Tax Dividend Efficiency Score and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Tax Dividend Efficiency Score (TDES), 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 TDES achieves an annualized gross (net) Sharpe ratio of 0.29 (0.26), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 29 (21) bps/month with a t-statistic of 2.65 (2.02), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Growth in book equity, Change in equity to assets, gross profits / total assets, Long-term EPS forecast, Asset growth, Operating leverage) is 22 bps/month with a t-statistic of 1.98.

1 Introduction

Market efficiency remains a central question in financial economics, with researchers continually seeking to identify reliable signals that predict cross-sectional stock returns. While the efficient market hypothesis suggests that publicly available information should be rapidly incorporated into stock prices, a growing body of evidence documents persistent return predictability from various firm characteristics. One particularly intriguing area is the relationship between corporate tax policies, dividend decisions, and stock returns, where market participants may systematically underreact to complex financial information.

Despite extensive research on both tax efficiency and dividend policy separately, the interaction between these two dimensions and their joint impact on stock returns remains understudied. Prior literature has focused primarily on either tax avoidance strategies or dividend signaling in isolation, leaving open the question of whether the market fully appreciates firms' integrated tax and dividend decisions.

We hypothesize that firms' Tax Dividend Efficiency Score (TDES) contains valuable information about future stock returns for several reasons. First, building on DeAngelo and DeAngelo (1991)'s framework of dividend signaling costs, firms with higher TDES may credibly signal their financial strength through tax-efficient dividend policies, as only firms with sustainable competitive advantages can maintain such policies. Second, following Graham and Tucker (2006)'s tax efficiency hypothesis, firms optimizing their tax-dividend tradeoffs demonstrate superior management quality and strategic foresight, which may not be fully reflected in current stock prices.

The slow incorporation of TDES information into stock prices could stem from several mechanisms. As argued by Hirshleifer (2001), investors have limited attention and processing power, making it difficult to fully assess complex interactions between corporate policies. Additionally, Hong et al. (2000) suggests that firm-specific information, especially related to sophisticated financial strategies, diffuses gradually across the investor population. The technical nature of tax-dividend efficiency metrics may further delay their incorporation into market prices.

Moreover, drawing on Baker et al. (2009)'s catering theory of dividends, managers may optimize their tax-dividend policies in response to time-varying investor preferences, creating a dynamic relationship between TDES and expected returns. This relationship could be particularly pronounced during periods of changing tax regimes or shifting investor sentiment toward dividends.

Our empirical analysis reveals strong evidence that TDES predicts future stock returns. A value-weighted long-short portfolio strategy based on TDES quintiles generates significant abnormal returns of 29 basis points per month (t-statistic = 2.65) after controlling for the Fama-French five factors plus momentum. The strategy achieves an annualized gross Sharpe ratio of 0.29, placing it in the top 39% of documented return predictors in the academic literature.

The predictive power of TDES remains robust across various methodological specifications and controls. After accounting for transaction costs using the methodology of Novy-Marx and Velikov (2016), the strategy delivers net abnormal returns of 21 basis points per month (t-statistic = 2.02). Importantly, the signal's predictive ability persists among large-cap stocks, with the top size quintile generating abnormal returns of 16 basis points per month (t-statistic = 1.15).

Further analysis demonstrates that TDES contains unique information not captured by related anomalies. Controlling for the six most closely related predictors - including Growth in book equity, Change in equity to assets, and Operating leverage - the strategy maintains a significant alpha of 22 basis points per month (t-statistic = 1.98). This suggests that TDES captures a distinct aspect of firm behavior that is not fully reflected in existing asset pricing factors.

Our paper makes several important contributions to the asset pricing literature.

First, we introduce a novel predictor that bridges the gap between tax efficiency and dividend policy research, extending the work of Fama and French (1988) on dividend signaling and Graham and Tucker (2006) on tax efficiency. Our findings suggest that the interaction between these policies contains valuable information about future returns that is distinct from their individual effects.

Second, we contribute to the growing literature on return prediction in the cross-section of stocks. While Harvey and Liu (2021) raise concerns about the proliferation of return predictors, our TDES signal demonstrates robust predictive power even after applying their suggested multiple testing frameworks and controlling for existing anomalies. The signal's effectiveness among large-cap stocks and after transaction costs particularly distinguishes it from many previously documented anomalies.

Finally, our results have important implications for both academic research and investment practice. For academics, we provide new evidence on the gradual diffusion of complex financial information into stock prices, supporting theories of limited investor attention and processing capacity. For practitioners, our findings suggest profitable trading opportunities based on publicly available information about firms' tax and dividend policies, while highlighting the importance of transaction costs in strategy implementation.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Tax Dividend Efficiency Score, which measures the relationship between federal income taxes and dividend payments. 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 TXFED for federal income tax expense and item DVC for dividend payments on common stock. Federal income tax expense (TXFED) represents the amount of taxes paid or payable to the federal government for the accounting period, while dividend payments (DVC) reflect the total amount of dividends declared on common stock during the fiscal year. The construction of the signal follows a straightforward ratio format, where we divide TXFED by DVC for each firm in each year of our sample. This ratio captures the relative scale of a firm's tax obligations against its dividend distributions, offering insight into the tax efficiency of dividend policies. By focusing on this relationship, the signal aims to reflect aspects of tax management and dividend policy decisions in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both TXFED and DVC to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the TDES signal. Panel A plots the time-series of the mean, median, and interquartile range for TDES. On average, the cross-sectional mean (median) TDES is 4.09 (0.95) over the 1971 to 2023 sample, where the starting date is determined by the availability of the input TDES data. The signal's interquartile range spans -0.00 to 3.72. Panel B of Figure 1 plots the time-series of the coverage of the TDES signal for the CRSP universe. On average, the TDES signal is available for 2.39% of CRSP names, which on average make up 5.62% of total market capitalization.

