# 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 numerous accounting-based anomalies have been documented, the relationship between firms' tax planning activities and future stock performance remains relatively unexplored. This gap is particularly notable given that tax strategies can significantly impact firms' cash flows and reveal information about managerial decision-making.

Prior literature has focused primarily on accounting accruals Sloan (1996), profitability measures Novy-Marx (2013), and investment patterns **?** as return predictors. However, these traditional metrics may not fully capture the information content embedded in firms' tax planning activities, which can signal both operational efficiency and financial sophistication.

We hypothesize that the Tax Dividend Coverage Metric (TDCM) contains valuable information about future stock returns for several reasons. First, following Miller and Modigliani (1961), a firm's dividend policy reflects management's confidence in sustainable future cash flows. The tax coverage of these dividends may therefore signal the quality and sustainability of earnings. Second, building on **?**, firms with higher TDCM likely have more sophisticated financial planning capabilities, suggesting better overall management quality.

The predictive power of TDCM may also stem from market participants' limited attention to complex tax information Hirshleifer and Teoh (2003). While investors readily process simple accounting metrics, they may underreact to signals requiring more sophisticated analysis of tax planning effectiveness. This cognitive constraint could lead to systematic mispricing that resolves as the implications of tax strategies become apparent.

Additionally, higher TDCM may indicate lower risk of regulatory scrutiny and tax-related costs, consistent with ?'s framework for analyzing corporate tax avoidance. Firms successfully managing their tax obligations while maintaining dividend payments demonstrate both financial strength and risk management capability, qualities that could predict superior future performance.

Our empirical analysis reveals that TDCM strongly predicts cross-sectional stock returns. A value-weighted long-short strategy based on TDCM quintiles generates a significant monthly alpha of 27 basis points (t-statistic = 2.56) relative to the Fama-French six-factor model. The strategy's economic magnitude is substantial, achieving an annualized gross Sharpe ratio of 0.32.

Importantly, TDCM's predictive power persists after controlling for known return predictors. The signal generates a monthly alpha of 20 basis points (t-statistic = 2.16) when controlling for six closely related anomalies, including gross profits, asset growth, and operating leverage. This finding suggests TDCM captures unique information not contained in traditional accounting-based signals.

The results are robust across various methodological specifications and firm sizes. While the effect is strongest among mid-cap stocks, we find significant predictability even among the largest quintile of firms, with a monthly alpha of 16 basis points (t-statistic = 1.18) for large-cap stocks.

Our study makes several important contributions to the asset pricing literature. First, we extend the work of Fama and French (2015) and Hou et al. (2015) by identifying a novel accounting-based signal that significantly improves the prediction of cross-sectional returns. Unlike previously documented tax-related anomalies, TDCM specifically captures the interaction between tax planning efficiency and dividend policy.

Second, we contribute to the literature on market efficiency and investor attention DellaVigna and Pollet (2009) by demonstrating that complex tax information is not fully incorporated into stock prices. Our findings suggest that sophisticated analysis of tax planning effectiveness can identify mispriced securities, challenging the strong-form market efficiency hypothesis.

Finally, our results have important implications for both academic research and investment practice. For researchers, we provide new evidence on the role of tax planning in asset pricing. For practitioners, TDCM represents a novel tool for portfolio formation that remains effective after accounting for transaction costs, with a net Sharpe ratio of 0.29.

## 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 dividend payments (DVT), on the other hand, captures the firm's cash distributions to shareholders, indicating its dividend policy and cash allocation decisions. 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 how a firm's tax obligations compare to its shareholder distributions, potentially offering information about the firm's financial flexibility and tax efficiency. By focusing on this relationship, the signal aims to capture 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 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 protfolio constructions. The first row reports the average returns and the alphas for the long/short strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios. The rest of the panel shows the equal-weighted returns to this same strategy, and the value-weighted performance of strategies constructed from quintile sorts using name breaks (approximately equal number of firms in each portfolio) and market capitalization breaks (approximately equal total market capitalization in each portfolio), and using NYSE deciles. The average return is lowest for the quintile sort using cap breakpoints and value-weighted portfolios, and equals 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 $80^{\text{th}}$ 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, 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.

[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 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 $\beta_{TDCM}$ 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 $\alpha$ 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

[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.

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 achieving 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 established factor models 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 existing pricing factors. 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.

[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 TDCM is available.

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 explored. Second, the study period may not fully capture the signal's behavior across different market regimes and economic cycles.

Future research could extend this work in several directions. Investigating TDCM's performance in international markets, examining its interaction with other established anomalies, and exploring its underlying economic mechanisms would provide valuable insights. Additionally, studying the signal's effectiveness across different market capitalizations and its sensitivity to varying market conditions could further enhance our understanding of its practical applications.

In conclusion, TDCM represents a promising addition to the investment practitioner's toolkit, offering meaningful predictive power for stock returns. While implementation costs somewhat diminish its profitability, the signal remains economically significant and robust to common risk factors and related anomalies.

