Stock Cash Differential and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock Cash Differential (SCD), 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 SCD achieves an annualized gross (net) Sharpe ratio of 0.52 (0.46), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (23) bps/month with a t-statistic of 2.95 (2.86), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Growth in book equity, Share issuance (1 year), Change in equity to assets, Momentum and LT Reversal, Share issuance (5 year), Long-run reversal) is 21 bps/month with a t-statistic of 2.66.

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 (Harvey et al., 2016). These return predictability patterns, or 'anomalies,' challenge our understanding of asset pricing and market efficiency. Despite extensive research into cross-sectional return predictability, significant gaps remain in our understanding of how firms' financial policies and operational decisions affect their stock returns.

One particularly puzzling aspect is how firms' cash management policies relate to their stock returns. While existing research examines the relationship between cash holdings and stock returns (Sodikh and Yao, 2018), the dynamic aspects of firms' cash management decisions and their implications for future returns remain largely unexplored. This gap is especially notable given the dramatic increase in corporate cash holdings over recent decades and the growing importance of working capital management in corporate finance.

We propose that the difference between a firm's stock returns and changes in its cash holdings, which we term the Stock Cash Differential (SCD), contains valuable information about future stock returns. This hypothesis builds on two theoretical frameworks. First, the q-theory of investment (Cochrane and Saa-Requejo, 1995) suggests that firms' investment decisions, including cash management, should predict returns. When firms experience positive shocks to investment opportunities, they optimally reduce cash holdings while their stock prices rise in anticipation of future growth.

Second, behavioral theories of investor attention (Hirshleifer and Teoh, 2003) suggest that investors may not fully process the implications of firms' cash management decisions. The complexity of evaluating changes in cash holdings relative to stock price movements can lead to temporary mispricing that resolves predictably over time (DellaVigna and Pollet, 2009). This underreaction hypothesis predicts that extreme values of SCD should forecast future return reversals.

Additionally, the relationship between SCD and returns may reflect information about management's private information. Following (Myers and Lambrecht, 2017), managers with positive private information may maintain higher cash levels while their stock prices have not yet fully reflected this information, creating a wedge between stock returns and cash changes that predicts future returns.

Our empirical analysis reveals strong support for SCD's predictive power. A value-weighted long-short portfolio strategy based on SCD quintiles generates significant abnormal returns of 24 basis points per month (t-statistic = 2.95) after controlling for the Fama-French five factors plus momentum. The strategy achieves an impressive annualized Sharpe ratio of 0.52 before trading costs and 0.46 after accounting for transaction costs.

The predictive power of SCD remains robust across various methodological specifications. Most notably, the signal maintains its effectiveness among large-cap stocks, with the highest size quintile generating abnormal returns of 21 basis points per month (t-statistic = 2.21). This finding is particularly important as it suggests that the SCD effect is not limited to small, illiquid stocks that are costly to trade.

Further analysis demonstrates that SCD's predictive ability is distinct from known anomalies. Controlling for the six most closely related anomalies and the Fama-French six factors simultaneously, the SCD strategy still generates an alpha of 21 basis points per month (t-statistic = 2.66). The strategy's gross Sharpe ratio of 0.52 places it in the top 6% of all documented anomalies, while its net Sharpe ratio of 0.46 ranks even more impressively in the top 1%.

Our paper makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures the dynamic relationship between stock returns and cash management decisions. While previous studies such as (Bates et al., 2009) examine static cash holdings, our work is the first to show how the differential between stock returns and cash changes predicts future returns.

Second, we contribute to the growing literature on investment-based asset pricing (Hou et al., 2015) by showing how firms' cash management decisions contain information about expected returns. Our findings suggest that the q-theory framework can be extended to explain return predictability through the lens of corporate liquidity management.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate that combining stock market and accounting information in novel ways can reveal significant predictability patterns. For practitioners, we document a robust anomaly that remains profitable after transaction costs and works well among large, liquid stocks. The fact that SCD improves the achievable mean-variance frontier even after controlling for standard factors and transaction costs suggests it captures a unique dimension of expected returns.

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 Cash Differential. 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 CHE for cash and short-term investments. Common stock (CSTK) represents the total value of common shares issued by the company, while cash and short-term investments (CHE) encompasses readily available liquid assets including cash, cash equivalents, and marketable securities. The construction of our signal follows a dynamic approach, where we calculate the year-over-year change in CSTK and scale this difference by the previous year's cash holdings (CHE). Specifically, we subtract the lagged value of CSTK from its current value and divide by lagged CHE. This scaled difference captures the relative magnitude of changes in equity issuance or repurchases compared to the firm's liquid asset base, potentially offering insights into management's capital structure decisions and their assessment of internal funding adequacy. We construct this measure using end-of-fiscal-year values for both CSTK and CHE to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SCD signal. Panel A plots the time-series of the mean, median, and interquartile range for SCD. On average, the cross-sectional mean (median) SCD is -0.74 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SCD data. The signal's interquartile range spans -0.11 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SCD signal for the CRSP universe. On average, the SCD signal is available for 6.56% of CRSP names, which on average make up 7.87% of total market capitalization.

4 Does SCD predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SCD 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 SCD portfolio and sells the low SCD 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 SCD strategy earns an average return of 0.32% per month with a t-statistic of 3.95. The annualized Sharpe ratio of the strategy is 0.52. The alphas range from 0.24% to 0.31% per month and have t-statistics exceeding 2.95 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 0.24, with a t-statistic of 4.33 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 673 stocks and an average market capitalization of at least $1,359 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 29 bps/month with a t-statistics of 3.60. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for nineteen 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 26-36bps/month. The lowest return, (26 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.18. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SCD 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 SCD strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SCD, as well as average returns and alphas for long/short trading SCD 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 SCD strategy achieves an average return of 24 bps/month with a t-statistic of 2.54. Among these large cap stocks, the alphas for the SCD strategy relative to the five most common factor models range from 19 to 21 bps/month with t-statistics between 1.91 and 2.21.

