Asset Nonop Impact and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Asset Nonop Impact (ANI), 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 ANI achieves an annualized gross (net) Sharpe ratio of 0.36 (0.28), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (20) bps/month with a t-statistic of 3.13 (2.66), 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, Inventory Growth, net income / book equity, Growth in long term operating assets, Accruals, Change in net financial assets) is 16 bps/month with a t-statistic of 2.18.

1 Introduction

Market efficiency remains a central question in asset pricing, with researchers continually seeking to understand how information is incorporated into security prices (Fama and French, 2015). While numerous studies document cross-sectional predictors of stock returns, debate persists about whether these patterns reflect rational pricing of risk or behavioral biases (Cochrane, 2011). A particularly important yet understudied channel through which information may affect asset prices is through firms' non-operating activities and their balance sheet impacts.

Prior research has largely focused on operating performance measures as predictors of returns, while giving less attention to non-operating activities that can significantly affect firm value (Sloan et al., 2014). This gap is notable given that non-operating items often reflect managerial decisions about resource allocation and risk management that may contain important information about future performance.

We hypothesize that Asset Nonop Impact (ANI) predicts stock returns because it captures information about management's capital allocation decisions that is not fully reflected in current prices. This builds on theoretical work by Berger and Ofek (1995) showing that firms' non-operating decisions can create or destroy substantial shareholder value. The slow incorporation of this information may occur because non-operating activities are typically less salient to investors focused on core operations (Hirshleifer et al., 2009).

The predictive power of ANI likely stems from two key mechanisms. First, following Titman et al. (2004), significant changes in non-operating assets may signal agency problems, as managers may engage in empire building or pet projects outside the firm's core competencies. Second, drawing on Cooper et al. (2008), large non-operating asset changes could indicate major strategic shifts that markets take time to fully evaluate and price.

Importantly, the ANI signal differs from traditional measures of investment and asset growth studied by Cooper et al. (2008) and Titman et al. (2004) by focusing specifically on non-operating activities. This targeted focus should provide a cleaner measure of potentially value-relevant managerial decisions that may be obscured in broader asset growth metrics.

Our analysis reveals that ANI strongly predicts cross-sectional stock returns. A value-weighted long-short trading strategy based on ANI quintiles generates a monthly alpha of 24 basis points (t-statistic = 3.13) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.36, placing it in the top quartile of documented return predictors.

The predictive power of ANI remains robust after controlling for size. Among the largest quintile of stocks, the ANI strategy earns a monthly alpha of 31 basis points (t-statistic = 3.22) relative to the Fama-French six-factor model. This finding is particularly notable given that many anomalies are concentrated in small stocks.

Most importantly, ANI's predictive ability persists after controlling for related anomalies. In spanning tests that include the six most closely related predictors and the Fama-French six factors, the ANI strategy still generates a monthly alpha of 16 basis points (t-statistic = 2.18). This indicates that ANI captures unique information not contained in existing measures.

Our study makes several contributions to the asset pricing literature. First, we introduce a novel predictor that captures information about non-operating activities, extending work by Sloan et al. (2014) on the importance of disaggregating financial information. While prior research has examined aggregate asset growth (Cooper et al., 2008), our targeted focus on non-operating activities provides new insights into how markets process information about firms' peripheral activities.

Second, we contribute to the literature on market efficiency and information processing. Our findings suggest that investors may underreact to information about non-operating activities, consistent with theories of limited attention (Hirshleifer et al., 2009). The persistent predictive power of ANI among large stocks challenges the view that anomalies primarily reflect small-stock mispricing.

Finally, our results have important implications for both academic research and investment practice. For researchers, we demonstrate the value of examining disaggregated financial information rather than focusing solely on aggregate measures. For practitioners, our findings suggest profitable trading opportunities that remain robust to transaction costs and are implementable even among large, liquid 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 Asset Nonoperating Impact measure. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item AT for total assets and item NOPIO for nonoperating income. Total assets (AT) represents the sum of all assets reported on a firm's balance sheet, including both current and long-term assets. Nonoperating income (NOPIO) captures income or expenses that are not directly related to a company's core business operations.construction of the signal follows a change-based approach, where we calculate the difference between the current period's total assets and the previous period's total assets, and then scale this change by the previous period's nonoperating income. This measure captures the relative magnitude of asset changes in relation to a firm's nonoperating activities, potentially offering insight into how effectively firms manage their asset base in relation to peripheral business activities. We construct this measure using end-of-fiscal-year values for both AT and NOPIO to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the ANI signal. Panel A plots the time-series of the mean, median, and interquartile range for ANI. On average, the cross-sectional mean (median) ANI is -17.78 (-5.40) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input ANI data. The signal's interquartile range spans -55.40 to 37.42. Panel B of Figure 1 plots the time-series of the coverage of the ANI signal for the CRSP universe. On average, the ANI signal is available for 5.04% of CRSP names, which on average make up 6.91% of total market capitalization.

