Equity-Debt Slant and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Equity-Debt Slant (EDS), 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 EDS achieves an annualized gross (net) Sharpe ratio of 0.50 (0.40), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 19 (16) bps/month with a t-statistic of 3.16 (2.68), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Change in financial liabilities, Accruals, Change in Net Working Capital, Net debt financing, Investment to revenue, Change in Net Noncurrent Op Assets) is 12 bps/month with a t-statistic of 2.13.

1 Introduction

Market efficiency remains a central question in financial economics, with mounting evidence that certain firm characteristics can predict future stock returns. While extensive research has documented various accounting-based signals, the literature has largely overlooked how firms' financing choices between equity and debt may contain information about future performance. This gap is particularly notable given that managers possess private information about firm prospects and demonstrate this through their financing decisions.

Prior research shows that managers time the market when choosing between equity and debt financing Baker and Wurgler (2002), but existing studies focus primarily on aggregate market timing rather than the cross-sectional implications of firm-level financing choices. Understanding how the relative use of equity versus debt financing relates to future stock returns could provide valuable insights into both market efficiency and corporate financial decision-making.

We propose that a firm's Equity-Debt Slant (EDS) - the relative intensity of equity versus debt financing - contains predictive information about future stock returns. This hypothesis builds on theoretical work by Myers and Majluf (1984) showing that managers, who are better informed than outside investors, prefer debt to equity financing when they believe their firm is undervalued. Consequently, firms that rely more heavily on equity financing may signal overvaluation.

The predictive power of EDS likely stems from two complementary mechanisms. First, following Baker (2009), managers actively time both equity and debt markets, choosing whichever financing source they view as relatively more attractive. Second, as demonstrated by Graham and Harvey (2001), CFOs consider their stock's valuation when making financing decisions, suggesting that financing choices reflect insider views about fundamental value.

Importantly, market participants may not fully incorporate the information contained in EDS because processing the relative mix of financing requires combining multiple pieces of information across different financial statements Hirshleifer and Teoh (2003). This limited attention to complex signals creates an opportunity for return predictability that persists in equilibrium.

Our empirical analysis reveals that EDS strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks with high EDS and shorts stocks with low EDS generates a monthly alpha of 19 basis points (t-statistic = 3.16) relative to the Fama-French six-factor model. The strategy achieves an annualized Sharpe ratio of 0.50 before trading costs and 0.40 after accounting for transaction costs.

The predictive power of EDS remains robust across various methodological specifications. The signal generates significant risk-adjusted returns using different portfolio construction approaches, with net returns ranging from -5 to 25 basis points per month. Importantly, EDS maintains its predictive ability among large-cap stocks, generating an average monthly return of 18 basis points (t-statistic = 2.29) in the largest size quintile.

Further analysis demonstrates that EDS contains unique information beyond existing anomalies. Controlling for the six most closely related anomalies and the Fama-French six factors simultaneously, the EDS strategy still generates a monthly alpha of 12 basis points (t-statistic = 2.13). This indicates that EDS captures a distinct aspect of mispricing not explained by known return predictors.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel return predictor that bridges the corporate finance and asset pricing literatures by showing how financing decisions contain information about future stock returns. This extends work by Baker and Wurgler (2002) and Bradshaw et al. (2006) by demonstrating the cross-sectional return implications of financing choices.

Second, we contribute to the growing literature on return prediction in efficient markets McLean and Pontiff (2016). Our finding that EDS predicts returns even among large-cap stocks challenges the notion that obvious mispricing should be quickly eliminated by sophisticated investors. The persistence of the EDS effect suggests that processing complex financing information poses meaningful limits to arbitrage.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the value of combining multiple financing signals into a single measure. For practitioners, we show that EDS offers a promising new tool for security selection that remains profitable after accounting for transaction costs and is implementable even among large, liquid stocks.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Equity-Debt Slant measure. 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 NP (Net Income) and CEQT (Total Common/Ordinary Equity) from the fundamental annual file. Net Income (NP) represents the company's total earnings or profit for a given period, while Total Common Equity (CEQT) reflects the total value of shareholders' equity in the company, including common stock and retained earnings. The construction of the Equity-Debt Slant follows a change-based format, where we calculate the difference between the current period's Net Income and its previous period value, then scale this difference by the previous period's Total Common Equity. This measure captures the relative change in profitability compared to the firm's equity base, providing insight into the dynamics of firm performance relative to its capital structure. By focusing on this relationship, the signal aims to reflect aspects of profitability growth and capital efficiency in a manner that is both economically meaningful and comparable across firms. We construct this measure using end-of-fiscal-year values for both NP and CEQT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the EDS signal. Panel A plots the time-series of the mean, median, and interquartile range for EDS. On average, the cross-sectional mean (median) EDS is -0.04 (-0.00) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input EDS data. The signal's interquartile range spans -0.10 to 0.08. Panel B of Figure 1 plots the time-series of the coverage of the EDS signal for the CRSP universe. On average, the EDS signal is available for 6.53% of CRSP names, which on average make up 7.90% of total market capitalization.

4 Does EDS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EDS 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 EDS portfolio and sells the low EDS 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 EDS strategy earns an average return of 0.23% per month with a t-statistic of 3.84. The annualized Sharpe ratio of the strategy is 0.50. The alphas range from 0.19% to 0.26% per month and have t-statistics exceeding 3.16 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 0.21, with a t-statistic of 5.18 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 637 stocks and an average market capitalization of at least $1,387 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 16 bps/month with a t-statistics of 2.49. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-four exceed two, and for twenty-one 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 -5-25bps/month. The lowest return, (-5 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of -1.05. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EDS trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in eighteen cases.