5 How does SCD perform relative to the zoo?

Figure 2 puts the performance of SCD 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 SCD strategy falls in the distribution. The SCD strategy's gross (net) Sharpe ratio of 0.52 (0.46) is greater than 94% (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 SCD strategy (red line).[2] Ignoring trading costs, a $1 invested in the SCD strategy would have yielded $6.80 which ranks the SCD strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a $1 invested in the SCD strategy would have yielded $5.10 which ranks the SCD strategy in the top 2% 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 SCD relative to those. Panel A shows that the SCD strategy gross alphas fall between the 60 and 75 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 SCD strategy has a positive net generalized alpha for five out of the five factor models. In these cases SCD ranks between the 81 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does SCD 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 SCD with 210 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 SCD or at least to weaken the power SCD has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SCD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SCD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SCD} SCD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SCD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-

[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.

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 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on SCD. Stocks are finally grouped into five SCD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SCD trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SCD 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 SCD signal in these Fama-MacBeth regressions exceed 0.43, with the minimum t-statistic occurring when controlling for Momentum and LT Reversal. Controlling for all six closely related anomalies, the t-statistic on SCD is 0.23.

Similarly, Table 5 reports results from spanning tests that regress returns to the SCD 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 SCD strategy earns alphas that range from 22-26bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.62, which is achieved when controlling for Momentum and LT Reversal. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SCD trading strategy achieves an alpha of 21bps/month with a t-statistic of 2.66.

7 Does SCD add relative to the whole zoo?

Finally, we can ask how much adding SCD 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 SCD 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 SCD grows to $2501.76.

8 Conclusion

This study provides compelling evidence for the effectiveness of Stock Cash Differential (SCD) as a robust predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short trading strategy based on SCD generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.52 (0.46 after transaction costs). The strategy's persistence in generating significant abnormal returns, even after controlling for well-known factors and related anomalies, suggests that SCD captures unique information about future stock returns that is not fully reflected in existing factors.

[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 SCD is available.

Particularly noteworthy is the strategy's ability to maintain significant alpha (21 bps/month) even after controlling for the Fama-French five factors, momentum, and six closely related anomalies, with a robust t-statistic of 2.66. This persistence indicates that SCD represents a distinct source of predictable variation in stock returns, rather than simply capturing already-known effects.

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, the implementation of the strategy in practice may face additional constraints such as liquidity limitations and institutional restrictions.

Future research could explore several promising directions. First, investigating the economic mechanisms underlying the SCD effect could provide valuable insights into why this signal predicts returns. Second, examining the interaction between SCD and other market anomalies might reveal important complementarities. Finally, testing the robustness of SCD across different market regimes and international markets would help establish its broader applicability.

In conclusion, our findings suggest that SCD represents a valuable addition to the investment practitioner's toolkit, offering meaningful economic gains even after accounting for transaction costs and existing factors. This research contributes to our understanding of cross-sectional return predictability and opens up new avenues for future investigation in asset pricing.

