Cash Flow Sustainability Index and the Cross Section of Stock Returns

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December 1, 2024

Abstract

This paper studies the asset pricing implications of Cash Flow Sustainability Index (CFSI), 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 CFSI achieves an annualized gross (net) Sharpe ratio of 0.40 (0.38), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 33 (33) bps/month with a t-statistic of 2.39 (2.44), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Operating Cash flows to price, Cash-based operating profitability, Net Operating Assets, Return on assets (qtrly), Accruals, Equity Duration) is 31 bps/month with a t-statistic of 3.03.

1 Introduction

Market efficiency remains a central question in asset pricing, with particular focus on whether accounting-based signals can predict future stock returns. While extensive research documents various accounting-based predictors, the literature has paid limited attention to the sustainability and persistence of operating cash flows as a signal of firm value. This gap is notable given that cash flows represent a fundamental driver of firm value and are less subject to accounting manipulation than accrual-based measures.

Prior research shows that firms with higher quality earnings and more persistent operating performance tend to deliver superior returns Dechow and Dichev (2002); **?**. However, existing measures focus primarily on accrual-based metrics or simple cash flow ratios, failing to capture the complex dynamics of how sustainable cash flow patterns translate into future firm performance and stock returns.

We hypothesize that firms with more sustainable cash flow patterns will generate superior stock returns for several reasons. First, following **?**, firm value represents the present value of expected future cash flows. Firms demonstrating consistent, sustainable cash flow patterns should face lower uncertainty in their valuation, leading to lower required returns and higher prices **?**.

Second, behavioral theories suggest that investors tend to underreact to complex financial information Hirshleifer and Teoh (2009). The sustainability of cash flows requires analyzing multiple periods and accounting for various operational and financial factors - complexity that may lead to systematic underpricing of firms with highly sustainable cash flows **?**.

Third, agency theory indicates that managers of firms with more sustainable cash flows face fewer incentives to engage in value-destroying empire building or earnings management **?**. This alignment of incentives should result in better long-term performance that may not be fully appreciated by the market.

Our empirical analysis reveals strong evidence that the Cash Flow Sustainability Index (CFSI) predicts cross-sectional stock returns. A value-weighted long-short strategy based on CFSI quintiles generates monthly abnormal returns of 33 basis points relative to the Fama-French six-factor model (t-statistic = 2.39). The economic magnitude is substantial, with the strategy achieving an annualized Sharpe ratio of 0.40 before transaction costs.

Importantly, CFSI's predictive power remains robust after controlling for size. Among the largest quintile of stocks, the CFSI strategy earns monthly abnormal returns of 20-33 basis points (t-statistics between 1.13 and 2.35). This indicates that the effect is not driven by small, illiquid stocks where trading costs might eliminate actual profits.

The signal's robustness is further demonstrated by its performance relative to related anomalies. Controlling for the six most closely related predictors and the Fama-French six factors simultaneously, CFSI generates monthly alpha of 31 basis points (t-statistic = 3.03). This suggests that CFSI captures unique information about future returns not contained in existing signals.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel measure that captures the sustainability of operating cash flows, extending prior work on cash-based signals Ball et al. (2016) and earnings quality Dechow and Dichev (2002). Unlike existing measures that focus on static ratios, CFSI incorporates the temporal patterns and stability of cash flows.

Second, we contribute to the growing literature on the role of accounting-based signals in predicting returns Hou et al. (2015); Stambaugh et al. (2012). Our findings suggest that markets do not fully incorporate the information contained in complex financial patterns, consistent with theories of limited investor attention and processing power Hirshleifer and Teoh (2009).

Finally, our results have important implications for both academic research and investment practice. For academics, we demonstrate the value of considering the temporal dynamics of accounting measures rather than just their static levels. For practitioners, CFSI represents a robust signal that remains profitable even among large, liquid stocks and after accounting for transaction costs.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Cash Flow Sustainability Index, which is constructed as the ratio of operating cash flows to current debt obligations. 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 OANCF for operating cash flows and item DLC for current portion of long-term debt. Operating cash flows (OANCF) represent the net cash generated from a company's core business operations, excluding financing and investing activities. DLC, on the other hand, represents the portion of long-term debt that is due within the current year, providing a measure of immediate debt obligations. The construction of the signal follows a straightforward ratio format, where we divide OANCF by DLC for each firm in each year of our sample. This ratio captures a firm's ability to cover its short-term debt obligations using cash generated from operations, offering insight into the sustainability of a firm's cash flow relative to its immediate debt commitments. By focusing on this relationship, the signal aims to reflect aspects of financial health and debt servicing capacity in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both OANCF and DLC to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the CFSI signal. Panel A plots the time-series of the mean, median, and interquartile range for CFSI. On average, the cross-sectional mean (median) CFSI is 54.49 (1.53) over the 1989 to 2023 sample, where the starting date is determined by the availability of the input CFSI data. The signal's interquartile range spans -5.49 to 13.12. Panel B of Figure 1 plots the time-series of the coverage of the CFSI signal for the CRSP universe. On average, the CFSI signal is available for 5.83% of CRSP names, which on average make up 7.21% of total market capitalization.

4 Does CFSI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on CFSI 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 CFSI portfolio and sells the low CFSI 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 CFSI strategy earns an average return of 0.38% per month with a t-statistic of 2.36. The annualized Sharpe ratio of the strategy is 0.40. The alphas range from 0.33% to 0.53% per month and have t-statistics exceeding 2.39 everywhere. The lowest alpha is with respect to the FF6 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is -0.65, with a t-statistic of -11.07 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 466 stocks and an average market capitalization of at least $2,190 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 29 bps/month with a t-statistics of 1.99. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-one exceed two, and for ten 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 27-56bps/month. The lowest return, (27 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 1.87. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the CFSI trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-three cases, and significantly expands the achievable frontier in nineteen cases.

