlling for the Fama-French five-factor model plus momentum, generating significant monthly abnormal returns of 25 basis points (26 bps net). The persistence of alpha even after controlling for six closely related factors from the factor zoo underscores IEOF's unique informational content and its potential complementarity to existing investment strategies.

These results have important implications for both academic research and practical investment management. For practitioners, our findings suggest that incorporating IEOF into investment strategies could enhance portfolio performance through improved stock selection. For academics, this study contributes to the growing literature on factor investing and inventory management's role in asset pricing.

ization on CRSP in the period for which IEOF is available.

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, the study period may not capture all market conditions, particularly recent market disruptions.

Future research could explore several promising directions: (1) examining IEOF's performance in international markets, (2) investigating potential interactions with other established factors, (3) analyzing the signal's effectiveness across different market regimes, and (4) studying the underlying economic mechanisms driving the relationship between inventory efficiency and stock returns. Additionally, research into the signal's implementation costs and capacity constraints would be valuable for institutional investors considering its practical application.

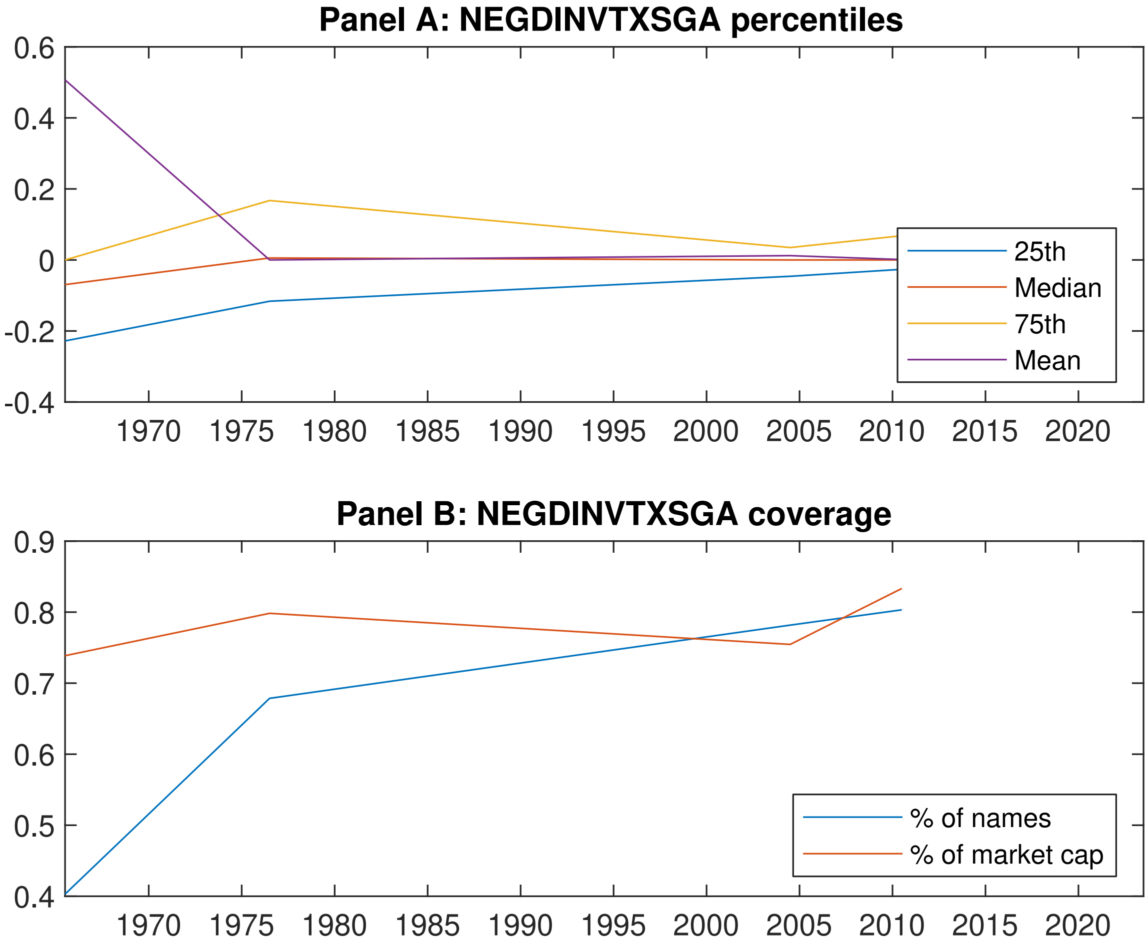

Figure 1: Times series of IEOF percentiles and coverage.
This figure plots descriptive statistics for IEOF. Panel A shows cross-sectional percentiles of IEOF over the sample. Panel B plots the monthly coverage of IEOF relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on IEOF. 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 IEOF-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.41	0.52	0.66	0.63	0.83	0.42
	[1.94]	[2.81]	[4.01]	[3.60]	[4.33]	[4.18]
α_{CAPM}	-0.25	-0.06	0.14	0.08	0.25	0.50
	[-3.62]	[-1.25]	[3.02]	[1.68]	[3.43]	[5.03]
