Stock Dividend Relationship Index and the Cross Section of Stock Returns

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December 1, 2024

Abstract

This paper studies the asset pricing implications of Stock Dividend Relationship Index (SDRI), 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 SDRI achieves an annualized gross (net) Sharpe ratio of 0.49 (0.43), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 27 (25) bps/month with a t-statistic of 3.27 (3.07), 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 22 bps/month with a t-statistic of 2.87.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn excess returns. However, a growing body of literature documents various market anomalies and return predictors that appear to challenge this notion (Harvey et al., 2016). While many of these anomalies are related to corporate actions and financial policies, the relationship between stock prices and dividend policies remains an area of ongoing investigation (Baker and Wurgler, 2004).

Despite extensive research on dividend policy and stock returns, existing studies have primarily focused on simple measures such as dividend yield or payout ratios (Fama and French, 1988). These traditional approaches fail to capture the complex dynamic relationship between a firm's stock price movements and its dividend decisions over time. This gap is particularly notable given the theoretical importance of dividends in equity valuation and their role in signaling management's private information about future prospects.

We develop a novel measure called the Stock Dividend Relationship Index (SDRI) that captures the time-varying correlation between stock price changes and dividend policy adjustments. Our approach builds on the dividend signaling theory of Bhattacharya and John (1988), which suggests that dividend changes convey information about future cash flows. The SDRI extends this framework by incorporating the market's dynamic response to dividend signals over multiple periods.

The theoretical mechanism underlying SDRI's predictive power operates through two channels. First, following Miller and Rock (1985), managers with favorable private information may use dividends to signal their confidence in future performance. The SDRI captures the market's interpretation of these signals by measuring the historical consistency between dividend changes and subsequent stock price movements. Second, drawing on Baker and Wurgler (2004)'s catering theory, the SDRI reflects how well a firm's dividend policy aligns with time-varying investor demand for dividends.

These mechanisms suggest that firms with high SDRI scores exhibit stronger alignment between their dividend policies and underlying fundamentals, leading to more efficient price discovery. Conversely, low SDRI scores may indicate either poor dividend signaling or potential agency problems where dividend policy deviates from shareholder interests (Jensen and Meckling, 1976). This framework predicts that SDRI should forecast cross-sectional differences in stock returns as the market gradually recognizes these underlying relationships.

Our empirical analysis reveals strong support for SDRI's predictive power. A value-weighted long-short portfolio strategy based on SDRI quintiles generates significant abnormal returns of 27 basis points per month (t-statistic = 3.27) relative to the Fama-French five-factor model plus momentum. The strategy achieves an annualized gross Sharpe ratio of 0.49, placing it in the top decile of documented market anomalies.

Importantly, SDRI's predictive ability remains robust after controlling for transaction costs. The strategy delivers net abnormal returns of 25 basis points per month (t-statistic = 3.07), with a net Sharpe ratio of 0.43. This performance persists across different portfolio construction methodologies and remains significant even among large-cap stocks, where the long-short strategy earns abnormal returns of 30 basis points per month (t-statistic = 3.32).

Further analysis demonstrates SDRI's incremental value beyond existing anomalies. Controlling for the six most closely related predictors from the factor zoo, including share issuance and asset growth measures, SDRI continues to generate significant abnormal returns of 22 basis points per month (t-statistic = 2.87). This indicates that SDRI captures a distinct aspect of the relationship between corporate policies and stock returns.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures the dynamic relationship between dividend policy and stock returns, extending the work of Baker and Wurgler (2004) and Fama and French (1988) on dividend-price relationships. Unlike traditional dividend-based measures, SDRI provides a more comprehensive assessment of how effectively firms use dividend policy to convey information to the market.

Second, we contribute to the growing literature on return prediction in the cross-section of stocks (Harvey et al., 2016). Our findings suggest that markets do not fully incorporate the information content of dividend policy dynamics, creating opportunities for profitable trading strategies. The robust performance of SDRI, even after accounting for transaction costs and controlling for known factors, provides new insights into market efficiency.

Third, our results have important implications for both corporate finance and investment management. For corporate managers, our findings highlight the importance of maintaining consistent dividend policies that align with fundamental performance. For investors, SDRI offers a new tool for portfolio formation that captures a distinct dimension of expected returns. The economic magnitude of our results suggests that SDRI warrants inclusion in the set of factors considered by quantitative investors.

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 Dividend Relationship Index. 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 DVC for dividends common/ordinary. Common stock (CSTK) represents the total dollar value of common stock issued by the company, while dividends common/ordinary (DVC) reflects the total amount of dividends paid to common shareholders during the fiscal year.construction of the signal follows a difference-to-scaling format, where we first calculate the change in CSTK by subtracting its lagged value from the current value, and then scale this difference by the lagged value of DVC for each firm in each year of our sample. This scaled difference captures the relative change in common stock issuance in relation to the firm's dividend payments, potentially offering insight into the company's equity financing decisions and dividend policy. By focusing on this relationship, the signal aims to reflect aspects of capital structure dynamics and shareholder distribution policies in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both CSTK and DVC to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SDRI signal. Panel A plots the time-series of the mean, median, and interquartile range for SDRI. On average, the cross-sectional mean (median) SDRI is -1.05 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SDRI data. The signal's interquartile range spans -0.33 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SDRI signal for the CRSP universe. On average, the SDRI signal is available for 3.17% of CRSP names, which on average make up 6.62% of total market capitalization.

