

Stock and Receivables Relationship and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock and Receivables Relationship (SRR), 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 SRR achieves an annualized gross (net) Sharpe ratio of 0.46 (0.42), and monthly average abnormal gross (net) return relative to the [Fama and French \(2015\)](#) five-factor model plus a momentum factor of 28 (25) bps/month with a t-statistic of 2.68 (2.43), 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, Change in equity to assets, Share issuance (5 year), Off season long-term reversal) is 26 bps/month with a t-statistic of 2.57.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that certain firm characteristics can predict future stock returns ([Harvey et al., 2016](#)). While many documented predictors stem from accounting fundamentals or market-based measures, the relationship between firms' inventory management and stock returns remains relatively unexplored. The interplay between inventory levels and accounts receivable may contain particularly valuable information about future firm performance, as it reflects both operational efficiency and working capital management.

Despite extensive research on working capital components individually, the literature has largely overlooked how the dynamic relationship between inventory and receivables might signal future stock performance. This gap is notable given that mismatches between these working capital components can indicate operational inefficiencies or aggressive revenue recognition practices that may not be immediately reflected in stock prices.

The predictive power of the Stock and Receivables Relationship (SRR) can be explained through several economic mechanisms. First, following [Thomas and Zhang \(2002\)](#), changes in inventory levels relative to receivables may signal future demand conditions before they are fully reflected in earnings. When inventory grows faster than receivables, it may indicate unexpected weakness in demand or operational inefficiencies that will eventually impact profitability.

Second, building on [Sloan \(1996\)](#), the relationship between inventory and receivables provides information about earnings quality. Firms maintaining balanced growth between these working capital components are likely executing sustainable business strategies, while significant mismatches may signal aggressive accounting practices or deteriorating business conditions. This information may be overlooked by investors focused on headline earnings numbers.

Third, as demonstrated by [Beneish and Lee \(2008\)](#), extreme divergences between inventory and receivables growth can indicate potential earnings manipulation, as firms attempting to inflate reported performance often show unusual patterns in working capital accounts. The market may initially misprice this information due to the complexity of analyzing multiple financial statement relationships simultaneously.

Our analysis reveals that a value-weighted long-short trading strategy based on SRR generates significant abnormal returns. The strategy achieves an annualized gross Sharpe ratio of 0.46 and delivers monthly average abnormal returns of 28 basis points relative to the Fama-French five-factor model plus momentum (t-statistic = 2.68). These results remain robust after accounting for transaction costs, with net returns maintaining statistical and economic significance.

Importantly, the predictive power of SRR persists across different size segments. Among the largest quintile of stocks, the strategy generates monthly returns of 27 basis points (t-statistic = 2.33), addressing potential concerns about implementability. The signal’s effectiveness among large-cap stocks suggests that the anomaly captures fundamental information rather than merely reflecting small-stock mispricing.

Further analysis demonstrates that SRR’s predictive power remains significant after controlling for related anomalies. When we control for the six most closely related predictors, including share issuance and growth in book equity, the strategy still generates an alpha of 26 basis points per month (t-statistic = 2.57). This finding indicates that SRR captures unique information not contained in previously documented signals.

Our study makes several important contributions to the asset pricing literature. First, we extend the work of [Thomas and Zhang \(2002\)](#) on inventory changes by showing how the joint dynamics of inventory and receivables provide incrementally valuable information for predicting returns. While previous research has examined these components in isolation, we demonstrate that their relationship contains unique

predictive power.

Second, we contribute to the literature on accounting-based anomalies pioneered by Sloan (1996) by identifying a novel signal that captures information about both operational efficiency and earnings quality. Our findings suggest that markets do not fully incorporate the information contained in complex financial relationships, even among large, widely-followed stocks.

Third, our work advances the growing literature on return prediction methodologies by applying the rigorous protocol of Novy-Marx and Velikov (2023). This approach provides comprehensive evidence on the robustness of the SRR signal across different implementation approaches and testing frameworks, establishing its validity as a reliable return predictor that survives transaction costs and holds among institutional-scale 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 relationship between stock capital and receivables. 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 stock capital and item RECCO for receivables. Stock capital (CSTK) represents the firm’s total common and preferred stock, while receivables (RECCO) captures the amounts owed to the company by its customers for goods or services delivered. construction of the signal follows a change-based approach, where we first calculate the year-over-year change in CSTK and then scale this difference by the previous year’s receivables (RECCO). This scaled difference captures the relative magnitude of changes in the firm’s equity capital structure in relation to its credit extension to customers. By focusing on

this relationship, the signal aims to reflect aspects of capital structure dynamics and working capital management in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both CSTK and RECCO to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SRR signal. Panel A plots the time-series of the mean, median, and interquartile range for SRR. On average, the cross-sectional mean (median) SRR is -1.18 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SRR data. The signal’s interquartile range spans -0.31 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SRR signal for the CRSP universe. On average, the SRR signal is available for 2.72% of CRSP names, which on average make up 3.80% of total market capitalization.

