Equity Share Deviation and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Equity Share Deviation (ESD), 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 ESD achieves an annualized gross (net) Sharpe ratio of 0.57 (0.51), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 23 (23) bps/month with a t-statistic of 2.84 (2.88), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth) is 18 bps/month with a t-statistic of 2.43.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents various market anomalies that appear to contradict this notion (Stambaugh and Yuan, 2017). Among these, equity issuance-related signals have emerged as particularly robust predictors of future returns (Pontiff and Woodgate, 2008).

While existing research has extensively studied the direct relationship between equity issuance and subsequent returns, less attention has been paid to how deviations from firms' typical equity financing patterns might signal future performance. This gap is notable given that firms' financing decisions often follow predictable patterns based on their life cycle and industry characteristics (DeAngelo et al., 2010).

We propose that significant deviations from a firm's historical equity financing patterns may contain valuable information about future stock returns. This hypothesis builds on the market timing theory of (Baker and Wurgler, 2002), which suggests that managers issue equity when they believe their stock is overvalued. However, we extend this framework by focusing on unexpected changes in equity financing relative to firm-specific patterns.

The predictive power of Equity Share Deviation (ESD) may stem from two complementary mechanisms. First, following (Daniel and Titman, 2006), managers likely have superior information about their firms' prospects and deviate from typical financing patterns when they perceive their stock as mispriced. Second, as suggested by (Frazzini and Pedersen, 2014), sudden changes in financing patterns may signal shifts in underlying business conditions that the market is slow to incorporate into prices.

Importantly, by measuring deviations from firm-specific patterns rather than absolute levels of equity issuance, ESD may capture information not reflected in traditional equity issuance measures. This approach builds on insights from (McLean and Pontiff, 2016) showing that the market's slow incorporation of financing-related signals creates persistent return predictability.

Our empirical analysis reveals that ESD is a robust predictor of future stock returns. A value-weighted long-short portfolio strategy based on ESD quintiles generates a significant monthly alpha of 23 basis points (t-statistic = 2.84) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.57, placing it in the top 5% of documented market anomalies.

The predictive power of ESD persists after controlling for transaction costs. The strategy maintains a significant net alpha of 23 basis points per month (t-statistic = 2.88) after accounting for trading frictions using the methodology of (Novy-Marx and Velikov, 2016). Importantly, ESD's predictive ability remains strong among large-cap stocks, with the long-short strategy earning a monthly alpha of 20 basis points (t-statistic = 2.09) within the largest size quintile.

Crucially, ESD contains incremental information beyond existing anomalies. Controlling for the six most closely related predictors and the Fama-French six factors, the strategy still generates a monthly alpha of 18 basis points (t-statistic = 2.43). This finding suggests that ESD captures a distinct aspect of mispricing not explained by known factors.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures unexpected deviations in firms' equity financing patterns, extending the literature on equity issuance anomalies pioneered by (Loughran and Ritter, 1995) and (Pontiff and Woodgate, 2008). Unlike existing measures that focus on absolute levels of issuance, ESD identifies firms that deviate from their typical financing behavior.

Second, we demonstrate that ESD's predictive power is distinct from known anomalies and robust to comprehensive controls. This finding contributes to the literature on the sources of cross-sectional return predictability (Hou et al., 2015), suggesting that market participants do not fully incorporate the information contained in unexpected changes to firms' financing patterns.

Third, our results have important implications for both academic research and investment practice. For researchers, we provide new evidence on the link between financing decisions and stock returns. For practitioners, we document a robust signal that remains profitable after transaction costs and works well 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 Share Deviation measure. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item CSTK for common stock and item CEQ for total common/ordinary equity. Common stock (CSTK) represents the total par or stated value of issued common stock, while common equity (CEQ) represents the total common shareholders' equity in the company.construction of our signal follows a difference-in-levels approach scaled by the equity base, where we calculate the change in CSTK from one period to the next and divide this difference by the previous period's CEQ. This measure captures the relative change in the par value of common stock relative to the firm's existing equity base, potentially indicating significant changes in the firm's equity structure or capital raising activities. By scaling the change by lagged common equity, we ensure comparability across firms of different sizes and control for the base level of equity capital. We construct this measure using end-of-fiscal-year values for both CSTK and CEQ to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the ESD signal. Panel A plots the time-series of the mean, median, and interquartile range for ESD. On average, the cross-sectional mean (median) ESD is -0.01 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input ESD 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 ESD signal for the CRSP universe. On average, the ESD signal is available for 6.65% of CRSP names, which on average make up 7.97% of total market capitalization.

4 Does ESD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on ESD 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 ESD portfolio and sells the low ESD 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 ESD strategy earns an average return of 0.34% per month with a t-statistic of 4.34. The annualized Sharpe ratio of the strategy is 0.57. The alphas range from 0.23% to 0.36% 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 5.74 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 617 stocks and an average market capitalization of at least $1,479 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 30 bps/month with a t-statistics of 3.86. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for nineteen 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 26-31bps/month. The lowest return, (26 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.40. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the ESD trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-five cases, and significantly expands the achievable frontier in twenty-five cases.

Table 3 provides direct tests for the role size plays in the ESD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and ESD, as well as average returns and alphas for long/short trading ESD 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 ESD strategy achieves an average return of 26 bps/month with a t-statistic of 2.73. Among these large cap stocks, the alphas for the ESD strategy relative to the five most common factor models range from 19 to 25 bps/month with t-statistics between 1.96 and 2.67.