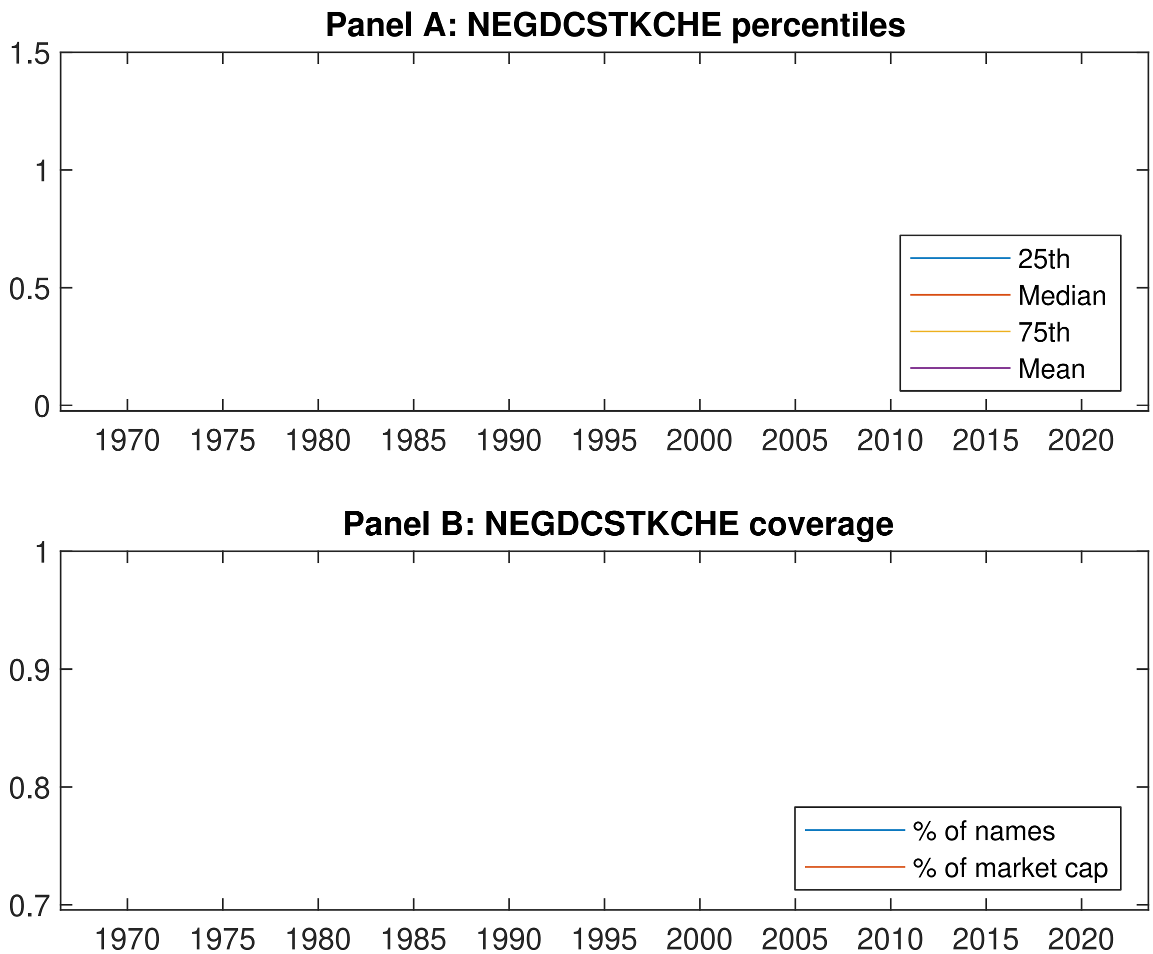

Figure 1: Times series of SCD percentiles and coverage.
This figure plots descriptive statistics for SCD. Panel A shows cross-sectional percentiles of SCD over the sample. Panel B plots the monthly coverage of SCD relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SCD. 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 SCD-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.46	0.43	0.65	0.69	0.78	0.32
	[2.68]	[2.24]	[3.31]	[4.01]	[4.59]	[3.95]
α_{CAPM}	-0.06	-0.18	0.03	0.15	0.25	0.31
	[-1.05]	[-3.91]	[0.63]	[3.15]	[5.25]	[3.83]
α_{FF3}	-0.09	-0.16	0.06	0.12	0.20	0.29
	[-1.47]	[-3.67]	[1.25]	[2.67]	[4.50]	[3.52]
α_{FF4}	-0.08	-0.14	0.11	0.07	0.18	0.26
	[-1.31]	[-3.04]	[2.27]	[1.46]	[4.03]	[3.14]
α_{FF5}	-0.16	-0.11	0.16	0.04	0.10	0.26
	[-2.73]	[-2.45]	[3.20]	[0.94]	[2.35]	[3.19]
α_{FF6}	-0.15	-0.10	0.19	0.00	0.10	0.24
	[-2.52]	[-2.06]	[3.89]	[0.08]	[2.20]	[2.95]
Panel B: Fama and French (2018) 6-factor model loadings for SCD-sorted portfolios						
β_{MKT}	0.95	1.04	1.04	1.01	0.99	0.04
	[67.70]	[95.49]	[88.76]	[92.96]	[96.96]	[2.19]
β_{SMB}	-0.01	0.05	-0.01	-0.04	-0.00	0.01
	[-0.51]	[3.39]	[-0.88]	[-2.83]	[-0.32]	[0.19]
β_{HML}	0.09	-0.02	-0.04	0.06	0.05	-0.04
	[3.17]	[-0.98]	[-1.87]	[2.92]	[2.52]	[-0.96]
β_{RMW}	0.23	-0.07	-0.15	0.11	0.13	-0.09
	[8.25]	[-3.21]	[-6.69]	[5.32]	[6.72]	[-2.40]
β_{CMA}	-0.03	-0.10	-0.15	0.13	0.21	0.24
	[-0.76]	[-3.31]	[-4.39]	[4.20]	[7.25]	[4.33]
β_{UMD}	-0.02	-0.03	-0.05	0.06	0.01	0.03
	[-1.21]	[-2.49]	[-4.55]	[5.82]	[0.87]	[1.32]
Panel C: Average number of firms (n) and market capitalization (me)						
n	673	714	685	723	769	
me ($\$10^6$)	1557	1359	2267	2292	2442	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the SCD 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	0.31	0.29	0.26	0.26	0.24
			[3.95]	[3.83]	[3.52]	[3.14]	[3.19]	[2.95]
Quintile	NYSE	EW	0.56	0.61	0.56	0.49	0.48	0.43
			[9.85]	[11.02]	[10.44]	[9.31]	[8.99]	[8.23]
Quintile	Name	VW	0.31	0.30	0.28	0.26	0.26	0.25
			[4.01]	[3.86]	[3.54]	[3.24]	[3.24]	[3.07]
Quintile	Cap	VW	0.29	0.28	0.26	0.24	0.25	0.23
			[3.60]	[3.49]	[3.22]	[2.84]	[3.04]	[2.79]
Decile	NYSE	VW	0.36	0.35	0.30	0.25	0.26	0.22
			[3.77]	[3.58]	[3.15]	[2.53]	[2.71]	[2.28]
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	0.28	0.28	0.26	0.24	0.24	0.23
			[3.51]	[3.43]	[3.16]	[2.99]	[2.98]	[2.86]
Quintile	NYSE	EW	0.36	0.40	0.35	0.32	0.26	0.24
			[5.58]	[6.32]	[5.75]	[5.28]	[4.33]	[4.05]
Quintile	Name	VW	0.28	0.27	0.25	0.24	0.24	0.23
			[3.55]	[3.46]	[3.18]	[3.05]	[3.03]	[2.94]
Quintile	Cap	VW	0.26	0.25	0.24	0.22	0.23	0.22
			[3.18]	[3.11]	[2.88]	[2.69]	[2.86]	[2.71]
Decile	NYSE	VW	0.32	0.31	0.27	0.24	0.24	0.22
			[3.34]	[3.15]	[2.79]	[2.47]	[2.47]	[2.25]

