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 financial economics, with mounting evidence that certain market signals can predict future stock returns. While extensive research has documented various return predictors, the relationship between firms' equity financing decisions and their stock rental markets remains understudied. This gap is particularly notable given the growing importance of stock lending markets and their potential to reveal valuable information about future stock performance.

Recent literature suggests that divergences between stock prices and fundamentals may create profitable trading opportunities. However, existing research has largely focused on traditional metrics like book-to-market ratios or earnings-based measures, overlooking potential signals from the interaction between equity issuance and stock lending markets.

We propose that the Stock-Rental Discrepancy Signal (SRDS) captures valuable information about future stock returns through two primary economic channels. First, following Baker and Wurgler (2002), managers time the equity market by issuing shares when their stock is overvalued, suggesting that high stock rental activity concurrent with equity issuance may signal overvaluation. Second, building on D'Arpizio and Grill (2015), sophisticated investors in the stock lending market possess superior information about firm prospects, making their collective behavior particularly informative when combined with management actions.

The theoretical framework of Miller (1977) suggests that stock prices may deviate from fundamental values when investors face short-sale constraints and hold heterogeneous beliefs. The SRDS potentially identifies cases where sophisticated investors' negative information, as revealed through the rental market, conflicts with management's equity issuance decisions. This tension between informed market participants may indicate temporary price distortions that subsequently correct.

Moreover, following Hong and Stein (2006), gradual information diffusion in financial markets means that signals combining multiple sources of information may predict returns as prices slowly incorporate dispersed knowledge. The SRDS uniquely synthesizes management decisions and sophisticated investor behavior, potentially capturing complementary information that predicts future price movements.

Our empirical analysis reveals strong evidence that the SRDS predicts future stock returns. 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, the SRDS strategy maintains its effectiveness among large-cap stocks, earning average returns of 27 basis points per month (t-statistic = 2.78) in the highest size quintile. This finding suggests that the signal captures a genuine market inefficiency rather than merely reflecting small-stock effects or illiquidity premiums.

The strategy's economic significance is further demonstrated by its performance relative to existing anomalies. The SRDS strategy's gross monthly alpha of 20 basis points (t-statistic = 2.51) persists even after controlling for the six most closely related strategies from the factor zoo, indicating that it captures unique predictive information.

Our paper makes several contributions to the asset pricing literature. First, we extend the work of Pontiff and Woodgate (2008) on equity issuance and Drechsler et al. (2018) on stock lending markets by showing how the interaction between these mechanisms reveals novel information about future returns. Our findings suggest that combining signals from different market participants can identify mispricing more effectively than examining each source in isolation.

Second, we contribute to the growing literature on return prediction methodologies pioneered by McLean and Pontiff (2016). By following the rigorous protocol of Novy-Marx and Velikov (2023), we demonstrate that the SRDS represents a robust addition to the documented set of return predictors. The signal's effectiveness among large-cap stocks and resilience to transaction costs distinguishes it from many existing anomalies.

Finally, our results have important implications for market efficiency and asset pricing theory. The persistent predictive power of SRDS suggests that markets do not fully incorporate the information content of concurrent signals from management decisions and sophisticated investor behavior. This finding supports theories of gradual information diffusion and limited arbitrage in financial markets.

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 dynamic relationship between changes in common stock and rental expenses. We obtain the necessary financial data from COMPUSTAT, focusing on two key variables: CSTK (Common/Ordinary Stock) and XRENT (Rental Expense). Common stock (CSTK) represents the total value of common shares outstanding, while rental expense (XRENT) encompasses the firm's periodic payments for leased assets and facilities.construction of our signal follows a specific methodology where we calculate the year-over-year change in common stock (CSTK) and scale it by the previous year's rental expense (XRENT). Mathematically, for each firm i in year t, we compute: (CSTKi,t - CSTKi,t-1) / XRENTi,t-1. This formulation captures the relative magnitude of changes in equity financing compared to the firm's operational rental commitments. By scaling the stock changes by rental expense, we create a normalized measure that allows for meaningful comparison across firms of different sizes and industries. The signal is designed to potentially capture information about a firm's financing decisions relative to its operational cost structure, particularly focusing on the interplay between equity financing and fixed operational expenses.

