# 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 financial economics, with substantial debate around whether and how quickly asset prices incorporate available information. While traditional theory suggests markets should rapidly reflect fundamental information, a growing body of evidence documents persistent return predictability from various accounting and market-based signals. One particularly understudied area is how the relationship between firms' inventory management and accounts receivable policies affects future stock returns.

Prior research has extensively examined inventory and receivables separately, but their joint dynamics may contain important information about future firm performance that is not fully reflected in stock prices. The interaction between these working capital components reflects fundamental business decisions about production, sales policies, and customer relationships that could signal future profitability and risk.

We hypothesize that the Stock and Receivables Relationship (SRR) predicts future returns through multiple economic channels. First, following Thomas and Zhang (2002), changes in inventory levels relative to receivables may indicate managers' private information about future demand conditions. When managers observe strong (weak) future demand, they are more likely to build up (draw down) inventory while maintaining tight (loose) credit terms with customers.

Second, building on Beneish and Lee (2002), the divergence between inventory and receivables growth could signal potential earnings management or deteriorating business conditions that investors fail to fully incorporate. Firms experiencing operational difficulties may extend more generous payment terms to maintain sales while simultaneously accumulating excess inventory.

Third, the SRR captures information about working capital efficiency and management quality that has implications for firm value, consistent with Aktas et al.

(2015). Firms that optimize their joint inventory-receivables positions demonstrate superior operational capabilities and risk management, which should translate into better future performance.

Our empirical analysis reveals that the SRR is a robust predictor of future stock returns. A value-weighted long-short portfolio strategy based on SRR quintiles generates monthly gross returns of 0.36% (t-statistic = 3.51) and a Sharpe ratio of 0.46. The strategy's performance remains strong after controlling for common risk factors, with monthly alphas ranging from 0.26% to 0.35% across various factor models.

Importantly, the predictive power of SRR persists after accounting for transaction costs. The strategy achieves net returns of 0.32% monthly (t-statistic = 3.16) and maintains significant alphas across all major factor models. The signal's effectiveness extends to large-cap stocks, with the top size quintile generating monthly returns of 0.27% (t-statistic = 2.33).

Further analysis demonstrates that SRR's predictive ability is distinct from known anomalies. Controlling for the six most closely related anomalies and standard risk factors simultaneously, the strategy maintains a significant monthly alpha of 0.26% (t-statistic = 2.57), indicating it captures unique information about future returns.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures the joint dynamics of key working capital components, extending work by Thomas and Zhang (2002) on inventory changes and Beneish and Lee (2002) on receivables growth. The SRR's robust performance across size groups and after trading costs suggests it reflects economically meaningful information.

Second, we contribute to the literature on accounting-based return predictability by showing how the interaction between operational metrics provides incremental information beyond their individual effects. Our findings complement recent work in the Journal of Financial Economics on the relationship between operational efficiency and stock returns Aktas et al. (2015).

Third, our results have implications for both academic research and investment practice. The persistence of SRR predictability, particularly among large stocks, challenges standard efficient market explanations and suggests sophisticated investors may benefit from incorporating this signal into their investment processes. The findings also highlight the importance of examining interactions between accounting variables when studying return predictability.

## 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 calculate the difference between the current period's CSTK and its lagged value, then scale this change by the lagged value of RECCO. This scaled difference captures the relative magnitude of changes in stock capital relative to the firm's receivables base, potentially offering insight into the firm's capital structure decisions in relation to its working capital position. By scaling the change in stock capital by receivables, the signal provides a standardized measure that facilitates comparison across firms of different sizes. We construct this measure using end-of-fiscal-year values 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 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 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 $80^{\text{th}}$ 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,

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

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 much it could have expanded the achievable investment frontier.

[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 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 $\beta_{SRR}$ 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 $\alpha$ 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 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

[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.

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.

[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 SRR 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 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. These findings suggest that SRR captures unique information about future stock returns that is not fully explained by well-known risk factors or similar anomalies.

From a practical perspective, our results indicate that SRR could be a valuable addition to quantitative investment strategies, offering meaningful diversification benefits and return enhancement opportunities. The signal's robustness to transaction costs further supports its practical implementation in portfolio management.

However, several limitations should be noted. Our study primarily focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be investigated. Additionally, the evolving nature of market efficiency may impact the signal's future performance.

Future research could explore the signal's performance in different market regimes, its interaction with other accounting-based anomalies, and its effectiveness in international markets. Furthermore, investigating the underlying economic mechanisms driving the SRR signal's predictive power could provide valuable insights into market inefficiencies and asset pricing theory.

