# Stock Depreciation Difference Signal and the Cross Section of Stock Returns

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**Abstract**

This paper studies the asset pricing implications of Stock Depreciation Difference Signal (SDDS), 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 SDDS achieves an annualized gross (net) Sharpe ratio of 0.58 (0.52), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 19 (20) bps/month with a t-statistic of 2.45 (2.61), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Net Payout Yield, Growth in book equity, Share issuance (5 year), Change in equity to assets, Asset growth) is 15 bps/month with a t-statistic of 2.13.

# 1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to understand how information is incorporated into security prices. While traditional asset pricing theory suggests that systematic risk factors should drive expected returns, a growing body of evidence documents various firm characteristics that predict future stock returns. One particularly understudied area is how firms' accounting choices and reporting practices may contain information about future performance that is not fully reflected in current prices.

Despite extensive research on accounting-based signals, the relationship between firms' depreciation practices and future stock returns has received limited attention. This gap is surprising given that depreciation represents one of management's most significant estimation decisions and directly impacts reported profitability. The discretion managers have in setting depreciation policies creates potential information content in the differences between firms' depreciation rates relative to industry peers.

We hypothesize that systematic differences in firms' depreciation rates relative to their industry peers contain information about future performance and stock returns. This hypothesis builds on two theoretical foundations. First, following Grossman and Stiglitz (1980), if gathering and processing detailed accounting information is costly, prices may not fully reflect the information content in firms' specific accounting choices. Second, as argued by Penman and Zhang (2002), conservative accounting practices like accelerated depreciation can create 'hidden reserves' that affect the quality and persistence of earnings.

The economic mechanism we propose operates through both signaling and real channels. Managers with private information about asset longevity and replacement costs may select depreciation policies that better match economic reality, creating a signal about future profitability. Additionally, as shown by Thomas and Zhang (2002), differences in depreciation policies directly affect reported earnings and investment behavior, potentially leading to systematic mispricing when investors fail to fully process these implications.

Critically, the Stock Depreciation Difference Signal (SDDS) we construct captures systematic deviations in a firm's depreciation rates from industry norms while controlling for asset composition. This design follows Sloan (1996) in isolating the discretionary component of accounting choices to better identify potential information content.

Our empirical analysis reveals that SDDS strongly predicts future stock returns. A value-weighted long-short trading strategy based on SDDS achieves an annualized gross Sharpe ratio of 0.58, with monthly abnormal returns of 19 basis points (t-statistic = 2.45) relative to the Fama-French five-factor model plus momentum. The predictive power of SDDS remains robust after controlling for transaction costs, with net returns maintaining a Sharpe ratio of 0.52.

Importantly, SDDS's predictive ability persists among large-cap stocks, with the long-short strategy earning average returns of 28 basis points per month (t-statistic = 2.87) among stocks above the 80th percentile of market capitalization. This finding suggests that the signal captures systematic mispricing rather than just small-stock effects or limits to arbitrage.

The economic significance of SDDS is further demonstrated by its performance relative to existing anomalies. When controlling for the six most closely related accounting-based anomalies and standard risk factors, SDDS continues to generate significant abnormal returns of 15 basis points per month (t-statistic = 2.13), indicating it captures unique information not contained in previously documented signals.

Our paper makes several contributions to the asset pricing and accounting literature. First, we extend the work of Fairfield et al. (2003) and Titman et al. (2004) on the investment-return relationship by showing how detailed analysis of depreciation policies provides incremental information about future returns. While these studies focus on aggregate investment levels, we demonstrate that the specific accounting choices firms make in reporting investment contain additional predictive power.

Second, we contribute to the literature on accounting quality and stock returns pioneered by Sloan (1996). While prior work has focused primarily on accruals and earnings management, we show that systematic analysis of a specific accounting choice - depreciation policy - can reveal information about future performance. This finding supports theories suggesting that detailed analysis of financial statements can identify mispricing even in large, liquid stocks.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the value of drilling down into specific accounting choices rather than focusing solely on aggregate measures. For practitioners, our findings suggest that systematic analysis of depreciation policies, despite their accounting complexity, can yield valuable investment signals that persist after trading costs and are robust across market capitalizations.

# 2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Stock Depreciation Difference Signal. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item CSTK for common stock and item DPACT for accumulated depreciation. CSTK represents the total value of common stock issued by the firm, while DPACT captures the cumulative amount of depreciation recorded for the firm's assets over time. The construction of the signal follows a difference-based approach, where we first calculate the change in CSTK by subtracting its lagged value from the current value, and then scale this difference by the lagged value of DPACT. This scaled difference aims to capture significant changes in a firm's equity structure relative to its historical depreciation base. By focusing on this relationship, the signal potentially reflects aspects of capital structure decisions and asset management efficiency in a manner that accounts for firm size and age effects. We construct this measure using end-of-fiscal-year values for both CSTK and DPACT to ensure consistency and comparability across firms and over time.

# 3 Signal diagnostics

Figure 1 plots descriptive statistics for the SDDS signal. Panel A plots the time-series of the mean, median, and interquartile range for SDDS. On average, the cross-sectional mean (median) SDDS is -0.24 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SDDS data. The signal's interquartile range spans -0.03 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SDDS signal for the CRSP universe. On average, the SDDS signal is available for 5.96% of CRSP names, which on average make up 7.36% of total market capitalization.

# 4 Does SDDS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SDDS 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 SDDS portfolio and sells the low SDDS 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 SDDS strategy earns an average return of 0.35% per month with a t-statistic of 4.39. The annualized Sharpe ratio of the strategy is 0.58. The alphas range from 0.19% to 0.40% per month and have t-statistics exceeding 2.45 everywhere. The lowest alpha is with respect to the FF6 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is 0.41, with a t-statistic of 8.09 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 505 stocks and an average market capitalization of at least $1,359 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

29 bps/month with a t-statistics of 3.63. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for fifteen 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 25-38bps/month. The lowest return, (25 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.18. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SDDS trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-five cases, and significantly expands the achievable frontier in twenty-five cases.

Table 3 provides direct tests for the role size plays in the SDDS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SDDS, as well as average returns and alphas for long/short trading SDDS 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 SDDS strategy achieves an average return of 28 bps/month with a t-statistic of 2.87. Among these large cap stocks, the alphas for the SDDS strategy relative to the five most common factor models range from 20 to 29 bps/month with t-statistics between 1.97 and 3.03.