α_{FF3}	-0.26	-0.03	0.18	0.10	0.15	0.40
	[-3.86]	[-0.61]	[3.89]	[2.21]	[2.24]	[4.24]
α_{FF4}	-0.19	0.01	0.17	0.10	0.12	0.31
	[-2.88]	[0.29]	[3.57]	[2.17]	[1.79]	[3.26]
α_{FF5}	-0.22	-0.03	0.07	0.14	0.09	0.31
	[-3.45]	[-0.60]	[1.61]	[2.89]	[1.40]	[3.57]
α_{FF6}	-0.17	0.01	0.07	0.13	0.08	0.25
	[-2.71]	[0.11]	[1.59]	[2.79]	[1.18]	[2.87]
Panel B: Fama and French (2018) 6-factor model loadings for IEOF-sorted portfolios						
β_{MKT}	1.09	1.01	0.96	0.99	1.08	-0.02
	[72.04]	[84.70]	[90.18]	[87.95]	[70.41]	[-0.88]
β_{SMB}	0.19	0.03	-0.06	-0.11	0.16	-0.04
	[8.76]	[1.94]	[-4.01]	[-6.81]	[7.08]	[-1.20]
β_{HML}	0.07	-0.07	-0.15	-0.01	0.06	-0.01
	[2.45]	[-2.97]	[-7.29]	[-0.36]	[1.99]	[-0.33]
β_{RMW}	0.11	0.09	0.19	-0.07	-0.07	-0.18
	[3.65]	[3.92]	[8.91]	[-3.19]	[-2.27]	[-4.37]
β_{CMA}	-0.29	-0.12	0.19	-0.05	0.39	0.68
	[-6.79]	[-3.45]	[6.34]	[-1.49]	[9.07]	[11.73]
β_{UMD}	-0.07	-0.05	-0.00	0.00	0.02	0.09
	[-4.66]	[-4.50]	[-0.01]	[0.38]	[1.30]	[4.40]
Panel C: Average number of firms (n) and market capitalization (me)						
n	594	547	595	651	612	
me ($\$10^6$)	1129	1949	2105	1729	1066	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the IEOF 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	0.42	0.50	0.40	0.31	0.31	0.25
			[4.18]	[5.03]	[4.24]	[3.26]	[3.57]	[2.87]
Quintile	NYSE	EW	0.53	0.58	0.52	0.45	0.51	0.46
			[7.78]	[8.54]	[7.89]	[6.89]	[8.40]	[7.65]
Quintile	Name	VW	0.42	0.49	0.38	0.28	0.31	0.24
			[4.29]	[5.09]	[4.19]	[3.13]	[3.66]	[2.87]
Quintile	Cap	VW	0.30	0.39	0.31	0.24	0.24	0.19
			[3.32]	[4.35]	[3.66]	[2.77]	[2.92]	[2.30]
Decile	NYSE	VW	0.59	0.64	0.52	0.41	0.49	0.41
			[4.98]	[5.42]	[4.59]	[3.62]	[4.44]	[3.71]
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	0.37	0.45	0.37	0.31	0.29	0.26
			[3.66]	[4.51]	[3.83]	[3.32]	[3.39]	[3.02]
Quintile	NYSE	EW	0.30	0.34	0.28	0.25	0.25	0.23
			[3.94]	[4.51]	[3.88]	[3.47]	[3.75]	[3.46]
Quintile	Name	VW	0.36	0.44	0.34	0.29	0.28	0.25
			[3.73]	[4.54]	[3.79]	[3.23]	[3.41]	[3.03]
Quintile	Cap	VW	0.26	0.35	0.28	0.24	0.22	0.19
			[2.85]	[3.88]	[3.28]	[2.81]	[2.76]	[2.43]
Decile	NYSE	VW	0.53	0.58	0.47	0.41	0.44	0.40
			[4.43]	[4.86]	[4.17]	[3.66]	[4.04]	[3.71]