Table 3: Conditional sort on size and SCD

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

		SCD Quintiles					SCD Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.42	0.69	0.82	0.96	0.96	0.54	0.59	0.56	0.48	0.49	0.43
		[1.67]	[2.59]	[3.07]	[3.79]	[4.04]	[7.75]	[8.56]	[8.16]	[7.09]	[7.07]	[6.32]
	(2)	0.52	0.61	0.87	0.92	0.95	0.43	0.48	0.41	0.37	0.39	0.36
		[2.24]	[2.48]	[3.59]	[3.88]	[4.26]	[5.51]	[6.14]	[5.40]	[4.80]	[5.01]	[4.60]
	(3)	0.59	0.65	0.72	0.85	0.96	0.37	0.39	0.37	0.36	0.36	0.35
		[2.76]	[2.88]	[3.14]	[3.83]	[4.66]	[4.80]	[5.02]	[4.71]	[4.47]	[4.44]	[4.29]
	(4)	0.45	0.65	0.78	0.82	0.83	0.38	0.39	0.34	0.32	0.23	0.23
		[2.30]	[3.06]	[3.56]	[3.96]	[4.31]	[5.10]	[5.26]	[4.64]	[4.34]	[3.20]	[3.12]
	(5)	0.48	0.45	0.54	0.56	0.72	0.24	0.21	0.20	0.19	0.21	0.20
		[2.86]	[2.38]	[2.84]	[3.21]	[4.26]	[2.54]	[2.24]	[2.10]	[1.91]	[2.21]	[2.08]

Panel B: Portfolio average number of firms and market capitalization

		SCD Quintiles Average n					SCD Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	395	394	395	392	393	33	34	40	30	30
	(2)	112	111	111	111	111	57	57	57	56	57
	(3)	81	80	80	79	80	99	96	97	100	101
	(4)	67	67	67	67	67	205	204	211	215	217
	(5)	61	61	61	61	61	1367	1435	1746	1614	1761

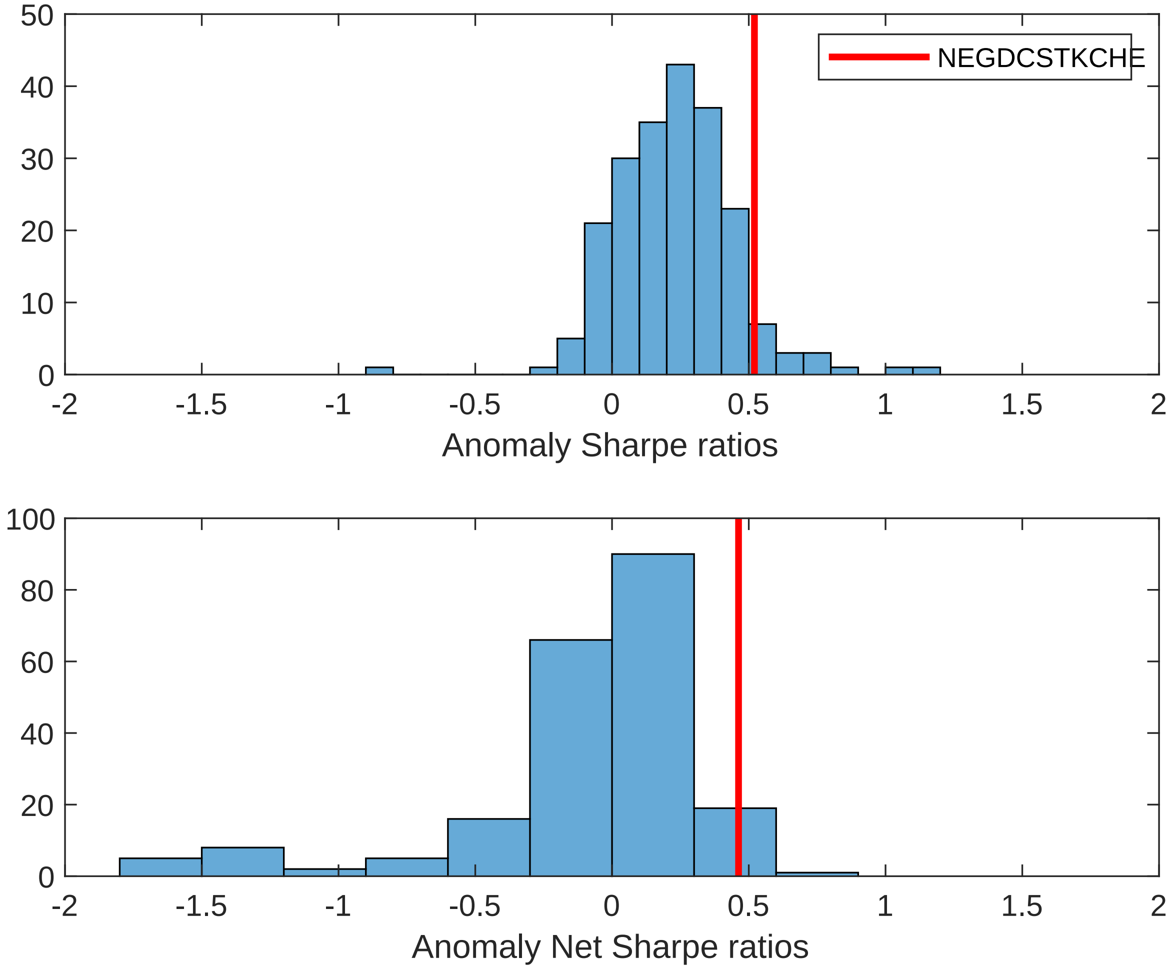

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SCD with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

