# Stock Liability Differential Signal and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

**Abstract**

This paper studies the asset pricing implications of Stock Liability Differential Signal (SLDS), 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 SLDS achieves an annualized gross (net) Sharpe ratio of 0.56 (0.50), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 21 (21) bps/month with a t-statistic of 2.52 (2.57), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth) is 17 bps/month with a t-statistic of 2.18.

# 1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (McLean and Pontiff, 2016). While many of these patterns stem from firm fundamentals or market frictions, the role of corporate liability structure in driving cross-sectional return predictability remains relatively unexplored. Understanding how changes in firms' liability composition affect expected returns is crucial for both asset pricing theory and investment practice.

We propose that the Stock Liability Differential Signal (SLDS) contains valuable information about future returns through multiple economic channels. First, changes in liability structure may signal management's private information about future investment opportunities and cash flow prospects (Myers and Majluf, 1984). When managers anticipate strong performance, they may adjust their liability mix to optimize capital structure, creating an informational link between liability changes and expected returns. Second, the composition of liabilities affects firms' exposure to systematic risk factors (Vassalou and Xing, 2004). Firms with different liability structures face varying degrees of financial constraints and distress risk, which theory suggests should be priced in equilibrium (Gomes et al., 2006). Third, liability structure changes can influence the agency conflicts between shareholders and debtholders, potentially affecting required returns through the cost of financial distress (Jensen and Meckling, 1976).

Our empirical analysis reveals that SLDS strongly predicts future stock returns. A value-weighted long-short portfolio formed on SLDS generates a monthly alpha of 21 basis points (t-statistic = 2.52) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized Sharpe ratio of 0.56 before trading costs and 0.50 after accounting for transaction costs. Importantly, the predictive power of SLDS persists among large-cap stocks, with the highest size quintile generating a monthly alpha of 19-25 basis points across various factor models. The signal's robustness to controlling for size suggests that the SLDS effect is distinct from well-known small-firm anomalies.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel return predictor based on changes in liability structure that is distinct from existing capital structure measures (Titman and Wessels, 1988). Second, we demonstrate that SLDS captures unique information not explained by related anomalies such as asset growth (Cooper et al., 2008) or external financing (Bradshaw, 2006). When controlling for six closely related anomalies and common risk factors, SLDS still generates a significant monthly alpha of 17 basis points (t-statistic = 2.18). Third, our findings extend the literature on how financing decisions affect expected returns (Baker and Wurgler, 2003) by showing that the composition of liabilities, not just their level, contains valuable predictive information.

## 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 Liability Differential Signal. 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 LCT for total current liabilities. Common stock (CSTK) represents the total value of common shares issued by the company, while total current liabilities (LCT) encompasses all debts and obligations due within one year, including accounts payable, short-term debt, and other current liabilities. The construction of the signal follows a differential format, where we calculate the change in CSTK between consecutive periods and scale this difference by the previous period's LCT. This scaled differential captures the relative magnitude of changes in equity financing compared to the firm's short-term obligations, potentially offering insight into changes in capital structure and financing decisions. By scaling the change in common stock by lagged current liabilities, the signal provides a standardized measure that facilitates comparison across firms of different sizes. We construct this measure using end-of-fiscal-year values for both CSTK and LCT to ensure consistency and comparability across firms and over time.

## 3 Signal diagnostics

Figure 1 plots descriptive statistics for the SLDS signal. Panel A plots the time-series of the mean, median, and interquartile range for SLDS. On average, the cross-sectional mean (median) SLDS is -0.03 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SLDS data. The signal's interquartile range spans -0.03 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SLDS signal for the CRSP universe. On average, the SLDS signal is available for 5.75% of CRSP names, which on average make up 6.88% of total market capitalization.

## 4 Does SLDS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SLDS 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 SLDS portfolio and sells the low SLDS 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 SLDS strategy earns an average return of 0.35% per month with a t-statistic of 4.28. The annualized Sharpe ratio of the strategy is 0.56. The alphas range from 0.21% to 0.37% per month and have t-statistics exceeding 2.52 everywhere. The lowest alpha is with respect to the FF6 factor model.

Panel B reports the six portfolios' loadings on the factors in the Fama and French (2018) six-factor model. The long/short strategy's most significant loading is 0.30, with a t-statistic of 5.42 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 517 stocks and an average market capitalization of at least $1,178 million.

Table 2 reports robustness results for alternative sorting methodologies, and accounting for transaction costs. These results are important, because many anomalies are far stronger among small cap stocks, but these small stocks are more expensive to trade. Construction methods, or even signal-size correlations, that over-weight small stocks can yield stronger paper performance without improving an investor's achievable investment opportunity set. Panel A reports gross returns and alphas for the long/short strategies made using various different protfolio constructions. The first row reports the average returns and the alphas for the long/short strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios. The rest of the panel shows the equal-weighted returns to this same strategy, and the value-weighted performance of strategies constructed from quintile sorts using name breaks (approximately equal number of firms in each portfolio) and market capitalization breaks (approximately equal total market capitalization in each portfolio), and using NYSE deciles. The average return is lowest for the quintile sort using cap breakpoints and value-weighted portfolios, and equals 31 bps/month with a t-statistics of 3.85. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for fourteen exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016). These generalized alphas measure the extent to which a test asset improves the ex-post mean-variance efficient portfolio, accounting for the costs of trading both the asset and the explanatory factors. The transaction costs are calculated as the high-frequency composite effective bid-ask half-spread measure from Chen and Velikov (2022). The net average returns reported in the first column range between 28-37bps/month. The lowest return, (28 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.41. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SLDS trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-five cases, and significantly expands the achievable frontier in twenty-five cases.

Table 3 provides direct tests for the role size plays in the SLDS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SLDS, as well as average returns and alphas for long/short trading SLDS 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 SLDS strategy achieves an average return of 27 bps/month with a t-statistic of 2.75. Among these large cap stocks, the alphas for the SLDS strategy relative to the five most common factor models range from 19 to 25 bps/month with t-statistics between 1.90 and 2.60.

# 5 How does SLDS perform relative to the zoo?

Figure 2 puts the performance of SLDS 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 SLDS strategy falls in the distribution. The SLDS strategy's gross (net) Sharpe ratio of 0.56 (0.50) is greater than 95% (99%) of anomaly Sharpe ratios, respectively.

