

Stock Inventory Delta and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock Inventory Delta (SID), 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 SID achieves an annualized gross (net) Sharpe ratio of 0.50 (0.44), and monthly average abnormal gross (net) return relative to the [Fama and French \(2015\)](#) five-factor model plus a momentum factor of 19 (18) bps/month with a t-statistic of 2.26 (2.23), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Long-run reversal) is 16 bps/month with a t-statistic of 2.04.

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 (McLean and Pontiff, 2016). While many of these patterns have been attributed to risk factors or behavioral biases, the role of firms’ operational decisions in driving stock returns remains relatively unexplored. One such operational decision - the management of inventory levels - represents a fundamental aspect of corporate policy that may contain valuable information about future firm performance and stock returns.

We propose that changes in firms’ stock inventory levels (Stock Inventory Delta or SID) provide a meaningful signal about future stock returns through several economic channels. First, following (Bernard et al., 2019), inventory changes reflect management’s private information about future demand conditions. Managers with positive demand forecasts are more likely to build up inventory, while those anticipating weakening demand typically reduce inventory levels. Second, as argued by (Thomas and Zhang, 2002), inventory changes affect firms’ operating leverage and risk exposure. Higher inventory levels increase fixed costs and amplify earnings sensitivity to demand shocks. Third, building on (Below and Liu, 2022), inventory management efficiency directly impacts firms’ working capital needs and cost of capital. Firms that optimize their inventory levels can reduce their reliance on external financing and improve their cost of capital. These mechanisms suggest that SID may contain valuable information about future stock returns that is not fully incorporated into prices.

Our empirical analysis reveals that SID strongly predicts future stock returns. A value-weighted long-short portfolio strategy based on SID quintiles generates a monthly alpha of 19 basis points (t -statistic = 2.26) relative to the Fama-French six-factor model. The strategy’s performance remains robust after controlling for

transaction costs, with a net alpha of 18 basis points per month (t-statistic = 2.23). Importantly, the predictive power of SID persists among large-cap stocks, with the top size quintile showing a monthly alpha of 18-20 basis points across various factor models. The signal’s economic significance is substantial, with an annualized gross (net) Sharpe ratio of 0.50 (0.44), placing it in the top decile of documented cross-sectional return predictors.

Our study makes several contributions to the asset pricing literature. First, we extend the work of (Thomas and Zhang, 2002) and (Bernard et al., 2019) by documenting a novel channel through which inventory information affects stock returns. While these studies focus on earnings prediction, we show that inventory changes directly forecast returns. Second, we complement the literature on operational efficiency and stock returns (Alan et al., 2019) by identifying a specific operational metric that predicts future performance. Third, our findings contribute to the growing literature on the real effects of corporate decisions on asset prices (Cooper and Priestley, 2016). The robustness of SID’s predictive power to transaction costs and its effectiveness among large-cap stocks suggest that it captures fundamental information about firm value that is not fully reflected in prices.

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 Inventory Delta measure. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT’s item CSTK for common stock and item INVT for inventory. Common stock (CSTK) represents the total value of common shares outstanding, while inventory (INVT) captures the value of goods held by the firm for sale or pro-

duction. construction of the signal follows a difference-based approach, where we first calculate the change in common stock by subtracting the previous period’s CSTK value from the current period’s value. This difference is then scaled by the previous period’s inventory value (INVT). This construction captures the relative change in equity capital relative to the firm’s inventory base, potentially offering insights into how firms adjust their capital structure in relation to their operational scale. By scaling the change in common stock by lagged inventory, the signal provides a normalized measure that facilitates comparison across firms of different sizes and across different time periods. We construct this measure using end-of-fiscal-year values to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SID signal. Panel A plots the time-series of the mean, median, and interquartile range for SID. On average, the cross-sectional mean (median) SID is -0.79 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SID data. The signal’s interquartile range spans -0.04 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SID signal for the CRSP universe. On average, the SID signal is available for 5.26% of CRSP names, which on average make up 6.96% of total market capitalization.

4 Does SID predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SID 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 SID portfolio and sells the low SID 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 SID strategy earns an average return of 0.31% per month with a t-statistic of 3.77. The annualized Sharpe ratio of the strategy is 0.50. The alphas range from 0.19% to 0.31% per month and have t-statistics exceeding 2.26 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 0.29, with a t-statistic of 5.24 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 479 stocks and an average market capitalization of at least \$1,229 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 25 bps/month with a t-statistics of 2.92. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-one exceed two, and for eleven 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 22-30bps/month. The lowest return, (22 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.54. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SID 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 nineteen cases.

Table 3 provides direct tests for the role size plays in the SID strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SID, as well as average returns and alphas for long/short trading SID strategies within each size quintile. Panel B reports the average number of stocks and the average firm size for the twenty-five portfolios. Among the largest stocks (those with market capitalization greater than the 80th NYSE percentile), the SID strategy achieves an average return of 24 bps/month with a t-statistic of 2.45. Among these large cap stocks, the alphas for the SID strategy relative to the five most common factor models range from 18 to 20 bps/month

with t-statistics between 1.79 and 2.10.

5 How does SID perform relative to the zoo?

Figure 2 puts the performance of SID 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 SID strategy falls in the distribution. The SID strategy’s gross (net) Sharpe ratio of 0.50 (0.44) is greater than 92% (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 SID strategy (red line).² Ignoring trading costs, a \$1 invested in the SID strategy would have yielded \$6.29 which ranks the SID strategy in the top 2% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the SID strategy would have yielded \$4.79 which ranks the SID 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 SID relative to those. Panel A shows that the SID strategy gross alphas fall between the 60 and 68 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

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

²The 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.

access to the factor models over the 196606 to 202306 sample. For example, 45% (53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The SID strategy has a positive net generalized alpha for five out of the five factor models. In these cases SID ranks between the 80 and 87 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does SID 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 SID 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 SID or at least to weaken the power SID has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SID conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SID} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SID}SID_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SID,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 filtered anomaly trading strategies at a time. The strategies

³When 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.

