Stock Dividend Impact and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock Dividend Impact (SDI), 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 SDI achieves an annualized gross (net) Sharpe ratio of 0.53 (0.48), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 29 (27) bps/month with a t-statistic of 3.55 (3.40), 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 25 bps/month with a t-statistic of 3.19.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency Fama and French (2008). While numerous studies have examined how corporate actions like share issuance and dividend policy affect stock returns, the specific impact of stock dividends on future returns remains understudied.

Stock dividends represent a unique corporate action that, while not directly affecting firm value, may signal management's private information about future prospects Brennan and Copeland (1988). Despite their potential information content, existing research has focused primarily on announcement effects rather than long-term return implications. This gap is particularly notable given that stock dividends involve no direct cash outlay yet may convey meaningful information about management's confidence in future growth.

We hypothesize that stock dividends serve as credible signals of management's private information for several reasons. First, following Spence (1973), effective signals must be costly to fake. Stock dividends create implicit commitments to maintain future dividend payments, imposing real constraints on firms' financial flexibility Lintner (1956). Second, managers with private information about strong future prospects can more confidently issue stock dividends, knowing they can sustain the expanded shareholder base.

The signaling value of stock dividends may be particularly meaningful because they represent a more subtle form of communication than traditional cash dividends or share repurchases Baker and Wurgler (2004). While cash payouts directly transfer wealth to shareholders, stock dividends primarily affect ownership structure and trading dynamics. This suggests stock dividends may convey information about operational prospects rather than just current financial strength.

Based on these theoretical foundations, we develop a novel measure called Stock Dividend Impact (SDI) that captures both the magnitude and frequency of a firm's stock dividend activity. If stock dividends indeed serve as credible signals, firms with higher SDI scores should earn superior future returns as their positive prospects are gradually revealed to the market Daniel and Titman (2006).

Our empirical analysis reveals that SDI strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on SDI quintiles generates monthly abnormal returns of 29 basis points relative to the Fama-French five-factor model plus momentum, with a t-statistic of 3.55. The strategy achieves an annualized Sharpe ratio of 0.53 before trading costs and 0.48 after costs.

Importantly, SDI's predictive power persists after controlling for size. Among the largest quintile of stocks by market capitalization, the SDI strategy earns monthly abnormal returns of 31 basis points (t-statistic = 3.32). This indicates that the signal's effectiveness is not limited to small, illiquid stocks where trading costs might impede implementation.

The robustness of SDI's predictive ability is further demonstrated by its performance relative to closely related anomalies. When controlling for six of the most similar known predictors including share issuance and asset growth, SDI continues to generate significant abnormal returns of 25 basis points per month (t-statistic = 3.19).

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel return predictor that captures information content in stock dividends, extending work by Michaely and Grullon (2012) on payout policy signals. Unlike existing measures focused on cash dividends or total payout yield, SDI isolates the unique information conveyed through stock dividends.

Second, we demonstrate that SDI's predictive power is distinct from known anomalies documented in Hou et al. (2020) and Chen and Zimmermann (2022). Our results suggest stock dividends contain incremental information beyond traditional measures of corporate actions and investment patterns. This finding enriches our understanding of how corporate decisions reveal management's private information.

Finally, our work has important implications for both academic research and investment practice. For researchers, we provide new evidence on the mechanisms through which corporate actions affect asset prices. For practitioners, we document a robust return predictor that remains effective among large, liquid stocks and maintains its performance after accounting for transaction costs.

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 Impact measure. 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 DVT for total dividends. Common stock (CSTK) represents the total value of common shares issued by the firm, while total dividends (DVT) captures all dividend distributions made to shareholders during the fiscal period.construction of the signal follows a difference-based approach, 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 DVT. This construction captures the relative magnitude of changes in common stock issuance compared to the firm's dividend distribution capacity. By focusing on this relationship, the signal aims to reflect aspects of capital structure decisions and dividend policy in a manner that is both economically meaningful and interpretable. We construct this measure using end-of-fiscal-year values for both CSTK and DVT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SDI signal. Panel A plots the time-series of the mean, median, and interquartile range for SDI. On average, the cross-sectional mean (median) SDI is -1.52 (-0.01) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SDI data. The signal's interquartile range spans -0.37 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SDI signal for the CRSP universe. On average, the SDI signal is available for 3.60% of CRSP names, which on average make up 6.78% of total market capitalization.

4 Does SDI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SDI 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 SDI portfolio and sells the low SDI 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 SDI strategy earns an average return of 0.32% per month with a t-statistic of 4.04. The annualized Sharpe ratio of the strategy is 0.53. The alphas range from 0.28% to 0.35% per month and have t-statistics exceeding 3.51 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 0.27, with a t-statistic of 4.98 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 332 stocks and an average market capitalization of at least $1,149 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 30 bps/month with a t-statistics of 3.76. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-five 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 24-32bps/month. The lowest return, (24 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 3.96. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SDI 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 SDI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SDI, as well as average returns and alphas for long/short trading SDI 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^{th} NYSE percentile), the SDI strategy achieves an average return of 31 bps/month with a t-statistic of 3.32. Among these large cap stocks, the alphas for the SDI strategy relative to the five most common factor models range from 30 to 33 bps/month with t-statistics between 3.12 and 3.52.

5 How does SDI perform relative to the zoo?

Figure 2 puts the performance of SDI 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 SDI strategy falls in the distribution. The SDI strategy's gross (net) Sharpe ratio of 0.53 (0.48) is greater than 95% (99%) of anomaly Sharpe ratios,

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

respectively.

