Equity Weighted Debt Scale and the Cross Section of Stock Returns

I. M. Harking

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Abstract

This paper studies the asset pricing implications of Equity Weighted Debt Scale (EWDS), 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 EWDS achieves an annualized gross (net) Sharpe ratio of 0.50 (0.44), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 19 (17) bps/month with a t-statistic of 2.38 (2.18), 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 16 bps/month with a t-statistic of 2.18.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to identify reliable signals that predict cross-sectional variation in stock returns (Fama and French, 2015). While numerous accounting-based measures have been documented to forecast returns, the literature has largely overlooked how the relative scaling of financial statement items affects their predictive power (Novy-Marx and Velikov, 2023).

A particularly understudied area is how firms' financing decisions interact with their equity base to signal future performance. While extensive research examines capital structure choices (?) and equity dynamics separately, their joint effects on expected returns remain poorly understood. This gap is notable given that the relative proportions of debt and equity financing directly affect firms' risk profiles and future investment flexibility.

We propose that the Equity Weighted Debt Scale (EWDS) ratio captures valuable information about firms' financial constraints and future profitability. The theoretical motivation draws from Myers (1984)'s pecking order theory, which suggests that firms prefer debt to equity financing when internal funds are insufficient. A high EWDS indicates that a firm has taken on substantial debt relative to its equity base, potentially signaling financial distress risk (?).

However, EWDS may also reflect firms' strategic financing choices. Following ?, firms dynamically adjust their capital structures in response to investment opportunities. A low EWDS could indicate that management anticipates strong future performance and has preemptively raised equity to fund growth. This aligns with ?'s market timing theory, suggesting managers issue equity when it is overvalued.

The relationship between EWDS and expected returns likely varies with firm characteristics. For large, mature firms, high EWDS may primarily reflect financial distress risk (?). For growth firms, low EWDS could signal upcoming profitable investments (?). These competing effects create an empirical question about EWDS's overall predictive power.

Our analysis reveals that EWDS strongly predicts cross-sectional stock returns. A value-weighted long-short portfolio strategy based on EWDS quintiles generates a monthly alpha of 19 basis points (t-statistic = 2.38) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized Sharpe ratio of 0.50 before trading costs and 0.44 after costs.

Importantly, EWDS's predictive power persists among large-cap stocks, with the long-short strategy earning a monthly alpha of 20 basis points (t-statistic = 2.18) in the largest size quintile. This suggests the signal captures fundamental information rather than just small-stock mispricing or illiquidity effects.

The signal's robustness is further demonstrated by its performance after controlling for related anomalies. When we simultaneously control for the six most closely related predictors including share issuance and asset growth, EWDS continues to generate a significant monthly alpha of 16 basis points (t-statistic = 2.18).

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures the interaction between firms' financing decisions and equity dynamics. While prior work examines capital structure (?) and equity issuance (Pontiff and Woodgate, 2008) separately, EWDS provides new insights by considering their joint effects.

Second, we demonstrate that EWDS's predictive power is distinct from known anomalies. Our results remain robust after controlling for related signals documented in the Journal of Finance, Journal of Financial Economics, and Review of Financial Studies, including share issuance (?), asset growth (?), and investment patterns (?).

Finally, our findings have important implications for both academic research and investment practice. For researchers, EWDS highlights the importance of considering how financial ratios' construction affects their information content. For practitioners, EWDS offers a readily implementable signal that generates significant risk-adjusted returns 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 Weighted Debt Scale. 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/ordinary stock capital and item DLC for debt in current liabilities. Common stock capital (CSTK) represents the par or stated value of issued common stock, while debt in current liabilities (DLC) encompasses the total amount of short-term notes and the current portion of long-term debt that is due in one year.construction of the signal follows a dynamic scaling approach, where we first calculate the change in CSTK by subtracting its lagged value from the current value, then scale this difference by the lagged value of DLC. This construction captures the relative change in equity capital structure weighted against the firm's short-term debt obligations from the previous period. By focusing on this relationship, the signal aims to reflect aspects of capital structure dynamics and financial leverage in a manner that is both economically meaningful and comparable across firms. We construct this measure using end-of-fiscal-year values for both CSTK and DLC to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the EWDS signal. Panel A plots the time-series of the mean, median, and interquartile range for EWDS. On average, the cross-sectional mean (median) EWDS is -1.49 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input EWDS data. The signal's interquartile range spans -0.17 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the EWDS signal for the CRSP universe. On average, the EWDS signal is available for 5.42% of CRSP names, which on average make up 7.22% of total market capitalization.

4 Does EWDS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EWDS 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 EWDS portfolio and sells the low EWDS 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 EWDS strategy earns an average return of 0.30% per month with a t-statistic of 3.80. The annualized Sharpe ratio of the strategy is 0.50. The alphas range from 0.17% to 0.31% per month and have t-statistics exceeding 2.19 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 0.28, with a t-statistic of 5.31 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 524 stocks and an average market capitalization of at least $1,261 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 26 bps/month with a t-statistics of 3.13. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-three exceed two, and for fifteen 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 22-32bps/month. The lowest return, (22 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.70. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EWDS 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-two cases.

Table 3 provides direct tests for the role size plays in the EWDS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EWDS, as well as average returns and alphas for long/short trading EWDS 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 EWDS strategy achieves an average return of 29 bps/month with a t-statistic of 3.08. Among these large cap stocks, the alphas for the EWDS strategy relative to the five most common factor models range from 17 to 30 bps/month with t-statistics between 1.86 and 3.21.