# 5 How does SDDS perform relative to the zoo?

Figure 2 puts the performance of SDDS 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 SDDS strategy falls in the distribution. The SDDS strategy's gross (net) Sharpe ratio of 0.58 (0.52) is greater than 95% (99%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a $1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a $1 invested in the SDDS strategy (red line).[2] Ignoring trading costs, a $1 invested in the SDDS strategy would have yielded $8.91 which ranks the SDDS strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the SDDS strategy would have yielded $6.68 which ranks the SDDS strategy in the top 0% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the SDDS relative to those. Panel A shows that the SDDS strategy gross alphas fall between the 62 and 74 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 196606 to 202306 sample. For example, 45%

[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.

(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 SDDS strategy has a positive net generalized alpha for five out of the five factor models. In these cases SDDS ranks between the 84 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

# 6 Does SDDS 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 SDDS with 210 filtered anomaly signals.[3] Figure 6 also shows an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

A closely related anomaly is also more likely to price SDDS or at least to weaken the power SDDS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SDDS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{SDDS}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SDDS} SDDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ from spanning tests of the form: $r_{SDDS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts,

[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.

value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on SDDS. Stocks are finally grouped into five SDDS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SDDS trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SDDS 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 SDDS signal in these Fama-MacBeth regressions exceed 1.91, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SDDS is 1.51.

Similarly, Table 5 reports results from spanning tests that regress returns to the SDDS 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 SDDS strategy earns alphas that range from 16-21bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.07, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SDDS trading strategy achieves an alpha of 15bps/month with a t-statistic of 2.13.

# 7 Does SDDS add relative to the whole zoo?

Finally, we can ask how much adding SDDS to the entire factor zoo could improve investment performance. Figure 8 plots the growth of $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). The combinations use either the 155 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 155 anomalies augmented with the SDDS 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 155-anomaly combination strategy grows to $2333.55, while $1 investment in the combination strategy that includes SDDS grows to $2174.06.

# 8 Conclusion

This study provides compelling evidence for the effectiveness of the Stock Depreciation Difference Signal (SDDS) as a valuable predictor of cross-sectional stock returns. Our findings demonstrate that SDDS-based trading strategies yield economically and statistically significant results, with impressive Sharpe ratios and consistent alpha generation even after accounting for transaction costs. The signal's robustness is particularly noteworthy, maintaining its predictive power when controlled for established factors and related anomalies from the factor zoo.

The empirical results show that a value-weighted long/short strategy based on

[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 SDDS is available.

SDDS delivers meaningful economic value, achieving an annualized net Sharpe ratio of 0.52 and generating significant abnormal returns of 20 basis points per month after costs. Importantly, the signal's predictive power persists even after controlling for the Fama-French five factors, momentum, and six closely related anomalies, suggesting that SDDS captures unique information not reflected in existing 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 behavior across different market regimes and economic cycles.

Future research could explore the signal's performance in international markets, its interaction with other accounting-based anomalies, and its behavior during different market conditions. Additionally, investigating the underlying economic mechanisms driving the SDDS effect could provide valuable insights into asset pricing theory. These findings contribute to the growing literature on return predictability and have practical implications for investment professionals seeking to enhance their portfolio management strategies.