Figure 3 plots the growth of a \$1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a \$1 invested in the SDI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the SDI strategy would have yielded \$7.29 which ranks the SDI strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the SDI strategy would have yielded \$5.53 which ranks the SDI 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 SDI relative to those. Panel A shows that the SDI strategy gross alphas fall between the 67 and 79 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 SDI strategy has a positive net generalized alpha for five out of the five factor models. In these cases SDI ranks between the 84 and 93 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does SDI 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

[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.

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 SDI with 205 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 SDI or at least to weaken the power SDI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SDI conditioning on each of the 205 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SDI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SDI} SDI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 205 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SDI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 205 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 205 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on SDI. Stocks are finally grouped into five SDI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SDI trading strategies conditioned on each of the 205 filtered anomalies.

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

[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.

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 SDI signal in these Fama-MacBeth regressions exceed 1.25, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SDI is 0.89.

Similarly, Table 5 reports results from spanning tests that regress returns to the SDI 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 SDI strategy earns alphas that range from 26-31bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.27, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SDI trading strategy achieves an alpha of 25bps/month with a t-statistic of 3.19.

7 Does SDI add relative to the whole zoo?

Finally, we can ask how much adding SDI 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 SDI 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,

[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 SDI 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 SDI grows to $2275.50.

8 Conclusion

This study provides compelling evidence for the significance of Stock Dividend Impact (SDI) as a robust predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short trading strategy based on SDI generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.53 (0.48 after transaction costs). The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that SDI captures unique information content not fully reflected in current asset pricing models.

Particularly noteworthy is the strategy's ability to maintain significant alpha (25 bps/month) when controlling for both the Fama-French five factors plus momentum and six closely related anomalies from the factor zoo. This robustness strengthens the case for SDI as a meaningful signal for portfolio management and asset allocation decisions.

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

Future research could explore several promising directions: (1) examining the interaction between SDI and other established anomalies, (2) investigating the signal's performance across different market regimes and economic cycles, (3) testing the signal's effectiveness in international markets, and (4) analyzing the underlying economic mechanisms driving the SDI effect. These extensions would further enhance our understanding of this promising return predictor and its role in asset pricing.

