

Tax Dividend Coverage Metric and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Tax Dividend Coverage Metric (TDCM), 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 TDCM achieves an annualized gross (net) Sharpe ratio of 0.32 (0.29), and monthly average abnormal gross (net) return relative to the [Fama and French \(2015\)](#) five-factor model plus a momentum factor of 27 (20) bps/month with a t-statistic of 2.56 (1.94), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (gross profits / total assets, Growth in book equity, Change in equity to assets, Asset growth, Payout Yield, Operating leverage) is 20 bps/month with a t-statistic of 2.16.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to identify reliable signals that predict cross-sectional stock returns. While hundreds of potential predictors have been documented in the literature (Harvey et al., 2016), many fail to survive careful scrutiny of their robustness and economic mechanisms (?). A particularly challenging puzzle is understanding how firms' tax and dividend policies jointly influence expected returns, as these decisions reflect both fundamental firm characteristics and managerial incentives.

Prior research has examined tax effects (Graham and Kumar, 2006) and dividend policy (Baker and Wurgler, 2004) separately, but their interaction remains understudied. This gap is notable given that tax considerations significantly influence payout decisions, while dividend policy signals information about future profitability (?). The Tax Dividend Coverage Metric (TDCM) offers a novel lens through which to examine this intersection.

We hypothesize that TDCM captures information about firms' financial strength and management quality through three channels. First, following (?), firms with higher tax coverage of dividends likely have more sustainable earnings and lower risk of dividend cuts, as tax payments represent a hard constraint that must be met before distributions to shareholders. This suggests TDCM may predict returns by proxying for earnings quality.

Second, building on (?), managers are reluctant to cut dividends due to the negative signal it sends to markets. Therefore, firms maintaining high TDCM demonstrate confidence in their ability to generate sufficient cash flows to meet both tax and dividend obligations, potentially indicating superior operating performance (?).

Third, consistent with (?), agency theory suggests that paying both substantial taxes and dividends constrains managers' ability to engage in empire-building or other value-destroying activities. Thus, high TDCM may identify firms with better

corporate governance and more efficient capital allocation.

Our empirical analysis reveals that TDCM strongly predicts stock returns. A value-weighted long-short strategy based on TDCM quintiles generates significant abnormal returns of 27 basis points per month (t-statistic = 2.56) relative to the Fama-French five-factor model plus momentum. The strategy achieves an annualized gross Sharpe ratio of 0.32, placing it in the top third of documented return predictors.

Importantly, TDCM’s predictive power persists after controlling for related anomalies. When we simultaneously control for the six most closely related predictors - including gross profitability, asset growth, and payout yield - TDCM continues to generate an alpha of 20 basis points monthly (t-statistic = 2.16). This indicates TDCM captures unique information about expected returns.

The signal’s robustness is further demonstrated by its effectiveness across different methodological choices. Using alternative portfolio construction approaches and accounting for transaction costs, TDCM consistently generates positive abnormal returns. The strategy’s net Sharpe ratio of 0.29 ranks in the top 10% of anomalies after incorporating trading costs.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that bridges the gap between tax and dividend research, building on work by (Graham and Kumar, 2006) on tax effects and (Baker and Wurgler, 2004) on dividend policy. TDCM provides new insights into how these corporate decisions jointly influence expected returns.

Second, we extend the literature on quality factors in asset pricing (Asness et al., 2013). While prior work has focused on earnings quality (?) and accruals (?), TDCM offers a unique measure that captures both earnings sustainability and management quality through the lens of tax and dividend coverage.

Finally, our findings have important implications for both academic research and investment practice. For researchers, we demonstrate the value of combining multiple

corporate decision signals to create more powerful return predictors. For practitioners, TDCM represents a novel tool for security selection that remains robust after transaction costs and across different implementation approaches.

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 Coverage Metric, 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 DVT for total dividend payments. Federal income tax expense (TXFED) represents the firm’s actual tax obligations to the federal government, reflecting the firm’s taxable income and effective tax management. Total dividends (DVT), on the other hand, captures the aggregate amount of dividend distributions made by the firm to its shareholders during the fiscal year. The construction of the signal follows a straightforward ratio format, where we divide TXFED by DVT for each firm in each year of our sample. This ratio provides insight into the relationship between a firm’s tax obligations and its dividend payout policy, potentially reflecting aspects of financial planning and cash flow management. By examining this relationship, the signal aims to capture information about a firm’s ability to balance tax obligations with shareholder distributions in a manner that is both measurable and comparable across firms. We construct this ratio using end-of-fiscal-year values for both TXFED and DVT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the TDCM signal. Panel A plots the time-series of the mean, median, and interquartile range for TDCM. On average, the cross-sectional mean (median) TDCM is 5.08 (0.78) over the 1971 to 2023 sample, where the starting date is determined by the availability of the input TDCM data. The signal’s interquartile range spans -0.00 to 3.65. Panel B of Figure 1 plots the time-series of the coverage of the TDCM signal for the CRSP universe. On average, the TDCM signal is available for 2.79% of CRSP names, which on average make up 5.73% of total market capitalization.

4 Does TDCM predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on TDCM 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 TDCM portfolio and sells the low TDCM 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 TDCM strategy earns an average return of 0.29% per month with a t-statistic of 2.33. The annualized Sharpe ratio of the strategy is 0.32. The alphas range from 0.21% to 0.34% per month and have t-statistics exceeding 1.67 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 0.52,

with a t-statistic of 10.91 on the RMW 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 254 stocks and an average market capitalization of at least \$825 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 portfolio 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 25 bps/month with a t-statistics of 2.20. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-one exceed two, and for seven 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 21-45bps/month. The lowest return, (21 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 1.53. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the TDCM trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-three cases, and significantly expands the achievable frontier in seventeen cases.

