

# Capital Scale Nonop Diff and the Cross Section of Stock Returns

I. M. Harking

December 1, 2024

## 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 unclear, 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 important 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 between operating and non-operating uses. Operating investments typically face greater scrutiny and are more closely tied to core business activities, while non-operating investments may reflect empire-building tendencies or inefficient cash deployment.

The theoretical framework of (Stein, 1996) suggests that market participants may have difficulty fully processing complex information about firms' capital allocation decisions. When managers deviate significantly from optimal capital deployment patterns by creating large disparities between operating and non-operating capital scale, this may signal potential agency problems or deteriorating investment opportunities that are not immediately reflected in stock prices (?).

This incomplete market response creates a predictable pattern in returns as information about the implications of capital allocation decisions is gradually incorporated into prices. Consistent with (Zhang, 2005), we expect firms with extreme CSND values to underperform as the market eventually recognizes and prices the inefficiencies in their capital deployment.

Our empirical analysis reveals that CSND strongly predicts future stock returns. A value-weighted long-short trading strategy based on CSND quintiles generates monthly abnormal returns of 31 basis points ( $t$ -statistic = 4.16) relative to the Fama-French five-factor model plus momentum. The strategy’s economic significance is substantial, achieving an annualized gross Sharpe ratio of 0.48.

Importantly, CSND’s predictive power remains robust after controlling for transaction costs. The strategy delivers net abnormal returns of 26 basis points per month ( $t$ -statistic = 3.63) and a net Sharpe ratio of 0.40. These results place CSND in the top 4% of documented anomalies in terms of net performance.

The signal’s predictive power persists across different size segments, with significant abnormal returns even among the largest stocks. In the top size quintile, the CSND strategy generates monthly alphas between 26 and 31 basis points ( $t$ -statistics ranging from 2.77 to 3.38) across various factor models, suggesting that the anomaly is not limited to small, illiquid stocks.

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 aggregate investment (Titman et al., 2004) and financing choices (Baker and Wurgler, 2003), we are the first to show that the differential between operating and non-operating capital scale contains significant predictive information.

Second, we extend the literature on investment-based anomalies by demonstrating that CSND’s predictive power is distinct from related phenomena. Our results remain

robust after controlling for established investment factors (Fama and French, 2015), accruals (Sloan, 1996), and net operating assets (Hirshleifer et al., 2004). The signal’s alpha of 24 basis points per month (t-statistic = 3.24) when controlling for six related anomalies indicates that CSND captures unique information.

Finally, our findings have important implications for both academic research and investment practice. For researchers, we provide new evidence on how market inefficiencies in processing complex corporate decisions can create predictable return patterns. For practitioners, we document a robust anomaly that remains profitable after transaction costs and is implementable even among large-cap stocks.

## 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 stockholders and debtholders, including both operating and non-operating assets. Non-operating income (NOPIO) captures income or expenses that are not directly related to the company’s core operations. The construction of the signal follows a difference-in-time approach, 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-core income, potentially offering insight into how efficiently the firm deploys new capital in relation to its non-operating activities. By focusing on this relationship, the signal aims to reflect aspects of cap-

ital allocation and non-operational financial management 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 portfolio 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<sup>th</sup> 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.<sup>1</sup> 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).<sup>2</sup> 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% (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

---

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

<sup>2</sup>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.



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.<sup>3</sup> 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  $\beta_{CSND}$  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  $\alpha$  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. Then, within each quintile, we sort stocks into quintiles based on CSND. Stocks are finally grouped into

---

<sup>3</sup>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.

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?