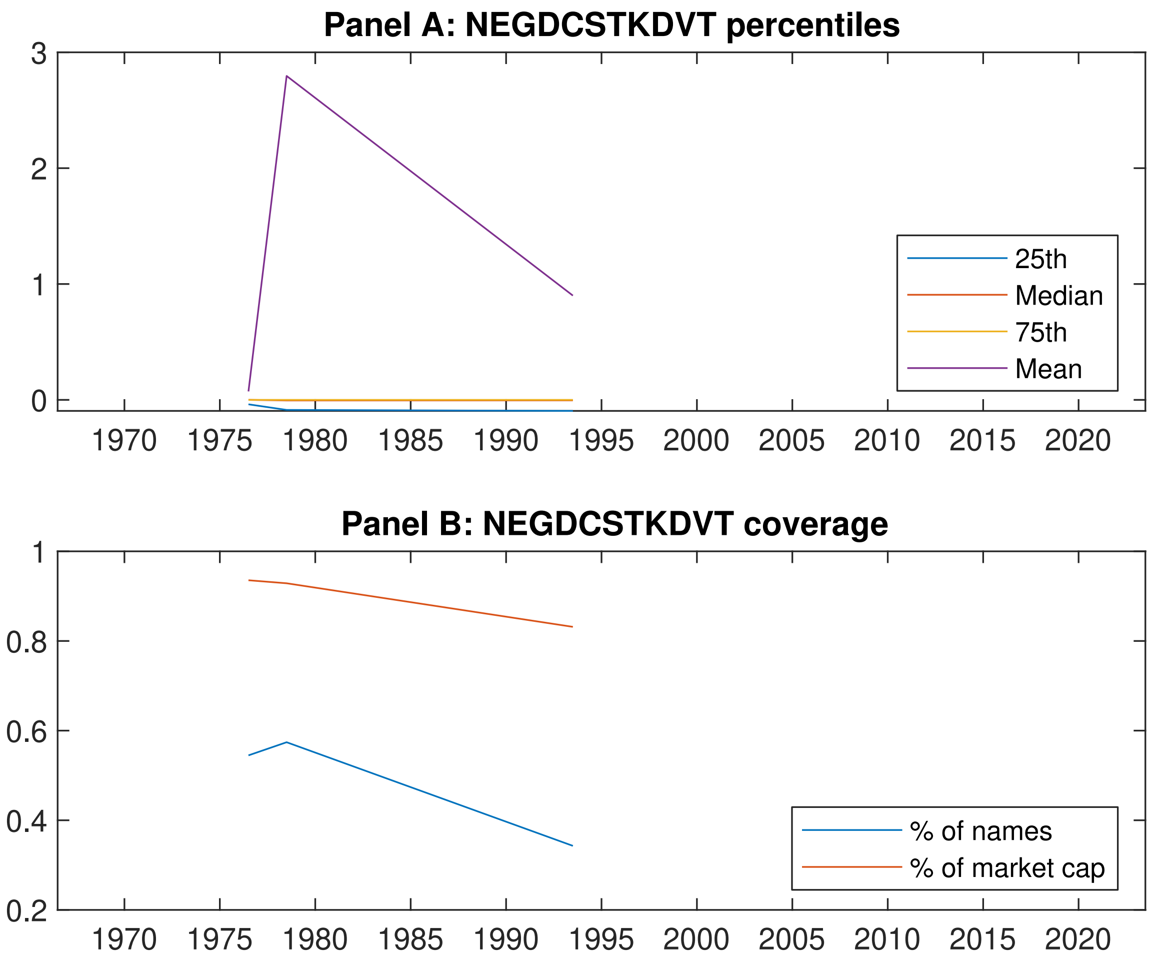

Figure 1: Times series of SDI percentiles and coverage.
This figure plots descriptive statistics for SDI. Panel A shows cross-sectional percentiles of SDI over the sample. Panel B plots the monthly coverage of SDI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SDI. 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 SDI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.41	0.56	0.60	0.60	0.73	0.32
	[2.29]	[3.14]	[3.44]	[3.63]	[4.37]	[4.04]
α_{CAPM}	-0.13	0.00	0.06	0.09	0.22	0.35
	[-2.15]	[0.09]	[1.09]	[1.68]	[3.89]	[4.38]
α_{FF3}	-0.17	-0.04	0.03	0.04	0.15	0.32
	[-2.75]	[-0.77]	[0.61]	[0.79]	[3.10]	[4.00]
α_{FF4}	-0.17	-0.03	0.05	0.02	0.16	0.32
	[-2.67]	[-0.57]	[0.88]	[0.37]	[3.09]	[3.93]
α_{FF5}	-0.25	-0.07	-0.04	-0.10	0.03	0.28
	[-4.28]	[-1.28]	[-0.87]	[-2.18]	[0.63]	[3.51]
α_{FF6}	-0.25	-0.06	-0.03	-0.10	0.04	0.29
	[-4.12]	[-1.09]	[-0.52]	[-2.26]	[0.89]	[3.55]
Panel B: Fama and French (2018) 6-factor model loadings for SDI-sorted portfolios						
β_{MKT}	0.99	1.00	1.00	0.98	0.98	-0.00
	[69.70]	[82.18]	[82.66]	[93.98]	[86.96]	[-0.17]
β_{SMB}	0.00	-0.03	-0.07	-0.12	-0.06	-0.06
	[0.06]	[-1.46]	[-3.78]	[-7.77]	[-3.63]	[-2.17]
β_{HML}	0.11	0.13	0.06	0.11	0.09	-0.02
	[4.04]	[5.74]	[2.56]	[5.34]	[4.03]	[-0.60]
β_{RMW}	0.26	0.09	0.18	0.22	0.19	-0.06
	[9.36]	[3.96]	[7.51]	[10.92]	[8.79]	[-1.72]
β_{CMA}	-0.03	-0.02	0.07	0.21	0.24	0.27
	[-0.68]	[-0.66]	[1.94]	[7.17]	[7.62]	[4.98]
β_{UMD}	-0.01	-0.01	-0.03	0.01	-0.02	-0.01
	[-0.72]	[-1.17]	[-2.32]	[0.67]	[-1.83]	[-0.55]
Panel C: Average number of firms (n) and market capitalization (me)						
n	425	371	332	368	413	
me ($\$10^6$)	1149	1165	1642	1755	1855	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the SDI 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	0.32	0.35	0.32	0.32	0.28	0.29
			[4.04]	[4.38]	[4.00]	[3.93]	[3.51]	[3.55]
Quintile	NYSE	EW	0.38	0.44	0.38	0.32	0.28	0.25
			[6.68]	[7.86]	[7.23]	[6.19]	[5.49]	[4.81]
Quintile	Name	VW	0.33	0.35	0.32	0.31	0.28	0.28
			[3.99]	[4.26]	[3.86]	[3.71]	[3.42]	[3.39]
Quintile	Cap	VW	0.30	0.32	0.30	0.30	0.28	0.28
			[3.76]	[4.01]	[3.82]	[3.67]	[3.47]	[3.43]
Decile	NYSE	VW	0.36	0.39	0.33	0.31	0.31	0.30
			[3.77]	[4.08]	[3.45]	[3.18]	[3.27]	[3.11]
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	0.29	0.32	0.29	0.29	0.27	0.27
			[3.61]	[4.00]	[3.66]	[3.66]	[3.38]	[3.40]
Quintile	NYSE	EW	0.24	0.29	0.23	0.21	0.13	0.12
			[3.96]	[4.85]	[4.19]	[3.75]	[2.50]	[2.29]
Quintile	Name	VW	0.29	0.32	0.29	0.29	0.27	0.27
			[3.55]	[3.90]	[3.54]	[3.48]	[3.30]	[3.30]
Quintile	Cap	VW	0.26	0.29	0.27	0.27	0.26	0.26
			[3.34]	[3.63]	[3.44]	[3.40]	[3.29]	[3.26]
Decile	NYSE	VW	0.32	0.36	0.30	0.29	0.29	0.29
			[3.33]	[3.68]	[3.16]	[3.03]	[3.02]	[2.98]