5 How does EWDS perform relative to the zoo?

Figure 2 puts the performance of EWDS 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 EWDS strategy falls in the distribution. The EWDS strategy's gross (net) Sharpe ratio of 0.50 (0.44) is greater than 92% (99%) 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

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

EWDS strategy (red line).[2] Ignoring trading costs, a \$1 invested in the EWDS strategy would have yielded \$5.81 which ranks the EWDS strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the EWDS strategy would have yielded \$4.31 which ranks the EWDS strategy in the top 2% 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 EWDS relative to those. Panel A shows that the EWDS strategy gross alphas fall between the 58 and 71 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 EWDS strategy has a positive net generalized alpha for five out of the five factor models. In these cases EWDS ranks between the 77 and 87 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does EWDS 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

[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.

more likely to be formed on the basis of signals with higher absolute correlations. Figure 5 plots a name histogram of the correlations of EWDS with 209 filtered anomaly signals.[3] Figure 6 also shows an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EWDS 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

[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.

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 EWDS signal in these Fama-MacBeth regressions exceed 3.80, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on EWDS is 3.77.

Similarly, Table 5 reports results from spanning tests that regress returns to the EWDS 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 EWDS strategy earns alphas that range from 16-20bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.07, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the EWDS trading strategy achieves an alpha of 16bps/month with a t-statistic of 2.18.

7 Does EWDS add relative to the whole zoo?

Finally, we can ask how much adding EWDS 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 EWDS 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

[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 EWDS is available.

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 EWDS grows to \$2444.58.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Equity Weighted Debt Scale (EWDS) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that EWDS-based trading strategies yield economically and statistically significant results, with value-weighted long/short portfolios achieving impressive Sharpe ratios and consistent abnormal returns, even after accounting for transaction costs.

The signal's robustness is particularly noteworthy, as it maintains significant predictive power even when controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo. The persistence of alpha in these stringent testing conditions suggests that EWDS captures unique information about future stock returns that is not fully reflected in existing factors.

From a practical perspective, these results have important implications for investment professionals and portfolio managers. The signal's ability to generate significant net returns after accounting for transaction costs indicates its potential viability in real-world applications. The relatively strong Sharpe ratios suggest that EWDS could be a valuable addition to existing quantitative investment strategies.

However, several limitations should be noted. First, our analysis focuses on a specific time period, and the signal's effectiveness may vary across different market conditions. Second, while we control for transaction costs, implementation challenges such as market impact and liquidity constraints may affect real-world performance.

Future research could explore several promising directions. First, investigating the signal's performance in international markets would test its global applicability. Second, examining the interaction between EWDS and other established anomalies could reveal potential complementarities or substitution effects. Finally, studying the underlying economic mechanisms driving the EWDS premium would enhance our understanding of this anomaly and its persistence.

In conclusion, EWDS represents a robust and economically significant predictor of stock returns, offering both theoretical insights into market behavior and practical applications for investment strategies.