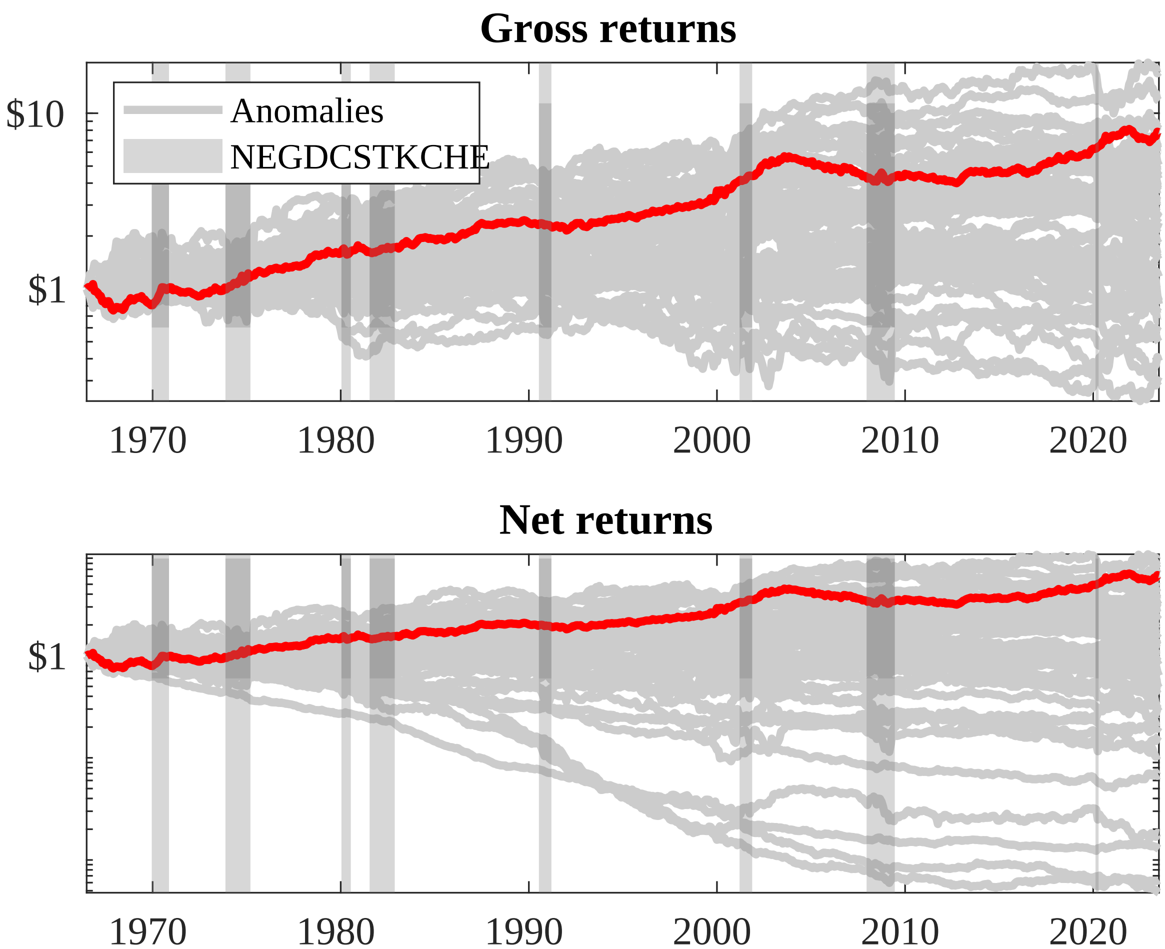

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SCD trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

