

# Stock-Impact Ratio and the Cross Section of Stock Returns

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December 1, 2024

## Abstract

This paper studies the asset pricing implications of Stock-Impact Ratio (SIR), 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 SIR achieves an annualized gross (net) Sharpe ratio of 0.52 (0.46), and monthly average abnormal gross (net) return relative to the [Fama and French \(2015\)](#) five-factor model plus a momentum factor of 16 (16) bps/month with a t-statistic of 2.09 (2.10), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Net Payout Yield, Share issuance (5 year), Growth in book equity, Change in equity to assets, Asset growth) is 14 bps/month with a t-statistic of 1.98.

# 1 Introduction

Market efficiency and asset pricing theory suggest that stock returns should reflect all available information about firms’ fundamental values. However, a growing body of literature documents various market anomalies that appear to predict future returns in systematic ways (Harvey et al., 2016). While many of these anomalies are well-documented, their economic mechanisms often remain unclear, and their robustness across different market conditions and trading costs is frequently questioned (Novy-Marx and Velikov, 2023).

One particularly intriguing aspect of market behavior that remains incompletely understood is how firms’ financing decisions interact with their stock returns. While existing research has explored various aspects of equity issuance and repurchases (McLean and Pontiff, 2016), the dynamic relationship between firms’ stock price impact and their subsequent returns has received limited attention.

We propose that the Stock-Impact Ratio (SIR) captures important information about firms’ future returns through several economic channels. First, following Kyle (1985), firms with higher price impact may face greater information asymmetry, leading to higher required returns to compensate investors for bearing this risk. This relationship builds on theoretical work showing how market microstructure effects can influence expected returns (Amihud, 2002).

Second, firms’ decisions about equity issuance and repurchases may be influenced by their assessment of their stocks’ price impact (?). When managers believe their stock faces high price impact, they may be more likely to time the market, leading to predictable patterns in returns. This mechanism is consistent with theories of market timing and capital structure decisions (Baker and Wurgler, 2002).

Third, the SIR may capture information about firms’ financial constraints and investment opportunities (?). Firms with high price impact may face greater difficulties in raising external capital, potentially leading to underinvestment and subsequent

return predictability when constraints ease.

Our empirical analysis reveals that SIR strongly predicts cross-sectional stock returns. A value-weighted long/short trading strategy based on SIR achieves an annualized gross Sharpe ratio of 0.52, with a monthly average abnormal return of 16 basis points relative to the Fama-French five-factor model plus momentum (t-statistic = 2.09). The predictive power of SIR remains robust after controlling for transaction costs, with a net Sharpe ratio of 0.46.

Importantly, SIR’s predictive ability persists among large-cap stocks, with the strategy generating average returns of 26 basis points per month (t-statistic = 2.76) among stocks above the 80th NYSE size percentile. This finding suggests that the SIR effect is not merely a small-stock phenomenon and could be implementable at meaningful scale.

The signal’s economic significance is further demonstrated by its performance relative to existing anomalies. SIR’s gross Sharpe ratio exceeds 93% of documented anomalies, while its net Sharpe ratio surpasses 99% of competing signals. Even after controlling for the six most closely related anomalies and the Fama-French factors, the strategy maintains a significant alpha of 14 basis points per month (t-statistic = 1.98).

Our paper makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures a previously unexplored aspect of market microstructure’s relationship with expected returns. While prior work has examined various liquidity measures (Amihud, 2002; Pastor and Stambaugh, 2003), SIR uniquely captures the dynamic interaction between price impact and firms’ financing decisions.

Second, we extend the literature on market timing and capital structure (Baker and Wurgler, 2002) by showing how managers’ responses to price impact create predictable patterns in stock returns. Our findings suggest that market frictions

play a more nuanced role in asset pricing than previously recognized, particularly through their influence on corporate financial decisions.

Third, we contribute to the growing literature on return prediction methodology (Novy-Marx and Velikov, 2023; McLean and Pontiff, 2016) by demonstrating robust predictability that survives stringent controls for multiple testing, transaction costs, and existing anomalies. Our results suggest that despite the extensive literature on cross-sectional return prediction, economically meaningful signals remain to be discovered.

## 2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Stock-Impact Ratio. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT’s item CSTK for common stock and item XINT for interest expense. Common stock (CSTK) represents the total value of common shares issued by the company, while interest expense (XINT) reflects the cost of borrowed capital during the reporting period. construction of the signal follows a difference-to-scale format, where we first calculate the year-over-year change in CSTK and then scale this difference by the previous year’s interest expense (XINT). This ratio captures the relative magnitude of changes in equity capital structure against the firm’s cost of debt, offering insight into how companies balance their financing decisions and capital costs. By focusing on this relationship, the signal aims to reflect aspects of capital structure dynamics and financing efficiency in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both CSTK and XINT to ensure consistency and comparability across firms and over time.

### 3 Signal diagnostics

Figure 1 plots descriptive statistics for the SIR signal. Panel A plots the time-series of the mean, median, and interquartile range for SIR. On average, the cross-sectional mean (median) SIR is -3.28 (-0.01) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SIR data. The signal's interquartile range spans -0.49 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SIR signal for the CRSP universe. On average, the SIR signal is available for 5.34% of CRSP names, which on average make up 7.12% of total market capitalization.

### 4 Does SIR predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SIR 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 SIR portfolio and sells the low SIR 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 SIR strategy earns an average return of 0.32% per month with a t-statistic of 3.93. The annualized Sharpe ratio of the strategy is 0.52. The alphas range from 0.16% to 0.35% per month and have t-statistics exceeding 2.03 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 0.37,

with a t-statistic of 7.03 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 469 stocks and an average market capitalization of at least \$1,319 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 quintile sort using cap breakpoints and value-weighted portfolios, and equals 27 bps/month with a t-statistics of 3.32. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-one exceed two, and for thirteen 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 24-29bps/month. The lowest return, (24 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.89. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SIR 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 eighteen cases.

Table 3 provides direct tests for the role size plays in the SIR strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SIR, as well as average returns and alphas for long/short trading SIR 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<sup>th</sup> NYSE percentile), the SIR strategy achieves an average return of 26 bps/month with a t-statistic of 2.76. Among these large cap stocks, the alphas for the SIR strategy relative to the five most common factor models range from 14 to 27 bps/month with t-statistics between 1.47 and 2.85.