Figure 3 plots the growth of a \$1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a \$1 invested in the SLDS strategy (red line).[2] Ignoring trading costs, a \$1 invested in the SLDS strategy would have yielded \$8.86 which ranks the SLDS strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the SLDS strategy would have yielded \$6.65 which ranks the SLDS strategy in the top 0% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the SLDS relative to those. Panel A shows that the SLDS strategy gross alphas fall between the 67 and 74 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%

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

[2] The figure assumes an initial investment of \$1 in T-bills and \$1 long/short in the two sides of the strategy. Returns are compounded each month, assuming, as in Detzel et al. (2022), that a capital cost is charged against the strategy's returns at the risk-free rate. This excess return corresponds more closely to the strategy's economic profitability.

(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 SLDS strategy has a positive net generalized alpha for five out of the five factor models. In these cases SLDS ranks between the 86 and 90 percentiles in terms of how much it could have expanded the achievable investment frontier.

## 6 Does SLDS 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 SLDS with 209 filtered anomaly signals.[3] Figure 6 also shows an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

A closely related anomaly is also more likely to price SLDS or at least to weaken the power SLDS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SLDS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{SLDS}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SLDS} SLDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SLDS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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,

[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.

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 SLDS. Stocks are finally grouped into five SLDS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SLDS trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SLDS 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 SLDS signal in these Fama-MacBeth regressions exceed 1.44, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SLDS is 1.25.

Similarly, Table 5 reports results from spanning tests that regress returns to the SLDS 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 SLDS strategy earns alphas that range from 18-23bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.18, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SLDS trading strategy achieves an alpha of 17bps/month with a t-statistic of 2.18.

# 7 Does SLDS add relative to the whole zoo?

Finally, we can ask how much adding SLDS 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 SLDS 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 SLDS grows to $1920.57.

# 8 Conclusion

This study provides compelling evidence for the effectiveness of the Stock Liability Differential Signal (SLDS) as a robust predictor of cross-sectional equity returns. Our findings demonstrate that SLDS-based trading strategies yield economically and statistically significant results, with a value-weighted long/short portfolio achieving impressive Sharpe ratios of 0.56 and 0.50 on a gross and net basis, respectively. The signal's predictive power remains strong even after controlling for well-established factors, including the Fama-French five-factor model and momentum factor, generating significant monthly abnormal returns of 21 basis points. Notably, the signal

[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 SLDS is available.

maintains its explanatory power when tested against the most closely related strategies from the factor zoo, producing a significant alpha of 17 basis points per month.

These results have important implications for both academic research and practical investment management. For academics, our findings contribute to the growing literature on return predictability and factor investing, suggesting that liability-related information contains valuable signals for asset pricing. For practitioners, SLDS presents a potentially profitable trading strategy that remains effective after accounting for transaction costs.

However, several limitations should be noted. First, our analysis focuses 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. Future research could explore the signal's performance in international markets, its interaction with other established factors, and its effectiveness during various market conditions. Additionally, investigating the underlying economic mechanisms driving the SLDS premium would provide valuable insights into asset pricing theory.

