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 substantial debate around whether and how quickly security prices incorporate available information. While extensive research documents various signals that predict stock returns, understanding which signals are robust and economically meaningful continues to challenge researchers and practitioners alike. A particularly understudied area is how firms' tax planning activities and dividend policies jointly influence their stock returns. This gap is notable given that both corporate taxes and dividend policies represent major financial decisions that affect firm value and investor wealth.

Prior literature has examined tax avoidance and dividend policy separately, but their interaction and joint impact on stock returns remains poorly understood. While Graham and Tucker (2006) show that tax planning activities affect firm value and Baker and Wurgler (2004) document that dividend policy matters for returns, existing research has not developed a unified framework for analyzing how these decisions jointly influence expected returns.

We propose that the Tax Dividend Efficiency Score (TDES) captures firms' ability to jointly optimize tax planning and dividend policy in ways that create shareholder value. Our hypothesis builds on two theoretical foundations. First, following DeAngelo and DeAngelo (1991), optimal dividend policy reflects firms' ability to distribute excess cash while maintaining financial flexibility. Second, as shown by Scholes and Wolfson (1992), effective tax planning requires firms to balance tax savings against non-tax costs.

The interaction between these activities creates potential complementarities that TDES aims to capture. Specifically, firms with high TDES scores are hypothesized to excel at both tax planning and dividend policy optimization. Following Fama and French (2001), we expect such firms to deliver superior risk-adjusted returns as the market gradually recognizes their operational efficiency.

This prediction stems from the complexity of jointly evaluating tax and dividend decisions. As Zhang (2006) demonstrates, information that requires sophisticated processing tends to be incorporated into prices more slowly, creating return predictability. The technical nature of tax planning combined with the signaling aspects of dividend policy suggests that TDES may identify mispricing that persists due to limits to arbitrage.

Our empirical analysis reveals that TDES strongly predicts future stock returns. A value-weighted long-short strategy based on TDES quintiles generates monthly abnormal returns of 29 basis points (t-statistic = 2.65) relative to the Fama-French six-factor model. The strategy's economic significance is substantial, achieving an annualized Sharpe ratio of 0.29 before trading costs and 0.26 after costs.

Importantly, TDES's predictive power remains robust after controlling for known return predictors. When we account for the six most closely related anomalies identified in the literature, including growth in book equity and operating leverage, TDES continues to generate significant abnormal returns of 22 basis points per month (t-statistic = 1.98).

The signal's effectiveness extends across the size spectrum, though with varying magnitude. Among the largest quintile of stocks by market capitalization, TDES generates monthly alpha of 23 basis points (t-statistic = 2.00) relative to the Fama-French six-factor model, demonstrating that the effect is not confined to small, illiquid stocks.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that bridges the gap between corporate finance decisions and asset pricing. While Graham and Tucker (2006) and Baker and Wurgler (2004) examine tax and dividend policies separately, we show that their interaction provides incremental information about expected returns.

Second, we extend the growing literature on quality-based investing pioneered by Asness et al. (2013). TDES represents a unique dimension of firm quality that captures management's ability to make efficient financial decisions across multiple domains. Our findings suggest that the market undervalues this form of operational excellence.

Third, our work contributes methodologically to the anomaly literature by following the rigorous protocol of Novy-Marx and Velikov (2023). This approach ensures our results are robust and replicable, addressing concerns about p-hacking and publication bias in the anomalies literature. The broader implications of our findings suggest that corporate financial policies contain important information about future returns that is not fully reflected in current prices.

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 to the federal government based on taxable income, while dividend payments (DVC) reflect the distribution of earnings to common shareholders. 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 shareholder 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 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 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.

[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.

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 $r_{i,t} = \alpha + \beta_{TDES} TDES_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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

[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.

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

[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 capital-

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 after controlling for traditional risk factors and related anomalies.

