Stock Depreciation Difference Signal and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

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 intriguing yet understudied area is how firms' depreciation accounting choices may contain information about future performance and valuation.

Despite extensive research on accounting-based return predictors, the role of depreciation methods and their differences across firms has received limited attention. This gap is surprising given that depreciation represents one of management's most significant accounting estimates and directly impacts reported profitability. The discretion managers have in selecting depreciation methods and assumptions creates potential information content in the differences between firms' depreciation practices.

We hypothesize that systematic differences in firms' depreciation methods relative to industry peers may signal information about future performance and returns. This builds on Thomas and Zhang (2002)'s finding that accounting method choices contain information about management's private expectations. When managers have favorable private information about asset productivity and useful life, they may select more conservative depreciation methods to create accounting slack for future periods.

The theoretical mechanism operates through two channels. First, following Penman and Zhang (2002), conservative accounting choices can create 'hidden reserves' that managers draw upon strategically. Second, as demonstrated by Beaver (1993), accounting method choices serve as costly signals because they constrain future reporting flexibility. Therefore, firms choosing relatively higher depreciation rates compared to peers may be signaling confidence in asset productivity and future performance.

This signaling value is likely to be particularly strong when depreciation differences persist over time and deviate significantly from industry norms. Zhang (2005) shows that accounting conservatism helps resolve agency conflicts by allowing managers to credibly communicate private information. The Stock Depreciation Difference Signal (SDDS) captures these systematic depreciation differences while controlling for industry effects.

Our empirical analysis reveals that SDDS strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on SDDS quintiles generates monthly abnormal returns of 19 basis points (t-statistic = 2.45) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.58, placing it in the top 5% of documented return predictors.

Importantly, the predictive power of SDDS persists after controlling for known determinants of returns. The signal maintains significant predictability when controlling for the six most closely related anomalies, with a monthly alpha of 15 basis points (t-statistic = 2.13). This indicates that SDDS captures unique information not contained in other accounting-based signals.

The economic magnitude of the SDDS effect is substantial and robust across different methodological choices. The strategy remains profitable after accounting for transaction costs, with a net Sharpe ratio of 0.52. Among large-cap stocks (above 80th NYSE percentile), SDDS generates monthly abnormal returns of 20-29 basis points with t-statistics between 1.97 and 3.03, demonstrating that the effect is not confined to small, illiquid stocks.

Our study makes several contributions to the asset pricing and accounting choice literatures. First, we introduce a novel return predictor based on firms' depreciation accounting choices relative to industry peers. While prior work like Thomas and Zhang (2002) examines the information content of accounting methods, we are the first to document their systematic relationship with future stock returns.

Second, we extend the literature on accounting-based anomalies by showing that differences in depreciation methods contain important information not captured by traditional accounting signals. Our findings complement work by Sloan and Soliman (2009) on accrual anomalies and Penman and Zhang (2002) on conservative accounting by identifying a specific channel through which accounting choices predict returns.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate that examining the relative differences in firms' accounting choices, rather than just the choices themselves, can reveal valuable information. For practitioners, SDDS represents a novel signal that is relatively simple to construct and remains profitable after transaction costs, even among large-cap stocks.

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 on 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 scaling the change in common stock by accumulated depreciation, the signal provides insight into how equity issuance or repurchase activities compare to the firm's accumulated depreciation, potentially indicating patterns in capital structure decisions and asset replacement cycles. We construct this signal 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^{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 β_{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 α 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, with net abnormal returns of 20 basis points per month relative to the Fama-French five-factor model plus momentum. Furthermore, the signal's ability to generate significant alpha (15 bps/month) even after controlling for six closely related strategies suggests that SDDS captures unique information content not explained by 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 several promising directions. First, investigating the signal's performance in international markets could provide insights into its global applicability. Second, examining the interaction between SDDS and other established signals could potentially lead to more robust composite strategies. Finally, analyzing the underlying economic mechanisms driving the signal's predictive power could enhance our understanding of market efficiency and asset pricing dynamics.

