Operating Expense Normalized Common Stock Difference and the Cross Section of Stock Returns

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December 1, 2024

Abstract

This paper studies the asset pricing implications of Operating Expense Normalized Common Stock Difference (OENCSD), 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 OENCSD achieves an annualized gross (net) Sharpe ratio of 0.64 (0.57), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 23 (23) bps/month with a t-statistic of 2.96 (3.01), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth) is 18 bps/month with a t-statistic of 2.58.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents persistent cross-sectional patterns in stock returns that challenge this view (Harvey et al., 2016). While many of these patterns appear to reflect rational pricing of risk or behavioral biases, the underlying economic mechanisms remain debated (McLean and Pontiff, 2016).

One particularly puzzling area involves the relationship between firms' operating activities and their stock returns. While operating expenses represent a fundamental aspect of business operations, their role in asset pricing has received limited attention. Recent evidence suggests that changes in operating activities may contain important information about future firm performance and risk that is not fully incorporated into prices (Cohen and Frazzini, 2008).

We propose that Operating Expense Normalized Common Stock Difference (OENCSD) contains valuable information about future stock returns through several potential channels. First, following Titman et al. (2004), changes in operating expenses relative to equity may signal management's investment decisions and future growth opportunities. When managers identify profitable projects, they often increase operating capacity before revenues materialize, leading to temporary increases in operating expenses relative to equity.

Second, building on Sloan and Soliman (2009), the relationship between operating expenses and equity financing choices may reveal information about management's private information. Managers with positive private information about future prospects may be more willing to fund current operations through equity issuance, leading to distinctive patterns in the OENCSD measure.

Third, consistent with Cooper et al. (2008), OENCSD may capture systematic risk exposure through operating leverage. Firms with higher fixed operating costs relative to equity face greater earnings volatility and systematic risk when demand fluctuates, potentially commanding higher expected returns.

Our empirical analysis reveals that OENCSD strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on OENCSD quintiles generates a monthly alpha of 23 basis points (t-statistic = 2.96) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.64, placing it in the top 3% of documented return predictors.

The predictive power of OENCSD remains robust across various methodological choices. The signal generates significant abnormal returns using both equal- and value-weighted portfolios, different sorting approaches, and after controlling for transaction costs. Importantly, the effect persists among large-cap stocks, with the long-short strategy earning a monthly alpha of 20 basis points (t-statistic = 2.09) in the largest size quintile.

Further analysis demonstrates that OENCSD's predictive ability is distinct from known anomalies. Controlling for the six most closely related predictors and the Fama-French six factors simultaneously, the strategy maintains a significant monthly alpha of 18 basis points (t-statistic = 2.58).

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures information about future returns through firms' operating activities and financing decisions. While prior work has examined operating leverage (Garcia-Feijoo and Kogan, 2021) and investment patterns (Titman et al., 2004) separately, OENCSD uniquely combines these dimensions to generate robust return predictability.

Second, we extend the literature on accounting-based anomalies by showing how the relationship between operating expenses and equity financing contains important pricing implications. Our findings complement work by Sloan and Soliman (2009) on operating accruals and Pontiff and Woodgate (2008) on share issuance, while identifying a distinct source of predictability.

Third, our results contribute to the broader debate on market efficiency and the economic sources of return predictability. The persistence of OENCSD's predictive power among large, liquid stocks and after controlling for transaction costs suggests it captures fundamental economic information that is not immediately impounded into prices. These findings have important implications for both academic research on asset pricing 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 the Operating Expense Normalized Common Stock Difference. 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 CSTK for common stock and item XOPR for operating expenses. Common stock (CSTK) represents the total par or stated value of common stock outstanding, while operating expenses (XOPR) capture the firm's regular costs associated with running its business operations.construction of the signal follows a difference-based approach normalized by operating expenses. Specifically, we calculate the year-over-year change in CSTK and scale this difference by the previous year's operating expenses (XOPR). This normalized difference provides insight into how changes in a firm's common stock value relate to its operational scale, as measured by operating expenses. By scaling the change in common stock by operating expenses, we create a measure that is comparable across firms of different sizes and operational scales. We construct this signal using end-of-fiscal-year values for both CSTK and XOPR to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the OENCSD signal. Panel A plots the time-series of the mean, median, and interquartile range for OENCSD. On average, the cross-sectional mean (median) OENCSD is -0.01 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input OENCSD data. The signal's interquartile range spans -0.01 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the OENCSD signal for the CRSP universe. On average, the OENCSD signal is available for 6.63% of CRSP names, which on average make up 7.96% of total market capitalization.

4 Does OENCSD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on OENCSD 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 OENCSD portfolio and sells the low OENCSD 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 OENCSD strategy earns an average return of 0.36% per month with a t-statistic of 4.82. The annualized Sharpe ratio of the strategy is 0.64. The alphas range from 0.23% to 0.38% per month and have t-statistics exceeding 2.96 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 0.29, with a t-statistic of 5.68 on the CMA 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 598 stocks and an average market capitalization of at least $1,429 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 32 bps/month with a t-statistics of 4.21. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty 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 29-37bps/month. The lowest return, (29 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.76. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the OENCSD 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-five cases.

Table 3 provides direct tests for the role size plays in the OENCSD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and OENCSD, as well as average returns and alphas for long/short trading OENCSD 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 OENCSD strategy achieves an average return of 28 bps/month with a t-statistic of 3.10. Among these large cap stocks, the alphas for the OENCSD strategy relative to the five most common factor models range from 20 to 27 bps/month with t-statistics between 2.09 and 2.92.

