Equity Liability Differential and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Equity Liability Differential (ELD), 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 ELD 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 22 (23) bps/month with a t-statistic of 2.84 (2.99), 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 19 bps/month with a t-statistic of 2.61.

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. While hundreds of potential predictors have been documented in the literature (Harvey et al., 2016), many fail to survive rigorous statistical testing or transaction costs. The relationship between firms' financing decisions and subsequent stock returns represents a particularly promising area of investigation, as theoretical work suggests that managers' choices between debt and equity financing may reveal private information about firm prospects (Myers and Majluf, 1984).

Despite extensive research on capital structure and stock returns, the literature has largely focused on examining debt and equity financing decisions in isolation. Studies have documented return predictability based on leverage changes (Baker and Wurgler, 2002) and equity issuance (Pontiff and Woodgate, 2008), but few have explored how the differential between equity and liability growth may contain unique information about future returns. This gap is notable given that managers actively manage both sides of the balance sheet in response to market conditions and growth opportunities.

We hypothesize that the Equity Liability Differential (ELD) - defined as the difference between the growth rates of equity and total liabilities - captures valuable information about future stock returns through multiple economic channels. First, following (Myers and Majluf, 1984), managers who perceive their equity as undervalued should prefer debt to equity financing, leading to a negative ELD. Conversely, overvalued firms may exploit their high valuations by issuing equity, resulting in positive ELD. This suggests that ELD may serve as a revealed preference measure of managers' private information about equity mispricing.

Second, the ELD may reflect firms' investment opportunities and financial constraints. As shown by (Fazzari et al., 1988), firms with valuable growth options but limited debt capacity may be forced to rely more heavily on equity financing, leading to positive ELD. In contrast, mature firms with stable cash flows can more readily access debt markets, potentially leading to negative ELD. The signal may therefore capture information about future profitability not fully reflected in current market prices.

Third, behavioral biases may cause investors to underreact to the information contained in firms' financing choices. (Daniel and Hirshleifer, 2020) document that investors often fail to fully process complex signals that require comparing multiple firm characteristics. Since ELD combines information from both sides of the balance sheet, limited investor attention may create predictable patterns in returns as the market gradually incorporates this information.

Our empirical analysis reveals that ELD strongly predicts future stock returns. A value-weighted long-short portfolio that buys stocks in the highest ELD quintile and shorts those in the lowest quintile generates monthly abnormal returns of 22 basis points (t-statistic = 2.84) after controlling for the Fama-French six factors. The strategy achieves an impressive annualized Sharpe ratio of 0.64 before transaction costs and 0.57 after accounting for trading frictions.

Importantly, the predictive power of ELD remains robust across various methodological choices and subsamples. The signal generates significant abnormal returns even among large-cap stocks, with a monthly alpha of 28 basis points (t-statistic = 3.07) in the largest size quintile. This suggests that the effect is not driven by small, illiquid stocks that are costly to trade.

Further analysis demonstrates that ELD contains unique information not captured by existing anomalies. Controlling for the six most closely related predictors from the literature - including share issuance, asset growth, and changes in equity-to-assets - the strategy still generates a monthly alpha of 19 basis points (t-statistic = 2.61). This indicates that ELD represents a novel source of return predictability rather than simply repackaging known effects.

Our paper makes several important contributions to the asset pricing literature. First, we introduce a new predictor that combines information from both equity and liability dynamics, extending prior work that has examined these financing channels separately (Baker and Wurgler, 2002; Pontiff and Woodgate, 2008). The strong performance of ELD suggests that considering the interaction between different financing choices provides additional insights beyond examining each in isolation.

Second, we contribute to the growing literature on investment-based asset pricing (Cochrane et al., 2023) by showing how firms' joint financing decisions reveal information about future returns. Our findings suggest that managers actively manage both sides of their balance sheets in ways that reflect their private information about investment opportunities and misvaluation.

Finally, our work has implications for the efficient market hypothesis and the broader debate about return predictability. The fact that ELD generates significant risk-adjusted returns, even among large stocks and after controlling for transaction costs, suggests either that markets are slow to incorporate the information in firms' financing choices or that ELD captures exposure to a priced risk factor. Either interpretation advances our understanding of the mechanisms driving cross-sectional return patterns.

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 Liability Differential. 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 LT for total liabilities.

Common stock (CSTK) represents the total value of common shares issued by the company, while total liabilities (LT) encompasses all of the firm's obligations, both current and long-term. The construction of the signal follows a difference-in-changes approach, where we first calculate the change in CSTK by subtracting its lagged value from the current value, and then scale this difference by the lagged value of total liabilities (LT). This scaled differential captures the relative change in equity financing compared to the firm's existing liability base, potentially offering insight into changes in the firm's capital structure and financing decisions. By focusing on this relationship, the signal aims to reflect aspects of financing policy and capital structure dynamics in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both CSTK and LT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the ELD signal. Panel A plots the time-series of the mean, median, and interquartile range for ELD. On average, the cross-sectional mean (median) ELD is -0.03 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input ELD 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 ELD signal for the CRSP universe. On average, the ELD signal is available for 6.63% of CRSP names, which on average make up 7.95% of total market capitalization.