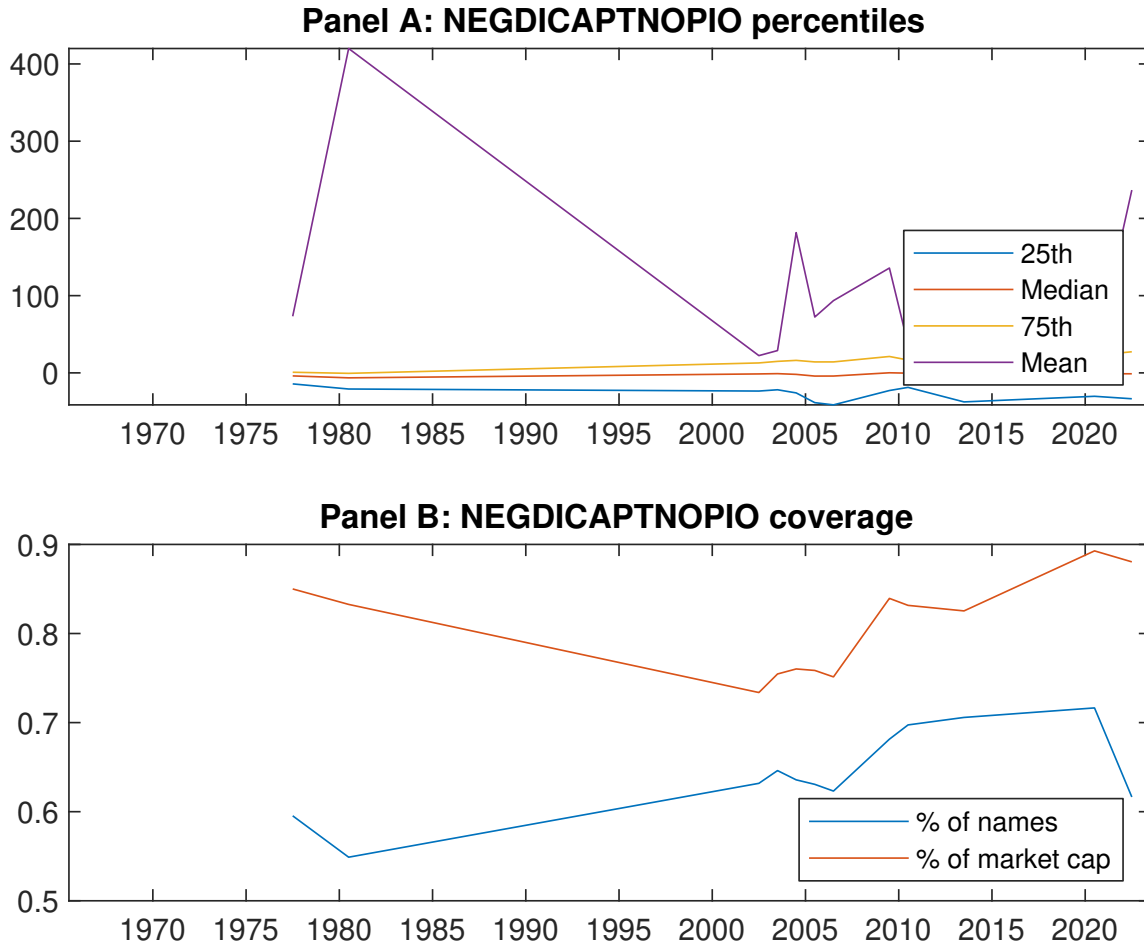
Finally, we can ask how much adding CSND to the entire factor zoo could improve investment performance. Figure 8 plots the growth of \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). The combinations use either the 155 anomalies from the zoo that satisfy our inclusion criteria

(blue lines) or these 155 anomalies augmented with the CSND signal.<sup>4</sup> 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.