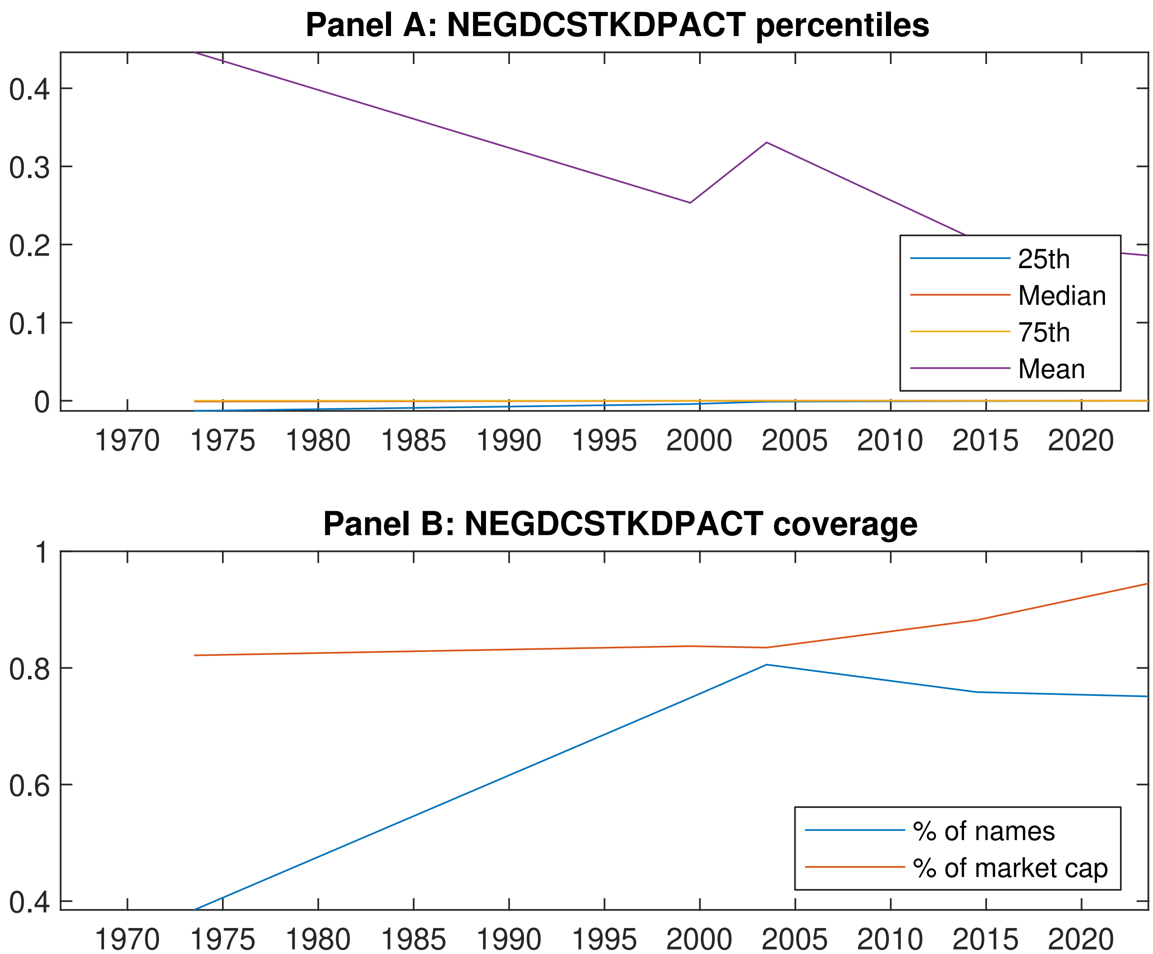



**Figure 1:** Times series of SDDS percentiles and coverage.
This figure plots descriptive statistics for SDDS. Panel A shows cross-sectional percentiles of SDDS over the sample. Panel B plots the monthly coverage of SDDS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SDDS. At the end of each month, we sort stocks into five portfolios based on their signal using NYSE breakpoints. Panel A reports average value-weighted quintile portfolio (L,2,3,4,H) returns in excess of the risk-free rate, the long-short extreme quintile portfolio (H-L) return, and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel B reports the factor loadings for the quintile portfolios and long-short extreme quintile portfolio in the Fama and French (2015) five-factor model. Panel C reports the average number of stocks and market capitalization of each portfolio. T-statistics are in brackets. The sample period is 196606 to 202306.

| Panel A: Excess returns and alphas on SDDS-sorted portfolios | | | | | | |
|---|---|---|---|---|---|---|
| | (L) | (2) | (3) | (4) | (H) | (H-L) |
| $r^e$ | 0.41 | 0.56 | 0.66 | 0.69 | 0.76 | 0.35 |
| | [2.24] | [2.98] | [3.51] | [4.12] | [4.51] | [4.39] |
| $\alpha_{CAPM}$ | -0.16 | -0.03 | 0.07 | 0.17 | 0.23 | 0.40 |
| | [-3.22] | [-0.67] | [1.37] | [3.39] | [4.85] | [5.01] |
| $\alpha_{FF3}$ | -0.13 | -0.00 | 0.10 | 0.15 | 0.21 | 0.33 |
| | [-2.56] | [-0.01] | [1.88] | [3.11] | [4.36] | [4.34] |
| $\alpha_{FF4}$ | -0.10 | 0.01 | 0.11 | 0.10 | 0.19 | 0.29 |
| | [-1.99] | [0.29] | [2.06] | [2.16] | [4.01] | [3.76] |
| $\alpha_{FF5}$ | -0.11 | 0.03 | 0.09 | 0.04 | 0.10 | 0.21 |
| | [-2.11] | [0.71] | [1.71] | [0.88] | [2.18] | [2.73] |
| $\alpha_{FF6}$ | -0.09 | 0.04 | 0.10 | 0.01 | 0.10 | 0.19 |
| | [-1.73] | [0.90] | [1.86] | [0.31] | [2.14] | [2.45] |
| Panel B: Fama and French (2018) 6-factor model loadings for SDDS-sorted portfolios | | | | | | |
| $\beta_{\text{MKT}}$ | 0.98 | 1.01 | 1.01 | 0.99 | 0.98 | 0.00 |
| | [81.19] | [88.85] | [79.38] | [92.82] | [90.59] | [0.24] |
| $\beta_{\text{SMB}}$ | 0.00 | 0.04 | 0.04 | -0.09 | -0.01 | -0.02 |
| | [0.07] | [2.48] | [2.21] | [-5.76] | [-0.91] | [-0.60] |
| $\beta_{\text{HML}}$ | -0.05 | -0.10 | -0.08 | -0.01 | -0.04 | 0.01 |
| | [-1.99] | [-4.57] | [-3.14] | [-0.61] | [-1.74] | [0.28] |
| $\beta_{\text{RMW}}$ | 0.04 | -0.07 | 0.04 | 0.10 | 0.12 | 0.08 |
| | [1.73] | [-3.35] | [1.78] | [4.84] | [5.90] | [2.40] |
| $\beta_{\text{CMA}}$ | -0.14 | -0.02 | -0.03 | 0.27 | 0.27 | 0.41 |
| | [-4.08] | [-0.58] | [-0.73] | [8.95] | [8.89] | [8.09] |
| $\beta_{\text{UMD}}$ | -0.03 | -0.01 | -0.01 | 0.04 | 0.00 | 0.03 |
| | [-2.46] | [-1.32] | [-1.16] | [3.83] | [0.07] | [1.69] |
| Panel C: Average number of firms ($n$) and market capitalization ($me$) | | | | | | |
| $n$ | 765 | 636 | 505 | 619 | 696 | |
| me ($\$10^6$) | 1610 | 1359 | 1818 | 2028 | 2258 | |

**Table 2:** Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the SDDS strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, and the choices are specified in the first three columns. For each strategy construction methodology, the table reports average excess returns and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel A reports average returns and alphas with no adjustment for trading costs. Panel B reports net average returns and Novy-Marx and Velikov (2016) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 196606 to 202306.

