Capital Scale Nonop Diff and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Capital Scale Nonop Diff (CSND), 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 CSND achieves an annualized gross (net) Sharpe ratio of 0.48 (0.40), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 31 (26) bps/month with a t-statistic of 4.16 (3.63), 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, Net Operating Assets, Change in equity to assets, Inventory Growth, change in net operating assets, Book-to-market and accruals) is 24 bps/month with a t-statistic of 3.24.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, making it difficult to systematically earn abnormal returns. However, a growing body of literature documents numerous market anomalies that appear to contradict this notion (Harvey et al., 2016). While many of these anomalies are well-documented, their economic mechanisms often remain poorly understood, and their robustness across different market conditions and methodological specifications is frequently questioned (Hou et al., 2020).

One particularly intriguing area of study involves the relationship between firms' capital allocation decisions and subsequent stock returns. While extensive research has examined how capital investment (Titman et al., 2004) and financing choices (Baker and Wurgler, 2003) affect stock prices, less attention has been paid to how the differential between operating and non-operating capital deployment impacts future returns.

We propose that the Capital Scale Non-operating Difference (CSND) signal captures valuable information about managerial decision-making and resource allocation efficiency. Building on agency theory (Jensen, 1986), we argue that managers face different incentives and constraints when deploying capital toward operating versus non-operating activities. Operating investments typically face greater scrutiny and are more closely tied to core business objectives, while non-operating investments may reflect agency problems or managerial empire-building tendencies.

The theoretical framework of (Stein, 1996) suggests that market participants may have difficulty fully processing complex accounting information, particularly when it requires combining multiple financial statement items. The CSND metric, which captures the difference between operating and non-operating capital deployment, represents exactly such a complex signal. This cognitive processing challenge could lead to systematic mispricing that becomes apparent only gradually as future performance materializes.

Furthermore, following (Richardson, 2006), we hypothesize that the relative scale of operating versus non-operating capital allocation provides a window into management quality and capital discipline. Firms maintaining better alignment between operating and non-operating capital deployment may benefit from more efficient resource allocation and stronger governance mechanisms, leading to superior future performance.

Our empirical analysis reveals that CSND strongly predicts future stock returns. A value-weighted long-short trading strategy based on CSND quintiles generates a monthly alpha of 31 basis points (t-statistic = 4.16) relative to the Fama-French six-factor model. This economic magnitude is substantial, translating to an annualized gross Sharpe ratio of 0.48.

Importantly, the predictive power of CSND remains robust across various methodological specifications. The signal maintains significance when using different portfolio construction approaches, with net returns (accounting for transaction costs) ranging from 16 to 24 basis points per month. The strategy's effectiveness persists even among large-cap stocks, where the monthly alpha ranges from 26 to 31 basis points with t-statistics between 2.77 and 3.38.

Further analysis demonstrates that CSND's predictive ability cannot be explained by known factors or closely related anomalies. Controlling for the six most closely related anomalies and the Fama-French six factors simultaneously, the CSND strategy still achieves an alpha of 24 basis points per month (t-statistic = 3.24), indicating its unique contribution to return prediction.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel signal that captures previously unexplored aspects of firms' capital allocation decisions. While prior work has examined various aspects of investment efficiency (Titman et al., 2004) and capital structure (Baker and Wurgler, 2003), CSND uniquely focuses on the relative scale of operating versus non-operating capital deployment.

Second, we extend the literature on investment-based asset pricing by demonstrating that the differential between operating and non-operating capital allocation contains important information about future returns. Our findings complement existing work on investment anomalies (Cooper et al., 2008) while highlighting a distinct mechanism through which capital allocation decisions affect firm value.

Finally, our results have important implications for both academic research and investment practice. For researchers, we provide new evidence on the links between corporate finance decisions and asset prices. For practitioners, CSND represents a robust signal that maintains its predictive power even after accounting for transaction costs and performs well across different size segments of the market.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the difference in invested capital scaled by non-operating income. 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 ICAPT for invested capital and item NOPIO for non-operating income. Invested capital (ICAPT) represents the total investment in the company by both shareholders and debtholders, including both operating and non-operating assets. Non-operating income (NOPIO) captures income derived from activities outside the company's core operations, such as interest income, dividend income, and other non-operating gains or losses. The construction of the signal follows a difference-in-time format, where we calculate the change in ICAPT from one period to the next and scale this difference by the previous period's

NOPIO. This scaled difference captures the relative change in a firm's total investment base relative to its non-operating income, potentially offering insight into how efficiently the firm deploys new capital in relation to its non-core income streams. By focusing on this relationship, the signal aims to reflect aspects of capital allocation efficiency and non-operating performance in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both ICAPT and NOPIO to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the CSND signal. Panel A plots the time-series of the mean, median, and interquartile range for CSND. On average, the cross-sectional mean (median) CSND is -13.75 (-3.47) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input CSND data. The signal's interquartile range spans -41.43 to 29.97. Panel B of Figure 1 plots the time-series of the coverage of the CSND signal for the CRSP universe. On average, the CSND signal is available for 4.87% of CRSP names, which on average make up 6.78% of total market capitalization.

4 Does CSND predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on CSND 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 CSND portfolio and sells the low CSND 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 CSND strategy earns an average return of 0.26% per month with a t-statistic of 3.70. The annualized Sharpe ratio of the strategy is 0.48. The alphas range from 0.27% to 0.31% per month and have t-statistics exceeding 3.71 everywhere. The lowest alpha is with respect to the FF3 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 -0.14, with a t-statistic of -3.97 on the RMW 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 452 stocks and an average market capitalization of at least $1,427 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 20 bps/month with a t-statistics of 2.94. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty-four 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 16-24bps/month. The lowest return, (16 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.36. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the CSND 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-three cases.

