Operating Efficiency Margin and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Operating Efficiency Margin (OEM), 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 OEM achieves an annualized gross (net) Sharpe ratio of 0.40 (0.39), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 54 (50) bps/month with a t-statistic of 4.45 (4.24), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (gross profits / total assets, Operating leverage, Total assets to market, Book to market using December ME, Market leverage, Cash Productivity) is 22 bps/month with a t-statistic of 2.37.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Harvey et al., 2016). While hundreds of return predictors have been documented, many fail to survive transaction costs or more rigorous statistical tests (Hou et al., 2020). This raises fundamental questions about which signals truly predict returns and through what economic mechanisms they operate.

Operating efficiency - how effectively firms convert inputs into outputs - represents a fundamental aspect of firm performance that may not be fully incorporated into stock prices. While accounting research has long studied operating efficiency metrics (Banker et al., 2011), their asset pricing implications remain underexplored. This gap is particularly notable given that operating efficiency directly impacts profitability and cash flows, which theory suggests should determine fundamental value.

We hypothesize that Operating Efficiency Margin (OEM) predicts stock returns through three potential channels. First, following (Zhang, 2005), firms with higher operating efficiency may be better positioned to scale operations in response to positive demand shocks, making them more valuable in equilibrium. The flexibility and adaptability reflected in superior operating efficiency represents a real option that should command a premium.

Second, building on (Novy-Marx, 2013), operating efficiency may serve as a cleaner signal of economic profitability compared to accounting-based measures. While standard profitability metrics can be distorted by one-time items and accounting choices, operating efficiency focuses on core business activities and may better capture sustainable competitive advantages (?).

Third, behavioral models suggest that investors may underreact to signals that require processing complex operating information (Hirshleifer and Teoh, 2003). Operating efficiency metrics typically require analyzing multiple financial statement items and understanding business processes. This complexity could lead to systematic underpricing of firms with superior operating efficiency until the value is gradually recognized.

Our analysis reveals that OEM strongly predicts stock returns in a manner robust to common risk adjustments. A value-weighted long-short portfolio formed on OEM generates monthly alphas of 54 basis points (t-statistic = 4.45) relative to the Fama-French six-factor model. The strategy achieves an annualized Sharpe ratio of 0.40, placing it in the 83rd percentile of documented anomalies.

Importantly, the predictive power of OEM persists among large, liquid stocks and survives transaction costs. Among stocks above the 80th percentile of market capitalization, the strategy earns monthly alphas of 37 basis points (t-statistic = 2.46). After accounting for trading frictions using the high-frequency spread estimates of (Chen and Velikov, 2022), the net Sharpe ratio remains an impressive 0.39.

The signal's robustness extends to controlling for related anomalies. When we simultaneously control for the six most closely related predictors - including gross profitability and operating leverage - OEM continues to generate significant abnormal returns of 22 basis points per month (t-statistic = 2.37). This indicates that OEM captures unique information about future returns not contained in known predictors.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures a fundamental aspect of firm performance and demonstrates robust predictive power for returns. Unlike many recently proposed signals that lack clear economic mechanisms, OEM has intuitive links to firm value through operational capabilities and competitive advantage.

Second, we extend the literature on profitability and operating performance anomalies (Novy-Marx, 2013; Ball et al., 2015). While prior work focuses primarily on accounting-based measures, we show that examining operational metrics provides incremental insights into the cross-section of returns. Our findings suggest that markets do not fully price the information contained in firms' operating efficiency.

Third, our results have implications for both academic research and investment practice. For researchers, we demonstrate the importance of examining granular operating metrics rather than focusing solely on summary accounting measures. For practitioners, we document a robust return predictor that remains profitable after transaction costs and works well among large, liquid stocks. The signal's effectiveness in combining with other anomalies also suggests valuable applications for quantitative portfolio management.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Operating Efficiency Margin, constructed as the ratio of invested capital to selling, general, and administrative expenses. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item ICAPT for invested capital and item XSGA for selling, general, and administrative expenses. Invested capital (ICAPT) represents the total investment in the company by shareholders and debtholders, including working capital, fixed assets, and other operating assets. Selling, general, and administrative expenses (XSGA) encompass all commercial expenses of operation, including marketing, overhead, and other non-production costs. The construction of the signal follows a straightforward ratio format, where we divide ICAPT by XSGA for each firm in each year of our sample. This ratio captures the capital intensity of a firm's operations relative to its overhead costs, offering insight into how efficiently the firm deploys capital in relation to its operational expenses. By focusing on this relationship, the signal aims to reflect aspects of operational efficiency and resource utilization in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both ICAPT and XSGA to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the OEM signal. Panel A plots the time-series of the mean, median, and interquartile range for OEM. On average, the cross-sectional mean (median) OEM is -6.61 (-3.21) over the 1964 to 2023 sample, where the starting date is determined by the availability of the input OEM data. The signal's interquartile range spans -9.15 to -1.30. Panel B of Figure 1 plots the time-series of the coverage of the OEM signal for the CRSP universe. On average, the OEM signal is available for 6.06% of CRSP names, which on average make up 6.61% of total market capitalization.