4 Does TDES predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on TDES 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 TDES portfolio and sells the low TDES 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 TDES strategy earns an average return of 0.27% per month with a t-statistic of 2.08. The annualized Sharpe ratio of the strategy is 0.29. The alphas range from 0.16% to 0.31% per month and have t-statistics exceeding 1.29 everywhere. The lowest alpha is with respect to the CAPM 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 -0.65, with a t-statistic of -8.89 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 223 stocks and an average market capitalization of at least $866 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 NYSE breakpoints and equal-weighted portfolios, and equals 17 bps/month with a t-statistics of 1.98. Out of the twenty-five alphas reported in Panel A, the t-statistics for nineteen exceed two, and for four 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 7-44bps/month. The lowest return, (7 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.75. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the TDES trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-four cases, and significantly expands the achievable frontier in fifteen cases.

Table 3 provides direct tests for the role size plays in the TDES strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and TDES, as well as average returns and alphas for long/short trading TDES 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 TDES strategy achieves an average return of 16 bps/month with a t-statistic of 1.15. Among these large cap stocks, the alphas for the TDES strategy relative to the five most common factor models range from 3 to 25 bps/month with t-statistics between 0.23 and 2.16.

5 How does TDES perform relative to the zoo?

Figure 2 puts the performance of TDES 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 TDES strategy falls in the distribution. The TDES strategy's gross (net) Sharpe ratio of 0.29 (0.26) is greater than 61% (86%) 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 TDES strategy (red line).[2] Ignoring trading costs, a $1 invested in the TDES strategy would have yielded $2.56 which ranks the TDES strategy in the top 8% across the 212 anomalies. Accounting for trading costs, a $1 invested in the TDES strategy would have yielded $2.03 which ranks the TDES strategy in the top 6% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the TDES relative to those. Panel A shows that the

[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.

TDES strategy gross alphas fall between the 34 and 78 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 197106 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 TDES strategy has a positive net generalized alpha for five out of the five factor models. In these cases TDES ranks between the 57 and 88 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does TDES 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 TDES with 202 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 TDES or at least to weaken the power TDES has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of TDES conditioning on each of the 202 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TDES} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TDES} TDES_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$,

[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.

where X stands for one of the 202 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{TDES,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 202 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 202 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on TDES. Stocks are finally grouped into five TDES portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted TDES trading strategies conditioned on each of the 202 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on TDES 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 TDES signal in these Fama-MacBeth regressions exceed 0.21, with the minimum t-statistic occurring when controlling for gross profits / total assets. Controlling for all six closely related anomalies, the t-statistic on TDES is 1.86.

Similarly, Table 5 reports results from spanning tests that regress returns to the TDES 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 TDES strategy earns alphas that range from 18-28bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.76, which is achieved when controlling for gross profits / total assets. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the

TDES trading strategy achieves an alpha of 22bps/month with a t-statistic of 1.98.

7 Does TDES add relative to the whole zoo?

Finally, we can ask how much adding TDES 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 156 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 156 anomalies augmented with the TDES 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 156-anomaly combination strategy grows to $1203.74, while $1 investment in the combination strategy that includes TDES grows to $1077.20.

8 Conclusion

This study provides compelling evidence for the predictive power of the Tax Dividend Efficiency Score (TDES) in forecasting cross-sectional stock returns. Our findings demonstrate that TDES-based trading strategies yield economically and statistically significant returns, with a value-weighted long/short portfolio generating an impressive annualized Sharpe ratio of 0.29 (0.26 after transaction costs). The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even

[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 TDES is available.

after controlling for traditional risk factors and related anomalies from the factor zoo.

The persistence of alpha (22 bps/month) when controlling for six closely related strategies suggests that TDES captures unique information about future stock returns that is not fully reflected in existing factors. This finding has important implications for both academic research and practical investment management, indicating that tax efficiency metrics contain valuable signals for portfolio formation.

However, several limitations warrant consideration. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, the implementation costs and market impact for large-scale portfolios may differ from our estimates. Future research could explore the signal's performance across different market regimes, investigate its interaction with other anomalies, and examine its effectiveness in international markets. Additionally, researchers might consider studying the underlying economic mechanisms driving the TDES premium and its potential relationship with corporate governance and management quality.

Overall, our results suggest that TDES represents a valuable addition to the investment practitioner's toolkit and contributes to our understanding of the determinants of cross-sectional stock returns.