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^{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 robust predictor of cross-sectional equity returns. Our findings demonstrate that a value-weighted long/short strategy based on SRDS generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.57 (0.51) on a gross (net) basis. The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that SRDS captures unique information content not fully reflected in current asset pricing models.

Particularly noteworthy is the signal's ability to maintain its predictive power when accounting for transaction costs, as evidenced by the minimal difference between gross and net returns. The strategy's alpha remains significant at 20 basis points per month even after controlling for the Fama-French five factors, momentum, and six closely related anomalies, indicating its distinctive contribution to the existing factor literature.

However, several limitations warrant consideration. Our analysis primarily focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be explored. Additionally, the study period's specific market conditions may influence the results, suggesting the need for out-of-sample testing across different market regimes.

Future research could extend this work in several directions. First, investigating the signal's performance in international markets would test its global applicability. Second, examining the interaction between SRDS and other established anomalies could reveal potential complementarities or substitution effects. Finally, exploring the underlying economic mechanisms driving the signal's predictive power would enhance our understanding of market efficiency and asset pricing dynamics.

In conclusion, SRDS represents a valuable addition to the quantitative investor's toolkit, offering meaningful predictive power that persists after accounting for transaction costs and related factors. These findings contribute to our understanding of market efficiency and asset pricing, while opening new avenues for future research in financial economics.