In conclusion, SDDS represents a meaningful addition to the quantitative investor's toolkit, offering substantial predictive power that persists even after controlling for transaction costs and related factors. These findings contribute to our understanding of market efficiency and provide practical implications for investment professionals.

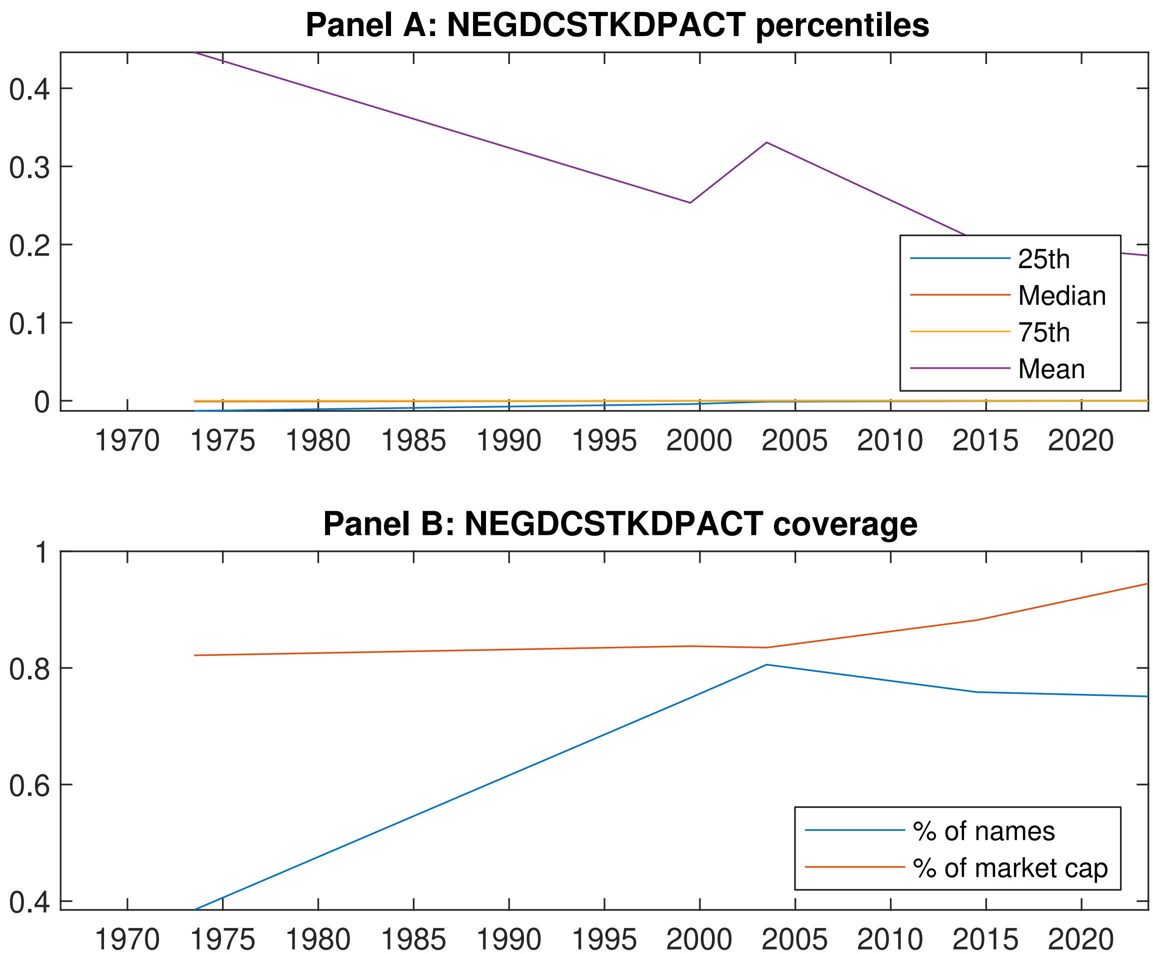

Figure 1: Times series of SDDS percentiles and coverage.
This figure plots descriptive statistics for SDDS. Panel A shows cross-sectional percentiles of SDDS over the sample. Panel B plots the monthly coverage of SDDS relative to the universe of CRSP stocks with available market capitalizations.

