Equity Debt Differential and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Equity Debt Differential (EDD), 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 EDD achieves an annualized gross (net) Sharpe ratio of 0.54 (0.48), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 19 (19) bps/month with a t-statistic of 2.51 (2.48), 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 17 bps/month with a t-statistic of 2.42.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (McLean and Pontiff, 2016). While many of these patterns have been attributed to risk factors or behavioral biases, the relationship between firms' financing decisions and subsequent stock returns remains an active area of research (Baker and Wurgler, 2002). In particular, the relative mix of equity and debt financing choices may contain important information about future stock performance that is not fully incorporated into prices.

Prior research has established that individual financing decisions, such as equity issuance (Loughran and Ritter, 1995) and debt issuance (Billet and Xue, 2007), predict future returns. However, the literature has largely examined these financing choices in isolation, potentially missing important information contained in their relative magnitudes and timing. This gap is particularly notable given that managers actively choose between equity and debt financing based on their private information about firm prospects.

We propose that the Equity Debt Differential (EDD), which captures the relative difference between a firm's equity and debt financing activities, provides a novel signal about future stock returns. The theoretical motivation draws from the pecking order theory of capital structure (Myers and Majluf, 1984), which suggests that managers prefer debt to equity financing due to information asymmetry costs. When managers deviate from this preference by issuing relatively more equity than debt, it may signal overvaluation.

The market timing hypothesis (Baker and Wurgler, 2002) further suggests that managers strategically issue equity when they believe their stock is overvalued and issue debt when they believe it is undervalued. Therefore, firms with high equity issuance relative to debt issuance (high EDD) may be more likely to be overvalued, leading to lower future returns. Conversely, firms with low EDD may be undervalued.

Additionally, the q-theory of investment (Cochrane and Saá-Requejo, 2000) implies that firms' financing choices reflect their investment opportunities. Firms with poor investment prospects may be more likely to issue equity rather than debt, as they face higher costs of debt financing. This suggests that high EDD firms may have lower expected returns due to both overvaluation and poor growth options.

Our empirical analysis reveals that EDD strongly predicts stock returns in the cross-section. A value-weighted long-short portfolio that buys stocks with low EDD and sells stocks with high EDD generates significant abnormal returns of 19 basis points per month (t-statistic = 2.51) relative to the Fama-French five-factor model plus momentum. The strategy achieves an annualized Sharpe ratio of 0.54 before trading costs and 0.48 after accounting for transaction costs.

The predictive power of EDD remains robust across various methodological choices. The signal performs consistently well across different size quintiles, with the long-short strategy generating significant abnormal returns even among the largest stocks (27 bps/month, t-statistic = 2.85). This suggests that the EDD effect is not confined to small, illiquid stocks where trading costs might prohibit implementation.

Most importantly, EDD's predictive power persists after controlling for related anomalies. When we control for the six most closely related financing-based anomalies and the Fama-French six factors simultaneously, the strategy still generates an alpha of 17 bps/month (t-statistic = 2.42). This indicates that EDD captures unique information about future returns not contained in existing factors or anomalies.

Our paper makes several contributions to the literature on financing decisions and asset pricing. First, we introduce a novel predictor that synthesizes information from both equity and debt financing activities, extending prior work that examined these channels separately (Loughran and Ritter, 1995; Billet and Xue, 2007). The strong performance of EDD among large stocks distinguishes it from many other financing-based anomalies documented in the literature.

Second, we contribute to the growing literature on the 'factor zoo' (Cochrane and Saá-Requejo, 2000) by showing that EDD's predictive power is distinct from existing anomalies. Our signal's gross (net) Sharpe ratio of 0.54 (0.48) places it in the top 5% (1%) of documented anomalies, suggesting it captures a unique dimension of cross-sectional return predictability.

Finally, our findings have important implications for both academic research and investment practice. For academics, our results highlight the importance of considering firms' joint equity and debt financing decisions when studying market efficiency. For practitioners, EDD represents a novel signal that can be implemented cost-effectively, even among large-cap stocks, and remains profitable after accounting for transaction costs.

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 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/ordinary stock capital and item DLTT for long-term debt. Common stock capital (CSTK) represents the par or stated value of issued common stock, while long-term debt (DLTT) encompasses all interest-bearing financial obligations due after one year. The construction of the signal follows a difference-in-levels approach scaled by debt, where we calculate the change in CSTK from one period to the next and divide this difference by the previous period's DLTT. Specifically, for each firm i in year t, we compute: (CSTK[t] - CSTK[t-1])/DLTT[t-1]. This ratio captures the relative change in equity capital structure compared to the firm's existing debt level, potentially offering insight into changes in the firm's capital structure and financing decisions. By scaling the equity change by lagged debt, the signal provides a standardized measure that facilitates comparison across firms of different sizes and capital structures. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the EDD signal. Panel A plots the time-series of the mean, median, and interquartile range for EDD. On average, the cross-sectional mean (median) EDD is -0.33 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input EDD data. The signal's interquartile range spans -0.04 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the EDD signal for the CRSP universe. On average, the EDD signal is available for 5.57% of CRSP names, which on average make up 7.51% of total market capitalization.