---

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

**Table 2:** Robustness to sorting methodology & trading costs

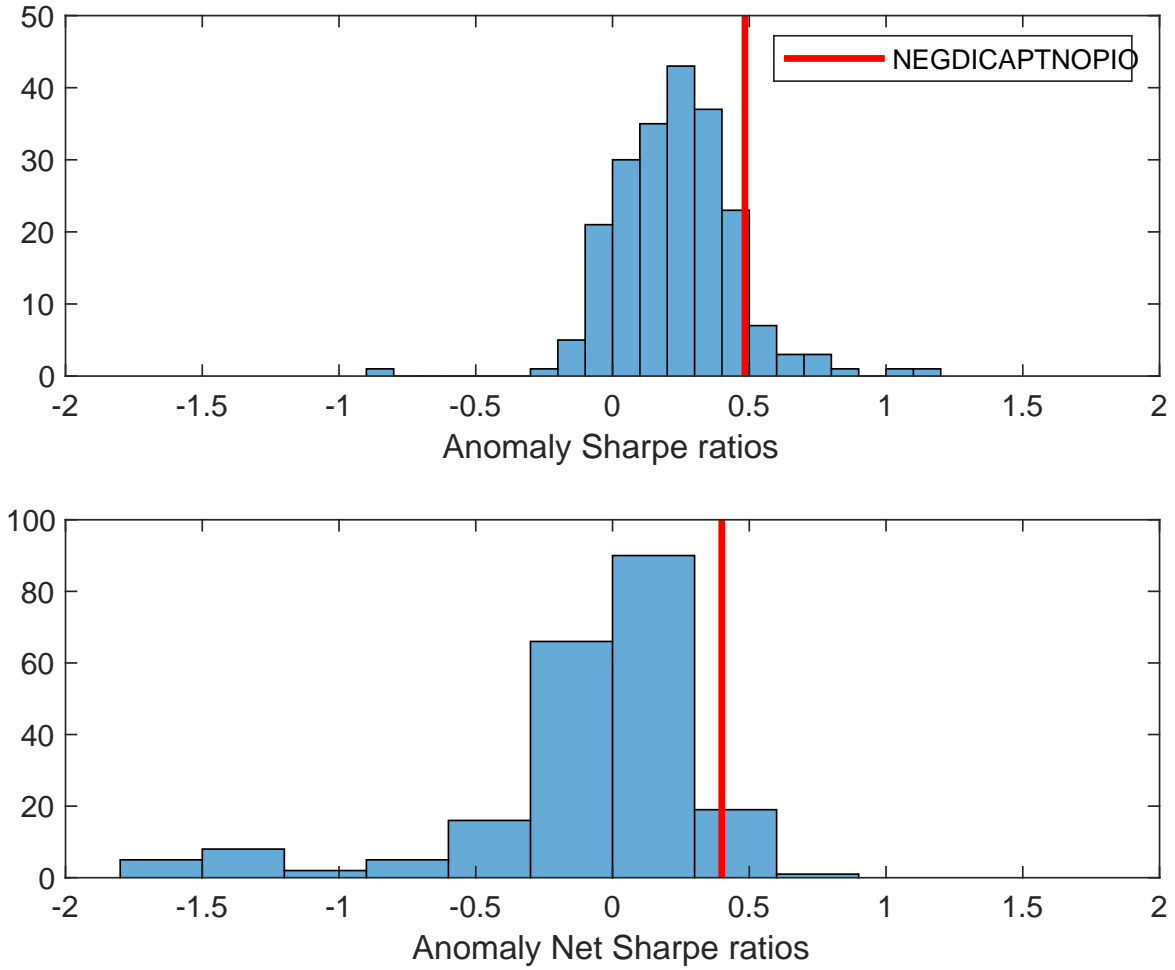
This table evaluates the robustness of the choices made in the CSND strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a 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	$r^e$	$\alpha_{\text{CAPM}}$	$\alpha_{\text{FF3}}$	$\alpha_{\text{FF4}}$	$\alpha_{\text{FF5}}$	$\alpha_{\text{FF6}}$
Quintile	NYSE	VW	0.26 [3.70]	0.28 [3.98]	0.27 [3.78]	0.27 [3.71]	0.31 [4.24]	0.31 [4.16]
Quintile	NYSE	EW	0.40 [7.43]	0.41 [7.48]	0.37 [7.22]	0.33 [6.44]	0.35 [6.97]	0.33 [6.41]
Quintile	Name	VW	0.26 [3.51]	0.28 [3.77]	0.28 [3.74]	0.28 [3.64]	0.33 [4.29]	0.33 [4.17]
Quintile	Cap	VW	0.20 [2.94]	0.24 [3.53]	0.23 [3.31]	0.20 [2.89]	0.26 [3.70]	0.23 [3.35]
Decile	NYSE	VW	0.30 [3.27]	0.32 [3.52]	0.33 [3.63]	0.31 [3.31]	0.36 [3.87]	0.34 [3.61]
Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	$r_{\text{net}}^e$	$\alpha_{\text{CAPM}}^*$	$\alpha_{\text{FF3}}^*$	$\alpha_{\text{FF4}}^*$	$\alpha_{\text{FF5}}^*$	$\alpha_{\text{FF6}}^*$
Quintile	NYSE	VW	0.22 [3.05]	0.25 [3.44]	0.23 [3.25]	0.24 [3.24]	0.26 [3.64]	0.26 [3.63]
Quintile	NYSE	EW	0.19 [2.96]	0.20 [3.08]	0.16 [2.57]	0.14 [2.32]	0.12 [1.96]	0.11 [1.81]
Quintile	Name	VW	0.22 [2.88]	0.25 [3.24]	0.24 [3.21]	0.24 [3.18]	0.28 [3.67]	0.28 [3.63]
Quintile	Cap	VW	0.16 [2.36]	0.21 [3.03]	0.19 [2.82]	0.18 [2.60]	0.22 [3.19]	0.21 [3.03]
Decile	NYSE	VW	0.24 [2.68]	0.28 [3.07]	0.29 [3.16]	0.28 [2.99]	0.31 [3.35]	0.30 [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.