| Panel A: Gross Returns and Alphas | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Portfolios | Breaks | Weights | $r^e$ | $\alpha_{\text{CAPM}}$ | $\alpha_{\text{FF3}}$ | $\alpha_{\text{FF4}}$ | $\alpha_{\text{FF5}}$ | $\alpha_{\text{FF6}}$ |
| Quintile | NYSE | VW | 0.35 | 0.40 | 0.33 | 0.29 | 0.21 | 0.19 |
| | | | [4.39] | [5.01] | [4.34] | [3.76] | [2.73] | [2.45] |
| Quintile | NYSE | EW | 0.59 | 0.69 | 0.58 | 0.48 | 0.38 | 0.33 |
| | | | [7.23] | [9.07] | [8.82] | [7.57] | [6.39] | [5.51] |
| Quintile | Name | VW | 0.35 | 0.38 | 0.32 | 0.28 | 0.20 | 0.19 |
| | | | [4.34] | [4.73] | [4.03] | [3.48] | [2.64] | [2.37] |
| Quintile | Cap | VW | 0.29 | 0.32 | 0.28 | 0.23 | 0.21 | 0.18 |
| | | | [3.63] | [4.01] | [3.53] | [2.93] | [2.63] | [2.26] |
| Decile | NYSE | VW | 0.36 | 0.40 | 0.31 | 0.27 | 0.26 | 0.23 |
| | | | [3.71] | [4.10] | [3.30] | [2.80] | [2.71] | [2.40] |
| 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 | 0.31 | 0.37 | 0.31 | 0.29 | 0.21 | 0.20 |
| | | | [3.92] | [4.58] | [4.01] | [3.72] | [2.74] | [2.61] |
| Quintile | NYSE | EW | 0.38 | 0.47 | 0.37 | 0.32 | 0.17 | 0.16 |
| | | | [4.38] | [5.73] | [5.19] | [4.64] | [2.65] | [2.38] |
| Quintile | Name | VW | 0.31 | 0.35 | 0.29 | 0.27 | 0.20 | 0.19 |
| | | | [3.87] | [4.33] | [3.74] | [3.47] | [2.65] | [2.52] |
| Quintile | Cap | VW | 0.25 | 0.29 | 0.25 | 0.23 | 0.20 | 0.18 |
| | | | [3.18] | [3.62] | [3.19] | [2.88] | [2.54] | [2.34] |
| Decile | NYSE | VW | 0.32 | 0.36 | 0.29 | 0.26 | 0.24 | 0.23 |
| | | | [3.27] | [3.69] | [3.01] | [2.76] | [2.52] | [2.40] |

**Table 3:** Conditional sort on size and SDDS

This table presents results for conditional double sorts on size and SDDS. 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 SDDS. 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 SDDS and short stocks with low SDDS .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196606 to 202306.

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

| | | SDDS Quintiles | | | | | SDDS Strategies | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (L) | (2) | (3) | (4) | (H) | $r^e$ | $\alpha_{CAPM}$ | $\alpha_{FF3}$ | $\alpha_{FF4}$ | $\alpha_{FF5}$ | $\alpha_{FF6}$ |
| Size quintiles | (1) | 0.32 | 0.69 | 0.89 | 1.00 | 0.99 | 0.68 | 0.78 | 0.67 | 0.58 | 0.47 | 0.42 |
| | | [1.07] | [2.52] | [3.41] | [3.74] | [3.98] | [6.58] | [7.78] | [7.55] | [6.60] | [5.65] | [5.00] |
| | (2) | 0.43 | 0.73 | 0.86 | 0.90 | 0.94 | 0.51 | 0.61 | 0.47 | 0.41 | 0.33 | 0.29 |
| | | [1.65] | [2.97] | [3.49] | [3.86] | [4.11] | [4.86] | [5.96] | [5.13] | [4.42] | [3.58] | [3.16] |
| | (3) | 0.63 | 0.54 | 0.84 | 0.82 | 0.93 | 0.30 | 0.37 | 0.26 | 0.24 | 0.14 | 0.14 |
| | | [2.76] | [2.43] | [3.58] | [3.89] | [4.50] | [3.19] | [4.12] | [3.15] | [2.89] | [1.72] | [1.67] |
| | (4) | 0.49 | 0.60 | 0.84 | 0.78 | 0.80 | 0.31 | 0.37 | 0.26 | 0.22 | 0.06 | 0.05 |
| | | [2.33] | [2.83] | [3.98] | [3.93] | [4.19] | [3.54] | [4.28] | [3.34] | [2.77] | [0.82] | [0.61] |
| | (5) | 0.45 | 0.49 | 0.51 | 0.55 | 0.73 | 0.28 | 0.29 | 0.26 | 0.22 | 0.22 | 0.20 |
| | | [2.56] | [2.60] | [2.83] | [3.21] | [4.36] | [2.87] | [3.03] | [2.67] | [2.20] | [2.27] | [1.97] |

Panel B: Portfolio average number of firms and market capitalization

| | | SDDS Quintiles | | | | | SDDS Quintiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Average $n$ | | | | | Average market capitalization ($\$10^6$) | | | | |
| | | (L) | (2) | (3) | (4) | (H) | (L) | (2) | (3) | (4) | (H) |
| Size quintiles | (1) | 354 | 355 | 354 | 352 | 353 | 26 | 30 | 34 | 25 | 25 |
| | (2) | 99 | 99 | 98 | 99 | 99 | 50 | 50 | 50 | 50 | 50 |
| | (3) | 72 | 72 | 72 | 72 | 72 | 87 | 86 | 87 | 89 | 89 |
| | (4) | 62 | 62 | 62 | 62 | 62 | 187 | 190 | 196 | 197 | 200 |
| | (5) | 57 | 57 | 57 | 57 | 57 | 1248 | 1373 | 1581 | 1451 | 1621 |