5 How does OENCSD perform relative to the zoo?

Figure 2 puts the performance of OENCSD 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 OENCSD strategy falls in the distribution. The OENCSD strategy's gross (net) Sharpe ratio of 0.64 (0.57) is greater than 97% (99%) of anomaly Sharpe

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

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 OENCSD strategy (red line).[2] Ignoring trading costs, a \$1 invested in the OENCSD strategy would have yielded \$9.88 which ranks the OENCSD strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the OENCSD strategy would have yielded \$7.53 which ranks the OENCSD 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 OENCSD relative to those. Panel A shows that the OENCSD strategy gross alphas fall between the 70 and 75 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 196606 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 OENCSD strategy has a positive net generalized alpha for five out of the five factor models. In these cases OENCSD ranks between the 86 and 91 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 OENCSD 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 OENCSD 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 OENCSD or at least to weaken the power OENCSD has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of OENCSD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{OENCSD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{OENCSD} OENCSD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{OENCSD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on OENCSD 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 OENCSD signal in these Fama-MacBeth regressions exceed 2.86, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on OENCSD is 2.38.

Similarly, Table 5 reports results from spanning tests that regress returns to the OENCSD 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 OENCSD strategy earns alphas that range from 20-24bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.64, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the OENCSD trading strategy achieves an alpha of 18bps/month with a t-statistic of 2.58.

7 Does OENCSD add relative to the whole zoo?

Finally, we can ask how much adding OENCSD to the entire factor zoo could improve investment performance. Figure 8 plots the growth of $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). The combinations use either the 155 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 155 anomalies augmented with the OENCSD signal.[4] We consider one different methods for combining signals.

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, \$1 investment in the 155-anomaly combination strategy grows to \$2333.55, while \$1 investment in the combination strategy that includes OENCSD grows to \$2268.09.

8 Conclusion

This study demonstrates that Operating Expense Normalized Common Stock Difference (OENCSD) serves as a significant predictor of stock returns, offering valuable insights for both academic research and practical investment applications. The empirical results reveal that a value-weighted long/short strategy based on OENCSD generates impressive risk-adjusted returns, with annualized Sharpe ratios of 0.64 (gross) and 0.57 (net). The strategy's robustness is evidenced by significant monthly abnormal returns of 23 basis points, even after accounting for transaction costs and controlling for the Fama-French five factors and momentum.

Particularly noteworthy is the signal's persistent predictive power when tested against the most closely related strategies from the factor zoo. The strategy maintains a significant monthly alpha of 18 basis points (t-statistic = 2.58), suggesting that OENCSD captures unique information about future stock returns that is not

[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 OENCSD is available.

explained by existing factors or similar signals.

However, several limitations should be considered. The study's findings may be sensitive to the specific time period examined and market conditions. Additionally, the implementation costs and market impact in real-world trading scenarios might differ from our estimates.

Future research could explore the economic mechanisms driving the OENCSD signal's predictive power, its interaction with other market anomalies, and its performance across different market regimes and international markets. Furthermore, investigating the signal's effectiveness in different asset classes and its potential application in portfolio optimization frameworks could yield valuable insights.

In conclusion, OENCSD represents a promising addition to the quantitative investor's toolkit, offering economically and statistically significant predictive power that appears robust to common risk factors and related signals.

