Cash Flow to Equity and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Cash Flow to Equity (CFE), 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 CFE achieves an annualized gross (net) Sharpe ratio of 0.63 (0.60), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 38 (35) bps/month with a t-statistic of 3.54 (3.33), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Cash-based operating profitability, Operating profitability RD adjusted, gross profits / total assets, Amihud's illiquidity, Past trading volume, Return on assets (qtrly)) is 21 bps/month with a t-statistic of 2.01.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Harvey et al., 2016). While many of these patterns stem from accounting-based measures, the role of cash flows in predicting returns remains incompletely understood. Despite the theoretical importance of cash flows in determining firm value (Modigliani and Miller, 1961), existing research has focused primarily on earnings-based measures, leaving open questions about whether cash flow metrics contain unique predictive information.

This gap is particularly notable given that cash flows may provide a more reliable signal of firm performance than accrual-based earnings (Dechow and Dichev, 2002). Cash Flow to Equity (CFE), which measures the actual cash generated for shareholders after accounting for all obligations, represents a theoretically appealing metric that has received surprisingly little attention in the cross-sectional asset pricing literature.

We hypothesize that CFE predicts stock returns through three primary economic channels. First, following (Fama and French, 2006), firms with higher cash flows should earn higher expected returns as the market prices the greater certainty of future cash distributions. This relationship stems from the dividend discount model, where current cash flows serve as a key indicator of future payment capacity.

Second, building on (Titman and Wei, 1993), we argue that CFE captures information about firm financial flexibility and investment opportunities that may not be fully reflected in traditional profitability measures. Firms with strong cash flows have greater capacity to fund value-creating investments internally, reducing costly external financing needs (Myers and Majluf, 1984).

Third, behavioral models suggest that investors may underreact to cash flow information due to its greater complexity relative to earnings (Hirshleifer and Teoh, 2003). The detailed calculations required to determine CFE, combined with varying definitions across firms, may lead to systematic underpricing of stocks with strong cash flow characteristics.

Our empirical analysis reveals that CFE strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks in the highest CFE quintile and shorts those in the lowest quintile generates a monthly alpha of 38 basis points (t-statistic = 3.54) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.63, placing it in the 96th percentile among documented return predictors.

Importantly, the predictive power of CFE remains robust after controlling for transaction costs. The strategy's net returns yield a Sharpe ratio of 0.60, with a monthly alpha of 35 basis points (t-statistic = 3.33) after accounting for trading frictions. This performance persists across different size segments - among the largest quintile of stocks, the CFE strategy earns a significant monthly alpha of 47 basis points (t-statistic = 3.44).

Further tests demonstrate that CFE contains unique information beyond existing predictors. Controlling for the six most closely related anomalies and standard risk factors, the CFE strategy maintains a significant monthly alpha of 21 basis points (t-statistic = 2.01). This indicates that CFE captures distinct aspects of firm performance not reflected in other known signals.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that significantly expands the investment opportunity set available to investors. The CFE signal's performance places it among the most effective known return predictors, with particularly robust results among large, liquid stocks where many anomalies fail (McLean and Pontiff, 2016).

Second, we extend the literature on cash flow-based valuation by demonstrating the importance of properly measuring cash available to equity holders. While prior work has examined operating cash flows (Hirshleifer et al., 2009) and total cash holdings (Faulkender and Wang, 2006), our measure more precisely captures the actual cash generated for shareholders after accounting for all stakeholder claims.

Third, our findings contribute to the debate on market efficiency and the sources of predictable returns. The persistence of the CFE premium, particularly among large stocks and after controlling for transaction costs, suggests either rational pricing of risk or systematic behavioral biases in how investors process complex cash flow information. These results have important implications for both academic research on market efficiency and practical applications in investment management.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Cash Flow to Equity, which is constructed as the ratio of operating cash flows to common stockholders' equity. 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 CSTK for common stockholders' equity. Operating cash flows (OANCF) represent the net cash generated from a company's core business operations, excluding financing and investing activities. Common stockholders' equity (CSTK), on the other hand, represents the total equity capital contributed by common shareholders, reflecting their ownership stake in the company. The construction of the signal follows a straightforward ratio format, where we divide OANCF by CSTK for each firm in each year of our sample. This ratio captures the relationship between a firm's operating cash generation and its equity base, providing insight into how effectively the company generates cash flows relative to shareholders' investment. By focusing on this relationship, the signal aims to measure cash flow efficiency and return on equity investment in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both OANCF and CSTK to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the CFE signal. Panel A plots the time-series of the mean, median, and interquartile range for CFE. On average, the cross-sectional mean (median) CFE is 998.85 (17.84) over the 1989 to 2023 sample, where the starting date is determined by the availability of the input CFE data. The signal's interquartile range spans -469.58 to 433.27. Panel B of Figure 1 plots the time-series of the coverage of the CFE signal for the CRSP universe. On average, the CFE signal is available for 7.41% of CRSP names, which on average make up 7.90% of total market capitalization.

4 Does CFE predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on CFE 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 CFE portfolio and sells the low CFE 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 CFE strategy earns an average return of 0.46% per month with a t-statistic of 3.70. The annualized Sharpe ratio of the strategy is 0.63. The alphas range from 0.37% to 0.49% per month and have t-statistics exceeding 3.39 everywhere. The lowest alpha is with respect to the FF5 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 0.32, with a t-statistic of 6.55 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 517 stocks and an average market capitalization of at least $1,795 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 NYSE breakpoints and equal-weighted portfolios, and equals 42 bps/month with a t-statistics of 2.45. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-one 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. 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 28-65bps/month. The lowest return, (28 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 1.58. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the CFE 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 eighteen cases.