Table 3: Conditional sort on size and IEOF

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

Size quintiles	IEOF Quintiles (L)	(2)	(3)	(4)	(H)	IEOF Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.52	0.82	0.78	0.85	1.02	0.50	0.53	0.49	0.36	0.45	0.36
	[2.00]	[3.34]	[3.12]	[3.44]	[3.77]	[4.28]	[4.58]	[4.18]	[3.08]	[3.98]	[3.14]
(2)	0.56	0.72	0.89	0.86	0.90	0.34	0.42	0.35	0.27	0.35	0.28
	[2.14]	[3.01]	[3.91]	[3.66]	[3.83]	[3.68]	[4.62]	[3.98]	[3.04]	[3.97]	[3.24]
(3)	0.57	0.78	0.81	0.87	0.84	0.28	0.34	0.26	0.23	0.29	0.27
	[2.27]	[3.50]	[3.87]	[4.02]	[3.65]	[2.89]	[3.59]	[2.81]	[2.40]	[3.21]	[2.89]
(4)	0.56	0.80	0.71	0.73	0.79	0.23	0.28	0.21	0.19	0.14	0.13
	[2.39]	[3.75]	[3.56]	[3.47]	[3.64]	[2.52]	[3.13]	[2.38]	[2.15]	[1.55]	[1.48]
(5)	0.41	0.56	0.56	0.59	0.72	0.31	0.40	0.33	0.25	0.22	0.17
	[1.97]	[3.14]	[3.39]	[3.28]	[4.06]	[2.65]	[3.50]	[2.86]	[2.14]	[2.08]	[1.61]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	IEOF Quintiles, Average n (L)	(2)	(3)	(4)	(H)	IEOF Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	347	346	341	342	340	31	29	28	27	26
(2)	94	94	93	93	93	47	48	47	47	48
(3)	65	65	65	65	64	80	80	80	80	79
(4)	52	52	52	52	52	165	166	163	162	163
(5)	47	47	47	47	46	965	1351	1526	1280	1259