Table 3 provides direct tests for the role size plays in the TDCM strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and TDCM, as well as average returns and alphas for long/short trading TDCM 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 80th NYSE percentile), the TDCM strategy achieves an average return of 16 bps/month with a t-statistic of 1.18. Among these large cap stocks, the alphas for the TDCM strategy relative to the five most common factor models range from 4 to 21 bps/month with t-statistics between 0.30 and 1.86.

5 How does TDCM perform relative to the zoo?

Figure 2 puts the performance of TDCM 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 TDCM strategy falls in the distribution. The TDCM strategy’s gross (net) Sharpe ratio of 0.32 (0.29) is greater than 67% (90%) of anomaly Sharpe ratios,

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

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 TDCM strategy (red line).² Ignoring trading costs, a \$1 invested in the TDCM strategy would have yielded \$3.18 which ranks the TDCM strategy in the top 6% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the TDCM strategy would have yielded \$2.49 which ranks the TDCM strategy in the top 4% 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 TDCM relative to those. Panel A shows that the TDCM strategy gross alphas fall between the 42 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 TDCM strategy has a positive net generalized alpha for five out of the five factor models. In these cases TDCM ranks between the 62 and 90 percentiles in terms of how much it could have expanded the achievable investment frontier.

²The 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 TDCM 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 TDCM with 203 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 TDCM or at least to weaken the power TDCM has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of TDCM conditioning on each of the 203 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TDCM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TDCM}TDCM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 203 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{TDCM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 203 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 203 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on TDCM. Stocks are finally grouped into five TDCM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these

³When 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.

conditional double-sorted TDCM trading strategies conditioned on each of the 203 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on TDCM 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 TDCM signal in these Fama-MacBeth regressions exceed -0.27, with the minimum t-statistic occurring when controlling for gross profits / total assets. Controlling for all six closely related anomalies, the t-statistic on TDCM is 0.99.

Similarly, Table 5 reports results from spanning tests that regress returns to the TDCM 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 TDCM strategy earns alphas that range from 16-29bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.62, 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 TDCM trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.16.

7 Does TDCM add relative to the whole zoo?

Finally, we can ask how much adding TDCM 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 TDCM 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 TDCM grows to \$1085.84.

8 Conclusion

This study provides compelling evidence for the predictive power of the Tax Dividend Coverage Metric (TDCM) in forecasting cross-sectional stock returns. Our findings demonstrate that TDCM-based trading strategies yield economically and statistically significant returns, with a value-weighted long/short portfolio generating an impressive annualized Sharpe ratio of 0.32 (0.29 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 TDCM’s predictive power, evidenced by monthly abnormal returns of 27 basis points (20 basis points net of costs) relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information not fully reflected in market prices. Furthermore, the signal’s ability to generate an alpha of 20 basis points per month even after controlling for six closely related anomalies indicates its distinctive contribution to the cross-section of expected returns.

⁴We 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 TDCM is available.

However, several limitations warrant consideration. First, our analysis period may not fully capture varying market conditions and regulatory environments. Second, the implementation costs might vary across different market segments and time periods. Future research could explore the signal's effectiveness in international markets, its interaction with other established anomalies, and its performance under different market regimes. Additionally, investigating the underlying economic mechanisms driving the TDCM effect could provide valuable insights for both academics and practitioners.

In conclusion, TDCM represents a valuable addition to the investment practitioner's toolkit, offering a robust signal for portfolio formation while contributing to our understanding of market efficiency and asset pricing.