Table 3 provides direct tests for the role size plays in the CSND strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and CSND, as well as average returns and alphas for long/short trading CSND strategies within each size quintile. Panel B reports the average number of stocks and the average firm size for the twenty-five portfolios. Among the largest stocks (those with market capitalization greater than the 80$^{\text{th}}$ NYSE percentile), the CSND strategy achieves an average return of 23 bps/month with a t-statistic of 2.55. Among these large cap stocks, the alphas for the CSND strategy relative to the five most common factor models range from 26 to 31 bps/month with t-statistics between 2.77 and 3.38.

5 How does CSND perform relative to the zoo?

Figure 2 puts the performance of CSND 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 CSND strategy falls in the distribution. The CSND strategy's gross (net) Sharpe ratio of 0.48 (0.40) is greater than 91% (96%) 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 CSND strategy (red line).[2] Ignoring trading costs, a $1 invested in the CSND strategy would have yielded $4.94 which ranks the CSND strategy in the top 6% across the 212 anomalies. Accounting for trading costs, a $1 invested in the CSND strategy would have yielded $3.33 which ranks the CSND strategy in the top 4% 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 CSND relative to those. Panel A shows that the CSND strategy gross alphas fall between the 55 and 81 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 196506 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 CSND strategy has a positive net generalized alpha for five out of the five factor models. In these cases CSND ranks between the 77 and 93 percentiles in terms of how much it could have expanded the achievable investment frontier.

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

A closely related anomaly is also more likely to price CSND or at least to weaken the power CSND has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of CSND conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CSND} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CSND} CSND_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{CSND,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts,

[3] When performing tests at the underlying signal level (e.g., the correlations plotted in Figure 5), we filter the 212 anomalies to avoid small sample issues. For each anomaly, we calculate the common stock observations in an average month for which both the anomaly and the test signal are available. In the filtered anomaly set, we drop anomalies with fewer than 100 common stock observations in an average month.

value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on CSND. Stocks are finally grouped into five CSND portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CSND trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on CSND 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 CSND signal in these Fama-MacBeth regressions exceed 1.19, with the minimum t-statistic occurring when controlling for Book-to-market and accruals. Controlling for all six closely related anomalies, the t-statistic on CSND is 0.61.

Similarly, Table 5 reports results from spanning tests that regress returns to the CSND 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 CSND strategy earns alphas that range from 28-32bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 3.80, which is achieved when controlling for Book-to-market and accruals. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the CSND trading strategy achieves an alpha of 24bps/month with a t-statistic of 3.24.

7 Does CSND add relative to the whole zoo?

Finally, we can ask how much adding CSND 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 CSND 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 $3027.42, while $1 investment in the combination strategy that includes CSND grows to $3270.71.

[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 CSND is available.