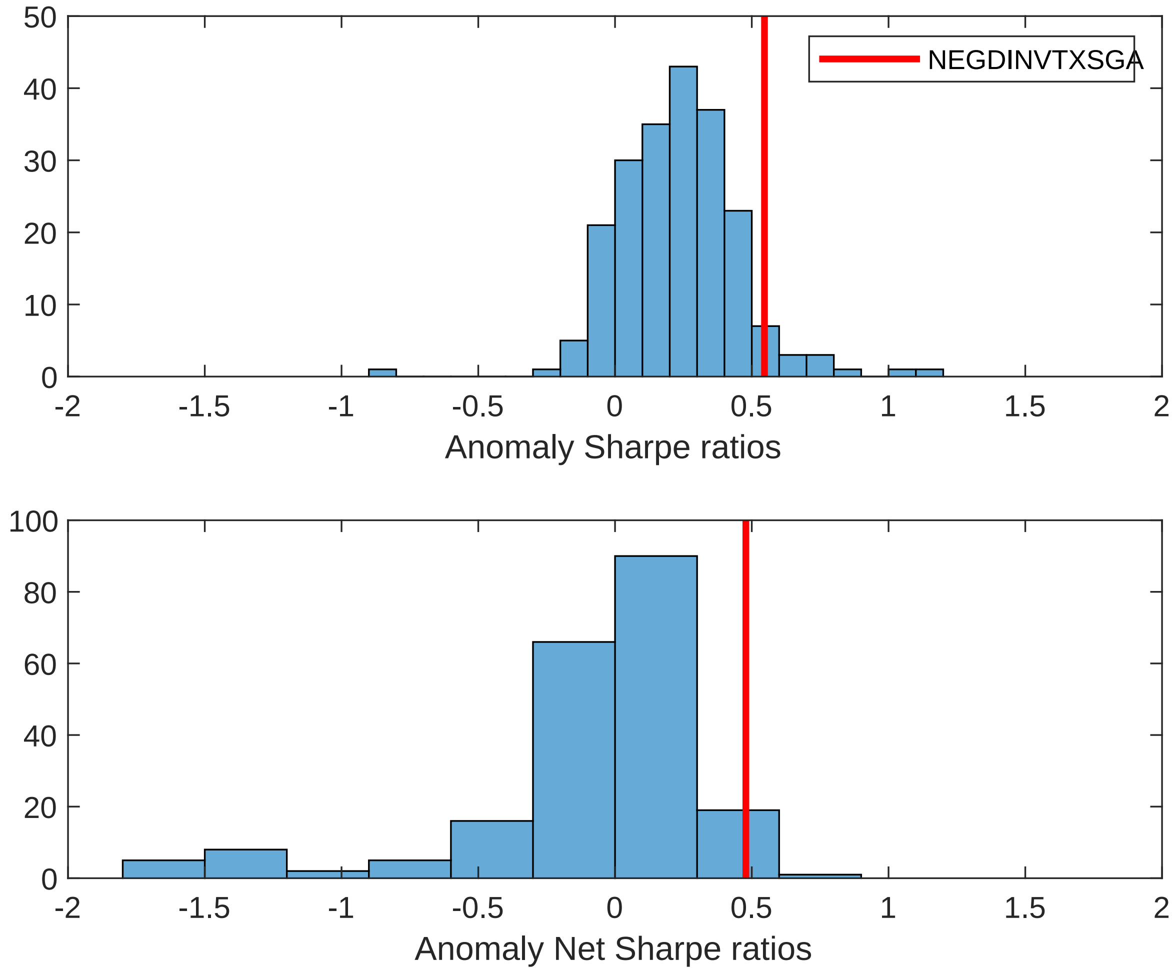

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the IEOF with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

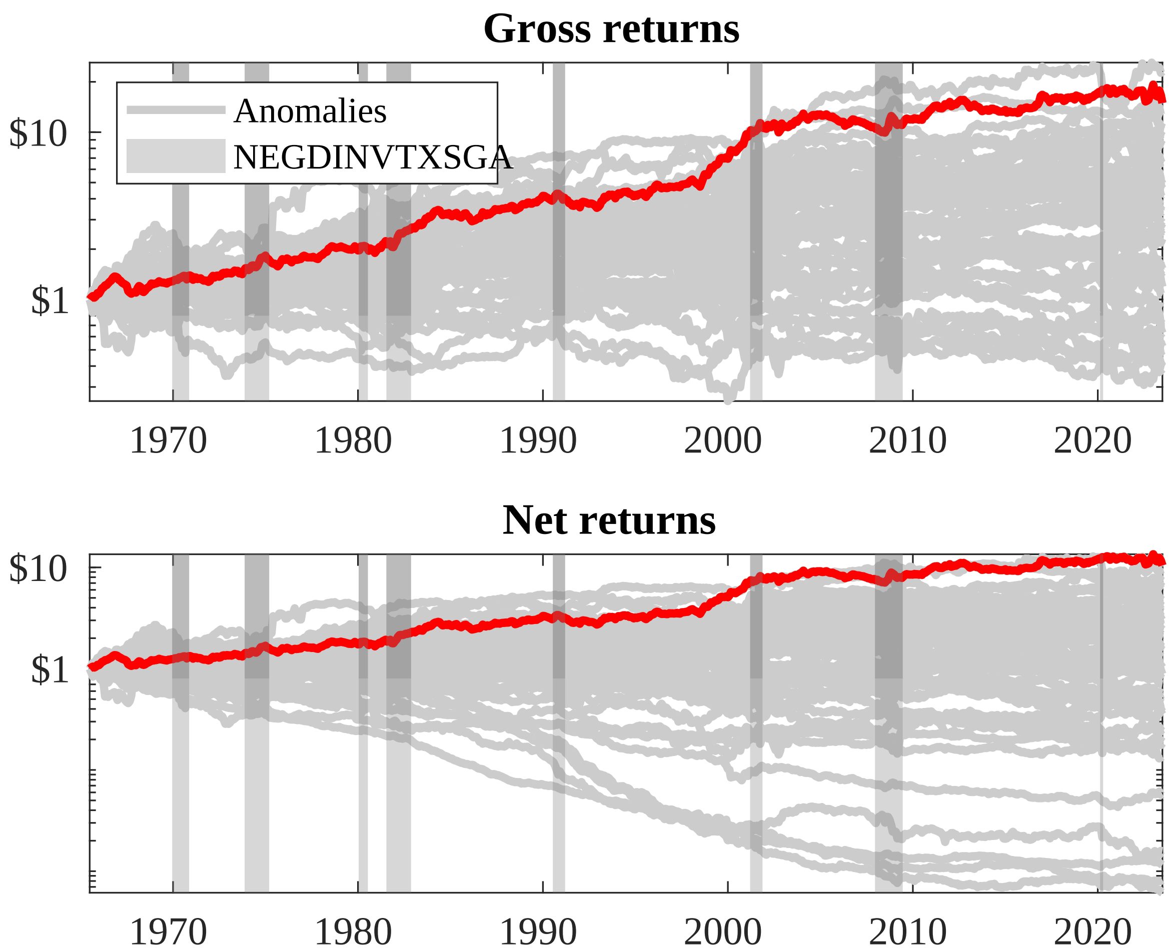

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the IEOF trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