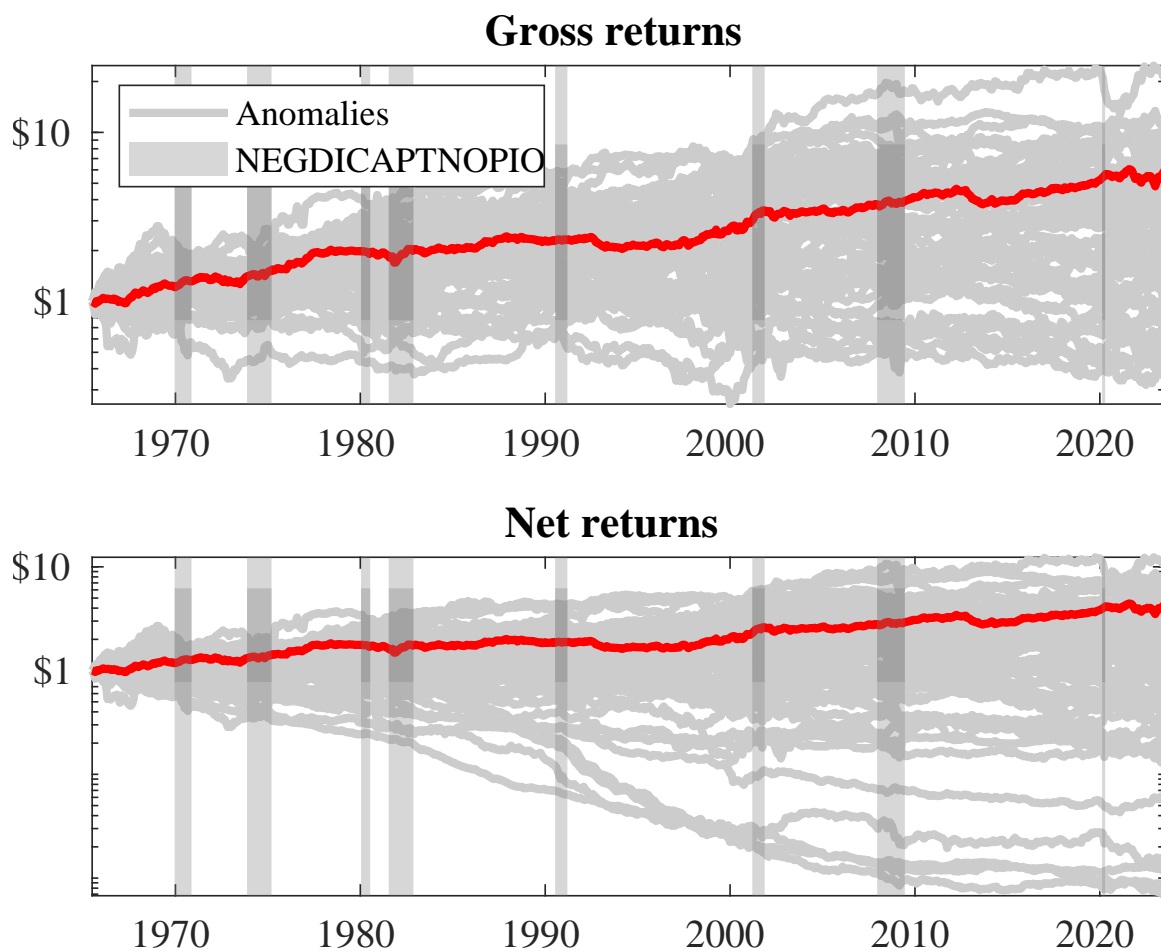
Panel A: portfolio average returns and time-series regression results												
Size quintiles	CSND Quintiles					CSND Strategies						
		(L)	(2)	(3)	(4)	(H)	$r^e$	$\alpha_{CAPM}$	$\alpha_{FF3}$	$\alpha_{FF4}$	$\alpha_{FF5}$	$\alpha_{FF6}$
	(1)	0.49 [1.86]	0.85 [3.34]	0.91 [3.66]	0.97 [3.63]	0.80 [2.94]	0.31 [3.90]	0.30 [3.73]	0.28 [3.53]	0.22 [2.69]	0.28 [3.33]	0.22 [2.68]
	(2)	0.69 [2.77]	0.70 [3.00]	0.88 [3.77]	0.84 [3.66]	0.90 [3.66]	0.21 [2.30]	0.22 [2.45]	0.20 [2.20]	0.24 [2.63]	0.22 [2.38]	0.26 [2.74]
	(3)	0.62 [2.78]	0.74 [3.43]	0.75 [3.65]	0.83 [4.07]	0.89 [3.97]	0.27 [3.27]	0.28 [3.30]	0.24 [2.92]	0.22 [2.59]	0.20 [2.36]	0.19 [2.19]
	(4)	0.61 [2.88]	0.64 [3.35]	0.68 [3.56]	0.72 [3.74]	0.84 [3.96]	0.23 [3.13]	0.23 [3.08]	0.19 [2.48]	0.17 [2.20]	0.16 [2.13]	0.15 [1.96]
	(5)	0.38 [1.97]	0.48 [2.68]	0.53 [3.38]	0.66 [4.06]	0.61 [3.35]	0.23 [2.55]	0.27 [3.04]	0.27 [2.93]	0.26 [2.77]	0.31 [3.38]	0.30 [3.23]
Panel B: Portfolio average number of firms and market capitalization												
Size quintiles	CSND Quintiles					CSND Quintiles						
		Average $n$					Average market capitalization (\$10 <sup>6</sup> )					
		(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.