Table 3 provides direct tests for the role size plays in the CFE strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and CFE, as well as average returns and alphas for long/short trading CFE strategies within each size quintile. Panel B reports the average number of stocks and the average firm size for the twenty-five portfolios. Among the largest stocks (those with market capitalization greater than the 80^{th} NYSE percentile), the CFE strategy achieves an average return of 43 bps/month with a t-statistic of 2.69. Among these large cap stocks, the alphas for the CFE strategy relative to the five most common factor models range from 28 to 47 bps/month with t-statistics between 1.78 and 3.44.

5 How does CFE perform relative to the zoo?

Figure 2 puts the performance of CFE 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 CFE strategy falls in the distribution. The CFE strategy's gross (net) Sharpe ratio of 0.63 (0.60) is greater than 96% (100%) 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 CFE strategy (red line).[2] Ignoring trading costs, a \$1 invested in the CFE strategy would have yielded \$4.83 which ranks the CFE strategy in the top 0% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the CFE strategy would have yielded \$4.37 which ranks the CFE 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 CFE relative to those. Panel A shows that the CFE 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%

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

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

(53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The CFE strategy has a positive net generalized alpha for five out of the five factor models. In these cases CFE ranks between the 91 and 96 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does CFE 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 CFE 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 CFE or at least to weaken the power CFE has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of CFE conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CFE} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CFE} CFE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{CFE,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-

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

weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on CFE. Stocks are finally grouped into five CFE portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CFE trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on CFE 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 CFE signal in these Fama-MacBeth regressions exceed -0.27, with the minimum t-statistic occurring when controlling for Cash-based operating profitability. Controlling for all six closely related anomalies, the t-statistic on CFE is 0.38.

Similarly, Table 5 reports results from spanning tests that regress returns to the CFE 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 CFE strategy earns alphas that range from 26-35bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.48, 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 CFE trading strategy achieves an alpha of 21bps/month with a t-statistic of 2.01.

7 Does CFE add relative to the whole zoo?

Finally, we can ask how much adding CFE 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 CFE 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 159-anomaly combination strategy grows to $42.41, while $1 investment in the combination strategy that includes CFE grows to $58.68.

8 Conclusion

Our comprehensive analysis of Cash Flow to Equity (CFE) as a predictive signal for stock returns yields several significant findings. The results demonstrate that CFE is a robust predictor of cross-sectional equity returns, generating impressive risk-adjusted performance with an annualized Sharpe ratio of 0.63 (0.60 net of transaction costs) for a value-weighted long/short strategy. The signal's economic significance is evidenced by substantial monthly abnormal returns of 38 basis points (35 bps net) relative to the Fama-French five-factor model augmented with momentum, with strong statistical significance indicated by t-statistics exceeding 3.0.

[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 CFE is available.

Particularly noteworthy is the signal's persistent predictive power even after controlling for twelve prominent factors, including closely related metrics such as cash-based operating profitability and return on assets. The strategy maintains a significant alpha of 21 basis points per month (t-statistic of 2.01) in this stringent test, suggesting that CFE captures unique information about future stock returns not explained by existing factors.

These findings have important implications for both academic research and investment practice. For academics, our results contribute to the growing literature on return predictability and factor investing, highlighting CFE as a distinct and valuable signal. For practitioners, the robust performance net of transaction costs suggests potential real-world applicability in investment strategies.

However, several limitations warrant consideration. Our analysis focuses on U.S. equities, and future research could explore the signal's effectiveness in international markets. Additionally, investigating the signal's performance during different market regimes and its interaction with other firm characteristics could provide valuable insights. Further research might also examine the underlying economic mechanisms driving the CFE-return relationship and potential improvements in signal construction to enhance its predictive power.