4 Does OEM predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on OEM 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 OEM portfolio and sells the low OEM 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 OEM strategy earns an average return of 0.41% per month with a t-statistic of 3.12. The annualized

Sharpe ratio of the strategy is 0.40. The alphas range from 0.44% to 0.64% per month and have t-statistics exceeding 3.34 everywhere. The lowest alpha is with respect to the CAPM 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 -0.56, with a t-statistic of -10.16 on the HML 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 506 stocks and an average market capitalization of at least $1,156 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 35 bps/month with a t-statistics of 2.62. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-three 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 24-51bps/month. The lowest return, (24 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 1.72. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the OEM 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 OEM strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and OEM, as well as average returns and alphas for long/short trading OEM 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 OEM strategy achieves an average return of 37 bps/month with a t-statistic of 2.46. Among these large cap stocks, the alphas for the OEM strategy relative to the five most common factor models range from 42 to 64 bps/month with t-statistics between 2.75 and 4.57.

5 How does OEM perform relative to the zoo?

Figure 2 puts the performance of OEM 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 OEM strategy falls in the distribution. The OEM strategy's gross (net) Sharpe ratio of 0.40 (0.39) is greater than 83% (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 OEM strategy (red line).[2] Ignoring trading costs, a $1 invested in the OEM strategy would have yielded $10.37 which ranks the OEM strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the OEM strategy would have yielded $9.32 which ranks the OEM 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 OEM relative to those. Panel A shows that the OEM strategy gross alphas fall between the 77 and 95 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 196406 to 202306 sample. For example, 45%

[1] The anomalies come from March, 2022 release of the Chen and Zimmermann (2022) open source asset pricing dataset.

[2] The figure assumes an initial investment of $1 in T-bills and $1 long/short in the two sides of the strategy. Returns are compounded each month, assuming, as in Detzel et al. (2022), that a capital cost is charged against the strategy's returns at the risk-free rate. This excess return corresponds more closely to the strategy's economic profitability.

(53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The OEM strategy has a positive net generalized alpha for five out of the five factor models. In these cases OEM ranks between the 92 and 99 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on OEM 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 OEM signal in these Fama-MacBeth regressions exceed 0.37, with the minimum t-statistic occurring when controlling for gross profits / total assets. Controlling for all six closely related anomalies, the t-statistic on OEM is 0.94.

Similarly, Table 5 reports results from spanning tests that regress returns to the OEM 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 OEM strategy earns alphas that range from 28-51bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.81, which is achieved when controlling for gross profits / total assets. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the OEM trading strategy achieves an alpha of 22bps/month with a t-statistic of 2.37.

7 Does OEM add relative to the whole zoo?

Finally, we can ask how much adding OEM 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 OEM 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 $3137.77, while $1 investment in the combination strategy that includes OEM grows to $3566.97.

[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 OEM is available.

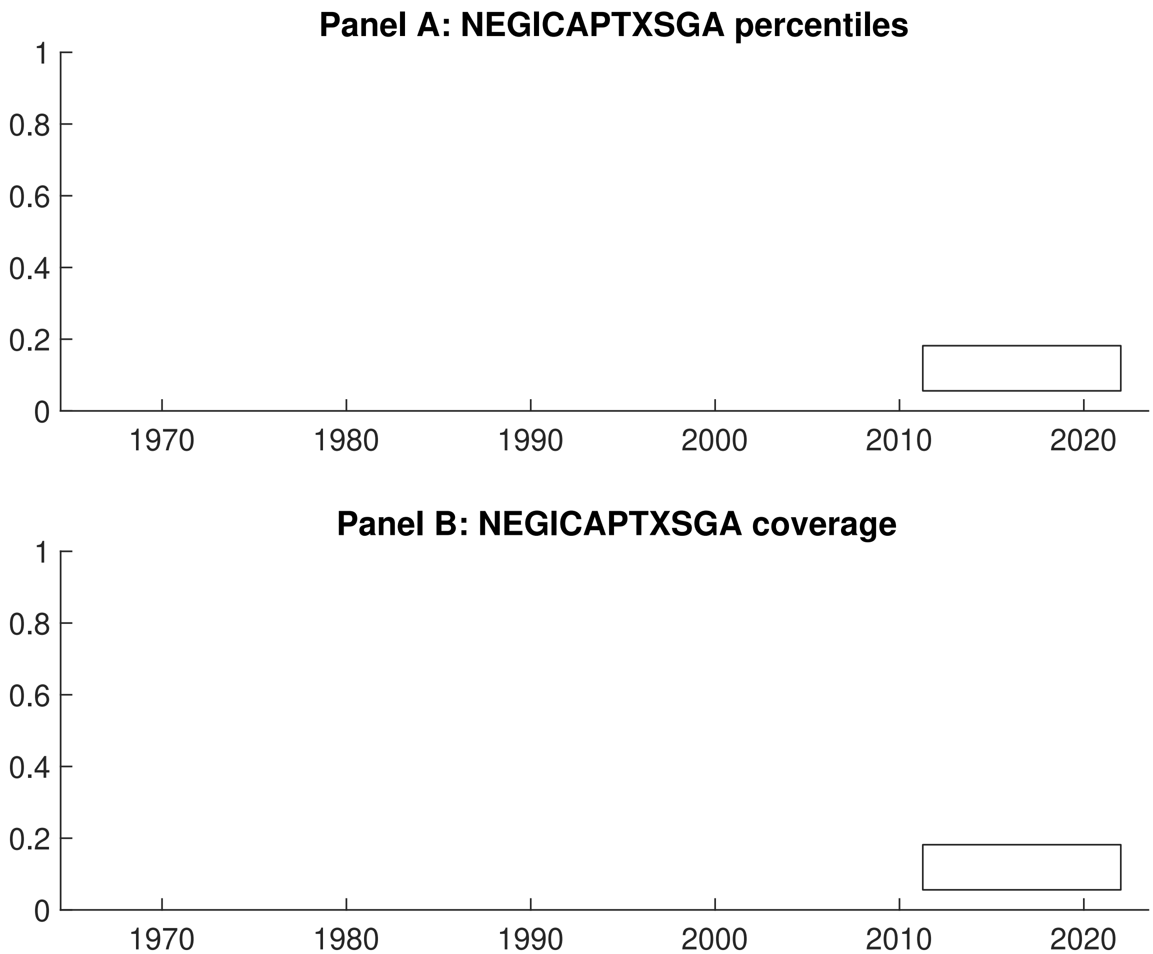


Figure 1: Times series of OEM percentiles and coverage.
This figure plots descriptive statistics for OEM. Panel A shows cross-sectional percentiles of OEM over the sample. Panel B plots the monthly coverage of OEM relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on OEM. 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 196406 to 202306.