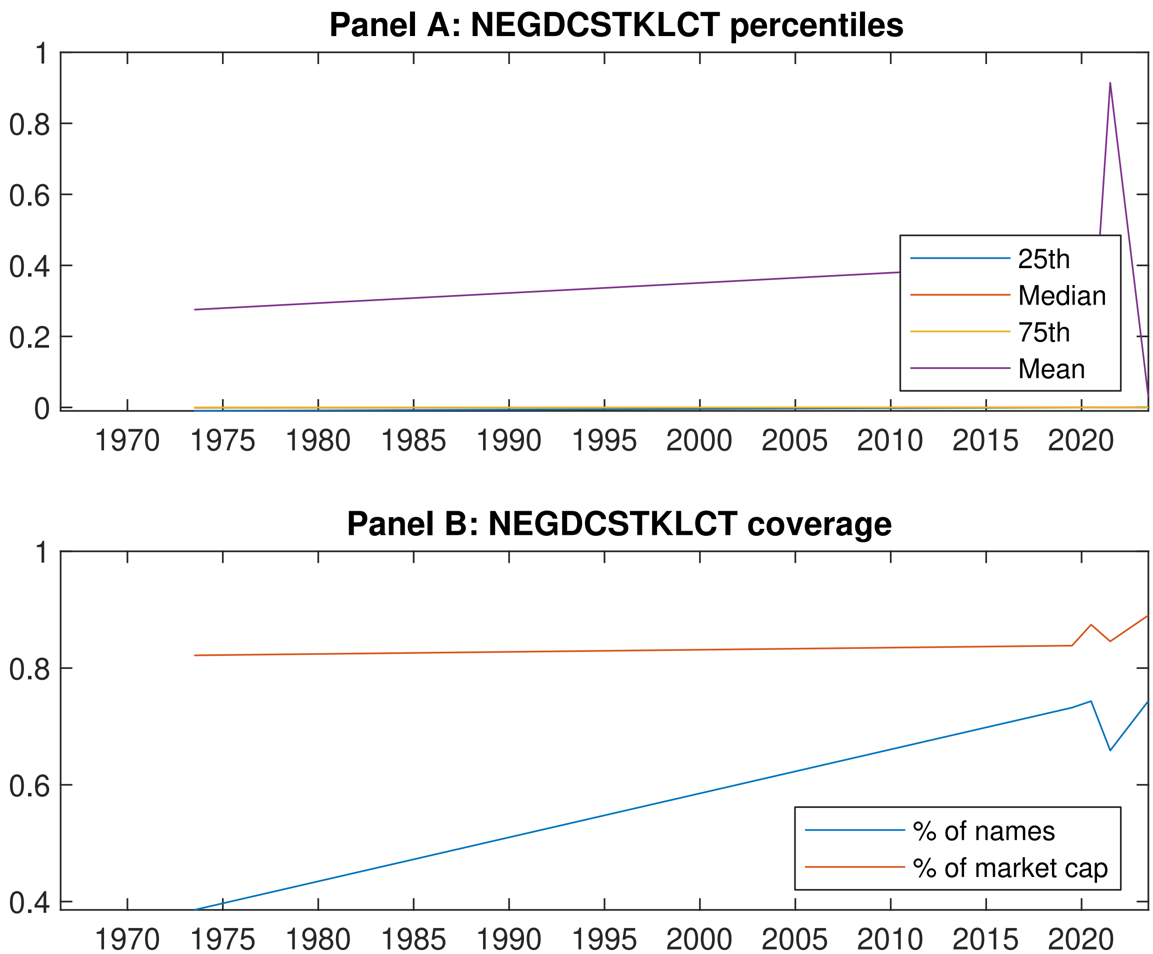


**Figure 1:** Times series of SLDS percentiles and coverage.
This figure plots descriptive statistics for SLDS. Panel A shows cross-sectional percentiles of SLDS over the sample. Panel B plots the monthly coverage of SLDS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SLDS. 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 SLDS-sorted portfolios | | | | | | |
|---|---|---|---|---|---|---|
| | (L) | (2) | (3) | (4) | (H) | (H-L) |
| $r^e$ | 0.42 | 0.53 | 0.62 | 0.73 | 0.77 | 0.35 |
| | [2.41] | [2.72] | [3.26] | [4.36] | [4.59] | [4.28] |
| $\alpha_{CAPM}$ | -0.12 | -0.08 | 0.03 | 0.21 | 0.25 | 0.37 |
| | [-2.14] | [-1.37] | [0.52] | [4.13] | [4.84] | [4.43] |
| $\alpha_{FF3}$ | -0.10 | -0.03 | 0.08 | 0.21 | 0.23 | 0.32 |
| | [-1.78] | [-0.56] | [1.49] | [4.12] | [4.40] | [3.93] |
| $\alpha_{FF4}$ | -0.08 | -0.02 | 0.11 | 0.15 | 0.20 | 0.29 |
| | [-1.45] | [-0.37] | [2.02] | [2.98] | [3.92] | [3.41] |
| $\alpha_{FF5}$ | -0.11 | 0.06 | 0.10 | 0.08 | 0.12 | 0.23 |
| | [-2.02] | [1.03] | [1.70] | [1.76] | [2.38] | [2.80] |
| $\alpha_{FF6}$ | -0.10 | 0.06 | 0.12 | 0.05 | 0.11 | 0.21 |
| | [-1.75] | [1.03] | [2.10] | [1.01] | [2.21] | [2.52] |
| Panel B: Fama and French (2018) 6-factor model loadings for SLDS-sorted portfolios | | | | | | |
| $\beta_{\text{MKT}}$ | 0.94 | 1.02 | 1.00 | 0.98 | 0.97 | 0.03 |
| | [69.39] | [79.03] | [75.67] | [88.15] | [81.74] | [1.71] |
| $\beta_{\text{SMB}}$ | -0.00 | 0.03 | 0.04 | -0.06 | 0.00 | 0.00 |
| | [-0.07] | [1.65] | [2.09] | [-3.70] | [0.07] | [0.09] |
| $\beta_{\text{HML}}$ | -0.04 | -0.10 | -0.14 | -0.07 | -0.05 | -0.00 |
| | [-1.71] | [-3.93] | [-5.68] | [-3.28] | [-2.00] | [-0.03] |
| $\beta_{\text{RMW}}$ | 0.07 | -0.16 | 0.01 | 0.13 | 0.12 | 0.05 |
| | [2.77] | [-6.44] | [0.48] | [6.04] | [5.23] | [1.25] |
| $\beta_{\text{CMA}}$ | -0.03 | -0.11 | -0.05 | 0.28 | 0.27 | 0.30 |
| | [-0.82] | [-3.13] | [-1.40] | [8.93] | [8.10] | [5.42] |
| $\beta_{\text{UMD}}$ | -0.02 | -0.00 | -0.04 | 0.06 | 0.01 | 0.03 |
| | [-1.66] | [-0.11] | [-2.77] | [5.12] | [0.93] | [1.69] |
| Panel C: Average number of firms ($n$) and market capitalization ($me$) | | | | | | |
| $n$ | 662 | 643 | 517 | 605 | 671 | |
| me ($\$10^6$) | 1423 | 1178 | 1807 | 1816 | 2098 | |

**Table 2:** Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the SLDS 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 | 0.35 | 0.37 | 0.32 | 0.29 | 0.23 | 0.21 |
| | | | [4.28] | [4.43] | [3.93] | [3.41] | [2.80] | [2.52] |
| Quintile | NYSE | EW | 0.58 | 0.65 | 0.55 | 0.48 | 0.37 | 0.33 |
| | | | [7.57] | [8.87] | [8.31] | [7.22] | [6.01] | [5.29] |
| Quintile | Name | VW | 0.35 | 0.36 | 0.32 | 0.29 | 0.24 | 0.23 |
| | | | [4.29] | [4.40] | [3.91] | [3.51] | [2.93] | [2.74] |
| Quintile | Cap | VW | 0.31 | 0.31 | 0.29 | 0.24 | 0.23 | 0.20 |
| | | | [3.85] | [3.83] | [3.54] | [2.91] | [2.77] | [2.36] |
| Decile | NYSE | VW | 0.34 | 0.33 | 0.28 | 0.25 | 0.24 | 0.22 |
| | | | [3.37] | [3.31] | [2.78] | [2.47] | [2.34] | [2.17] |
| 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 | 0.34 | 0.30 | 0.28 | 0.22 | 0.21 |
| | | | [3.83] | [4.02] | [3.58] | [3.33] | [2.71] | [2.57] |
| Quintile | NYSE | EW | 0.37 | 0.44 | 0.35 | 0.31 | 0.16 | 0.15 |
| | | | [4.52] | [5.49] | [4.81] | [4.34] | [2.41] | [2.22] |
| Quintile | Name | VW | 0.31 | 0.33 | 0.30 | 0.28 | 0.23 | 0.23 |
| | | | [3.84] | [4.05] | [3.63] | [3.44] | [2.89] | [2.79] |
| Quintile | Cap | VW | 0.28 | 0.29 | 0.26 | 0.24 | 0.22 | 0.20 |
| | | | [3.41] | [3.49] | [3.23] | [2.91] | [2.70] | [2.48] |
| Decile | NYSE | VW | 0.29 | 0.30 | 0.25 | 0.23 | 0.22 | 0.21 |
| | | | [2.96] | [2.96] | [2.50] | [2.35] | [2.18] | [2.10] |