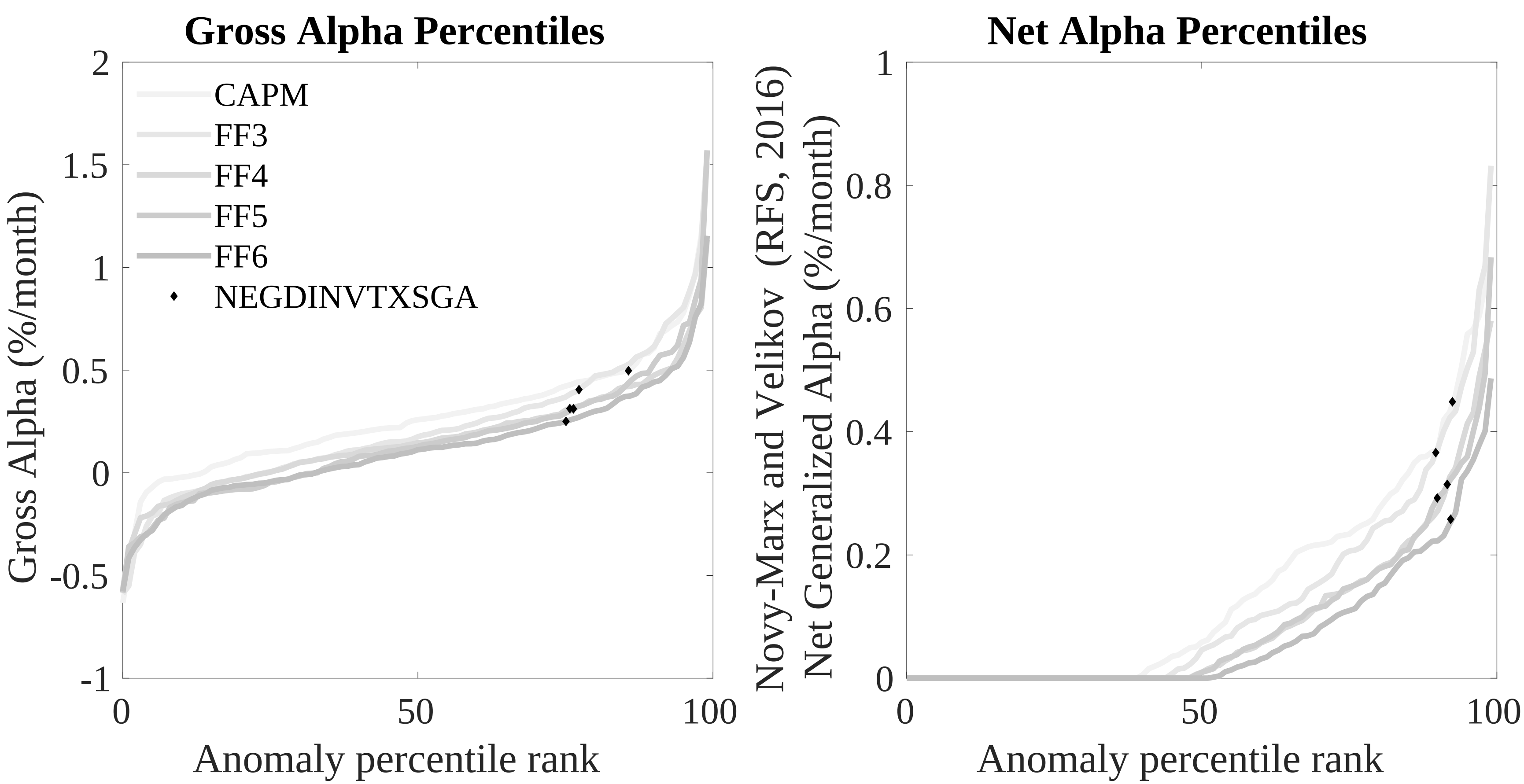

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the IEOF trading strategy alphas (diamonds). The strategies are constructed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

