Assaying Anomalies Performance Report for Cross-Sectional Return Predictor Operating Cash Flow to Investment

Robert Novy-Marx Mihail Velikov

November 21, 2026

Abstract

This report studies the asset pricing implications of Operating Cash Flow to Investment (OCFI), and its robustness in predicting returns in the cross-section of equities using the protocol proposed by Novy-Marx and Velikov (2026). A value-weighted long/short trading strategy based on OCFI achieves an annualized gross (net) Sharpe ratio of 0.57 (0.54), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 39 (40) bps/month with a t-statistic of 3.44 (3.59), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net external financing, Cash-based operating profitability, Operating profitability R&D adjusted, net income / book equity, Analyst earnings per share, Idiosyncratic risk (AHT)) is 22 bps/month with a t-statistic of 2.19.

1 Introduction

The following automatically generated report tests the asset pricing implications of Operating Cash Flow to Investment (OCFI), and its robustness in predicting returns in the cross-section of equities. It is produced using the methodology of Novy-Marx and Velikov (2026), from input data consisting of firm-month observations for the proposed predictor.[1]

2 Signal diagnostics

Figure 1 plots descriptive statistics for the OCFI signal. Panel A plots the time-series of the mean, median, and interquartile range for OCFI. On average, the cross-sectional mean (median) OCFI is −18.94 (1.41) over the 1988 to 2025 sample, where the starting date is determined by the availability of the input OCFI data. The signal's interquartile range spans −8.72 to 6.43. Panel B of Figure 1 plots the time-series of the coverage of the OCFI signal for the CRSP universe. On average over the months in which it has values, the OCFI signal is available for 77.80% of CRSP names, which on average make up 87.50% of total market capitalization.

3 Does OCFI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on OCFI 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 OCFI portfolio and sells the low OCFI 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

[1]It used version 0.9.0 of the publicly available code repository at https://github.com/velikov-mihail/AssayingAnomalies. See more details at https://AssayingAnomalies.com.

model (FF3) and its variation that adds momentum (FF4), the Fama and French (2015) five-factor model (FF5), and its variation that adds the momentum factor, used in Fama and French (2018) (FF6). The table shows that the long/short OCFI strategy earns an average return of 0.55% per month with a t-statistic of 3.50. The annualized Sharpe ratio of the strategy is 0.57. The alphas range from 0.39% to 0.73% per month and have t-statistics of at least 3.44. 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 0.62, with a t-statistic of 12.07 on the RMW 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 503 stocks and an average market capitalization of at least $1,049 million.

Table 2 reports robustness results for alternative sorting methodologies, and accounting for trading 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. Trading costs throughout this report are the Chen–Velikov (C-V) effective-spread costs of Chen and Velikov (2023). A stock's cost is its effective bid-ask half-spread, taken from high-frequency TAQ and ISSM trade and quote data where these are available; otherwise from the average of four low-frequency estimators (the Gibbs sampler of Hasbrouck (2009) and the estimators of Corwin and Schultz (2012), Abdi and Ranaldo (2017), and Kyle and Obizhaeva (2016)); and, for stock-months with none of these, from stocks matched on size and idiosyncratic volatility. Panel A reports gross returns and alphas for the long/short strategies made using various different portfolio 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 name breakpoints and value-weighted portfolios, and equals 32 bps/month with a t-statistic of 1.38. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for seventeen 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. Each portfolio is bought in a month in which the signal is available and held, without rebalancing, until the next such month, when each leg is set back to one dollar. Net returns are gross returns less the cost of the trades made in those months, charged at the C-V effective spreads; the cost of the initial purchase is not charged. The factors' trading costs are those of the 2×3 portfolios held between trades, each side brought back to equal shares every month, under the same convention. The net average returns reported in the first column range from 28 to 58 bps/month. The lowest return, 28 bps/month, is achieved by the quintile sort using name breakpoints and value-weighted portfolios, and has an associated t-statistic of 1.22. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the OCFI 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-one cases.

Table 3 examines the stability of the strategy's performance over time. It reports the average return and alphas of the long/short OCFI strategy from Table 1 over the full sample and splits the sample into three subsamples of roughly equal length. The strategy's average return is positive in all three subsamples, ranging from 0.36% per month (t-statistic of 1.56, 200101–201306) to 0.65% per month (t-statistic of 2.09, 198807–200012). Its alpha relative to the FF6 factor model ranges from 0.31% to 0.34% per month across the subsamples, with t-statistics between 1.49 and 1.84.

Table 4 provides direct tests for the role size plays in the OCFI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and OCFI, as well as average returns and alphas for long/short OCFI trading 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 OCFI strategy achieves an average return of 48 bps/month with a t-statistic of 3.26. Among these large cap stocks, the alphas for the OCFI strategy relative to the five most common factor models range from 32 to 54 bps/month with t-statistics between 2.20 and 3.68.

4 How does OCFI perform relative to the zoo?

Figure 2 puts the performance of OCFI 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 (Panels A and B, respectively), for 159 documented anomalies in the zoo.[2] The vertical red line shows where the Sharpe ratio for the OCFI strategy falls in the distribution. The OCFI strategy's gross (net)

[2]The anomalies come from the October 2026 release of the Chen and Zimmermann (2022) open source asset pricing dataset. We filter their 212 anomalies and require for each anomaly more than ten years of data and, in the average month, a signal for more than 40% of the stocks with market capitalization on CRSP in the sample period of this report.

Sharpe ratio of 0.57 (0.54) is greater than 96% (99%) of anomaly Sharpe ratios, respectively. Each anomaly's Sharpe ratio is calculated over all months in which the anomaly strategy has returns, and that of OCFI over 198807 to 202512.

Figure 3 plots the growth of $1 invested in these same 159 anomaly trading strategies (gray lines), and compares those with the growth of $1 invested in the OCFI strategy (red line).[3] The figure covers 198807 to 202512, the months in which the OCFI strategy has returns. In a month of this period in which an anomaly strategy has no return, it is given the return of the OCFI strategy. Ignoring trading costs, $1 invested in the OCFI strategy grew to $9.20, which ranks the OCFI strategy in the top 5% across the 159 anomalies. Accounting for trading costs, $1 invested in the OCFI strategy grew to $8.18, which ranks the OCFI strategy in the top 1% across the 159 anomalies.

Figure 4 plots percentile ranks for the 159 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 OCFI relative to those. Panel A shows that the OCFI strategy gross alphas fall between the 85th and 97th 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. For example, 43% (49%) of the 159 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. Each strategy's alphas are estimated over all months in which the strategy and the model's factors have returns. The OCFI strategy has a positive net generalized alpha for all five factor models. In these cases OCFI ranks between the 96th and 100th percentiles in terms of how

[3]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.

much it could have expanded the achievable investment frontier.

5 Does OCFI 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 OCFI with the 159 anomaly signals. Figure 6 also shows an agglomerative hierarchical cluster plot of the long/short strategy returns, built with Ward's minimum-variance linkage; links below the 75th percentile of the linkage distances are colored by cluster. The plot uses the months from July 1988 to December 2025, in which OCFI has a return, and the 148 of the 159 anomalies with a return in every one of those months.

