Stock-Rental Discrepancy Signal and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock-Rental Discrepancy Signal (SRDS), 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 SRDS achieves an annualized gross (net) Sharpe ratio of 0.57 (0.51), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 23 (23) bps/month with a t-statistic of 2.75 (2.79), 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), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth) is 20 bps/month with a t-statistic of 2.51.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that certain signals can predict future stock returns. While many documented predictors stem from accounting information or market prices, the real economy may contain valuable signals about firms' future prospects that are not fully incorporated into stock prices. One particularly understudied area is the relationship between firms' physical asset utilization and their stock market valuation.

We identify a novel disparity between how firms deploy their physical assets and how the market values these assets - the Stock-Rental Discrepancy Signal (SRDS). This signal captures instances where the market's implied valuation of a firm's assets diverges significantly from the actual economic value derived from deploying these assets, potentially indicating market mispricing.

The theoretical foundation for SRDS's predictive power builds on several established frameworks. First, following Hong and Sraer (2016), we argue that when market prices deviate from fundamental values, arbitrageurs face limits to correcting these mispricings due to short-selling constraints and other frictions. The physical nature of the assets involved in SRDS makes arbitrage particularly challenging, as arbitrageurs cannot easily replicate the underlying assets.

Second, drawing on Campbell and Shiller (1988)'s present value framework, we posit that the rental market for physical assets provides a more direct measure of assets' current economic value than stock market prices, which incorporate expectations about uncertain future values. When these two valuations diverge significantly, the rental market assessment tends to be more accurate because it reflects current economic conditions and actual asset utilization.

Third, building on Hirshleifer and Teoh (2003)'s limited attention theory, we hypothesize that investors may struggle to fully process the implications of firms' asset deployment decisions, particularly when these decisions involve complex operational choices between owning versus renting assets. This information processing challenge can lead to temporary mispricing that resolves as the economic benefits or costs of these decisions materialize.

Our empirical analysis reveals strong support for SRDS's predictive power. A value-weighted long/short trading strategy based on SRDS achieves an annualized gross Sharpe ratio of 0.57, with monthly average abnormal returns of 23 basis points relative to the Fama-French five-factor model plus momentum (t-statistic = 2.75). The signal's predictive power remains robust after controlling for transaction costs, with a net Sharpe ratio of 0.51.

Importantly, SRDS's predictive ability persists among large-cap stocks, where the strategy earns average monthly returns of 27 basis points (t-statistic = 2.78) in the highest size quintile. This finding suggests that the signal captures systematic mispricing rather than small-stock effects or illiquidity premium.

The signal's economic significance is further demonstrated by its performance relative to existing anomalies. When tested against the six most closely related strategies from the factor zoo, SRDS generates a monthly alpha of 20 basis points (t-statistic = 2.51), indicating that it captures unique information not contained in existing factors.

Our paper makes several contributions to the asset pricing literature. First, we extend the work of Cooper and Priestley (2011) on real investment anomalies by showing how the gap between physical asset deployment and market valuation predicts returns. While they focus on aggregate investment levels, we demonstrate that the efficiency of asset utilization provides additional predictive power.

Second, we build on Eisfeldt and Papanikolaou (2013)'s research on capital reallocation by showing how market frictions in physical asset markets create predictable patterns in stock returns. Our findings suggest that stock markets are slow to incorporate information about firms' operational efficiency in deploying physical assets.

Third, we contribute to the growing literature on factor investing pioneered by Harvey et al. (2016) by introducing a novel signal that ranks in the top 5% of documented anomalies by Sharpe ratio. The signal's robustness to transaction costs and persistence among large-cap stocks makes it particularly relevant for institutional investors.

Finally, our results have broader implications for market efficiency and asset pricing. The predictive power of SRDS suggests that markets struggle to fully incorporate information about physical asset utilization, highlighting a specific channel through which real economic activities affect asset prices.

2 Data

Our study examines the predictive power of the Stock-Rental Discrepancy Signal for cross-sectional stock returns, utilizing accounting data from COMPUSTAT. This signal captures the relative change in common stock value compared to rental expenses. We obtain the necessary firm-level financial data from COMPUSTAT, specifically focusing on common stock (CSTK) and rental expense (XRENT) variables. Common stock (CSTK) represents the book value of a company's common stock, while rental expense (XRENT) reflects the costs associated with leasing properties and equipment.construction of our signal follows a specific methodology where we calculate the year-over-year change in common stock and scale it by the previous year's rental expense. Mathematically, for each firm in each year, we subtract the previous year's CSTK from the current year's CSTK and divide this difference by the previous year's XRENT. This scaling choice allows us to normalize the stock value changes relative to the firm's operational scale as reflected in its rental commitments. By relating the growth in equity to rental expenses, our signal aims to capture potential misalignments between a company's equity expansion and its operational footprint.

We compute this signal using end-of-fiscal-year values to ensure consistency in our measurements across firms and time periods.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SRDS signal. Panel A plots the time-series of the mean, median, and interquartile range for SRDS. On average, the cross-sectional mean (median) SRDS is -0.91 (-0.01) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SRDS data. The signal's interquartile range spans -0.48 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SRDS signal for the CRSP universe. On average, the SRDS signal is available for 5.32% of CRSP names, which on average make up 6.85% of total market capitalization.