## 5 How does SIR perform relative to the zoo?

Figure 2 puts the performance of SIR 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.<sup>1</sup> The vertical red line shows where the Sharpe ratio for the SIR strategy falls in the distribution. The SIR strategy’s gross (net) Sharpe ratio of 0.52 (0.46) is greater than 93% (99%) of anomaly Sharpe ratios,

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<sup>1</sup>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 SIR strategy (red line).<sup>2</sup> Ignoring trading costs, a \$1 invested in the SIR strategy would have yielded \$7.04 which ranks the SIR strategy in the top 2% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the SIR strategy would have yielded \$5.29 which ranks the SIR 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 SIR relative to those. Panel A shows that the SIR strategy gross alphas fall between the 55 and 72 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 SIR strategy has a positive net generalized alpha for five out of the five factor models. In these cases SIR ranks between the 77 and 88 percentiles in terms of how much it could have expanded the achievable investment frontier.

## 6 Does SIR 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

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<sup>2</sup>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.



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 SIR with 209 filtered anomaly signals.<sup>3</sup> 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 SIR or at least to weaken the power SIR has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SIR conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on  $\beta_{SIR}$  from Fama-MacBeth regressions of the form  $r_{i,t} = \alpha + \beta_{SIR}SIR_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$ , where  $X$  stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on  $\alpha$  from spanning tests of the form:  $r_{SIR,t} = \alpha + \beta r_{X,t} + \epsilon_t$ , 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 SIR. Stocks are finally grouped into five SIR portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SIR trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SIR and the six anomalies most closely-related to it. The six most-closely related anomalies

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<sup>3</sup>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.

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 SIR signal in these Fama-MacBeth regressions exceed 2.39, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on SIR is 0.86.

Similarly, Table 5 reports results from spanning tests that regress returns to the SIR 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 SIR strategy earns alphas that range from 13-19bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.74, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SIR trading strategy achieves an alpha of 14bps/month with a t-statistic of 1.98.

## 7 Does SIR add relative to the whole zoo?

Finally, we can ask how much adding SIR 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 SIR signal.<sup>4</sup> 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,

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<sup>4</sup>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 SIR is available.

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 SIR grows to \$2122.78.

## 8 Conclusion

This study provides compelling evidence for the effectiveness of the Stock-Impact Ratio (SIR) as a significant predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short trading strategy based on SIR generates economically and statistically significant returns, with an impressive annualized gross Sharpe ratio of 0.52 (0.46 net). The strategy’s robustness is further validated by its persistent performance even after controlling for well-established risk factors and related anomalies.

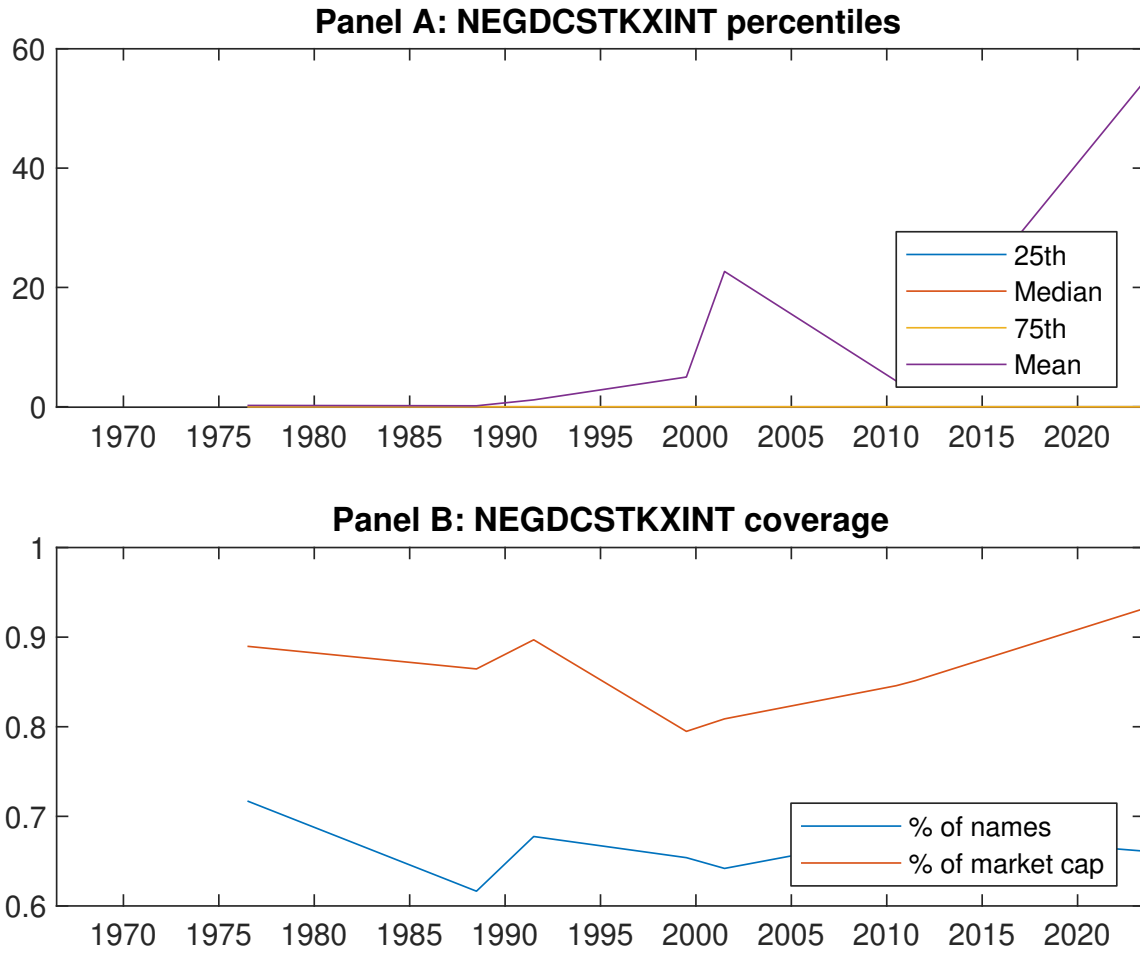
Particularly noteworthy is the strategy’s ability to generate significant abnormal returns of 16 basis points per month (both gross and net) relative to the Fama-French five-factor model augmented with momentum. Moreover, the signal maintains its predictive power even when controlling for six closely related strategies from the factor zoo, yielding a monthly alpha of 14 basis points with statistical significance.