A closely related anomaly is also more likely to price OCFI or at least to weaken the power OCFI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of OCFI conditioning on each of the 159 anomaly signals one at a time. Panel A reports t-statistics on β_{OCFI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{OCFI} OCFI_{i,t-1} + \beta_X X_{i,t-1} + \epsilon_{i,t}$, where X stands for one of the 159 anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{OCFI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 159 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 in which both signals are available, we sort stocks into quintiles based on one of the 159 anomaly signals. Then,

within each quintile, we sort stocks into quintiles based on OCFI. Stocks are finally grouped into five OCFI portfolios by combining stocks within each anomaly sorting portfolio. The portfolios are value-weighted, with weights reset every month. The panel plots the t-statistics on the average returns of these conditional double-sorted OCFI trading strategies conditioned on each of the 159 anomalies.

Table 5 reports Fama-MacBeth cross-sectional regressions of returns on OCFI 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 rank correlations in Panel A of Figure 5 and the adjusted R^2 from regressions of the signal's long/short returns on each anomaly's long/short returns, the regressions behind Figure 7, Panel B. On its own, OCFI has a t-statistic of 0.63. Controlling for these signals one at a time, the t-statistics on the OCFI signal in these Fama-MacBeth regressions are at least -1.59, with the minimum t-statistic occurring when controlling for Cash-based operating profitability. Controlling for all six closely related anomalies, the t-statistic on OCFI is -0.17. The average cross-sectional adjusted R^2 rises from 0.40% with OCFI alone to 3.44% in the joint regression.

Similarly, Table 6 reports results from spanning tests that regress returns to the OCFI 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 OCFI strategy earns alphas that range from 23 to 39 bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.22, which is achieved when controlling for Cash-based operating profitability. Controlling for all six closely related anomalies and the six Fama-French factors simultaneously, the OCFI trading strategy achieves an alpha of 22 bps/month with a t-statistic of 2.19. The adjusted R^2 of this joint spanning regression is 65%.

6 Does OCFI add relative to the whole zoo?

Finally, we can ask how much adding OCFI 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 (2023). The combinations use either the 159 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 159 anomalies augmented with the OCFI signal. We consider six different methods for combining signals.

The average rank uses OCFI from the first month in which it has data, and the other methods once it has ten years of data, so that their estimation windows contain it throughout. In each panel the two strategies start in the same month, the first in which the method uses OCFI, and the figure starts in OCFI's first month.

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. From July 1988 to December 2025, $1 investment in the 159-anomaly combination strategy grows to $40.02, while $1 investment in the combination strategy that includes OCFI grows to $36.40.

Panel B shows results using "Weighted-Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated as their weighted-average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns and the weights are determined by the average returns over the past ten years to the long/short strategies based on the individual signals. From July 1998 to December 2025, $1 investment in the 159-anomaly combination strategy grows to $4.20, while $1 investment in the combination strategy that includes OCFI grows to $5.15.

Panel C shows results using "Fama-MacBeth" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated from Fama and MacBeth (1973) regressions following Haugen and Baker (1996) and Lewellen (2015) using only data in the investor's information set at the time of portfolio formation, given the anomalies selected on the full sample. The estimation uses rolling ten years of data, so the actual strategies begin ten years later for this combination method. From July 1998 to December 2025, $1 investment in the 159-anomaly combination strategy grows to $104.66, while $1 investment in the combination strategy that includes OCFI grows to $105.45.

Panel D shows results using "Partial Least Squares" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated from the partial least squares (PLS) filtering procedure following Light et al. (2017) using only data in the investor's information set at the time of portfolio formation, given the anomalies selected on the full sample. Each month's forecasts use only that month's cross-sectional regressions, so this method needs no estimation window. From July 1998 to December 2025, $1 investment in the 159-anomaly combination strategy grows to $4.56, while $1 investment in the combination strategy that includes OCFI grows to $5.89.

Panel E shows results using "IPCA" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated from the instrumented principal component analysis (IPCA) procedure of Kelly et al. (2019) using only data in the investor's information set at the time of portfolio formation, given the anomalies selected on the full sample. The estimation uses rolling ten years of data, so the actual strategies begin ten years later for this combination method. From July 1998 to December 2025, $1 investment in the 159-anomaly combination strategy grows to $20.26, while $1 investment in the combination strategy that includes OCFI grows to $16.28.

Panel F shows results using "LASSO" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are estimated by the least absolute shrinkage and selection operator (LASSO) using only data in the investor's information set at the time of portfolio formation, given the anomalies selected on the full sample. Following Chen and Velikov (2023), the LASSO penalty (λ) is selected by minimizing the mean squared error (MSE) estimated by 5-fold cross validation. The estimation uses rolling ten years of data, so the actual strategies begin ten years later for this combination method. From July 1998 to December 2025, \$1 investment in the 159-anomaly combination strategy grows to \$74.65, while \$1 investment in the combination strategy that includes OCFI grows to \$79.81.