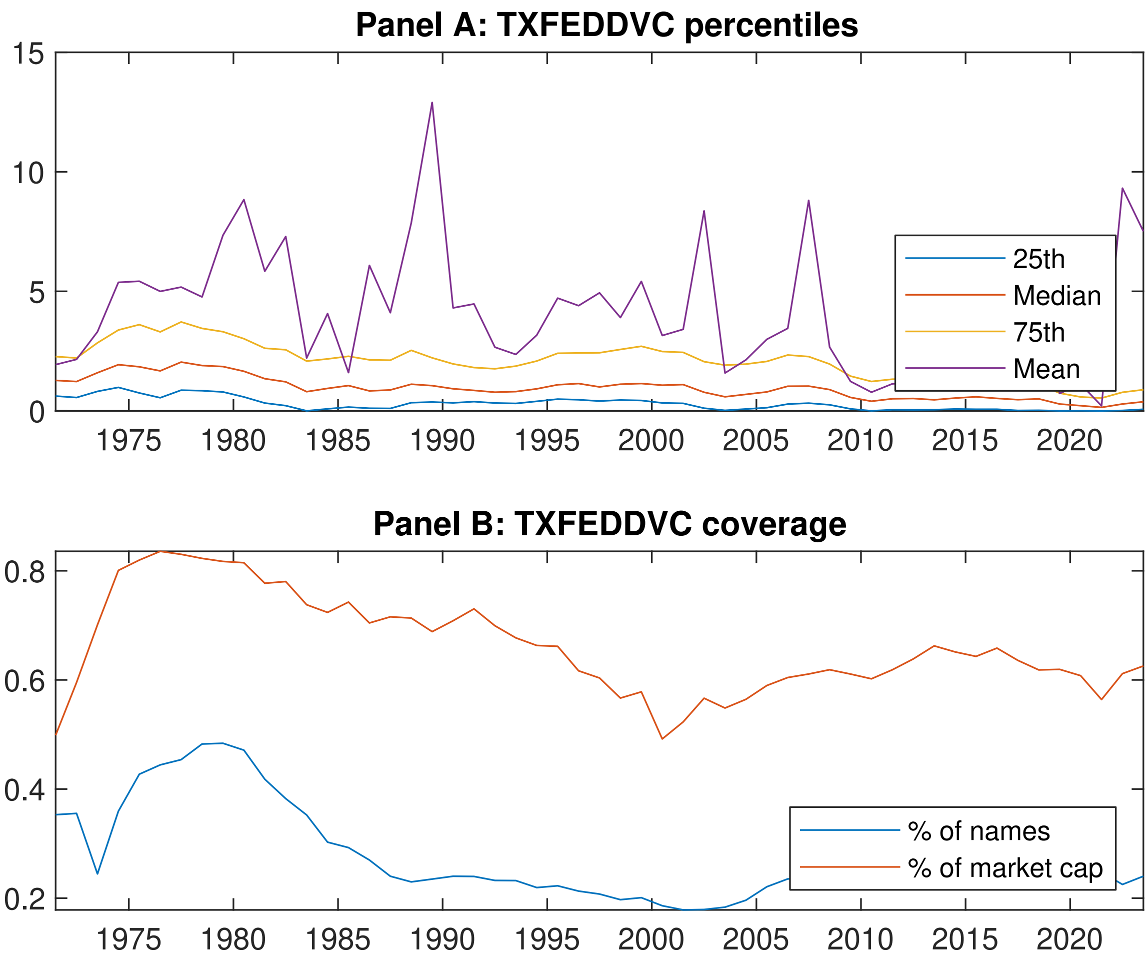


Figure 1: Times series of TDES percentiles and coverage.
This figure plots descriptive statistics for TDES. Panel A shows cross-sectional percentiles of TDES over the sample. Panel B plots the monthly coverage of TDES relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on TDES. 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 197106 to 202306.

Panel A: Excess returns and alphas on TDES-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.52	0.58	0.55	0.70	0.79	0.27
	[2.68]	[3.54]	[3.21]	[3.69]	[3.59]	[2.08]
α_{CAPM}	-0.05	0.09	0.04	0.11	0.11	0.16
	[-0.60]	[1.33]	[0.59]	[1.89]	[1.50]	[1.29]
α_{FF3}	-0.19	0.04	0.01	0.11	0.12	0.31
	[-2.54]	[0.64]	[0.09]	[1.99]	[1.66]	[2.66]
α_{FF4}	-0.15	0.01	-0.00	0.14	0.15	0.31
	[-2.07]	[0.15]	[-0.04]	[2.38]	[2.00]	[2.57]
α_{FF5}	-0.24	-0.13	-0.19	0.01	0.06	0.30
	[-3.50]	[-2.47]	[-3.22]	[0.10]	[0.85]	[2.85]
α_{FF6}	-0.20	-0.14	-0.18	0.03	0.08	0.29
	[-2.92]	[-2.58]	[-3.05]	[0.61]	[1.16]	[2.65]
Panel B: Fama and French (2018) 6-factor model loadings for TDES-sorted portfolios						
β_{MKT}	1.03	0.93	0.94	1.01	1.08	0.06
	[62.93]	[73.75]	[67.63]	[78.13]	[65.65]	[2.32]
β_{SMB}	-0.04	-0.19	-0.15	0.03	0.21	0.25
	[-1.64]	[-10.30]	[-7.01]	[1.66]	[8.31]	[6.52]
β_{HML}	0.16	0.05	0.03	-0.09	-0.01	-0.17
	[5.12]	[1.89]	[1.09]	[-3.68]	[-0.42]	[-3.59]
β_{RMW}	-0.11	0.25	0.41	0.25	0.31	0.42
	[-3.32]	[10.20]	[14.95]	[10.11]	[9.70]	[8.52]
β_{CMA}	0.46	0.32	0.21	0.10	-0.18	-0.65
	[9.82]	[8.81]	[5.11]	[2.78]	[-3.85]	[-8.89]
β_{UMD}	-0.06	0.01	-0.01	-0.04	-0.03	0.03
	[-3.64]	[0.87]	[-0.88]	[-3.31]	[-2.03]	[1.03]
Panel C: Average number of firms (n) and market capitalization (me)						
n	255	223	240	273	344	
me ($\$10^6$)	866	1646	1740	1512	1109	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the TDES 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 197106 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	0.27	0.16	0.31	0.31	0.30	0.29
			[2.08]	[1.29]	[2.66]	[2.57]	[2.85]	[2.65]
Quintile	NYSE	EW	0.17	0.15	0.23	0.18	0.14	0.10
			[1.98]	[1.72]	[2.65]	[2.03]	[1.76]	[1.23]
Quintile	Name	VW	0.29	0.16	0.31	0.31	0.31	0.30
			[2.09]	[1.21]	[2.56]	[2.53]	[2.78]	[2.64]
Quintile	Cap	VW	0.21	0.11	0.25	0.25	0.28	0.26
			[1.78]	[0.94]	[2.36]	[2.28]	[2.83]	[2.62]
Decile	NYSE	VW	0.48	0.39	0.58	0.62	0.57	0.59
			[3.14]	[2.56]	[4.31]	[4.49]	[4.36]	[4.45]