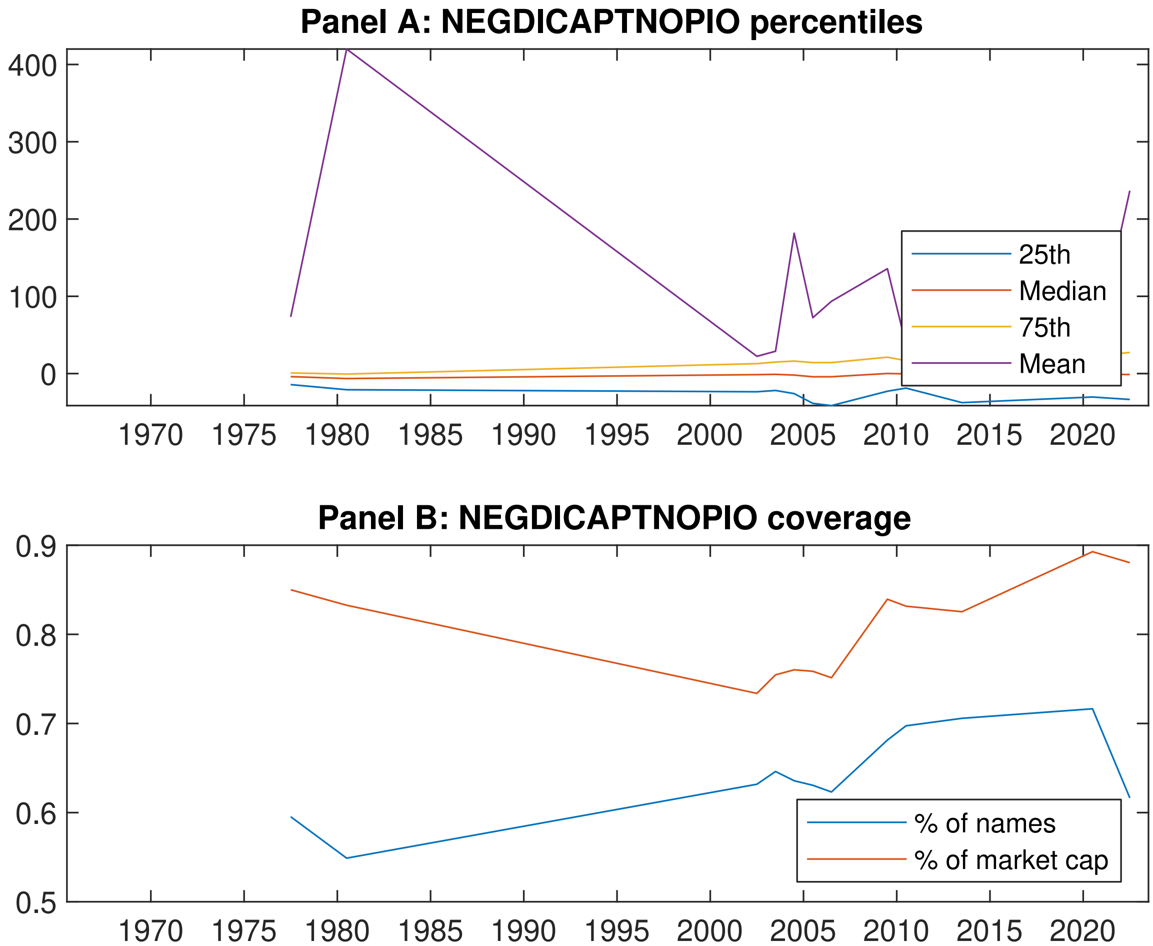

Figure 1: Times series of CSND percentiles and coverage.
This figure plots descriptive statistics for CSND. Panel A shows cross-sectional percentiles of CSND over the sample. Panel B plots the monthly coverage of CSND relative to the universe of CRSP stocks with available market capitalizations.

Table 1: Basic sort: VW, quintile, NYSE-breaks
This table reports average excess returns and alphas for portfolios sorted on CSND. 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 196506 to 202306.

Panel A: Excess returns and alphas on CSND-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.45	0.55	0.54	0.65	0.71	0.26
	[2.29]	[3.12]	[3.46]	[3.90]	[3.72]	[3.70]
α_{CAPM}	-0.17	-0.01	0.06	0.13	0.11	0.28
	[-3.65]	[-0.14]	[1.13]	[2.49]	[2.01]	[3.98]
α_{FF3}	-0.13	0.04	0.04	0.10	0.15	0.27
	[-2.88]	[0.79]	[0.86]	[2.04]	[2.73]	[3.78]
α_{FF4}	-0.11	0.05	0.03	0.08	0.16	0.27
	[-2.50]	[1.13]	[0.63]	[1.58]	[2.94]	[3.71]
α_{FF5}	-0.11	0.05	-0.04	-0.01	0.20	0.31
	[-2.52]	[0.99]	[-0.98]	[-0.33]	[3.62]	[4.24]
α_{FF6}	-0.10	0.06	-0.04	-0.02	0.21	0.31
	[-2.28]	[1.22]	[-0.98]	[-0.41]	[3.72]	[4.16]
Panel B: Fama and French (2018) 6-factor model loadings for CSND-sorted portfolios						
β_{MKT}	1.05	0.98	0.93	1.00	1.01	-0.04
	[99.27]	[90.17]	[85.54]	[91.75]	[77.10]	[-2.07]
β_{SMB}	0.08	-0.07	-0.11	-0.10	0.06	-0.02
	[5.02]	[-4.31]	[-6.85]	[-6.12]	[3.15]	[-0.66]
β_{HML}	-0.10	-0.04	0.01	-0.07	-0.10	0.01
	[-5.19]	[-2.09]	[0.36]	[-3.29]	[-3.92]	[0.19]
β_{RMW}	0.04	0.05	0.12	0.06	-0.10	-0.14
	[1.88]	[2.19]	[5.54]	[2.91]	[-3.78]	[-3.97]
β_{CMA}	-0.12	-0.12	0.19	0.44	-0.06	0.06
	[-4.00]	[-3.85]	[6.10]	[14.24]	[-1.72]	[1.12]
β_{UMD}	-0.01	-0.02	0.00	0.01	-0.01	0.00
	[-1.31]	[-1.52]	[0.06]	[0.54]	[-0.89]	[0.12]
Panel C: Average number of firms (n) and market capitalization (me)						
n	564	465	452	500	599	
me ($\$10^6$)	1478	1699	2145	1551	1427	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the CSND 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 196506 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	0.26	0.28	0.27	0.27	0.31	0.31
			[3.70]	[3.98]	[3.78]	[3.71]	[4.24]	[4.16]
Quintile	NYSE	EW	0.40	0.41	0.37	0.33	0.35	0.33
			[7.43]	[7.48]	[7.22]	[6.44]	[6.97]	[6.41]
Quintile	Name	VW	0.26	0.28	0.28	0.28	0.33	0.33
			[3.51]	[3.77]	[3.74]	[3.64]	[4.29]	[4.17]
Quintile	Cap	VW	0.20	0.24	0.23	0.20	0.26	0.23
			[2.94]	[3.53]	[3.31]	[2.89]	[3.70]	[3.35]
Decile	NYSE	VW	0.30	0.32	0.33	0.31	0.36	0.34
			[3.27]	[3.52]	[3.63]	[3.31]	[3.87]	[3.61]
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	0.22	0.25	0.23	0.24	0.26	0.26
			[3.05]	[3.44]	[3.25]	[3.24]	[3.64]	[3.63]
Quintile	NYSE	EW	0.19	0.20	0.16	0.14	0.12	0.11
			[2.96]	[3.08]	[2.57]	[2.32]	[1.96]	[1.81]
Quintile	Name	VW	0.22	0.25	0.24	0.24	0.28	0.28
			[2.88]	[3.24]	[3.21]	[3.18]	[3.67]	[3.63]
Quintile	Cap	VW	0.16	0.21	0.19	0.18	0.22	0.21
			[2.36]	[3.03]	[2.82]	[2.60]	[3.19]	[3.03]
Decile	NYSE	VW	0.24	0.28	0.29	0.28	0.31	0.30
			[2.68]	[3.07]	[3.16]	[2.99]	[3.35]	[3.20]

Table 3: Conditional sort on size and CSND

This table presents results for conditional double sorts on size and CSND. 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 CSND. 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 CSND and short stocks with low CSND .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196506 to 202306.