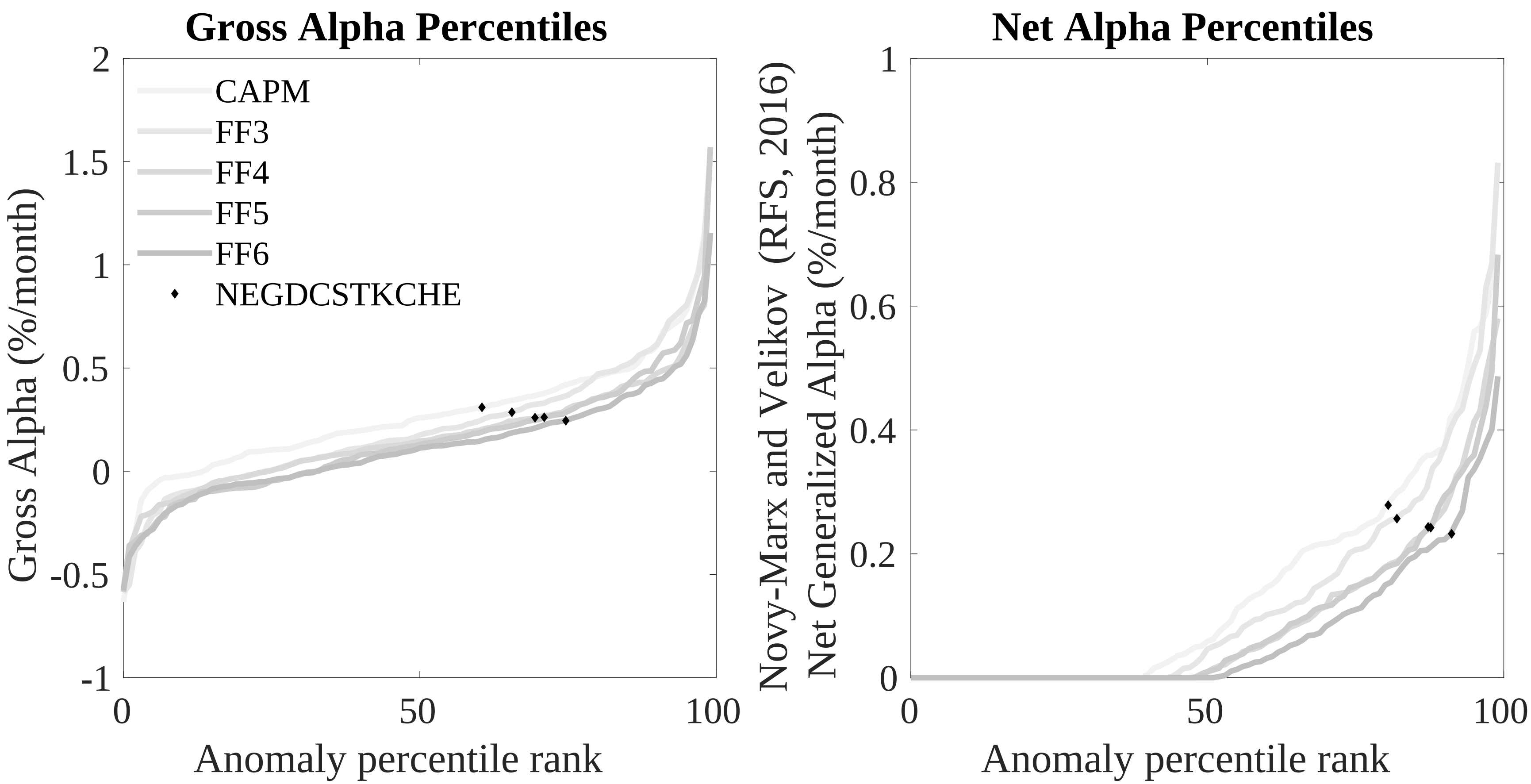

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SCD trading strategy alphas (diamonds). The strategies are constructed using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

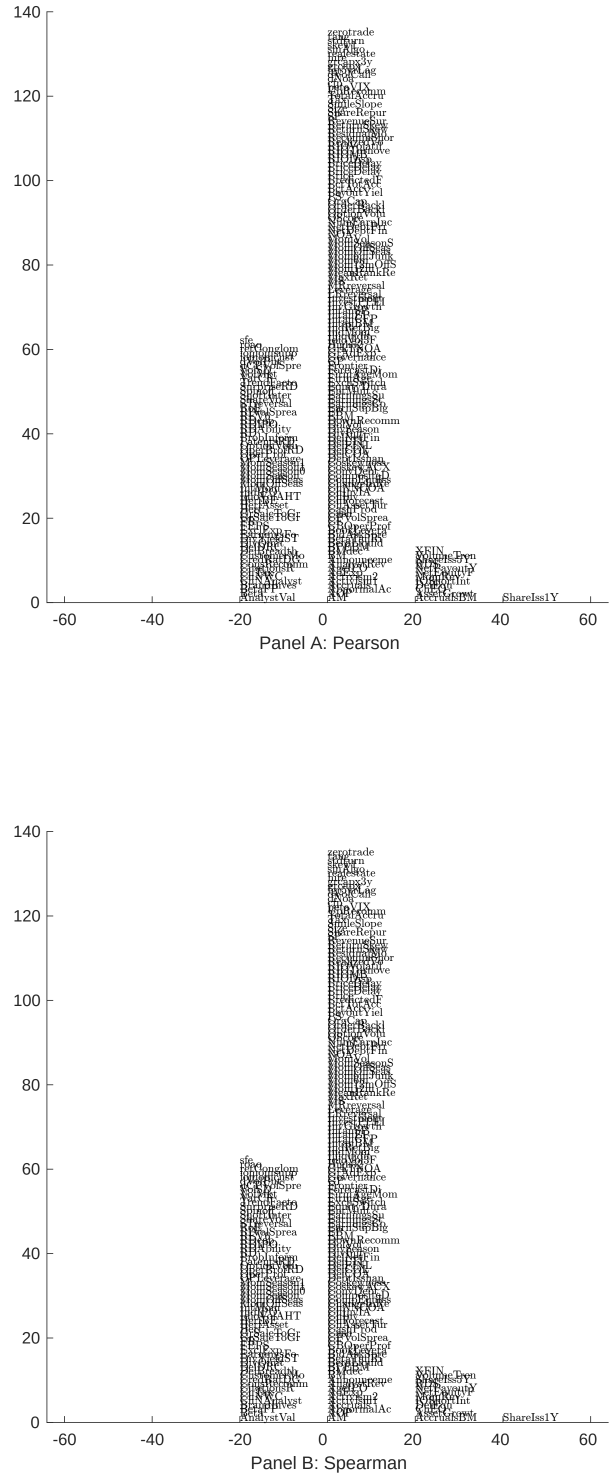

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with SCD. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