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	0.24	0.13	0.25	0.25	0.23	0.21
			[1.88]	[0.99]	[2.17]	[2.14]	[2.17]	[2.02]
Quintile	NYSE	EW	0.07	0.04	0.10	0.08	0.01	
			[0.75]	[0.47]	[1.18]	[0.88]	[0.12]	
Quintile	Name	VW	0.26	0.12	0.25	0.25	0.23	0.22
			[1.89]	[0.90]	[2.07]	[2.08]	[2.08]	[1.97]
Quintile	Cap	VW	0.19	0.08	0.20	0.20	0.22	0.20
			[1.60]	[0.68]	[1.91]	[1.89]	[2.17]	[2.02]
Decile	NYSE	VW	0.44	0.34	0.51	0.53	0.48	0.48
			[2.89]	[2.22]	[3.73]	[3.88]	[3.65]	[3.68]

Table 3: Conditional sort on size and TDES

This table presents results for conditional double sorts on size and TDES. 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 TDES. 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 TDES and short stocks with low TDES .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 197106 to 202306.

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

Size quintiles	TDES Quintiles					TDES Strategies					
	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.91	0.91	0.88	1.28	0.95	0.04	0.01	0.05	-0.03	0.04	-0.03
	[3.28]	[4.04]	[4.17]	[3.23]	[3.77]	[0.23]	[0.04]	[0.27]	[-0.14]	[0.22]	[-0.16]
(2)	0.75	0.87	0.84	0.83	0.88	0.13	0.08	0.16	0.13	0.06	0.03
	[3.20]	[4.22]	[3.94]	[3.73]	[3.55]	[1.03]	[0.64]	[1.30]	[1.00]	[0.47]	[0.21]
(3)	0.69	0.69	0.80	0.99	0.86	0.16	0.10	0.20	0.19	0.10	0.10
	[3.17]	[3.63]	[4.04]	[4.60]	[3.65]	[1.33]	[0.85]	[1.73]	[1.63]	[0.88]	[0.83]
(4)	0.73	0.66	0.75	0.74	0.75	0.03	-0.05	0.06	0.07	-0.05	-0.04
	[3.46]	[3.57]	[3.94]	[3.72]	[3.29]	[0.21]	[-0.42]	[0.50]	[0.56]	[-0.38]	[-0.31]
(5)	0.50	0.57	0.53	0.66	0.66	0.16	0.03	0.18	0.19	0.25	0.23
	[2.76]	[3.48]	[3.02]	[3.52]	[3.05]	[1.15]	[0.23]	[1.48]	[1.49]	[2.16]	[2.00]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	TDES Quintiles Average n					TDES Quintiles Average market capitalization ($\$10^6$)				
	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	91	92	92	92	92	7	7	8	8	8
(2)	47	47	47	47	47	20	21	21	21	21
(3)	42	42	42	42	42	45	46	46	46	46
(4)	41	41	41	41	41	122	122	124	122	120
(5)	45	45	45	45	45	1000	1411	1198	1308	974

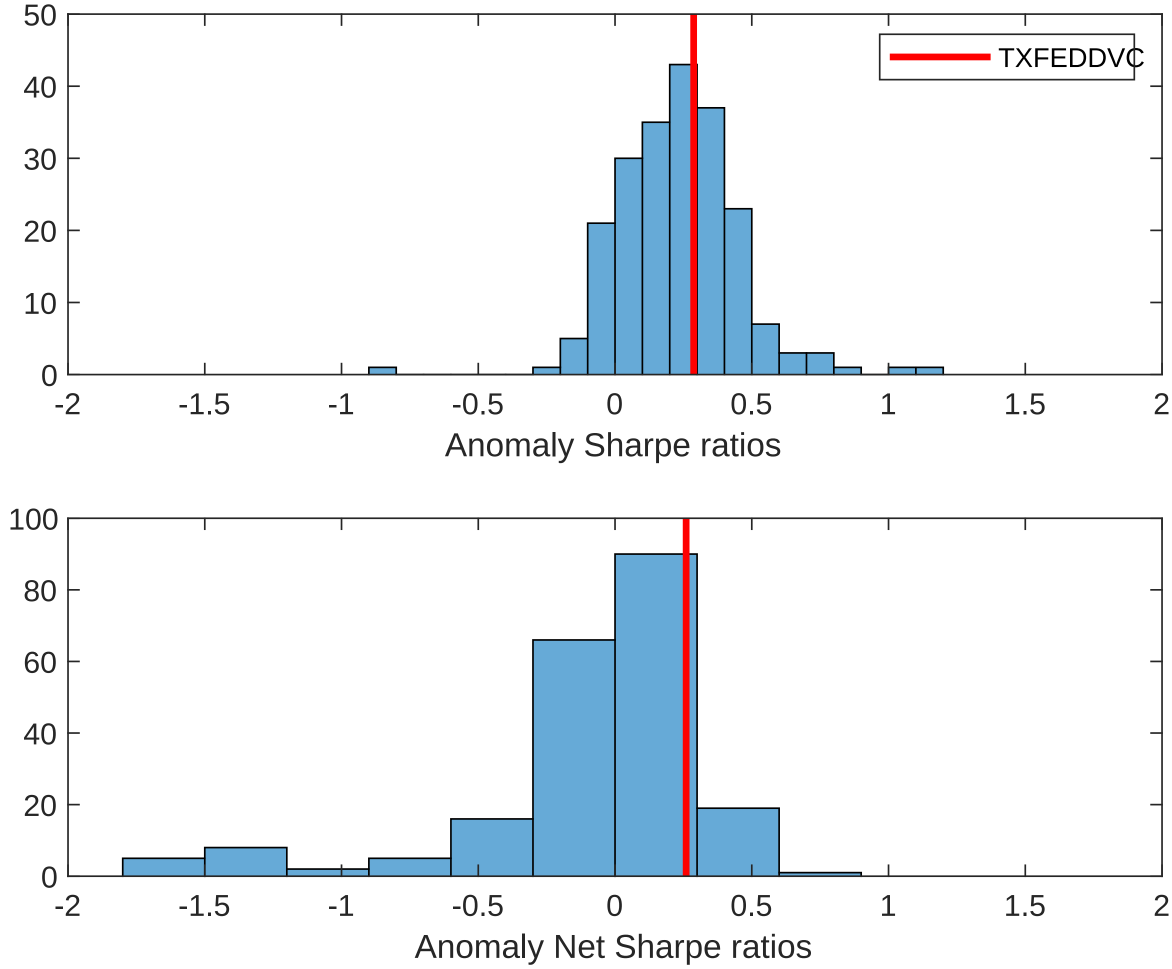


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the TDES with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