Table 3: Conditional sort on size and SDI

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

		SDI Quintiles					SDI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.63	0.76	0.79	1.05	0.93	0.30	0.34	0.29	0.26	0.18	0.17
		[2.70]	[3.23]	[3.34]	[3.84]	[4.26]	[3.55]	[4.12]	[3.60]	[3.25]	[2.26]	[2.09]
	(2)	0.60	0.75	0.84	0.89	0.86	0.26	0.29	0.22	0.22	0.15	0.16
		[2.70]	[3.46]	[3.90]	[4.18]	[4.02]	[2.90]	[3.32]	[2.60]	[2.57]	[1.75]	[1.83]
	(3)	0.65	0.66	0.80	0.76	0.92	0.28	0.30	0.25	0.25	0.21	0.21
		[3.17]	[3.15]	[3.92]	[3.86]	[4.67]	[3.43]	[3.74]	[3.12]	[3.07]	[2.58]	[2.60]
	(4)	0.49	0.67	0.73	0.78	0.75	0.26	0.30	0.24	0.24	0.15	0.16
		[2.48]	[3.40]	[3.66]	[4.15]	[4.00]	[3.40]	[3.93]	[3.29]	[3.25]	[2.01]	[2.13]
	(5)	0.39	0.52	0.51	0.54	0.70	0.31	0.33	0.31	0.30	0.30	0.30
		[2.22]	[2.95]	[2.98]	[3.18]	[4.21]	[3.32]	[3.52]	[3.24]	[3.12]	[3.16]	[3.12]

Panel B: Portfolio average number of firms and market capitalization

		SDI Quintiles					SDI Quintiles				
		Average n					Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	157	157	157	156	157	15	14	15	12	13
	(2)	65	65	65	65	65	28	28	28	28	28
	(3)	55	55	55	54	55	57	56	57	58	57
	(4)	51	51	51	51	51	135	137	143	140	142
	(5)	54	54	53	54	54	1030	1265	1360	1280	1443

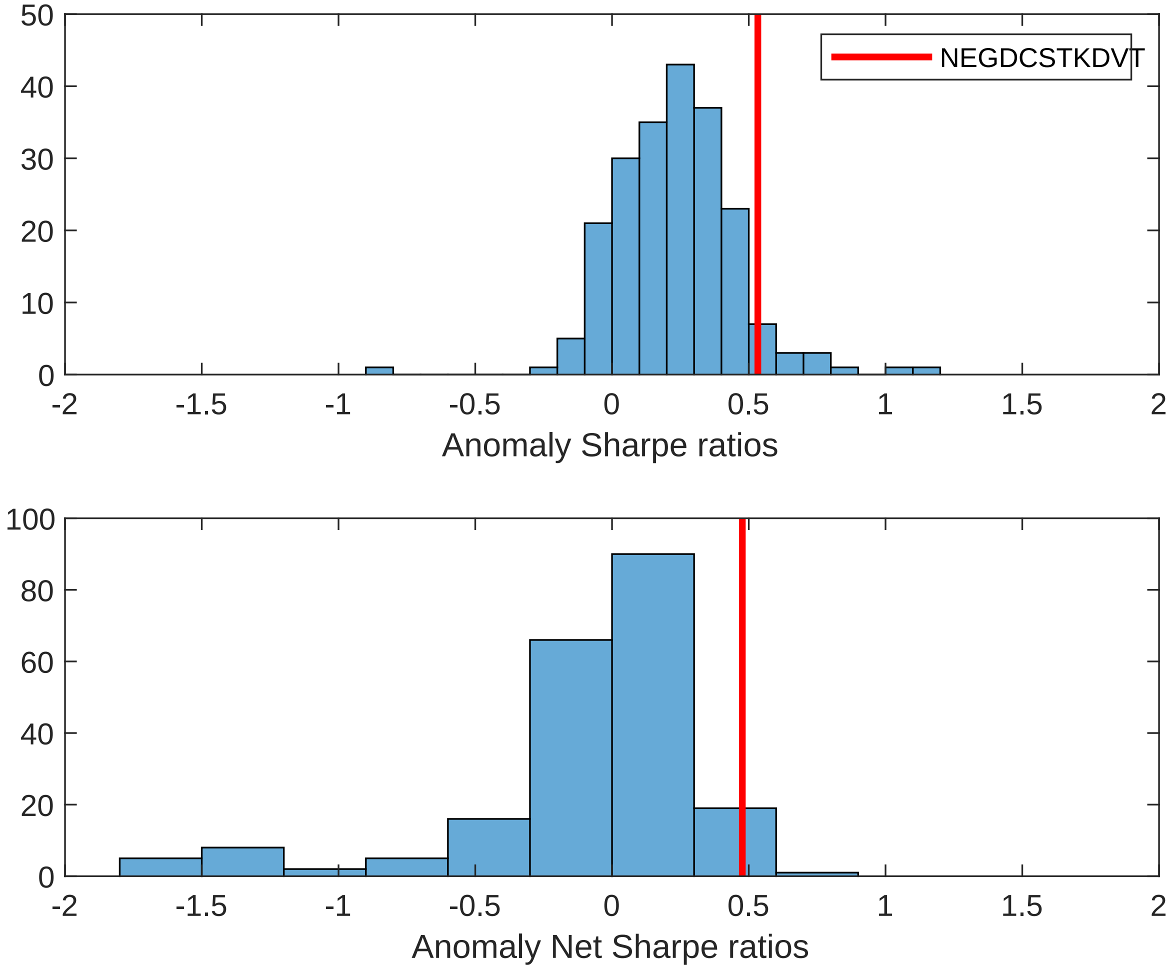

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SDI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