4 Does EDD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on EDD 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 EDD portfolio and sells the low EDD 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 EDD strategy earns an average return of 0.33% per month with a t-statistic of 4.13. The annualized Sharpe ratio of the strategy is 0.54. The alphas range from 0.19% to 0.36% per month and have t-statistics exceeding 2.47 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 0.36, with a t-statistic of 7.07 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 481 stocks and an average market capitalization of at least $1,400 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 30 bps/month with a t-statistics of 3.25. Out of the twenty-five alphas reported in

Panel A, the t-statistics for twenty-five exceed two, and for sixteen 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 26-29bps/month. The lowest return, (26 bps/month), is achieved from the decile sort using NYSE breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.82. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the EDD 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 EDD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and EDD, as well as average returns and alphas for long/short trading EDD 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 EDD strategy achieves an average return of 27 bps/month with a t-statistic of 2.85. Among these large cap stocks, the alphas for the EDD strategy relative to the five most common factor models range from 21 to 28 bps/month with t-statistics between 2.26 and 2.94.

5 How does EDD perform relative to the zoo?

Figure 2 puts the performance of EDD 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 EDD strategy falls in the distribution. The EDD strategy's gross (net) Sharpe ratio of 0.54 (0.48) is greater than 95% (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 EDD strategy (red line).[2] Ignoring trading costs, a $1 invested in the EDD strategy would have yielded $7.30 which ranks the EDD strategy in the top 2% across the 212 anomalies. Accounting for trading costs, a $1 invested in the EDD strategy would have yielded $5.50 which ranks the EDD strategy in the top 1% 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 EDD relative to those. Panel A shows that the EDD strategy gross alphas fall between the 60 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%

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

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

(53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The EDD strategy has a positive net generalized alpha for five out of the five factor models. In these cases EDD ranks between the 82 and 90 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does EDD 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 EDD 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 EDD or at least to weaken the power EDD has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of EDD conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EDD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EDD} EDD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EDD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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-

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

weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on EDD. Stocks are finally grouped into five EDD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EDD trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on EDD 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 EDD signal in these Fama-MacBeth regressions exceed 1.04, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on EDD is 0.40.

Similarly, Table 5 reports results from spanning tests that regress returns to the EDD 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 EDD strategy earns alphas that range from 16-22bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.20, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the EDD trading strategy achieves an alpha of 17bps/month with a t-statistic of 2.42.

7 Does EDD add relative to the whole zoo?

Finally, we can ask how much adding EDD 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 EDD 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 EDD grows to $2166.12.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Equity Debt Differential (EDD) as a significant predictor of stock returns. Our analysis demonstrates that EDD-based trading strategies yield economically and statistically significant results, with a value-weighted long/short strategy achieving impressive Sharpe ratios of 0.54 and 0.48 on a gross and net basis, respectively. The signal's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for established factors and related anomalies from the factor zoo.

The persistence of EDD's predictive power, evidenced by monthly abnormal re-

[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 EDD is available.

turns of 19 basis points relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information about future stock returns that is not fully incorporated in existing factors. Furthermore, the signal's ability to generate an alpha of 17 basis points per month even after controlling for six closely related strategies indicates its distinctive contribution to the cross-section of stock returns.

However, several limitations warrant consideration. First, our analysis focuses primarily on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, the study period may not fully capture the signal's behavior across different market regimes and economic cycles.

Future research could explore the signal's performance in international markets, its interaction with other established anomalies, and its behavior during different market conditions. Additionally, investigating the underlying economic mechanisms driving the EDD signal's predictive power could provide valuable insights for both academics and practitioners. Finally, examining the signal's robustness to alternative implementation approaches and transaction cost models could further validate its practical utility for investment professionals.

