Operating Efficiency Margin and the Cross Section of Stock Returns

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December 1, 2024

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, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Fama and French, 2008). While many of these patterns have been attributed to risk factors or behavioral biases, the underlying economic mechanisms remain debated (Hou et al., 2020).

One particularly puzzling aspect is how operational efficiency metrics relate to future stock returns. While traditional asset pricing models focus primarily on financial metrics, recent research suggests that operational characteristics may contain important information about firms' future performance and risk (Novy-Marx, 2013). The relationship between operational efficiency and stock returns remains incompletely understood, presenting an opportunity to expand our understanding of the cross-section of expected returns.

We propose that Operating Efficiency Margin (OEM) contains valuable information about future firm performance through multiple economic channels. First, firms with higher operational efficiency likely have stronger competitive advantages and barriers to entry, leading to more sustainable profits (?). These competitive advantages should translate into lower risk and higher future returns (Fama and French, 2015).

Second, operational efficiency may signal management quality and organizational capital (Eisenfeldt and Papanikolaou, 2013). More capable managers implement better operational practices, resulting in both higher efficiency and superior long-term performance. This organizational capital represents an important intangible asset that is often not fully reflected in traditional financial metrics (?).

Third, investors may systematically underestimate the persistence and importance of operational efficiency (?). Due to limited attention and processing capacity,

market participants could fail to fully incorporate the implications of complex operational metrics into stock prices, creating predictable patterns in returns as this information is gradually recognized (**?**).

Our empirical analysis reveals that OEM strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on OEM quintiles generates monthly abnormal returns 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 among documented return predictors.

Importantly, the predictive power of OEM remains robust after controlling for size. Among the largest quintile of stocks, the OEM strategy earns monthly abnormal returns of 37 basis points (t-statistic = 2.46). This indicates that the effect is not confined to small, illiquid stocks where trading costs might eliminate real-world profitability.

Most critically, OEM continues to predict returns even after controlling for the six most closely related anomalies identified in the literature. In spanning tests that include these related predictors plus the Fama-French six factors, the OEM strategy still generates monthly alpha of 22 basis points (t-statistic = 2.37), demonstrating that it captures unique information not contained in existing factors.

Our paper makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures operational efficiency in a more comprehensive way than existing metrics like gross profitability (Novy-Marx, 2013) or operating leverage (**?**). The robust predictive power of OEM suggests that operational characteristics contain important information about expected returns that is not fully captured by traditional financial ratios.

Second, we advance the literature on intangible capital and stock returns (Eisenfeldt and Papanikolaou, 2013; **?**) by showing how operational efficiency metrics can help identify firms with valuable organizational capital and management qual-

ity. Our findings suggest that the market does not fully price these important but hard-to-measure assets.

Finally, our results contribute to the broader debate about market efficiency and the proliferation of return predictors (**?**Chen and Zimmermann, 2022). The fact that OEM generates significant alpha even after controlling for hundreds of existing anomalies suggests that there remain important aspects of firm value that are not fully reflected in stock prices, particularly related to operational characteristics.

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, which is 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 both shareholders and debtholders, including working capital, fixed assets, and other operating assets. Selling, general, and administrative expenses (XSGA) encompass all commercial expenses of operation not directly related to product production, including marketing, overhead, and administrative 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 relationship between a firm's total invested capital and its operational overhead expenses, providing insight into how efficiently the company deploys its capital relative to its administrative cost structure. 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 80th 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% (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

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[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.

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-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

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[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.

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.

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[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.