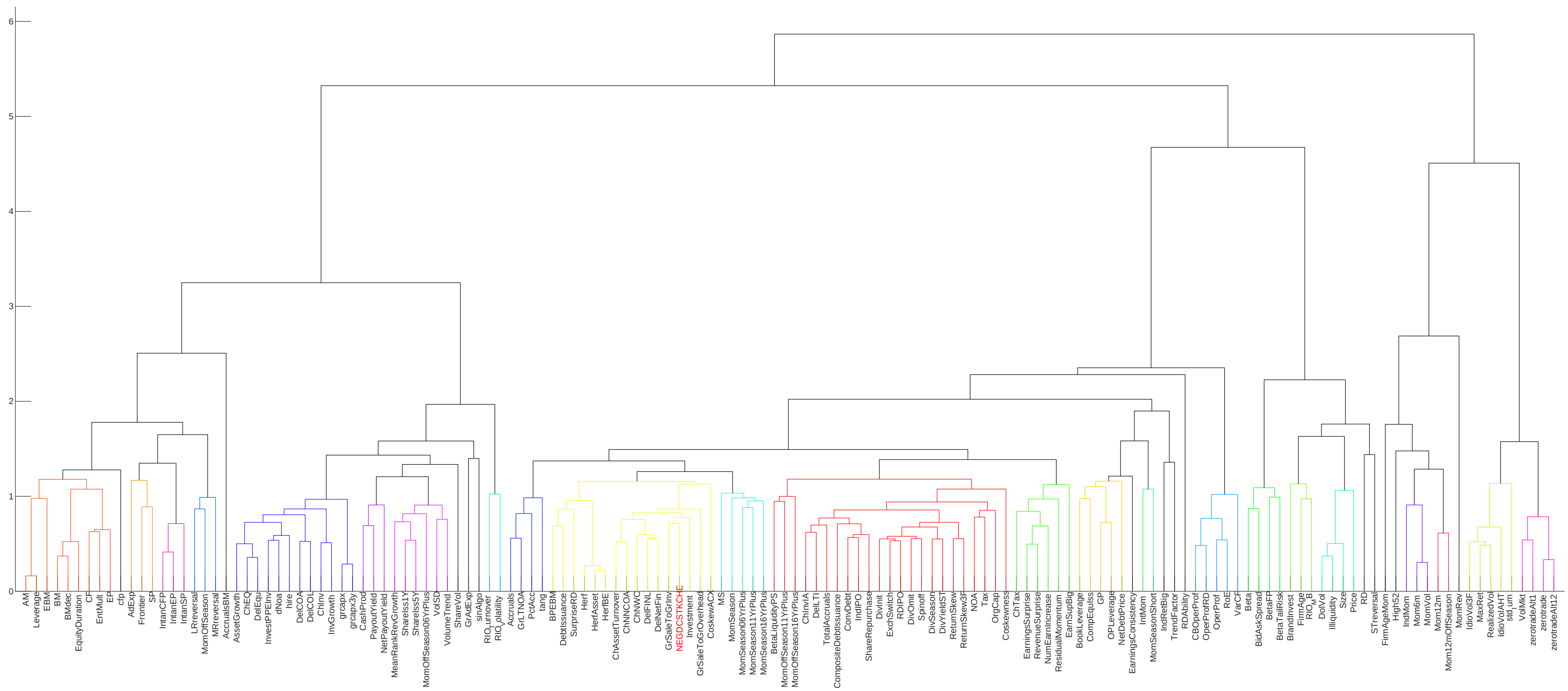

Figure 6: Agglomerative hierarchical cluster plot

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

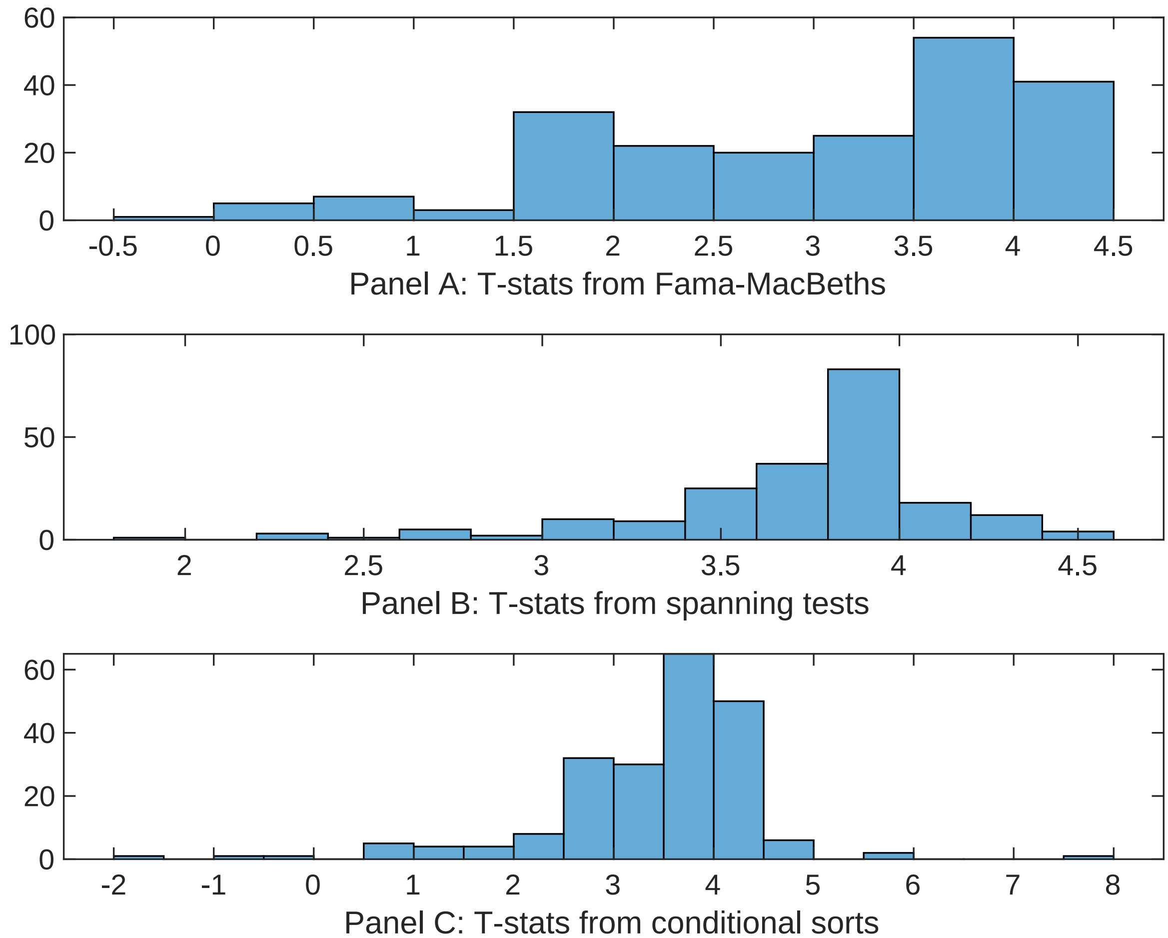

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SCD conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SCD} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SCD} SCD_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{SCD,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 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 210 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on SCD. Stocks are finally grouped into five SCD portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SCD trading strategies conditioned on each of the 210 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on SCD. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SCD} SCD_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Growth in book equity, Share issuance (1 year), Change in equity to assets, Momentum and LT Reversal, Share issuance (5 year), Long-run reversal. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.18	0.13	0.13	0.44	0.13	0.13	0.15
	[7.45]	[5.63]	[5.55]	[1.29]	[6.01]	[5.75]	[3.47]
SCD	0.13	0.17	0.14	0.10	0.18	0.18	0.84
	[2.50]	[3.36]	[2.81]	[0.43]	[3.44]	[3.53]	[0.23]
Anomaly 1	0.52						0.69
	[4.92]						[2.72]
Anomaly 2		0.27					-0.13
		[6.02]					[-0.96]
Anomaly 3			0.16				-0.14
			[4.65]				[-1.82]
Anomaly 4				0.11			0.81
				[4.22]			[2.45]
Anomaly 5					0.39		0.42
					[4.49]		[1.44]
Anomaly 6						0.28	-0.31
						[3.08]	[-0.23]