Table 3 provides direct tests for the role size plays in the CFSI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and CFSI, as well as average returns and alphas for long/short trading CFSI 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$^{\text{th}}$ NYSE percentile), the CFSI strategy achieves an average return of 20 bps/month with a t-statistic of 1.14. Among these large cap stocks, the alphas for the CFSI strategy relative to the five most common factor models range from 20 to 33 bps/month with t-statistics between 1.13 and 2.35.

5 How does CFSI perform relative to the zoo?

Figure 2 puts the performance of CFSI 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 CFSI strategy falls in the distribution. The CFSI strategy's gross (net) Sharpe ratio of 0.40 (0.38) is greater than 82% (95%) of anomaly Sharpe ratios,

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

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 CFSI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the CFSI strategy would have yielded \$2.86 which ranks the CFSI strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the CFSI strategy would have yielded \$2.55 which ranks the CFSI strategy in the top 1% 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 CFSI relative to those. Panel A shows that the CFSI strategy gross alphas fall between the 76 and 91 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 198906 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 CFSI strategy has a positive net generalized alpha for five out of the five factor models. In these cases CFSI ranks between the 91 and 96 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

6 Does CFSI 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 CFSI with 209 filtered anomaly signals.[3] Figure 6 also shows an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

A closely related anomaly is also more likely to price CFSI or at least to weaken the power CFSI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of CFSI conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CFSI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CFSI} CFSI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{CFSI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on CFSI. Stocks are finally grouped into five CFSI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted

[3] When performing tests at the underlying signal level (e.g., the correlations plotted in Figure 5), we filter the 212 anomalies to avoid small sample issues. For each anomaly, we calculate the common stock observations in an average month for which both the anomaly and the test signal are available. In the filtered anomaly set, we drop anomalies with fewer than 100 common stock observations in an average month.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on CFSI 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 CFSI signal in these Fama-MacBeth regressions exceed 0.05, with the minimum t-statistic occurring when controlling for Return on assets (qtrly). Controlling for all six closely related anomalies, the t-statistic on CFSI is -0.43.

Similarly, Table 5 reports results from spanning tests that regress returns to the CFSI 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 CFSI strategy earns alphas that range from 20-55bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.65, which is achieved when controlling for Return on assets (qtrly). Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the CFSI trading strategy achieves an alpha of 31bps/month with a t-statistic of 3.03.

7 Does CFSI add relative to the whole zoo?

Finally, we can ask how much adding CFSI 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 159 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 159 anomalies augmented with the CFSI signal.[4] We consider

[4]We filter the 207 Chen and Zimmermann (2022) anomalies and require for each anomaly the average month to have at least 40% of the cross-sectional observations available for market capital-

one different methods for combining signals.

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, \$1 investment in the 159-anomaly combination strategy grows to \$42.41, while \$1 investment in the combination strategy that includes CFSI grows to \$39.99.