Panel A: portfolio average returns and time-series regression results

	CSND Quintiles					CSND Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.49	0.85	0.91	0.97	0.80	0.31	0.30	0.28	0.22	0.28	0.22
	[1.86]	[3.34]	[3.66]	[3.63]	[2.94]	[3.90]	[3.73]	[3.53]	[2.69]	[3.33]	[2.68]
(2)	0.69	0.70	0.88	0.84	0.90	0.21	0.22	0.20	0.24	0.22	0.26
	[2.77]	[3.00]	[3.77]	[3.66]	[3.66]	[2.30]	[2.45]	[2.20]	[2.63]	[2.38]	[2.74]
(3)	0.62	0.74	0.75	0.83	0.89	0.27	0.28	0.24	0.22	0.20	0.19
	[2.78]	[3.43]	[3.65]	[4.07]	[3.97]	[3.27]	[3.30]	[2.92]	[2.59]	[2.36]	[2.19]
(4)	0.61	0.64	0.68	0.72	0.84	0.23	0.23	0.19	0.17	0.16	0.15
	[2.88]	[3.35]	[3.56]	[3.74]	[3.96]	[3.13]	[3.08]	[2.48]	[2.20]	[2.13]	[1.96]
(5)	0.38	0.48	0.53	0.66	0.61	0.23	0.27	0.27	0.26	0.31	0.30
	[1.97]	[2.68]	[3.38]	[4.06]	[3.35]	[2.55]	[3.04]	[2.93]	[2.77]	[3.38]	[3.23]

Panel B: Portfolio average number of firms and market capitalization

	CSND Quintiles					CSND Quintiles				
	Average n					Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	267	268	268	265	263	24	24	22	21	22
(2)	81	81	81	80	80	42	42	43	42	43
(3)	62	62	62	62	62	77	77	76	77	77
(4)	55	55	55	55	55	179	173	178	174	175
(5)	52	52	52	52	52	1072	1242	1783	1437	1179

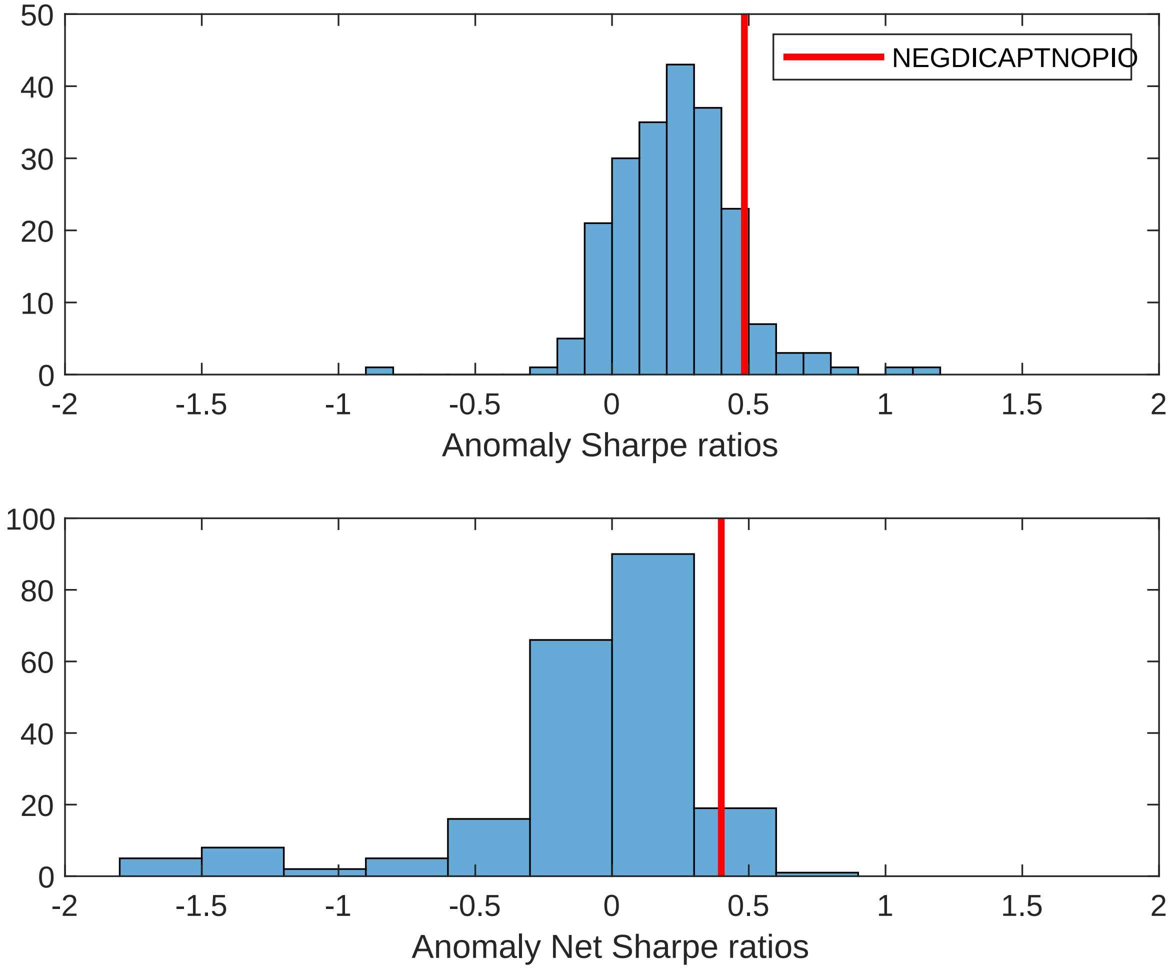

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CSND with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