4 Does SRR predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SRR 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 SRR portfolio and sells the low SRR 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 SRR strategy earns an average return of 0.36% per month with a t-statistic of 3.51. The annualized

Sharpe ratio of the strategy is 0.46. The alphas range from 0.26% to 0.35% per month and have t-statistics exceeding 2.45 everywhere. The lowest alpha is with respect to the FF5 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 0.25, with a t-statistic of 3.51 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 221 stocks and an average market capitalization of at least \$628 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 portfolio 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 decile sort using NYSE breakpoints and value-weighted portfolios, and equals 27 bps/month with a t-statistics of 2.11. Out of the twenty-five alphas reported in Panel A, the t-statistics for eighteen exceed two, and for seven exceed three.

Panel B reports for these same strategies the average monthly net returns and the

generalized net alphas of [Novy-Marx and Velikov \(2016\)](#). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from [Chen and Velikov \(2022\)](#). The net average returns reported in the first column range between 23-38bps/month. The lowest return, (23 bps/month), is achieved from the decile sort using NYSE breakpoints and value-weighted portfolios, and has an associated t-statistic of 1.82. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SRR 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 fourteen cases.

Table 3 provides direct tests for the role size plays in the SRR strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SRR, as well as average returns and alphas for long/short trading SRR 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 80th NYSE percentile), the SRR strategy achieves an average return of 27 bps/month with a t-statistic of 2.33. Among these large cap stocks, the alphas for the SRR strategy relative to the five most common factor models range from 17 to 25 bps/month with t-statistics between 1.37 and 2.08.

5 How does SRR perform relative to the zoo?

Figure 2 puts the performance of SRR 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 SRR strategy falls in the distribution. The SRR strategy’s gross (net) Sharpe ratio of 0.46 (0.42) is greater than 89% (98%) 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 SRR strategy (red line).² Ignoring trading costs, a \$1 invested in the SRR strategy would have yielded \$8.14 which ranks the SRR strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the SRR strategy would have yielded \$6.18 which ranks the SRR strategy in the top 1% 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 SRR relative to those. Panel A shows that the SRR strategy gross alphas fall between the 66 and 78 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 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 SRR strategy has a positive net generalized alpha for five out of the five factor models. In these cases SRR ranks between the 83 and 92 percentiles in terms of how

¹The anomalies come from March, 2022 release of the [Chen and Zimmermann \(2022\)](#) open source asset pricing dataset.

²The 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.

much it could have expanded the achievable investment frontier.

6 Does SRR 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 SRR with 204 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 SRR or at least to weaken the power SRR has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SRR conditioning on each of the 204 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SRR} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SRR}SRR_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 204 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SRR,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 204 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 204 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on SRR. Stocks are finally grouped into

³When 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.

five SRR portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SRR trading strategies conditioned on each of the 204 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SRR 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 SRR signal in these Fama-MacBeth regressions exceed 2.55, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SRR is 0.84.

Similarly, Table 5 reports results from spanning tests that regress returns to the SRR 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 SRR strategy earns alphas that range from 24-30bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.35, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SRR trading strategy achieves an alpha of 26bps/month with a t-statistic of 2.57.

7 Does SRR add relative to the whole zoo?

Finally, we can ask how much adding SRR 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 SRR 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 SRR grows to \$2202.19.

8 Conclusion

Our comprehensive analysis of the Stock and Receivables Relationship (SRR) signal demonstrates its significant value as a predictor of cross-sectional stock returns. The empirical results reveal that a value-weighted long/short strategy based on SRR generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.46 (0.42 net of transaction costs). The strategy’s robustness is evidenced by its persistent abnormal returns of 28 basis points per month (25 bps net) relative to the Fama-French five-factor model augmented with momentum, maintaining statistical significance with t-statistics above conventional thresholds.

Particularly noteworthy is the signal’s continued effectiveness even after controlling for six closely related factors from the factor zoo, yielding a significant monthly alpha of 26 basis points. This finding suggests that SRR captures unique information about future stock returns that is not subsumed by well-known risk factors or similar anomalies.

From a practical perspective, these results have important implications for in-

⁴We 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 SRR is available.

vestment professionals and portfolio managers. The signal’s economic significance, coupled with its resilience to transaction costs, suggests that SRR could be valuable in constructing investment strategies and enhancing portfolio performance.

However, several limitations should be noted. Our analysis primarily focuses on U.S. equity markets, and the signal’s effectiveness in international markets remains to be explored. Additionally, the evolving nature of market efficiency may impact the signal’s future predictive power.

Future research could extend this work by examining the signal’s performance in different market regimes, investigating its interaction with other established anomalies, and testing its applicability in international markets. Furthermore, exploring the underlying economic mechanisms driving the SRR effect could provide valuable insights into market behavior and asset pricing theory.