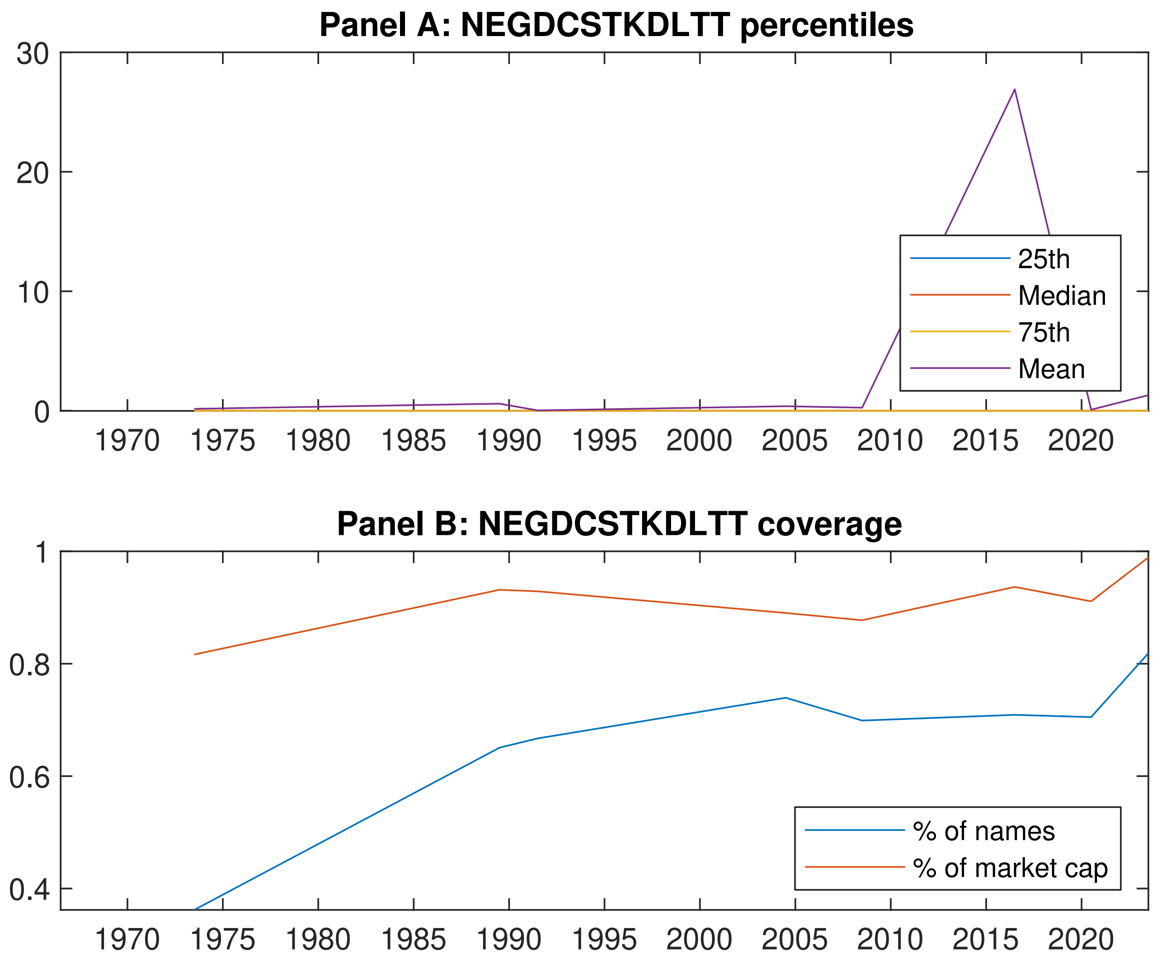

Figure 1: Times series of EDD percentiles and coverage.
This figure plots descriptive statistics for EDD. Panel A shows cross-sectional percentiles of EDD over the sample. Panel B plots the monthly coverage of EDD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on EDD. 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 EDD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.43	0.52	0.64	0.66	0.75	0.33
	[2.42]	[2.88]	[3.49]	[3.94]	[4.48]	[4.13]
α_{CAPM}	-0.13	-0.05	0.07	0.14	0.23	0.36
	[-2.63]	[-1.32]	[1.30]	[2.81]	[4.44]	[4.56]
α_{FF3}	-0.11	-0.08	0.04	0.09	0.18	0.29
	[-2.38]	[-1.89]	[0.74]	[2.01]	[3.75]	[3.87]
α_{FF4}	-0.11	-0.06	0.05	0.05	0.18	0.29
	[-2.22]	[-1.43]	[0.96]	[1.19]	[3.62]	[3.69]
α_{FF5}	-0.13	-0.07	-0.01	-0.00	0.06	0.19
	[-2.73]	[-1.71]	[-0.19]	[-0.03]	[1.21]	[2.47]
α_{FF6}	-0.13	-0.06	0.00	-0.02	0.06	0.19
	[-2.61]	[-1.37]	[0.07]	[-0.50]	[1.40]	[2.51]
Panel B: Fama and French (2018) 6-factor model loadings for EDD-sorted portfolios						
β_{MKT}	0.97	1.02	1.02	1.00	0.99	0.02
	[84.42]	[101.69]	[84.86]	[98.60]	[91.31]	[1.03]
β_{SMB}	-0.01	0.01	0.03	-0.08	-0.05	-0.04
	[-0.40]	[0.89]	[1.52]	[-5.67]	[-2.87]	[-1.47]
β_{HML}	0.01	0.07	0.04	0.09	0.05	0.03
	[0.64]	[3.59]	[1.80]	[4.55]	[2.30]	[0.98]
β_{RMW}	0.11	0.02	0.10	0.10	0.18	0.07
	[4.91]	[0.82]	[4.40]	[4.93]	[8.54]	[2.00]
β_{CMA}	-0.10	-0.03	0.06	0.21	0.26	0.36
	[-2.98]	[-1.20]	[1.66]	[7.14]	[8.57]	[7.07]
β_{UMD}	-0.01	-0.02	-0.02	0.03	-0.01	-0.01
	[-0.58]	[-2.20]	[-1.74]	[3.16]	[-1.34]	[-0.43]
Panel C: Average number of firms (n) and market capitalization (me)						
n	741	557	481	583	651	
me ($\$10^6$)	1603	1400	1907	2121	2308	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the EDD 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	0.33	0.36	0.29	0.29	0.19	0.19
			[4.13]	[4.56]	[3.87]	[3.69]	[2.47]	[2.51]
Quintile	NYSE	EW	0.46	0.54	0.44	0.37	0.27	0.23
			[6.56]	[7.98]	[7.51]	[6.38]	[5.00]	[4.24]
Quintile	Name	VW	0.31	0.32	0.27	0.27	0.20	0.21
			[3.82]	[3.94]	[3.35]	[3.26]	[2.45]	[2.51]
Quintile	Cap	VW	0.31	0.33	0.28	0.27	0.24	0.24
			[3.85]	[4.08]	[3.50]	[3.32]	[3.05]	[3.00]
Decile	NYSE	VW	0.30	0.32	0.23	0.24	0.19	0.20
			[3.25]	[3.42]	[2.61]	[2.61]	[2.16]	[2.25]
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	0.29	0.33	0.27	0.27	0.18	0.19
			[3.67]	[4.13]	[3.54]	[3.47]	[2.43]	[2.48]
Quintile	NYSE	EW	0.27	0.34	0.24	0.21	0.07	0.06
			[3.49]	[4.52]	[3.76]	[3.27]	[1.16]	[0.99]
Quintile	Name	VW	0.28	0.30	0.25	0.25	0.19	0.20
			[3.37]	[3.59]	[3.08]	[3.06]	[2.37]	[2.43]
Quintile	Cap	VW	0.27	0.30	0.25	0.25	0.23	0.23
			[3.41]	[3.69]	[3.19]	[3.12]	[2.89]	[2.89]
Decile	NYSE	VW	0.26	0.28	0.20	0.21	0.17	0.18
			[2.82]	[3.00]	[2.30]	[2.32]	[1.89]	[2.00]