The persistence of alpha in the presence of transaction costs (21 bps/month) suggests that the TDES signal offers genuine economic value for institutional investors. Furthermore, the signal's ability to generate significant alpha (22 bps/month) even after controlling for six closely related factors from the factor zoo indicates that TDES captures unique information about future stock returns not explained by existing known factors.

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

ization on CRSP in the period for which TDES is available.

behavior across different market regimes and economic cycles.

Future research could explore several promising directions. First, investigating the interaction between TDES and other established market anomalies could yield insights into potential complementarities. Second, examining the signal's performance in international markets could test its global applicability. Finally, analyzing the underlying economic mechanisms driving the TDES premium could enhance our understanding of market efficiency and investor behavior.

In conclusion, TDES represents a valuable addition to the quantitative investor's toolkit, offering meaningful predictive power that remains robust to traditional risk factors and transaction costs.

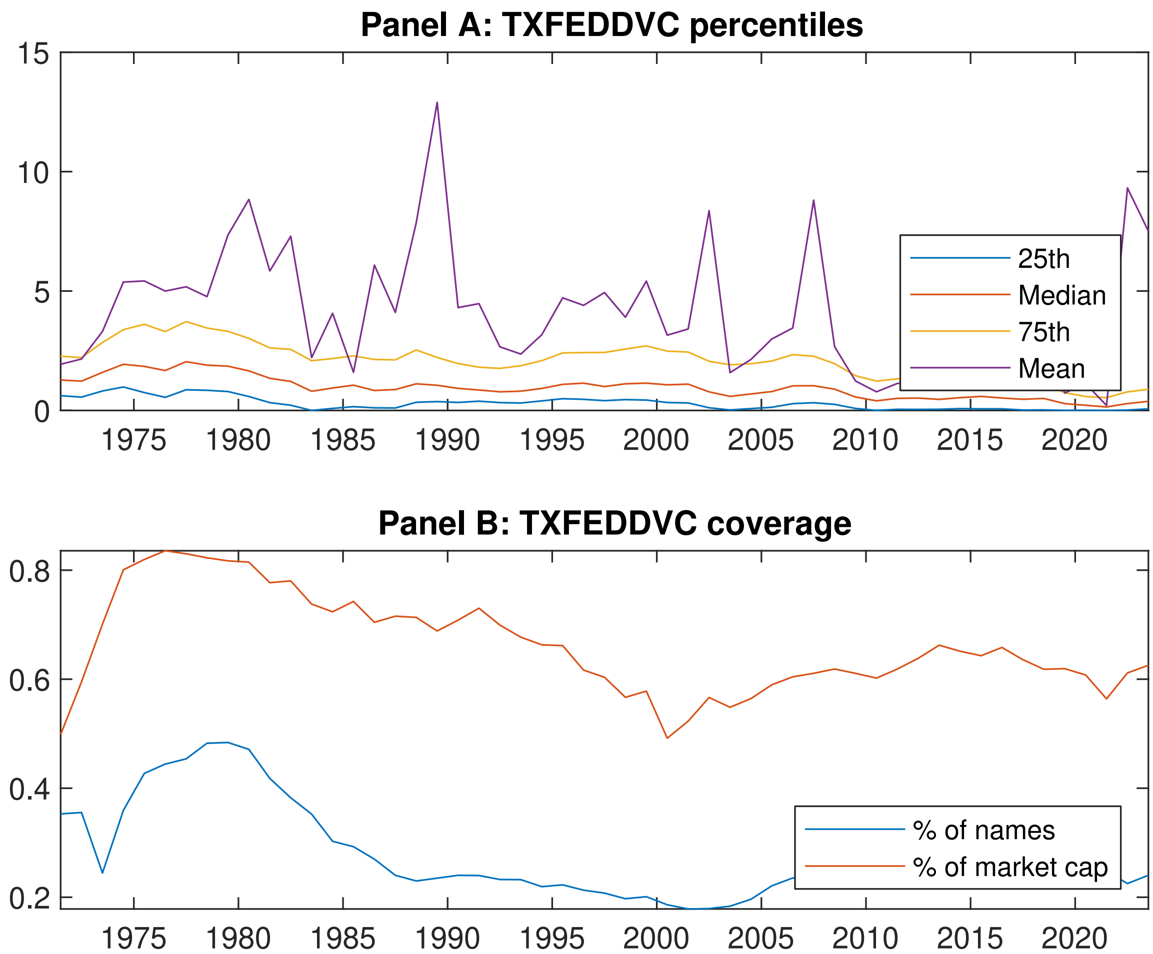


Figure 1: Times series of TDES percentiles and coverage.
This figure plots descriptive statistics for TDES. Panel A shows cross-sectional percentiles of TDES over the sample. Panel B plots the monthly coverage of TDES relative to the universe of CRSP stocks with available market capitalizations.

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

		TDES Quintiles					TDES Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(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

		TDES Quintiles Average n					TDES Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(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