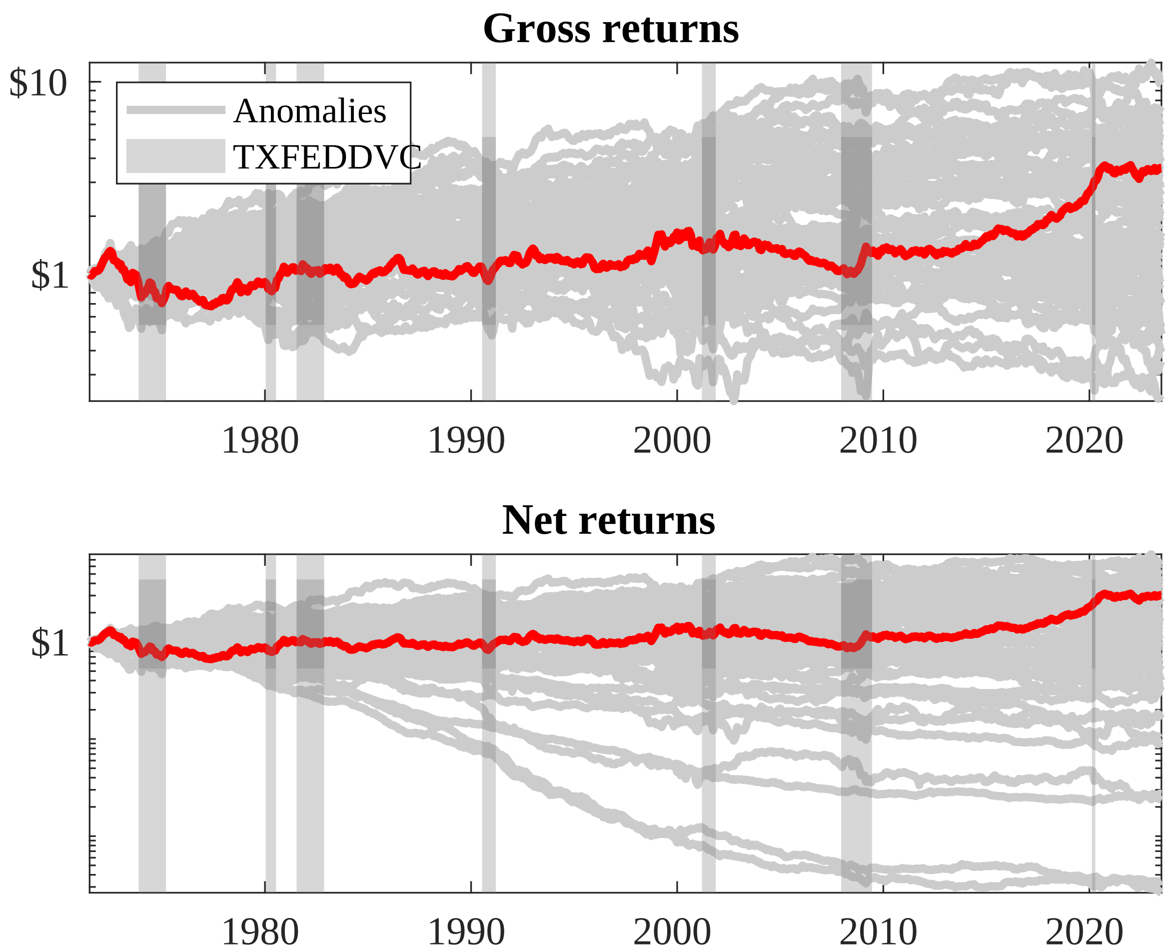


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the TDES trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