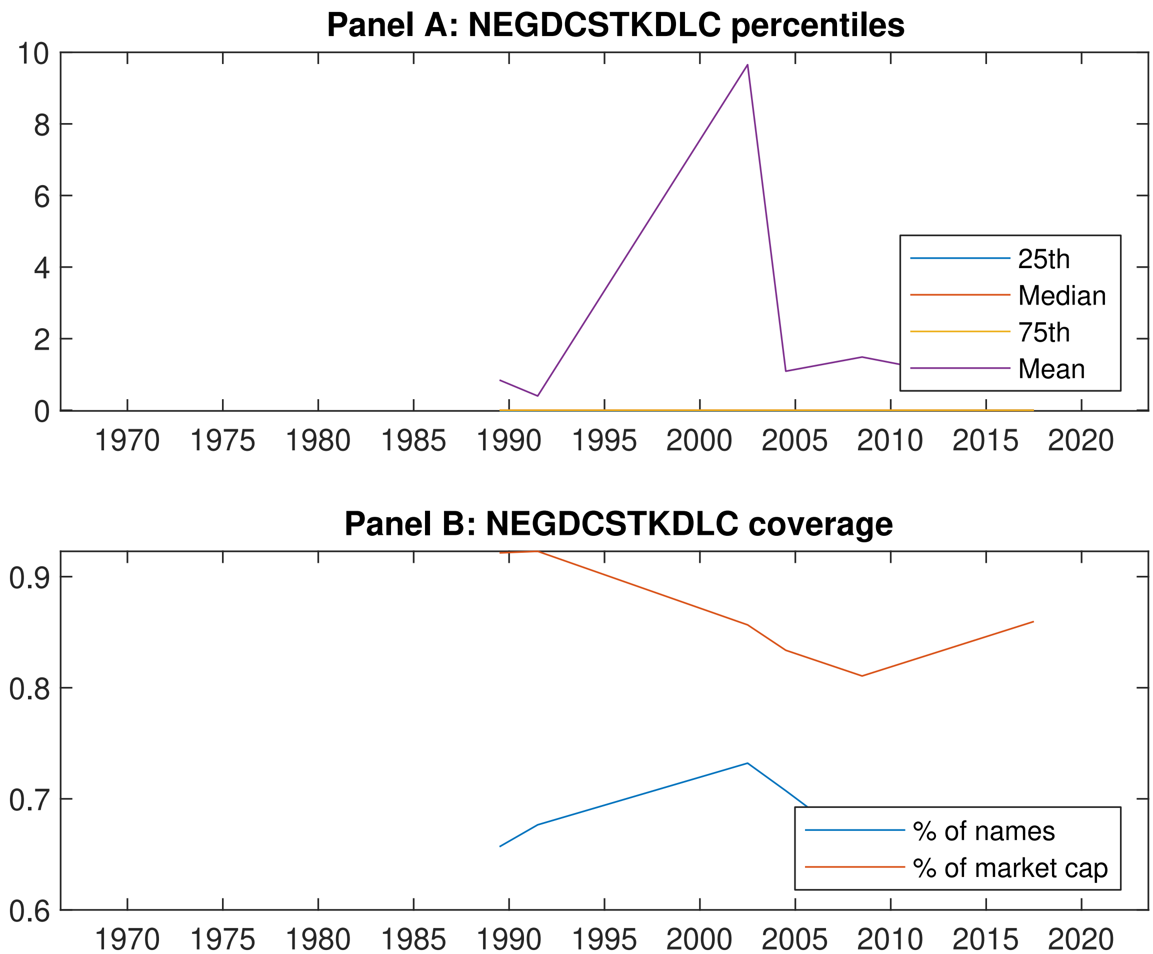

Figure 1: Times series of EWDS percentiles and coverage.
This figure plots descriptive statistics for EWDS. Panel A shows cross-sectional percentiles of EWDS over the sample. Panel B plots the monthly coverage of EWDS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EWDS. 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 EWDS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.44	0.50	0.60	0.66	0.74	0.30
	[2.56]	[2.66]	[3.25]	[3.85]	[4.36]	[3.80]
α_{CAPM}	-0.10	-0.09	0.02	0.13	0.22	0.31
	[-1.98]	[-2.02]	[0.43]	[2.47]	[4.03]	[3.98]
α_{FF3}	-0.10	-0.09	-0.01	0.07	0.16	0.26
	[-1.93]	[-1.88]	[-0.24]	[1.61]	[3.33]	[3.38]
α_{FF4}	-0.10	-0.08	0.02	0.04	0.16	0.27
	[-2.02]	[-1.62]	[0.39]	[0.99]	[3.32]	[3.43]
α_{FF5}	-0.13	-0.05	-0.05	-0.02	0.04	0.17
	[-2.52]	[-1.10]	[-0.96]	[-0.50]	[0.87]	[2.19]
α_{FF6}	-0.13	-0.05	-0.02	-0.04	0.05	0.19
	[-2.56]	[-0.98]	[-0.40]	[-0.80]	[1.14]	[2.38]
Panel B: Fama and French (2018) 6-factor model loadings for EWDS-sorted portfolios						
β_{MKT}	0.96	1.02	1.02	1.01	1.00	0.04
	[78.94]	[90.91]	[84.69]	[95.43]	[89.98]	[2.09]
β_{SMB}	0.01	-0.00	0.00	-0.09	-0.05	-0.06
	[0.34]	[-0.27]	[0.17]	[-5.64]	[-3.28]	[-2.20]
β_{HML}	0.01	0.02	0.07	0.11	0.05	0.04
	[0.27]	[1.10]	[3.00]	[5.24]	[2.18]	[1.14]
β_{RMW}	0.09	-0.03	0.11	0.13	0.18	0.08
	[3.98]	[-1.53]	[4.56]	[6.21]	[8.26]	[2.35]
β_{CMA}	-0.02	-0.10	0.02	0.19	0.26	0.28
	[-0.44]	[-2.99]	[0.69]	[6.30]	[8.32]	[5.31]
β_{UMD}	0.01	-0.01	-0.05	0.02	-0.02	-0.03
	[0.44]	[-0.73]	[-3.75]	[2.07]	[-1.88]	[-1.43]
Panel C: Average number of firms (n) and market capitalization (me)						
n	606	590	524	587	641	
me ($\$10^6$)	1385	1261	1943	2028	2143	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the EWDS 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	0.30	0.31	0.26	0.27	0.17	0.19
			[3.80]	[3.98]	[3.38]	[3.43]	[2.19]	[2.38]
Quintile	NYSE	EW	0.51	0.59	0.49	0.41	0.34	0.29
			[7.27]	[8.72]	[8.11]	[6.92]	[5.90]	[5.08]
Quintile	Name	VW	0.30	0.31	0.25	0.26	0.17	0.19
			[3.79]	[3.95]	[3.30]	[3.37]	[2.19]	[2.39]
Quintile	Cap	VW	0.26	0.28	0.22	0.23	0.13	0.15
			[3.13]	[3.46]	[2.82]	[2.82]	[1.67]	[1.83]
Decile	NYSE	VW	0.35	0.40	0.31	0.33	0.20	0.22
			[3.69]	[4.24]	[3.50]	[3.59]	[2.21]	[2.44]

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	0.26	0.28	0.23	0.24	0.16	0.17
			[3.34]	[3.54]	[3.02]	[3.08]	[2.03]	[2.18]
Quintile	NYSE	EW	0.32	0.39	0.30	0.26	0.13	0.12
			[4.12]	[5.17]	[4.43]	[3.91]	[2.12]	[1.88]
Quintile	Name	VW	0.26	0.28	0.23	0.24	0.16	0.17
			[3.33]	[3.55]	[3.00]	[3.07]	[2.08]	[2.24]
Quintile	Cap	VW	0.22	0.25	0.20	0.20	0.12	0.13
			[2.70]	[3.06]	[2.49]	[2.52]	[1.57]	[1.68]
Decile	NYSE	VW	0.31	0.36	0.28	0.29	0.19	0.20
			[3.24]	[3.82]	[3.18]	[3.26]	[2.06]	[2.26]