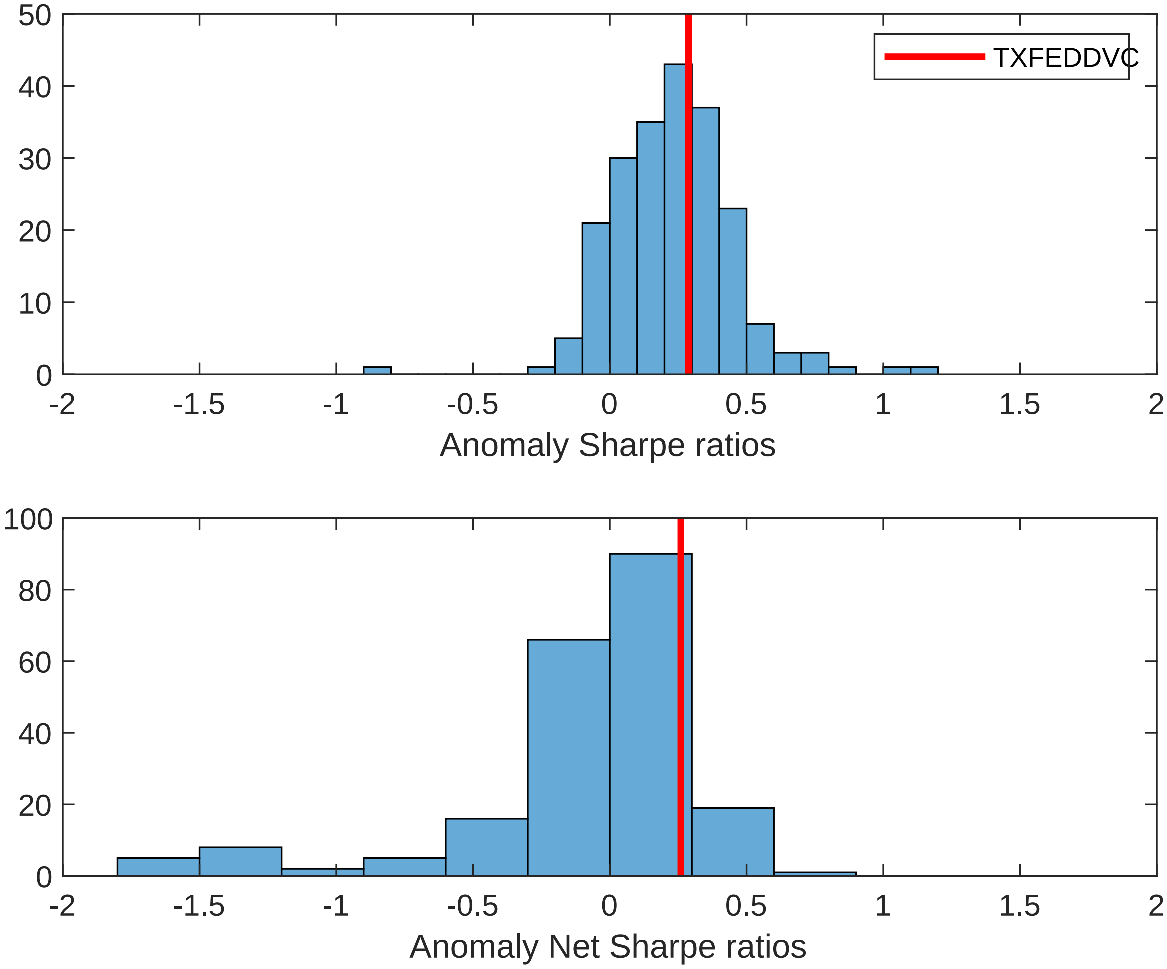


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the TDES with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