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

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

| | | SLDS Quintiles | | | | | SLDS Strategies | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (L) | (2) | (3) | (4) | (H) | $r^e$ | $\alpha_{CAPM}$ | $\alpha_{FF3}$ | $\alpha_{FF4}$ | $\alpha_{FF5}$ | $\alpha_{FF6}$ |
| Size quintiles | (1) | 0.35 | 0.61 | 0.90 | 0.97 | 0.96 | 0.61 | 0.69 | 0.60 | 0.53 | 0.44 | 0.40 |
| | | [1.24] | [2.16] | [3.36] | [3.63] | [3.85] | [6.74] | [7.81] | [7.36] | [6.49] | [5.56] | [4.99] |
| | (2) | 0.49 | 0.66 | 0.83 | 0.89 | 0.93 | 0.44 | 0.51 | 0.38 | 0.36 | 0.25 | 0.24 |
| | | [1.96] | [2.62] | [3.32] | [3.71] | [4.04] | [4.46] | [5.36] | [4.42] | [4.02] | [2.90] | [2.73] |
| | (3) | 0.60 | 0.61 | 0.78 | 0.80 | 0.93 | 0.34 | 0.37 | 0.28 | 0.28 | 0.19 | 0.19 |
| | | [2.78] | [2.60] | [3.32] | [3.68] | [4.54] | [3.96] | [4.36] | [3.52] | [3.35] | [2.31] | [2.30] |
| | (4) | 0.48 | 0.63 | 0.77 | 0.85 | 0.81 | 0.33 | 0.36 | 0.29 | 0.26 | 0.10 | 0.09 |
| | | [2.35] | [2.98] | [3.54] | [4.19] | [4.24] | [3.88] | [4.25] | [3.50] | [3.10] | [1.25] | [1.15] |
| | (5) | 0.47 | 0.45 | 0.51 | 0.56 | 0.74 | 0.27 | 0.25 | 0.24 | 0.20 | 0.22 | 0.19 |
| | | [2.82] | [2.39] | [2.77] | [3.24] | [4.46] | [2.75] | [2.60] | [2.47] | [2.01] | [2.21] | [1.90] |

Panel B: Portfolio average number of firms and market capitalization

| | | SLDS Quintiles<br>Average $n$ | | | | | SLDS Quintiles<br>Average market capitalization ($\$10^6$) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (L) | (2) | (3) | (4) | (H) | (L) | (2) | (3) | (4) | (H) |
| Size quintiles | (1) | 347 | 346 | 345 | 343 | 345 | 26 | 28 | 33 | 25 | 24 |
| | (2) | 95 | 94 | 94 | 94 | 94 | 47 | 47 | 48 | 47 | 48 |
| | (3) | 69 | 68 | 68 | 68 | 68 | 81 | 80 | 81 | 82 | 83 |
| | (4) | 59 | 58 | 58 | 58 | 59 | 175 | 177 | 180 | 184 | 186 |
| | (5) | 53 | 53 | 53 | 53 | 53 | 1180 | 1157 | 1497 | 1284 | 1522 |

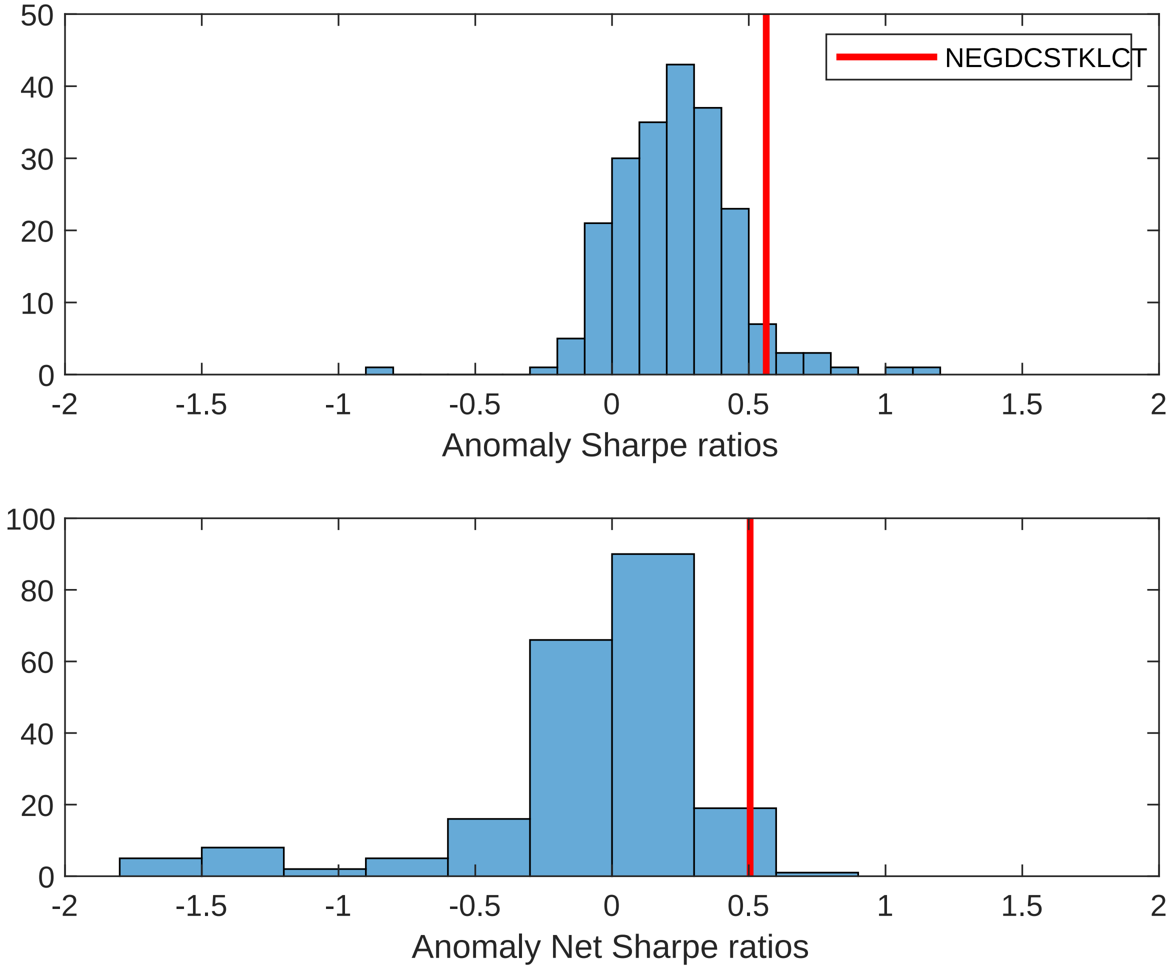


**Figure 2:** Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SLDS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