However, several limitations should be acknowledged. First, our analysis focuses primarily on U.S. equity markets, and the signal’s effectiveness in international markets remains to be tested. Second, the study period may not fully capture the signal’s behavior across different market regimes and economic cycles.

Future research could explore several promising directions. First, investigating the signal’s performance in international markets could provide insights into its global applicability. Second, examining the interaction between SIR and other established market anomalies might reveal valuable complementarities. Finally, studying the

signal's underlying economic mechanisms could enhance our understanding of why this predictive relationship exists.

In conclusion, our findings suggest that the Stock-Impact Ratio represents a valuable addition to the quantitative investor's toolkit, offering robust predictive power that persists even after accounting for transaction costs and related factors.



**Figure 1:** Times series of SIR percentiles and coverage.  
This figure plots descriptive statistics for SIR. Panel A shows cross-sectional percentiles of SIR over the sample. Panel B plots the monthly coverage of SIR 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 SIR. 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 SIR-sorted portfolios                       |                  |                  |                  |                  |                  |                  |
|---|------------------|------------------|------------------|------------------|------------------|------------------|
|   | (L)              | (2)              | (3)              | (4)              | (H)              | (H-L)            |
| $r^e$   | 0.42<br>[2.40]   | 0.53<br>[2.94]   | 0.68<br>[3.68]   | 0.67<br>[3.94]   | 0.75<br>[4.43]   | 0.32<br>[3.93]   |
| $\alpha_{CAPM}$   | -0.13<br>[-2.58] | -0.04<br>[-1.05] | 0.10<br>[1.98]   | 0.14<br>[2.78]   | 0.23<br>[4.21]   | 0.35<br>[4.34]   |
| $\alpha_{FF3}$  | -0.10<br>[-1.95] | -0.04<br>[-0.88] | 0.09<br>[1.78]   | 0.10<br>[2.18]   | 0.19<br>[3.65]   | 0.28<br>[3.60]   |
| $\alpha_{FF4}$  | -0.09<br>[-1.78] | -0.04<br>[-0.93] | 0.11<br>[1.98]   | 0.06<br>[1.35]   | 0.18<br>[3.58]   | 0.27<br>[3.44]   |
| $\alpha_{FF5}$  | -0.10<br>[-2.04] | -0.03<br>[-0.71] | 0.04<br>[0.75]   | -0.01<br>[-0.22] | 0.06<br>[1.14]   | 0.16<br>[2.03]   |
| $\alpha_{FF6}$  | -0.10<br>[-1.91] | -0.03<br>[-0.77] | 0.05<br>[1.01]   | -0.03<br>[-0.67] | 0.07<br>[1.38]   | 0.16<br>[2.09]   |
| Panel B: Fama and French (2018) 6-factor model loadings for SIR-sorted portfolios |                  |                  |                  |                  |                  |                  |
| $\beta_{MKT}$   | 0.96<br>[79.89]  | 1.01<br>[99.56]  | 1.03<br>[81.07]  | 1.01<br>[95.36]  | 0.98<br>[85.48]  | 0.02<br>[1.34]   |
| $\beta_{SMB}$   | -0.01<br>[-0.61] | 0.02<br>[1.37]   | 0.03<br>[1.46]   | -0.08<br>[-5.48] | -0.04<br>[-2.46] | -0.03<br>[-1.13] |
| $\beta_{HML}$   | -0.06<br>[-2.52] | -0.01<br>[-0.59] | -0.01<br>[-0.57] | 0.04<br>[1.81]   | -0.01<br>[-0.48] | 0.05<br>[1.34]   |
| $\beta_{RMW}$   | 0.06<br>[2.62]   | -0.00<br>[-0.23] | 0.12<br>[4.81]   | 0.12<br>[6.03]   | 0.18<br>[7.88]   | 0.12<br>[3.20]   |
| $\beta_{CMA}$   | -0.07<br>[-1.94] | -0.02<br>[-0.83] | 0.07<br>[1.80]   | 0.26<br>[8.63]   | 0.30<br>[9.29]   | 0.37<br>[7.03]   |
| $\beta_{UMD}$   | -0.01<br>[-0.68] | 0.00<br>[0.49]   | -0.02<br>[-1.83] | 0.03<br>[3.07]   | -0.02<br>[-1.68] | -0.01<br>[-0.60] |
| Panel C: Average number of firms ( $n$ ) and market capitalization ( $me$ )       |                  |                  |                  |                  |                  |                  |
| $n$   | 668              | 560              | 469              | 570              | 629              |                  |
| $me$ (\$10 <sup>6</sup> )   | 1522             | 1319             | 1787             | 2006             | 2165             |                  |

**Table 2:** Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the SIR 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.