Panel A: NEGICAPTXSGA percentiles
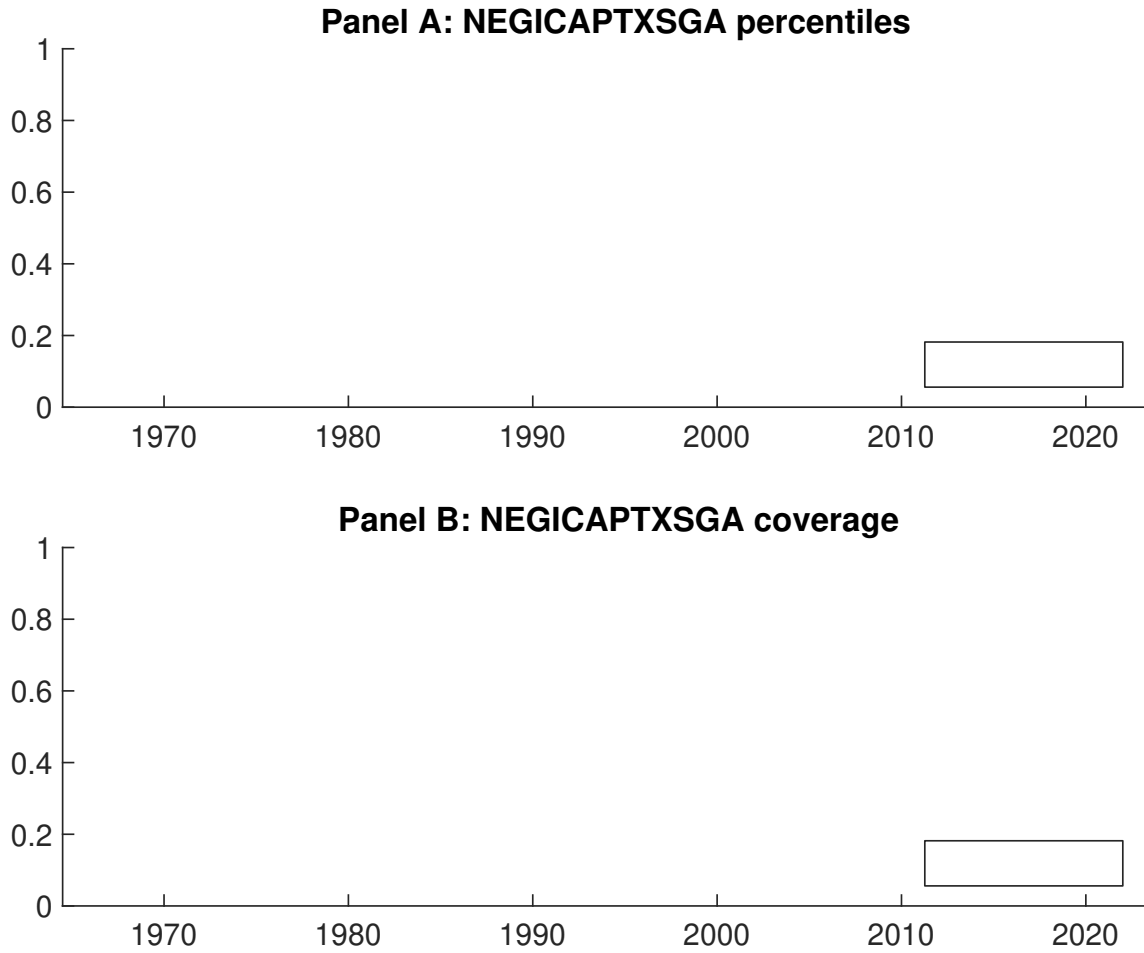

Panel B: NEGICAPTXSGA coverage

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.

	(L)	(2)	(3)	(4)	(H)	(H-L)
Panel A: Excess returns and alphas on OEM-sorted portfolios						
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