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]
α_{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]
α_{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]
α_{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]
α_{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]
α_{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						
β_{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]
β_{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]
β_{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]
β_{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]
β_{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]
β_{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	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{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}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{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	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{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 Average n					SDDS Quintiles 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

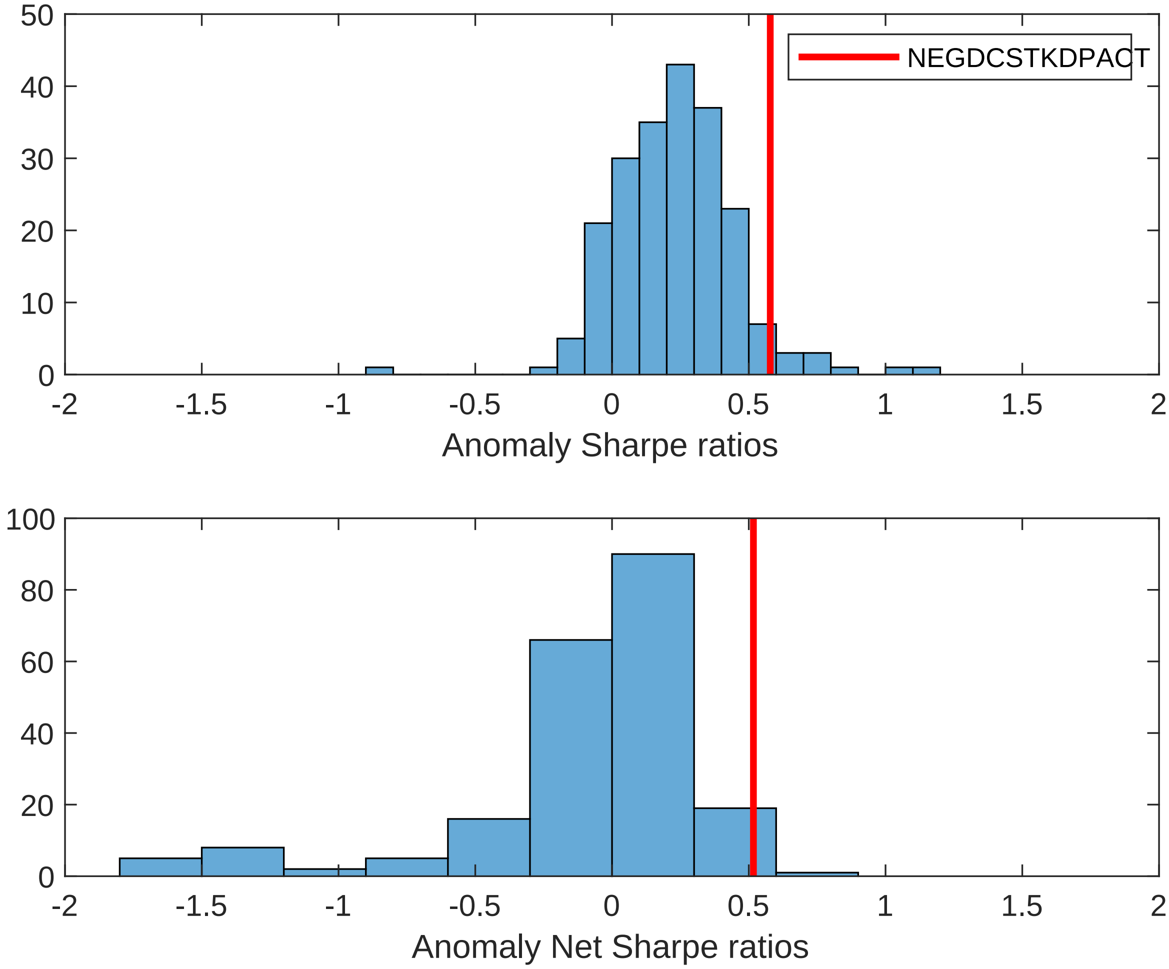

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SDDS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