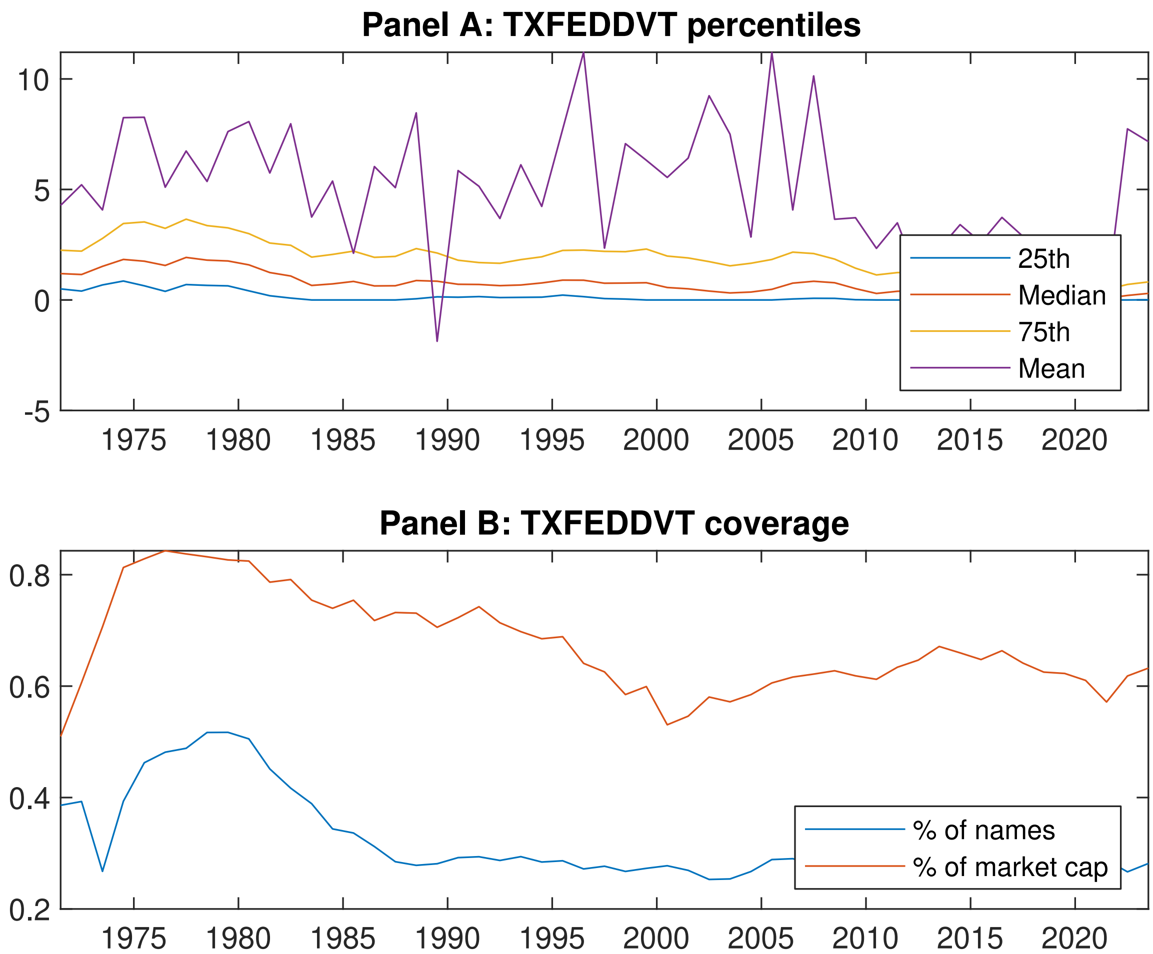


**Figure 1:** Times series of TDCM percentiles and coverage.
This figure plots descriptive statistics for TDCM. Panel A shows cross-sectional percentiles of TDCM over the sample. Panel B plots the monthly coverage of TDCM relative to the universe of CRSP stocks with available market capitalizations.