Table 3: Conditional sort on size and EDD

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

		EDD Quintiles					EDD Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.45	0.70	0.83	0.96	0.98	0.53	0.60	0.51	0.45	0.36	0.32
		[1.71]	[2.65]	[3.27]	[3.59]	[4.10]	[6.24]	[7.32]	[6.78]	[5.87]	[4.89]	[4.31]
	(2)	0.58	0.63	0.90	0.85	0.94	0.36	0.42	0.29	0.28	0.18	0.18
		[2.44]	[2.66]	[3.70]	[3.64]	[4.19]	[3.87]	[4.57]	[3.58]	[3.30]	[2.23]	[2.14]
	(3)	0.57	0.64	0.80	0.77	0.94	0.38	0.42	0.34	0.33	0.22	0.22
		[2.62]	[2.93]	[3.53]	[3.63]	[4.63]	[4.50]	[4.96]	[4.34]	[4.12]	[2.80]	[2.78]
	(4)	0.52	0.64	0.73	0.80	0.80	0.28	0.33	0.22	0.20	0.04	0.04
		[2.56]	[3.11]	[3.48]	[4.02]	[4.19]	[3.13]	[3.75]	[2.86]	[2.56]	[0.52]	[0.52]
	(5)	0.44	0.46	0.53	0.56	0.70	0.27	0.28	0.22	0.21	0.22	0.22
		[2.52]	[2.48]	[2.98]	[3.35]	[4.19]	[2.85]	[2.94]	[2.38]	[2.26]	[2.37]	[2.31]

Panel B: Portfolio average number of firms and market capitalization

		EDD Quintiles					EDD Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	316	316	314	313	314	25	27	31	23	23
	(2)	96	95	95	95	95	48	47	48	47	47
	(3)	73	72	72	71	72	86	85	86	88	89
	(4)	62	62	62	62	63	186	188	196	198	198
	(5)	59	59	59	59	59	1305	1425	1624	1515	1704

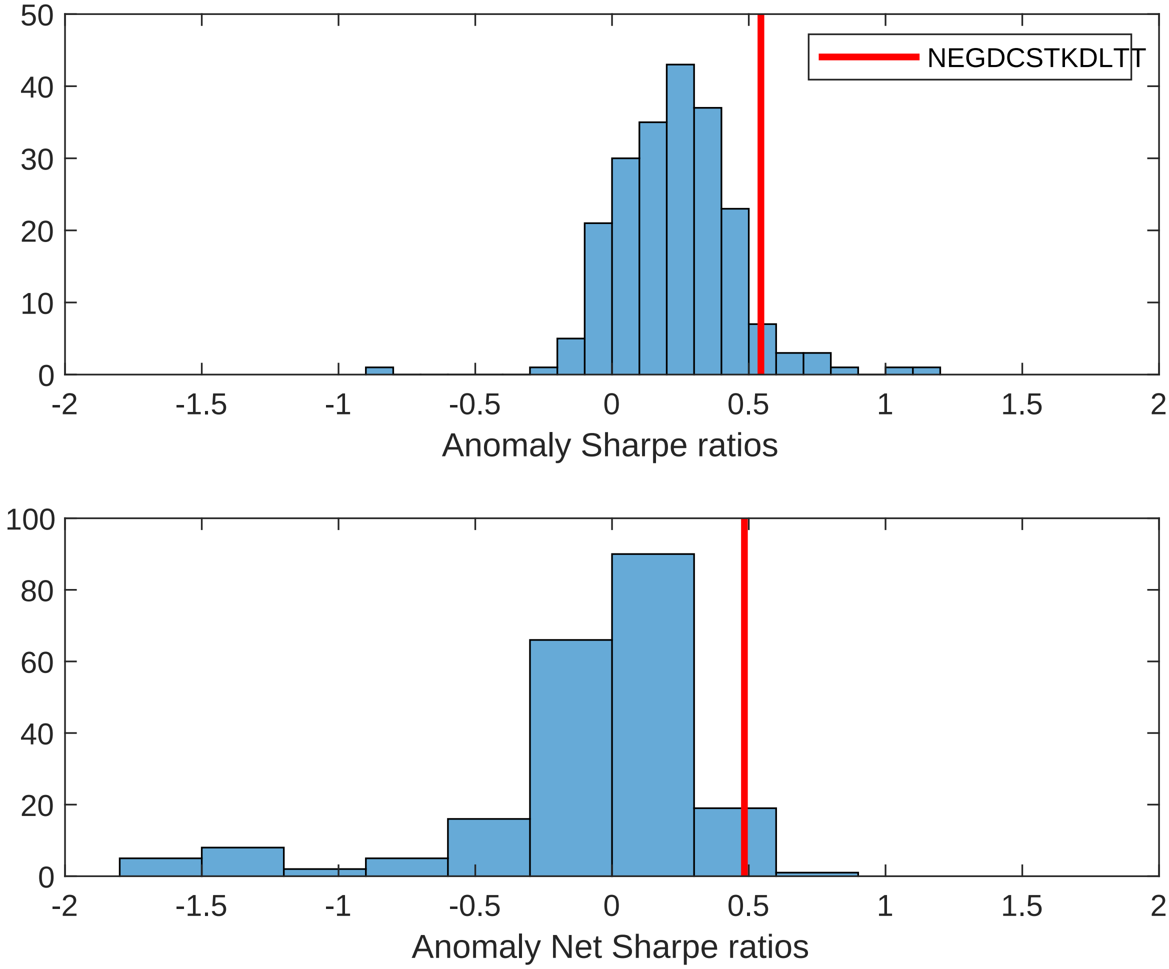

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the EDD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