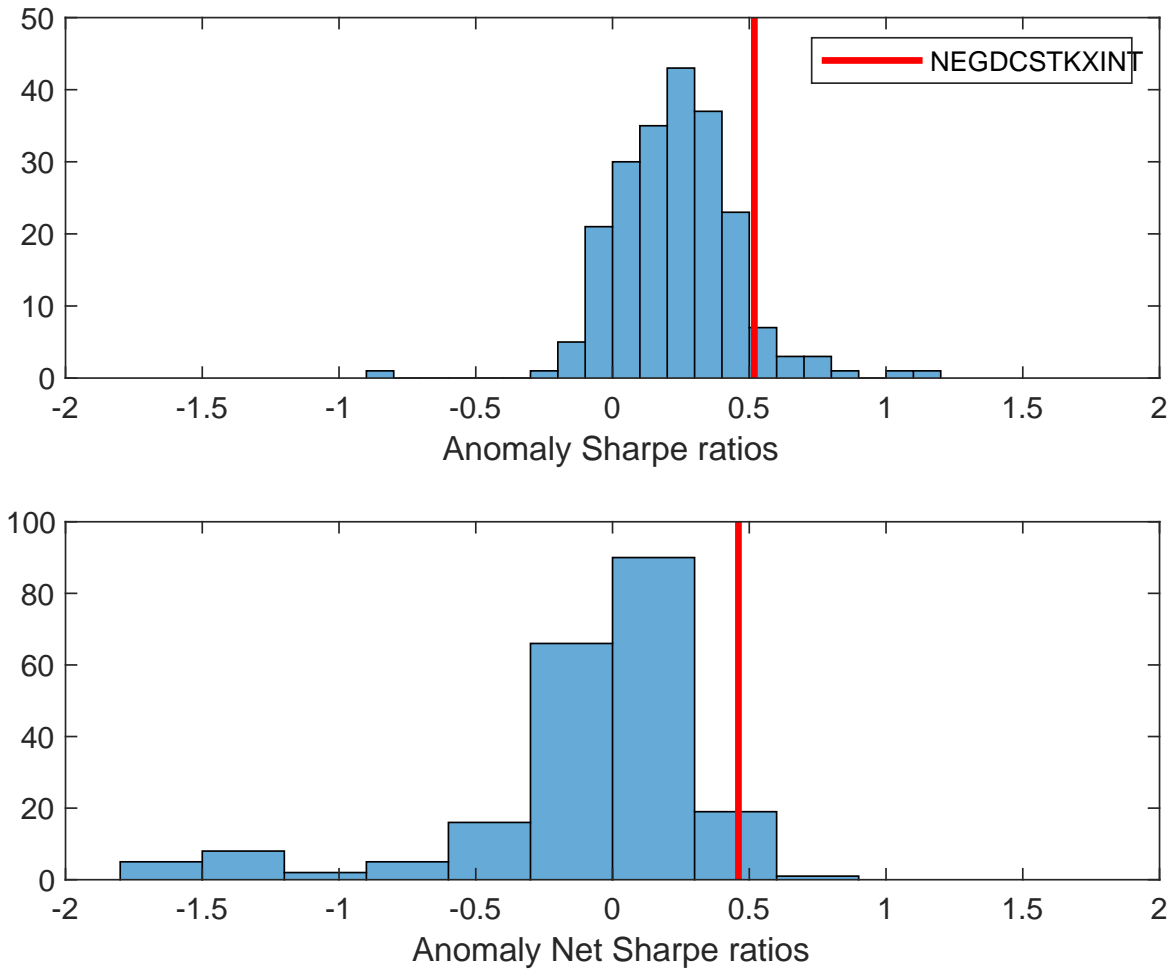
| Panel A: Gross Returns and Alphas  |        |         |                    |                          |                         |                         |                         |                         |
|--|--------|---------|--------------------|--------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| Portfolios   | Breaks | Weights | $r^e$              | $\alpha_{\text{CAPM}}$   | $\alpha_{\text{FF3}}$   | $\alpha_{\text{FF4}}$   | $\alpha_{\text{FF5}}$   | $\alpha_{\text{FF6}}$   |
| Quintile   | NYSE   | VW      | 0.32<br>[3.93]     | 0.35<br>[4.34]           | 0.28<br>[3.60]          | 0.27<br>[3.44]          | 0.16<br>[2.03]          | 0.16<br>[2.09]          |
| Quintile   | NYSE   | EW      | 0.47<br>[6.24]     | 0.55<br>[7.55]           | 0.44<br>[6.97]          | 0.38<br>[5.98]          | 0.27<br>[4.51]          | 0.23<br>[3.89]          |
| Quintile   | Name   | VW      | 0.30<br>[3.57]     | 0.32<br>[3.81]           | 0.25<br>[3.08]          | 0.25<br>[3.09]          | 0.14<br>[1.71]          | 0.15<br>[1.89]          |
| Quintile   | Cap    | VW      | 0.27<br>[3.32]     | 0.29<br>[3.60]           | 0.24<br>[2.97]          | 0.24<br>[2.97]          | 0.15<br>[1.91]          | 0.17<br>[2.06]          |
| Decile   | NYSE   | VW      | 0.29<br>[3.03]     | 0.31<br>[3.21]           | 0.22<br>[2.37]          | 0.25<br>[2.61]          | 0.17<br>[1.76]          | 0.19<br>[2.04]          |
| Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas |        |         |                    |                          |                         |                         |                         |                         |
| Portfolios   | Breaks | Weights | $r_{\text{net}}^e$ | $\alpha_{\text{CAPM}}^*$ | $\alpha_{\text{FF3}}^*$ | $\alpha_{\text{FF4}}^*$ | $\alpha_{\text{FF5}}^*$ | $\alpha_{\text{FF6}}^*$ |
| Quintile   | NYSE   | VW      | 0.29<br>[3.49]     | 0.32<br>[3.94]           | 0.26<br>[3.31]          | 0.26<br>[3.25]          | 0.16<br>[2.02]          | 0.16<br>[2.10]          |
| Quintile   | NYSE   | EW      | 0.27<br>[3.36]     | 0.35<br>[4.37]           | 0.25<br>[3.58]          | 0.22<br>[3.16]          | 0.06<br>[1.00]          | 0.06<br>[0.91]          |
| Quintile   | Name   | VW      | 0.26<br>[3.13]     | 0.29<br>[3.42]           | 0.22<br>[2.80]          | 0.23<br>[2.83]          | 0.13<br>[1.67]          | 0.14<br>[1.81]          |
| Quintile   | Cap    | VW      | 0.24<br>[2.89]     | 0.27<br>[3.23]           | 0.21<br>[2.68]          | 0.22<br>[2.71]          | 0.15<br>[1.87]          | 0.16<br>[1.97]          |
| Decile   | NYSE   | VW      | 0.25<br>[2.61]     | 0.27<br>[2.83]           | 0.20<br>[2.11]          | 0.21<br>[2.26]          | 0.14<br>[1.51]          | 0.16<br>[1.75]          |