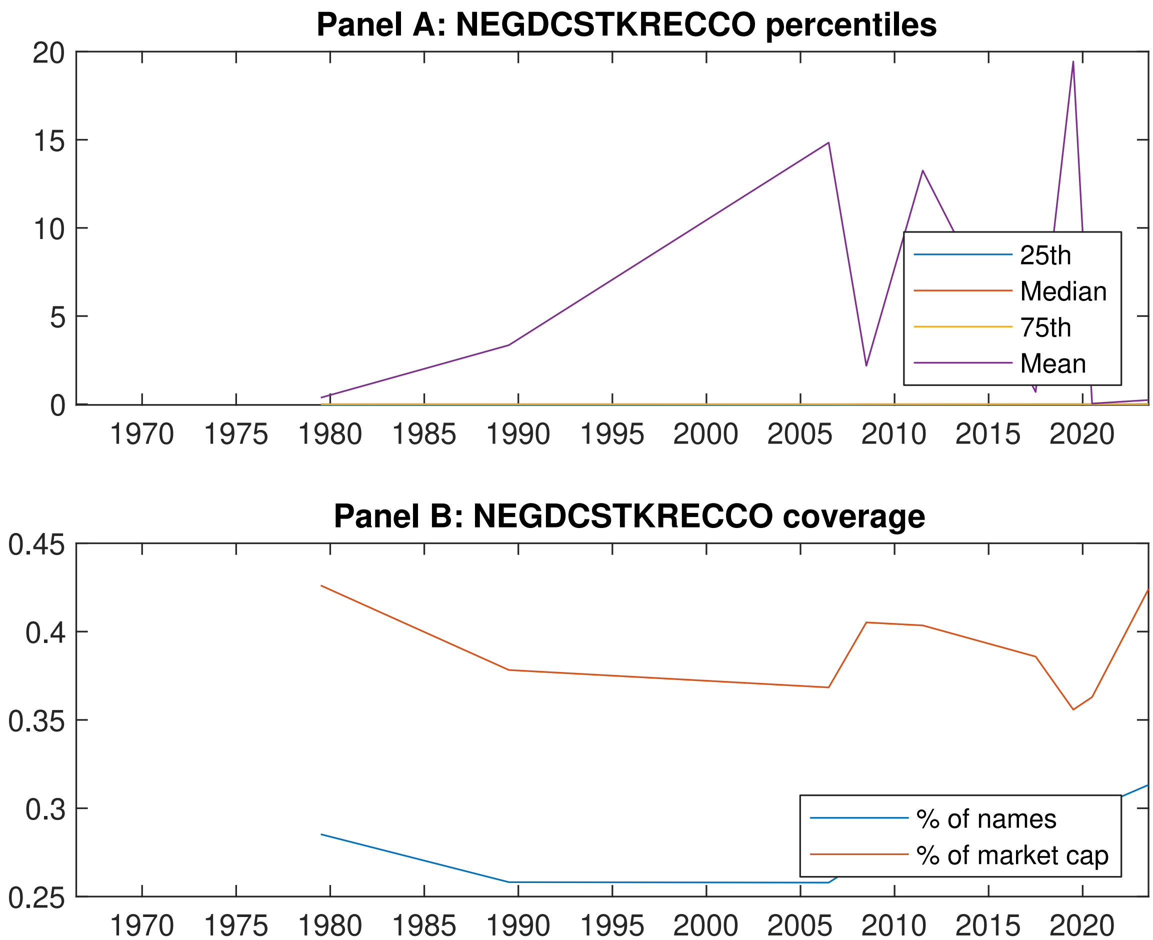


**Figure 1:** Times series of SRR percentiles and coverage.
This figure plots descriptive statistics for SRR. Panel A shows cross-sectional percentiles of SRR over the sample. Panel B plots the monthly coverage of SRR relative to the universe of CRSP stocks with available market capitalizations.