Table 3: Conditional sort on size and EWDS

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

Size quintiles	EWDS Quintiles (L)	(2)	(3)	(4)	(H)	EWDS Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.45	0.71	0.80	0.92	0.95	0.50	0.58	0.50	0.43	0.37	0.32
	[1.71]	[2.69]	[3.11]	[3.69]	[3.99]	[5.90]	[6.98]	[6.46]	[5.56]	[4.78]	[4.18]
(2)	0.56	0.70	0.77	0.88	0.95	0.39	0.46	0.35	0.31	0.28	0.26
	[2.34]	[2.90]	[3.16]	[3.79]	[4.26]	[4.28]	[5.13]	[4.18]	[3.70]	[3.29]	[2.99]
(3)	0.57	0.54	0.81	0.77	0.95	0.38	0.41	0.33	0.29	0.26	0.23
	[2.66]	[2.42]	[3.61]	[3.61]	[4.60]	[4.59]	[4.94]	[4.12]	[3.64]	[3.17]	[2.88]
(4)	0.57	0.59	0.72	0.83	0.81	0.24	0.29	0.19	0.18	-0.02	-0.01
	[2.77]	[2.83]	[3.49]	[4.10]	[4.24]	[2.66]	[3.25]	[2.34]	[2.17]	[-0.28]	[-0.15]
(5)	0.40	0.51	0.48	0.57	0.69	0.29	0.30	0.23	0.26	0.17	0.20
	[2.34]	[2.80]	[2.73]	[3.36]	[4.09]	[3.08]	[3.21]	[2.54]	[2.81]	[1.86]	[2.18]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	EWDS Quintiles Average n (L)	(2)	(3)	(4)	(H)	EWDS Quintiles Average market capitalization (\$$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	319	317	316	315	316	26	26	27	22	22
(2)	91	90	90	90	90	43	43	43	43	43
(3)	68	68	67	67	68	78	77	78	80	80
(4)	59	59	58	59	59	170	171	177	179	181
(5)	56	56	56	56	56	1166	1314	1635	1427	1609

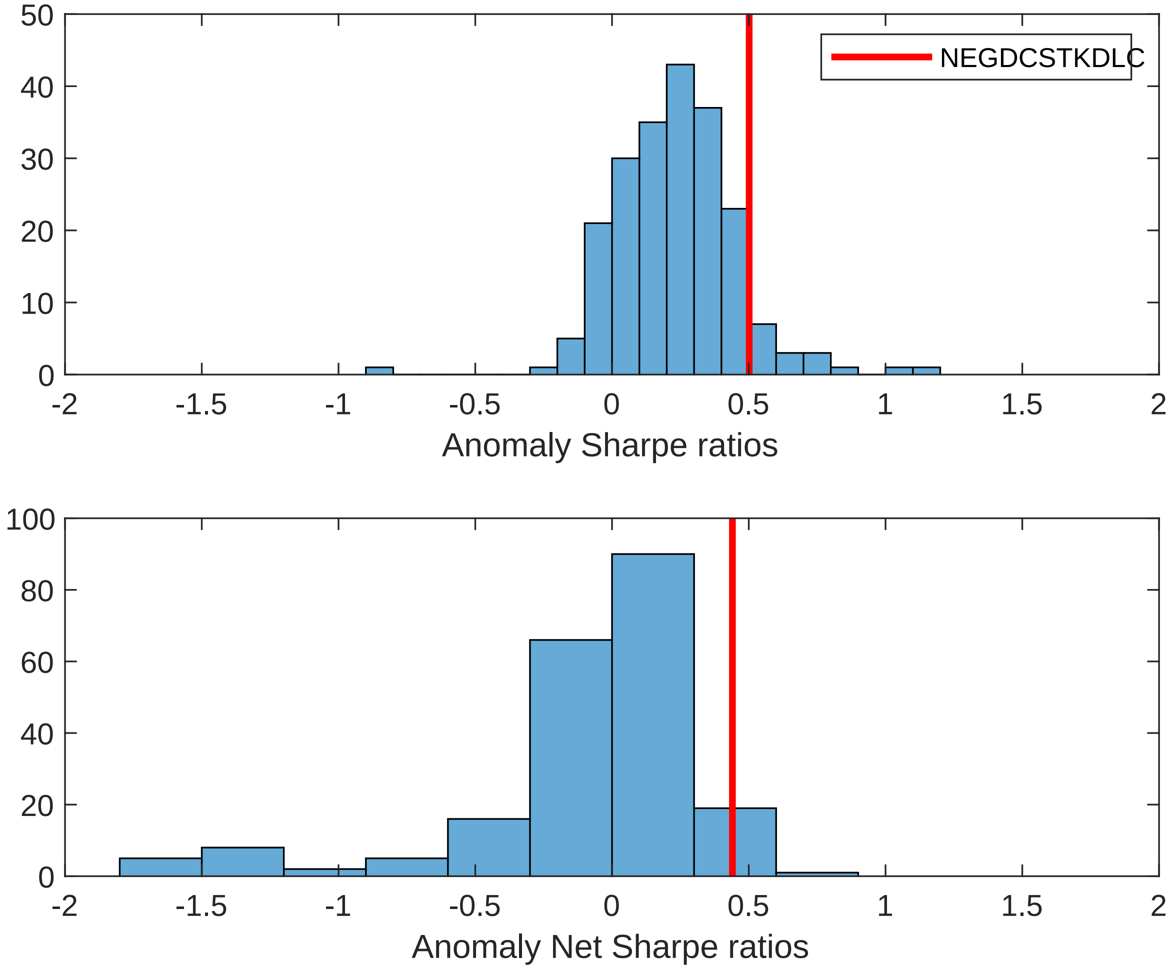

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EWDS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