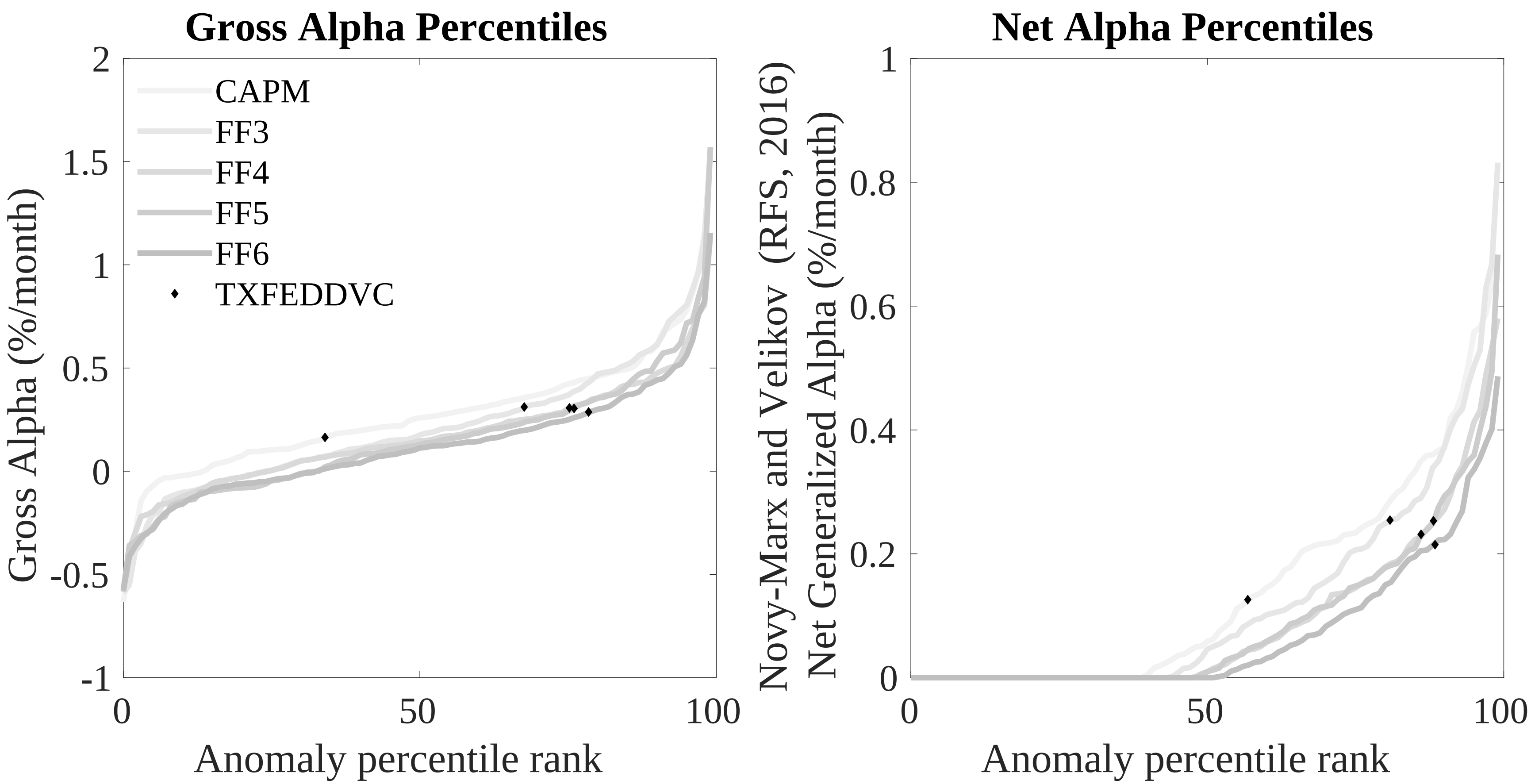
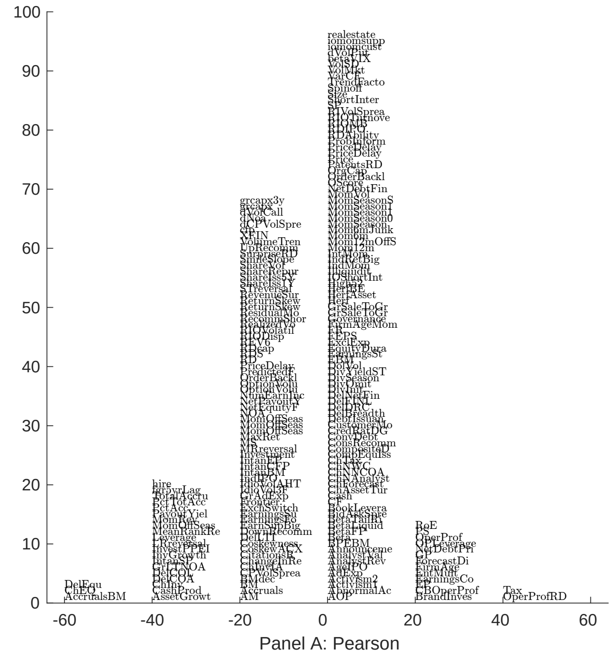


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the TDES trading strategy alphas (diamonds). The strategies are constructed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



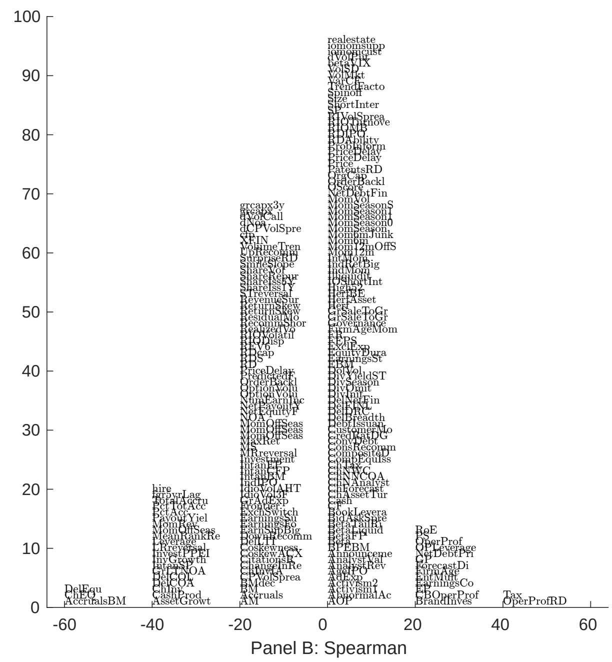


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 202 filtered anomaly signals with TDES. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