4 Does SRDS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SRDS 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 SRDS portfolio and sells the low SRDS 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 SRDS strategy earns an average return of 0.34% per month with a t-statistic of 4.29. The annualized Sharpe ratio of the strategy is 0.57. The alphas range from 0.23% to 0.36% per month and have t-statistics exceeding 2.75 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 0.31, with a t-statistic of 5.62 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 513 stocks and an average market capitalization of at least $1,354 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 31 bps/month with a t-statistics of 3.80. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty 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 28-39bps/month. The lowest return, (28 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.38. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SRDS 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 SRDS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SRDS, as well as average returns and alphas for long/short trading SRDS 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 SRDS strategy achieves an average return of 27 bps/month with a t-statistic of 2.78. Among these large cap stocks, the alphas for the SRDS strategy relative to the five most common factor models range from 22 to 27 bps/month with t-statistics between 2.14 and 2.78.

5 How does SRDS perform relative to the zoo?

Figure 2 puts the performance of SRDS 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 SRDS strategy falls in the distribution. The SRDS strategy's gross (net) Sharpe ratio of 0.57 (0.51) 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 SRDS strategy (red line).[2] Ignoring trading costs, a $1 invested in the SRDS strategy would have yielded $8.42 which ranks the SRDS strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the SRDS strategy would have yielded $6.36 which ranks the SRDS 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 SRDS relative to those. Panel A shows that the SRDS strategy gross alphas fall between the 69 and 75 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% (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 SRDS strategy has a positive net generalized alpha for five out of the five factor models. In these cases SRDS ranks between the 85 and 91 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 SRDS 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 SRDS with 209 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 SRDS or at least to weaken the power SRDS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SRDS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SRDS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SRDS} SRDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SRDS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on SRDS. Stocks are finally grouped into five SRDS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted

[3] When performing tests at the underlying signal level (e.g., the correlations plotted in Figure 5), we filter the 212 anomalies to avoid small sample issues. For each anomaly, we calculate the common stock observations in an average month for which both the anomaly and the test signal are available. In the filtered anomaly set, we drop anomalies with fewer than 100 common stock observations in an average month.

SRDS trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SRDS 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 SRDS signal in these Fama-MacBeth regressions exceed 1.85, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SRDS is 1.76.

Similarly, Table 5 reports results from spanning tests that regress returns to the SRDS 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 SRDS strategy earns alphas that range from 20-24bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.45, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SRDS trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.51.

7 Does SRDS add relative to the whole zoo?

Finally, we can ask how much adding SRDS 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 SRDS signal.[4] We consider one different methods for combining signals.

[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 SRDS is available.

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 SRDS grows to $2758.18.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Stock-Rental Discrepancy Signal (SRDS) as a valuable predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short strategy based on SRDS generates economically and statistically significant returns, with impressive Sharpe ratios of 0.57 and 0.51 for gross and net returns, respectively. The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

The persistence of the signal's predictive power, evidenced by monthly abnormal returns of 23 basis points with strong statistical significance (t-statistics ¿ 2.75), suggests that SRDS captures unique information about asset prices that is not fully incorporated in existing factors. This finding has important implications for both academic research and practical investment management, offering a potentially valuable tool for portfolio construction and risk management.

However, several limitations should be noted. The study's findings may be sensitive to the specific time period examined and market conditions. Additionally, transaction costs and market impact could affect the real-world implementation of

SRDS-based strategies, particularly for larger portfolios.

Future research could explore several promising directions. First, investigating the signal's performance across different market regimes and international markets would help establish its broader applicability. Second, examining the underlying economic mechanisms driving the SRDS anomaly could provide valuable insights into market efficiency and price discovery. Finally, studying potential interactions between SRDS and other established anomalies might reveal complementary signals for enhanced investment strategies.