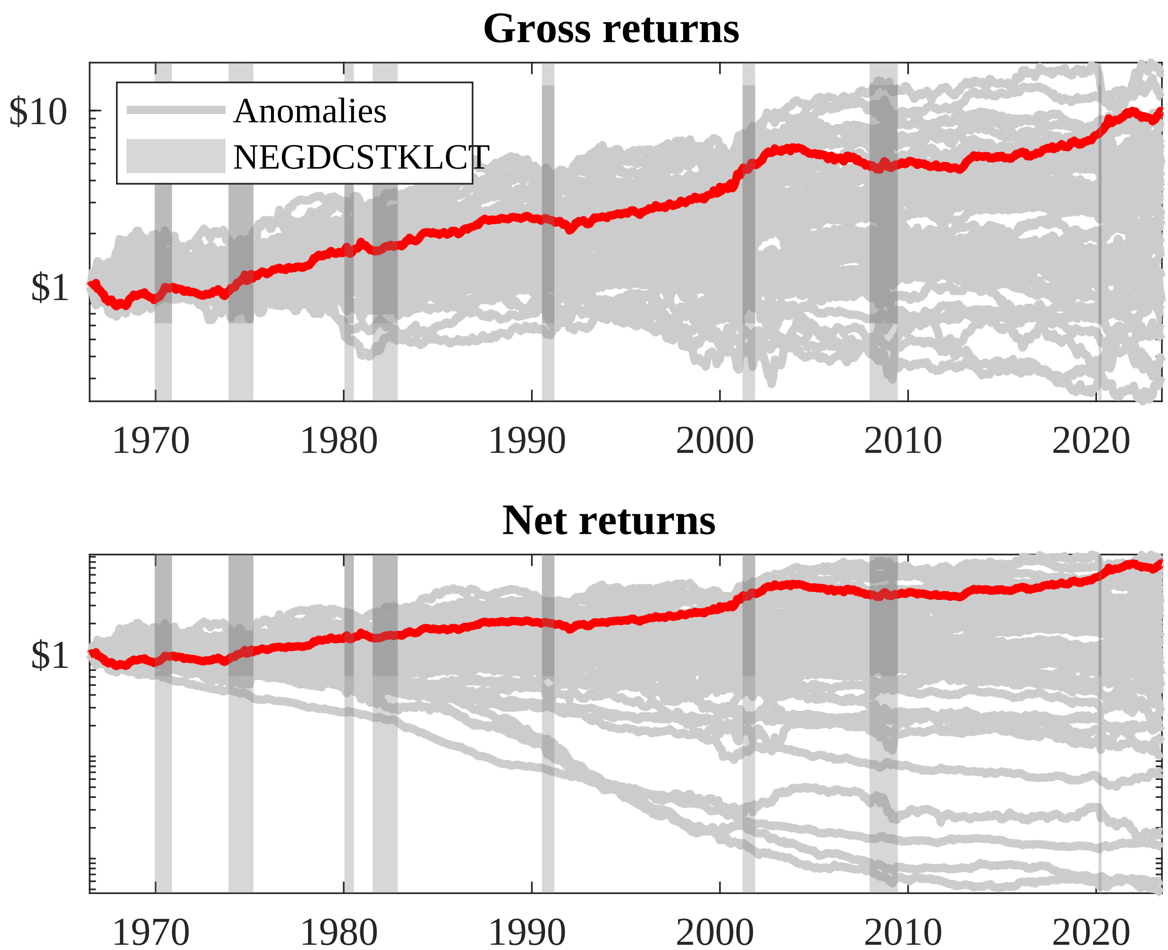


**Figure 3:** Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SLDS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results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