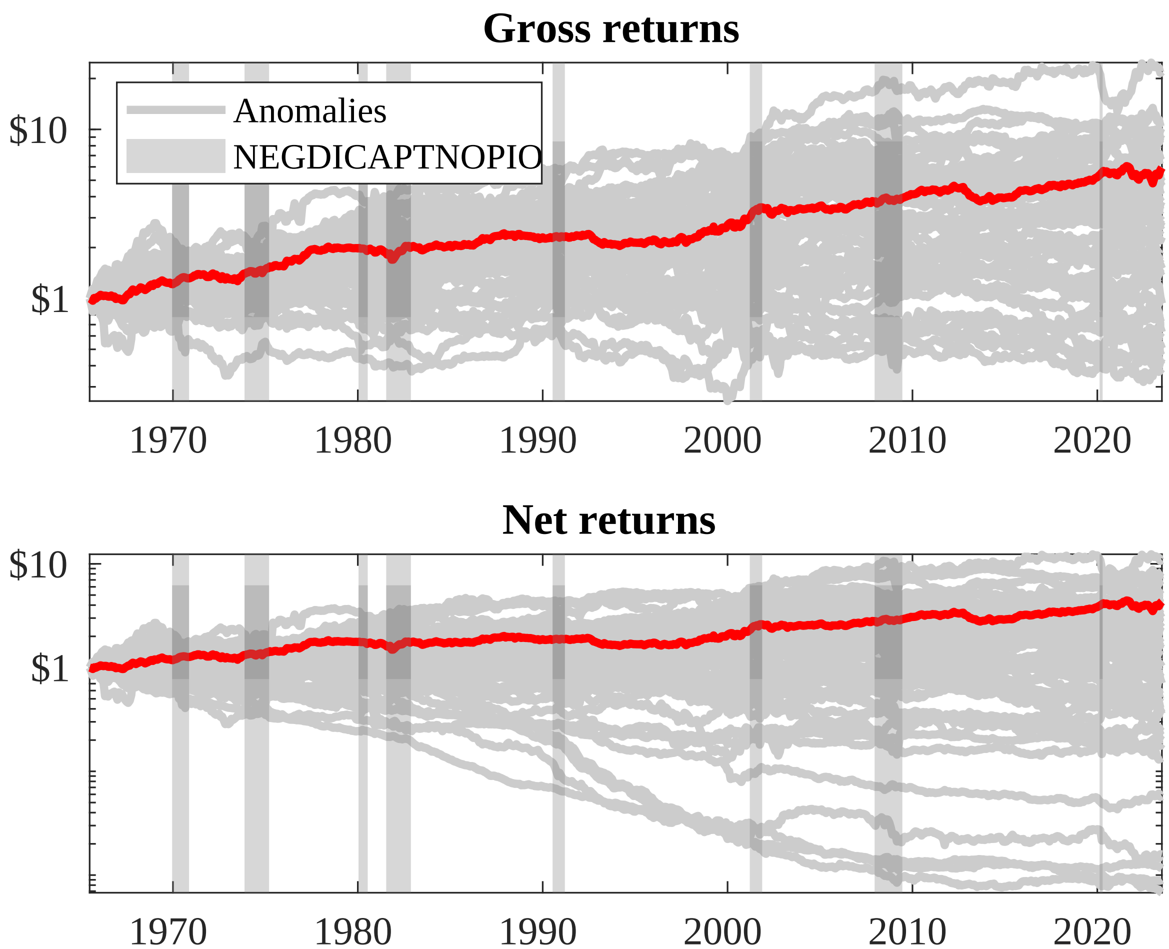

Figure 3: Dollar invested.
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CSND trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for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