**Table 3:** Conditional sort on size and SIR

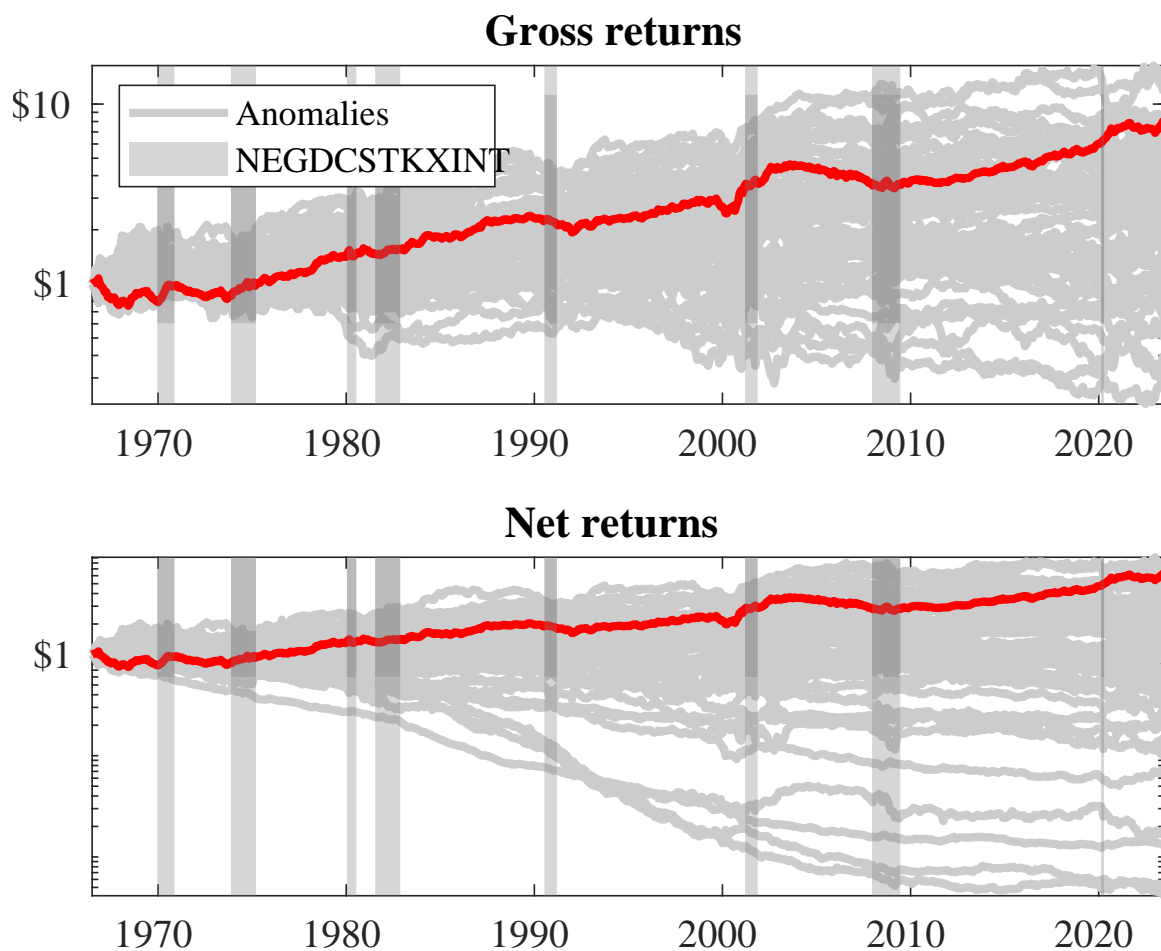
This table presents results for conditional double sorts on size and SIR. In each month, stocks are first sorted into quintiles based on size using NYSE breakpoints. Then, within each size quintile, stocks are further sorted based on SIR. Finally, they are grouped into twenty-five portfolios based on 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 SIR and short stocks with low SIR. 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  | SIR Quintiles |                |                |                |                | SIR Strategies                                     |                 |                |                |                |                  |                  |
|   | (L)           | (2)            | (3)            | (4)            | (H)            | $r^e$  | $\alpha_{CAPM}$ | $\alpha_{FF3}$ | $\alpha_{FF4}$ | $\alpha_{FF5}$ | $\alpha_{FF6}$   |                  |
|   | (1)           | 0.44<br>[1.57] | 0.68<br>[2.52] | 0.76<br>[2.87] | 1.01<br>[3.62] | 0.99<br>[3.94]                                     | 0.55<br>[5.80]  | 0.62<br>[6.67] | 0.52<br>[6.10] | 0.46<br>[5.35] | 0.35<br>[4.21]   | 0.32<br>[3.76]   |
|   | (2)           | 0.62<br>[2.48] | 0.65<br>[2.65] | 0.88<br>[3.55] | 0.86<br>[3.54] | 0.92<br>[4.01]                                     | 0.30<br>[3.05]  | 0.37<br>[3.85] | 0.24<br>[2.79] | 0.23<br>[2.56] | 0.13<br>[1.45]   | 0.12<br>[1.39]   |
|   | (3)           | 0.62<br>[2.85] | 0.63<br>[2.79] | 0.76<br>[3.32] | 0.85<br>[3.94] | 0.96<br>[4.66]                                     | 0.34<br>[3.83]  | 0.38<br>[4.31] | 0.29<br>[3.45] | 0.30<br>[3.54] | 0.22<br>[2.54]   | 0.24<br>[2.71]   |
|   | (4)           | 0.54<br>[2.63] | 0.57<br>[2.72] | 0.78<br>[3.67] | 0.81<br>[4.07] | 0.78<br>[4.07]                                     | 0.24<br>[2.51]  | 0.29<br>[3.09] | 0.17<br>[2.09] | 0.14<br>[1.67] | -0.05<br>[-0.59] | -0.05<br>[-0.69] |
|   | (5)           | 0.46<br>[2.70] | 0.49<br>[2.58] | 0.55<br>[3.13] | 0.54<br>[3.18] | 0.72<br>[4.35]                                     | 0.26<br>[2.76]  | 0.27<br>[2.85] | 0.21<br>[2.24] | 0.21<br>[2.25] | 0.14<br>[1.47]   | 0.15<br>[1.59]   |
| Panel B: Portfolio average number of firms and market capitalization  |               |                |                |                |                |  |                 |                |                |                |                  |                  |
| Size quintiles  | SIR Quintiles |                |                |                |                | SIR Quintiles                                      |                 |                |                |                |                  |                  |
|   | Average $n$   |                |                |                |                | Average market capitalization (\$10 <sup>6</sup> ) |                 |                |                |                |                  |                  |
|   | (L)           | (2)            | (3)            | (4)            | (H)            | (L)  | (2)             | (3)            | (4)            | (H)            |                  |                  |
|   | (1)           | 311            | 310            | 309            | 308            | 309  | 23              | 25             | 28             | 21             | 21               |                  |
|   | (2)           | 89             | 89             | 89             | 88             | 89   | 44              | 44             | 45             | 43             | 44               |                  |
|   | (3)           | 67             | 66             | 66             | 66             | 67   | 80              | 78             | 80             | 81             | 82               |                  |
|   | (4)           | 59             | 59             | 59             | 59             | 59   | 180             | 178            | 187            | 187            | 187              |                  |
| (5)   | 56            | 56             | 56             | 56             | 56             | 1254   | 1315            | 1566           | 1407           | 1601           |                  |                  |