Panel A: Excess returns and alphas on OEM-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.32	0.50	0.68	0.61	0.73	0.41
	[1.67]	[2.80]	[3.54]	[3.35]	[4.15]	[3.12]
α_{CAPM}	-0.25	-0.06	0.08	0.05	0.19	0.44
	[-2.96]	[-1.02]	[1.32]	[0.74]	[2.98]	[3.34]
α_{FF3}	-0.37	-0.15	0.14	0.13	0.27	0.64
	[-4.83]	[-3.16]	[2.44]	[2.29]	[4.55]	[5.45]
α_{FF4}	-0.36	-0.12	0.19	0.13	0.25	0.61
	[-4.65]	[-2.47]	[3.34]	[2.22]	[4.18]	[5.13]
α_{FF5}	-0.36	-0.17	0.17	0.12	0.19	0.55
	[-4.65]	[-3.43]	[2.98]	[2.04]	[3.19]	[4.64]
α_{FF6}	-0.36	-0.14	0.22	0.11	0.18	0.54
	[-4.51]	[-2.86]	[3.68]	[1.98]	[3.00]	[4.45]
Panel B: Fama and French (2018) 6-factor model loadings for OEM-sorted portfolios						
β_{MKT}	1.08	1.04	1.02	0.98	0.96	-0.12
	[57.31]	[87.25]	[73.22]	[71.59]	[67.46]	[-4.27]
β_{SMB}	-0.03	0.00	0.06	0.03	0.04	0.07
	[-1.09]	[0.08]	[3.16]	[1.59]	[2.14]	[1.78]
β_{HML}	0.32	0.25	-0.20	-0.19	-0.24	-0.56
	[8.83]	[10.93]	[-7.55]	[-7.40]	[-8.77]	[-10.16]
β_{RMW}	-0.04	0.05	-0.05	0.10	0.22	0.26
	[-1.20]	[2.23]	[-1.83]	[3.78]	[7.81]	[4.66]
β_{CMA}	0.05	0.02	-0.03	-0.11	0.02	-0.03
	[0.98]	[0.61]	[-0.82]	[-2.82]	[0.56]	[-0.37]
β_{UMD}	-0.01	-0.04	-0.06	0.00	0.01	0.02
	[-0.51]	[-3.58]	[-4.47]	[0.18]	[0.97]	[0.81]
Panel C: Average number of firms (n) and market capitalization (me)						
n	506	594	613	667	883	
me ($\$10^6$)	1156	1574	1815	2029	1527	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the OEM 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 196406 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	0.41	0.44	0.64	0.61	0.55	0.54
			[3.12]	[3.34]	[5.45]	[5.13]	[4.64]	[4.45]
Quintile	NYSE	EW	0.37	0.30	0.42	0.50	0.59	0.65
			[2.65]	[2.12]	[3.52]	[4.19]	[5.03]	[5.51]
Quintile	Name	VW	0.43	0.45	0.65	0.61	0.57	0.54
			[3.15]	[3.27]	[5.41]	[4.96]	[4.66]	[4.36]
Quintile	Cap	VW	0.35	0.38	0.58	0.54	0.48	0.45
			[2.62]	[2.84]	[4.90]	[4.46]	[4.00]	[3.73]
Decile	NYSE	VW	0.53	0.55	0.76	0.76	0.73	0.73
			[3.10]	[3.18]	[4.72]	[4.64]	[4.41]	[4.37]

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	0.40	0.42	0.59	0.58	0.51	0.50
			[3.02]	[3.19]	[5.06]	[4.93]	[4.34]	[4.24]
Quintile	NYSE	EW	0.24	0.19	0.29	0.34	0.41	0.44
			[1.72]	[1.32]	[2.38]	[2.82]	[3.40]	[3.69]
Quintile	Name	VW	0.41	0.44	0.61	0.59	0.53	0.51
			[3.05]	[3.17]	[5.06]	[4.84]	[4.37]	[4.21]
Quintile	Cap	VW	0.33	0.36	0.53	0.51	0.44	0.42
			[2.52]	[2.70]	[4.50]	[4.29]	[3.69]	[3.53]
Decile	NYSE	VW	0.51	0.53	0.71	0.71	0.68	0.67
			[2.98]	[3.07]	[4.43]	[4.42]	[4.12]	[4.09]

Table 3: Conditional sort on size and OEM

This table presents results for conditional double sorts on size and OEM. 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 OEM. 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 OEM and short stocks with low OEM .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196406 to 202306.