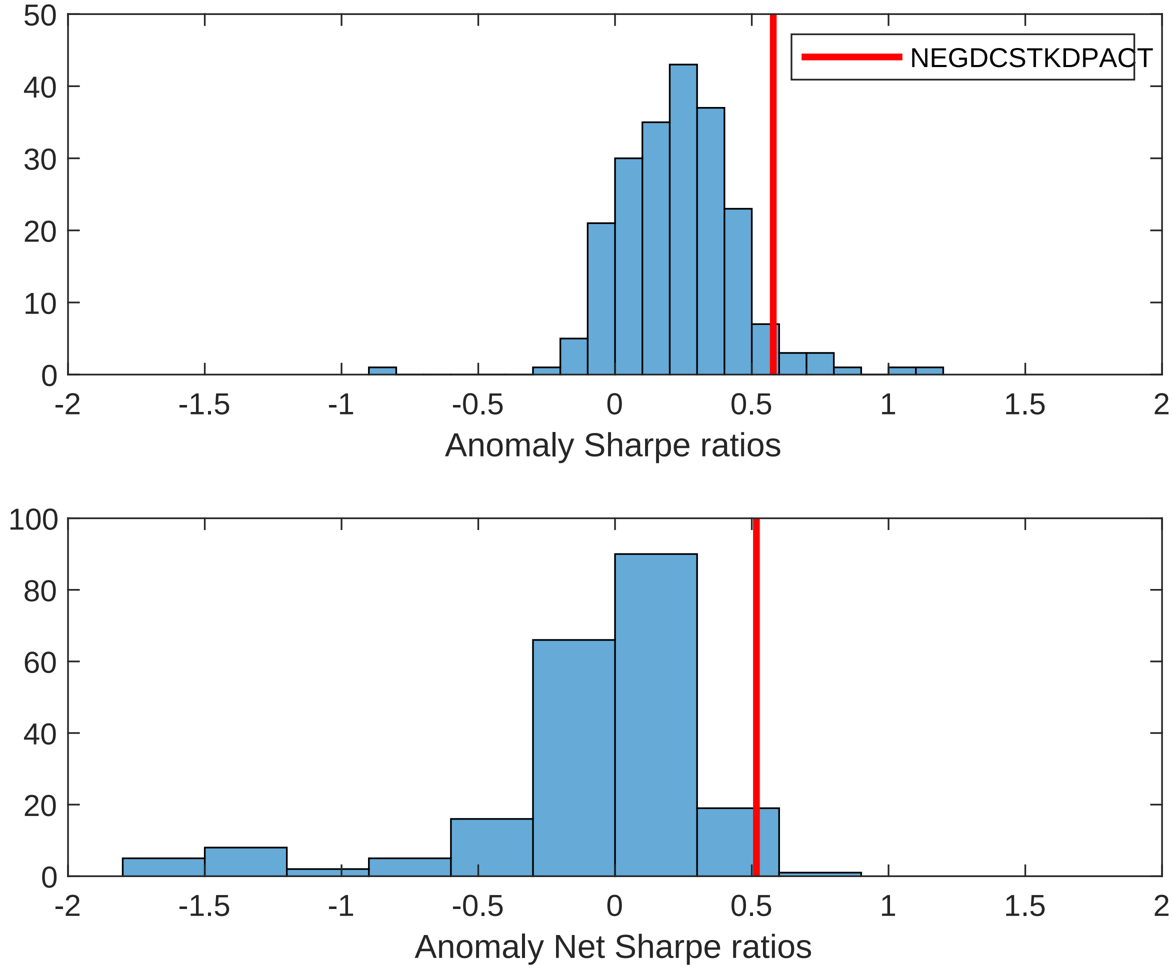



**Figure 2:** Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SDDS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

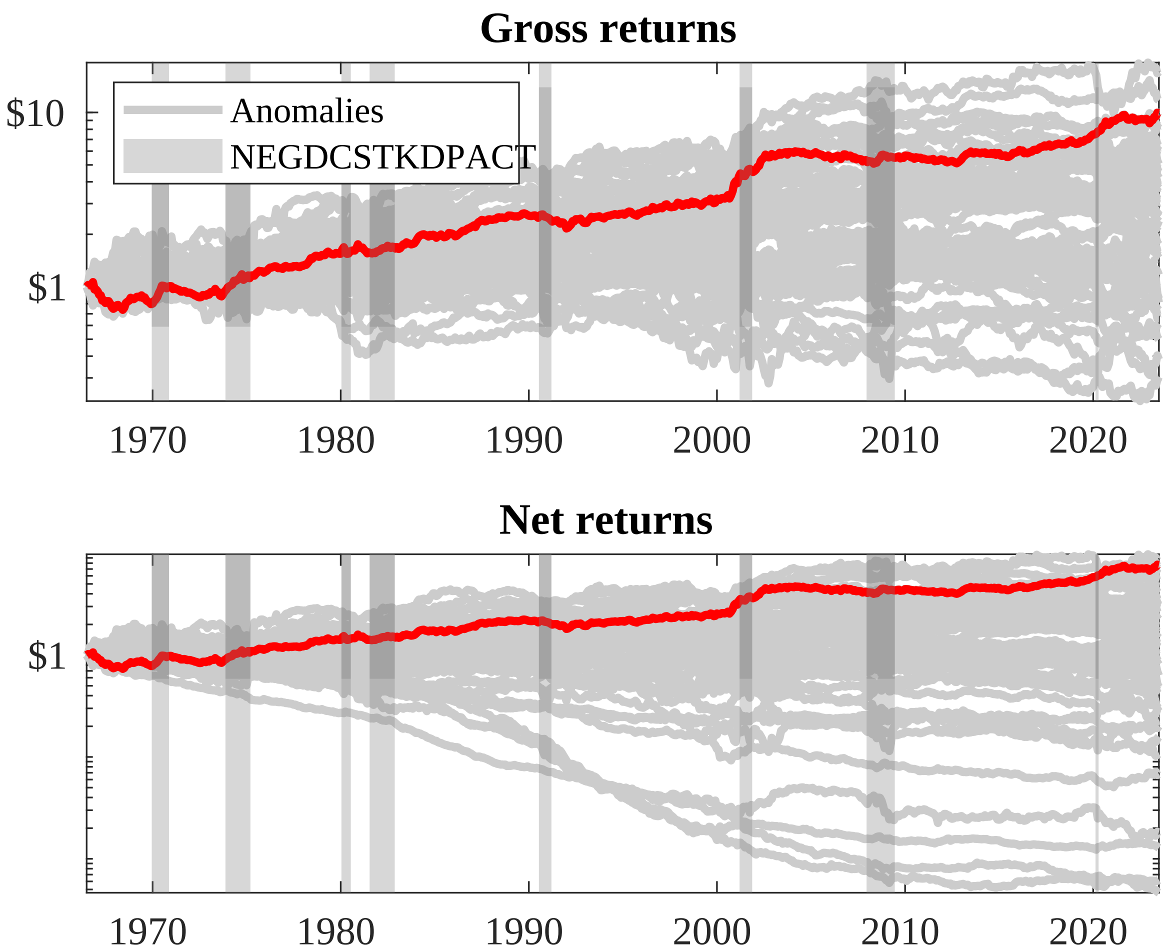



**Figure 3:** Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SDDS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