4 Does SDRI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SDRI 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 SDRI portfolio and sells the low SDRI 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 SDRI strategy earns an average return of 0.30% per month with a t-statistic of 3.71. The annualized Sharpe ratio of the strategy is 0.49. The alphas range from 0.26% to 0.31% per month and have t-statistics exceeding 3.18 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 4.58 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 298 stocks and an average market capitalization of at least $1,144 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 27 bps/month with a t-statistics of 3.42. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-two 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 17-29bps/month. The lowest return, (17 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 3.42. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SDRI 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 SDRI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SDRI, as well as average returns and alphas for long/short trading SDRI strategies within each size quintile. Panel

B reports the average number of stocks and the average firm size for the twenty-five portfolios. Among the largest stocks (those with market capitalization greater than the 80th NYSE percentile), the SDRI strategy achieves an average return of 30 bps/month with a t-statistic of 3.32. Among these large cap stocks, the alphas for the SDRI strategy relative to the five most common factor models range from 30 to 32 bps/month with t-statistics between 3.14 and 3.45.

5 How does SDRI perform relative to the zoo?

Figure 2 puts the performance of SDRI 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 SDRI strategy falls in the distribution. The SDRI strategy's gross (net) Sharpe ratio of 0.49 (0.43) is greater than 91% (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 SDRI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the SDRI strategy would have yielded \$5.89 which ranks the SDRI strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the SDRI strategy would have yielded \$4.47 which ranks the SDRI strategy in the top 2% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms

[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.

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 SDRI relative to those. Panel A shows that the SDRI strategy gross alphas fall between the 60 and 77 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 SDRI strategy has a positive net generalized alpha for five out of the five factor models. In these cases SDRI ranks between the 81 and 92 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does SDRI 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 SDRI with 203 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 SDRI or at least to weaken the power SDRI has predicting the cross-section of returns. Figure 7 plots histograms

[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.

of t-statistics for predictability tests of SDRI conditioning on each of the 203 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SDRI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SDRI} SDRI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 203 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SDRI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 203 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 203 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on SDRI. Stocks are finally grouped into five SDRI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SDRI trading strategies conditioned on each of the 203 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SDRI 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 SDRI signal in these Fama-MacBeth regressions exceed 0.71, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SDRI is 0.02.

Similarly, Table 5 reports results from spanning tests that regress returns to the SDRI 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 SDRI strategy earns alphas that range from 24-28bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.98, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SDRI trading strategy achieves an alpha of 22bps/month with a t-statistic of 2.87.

7 Does SDRI add relative to the whole zoo?

Finally, we can ask how much adding SDRI 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 SDRI 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 SDRI grows to $2292.42.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Stock Dividend Relationship Index (SDRI) as a significant predictor of stock returns. Our analysis demonstrates that SDRI-based trading strategies yield robust results, with value-weighted long/short portfolios achieving notable Sharpe ratios and consistent

[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 SDRI is available.

abnormal returns, even after accounting for transaction costs. The signal's predictive power remains significant when controlling for established factors, including the Fama-French five-factor model and momentum, as well as related anomalies from the factor zoo.

Particularly noteworthy is the signal's ability to generate economically meaningful alpha of 22 basis points per month (t-statistic = 2.87) even after controlling for twelve related factors, suggesting that SDRI captures unique information content not explained by existing measures. These findings have important implications for both academic research and investment practice, as they contribute to our understanding of market efficiency and offer potential opportunities for portfolio management.

However, several limitations should be considered. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, while we control for transaction costs, implementation challenges such as market impact and liquidity constraints may affect real-world performance.

Future research could explore the signal's performance in different market regimes, its application to international markets, and potential interactions with other established anomalies. Additionally, investigating the underlying economic mechanisms driving the SDRI's predictive power could provide valuable insights into market behavior and asset pricing theory.