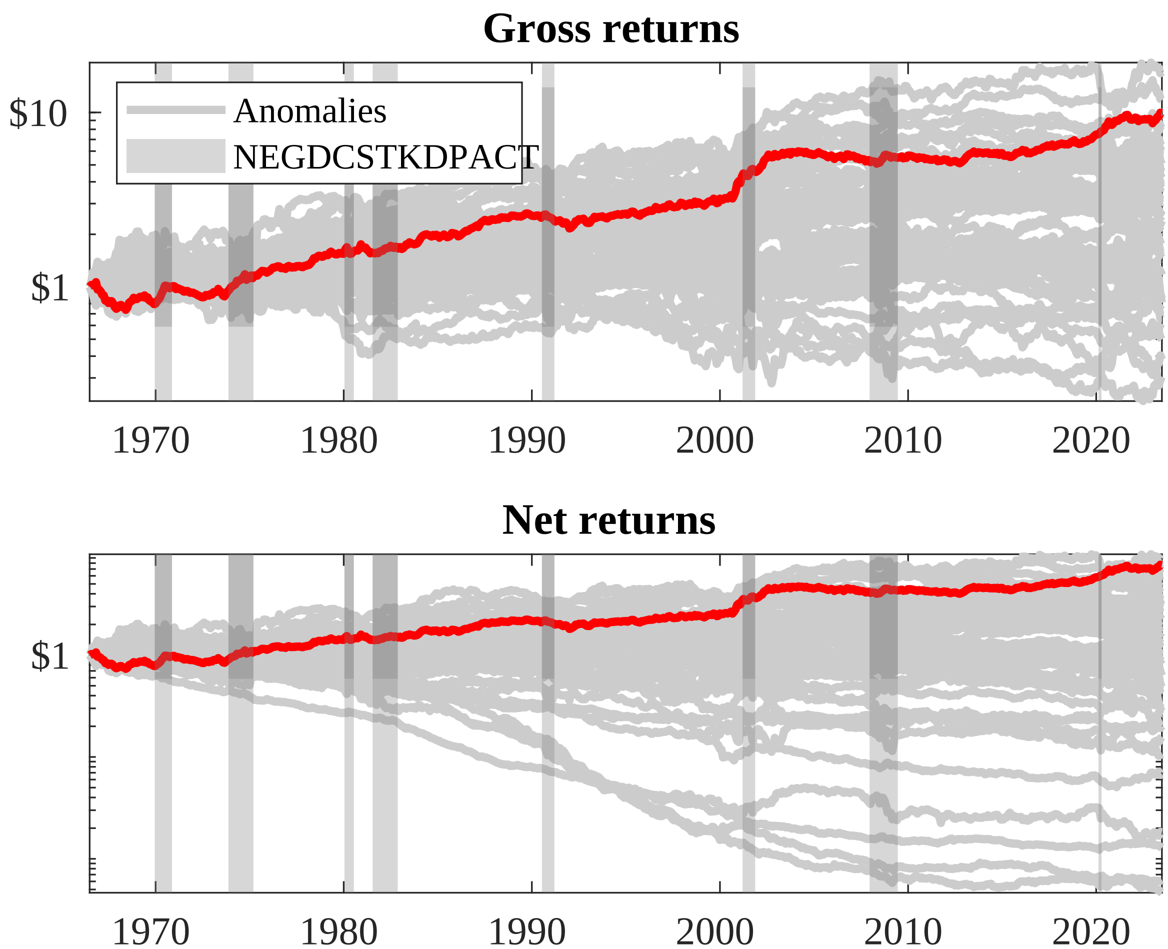

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SDDS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