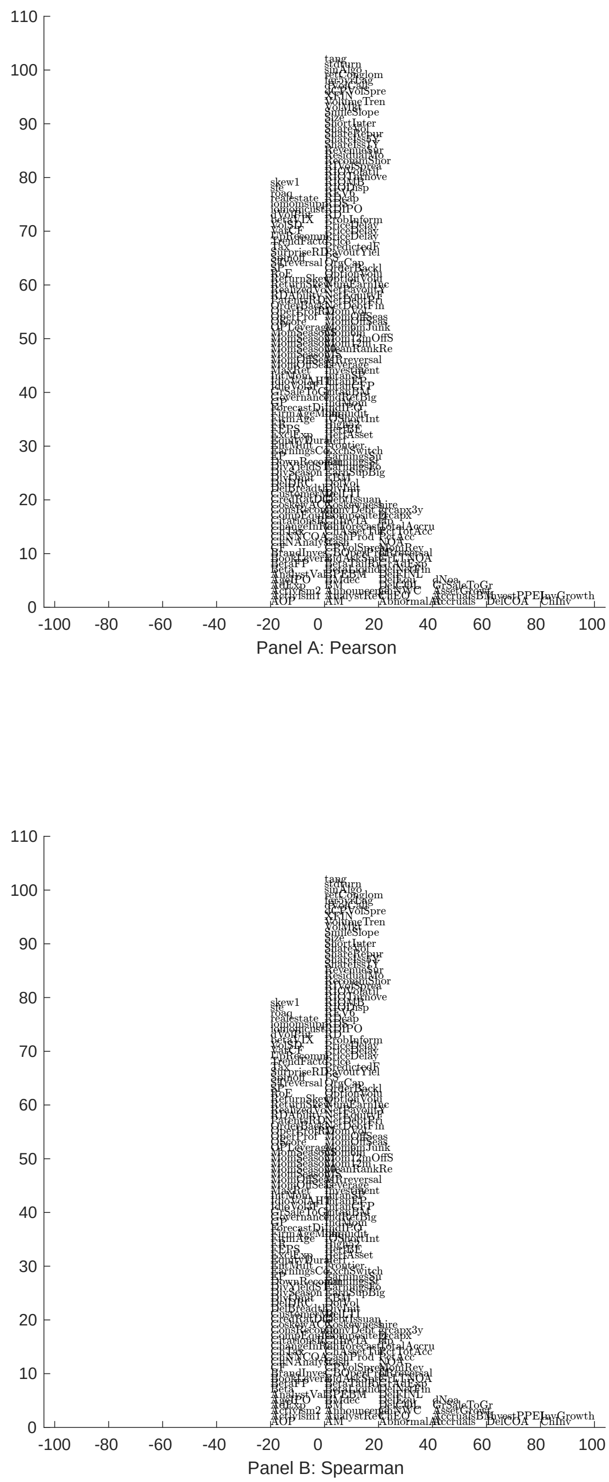

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with IEOF. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