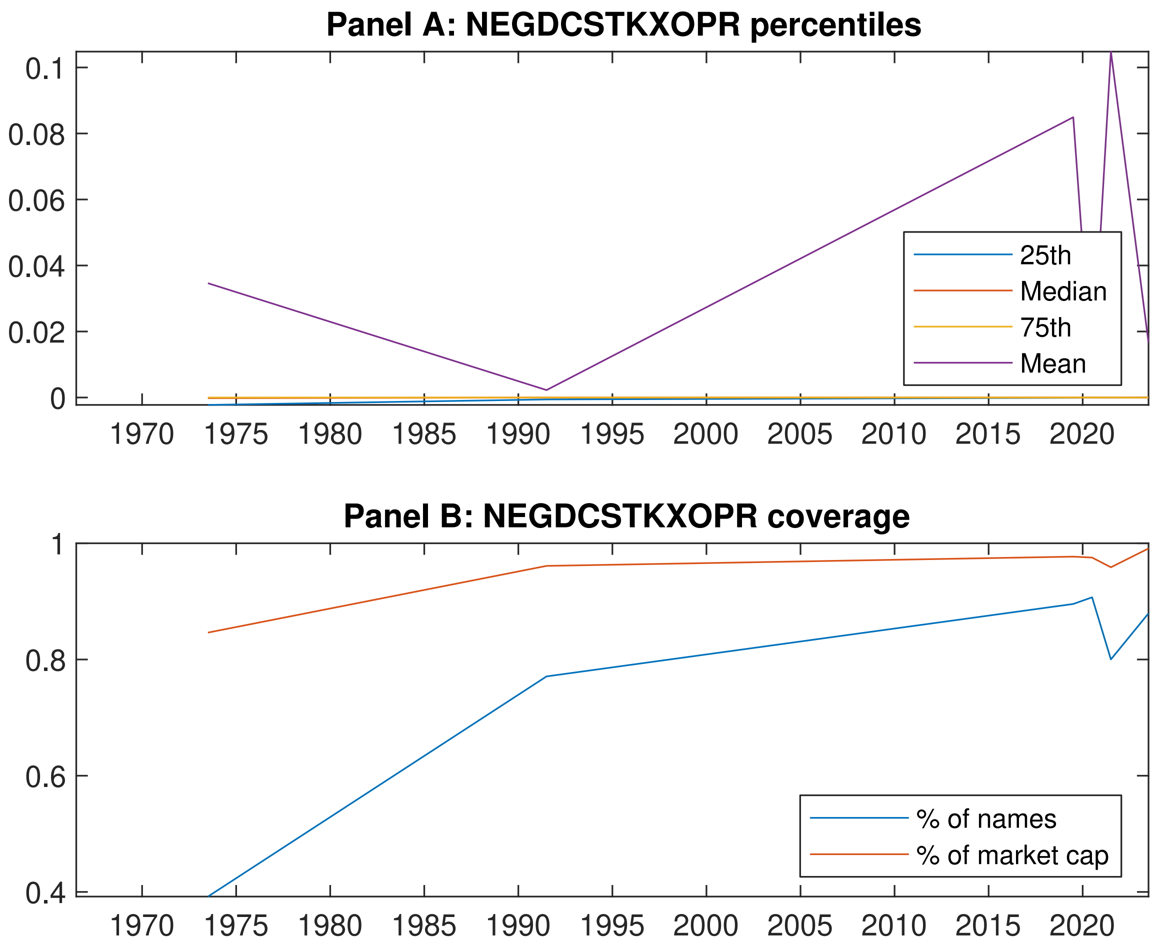


Figure 1: Times series of OENCSD percentiles and coverage.
This figure plots descriptive statistics for OENCSD. Panel A shows cross-sectional percentiles of OENCSD over the sample. Panel B plots the monthly coverage of OENCSD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on OENCSD. 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 196606 to 202306.

Panel A: Excess returns and alphas on OENCSD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.40	0.52	0.66	0.69	0.77	0.36
	[2.34]	[2.67]	[3.43]	[4.09]	[4.56]	[4.82]
α_{CAPM}	-0.13	-0.09	0.06	0.16	0.24	0.38
	[-2.62]	[-1.98]	[1.08]	[3.44]	[5.14]	[4.96]
α_{FF3}	-0.15	-0.08	0.07	0.13	0.19	0.34
	[-2.90]	[-1.59]	[1.40]	[2.86]	[4.41]	[4.50]
α_{FF4}	-0.12	-0.04	0.09	0.09	0.18	0.30
	[-2.42]	[-0.94]	[1.70]	[1.95]	[3.94]	[3.91]
α_{FF5}	-0.15	-0.01	0.10	0.03	0.10	0.25
	[-2.98]	[-0.17]	[1.89]	[0.59]	[2.25]	[3.29]
α_{FF6}	-0.14	0.01	0.11	0.00	0.09	0.23
	[-2.61]	[0.23]	[2.07]	[0.03]	[2.10]	[2.96]
Panel B: Fama and French (2018) 6-factor model loadings for OENCSD-sorted portfolios						
β_{MKT}	0.96	1.04	1.03	1.00	0.99	0.02
	[78.27]	[90.99]	[78.92]	[99.24]	[97.30]	[1.38]
β_{SMB}	-0.06	0.01	0.07	-0.06	-0.01	0.05
	[-3.41]	[0.80]	[3.81]	[-4.11]	[-1.01]	[1.75]
β_{HML}	0.07	-0.02	-0.03	0.05	0.05	-0.03
	[3.16]	[-0.74]	[-1.26]	[2.54]	[2.36]	[-0.82]
β_{RMW}	0.07	-0.09	-0.01	0.13	0.13	0.06
	[2.97]	[-4.28]	[-0.28]	[6.66]	[6.41]	[1.58]
β_{CMA}	-0.07	-0.12	-0.10	0.20	0.22	0.29
	[-1.99]	[-3.86]	[-2.59]	[7.11]	[7.69]	[5.68]
β_{UMD}	-0.03	-0.03	-0.02	0.04	0.01	0.04
	[-2.26]	[-2.65]	[-1.37]	[3.70]	[0.82]	[2.00]
Panel C: Average number of firms (n) and market capitalization (me)						
n	784	732	598	701	775	
me ($\$10^6$)	1826	1429	1979	2254	2443	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the OENCSD 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 196606 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	0.36	0.38	0.34	0.30	0.25	0.23
			[4.82]	[4.96]	[4.50]	[3.91]	[3.29]	[2.96]
Quintile	NYSE	EW	0.57	0.63	0.55	0.48	0.41	0.36
			[8.75]	[9.88]	[9.27]	[8.17]	[7.15]	[6.43]
Quintile	Name	VW	0.34	0.35	0.32	0.29	0.25	0.24
			[4.58]	[4.58]	[4.22]	[3.83]	[3.30]	[3.10]
Quintile	Cap	VW	0.32	0.32	0.30	0.25	0.24	0.21
			[4.21]	[4.16]	[3.86]	[3.23]	[3.04]	[2.64]
Decile	NYSE	VW	0.39	0.36	0.33	0.26	0.27	0.22
			[4.15]	[3.90]	[3.52]	[2.77]	[2.86]	[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	0.33	0.34	0.31	0.29	0.24	0.23
			[4.35]	[4.54]	[4.14]	[3.85]	[3.19]	[3.01]
Quintile	NYSE	EW	0.37	0.43	0.35	0.32	0.20	0.19
			[5.20]	[5.99]	[5.34]	[4.88]	[3.21]	[2.98]
Quintile	Name	VW	0.31	0.32	0.29	0.28	0.24	0.23
			[4.10]	[4.20]	[3.88]	[3.70]	[3.17]	[3.06]
Quintile	Cap	VW	0.29	0.29	0.27	0.25	0.23	0.21
			[3.76]	[3.78]	[3.50]	[3.19]	[2.91]	[2.69]
Decile	NYSE	VW	0.35	0.33	0.30	0.26	0.25	0.23
			[3.73]	[3.55]	[3.23]	[2.84]	[2.72]	[2.45]

Table 3: Conditional sort on size and OENCSD

This table presents results for conditional double sorts on size and OENCSD. 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 OENCSD. 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 OENCSD and short stocks with low OENCSD .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196606 to 202306.