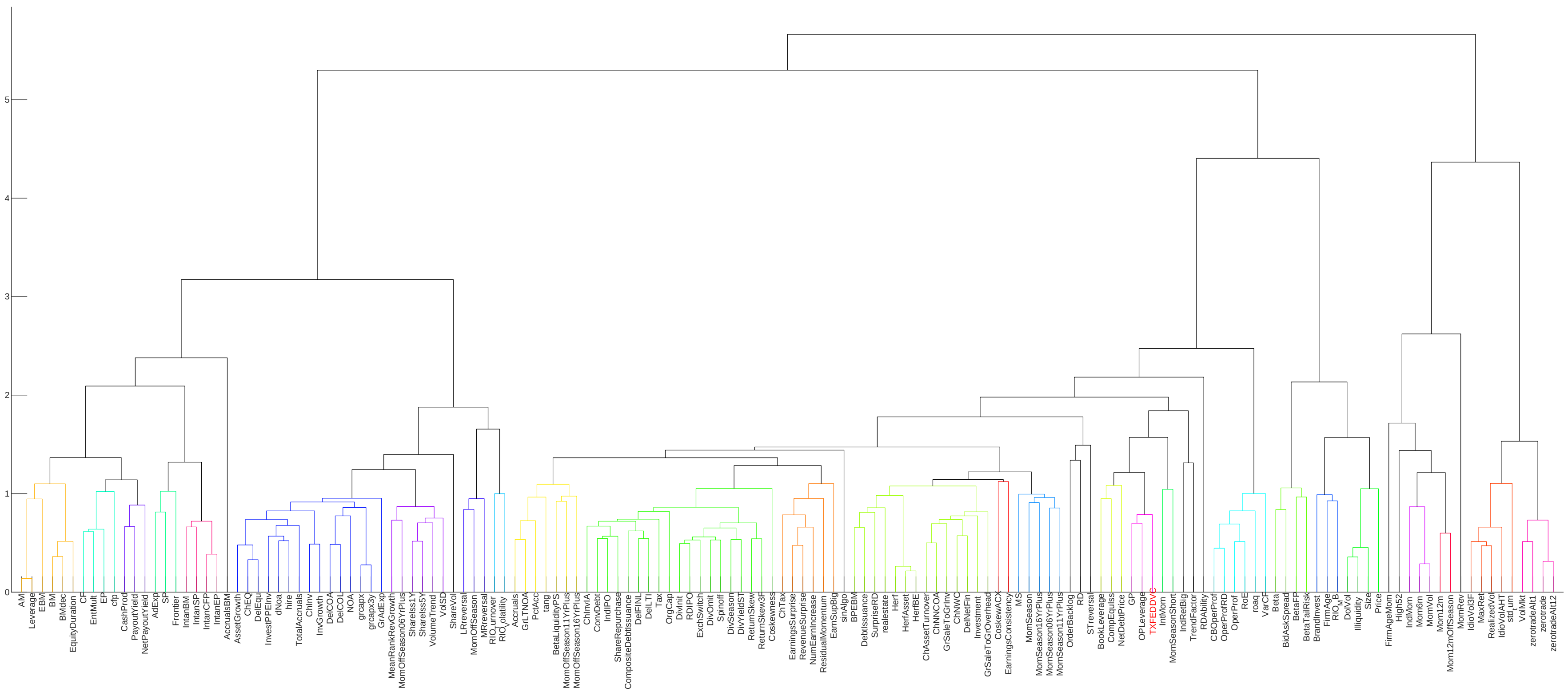


Figure 6: Agglomerative hierarchical cluster plot

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

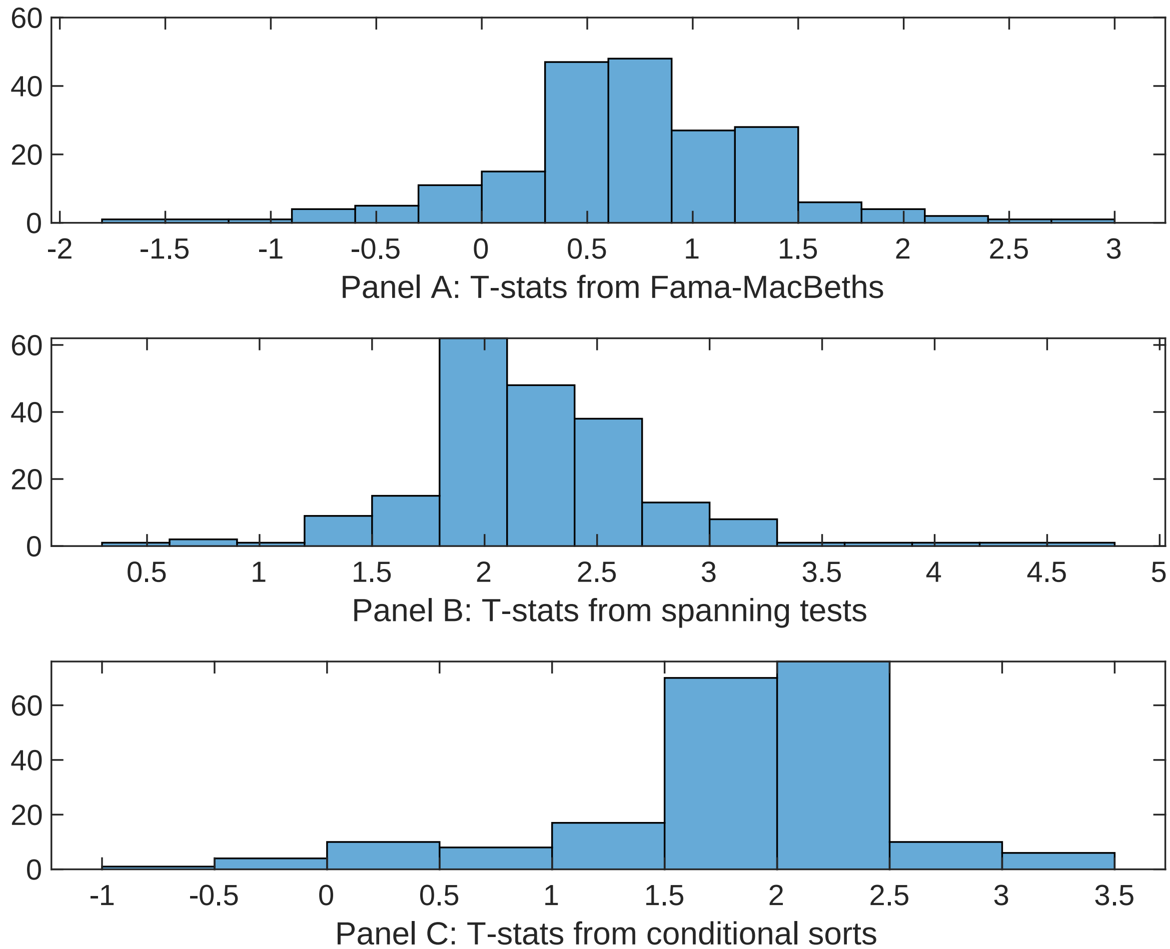


Figure 7: Distribution of t-stats on conditioning strategies

This figure plots histograms of t-statistics for predictability tests of TDES conditioning on each of the 202 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TDES} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TDES} TDES_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 202 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{TDES,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 202 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 202 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on TDES. Stocks are finally grouped into five TDES portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted TDES trading strategies conditioned on each of the 202 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies

This table presents Fama-MacBeth results of returns on TDES. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{TDES}TDES_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^k + \epsilon_{i,t}$. The six most closely related anomalies, X, are Growth in book equity, Change in equity to assets, gross profits / total assets, Long-term EPS forecast, Asset growth, Operating leverage. 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 197106 to 202306.

Intercept	0.19	0.13	0.11	0.13	0.13	0.11	0.13
	[7.71]	[6.39]	[5.76]	[7.08]	[6.73]	[5.91]	[5.87]
TDES	0.15	0.18	0.25	0.30	0.13	0.55	0.30
	[1.36]	[1.70]	[0.21]	[2.11]	[1.17]	[0.47]	[1.86]
Anomaly 1	0.61						0.37
	[4.48]						[0.28]
Anomaly 2		0.16					0.55
		[3.92]					[1.01]
Anomaly 3			0.24				0.18
			[1.69]				[1.04]
Anomaly 4				0.10			0.62
				[1.31]			[0.79]
Anomaly 5					0.84		0.29
					[6.89]		[2.29]