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

		OEM Quintiles					OEM Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.50	0.70	0.83	0.90	0.76	0.26	0.11	0.24	0.27	0.50	0.51
		[2.24]	[2.97]	[3.23]	[3.33]	[2.52]	[1.42]	[0.59]	[1.49]	[1.65]	[3.19]	[3.21]
	(2)	0.64	0.75	0.75	0.79	0.85	0.21	0.15	0.30	0.34	0.37	0.40
		[2.70]	[3.29]	[3.14]	[3.22]	[3.34]	[1.49]	[1.08]	[2.42]	[2.67]	[2.93]	[3.12]
	(3)	0.67	0.67	0.72	0.85	0.86	0.19	0.17	0.33	0.38	0.37	0.40
		[2.90]	[3.04]	[3.27]	[3.66]	[3.74]	[1.36]	[1.25]	[2.54]	[2.87]	[2.76]	[3.01]
	(4)	0.52	0.59	0.72	0.78	0.90	0.39	0.41	0.57	0.58	0.59	0.61
		[2.30]	[2.75]	[3.36]	[3.62]	[4.26]	[2.72]	[2.88]	[4.30]	[4.35]	[4.38]	[4.43]
	(5)	0.31	0.49	0.65	0.57	0.68	0.37	0.42	0.64	0.61	0.54	0.52
		[1.58]	[2.74]	[3.40]	[3.23]	[3.95]	[2.46]	[2.75]	[4.57]	[4.30]	[3.81]	[3.65]

Panel B: Portfolio average number of firms and market capitalization

		OEM Quintiles Average n					OEM Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	382	385	384	381	369	35	34	33	29	23
	(2)	101	102	102	102	101	51	52	51	50	51
	(3)	69	69	69	69	69	84	85	84	85	85
	(4)	54	54	54	54	54	169	169	169	173	172
	(5)	47	47	48	47	48	962	1277	1622	1314	1244

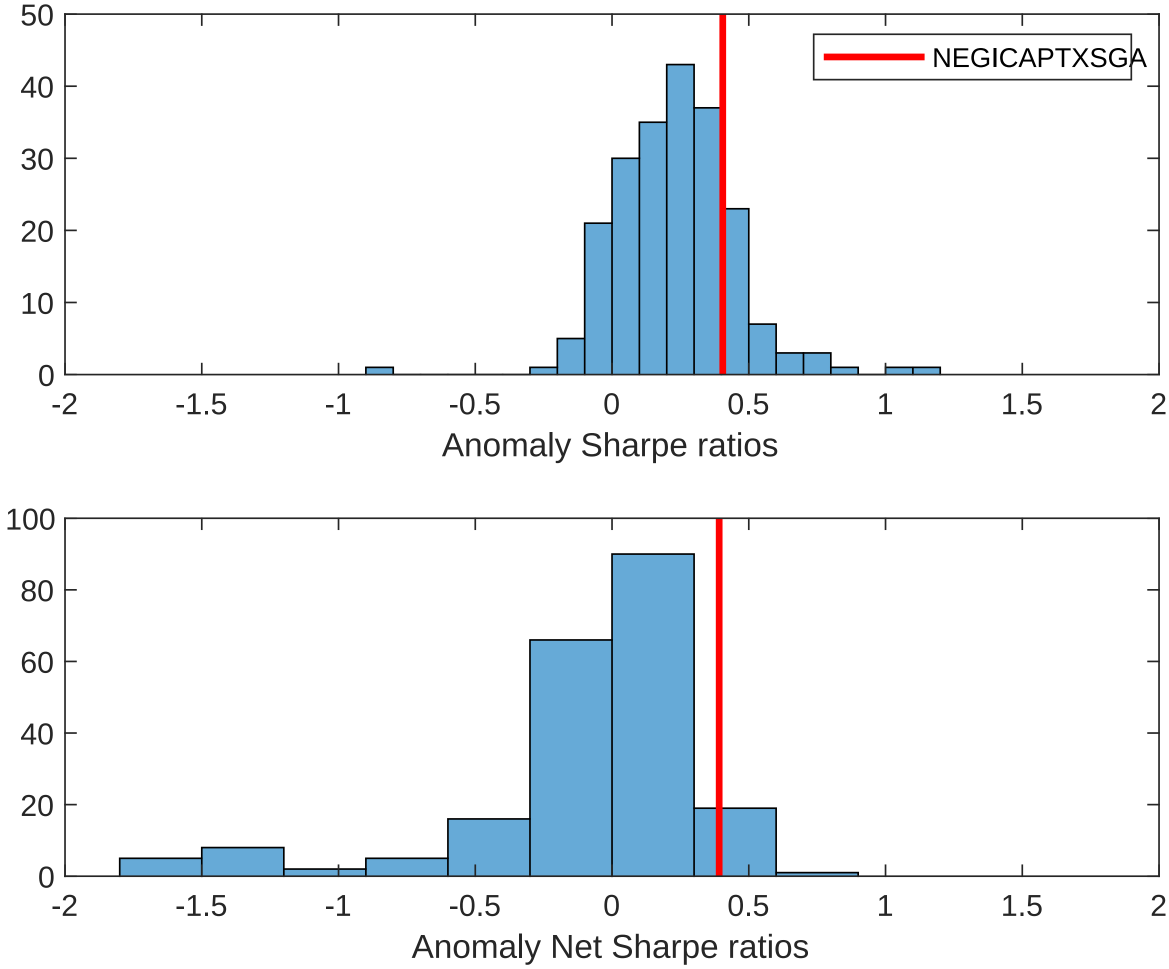


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the OEM with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