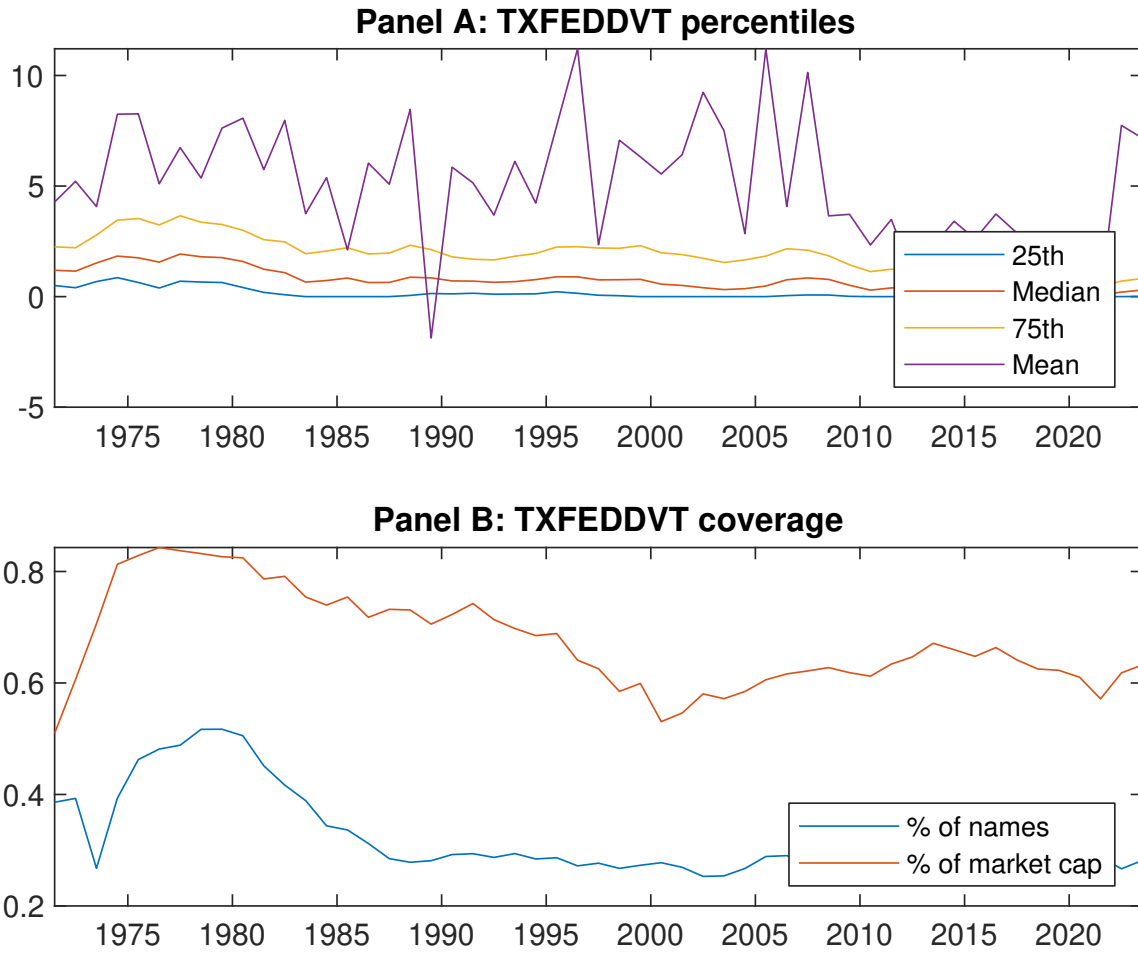


Figure 1: Times series of TDCM percentiles and coverage.
This figure plots descriptive statistics for TDCM. Panel A shows cross-sectional percentiles of TDCM over the sample. Panel B plots the monthly coverage of TDCM relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on TDCM. 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 TDCM-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.48 [2.41]	0.55 [3.34]	0.55 [3.22]	0.71 [3.79]	0.77 [3.52]	0.29 [2.33]
α_{CAPM}	-0.11 [-1.35]	0.06 [0.84]	0.04 [0.61]	0.12 [2.21]	0.09 [1.29]	0.21 [1.67]
α_{FF3}	-0.23 [-3.08]	-0.01 [-0.11]	0.00 [0.05]	0.14 [2.40]	0.11 [1.58]	0.34 [2.96]
α_{FF4}	-0.19 [-2.55]	-0.02 [-0.42]	-0.01 [-0.15]	0.15 [2.58]	0.14 [1.99]	0.34 [2.86]
α_{FF5}	-0.23 [-3.30]	-0.14 [-2.65]	-0.19 [-3.26]	0.02 [0.37]	0.05 [0.76]	0.28 [2.72]
α_{FF6}	-0.19 [-2.73]	-0.14 [-2.62]	-0.19 [-3.15]	0.04 [0.71]	0.08 [1.13]	0.27 [2.56]
Panel B: Fama and French (2018) 6-factor model loadings for TDCM-sorted portfolios						
β_{MKT}	1.04 [63.48]	0.94 [73.63]	0.94 [68.59]	1.00 [81.41]	1.09 [68.32]	0.05 [2.02]
β_{SMB}	-0.00 [-0.08]	-0.19 [-10.07]	-0.14 [-7.05]	0.02 [1.12]	0.21 [8.80]	0.21 [5.78]
β_{HML}	0.13 [4.23]	0.07 [2.70]	0.04 [1.50]	-0.08 [-3.46]	-0.05 [-1.57]	-0.18 [-3.85]
β_{RMW}	-0.23 [-7.24]	0.17 [6.66]	0.39 [14.76]	0.28 [11.83]	0.29 [9.32]	0.52 [10.91]
β_{CMA}	0.41 [8.72]	0.32 [8.73]	0.20 [5.17]	0.07 [2.02]	-0.15 [-3.36]	-0.57 [-8.02]
β_{UMD}	-0.06 [-3.60]	0.00 [0.06]	-0.01 [-0.42]	-0.03 [-2.23]	-0.04 [-2.44]	0.02 [0.82]
Panel C: Average number of firms (n) and market capitalization (me)						
n	364	264	254	294	389	
me (\$10 ⁶)	825	1585	1832	1626	1124	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the TDCM 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	0.29 [2.33]	0.21 [1.67]	0.34 [2.96]	0.34 [2.86]	0.28 [2.72]	0.27 [2.56]
Quintile	NYSE	EW	0.35 [2.62]	0.41 [3.03]	0.39 [2.95]	0.27 [2.06]	0.05 [0.49]	-0.03 [-0.23]
Quintile	Name	VW	0.40 [3.04]	0.33 [2.55]	0.47 [3.76]	0.44 [3.52]	0.32 [2.84]	0.30 [2.66]
Quintile	Cap	VW	0.25 [2.20]	0.17 [1.50]	0.30 [2.84]	0.30 [2.78]	0.27 [2.87]	0.26 [2.72]
Decile	NYSE	VW	0.49 [3.31]	0.44 [2.96]	0.62 [4.52]	0.66 [4.73]	0.53 [4.10]	0.56 [4.27]
Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	r_{net}^e	α_{CAPM}^*	α_{FF3}^*	α_{FF4}^*	α_{FF5}^*	α_{FF6}^*
Quintile	NYSE	VW	0.26 [2.09]	0.17 [1.33]	0.28 [2.44]	0.28 [2.41]	0.22 [2.07]	0.20 [1.94]
Quintile	NYSE	EW	0.21 [1.53]	0.24 [1.72]	0.21 [1.58]	0.15 [1.11]		
Quintile	Name	VW	0.36 [2.78]	0.29 [2.20]	0.40 [3.24]	0.39 [3.14]	0.27 [2.35]	0.24 [2.20]
Quintile	Cap	VW	0.23 [2.00]	0.14 [1.22]	0.25 [2.38]	0.25 [2.37]	0.22 [2.27]	0.20 [2.14]
Decile	NYSE	VW	0.45 [3.04]	0.39 [2.59]	0.54 [3.94]	0.57 [4.10]	0.45 [3.48]	0.45 [3.54]