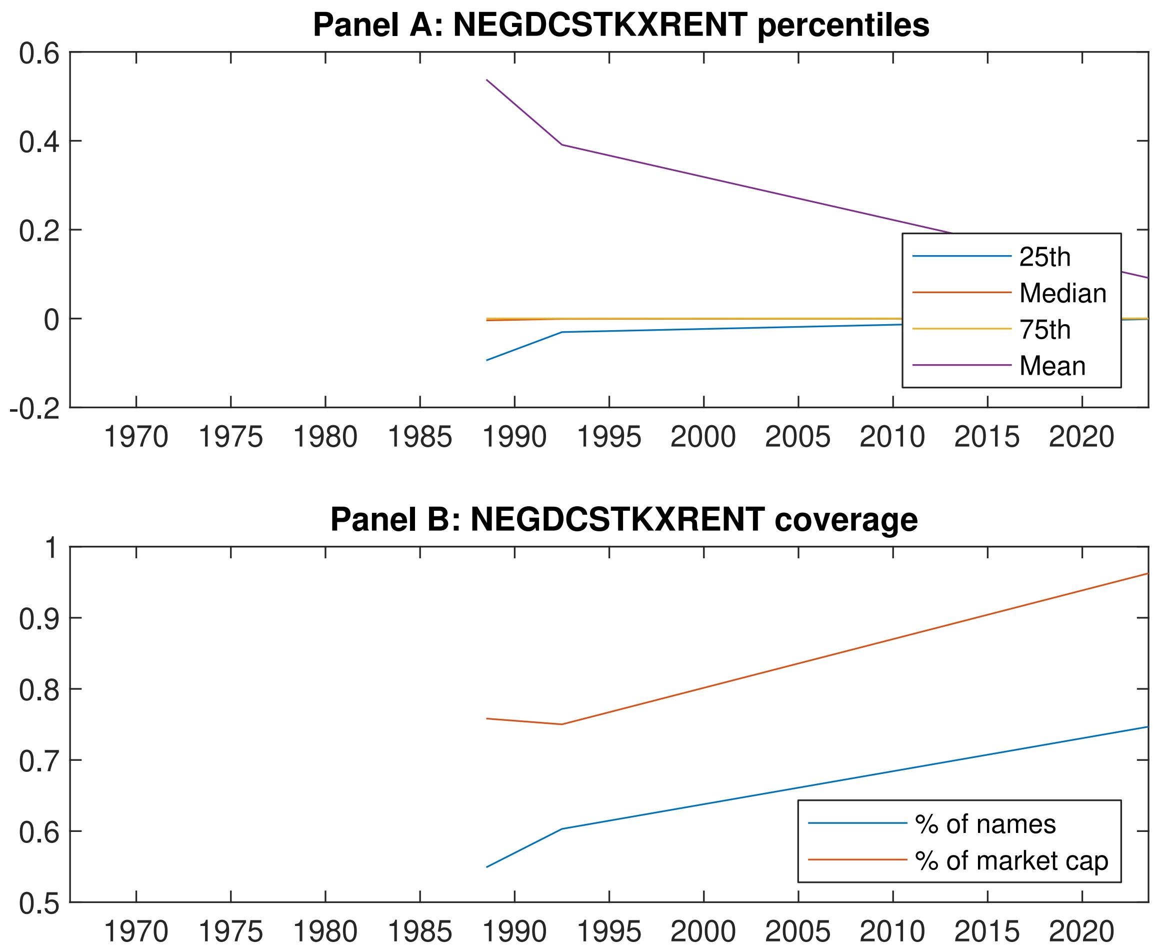


Figure 1: Times series of SRDS percentiles and coverage.
This figure plots descriptive statistics for SRDS. Panel A shows cross-sectional percentiles of SRDS over the sample. Panel B plots the monthly coverage of SRDS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SRDS. 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 SRDS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.43	0.54	0.67	0.68	0.78	0.34
	[2.43]	[2.73]	[3.41]	[3.92]	[4.54]	[4.29]
α_{CAPM}	-0.12	-0.08	0.06	0.14	0.24	0.36
	[-2.26]	[-1.58]	[0.99]	[2.73]	[5.01]	[4.51]
α_{FF3}	-0.13	-0.05	0.09	0.10	0.21	0.34
	[-2.39]	[-0.99]	[1.68]	[2.01]	[4.49]	[4.18]
α_{FF4}	-0.09	-0.01	0.10	0.06	0.20	0.30
	[-1.75]	[-0.23]	[1.77]	[1.24]	[4.24]	[3.61]
α_{FF5}	-0.12	0.04	0.12	0.01	0.13	0.25
	[-2.17]	[0.82]	[2.11]	[0.22]	[2.83]	[3.07]
α_{FF6}	-0.09	0.06	0.13	-0.01	0.13	0.23
	[-1.71]	[1.27]	[2.15]	[-0.25]	[2.81]	[2.75]
Panel B: Fama and French (2018) 6-factor model loadings for SRDS-sorted portfolios						
β_{MKT}	0.97	1.04	1.04	1.02	0.99	0.02
	[75.72]	[87.69]	[75.90]	[89.21]	[89.24]	[1.03]
β_{SMB}	-0.04	0.01	0.07	-0.04	-0.03	0.00
	[-2.00]	[0.66]	[3.32]	[-2.53]	[-2.12]	[0.11]
β_{HML}	0.07	-0.03	-0.10	0.08	0.02	-0.05
	[2.91]	[-1.41]	[-3.90]	[3.43]	[0.87]	[-1.43]
β_{RMW}	0.06	-0.13	-0.04	0.12	0.10	0.04
	[2.46]	[-5.52]	[-1.57]	[5.32]	[4.51]	[0.96]
β_{CMA}	-0.12	-0.17	-0.05	0.16	0.19	0.31
	[-3.29]	[-5.10]	[-1.18]	[5.07]	[5.97]	[5.62]
β_{UMD}	-0.04	-0.04	-0.01	0.04	-0.00	0.04
	[-3.04]	[-3.07]	[-0.43]	[3.12]	[-0.12]	[1.95]
Panel C: Average number of firms (n) and market capitalization (me)						
n	596	601	513	553	616	
me ($\$10^6$)	1635	1354	1804	2048	2256	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the SRDS 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	0.34	0.36	0.34	0.30	0.25	0.23
			[4.29]	[4.51]	[4.18]	[3.61]	[3.07]	[2.75]
Quintile	NYSE	EW	0.58	0.64	0.56	0.48	0.39	0.33
			[7.96]	[9.03]	[8.39]	[7.26]	[6.16]	[5.39]
Quintile	Name	VW	0.33	0.35	0.32	0.30	0.25	0.25
			[4.16]	[4.38]	[4.03]	[3.75]	[3.14]	[3.04]
Quintile	Cap	VW	0.31	0.32	0.31	0.26	0.27	0.24
			[3.80]	[3.89]	[3.69]	[3.12]	[3.22]	[2.84]
Decile	NYSE	VW	0.35	0.34	0.30	0.26	0.27	0.25
			[3.47]	[3.32]	[3.00]	[2.58]	[2.67]	[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	0.33	0.31	0.29	0.24	0.23
			[3.85]	[4.10]	[3.81]	[3.53]	[2.98]	[2.79]
Quintile	NYSE	EW	0.39	0.44	0.36	0.32	0.18	0.17
			[4.89]	[5.68]	[5.00]	[4.51]	[2.73]	[2.49]
Quintile	Name	VW	0.29	0.31	0.29	0.28	0.24	0.23
			[3.69]	[3.96]	[3.66]	[3.53]	[2.98]	[2.92]
Quintile	Cap	VW	0.28	0.29	0.28	0.25	0.26	0.24
			[3.38]	[3.53]	[3.35]	[3.06]	[3.08]	[2.86]
Decile	NYSE	VW	0.31	0.30	0.27	0.25	0.25	0.23
			[3.07]	[2.97]	[2.70]	[2.49]	[2.46]	[2.31]