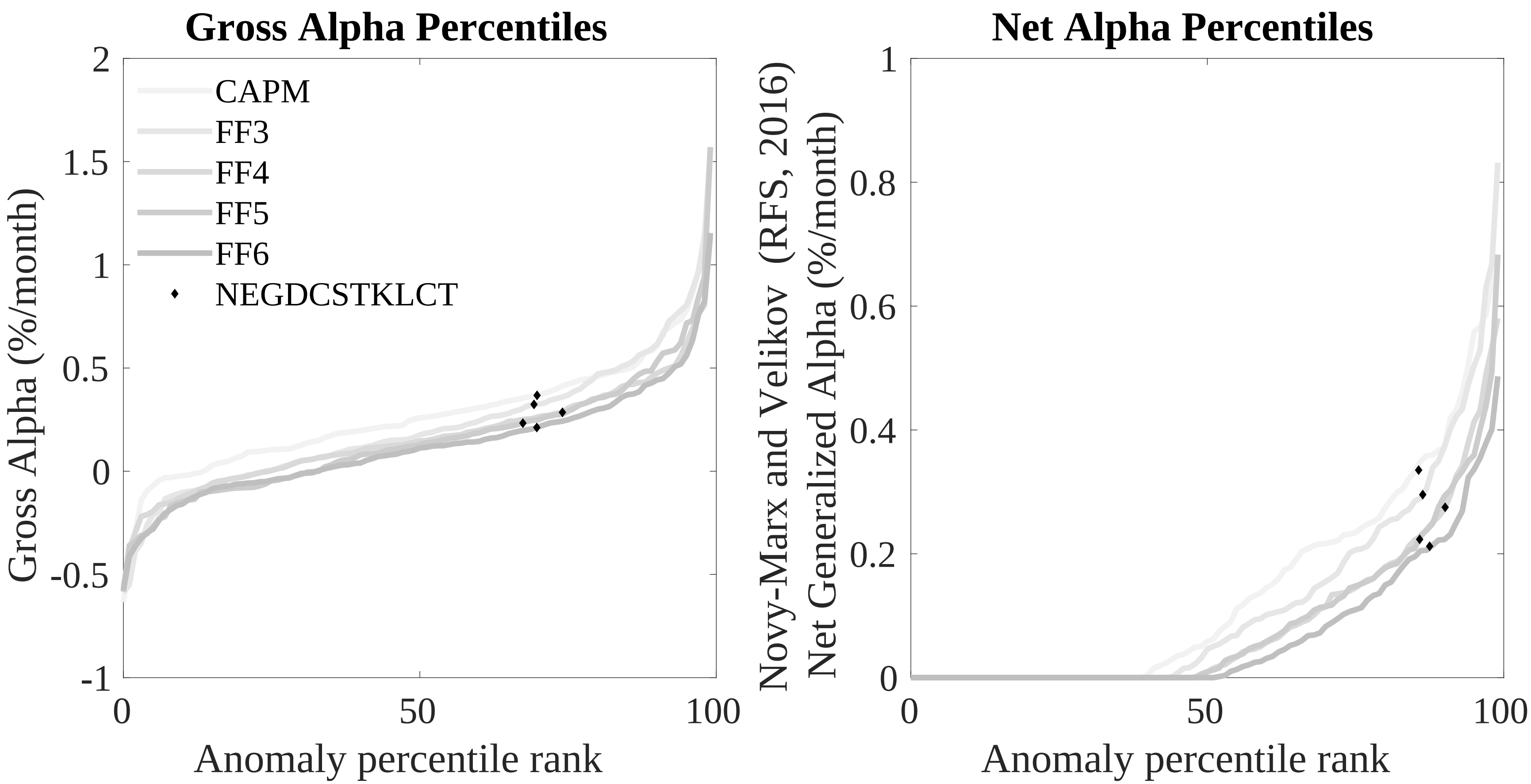


**Figure 4:** Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SLDS trading strategy alphas (diamonds). The strategies are constructed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

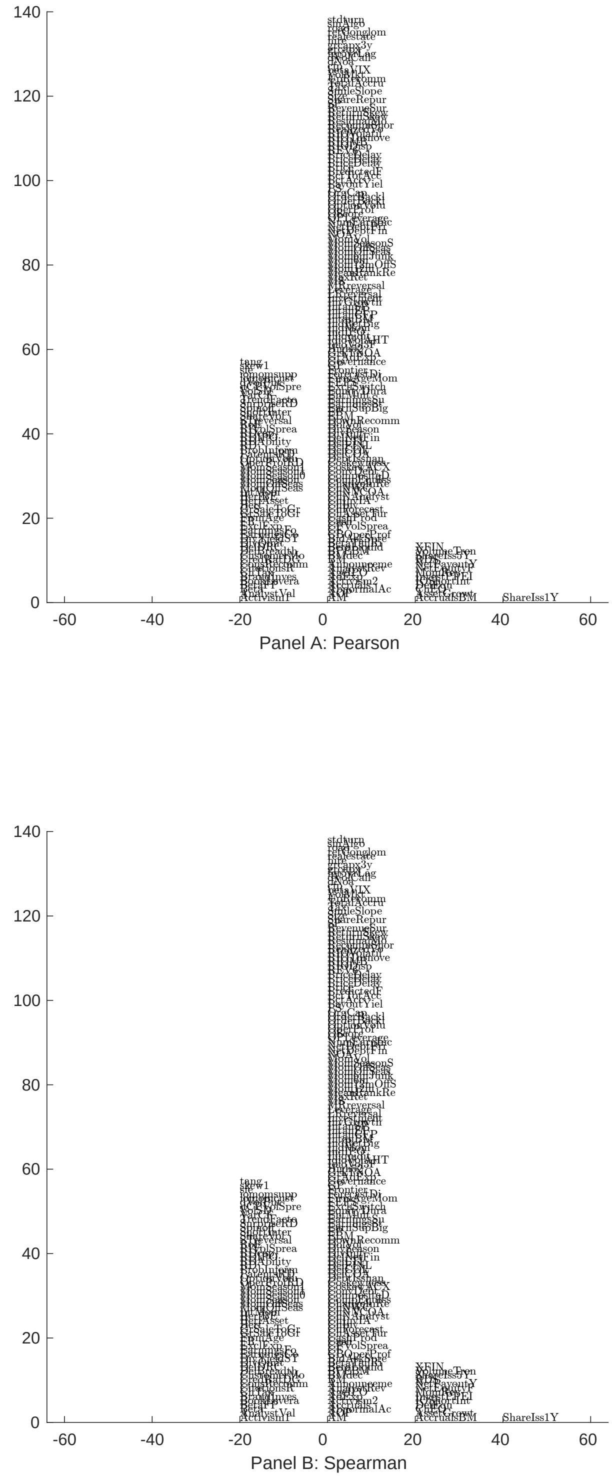


**Figure 5:** Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with SLDS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