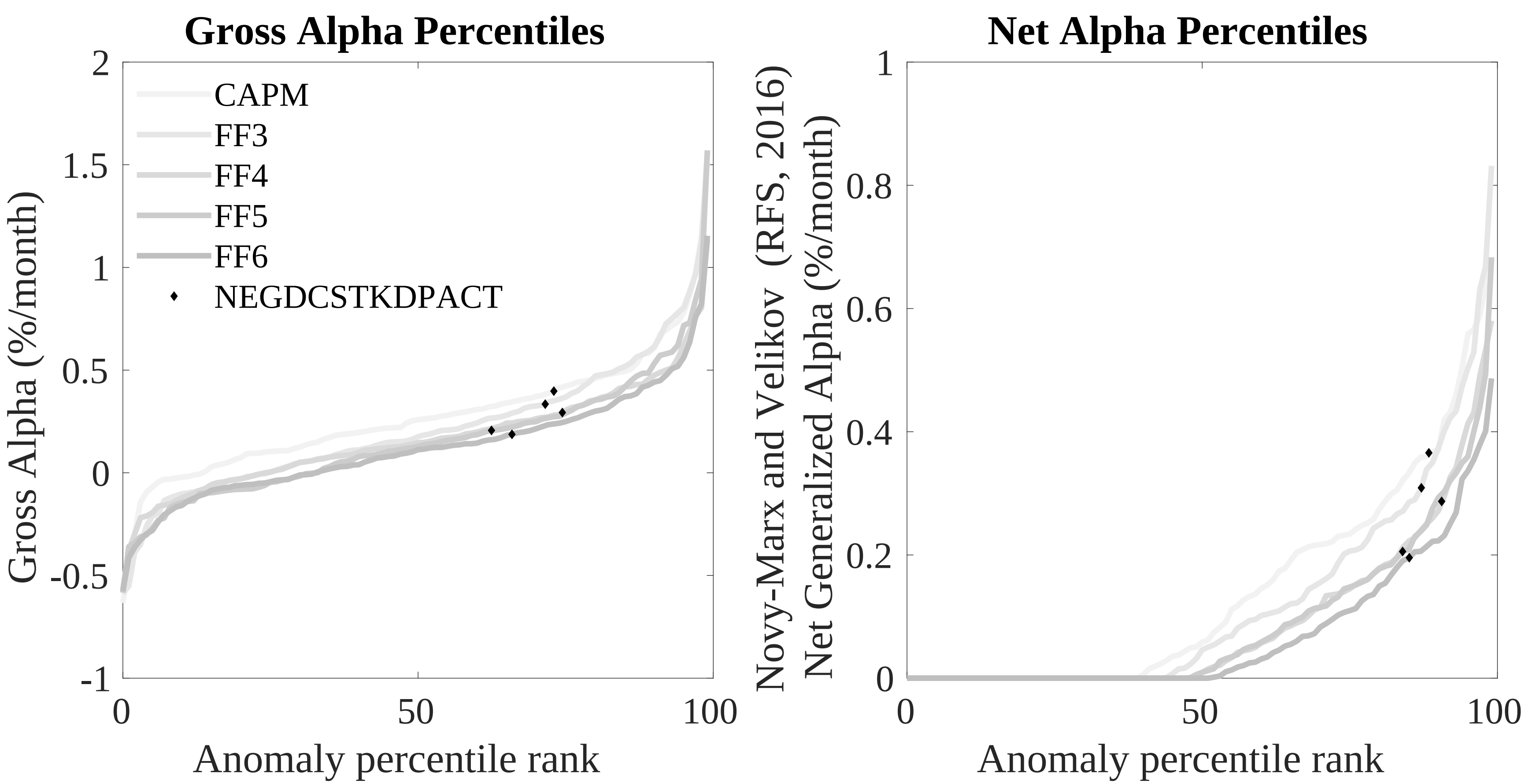
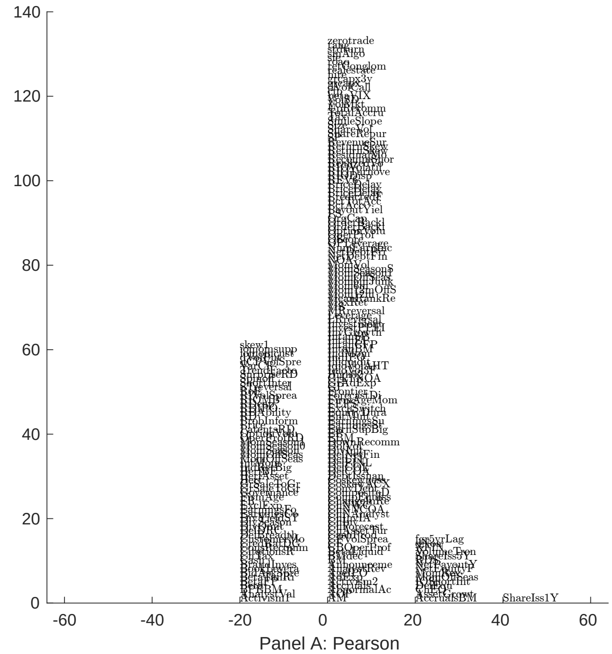



**Figure 4:** Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SDDS trading strategy alphas (diamonds). The strategies are constructed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



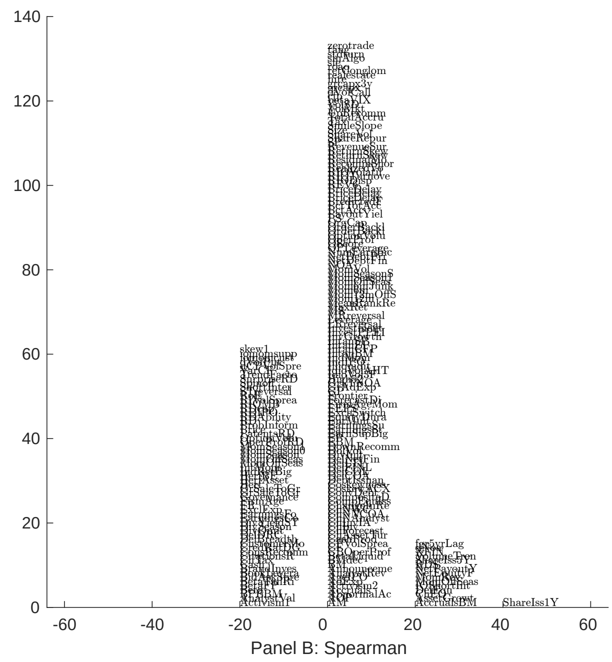




**Figure 5:** Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with SDDS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