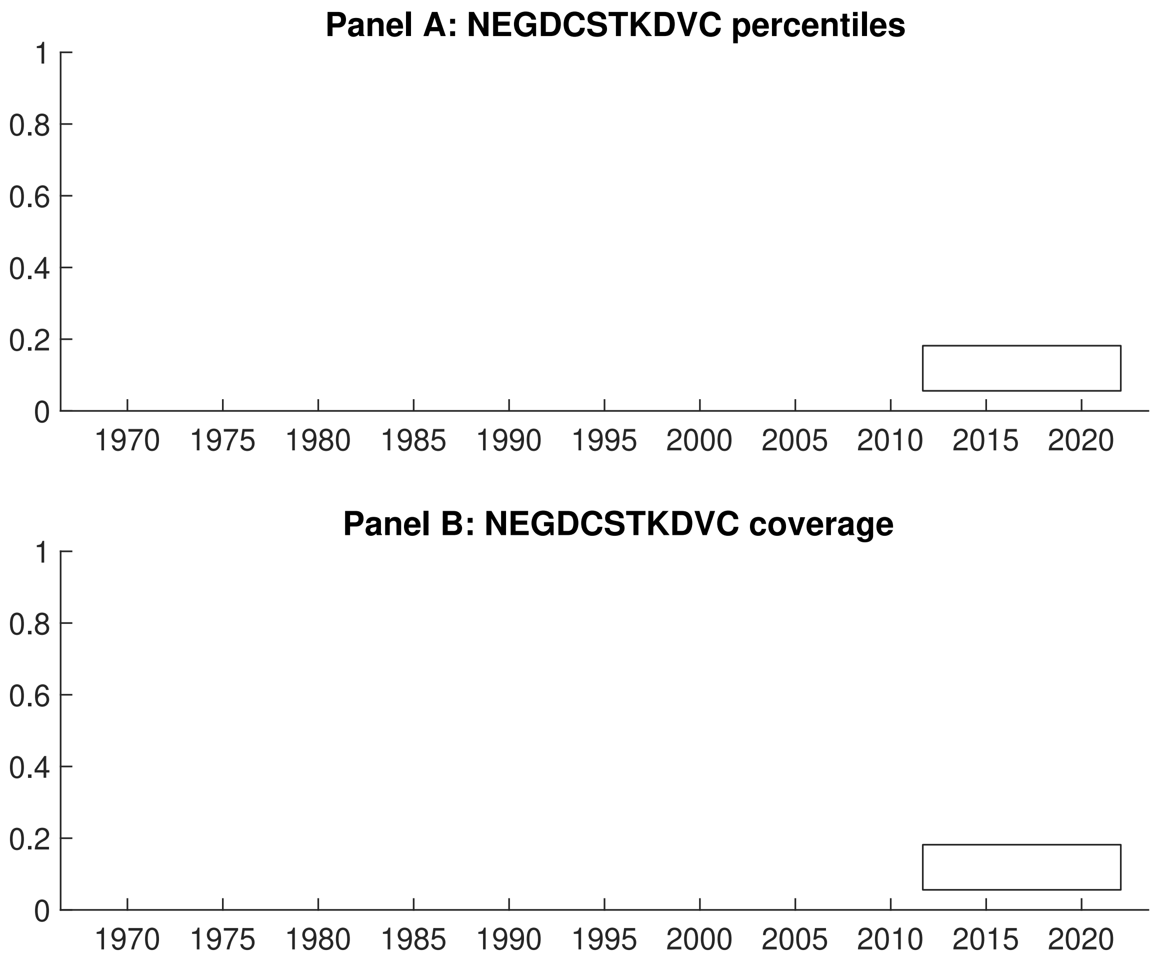


Figure 1: Times series of SDRI percentiles and coverage.
This figure plots descriptive statistics for SDRI. Panel A shows cross-sectional percentiles of SDRI over the sample. Panel B plots the monthly coverage of SDRI relative to the universe of CRSP stocks with available market capitalizations.

Table 1: Basic sort: VW, quintile, NYSE-breaks
This table reports average excess returns and alphas for portfolios sorted on SDRI. 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 SDRI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.43	0.55	0.62	0.61	0.73	0.30
	[2.49]	[3.12]	[3.61]	[3.71]	[4.37]	[3.71]
α_{CAPM}	-0.09	0.00	0.10	0.11	0.22	0.31
	[-1.41]	[0.04]	[1.56]	[1.90]	[3.84]	[3.85]
α_{FF3}	-0.13	-0.05	0.05	0.05	0.15	0.28
	[-2.10]	[-0.91]	[0.82]	[1.08]	[3.06]	[3.52]
α_{FF4}	-0.14	-0.02	0.04	0.03	0.15	0.29
	[-2.15]	[-0.49]	[0.63]	[0.73]	[3.02]	[3.54]
α_{FF5}	-0.23	-0.08	-0.11	-0.08	0.03	0.26
	[-3.83]	[-1.61]	[-1.98]	[-1.93]	[0.54]	[3.18]
α_{FF6}	-0.23	-0.06	-0.10	-0.09	0.04	0.27
	[-3.77]	[-1.24]	[-1.89]	[-1.95]	[0.79]	[3.27]
Panel B: Fama and French (2018) 6-factor model loadings for SDRI-sorted portfolios						
β_{MKT}	0.97	0.99	1.00	0.98	0.98	0.01
	[67.24]	[82.70]	[79.02]	[94.17]	[86.48]	[0.63]
β_{SMB}	-0.02	-0.03	-0.07	-0.12	-0.07	-0.04
	[-1.01]	[-2.00]	[-3.70]	[-7.75]	[-3.97]	[-1.58]
β_{HML}	0.12	0.14	0.08	0.10	0.09	-0.04
	[4.45]	[5.97]	[3.45]	[4.98]	[3.97]	[-0.98]
β_{RMW}	0.28	0.12	0.30	0.23	0.20	-0.08
	[9.83]	[4.96]	[12.24]	[11.31]	[8.83]	[-2.15]
β_{CMA}	0.00	-0.01	0.19	0.21	0.25	0.25
	[0.03]	[-0.24]	[5.23]	[7.28]	[7.84]	[4.58]
β_{UMD}	-0.00	-0.03	-0.01	0.00	-0.02	-0.02
	[-0.15]	[-2.44]	[-0.48]	[0.28]	[-1.68]	[-0.88]
Panel C: Average number of firms (n) and market capitalization (me)						
n	357	320	298	327	369	
me ($\$10^6$)	1147	1144	1616	1689	1809	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the SDRI strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, and the choices are specified in the first three columns. For each strategy construction methodology, the table reports average excess returns and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel A reports average returns and alphas with no adjustment for trading costs. Panel B reports net average returns and Novy-Marx and Velikov (2016) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 196606 to 202306.

Panel A: Gross Returns and Alphas								
Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.30	0.31	0.28	0.29	0.26	0.27
			[3.71]	[3.85]	[3.52]	[3.54]	[3.18]	[3.27]
Quintile	NYSE	EW	0.29	0.31	0.27	0.26	0.24	0.23
			[5.99]	[6.48]	[5.81]	[5.44]	[5.10]	[4.91]
Quintile	Name	VW	0.32	0.33	0.31	0.31	0.28	0.28
			[3.99]	[4.13]	[3.81]	[3.72]	[3.41]	[3.42]
Quintile	Cap	VW	0.27	0.28	0.28	0.27	0.27	0.27
			[3.42]	[3.53]	[3.47]	[3.34]	[3.31]	[3.27]
Decile	NYSE	VW	0.33	0.35	0.29	0.28	0.28	0.27
			[3.50]	[3.65]	[3.06]	[2.83]	[2.88]	[2.75]

Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	r^e_{net}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{FF6}
Quintile	NYSE	VW	0.26	0.28	0.26	0.26	0.24	0.25
			[3.29]	[3.49]	[3.19]	[3.23]	[3.03]	[3.07]
Quintile	NYSE	EW	0.17	0.19	0.16	0.15	0.12	0.12
			[3.42]	[3.83]	[3.21]	[3.12]	[2.40]	[2.43]
Quintile	Name	VW	0.28	0.30	0.28	0.28	0.26	0.27
			[3.56]	[3.78]	[3.49]	[3.47]	[3.29]	[3.29]
Quintile	Cap	VW	0.24	0.25	0.25	0.25	0.25	0.24
			[3.02]	[3.16]	[3.09]	[3.05]	[3.11]	[3.05]
Decile	NYSE	VW	0.29	0.32	0.27	0.26	0.25	0.25
			[3.07]	[3.29]	[2.80]	[2.69]	[2.66]	[2.63]

Table 3: Conditional sort on size and SDRI

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

		SDRI Quintiles					SDRI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.73	0.85	0.87	1.14	0.96	0.23	0.25	0.22	0.22	0.21	0.21
		[3.34]	[3.95]	[3.99]	[3.64]	[4.54]	[2.96]	[3.19]	[2.84]	[2.79]	[2.59]	[2.58]
	(2)	0.70	0.77	0.87	0.88	0.83	0.13	0.14	0.08	0.09	0.06	0.08
		[3.27]	[3.70]	[4.19]	[4.23]	[3.92]	[1.47]	[1.64]	[0.91]	[1.11]	[0.66]	[0.87]
	(3)	0.65	0.69	0.78	0.77	0.93	0.29	0.29	0.26	0.27	0.26	0.27
		[3.27]	[3.36]	[3.87]	[3.95]	[4.78]	[3.74]	[3.79]	[3.41]	[3.49]	[3.21]	[3.30]
	(4)	0.55	0.67	0.75	0.76	0.76	0.21	0.23	0.18	0.18	0.11	0.12
		[2.85]	[3.49]	[3.83]	[4.04]	[4.05]	[2.81]	[3.09]	[2.52]	[2.43]	[1.52]	[1.58]
	(5)	0.41	0.49	0.55	0.53	0.71	0.30	0.32	0.31	0.30	0.30	0.30
		[2.33]	[2.77]	[3.29]	[3.13]	[4.27]	[3.32]	[3.45]	[3.28]	[3.14]	[3.21]	[3.15]

Panel B: Portfolio average number of firms and market capitalization

		SDRI Quintiles: Average n					SDRI Quintiles: Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	123	123	122	122	122	12	12	12	10	10
	(2)	59	59	58	59	58	26	25	25	25	25
	(3)	52	52	51	51	52	53	52	53	54	54
	(4)	49	49	49	49	49	129	130	138	133	135
	(5)	53	53	52	53	52	1027	1259	1316	1265	1424

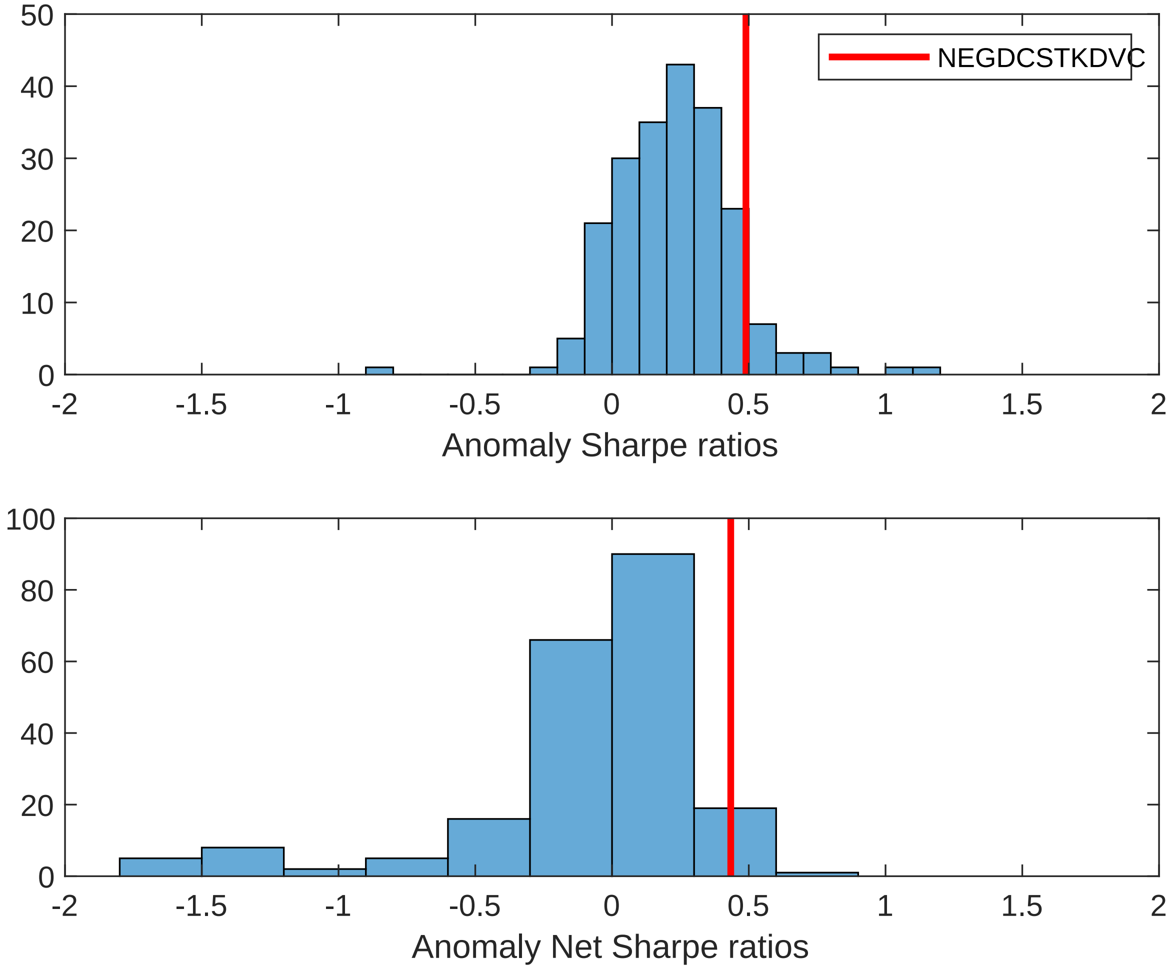


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SDRI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