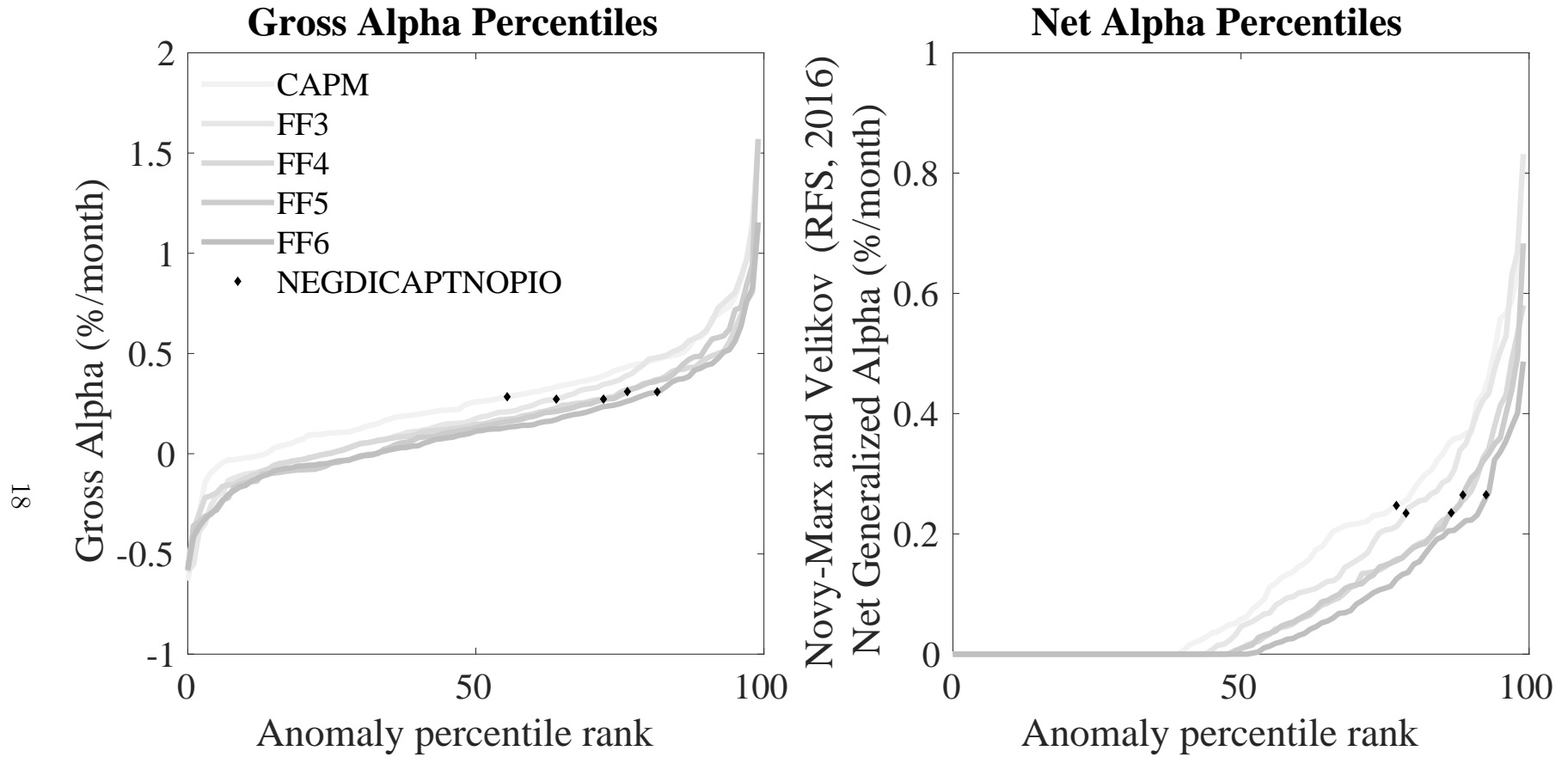
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the CSND with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.