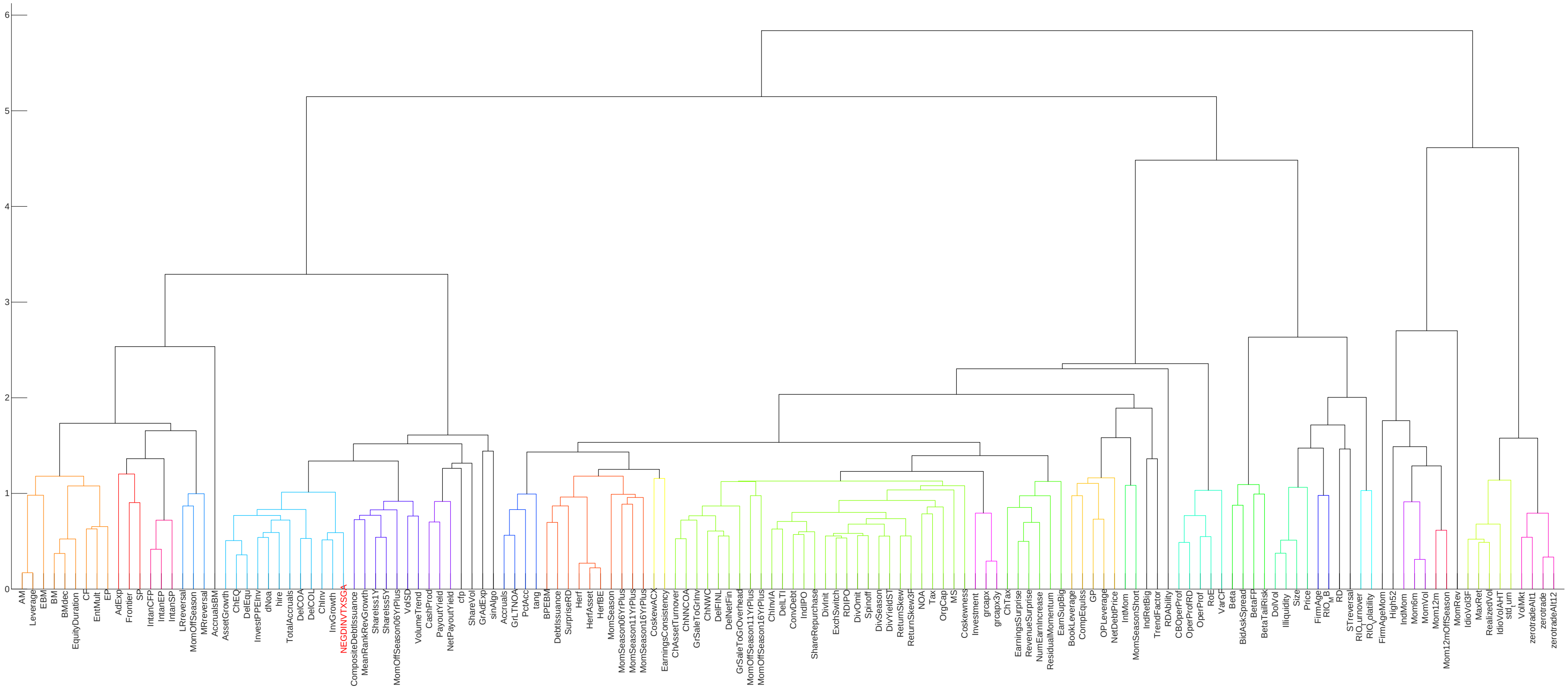

Figure 6: Agglomerative hierarchical cluster plot

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

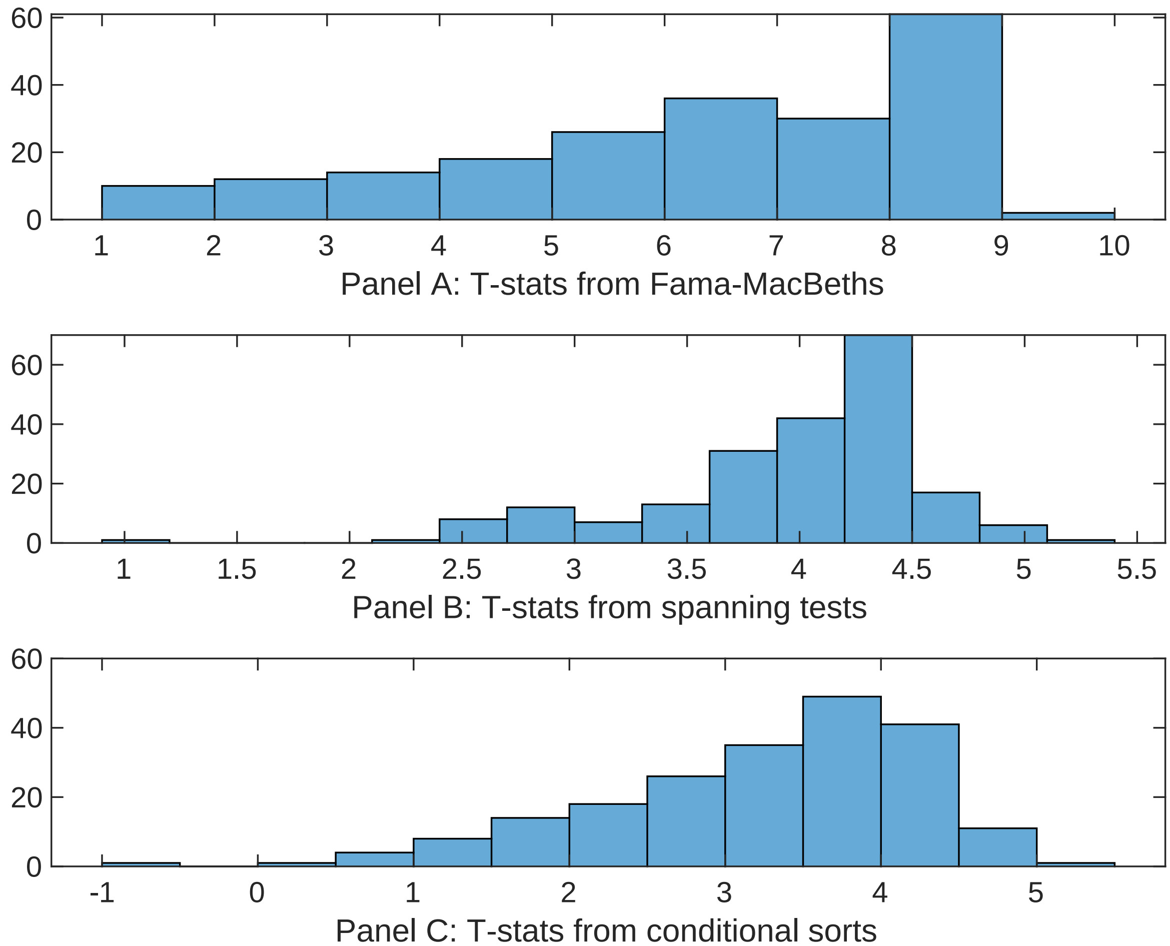

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of IEOF conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{IEOF} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{IEOF} IEOF_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{IEOF,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on IEOF. Stocks are finally grouped into five IEOF portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted IEOF trading strategies conditioned on each of the 209 filtered anomalies.