5 How does ESD perform relative to the zoo?

Figure 2 puts the performance of ESD 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

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

ratio for the ESD strategy falls in the distribution. The ESD strategy's gross (net) Sharpe ratio of 0.57 (0.51) 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 ESD strategy (red line).[2] Ignoring trading costs, a $1 invested in the ESD strategy would have yielded $8.34 which ranks the ESD strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the ESD strategy would have yielded $6.25 which ranks the ESD 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 ESD relative to those. Panel A shows that the ESD strategy gross alphas fall between the 68 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 ESD strategy has a positive net generalized alpha for five out of the five factor models. In these cases ESD ranks between the 84 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

6 Does ESD 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 ESD 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 ESD or at least to weaken the power ESD has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of ESD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ESD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ESD} ESD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{ESD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 ESD. Stocks are finally grouped into five ESD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted

[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.

ESD trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on ESD 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 ESD signal in these Fama-MacBeth regressions exceed 2.59, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on ESD is 1.99.

Similarly, Table 5 reports results from spanning tests that regress returns to the ESD 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 ESD strategy earns alphas that range from 20-25bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.49, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the ESD trading strategy achieves an alpha of 18bps/month with a t-statistic of 2.43.

7 Does ESD add relative to the whole zoo?

Finally, we can ask how much adding ESD 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 ESD signal.[4] We consider one different methods for combining signals.

[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 ESD is available.

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 ESD grows to $2316.52.

8 Conclusion

This study provides compelling evidence for the effectiveness of Equity Share Deviation (ESD) as a robust predictor of stock returns. Our findings demonstrate that ESD-based trading strategies yield economically and statistically significant results, with a value-weighted long/short strategy achieving impressive Sharpe ratios of 0.57 and 0.51 on a gross and net basis, respectively. The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, underscores its unique contribution to the asset pricing literature.

Particularly noteworthy is the signal's ability to maintain its predictive power when tested against the Fama-French five-factor model plus momentum, generating monthly abnormal returns of 23 basis points. Furthermore, the strategy's alpha remains significant at 18 basis points per month even after controlling for six closely related anomalies from the factor zoo, suggesting that ESD captures distinct information not fully explained by existing factors.

However, several limitations warrant consideration. The study's findings may be sensitive to the specific time period examined, and transaction costs could impact real-world implementation. Future research could explore the signal's effectiveness across different market regimes, international markets, and asset classes. Additionally, investigating the underlying economic mechanisms driving the ESD effect and its interaction with other market anomalies could provide valuable insights.

In conclusion, our results suggest that ESD represents a valuable addition to the quantitative investor's toolkit, offering meaningful predictive power for stock returns. The signal's robustness to controls and transaction costs makes it particularly relevant for practical applications in investment management.