**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 | 0.55 | 0.64 | 0.64 | 0.75 | 0.36 |
| | [2.30] | [2.85] | [3.33] | [3.57] | [4.32] | [3.51] |
| $\alpha_{CAPM}$ | -0.11 | -0.04 | 0.06 | 0.10 | 0.23 | 0.35 |
| | [-1.54] | [-0.61] | [0.83] | [1.46] | [3.30] | [3.37] |
| $\alpha_{FF3}$ | -0.12 | -0.06 | 0.03 | 0.02 | 0.18 | 0.30 |
| | [-1.65] | [-0.88] | [0.43] | [0.29] | [2.60] | [2.89] |
| $\alpha_{FF4}$ | -0.12 | -0.06 | 0.02 | -0.01 | 0.20 | 0.32 |
| | [-1.67] | [-0.88] | [0.29] | [-0.17] | [2.88] | [3.09] |
| $\alpha_{FF5}$ | -0.18 | -0.07 | 0.01 | -0.07 | 0.08 | 0.26 |
| | [-2.43] | [-1.01] | [0.14] | [-1.12] | [1.13] | [2.45] |
| $\alpha_{FF6}$ | -0.18 | -0.07 | 0.00 | -0.08 | 0.10 | 0.28 |
| | [-2.40] | [-1.00] | [0.05] | [-1.36] | [1.52] | [2.68] |
| Panel B: Fama and French (2018) 6-factor model loadings for SRR-sorted portfolios | | | | | | |
| $\beta_{\text{MKT}}$ | 0.92 | 1.03 | 1.04 | 1.03 | 0.98 | 0.06 |
| | [52.38] | [63.52] | [57.14] | [70.97] | [60.65] | [2.39] |
| $\beta_{\text{SMB}}$ | -0.03 | 0.04 | 0.03 | -0.07 | -0.05 | -0.02 |
| | [-1.20] | [1.81] | [0.96] | [-3.35] | [-2.20] | [-0.58] |
| $\beta_{\text{HML}}$ | 0.05 | 0.05 | 0.07 | 0.19 | 0.07 | 0.02 |
| | [1.41] | [1.54] | [2.02] | [6.85] | [2.10] | [0.37] |
| $\beta_{\text{RMW}}$ | 0.17 | 0.04 | 0.04 | 0.13 | 0.15 | -0.03 |
| | [5.10] | [1.30] | [1.16] | [4.46] | [4.74] | [-0.52] |
| $\beta_{\text{CMA}}$ | -0.02 | -0.02 | 0.02 | 0.15 | 0.22 | 0.25 |
| | [-0.46] | [-0.39] | [0.43] | [3.74] | [4.91] | [3.51] |
| $\beta_{\text{UMD}}$ | -0.00 | 0.00 | 0.01 | 0.02 | -0.04 | -0.04 |
| | [-0.00] | [0.04] | [0.59] | [1.68] | [-2.64] | [-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 | $r^e$ | $\alpha_{\text{CAPM}}$ | $\alpha_{\text{FF3}}$ | $\alpha_{\text{FF4}}$ | $\alpha_{\text{FF5}}$ | $\alpha_{\text{FF6}}$ |
| Quintile | NYSE | VW | 0.36 | 0.35 | 0.30 | 0.32 | 0.26 | 0.28 |
| | | | [3.51] | [3.37] | [2.89] | [3.09] | [2.45] | [2.68] |
| Quintile | NYSE | EW | 0.61 | 0.69 | 0.60 | 0.54 | 0.46 | 0.43 |
| | | | [7.23] | [8.62] | [8.07] | [7.28] | [6.31] | [5.83] |
| Quintile | Name | VW | 0.30 | 0.29 | 0.24 | 0.27 | 0.22 | 0.25 |
| | | | [2.89] | [2.74] | [2.34] | [2.57] | [2.04] | [2.28] |
| Quintile | Cap | VW | 0.29 | 0.27 | 0.23 | 0.25 | 0.19 | 0.22 |
| | | | [2.62] | [2.46] | [2.08] | [2.24] | [1.70] | [1.90] |
| Decile | NYSE | VW | 0.27 | 0.26 | 0.21 | 0.22 | 0.21 | 0.22 |
| | | | [2.11] | [1.98] | [1.58] | [1.66] | [1.55] | [1.64] |
| Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas | | | | | | | | |
| Portfolios | Breaks | Weights | $r^e_{net}$ | $\alpha^*_{\text{CAPM}}$ | $\alpha^*_{\text{FF3}}$ | $\alpha^*_{\text{FF4}}$ | $\alpha^*_{\text{FF5}}$ | $\alpha^*_{\text{FF6}}$ |
| Quintile | NYSE | VW | 0.32 | 0.31 | 0.27 | 0.28 | 0.23 | 0.25 |
| | | | [3.16] | [3.03] | [2.61] | [2.75] | [2.26] | [2.43] |
| Quintile | NYSE | EW | 0.38 | 0.47 | 0.38 | 0.35 | 0.23 | 0.22 |
| | | | [4.11] | [5.26] | [4.62] | [4.32] | [2.81] | [2.75] |
| Quintile | Name | VW | 0.26 | 0.24 | 0.20 | 0.22 | 0.18 | 0.20 |
| | | | [2.54] | [2.36] | [1.98] | [2.14] | [1.76] | [1.92] |
| Quintile | Cap | VW | 0.25 | 0.24 | 0.20 | 0.21 | 0.17 | 0.19 |
| | | | [2.31] | [2.17] | [1.82] | [1.94] | [1.56] | [1.69] |
| Decile | NYSE | VW | 0.23 | 0.22 | 0.17 | 0.18 | 0.18 | 0.19 |
| | | | [1.82] | [1.70] | [1.34] | [1.41] | [1.38] | [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

| | SRR Quintiles | | | | | SRR Strategies | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Size quintiles | (L) | (2) | (3) | (4) | (H) | $r^e$ | $\alpha_{CAPM}$ | $\alpha_{FF3}$ | $\alpha_{FF4}$ | $\alpha_{FF5}$ | $\alpha_{FF6}$ |
| (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

| | SRR Quintiles | | | | | SRR Quintiles | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Average $n$ | | | | | Average market capitalization ($\$10^6$) | | | | |
| Size quintiles | (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 |