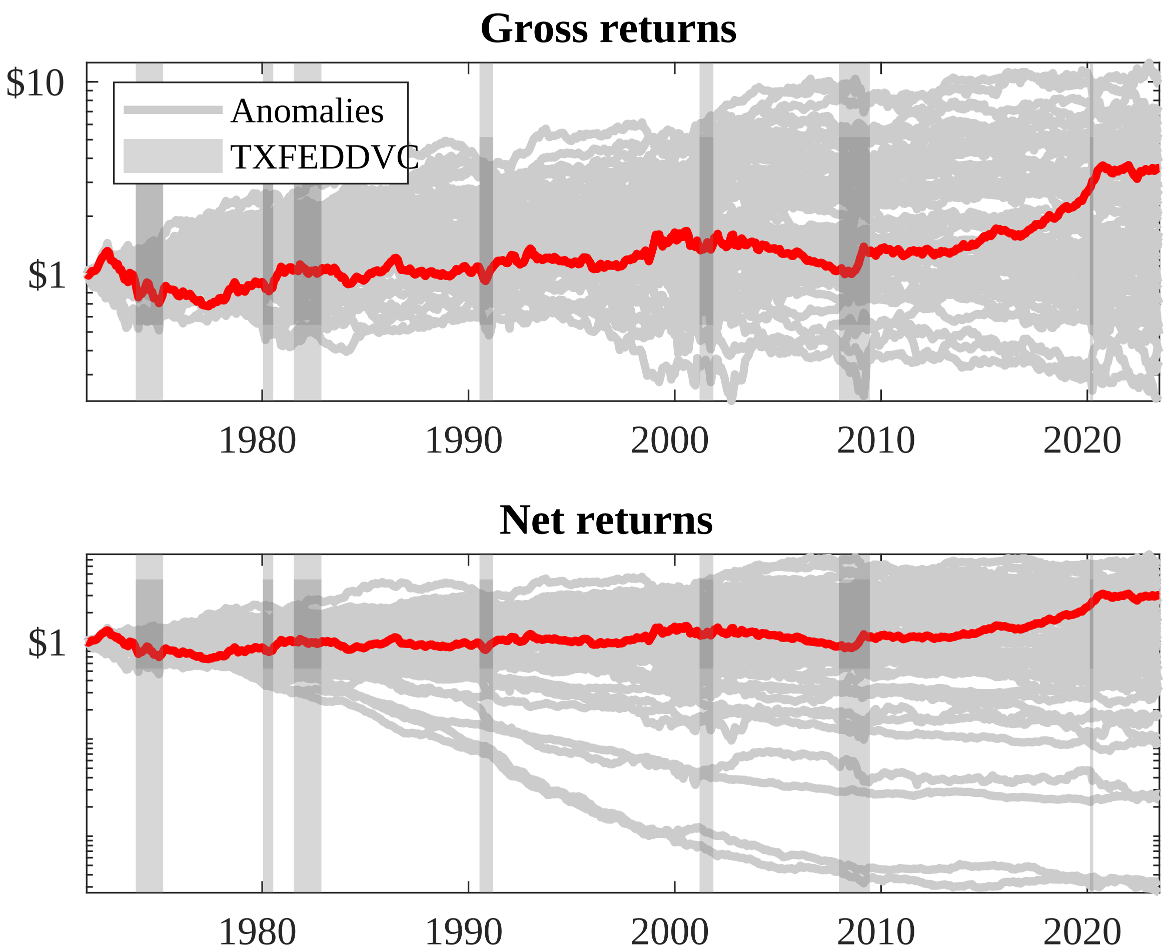


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the TDES trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