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

		OENCSD Quintiles					OENCSD Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.37	0.66	0.89	0.96	0.96	0.59	0.64	0.58	0.53	0.45	0.41
		[1.42]	[2.45]	[3.44]	[3.80]	[4.02]	[7.72]	[8.46]	[8.05]	[7.21]	[6.31]	[5.78]
	(2)	0.47	0.73	0.82	0.90	0.95	0.48	0.52	0.44	0.41	0.34	0.32
		[2.03]	[2.99]	[3.33]	[3.90]	[4.27]	[5.66]	[6.16]	[5.40]	[4.92]	[4.14]	[3.89]
	(3)	0.54	0.64	0.81	0.79	0.94	0.40	0.42	0.38	0.37	0.31	0.31
		[2.59]	[2.83]	[3.51]	[3.71]	[4.65]	[5.33]	[5.56]	[5.08]	[4.82]	[3.99]	[3.90]
	(4)	0.47	0.62	0.80	0.80	0.80	0.34	0.36	0.30	0.28	0.11	0.11
		[2.41]	[2.89]	[3.73]	[4.00]	[4.26]	[4.16]	[4.39]	[3.79]	[3.50]	[1.41]	[1.43]
	(5)	0.43	0.50	0.51	0.54	0.71	0.28	0.27	0.26	0.21	0.23	0.20
		[2.54]	[2.66]	[2.78]	[3.15]	[4.25]	[3.10]	[2.92]	[2.76]	[2.28]	[2.41]	[2.09]

Panel B: Portfolio average number of firms and market capitalization

		OENCSD Quintiles					OENCSD Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	396	396	396	393	395	33	34	40	30	30
	(2)	112	111	111	111	111	57	57	58	56	57
	(3)	82	81	81	80	81	99	96	99	100	101
	(4)	68	68	68	68	68	205	206	211	215	218
	(5)	62	62	62	62	62	1383	1438	1734	1609	1765

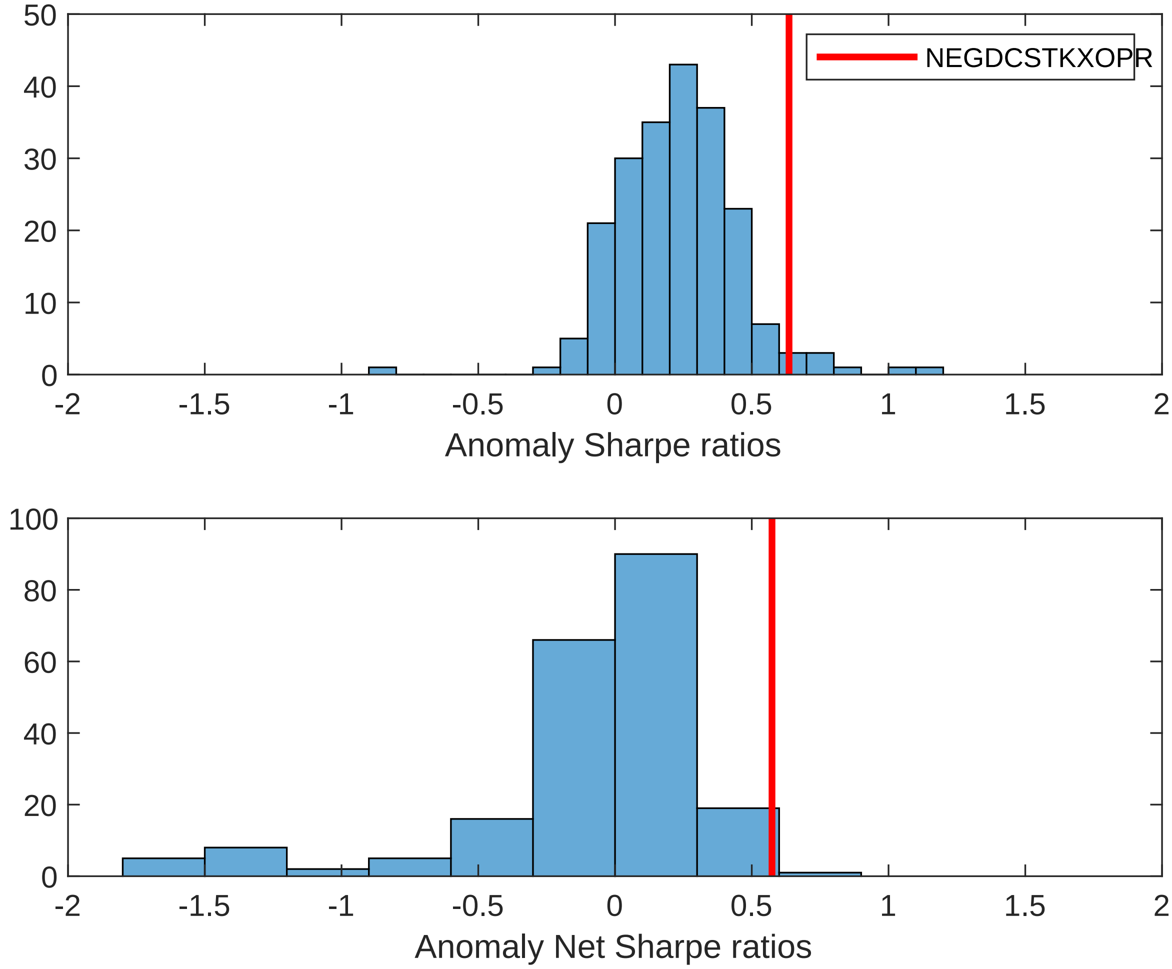


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the OENCSD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