Table 3: Conditional sort on size and TDCM

This table presents results for conditional double sorts on size and TDCM. 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 TDCM. 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 TDCM and short stocks with low TDCM .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	TDCM Quintiles					TDCM Strategies						
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
	(1)	0.66 [2.16]	0.33 [0.98]	0.67 [2.77]	1.12 [3.54]	0.90 [3.60]	0.24 [1.31]	0.29 [1.58]	0.24 [1.36]	0.26 [1.44]	-0.00 [-0.00]	0.02 [0.12]
	(2)	0.50 [1.91]	0.71 [3.15]	0.84 [3.92]	0.82 [3.68]	0.83 [3.33]	0.33 [2.48]	0.37 [2.68]	0.37 [2.71]	0.35 [2.49]	0.09 [0.77]	0.08 [0.70]
	(3)	0.71 [2.87]	0.66 [3.32]	0.78 [3.92]	0.99 [4.61]	0.83 [3.52]	0.12 [0.85]	0.14 [0.99]	0.16 [1.13]	0.19 [1.31]	-0.14 [-1.15]	-0.10 [-0.83]
	(4)	0.64 [2.89]	0.65 [3.46]	0.73 [3.80]	0.74 [3.72]	0.79 [3.47]	0.15 [1.15]	0.12 [0.89]	0.19 [1.50]	0.17 [1.27]	-0.02 [-0.19]	-0.04 [-0.31]
	(5)	0.49 [2.65]	0.54 [3.28]	0.57 [3.28]	0.66 [3.48]	0.64 [2.98]	0.16 [1.18]	0.04 [0.30]	0.19 [1.54]	0.20 [1.62]	0.21 [1.86]	0.21 [1.79]
Panel B: Portfolio average number of firms and market capitalization												
Size quintiles	TDCM Quintiles					TDCM Quintiles						
		Average n					Average market capitalization (\$10 ⁶)					
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)	
	(1)	125	124	127	128	128	9	7	10	12	12	
	(2)	53	53	53	53	53	22	23	24	24	24	
	(3)	45	45	45	45	45	49	49	49	50	49	
	(4)	43	43	43	43	43	127	128	131	127	126	
(5)	46	46	46	46	46	983	1440	1218	1324	974		

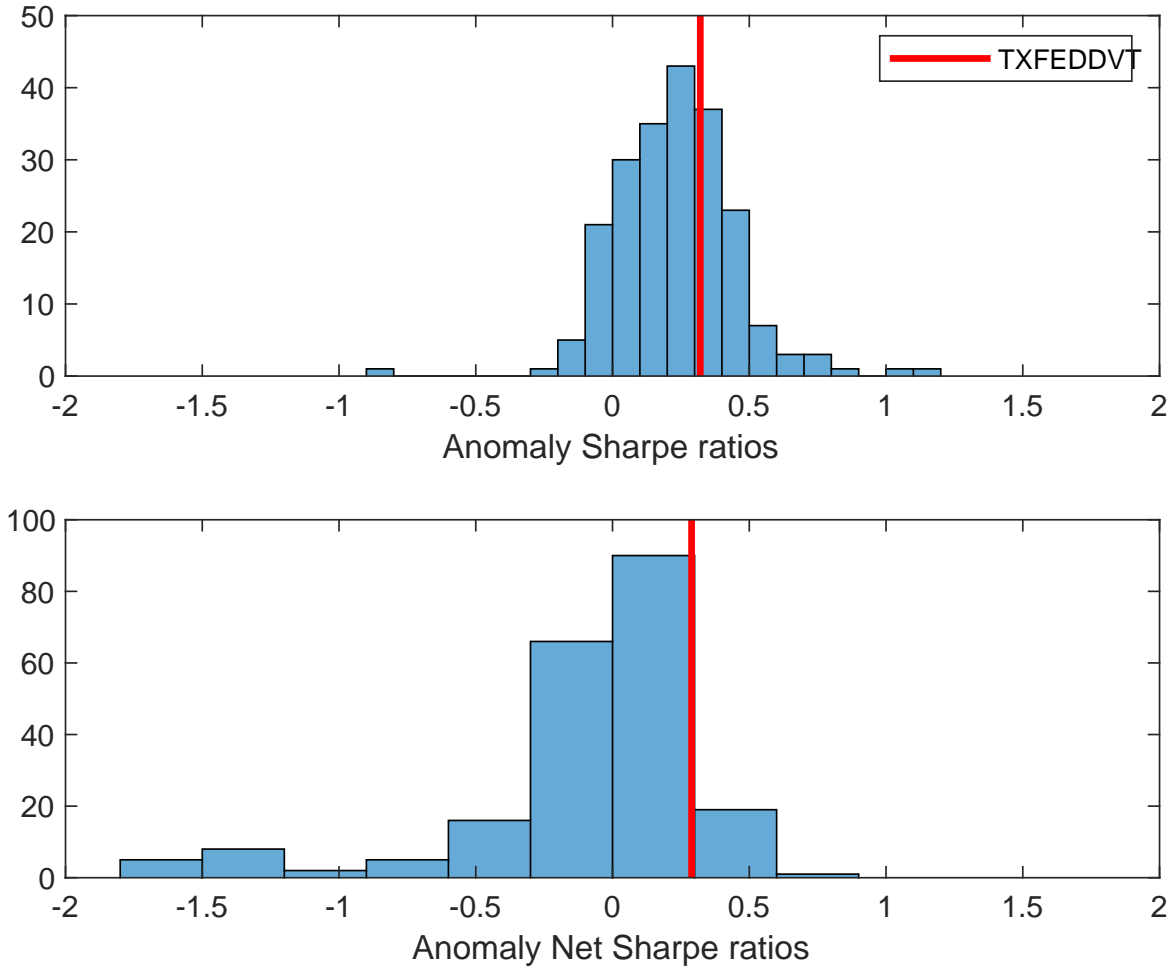


Figure 2: Distribution of Sharpe ratios. This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the TDCM with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