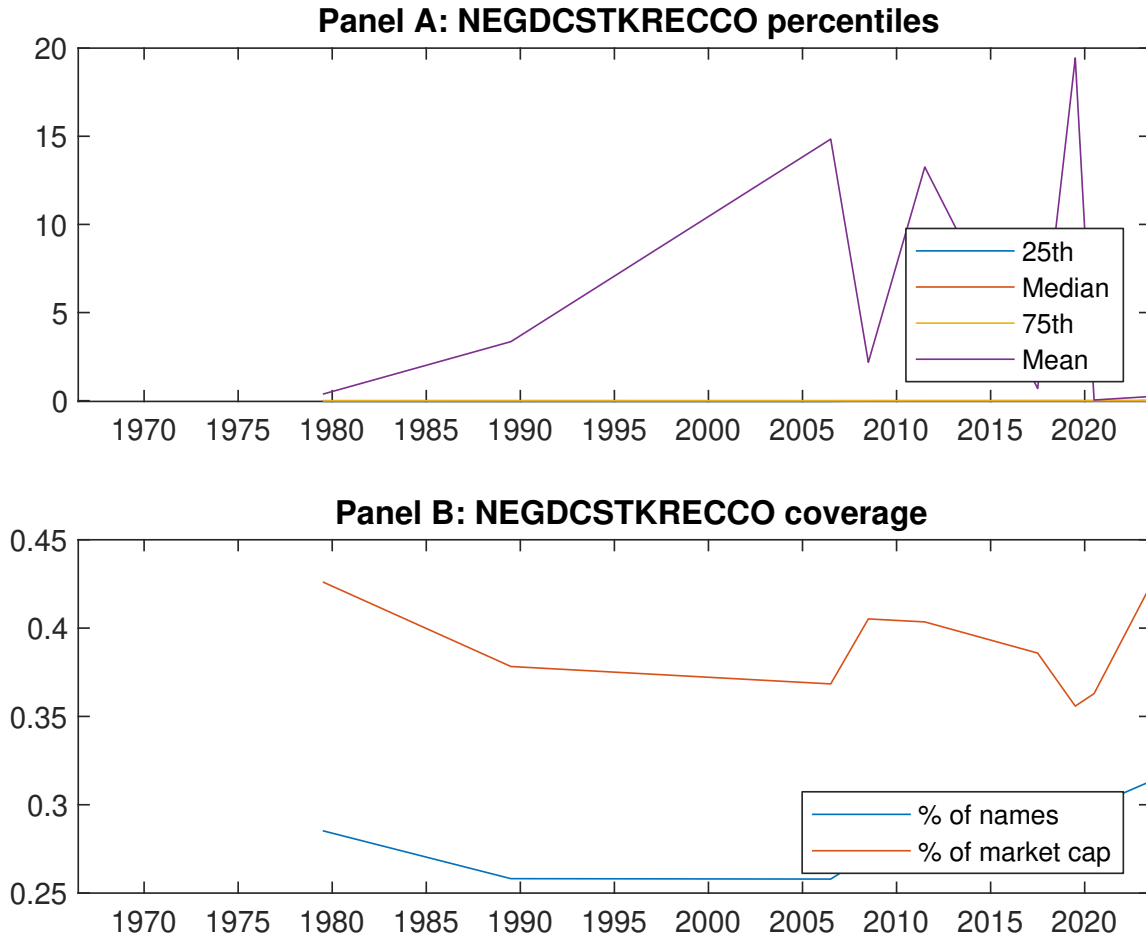


Figure 1: Times series of SRR percentiles and coverage. This figure plots descriptive statistics for SRR. Panel A shows cross-sectional percentiles of SRR over the sample. Panel B plots the monthly coverage of SRR relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SRR. 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 SRR-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.40 [2.30]	0.55 [2.85]	0.64 [3.33]	0.64 [3.57]	0.75 [4.32]	0.36 [3.51]
α_{CAPM}	-0.11 [-1.54]	-0.04 [-0.61]	0.06 [0.83]	0.10 [1.46]	0.23 [3.30]	0.35 [3.37]
α_{FF3}	-0.12 [-1.65]	-0.06 [-0.88]	0.03 [0.43]	0.02 [0.29]	0.18 [2.60]	0.30 [2.89]
α_{FF4}	-0.12 [-1.67]	-0.06 [-0.88]	0.02 [0.29]	-0.01 [-0.17]	0.20 [2.88]	0.32 [3.09]
α_{FF5}	-0.18 [-2.43]	-0.07 [-1.01]	0.01 [0.14]	-0.07 [-1.12]	0.08 [1.13]	0.26 [2.45]
α_{FF6}	-0.18 [-2.40]	-0.07 [-1.00]	0.00 [0.05]	-0.08 [-1.36]	0.10 [1.52]	0.28 [2.68]
Panel B: Fama and French (2018) 6-factor model loadings for SRR-sorted portfolios						
β_{MKT}	0.92 [52.38]	1.03 [63.52]	1.04 [57.14]	1.03 [70.97]	0.98 [60.65]	0.06 [2.39]
β_{SMB}	-0.03 [-1.20]	0.04 [1.81]	0.03 [0.96]	-0.07 [-3.35]	-0.05 [-2.20]	-0.02 [-0.58]
β_{HML}	0.05 [1.41]	0.05 [1.54]	0.07 [2.02]	0.19 [6.85]	0.07 [2.10]	0.02 [0.37]
β_{RMW}	0.17 [5.10]	0.04 [1.30]	0.04 [1.16]	0.13 [4.46]	0.15 [4.74]	-0.03 [-0.52]
β_{CMA}	-0.02 [-0.46]	-0.02 [-0.39]	0.02 [0.43]	0.15 [3.74]	0.22 [4.91]	0.25 [3.51]
β_{UMD}	-0.00 [-0.00]	0.00 [0.04]	0.01 [0.59]	0.02 [1.68]	-0.04 [-2.64]	-0.04 [-1.71]
Panel C: Average number of firms (n) and market capitalization (me)						
n	296	270	221	294	296	
me (\$10 ⁶)	687	628	748	862	955	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the SRR 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	0.36 [3.51]	0.35 [3.37]	0.30 [2.89]	0.32 [3.09]	0.26 [2.45]	0.28 [2.68]
Quintile	NYSE	EW	0.61 [7.23]	0.69 [8.62]	0.60 [8.07]	0.54 [7.28]	0.46 [6.31]	0.43 [5.83]
Quintile	Name	VW	0.30 [2.89]	0.29 [2.74]	0.24 [2.34]	0.27 [2.57]	0.22 [2.04]	0.25 [2.28]
Quintile	Cap	VW	0.29 [2.62]	0.27 [2.46]	0.23 [2.08]	0.25 [2.24]	0.19 [1.70]	0.22 [1.90]
Decile	NYSE	VW	0.27 [2.11]	0.26 [1.98]	0.21 [1.58]	0.22 [1.66]	0.21 [1.55]	0.22 [1.64]
Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	r_{net}^e	α_{CAPM}^*	α_{FF3}^*	α_{FF4}^*	α_{FF5}^*	α_{FF6}^*
Quintile	NYSE	VW	0.32 [3.16]	0.31 [3.03]	0.27 [2.61]	0.28 [2.75]	0.23 [2.26]	0.25 [2.43]
Quintile	NYSE	EW	0.38 [4.11]	0.47 [5.26]	0.38 [4.62]	0.35 [4.32]	0.23 [2.81]	0.22 [2.75]
Quintile	Name	VW	0.26 [2.54]	0.24 [2.36]	0.20 [1.98]	0.22 [2.14]	0.18 [1.76]	0.20 [1.92]
Quintile	Cap	VW	0.25 [2.31]	0.24 [2.17]	0.20 [1.82]	0.21 [1.94]	0.17 [1.56]	0.19 [1.69]
Decile	NYSE	VW	0.23 [1.82]	0.22 [1.70]	0.17 [1.34]	0.18 [1.41]	0.18 [1.38]	0.19 [1.46]

Table 3: Conditional sort on size and SRR

This table presents results for conditional double sorts on size and SRR. 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 SRR. 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 SRR and short stocks with low SRR. 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	SRR Quintiles					SRR Strategies						
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
	(1)	0.24	0.55	0.79	0.95	0.93	0.69	0.78	0.70	0.66	0.55	0.53
		[0.84]	[1.86]	[2.94]	[2.89]	[3.72]	[5.42]	[6.32]	[5.81]	[5.39]	[4.56]	[4.33]
	(2)	0.55	0.51	0.81	0.96	0.96	0.41	0.48	0.35	0.35	0.33	0.33
		[2.17]	[1.94]	[3.15]	[3.95]	[4.12]	[3.20]	[3.75]	[2.91]	[2.87]	[2.63]	[2.61]
	(3)	0.66	0.69	0.70	0.81	1.01	0.35	0.41	0.34	0.31	0.30	0.29
	[2.93]	[2.82]	[2.92]	[3.61]	[4.95]	[3.11]	[3.63]	[3.05]	[2.79]	[2.69]	[2.50]	
(4)	0.40	0.50	0.68	0.98	0.81	0.40	0.44	0.34	0.32	0.24	0.23	
	[1.91]	[2.29]	[3.14]	[4.75]	[4.05]	[3.74]	[4.05]	[3.26]	[3.00]	[2.23]	[2.14]	
(5)	0.44	0.51	0.50	0.54	0.72	0.27	0.25	0.21	0.24	0.17	0.19	
	[2.56]	[2.70]	[2.74]	[3.04]	[4.02]	[2.33]	[2.08]	[1.79]	[1.96]	[1.37]	[1.58]	
Panel B: Portfolio average number of firms and market capitalization												
Size quintiles	SRR Quintiles					SRR Quintiles						
	Average n					Average market capitalization (\$10 ⁶)						
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)	
	(1)	152	151	150	150	151	10	11	12	9	9	
	(2)	40	40	40	40	40	18	18	18	18	18	
	(3)	31	31	31	30	31	32	33	33	34	34	
	(4)	27	27	26	27	27	73	73	75	76	77	
(5)	28	28	27	27	27	589	664	603	582	762		