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. Then, within each quintile, we sort stocks into quintiles based on SID. Stocks are finally grouped into five SID portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SID trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SID 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 SID signal in these Fama-MacBeth regressions exceed 3.15, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SID is 2.30.

Similarly, Table 5 reports results from spanning tests that regress returns to the SID 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 SID strategy earns alphas that range from 16-21bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.90, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SID trading strategy achieves an alpha of 16bps/month with a t-statistic of 2.04.

7 Does SID add relative to the whole zoo?

Finally, we can ask how much adding SID 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 SID 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 SID grows to \$2348.91.

8 Conclusion

This study provides compelling evidence for the significance of Stock Inventory Delta (SID) as a robust predictor of cross-sectional equity returns. Our findings demonstrate that a value-weighted long/short trading strategy based on SID generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.50 (0.44 after transaction costs). The strategy’s persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that SID captures unique information content not fully reflected in current asset pricing models.

⁴We 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 SID is available.

Particularly noteworthy is the signal’s ability to maintain its predictive power when tested against the Fama-French five-factor model augmented with momentum, yielding monthly abnormal returns of 19 basis points (18 basis points net). The robustness of these results is further reinforced by the signal’s performance when controlling for six closely related anomalies, where it continues to generate significant alpha of 16 basis points per month.

However, several limitations warrant consideration. First, our analysis focuses primarily on U.S. equity markets, and the signal’s effectiveness in international markets remains to be tested. Second, the study period may not fully capture the signal’s behavior across different market regimes and economic cycles.

Future research could explore the signal’s performance in international markets, its interaction with other established anomalies, and its behavior during specific market conditions. Additionally, investigating the underlying economic mechanisms driving the SID effect could provide valuable insights for both academics and practitioners. These findings contribute to the growing literature on return predictability and have important implications for investment strategy development and portfolio management.