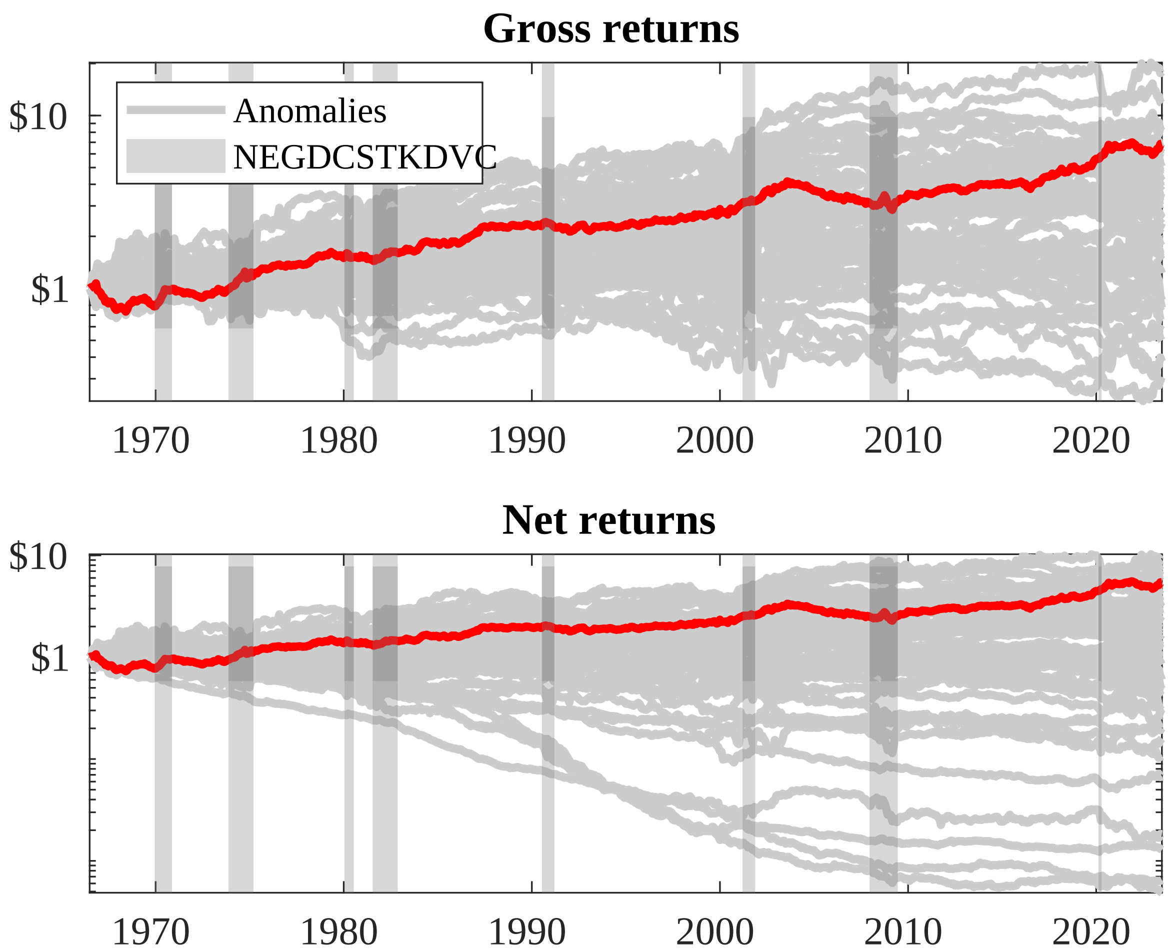


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SDRI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