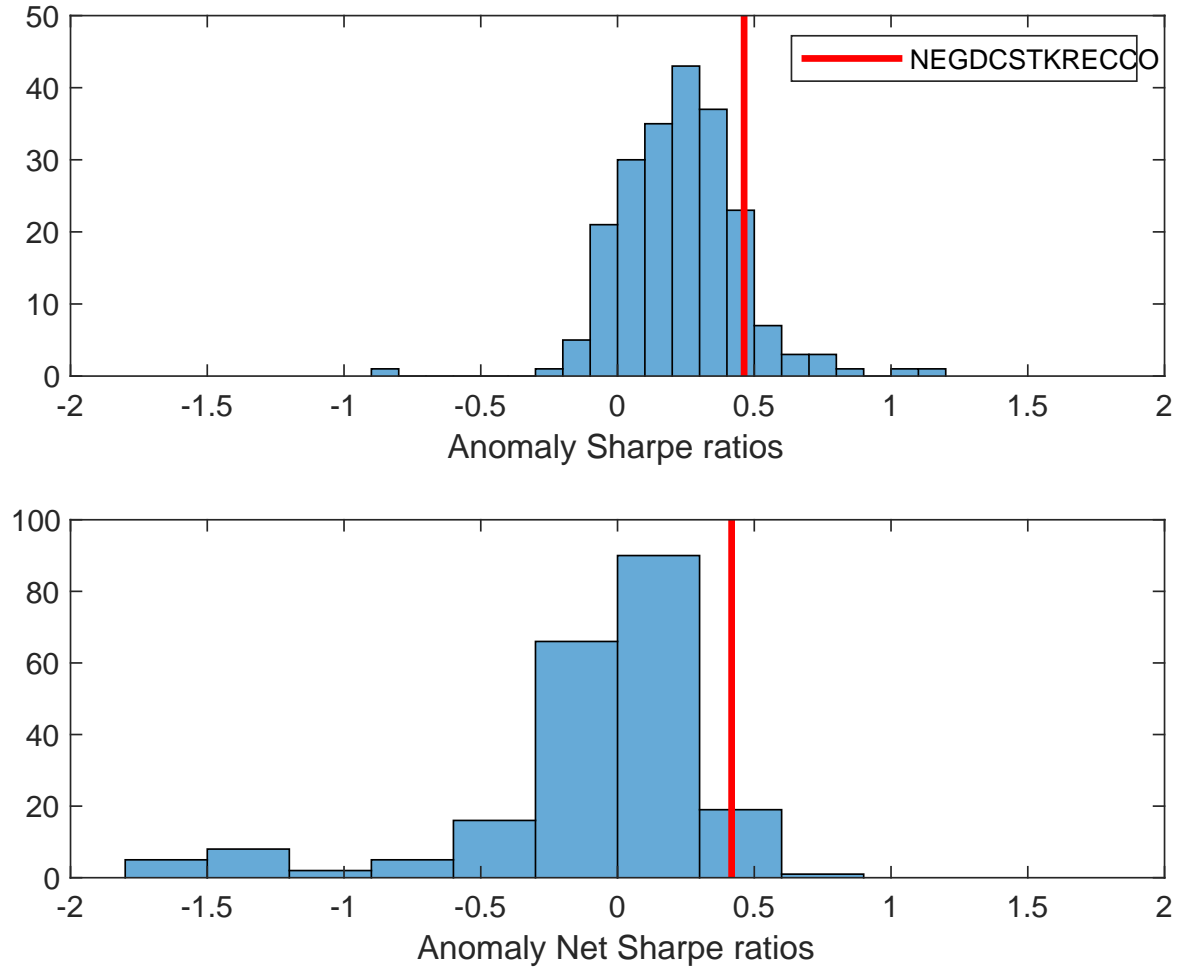


Figure 2: Distribution of Sharpe ratios.