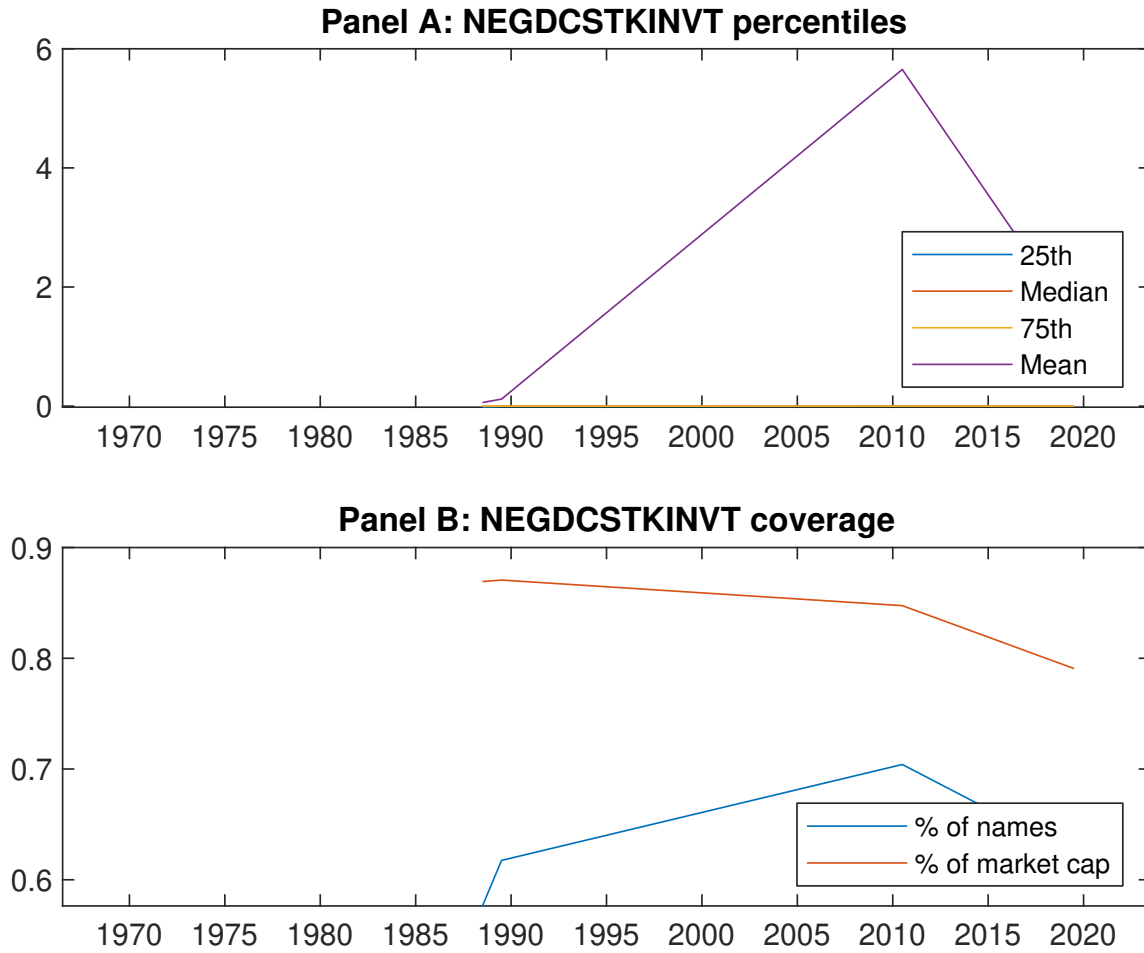


Figure 1: Times series of SID percentiles and coverage.
This figure plots descriptive statistics for SID. Panel A shows cross-sectional percentiles of SID over the sample. Panel B plots the monthly coverage of SID relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SID. 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 SID-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.46 [2.70]	0.50 [2.61]	0.67 [3.52]	0.66 [3.86]	0.77 [4.54]	0.31 [3.77]
α_{CAPM}	-0.06 [-1.15]	-0.10 [-2.13]	0.08 [1.40]	0.13 [2.44]	0.24 [4.69]	0.31 [3.76]
α_{FF3}	-0.07 [-1.34]	-0.10 [-2.06]	0.07 [1.21]	0.09 [1.80]	0.20 [4.00]	0.27 [3.32]
α_{FF4}	-0.06 [-1.12]	-0.08 [-1.52]	0.08 [1.49]	0.05 [0.99]	0.19 [3.75]	0.25 [3.02]
α_{FF5}	-0.11 [-1.99]	-0.09 [-1.77]	0.04 [0.69]	-0.02 [-0.47]	0.09 [1.78]	0.20 [2.38]
α_{FF6}	-0.10 [-1.78]	-0.07 [-1.39]	0.05 [0.95]	-0.05 [-0.94]	0.09 [1.82]	0.19 [2.26]
Panel B: Fama and French (2018) 6-factor model loadings for SID-sorted portfolios						
β_{MKT}	0.95 [70.77]	1.04 [88.22]	1.03 [77.96]	1.00 [86.93]	0.99 [86.37]	0.04 [1.87]
β_{SMB}	-0.05 [-2.78]	0.05 [2.87]	0.07 [3.51]	-0.05 [-2.71]	-0.01 [-0.65]	0.04 [1.51]
β_{HML}	0.06 [2.29]	0.00 [0.00]	0.00 [0.13]	0.05 [2.17]	0.02 [1.02]	-0.04 [-0.97]
β_{RMW}	0.13 [5.15]	0.03 [1.35]	0.09 [3.59]	0.17 [7.36]	0.16 [7.05]	0.02 [0.58]
β_{CMA}	-0.04 [-1.14]	-0.08 [-2.27]	-0.00 [-0.09]	0.21 [6.32]	0.25 [7.73]	0.29 [5.24]
β_{UMD}	-0.02 [-1.25]	-0.03 [-2.48]	-0.02 [-1.81]	0.04 [3.15]	-0.01 [-0.45]	0.01 [0.59]
Panel C: Average number of firms (n) and market capitalization (me)						
n	623	572	479	564	627	
me (\$10 ⁶)	1580	1229	1537	1872	2090	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the SID 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	0.31 [3.77]	0.31 [3.76]	0.27 [3.32]	0.25 [3.02]	0.20 [2.38]	0.19 [2.26]
Quintile	NYSE	EW	0.49 [7.51]	0.54 [8.47]	0.47 [7.76]	0.40 [6.73]	0.34 [5.81]	0.30 [5.13]
Quintile	Name	VW	0.30 [3.66]	0.29 [3.49]	0.27 [3.22]	0.27 [3.14]	0.23 [2.64]	0.23 [2.66]
Quintile	Cap	VW	0.25 [2.92]	0.23 [2.67]	0.22 [2.54]	0.19 [2.20]	0.17 [2.00]	0.16 [1.82]
Decile	NYSE	VW	0.31 [3.15]	0.27 [2.71]	0.23 [2.33]	0.20 [1.96]	0.20 [2.01]	0.18 [1.77]
Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	r_{net}^e	α_{CAPM}^*	α_{FF3}^*	α_{FF4}^*	α_{FF5}^*	α_{FF6}^*
Quintile	NYSE	VW	0.27 [3.36]	0.28 [3.41]	0.25 [3.03]	0.24 [2.89]	0.19 [2.30]	0.18 [2.23]
Quintile	NYSE	EW	0.30 [4.16]	0.34 [4.80]	0.27 [4.08]	0.24 [3.65]	0.13 [2.10]	0.12 [1.90]
Quintile	Name	VW	0.27 [3.26]	0.27 [3.21]	0.25 [2.97]	0.25 [2.95]	0.22 [2.55]	0.22 [2.55]
Quintile	Cap	VW	0.22 [2.54]	0.21 [2.41]	0.20 [2.28]	0.18 [2.12]	0.17 [1.94]	0.16 [1.80]
Decile	NYSE	VW	0.28 [2.78]	0.24 [2.41]	0.21 [2.07]	0.19 [1.90]	0.19 [1.84]	0.18 [1.74]