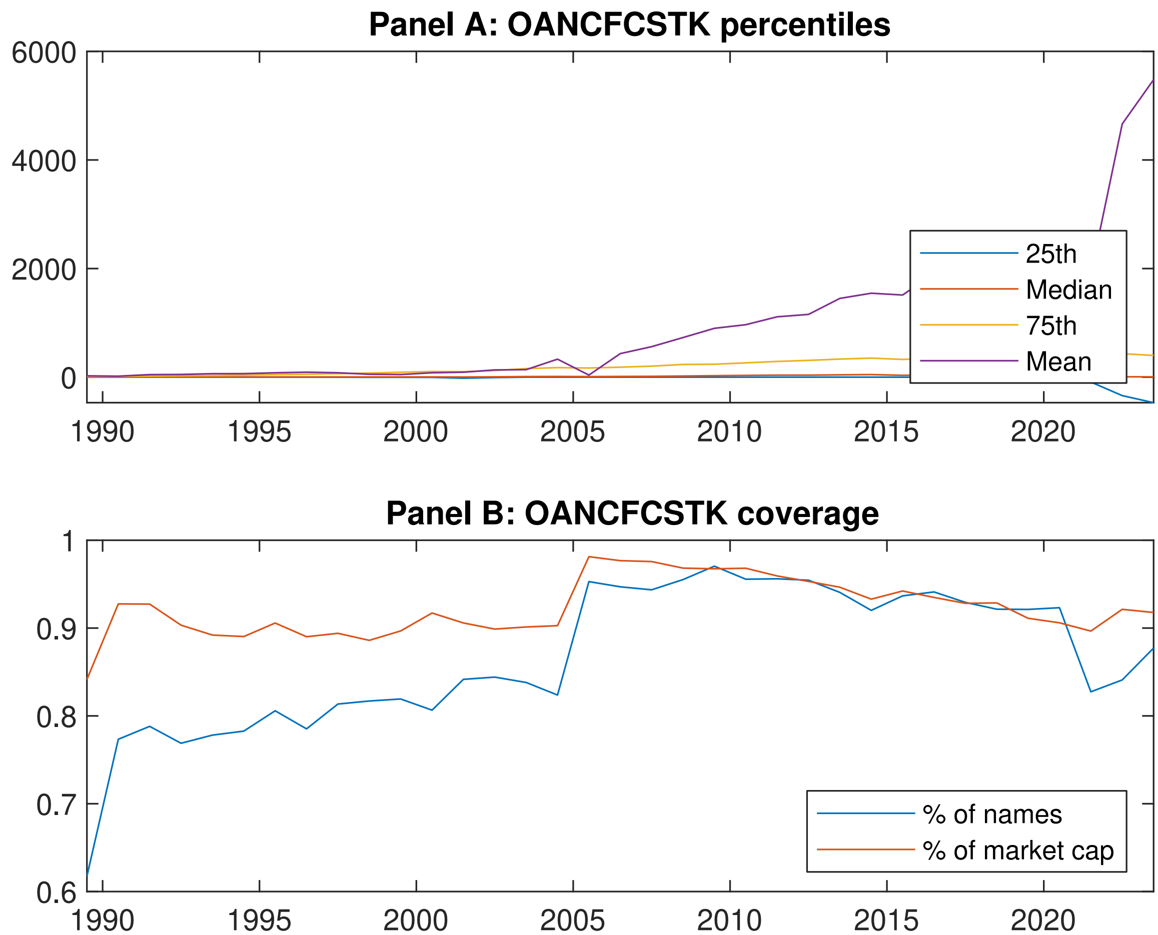

Figure 1: Times series of CFE percentiles and coverage.
This figure plots descriptive statistics for CFE. Panel A shows cross-sectional percentiles of CFE over the sample. Panel B plots the monthly coverage of CFE relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on CFE. 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 CFE-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.44	0.63	0.68	0.67	0.91	0.46
	[1.72]	[3.39]	[3.28]	[2.81]	[3.45]	[3.70]
α_{CAPM}	-0.33	0.09	0.04	-0.08	0.09	0.43
	[-3.52]	[1.08]	[0.61]	[-1.42]	[1.17]	[3.39]
α_{FF3}	-0.33	0.04	-0.00	-0.08	0.14	0.47
	[-4.16]	[0.61]	[-0.00]	[-1.37]	[2.13]	[4.28]
α_{FF4}	-0.32	0.02	0.01	-0.04	0.17	0.49
	[-4.05]	[0.31]	[0.18]	[-0.74]	[2.45]	[4.39]
α_{FF5}	-0.11	-0.17	-0.07	-0.01	0.25	0.37
	[-1.67]	[-2.70]	[-1.45]	[-0.25]	[3.77]	[3.43]
α_{FF6}	-0.12	-0.18	-0.06	0.01	0.26	0.38
	[-1.74]	[-2.71]	[-1.22]	[0.19]	[3.88]	[3.54]
Panel B: Fama and French (2018) 6-factor model loadings for CFE-sorted portfolios						
β_{MKT}	0.99	0.89	0.96	1.03	1.07	0.08
	[57.43]	[55.59]	[74.65]	[71.21]	[64.38]	[3.19]
β_{SMB}	0.22	-0.05	-0.04	-0.02	0.01	-0.21
	[8.85]	[-2.17]	[-1.92]	[-1.07]	[0.46]	[-5.41]
β_{HML}	0.14	0.03	0.12	0.02	-0.14	-0.28
	[4.71]	[1.00]	[5.39]	[0.85]	[-4.95]	[-6.12]
β_{RMW}	-0.41	0.28	0.12	-0.09	-0.09	0.32
	[-13.16]	[9.67]	[5.27]	[-3.59]	[-3.08]	[6.55]
β_{CMA}	-0.10	0.36	0.09	-0.06	-0.26	-0.16
	[-2.41]	[9.08]	[2.80]	[-1.60]	[-6.23]	[-2.33]
β_{UMD}	0.01	0.00	-0.02	-0.04	-0.02	-0.02
	[0.63]	[0.28]	[-1.77]	[-3.52]	[-1.04]	[-1.06]
Panel C: Average number of firms (n) and market capitalization (me)						
n	1514	517	680	690	711	
me ($\$10^6$)	1795	3288	2791	2662	4555	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the CFE 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	0.46	0.43	0.47	0.49	0.37	0.38
			[3.70]	[3.39]	[4.28]	[4.39]	[3.43]	[3.54]
Quintile	NYSE	EW	0.42	0.46	0.38	0.32	0.03	-0.01
			[2.45]	[2.68]	[2.64]	[2.17]	[0.26]	[-0.09]
Quintile	Name	VW	0.49	0.74	0.70	0.65	0.28	0.25
			[2.30]	[3.70]	[4.09]	[3.75]	[1.81]	[1.64]
Quintile	Cap	VW	0.46	0.33	0.42	0.45	0.50	0.51
			[3.20]	[2.37]	[3.60]	[3.81]	[4.28]	[4.35]
Decile	NYSE	VW	0.68	0.81	0.82	0.79	0.57	0.55
			[3.66]	[4.41]	[5.10]	[4.83]	[3.68]	[3.53]
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	0.44	0.40	0.42	0.44	0.34	0.35
			[3.54]	[3.21]	[3.88]	[4.01]	[3.22]	[3.33]
Quintile	NYSE	EW	0.28	0.28	0.21	0.18		
			[1.58]	[1.56]	[1.42]	[1.17]		
Quintile	Name	VW	0.46	0.70	0.66	0.63	0.28	0.27
			[2.15]	[3.56]	[3.89]	[3.71]	[1.85]	[1.75]
Quintile	Cap	VW	0.45	0.31	0.37	0.40	0.46	0.47
			[3.11]	[2.21]	[3.19]	[3.37]	[3.91]	[4.00]
Decile	NYSE	VW	0.65	0.78	0.77	0.76	0.55	0.54
			[3.48]	[4.29]	[4.82]	[4.70]	[3.59]	[3.52]