4 Does ELD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on ELD 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 ELD portfolio and sells the low ELD 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 ELD strategy earns an average return of 0.38% per month with a t-statistic of 4.82. The annualized Sharpe ratio of the strategy is 0.64. The alphas range from 0.22% to 0.41% per month and have t-statistics exceeding 2.84 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 0.31, with a t-statistic of 5.94 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 566 stocks and an average market capitalization of at least $1,456 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 decile sort using NYSE breakpoints and value-weighted portfolios, and equals 27 bps/month with a t-statistics of 2.83. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-two exceed two, and for seventeen exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from Chen and Velikov (2022). The net average returns reported in the first column range between 22-34bps/month. The lowest return, (22 bps/month), is achieved from the decile sort using NYSE breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.39. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the ELD 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 nineteen cases.

Table 3 provides direct tests for the role size plays in the ELD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and ELD, as well as average returns and alphas for long/short trading ELD 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 ELD strategy achieves an average return of 28 bps/month with a t-statistic of 3.07. Among these large cap stocks, the alphas for the ELD strategy relative to the five most common factor models range from 19 to 28 bps/month with t-statistics between 2.07 and 3.03.

5 How does ELD perform relative to the zoo?

Figure 2 puts the performance of ELD 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 ELD strategy falls in the distribution. The ELD strategy's gross (net) Sharpe ratio of 0.64 (0.57) is greater than 97% (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 ELD strategy (red line).[2] Ignoring trading costs, a $1 invested in the ELD strategy would have yielded $11.04 which ranks the ELD strategy in the top 0% across the 212 anomalies. Accounting for trading costs, a $1 invested in the ELD strategy would have yielded $8.34 which ranks the ELD 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 ELD relative to those. Panel A shows that

[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.

the ELD strategy gross alphas fall between the 70 and 74 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 ELD strategy has a positive net generalized alpha for five out of the five factor models. In these cases ELD ranks between the 88 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does ELD 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 ELD 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 ELD or at least to weaken the power ELD has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of ELD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ELD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ELD} ELD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X

[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.

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: $r_{ELD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 ELD. Stocks are finally grouped into five ELD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted ELD trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on ELD 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 ELD signal in these Fama-MacBeth regressions exceed 1.36, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on ELD is 0.85.

Similarly, Table 5 reports results from spanning tests that regress returns to the ELD 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 ELD strategy earns alphas that range from 19-24bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.52, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the ELD trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.61.

7 Does ELD add relative to the whole zoo?

Finally, we can ask how much adding ELD 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 ELD 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 ELD grows to $2262.40.

[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 ELD is available.