Table 3 provides direct tests for the role size plays in the EDS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EDS, as well as average returns and alphas for long/short trading EDS 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 EDS strategy achieves an average return of 18 bps/month with a t-statistic of 2.29. Among these large cap stocks, the alphas for the EDS strategy relative to the five most common factor models range from 11 to 21 bps/month with t-statistics between 1.44 and 2.63.

5 How does EDS perform relative to the zoo?

Figure 2 puts the performance of EDS 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 EDS strategy falls in the distribution. The EDS strategy's gross (net) Sharpe ratio of 0.50 (0.40) is greater than 92% (97%) 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 EDS strategy (red line).[2] Ignoring trading costs, a \$1 invested in the EDS strategy would have yielded \$3.66 which ranks the EDS strategy in the top 8% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the EDS strategy would have yielded \$2.38 which ranks the EDS strategy in the top 6% 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 EDS relative to those. Panel A shows that the EDS strategy gross alphas fall between the 49 and 66 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 196506 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 EDS strategy has a positive net generalized alpha for five out of the five factor models. In these cases EDS ranks between the 66 and 82 percentiles in terms of how

[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.

much it could have expanded the achievable investment frontier.

6 Does EDS 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 EDS 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 EDS or at least to weaken the power EDS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of EDS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EDS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EDS} EDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EDS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on EDS. Stocks are finally grouped into

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

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EDS 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 EDS signal in these Fama-MacBeth regressions exceed 1.25, with the minimum t-statistic occurring when controlling for Change in financial liabilities. Controlling for all six closely related anomalies, the t-statistic on EDS is 0.17.

Similarly, Table 5 reports results from spanning tests that regress returns to the EDS 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 EDS strategy earns alphas that range from 14-18bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.34, which is achieved when controlling for Change in financial liabilities. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the EDS trading strategy achieves an alpha of 12bps/month with a t-statistic of 2.13.

7 Does EDS add relative to the whole zoo?

Finally, we can ask how much adding EDS 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 EDS 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 $3027.42, while $1 investment in the combination strategy that includes EDS grows to $3275.67.

8 Conclusion

This study provides compelling evidence for the effectiveness of Equity-Debt Slant (EDS) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on EDS generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.50 (0.40 net of transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

The persistence of the signal's predictive power, evidenced by a monthly alpha of 12 bps (t-statistic = 2.13) after controlling for related factors, suggests that EDS captures unique information about future stock returns that is not fully reflected in existing asset pricing factors. This has important implications for both academic research and practical investment management, as it contributes to our understanding of market efficiency and offers potential opportunities for portfolio enhancement.

[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 EDS is available.

However, several limitations should be noted. First, the study's findings may be sensitive to the specific time period examined and market conditions. Second, transaction costs and market impact could affect the real-world implementation of EDS-based strategies, particularly for large-scale portfolios. Future research could explore the international validity of the EDS signal, its interaction with other market anomalies, and its performance during different market regimes. Additionally, investigating the underlying economic mechanisms driving the EDS effect could provide valuable insights into asset pricing theory and market behavior.