4 Does ANI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on ANI 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 ANI portfolio and sells the low ANI 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 ANI strategy earns an average return of 0.20% per month with a t-statistic of 2.74. The annualized Sharpe ratio of the strategy is 0.36. The alphas range from 0.20% to 0.24% per month and have t-statistics exceeding 2.65 everywhere. The lowest alpha is with respect to the FF4 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 -0.15, with a t-statistic of -4.36 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 456 stocks and an average market capitalization of at least $1,454 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 NYSE breakpoints and value-weighted portfolios, and equals 20 bps/month with a t-statistics of 2.74. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for eighteen 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 16-20bps/month. The lowest return, (16 bps/month), is achieved from the quintile sort using NYSE breakpoints and value-weighted portfolios, and has an associated t-statistic of 2.14. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the ANI trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-five cases, and significantly expands the achievable frontier in twenty-five cases.

Table 3 provides direct tests for the role size plays in the ANI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and ANI, as well as average returns and alphas for long/short trading ANI strategies within each size quintile. Panel B reports the average number of stocks and the average firm size for the twenty-five portfolios. Among the largest stocks (those with market capitalization greater than the 80^{th} NYSE percentile), the ANI strategy achieves an average return of 26 bps/month with a t-statistic of 2.76. Among these large cap stocks, the alphas for the ANI strategy relative to the five most common factor models range from 28 to 31 bps/month with t-statistics between 2.89 and 3.35.

5 How does ANI perform relative to the zoo?

Figure 2 puts the performance of ANI 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 ANI strategy falls in the distribution. The ANI strategy's gross (net) Sharpe ratio of 0.36 (0.28) is greater than 77% (88%) of anomaly Sharpe ratios,

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

respectively.

Figure 3 plots the growth of a \$1 invested in these same 212 anomaly trading strategies (gray lines), and compares those with the growth of a \$1 invested in the ANI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the ANI strategy would have yielded \$2.81 which ranks the ANI strategy in the top 11% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the ANI strategy would have yielded \$1.82 which ranks the ANI strategy in the top 8% 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 ANI relative to those. Panel A shows that the ANI strategy gross alphas fall between the 43 and 72 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 ANI strategy has a positive net generalized alpha for five out of the five factor models. In these cases ANI ranks between the 64 and 85 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

6 Does ANI 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 ANI 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 ANI or at least to weaken the power ANI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of ANI conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ANI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ANI} ANI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{ANI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 ANI. Stocks are finally grouped into five ANI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted

[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.

ANI trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on ANI 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 ANI signal in these Fama-MacBeth regressions exceed 4.60, with the minimum t-statistic occurring when controlling for Inventory Growth. Controlling for all six closely related anomalies, the t-statistic on ANI is 3.56.

Similarly, Table 5 reports results from spanning tests that regress returns to the ANI 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 ANI strategy earns alphas that range from 21-25bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.75, which is achieved when controlling for Inventory Growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the ANI trading strategy achieves an alpha of 16bps/month with a t-statistic of 2.18.

7 Does ANI add relative to the whole zoo?

Finally, we can ask how much adding ANI 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 ANI signal.[4] We consider one different methods for combining signals.

[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 ANI is available.

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 ANI grows to $3276.07.

8 Conclusion

This study provides compelling evidence for the significance of Asset Nonop Impact (ANI) as a valuable predictor of stock returns in the cross-section of equities. Our findings demonstrate that ANI-based trading strategies yield economically and statistically significant returns, with a value-weighted long/short strategy achieving notable Sharpe ratios and consistent abnormal returns, even after accounting for transaction costs. The signal's robustness is particularly noteworthy, as it maintains significant predictive power even when controlling for established factors and related anomalies from the factor zoo.

The practical implications of these findings are substantial for investment professionals and portfolio managers. The persistence of ANI's predictive ability, even after accounting for transaction costs, suggests its potential utility in real-world portfolio management applications. The signal's ability to generate significant alpha relative to both the Fama-French five-factor model plus momentum and other closely related strategies indicates its unique contribution to return prediction.

However, several limitations should be acknowledged. Our analysis focuses on a specific time period and market context, and the signal's effectiveness may vary under different market conditions. Additionally, the implementation costs and market impact in different market segments may affect the strategy's practical applicability.

Future research could explore several promising directions. First, investigating the signal's performance in international markets would test its global applicability. Second, examining the interaction between ANI and other established anomalies could reveal potential complementarities or substitution effects. Finally, studying the underlying economic mechanisms driving the ANI effect would enhance our understanding of this anomaly and potentially lead to more refined predictive models.