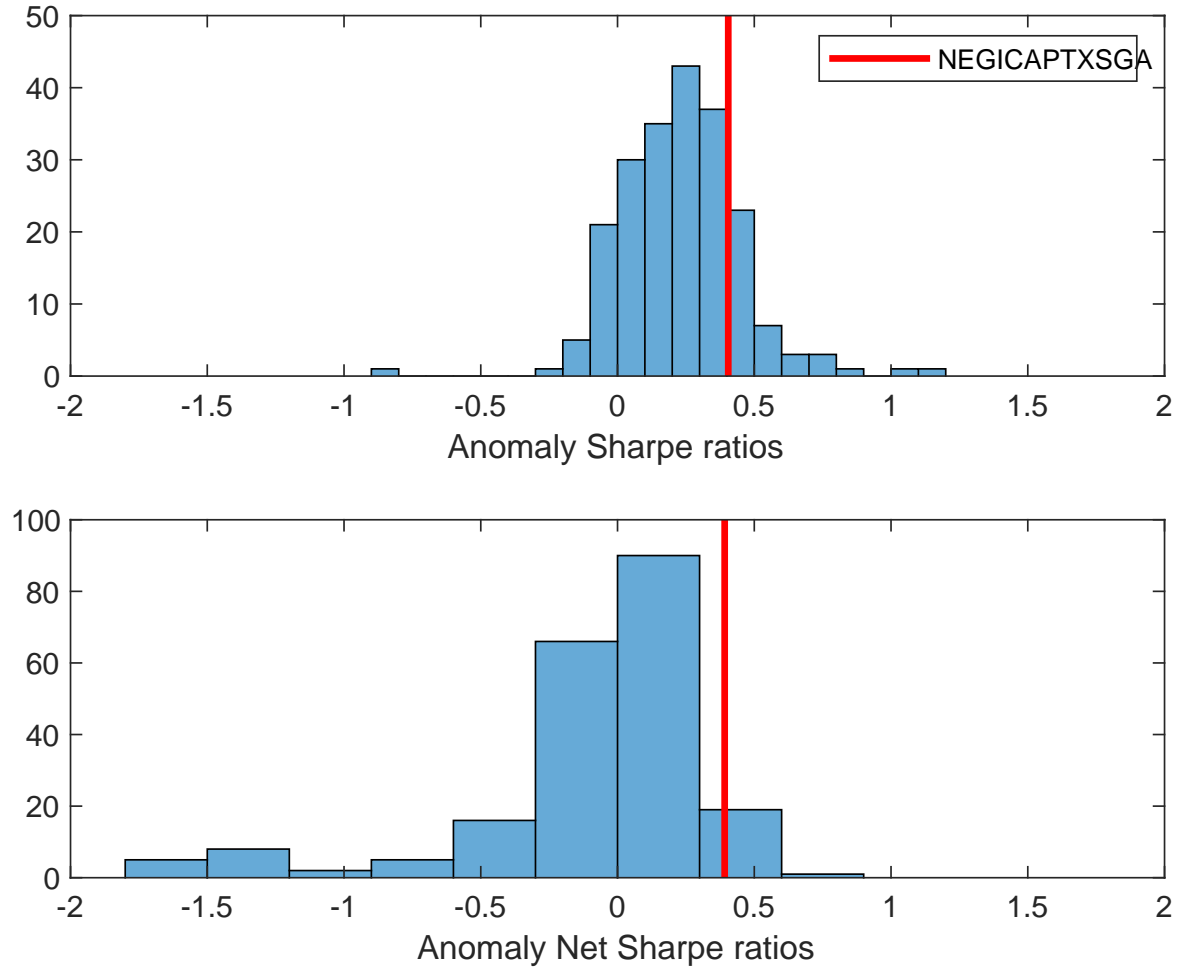|		OEM Quintiles					OEM Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	382	385	384	381	369	35	34	33	29	23
	(2)	101	102	102	102	101	51	52	51	50	51
	(3)	69	69	69	69	69	84	85	84	85	85
	(4)	54	54	54	54	54	169	169	169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