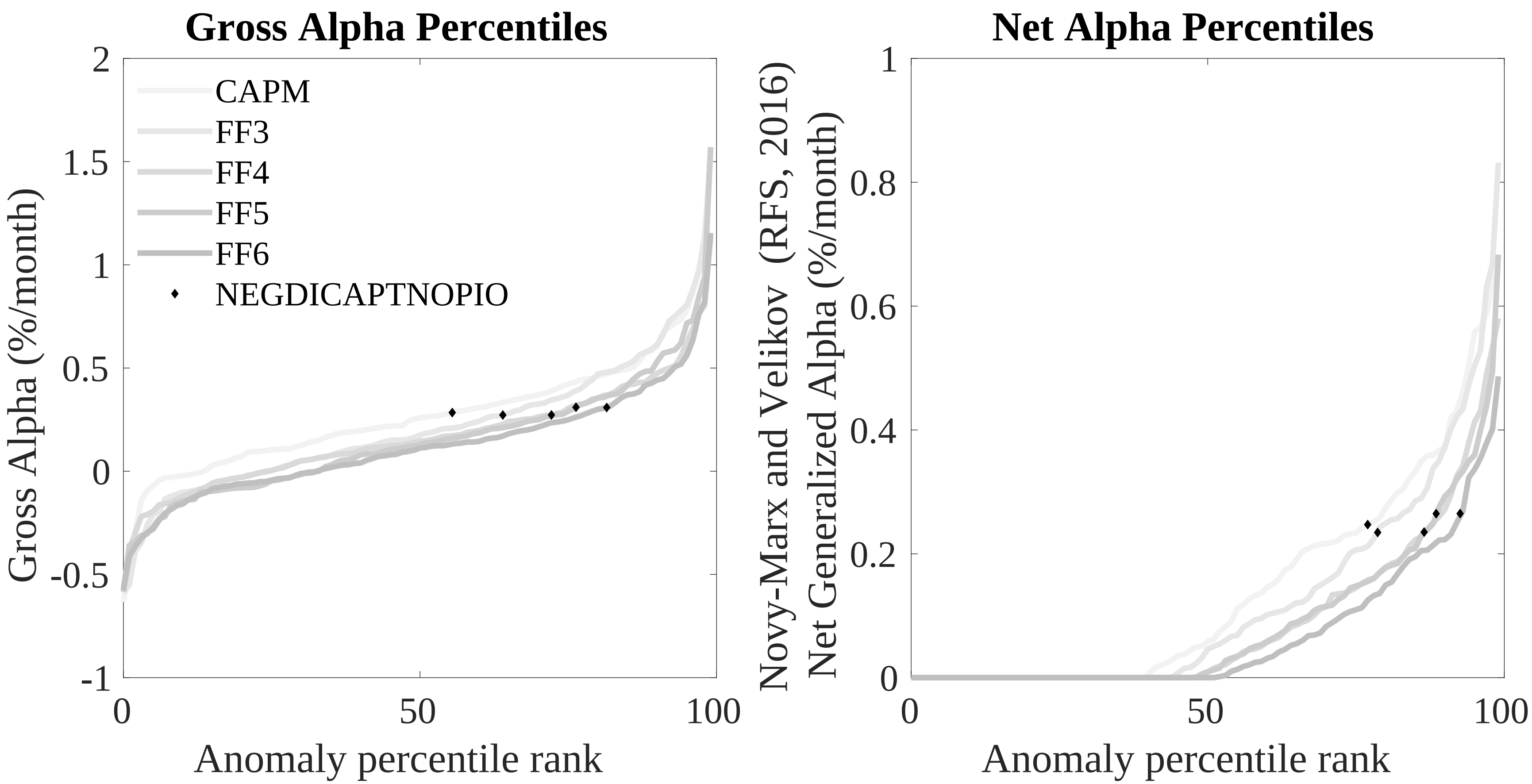

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CSND trading strategy alphas (diamonds). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. The alphas include those with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). The left panel plots alphas with no adjustment for trading costs. The right panel plots Novy-Marx and Velikov (2016) net generalized alphas.

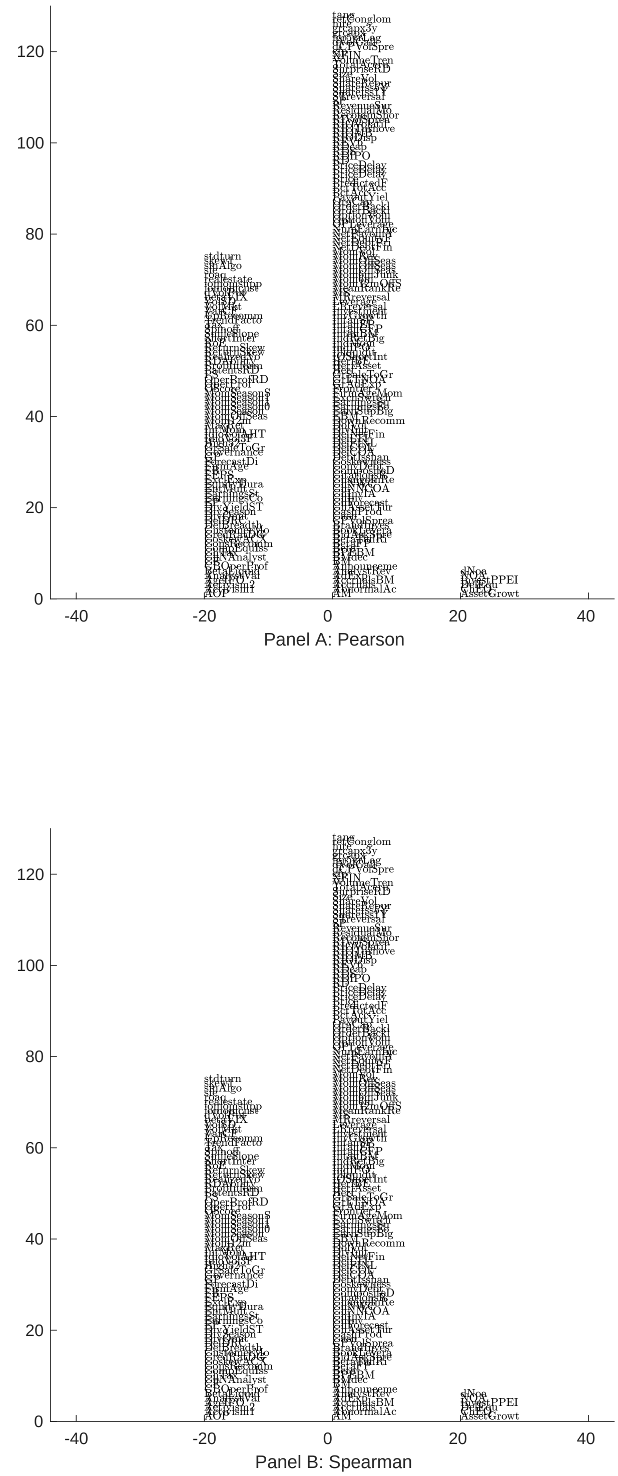

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with CSND. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