Table 3: Conditional sort on size and SID

This table presents results for conditional double sorts on size and SID. 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 SID. 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 SID and short stocks with low SID. 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												
Size quintiles	SID Quintiles					SID Strategies						
	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}	
	(1)	0.45 [1.75]	0.72 [2.77]	0.86 [3.30]	1.02 [3.76]	0.97 [4.15]	0.52 [6.27]	0.57 [6.93]	0.51 [6.55]	0.48 [6.08]	0.38 [4.97]	0.36 [4.73]
	(2)	0.60 [2.63]	0.72 [2.93]	0.81 [3.23]	0.89 [3.74]	0.87 [3.83]	0.27 [3.15]	0.29 [3.40]	0.22 [2.61]	0.19 [2.23]	0.13 [1.50]	0.11 [1.32]
	(3)	0.57 [2.74]	0.68 [2.97]	0.77 [3.31]	0.85 [3.87]	0.93 [4.48]	0.35 [4.09]	0.37 [4.19]	0.32 [3.72]	0.33 [3.68]	0.26 [2.94]	0.27 [3.00]
	(4)	0.51 [2.60]	0.68 [3.11]	0.78 [3.53]	0.82 [3.95]	0.80 [4.13]	0.29 [3.24]	0.30 [3.41]	0.23 [2.62]	0.23 [2.59]	0.07 [0.76]	0.08 [0.92]
	(5)	0.49 [2.94]	0.45 [2.40]	0.50 [2.75]	0.55 [3.21]	0.72 [4.29]	0.24 [2.45]	0.20 [2.10]	0.20 [2.06]	0.19 [1.89]	0.19 [1.88]	0.18 [1.79]
Panel B: Portfolio average number of firms and market capitalization												
Size quintiles	SID Quintiles					SID Quintiles						
	Average n					Average market capitalization (\$10 ⁶)						
	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)		
	(1)	313	313	313	311	312	25	26	29	22	22	
	(2)	88	88	88	88	88	43	43	43	43	43	
	(3)	65	65	65	64	65	75	74	75	76	77	
	(4)	55	55	55	55	55	160	159	165	165	165	
(5)	53	53	53	53	53	1190	1237	1447	1369	1534		

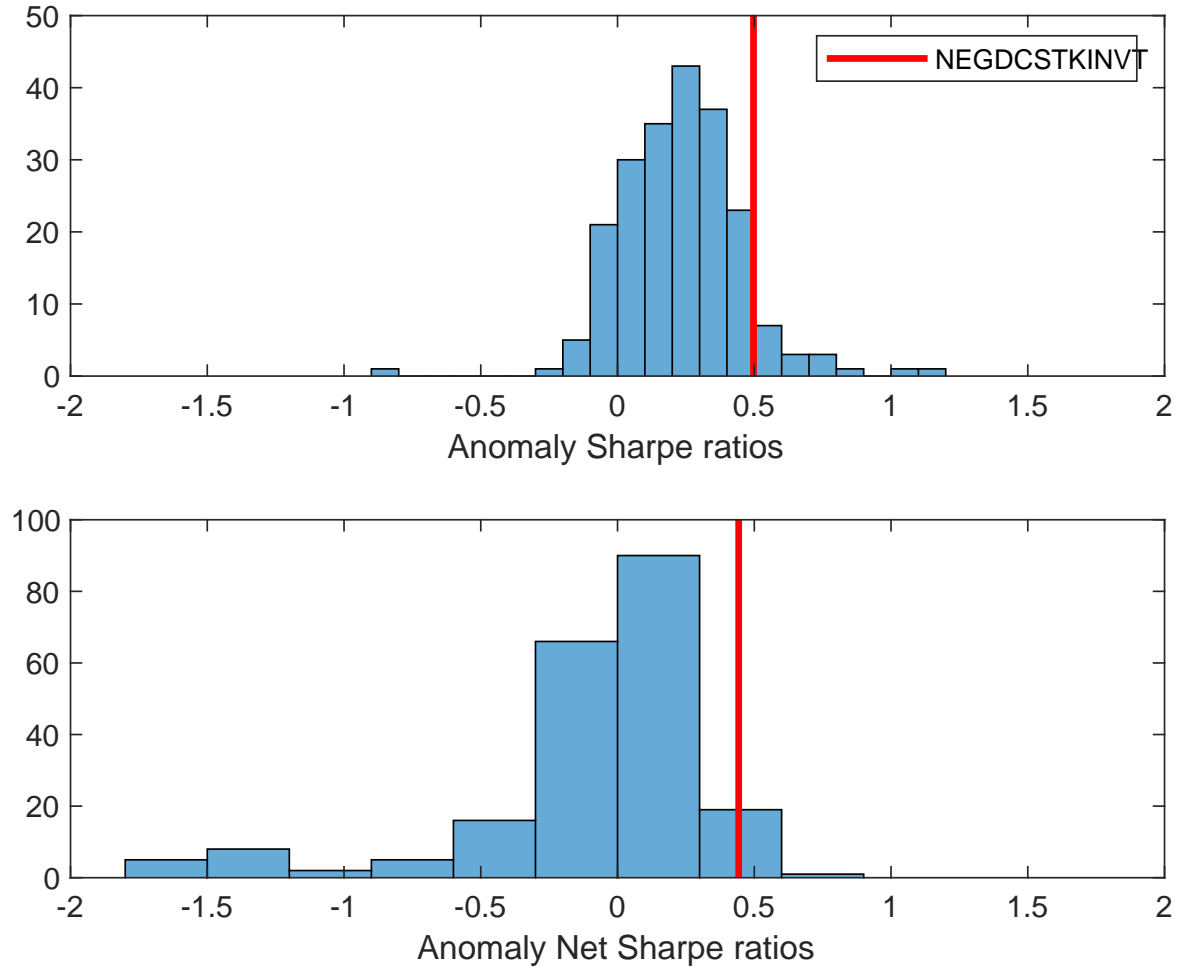


Figure 2: Distribution of Sharpe ratios.