Table 3: Conditional sort on size and CFE

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

		CFE Quintiles					CFE Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.31	0.29	0.75	0.88	1.01	0.70	0.91	0.74	0.69	0.25	0.22
		[0.69]	[0.75]	[2.65]	[3.08]	[3.16]	[2.55]	[3.38]	[3.44]	[3.18]	[1.29]	[1.15]
	(2)	0.27	0.54	0.89	0.94	0.96	0.69	0.91	0.78	0.75	0.34	0.33
		[0.65]	[1.95]	[3.20]	[3.22]	[3.27]	[3.01]	[4.15]	[4.47]	[4.24]	[2.32]	[2.21]
	(3)	0.35	0.70	0.83	0.84	1.00	0.65	0.75	0.69	0.63	0.32	0.29
		[1.05]	[2.74]	[2.91]	[3.06]	[3.49]	[3.85]	[4.46]	[4.30]	[3.90]	[2.18]	[1.94]
	(4)	0.53	0.76	0.81	0.81	1.04	0.51	0.51	0.49	0.46	0.28	0.26
		[1.90]	[3.18]	[3.22]	[3.14]	[3.81]	[4.07]	[4.07]	[3.93]	[3.62]	[2.29]	[2.11]
	(5)	0.46	0.67	0.63	0.64	0.89	0.43	0.28	0.37	0.40	0.45	0.47
		[2.07]	[3.60]	[3.04]	[2.77]	[3.24]	[2.69]	[1.78]	[2.79]	[2.97]	[3.38]	[3.44]

Panel B: Portfolio average number of firms and market capitalization

		CFE Quintiles					CFE Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	448	453	464	462	460	46	40	52	56	69
	(2)	134	135	134	134	134	87	91	93	94	95
	(3)	90	91	91	90	90	149	157	154	159	157
	(4)	75	75	74	74	74	321	330	325	325	331
	(5)	66	66	66	66	66	1883	2468	2315	1942	3355

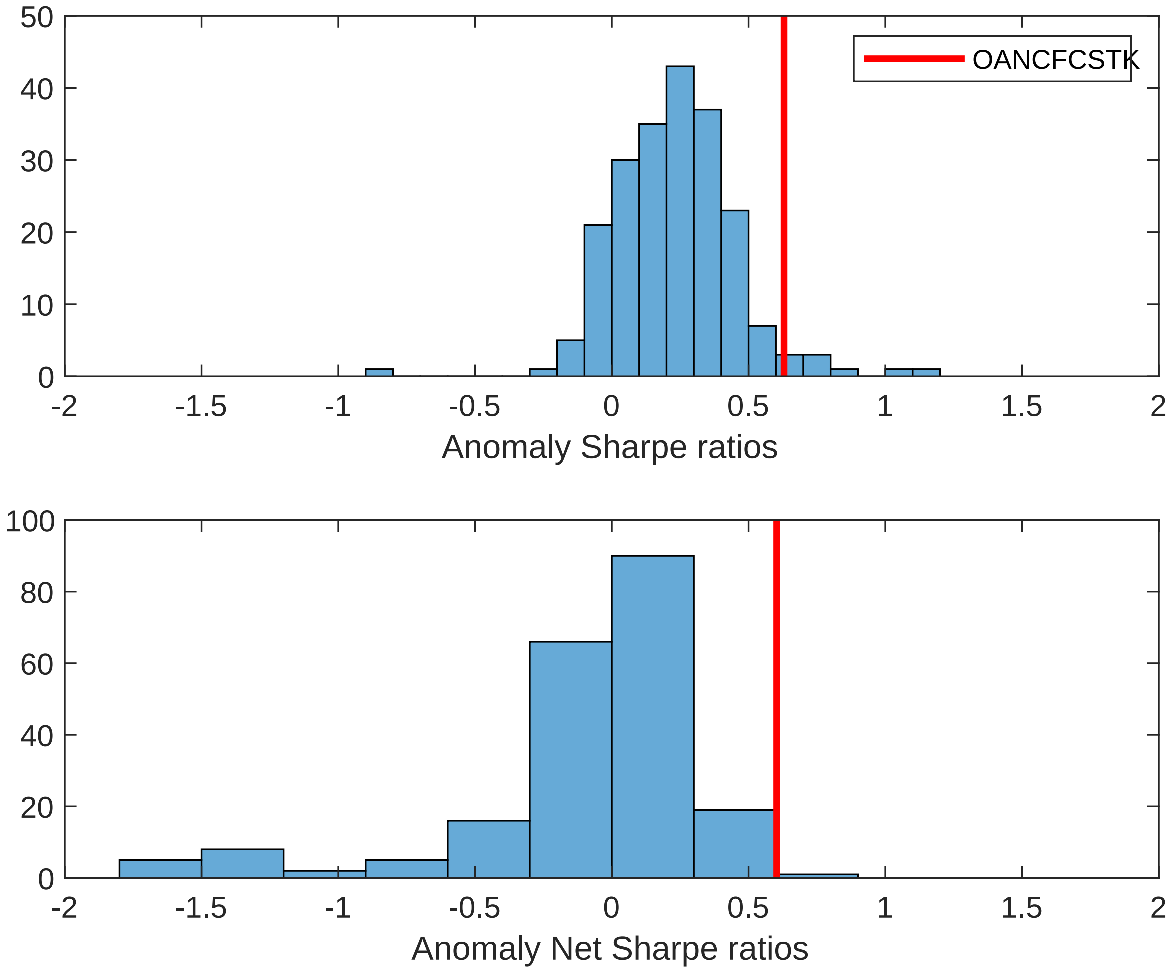

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CFE with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