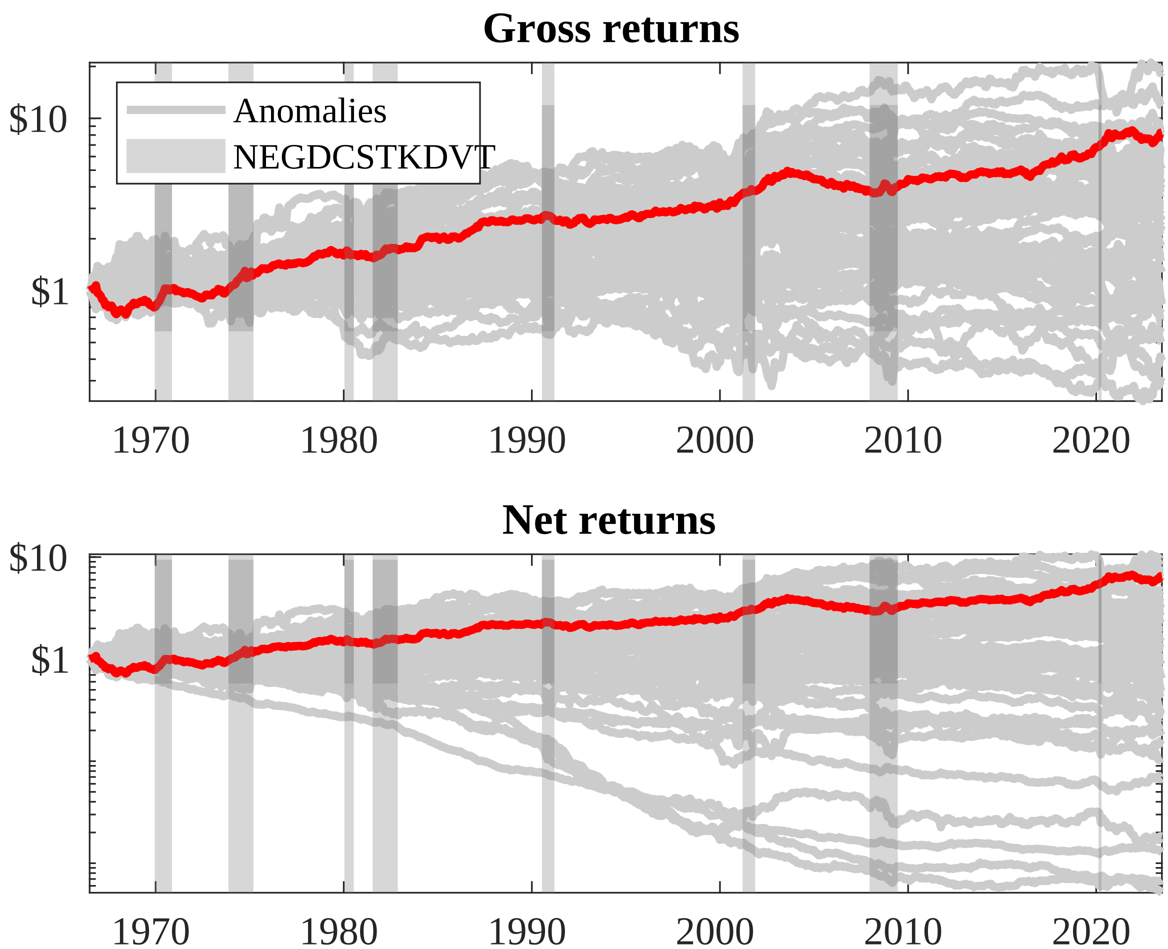

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SDI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