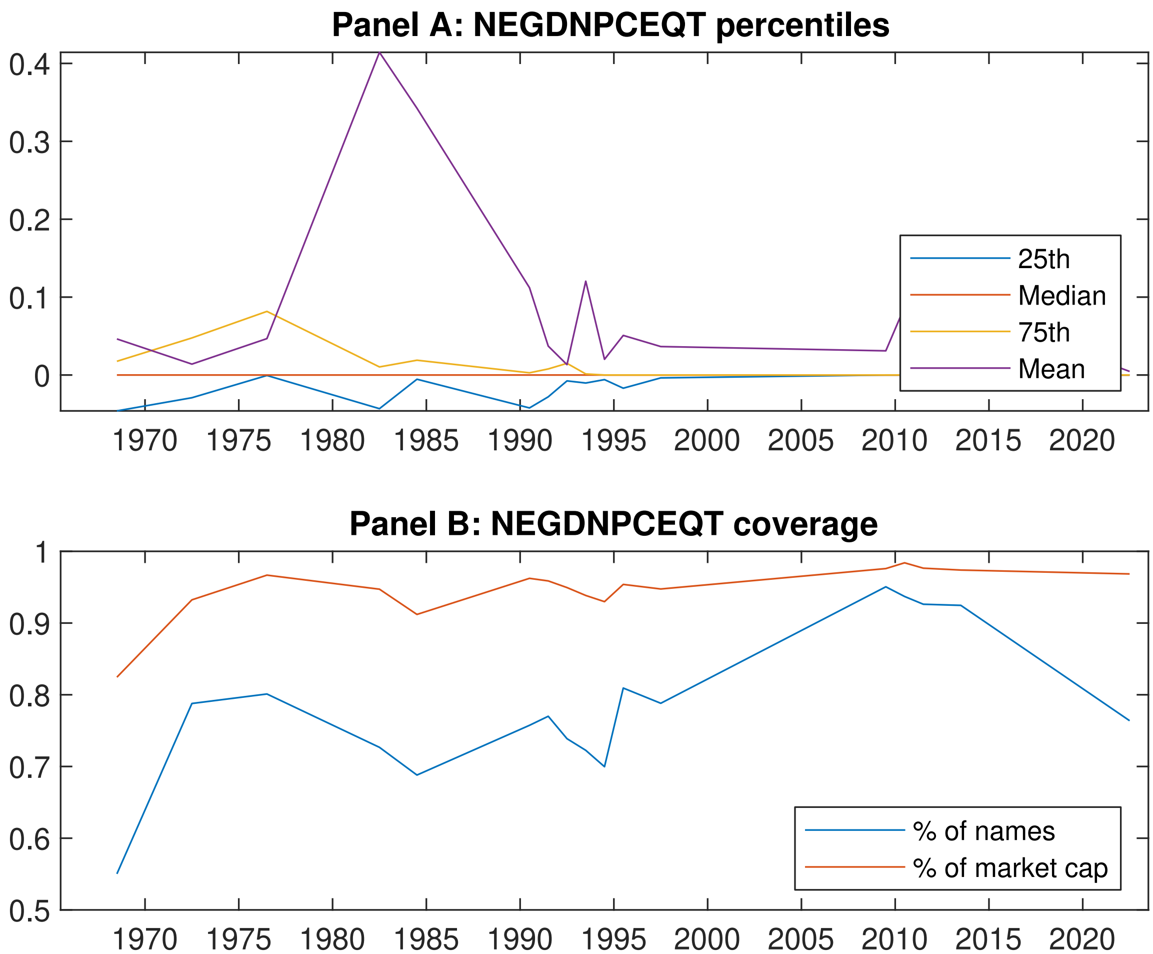

Figure 1: Times series of EDS percentiles and coverage.
This figure plots descriptive statistics for EDS. Panel A shows cross-sectional percentiles of EDS over the sample. Panel B plots the monthly coverage of EDS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EDS. 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 196506 to 202306.

Panel A: Excess returns and alphas on EDS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.41	0.54	0.69	0.63	0.64	0.23
	[2.30]	[3.00]	[3.51]	[3.41]	[3.78]	[3.84]
α_{CAPM}	-0.14	-0.02	0.07	0.05	0.11	0.25
	[-2.63]	[-0.47]	[1.31]	[0.98]	[2.35]	[4.13]
α_{FF3}	-0.19	0.00	0.12	0.08	0.06	0.26
	[-3.91]	[0.09]	[2.42]	[1.52]	[1.46]	[4.25]
α_{FF4}	-0.16	0.08	0.12	0.05	0.05	0.21
	[-3.22]	[1.65]	[2.53]	[1.03]	[1.14]	[3.46]
α_{FF5}	-0.26	0.05	0.19	0.11	-0.03	0.23
	[-5.39]	[1.04]	[3.82]	[2.09]	[-0.83]	[3.71]
α_{FF6}	-0.23	0.11	0.19	0.09	-0.04	0.19
	[-4.75]	[2.28]	[3.79]	[1.66]	[-0.87]	[3.16]
Panel B: Fama and French (2018) 6-factor model loadings for EDS-sorted portfolios						
β_{MKT}	1.02	0.98	1.04	1.01	1.00	-0.02
	[89.49]	[83.56]	[88.13]	[80.60]	[99.74]	[-1.69]
β_{SMB}	-0.06	-0.11	0.11	0.02	0.01	0.07
	[-3.58]	[-6.50]	[6.36]	[0.94]	[0.67]	[3.29]
β_{HML}	0.17	-0.06	-0.13	-0.08	0.05	-0.12
	[7.79]	[-2.65]	[-5.86]	[-3.29]	[2.56]	[-4.39]
β_{RMW}	0.22	-0.08	-0.13	-0.10	0.16	-0.05
	[9.65]	[-3.69]	[-5.70]	[-4.14]	[8.37]	[-1.83]
β_{CMA}	-0.03	-0.03	-0.10	0.01	0.18	0.21
	[-1.01]	[-0.97]	[-2.89]	[0.17]	[6.33]	[5.18]
β_{UMD}	-0.04	-0.09	-0.00	0.03	0.00	0.05
	[-3.93]	[-7.60]	[-0.10]	[2.59]	[0.31]	[3.33]
Panel C: Average number of firms (n) and market capitalization (me)						
n	677	658	840	715	637	
me ($\$10^6$)	2777	1608	1387	1488	2474	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the EDS 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 196506 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	0.23	0.25	0.26	0.21	0.23	0.19
			[3.84]	[4.13]	[4.25]	[3.46]	[3.71]	[3.16]
Quintile	NYSE	EW	0.18	0.18	0.19	0.20	0.20	0.21
			[4.62]	[4.51]	[4.65]	[4.84]	[4.99]	[5.14]
Quintile	Name	VW	0.24	0.25	0.26	0.21	0.25	0.21
			[3.87]	[4.10]	[4.28]	[3.44]	[4.00]	[3.38]
Quintile	Cap	VW	0.16	0.19	0.21	0.16	0.16	0.13
			[2.49]	[2.95]	[3.13]	[2.41]	[2.42]	[1.93]
Decile	NYSE	VW	0.30	0.32	0.31	0.28	0.25	0.23
			[4.12]	[4.38]	[4.29]	[3.80]	[3.43]	[3.15]

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	0.19	0.21	0.21	0.18	0.18	0.16
			[3.07]	[3.34]	[3.44]	[3.03]	[2.99]	[2.68]
Quintile	NYSE	EW	-0.05					
			[-1.05]					
Quintile	Name	VW	0.19	0.21	0.22	0.19	0.20	0.18
			[3.10]	[3.32]	[3.47]	[3.03]	[3.23]	[2.88]
Quintile	Cap	VW	0.12	0.15	0.16	0.13	0.12	0.10
			[1.83]	[2.26]	[2.41]	[2.02]	[1.83]	[1.50]
Decile	NYSE	VW	0.25	0.27	0.26	0.25	0.21	0.20
			[3.40]	[3.65]	[3.58]	[3.32]	[2.88]	[2.70]

Table 3: Conditional sort on size and EDS

This table presents results for conditional double sorts on size and EDS. 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 EDS. 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 EDS and short stocks with low EDS .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196506 to 202306.