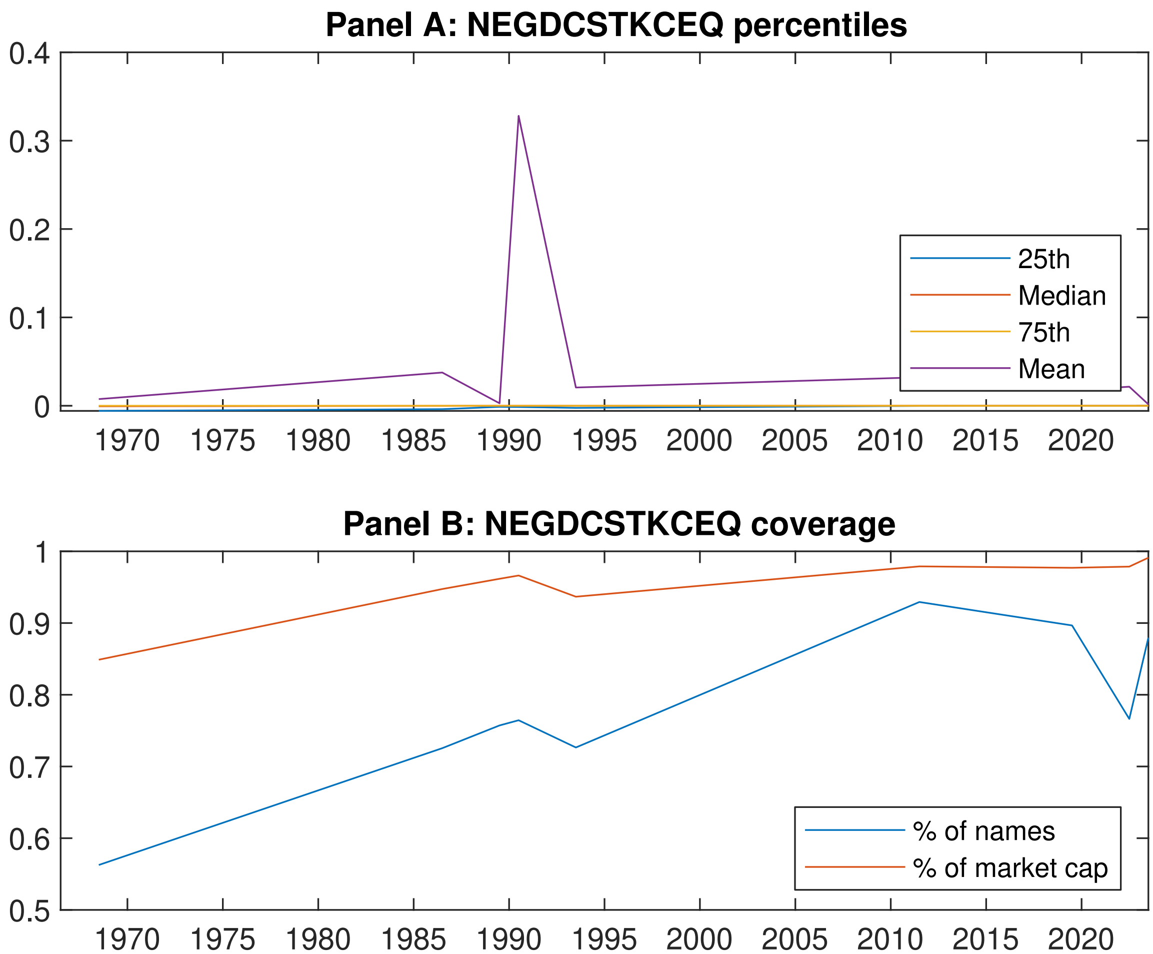


Figure 1: Times series of ESD percentiles and coverage.
This figure plots descriptive statistics for ESD. Panel A shows cross-sectional percentiles of ESD over the sample. Panel B plots the monthly coverage of ESD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on ESD. 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 ESD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.42	0.48	0.68	0.67	0.76	0.34
	[2.39]	[2.50]	[3.61]	[3.91]	[4.51]	[4.34]
α_{CAPM}	-0.13	-0.13	0.09	0.13	0.23	0.36
	[-2.38]	[-2.77]	[1.78]	[2.76]	[4.94]	[4.53]
α_{FF3}	-0.14	-0.11	0.11	0.10	0.19	0.32
	[-2.58]	[-2.51]	[2.24]	[2.19]	[4.17]	[4.07]
α_{FF4}	-0.11	-0.08	0.12	0.06	0.17	0.28
	[-2.11]	[-1.85]	[2.53]	[1.27]	[3.69]	[3.50]
α_{FF5}	-0.16	-0.06	0.14	0.01	0.10	0.25
	[-2.92]	[-1.23]	[2.83]	[0.22]	[2.22]	[3.18]
α_{FF6}	-0.14	-0.04	0.15	-0.02	0.09	0.23
	[-2.55]	[-0.81]	[3.02]	[-0.36]	[2.04]	[2.84]
Panel B: Fama and French (2018) 6-factor model loadings for ESD-sorted portfolios						
β_{MKT}	0.97	1.03	1.01	1.01	0.99	0.02
	[76.60]	[94.37]	[85.88]	[96.41]	[94.58]	[1.02]
β_{SMB}	-0.02	0.02	0.04	-0.08	-0.00	0.02
	[-1.15]	[1.16]	[2.33]	[-5.01]	[-0.30]	[0.60]
β_{HML}	0.07	-0.01	-0.07	0.06	0.05	-0.02
	[2.98]	[-0.59]	[-3.09]	[3.07]	[2.37]	[-0.68]
β_{RMW}	0.12	-0.09	-0.07	0.11	0.11	-0.01
	[5.02]	[-4.11]	[-2.94]	[5.56]	[5.37]	[-0.39]
β_{CMA}	-0.10	-0.09	-0.02	0.17	0.21	0.31
	[-2.77]	[-2.98]	[-0.51]	[5.86]	[7.03]	[5.74]
β_{UMD}	-0.03	-0.03	-0.02	0.04	0.01	0.04
	[-2.30]	[-2.74]	[-1.49]	[3.90]	[1.05]	[2.12]
Panel C: Average number of firms (n) and market capitalization (me)						
n	754	726	617	715	788	
me ($\$10^6$)	1740	1479	2085	2281	2349	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the ESD 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	0.34	0.36	0.32	0.28	0.25	0.23
			[4.34]	[4.53]	[4.07]	[3.50]	[3.18]	[2.84]
Quintile	NYSE	EW	0.48	0.53	0.48	0.42	0.38	0.34
			[8.46]	[9.59]	[8.94]	[7.90]	[7.21]	[6.53]
Quintile	Name	VW	0.34	0.35	0.32	0.29	0.25	0.23
			[4.34]	[4.49]	[4.05]	[3.57]	[3.19]	[2.92]
Quintile	Cap	VW	0.30	0.31	0.28	0.24	0.25	0.22
			[3.86]	[3.91]	[3.59]	[2.99]	[3.13]	[2.73]
Decile	NYSE	VW	0.35	0.35	0.30	0.26	0.27	0.25
			[3.93]	[3.84]	[3.31]	[2.85]	[3.03]	[2.72]
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	0.31	0.33	0.30	0.27	0.24	0.23
			[3.87]	[4.11]	[3.72]	[3.43]	[3.06]	[2.88]
Quintile	NYSE	EW	0.28	0.33	0.27	0.24	0.16	0.15
			[4.35]	[5.12]	[4.46]	[4.04]	[2.77]	[2.55]
Quintile	Name	VW	0.30	0.32	0.29	0.27	0.24	0.23
			[3.87]	[4.07]	[3.69]	[3.46]	[3.08]	[2.93]
Quintile	Cap	VW	0.26	0.28	0.25	0.23	0.23	0.22
			[3.40]	[3.53]	[3.25]	[2.94]	[2.99]	[2.77]
Decile	NYSE	VW	0.31	0.31	0.26	0.25	0.25	0.23
			[3.45]	[3.41]	[2.96]	[2.73]	[2.74]	[2.61]