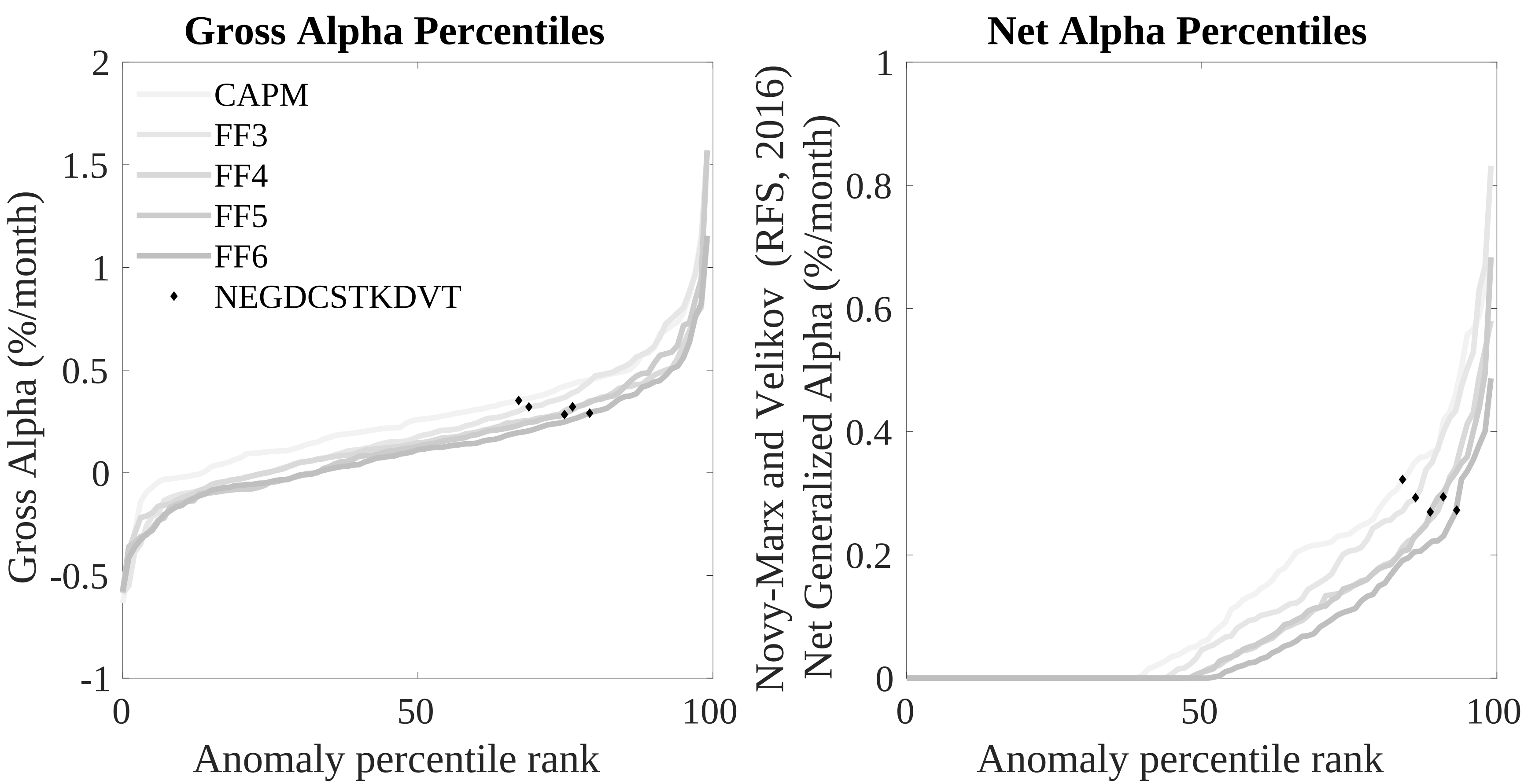

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models

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

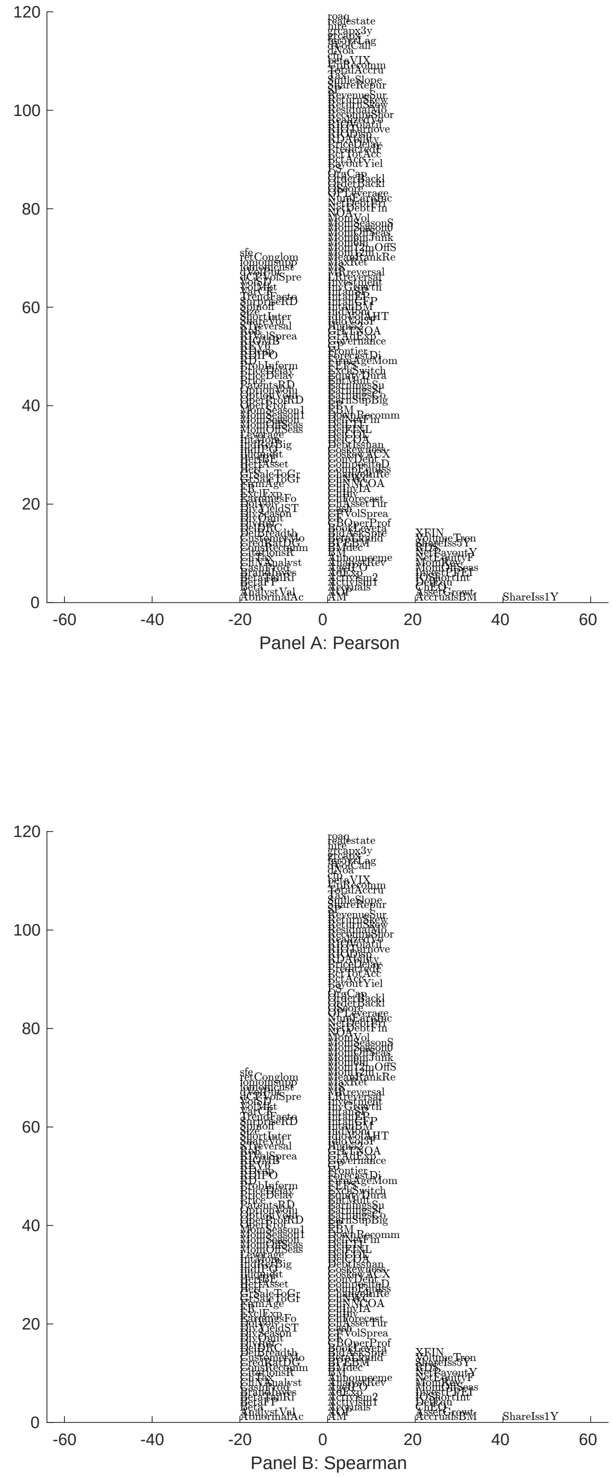

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 205 filtered anomaly signals with SDI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