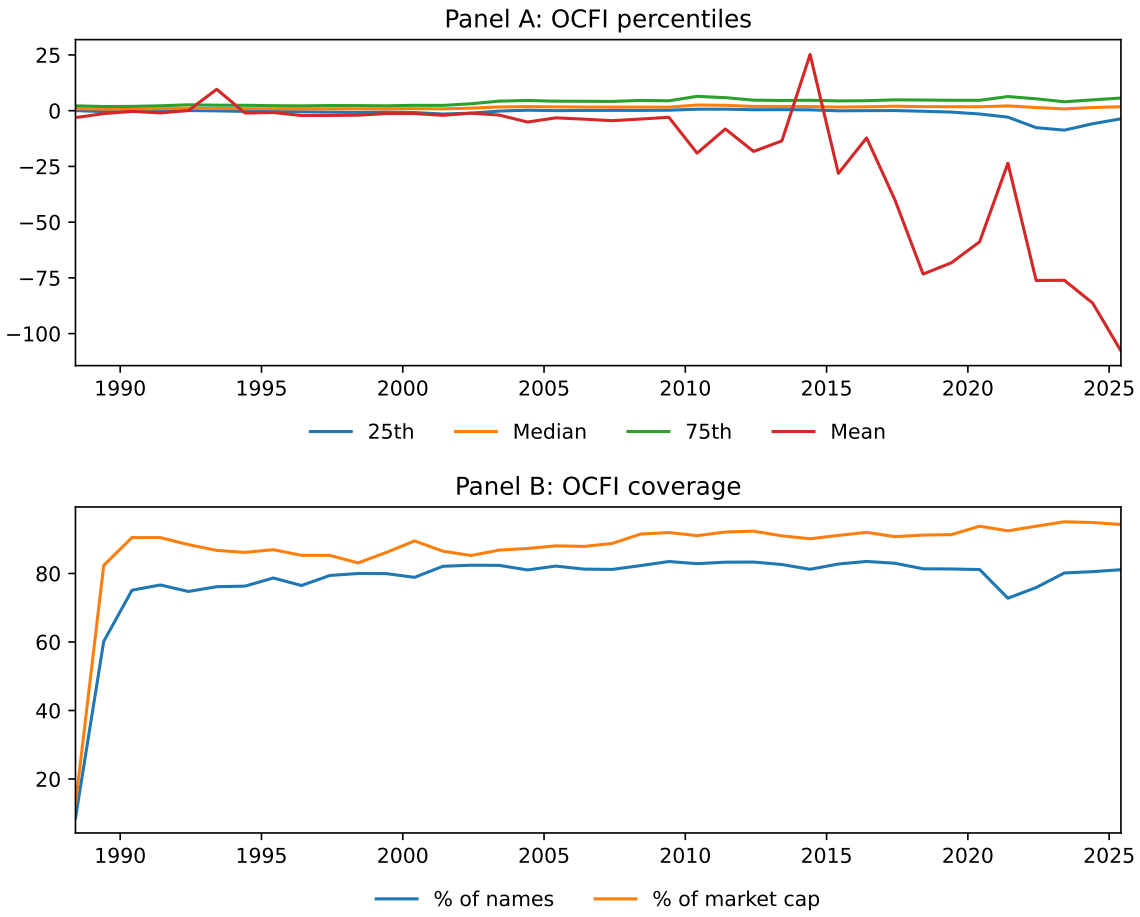

Figure 1: Time series of OCFI percentiles and coverage.
This figure plots descriptive statistics for OCFI. Panel A shows cross-sectional percentiles of OCFI over the sample. Panel B plots the coverage of OCFI relative to the universe of CRSP stocks with available market capitalizations. Both panels show the months in which the signal has values.

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

This table reports average excess returns and alphas for portfolios sorted on OCFI. In each month in which the signal is available, we sort stocks into five portfolios based on their signal using NYSE breakpoints. The portfolios are held, without rebalancing, until the next such month. 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 augmented with the Carhart (1997) momentum factor. Panel C reports the average number of stocks and market capitalization of each portfolio. T-statistics are in brackets. The sample period is 198807 to 202512.

Panel A: Excess returns and alphas on OCFI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.37	0.69	0.65	0.87	0.92	0.55
	[1.29]	[3.19]	[3.32]	[4.74]	[4.18]	[3.50]
α_{CAPM}	-0.58	-0.05	-0.03	0.23	0.15	0.73
	[-4.65]	[-0.68]	[-0.60]	[4.19]	[2.41]	[4.82]
α_{FF3}	-0.50	-0.06	-0.05	0.23	0.17	0.66
	[-5.22]	[-0.83]	[-0.95]	[4.36]	[2.88]	[5.36]
α_{FF4}	-0.47	-0.03	-0.02	0.20	0.17	0.64
	[-4.82]	[-0.44]	[-0.36]	[3.80]	[2.94]	[5.08]
α_{FF5}	-0.25	-0.07	-0.14	0.15	0.15	0.40
	[-3.04]	[-0.98]	[-2.49]	[2.86]	[2.54]	[3.57]
α_{FF6}	-0.24	-0.05	-0.10	0.13	0.15	0.39
	[-2.83]	[-0.66]	[-1.86]	[2.49]	[2.58]	[3.44]
Panel B: Fama and French (2018) 6-factor model loadings for OCFI-sorted portfolios						
β_{MKT}	1.09	0.97	0.96	0.91	1.04	-0.06
	[52.25]	[50.57]	[70.21]	[70.47]	[70.07]	[-1.95]
β_{SMB}	0.36	0.08	-0.05	-0.08	-0.04	-0.41
	[12.22]	[2.78]	[-2.39]	[-4.24]	[-2.13]	[-10.13]
β_{HML}	-0.01	0.05	-0.08	-0.10	-0.11	-0.10
	[-0.18]	[1.57]	[-3.21]	[-4.38]	[-4.14]	[-2.03]
β_{RMW}	-0.53	0.06	0.12	0.13	0.09	0.62
	[-14.02]	[1.66]	[4.89]	[5.70]	[3.31]	[12.07]
β_{CMA}	-0.18	-0.02	0.20	0.12	-0.08	0.10
	[-3.40]	[-0.45]	[5.99]	[3.57]	[-2.17]	[1.37]
β_{MOM}	-0.02	-0.04	-0.05	0.03	-0.01	0.02
	[-1.18]	[-2.14]	[-4.48]	[2.42]	[-0.47]	[0.62]
Panel C: Average number of firms (n) and market capitalization (me)						
n	1397	543	503	529	720	
me ($\$10^6$)	1049	5428	9040	8264	7400	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the OCFI 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), net of trading costs, measured as Chen–Velikov (C-V) effective spreads (Chen and Velikov, 2023). T-statistics are in brackets. The sample period is 198807 to 202512.

Panel A: Gross Returns and Alphas								
Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.55	0.73	0.66	0.64	0.40	0.39
			[3.50]	[4.82]	[5.36]	[5.08]	[3.57]	[3.44]
Quintile	NYSE	EW	0.58	0.76	0.64	0.59	0.39	0.35
			[3.50]	[4.66]	[4.88]	[4.43]	[3.33]	[2.96]
Quintile	Name	VW	0.32	0.61	0.47	0.49	0.07	0.10
			[1.38]	[2.81]	[2.75]	[2.79]	[0.46]	[0.66]
Quintile	Cap	VW	0.37	0.44	0.43	0.40	0.30	0.28
			[3.10]	[3.67]	[3.84]	[3.54]	[2.73]	[2.53]
Decile	NYSE	VW	0.61	0.88	0.77	0.71	0.50	0.45
			[3.18]	[4.87]	[5.24]	[4.75]	[3.69]	[3.32]
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	0.52	0.70	0.63	0.61	0.41	0.40
			[3.33]	[4.64]	[5.09]	[4.95]	[3.69]	[3.59]
Quintile	NYSE	EW	0.42	0.59	0.47	0.44	0.21	0.19
			[2.45]	[3.49]	[3.46]	[3.24]	[1.76]	[1.60]
Quintile	Name	VW	0.28	0.57	0.44	0.45	0.08	0.10
			[1.22]	[2.63]	[2.53]	[2.58]	[0.52]	[0.66]
Quintile	Cap	VW	0.35	0.42	0.40	0.39	0.30	0.29
			[2.95]	[3.52]	[3.64]	[3.48]	[2.79]	[2.65]
Decile	NYSE	VW	0.58	0.84	0.73	0.69	0.49	0.46
			[3.00]	[4.67]	[4.99]	[4.71]	[3.67]	[3.43]

Table 3: Performance across subsamples

This table reports the performance of the long/short OCFI strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios, in different parts of the sample. The first row reports results for the full sample. The following rows split the sample into three contiguous subsamples of approximately equal length, labelled by their first and last month. For each sample, the table reports the average excess 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), all in percent per month. T-statistics are in brackets. The sample period is 198807 to 202512.

Sample	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Full sample	0.55	0.73	0.66	0.64	0.40	0.39
	[3.50]	[4.82]	[5.36]	[5.08]	[3.57]	[3.44]
198807–200012	0.65	0.87	0.68	0.72	0.47	0.32
	[2.09]	[2.85]	[3.10]	[3.02]	[2.52]	[1.60]
200101–201306	0.36	0.46	0.54	0.53	0.32	0.31
	[1.56]	[2.26]	[2.66]	[2.61]	[1.53]	[1.49]
201307–202512	0.64	0.81	0.50	0.47	0.40	0.34
	[2.36]	[2.98]	[2.36]	[2.20]	[2.15]	[1.84]

Table 4: Conditional sort on size and OCFI

This table presents results for conditional double sorts on size and OCFI. In each month in which the signal is available, stocks are first sorted into quintiles based on size using NYSE breakpoints. Then, within each size quintile, stocks are further sorted based on OCFI. Finally, they are grouped into twenty-five portfolios based on the intersection of the two sorts. The portfolios are value-weighted, with weights reset every month. Panel A presents the average returns to the 25 portfolios, as well as strategies that go long stocks with high OCFI and short stocks with low OCFI. Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 198807 to 202512.