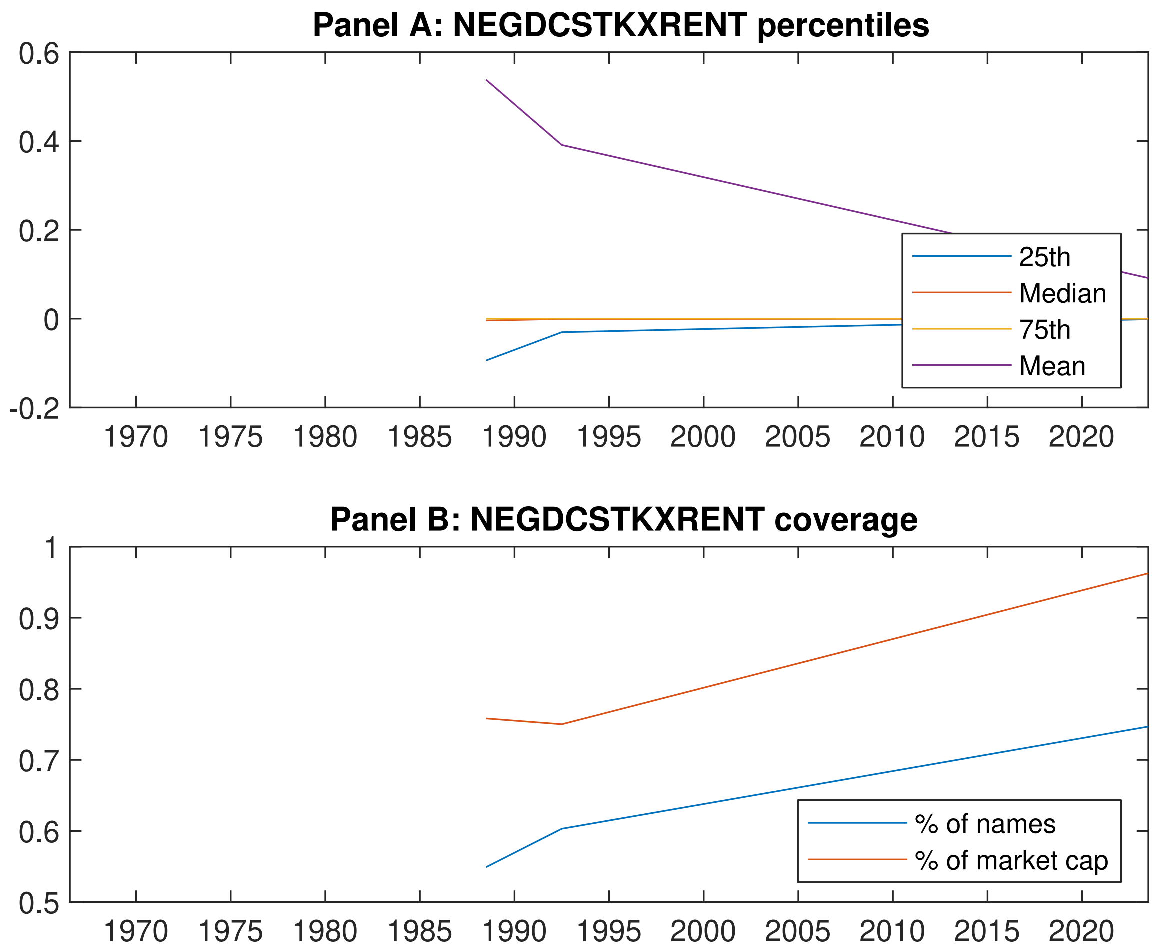

Figure 1: Times series of SRDS percentiles and coverage.
This figure plots descriptive statistics for SRDS. Panel A shows cross-sectional percentiles of SRDS over the sample. Panel B plots the monthly coverage of SRDS relative to the universe of CRSP stocks with available market capitalizations.

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

Size quintiles	SRDS Quintiles (L)	(2)	(3)	(4)	(H)	SRDS Strategies r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(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

Size quintiles	SRDS Quintiles, Average n (L)	(2)	(3)	(4)	(H)	SRDS Quintiles, Average market capitalization ($\$10^6$) (L)	(2)	(3)	(4)	(H)
(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