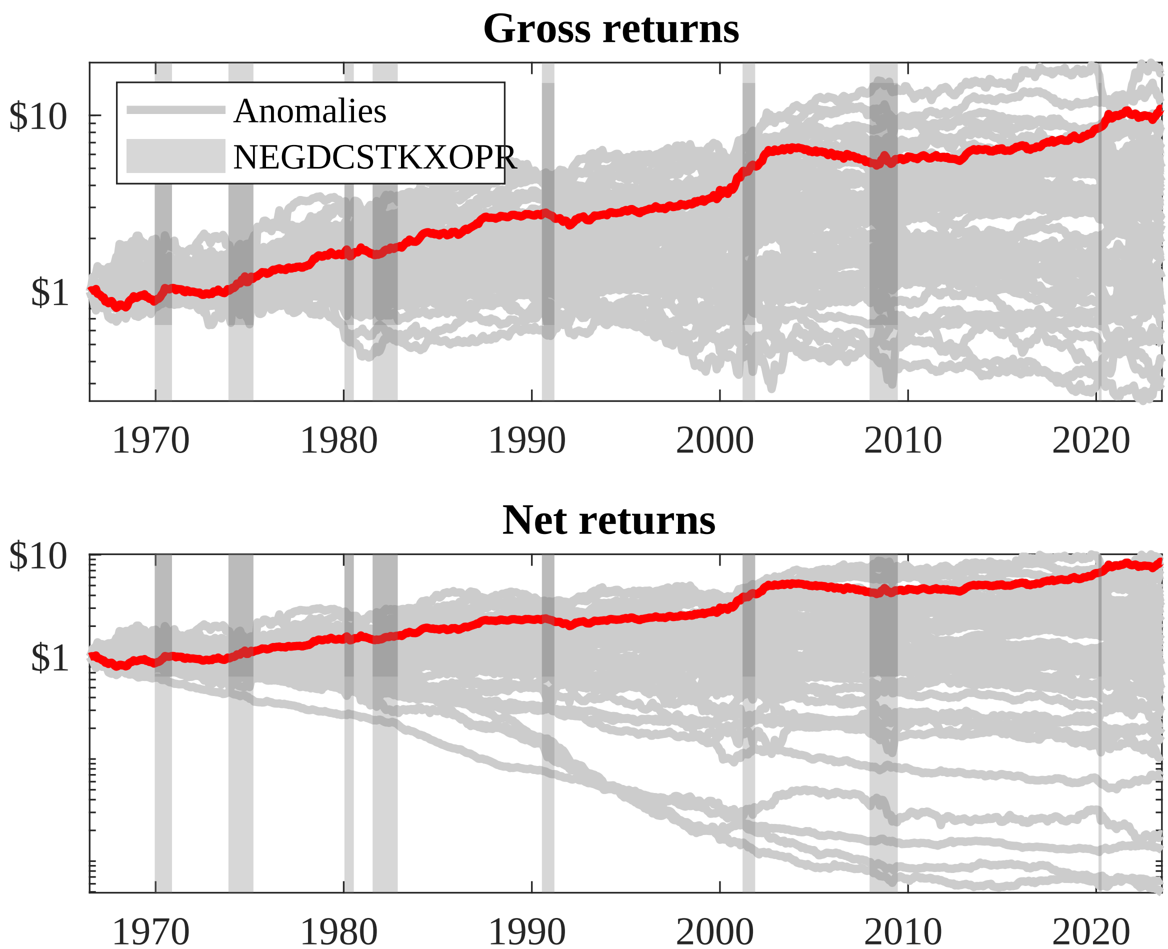


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the OENCSD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