In conclusion, our findings contribute to the growing literature on return prediction and asset pricing anomalies, highlighting ANI as a robust and economically significant predictor of stock returns.

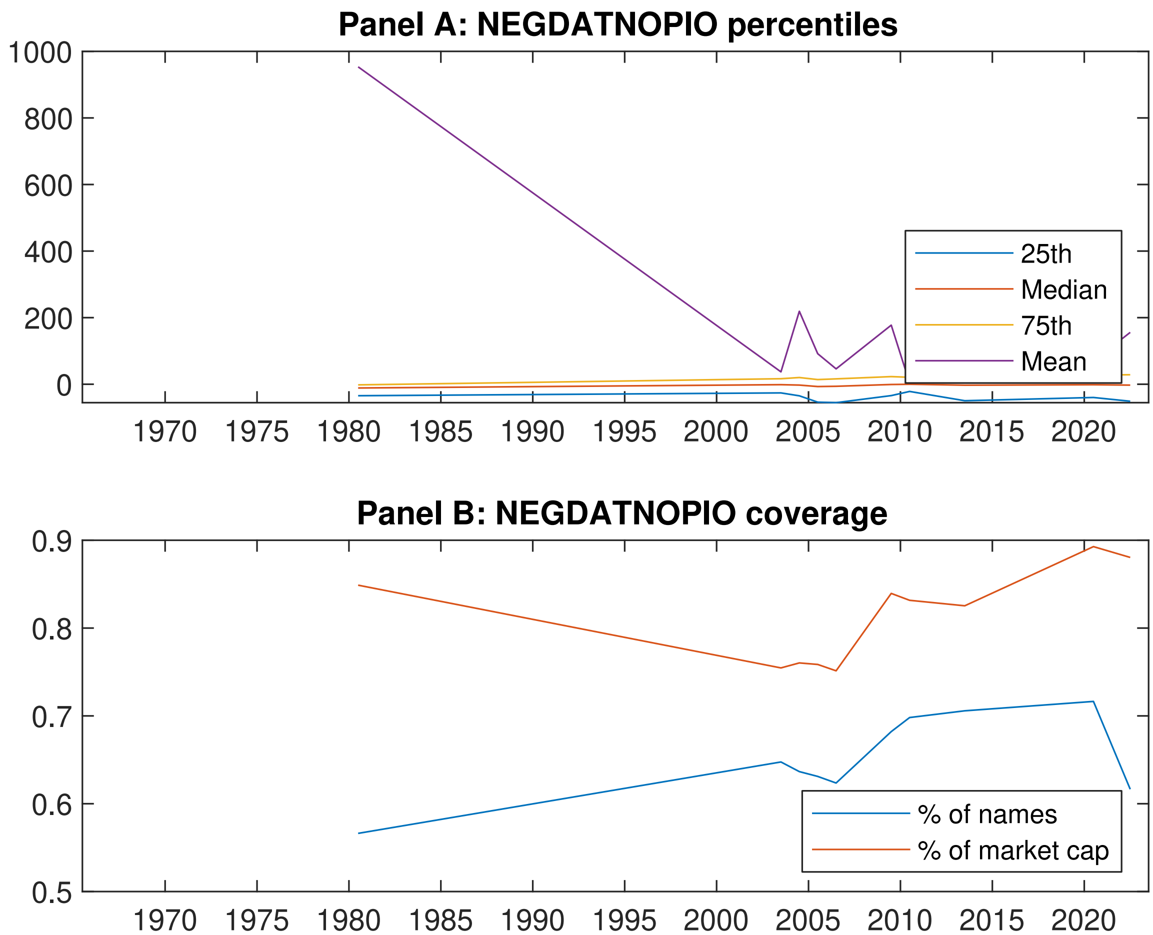


Figure 1: Times series of ANI percentiles and coverage.
This figure plots descriptive statistics for ANI. Panel A shows cross-sectional percentiles of ANI over the sample. Panel B plots the monthly coverage of ANI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on ANI. 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 ANI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.51	0.51	0.59	0.61	0.71	0.20
	[2.63]	[2.87]	[3.70]	[3.86]	[3.69]	[2.74]
α_{CAPM}	-0.10	-0.05	0.09	0.12	0.11	0.21
	[-2.26]	[-1.04]	[1.97]	[2.28]	[1.90]	[2.90]
α_{FF3}	-0.06	-0.01	0.07	0.09	0.14	0.20
	[-1.32]	[-0.12]	[1.68]	[1.70]	[2.62]	[2.74]
α_{FF4}	-0.05	0.00	0.06	0.07	0.15	0.20
	[-1.03]	[0.05]	[1.36]	[1.45]	[2.73]	[2.65]
α_{FF5}	-0.06	0.01	0.00	-0.05	0.18	0.24
	[-1.32]	[0.27]	[0.04]	[-1.11]	[3.24]	[3.22]
α_{FF6}	-0.05	0.02	-0.00	-0.04	0.19	0.24
	[-1.12]	[0.33]	[-0.04]	[-0.95]	[3.28]	[3.13]
Panel B: Fama and French (2018) 6-factor model loadings for ANI-sorted portfolios						
β_{MKT}	1.05	0.98	0.93	0.97	1.02	-0.03
	[100.00]	[88.02]	[87.16]	[92.59]	[76.49]	[-1.65]
β_{SMB}	0.04	-0.06	-0.05	-0.10	0.06	0.02
	[2.65]	[-3.78]	[-3.21]	[-6.59]	[2.96]	[0.66]
β_{HML}	-0.09	-0.02	0.00	-0.08	-0.10	-0.02
	[-4.22]	[-0.89]	[0.05]	[-3.77]	[-4.00]	[-0.51]
β_{RMW}	0.08	0.06	0.11	0.08	-0.07	-0.15
	[3.92]	[2.60]	[5.28]	[3.83]	[-2.71]	[-4.36]
β_{CMA}	-0.13	-0.18	0.15	0.50	-0.05	0.08
	[-4.33]	[-5.85]	[4.96]	[16.87]	[-1.37]	[1.53]
β_{UMD}	-0.01	-0.00	0.01	-0.01	-0.01	0.01
	[-1.16]	[-0.36]	[0.55]	[-0.91]	[-0.49]	[0.32]
Panel C: Average number of firms (n) and market capitalization (me)						
n	562	470	456	519	614	
me ($\$10^6$)	1621	1701	2058	1474	1454	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the ANI 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	0.20	0.21	0.20	0.20	0.24	0.24