**Figure 3:** Dollar invested.

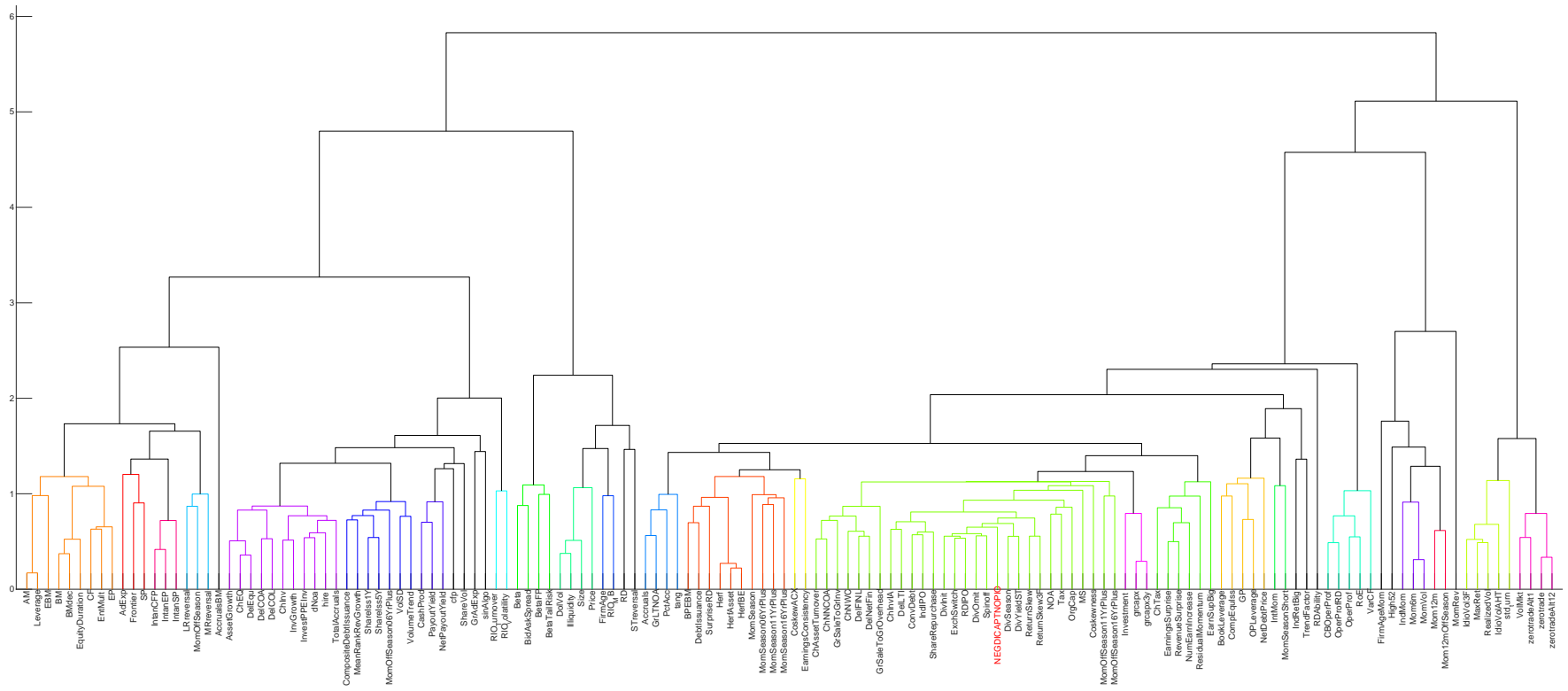
This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the CSND trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross strategy returns. Panel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