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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.
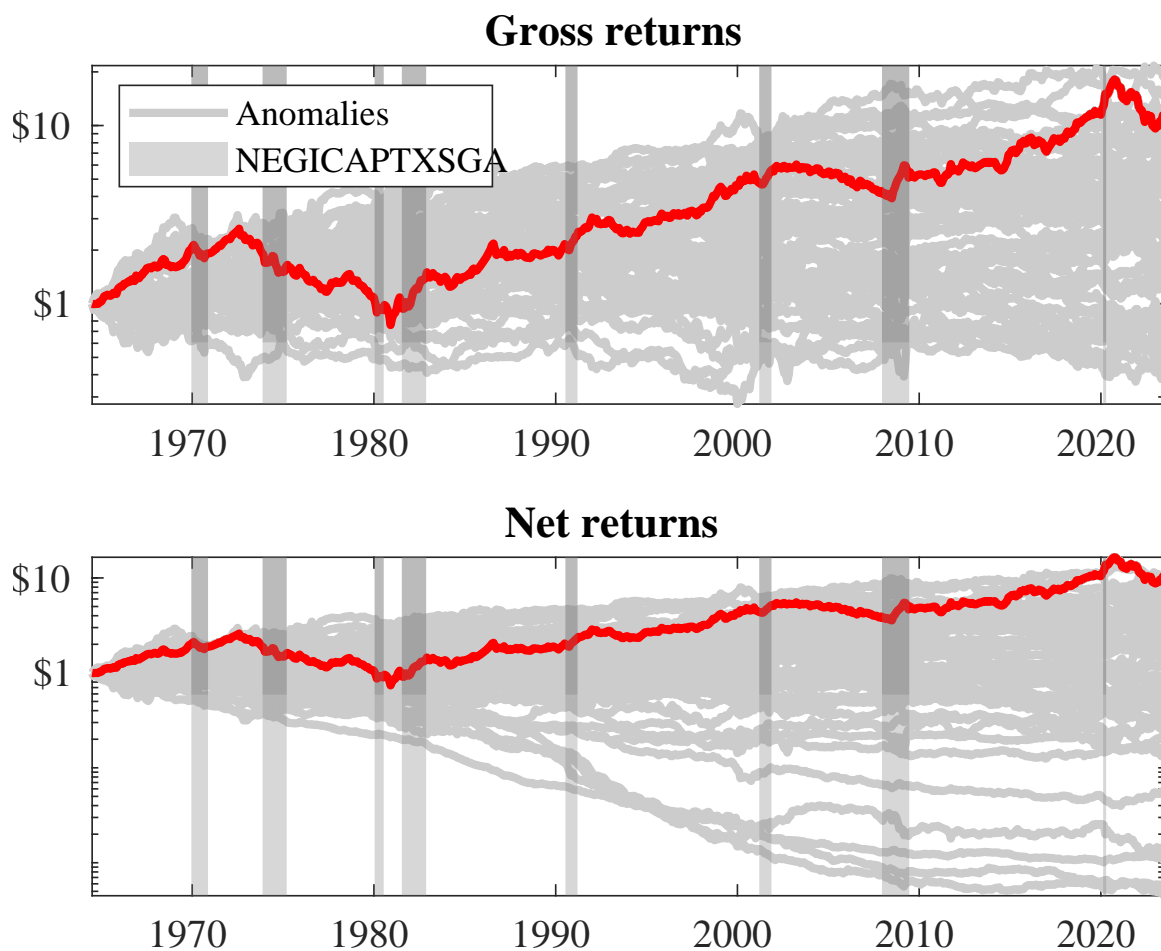
Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the OEM trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross strategy