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

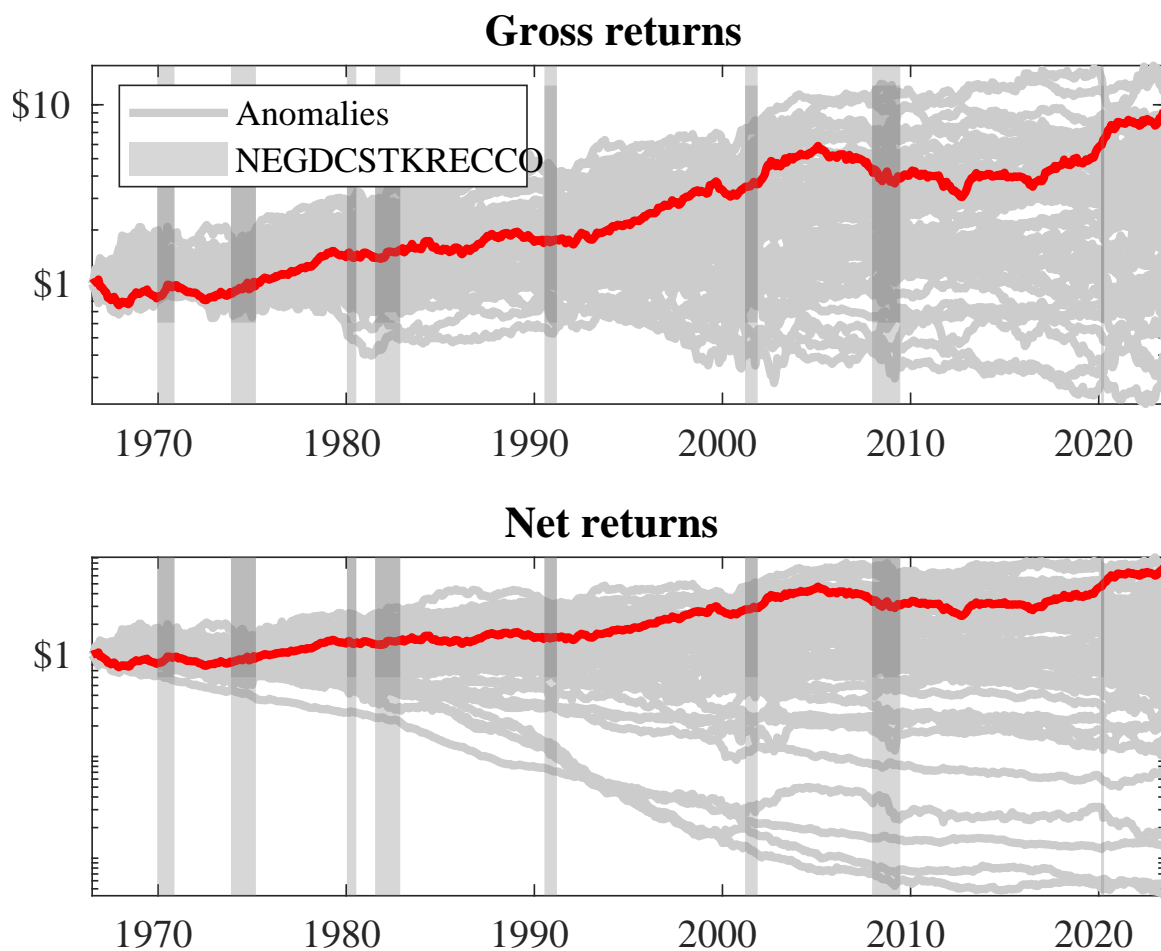


Figure 3: Dollar invested.

This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SRR 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 strategy returns.