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

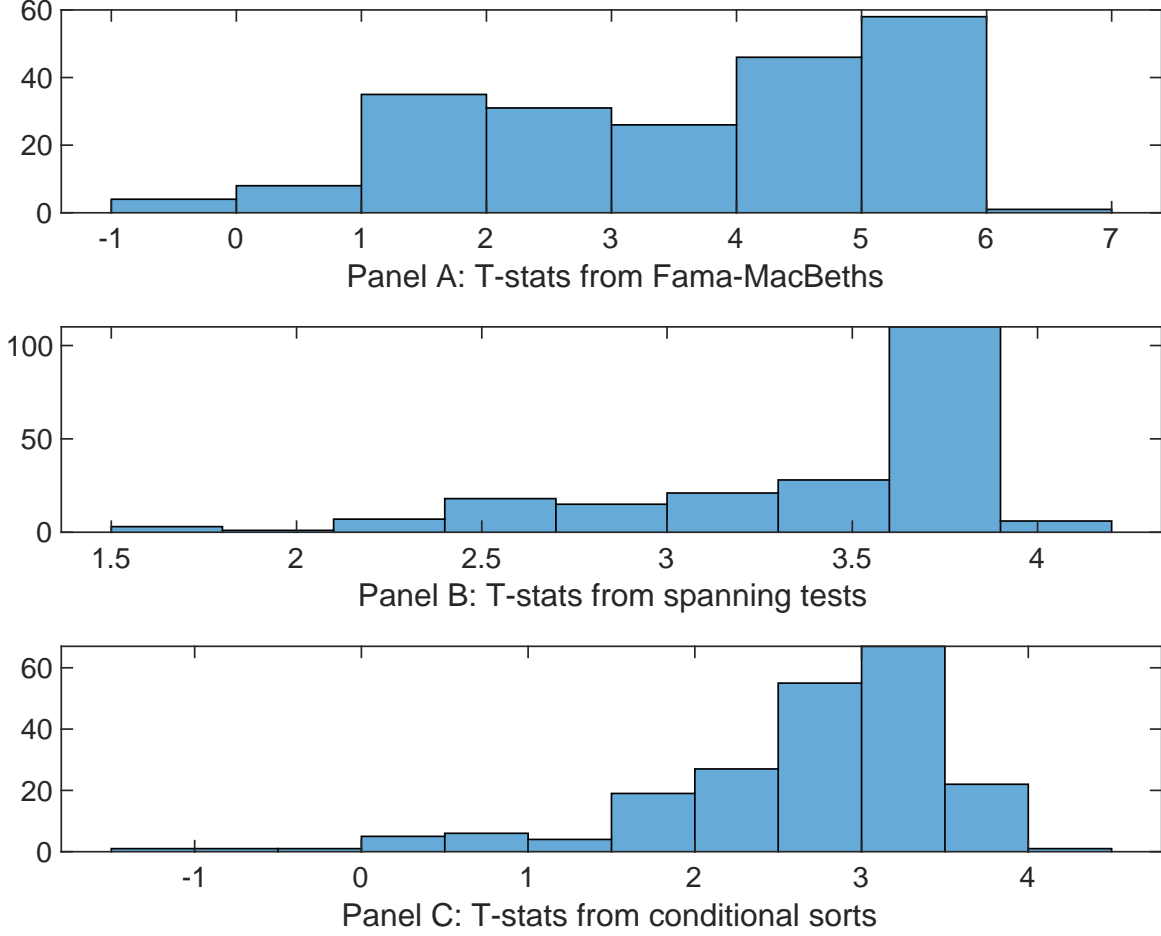
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the CSND trading strategy alphas (diamonds). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. The alphas include those with respect 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 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  $\beta_{CSND}$  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  $\alpha$  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 on 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