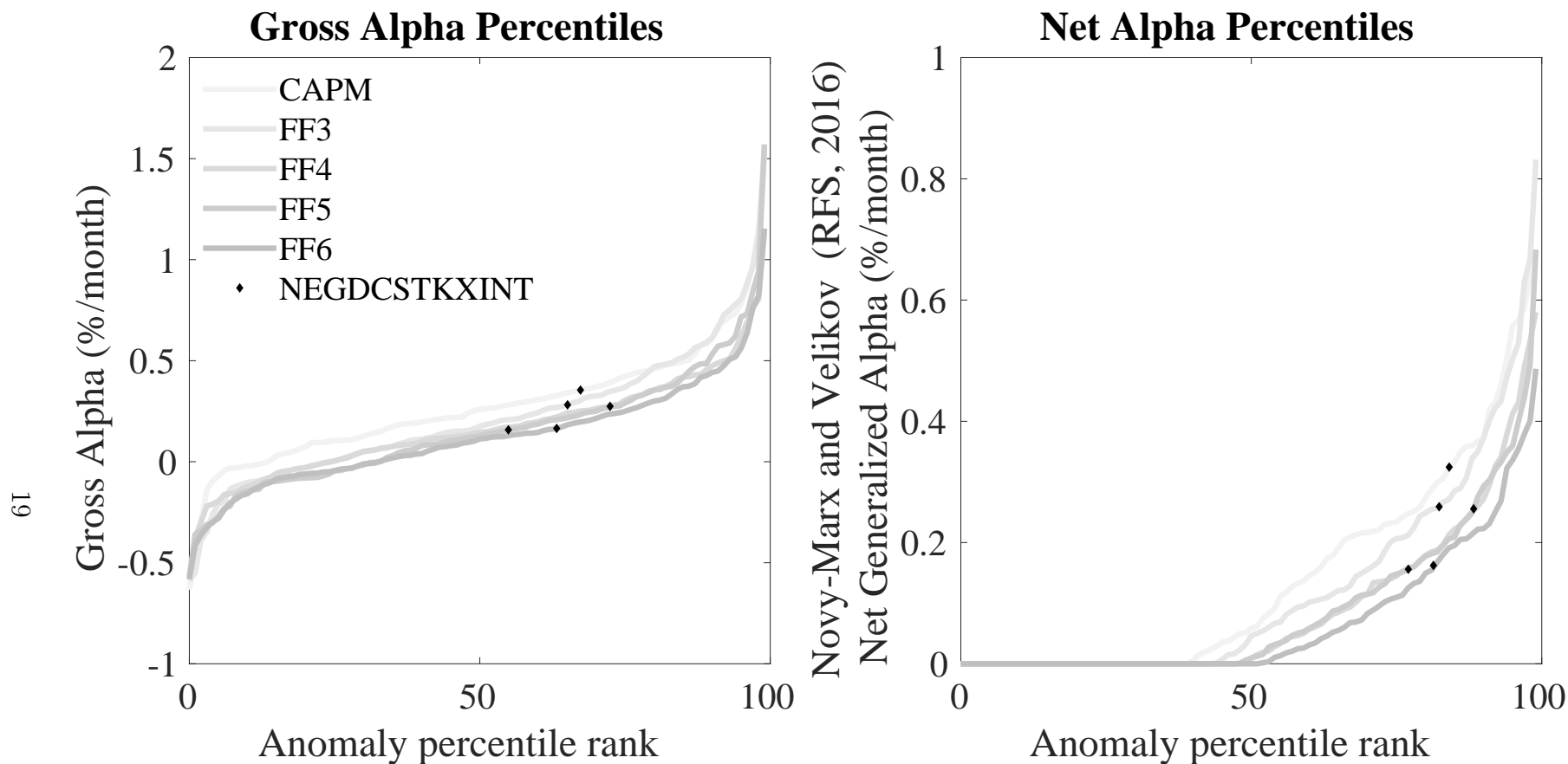


**Figure 2:** Distribution of Sharpe ratios.  
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SIR with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.