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

		OCFI Quintiles					OCFI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.49	0.40	0.71	1.05	1.01	0.52	0.76	0.56	0.50	0.08	0.05
		[1.12]	[1.01]	[2.20]	[3.63]	[3.43]	[1.85]	[2.75]	[2.32]	[2.04]	[0.39]	[0.24]
	(2)	0.41	0.55	0.85	0.95	0.93	0.52	0.86	0.67	0.60	0.26	0.22
		[1.01]	[1.74]	[3.15]	[3.56]	[3.60]	[2.26]	[3.96]	[3.83]	[3.38]	[1.78]	[1.44]
	(3)	0.30	0.80	0.83	0.94	0.90	0.60	0.90	0.79	0.70	0.46	0.39
		[0.86]	[3.06]	[3.30]	[3.69]	[3.67]	[3.19]	[5.26]	[5.11]	[4.47]	[3.20]	[2.72]
	(4)	0.61	0.76	0.80	0.93	0.91	0.30	0.53	0.43	0.36	0.17	0.11
		[1.89]	[3.14]	[3.47]	[4.20]	[3.88]	[1.82]	[3.33]	[3.00]	[2.46]	[1.24]	[0.83]
	(5)	0.46	0.72	0.70	0.89	0.93	0.48	0.54	0.54	0.49	0.36	0.32
		[1.79]	[3.57]	[3.74]	[4.43]	[4.09]	[3.26]	[3.68]	[3.67]	[3.29]	[2.45]	[2.20]

Panel B: Portfolio average number of firms and market capitalization

		OCFI Quintiles					OCFI Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	390	395	402	406	406	99	108	142	161	150
	(2)	122	123	122	123	123	699	729	747	747	754
	(3)	83	84	83	84	84	1742	1816	1836	1842	1838
	(4)	70	70	70	70	70	4469	4531	4648	4687	4769
	(5)	62	62	62	62	62	28477	47862	40486	43369	40183

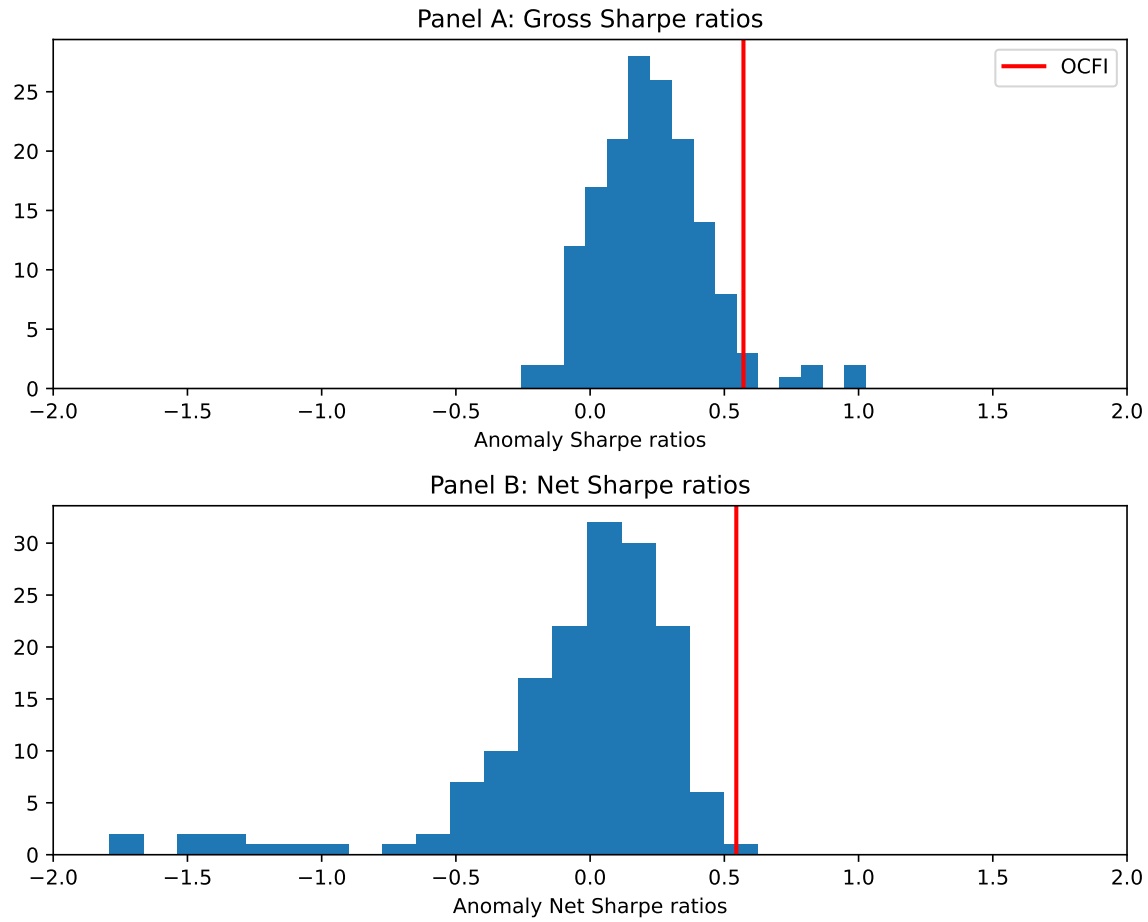

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 159 anomalies, and compares the Sharpe ratio of OCFI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for Sharpe ratios net of trading costs, measured as Chen–Velikov (C-V) effective spreads (Chen and Velikov, 2023). Each anomaly's Sharpe ratio is calculated over all months in which the anomaly strategy has returns; that of OCFI over 198807 to 202512.