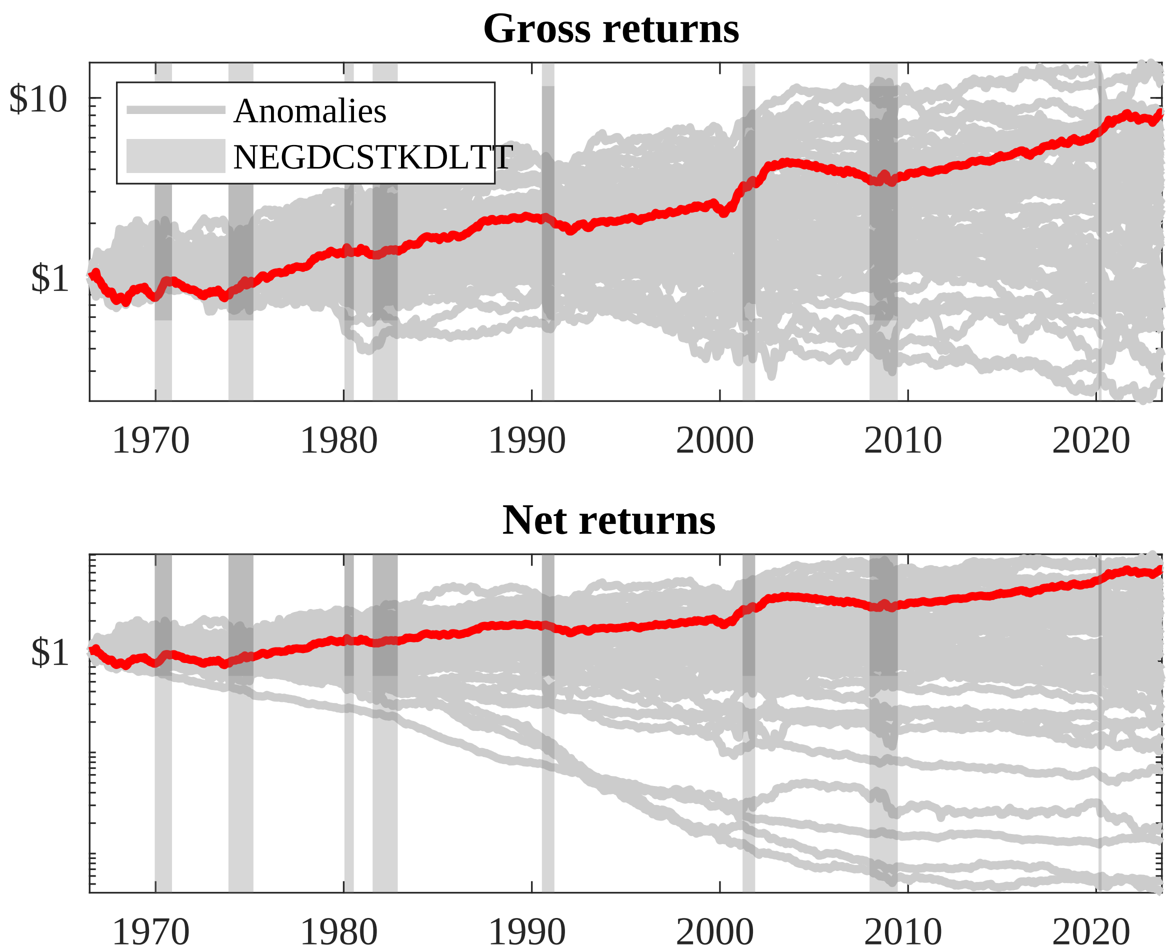

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the EDD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