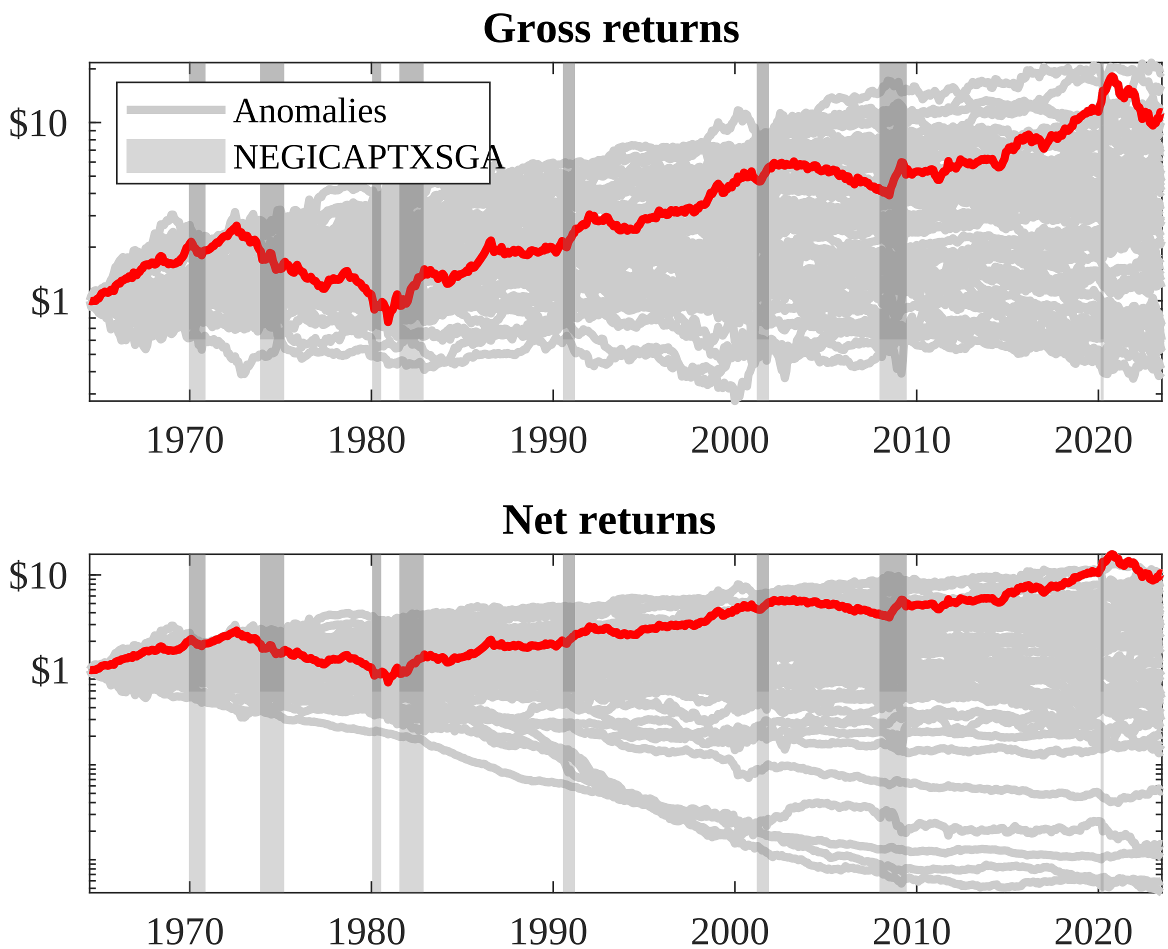


Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the OEM trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