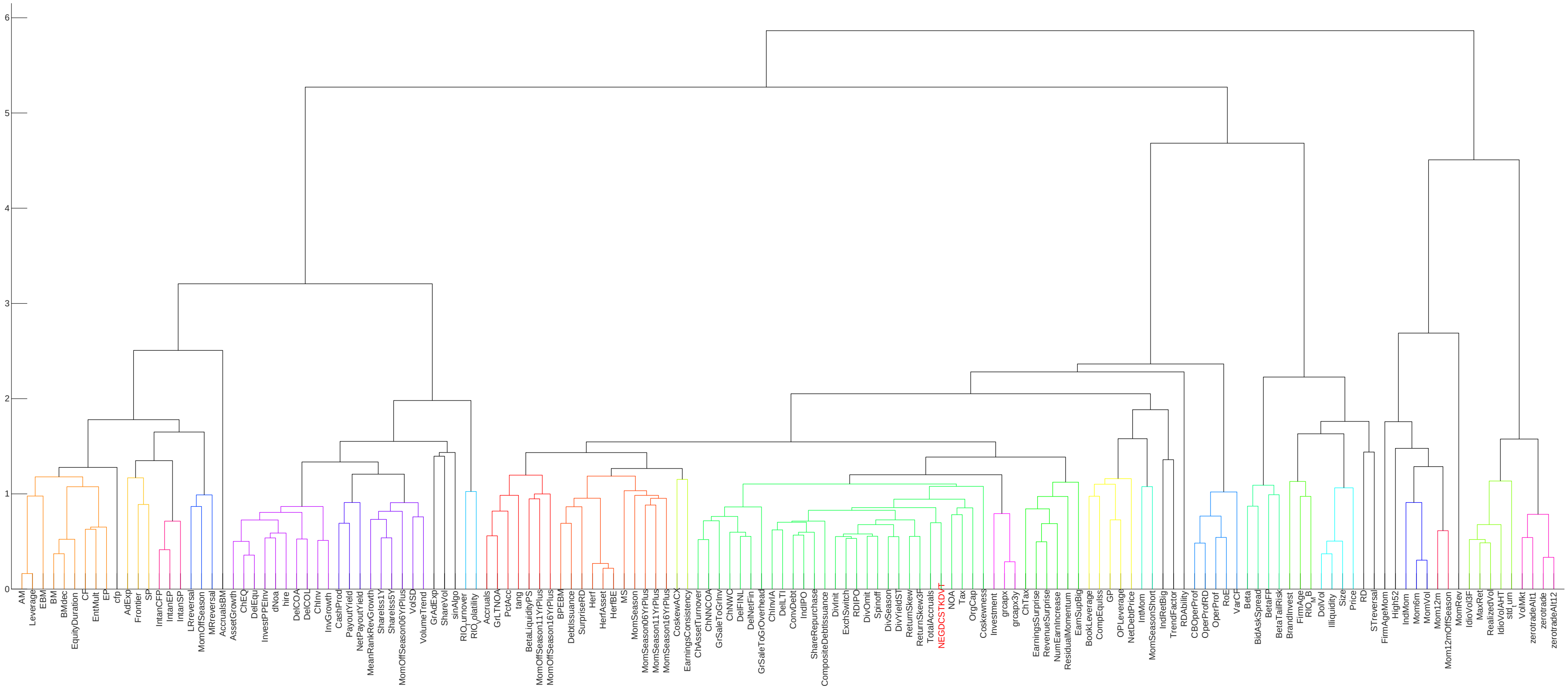

Figure 6: Agglomerative hierarchical cluster plot

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

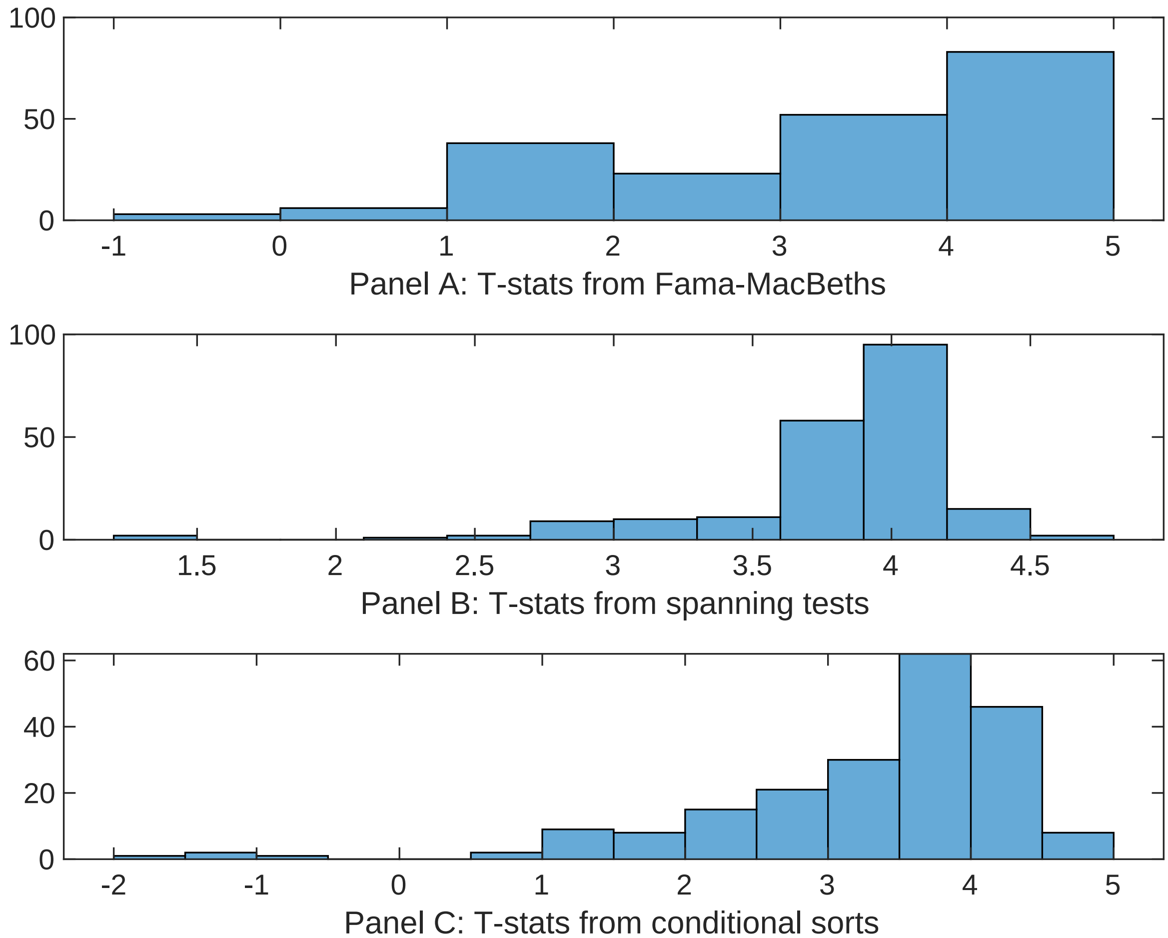

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SDI conditioning on each of the 205 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SDI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SDI} SDI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 205 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SDI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 205 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 205 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on SDI. Stocks are finally grouped into five SDI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SDI trading strategies conditioned on each of the 205 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on SDI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SDI} SDI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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	0.13
	[6.16]	[6.97]	[5.35]	[6.37]	[6.13]	[6.50]	[5.11]
SDI	0.57	0.41	0.31	0.53	0.45	0.43	0.23
	[4.00]	[2.84]	[1.25]	[3.51]	[3.14]	[3.04]	[0.89]
Anomaly 1	0.20						0.35
	[4.45]						[0.66]
Anomaly 2		0.40					0.14
		[3.25]					[0.76]
Anomaly 3			0.29				0.23
			[2.57]				[2.08]
Anomaly 4				0.30			0.37
				[3.73]			[0.04]
Anomaly 5					0.15		-0.22
					[3.65]		[-0.35]
Anomaly 6						0.80	0.53
						[6.29]	[4.43]