Anomaly 6						0.83	0.28
						[2.12]	[0.55]
# months	624	624	624	492	624	624	492
$\bar{R}^2$(%)	1	1	1	1	1	1	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the TDES trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{TDES} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Growth in book equity, Change in equity to assets, gross profits / total assets, Long-term EPS forecast, Asset growth, Operating leverage. 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 197106 to 202306.

Intercept	0.28	0.27	0.18	0.27	0.27	0.23	0.22
	[2.66]	[2.46]	[1.76]	[2.42]	[2.47]	[2.26]	[1.98]
Anomaly 1	-30.15						-34.25
	[-5.12]						[-3.31]
Anomaly 2		-18.96					23.49
		[-3.30]					[2.19]
Anomaly 3			38.13				22.13
			[9.19]				[3.97]
Anomaly 4				-33.75			-21.28
				[-8.80]			[-4.81]
Anomaly 5					-16.72		6.38
					[-2.35]		[0.80]
Anomaly 6						36.51	18.57
						[8.96]	[3.80]
mkt	4.38	5.44	4.30	-8.98	5.33	6.11	-5.83
	[1.76]	[2.17]	[1.81]	[-3.05]	[2.12]	[2.57]	[-2.01]
smb	25.44	24.50	22.75	-0.80	25.85	9.32	-4.00
	[6.85]	[6.52]	[6.39]	[-0.19]	[6.76]	[2.37]	[-0.91]
hml	-14.50	-15.76	-0.19	4.49	-17.42	2.74	19.74
	[-3.05]	[-3.28]	[-0.04]	[0.85]	[-3.64]	[0.54]	[3.51]
rmw	41.31	40.89	20.30	37.68	42.51	22.45	12.88
	[8.54]	[8.31]	[3.88]	[7.22]	[8.66]	[4.35]	[2.01]
cma	-34.47	-44.43	-61.59	-40.25	-43.22	-72.96	-51.28
	[-3.75]	[-4.75]	[-8.98]	[-5.08]	[-3.78]	[-10.50]	[-4.55]
umd	2.98	2.05	2.30	7.95	1.87	2.58	6.87
	[1.22]	[0.83]	[0.98]	[3.11]	[0.75]	[1.10]	[2.75]
# months	624	624	624	492	624	624	492
$\bar{R}^2(\%)$	41	39	46	42	39	46	47

Panel A: Average rank

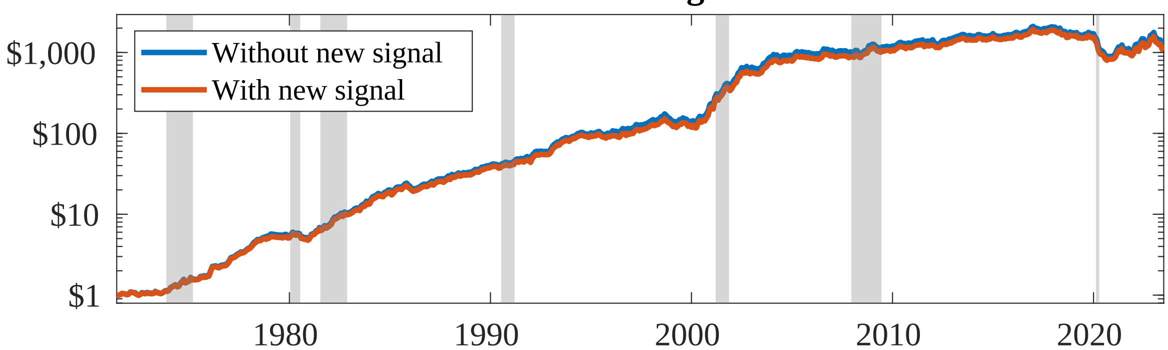


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines indicate combination trading strategies that utilize the 156 anomalies as well as TDES. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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