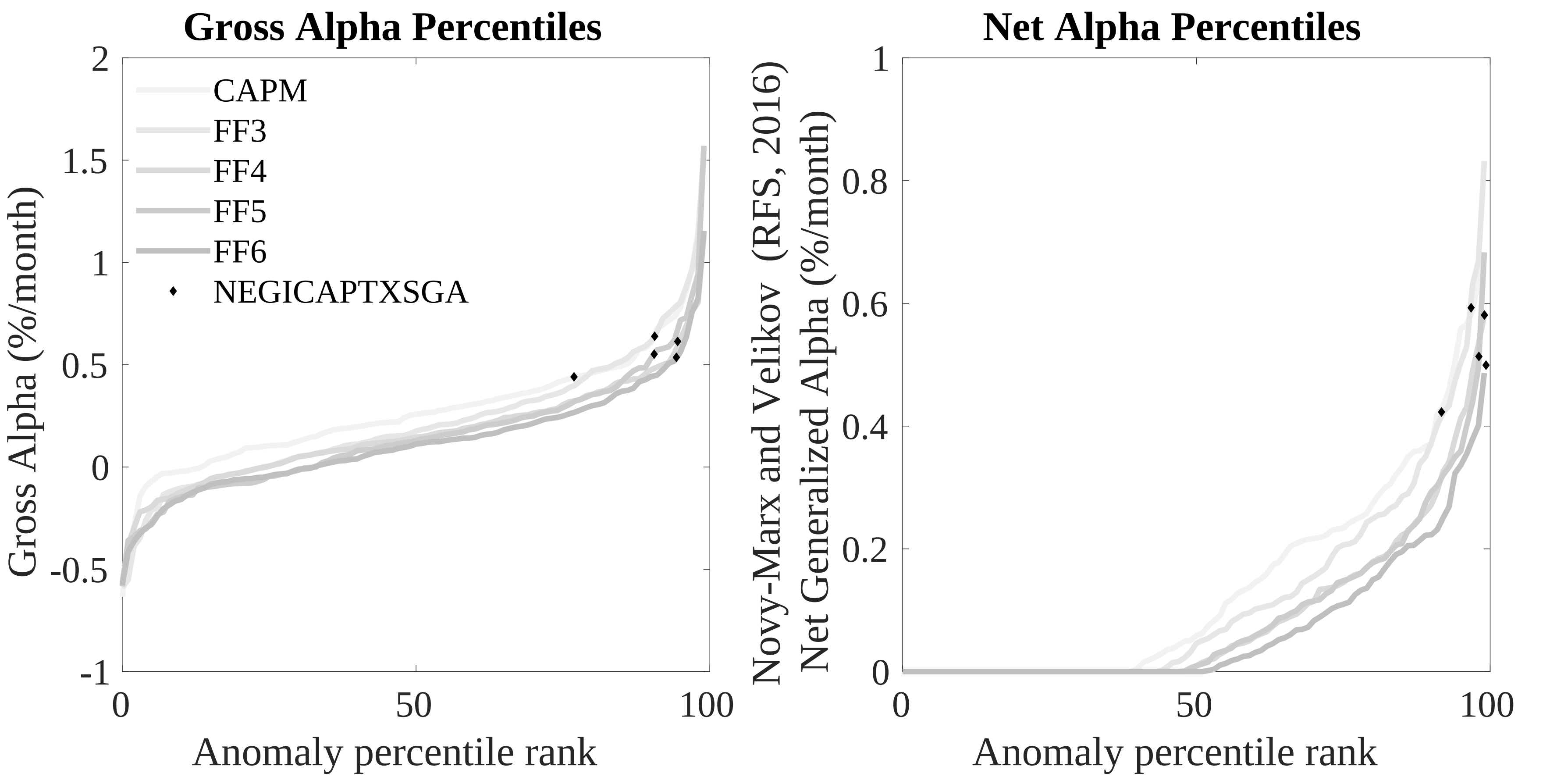
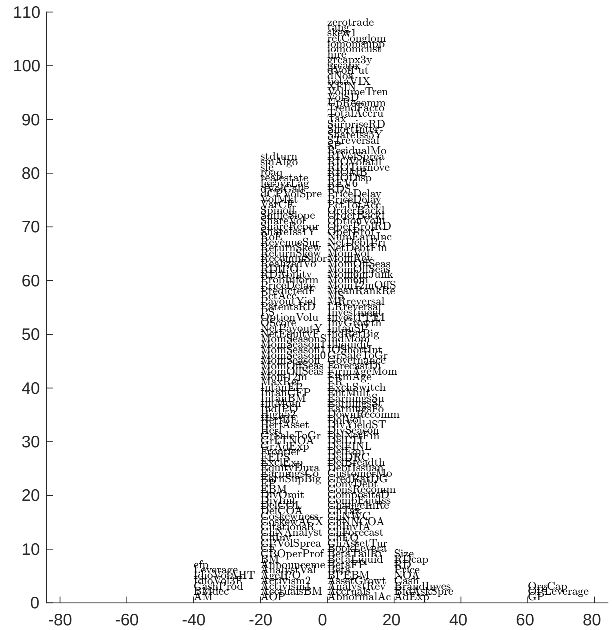


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the OEM trading strategy alphas (diamonds). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. The alphas include those with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). The left panel plots alphas with no adjustment for trading costs. The right panel plots Novy-Marx and Velikov (2016) net generalized alphas.



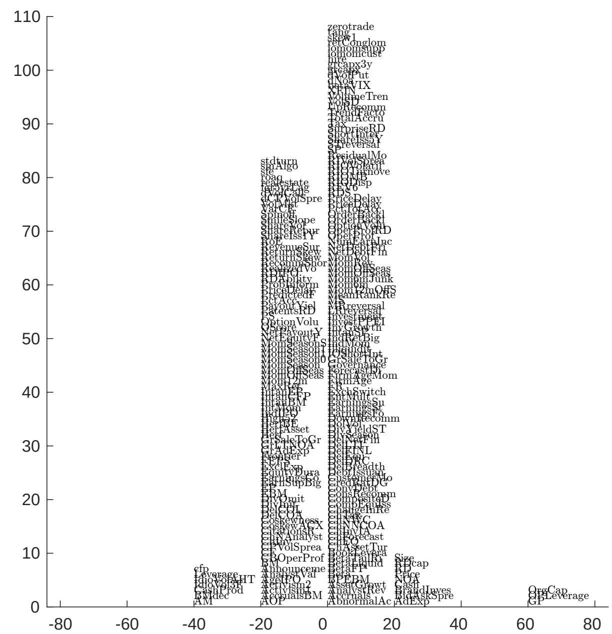


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with OEM. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