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

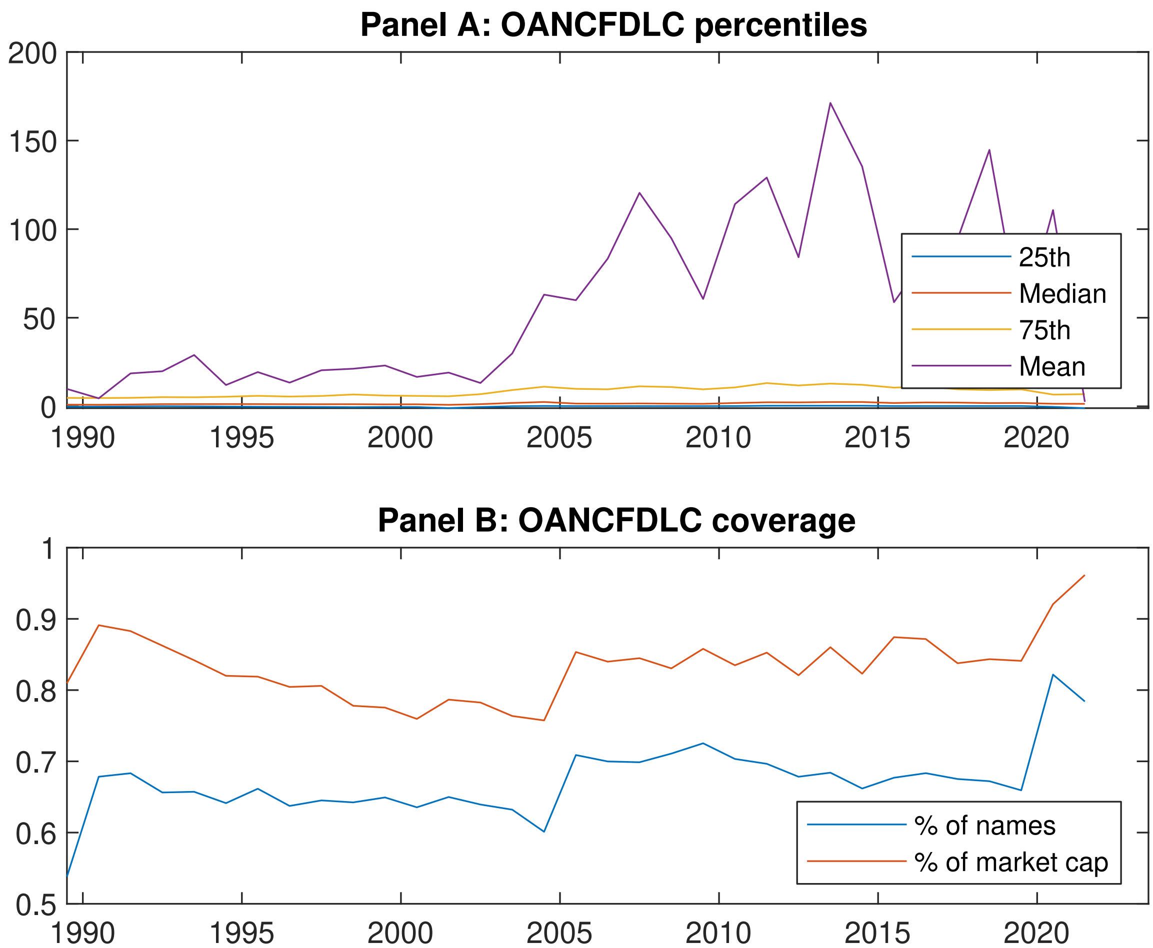

Figure 1: Times series of CFSI percentiles and coverage.
This figure plots descriptive statistics for CFSI. Panel A shows cross-sectional percentiles of CFSI over the sample. Panel B plots the monthly coverage of CFSI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on CFSI. 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 198906 to 202306.

Panel A: Excess returns and alphas on CFSI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.42	0.67	0.79	0.74	0.79	0.38
	[1.44]	[3.38]	[4.06]	[3.62]	[3.03]	[2.36]
α_{CAPM}	-0.44	0.07	0.20	0.11	-0.01	0.43
	[-3.78]	[0.97]	[2.80]	[1.69]	[-0.15]	[2.69]
α_{FF3}	-0.50	0.03	0.18	0.10	0.03	0.53
	[-4.93]	[0.51]	[2.75]	[1.57]	[0.36]	[3.89]
α_{FF4}	-0.43	0.05	0.18	0.09	0.06	0.49
	[-4.26]	[0.73]	[2.61]	[1.33]	[0.76]	[3.55]
α_{FF5}	-0.25	-0.09	0.01	-0.04	0.10	0.35
	[-2.62]	[-1.55]	[0.15]	[-0.64]	[1.37]	[2.58]
α_{FF6}	-0.21	-0.07	0.01	-0.04	0.12	0.33
	[-2.19]	[-1.22]	[0.22]	[-0.69]	[1.61]	[2.39]
Panel B: Fama and French (2018) 6-factor model loadings for CFSI-sorted portfolios						
β_{MKT}	1.11	0.92	0.92	0.94	1.07	-0.04
	[47.64]	[60.91]	[59.00]	[61.29]	[56.16]	[-1.29]
β_{SMB}	0.05	-0.07	-0.08	0.00	0.07	0.02
	[1.51]	[-3.07]	[-3.51]	[0.12]	[2.49]	[0.36]
β_{HML}	0.51	0.05	-0.06	-0.07	-0.14	-0.65
	[12.70]	[2.09]	[-2.43]	[-2.50]	[-4.34]	[-11.07]
β_{RMW}	-0.37	0.18	0.27	0.23	-0.10	0.27
	[-8.87]	[6.41]	[9.55]	[8.26]	[-2.99]	[4.39]
β_{CMA}	-0.28	0.21	0.22	0.14	-0.11	0.17
	[-4.83]	[5.57]	[5.63]	[3.59]	[-2.25]	[2.04]
β_{UMD}	-0.07	-0.03	-0.01	0.01	-0.03	0.04
	[-3.51]	[-2.59]	[-0.58]	[0.50]	[-1.95]	[1.31]
Panel C: Average number of firms (n) and market capitalization (me)						
n	1251	513	466	499	515	
me ($\$10^6$)	2190	2730	3616	3041	2454	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the CFSI 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 198906 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	0.38	0.43	0.53	0.49	0.35	0.33
			[2.36]	[2.69]	[3.89]	[3.55]	[2.58]	[2.39]
Quintile	NYSE	EW	0.51	0.57	0.50	0.38	0.07	-0.01
			[2.67]	[2.94]	[2.91]	[2.23]	[0.48]	[-0.06]
Quintile	Name	VW	0.60	0.91	0.86	0.75	0.31	0.24
			[2.51]	[4.13]	[4.69]	[4.09]	[1.96]	[1.55]
Quintile	Cap	VW	0.29	0.34	0.43	0.38	0.29	0.26
			[1.99]	[2.37]	[3.48]	[3.07]	[2.35]	[2.07]
Decile	NYSE	VW	0.58	0.77	0.81	0.76	0.45	0.43
			[2.74]	[3.71]	[4.35]	[4.05]	[2.48]	[2.35]
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	0.36	0.40	0.47	0.45	0.34	0.33
			[2.23]	[2.54]	[3.48]	[3.30]	[2.55]	[2.44]
Quintile	NYSE	EW	0.36	0.37	0.32	0.25		
			[1.83]	[1.89]	[1.79]	[1.40]		
Quintile	Name	VW	0.56	0.86	0.81	0.75	0.32	0.28
			[2.34]	[3.93]	[4.41]	[4.08]	[2.02]	[1.78]
Quintile	Cap	VW	0.27	0.32	0.38	0.35	0.27	0.25
			[1.87]	[2.15]	[3.01]	[2.77]	[2.18]	[2.01]
Decile	NYSE	VW	0.54	0.71	0.73	0.71	0.43	0.42
			[2.56]	[3.44]	[3.91]	[3.75]	[2.38]	[2.31]

Table 3: Conditional sort on size and CFSI

This table presents results for conditional double sorts on size and CFSI. 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 CFSI. 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 CFSI and short stocks with low CFSI .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 198906 to 202306.