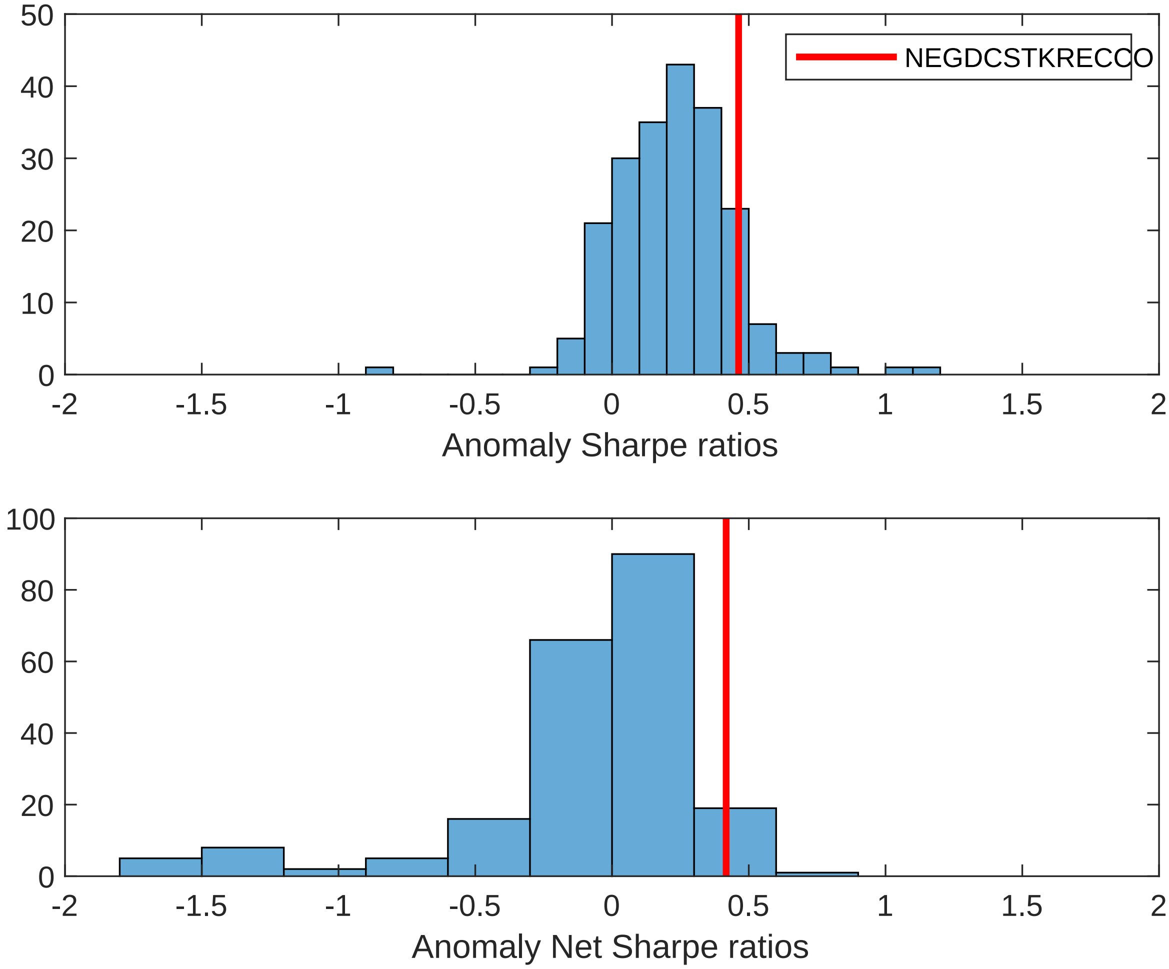


**Figure 2:** Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SRR with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