**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 | 0.55 | 0.55 | 0.71 | 0.77 | 0.29 |
| | [2.41] | [3.34] | [3.22] | [3.79] | [3.52] | [2.33] |
| $\alpha_{CAPM}$ | -0.11 | 0.06 | 0.04 | 0.12 | 0.09 | 0.21 |
| | [-1.35] | [0.84] | [0.61] | [2.21] | [1.29] | [1.67] |
| $\alpha_{FF3}$ | -0.23 | -0.01 | 0.00 | 0.14 | 0.11 | 0.34 |
| | [-3.08] | [-0.11] | [0.05] | [2.40] | [1.58] | [2.96] |
| $\alpha_{FF4}$ | -0.19 | -0.02 | -0.01 | 0.15 | 0.14 | 0.34 |
| | [-2.55] | [-0.42] | [-0.15] | [2.58] | [1.99] | [2.86] |
| $\alpha_{FF5}$ | -0.23 | -0.14 | -0.19 | 0.02 | 0.05 | 0.28 |
| | [-3.30] | [-2.65] | [-3.26] | [0.37] | [0.76] | [2.72] |
| $\alpha_{FF6}$ | -0.19 | -0.14 | -0.19 | 0.04 | 0.08 | 0.27 |
| | [-2.73] | [-2.62] | [-3.15] | [0.71] | [1.13] | [2.56] |
| Panel B: Fama and French (2018) 6-factor model loadings for TDCM-sorted portfolios | | | | | | |
| $\beta_{\text{MKT}}$ | 1.04 | 0.94 | 0.94 | 1.00 | 1.09 | 0.05 |
| | [63.48] | [73.63] | [68.59] | [81.41] | [68.32] | [2.02] |
| $\beta_{\text{SMB}}$ | -0.00 | -0.19 | -0.14 | 0.02 | 0.21 | 0.21 |
| | [-0.08] | [-10.07] | [-7.05] | [1.12] | [8.80] | [5.78] |
| $\beta_{\text{HML}}$ | 0.13 | 0.07 | 0.04 | -0.08 | -0.05 | -0.18 |
| | [4.23] | [2.70] | [1.50] | [-3.46] | [-1.57] | [-3.85] |
| $\beta_{\text{RMW}}$ | -0.23 | 0.17 | 0.39 | 0.28 | 0.29 | 0.52 |
| | [-7.24] | [6.66] | [14.76] | [11.83] | [9.32] | [10.91] |
| $\beta_{\text{CMA}}$ | 0.41 | 0.32 | 0.20 | 0.07 | -0.15 | -0.57 |
| | [8.72] | [8.73] | [5.17] | [2.02] | [-3.36] | [-8.02] |
| $\beta_{\text{UMD}}$ | -0.06 | 0.00 | -0.01 | -0.03 | -0.04 | 0.02 |
| | [-3.60] | [0.06] | [-0.42] | [-2.23] | [-2.44] | [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 | $r^e$ | $\alpha_{\text{CAPM}}$ | $\alpha_{\text{FF3}}$ | $\alpha_{\text{FF4}}$ | $\alpha_{\text{FF5}}$ | $\alpha_{\text{FF6}}$ |
| Quintile | NYSE | VW | 0.29 | 0.21 | 0.34 | 0.34 | 0.28 | 0.27 |
| | | | [2.33] | [1.67] | [2.96] | [2.86] | [2.72] | [2.56] |
| Quintile | NYSE | EW | 0.35 | 0.41 | 0.39 | 0.27 | 0.05 | -0.03 |
| | | | [2.62] | [3.03] | [2.95] | [2.06] | [0.49] | [-0.23] |
| Quintile | Name | VW | 0.40 | 0.33 | 0.47 | 0.44 | 0.32 | 0.30 |
| | | | [3.04] | [2.55] | [3.76] | [3.52] | [2.84] | [2.66] |
| Quintile | Cap | VW | 0.25 | 0.17 | 0.30 | 0.30 | 0.27 | 0.26 |
| | | | [2.20] | [1.50] | [2.84] | [2.78] | [2.87] | [2.72] |
| Decile | NYSE | VW | 0.49 | 0.44 | 0.62 | 0.66 | 0.53 | 0.56 |
| | | | [3.31] | [2.96] | [4.52] | [4.73] | [4.10] | [4.27] |
| Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas | | | | | | | | |
| Portfolios | Breaks | Weights | $r^e_{net}$ | $\alpha^*_{\text{CAPM}}$ | $\alpha^*_{\text{FF3}}$ | $\alpha^*_{\text{FF4}}$ | $\alpha^*_{\text{FF5}}$ | $\alpha^*_{\text{FF6}}$ |
| Quintile | NYSE | VW | 0.26 | 0.17 | 0.28 | 0.28 | 0.22 | 0.20 |
| | | | [2.09] | [1.33] | [2.44] | [2.41] | [2.07] | [1.94] |
| Quintile | NYSE | EW | 0.21 | 0.24 | 0.21 | 0.15 | | |
| | | | [1.53] | [1.72] | [1.58] | [1.11] | | |
| Quintile | Name | VW | 0.36 | 0.29 | 0.40 | 0.39 | 0.27 | 0.24 |
| | | | [2.78] | [2.20] | [3.24] | [3.14] | [2.35] | [2.20] |
| Quintile | Cap | VW | 0.23 | 0.14 | 0.25 | 0.25 | 0.22 | 0.20 |
| | | | [2.00] | [1.22] | [2.38] | [2.37] | [2.27] | [2.14] |
| Decile | NYSE | VW | 0.45 | 0.39 | 0.54 | 0.57 | 0.45 | 0.45 |
| | | | [3.04] | [2.59] | [3.94] | [4.10] | [3.48] | [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

| | | TDCM Quintiles | | | | | TDCM Strategies | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (L) | (2) | (3) | (4) | (H) | $r^e$ | $\alpha_{CAPM}$ | $\alpha_{FF3}$ | $\alpha_{FF4}$ | $\alpha_{FF5}$ | $\alpha_{FF6}$ |
| Size quintiles | (1) | 0.66 | 0.33 | 0.67 | 1.12 | 0.90 | 0.24 | 0.29 | 0.24 | 0.26 | -0.00 | 0.02 |
| | | [2.16] | [0.98] | [2.77] | [3.54] | [3.60] | [1.31] | [1.58] | [1.36] | [1.44] | [-0.00] | [0.12] |
| | (2) | 0.50 | 0.71 | 0.84 | 0.82 | 0.83 | 0.33 | 0.37 | 0.37 | 0.35 | 0.09 | 0.08 |
| | | [1.91] | [3.15] | [3.92] | [3.68] | [3.33] | [2.48] | [2.68] | [2.71] | [2.49] | [0.77] | [0.70] |
| | (3) | 0.71 | 0.66 | 0.78 | 0.99 | 0.83 | 0.12 | 0.14 | 0.16 | 0.19 | -0.14 | -0.10 |
| | | [2.87] | [3.32] | [3.92] | [4.61] | [3.52] | [0.85] | [0.99] | [1.13] | [1.31] | [-1.15] | [-0.83] |
| | (4) | 0.64 | 0.65 | 0.73 | 0.74 | 0.79 | 0.15 | 0.12 | 0.19 | 0.17 | -0.02 | -0.04 |
| | | [2.89] | [3.46] | [3.80] | [3.72] | [3.47] | [1.15] | [0.89] | [1.50] | [1.27] | [-0.19] | [-0.31] |
| | (5) | 0.49 | 0.54 | 0.57 | 0.66 | 0.64 | 0.16 | 0.04 | 0.19 | 0.20 | 0.21 | 0.21 |
| | | [2.65] | [3.28] | [3.28] | [3.48] | [2.98] | [1.18] | [0.30] | [1.54] | [1.62] | [1.86] | [1.79] |