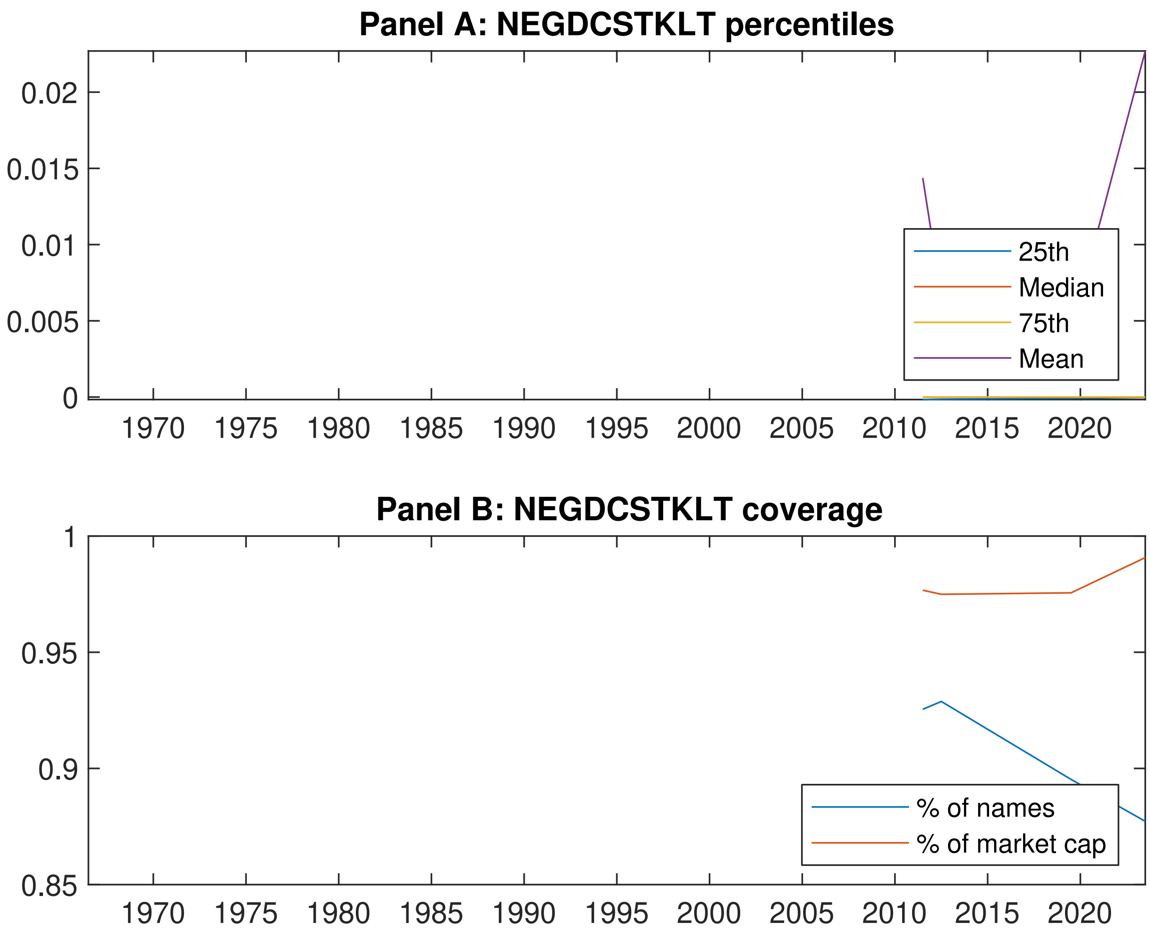


Figure 1: Times series of ELD percentiles and coverage.
This figure plots descriptive statistics for ELD. Panel A shows cross-sectional percentiles of ELD over the sample. Panel B plots the monthly coverage of ELD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on ELD. 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 ELD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.38	0.55	0.65	0.67	0.76	0.38
	[2.15]	[2.97]	[3.40]	[3.93]	[4.53]	[4.82]
α_{CAPM}	-0.17	-0.04	0.05	0.14	0.24	0.41
	[-3.32]	[-0.94]	[0.99]	[2.83]	[5.07]	[5.16]
α_{FF3}	-0.16	-0.03	0.04	0.09	0.19	0.35
	[-3.01]	[-0.68]	[0.82]	[2.10]	[4.39]	[4.50]
α_{FF4}	-0.12	-0.03	0.08	0.05	0.17	0.29
	[-2.34]	[-0.67]	[1.70]	[1.22]	[3.90]	[3.79]
α_{FF5}	-0.16	0.02	0.06	-0.00	0.09	0.25
	[-3.02]	[0.41]	[1.22]	[-0.03]	[2.20]	[3.27]
α_{FF6}	-0.13	0.01	0.09	-0.02	0.09	0.22
	[-2.52]	[0.31]	[1.88]	[-0.56]	[2.03]	[2.84]
Panel B: Fama and French (2018) 6-factor model loadings for ELD-sorted portfolios						
β_{MKT}	0.96	1.01	1.04	1.01	0.99	0.03
	[77.10]	[104.10]	[90.70]	[100.44]	[98.96]	[1.40]
β_{SMB}	-0.01	0.03	0.01	-0.08	-0.03	-0.01
	[-0.67]	[2.32]	[0.38]	[-5.30]	[-1.83]	[-0.54]
β_{HML}	-0.02	-0.00	0.04	0.08	0.04	0.06
	[-0.63]	[-0.05]	[1.80]	[4.35]	[2.12]	[1.59]
β_{RMW}	0.08	-0.07	0.02	0.12	0.12	0.05
	[3.15]	[-3.55]	[0.89]	[6.04]	[6.34]	[1.32]
β_{CMA}	-0.08	-0.09	-0.09	0.19	0.23	0.31
	[-2.29]	[-3.16]	[-2.66]	[6.51]	[7.97]	[5.94]
β_{UMD}	-0.04	0.01	-0.05	0.04	0.01	0.05
	[-3.27]	[0.63]	[-4.41]	[3.54]	[0.94]	[2.75]
Panel C: Average number of firms (n) and market capitalization (me)						
n	849	703	566	697	775	
me ($\$10^6$)	1683	1456	2095	2247	2435	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the ELD 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	0.38	0.41	0.35	0.29	0.25	0.22
			[4.82]	[5.16]	[4.50]	[3.79]	[3.27]	[2.84]
Quintile	NYSE	EW	0.51	0.60	0.50	0.41	0.33	0.27
			[6.99]	[8.73]	[8.36]	[7.08]	[5.97]	[5.06]
Quintile	Name	VW	0.35	0.37	0.31	0.28	0.25	0.24
			[4.47]	[4.63]	[3.98]	[3.55]	[3.21]	[2.97]
Quintile	Cap	VW	0.32	0.33	0.28	0.24	0.25	0.22
			[4.08]	[4.22]	[3.68]	[3.08]	[3.18]	[2.78]
Decile	NYSE	VW	0.27	0.28	0.20	0.17	0.18	0.15
			[2.83]	[2.98]	[2.18]	[1.78]	[1.89]	[1.63]
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	0.34	0.38	0.32	0.29	0.24	0.23
			[4.35]	[4.73]	[4.17]	[3.82]	[3.18]	[2.99]
Quintile	NYSE	EW	0.31	0.39	0.29	0.25	0.12	0.10
			[3.90]	[5.15]	[4.48]	[3.91]	[1.94]	[1.68]
Quintile	Name	VW	0.32	0.34	0.29	0.27	0.24	0.23
			[4.00]	[4.23]	[3.67]	[3.46]	[3.05]	[2.97]
Quintile	Cap	VW	0.28	0.30	0.26	0.23	0.23	0.21
			[3.62]	[3.80]	[3.33]	[3.03]	[2.98]	[2.80]
Decile	NYSE	VW	0.22	0.25	0.17	0.16	0.15	0.14
			[2.39]	[2.58]	[1.90]	[1.69]	[1.61]	[1.54]