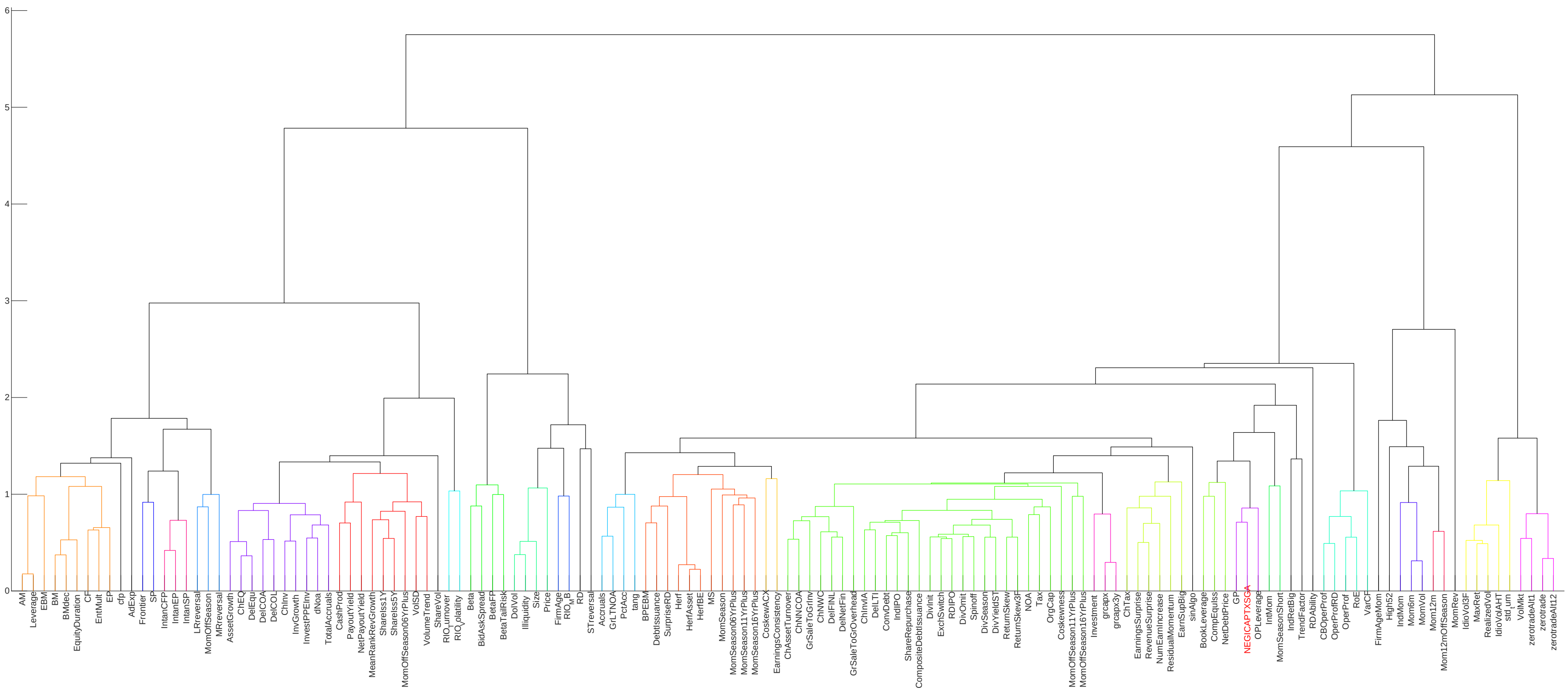


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

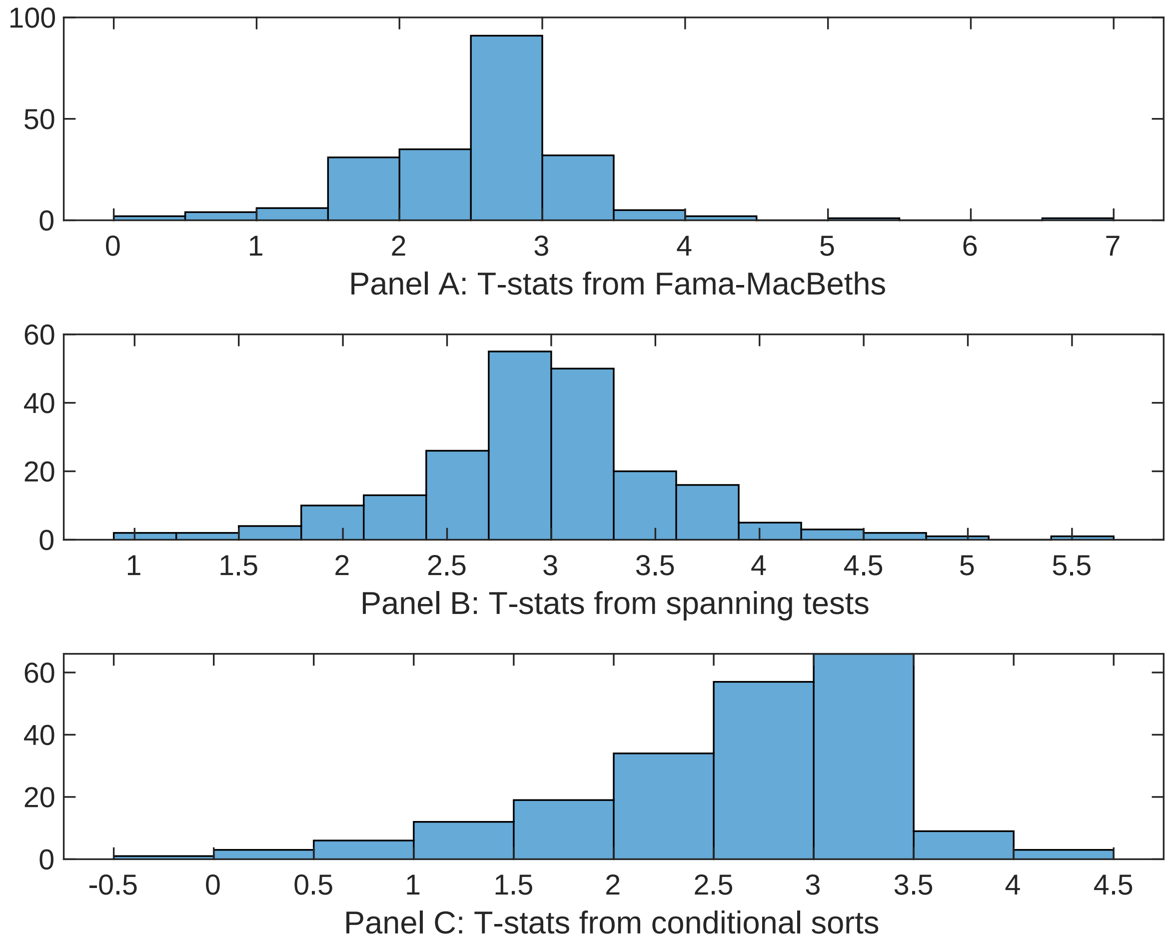


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of OEM conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{OEM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{OEM} OEM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{OEM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 OEM. Stocks are finally grouped into five OEM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted OEM 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 OEM. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{OEM} OEM_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are gross profits / total assets, Operating leverage, Total assets to market, Book to market using December ME, Market leverage, Cash Productivity. 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 196406 to 202306.

Intercept	0.84	0.11	0.11	0.99	0.12	0.12	0.49
	[2.88]	[4.60]	[4.82]	[4.09]	[5.01]	[5.23]	[1.75]
OEM	0.21	0.79	0.15	0.17	0.14	0.14	0.49
	[0.37]	[1.75]	[3.05]	[3.50]	[2.85]	[2.80]	[0.94]
Anomaly 1	0.91						0.11
	[5.67]						[7.03]
Anomaly 2		0.13					-0.29
		[3.52]					[-0.77]
Anomaly 3			0.49				0.23
			[3.34]				[2.69]
Anomaly 4				0.37			0.16
				[5.78]			[1.38]
Anomaly 5					0.51		-0.22
					[2.91]		[-2.32]
Anomaly 6						0.21	-0.25
						[2.07]	[-0.34]