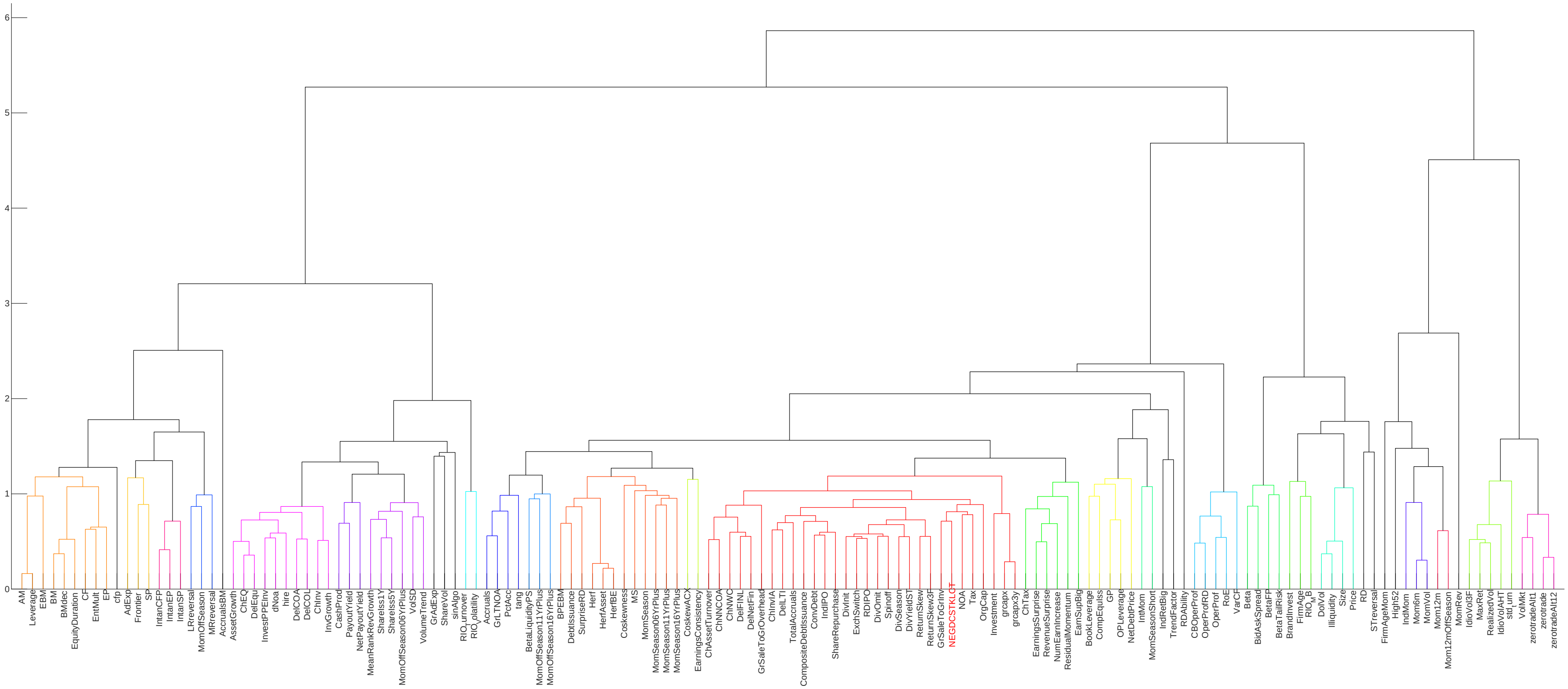


**Figure 6:** Agglomerative hierarchical cluster plot

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

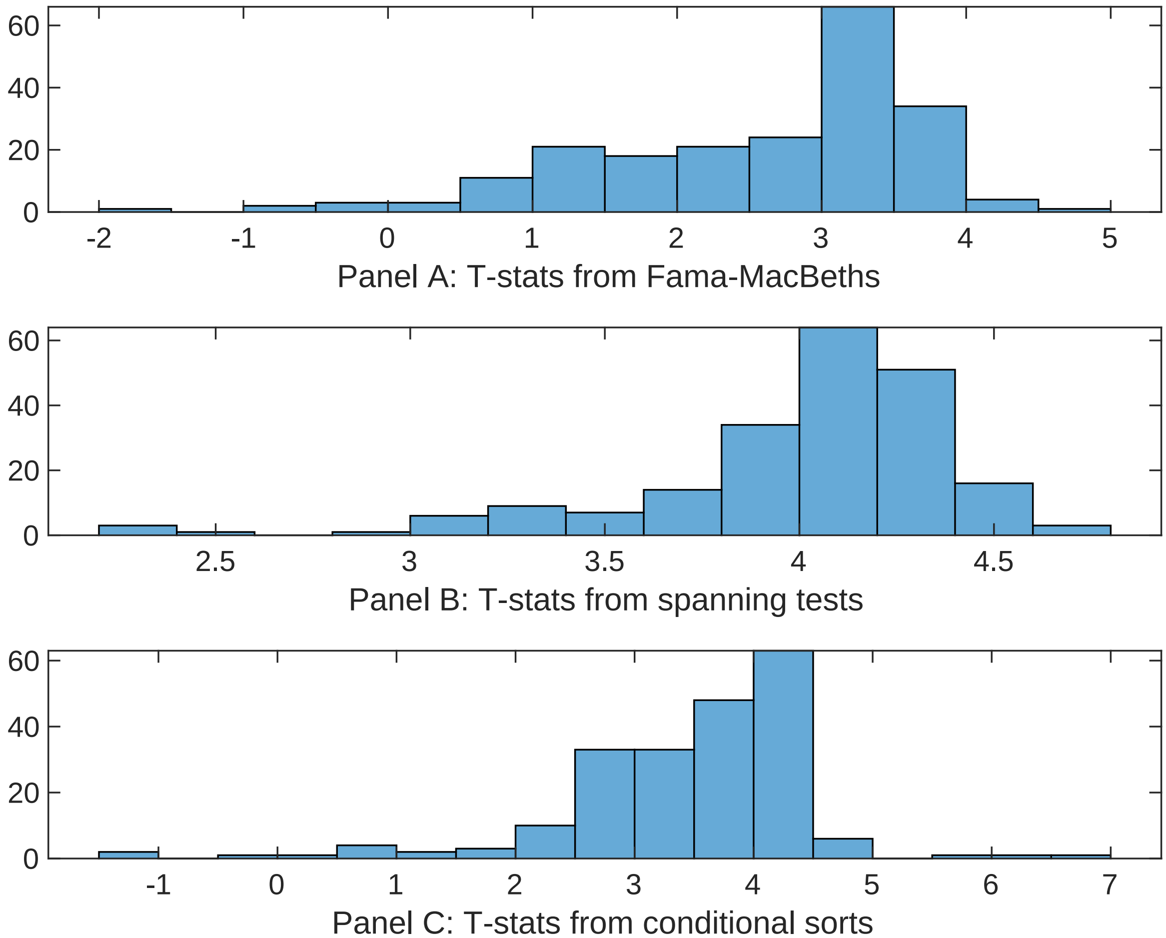


**Figure 7:** Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SLDS conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on $\beta_{SLDS}$ from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SLDS} SLDS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SLDS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SLDS. Stocks are finally grouped into five SLDS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SLDS 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 SLDS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SLDS} SLDS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, $X$, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the $R^2$ from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.13 | 0.18 | 0.12 | 0.13 | 0.13 | 0.14 | 0.13 |
| | [5.48] | [7.14] | [5.22] | [5.86] | [5.39] | [5.84] | [5.20] |
| SLDS | 0.75 | 0.61 | 0.40 | 0.83 | 0.62 | 0.41 | 0.33 |
| | [2.93] | [2.39] | [1.44] | [3.30] | [2.34] | [1.56] | [1.25] |
| Anomaly 1 | 0.27 | | | | | | 0.98 |
| | [5.82] | | | | | | [2.42] |
| Anomaly 2 | | 0.49 | | | | | -0.20 |
| | | [4.47] | | | | | [-0.01] |
| Anomaly 3 | | | 0.28 | | | | 0.24 |
| | | | [2.49] | | | | [2.19] |
| Anomaly 4 | | | | 0.32 | | | 0.31 |
| | | | | [3.37] | | | [0.34] |
| Anomaly 5 | | | | | 0.15 | | -0.21 |
| | | | | | [4.17] | | [-0.39] |
| Anomaly 6 | | | | | | 0.10 | 0.69 |
| | | | | | | [8.93] | [6.64] |
| # months | 679 | 684 | 679 | 679 | 684 | 684 | 679 |
| $\bar{R}^2$(%) | 0 | 0 | 1 | 0 | 0 | 0 | 0 |

**Table 5:** Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the SLDS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SLDS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, where $X_k$ indicates each of the six most-closely related anomalies and $f_j$ indicates the six factors from the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor. The six most closely related anomalies, $X$, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the $R^2$ from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Intercept | 0.19 | 0.21 | 0.20 | 0.18 | 0.23 | 0.22 | 0.17 |
| | [2.27] | [2.59] | [2.47] | [2.18] | [2.79] | [2.57] | [2.18] |
| Anomaly 1 | 24.01 | | | | | | 15.00 |
| | [5.70] | | | | | | [3.07] |
| Anomaly 2 | | 34.41 | | | | | 34.15 |
| | | [7.63] | | | | | [5.17] |