Table 3: Conditional sort on size and ELD

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

		ELD Quintiles					ELD Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.39	0.64	0.88	0.93	0.96	0.57	0.66	0.57	0.50	0.41	0.36
		[1.42]	[2.39]	[3.47]	[3.71]	[4.04]	[6.56]	[7.88]	[7.51]	[6.59]	[5.58]	[4.98]
	(2)	0.49	0.67	0.87	0.88	0.95	0.47	0.55	0.41	0.38	0.30	0.28
		[1.98]	[2.79]	[3.64]	[3.90]	[4.30]	[4.92]	[6.02]	[5.16]	[4.63]	[3.71]	[3.42]
	(3)	0.57	0.62	0.79	0.81	0.93	0.37	0.42	0.33	0.31	0.25	0.24
		[2.61]	[2.77]	[3.50]	[3.85]	[4.63]	[4.47]	[5.21]	[4.38]	[4.02]	[3.30]	[3.11]
	(4)	0.47	0.56	0.84	0.79	0.81	0.34	0.39	0.28	0.26	0.11	0.10
		[2.32]	[2.72]	[3.98]	[3.98]	[4.28]	[3.97]	[4.61]	[3.78]	[3.38]	[1.46]	[1.35]
	(5)	0.43	0.50	0.47	0.57	0.72	0.28	0.28	0.24	0.19	0.23	0.20
		[2.52]	[2.63]	[2.63]	[3.28]	[4.27]	[3.07]	[3.03]	[2.58]	[2.07]	[2.47]	[2.10]

Panel B: Portfolio average number of firms and market capitalization

		ELD Quintiles					ELD Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	397	396	395	394	395	32	35	41	30	30
	(2)	112	112	111	111	111	57	57	58	56	57
	(3)	81	81	80	80	81	98	97	99	100	101
	(4)	68	68	68	68	68	202	206	214	214	217
	(5)	62	62	62	62	62	1390	1436	1719	1609	1763

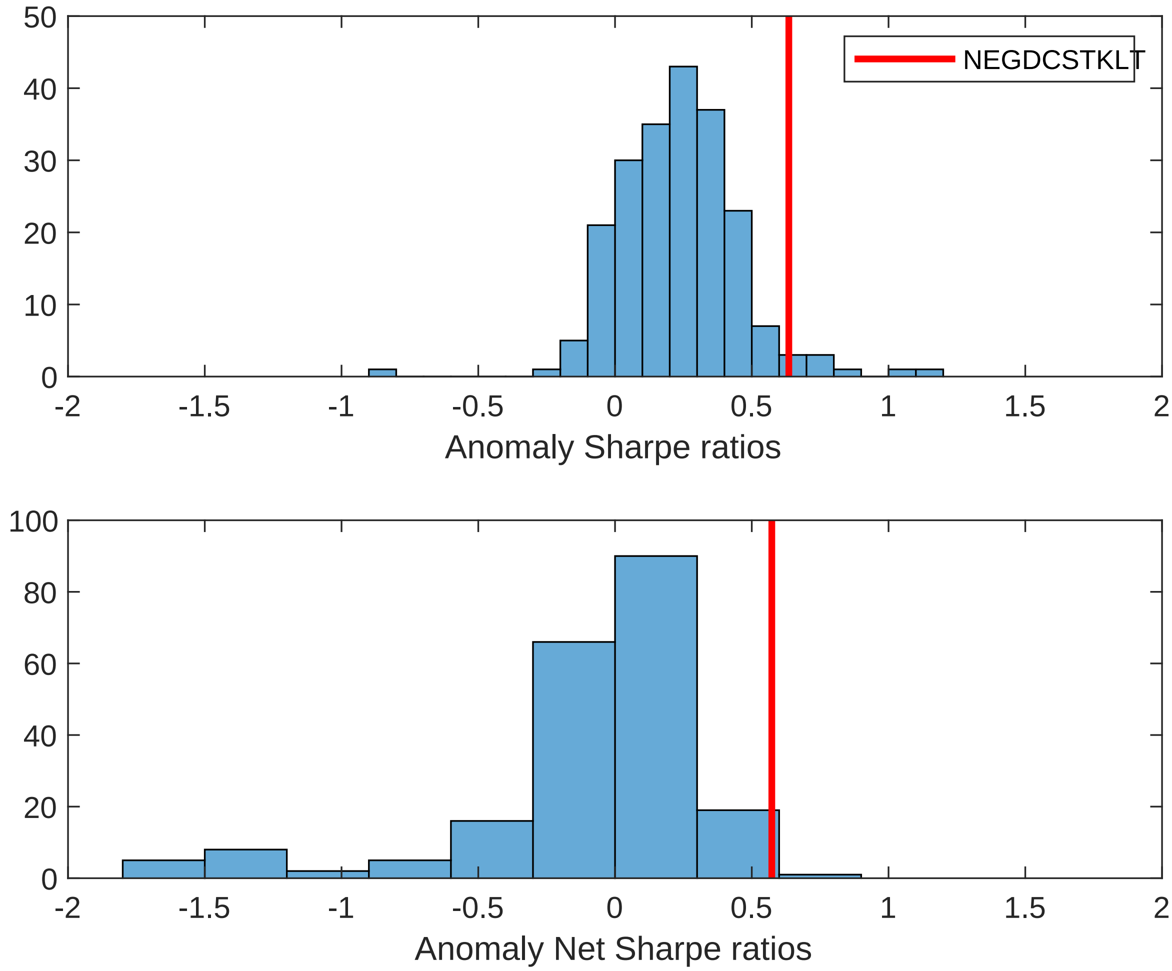


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the ELD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