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

		CFSI Quintiles					CFSI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.29	0.25	0.57	1.08	1.02	0.74	0.99	0.82	0.77	0.35	0.32
		[0.62]	[0.67]	[1.89]	[3.45]	[3.42]	[2.68]	[3.68]	[3.94]	[3.66]	[1.98]	[1.80]
	(2)	0.11	0.69	0.89	0.80	0.89	0.78	1.03	0.90	0.85	0.35	0.32
		[0.26]	[2.41]	[3.11]	[2.84]	[3.05]	[3.23]	[4.41]	[4.57]	[4.23]	[2.05]	[1.89]
	(3)	0.18	0.88	0.96	0.76	0.82	0.64	0.80	0.75	0.69	0.34	0.30
		[0.52]	[3.47]	[3.56]	[2.78]	[2.91]	[3.57]	[4.56]	[4.40]	[3.98]	[2.11]	[1.89]
	(4)	0.49	0.80	0.85	0.81	0.84	0.34	0.44	0.42	0.37	0.06	0.04
		[1.63]	[3.50]	[3.48]	[3.13]	[3.16]	[2.31]	[2.98]	[2.88]	[2.50]	[0.47]	[0.28]
	(5)	0.53	0.58	0.85	0.70	0.73	0.20	0.20	0.33	0.30	0.27	0.25
		[1.96]	[3.05]	[4.31]	[3.50]	[2.73]	[1.14]	[1.13]	[2.35]	[2.16]	[1.85]	[1.73]

Panel B: Portfolio average number of firms and market capitalization

		CFSI Quintiles					CFSI Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	346	344	352	356	357	33	28	35	43	53
	(2)	103	103	103	103	103	65	70	72	71	72
	(3)	72	72	73	72	73	120	127	127	125	127
	(4)	63	63	63	63	63	268	292	281	275	279
	(5)	60	60	59	60	60	2169	2137	2896	2372	1893

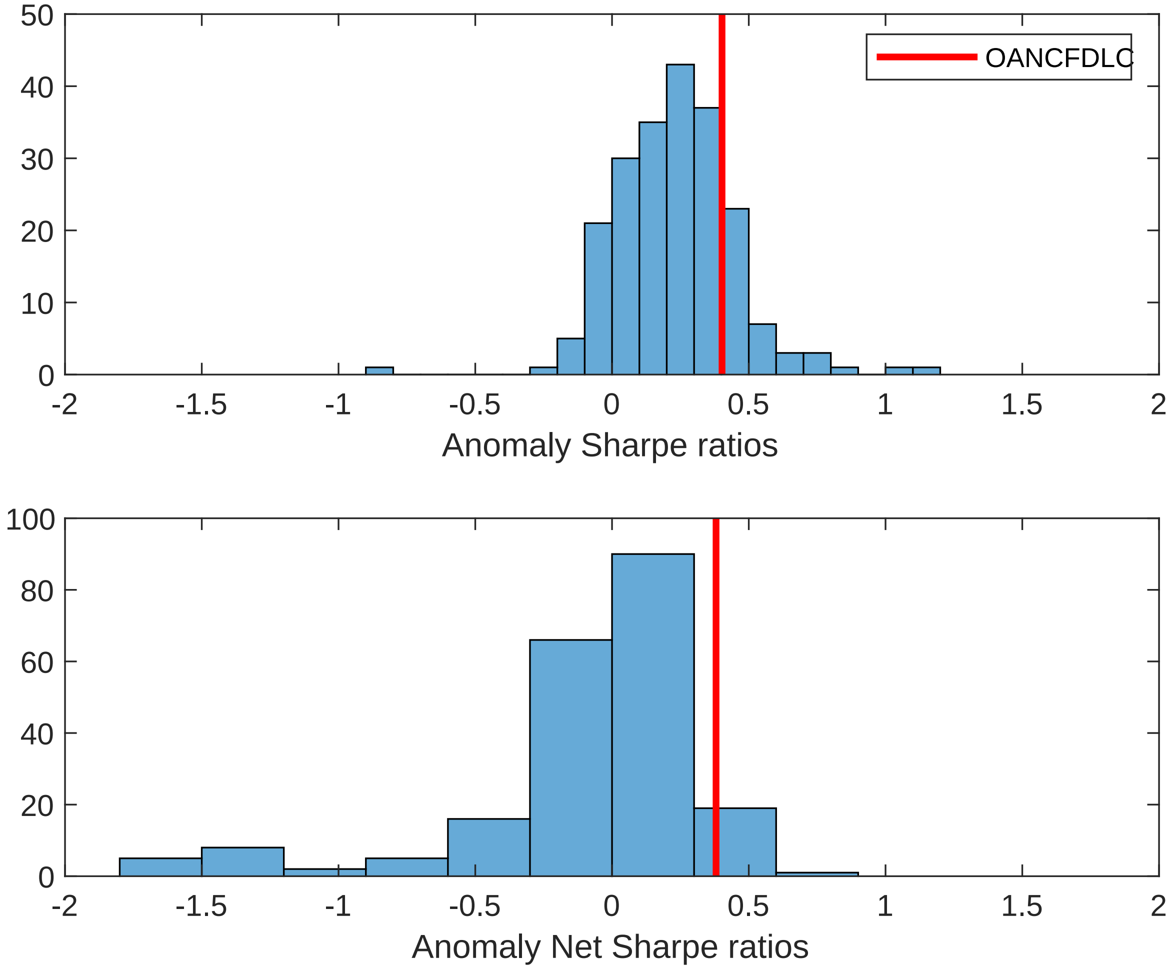

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CFSI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