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

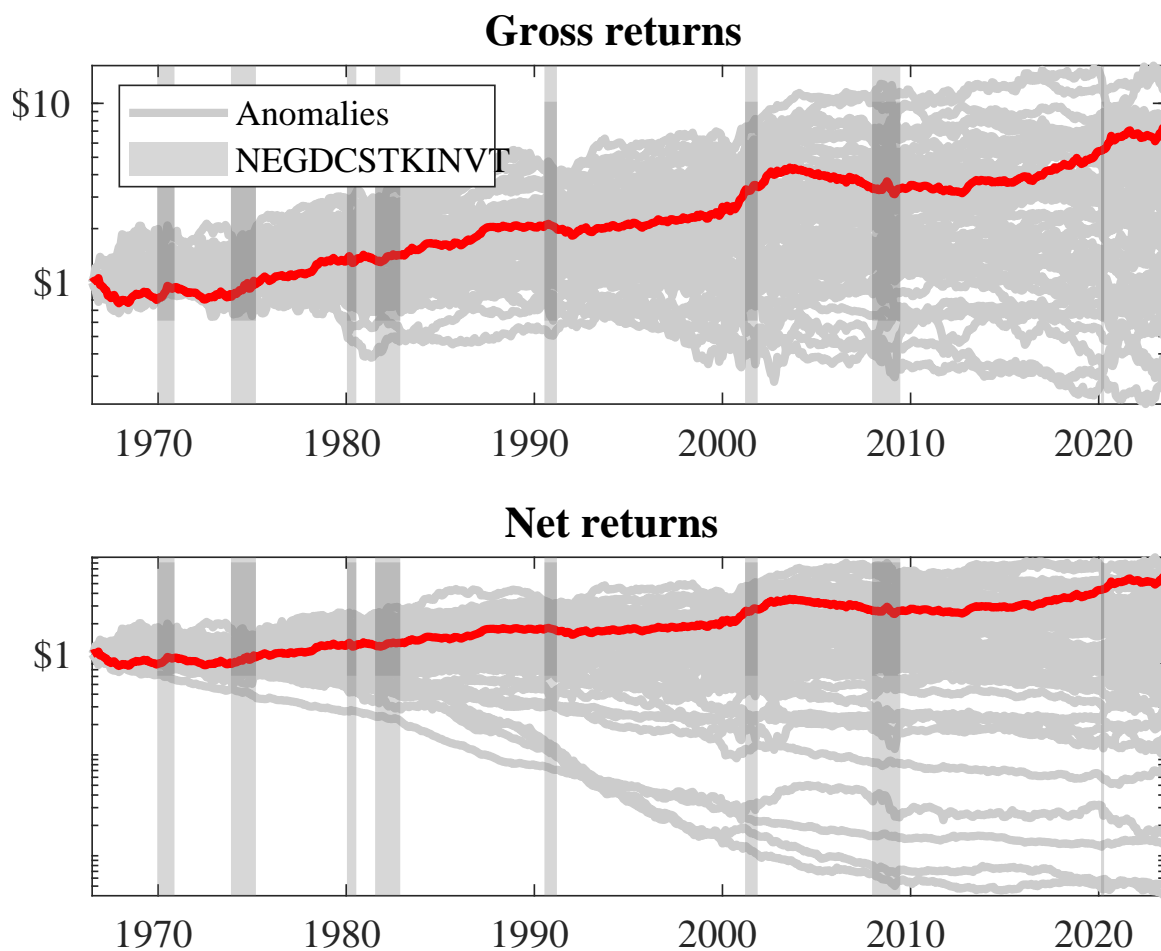


Figure 3: Dollar invested.

This figure plots the growth of a \$1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SID 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.