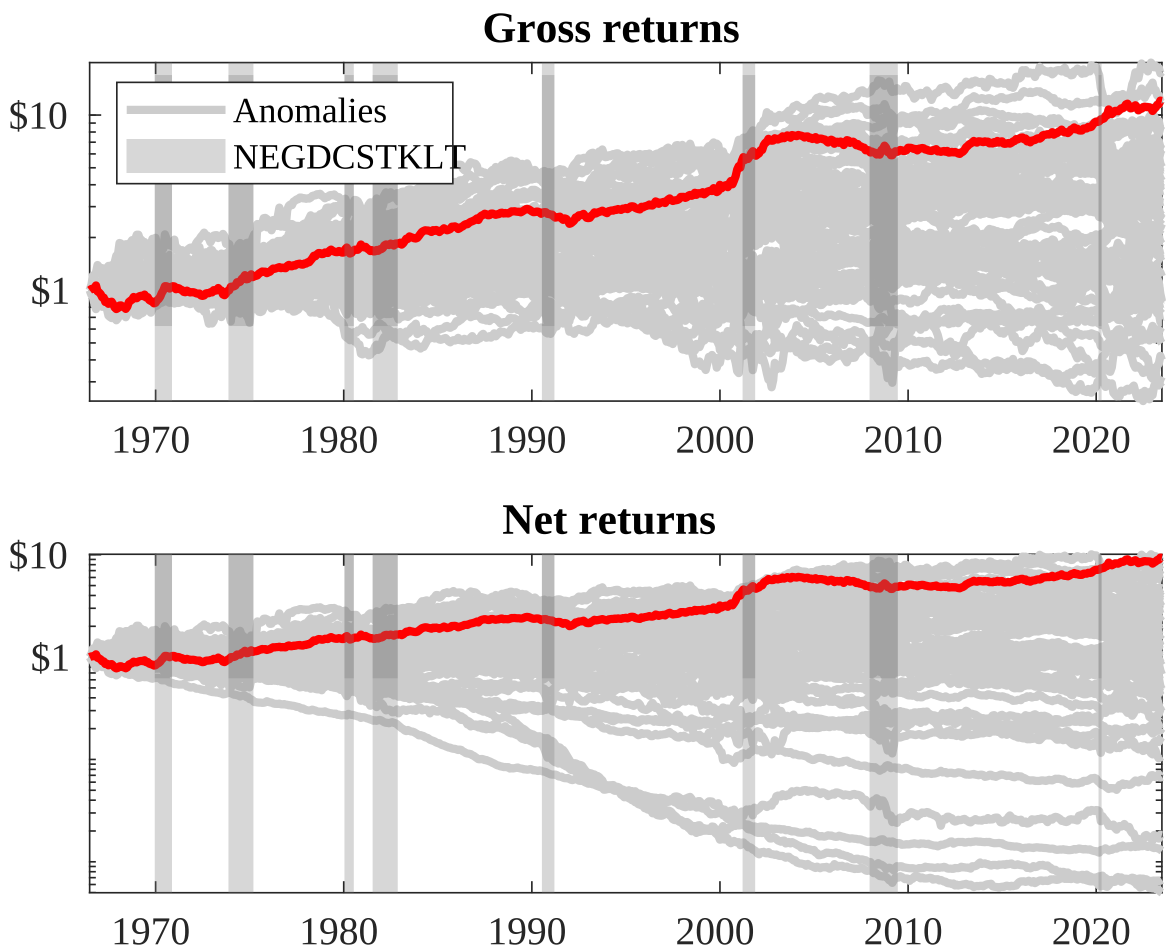


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the ELD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