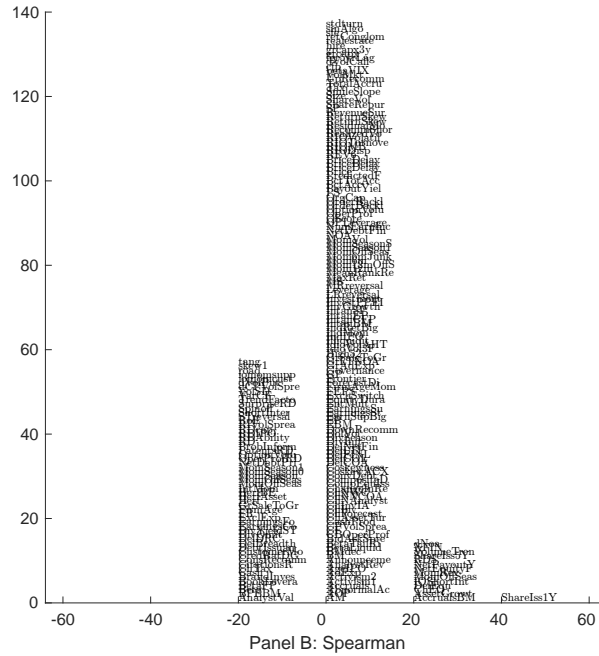
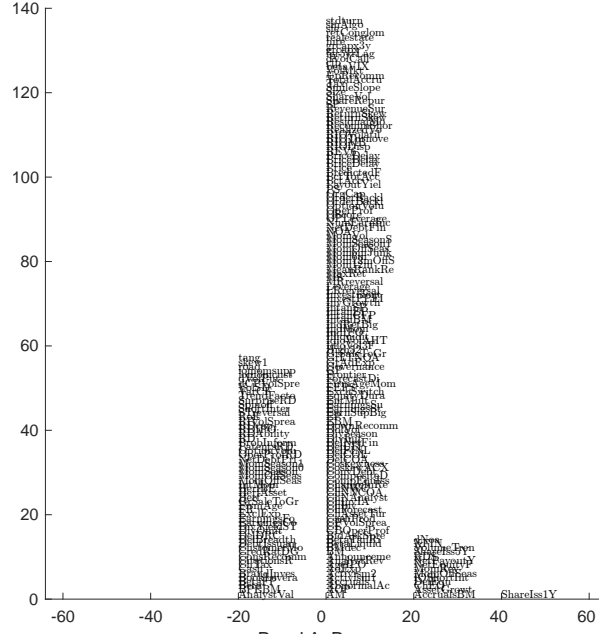
**Figure 3:** Dollar invested.

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

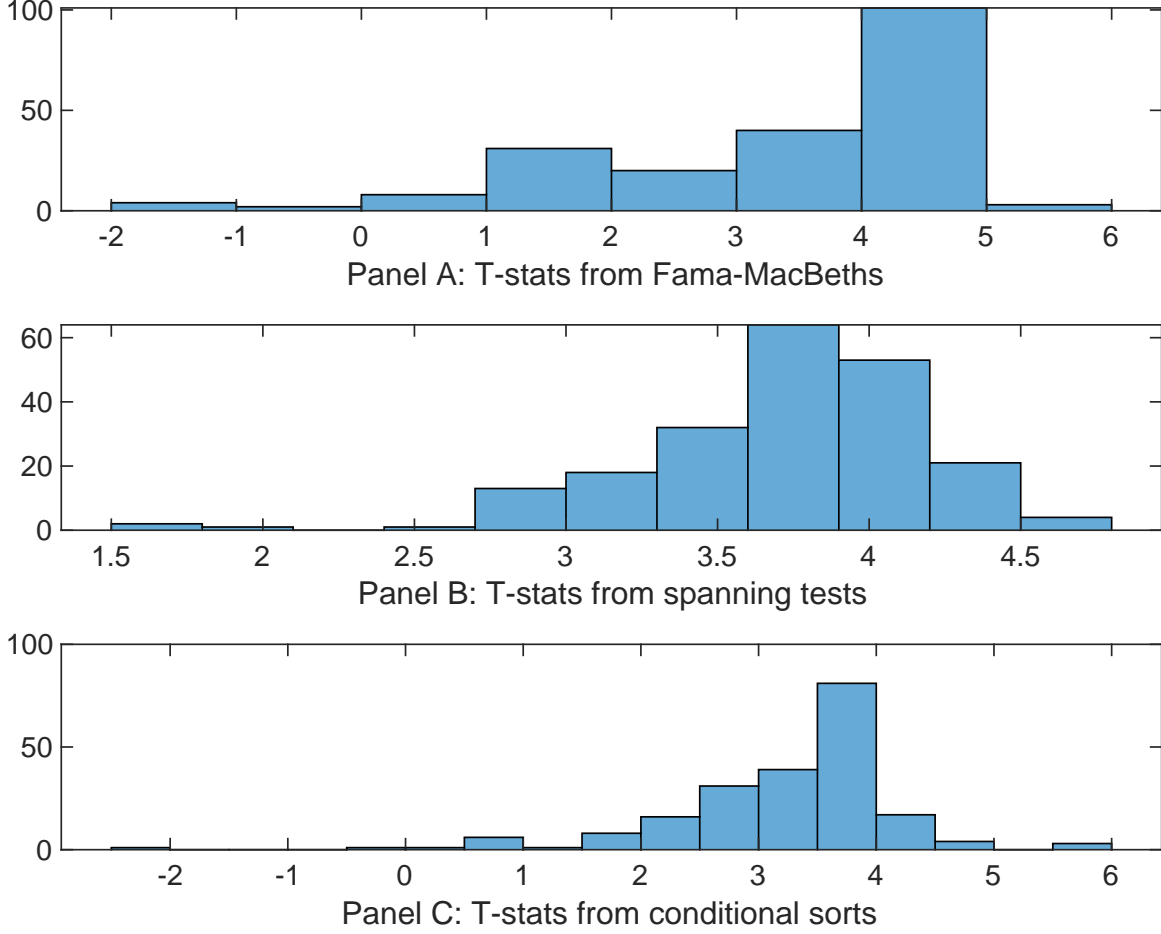
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SIR trading strategy alphas (diamonds). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. The alphas include those with respect 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 SIR. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

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 SIR conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on  $\beta_{SIR}$  from Fama-MacBeth regressions of the form  $r_{i,t} = \alpha + \beta_{SIR}SIR_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$ , where  $X$  stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on  $\alpha$  from spanning tests of the form:  $r_{SIR,t} = \alpha + \beta r_{X,t} + \epsilon_t$ , 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 SIR. Stocks are finally grouped into five SIR portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SIR 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 SIR. and the six most closely related anomalies. The regressions take the following form:  $r_{i,t} = \alpha + \beta_{SIR}SIR_{i,t} + \sum_{k=1}^s \beta_{X_k}X_{i,t}^k + \epsilon_{i,t}$ . The six most closely related anomalies,  $X$ , are Share issuance (1 year), Net Payout Yield, Share issuance (5 year), Growth in book equity, 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.