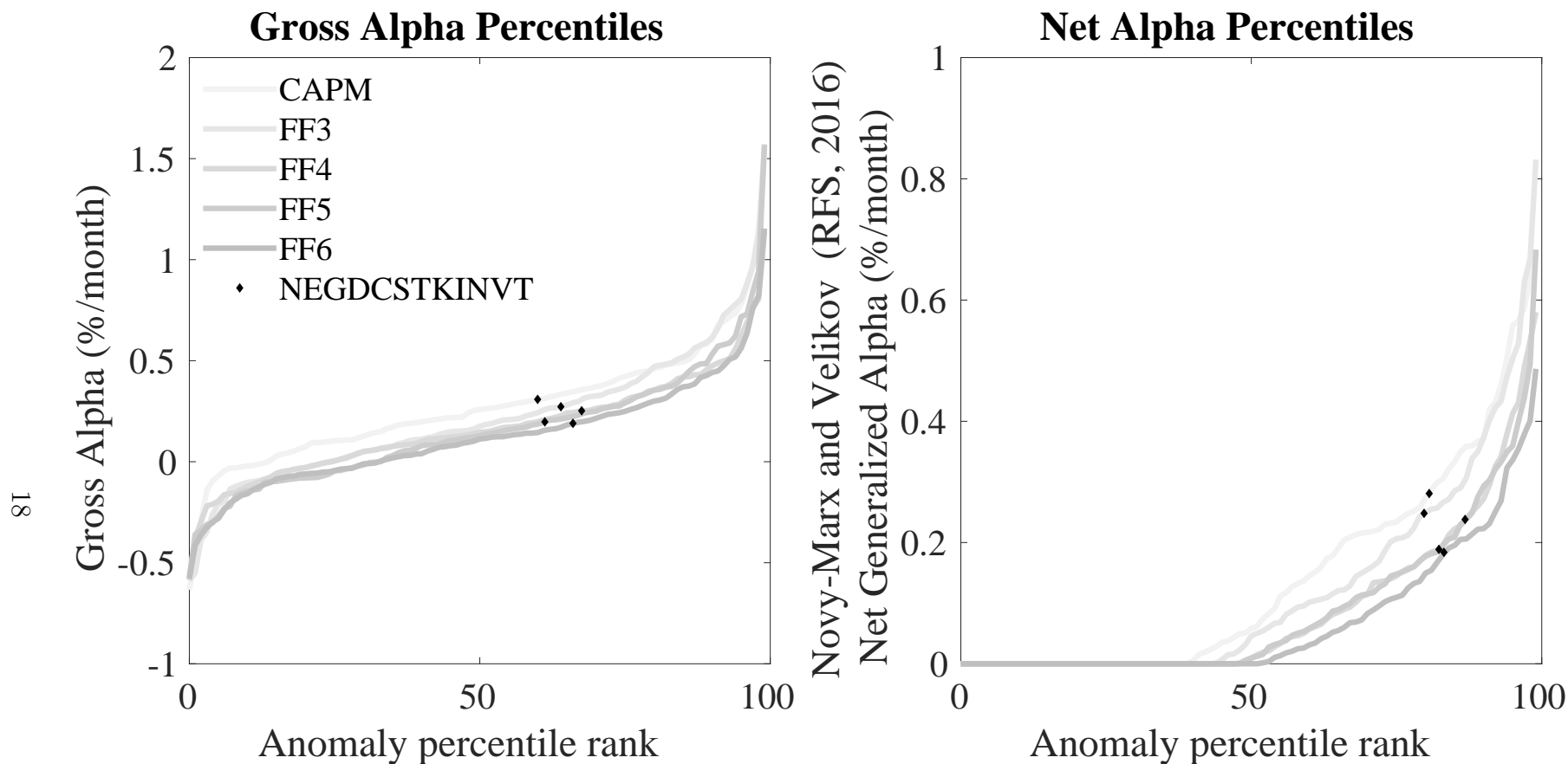


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models

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

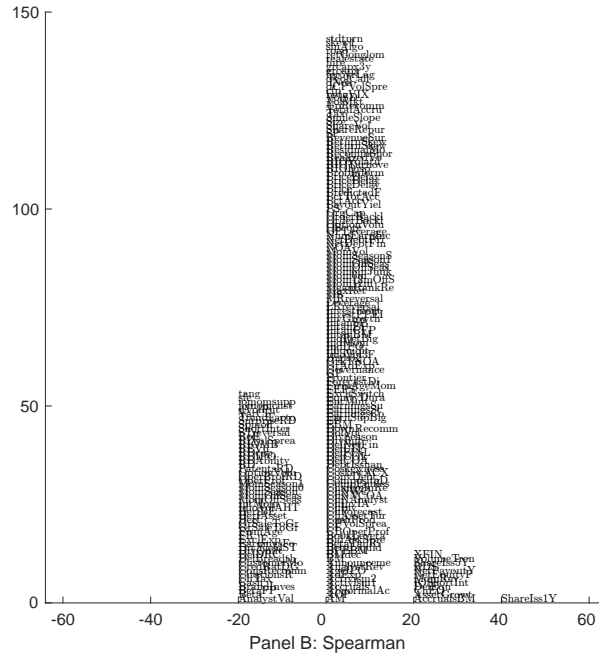
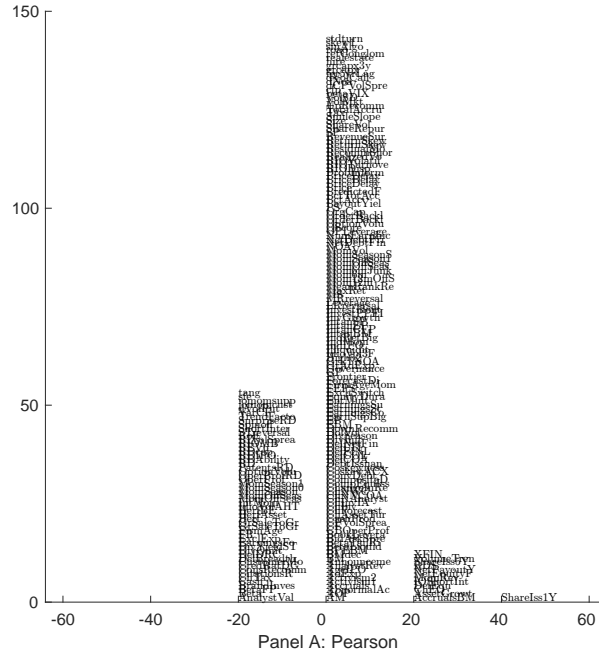


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with SID. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