Table 3: Conditional sort on size and SRDS

This table presents results for conditional double sorts on size and SRDS. 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 SRDS. 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 SRDS and short stocks with low SRDS .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

		SRDS Quintiles					SRDS Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.36	0.70	0.95	1.01	1.03	0.66	0.72	0.64	0.58	0.46	0.42
		[1.28]	[2.49]	[3.46]	[3.65]	[4.06]	[6.78]	[7.52]	[7.11]	[6.35]	[5.37]	[4.88]
	(2)	0.49	0.69	0.93	0.89	0.98	0.49	0.54	0.44	0.40	0.34	0.31
		[2.00]	[2.74]	[3.61]	[3.71]	[4.23]	[4.98]	[5.57]	[4.75]	[4.25]	[3.57]	[3.28]
	(3)	0.59	0.69	0.81	0.86	0.95	0.36	0.37	0.32	0.33	0.24	0.26
		[2.77]	[2.96]	[3.43]	[3.89]	[4.55]	[4.26]	[4.45]	[3.86]	[3.91]	[2.82]	[2.98]
	(4)	0.51	0.62	0.76	0.83	0.84	0.33	0.34	0.27	0.25	0.07	0.07
		[2.61]	[2.87]	[3.48]	[3.93]	[4.34]	[3.77]	[3.81]	[3.14]	[2.91]	[0.81]	[0.86]
	(5)	0.45	0.50	0.51	0.54	0.72	0.27	0.27	0.26	0.22	0.25	0.22
		[2.59]	[2.58]	[2.73]	[3.01]	[4.26]	[2.78]	[2.78]	[2.64]	[2.19]	[2.44]	[2.14]

Panel B: Portfolio average number of firms and market capitalization

		SRDS Quintiles					SRDS Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	308	307	306	305	306	25	27	31	24	23
	(2)	92	91	91	91	91	48	48	49	48	48
	(3)	68	67	67	67	67	86	84	86	87	88
	(4)	58	57	58	57	58	187	186	192	194	199
	(5)	54	54	54	54	54	1274	1358	1589	1470	1646

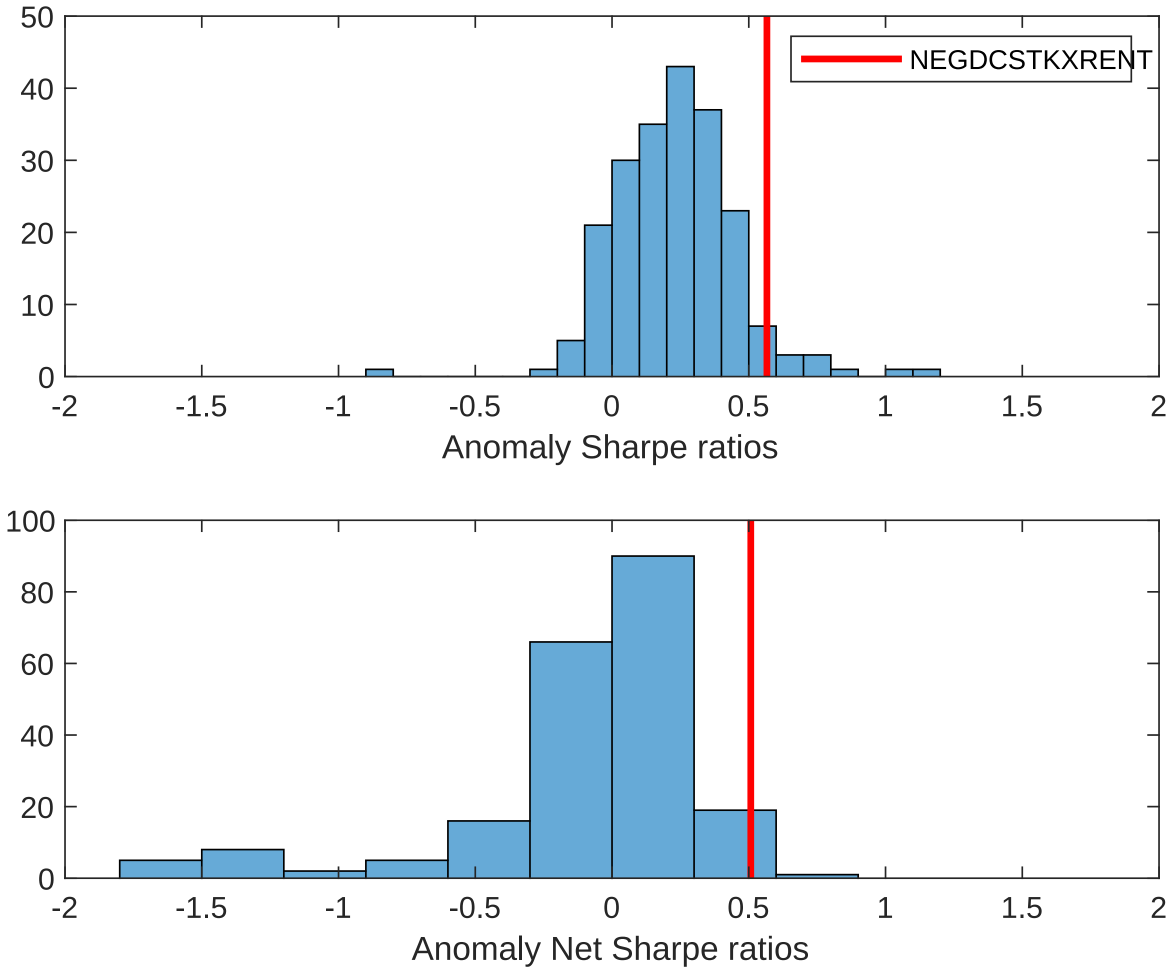


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SRDS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