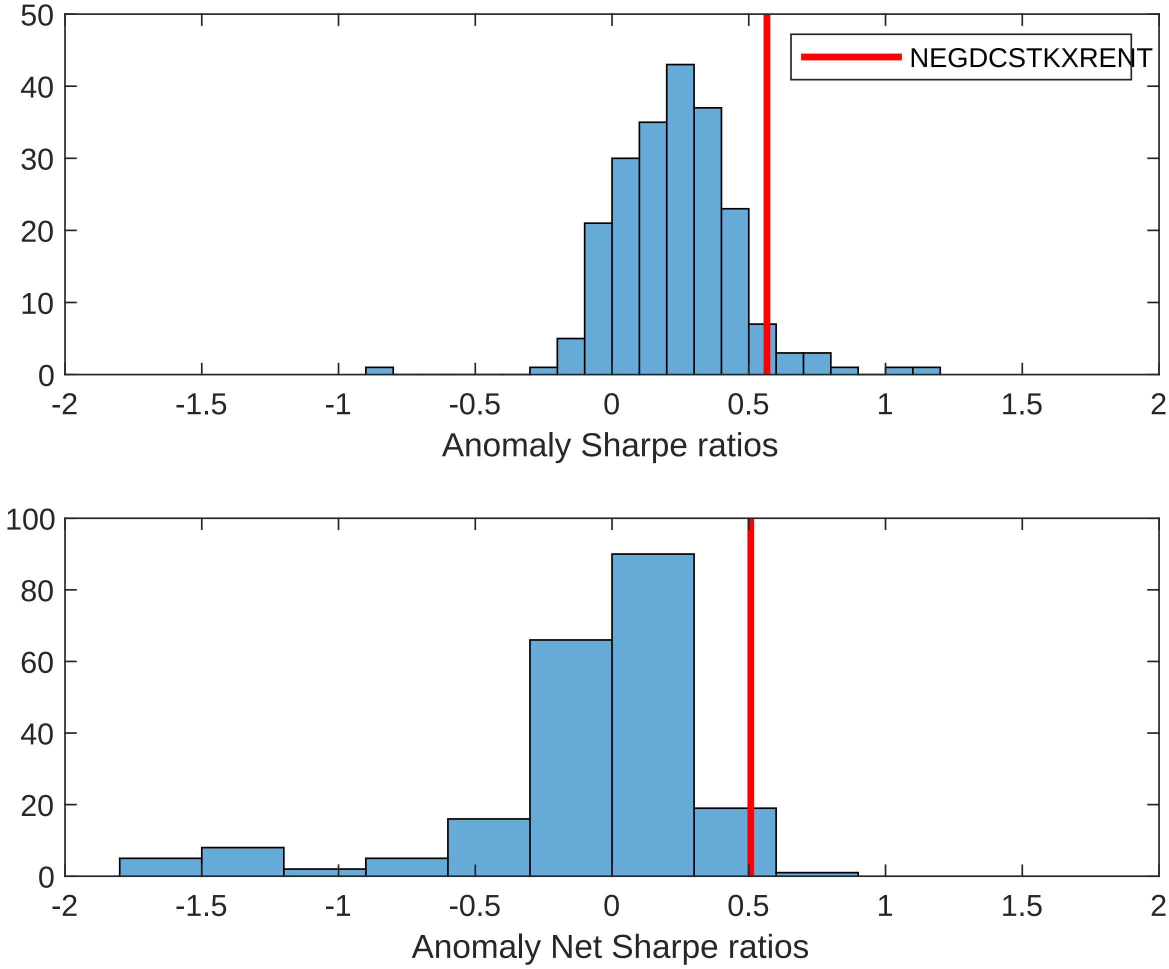

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SRDS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