returns. Panel B plots results for net strtaegy returns.
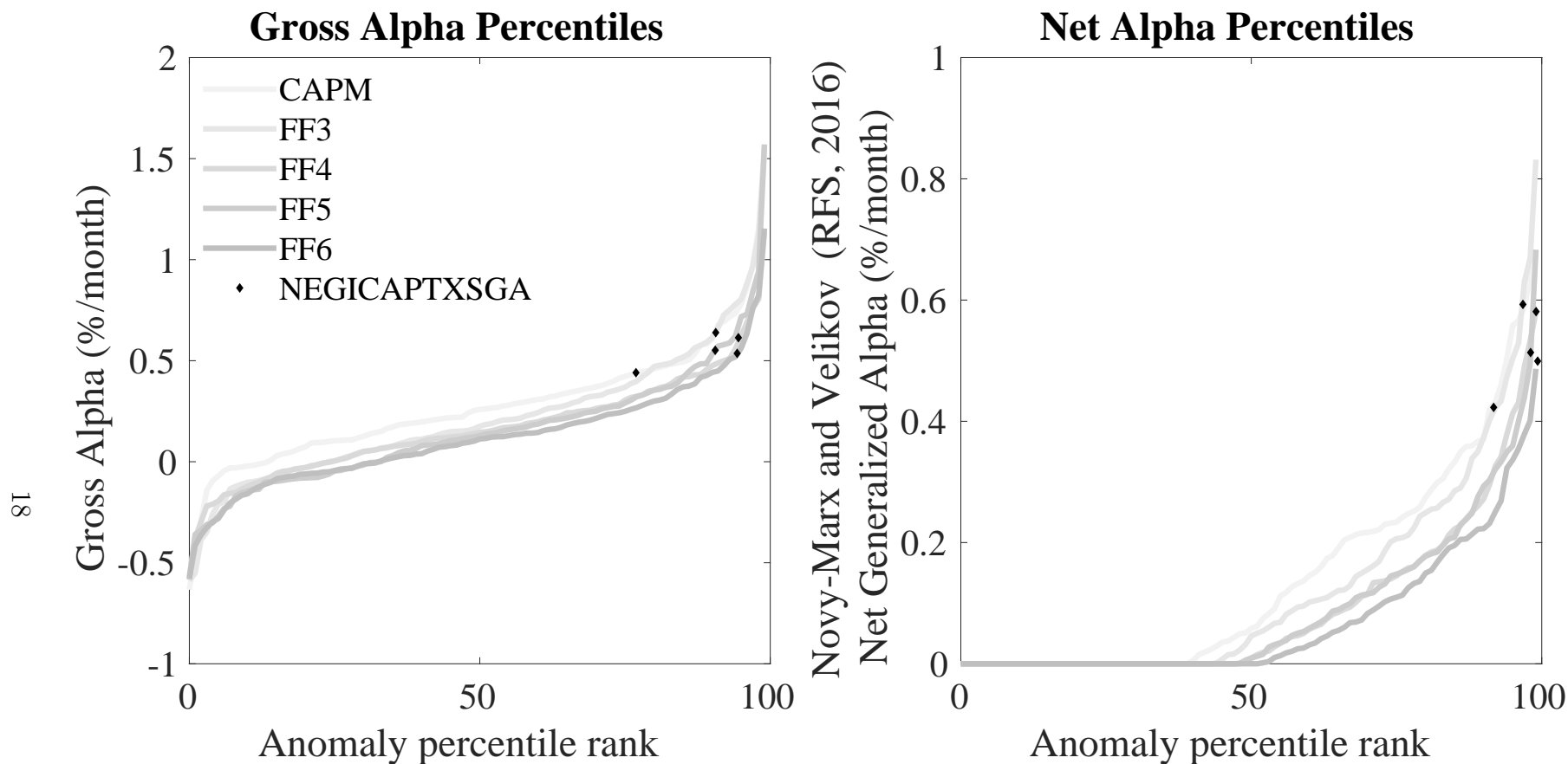
Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the OEM trading strategy alphas (diamonds). The strategies are constructed using 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.