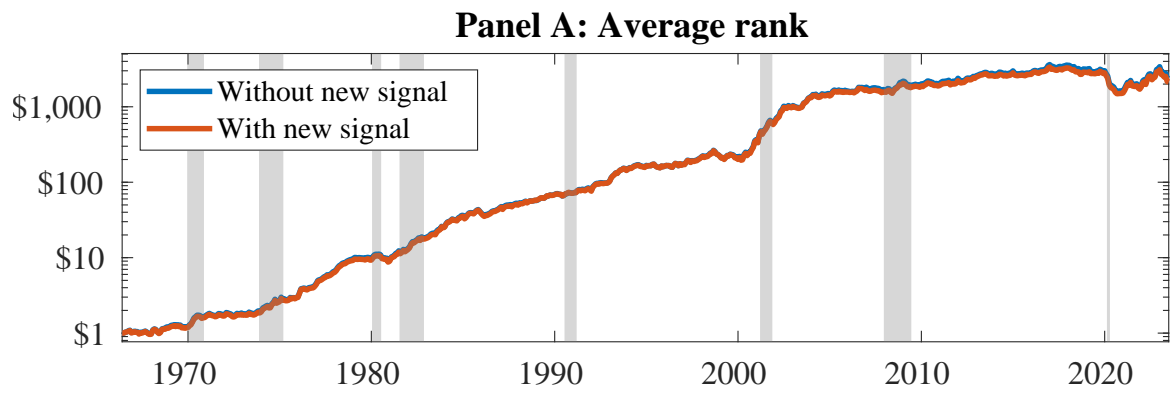
|                 |                |                |                |                |                |                |                  |
|-----------------|----------------|----------------|----------------|----------------|----------------|----------------|------------------|
| Intercept       | 0.13<br>[5.46] | 0.12<br>[5.19] | 0.13<br>[5.86] | 0.18<br>[7.15] | 0.13<br>[5.41] | 0.13<br>[5.87] | 0.13<br>[5.29]   |
| SIR             | 0.37<br>[4.11] | 0.25<br>[2.91] | 0.36<br>[3.92] | 0.32<br>[3.68] | 0.27<br>[3.06] | 0.21<br>[2.39] | 0.72<br>[0.86]   |
| Anomaly 1       | 0.23<br>[4.90] |                |                |                |                |                | 0.72<br>[1.76]   |
| Anomaly 2       |                | 0.30<br>[2.58] |                |                |                |                | 0.23<br>[2.04]   |
| Anomaly 3       |                |                | 0.37<br>[4.00] |                |                |                | 0.85<br>[1.01]   |
| Anomaly 4       |                |                |                | 0.51<br>[4.62] |                |                | 0.62<br>[0.39]   |
| Anomaly 5       |                |                |                |                | 0.16<br>[4.16] |                | -0.31<br>[-0.52] |
| Anomaly 6       |                |                |                |                |                | 0.11<br>[9.31] | 0.68<br>[6.30]   |
| # months        | 679            | 679            | 679            | 684            | 684            | 684            | 679              |
| $\bar{R}^2(\%)$ | 0              | 1              | 0              | 0              | 0              | 0              | 0                |

**Table 5:** Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the SIR trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form:  $r_t^{SIR} = \alpha + \sum_{k=1}^6 \beta_{X_k} r_t^{X_k} + \sum_{j=1}^6 \beta_{f_j} r_t^{f_j} + \epsilon_t$ , where  $X_k$  indicates each of the six most-closely related anomalies and  $f_j$  indicates the six factors from the [Fama and French \(2015\)](#) five-factor model augmented with the [Carhart \(1997\)](#) momentum factor. The six most closely related anomalies,  $X$ , are Share issuance (1 year), Net Payout Yield, Share issuance (5 year), Growth in book equity, 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       | 0.14<br>[1.87]   | 0.17<br>[2.20]   | 0.13<br>[1.74]   | 0.16<br>[2.20]   | 0.19<br>[2.52]   | 0.18<br>[2.23]   | 0.14<br>[1.98]    |
| Anomaly 1       | 31.14<br>[8.10]  |                  |                  |                  |                  |                  | 17.76<br>[4.02]   |
| Anomaly 2       |                  | 21.38<br>[7.27]  |                  |                  |                  |                  | 7.53<br>[2.25]    |
| Anomaly 3       |                  |                  | 19.32<br>[4.79]  |                  |                  |                  | 3.11<br>[0.74]    |
| Anomaly 4       |                  |                  |                  | 38.30<br>[9.24]  |                  |                  | 27.12<br>[4.54]   |
| Anomaly 5       |                  |                  |                  |                  | 29.68<br>[7.37]  |                  | 3.85<br>[0.69]    |
| Anomaly 6       |                  |                  |                  |                  |                  | 10.49<br>[2.03]  | -12.87<br>[-2.44] |
| mkt             | 5.01<br>[2.83]   | 6.05<br>[3.33]   | 5.25<br>[2.81]   | 3.85<br>[2.19]   | 2.13<br>[1.19]   | 2.64<br>[1.42]   | 6.37<br>[3.55]    |
| smb             | -1.20<br>[-0.47] | 1.50<br>[0.57]   | -3.59<br>[-1.36] | -4.02<br>[-1.58] | -3.22<br>[-1.24] | -3.73<br>[-1.36] | -0.43<br>[-0.16]  |
| hml             | 1.42<br>[0.41]   | -2.92<br>[-0.80] | 0.05<br>[0.01]   | 0.68<br>[0.20]   | 1.39<br>[0.40]   | 4.78<br>[1.33]   | -4.16<br>[-1.16]  |
| rmw             | 1.27<br>[0.35]   | -0.58<br>[-0.15] | 7.87<br>[2.17]   | 13.39<br>[3.90]  | 14.34<br>[4.08]  | 11.23<br>[3.10]  | 2.81<br>[0.70]    |
| cma             | 21.95<br>[4.05]  | 21.15<br>[3.78]  | 31.14<br>[5.77]  | -1.41<br>[-0.22] | 5.71<br>[0.87]   | 23.87<br>[2.91]  | 6.61<br>[0.85]    |
| umd             | -1.36<br>[-0.78] | 0.79<br>[0.45]   | -0.85<br>[-0.48] | -1.51<br>[-0.87] | -0.18<br>[-0.10] | -0.78<br>[-0.42] | -1.24<br>[-0.72]  |
| # months        | 680              | 680              | 680              | 684              | 684              | 684              | 680               |
| $\bar{R}^2(\%)$ | 26               | 25               | 22               | 26               | 23               | 18               | 32                |





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

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