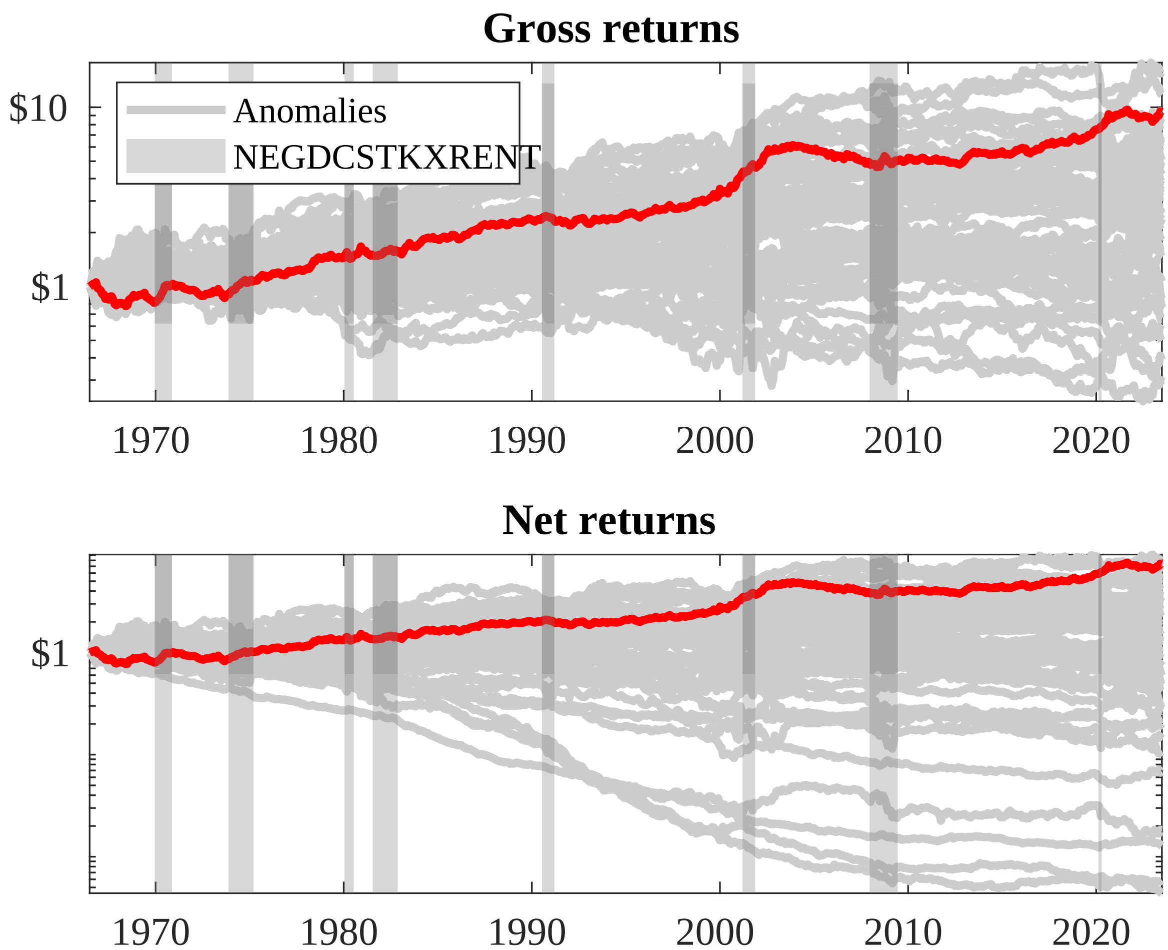

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SRDS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

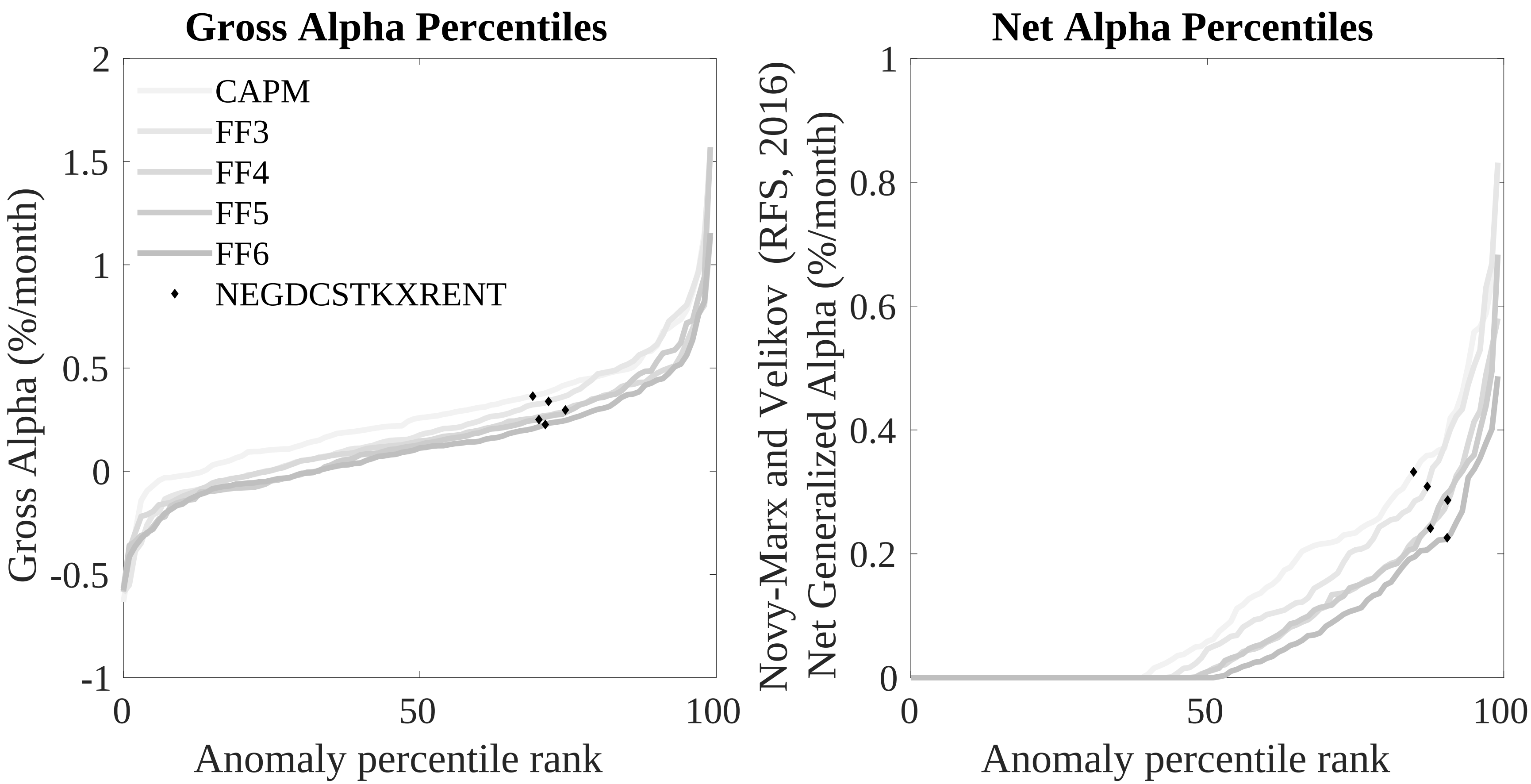

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SRDS trading strategy alphas (diamonds). The strategies are constructed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