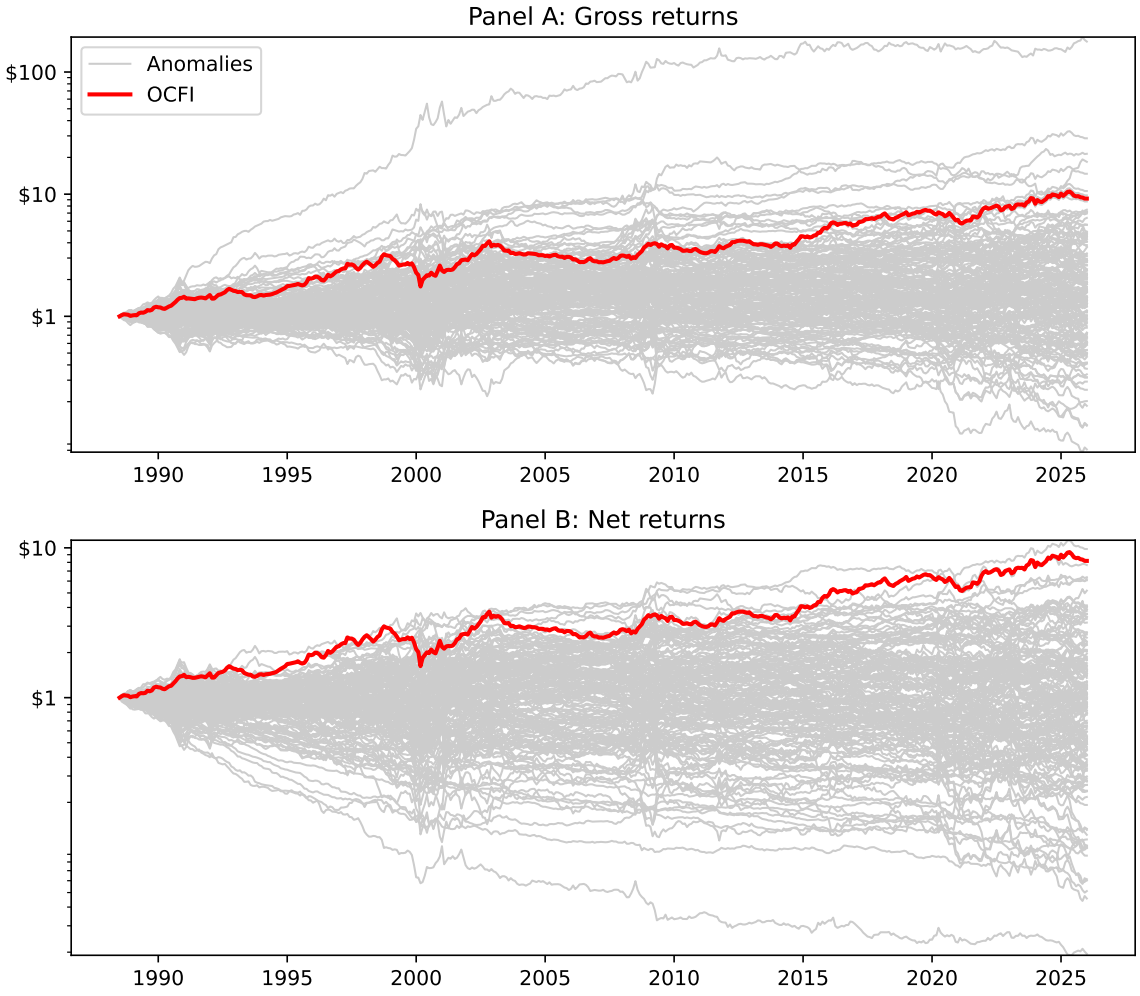

Figure 3: Dollar invested.
This figure plots the growth of $1 invested in 159 anomaly trading strategies (gray lines), and compares those with the OCFI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross strategy returns. Panel B plots results for strategy returns net of trading costs, measured as Chen–Velikov (C-V) effective spreads (Chen and Velikov, 2023). The figure covers 198807 to 202512, the months in which the OCFI strategy has returns; every strategy starts at $1. In a month in which an anomaly strategy has no return it is given the return of the OCFI strategy.

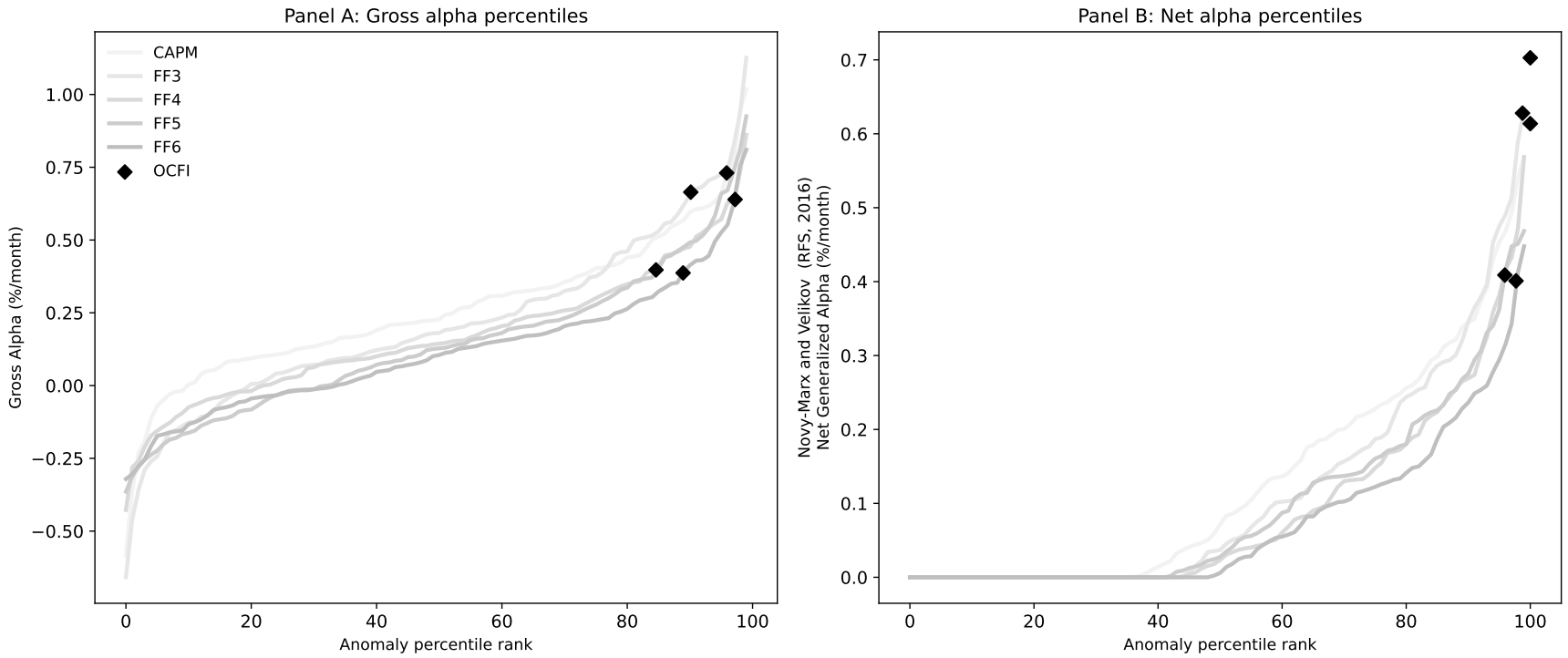

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 159 anomaly trading strategies in terms of alphas (solid lines), and compares those with the OCFI trading strategy alphas (diamonds). The strategies are constructed 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). Panel A plots alphas with no adjustment for trading costs. Panel B plots Novy-Marx and Velikov (2016) generalized alphas net of trading costs, measured as Chen–Velikov (C-V) effective spreads (Chen and Velikov, 2023). Each strategy's alphas are estimated over all months in which the strategy and the model's factors have returns.