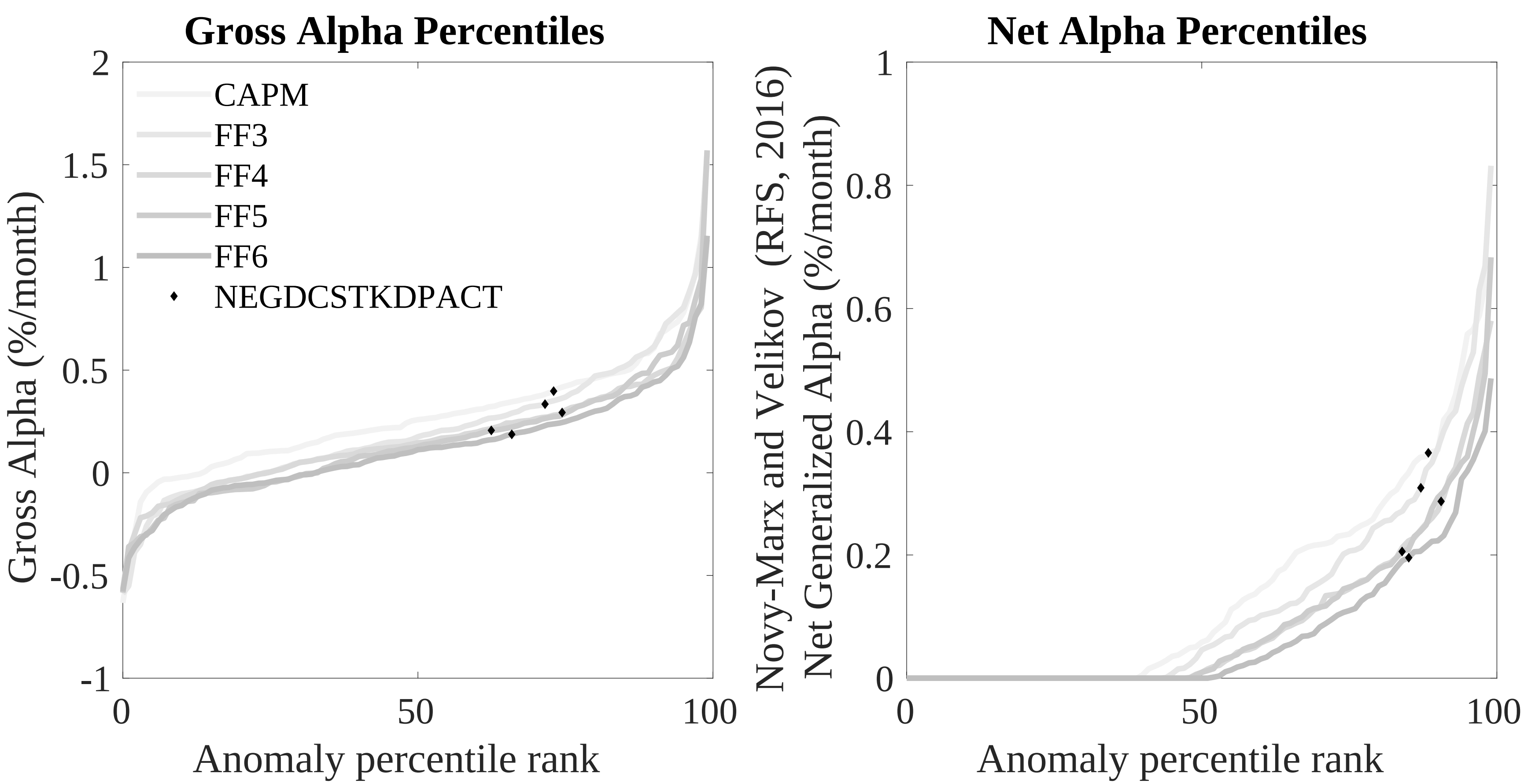

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SDDS trading strategy alphas (diamonds). The strategies are constructed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