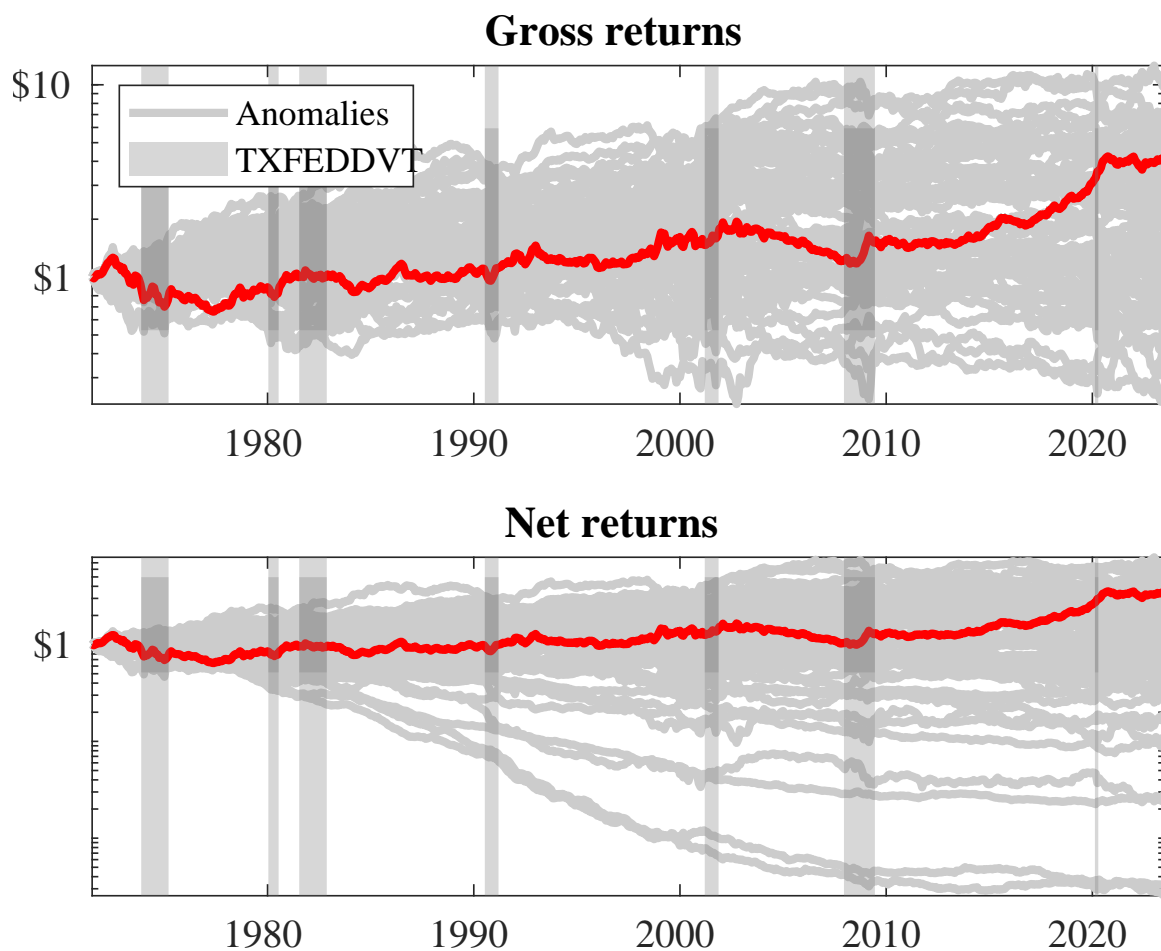


Figure 3: Dollar invested.

This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the TDCM 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 strategy returns.