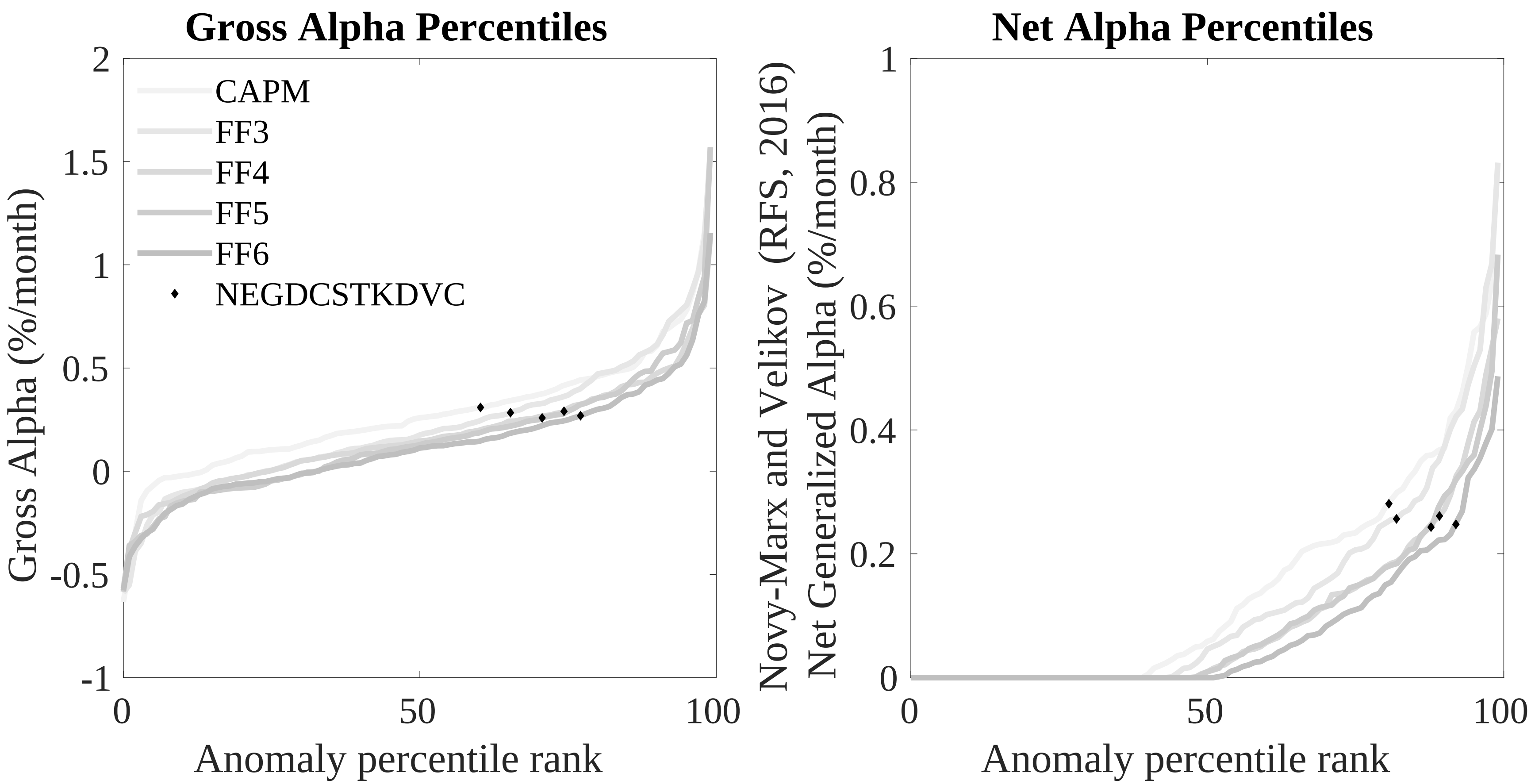
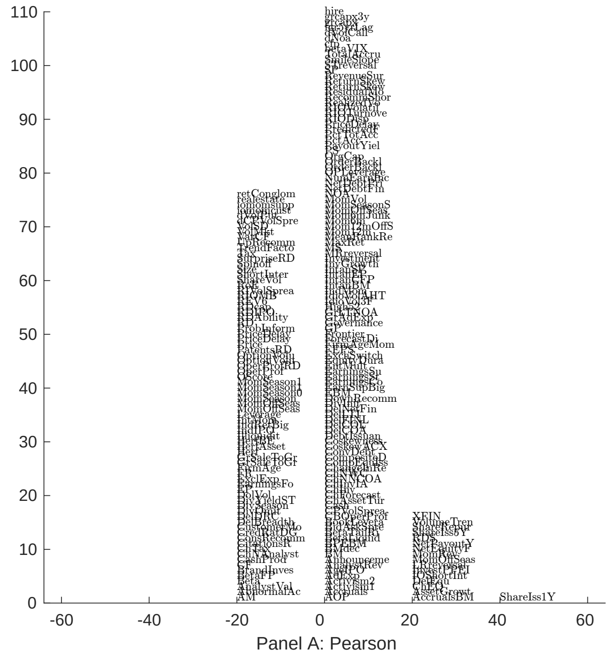


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SDRI trading strategy alphas (diamonds). The strategies are constructed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



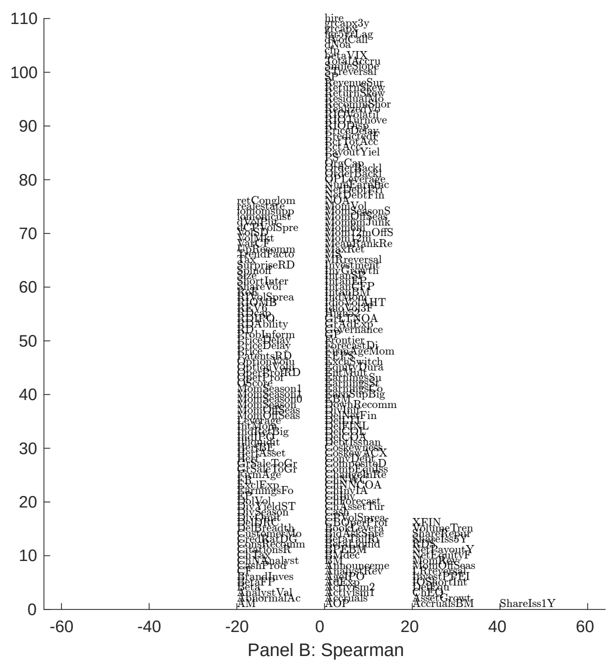


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 203 filtered anomaly signals with SDRI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