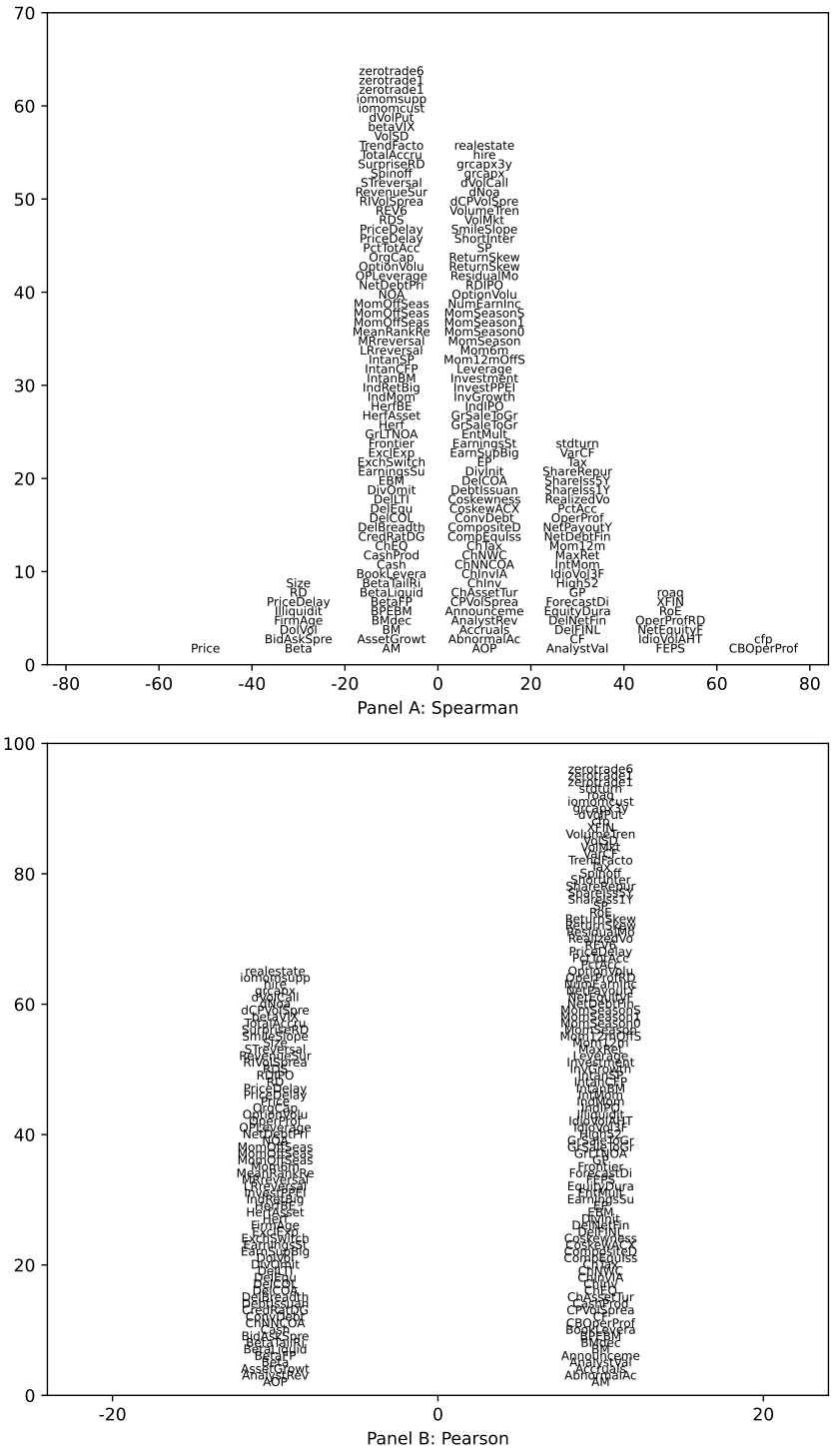

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 159 anomaly signals with OCFI. The correlations are pooled. Panel A plots Spearman rank correlations, while Panel B plots Pearson correlations.

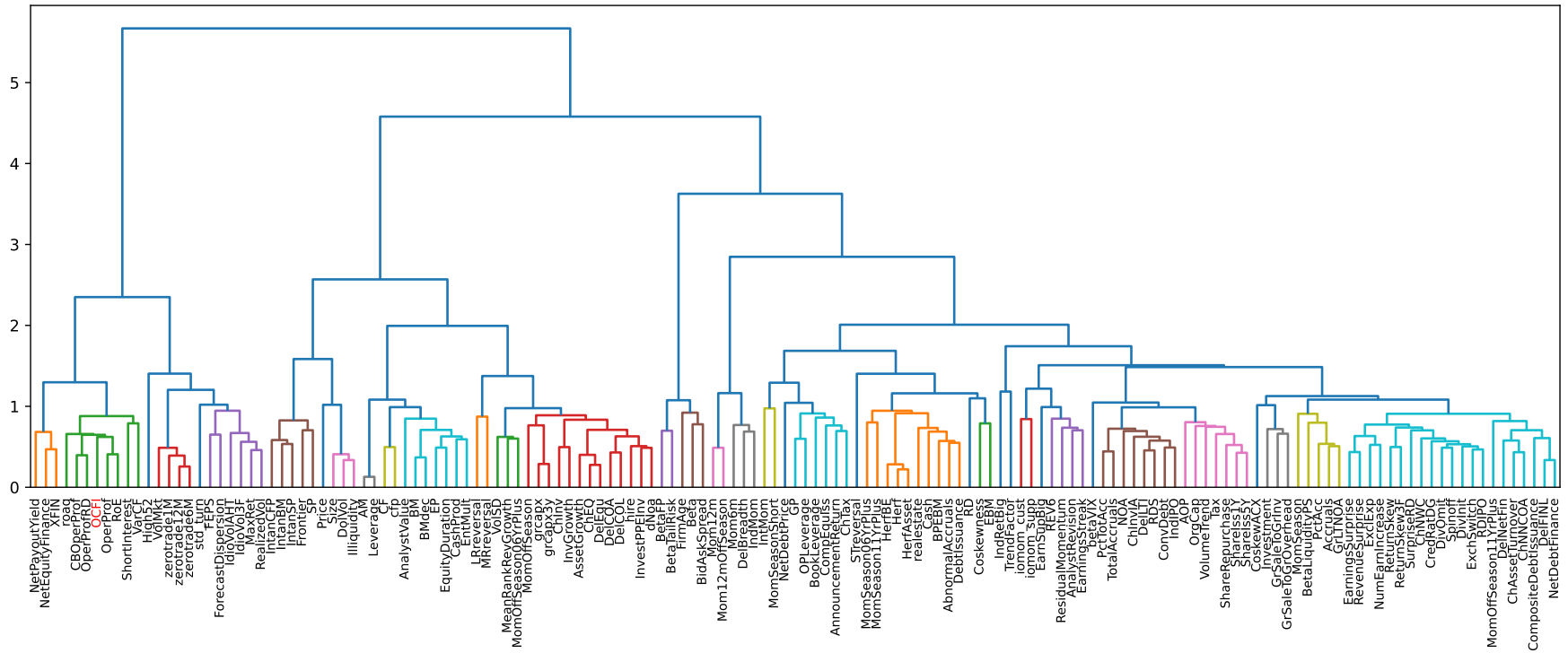

Figure 6: Agglomerative hierarchical cluster plot

This figure plots an agglomerative hierarchical cluster plot of the monthly long/short returns of OCFI and the 148 anomaly strategies with a return in every month from July 1988 to December 2025, using Ward's minimum-variance linkage on Euclidean distances. Links below the 75th percentile of the linkage distances are colored by cluster.