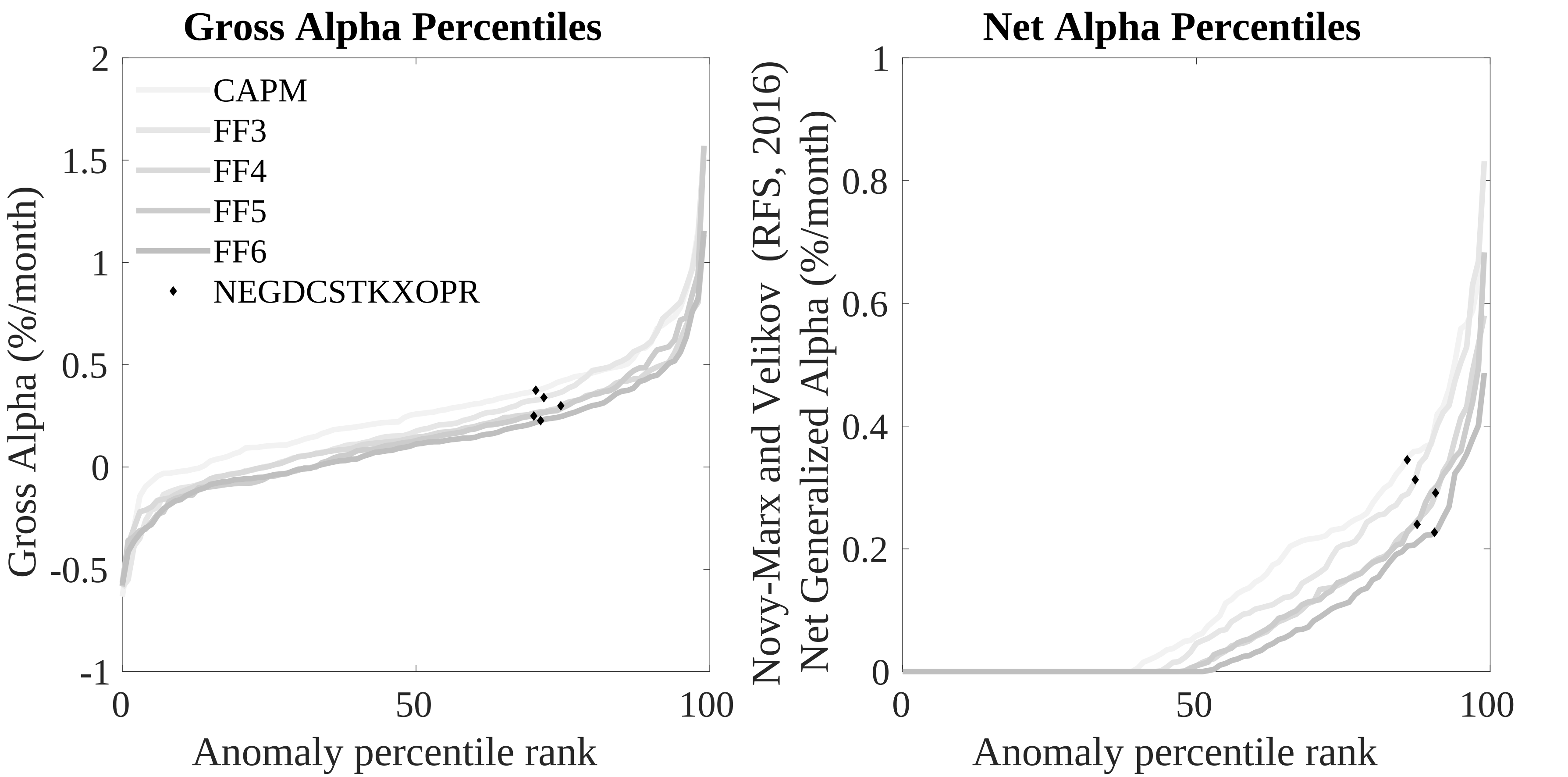
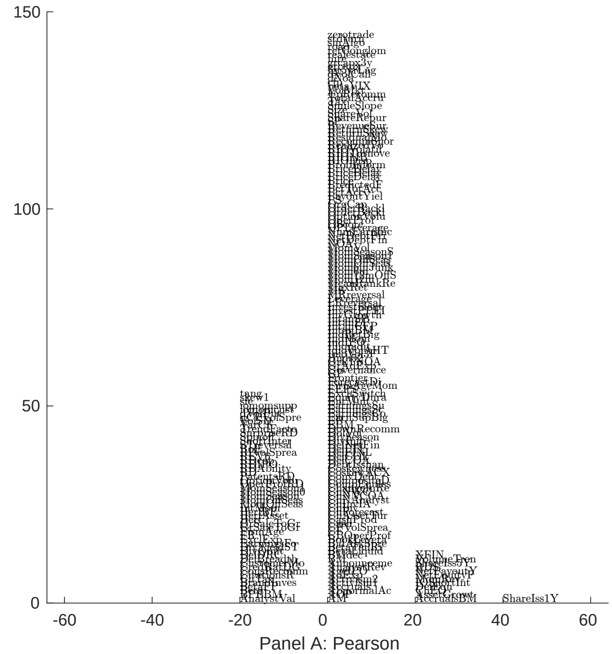


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the OENCSD trading strategy alphas (diamonds). The strategies are constructed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



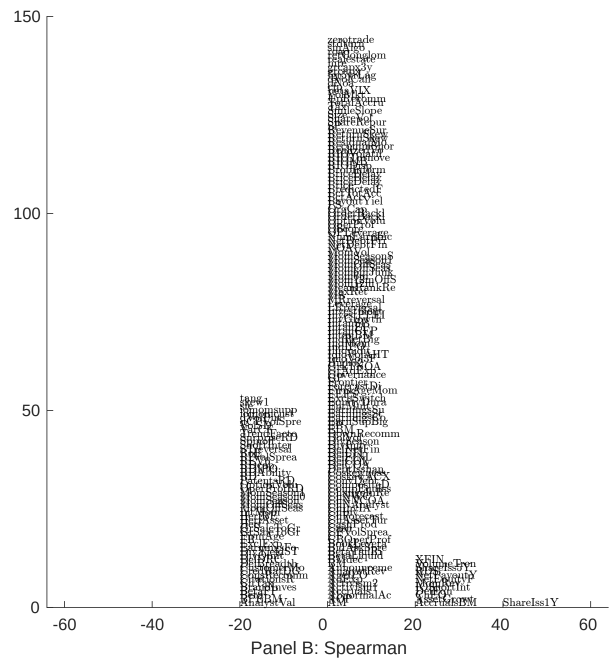


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with OENCSD. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