| Anomaly 3 | | | 14.93 | | | | 3.40 |
| | | | [4.64] | | | | [0.92] |
| Anomaly 4 | | | | 12.40 | | | -0.45 |
| | | | | [2.85] | | | [-0.10] |
| Anomaly 5 | | | | | 21.92 | | -2.78 |
| | | | | | [4.99] | | [-0.45] |
| Anomaly 6 | | | | | | 3.48 | -18.02 |
| | | | | | | [0.63] | [-3.09] |
| mkt | 5.57 | 4.71 | 6.15 | 5.46 | 3.24 | 3.59 | 6.51 |
| | [2.87] | [2.46] | [3.09] | [2.71] | [1.66] | [1.81] | [3.29] |
| smb | 1.96 | -0.63 | 3.80 | 0.34 | 0.18 | 0.22 | 2.85 |
| | [0.70] | [-0.23] | [1.33] | [0.12] | [0.06] | [0.08] | [0.99] |
| hml | -2.23 | -3.73 | -4.91 | -2.48 | -2.47 | 0.22 | -5.38 |
| | [-0.59] | [-1.00] | [-1.23] | [-0.61] | [-0.65] | [0.06] | [-1.35] |
| rmw | -3.12 | 6.27 | -3.64 | 2.48 | 6.64 | 4.39 | -0.18 |
| | [-0.78] | [1.68] | [-0.86] | [0.63] | [1.73] | [1.13] | [-0.04] |
| cma | 19.19 | -3.99 | 19.85 | 27.25 | 7.35 | 25.94 | 12.49 |
| | [3.23] | [-0.57] | [3.24] | [4.67] | [1.02] | [2.95] | [1.45] |
| umd | 3.27 | 3.00 | 4.82 | 3.69 | 4.04 | 3.44 | 2.55 |
| | [1.72] | [1.59] | [2.50] | [1.90] | [2.08] | [1.73] | [1.34] |
| # months | 680 | 684 | 680 | 680 | 684 | 684 | 680 |
| $\bar{R}^2$(%) | 13 | 15 | 12 | 10 | 11 | 7 | 18 |

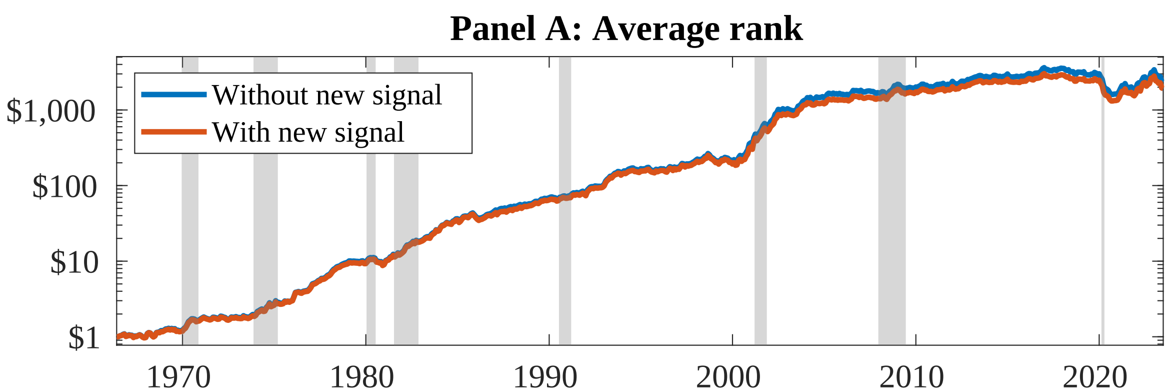


**Figure 8:** Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

## References


Baker, M. and Wurgler, J. (2003). Market timing and capital structure. *Journal of Finance*, 57(1):1–32.

Bradshaw, M. T. (2006). The use of target prices to justify sell-side analysts' stock recommendations. *Accounting Horizons*, 20(2):267–286.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.

Cooper, M. J., Gulen, H., and Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *Journal of Finance*, 63(4):1609–1651.

Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance, Forthcoming*.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Gomes, J., Kogan, L., and Zhang, L. (2006). Equilibrium cross section of returns. *Journal of Political Economy*, 114(4):678–714.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

McLean, R. D. and Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance*, 71(1):5–32.

Myers, S. C. and Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2):187–221.

Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper*.

Titman, S. and Wessels, R. (1988). The determinants of capital structure choice. *Journal of Finance*, 43(1):1–19.

Vassalou, M. and Xing, Y. (2004). Default risk in equity returns. *Journal of Finance*, 59(2):831–868.