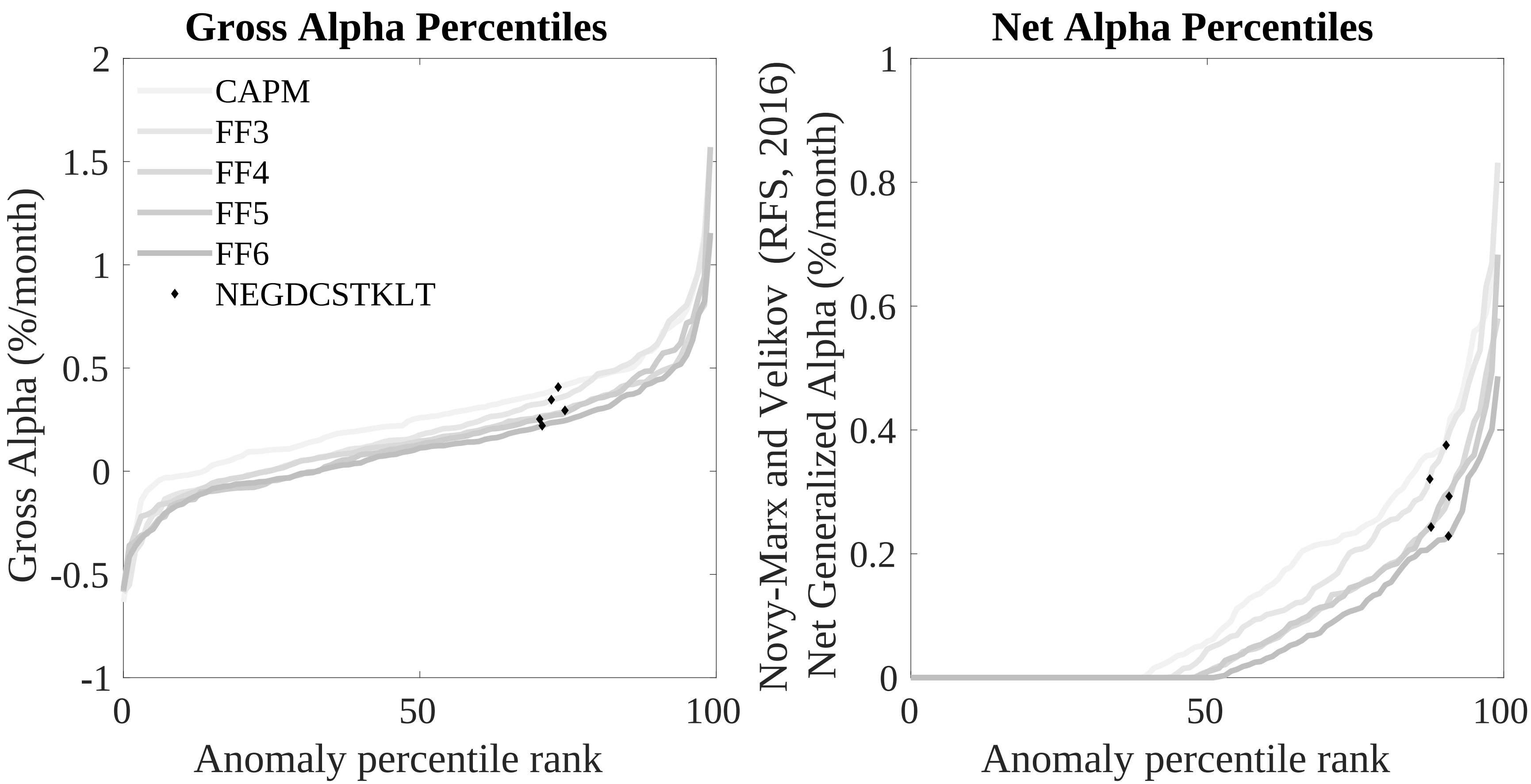
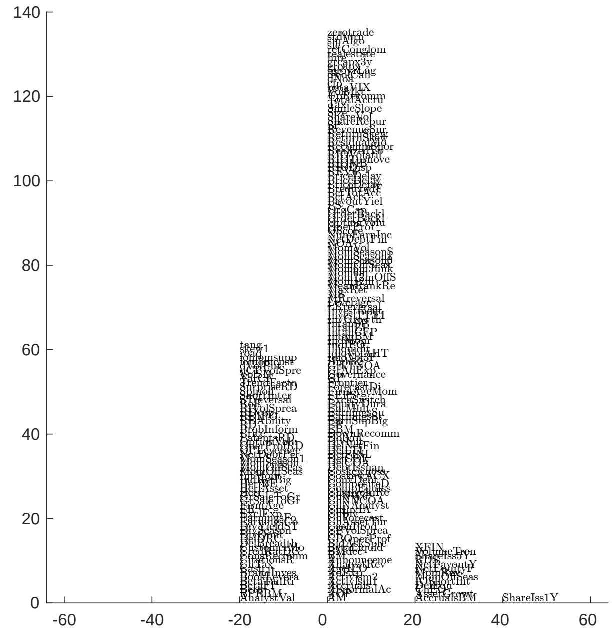
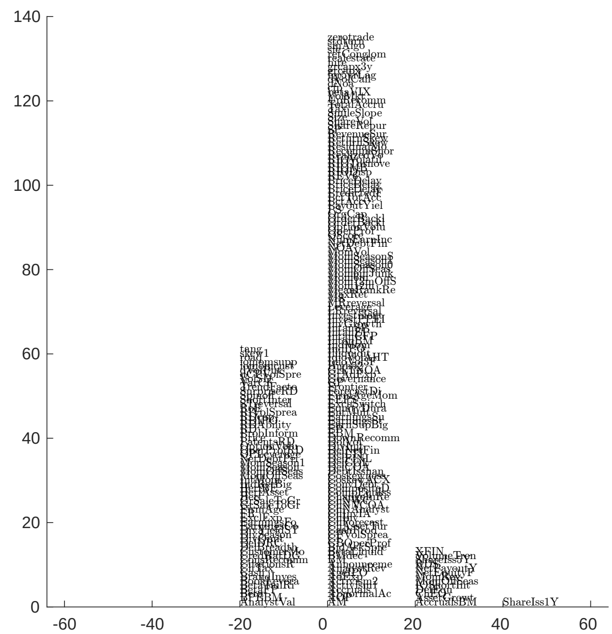


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models

This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the ELD 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.