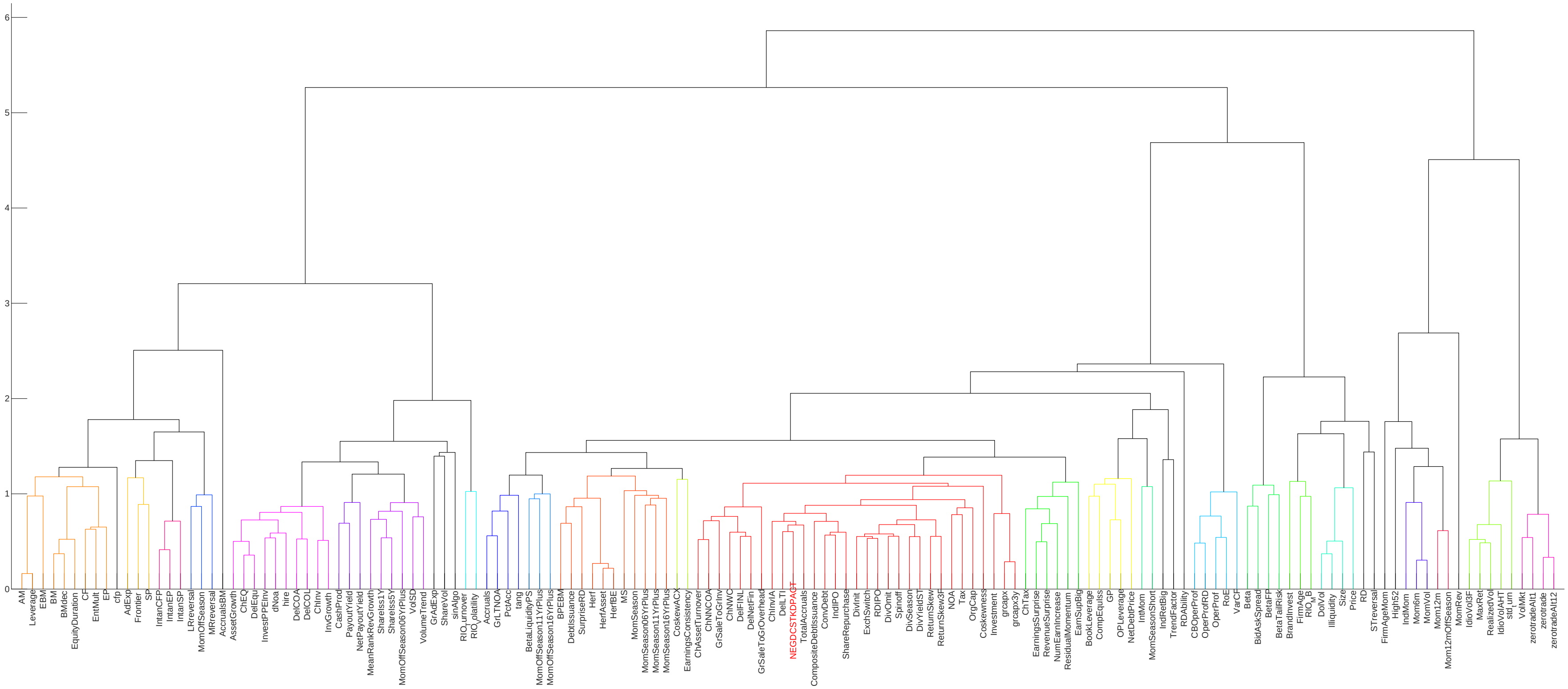



**Figure 6:** Agglomerative hierarchical cluster plot

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

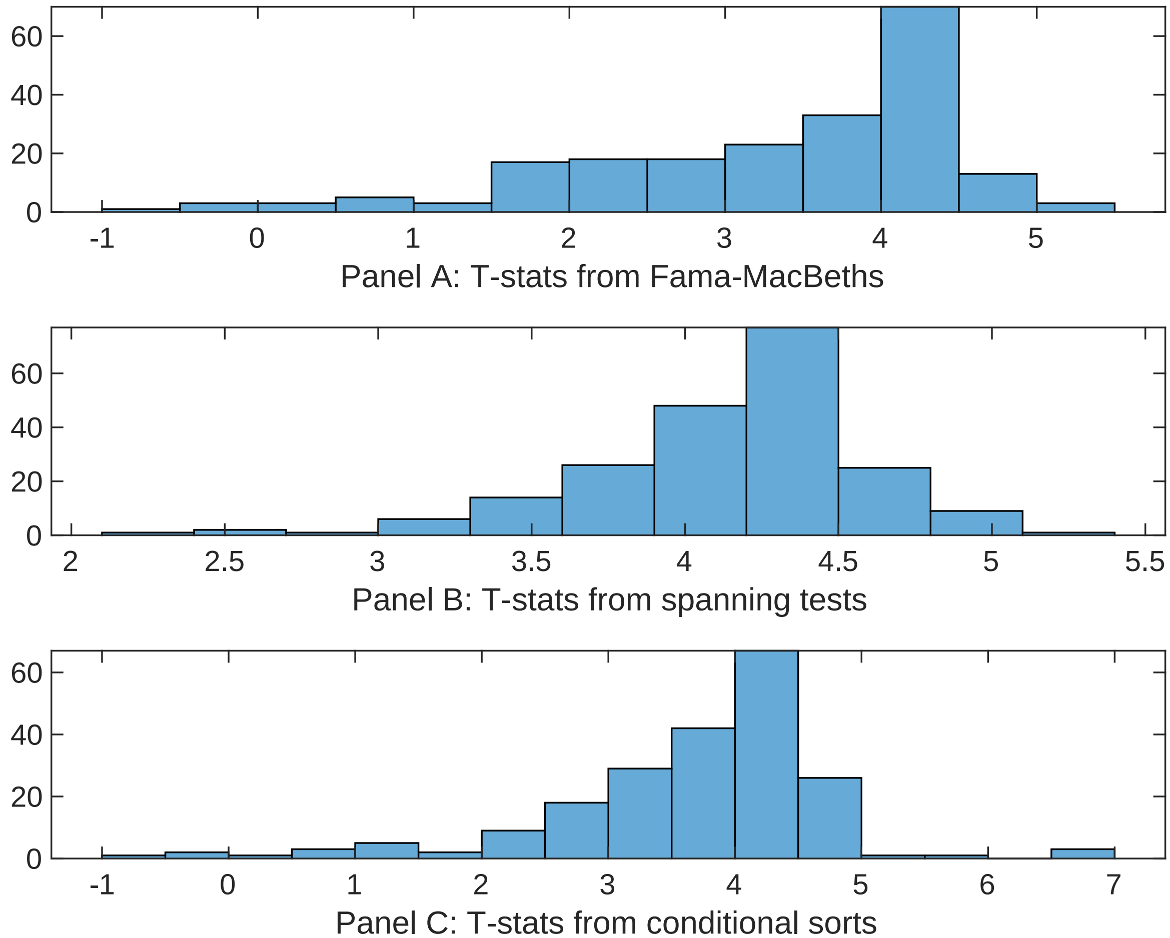



**Figure 7:** Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SDDS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{SDDS}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SDDS} SDDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ from spanning tests of the form: $r_{SDDS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on SDDS. Stocks are finally grouped into five SDDS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SDDS trading strategies conditioned on each of the 210 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on SDDS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SDDS} SDDS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, $X$, are Share issuance (1 year), Net Payout Yield, Growth in book equity, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the $R^2$ from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.13 | 0.12 | 0.18 | 0.13 | 0.13 | 0.14 | 0.13 |
| | [5.55] | [5.25] | [7.05] | [5.92] | [5.47] | [5.91] | [5.11] |
| SDDS | 0.69 | 0.35 | 0.59 | 0.71 | 0.65 | 0.49 | 0.26 |
| | [3.80] | [1.91] | [3.39] | [3.97] | [3.56] | [2.83] | [1.51] |
| Anomaly 1 | 0.27 | | | | | | 0.11 |
| | [5.82] | | | | | | [2.66] |
| Anomaly 2 | | 0.28 | | | | | 0.23 |
| | | [2.52] | | | | | [2.17] |
| Anomaly 3 | | | 0.48 | | | | -0.11 |
| | | | [4.42] | | | | [-0.01] |
| Anomaly 4 | | | | 0.33 | | | 0.34 |
| | | | | [3.54] | | | [0.38] |
| Anomaly 5 | | | | | 0.15 | | -0.19 |
| | | | | | [4.12] | | [-0.34] |
| Anomaly 6 | | | | | | 0.10 | 0.68 |
| | | | | | | [8.79] | [6.45] |
| # months | 679 | 679 | 684 | 679 | 684 | 684 | 679 |
| $\bar{R}^2$(%) | 0 | 1 | 0 | 0 | 0 | 0 | 0 |