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

Size quintiles	EDS Quintiles (L)	(2)	(3)	(4)	(H)	EDS Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.53	0.85	0.96	0.85	0.73	0.20	0.19	0.20	0.20	0.23	0.22
	[2.13]	[3.41]	[3.63]	[3.30]	[2.92]	[2.91]	[2.84]	[2.92]	[2.85]	[3.22]	[3.15]
(2)	0.63	0.77	0.82	0.84	0.92	0.29	0.29	0.30	0.28	0.32	0.29
	[2.77]	[3.28]	[3.46]	[3.57]	[4.02]	[4.07]	[3.99]	[4.24]	[3.82]	[4.30]	[3.96]
(3)	0.69	0.69	0.82	0.82	0.73	0.04	0.03	0.05	0.06	0.04	0.05
	[3.33]	[3.27]	[3.70]	[3.75]	[3.54]	[0.52]	[0.41]	[0.70]	[0.79]	[0.50]	[0.63]
(4)	0.61	0.66	0.68	0.80	0.74	0.13	0.13	0.16	0.14	0.19	0.17
	[3.16]	[3.33]	[3.28]	[3.88]	[3.89]	[2.06]	[2.04]	[2.42]	[2.16]	[2.87]	[2.65]
(5)	0.39	0.42	0.62	0.58	0.57	0.18	0.21	0.20	0.15	0.15	0.11
	[2.20]	[2.51]	[3.19]	[3.25]	[3.44]	[2.29]	[2.63]	[2.57]	[1.91]	[1.88]	[1.44]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	EDS Quintiles, Average n (L)	(2)	(3)	(4)	(H)	EDS Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	386	389	389	390	387	30	34	34	34	31
(2)	110	110	109	109	110	56	56	56	56	56
(3)	80	79	79	79	80	99	96	96	96	98
(4)	67	67	67	67	67	213	204	202	206	210
(5)	61	62	61	62	61	1857	1510	1328	1352	1723

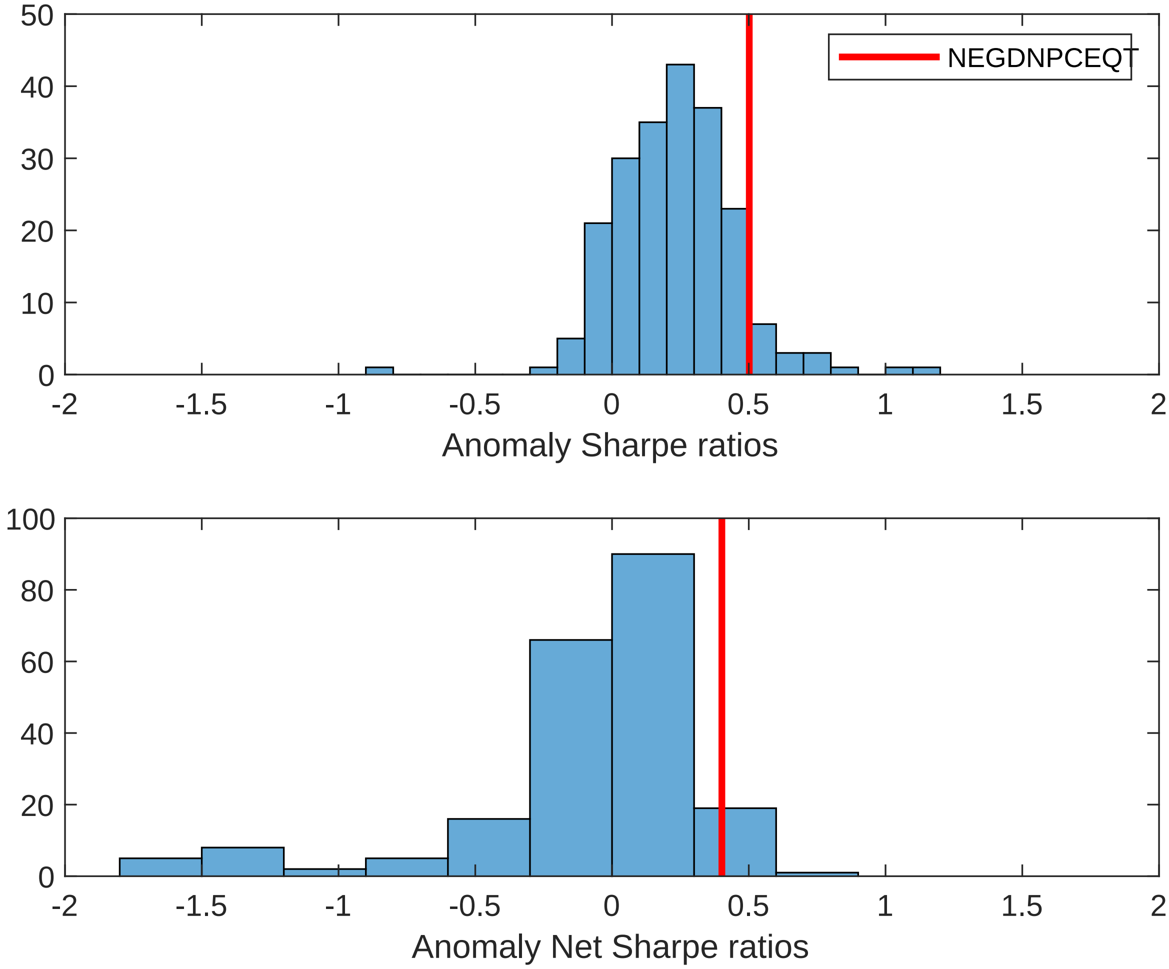

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EDS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