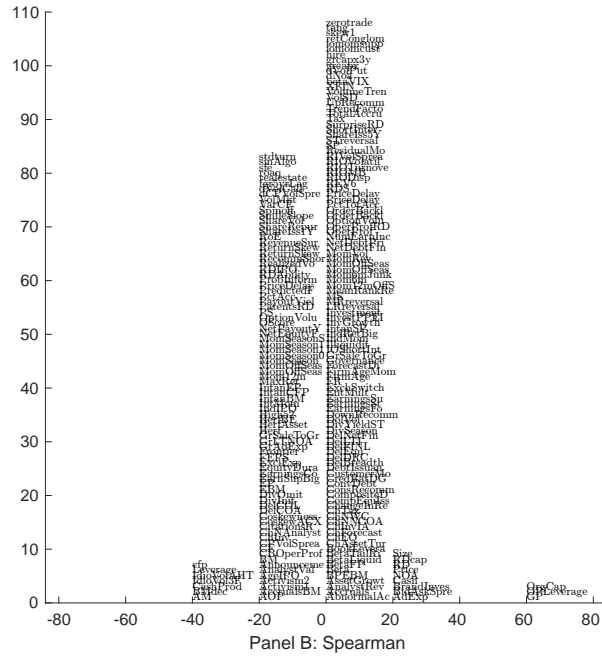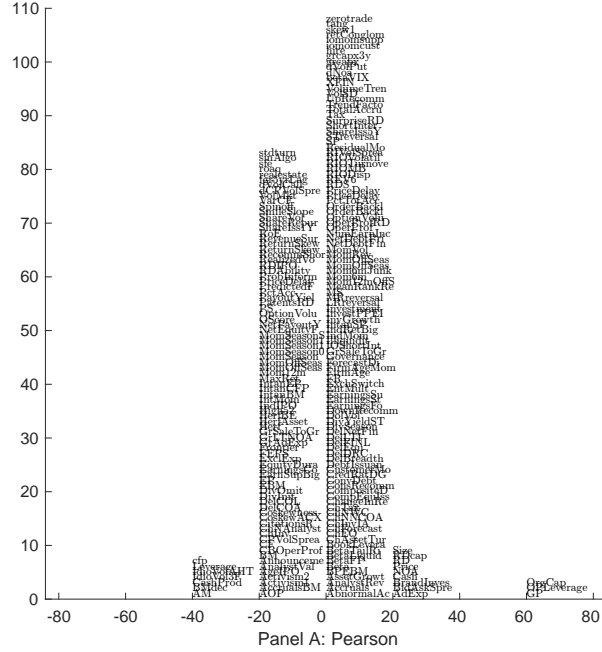
Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with OEM. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.
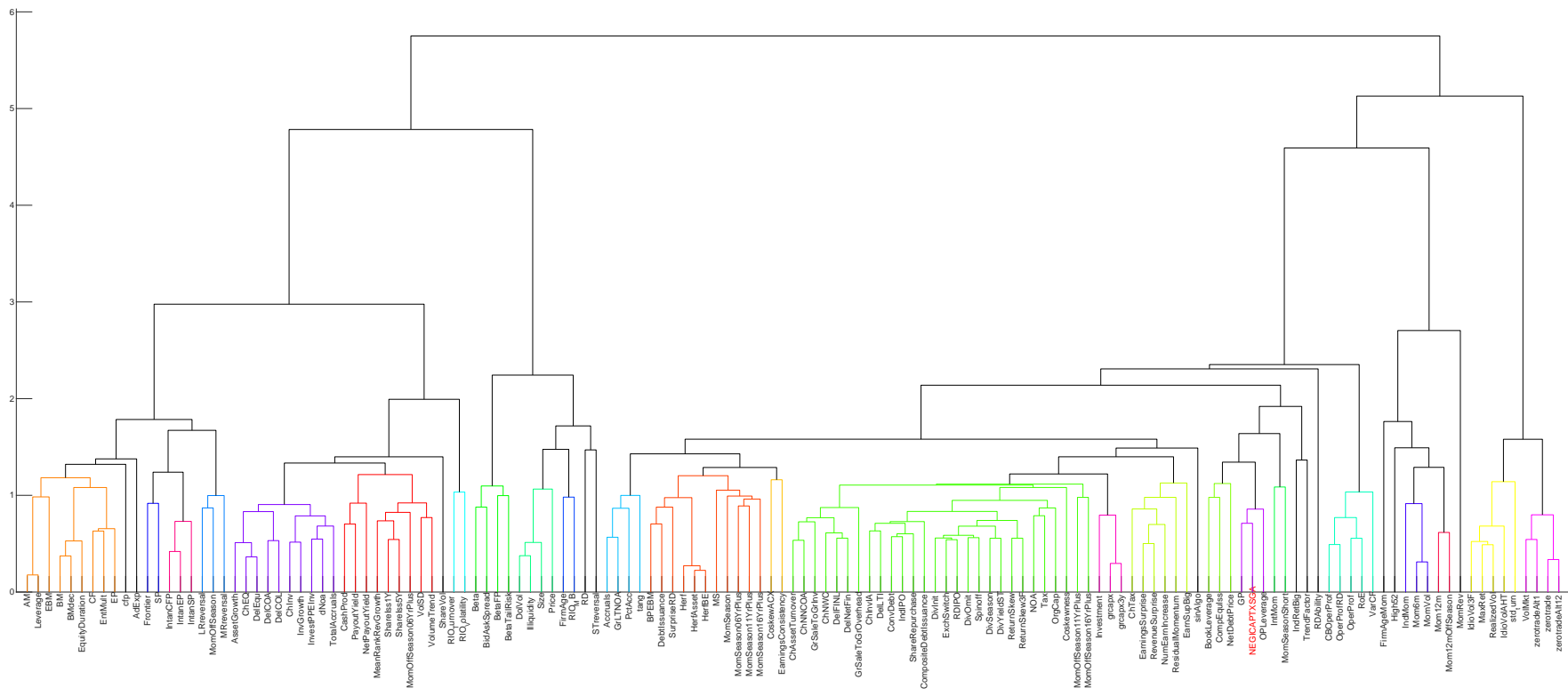
Figure 6: Agglomerative hierarchical cluster plot