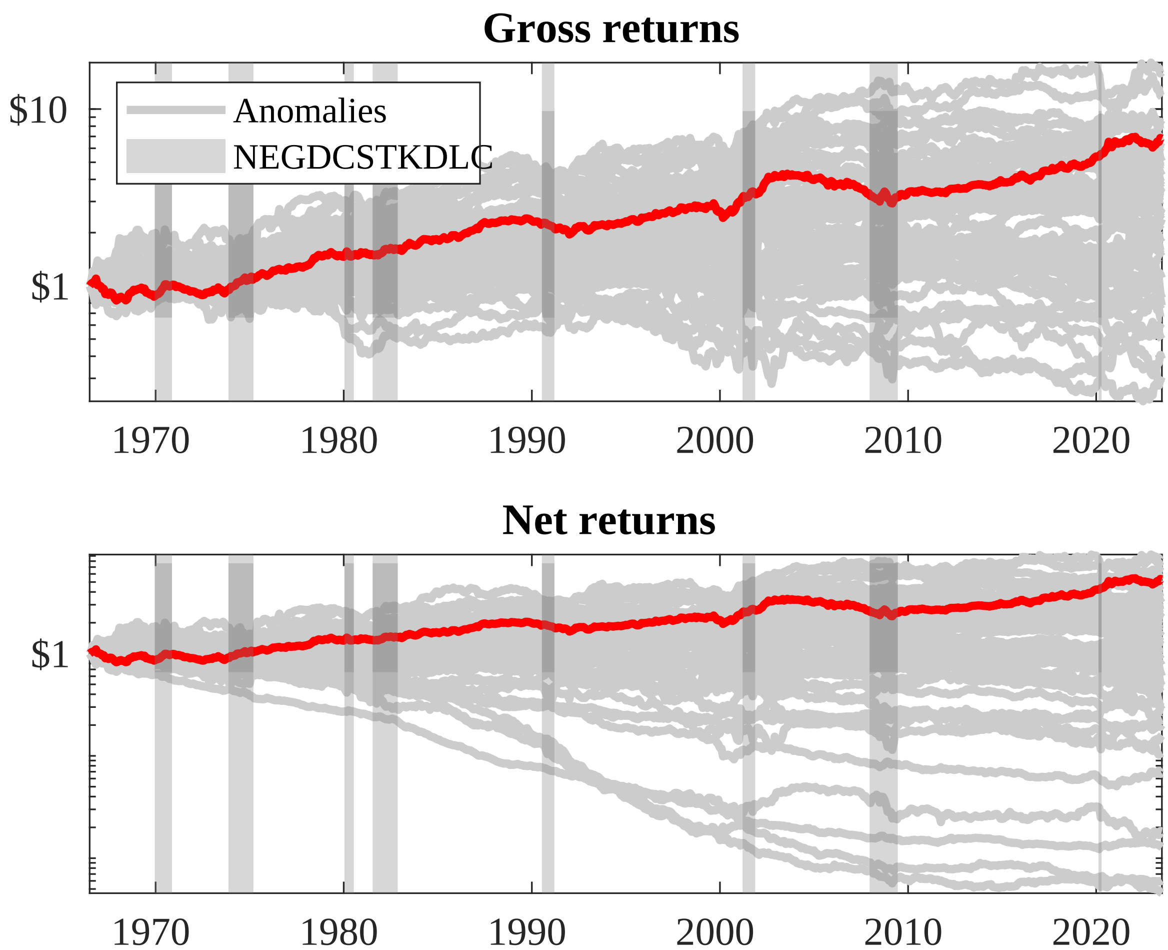

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EWDS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