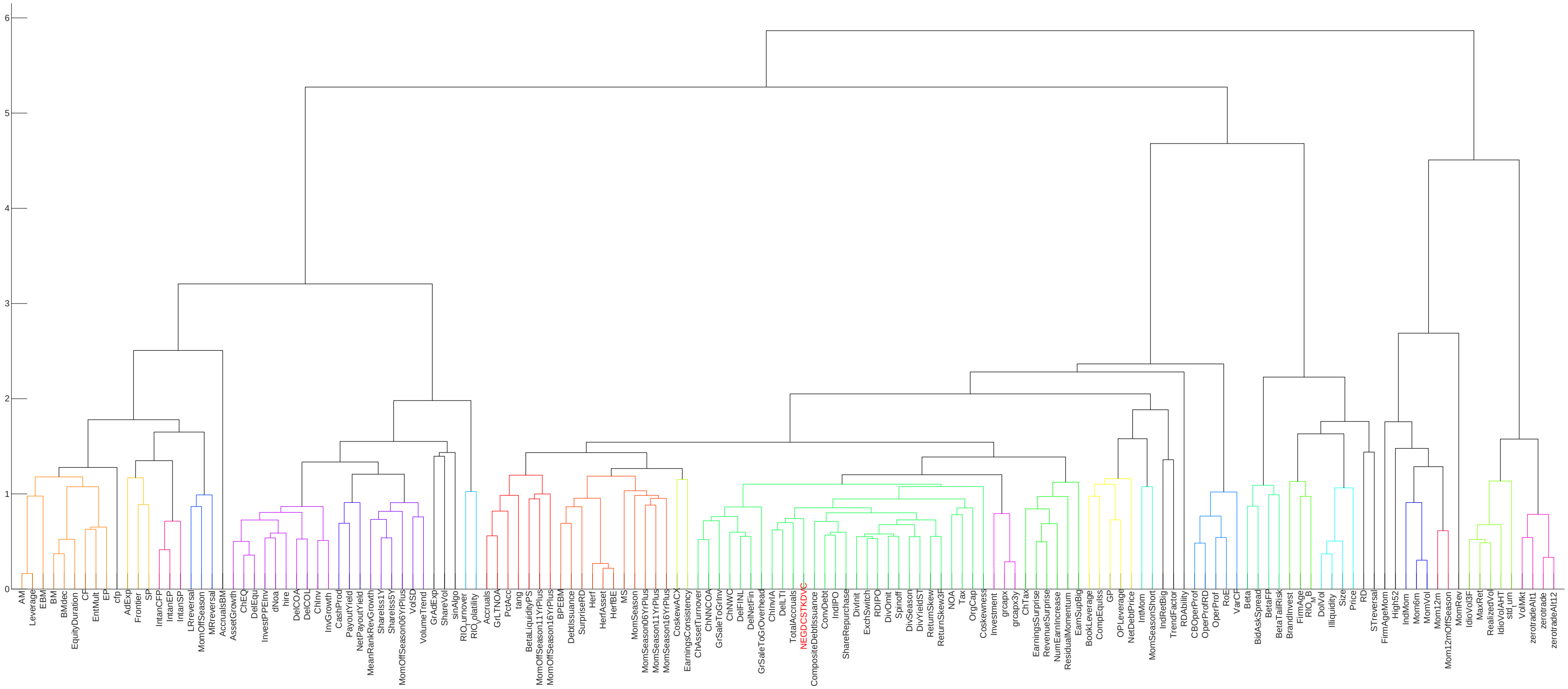


Figure 6: Agglomerative hierarchical cluster plot

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

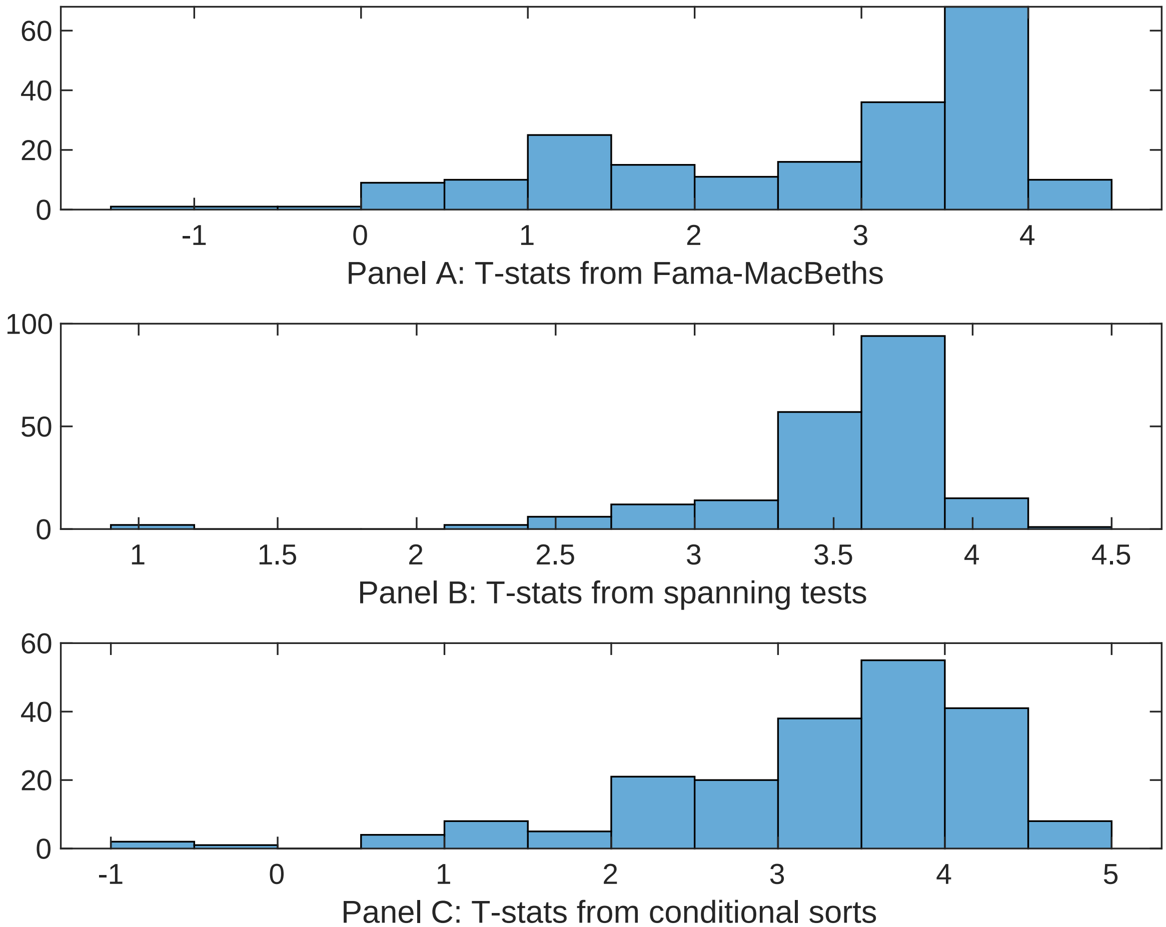


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SDRI conditioning on each of the 203 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SDRI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SDRI} SDRI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 203 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SDRI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 203 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 203 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on SDRI. Stocks are finally grouped into five SDRI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SDRI trading strategies conditioned on each of the 203 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on SDRI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SDRI} SDRI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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	0.12	0.16	0.11	0.12	0.12	0.13	0.12
	[6.48]	[6.73]	[5.69]	[6.66]	[6.47]	[6.82]	[3.94]
SDRI	0.56	0.42	0.19	0.46	0.45	0.37	0.67
	[3.48]	[2.64]	[0.71]	[2.72]	[2.82]	[2.40]	[0.02]
Anomaly 1	0.12						-0.47
	[2.90]						[-0.10]
Anomaly 2		0.39					-0.59
		[2.80]					[-0.03]
Anomaly 3			0.21				0.21
			[1.90]				[1.91]
Anomaly 4				0.20			-0.50
				[2.61]			[-0.47]
Anomaly 5					0.11		0.47
					[2.69]		[0.07]
Anomaly 6						0.68	0.49