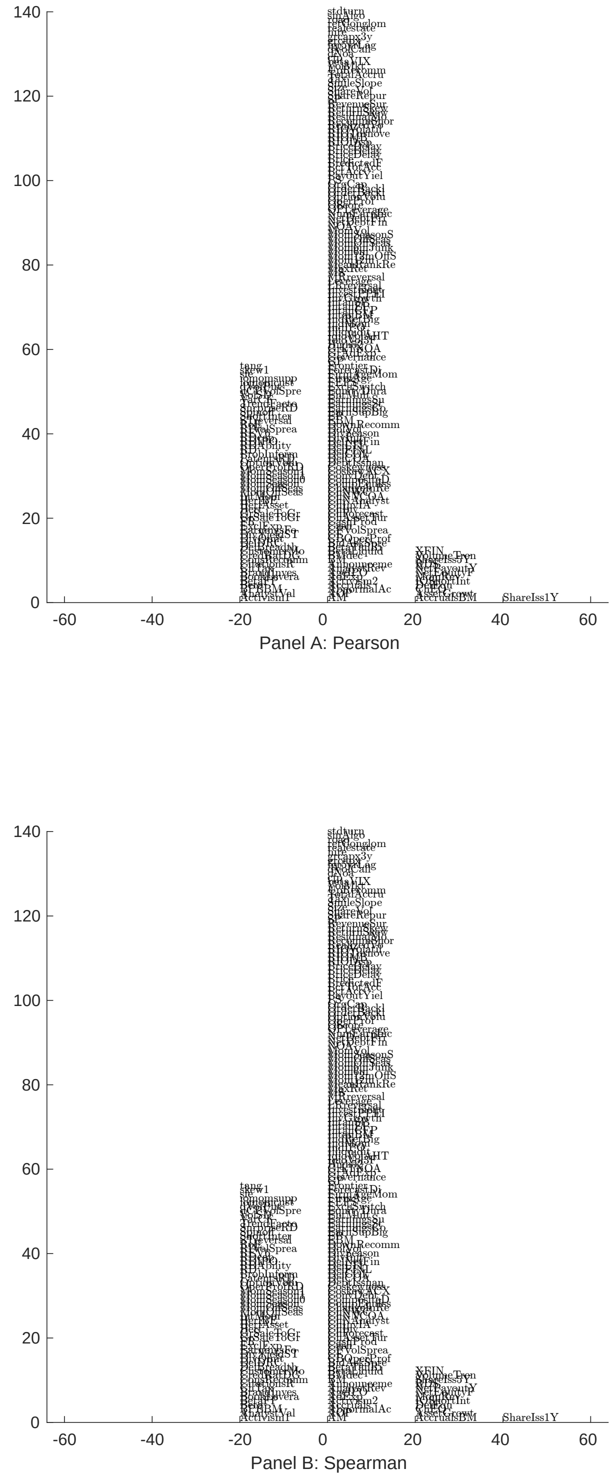

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with SRDS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