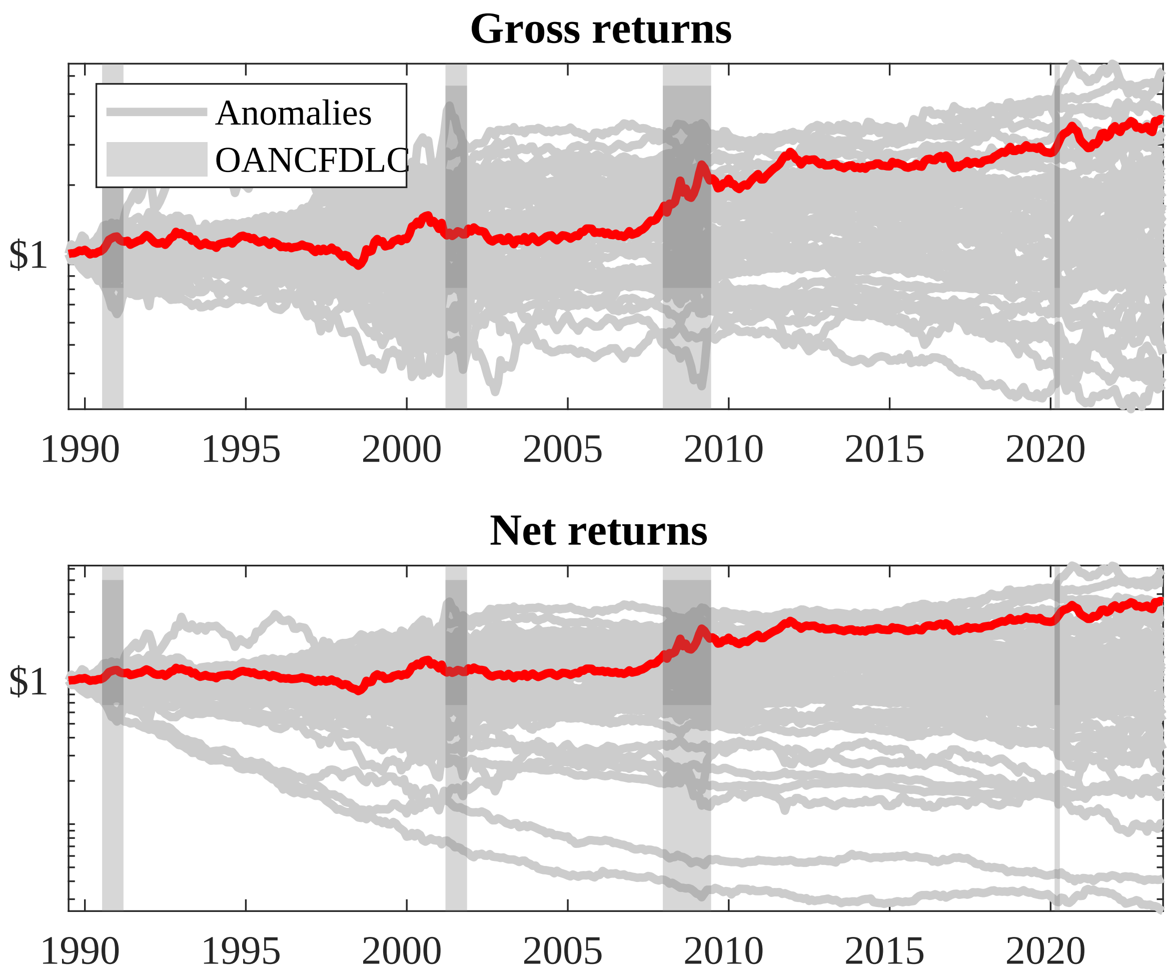

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CFSI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