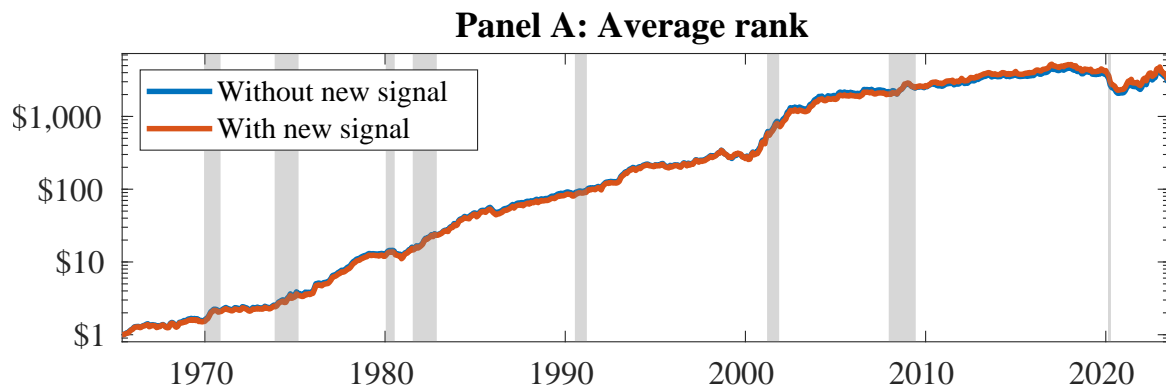
This table presents Fama-MacBeth results of returns on CSND. and the six most closely related anomalies. The regressions take the following form:  $r_{i,t} = \alpha + \beta_{CSND}CSND_{i,t} + \sum_{k=1}^s \beta_{X_k} X_{i,t}^k + \epsilon_{i,t}$ . The six most closely related anomalies,  $X$ , are Growth 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 [7.04]	0.18 [6.94]	0.12 [5.51]	0.12 [5.45]	0.13 [5.80]	0.69 [2.33]	0.12 [3.06]
CSND	0.38 [4.27]	0.26 [3.06]	0.36 [4.09]	0.39 [4.30]	0.16 [1.89]	0.36 [1.19]	0.19 [0.61]
Anomaly 1	0.45 [4.04]						-0.14 [-0.59]
Anomaly 2		0.86 [6.93]					0.49 [1.66]
Anomaly 3			0.15 [4.09]				0.75 [0.92]
Anomaly 4				0.30 [5.48]			0.12 [1.01]
Anomaly 5					0.13 [9.15]		0.90 [2.11]
Anomaly 6						0.16 [6.78]	0.11 [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 [4.30]	0.29 [3.93]	0.32 [4.34]	0.30 [4.04]	0.31 [4.21]	0.28 [3.80]	0.24 [3.24]
Anomaly 1	17.46 [4.28]						27.03 [4.72]
Anomaly 2		11.25 [3.61]					10.98 [3.50]
Anomaly 3			5.33 [1.36]				-14.87 [-2.70]
Anomaly 4				10.09 [2.70]			5.66 [1.48]
Anomaly 5					4.35 [1.01]		-3.33 [-0.73]
Anomaly 6						2.02 [1.89]	1.61 [1.51]
mkt	-2.69 [-1.55]	-3.63 [-2.08]	-3.34 [-1.90]	-3.00 [-1.72]	-3.24 [-1.85]	-3.19 [-1.84]	-2.29 [-1.33]
smb	-2.48 [-0.99]	0.01 [0.01]	-1.93 [-0.76]	-0.58 [-0.22]	-1.74 [-0.69]	-2.41 [-0.95]	-0.60 [-0.23]
hml	-0.59 [-0.17]	-1.33 [-0.39]	0.88 [0.26]	0.89 [0.27]	1.24 [0.37]	-0.16 [-0.05]	-4.29 [-1.23]
rmw	-13.49 [-3.98]	-15.45 [-4.54]	-13.92 [-4.04]	-12.63 [-3.64]	-14.34 [-4.19]	-12.81 [-3.74]	-13.11 [-3.82]
cma	-12.50 [-1.97]	4.34 [0.88]	-0.80 [-0.12]	-1.86 [-0.34]	1.43 [0.24]	6.24 [1.25]	-6.38 [-0.92]
umd	0.19 [0.11]	-0.01 [-0.01]	0.54 [0.31]	-0.24 [-0.14]	0.27 [0.16]	2.06 [1.10]	0.33 [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.



## References

- Baker, M. and Wurgler, J. (2003). Market timing and capital structure. *Journal of Finance*, 58(1):1–32.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.
- Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.
- Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.
- Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance*, Forthcoming.
- Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.
- Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.
- Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.
- Harvey, C. R., Liu, Y., and Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.
- Hirshleifer, D., Hou, K., Teoh, S. H., and Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, 38:297–331.

- Hou, K., Mo, H., Xue, C., and Zhang, L. (2020). An empirical evaluation of asset pricing models: Replication and extension. *Journal of Finance*, 75(1):464–503.
- Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review*, 76(2):323–329.
- Novy-Marx, R. and Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.
- Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper*.
- Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3):289–315.
- Stein, J. C. (1996). Rational capital budgeting in an irrational world. *Journal of Business*, 69(4):429–455.
- Titman, S., Wei, K. J., and Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39(4):677–700.
- Zhang, L. (2005). The value premium. *Journal of Finance*, 60(1):67–103.