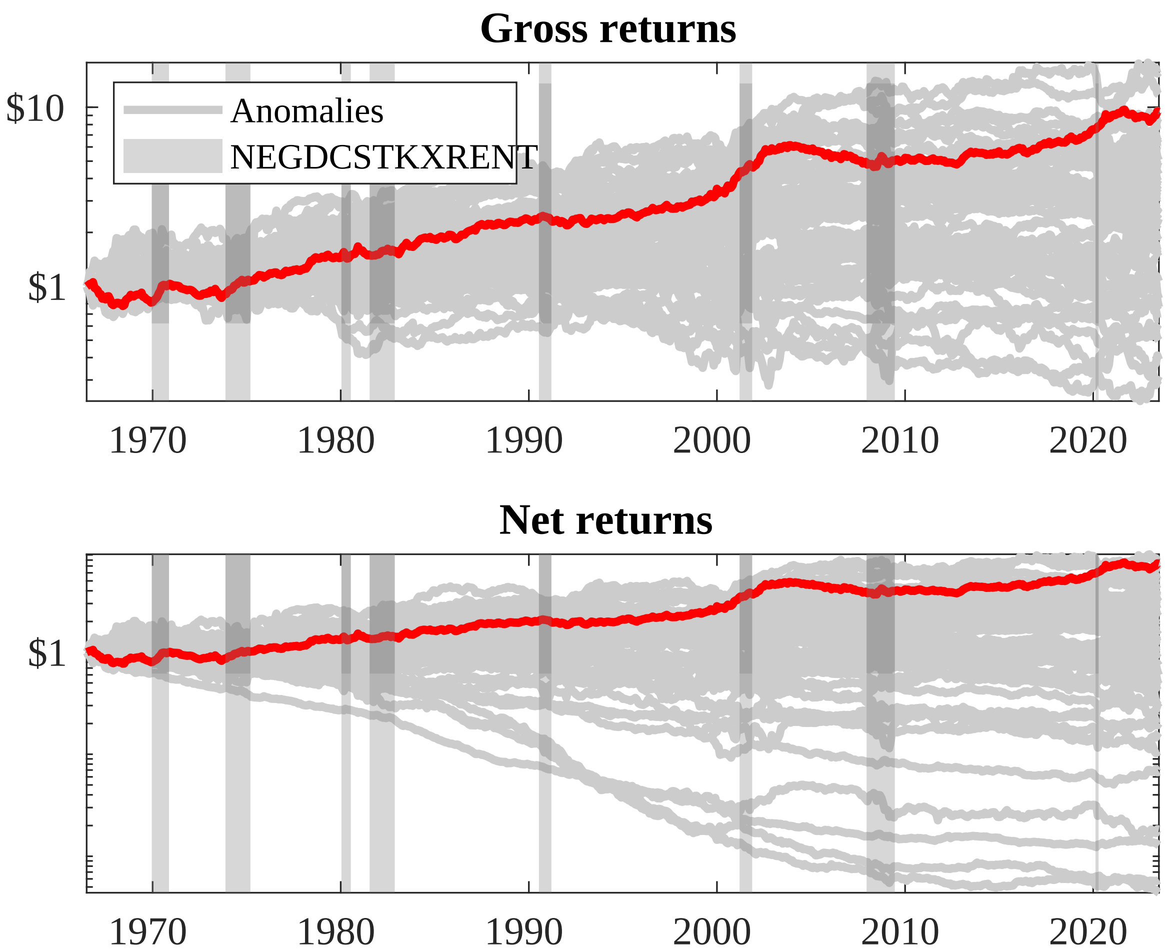


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SRDS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