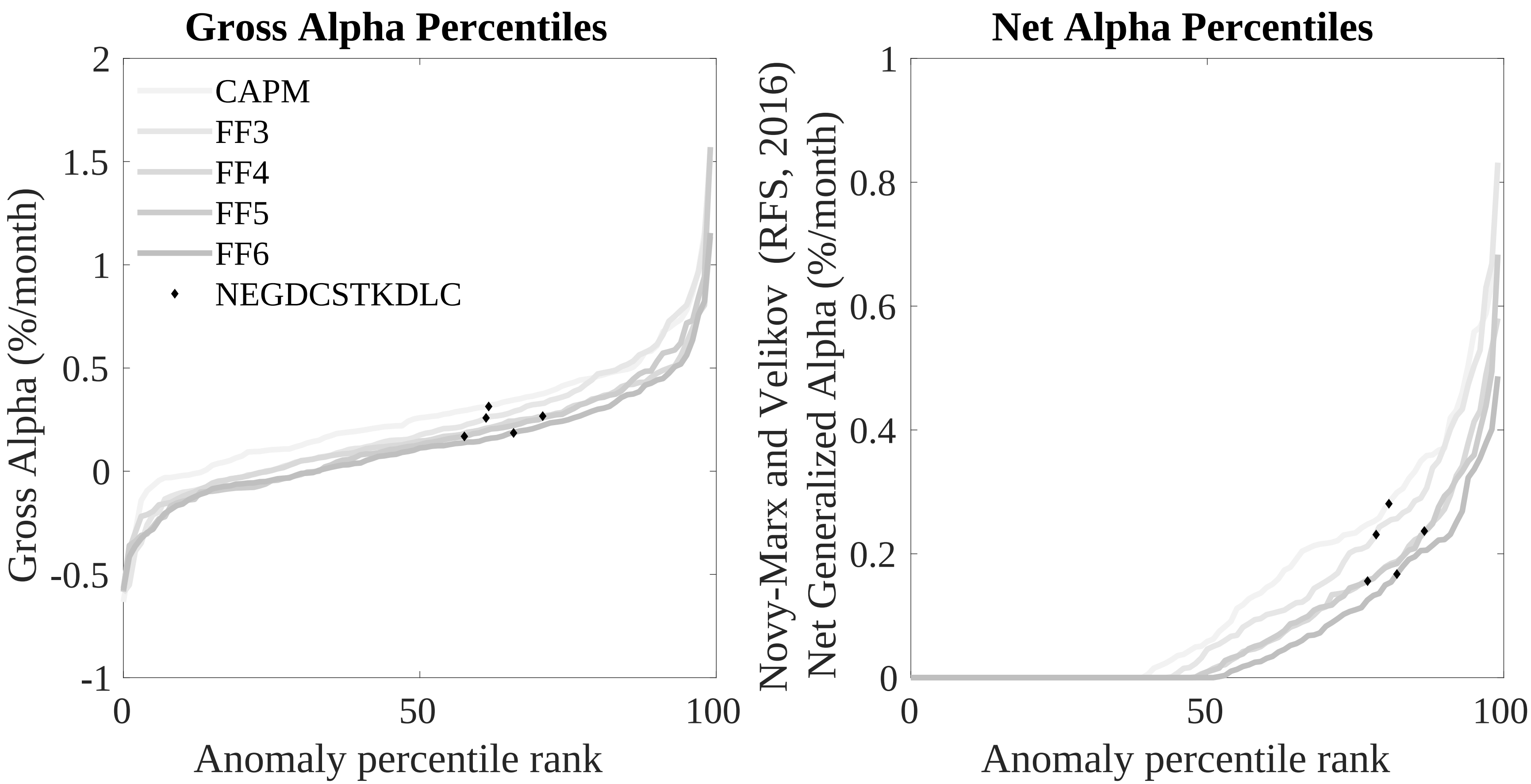

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EWDS trading strategy alphas (diamonds). The strategies are constructed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

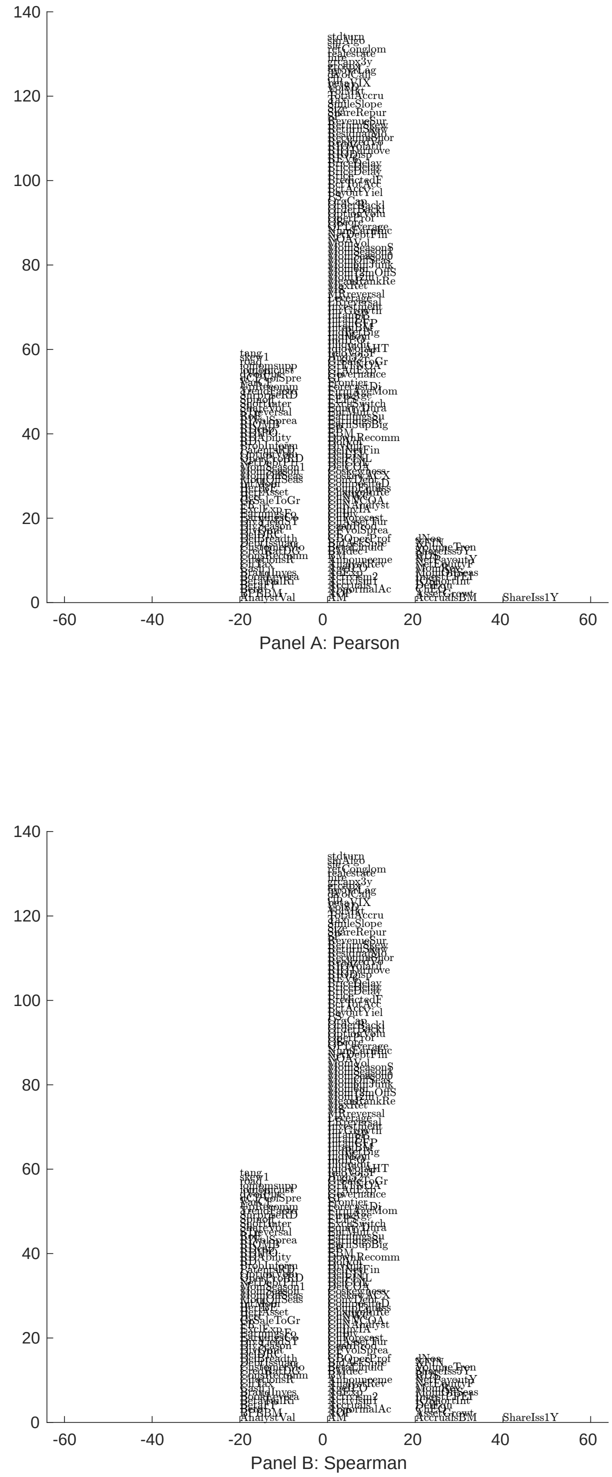

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with EWDS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