						[5.46]	[4.13]
# months	679	684	679	679	684	684	679
$\bar{R}^2(\%)$	0	0	1	0	1	0	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the SDRI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SDRI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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	0.25	0.27	0.26	0.24	0.28	0.27	0.22
	[3.10]	[3.37]	[3.21]	[2.98]	[3.47]	[3.31]	[2.87]
Anomaly 1	25.55						19.02
	[6.22]						[3.97]
Anomaly 2		29.21					35.95
		[6.57]					[5.55]
Anomaly 3			12.52				1.90
			[3.96]				[0.52]
Anomaly 4				14.69			2.74
				[3.45]			[0.60]
Anomaly 5					13.76		-13.47
					[3.18]		[-2.22]
Anomaly 6						0.16	-18.38
						[0.03]	[-3.22]
mkt	3.66	2.60	3.79	3.72	1.42	1.63	5.13
	[1.93]	[1.38]	[1.94]	[1.88]	[0.74]	[0.84]	[2.64]
smb	-2.87	-5.08	-1.45	-4.72	-4.31	-4.08	-2.28
	[-1.05]	[-1.86]	[-0.52]	[-1.69]	[-1.54]	[-1.42]	[-0.81]
hml	-6.13	-6.38	-7.53	-6.88	-4.69	-2.91	-8.86
	[-1.66]	[-1.74]	[-1.91]	[-1.74]	[-1.25]	[-0.78]	[-2.27]
rmw	-17.11	-7.35	-15.69	-11.45	-7.52	-8.92	-15.80
	[-4.37]	[-2.00]	[-3.78]	[-2.99]	[-1.99]	[-2.36]	[-3.64]
cma	13.20	-4.10	16.65	21.20	10.57	24.71	14.96
	[2.28]	[-0.59]	[2.76]	[3.72]	[1.49]	[2.88]	[1.77]
umd	-1.83	-1.93	-0.42	-1.40	-1.22	-1.67	-3.11
	[-0.98]	[-1.04]	[-0.22]	[-0.74]	[-0.64]	[-0.86]	[-1.67]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	11	11	8	8	6	5	15

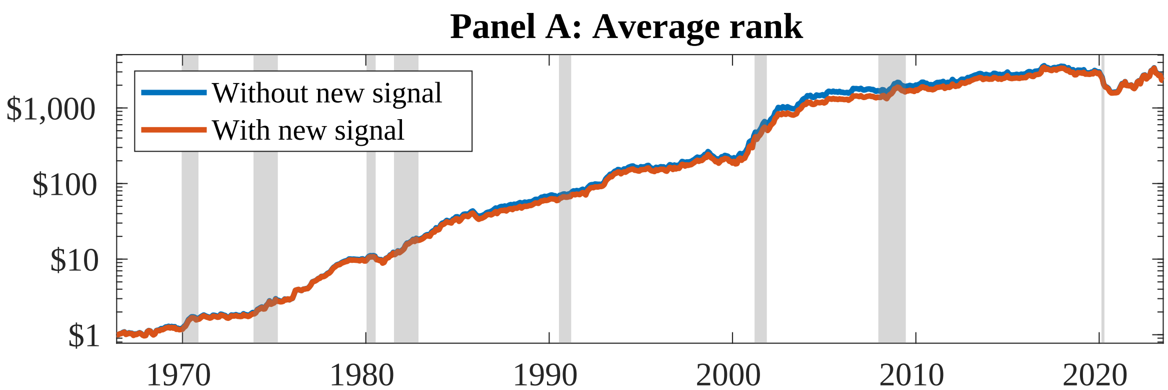


Figure 8: Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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