Table 5: Fama-MacBeth regressions controlling for the most closely related anomalies

This table presents Fama-MacBeth results of returns on OCFI and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{OCFI} OCFI_{i,t-1} + \sum_{k=1}^{6} \beta_{X_k} X^k_{i,t-1} + \epsilon_{i,t}$, with returns in percent per month. The six most closely related anomalies, X, are Net external financing, Cash-based operating profitability, Operating profitability R&D adjusted, net income / book equity, Analyst earnings per share, Idiosyncratic risk (AHT). These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman rank correlations in Panel A of Figure 5 and the adjusted R^2 from regressions of the signal's long/short returns on each anomaly's long/short returns, the regressions behind Figure 7, Panel B. The first column reports the regression on OCFI alone, the last column the regression on all of them jointly. The slopes on OCFI are multiplied by 10^2. The row # months reports the number of monthly cross-sections and the last row the average cross-sectional adjusted R^2 in percent. The sample period is 198807 to 202512; each regression uses the months in which all of its variables are available.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.08	1.23	0.93	0.91	1.08	0.94	1.20	0.98
	[3.79]	[4.47]	[3.05]	[2.85]	[3.80]	[2.84]	[5.21]	[4.10]
OCFI $\times 10^2$	0.23	-0.42	-0.56	-0.04	0.23	0.50	0.42	-0.06
	[0.63]	[-1.46]	[-1.59]	[-0.14]	[0.73]	[1.84]	[2.16]	[-0.17]
Anomaly 1		1.84						0.96
		[6.21]						[3.85]
Anomaly 2			2.03					1.09
			[5.29]					[2.53]
Anomaly 3				1.79				0.44
				[3.86]				[0.90]
Anomaly 4					0.06			-0.04
					[1.12]			[-0.55]
Anomaly 5						0.04		-0.02
						[0.59]		[-0.48]
Anomaly 6							8.65	6.52
							[1.48]	[1.00]
# months	450	450	450	450	450	450	450	450
$\bar{R}^2$ (%)	0.40	1.04	0.95	1.03	0.61	1.64	1.99	3.44

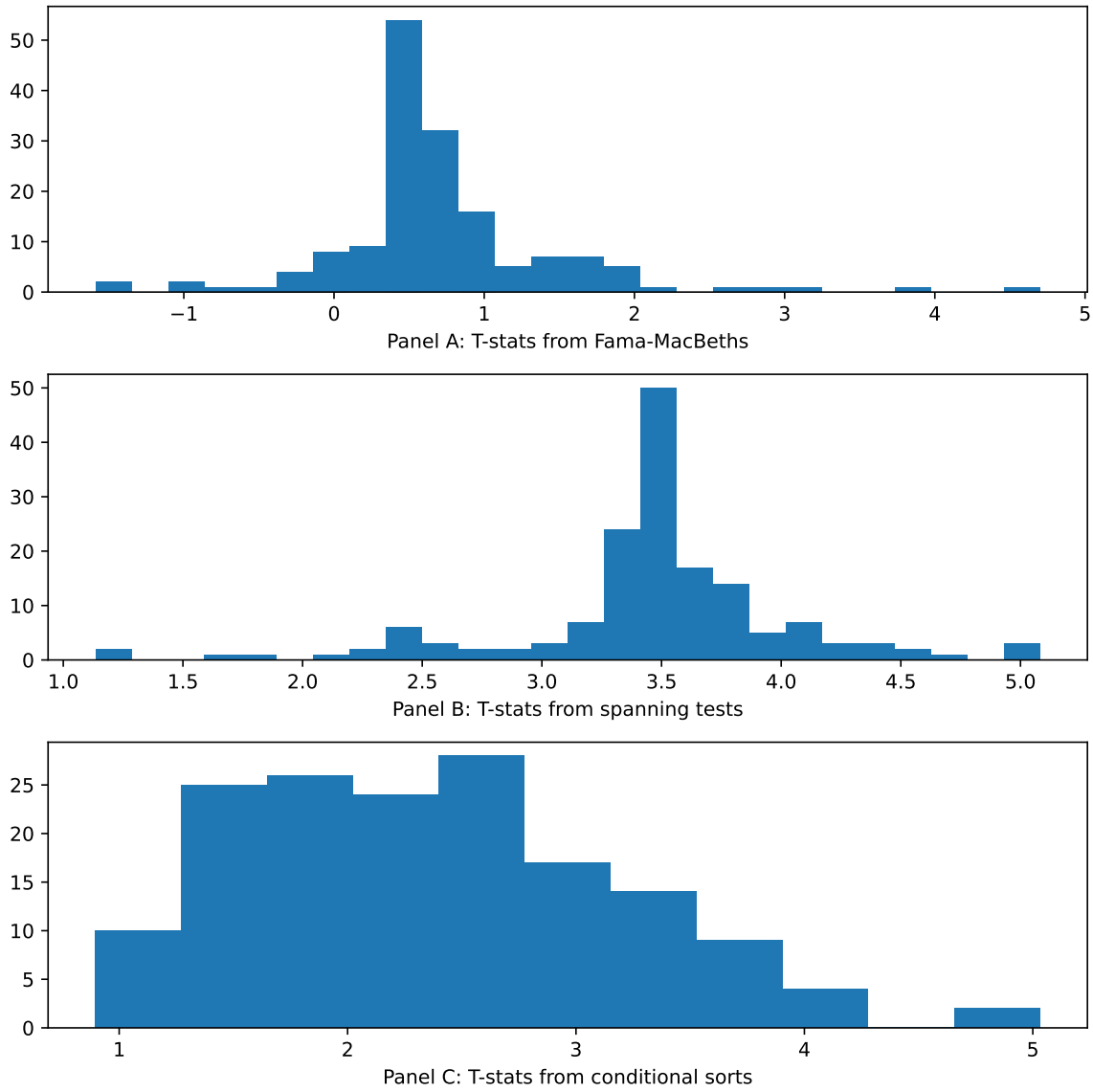

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of OCFI conditioning on each of the 159 anomaly signals one at a time. Panel A reports t-statistics on β_{OCFI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{OCFI} OCFI_{i,t-1} + \beta_X X_{i,t-1} + \epsilon_{i,t}$, where X stands for one of the 159 anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{OCFI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 159 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 in which both signals are available, we sort stocks into quintiles based on one of the 159 anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on OCFI. Stocks are finally grouped into five OCFI portfolios by combining stocks within each anomaly sorting portfolio. The portfolios are value-weighted, with weights reset every month. The panel plots the t-statistics on the average returns of these conditional double-sorted OCFI trading strategies conditioned on each of the 159 anomalies.