**Table 5:** Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the SDDS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SDDS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where $X_k$ indicates each of the six most-closely related anomalies and $f_j$ indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, $X$, are Share issuance (1 year), Net Payout Yield, Growth in book equity, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the $R^2$ from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.16 | 0.18 | 0.19 | 0.16 | 0.21 | 0.19 | 0.15 |
| | [2.20] | [2.46] | [2.54] | [2.07] | [2.73] | [2.53] | [2.13] |
| Anomaly 1 | 27.71 | | | | | | 18.11 |
| | [7.37] | | | | | | [4.18] |
| Anomaly 2 | | 17.38 | | | | | 6.15 |
| | | [6.02] | | | | | [1.88] |
| Anomaly 3 | | | 34.90 | | | | 34.43 |
| | | | [8.60] | | | | [5.87] |
| Anomaly 4 | | | | 14.25 | | | -0.37 |
| | | | | [3.62] | | | [-0.09] |
| Anomaly 5 | | | | | 20.84 | | -8.10 |
| | | | | | [5.23] | | [-1.48] |
| Anomaly 6 | | | | | | 6.75 | -14.01 |
| | | | | | | [1.34] | [-2.71] |
| mkt | 2.86 | 3.55 | 1.79 | 2.73 | 0.32 | 0.67 | 4.28 |
| | [1.65] | [1.99] | [1.04] | [1.50] | [0.18] | [0.37] | [2.43] |
| smb | 0.15 | 2.29 | -2.49 | -1.71 | -1.65 | -1.95 | 1.14 |
| | [0.06] | [0.90] | [-1.00] | [-0.66] | [-0.64] | [-0.73] | [0.45] |
| hml | -1.82 | -4.97 | -2.71 | -2.09 | -1.25 | 1.15 | -5.59 |
| | [-0.54] | [-1.38] | [-0.81] | [-0.57] | [-0.36] | [0.33] | [-1.58] |
| rmw | -0.83 | -1.52 | 9.88 | 5.65 | 10.12 | 7.94 | 0.12 |
| | [-0.23] | [-0.40] | [2.94] | [1.60] | [2.91] | [2.25] | [0.03] |
| cma | 28.22 | 28.86 | 6.40 | 37.55 | 19.35 | 32.84 | 19.95 |
| | [5.33] | [5.25] | [1.01] | [7.12] | [2.97] | [4.11] | [2.61] |
| umd | 2.89 | 4.69 | 2.70 | 3.37 | 3.70 | 3.26 | 2.35 |
| | [1.70] | [2.71] | [1.59] | [1.92] | [2.10] | [1.81] | [1.39] |
| # months | 680 | 680 | 684 | 680 | 684 | 684 | 680 |
| $\bar{R}^2(\%)$ | 27 | 25 | 27 | 22 | 22 | 19 | 32 |

## Panel A: Average rank

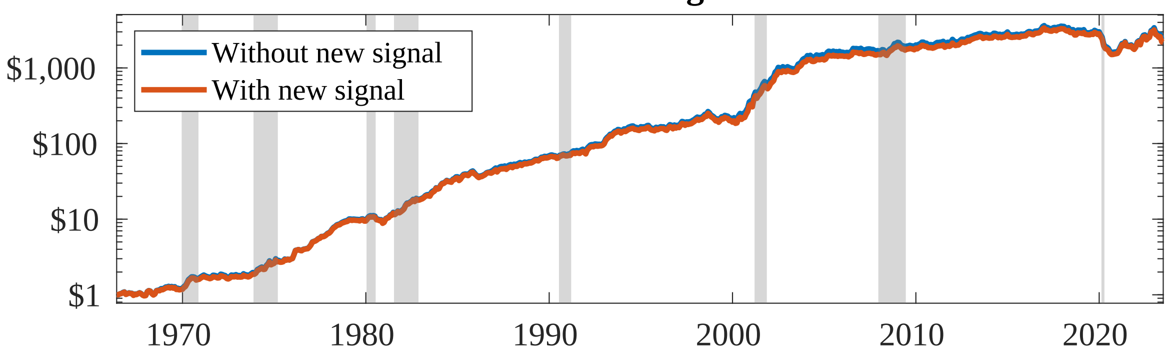



**Figure 8:** Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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