Table 3: Conditional sort on size and ESD

This table presents results for conditional double sorts on size and ESD. 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 ESD. 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 ESD and short stocks with low ESD .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	ESD Quintiles (L)	(2)	(3)	(4)	(H)	ESD Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.43	0.65	0.86	0.92	0.94	0.51	0.54	0.51	0.46	0.44	0.40
	[1.66]	[2.45]	[3.35]	[3.69]	[3.83]	[7.47]	[7.98]	[7.61]	[6.82]	[6.37]	[5.85]
(2)	0.56	0.66	0.84	0.89	0.92	0.36	0.40	0.34	0.30	0.29	0.26
	[2.40]	[2.70]	[3.45]	[3.88]	[4.08]	[4.43]	[4.85]	[4.21]	[3.65]	[3.55]	[3.20]
(3)	0.53	0.67	0.76	0.81	0.95	0.42	0.43	0.39	0.39	0.36	0.36
	[2.55]	[2.96]	[3.33]	[3.84]	[4.62]	[5.68]	[5.76]	[5.34]	[5.16]	[4.78]	[4.71]
(4)	0.51	0.63	0.75	0.83	0.77	0.27	0.29	0.23	0.21	0.11	0.11
	[2.57]	[3.02]	[3.51]	[4.16]	[4.05]	[3.55]	[3.80]	[3.15]	[2.84]	[1.52]	[1.44]
(5)	0.46	0.46	0.52	0.53	0.71	0.26	0.25	0.23	0.19	0.23	0.20
	[2.64]	[2.43]	[2.86]	[3.09]	[4.24]	[2.73]	[2.67]	[2.41]	[1.96]	[2.41]	[2.09]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	ESD Quintiles, Average n (L)	(2)	(3)	(4)	(H)	ESD Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(1)	397	398	398	395	394	32	34	41	30	31
(2)	113	112	112	111	112	57	57	58	57	57
(3)	82	81	81	80	81	99	96	99	100	101
(4)	68	68	68	68	68	207	204	212	217	217
(5)	62	62	62	62	62	1422	1424	1726	1614	1745

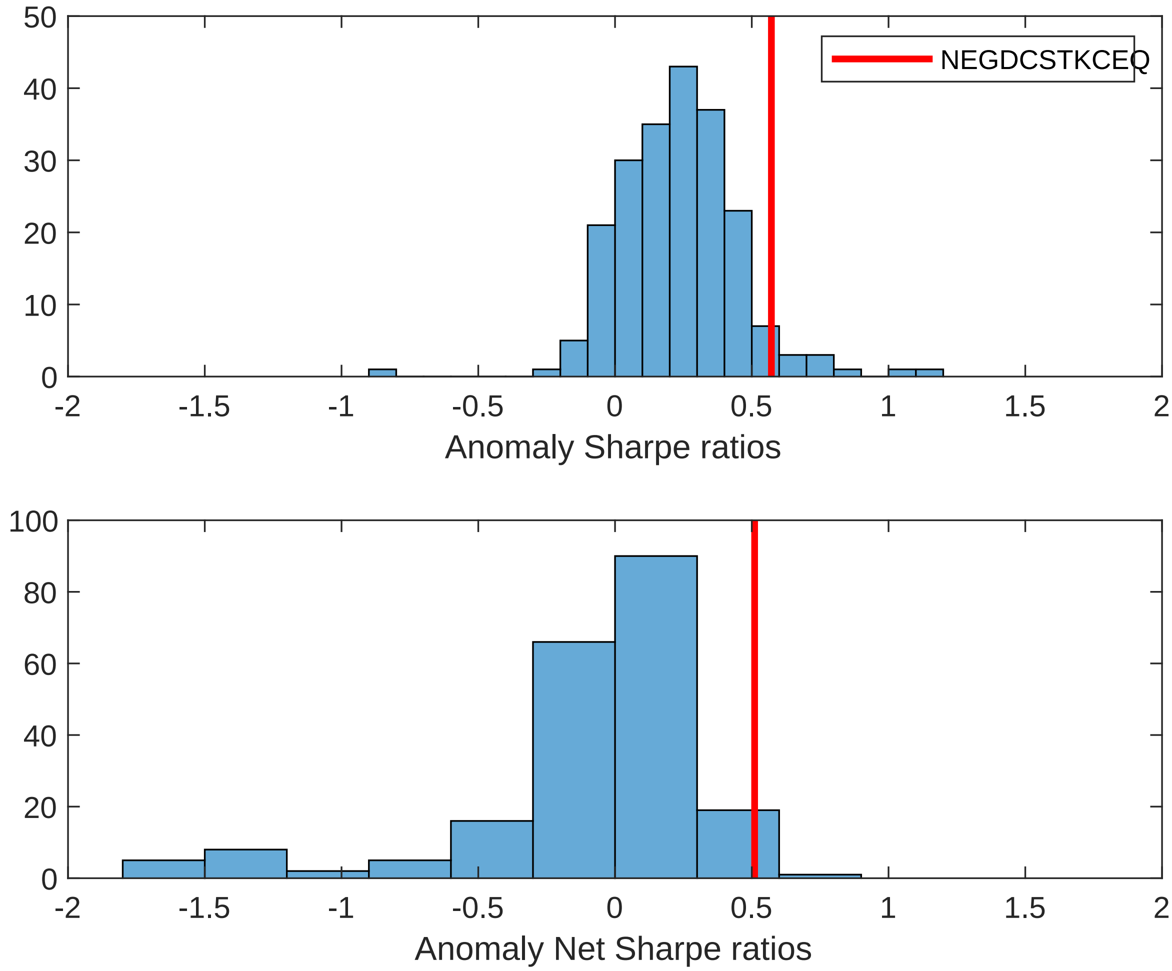


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the ESD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