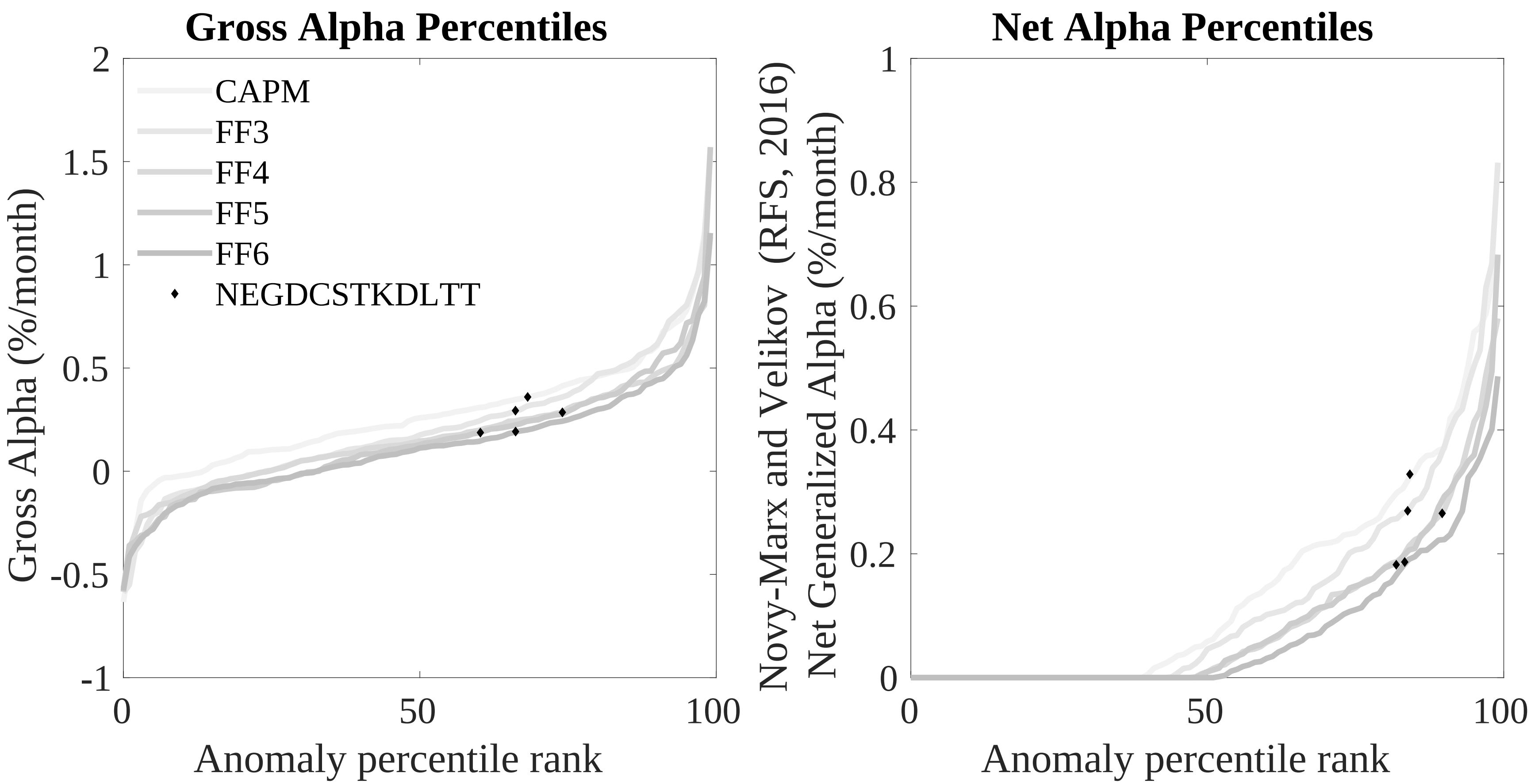

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the EDD trading strategy alphas (diamonds). The strategies are constructed using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

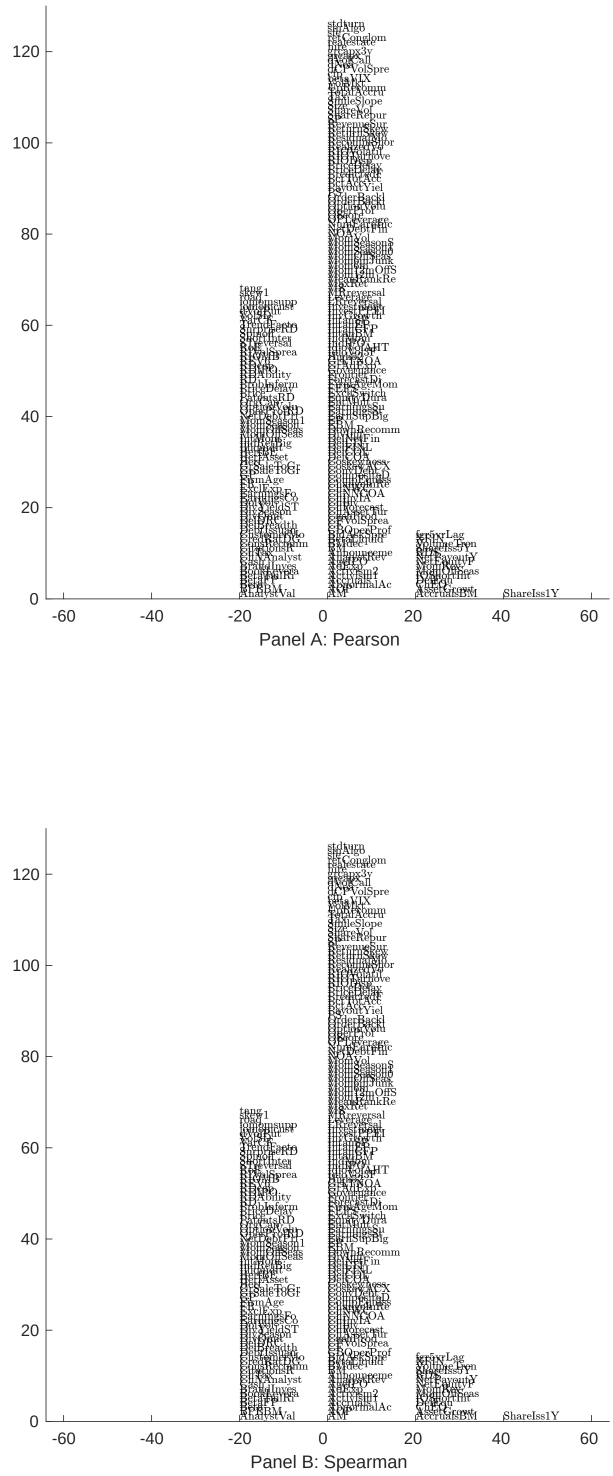

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with EDD. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