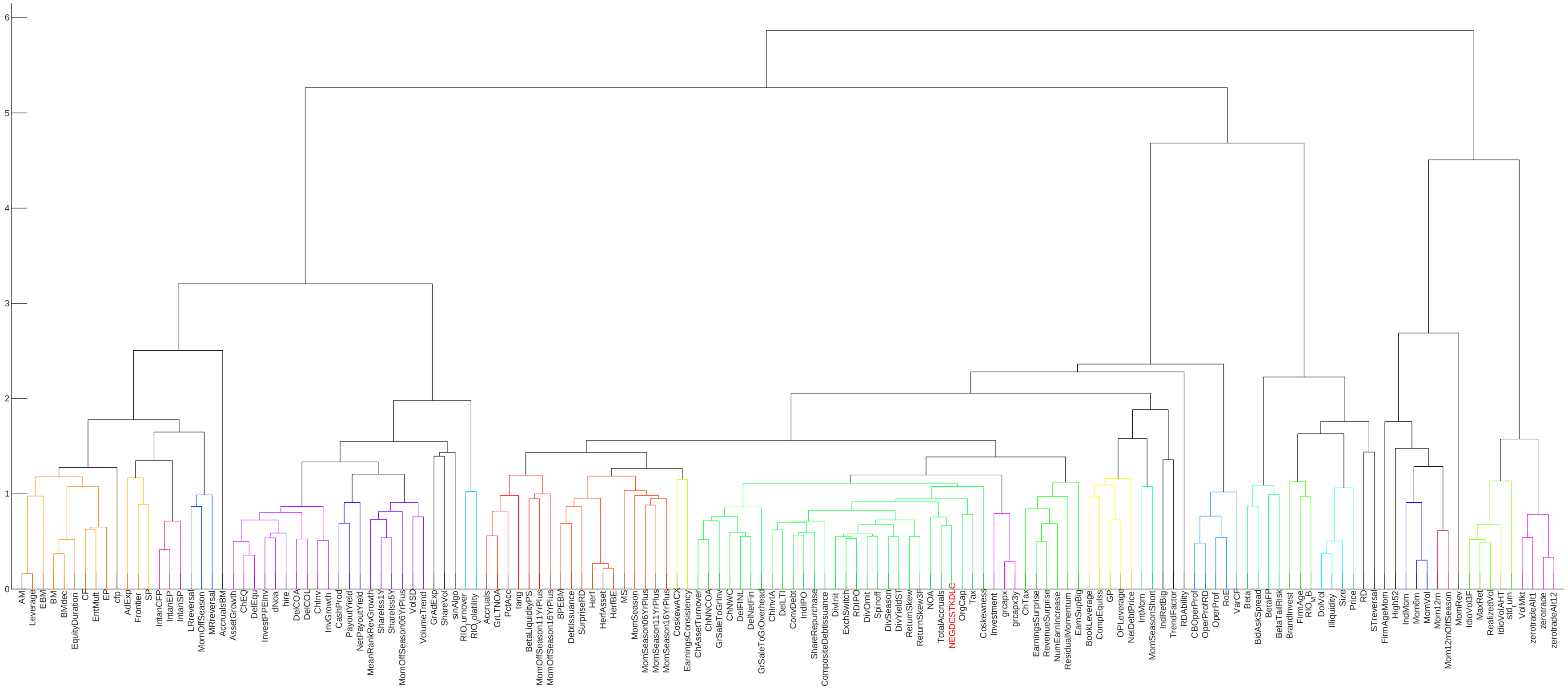

Figure 6: Agglomerative hierarchical cluster plot

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

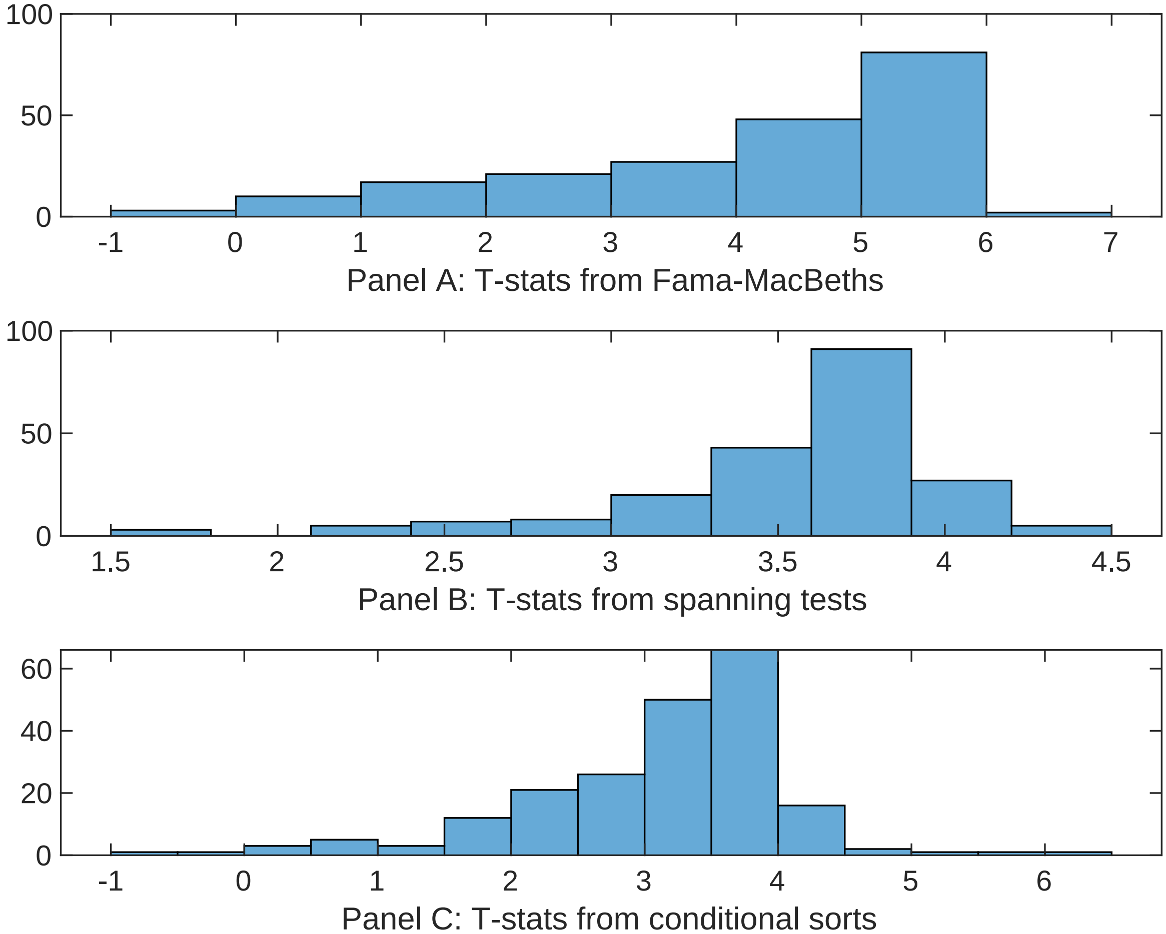

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EWDS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EWDS} from Fama-MacBeth regressions of the form $r_{i,t}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

Table 4: Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on EWDS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EWDS}EWDS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k}X_{i,t}^{k} + \epsilon_{i,t}$. 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	0.12	0.13	0.13
	[5.58]	[7.24]	[5.25]	[5.98]	[5.52]	[5.99]	[5.05]
EWDS	0.66	0.58	0.66	0.70	0.56	0.49	0.49
	[4.73]	[4.59]	[4.76]	[4.93]	[4.38]	[3.80]	[3.77]
Anomaly 1	0.24						0.76
	[4.87]						[1.57]
Anomaly 2		0.50					0.31
		[4.42]					[0.18]
Anomaly 3			0.27				0.22
			[2.33]				[1.99]
Anomaly 4				0.40			0.71
				[4.34]			[0.70]
Anomaly 5					0.15		-0.13
					[4.00]		[-0.22]
Anomaly 6						0.11	0.65
						[8.95]	[5.97]