# months	679	684	679	679	684	684	679
$\bar{R}^2(\%)$	0	1	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 SDI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SDI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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	0.27	0.29	0.28	0.26	0.31	0.29	0.25
	[3.40]	[3.66]	[3.54]	[3.27]	[3.75]	[3.58]	[3.19]
Anomaly 1	27.68						20.69
	[6.81]						[4.38]
Anomaly 2		29.46					35.57
		[6.66]					[5.56]
Anomaly 3			14.18				3.27
			[4.52]				[0.91]
Anomaly 4				16.50			3.52
				[3.91]			[0.78]
Anomaly 5					14.03		-14.10
					[3.26]		[-2.36]
Anomaly 6						-0.61	-19.61
						[-0.11]	[-3.47]
mkt	2.23	1.02	2.47	2.37	-0.17	0.04	3.96
	[1.19]	[0.54]	[1.27]	[1.21]	[-0.09]	[0.02]	[2.07]
smb	-4.52	-6.75	-2.89	-6.58	-5.97	-5.66	-3.64
	[-1.68]	[-2.48]	[-1.04]	[-2.37]	[-2.15]	[-1.98]	[-1.31]
hml	-5.22	-5.05	-7.00	-6.22	-3.36	-1.52	-8.53
	[-1.43]	[-1.39]	[-1.79]	[-1.59]	[-0.90]	[-0.41]	[-2.22]
rmw	-16.03	-5.59	-14.86	-10.03	-5.75	-7.17	-15.61
	[-4.14]	[-1.53]	[-3.61]	[-2.64]	[-1.53]	[-1.90]	[-3.64]
cma	14.31	-2.30	17.55	22.74	12.33	27.69	17.41
	[2.50]	[-0.33]	[2.94]	[4.02]	[1.75]	[3.24]	[2.09]
umd	-1.24	-1.29	0.33	-0.78	-0.57	-1.06	-2.49
	[-0.68]	[-0.70]	[0.17]	[-0.42]	[-0.30]	[-0.55]	[-1.35]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	14	13	11	10	8	7	18

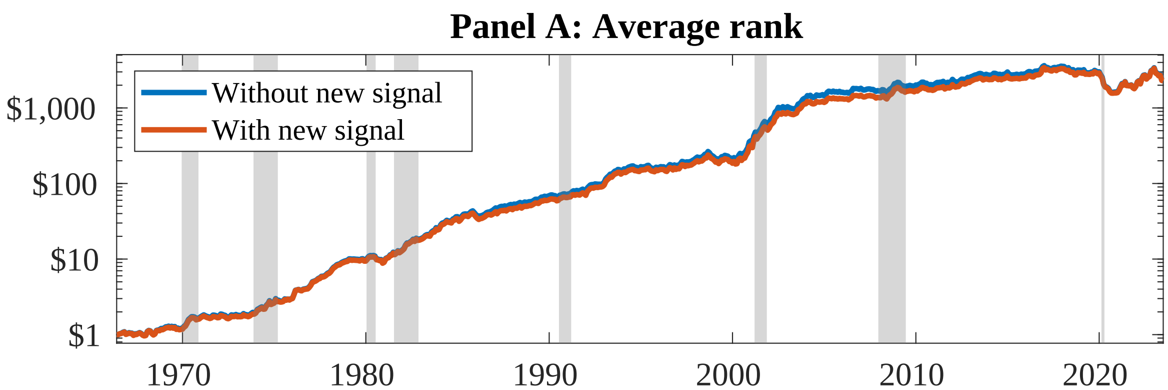

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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