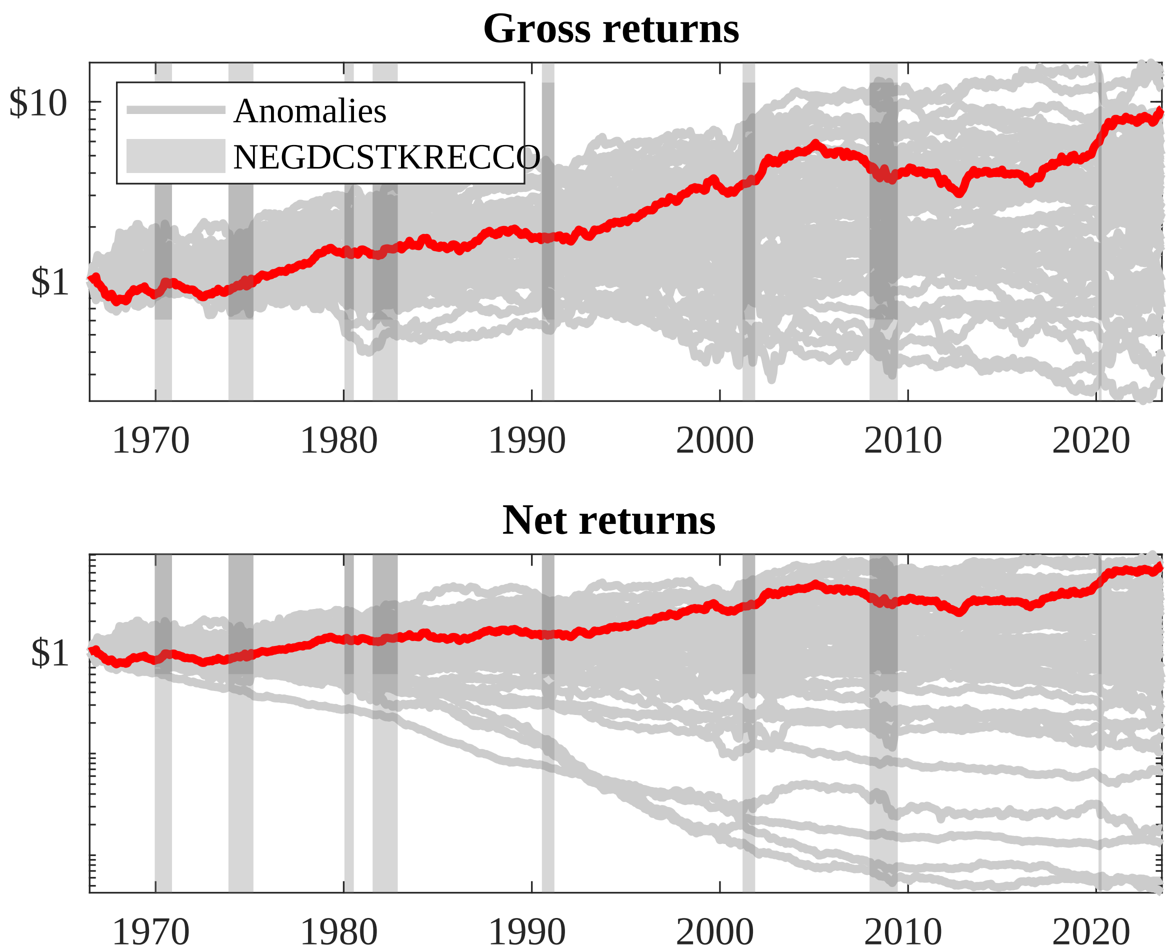


**Figure 3:** Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SRR trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

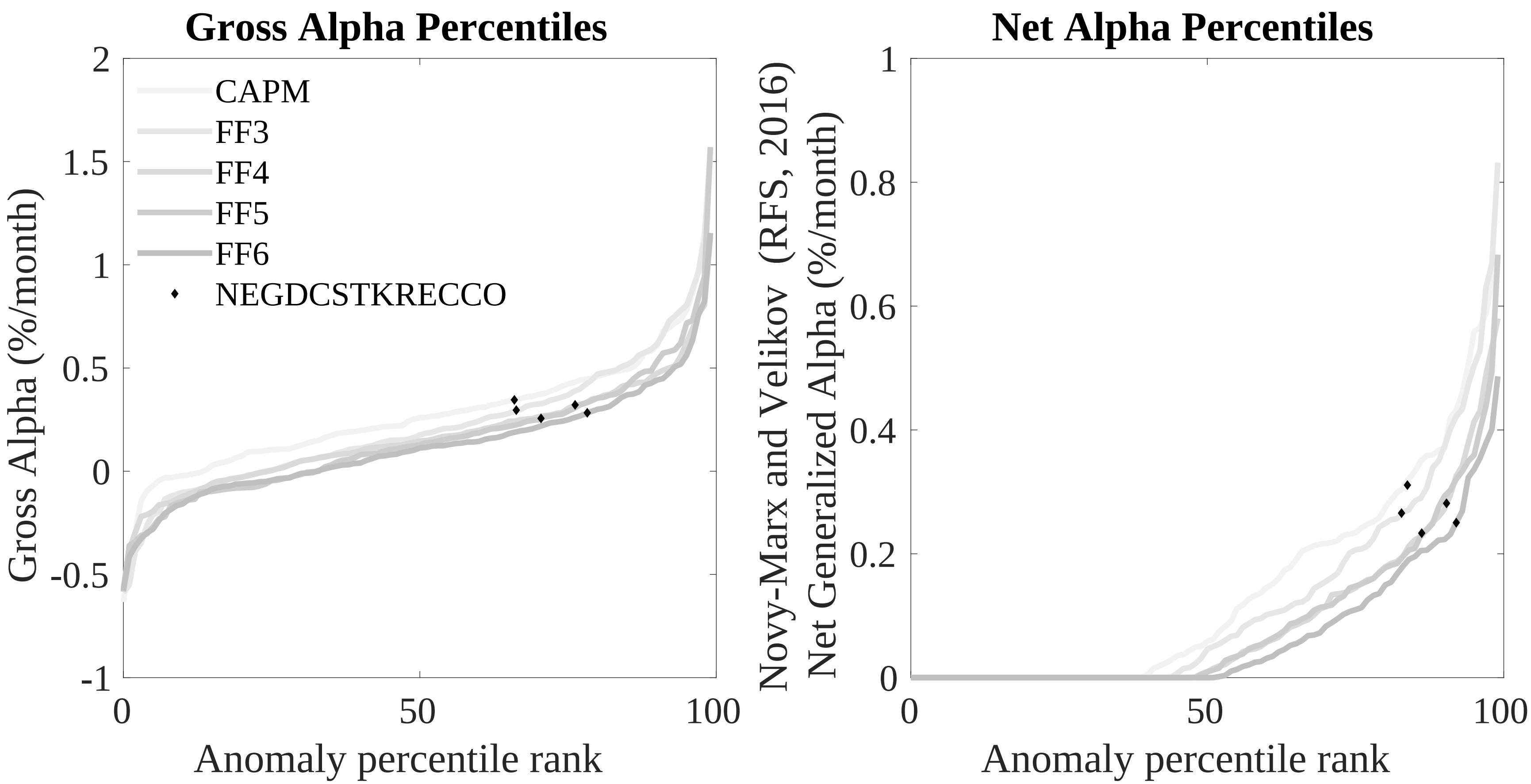


**Figure 4:** Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SRR trading strategy alphas (diamonds). The strategies are constructed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