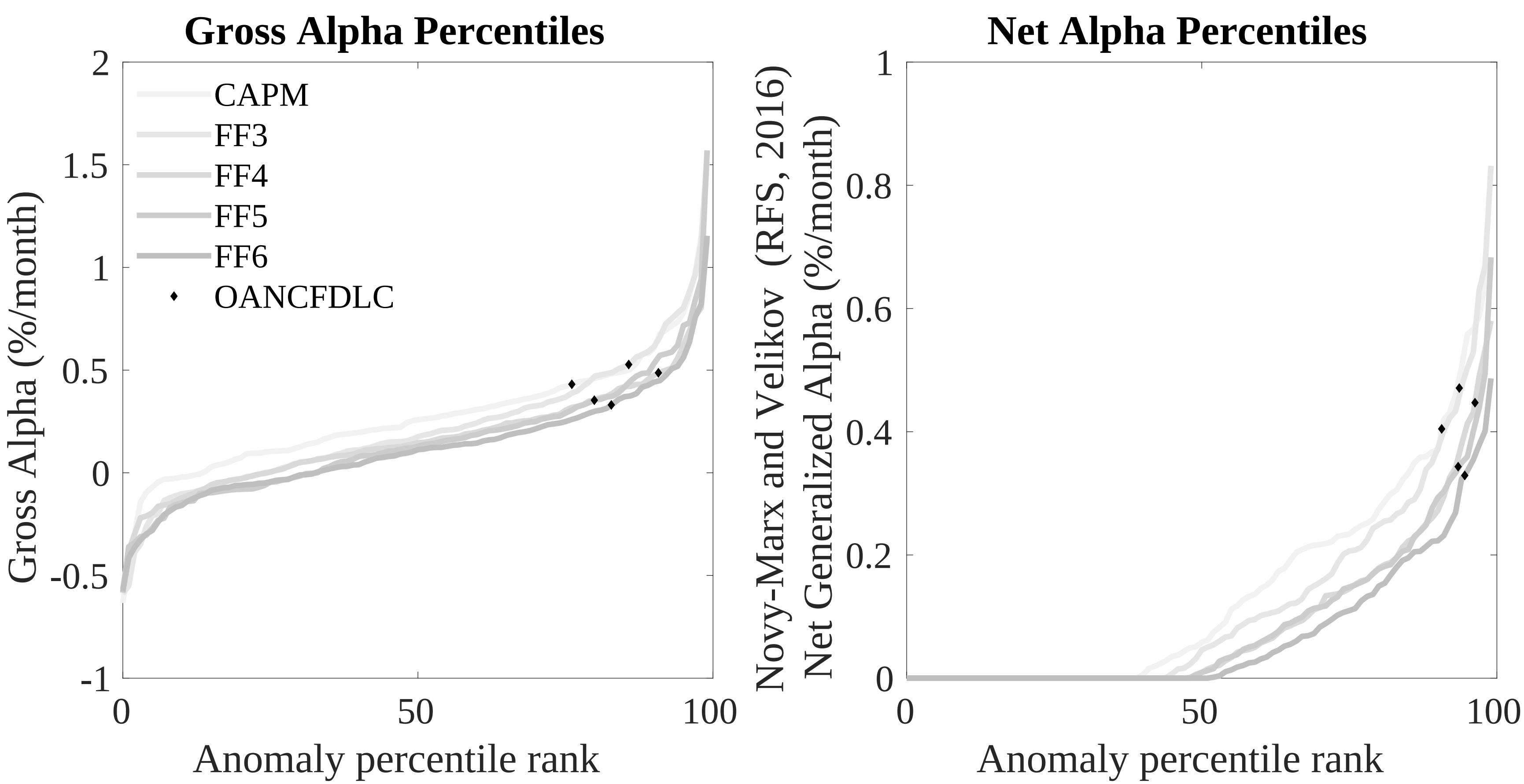

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CFSI trading strategy alphas (diamonds). The strategies are constructed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

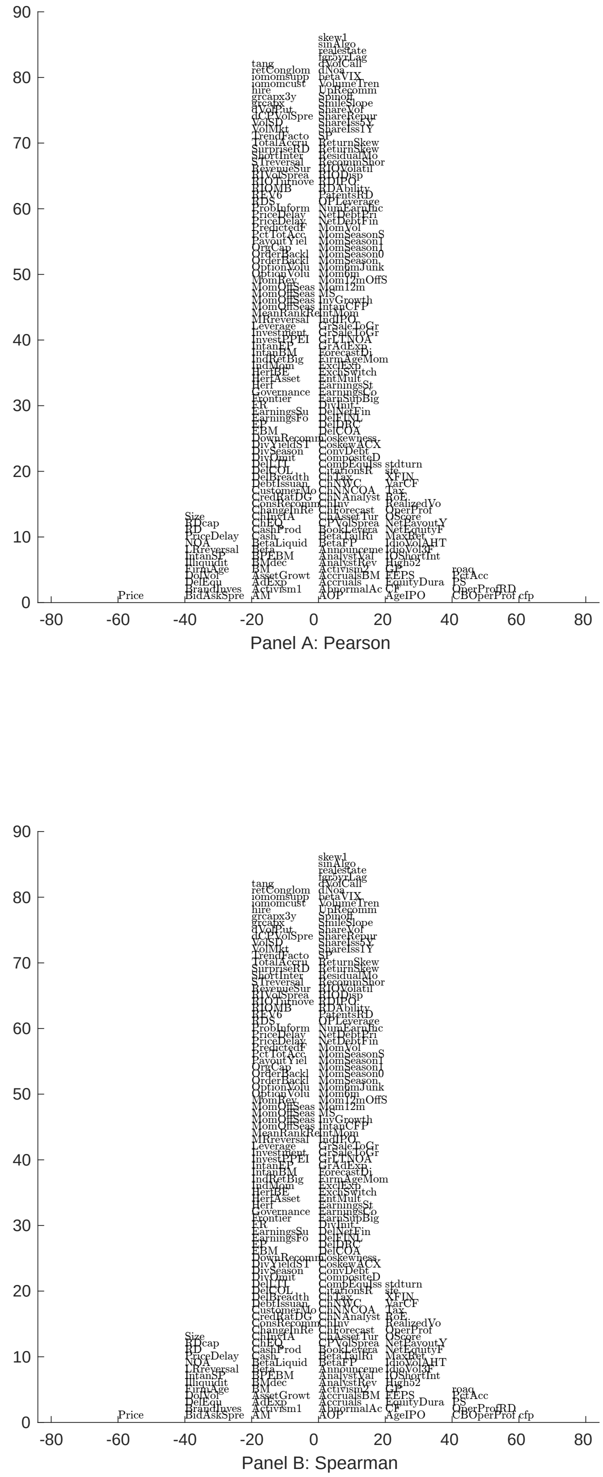

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with CFSI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