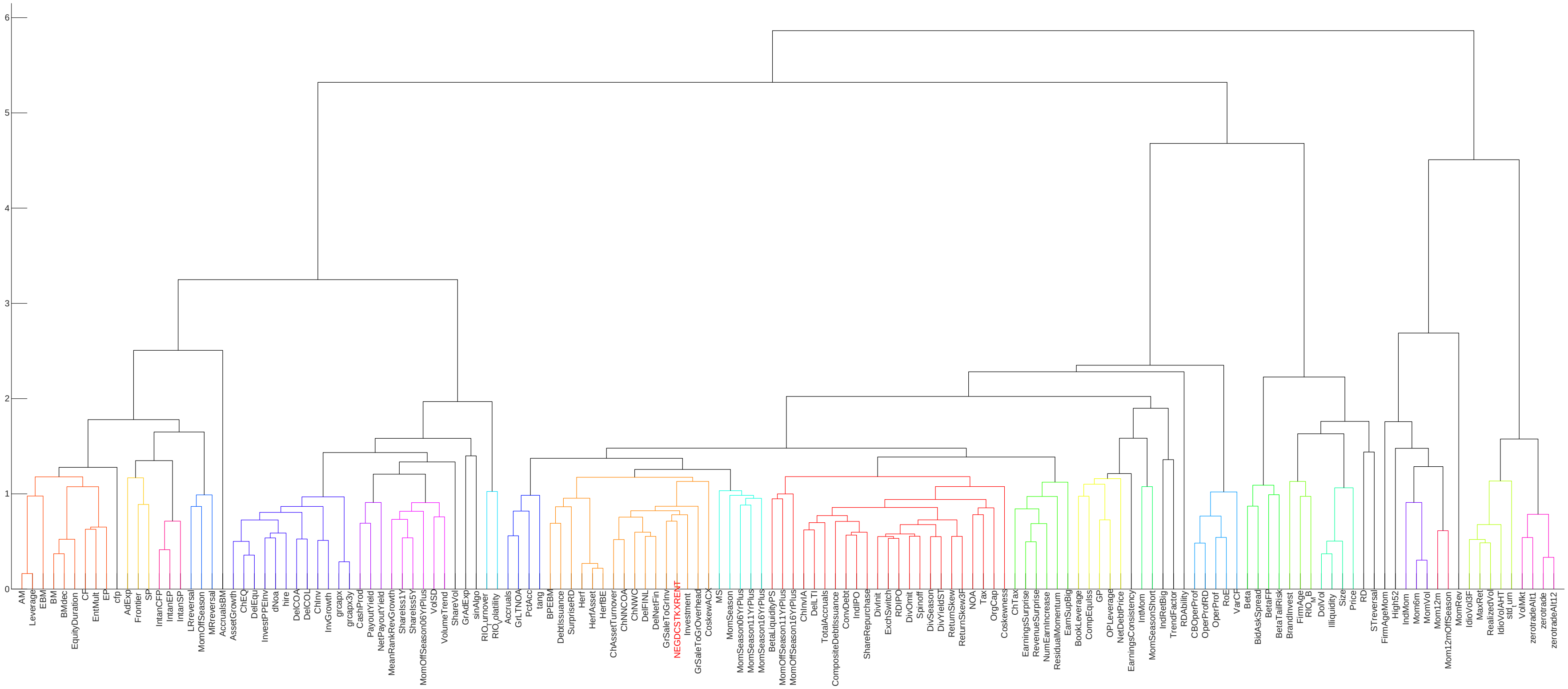

Figure 6: Agglomerative hierarchical cluster plot

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

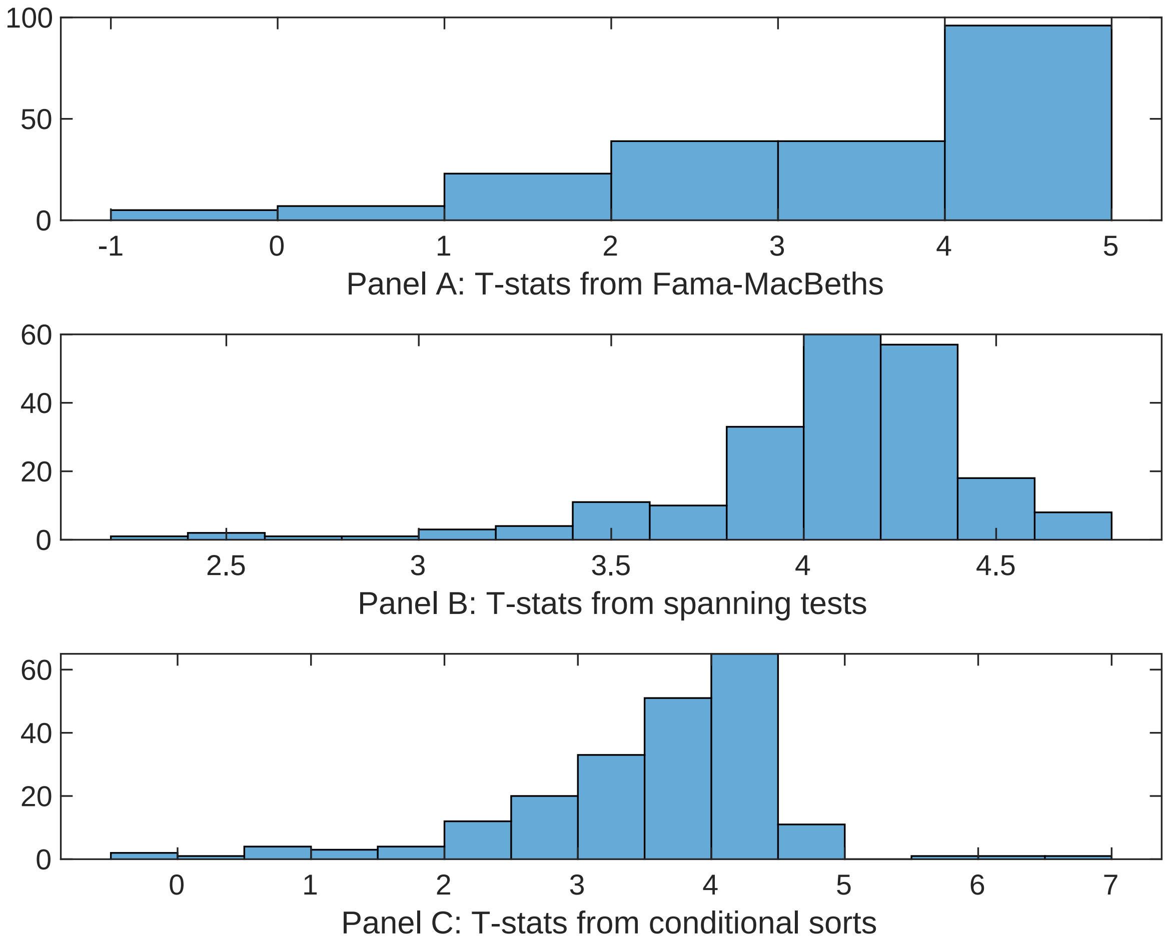

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SRDS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SRDS