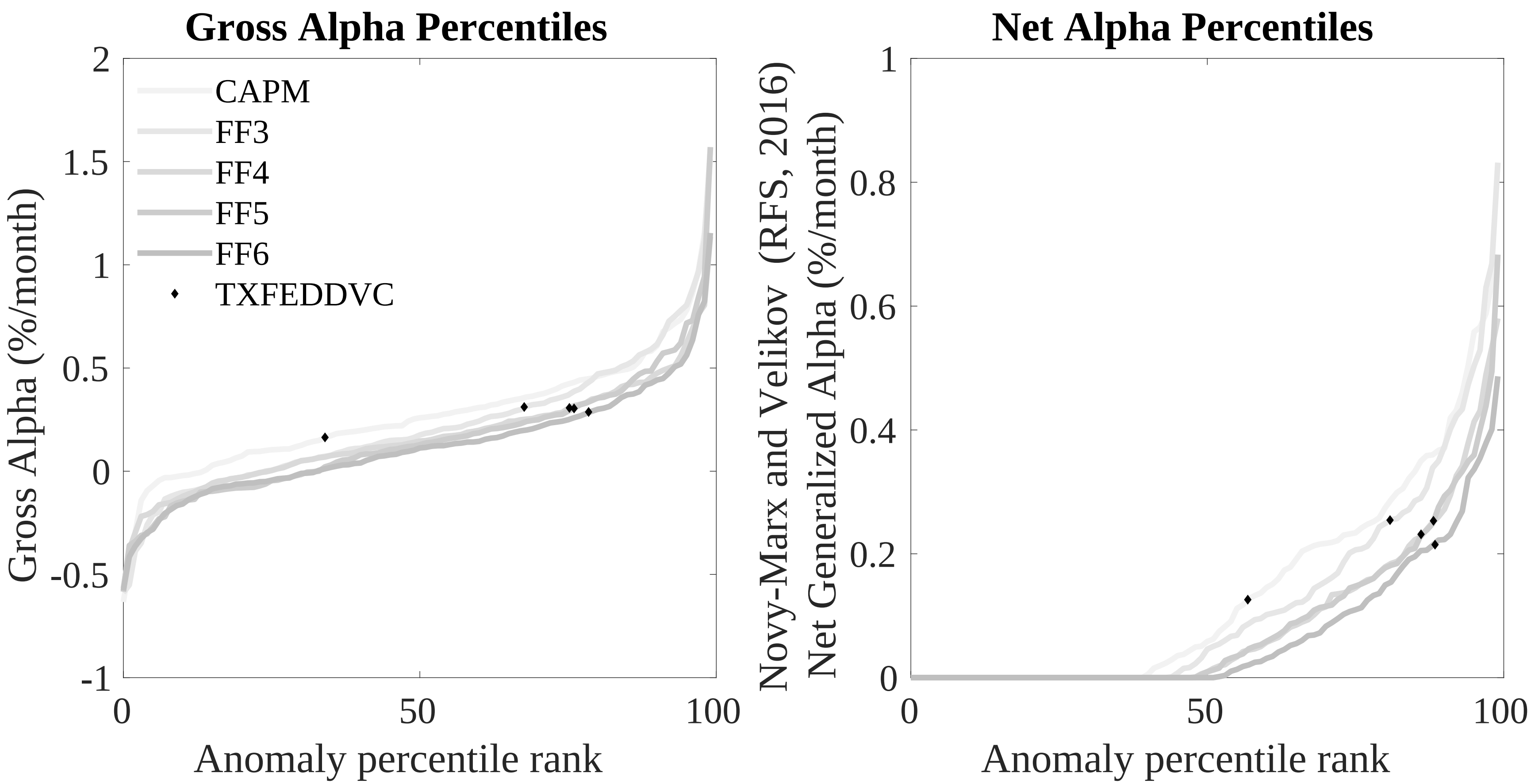
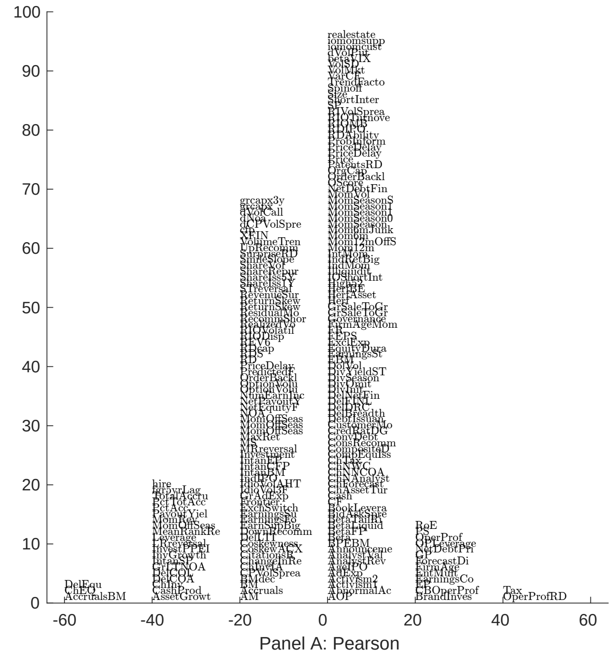