This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.
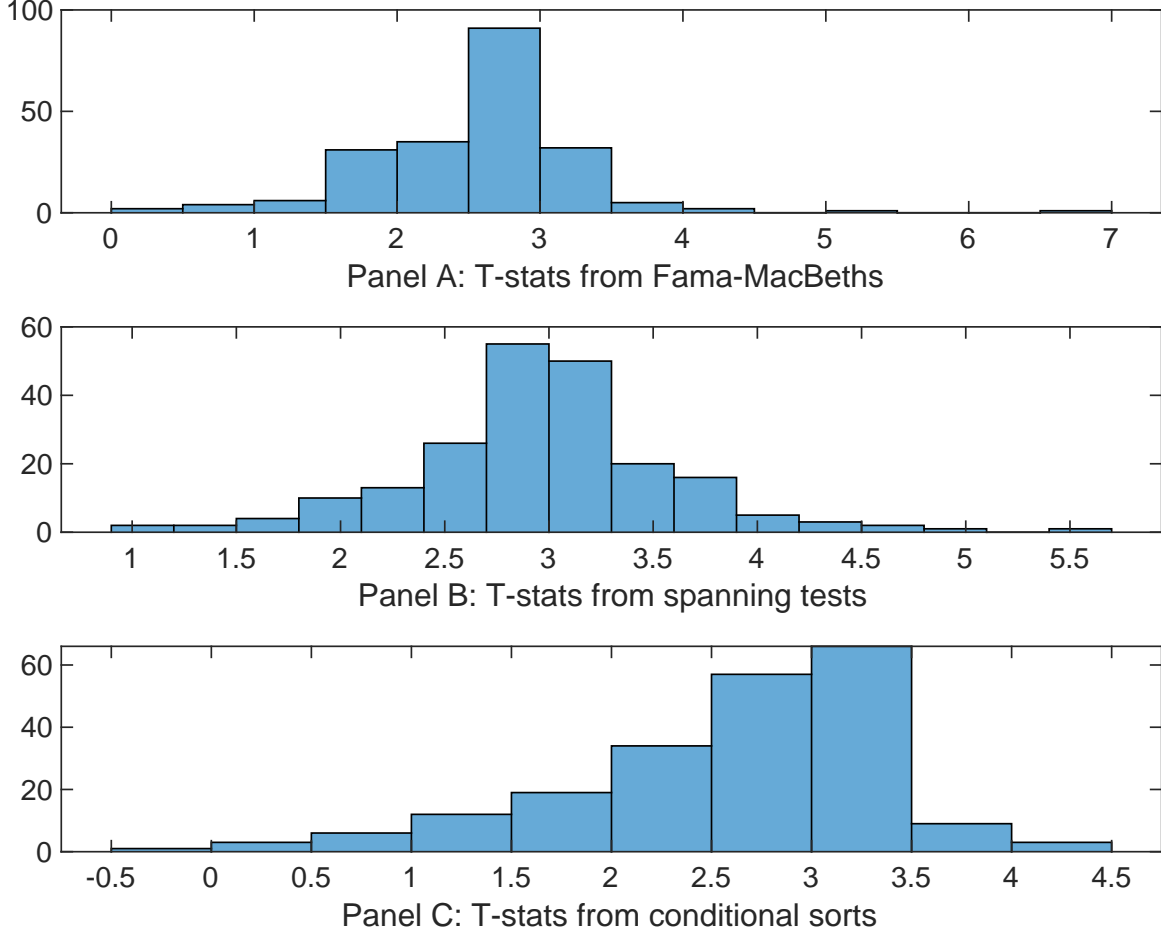
Figure 7: Distribution of t-stats on conditioning strategies