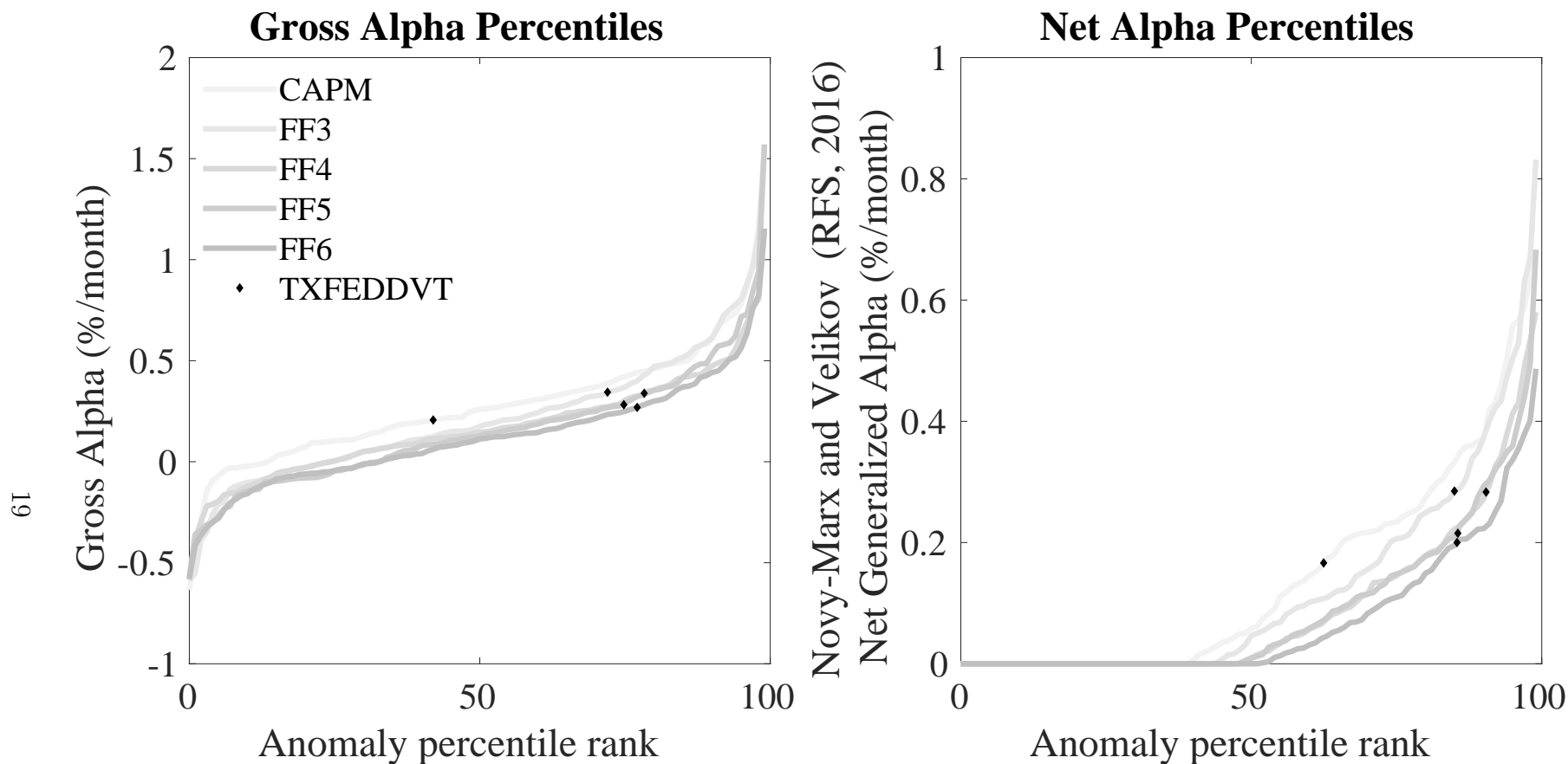


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models

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

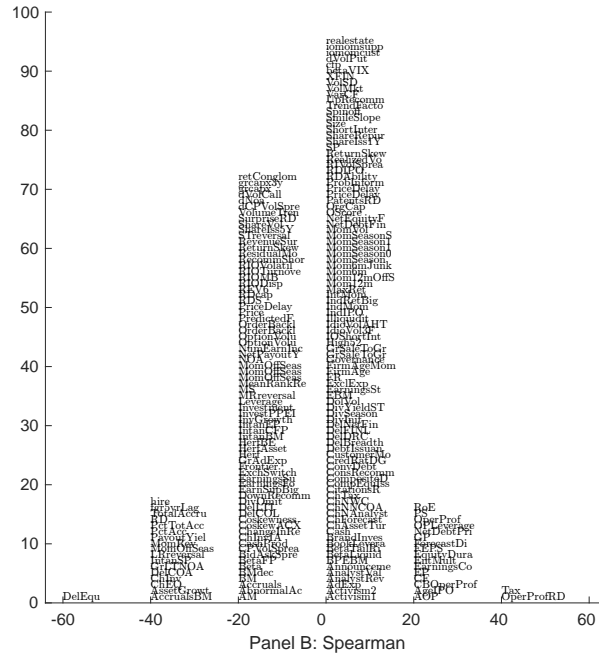
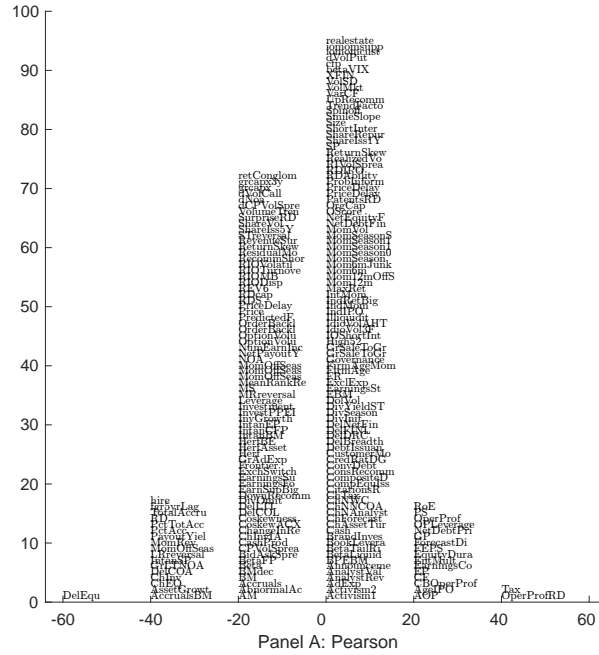


Figure 5: Distribution of correlations.

This figure plots a name histogram of correlations of 203 filtered anomaly signals with TDCM. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