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the TDES trading strategy alphas (diamonds). The strategies are constructed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



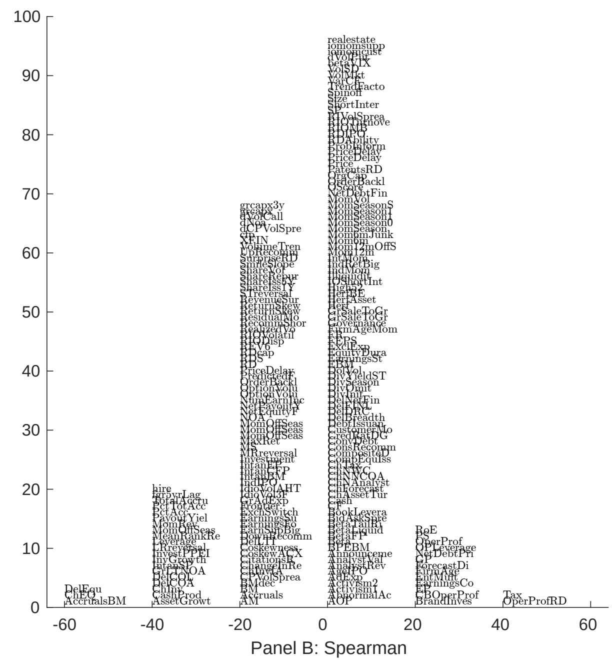


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 202 filtered anomaly signals with TDES. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