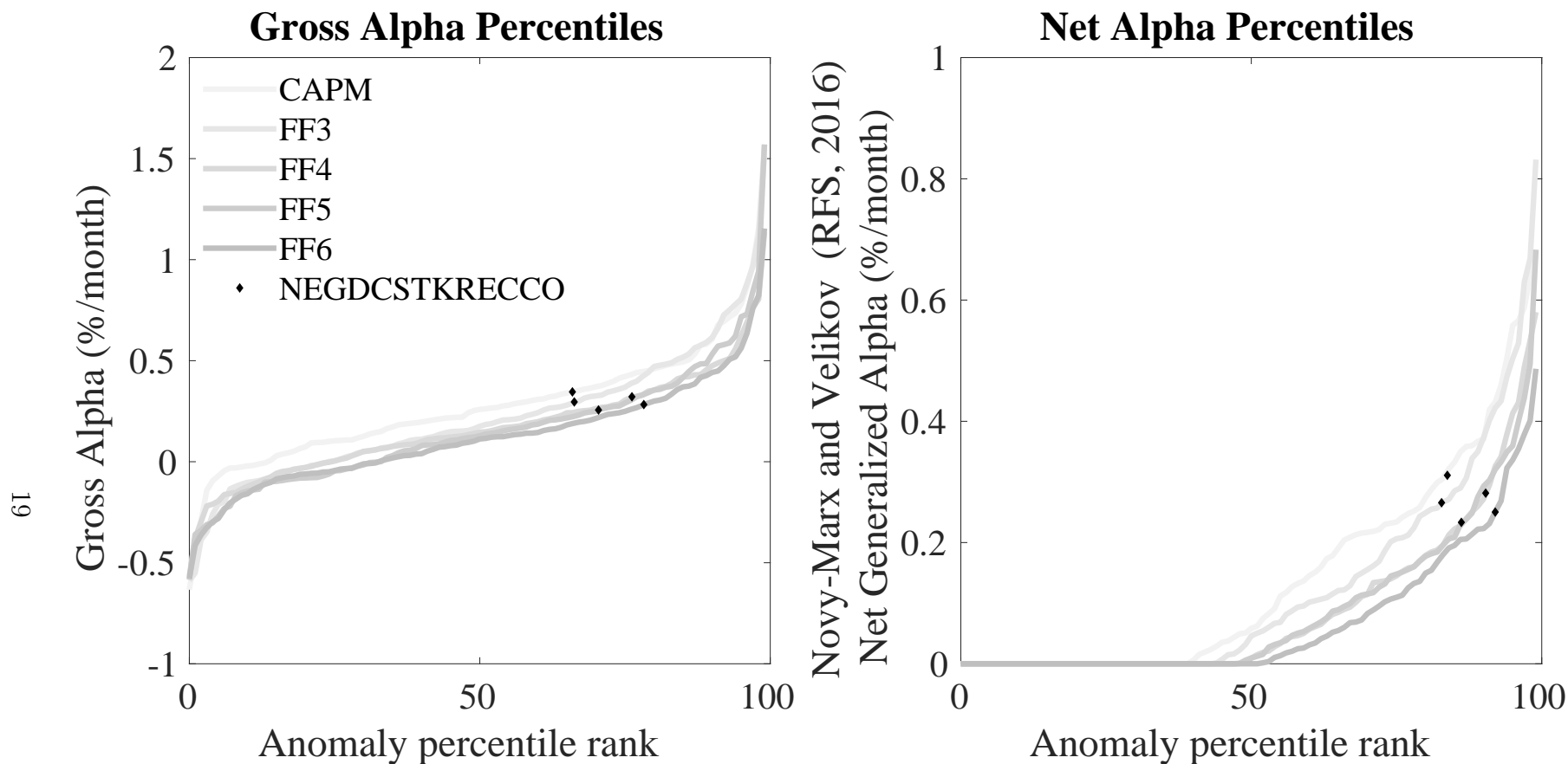


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models

This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SRR 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.