Panel B: Portfolio average number of firms and market capitalization

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

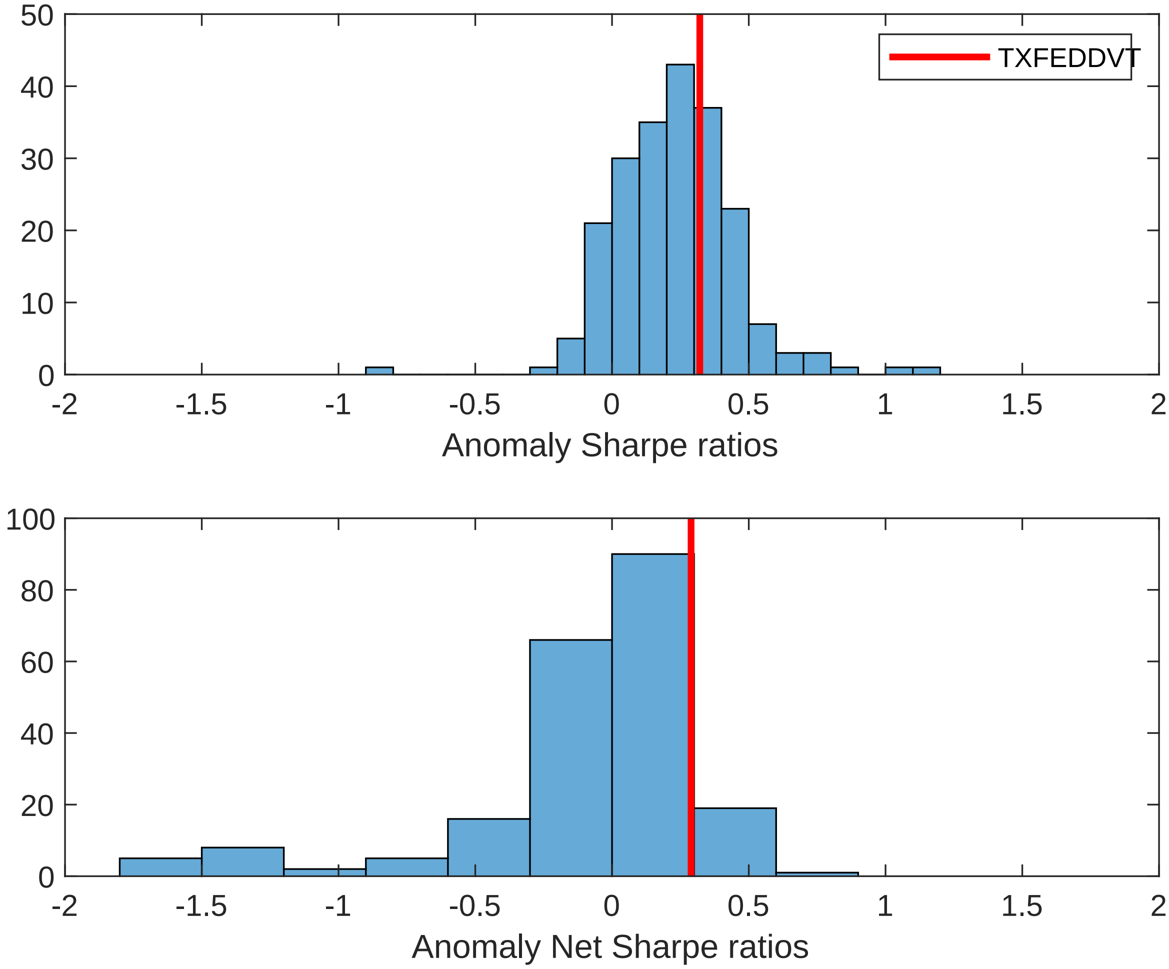


**Figure 2:** Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the TDCM with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