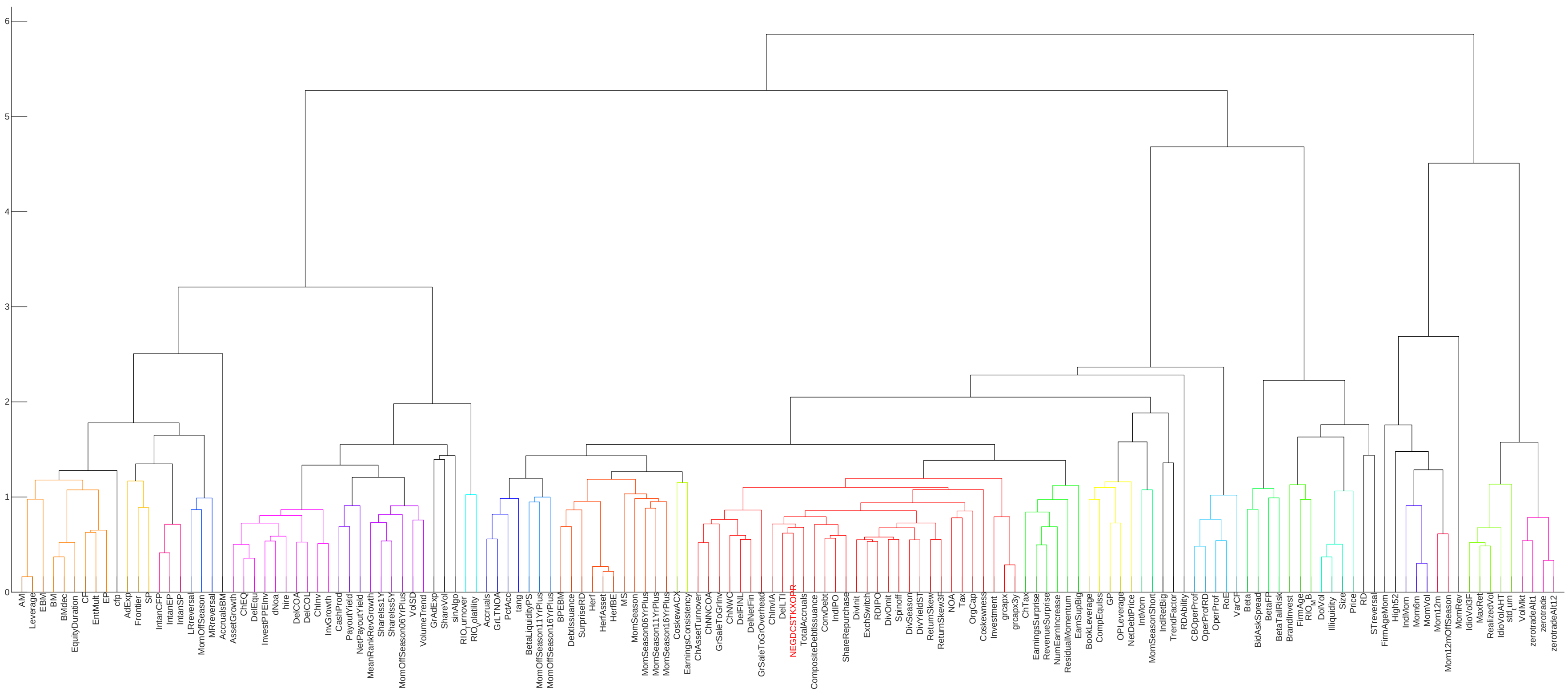


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

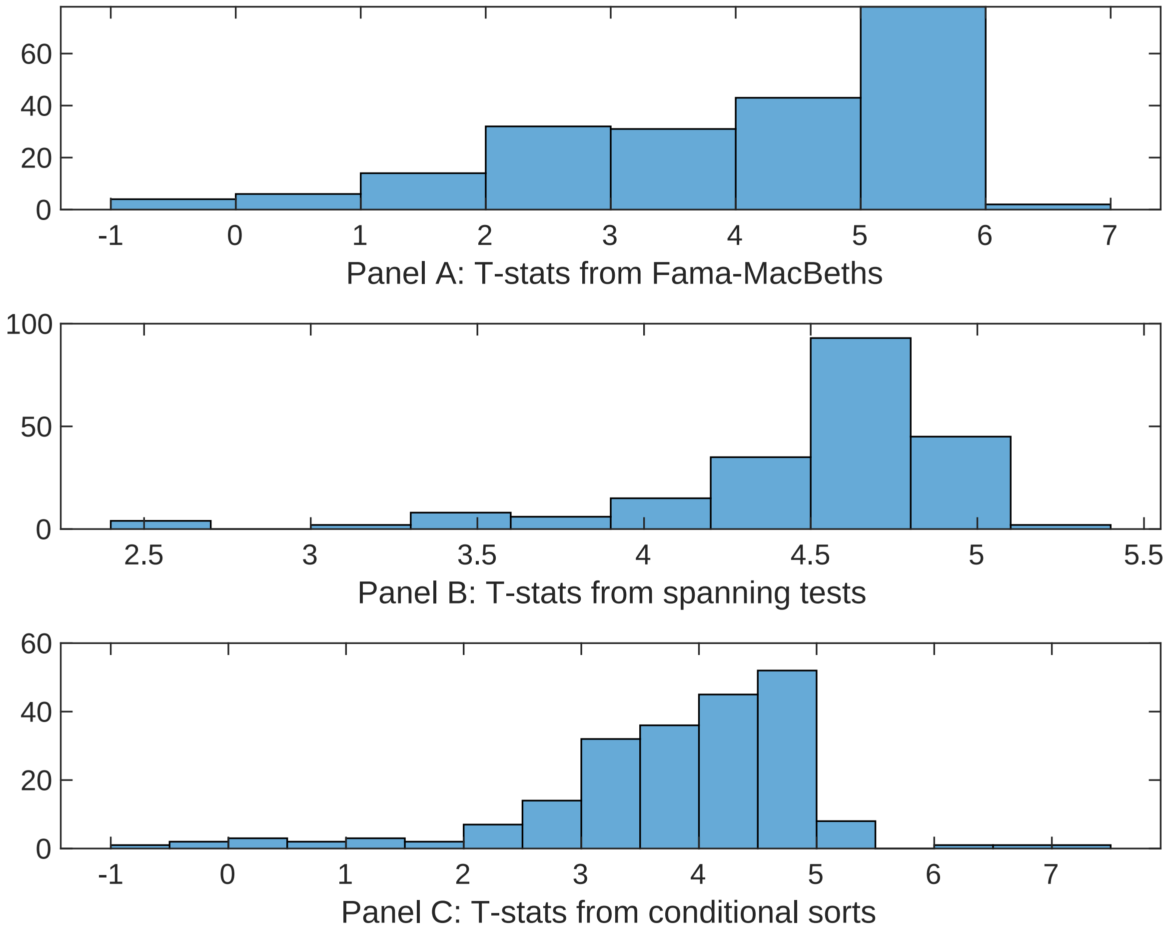


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of OENCSD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{OENCSD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{OENCSD} OENCSD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{OENCSD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 OENCSD. Stocks are finally grouped into five OENCSD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted OENCSD 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 OENCSD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{OENCSD} OENCSD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. 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 196606 to 202306.

Intercept	0.13	0.18	0.12	0.13	0.13	0.13	0.13
	[5.65]	[7.33]	[5.21]	[6.01]	[5.56]	[6.02]	[5.28]
OENCSD	0.27	0.24	0.20	0.25	0.25	0.20	0.17
	[5.03]	[4.51]	[2.86]	[4.40]	[4.76]	[3.68]	[2.38]
Anomaly 1	0.27						0.98
	[5.91]						[2.44]
Anomaly 2		0.48					-0.11
		[4.33]					[-0.07]
Anomaly 3			0.27				0.23
			[2.43]				[2.11]
Anomaly 4				0.38			0.40
				[4.37]			[0.45]
Anomaly 5					0.14		-0.15
					[4.09]		[-0.28]
Anomaly 6						0.10	0.69
						[8.75]	[6.60]