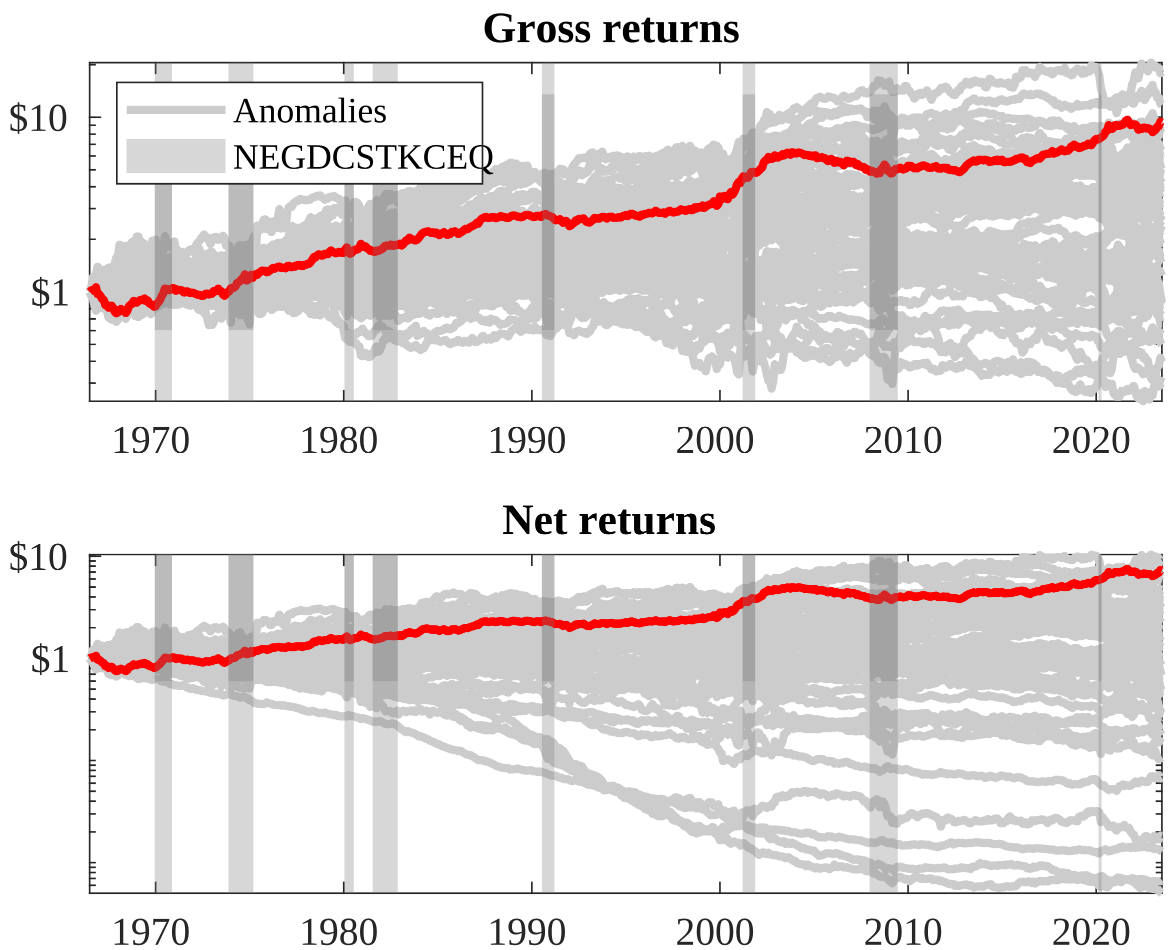


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the ESD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