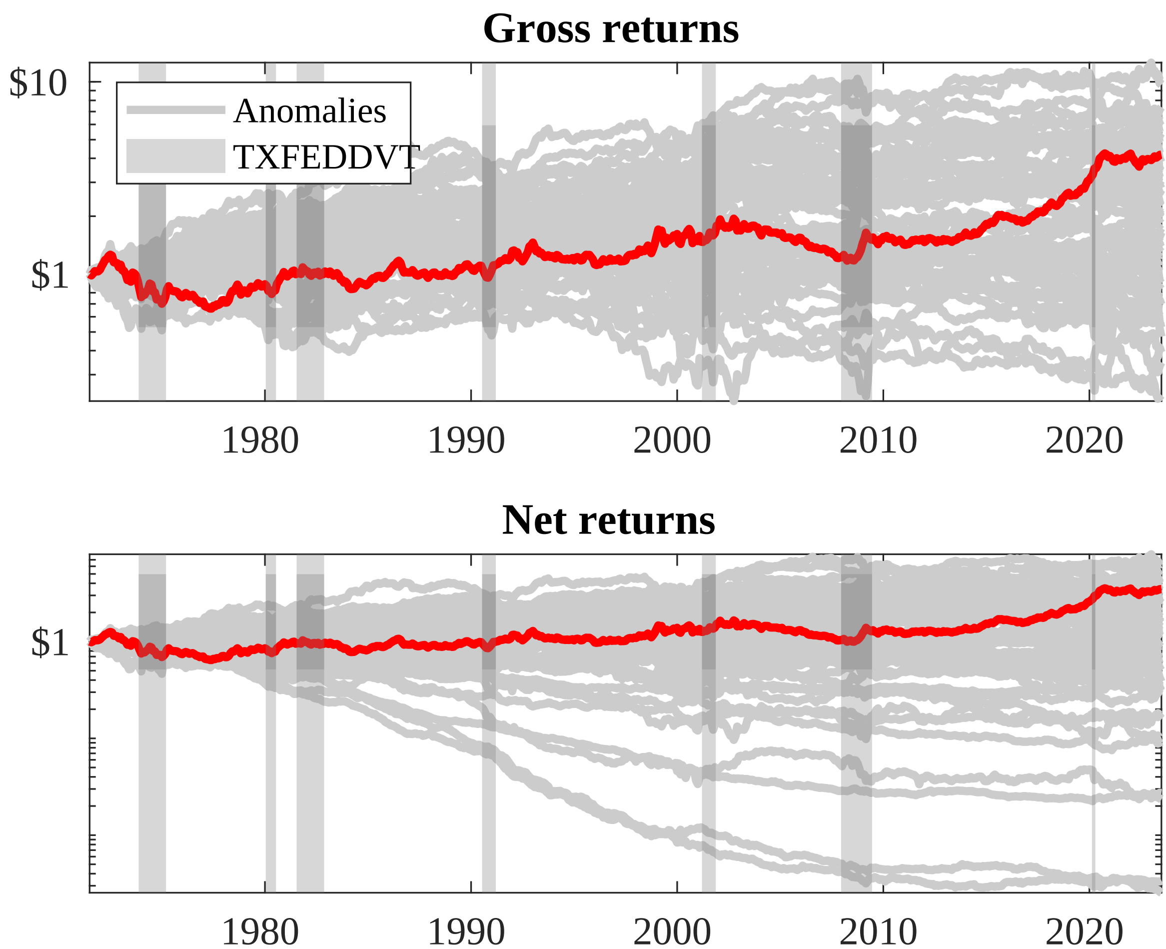


**Figure 3:** Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the TDCM trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

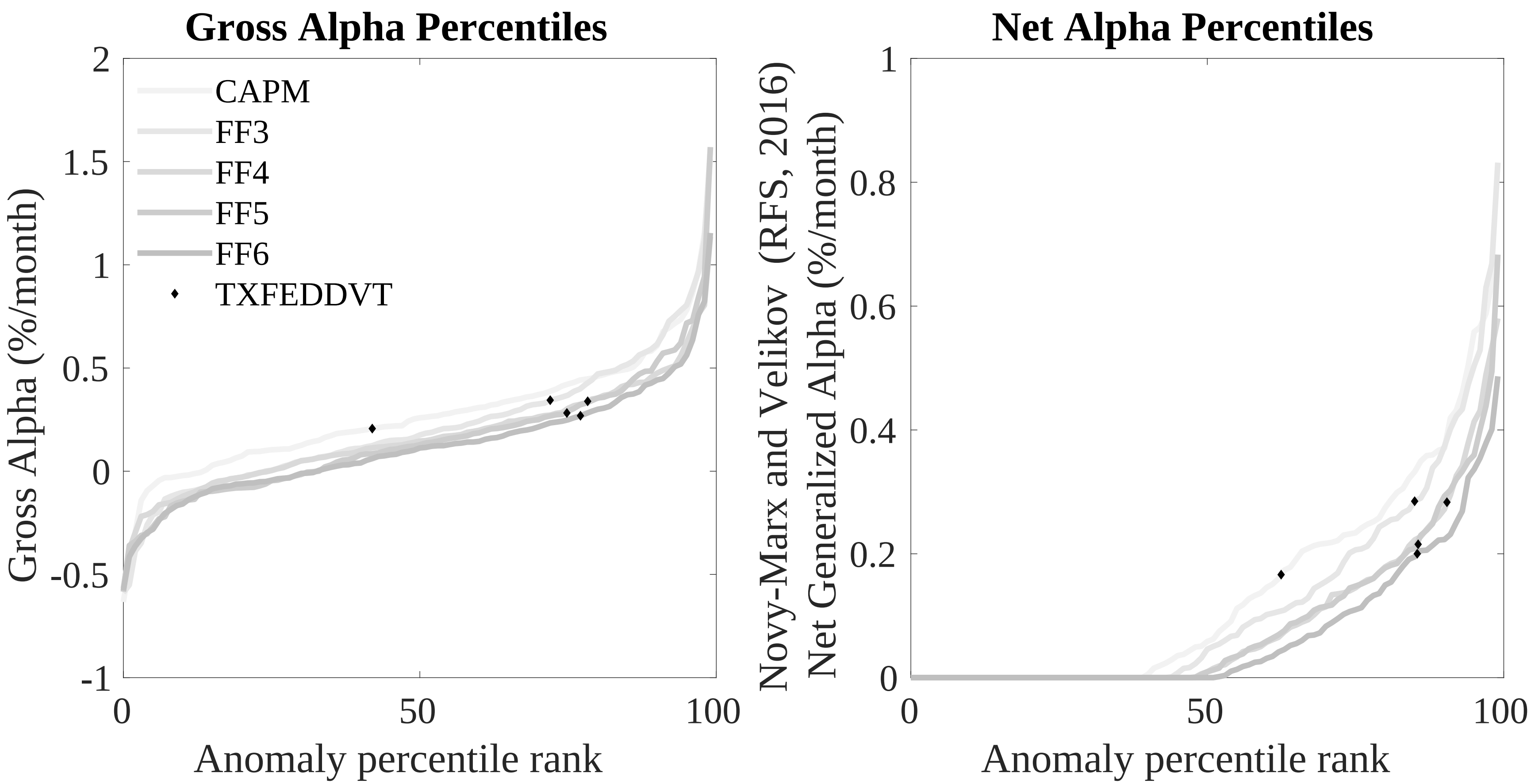


**Figure 4:** Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the TDCM trading strategy alphas (diamonds). The strategies are constructed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