Panel A: Pearson



Panel B: Spearman

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

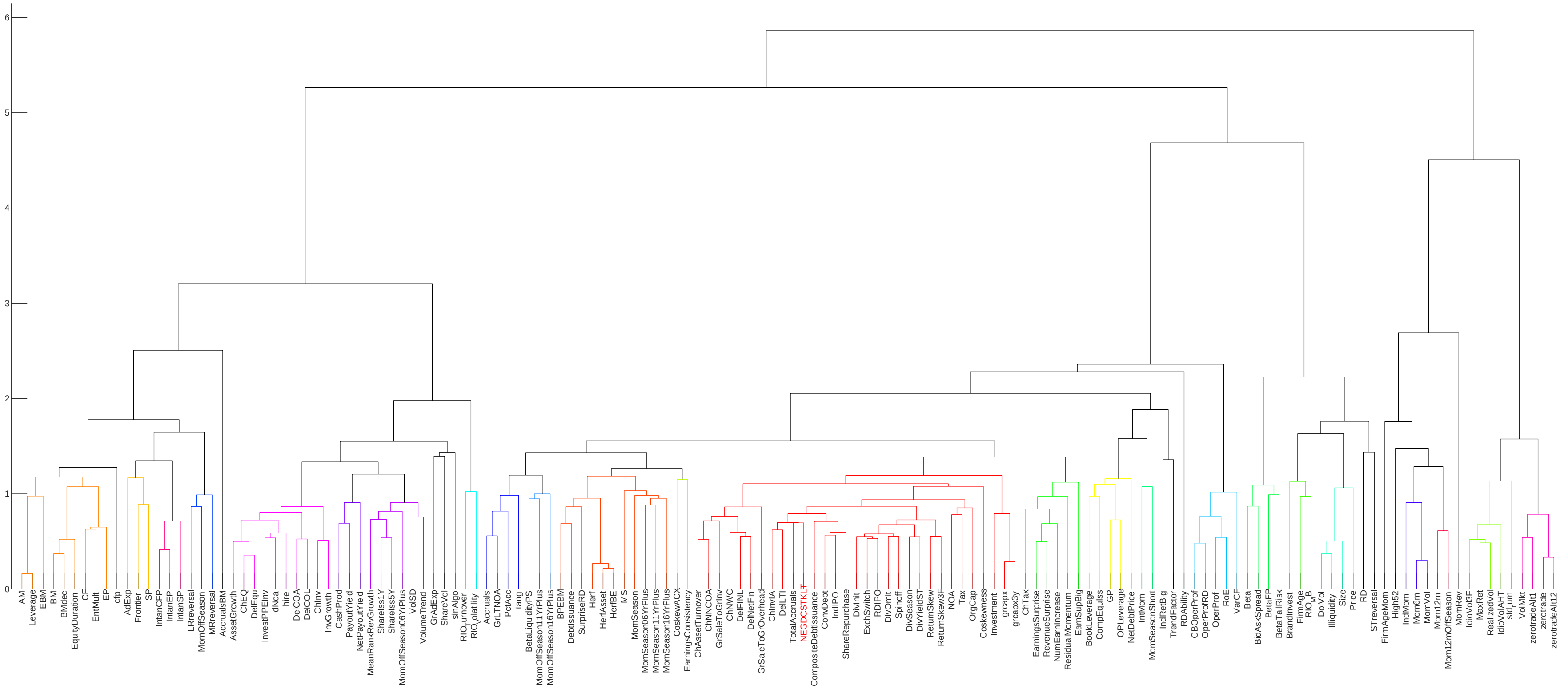


Figure 6: Agglomerative hierarchical cluster plot

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

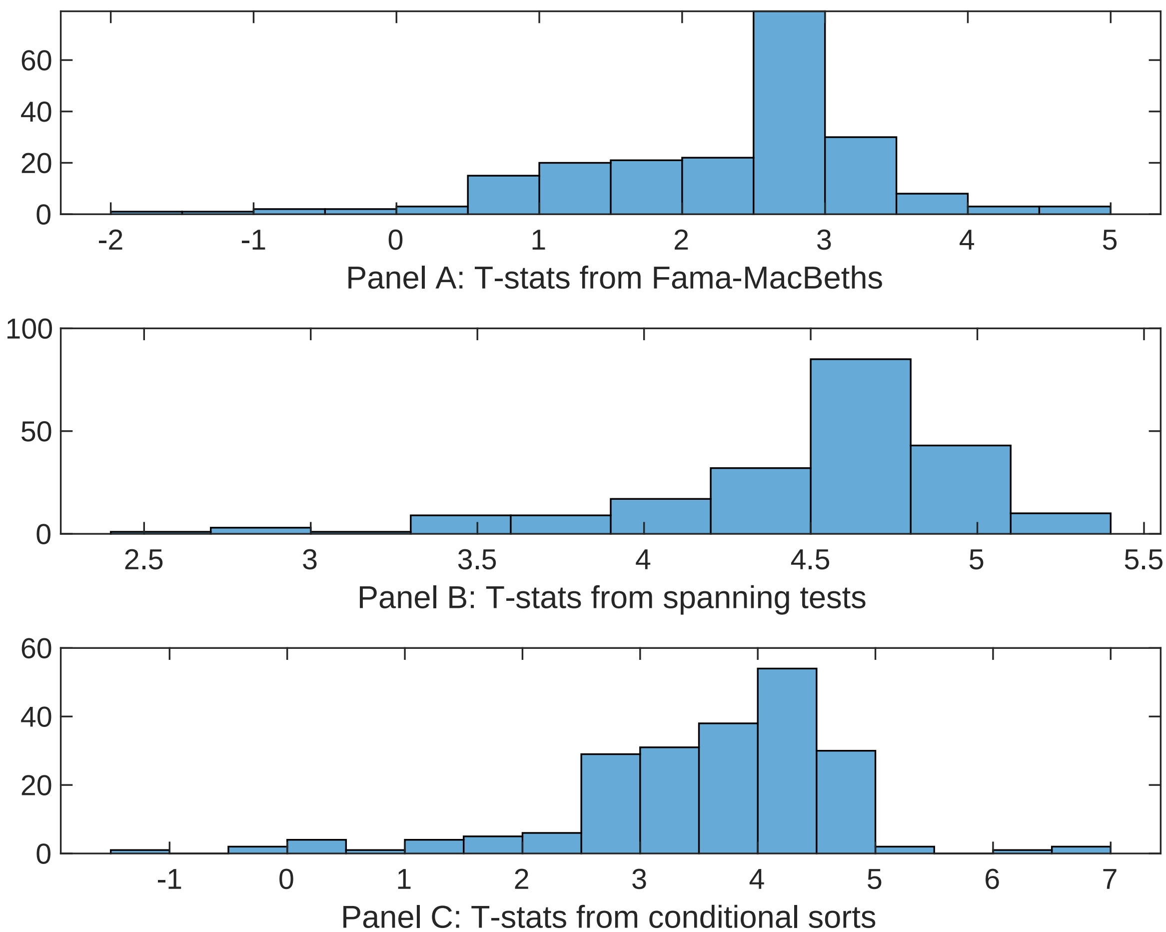


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of ELD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ELD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ELD} ELD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{ELD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 ELD. Stocks are finally grouped into five ELD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted ELD 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 ELD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{ELD} ELD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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
	[5.66]	[7.32]	[5.24]	[6.03]	[5.56]	[6.04]	[5.21]
ELD	0.20	0.15	0.11	0.22	0.16	0.11	0.61
	[2.45]	[2.01]	[1.41]	[2.84]	[1.96]	[1.36]	[0.85]
Anomaly 1	0.27						1.00
	[5.99]						[2.50]
Anomaly 2		0.49					0.14
		[4.55]					[0.09]
Anomaly 3			0.28				0.23
			[2.51]				[2.12]
Anomaly 4				0.38			0.46
				[4.40]			[0.51]
Anomaly 5					0.14		-0.20
					[4.13]		[-0.35]
Anomaly 6						0.10	0.68
						[8.96]	[6.40]