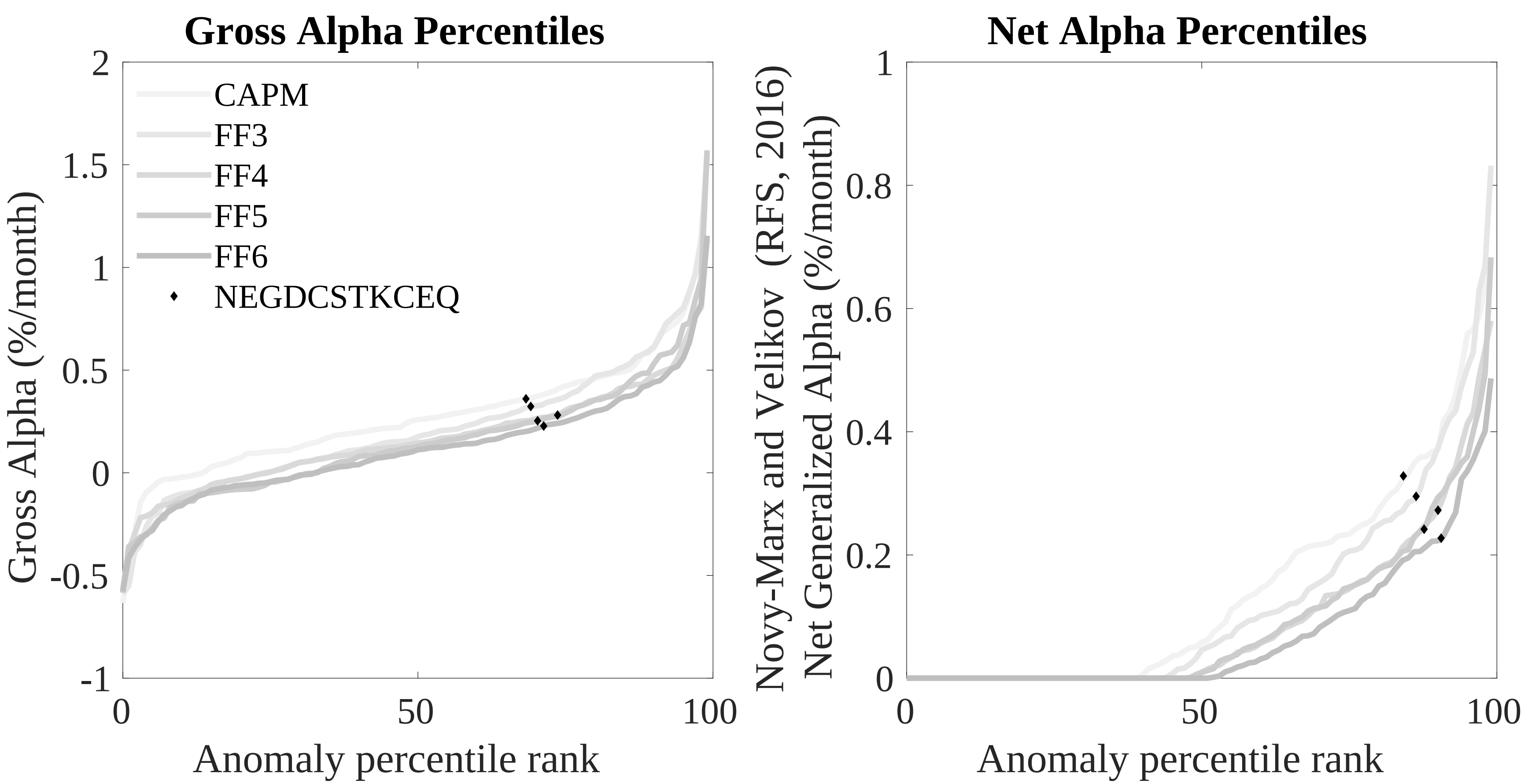
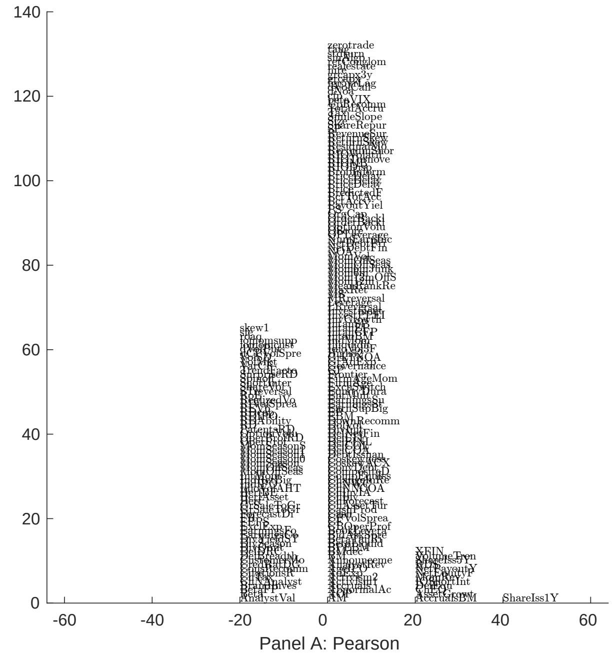


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the ESD trading strategy alphas (diamonds). The strategies are constructed using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



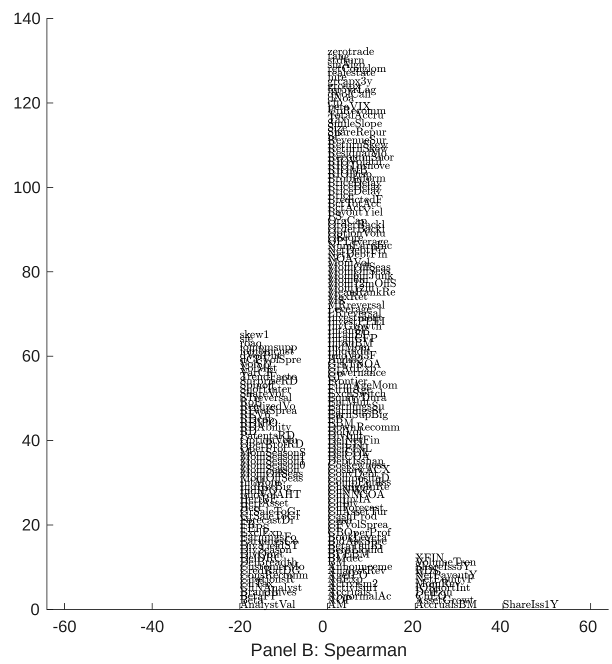


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with ESD. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