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.

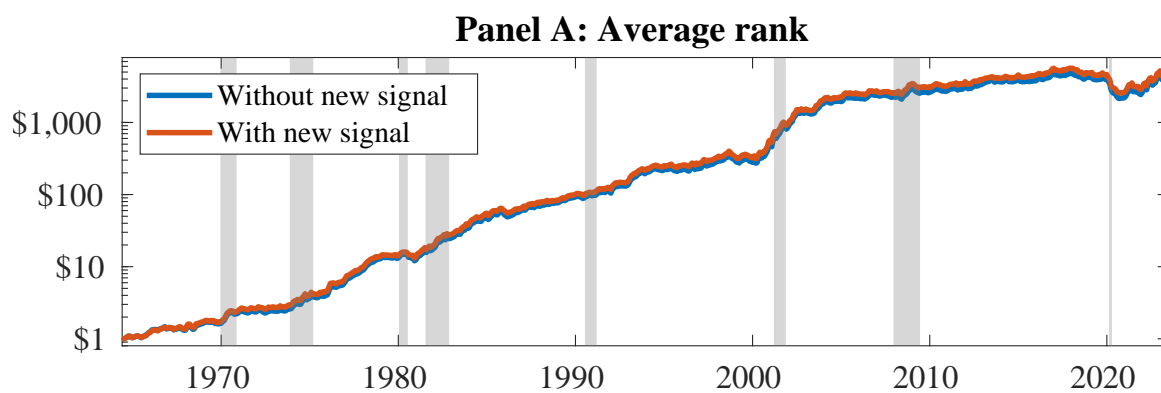|							
Intercept	0.28	0.46	0.51	0.46	0.51	0.51	0.22
	[2.81]	[4.02]	[4.19]	[3.90]	[4.16]	[4.23]	[2.37]
Anomaly 1	76.76						79.59
	[19.18]						[15.84]
Anomaly 2		42.63					21.21
		[9.35]					[4.64]
Anomaly 3			-1.81				-12.80
			[-0.35]				[-0.85]
Anomaly 4				-55.53			-25.66
				[-7.40]			[-3.95]
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

Panel A: Average rank

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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