Table 6: Spanning tests controlling for the most closely related anomalies

This table presents spanning-test results of regressing returns to the OCFI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{OCFI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Net external financing, Cash-based operating profitability, Operating profitability R&D adjusted, net income / book equity, Analyst earnings per share, Idiosyncratic risk (AHT). These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman rank correlations in Panel A of Figure 5 and the adjusted R^2 from regressions of the signal's long/short returns on each anomaly's long/short returns, the regressions behind Figure 7, Panel B. The last column reports the regression on all of them jointly. The row # months reports the number of months in each regression and the last row the adjusted R^2 in percent. The sample period is 198807 to 202512; each regression uses the months in which all of its strategies have returns.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.30	0.23	0.24	0.36	0.39	0.39	0.22
	[2.90]	[2.22]	[2.23]	[3.35]	[3.44]	[3.57]	[2.19]
Anomaly 1	0.44						0.24
	[8.57]						[4.19]
Anomaly 2		0.43					0.29
		[9.53]					[4.48]
Anomaly 3			0.34				0.03
			[7.89]				[0.49]
Anomaly 4				0.39			0.13
				[5.93]			[1.98]
Anomaly 5					0.10		-0.10
					[2.41]		[-2.08]
Anomaly 6						0.14	0.10
						[4.36]	[2.82]
mkt	0.01	-0.02	0.00	-0.00	-0.03	0.01	0.05
	[0.34]	[-0.89]	[0.03]	[-0.05]	[-1.08]	[0.22]	[1.68]
smb	-0.26	-0.30	-0.31	-0.28	-0.35	-0.29	-0.17
	[-6.28]	[-7.79]	[-7.97]	[-6.40]	[-7.29]	[-6.01]	[-3.77]
hml	-0.04	0.08	0.04	-0.05	-0.12	-0.14	0.07
	[-0.94]	[1.58]	[0.85]	[-1.10]	[-2.35]	[-2.89]	[1.37]
rmw	0.36	0.40	0.36	0.28	0.50	0.46	0.19
	[6.35]	[7.76]	[6.27]	[3.69]	[7.17]	[7.57]	[2.52]
cma	-0.19	0.01	0.08	0.13	0.07	0.04	-0.12
	[-2.59]	[0.13]	[1.18]	[1.97]	[0.93]	[0.61]	[-1.66]
umd	0.00	-0.02	-0.03	-0.00	-0.01	-0.01	-0.02
	[0.17]	[-0.76]	[-1.16]	[-0.16]	[-0.23]	[-0.54]	[-1.02]
# months	450	450	450	450	450	450	450
$\bar{R}^2$ (%)	61	62	60	57	55	56	65

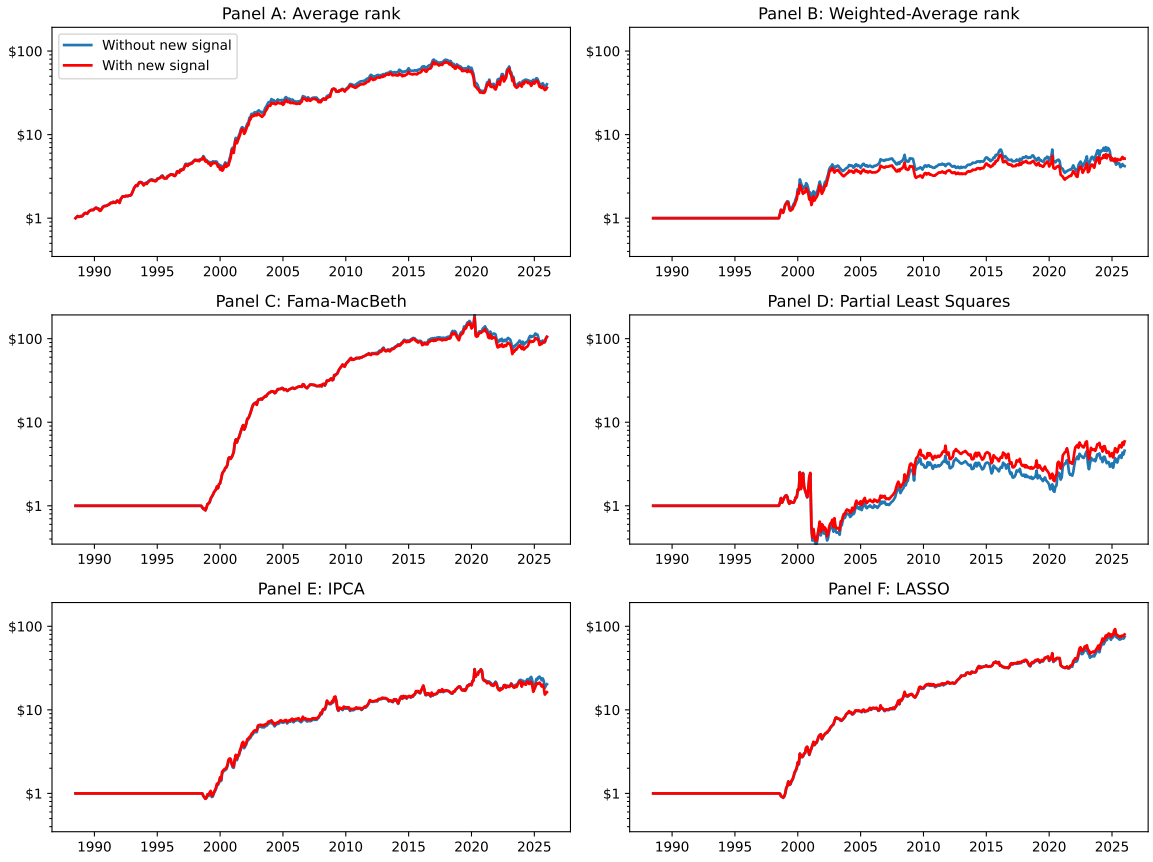

Figure 8: Combination strategy performance
This figure plots the growth of $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2023). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines indicate combination trading strategies that utilize the 159 anomalies as well as OCFI. Panel A shows results using "Average rank" as the combination method. Panel B shows results using "Weighted-Average rank" as the combination method. Panel C shows results using "Fama-MacBeth" as the combination method. Panel D shows results using "Partial Least Squares" as the combination method. Panel E shows results using "IPCA" as the combination method. Panel F shows results using "LASSO" as the combination method. The figure starts in the first month in which OCFI has data. In each panel both strategies start in the first month in which the method uses OCFI: that month for the average rank, and ten years later for the other methods. See Section 6 for details on the combination methods.

References

Abdi, F. and Ranaldo, A. (2017). A simple estimation of bid-ask spreads from daily close, high, and low prices. *Review of Financial Studies*, 30(12):4437–4480.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Chen, A. and Velikov, M. (2023). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, 58(3):968–1004.

Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.

Corwin, S. A. and Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance*, 67(2):719–760.

Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance, Forthcoming*.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: empirical tests. *Journal of Political Economy*, 81(3):607–636.

Hasbrouck, J. (2009). Trading costs and returns for U.S. equities: Estimating effective costs from daily data. *Journal of Finance*, 64(3):1445–1477.

Haugen, R. A. and Baker, N. L. (1996). Commonality in the determinants of expected stock returns. *Journal of Financial Economics*, 41(3):401–439.

Kelly, B. T., Pruitt, S., and Su, Y. (2019). Characteristics are covariances: A unified model of risk and return. *Journal of Financial Economics*, 134(3):501–524.

Kyle, A. S. and Obizhaeva, A. A. (2016). Market microstructure invariance: Empirical hypotheses. *Econometrica*, 84(4):1345–1404.

Lewellen, J. (2015). The cross-section of expected returns. *Critical Finance Review*, 4(1):1–44.

Light, N., Maslov, D., and Rytchkov, O. (2017). Aggregation of information about the cross section of stock returns: A latent variable approach. *Review of Financial Studies*, 30:1339–1381.

Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2026). Assaying anomalies. *Working paper*.