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

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

Intercept	0.13	0.13	0.14	0.13	0.13	0.14	0.14
	[5.59]	[5.54]	[5.83]	[5.65]	[5.59]	[6.03]	[5.93]
IEOF	0.23	0.23	0.10	0.24	0.29	0.17	0.93
	[4.17]	[3.69]	[1.91]	[5.06]	[6.27]	[3.72]	[1.35]
Anomaly 1	0.25						0.21
	[4.03]						[0.23]
Anomaly 2		0.42					-0.18
		[6.45]					[-0.24]
Anomaly 3			0.16				0.53
			[7.64]				[1.75]
Anomaly 4				0.19			0.40
				[5.92]			[1.14]
Anomaly 5					0.81		-0.12
					[5.56]		[-0.86]
Anomaly 6						0.10	0.69
						[8.33]	[4.79]
# 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 IEOF trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{IEOF} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Employment growth, 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 196506 to 202306.

Intercept	0.15	0.25	0.25	0.26	0.30	0.25	0.15
	[1.88]	[3.25]	[2.91]	[3.06]	[3.41]	[2.93]	[1.98]
Anomaly 1	54.63						33.79
	[14.05]						[7.07]
Anomaly 2		45.39					32.17
		[14.91]					[8.51]
Anomaly 3			24.42				7.78
			[6.05]				[2.04]
Anomaly 4				21.93			-2.75
				[5.18]			[-0.66]
Anomaly 5					16.34		-8.28
					[3.48]		[-1.85]
Anomaly 6						10.16	-10.89
						[1.78]	[-2.08]
mkt	-0.39	-2.86	-2.34	-1.98	-1.56	-1.70	-1.99
	[-0.21]	[-1.60]	[-1.16]	[-0.98]	[-0.77]	[-0.83]	[-1.15]
smb	3.98	0.76	-3.53	1.57	-2.00	-3.77	3.75
	[1.49]	[0.29]	[-1.22]	[0.52]	[-0.67]	[-1.25]	[1.40]
hml	-4.71	-3.76	-3.71	-9.42	-3.98	-1.45	-3.09
	[-1.35]	[-1.09]	[-0.96]	[-2.24]	[-0.99]	[-0.37]	[-0.85]
rmw	-7.93	-12.19	-17.61	-14.88	-17.44	-17.93	-8.13
	[-2.19]	[-3.47]	[-4.49]	[-3.73]	[-4.38]	[-4.47]	[-2.36]
cma	32.85	31.63	49.85	56.42	54.22	56.20	36.39
	[5.73]	[5.61]	[7.71]	[9.13]	[7.64]	[6.20]	[4.63]
umd	5.47	4.02	8.72	9.75	7.89	9.18	3.23
	[3.03]	[2.24]	[4.40]	[4.86]	[3.89]	[4.49]	[1.81]
# months	696	696	696	696	696	696	696
$\bar{R}^2$(%)	48	50	37	36	35	34	54

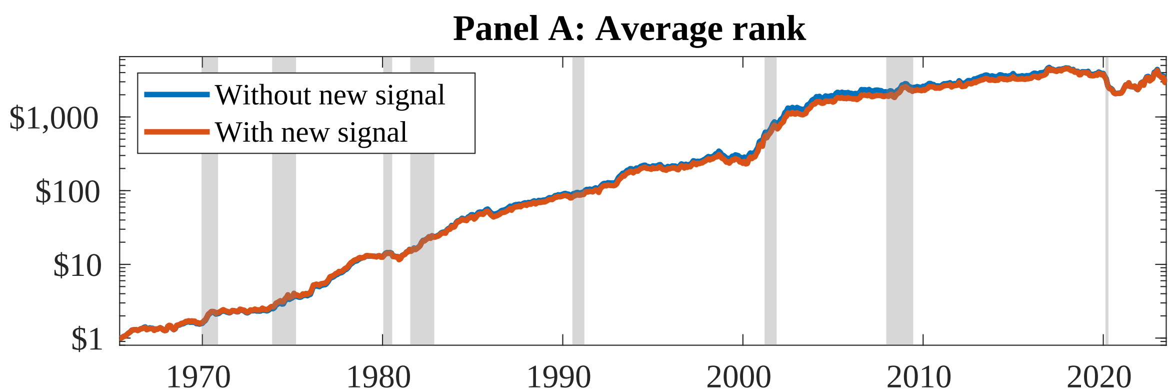

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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