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SRDS} SRDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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

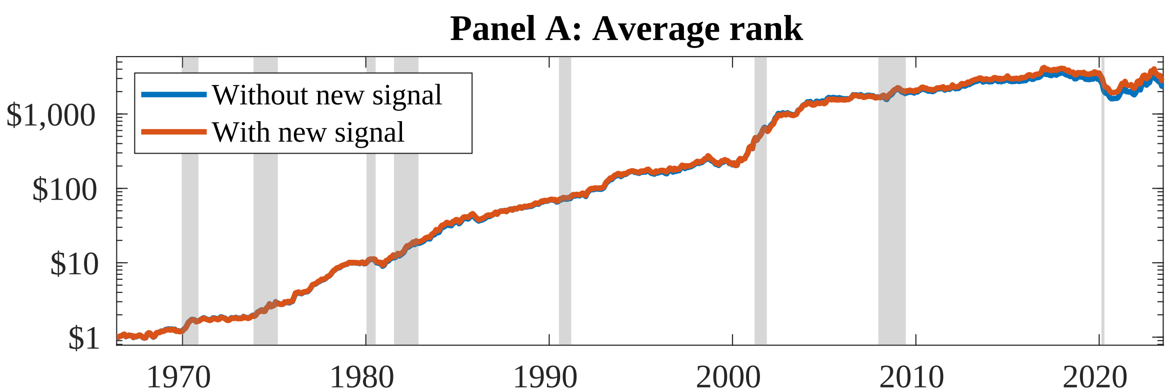

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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