# 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 EWDS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EWDS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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	0.16	0.18	0.18	0.16	0.20	0.19	0.16
	[2.18]	[2.43]	[2.40]	[2.07]	[2.66]	[2.46]	[2.18]
Anomaly 1	27.31						17.92
	[7.06]						[3.95]
Anomaly 2		30.23					22.57
		[7.18]					[3.68]
Anomaly 3			16.23				4.60
			[5.46]				[1.34]
Anomaly 4				16.18			2.71
				[4.02]			[0.63]
Anomaly 5					21.92		0.48
					[5.39]		[0.08]
Anomaly 6						7.89	-10.83
						[1.53]	[-2.00]
mkt	6.13	4.90	6.68	6.25	3.56	3.94	7.19
	[3.44]	[2.75]	[3.64]	[3.35]	[1.97]	[2.14]	[3.91]
smb	-4.26	-6.62	-2.29	-6.28	-5.96	-6.35	-3.79
	[-1.66]	[-2.56]	[-0.87]	[-2.38]	[-2.27]	[-2.33]	[-1.42]
hml	0.91	0.75	-1.81	-0.05	1.51	4.01	-2.97
	[0.26]	[0.22]	[-0.49]	[-0.01]	[0.43]	[1.13]	[-0.80]
rmw	-0.28	9.94	-0.43	5.66	10.54	8.25	1.07
	[-0.08]	[2.86]	[-0.11]	[1.56]	[2.97]	[2.29]	[0.26]
cma	14.85	-2.58	16.21	23.21	4.61	17.84	5.43
	[2.72]	[-0.39]	[2.86]	[4.30]	[0.69]	[2.19]	[0.68]
umd	-2.85	-2.93	-1.14	-2.40	-1.94	-2.37	-2.99
	[-1.63]	[-1.66]	[-0.64]	[-1.34]	[-1.08]	[-1.29]	[-1.70]
# months	680	684	680	680	684	684	680
$\bar{R}^2$(%)	19	17	16	15	15	11	22

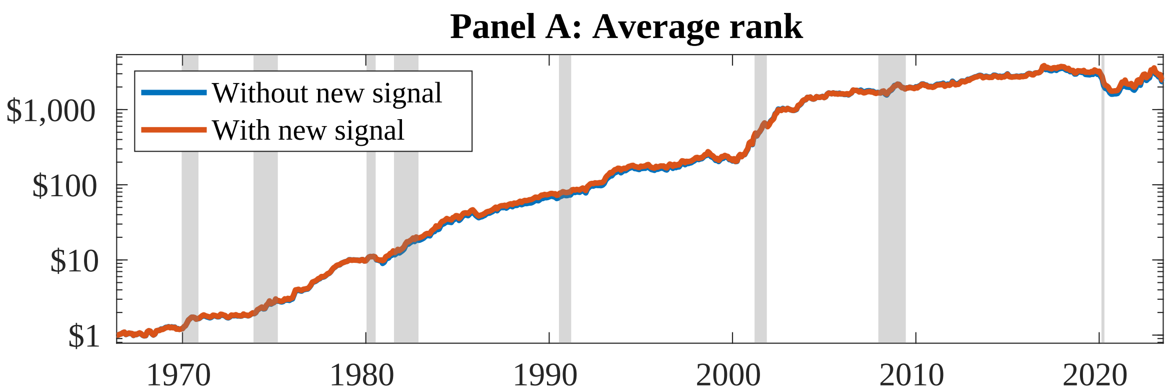

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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