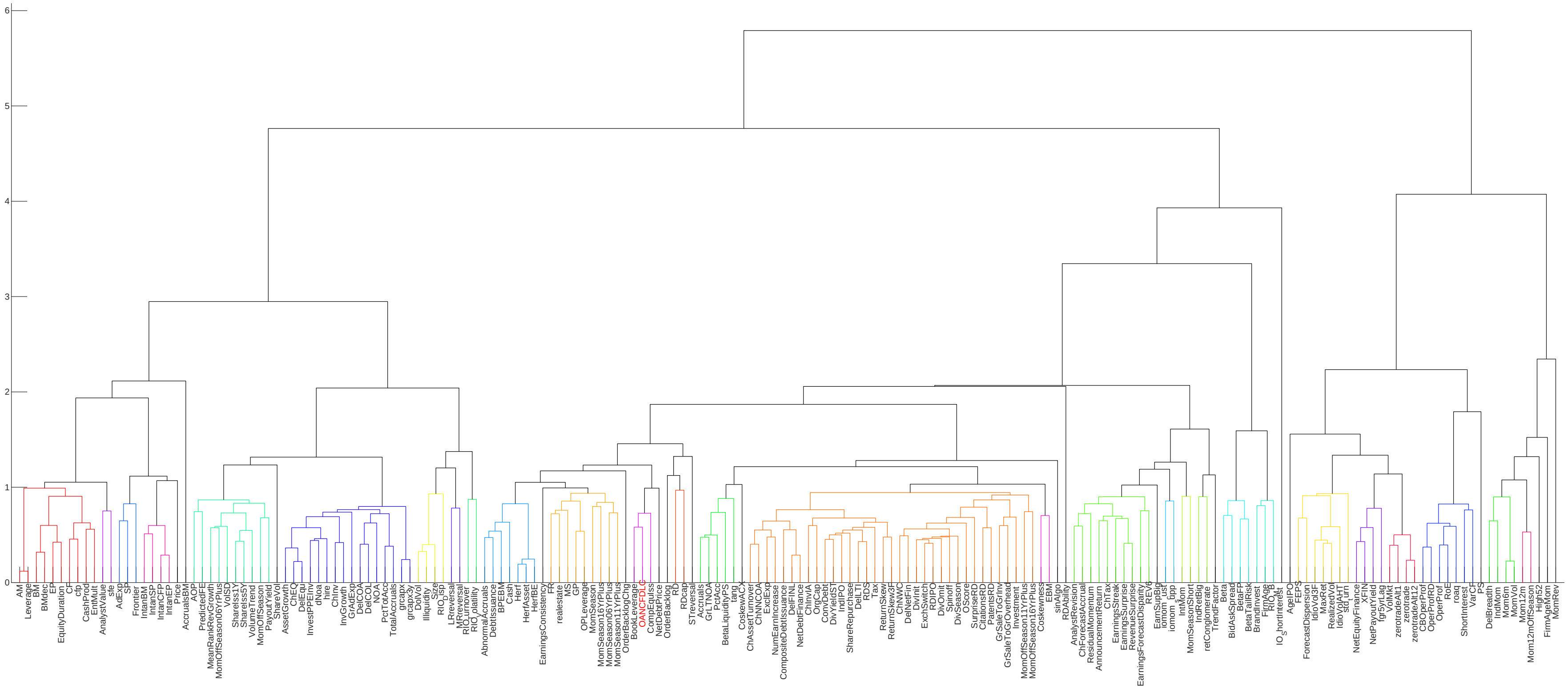

Figure 6: Agglomerative hierarchical cluster plot

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

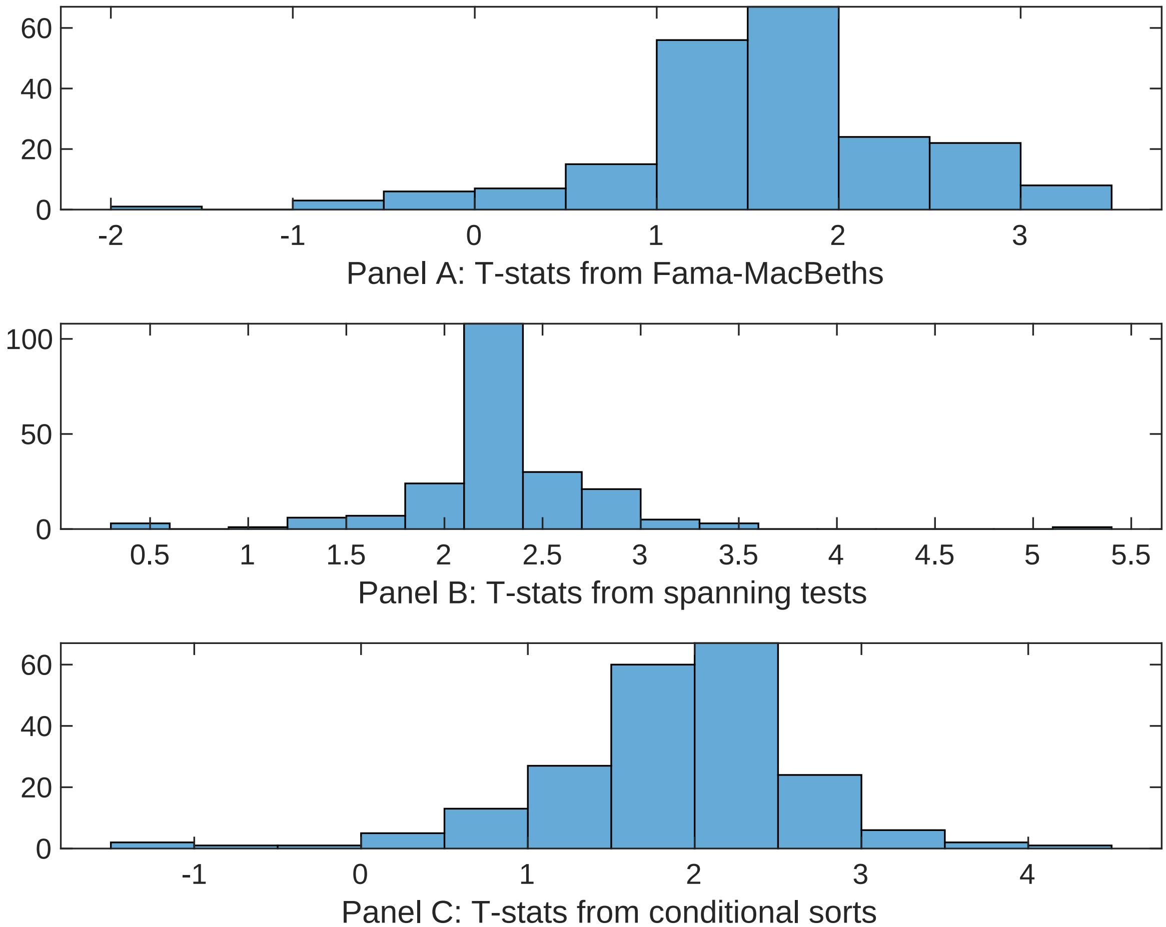

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CFSI conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CFSI} from Fama-MacBeth regressions of the form $r_{i,t}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