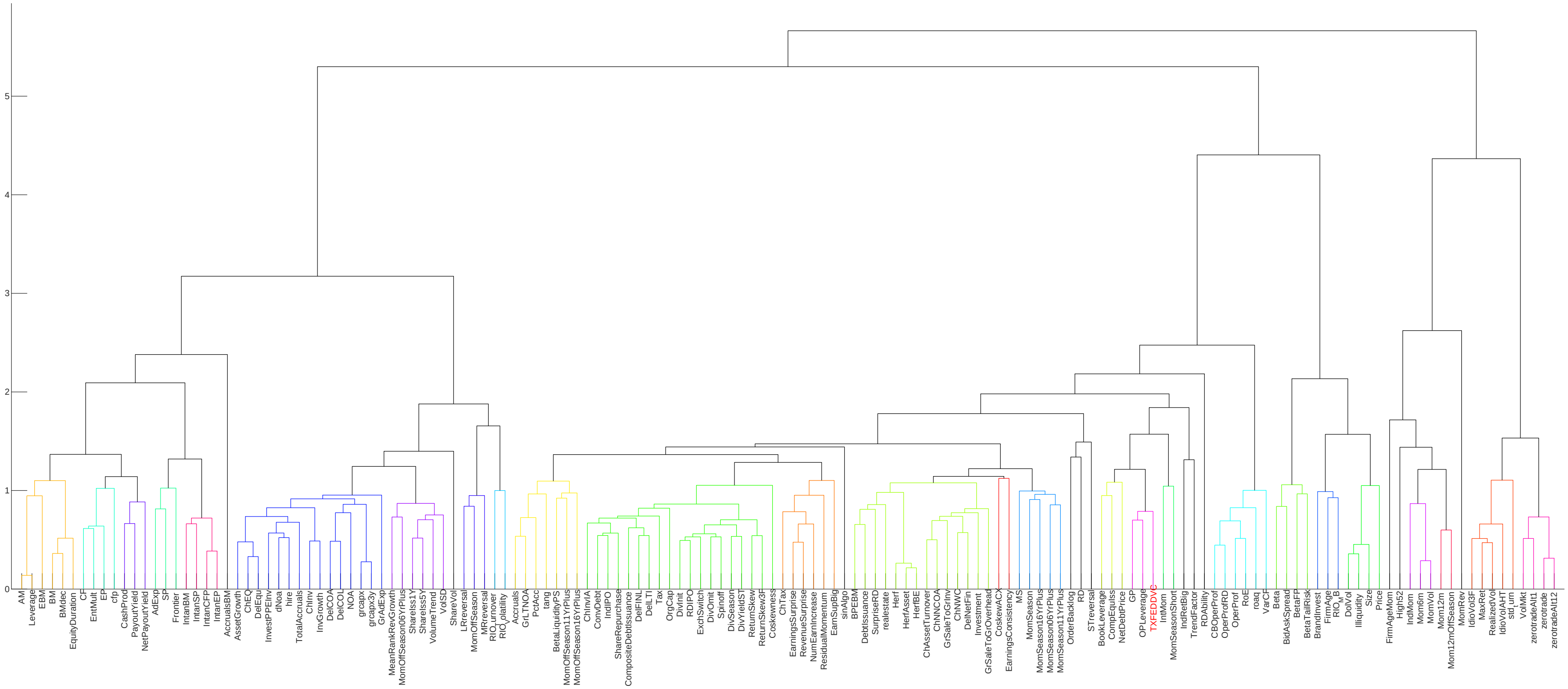


Figure 6: Agglomerative hierarchical cluster plot

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

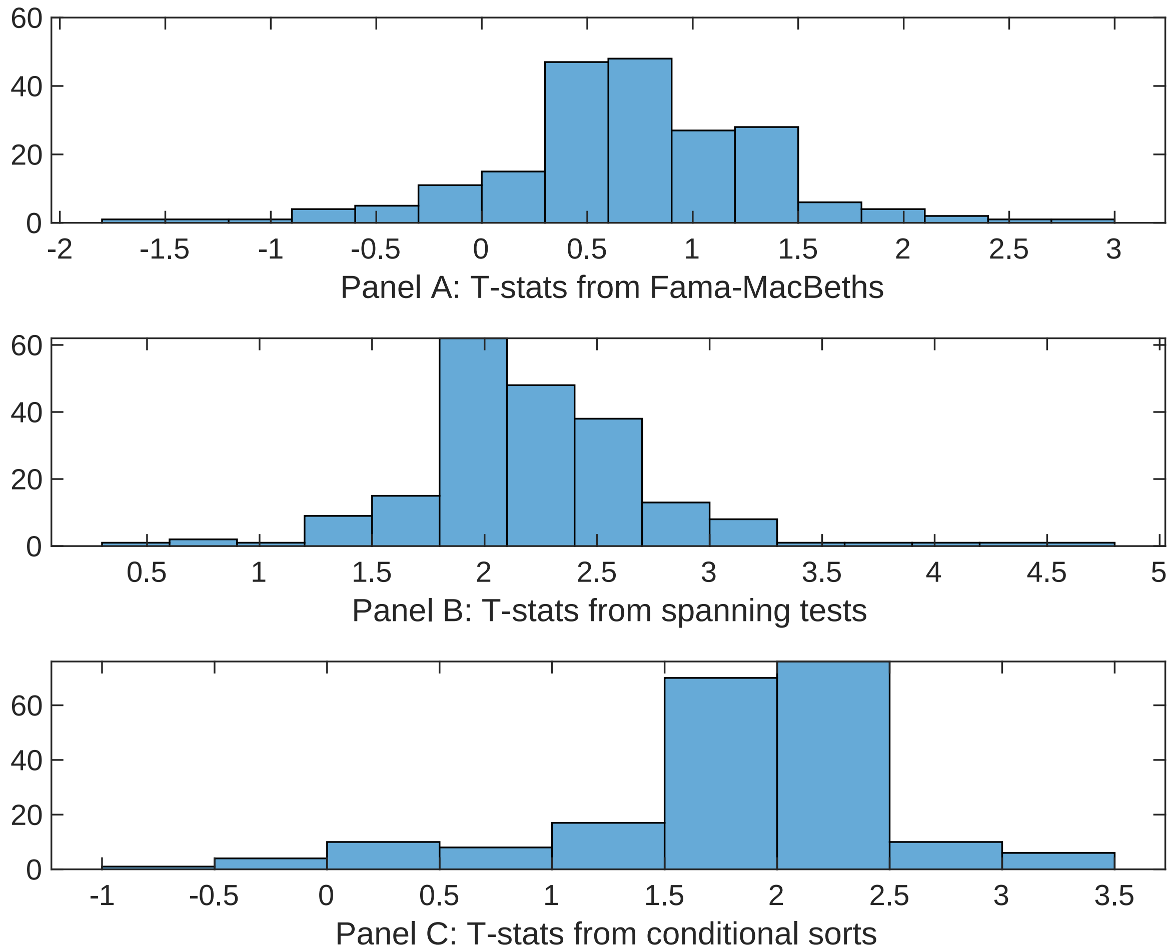


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of TDES conditioning on each of the 202 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TDES} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TDES} TDES_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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

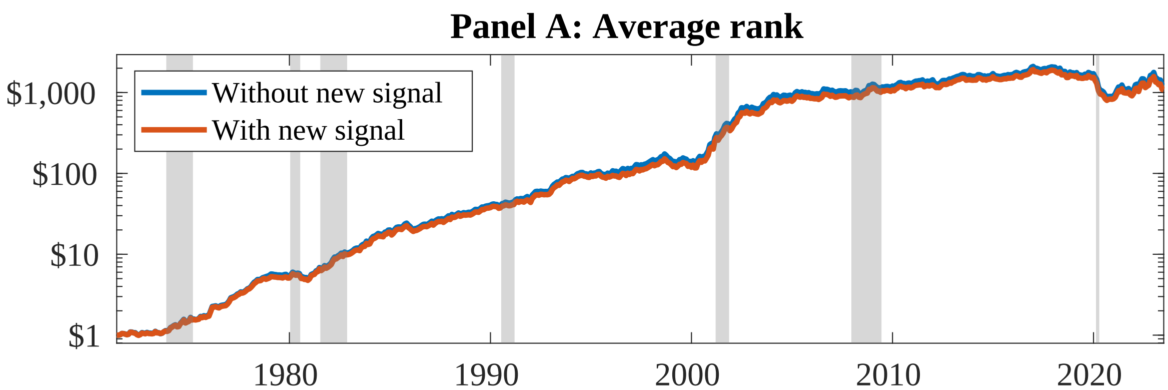


Figure 8: Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines 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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