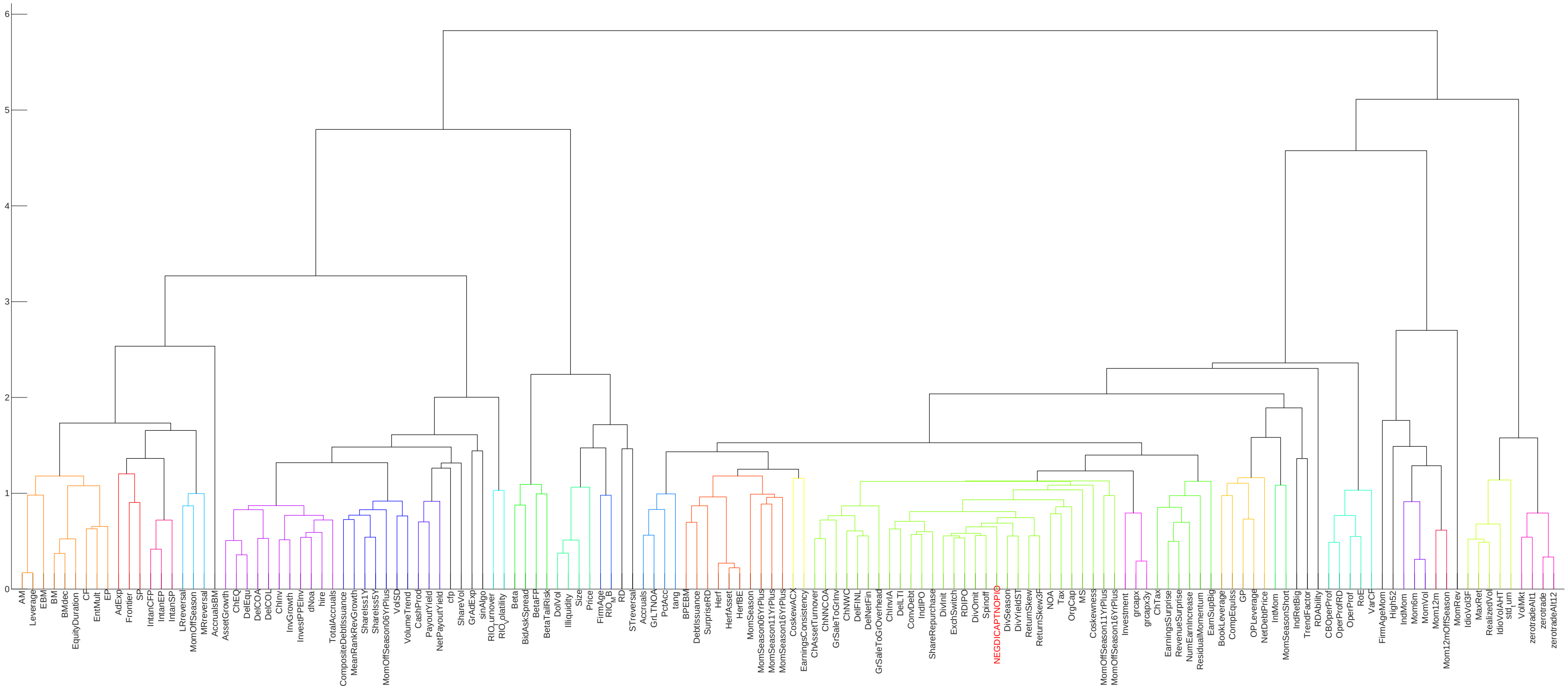

Figure 6: Agglomerative hierarchical cluster plot

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

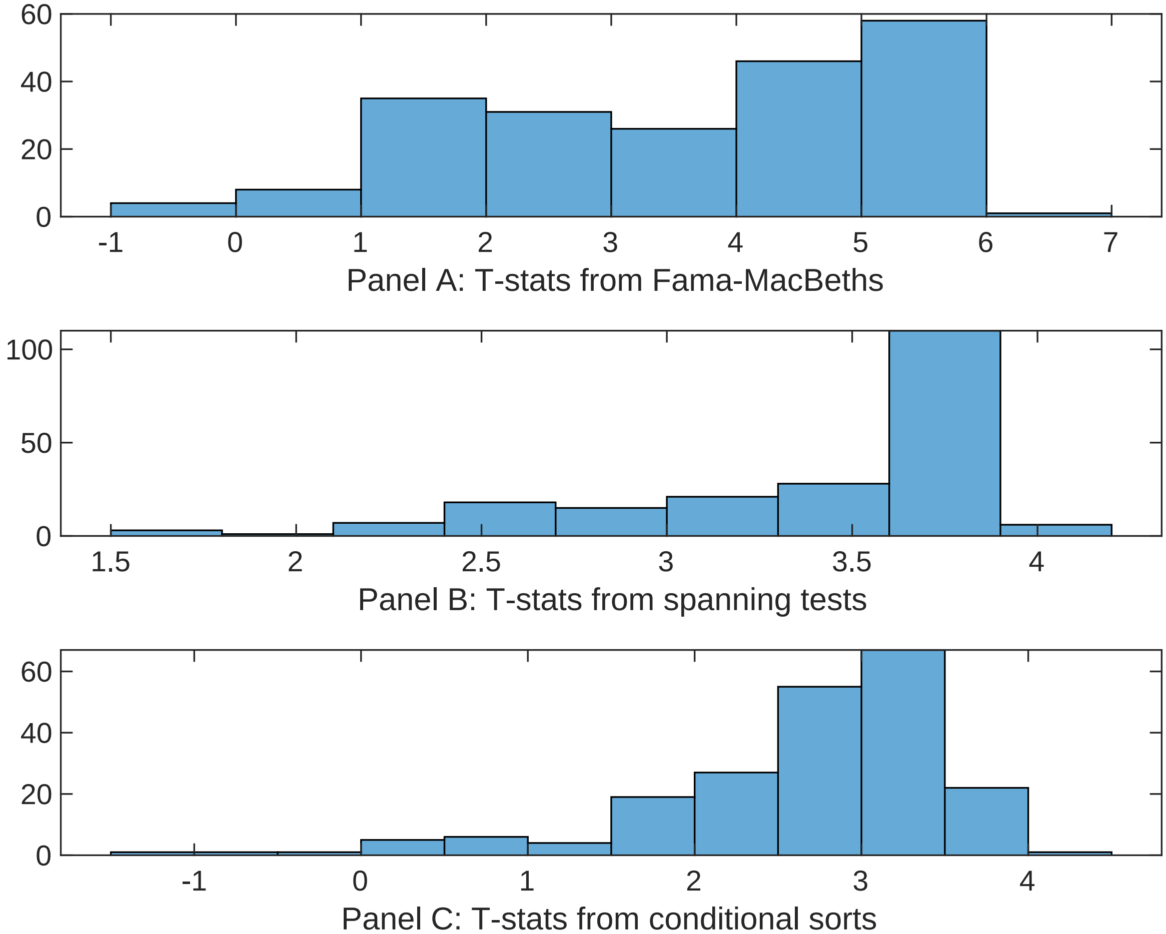

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of CSND conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{CSND} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{CSND} CSND_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{CSND,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 209 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on CSND. Stocks are finally grouped into five CSND portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted CSND trading strategies conditioned on each of the 209 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on CSND. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{CSND} CSND_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Growth in book equity, Net Operating Assets, Change in equity to assets, Inventory Growth, change in net operating assets, Book-to-market and accruals. 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 196506 to 202306.

Intercept	0.17	0.18	0.12	0.12	0.13	0.69	0.12
	[7.04]	[6.94]	[5.51]	[5.45]	[5.80]	[2.33]	[3.06]
CSND	0.38	0.26	0.36	0.39	0.16	0.36	0.19
	[4.27]	[3.06]	[4.09]	[4.30]	[1.89]	[1.19]	[0.61]
Anomaly 1	0.45						-0.14
	[4.04]						[-0.59]
Anomaly 2		0.86					0.49
		[6.93]					[1.66]
Anomaly 3			0.15				0.75
			[4.09]				[0.92]
Anomaly 4				0.30			0.12
				[5.48]			[1.01]
Anomaly 5					0.13		0.90
					[9.15]		[2.11]
Anomaly 6						0.16	0.11
						[6.78]	[4.29]