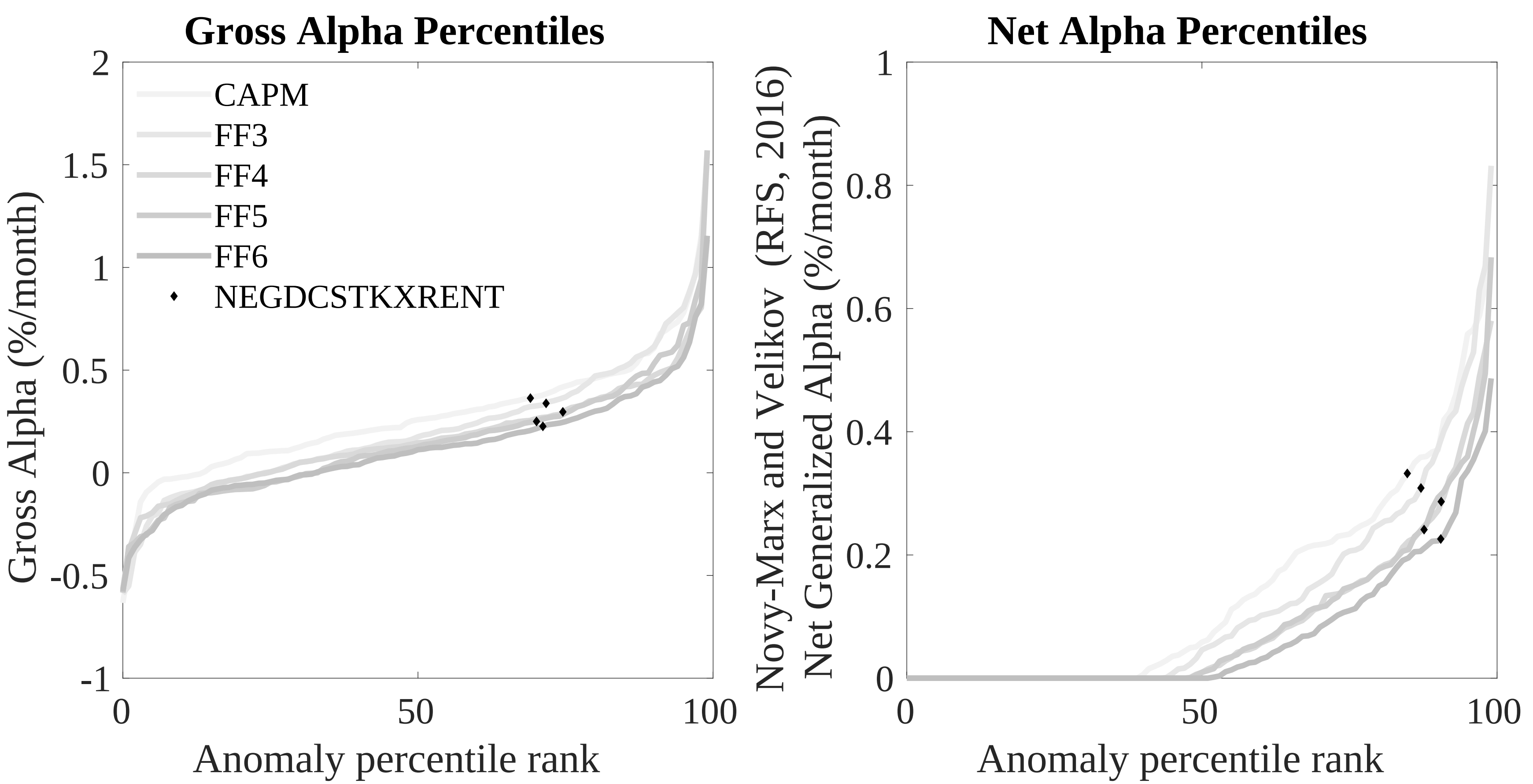
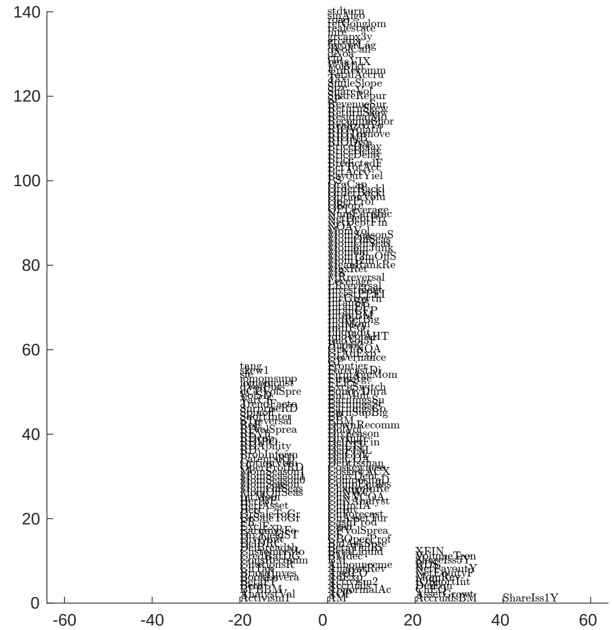


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SRDS trading strategy alphas (diamonds). The strategies are constructed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



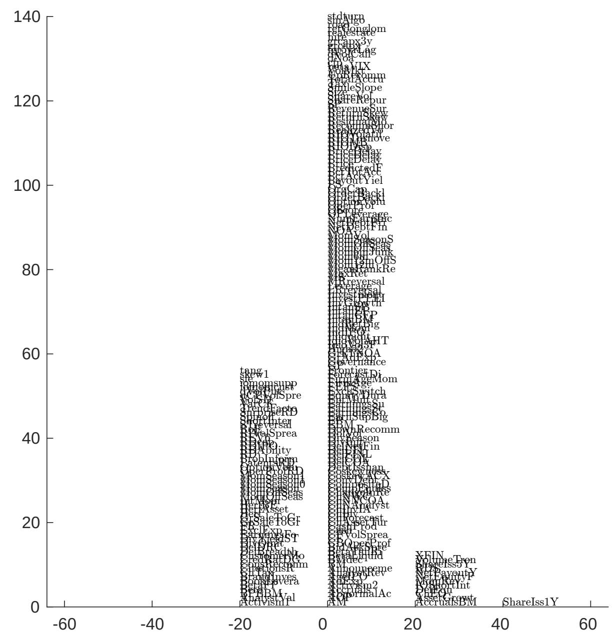


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with SRDS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