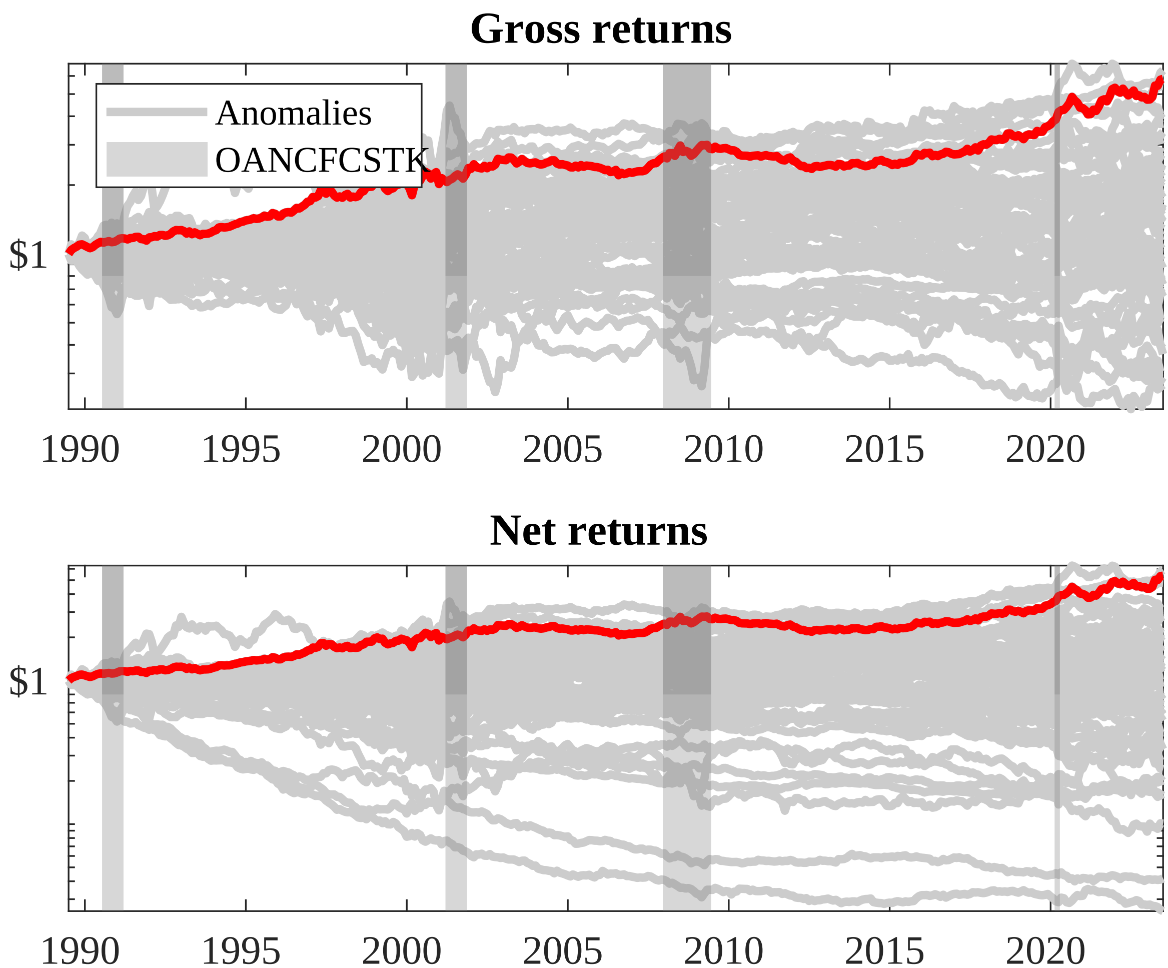

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CFE trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