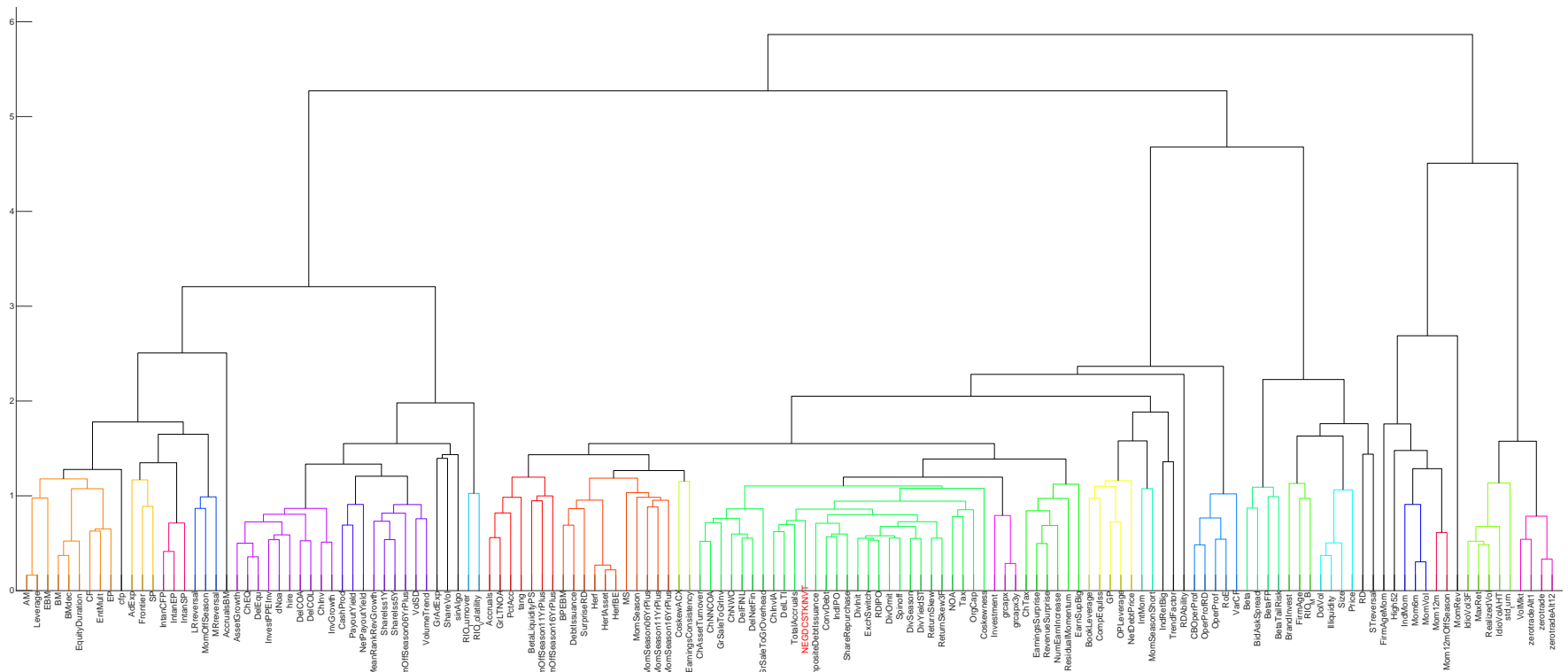


Figure 6: Agglomerative hierarchical cluster plot

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

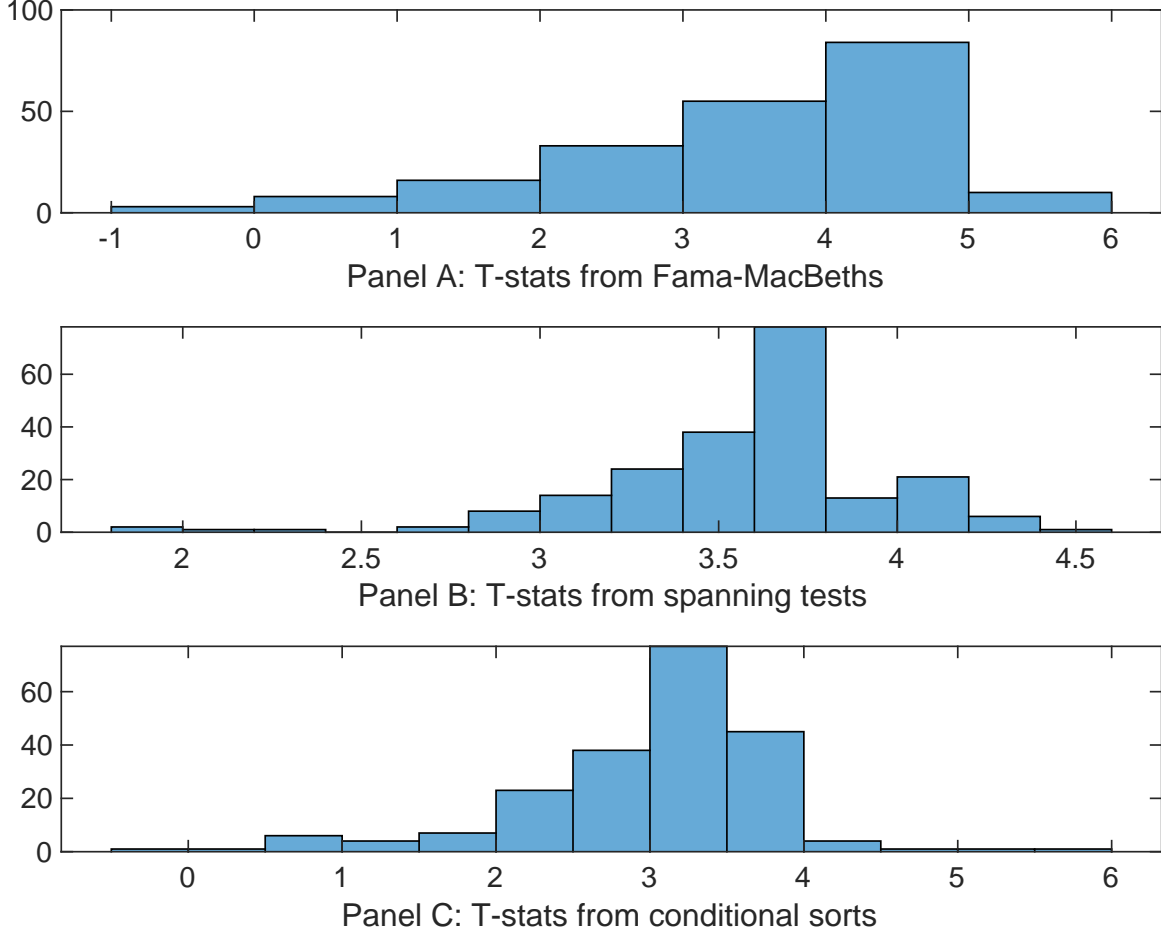


Figure 7: Distribution of t-stats on conditioning strategies

This figure plots histograms of t-statistics for predictability tests of SID conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SID} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SID}SID_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SID,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SID. Stocks are finally grouped into five SID portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SID 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 SID. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SID}SID_{i,t} + \sum_{k=1}^s \beta_{X_k}X_{i,t}^k + \epsilon_{i,t}$. The six most closely related anomalies, X , are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, 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	0.13 [5.63]	0.18 [7.44]	0.12 [5.19]	0.13 [5.97]	0.13 [5.62]	0.13 [5.75]	0.13 [6.00]
SID	0.29 [4.59]	0.27 [4.57]	0.23 [3.15]	0.23 [3.34]	0.27 [4.59]	0.24 [4.16]	0.17 [2.30]
Anomaly 1	0.24 [4.91]						0.66 [1.52]
Anomaly 2		0.53 [4.89]					0.11 [0.67]
Anomaly 3			0.33 [3.21]				0.26 [2.72]
Anomaly 4				0.39 [4.54]			0.48 [0.50]
Anomaly 5					0.17 [4.58]		0.74 [0.14]
Anomaly 6						0.26 [2.78]	0.20 [2.62]