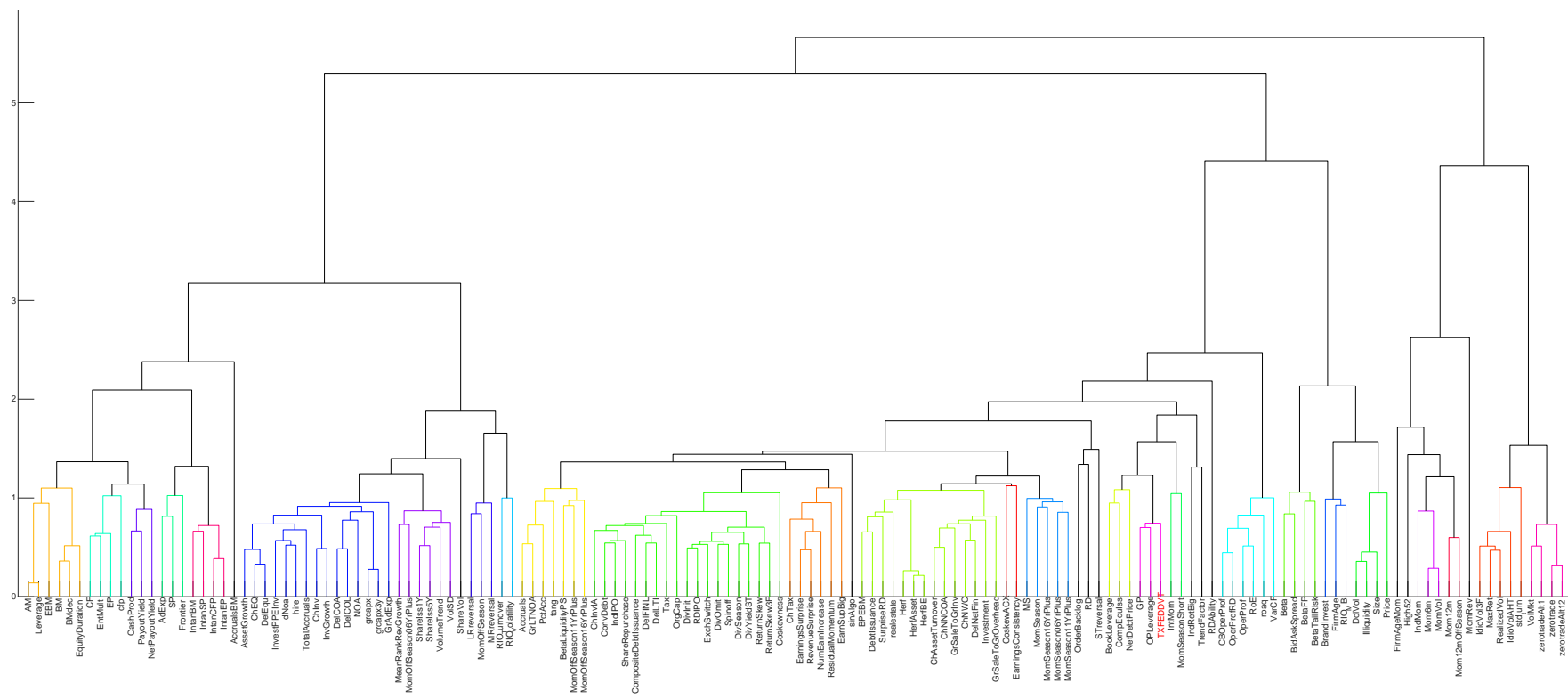


Figure 6: Agglomerative hierarchical cluster plot

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

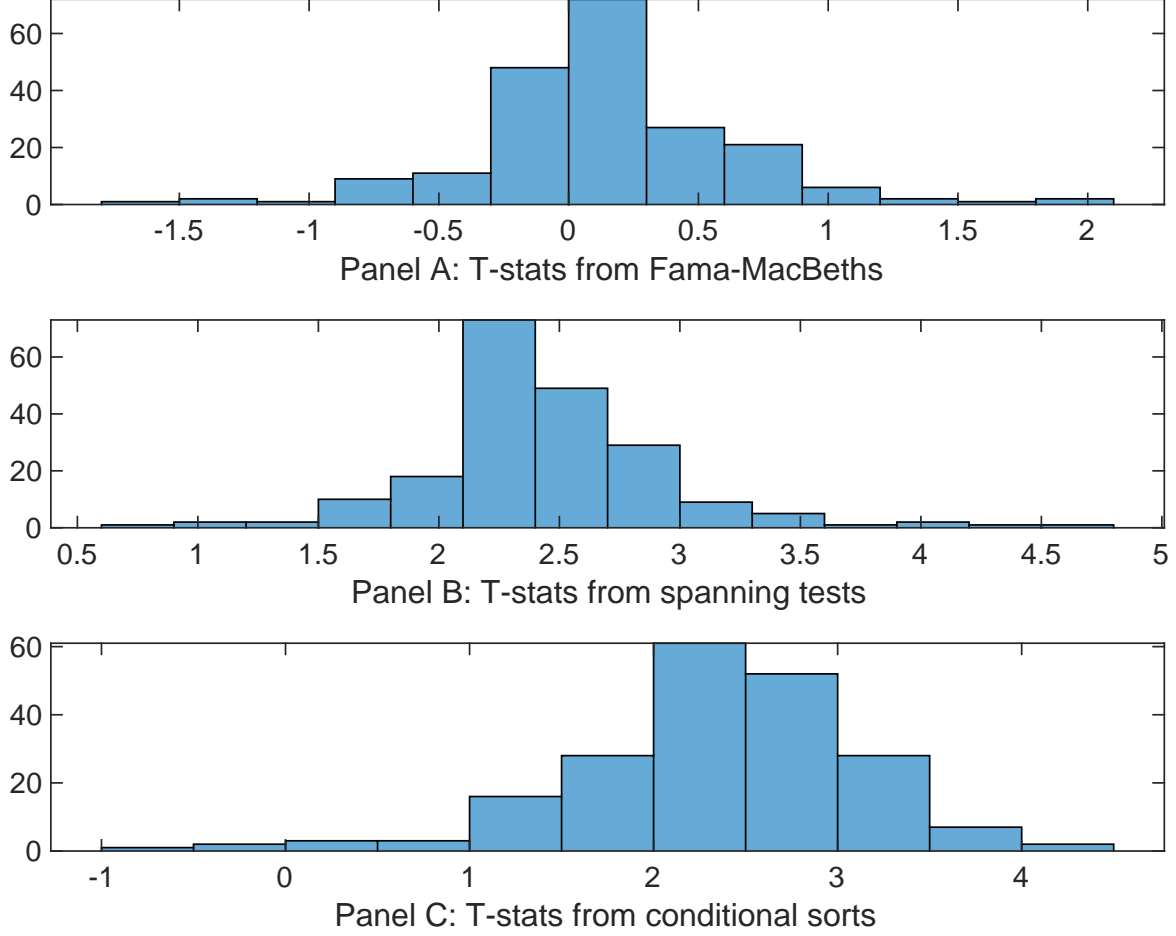


Figure 7: Distribution of t-stats on conditioning strategies

This figure plots histograms of t-statistics for predictability tests of TDCM conditioning on each of the 203 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{TDCM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TDCM}TDCM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 203 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{TDCM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 203 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 on one of the 203 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on TDCM. Stocks are finally grouped into five TDCM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted TDCM trading strategies conditioned on each of the 203 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on TDCM. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{TDCM}TDCM_{i,t} + \sum_{k=1}^s \beta_{X_k}X_{i,t}^k + \epsilon_{i,t}$. The six most closely related anomalies, X , are gross profits / total assets, Growth in book equity, Change in equity to assets, Asset growth, Payout Yield, 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	0.92 [4.06]	0.18 [7.59]	0.12 [5.70]	0.13 [6.12]	0.12 [5.89]	0.10 [4.84]	0.12 [5.04]
TDCM	-0.26 [-0.27]	0.46 [0.52]	0.69 [0.79]	0.45 [0.48]	0.64 [0.87]	-0.95 [-0.09]	0.70 [0.99]
Anomaly 1	0.59 [3.44]						0.37 [2.36]
Anomaly 2		0.57 [4.78]					0.69 [0.45]
Anomaly 3			0.19 [4.74]				0.69 [1.24]
Anomaly 4				1.00 [8.12]			0.64 [5.57]
Anomaly 5					-0.38 [-0.96]		-0.50 [-1.26]
Anomaly 6						0.12 [2.71]	0.35 [0.78]