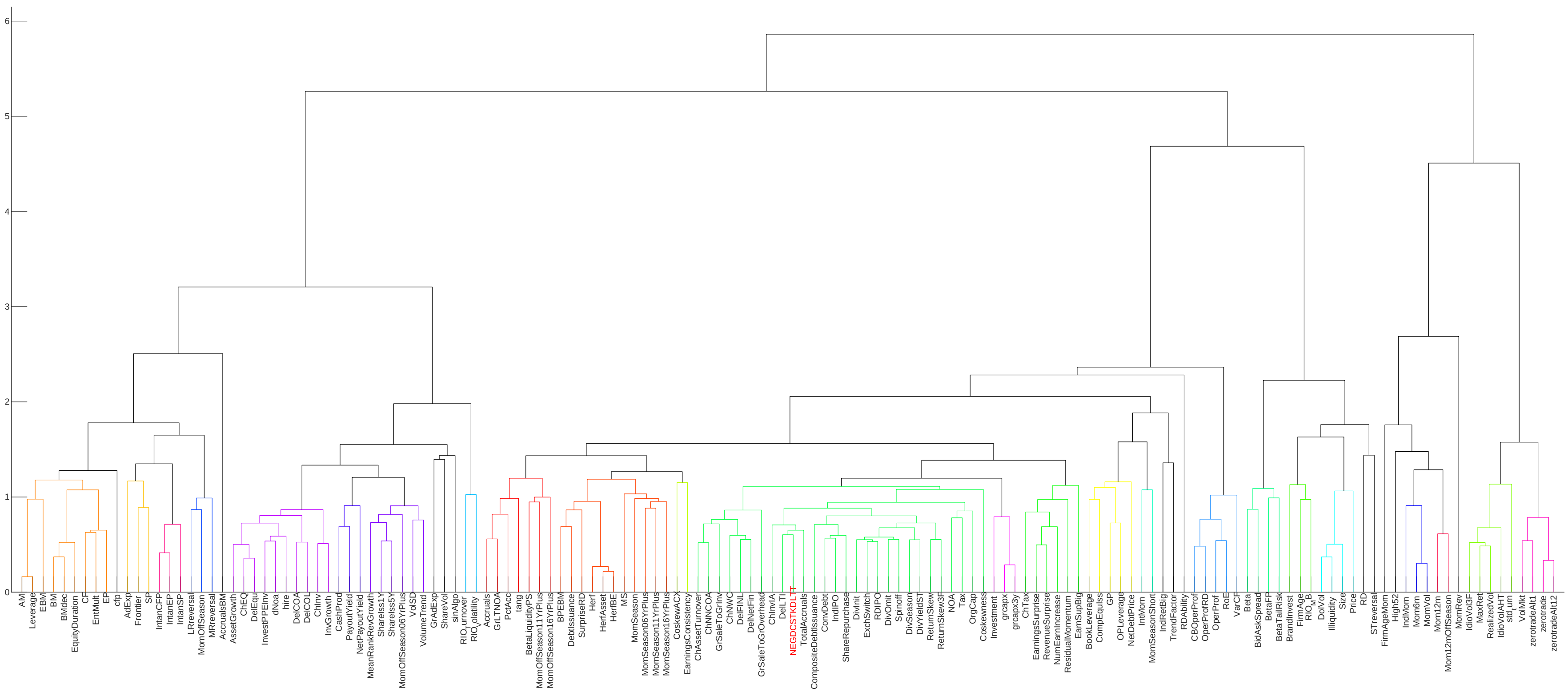

Figure 6: Agglomerative hierarchical cluster plot

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

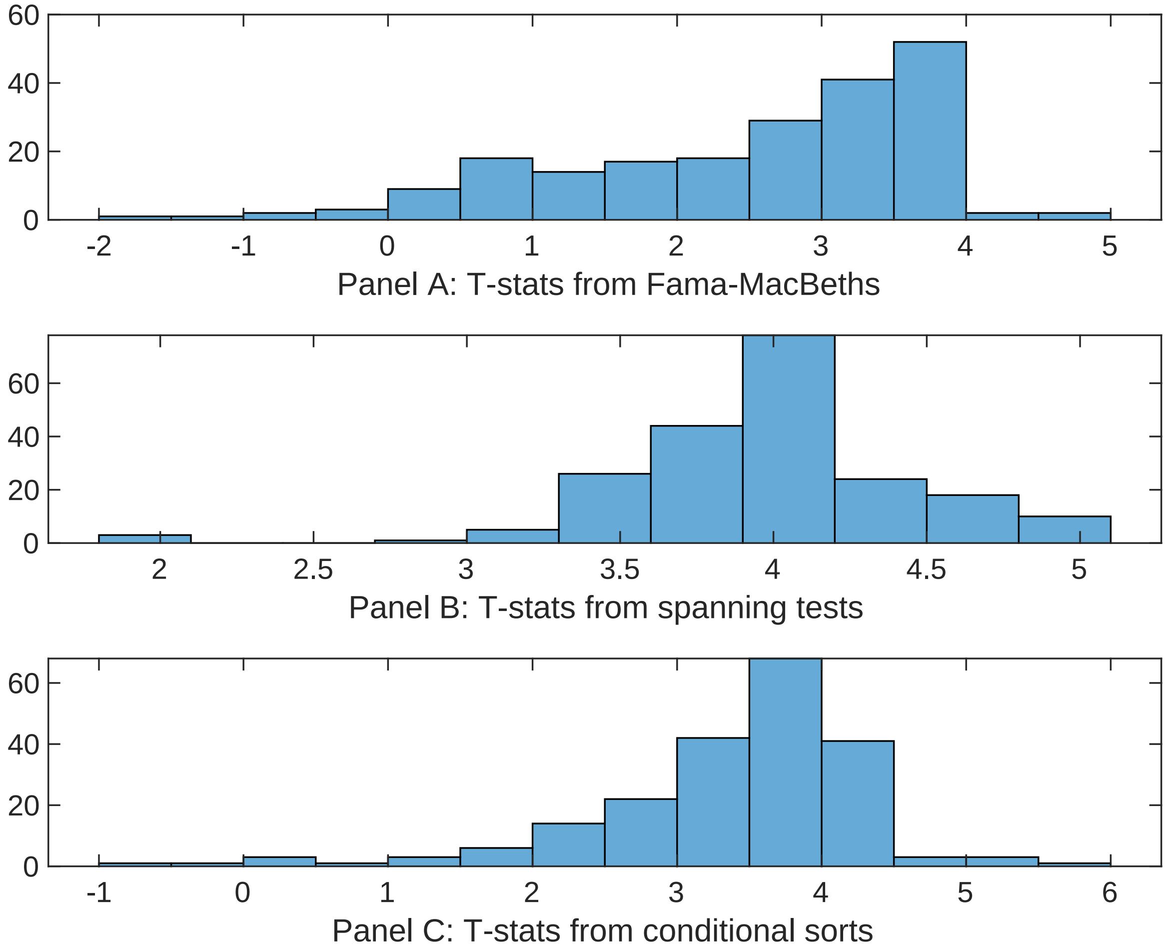

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of EDD conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{EDD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{EDD} EDD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{EDD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 EDD. Stocks are finally grouped into five EDD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted EDD 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 EDD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{EDD} EDD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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	0.12	0.17	0.12	0.13	0.12	0.13	0.13
	[5.57]	[7.04]	[5.19]	[5.96]	[5.51]	[5.96]	[5.01]
EDD	0.26	0.24	0.10	0.27	0.21	0.16	0.41
	[3.12]	[3.04]	[1.04]	[3.02]	[2.71]	[2.07]	[0.40]
Anomaly 1	0.22						0.81
	[4.89]						[1.90]
Anomaly 2		0.45					0.16
		[4.14]					[0.01]
Anomaly 3			0.29				0.23
			[2.56]				[2.12]
Anomaly 4				0.40			0.96
				[4.61]			[1.06]
Anomaly 5					0.14		-0.19
					[3.84]		[-0.31]
Anomaly 6						0.10	0.68
						[8.71]	[6.27]