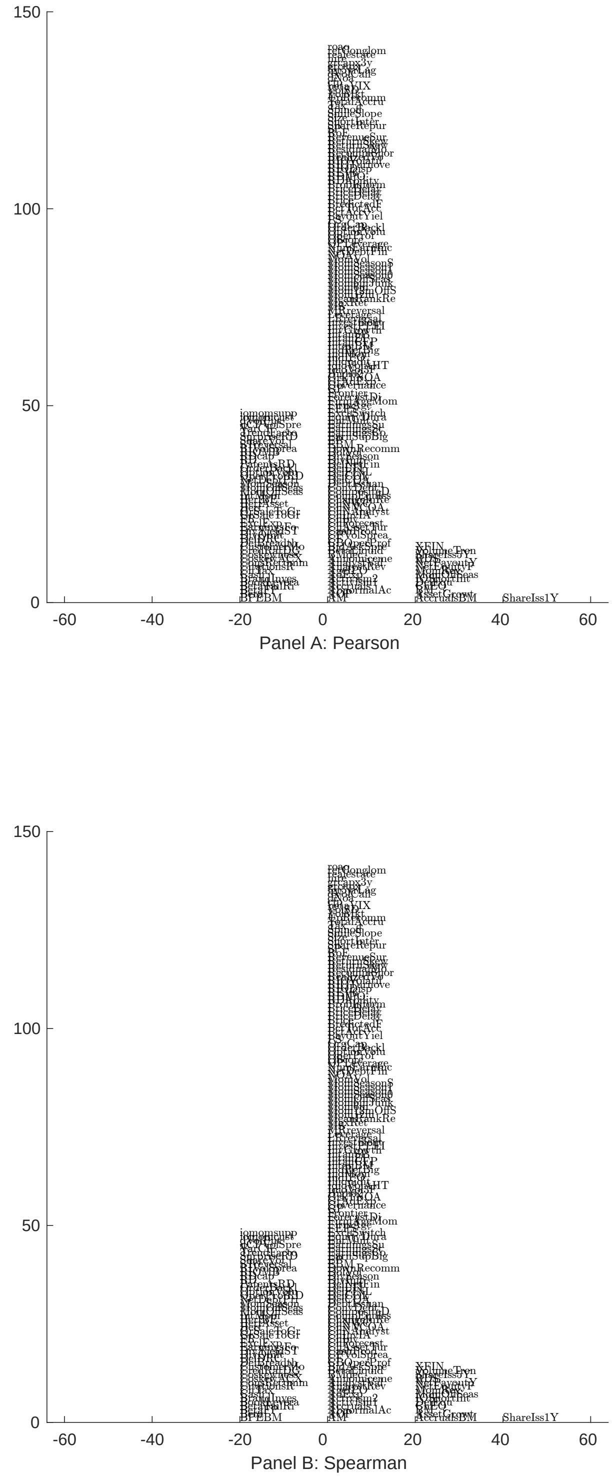


**Figure 5:** Distribution of correlations.
This figure plots a name histogram of correlations of 204 filtered anomaly signals with SRR. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