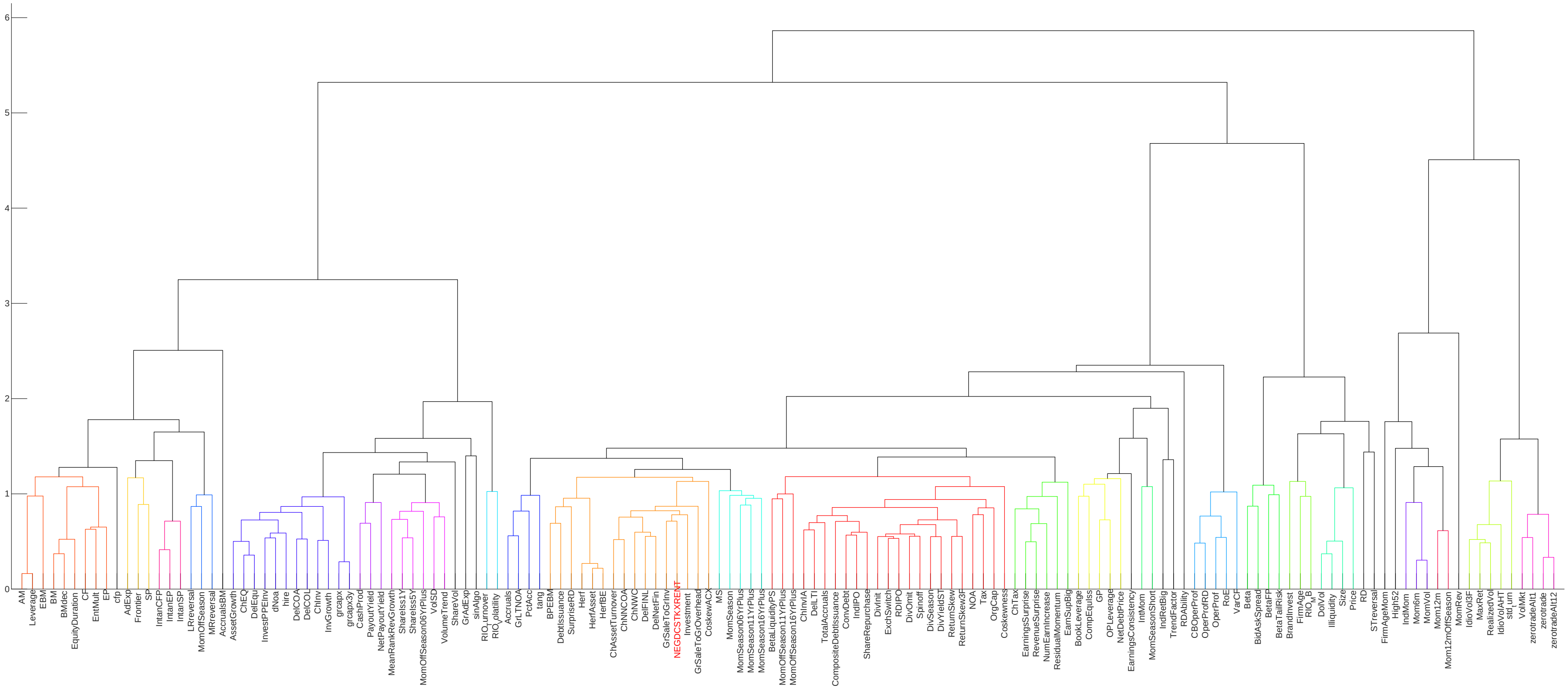


Figure 6: Agglomerative hierarchical cluster plot

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

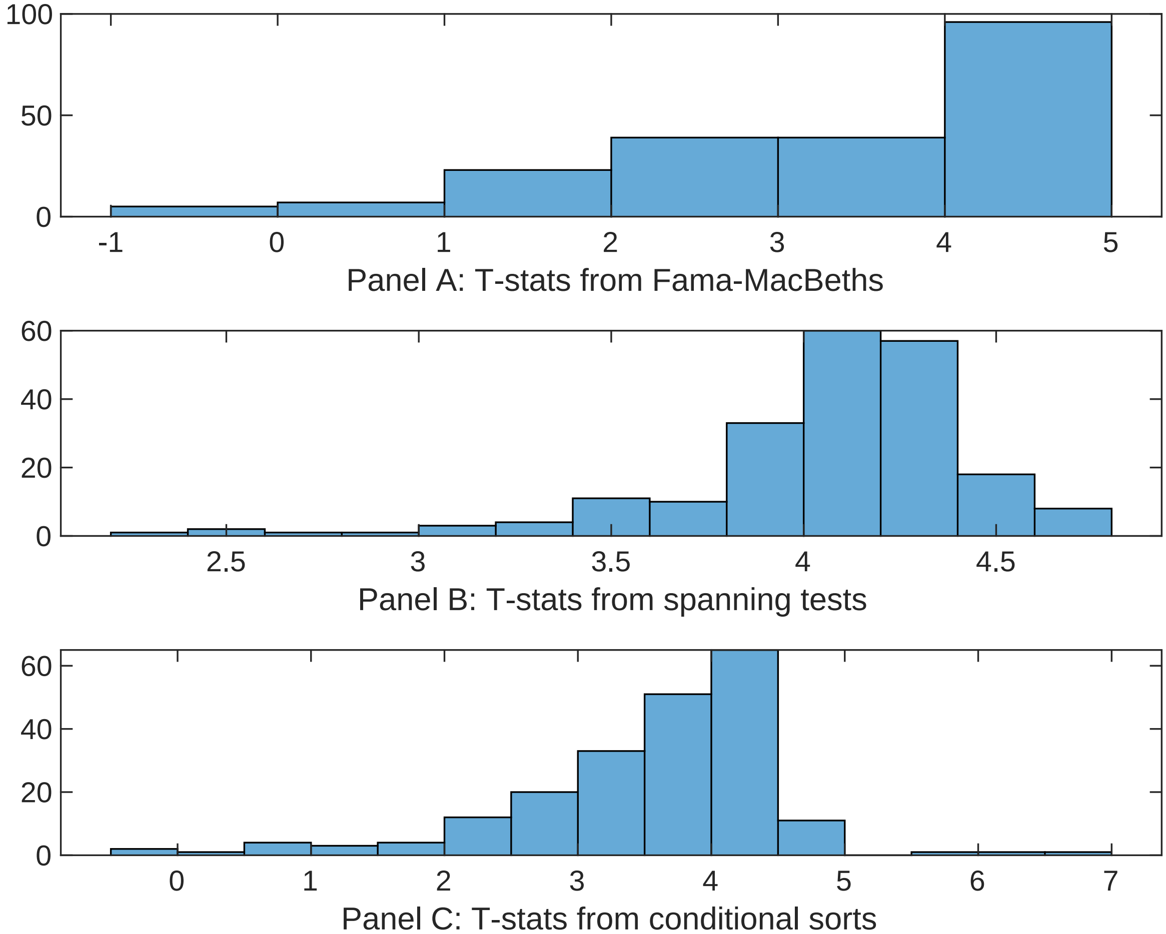


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SRDS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SRDS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SRDS} SRDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SRDS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on SRDS. Stocks are finally grouped into five SRDS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SRDS trading strategies conditioned on each of the 209 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on SRDS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SRDS} SRDS_{i,t} + \sum_{k=1}^{s} ix \beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, 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	0.18	0.12	0.13	0.13	0.14	0.13
	[5.46]	[7.14]	[5.19]	[5.85]	[5.41]	[5.86]	[5.38]
SRDS	0.48	0.38	0.26	0.51	0.40	0.31	0.24
	[4.01]	[3.12]	[1.85]	[4.32]	[3.18]	[2.49]	[1.76]
Anomaly 1	0.26						0.10
	[5.40]						[2.47]
Anomaly 2		0.52					0.13
		[4.50]					[0.01]
Anomaly 3			0.27				0.22
			[2.36]				[2.00]
Anomaly 4				0.33			0.58
				[3.50]			[0.69]
Anomaly 5					0.15		-0.29
					[4.07]		[-0.49]
Anomaly 6						0.11	0.76
						[8.57]	[6.94]