# months	679	684	679	679	684	679	679
$\bar{R}^2(\%)$	0	0	1	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 SID trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SID} = \alpha + \sum_{k=1}^6 \beta_{X_k} r_t^{X_k} + \sum_{j=1}^6 \beta_{f_j} r_t^{f_j} + \epsilon_t$, where X_k indicates each of the six most-closely related anomalies and f_j indicates the six factors from the [Fama and French \(2015\)](#) five-factor model augmented with the [Carhart \(1997\)](#) momentum factor. The six most closely related anomalies, X , are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, 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	0.16 [2.00]	0.19 [2.35]	0.18 [2.26]	0.16 [1.90]	0.21 [2.54]	0.16 [1.92]	0.16 [2.04]
Anomaly 1	28.06 [6.75]						14.37 [2.98]
Anomaly 2		37.28 [8.35]					32.49 [5.04]
Anomaly 3			18.34 [5.77]				7.16 [1.97]
Anomaly 4				17.32 [4.01]			3.72 [0.81]
Anomaly 5					21.92 [5.00]		-10.93 [-1.81]
Anomaly 6						7.74 [3.17]	2.63 [1.10]
mkt	6.01 [3.14]	5.00 [2.64]	6.81 [3.47]	6.21 [3.11]	3.43 [1.76]	3.67 [1.88]	7.65 [3.90]
smb	6.26 [2.28]	3.41 [1.24]	8.55 [3.03]	4.12 [1.45]	4.32 [1.53]	2.38 [0.79]	4.58 [1.54]
hml	-6.31 [-1.69]	-7.66 [-2.08]	-9.82 [-2.49]	-7.52 [-1.88]	-6.07 [-1.60]	-4.74 [-1.22]	-12.16 [-3.04]
rmw	-6.97 [-1.76]	4.02 [1.09]	-8.10 [-1.94]	-1.01 [-0.26]	4.24 [1.11]	5.74 [1.46]	-5.51 [-1.23]
cma	16.01 [2.73]	-7.91 [-1.14]	16.06 [2.65]	24.34 [4.21]	6.28 [0.88]	25.23 [4.31]	-6.63 [-0.93]
umd	1.00 [0.53]	0.74 [0.39]	2.88 [1.51]	1.47 [0.76]	1.80 [0.93]	2.11 [1.09]	1.22 [0.65]
# months	680	684	680	680	684	680	680
$\bar{R}^2(\%)$	13	14	11	9	8	8	18

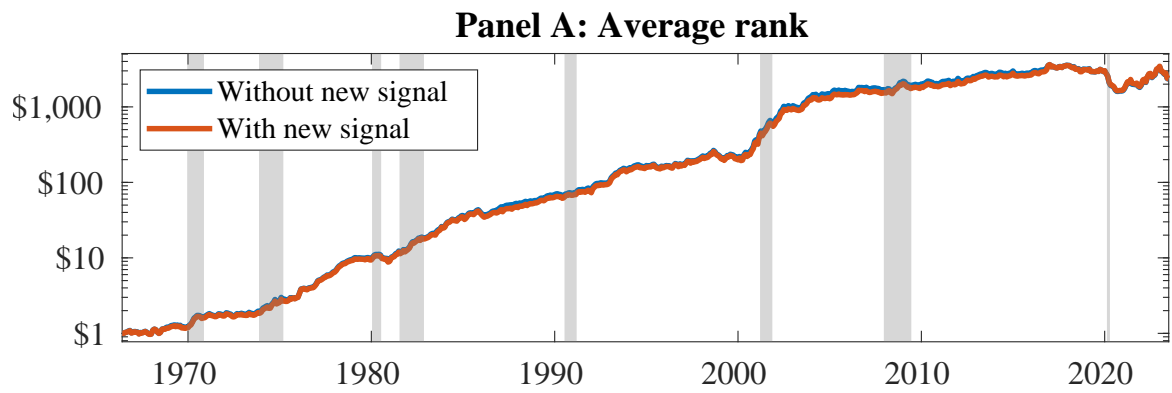


Figure 8: Combination strategy performance

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

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