# 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 EDD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{EDD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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	0.17	0.19	0.20	0.16	0.22	0.20	0.17
	[2.33]	[2.62]	[2.67]	[2.20]	[2.90]	[2.61]	[2.42]
Anomaly 1	30.72						16.67
	[8.19]						[3.88]
Anomaly 2		37.39					28.89
		[9.27]					[4.97]
Anomaly 3			21.30				7.69
			[7.43]				[2.37]
Anomaly 4				21.63			6.23
				[5.53]			[1.52]
Anomaly 5					27.43		0.27
					[6.97]		[0.05]
Anomaly 6						9.09	-13.44
						[1.80]	[-2.62]
mkt	4.32	3.17	5.38	4.85	1.51	1.98	6.13
	[2.50]	[1.85]	[3.03]	[2.68]	[0.86]	[1.10]	[3.52]
smb	-2.12	-4.80	0.57	-4.70	-3.99	-4.41	-1.56
	[-0.86]	[-1.94]	[0.23]	[-1.83]	[-1.57]	[-1.65]	[-0.62]
hml	-0.15	-0.68	-4.52	-2.33	0.21	3.37	-6.43
	[-0.05]	[-0.20]	[-1.27]	[-0.64]	[0.06]	[0.97]	[-1.84]
rmw	-3.06	8.87	-5.01	2.91	9.64	6.77	-2.31
	[-0.85]	[2.66]	[-1.33]	[0.83]	[2.80]	[1.92]	[-0.59]
cma	21.37	-1.19	20.41	29.44	7.37	24.87	7.72
	[4.04]	[-0.19]	[3.74]	[5.62]	[1.14]	[3.11]	[1.02]
umd	-1.09	-1.18	1.04	-0.61	0.06	-0.51	-1.12
	[-0.64]	[-0.70]	[0.61]	[-0.35]	[0.04]	[-0.28]	[-0.67]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	25	25	24	21	22	16	31

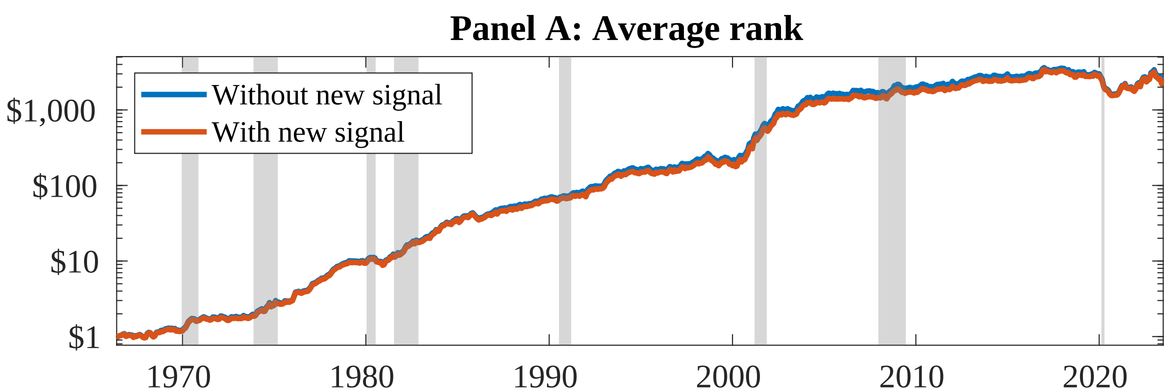

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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