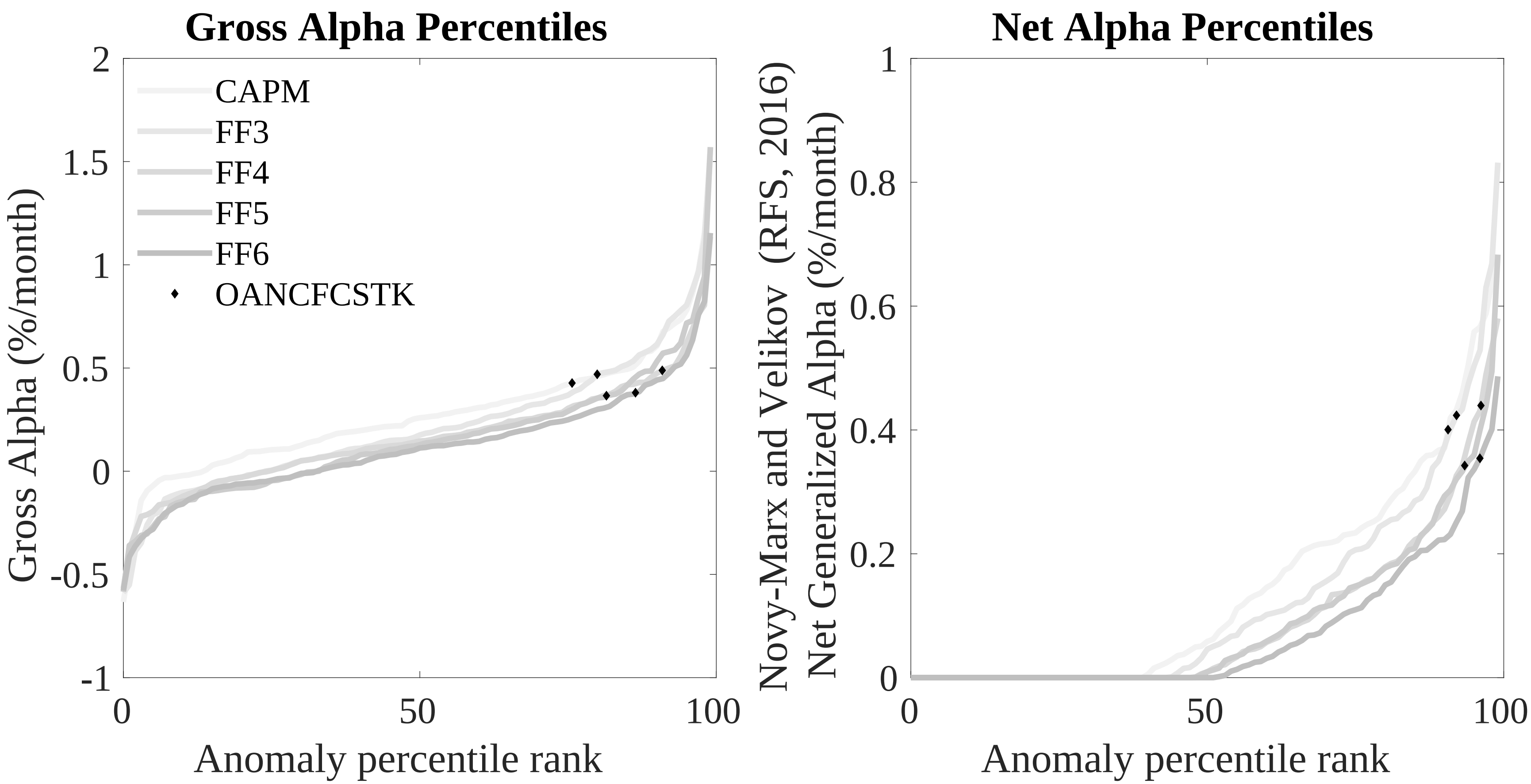

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CFE trading strategy alphas (diamonds). The strategies are constructed using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

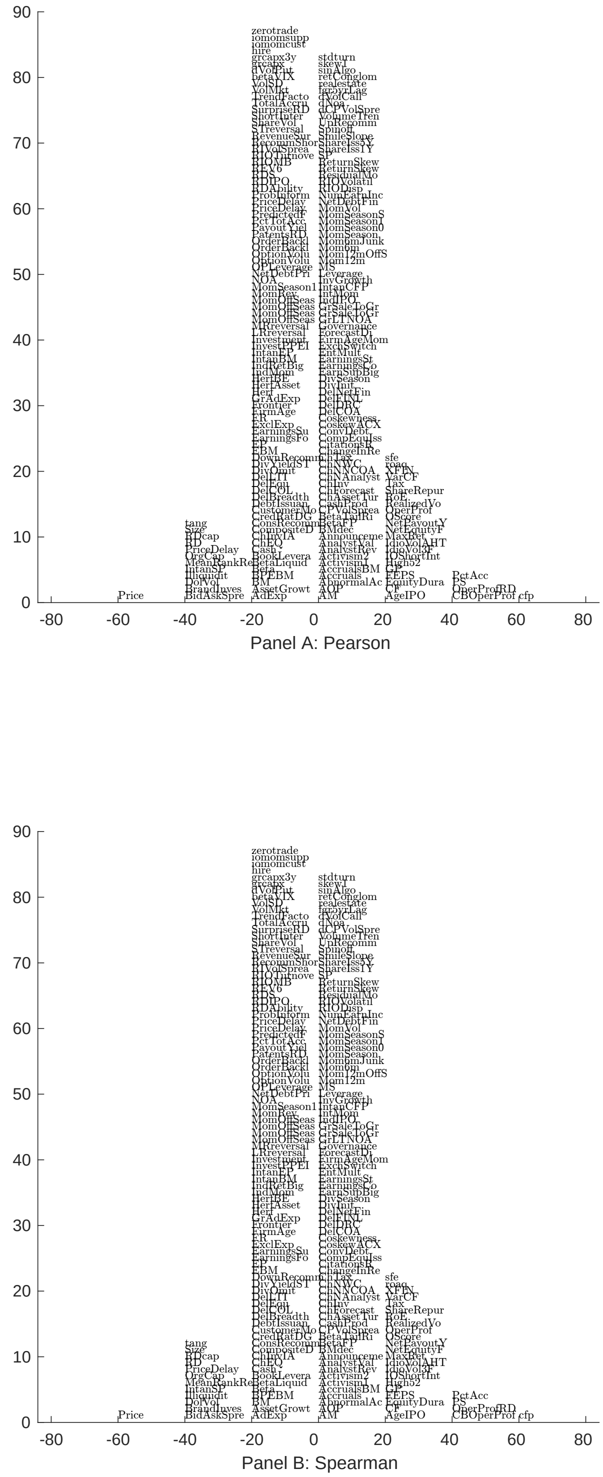

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with CFE. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