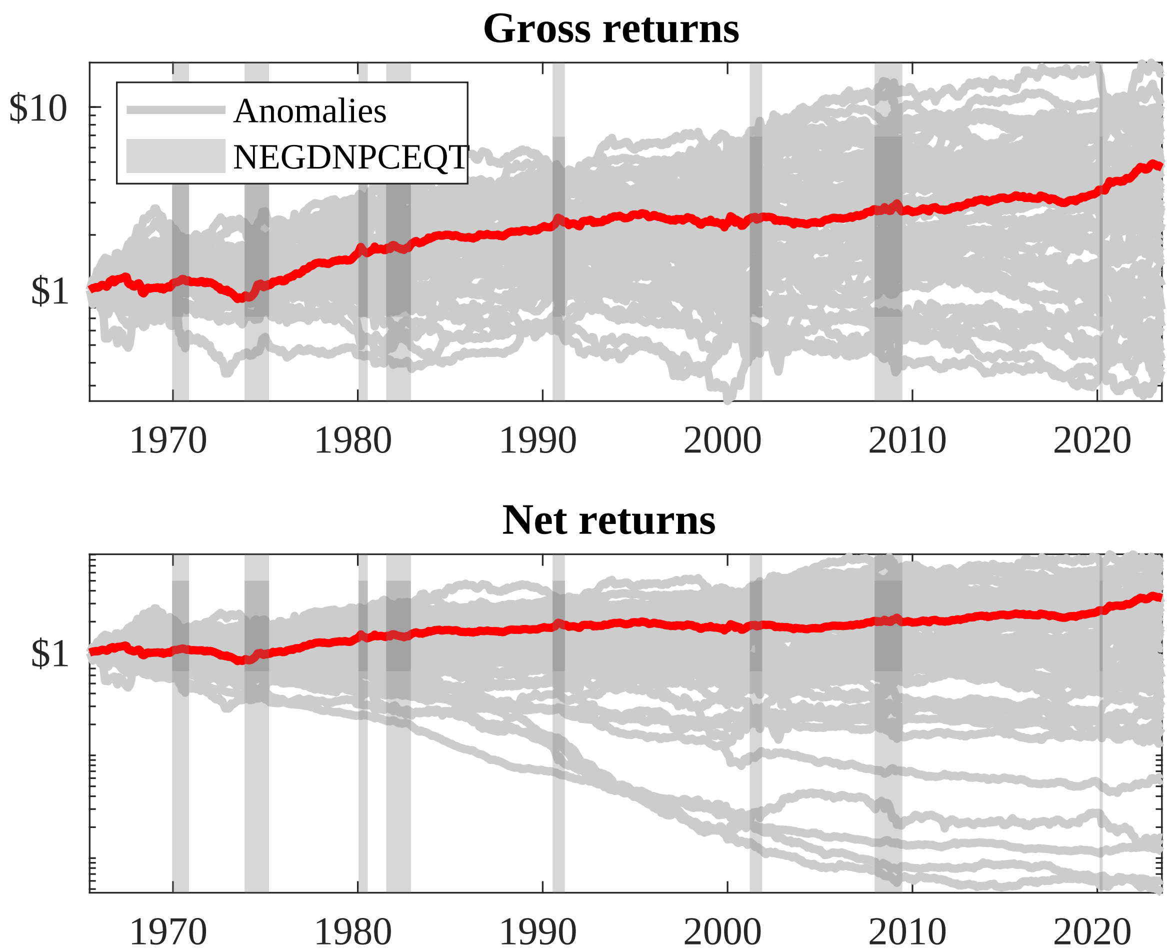

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EDS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