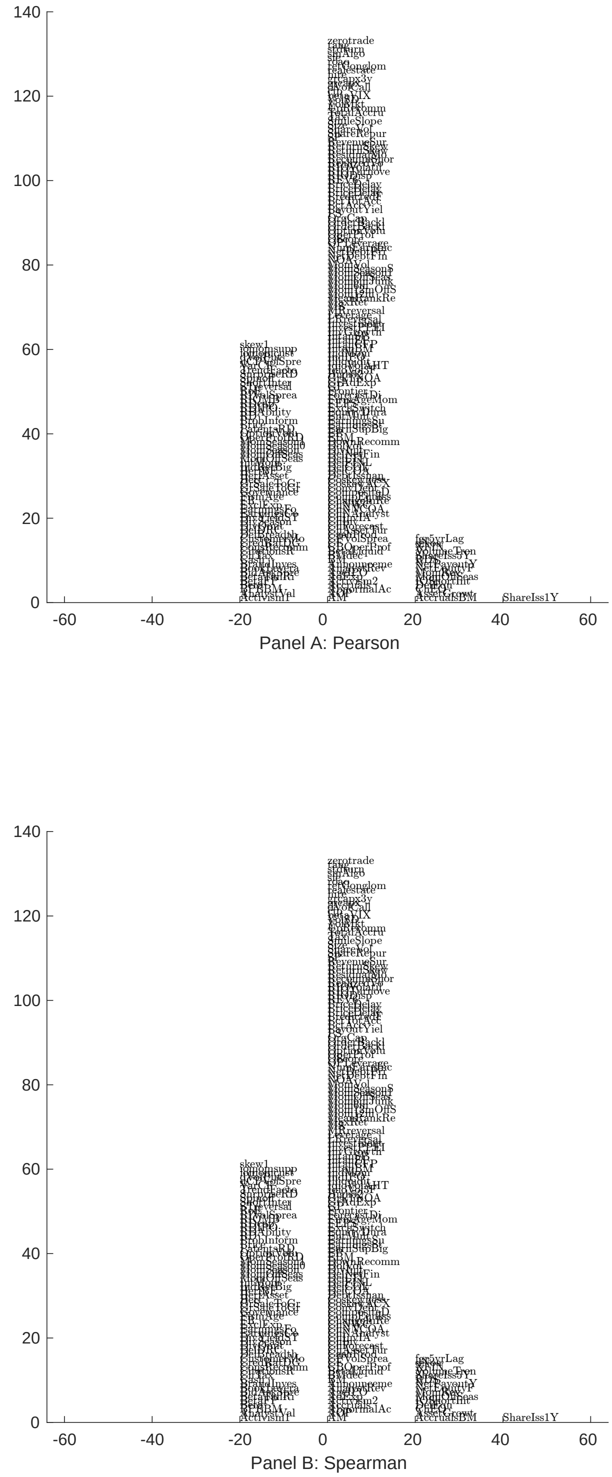

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with SDDS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