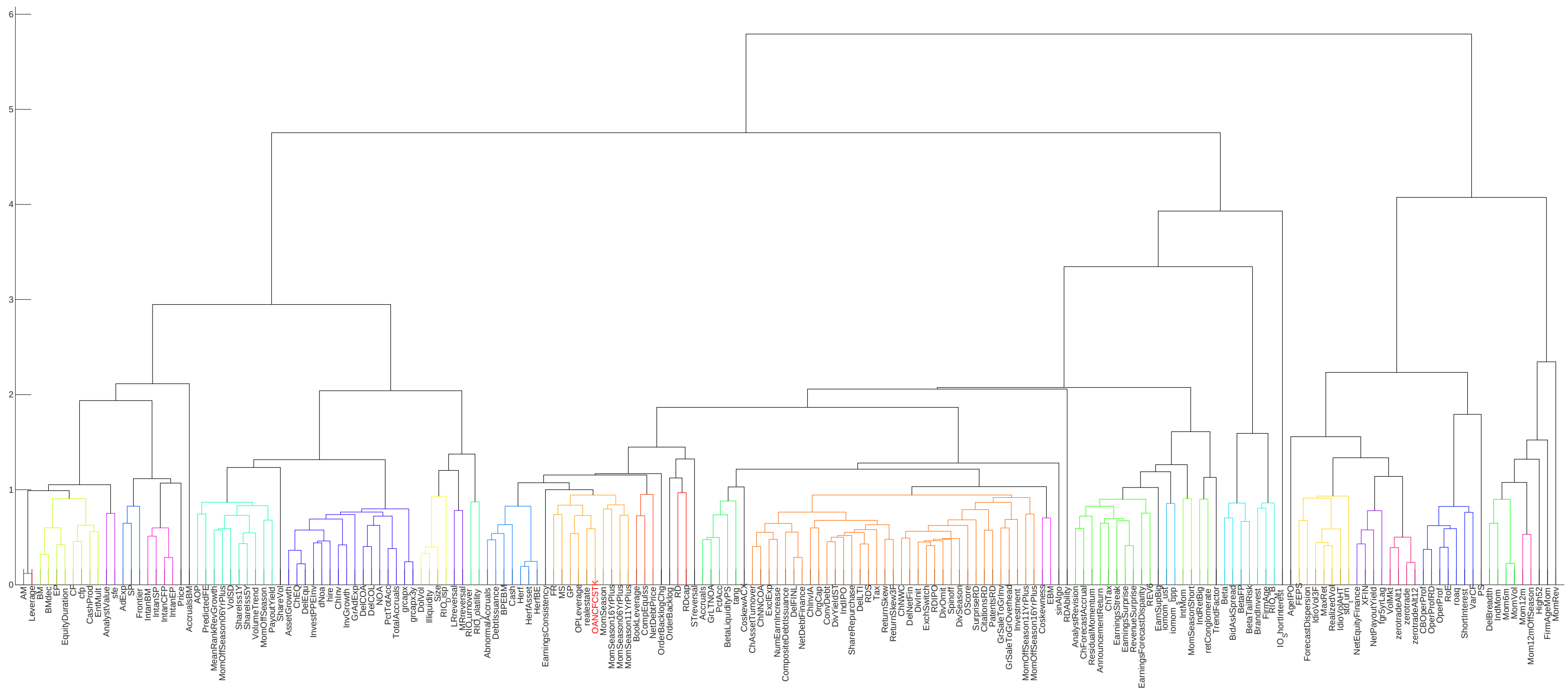

Figure 6: Agglomerative hierarchical cluster plot

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

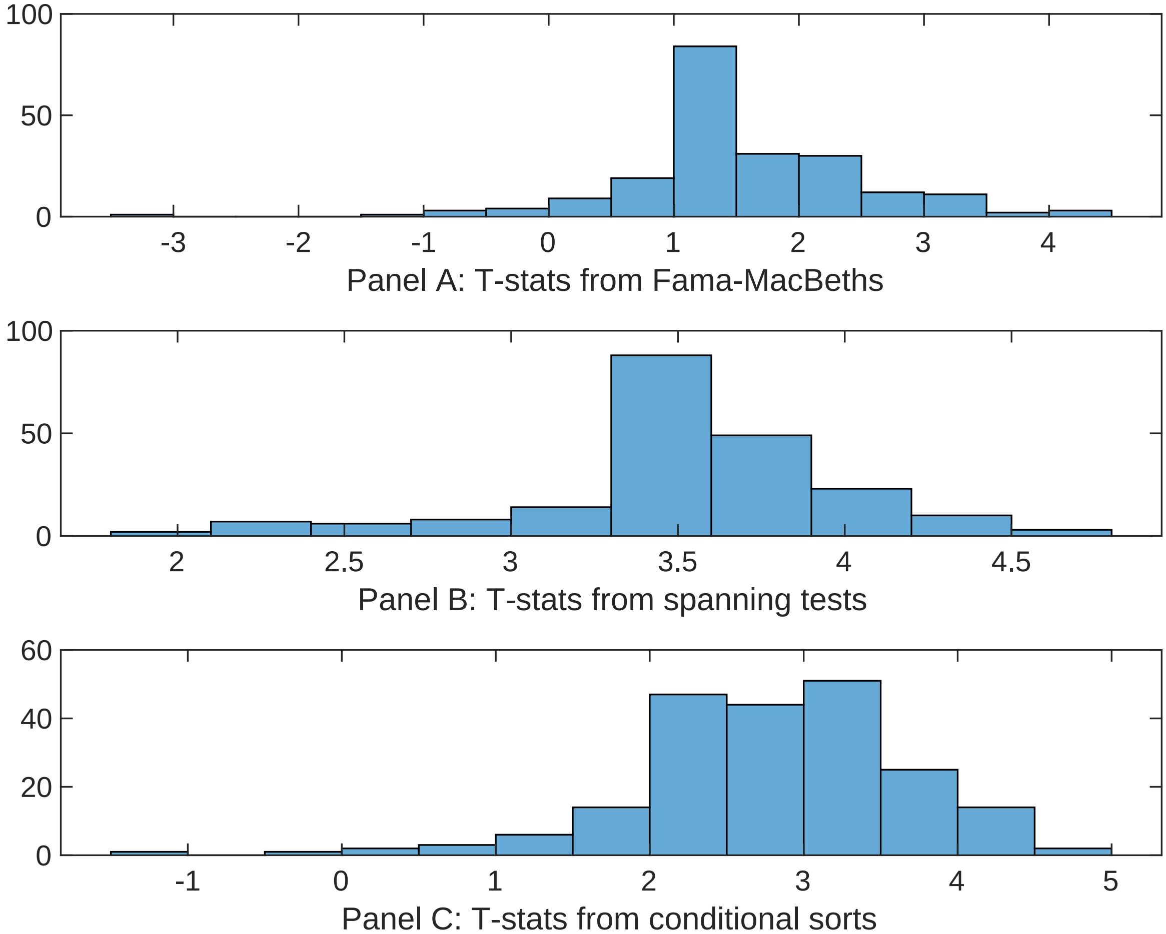

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CFE conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CFE} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CFE} CFE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{CFE,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 CFE. Stocks are finally grouped into five CFE portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CFE 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 CFE. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{CFE} CFE_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Cash-based operating profitability, Operating profitability RD adjusted, gross profits / total assets, Amihud's illiquidity, Past trading volume, Return on assets (qtrly). 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	0.10	0.96	0.86	0.96	0.12	0.11	0.10
	[3.01]	[2.78]	[2.55]	[3.19]	[3.92]	[4.00]	[3.17]
CFE	-0.20	0.12	0.11	0.22	0.24	0.61	0.23
	[-0.27]	[1.74]	[1.07]	[2.21]	[2.75]	[0.85]	[0.38]
Anomaly 1	0.17						0.15
	[3.77]						[4.17]
Anomaly 2		0.15					-0.20
		[2.86]					[-0.43]
Anomaly 3			0.66				0.42
			[3.40]				[1.78]
Anomaly 4				0.40			0.56
				[2.67]			[2.02]
Anomaly 5					0.87		0.82
					[2.77]		[2.89]
Anomaly 6						0.34	0.34
						[1.99]	[2.32]