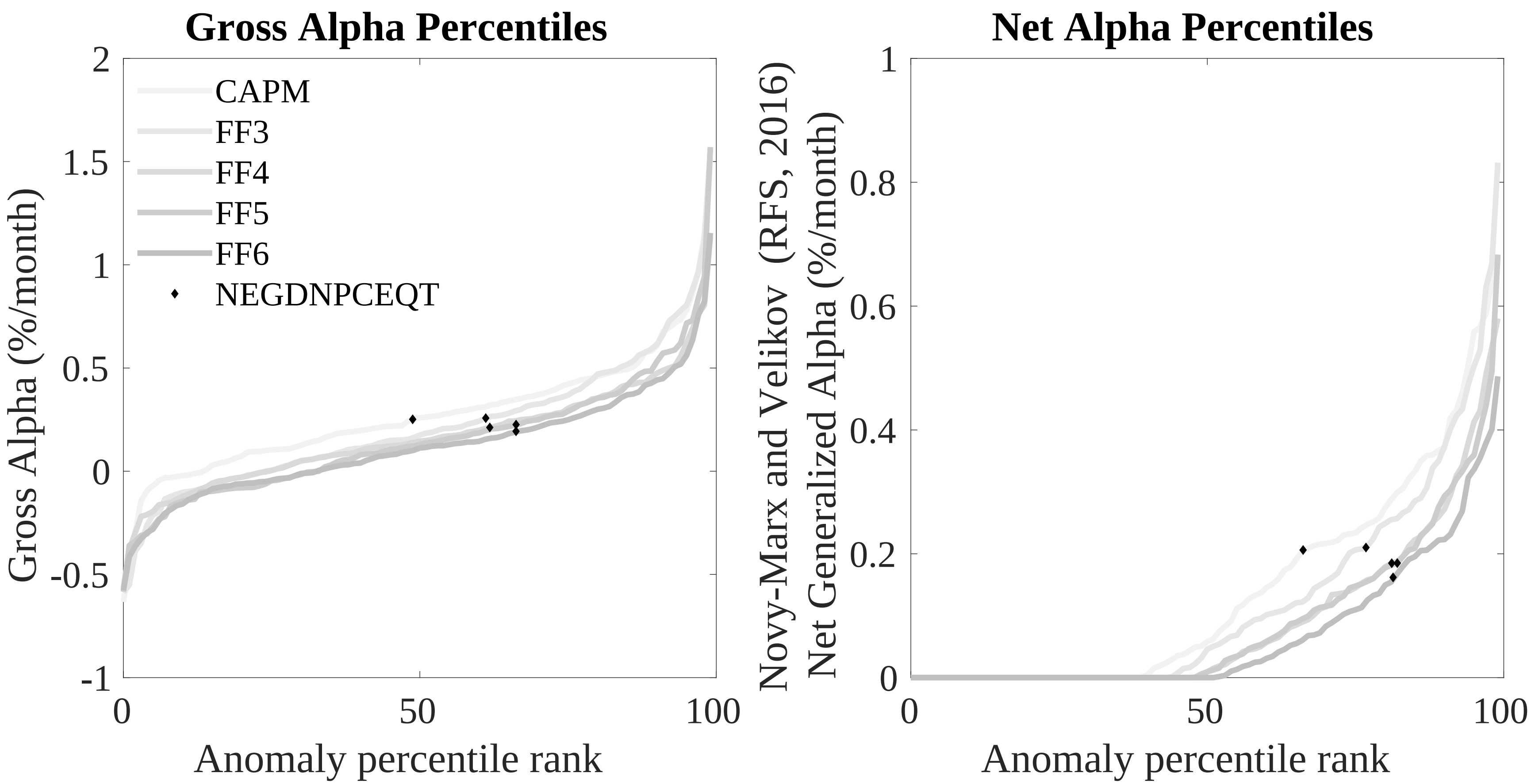

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EDS trading strategy alphas (diamonds). The strategies are constructed using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

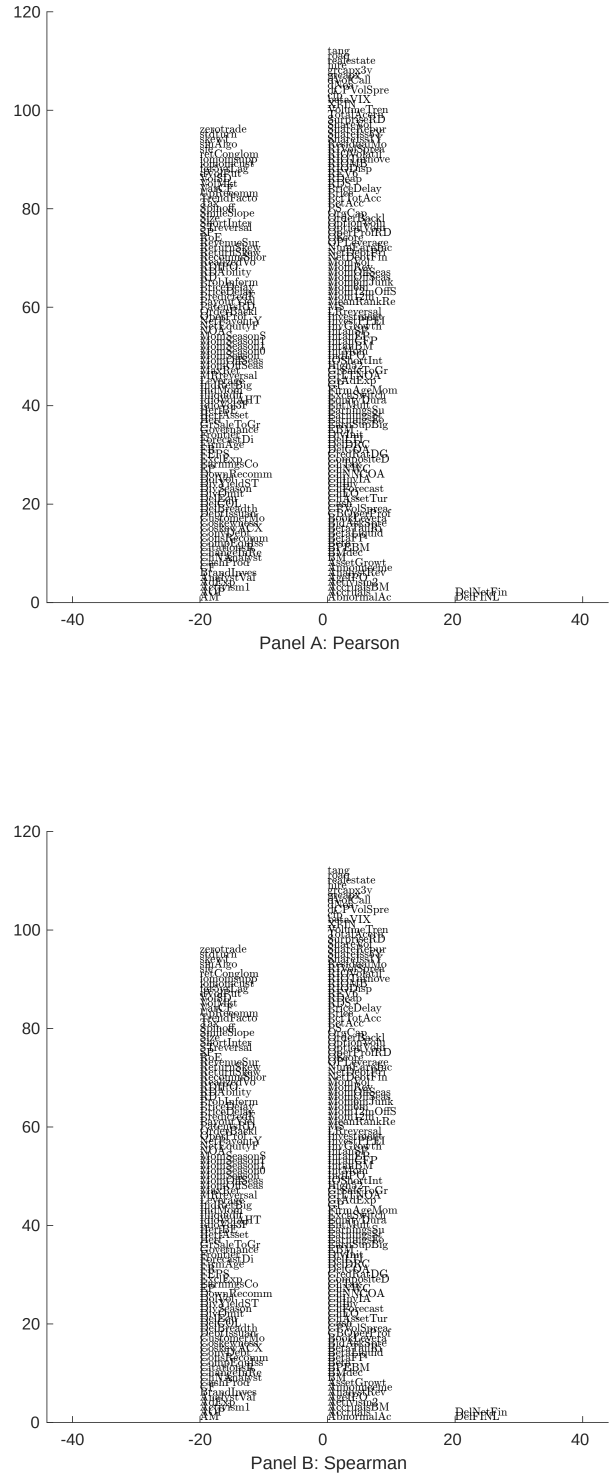

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with EDS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