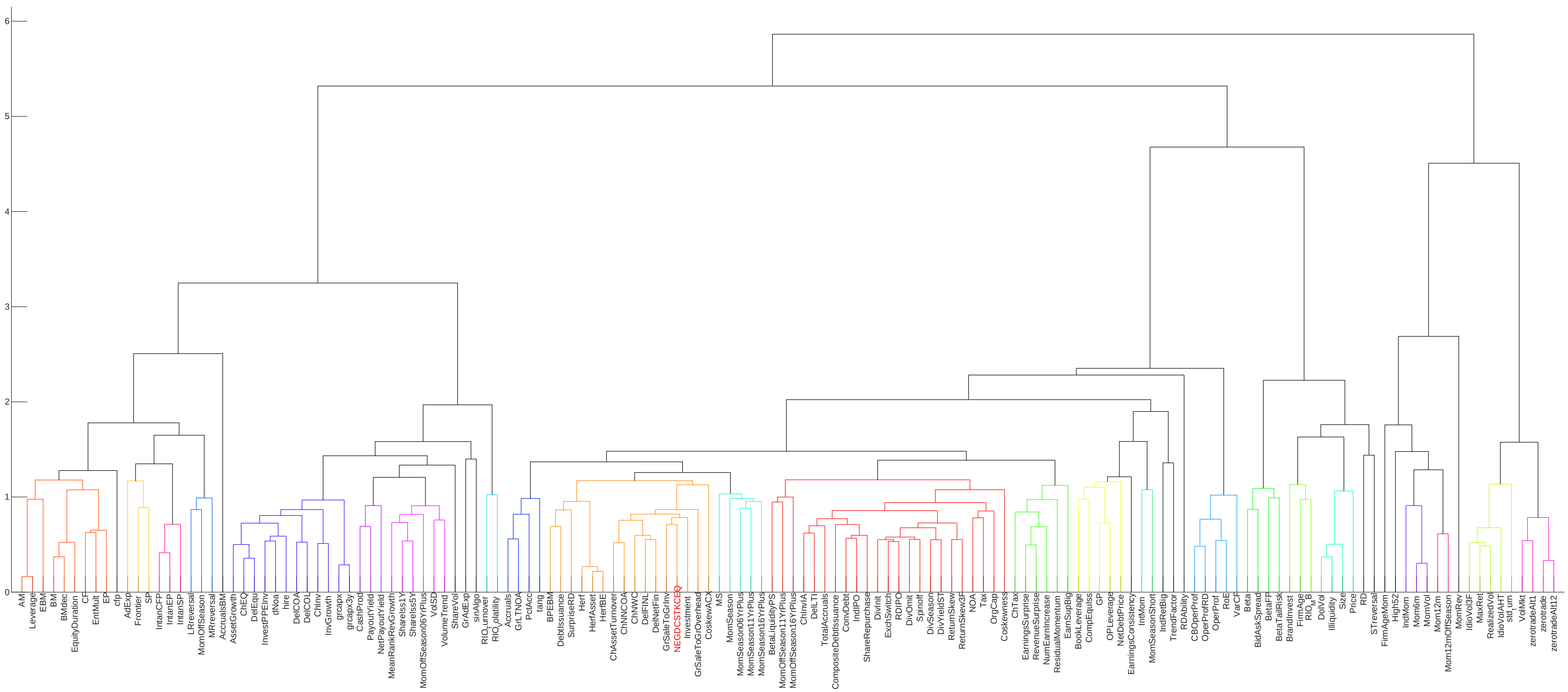


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

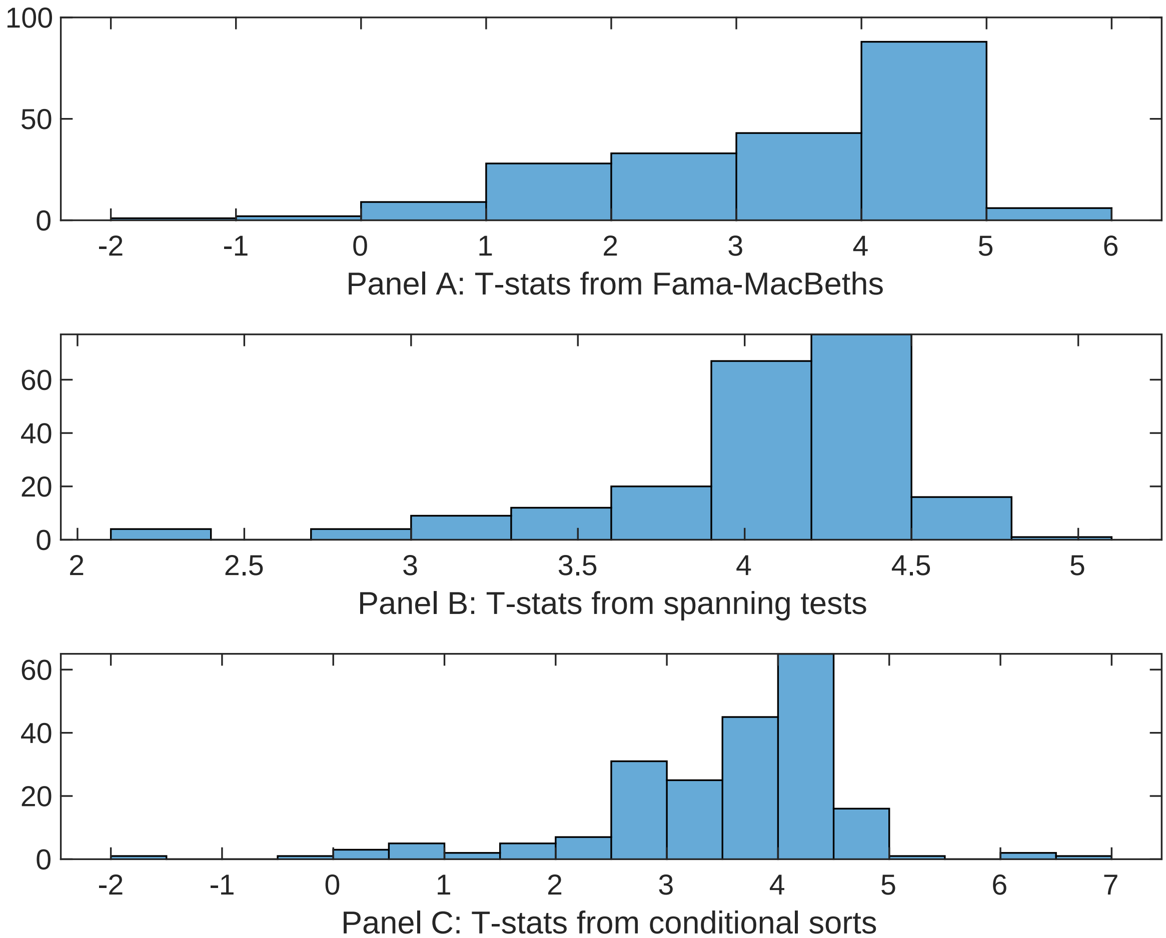


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of ESD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ESD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ESD} ESD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{ESD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 ESD. Stocks are finally grouped into five ESD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted ESD 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 ESD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{ESD} ESD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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	0.17	0.12	0.13	0.12	0.13	0.13
	[5.65]	[7.19]	[5.24]	[6.02]	[5.55]	[6.03]	[5.10]
ESD	0.21	0.19	0.16	0.22	0.19	0.15	0.12
	[3.98]	[3.96]	[2.59]	[3.96]	[3.68]	[2.91]	[1.99]
Anomaly 1	0.27						0.98
	[5.88]						[2.45]
Anomaly 2		0.46					-0.37
		[4.21]					[-0.25]
Anomaly 3			0.27				0.23
			[2.43]				[2.12]
Anomaly 4				0.38			0.38
				[4.38]			[0.43]
Anomaly 5					0.14		-0.11
					[4.10]		[-0.19]
Anomaly 6						0.10	0.69
						[8.82]	[6.52]