# months	403	403	408	403	403	403	403
$\bar{R}^2(\%)$	1	1	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 CFE trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{CFE} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Cash-based operating profitability, Operating profitability RD adjusted, gross profits / total assets, Amihud's illiquidity, Past trading volume, Return on assets (qtrly). 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	0.26	0.26	0.29	0.35	0.34	0.31	0.21
	[2.49]	[2.48]	[2.79]	[3.26]	[3.17]	[2.98]	[2.01]
Anomaly 1	24.60						13.66
	[5.39]						[1.95]
Anomaly 2		18.79					-1.39
		[4.39]					[-0.22]
Anomaly 3			25.78				17.12
			[6.05]				[3.33]
Anomaly 4				-8.10			-26.98
				[-0.98]			[-2.23]
Anomaly 5					5.34		33.49
					[0.73]		[3.13]
Anomaly 6						17.46	12.35
						[3.79]	[2.56]
mkt	10.79	11.97	8.14	7.98	10.29	11.66	15.44
	[4.19]	[4.48]	[3.18]	[2.79]	[3.26]	[4.33]	[4.77]
smb	-12.50	-13.16	-20.73	-9.33	-22.95	-14.63	-14.89
	[-3.28]	[-3.40]	[-5.65]	[-0.96]	[-3.00]	[-3.81]	[-1.59]
hml	-16.33	-18.05	-17.13	-24.35	-26.94	-19.98	-14.77
	[-3.42]	[-3.75]	[-3.61]	[-5.10]	[-5.41]	[-4.20]	[-2.94]
rmw	18.48	16.84	16.70	28.74	30.49	14.89	-1.64
	[3.61]	[3.00]	[3.23]	[5.63]	[6.39]	[2.38]	[-0.24]
cma	-18.97	-15.01	-9.99	-13.26	-14.06	-14.98	-14.32
	[-2.91]	[-2.30]	[-1.55]	[-1.98]	[-2.10]	[-2.28]	[-2.19]
umd	-4.34	-4.71	-3.78	-2.48	-1.44	-6.61	-3.09
	[-1.90]	[-2.01]	[-1.68]	[-1.06]	[-0.57]	[-2.58]	[-1.14]
# months	404	404	408	404	404	404	404
$\bar{R}^2$(%)	35	33	38	30	30	33	39

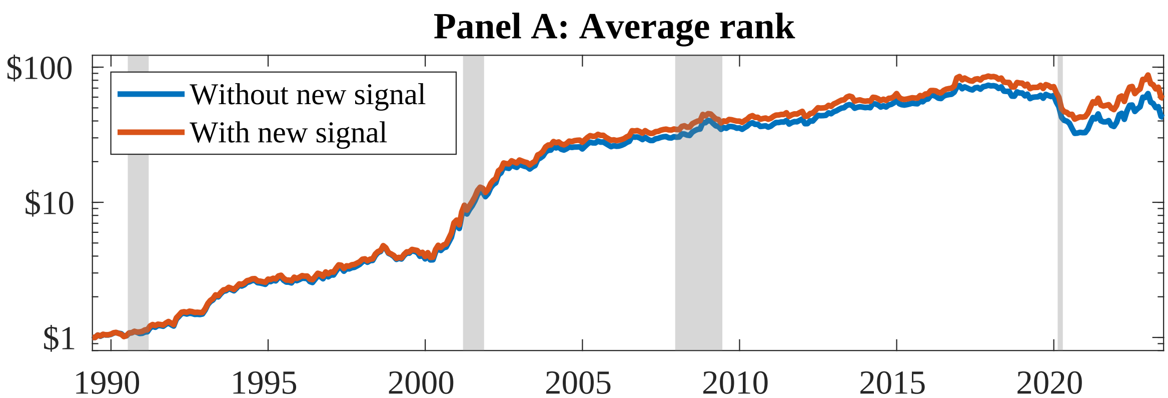

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines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

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