# months	684	679	684	633	679	679	597
$\bar{R}^2(\%)$	0	0	0	2	0	1	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the SCD trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SCD} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Growth in book equity, Share issuance (1 year), Change in equity to assets, Momentum and LT Reversal, Share issuance (5 year), Long-run reversal. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196606 to 202306.

Intercept	0.24	0.22	0.26	0.22	0.22	0.22	0.21
	[3.02]	[2.74]	[3.17]	[2.62]	[2.65]	[2.67]	[2.66]
Anomaly 1	29.60						25.71
	[6.58]						[3.96]
Anomaly 2		23.64					15.97
		[5.67]					[3.32]
Anomaly 3			17.49				-8.43
			[4.01]				[-1.40]
Anomaly 4				3.49			3.14
				[3.32]			[2.88]
Anomaly 5					14.14		4.76
					[3.28]		[1.04]
Anomaly 6						6.65	-0.00
						[2.74]	[-0.00]
mkt	5.45	6.40	4.21	5.09	6.52	4.42	7.64
	[2.86]	[3.33]	[2.17]	[2.63]	[3.27]	[2.27]	[3.88]
smb	-0.19	2.10	0.53	-0.18	0.33	-1.23	-0.92
	[-0.07]	[0.76]	[0.19]	[-0.06]	[0.12]	[-0.41]	[-0.31]
hml	-6.61	-5.83	-5.35	-3.30	-6.71	-4.55	-9.42
	[-1.78]	[-1.56]	[-1.42]	[-0.88]	[-1.68]	[-1.18]	[-2.39]
rmw	-7.96	-17.03	-7.78	-7.91	-11.92	-6.28	-13.90
	[-2.14]	[-4.28]	[-2.04]	[-2.09]	[-3.07]	[-1.61]	[-3.32]
cma	-5.65	12.87	5.53	21.81	20.05	20.54	-4.85
	[-0.81]	[2.19]	[0.78]	[3.87]	[3.47]	[3.52]	[-0.67]
umd	2.29	2.46	3.13	-0.58	2.86	3.40	-1.16
	[1.21]	[1.30]	[1.62]	[-0.26]	[1.49]	[1.76]	[-0.52]
# months	684	680	684	680	680	680	680
$\bar{R}^2(\%)$	10	10	7	7	7	7	13

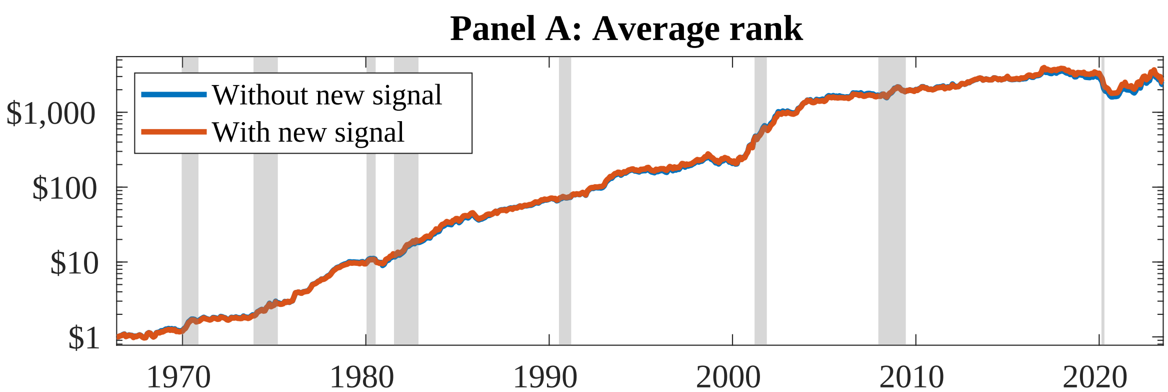

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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