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

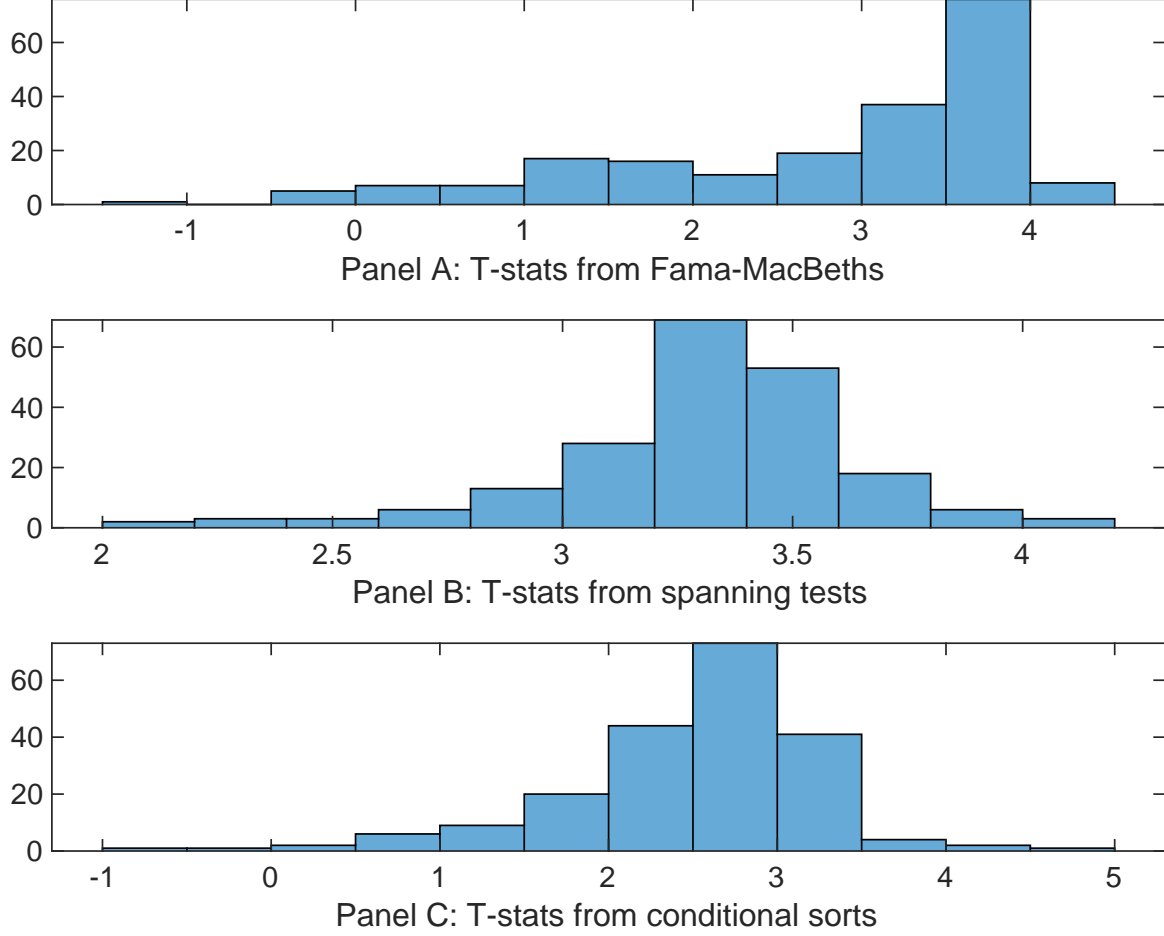


Figure 7: Distribution of t-stats on conditioning strategies

This figure plots histograms of t-statistics for predictability tests of SRR conditioning on each of the 204 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SRR} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SRR}SRR_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 204 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SRR,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 204 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 204 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on SRR. Stocks are finally grouped into five SRR portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SRR trading strategies conditioned on each of the 204 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on SRR. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SRR}SRR_{i,t} + \sum_{k=1}^s \beta_{X_k} X_{i,t}^k + \epsilon_{i,t}$. The six most closely related anomalies, X , are Share issuance (1 year), Growth in book equity, Net Payout Yield, Change in equity to assets, Share issuance (5 year), Off season long-term reversal. 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	0.12 [5.29]	0.19 [7.34]	0.12 [4.98]	0.12 [5.25]	0.13 [5.74]	0.13 [5.91]	0.14 [5.88]
SRR	0.22 [3.69]	0.21 [3.80]	0.16 [2.55]	0.17 [3.27]	0.19 [2.55]	0.14 [2.84]	0.55 [0.84]
Anomaly 1	0.25 [4.69]						0.66 [1.01]
Anomaly 2		0.60 [5.49]					-0.30 [-0.17]
Anomaly 3			0.35 [3.32]				0.19 [2.00]
Anomaly 4				0.19 [4.94]			0.48 [0.74]
Anomaly 5					0.28 [2.47]		-0.19 [-1.42]
Anomaly 6						0.16 [6.19]	0.17 [5.34]
# months	679	684	679	684	679	679	679
$\bar{R}^2(\%)$	0	0	1	0	0	1	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the SRR trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SRR} = \alpha + \sum_{k=1}^6 \beta_{X_k} r_t^{X_k} + \sum_{j=1}^6 \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Change in equity to assets, Share issuance (5 year), Off season long-term reversal. 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	0.25 [2.44]	0.28 [2.70]	0.28 [2.68]	0.30 [2.90]	0.24 [2.35]	0.24 [2.35]	0.26 [2.57]
Anomaly 1	30.90 [5.86]						17.47 [2.81]
Anomaly 2		32.26 [5.62]					16.92 [2.04]
Anomaly 3			21.02 [5.23]				9.32 [1.98]
Anomaly 4				24.55 [4.46]			-0.55 [-0.07]
Anomaly 5					20.28 [3.73]		4.23 [0.70]
Anomaly 6						11.42 [3.09]	3.38 [0.89]
mkt	8.49 [3.50]	7.12 [2.93]	9.49 [3.82]	5.68 [2.32]	8.85 [3.51]	7.79 [3.14]	10.40 [4.10]
smb	0.22 [0.06]	-2.47 [-0.70]	2.87 [0.80]	-1.78 [-0.50]	-2.25 [-0.63]	-3.06 [-0.84]	-0.40 [-0.11]
hml	-1.35 [-0.28]	-1.49 [-0.32]	-5.57 [-1.11]	-0.83 [-0.17]	-3.07 [-0.61]	-2.88 [-0.56]	-8.61 [-1.63]
rmw	-13.10 [-2.61]	-1.43 [-0.30]	-14.83 [-2.82]	-0.67 [-0.14]	-6.79 [-1.39]	-2.37 [-0.50]	-13.90 [-2.45]
cma	10.44 [1.40]	-7.38 [-0.83]	9.81 [1.28]	-0.91 [-0.10]	19.14 [2.63]	20.64 [2.83]	-9.66 [-1.06]
umd	-4.48 [-1.88]	-4.66 [-1.93]	-2.36 [-0.98]	-3.55 [-1.46]	-3.98 [-1.64]	-3.23 [-1.33]	-3.60 [-1.49]
# months	680	684	680	684	680	680	680
$\bar{R}^2(\%)$	10	8	9	7	7	6	12

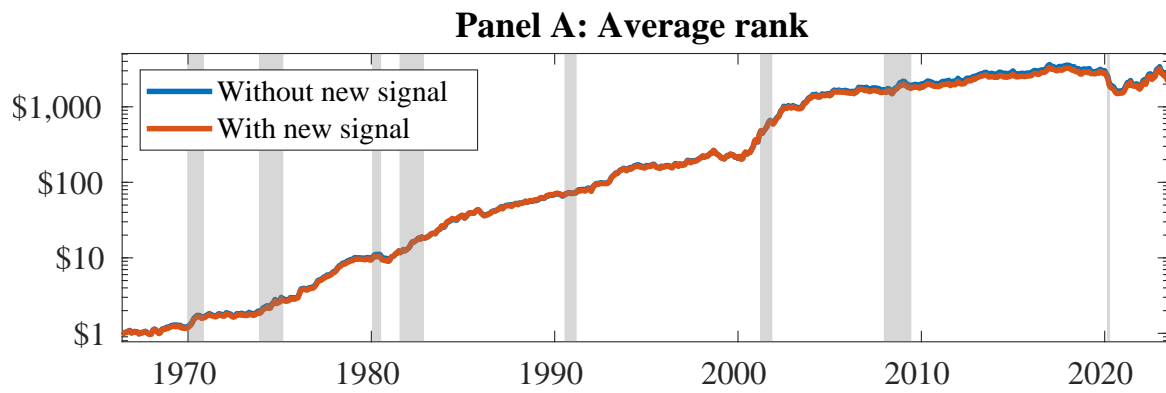


Figure 8: Combination strategy performance

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 SRR. Panel A shows results using "Average rank" as the combination method. See [Section 7](#) for details on the combination methods.

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