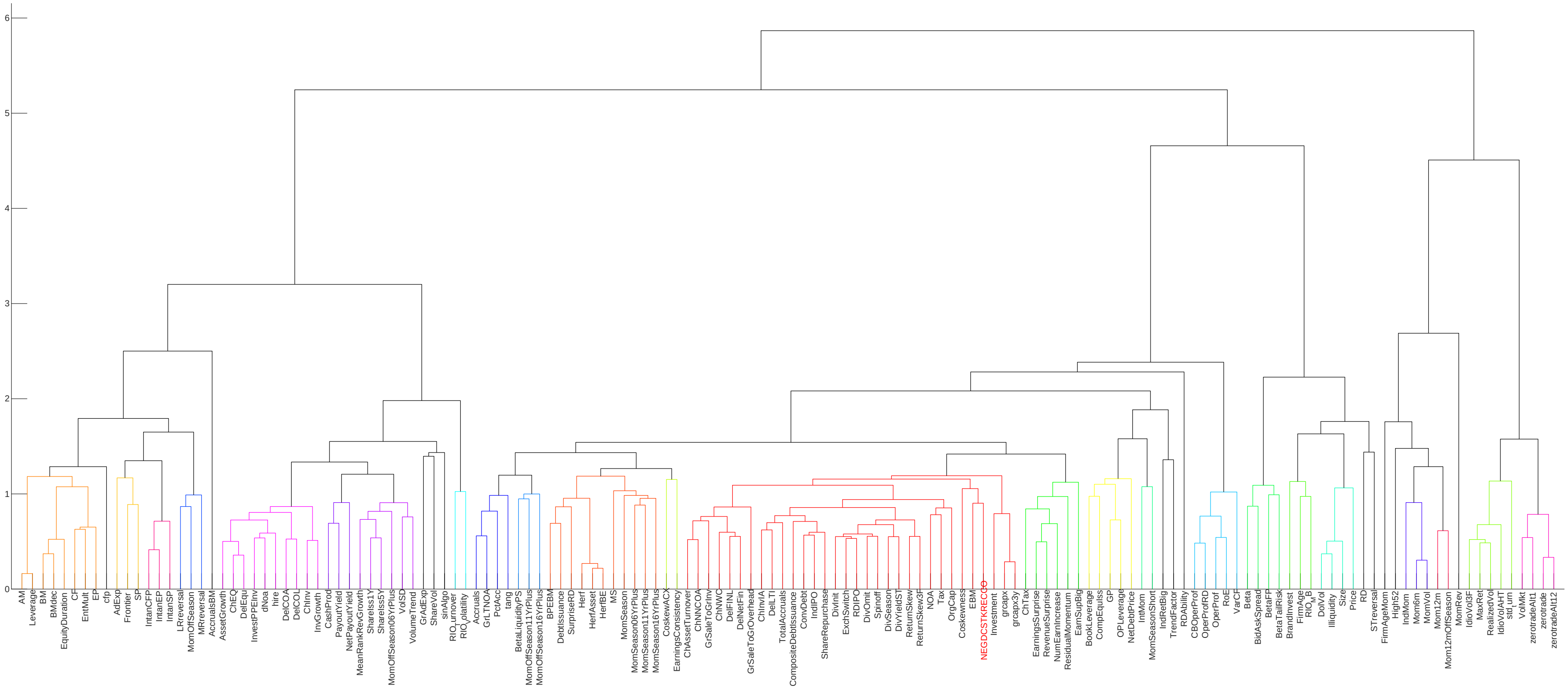


**Figure 6:** Agglomerative hierarchical cluster plot

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

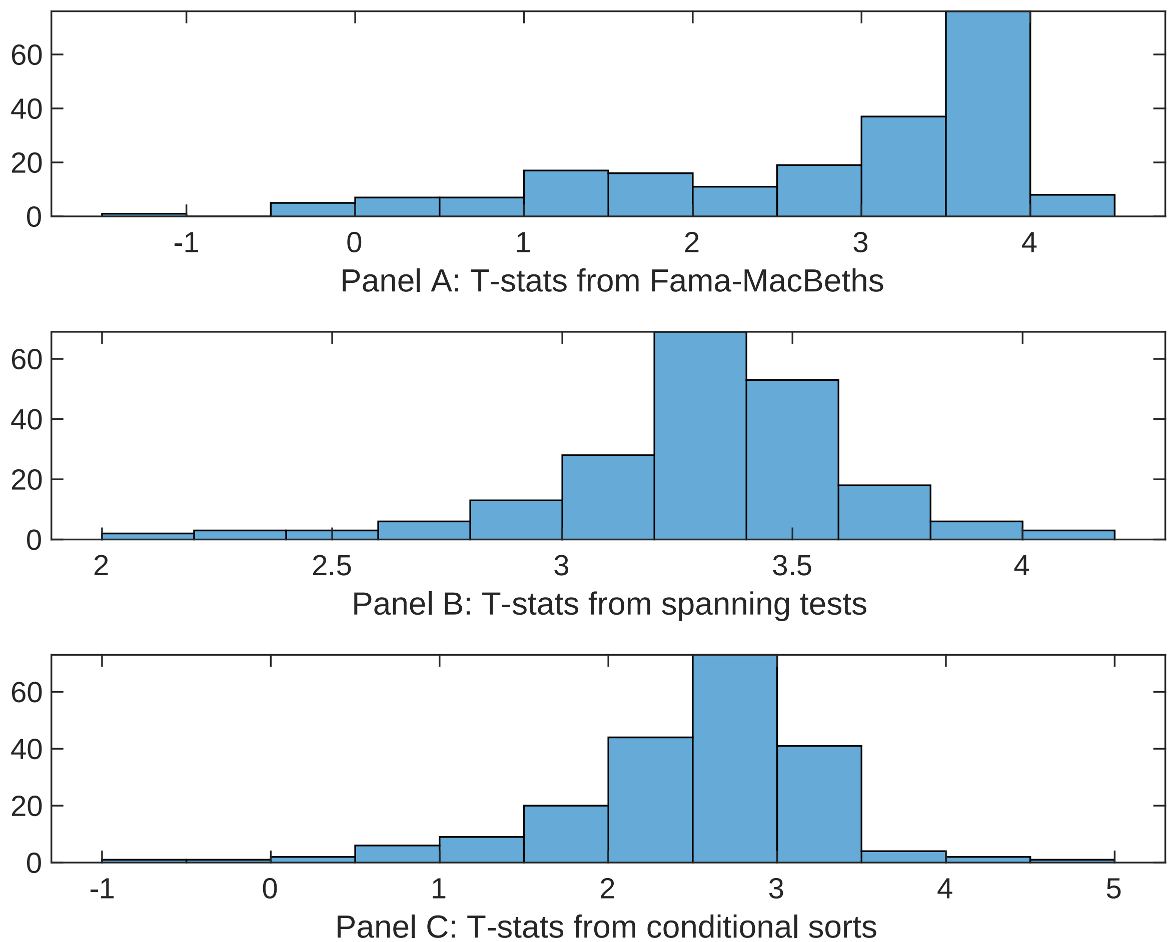


**Figure 7:** Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SRR conditioning on each of the 204 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{SRR}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SRR} SRR_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where $X$ stands for one of the 204 filtered anomaly signals at a time. Panel B plots t-statistics on $\alpha$ 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: $r_{i,t} = \alpha + \beta_{SRR} SRR_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, $X$, are Share issuance (1 year), Growth in book equity, Net Payout Yield, 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 | 0.19 | 0.12 | 0.12 | 0.13 | 0.13 | 0.14 |
| | [5.29] | [7.34] | [4.98] | [5.25] | [5.74] | [5.91] | [5.88] |
| SRR | 0.22 | 0.21 | 0.16 | 0.17 | 0.19 | 0.14 | 0.55 |
| | [3.69] | [3.80] | [2.55] | [3.27] | [2.55] | [2.84] | [0.84] |
| Anomaly 1 | 0.25 | | | | | | 0.66 |
| | [4.69] | | | | | | [1.01] |
| Anomaly 2 | | 0.60 | | | | | -0.30 |
| | | [5.49] | | | | | [-0.17] |
| Anomaly 3 | | | 0.35 | | | | 0.19 |
| | | | [3.32] | | | | [2.00] |
| Anomaly 4 | | | | 0.19 | | | 0.48 |
| | | | | [4.94] | | | [0.74] |
| Anomaly 5 | | | | | 0.28 | | -0.19 |
| | | | | | [2.47] | | [-1.42] |
| Anomaly 6 | | | | | | 0.16 | 0.17 |
| | | | | | | [6.19] | [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 | 0.28 | 0.28 | 0.30 | 0.24 | 0.24 | 0.26 |