# 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 ESD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{ESD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.20	0.23	0.22	0.20	0.25	0.23	0.18
	[2.63]	[2.94]	[2.78]	[2.49]	[3.09]	[2.88]	[2.43]
Anomaly 1	28.54						20.09
	[7.18]						[4.39]
Anomaly 2		36.41					40.65
		[8.51]					[6.56]
Anomaly 3			14.69				1.89
			[4.78]				[0.55]
Anomaly 4				14.99			1.02
				[3.61]			[0.23]
Anomaly 5					19.85		-10.38
					[4.71]		[-1.79]
Anomaly 6						3.93	-18.51
						[0.74]	[-3.38]
mkt	4.36	3.27	4.61	4.26	1.76	2.09	5.62
	[2.38]	[1.81]	[2.43]	[2.21]	[0.94]	[1.10]	[3.03]
smb	3.36	0.65	5.06	1.41	1.57	1.53	3.82
	[1.28]	[0.25]	[1.85]	[0.52]	[0.58]	[0.55]	[1.42]
hml	-5.47	-6.40	-7.34	-5.85	-4.64	-2.24	-8.35
	[-1.53]	[-1.82]	[-1.92]	[-1.52]	[-1.27]	[-0.61]	[-2.24]
rmw	-10.80	0.25	-9.64	-4.19	0.31	-1.75	-7.90
	[-2.85]	[0.07]	[-2.39]	[-1.12]	[0.08]	[-0.47]	[-1.90]
cma	17.17	-5.60	20.45	26.65	9.87	25.76	12.92
	[3.06]	[-0.84]	[3.49]	[4.79]	[1.43]	[3.06]	[1.60]
umd	3.81	3.65	5.43	4.30	4.63	4.11	2.62
	[2.12]	[2.03]	[2.94]	[2.32]	[2.48]	[2.17]	[1.47]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	15	16	12	11	10	8	21

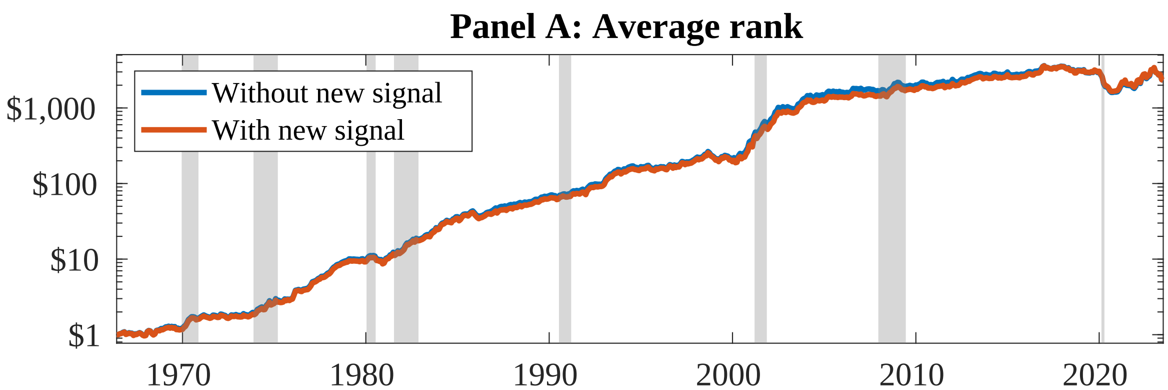


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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