# months	696	696	696	696	696	619	619
$\bar{R}^2(\%)$	0	0	0	0	0	1	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the CSND trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{CSND} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Net Operating Assets, Change in equity to assets, Inventory Growth, change in net operating assets, Book-to-market and accruals. 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 196506 to 202306.

Intercept	0.32	0.29	0.32	0.30	0.31	0.28	0.24
	[4.30]	[3.93]	[4.34]	[4.04]	[4.21]	[3.80]	[3.24]
Anomaly 1	17.46						27.03
	[4.28]						[4.72]
Anomaly 2		11.25					10.98
		[3.61]					[3.50]
Anomaly 3			5.33				-14.87
			[1.36]				[-2.70]
Anomaly 4				10.09			5.66
				[2.70]			[1.48]
Anomaly 5					4.35		-3.33
					[1.01]		[-0.73]
Anomaly 6						2.02	1.61
						[1.89]	[1.51]
mkt	-2.69	-3.63	-3.34	-3.00	-3.24	-3.19	-2.29
	[-1.55]	[-2.08]	[-1.90]	[-1.72]	[-1.85]	[-1.84]	[-1.33]
smb	-2.48	0.01	-1.93	-0.58	-1.74	-2.41	-0.60
	[-0.99]	[0.01]	[-0.76]	[-0.22]	[-0.69]	[-0.95]	[-0.23]
hml	-0.59	-1.33	0.88	0.89	1.24	-0.16	-4.29
	[-0.17]	[-0.39]	[0.26]	[0.27]	[0.37]	[-0.05]	[-1.23]
rmw	-13.49	-15.45	-13.92	-12.63	-14.34	-12.81	-13.11
	[-3.98]	[-4.54]	[-4.04]	[-3.64]	[-4.19]	[-3.74]	[-3.82]
cma	-12.50	4.34	-0.80	-1.86	1.43	6.24	-6.38
	[-1.97]	[0.88]	[-0.12]	[-0.34]	[0.24]	[1.25]	[-0.92]
umd	0.19	-0.01	0.54	-0.24	0.27	2.06	0.33
	[0.11]	[-0.01]	[0.31]	[-0.14]	[0.16]	[1.10]	[0.18]
# months	696	696	696	696	696	692	692
$\bar{R}^2(\%)$	5	5	3	4	3	4	9

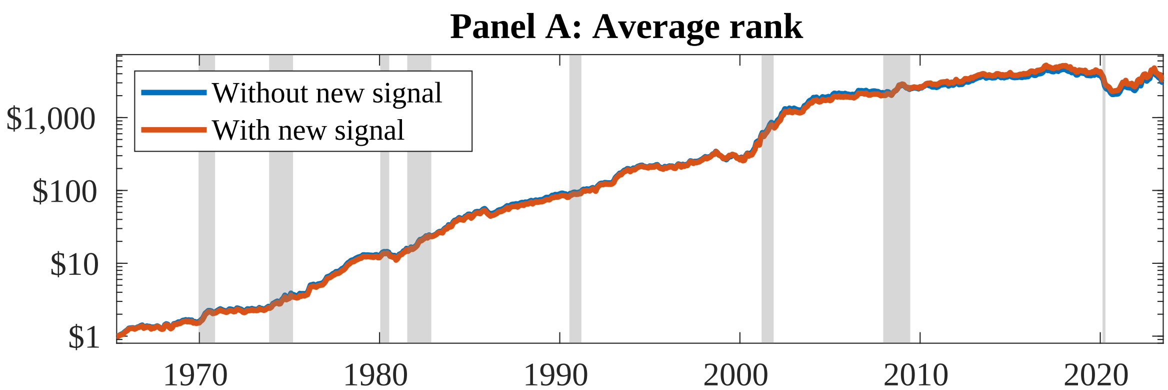

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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