# months	624	624	624	624	619	624	619
$\bar{R}^2(\%)$	1	1	1	1	1	0	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the TDCM trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{TDCM} = \alpha + \sum_{k=1}^6 \beta_{X_k} r_t^{X_k} + \sum_{j=1}^6 \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 gross profits / total assets, Growth in book equity, Change in equity to assets, Asset growth, Payout Yield, 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	0.16 [1.62]	0.26 [2.57]	0.25 [2.37]	0.25 [2.38]	0.29 [2.80]	0.21 [2.16]	0.20 [2.16]
Anomaly 1	39.18 [9.81]						29.87 [7.08]
Anomaly 2		-30.79 [-5.40]					-51.87 [-6.69]
Anomaly 3			-18.68 [-3.35]				25.24 [3.29]
Anomaly 4				-16.20 [-2.35]			5.24 [0.77]
Anomaly 5					-13.48 [-3.53]		3.24 [0.82]
Anomaly 6						36.96 [9.41]	30.73 [7.52]
mkt	3.35 [1.47]	3.44 [1.43]	4.52 [1.86]	4.41 [1.81]	1.79 [0.71]	5.20 [2.27]	2.97 [1.31]
smb	19.31 [5.64]	22.07 [6.14]	21.10 [5.79]	22.41 [6.04]	18.89 [5.15]	5.74 [1.51]	8.05 [2.21]
hml	-0.36 [-0.08]	-15.09 [-3.28]	-16.46 [-3.53]	-18.10 [-3.90]	-12.65 [-2.50]	2.34 [0.48]	12.99 [2.68]
rmw	29.86 [5.94]	51.45 [10.99]	51.09 [10.71]	52.69 [11.06]	51.43 [10.81]	32.38 [6.51]	18.86 [3.86]
cma	-53.43 [-8.10]	-25.75 [-2.90]	-36.62 [-4.04]	-35.77 [-3.23]	-50.34 [-6.88]	-64.98 [-9.69]	-46.07 [-4.57]
umd	1.69 [0.75]	2.39 [1.01]	1.45 [0.60]	1.29 [0.53]	-0.65 [-0.26]	1.98 [0.87]	3.50 [1.58]
# months	624	624	624	624	620	624	620
$\bar{R}^2(\%)$	46	41	39	38	40	46	54

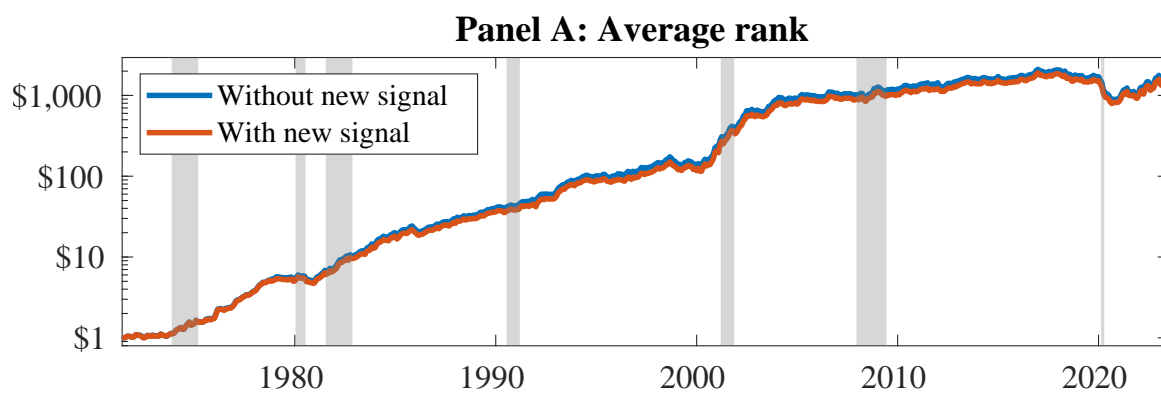


Figure 8: Combination strategy performance

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 TDCM. Panel A shows results using "Average rank" as the combination method. See [Section 7](#) for details on the combination methods.

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