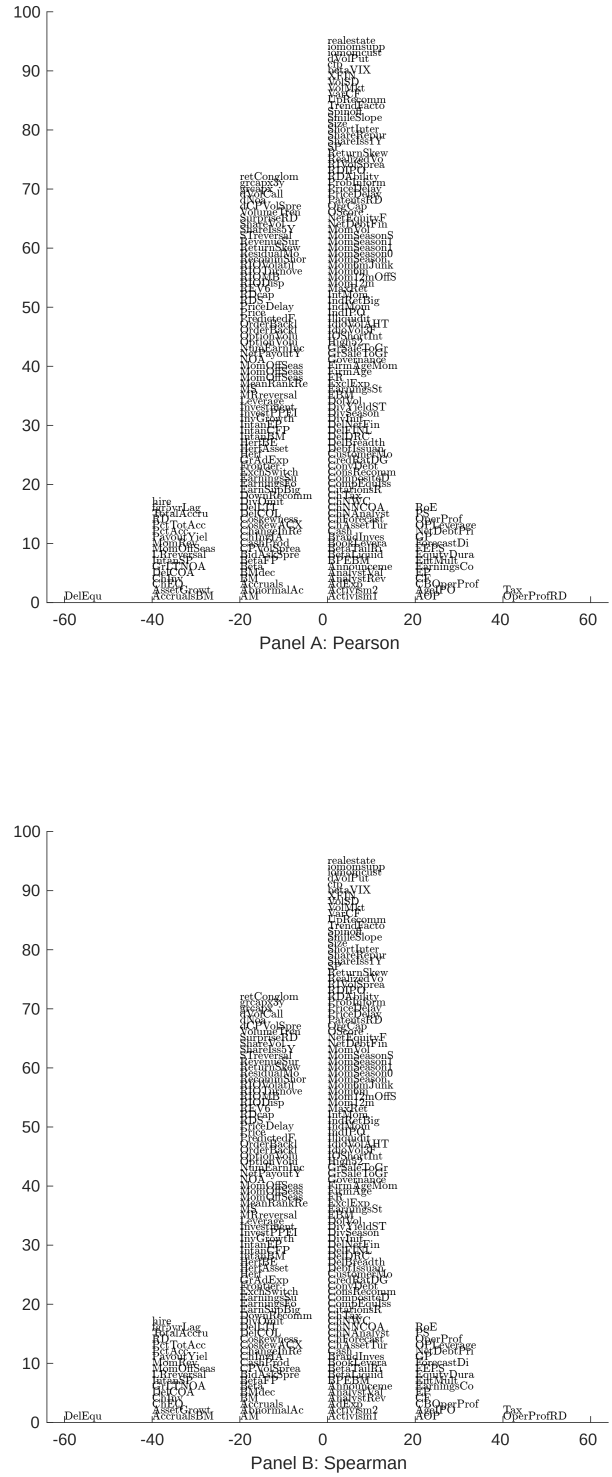


**Figure 5:** Distribution of correlations.
This figure plots a name histogram of correlations of 203 filtered anomaly signals with TDCM. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