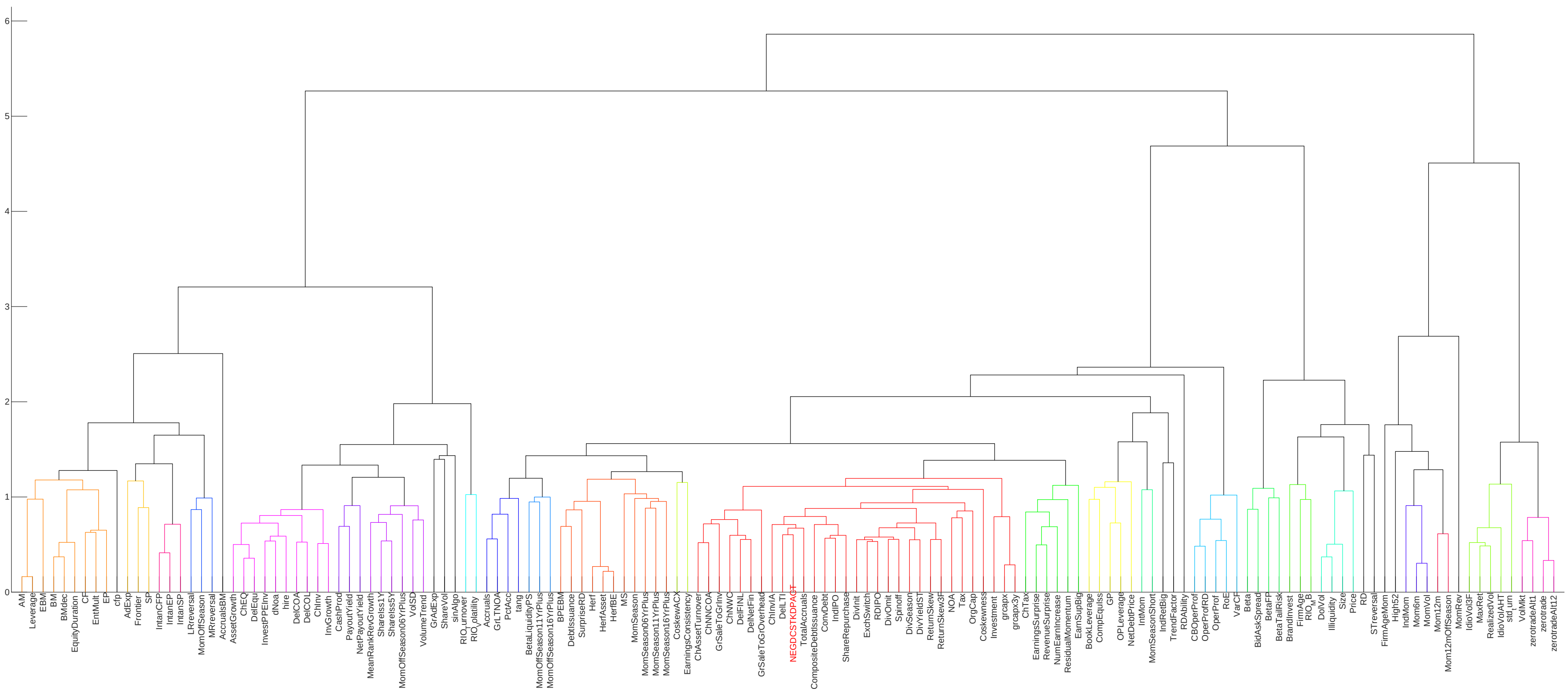

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

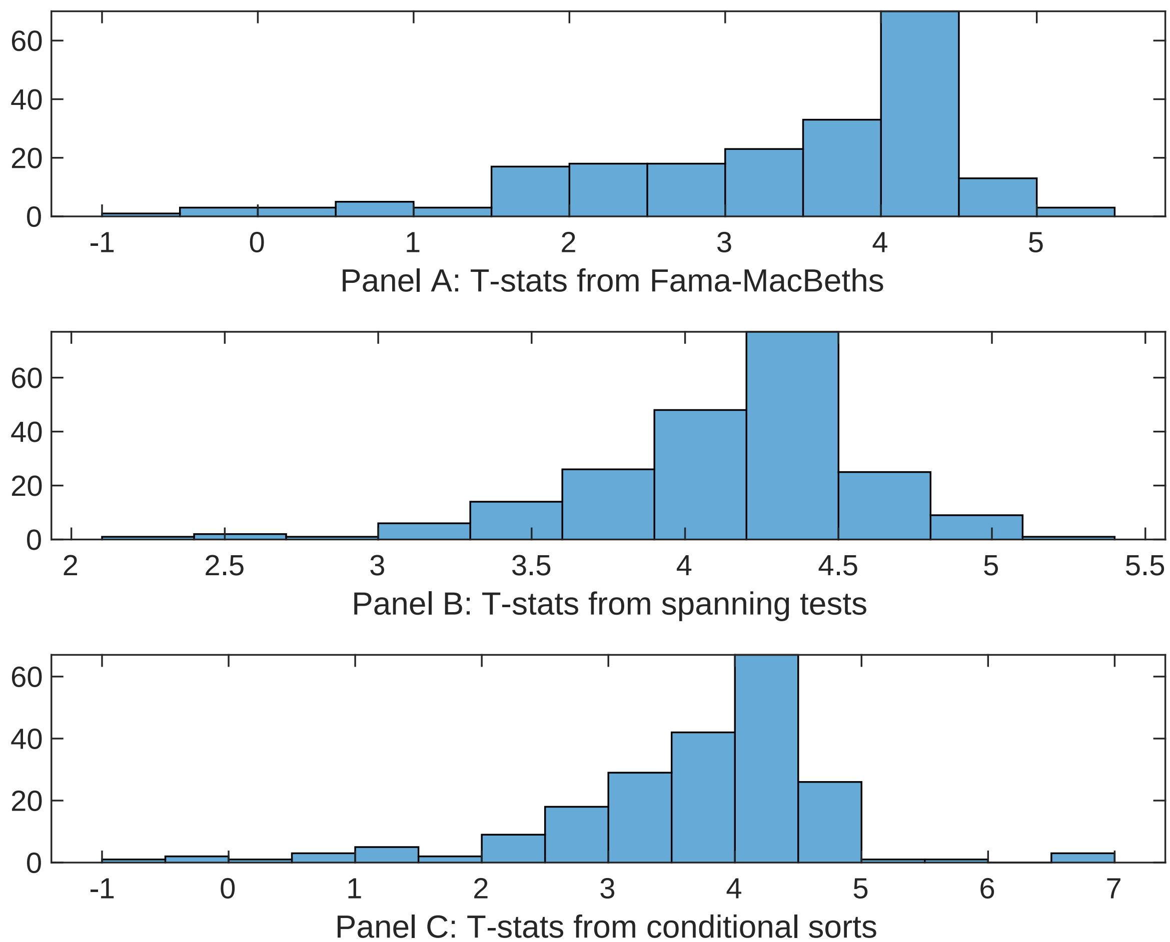

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SDDS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SDDS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SDDS} SDDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α 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

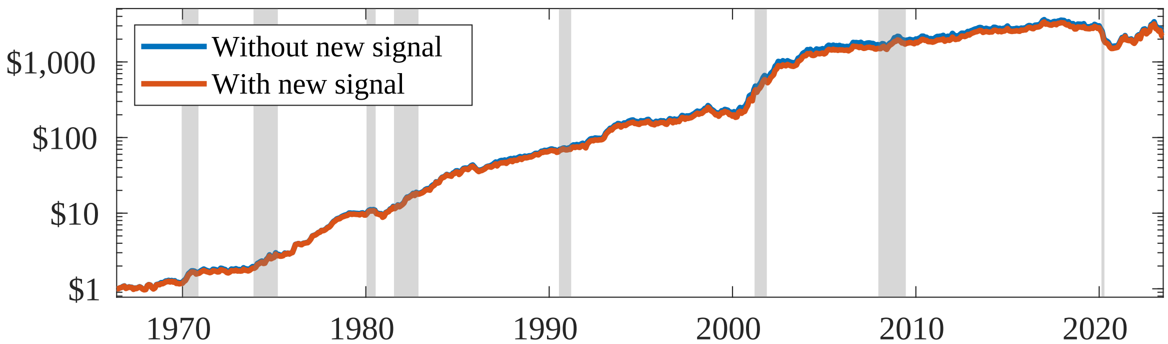

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines 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.

References

Beaver, W. H. (1993). Differential pricing of alternative accounting choice. *Journal of Accounting Research*, 31(1):38–62.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.

Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance, Forthcoming.*

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper.*

Penman, S. H. and Zhang, X.-J. (2002). Accounting conservatism, the quality of earnings, and stock returns. *The Accounting Review*, 77(2):237–264.

Sloan, R. G. and Soliman, M. T. (2009). The extreme accruals anomaly: International evidence. *The Accounting Review*, 84(6):1995–2033.

Thomas, J. K. and Zhang, H. (2002). Inventory changes and future returns. *Review of Accounting Studies*, 7(2):163–187.

Zhang, J. (2005). The contracting benefits of accounting conservatism to lenders and borrowers. *Journal of Accounting and Economics*, 45(1):27–54.