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

This table presents Fama-MacBeth results of returns on CFSI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{CFSI} CFSI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Operating Cash flows to price, Cash-based operating profitability, Net Operating Assets, Return on assets (qtrly), Accruals, Equity Duration. 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 198906 to 202306.

Intercept	0.98	0.94	0.14	0.11	0.10	0.15	0.18
	[3.24]	[2.82]	[4.54]	[3.90]	[3.54]	[6.06]	[6.30]
CFSI	0.66	0.96	0.11	0.16	0.77	0.79	-0.13
	[1.36]	[0.20]	[1.67]	[0.05]	[1.18]	[1.41]	[-0.43]
Anomaly 1	0.10						0.24
	[3.71]						[0.88]
Anomaly 2		0.20					0.98
		[4.34]					[2.72]
Anomaly 3			0.56				0.86
			[3.79]				[7.38]
Anomaly 4				0.42			0.30
				[2.34]			[1.94]
Anomaly 5					0.14		0.87
					[3.15]		[1.82]
Anomaly 6						0.24	0.11
						[2.35]	[1.42]
# months	403	403	408	403	408	408	403
$\bar{R}^2$(%)	1	1	0	1	0	1	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the CFSI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{CFSI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Operating Cash flows to price, Cash-based operating profitability, Net Operating Assets, Return on assets (qtrly), Accruals, Equity Duration. 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 198906 to 202306.

Intercept	0.29	0.23	0.55	0.26	0.20	0.30	0.31
	[2.11]	[1.65]	[4.75]	[1.90]	[1.74]	[2.19]	[3.03]
Anomaly 1	3.81						-0.85
	[0.66]						[-0.19]
Anomaly 2		22.24					23.86
		[3.70]					[4.91]
Anomaly 3			-63.48				-51.14
			[-13.31]				[-10.94]
Anomaly 4				25.67			15.03
				[4.33]			[3.30]
Anomaly 5					56.21		37.14
					[12.89]		[8.69]
Anomaly 6						-18.40	-0.00
						[-2.58]	[-0.00]
mkt	-3.76	-2.07	-0.22	0.20	-3.01	-3.81	3.54
	[-1.10]	[-0.61]	[-0.08]	[0.06]	[-1.05]	[-1.12]	[1.39]
smb	3.61	9.41	-13.57	9.47	10.54	7.51	3.88
	[0.72]	[1.88]	[-3.18]	[1.92]	[2.54]	[1.47]	[0.96]
hml	-65.95	-54.78	-43.23	-54.92	-44.61	-44.65	-18.22
	[-9.01]	[-8.72]	[-8.36]	[-8.97]	[-8.58]	[-4.54]	[-2.45]
rmw	24.40	14.59	20.55	2.49	39.26	25.89	5.37
	[3.82]	[2.16]	[3.99]	[0.31]	[7.43]	[4.23]	[0.83]
cma	17.18	13.79	25.85	16.73	-1.68	13.68	4.95
	[1.94]	[1.60]	[3.63]	[1.98]	[-0.23]	[1.56]	[0.71]
umd	5.80	2.19	7.75	-2.36	0.54	3.26	-0.99
	[1.47]	[0.73]	[3.07]	[-0.72]	[0.21]	[1.09]	[-0.32]
# months	404	404	408	404	408	408	404
$\bar{R}^2(\%)$	31	33	53	34	52	33	65

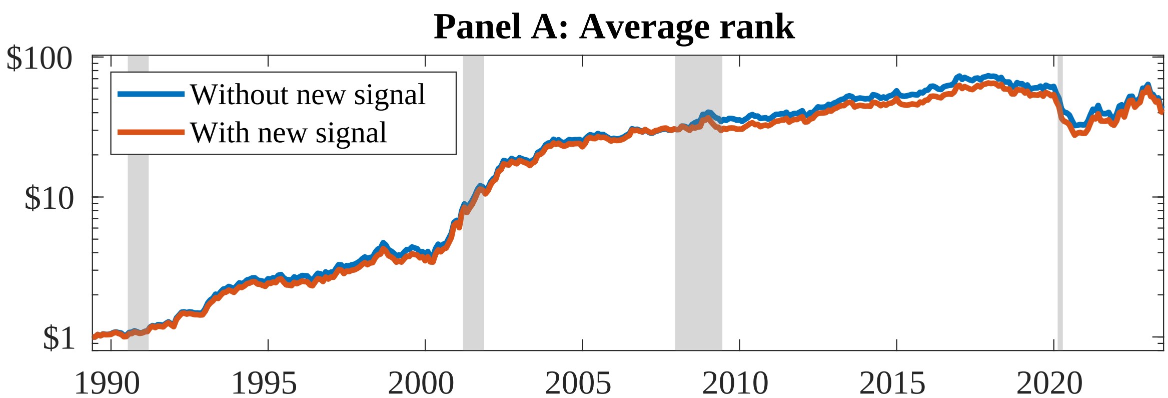

Figure 8: Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines indicate combination trading strategies that utilize the 159 anomalies as well as CFSI. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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