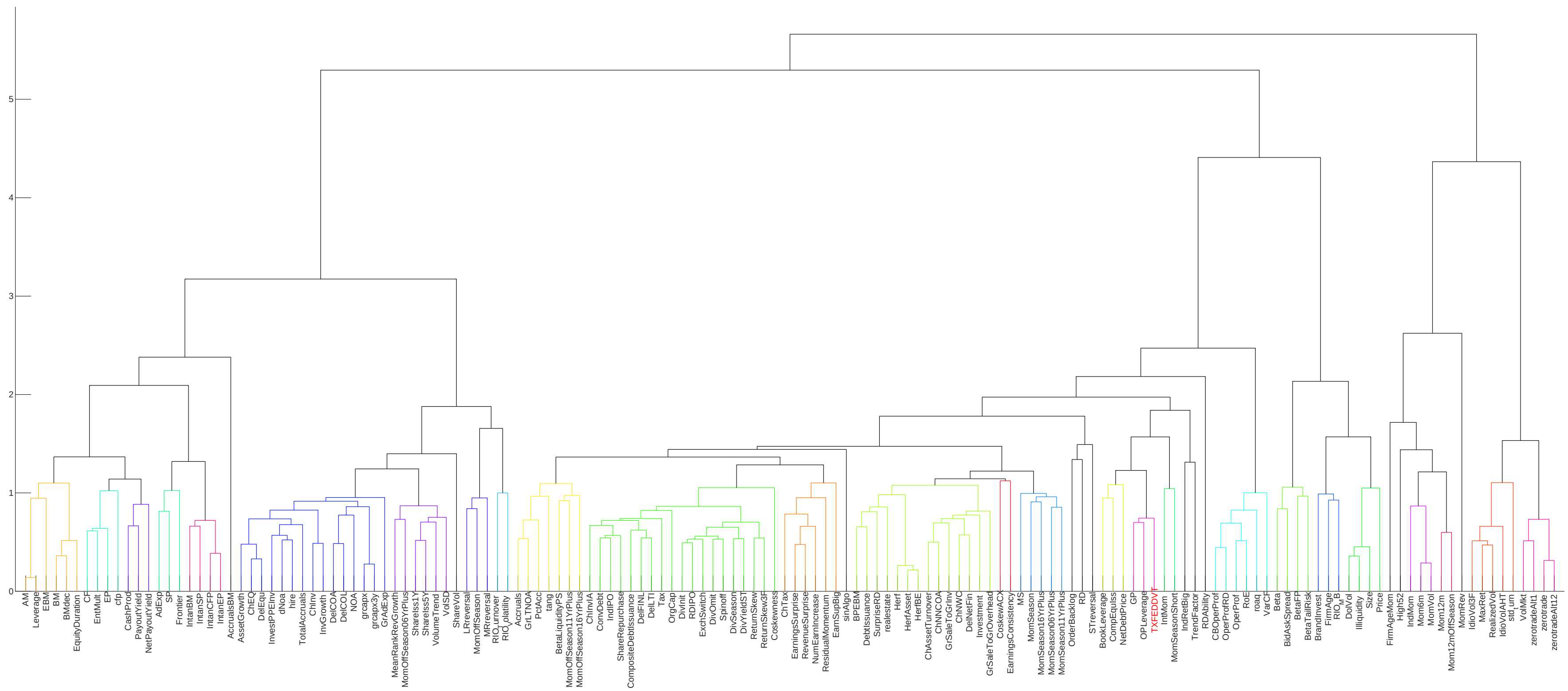


**Figure 6:** Agglomerative hierarchical cluster plot

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

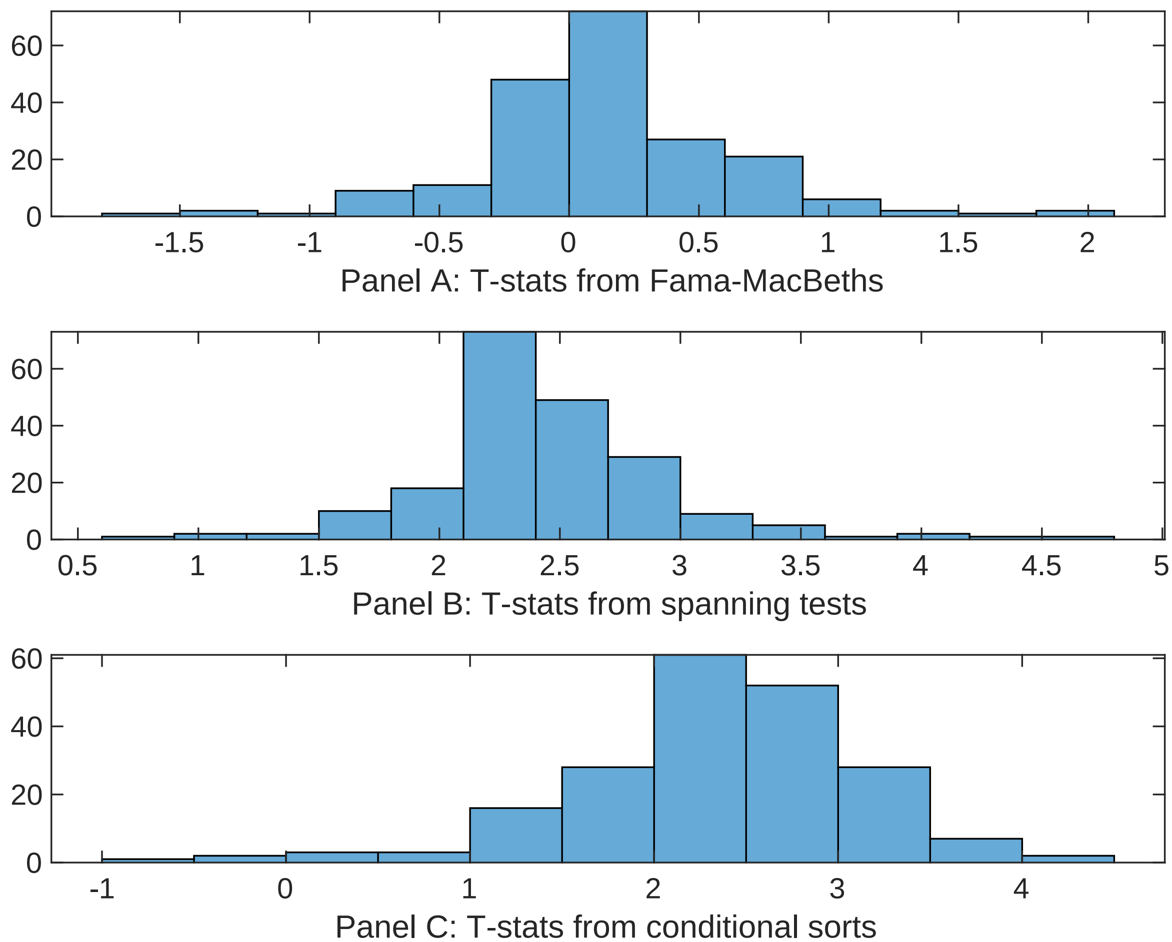


**Figure 7:** Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of TDCM conditioning on each of the 203 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{TDCM}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{TDCM} TDCM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 203 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ 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 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: $r_{i,t} = \alpha + \beta_{TDCM}TDCM_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k}X_{i,t}^{k} + \epsilon_{i,t}$. 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 | 0.18 | 0.12 | 0.13 | 0.12 | 0.10 | 0.12 |
| | [4.06] | [7.59] | [5.70] | [6.12] | [5.89] | [4.84] | [5.04] |
| TDCM | -0.26 | 0.46 | 0.69 | 0.45 | 0.64 | -0.95 | 0.70 |
| | [-0.27] | [0.52] | [0.79] | [0.48] | [0.87] | [-0.09] | [0.99] |
| Anomaly 1 | 0.59 | | | | | | 0.37 |
| | [3.44] | | | | | | [2.36] |
| Anomaly 2 | | 0.57 | | | | | 0.69 |
| | | [4.78] | | | | | [0.45] |
| Anomaly 3 | | | 0.19 | | | | 0.69 |
| | | | [4.74] | | | | [1.24] |
| Anomaly 4 | | | | 1.00 | | | 0.64 |
| | | | | [8.12] | | | [5.57] |
| Anomaly 5 | | | | | -0.38 | | -0.50 |
| | | | | | [-0.96] | | [-1.26] |
| Anomaly 6 | | | | | | 0.12 | 0.35 |
| | | | | | | [2.71] | [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 | 0.26 | 0.25 | 0.25 | 0.29 | 0.21 | 0.20 |