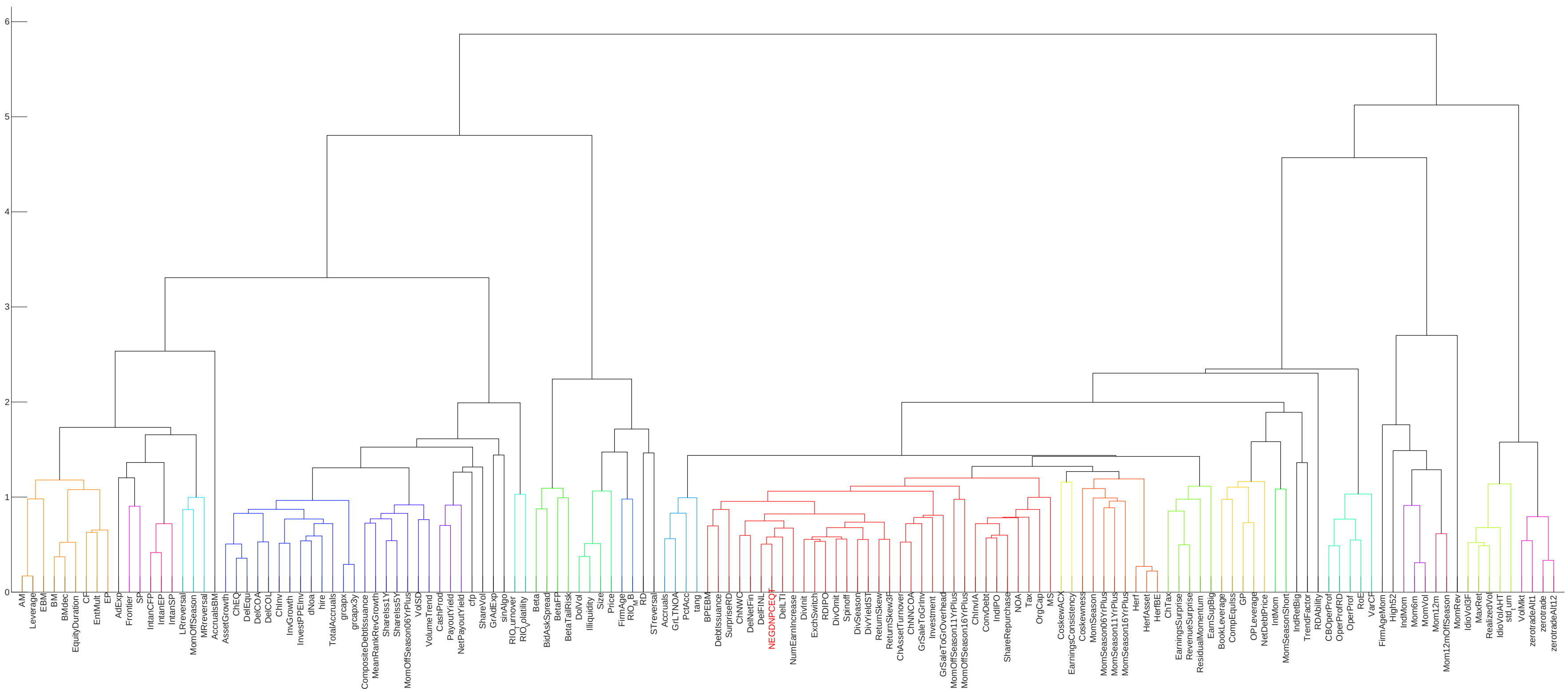

Figure 6: Agglomerative hierarchical cluster plot

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

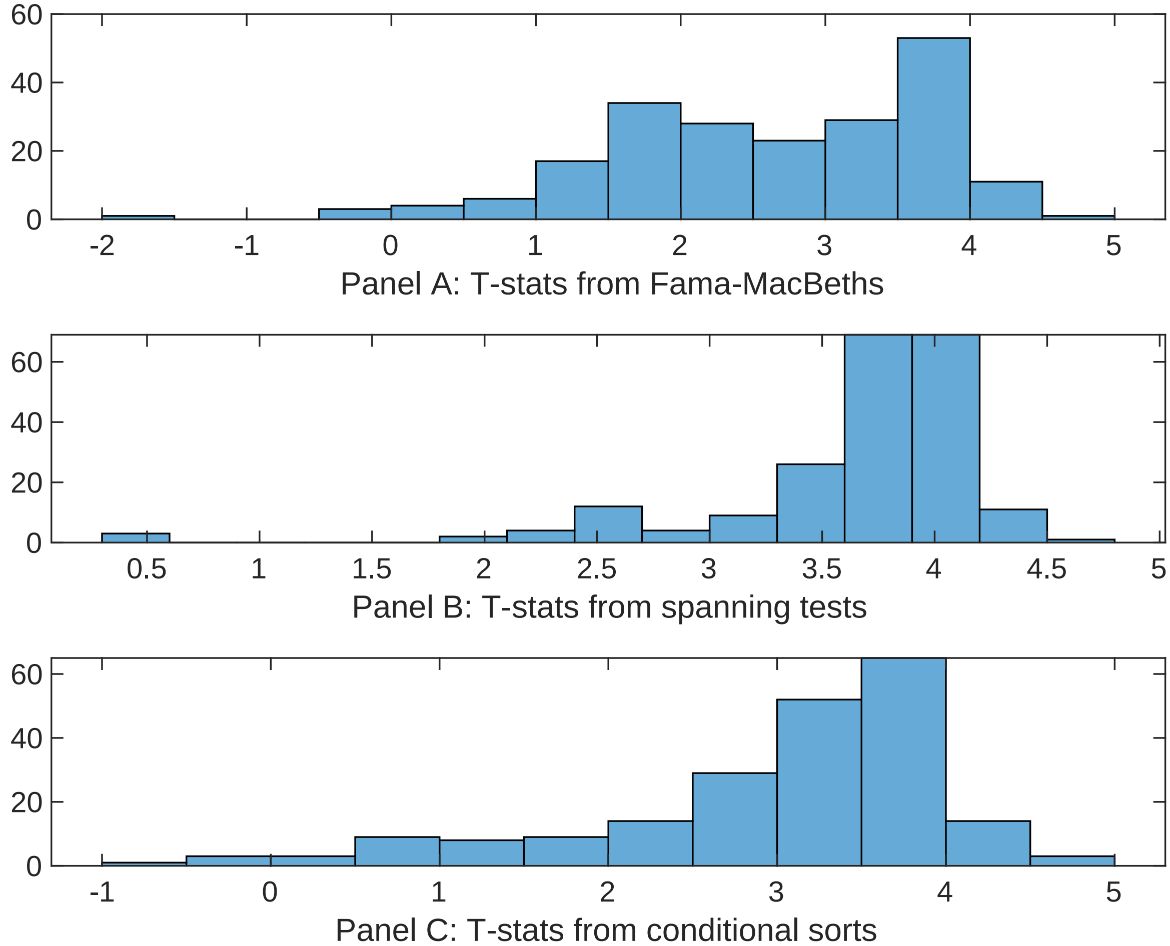

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EDS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EDS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EDS} EDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EDS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EDS. Stocks are finally grouped into five EDS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EDS 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 EDS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EDS}EDS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k}X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in financial liabilities, Accruals, Change in Net Working Capital, Net debt financing, Investment to revenue, Change in Net Noncurrent Op Assets. 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 196506 to 202306.