# months	708	708	703	703	703	703	703
$\bar{R}^2(\%)$	1	0	1	1	1	1	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the OEM trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{OEM} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 gross profits / total assets, Operating leverage, Total assets to market, Book to market using December ME, Market leverage, Cash Productivity. 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 196406 to 202306.

Intercept	0.28	0.46	0.51	0.46	0.51	0.51	0.22
	[2.81]	[4.02]	[4.19]	[3.90]	[4.16]	[4.23]	[2.37]
Anomaly 1	76.76						79.59
	[19.18]						[15.84]
Anomaly 2		42.63					21.21
		[9.35]					[4.64]
Anomaly 3			-1.81				-12.80
			[-0.35]				[-0.85]
Anomaly 4				-55.53			-25.66
				[-7.40]			[-3.95]
Anomaly 5					-6.14		22.22
					[-1.22]		[1.52]
Anomaly 6						-13.11	38.97
						[-2.18]	[7.08]
mkt	-13.53	-12.20	-12.15	-11.41	-11.54	-13.67	-10.18
	[-5.81]	[-4.50]	[-4.08]	[-4.10]	[-3.88]	[-4.66]	[-4.24]
smb	2.27	-11.41	8.15	26.77	8.58	8.69	-2.09
	[0.67]	[-2.58]	[1.93]	[5.63]	[2.04]	[2.08]	[-0.48]
hml	-23.57	-34.36	-54.36	0.10	-49.59	-46.78	-24.80
	[-4.93]	[-6.01]	[-6.68]	[0.01]	[-6.28]	[-6.60]	[-2.88]
rmw	-18.17	3.66	27.48	14.74	27.42	26.34	-33.43
	[-3.54]	[0.62]	[4.84]	[2.58]	[4.86]	[4.65]	[-6.16]
cma	9.28	-9.95	-1.20	2.92	-1.84	0.47	5.87
	[1.40]	[-1.29]	[-0.15]	[0.37]	[-0.22]	[0.06]	[0.91]
umd	0.19	1.37	1.68	3.75	0.56	-0.74	11.33
	[0.08]	[0.51]	[0.52]	[1.36]	[0.18]	[-0.24]	[4.24]
# months	708	708	704	704	704	704	704
$\bar{R}^2$(%)	51	33	25	30	25	25	56

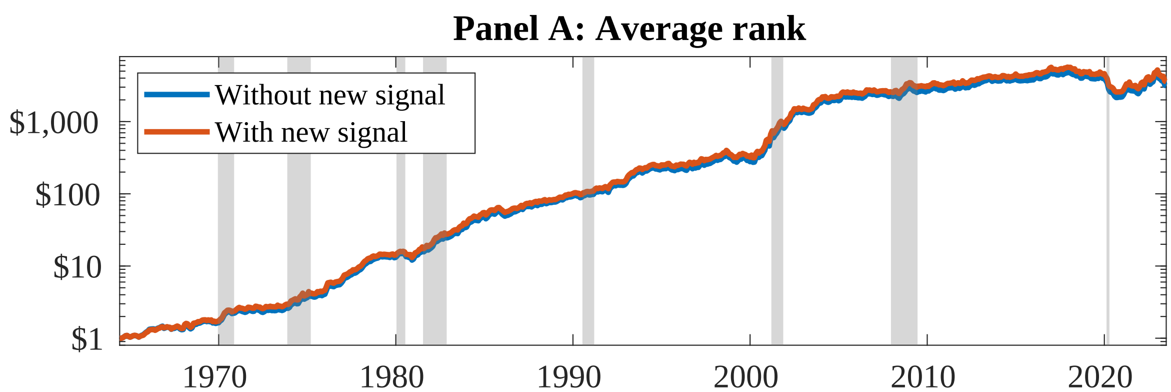


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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