| | [1.62] | [2.57] | [2.37] | [2.38] | [2.80] | [2.16] | [2.16] |
| Anomaly 1 | 39.18 | | | | | | 29.87 |
| | [9.81] | | | | | | [7.08] |
| Anomaly 2 | | -30.79 | | | | | -51.87 |
| | | [-5.40] | | | | | [-6.69] |
| Anomaly 3 | | | -18.68 | | | | 25.24 |
| | | | [-3.35] | | | | [3.29] |
| Anomaly 4 | | | | -16.20 | | | 5.24 |
| | | | | [-2.35] | | | [0.77] |
| Anomaly 5 | | | | | -13.48 | | 3.24 |
| | | | | | [-3.53] | | [0.82] |
| Anomaly 6 | | | | | | 36.96 | 30.73 |
| | | | | | | [9.41] | [7.52] |
| mkt | 3.35 | 3.44 | 4.52 | 4.41 | 1.79 | 5.20 | 2.97 |
| | [1.47] | [1.43] | [1.86] | [1.81] | [0.71] | [2.27] | [1.31] |
| smb | 19.31 | 22.07 | 21.10 | 22.41 | 18.89 | 5.74 | 8.05 |
| | [5.64] | [6.14] | [5.79] | [6.04] | [5.15] | [1.51] | [2.21] |
| hml | -0.36 | -15.09 | -16.46 | -18.10 | -12.65 | 2.34 | 12.99 |
| | [-0.08] | [-3.28] | [-3.53] | [-3.90] | [-2.50] | [0.48] | [2.68] |
| rmw | 29.86 | 51.45 | 51.09 | 52.69 | 51.43 | 32.38 | 18.86 |
| | [5.94] | [10.99] | [10.71] | [11.06] | [10.81] | [6.51] | [3.86] |
| cma | -53.43 | -25.75 | -36.62 | -35.77 | -50.34 | -64.98 | -46.07 |
| | [-8.10] | [-2.90] | [-4.04] | [-3.23] | [-6.88] | [-9.69] | [-4.57] |
| umd | 1.69 | 2.39 | 1.45 | 1.29 | -0.65 | 1.98 | 3.50 |
| | [0.75] | [1.01] | [0.60] | [0.53] | [-0.26] | [0.87] | [1.58] |
| # months | 624 | 624 | 624 | 624 | 620 | 624 | 620 |
| $\bar{R}^2(\%)$ | 46 | 41 | 39 | 38 | 40 | 46 | 54 |

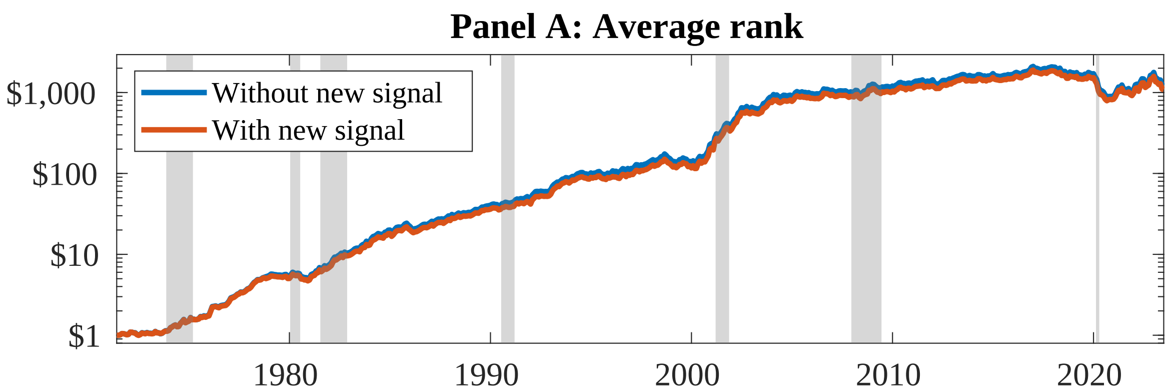


**Figure 8:** Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 156 anomalies. The red solid lines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