# 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 ELD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{ELD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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	0.22	0.22	0.19	0.24	0.23	0.19
	[2.66]	[2.98]	[2.87]	[2.52]	[3.20]	[2.94]	[2.61]
Anomaly 1	28.42						18.65
	[7.42]						[4.22]
Anomaly 2		36.89					33.78
		[8.99]					[5.65]
Anomaly 3			16.45				3.31
			[5.57]				[0.99]
Anomaly 4				14.59			-0.03
				[3.64]			[-0.01]
Anomaly 5					24.73		-1.83
					[6.15]		[-0.33]
Anomaly 6						7.19	-15.68
						[1.41]	[-2.97]
mkt	4.95	3.94	5.46	4.81	2.34	2.75	5.86
	[2.80]	[2.26]	[2.99]	[2.59]	[1.31]	[1.50]	[3.27]
smb	0.27	-2.39	2.25	-1.64	-1.55	-1.82	0.85
	[0.11]	[-0.95]	[0.86]	[-0.62]	[-0.60]	[-0.67]	[0.33]
hml	2.66	1.72	0.02	2.39	2.90	5.79	-0.64
	[0.77]	[0.51]	[0.01]	[0.64]	[0.83]	[1.64]	[-0.18]
rmw	-4.79	6.33	-4.70	1.86	6.85	4.28	-1.57
	[-1.31]	[1.87]	[-1.21]	[0.52]	[1.95]	[1.20]	[-0.39]
cma	17.05	-6.15	18.82	26.62	4.72	21.73	7.20
	[3.16]	[-0.96]	[3.35]	[4.95]	[0.72]	[2.68]	[0.93]
umd	4.79	4.64	6.54	5.28	5.79	5.24	4.20
	[2.76]	[2.70]	[3.69]	[2.96]	[3.26]	[2.86]	[2.45]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	21	22	19	17	18	13	27

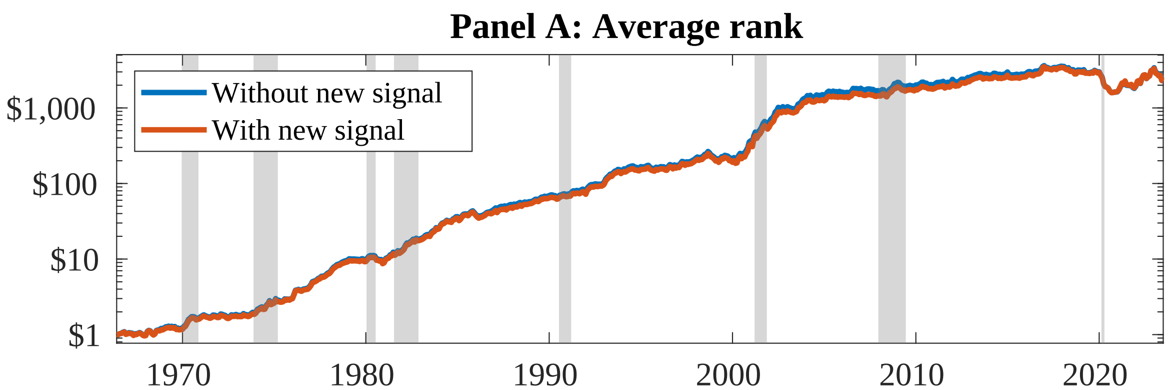


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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