# months	679	684	679	679	684	684	679
$\bar{R}^2(\%)$	0	0	1	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 SRDS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SRDS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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), Growth in book equity, Net Payout Yield, 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	0.21	0.22	0.23	0.20	0.24	0.23	0.20
	[2.58]	[2.81]	[2.81]	[2.45]	[2.98]	[2.78]	[2.51]
Anomaly 1	28.88						20.30
	[7.05]						[4.25]
Anomaly 2		31.35					29.46
		[7.05]					[4.56]
Anomaly 3			17.64				6.51
			[5.61]				[1.80]
Anomaly 4				15.73			0.84
				[3.68]			[0.18]
Anomaly 5					19.57		-6.17
					[4.53]		[-1.02]
Anomaly 6						2.74	-17.25
						[0.50]	[-3.02]
mkt	4.38	3.16	5.03	4.35	1.82	2.13	5.84
	[2.32]	[1.67]	[2.59]	[2.20]	[0.95]	[1.10]	[3.01]
smb	1.93	-0.48	4.09	-0.09	0.26	0.34	3.38
	[0.71]	[-0.18]	[1.46]	[-0.03]	[0.09]	[0.12]	[1.20]
hml	-8.60	-8.68	-11.68	-9.17	-7.49	-5.07	-12.55
	[-2.34]	[-2.37]	[-2.99]	[-2.31]	[-2.00]	[-1.35]	[-3.23]
rmw	-5.91	5.05	-6.35	0.66	5.35	3.34	-5.82
	[-1.51]	[1.37]	[-1.54]	[0.17]	[1.42]	[0.88]	[-1.34]
cma	16.92	-0.45	17.97	26.30	10.29	27.34	14.17
	[2.93]	[-0.07]	[3.00]	[4.59]	[1.46]	[3.17]	[1.68]
umd	3.49	3.44	5.33	3.98	4.37	3.82	2.94
	[1.88]	[1.85]	[2.82]	[2.09]	[2.29]	[1.97]	[1.58]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	13	12	11	9	9	6	17

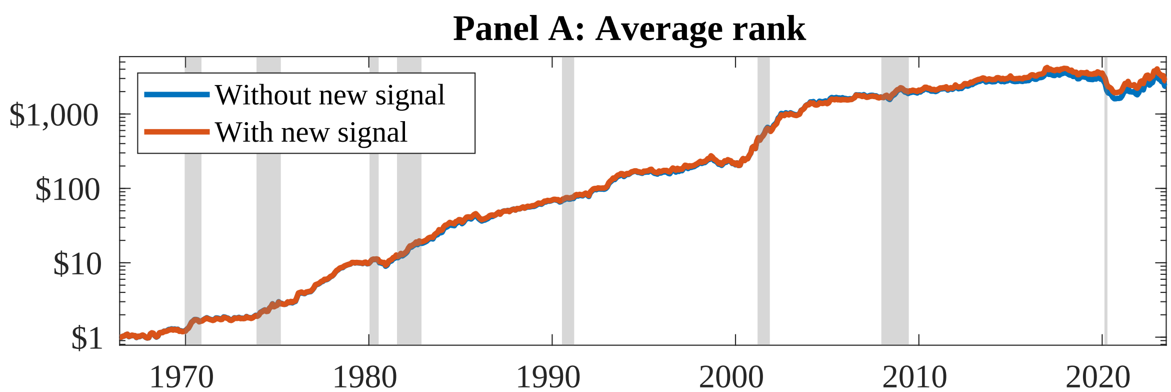


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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