Intercept	0.12	0.12	0.12	0.13	0.15	0.12	0.14
	[5.61]	[5.24]	[5.35]	[5.15]	[6.37]	[5.36]	[5.54]
EDS	0.78	0.17	0.21	0.17	0.10	0.22	0.11
	[1.25]	[2.85]	[3.31]	[2.75]	[1.40]	[3.53]	[0.17]
Anomaly 1	0.17						0.53
	[9.09]						[1.75]
Anomaly 2		0.13					0.22
		[4.06]					[3.84]
Anomaly 3			0.68				-0.16
			[2.56]				[-3.06]
Anomaly 4				0.20			0.97
				[9.30]			[2.64]
Anomaly 5					0.24		0.14
					[6.19]		[3.20]
Anomaly 6						0.74	0.15
						[3.98]	[0.62]
# months	696	696	696	618	696	696	618
$\bar{R}^2(\%)$	0	0	0	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 EDS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EDS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Change in financial liabilities, Accruals, Change in Net Working Capital, Net debt financing, Investment to revenue, Change in Net Noncurrent Op Assets. 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 196506 to 202306.

Intercept	0.16	0.14	0.16	0.18	0.18	0.18	0.12
	[2.66]	[2.34]	[2.54]	[2.95]	[2.88]	[3.03]	[2.13]
Anomaly 1	28.69						25.78
	[8.33]						[5.73]
Anomaly 2		16.19					11.42
		[6.66]					[4.58]
Anomaly 3			14.89				2.92
			[4.71]				[0.89]
Anomaly 4				13.11			-8.92
				[3.78]			[-2.10]
Anomaly 5					11.15		3.48
					[4.48]		[1.46]
Anomaly 6						17.50	9.77
						[6.27]	[3.38]
mkt	-1.80	-1.14	-2.55	-0.80	-2.59	-2.37	0.22
	[-1.29]	[-0.80]	[-1.78]	[-0.55]	[-1.80]	[-1.67]	[0.16]
smb	4.06	10.09	7.26	6.66	4.73	6.26	7.14
	[1.99]	[4.81]	[3.50]	[3.04]	[2.22]	[3.05]	[3.32]
hml	-9.91	-8.86	-11.13	-11.62	-11.28	-12.65	-7.56
	[-3.70]	[-3.21]	[-4.03]	[-4.23]	[-4.08]	[-4.64]	[-2.90]
rmw	-7.58	0.34	-3.54	-5.19	-4.34	-7.33	-1.91
	[-2.78]	[0.12]	[-1.25]	[-1.83]	[-1.54]	[-2.63]	[-0.68]
cma	10.34	16.48	20.42	18.08	20.22	21.17	10.60
	[2.49]	[4.05]	[5.02]	[4.21]	[4.96]	[5.27]	[2.57]
umd	2.50	3.43	4.03	4.11	3.43	2.68	0.62
	[1.78]	[2.44]	[2.83]	[2.84]	[2.36]	[1.86]	[0.45]
# months	696	696	696	618	696	696	618
$\bar{R}^2(\%)$	17	15	12	12	12	14	24

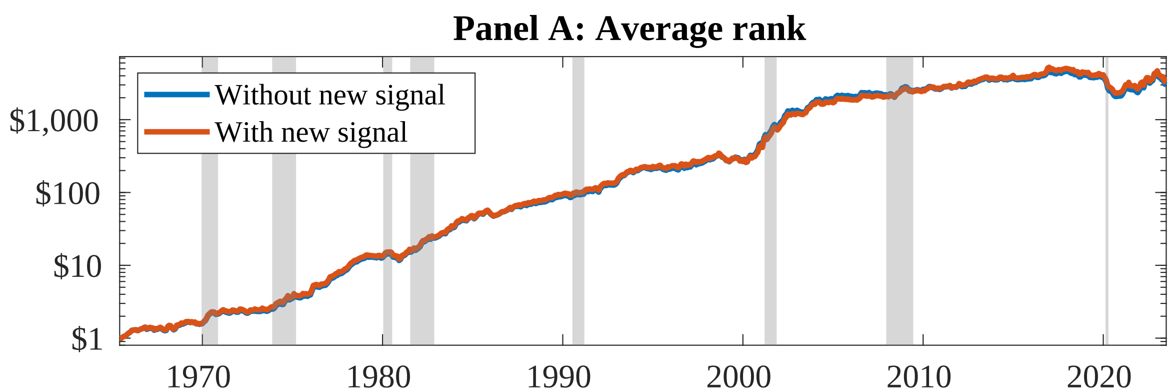

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

References

Baker, M. (2009). Market timing and capital structure. *Journal of Finance*, 64(6):2529–2563.

Baker, M. and Wurgler, J. (2002). Market timing and capital structure. *Journal of Finance*, 57(1):1–32.

Bradshaw, M. T., Richardson, S. A., and Sloan, R. G. (2006). The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics*, 42(1-2):53–85.

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

Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.

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

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

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

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

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

Graham, J. R. and Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics*, 60(2-3):187–243.

Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3):337–386.

McLean, R. D. and Pontiff, J. (2016). Does mispricing drive the anomaly zoo? *Journal of Finance*, 71(2):651–686.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221.

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

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper*.