# months	679	684	679	679	684	684	679
$\bar{R}^2(\%)$	0	0	1	0	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the OENCSD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{OENCSD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. 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 196606 to 202306.

Intercept	0.20	0.23	0.22	0.20	0.24	0.23	0.18
	[2.76]	[3.08]	[2.93]	[2.64]	[3.22]	[3.02]	[2.58]
Anomaly 1	26.28						17.17
	[6.91]						[3.93]
Anomaly 2		35.57					40.11
		[8.76]					[6.78]
Anomaly 3			14.15				1.88
			[4.82]				[0.57]
Anomaly 4				15.12			2.36
				[3.81]			[0.56]
Anomaly 5					19.32		-10.24
					[4.82]		[-1.85]
Anomaly 6						4.43	-17.10
						[0.88]	[-3.28]
mkt	4.67	3.80	5.00	4.73	2.32	2.64	6.03
	[2.67]	[2.20]	[2.75]	[2.58]	[1.30]	[1.46]	[3.40]
smb	6.24	3.66	7.90	4.33	4.56	4.46	6.44
	[2.48]	[1.47]	[3.03]	[1.66]	[1.76]	[1.67]	[2.50]
hml	-5.47	-6.64	-7.45	-6.24	-4.91	-2.60	-8.68
	[-1.60]	[-1.98]	[-2.04]	[-1.70]	[-1.41]	[-0.74]	[-2.44]
rmw	-3.22	7.17	-2.51	2.59	7.22	5.22	-0.39
	[-0.89]	[2.13]	[-0.65]	[0.73]	[2.06]	[1.48]	[-0.10]
cma	16.33	-6.50	18.84	24.55	8.70	23.44	10.61
	[3.04]	[-1.03]	[3.37]	[4.62]	[1.33]	[2.92]	[1.38]
umd	3.42	3.23	4.96	3.86	4.19	3.71	2.30
	[1.98]	[1.89]	[2.81]	[2.19]	[2.36]	[2.05]	[1.35]
# months	680	684	680	680	684	684	680
$\bar{R}^2$(%)	15	16	12	10	10	7	21

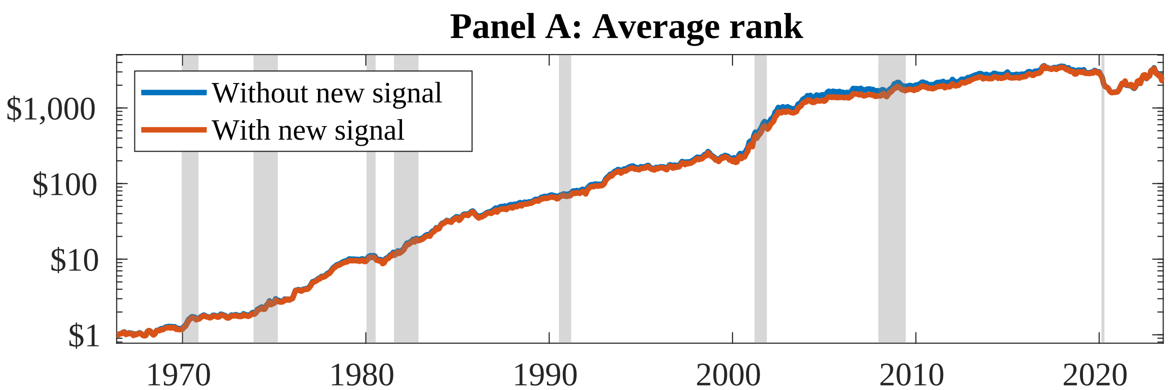


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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