| | [2.44] | [2.70] | [2.68] | [2.90] | [2.35] | [2.35] | [2.57] |
| Anomaly 1 | 30.90 | | | | | | 17.47 |
| | [5.86] | | | | | | [2.81] |
| Anomaly 2 | | 32.26 | | | | | 16.92 |
| | | [5.62] | | | | | [2.04] |
| Anomaly 3 | | | 21.02 | | | | 9.32 |
| | | | [5.23] | | | | [1.98] |
| Anomaly 4 | | | | 24.55 | | | -0.55 |
| | | | | [4.46] | | | [-0.07] |
| Anomaly 5 | | | | | 20.28 | | 4.23 |
| | | | | | [3.73] | | [0.70] |
| Anomaly 6 | | | | | | 11.42 | 3.38 |
| | | | | | | [3.09] | [0.89] |
| mkt | 8.49 | 7.12 | 9.49 | 5.68 | 8.85 | 7.79 | 10.40 |
| | [3.50] | [2.93] | [3.82] | [2.32] | [3.51] | [3.14] | [4.10] |
| smb | 0.22 | -2.47 | 2.87 | -1.78 | -2.25 | -3.06 | -0.40 |
| | [0.06] | [-0.70] | [0.80] | [-0.50] | [-0.63] | [-0.84] | [-0.11] |
| hml | -1.35 | -1.49 | -5.57 | -0.83 | -3.07 | -2.88 | -8.61 |
| | [-0.28] | [-0.32] | [-1.11] | [-0.17] | [-0.61] | [-0.56] | [-1.63] |
| rmw | -13.10 | -1.43 | -14.83 | -0.67 | -6.79 | -2.37 | -13.90 |
| | [-2.61] | [-0.30] | [-2.82] | [-0.14] | [-1.39] | [-0.50] | [-2.45] |
| cma | 10.44 | -7.38 | 9.81 | -0.91 | 19.14 | 20.64 | -9.66 |
| | [1.40] | [-0.83] | [1.28] | [-0.10] | [2.63] | [2.83] | [-1.06] |
| umd | -4.48 | -4.66 | -2.36 | -3.55 | -3.98 | -3.23 | -3.60 |
| | [-1.88] | [-1.93] | [-0.98] | [-1.46] | [-1.64] | [-1.33] | [-1.49] |
| # months | 680 | 684 | 680 | 684 | 680 | 680 | 680 |
| $\bar{R}^2$(%) | 10 | 8 | 9 | 7 | 7 | 6 | 12 |

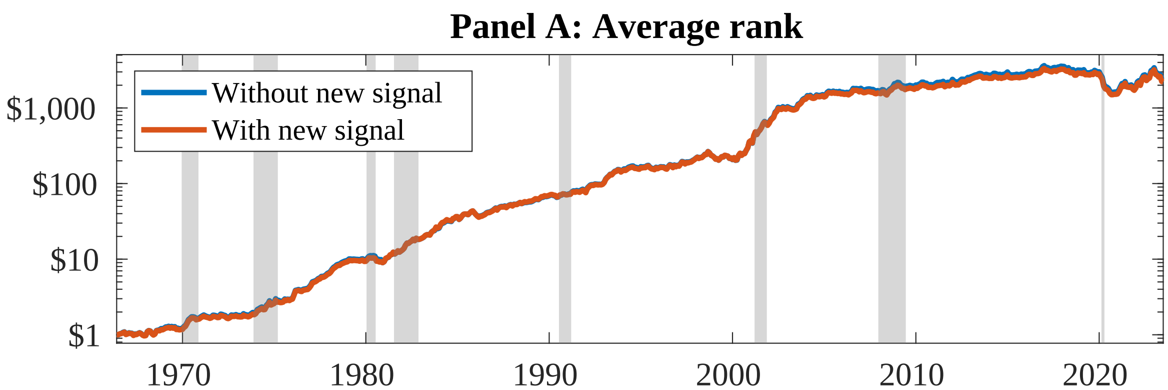


**Figure 8:** Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid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