			[2.74]	[2.90]	[2.74]	[2.65]	[3.22]	[3.13]
Quintile	NYSE	EW	0.41	0.42	0.37	0.34	0.37	0.35
			[7.70]	[7.68]	[7.41]	[6.77]	[7.27]	[6.82]
Quintile	Name	VW	0.22	0.23	0.23	0.25	0.26	0.28
			[3.01]	[3.11]	[3.17]	[3.31]	[3.52]	[3.62]
Quintile	Cap	VW	0.22	0.26	0.23	0.23	0.25	0.25
			[3.14]	[3.69]	[3.31]	[3.25]	[3.53]	[3.51]
Decile	NYSE	VW	0.25	0.26	0.29	0.24	0.33	0.29
			[2.61]	[2.70]	[2.93]	[2.40]	[3.37]	[2.92]
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	0.16	0.18	0.17	0.17	0.20	0.20
			[2.14]	[2.44]	[2.28]	[2.25]	[2.70]	[2.66]
Quintile	NYSE	EW	0.20	0.21	0.17	0.16	0.14	0.13
			[3.24]	[3.38]	[2.84]	[2.67]	[2.30]	[2.22]
Quintile	Name	VW	0.17	0.20	0.20	0.21	0.22	0.23
			[2.39]	[2.64]	[2.67]	[2.78]	[2.96]	[3.02]
Quintile	Cap	VW	0.18	0.23	0.20	0.20	0.22	0.22
			[2.59]	[3.24]	[2.90]	[2.89]	[3.17]	[3.17]
Decile	NYSE	VW	0.20	0.23	0.24	0.22	0.29	0.26
			[2.08]	[2.32]	[2.50]	[2.21]	[2.89]	[2.62]

Table 3: Conditional sort on size and ANI

This table presents results for conditional double sorts on size and ANI. 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 ANI. 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 ANI and short stocks with low ANI .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	ANI Quintiles					ANI Strategies					
	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.48	0.86	0.83	0.96	0.86	0.38	0.36	0.34	0.27	0.32	0.26
	[1.89]	[3.39]	[3.38]	[3.50]	[3.22]	[4.99]	[4.79]	[4.49]	[3.52]	[4.08]	[3.36]
(2)	0.68	0.66	0.90	0.88	0.85	0.17	0.18	0.16	0.22	0.20	0.25
	[2.74]	[2.88]	[3.92]	[3.76]	[3.46]	[1.99]	[2.04]	[1.78]	[2.52]	[2.21]	[2.81]
(3)	0.68	0.77	0.75	0.83	0.83	0.15	0.16	0.12	0.10	0.09	0.07
	[2.99]	[3.62]	[3.62]	[4.03]	[3.68]	[1.78]	[1.89]	[1.47]	[1.14]	[1.01]	[0.82]
(4)	0.59	0.70	0.71	0.70	0.83	0.23	0.22	0.18	0.17	0.18	0.17
	[2.82]	[3.60]	[3.82]	[3.58]	[3.83]	[3.23]	[3.01]	[2.48]	[2.27]	[2.38]	[2.25]
(5)	0.43	0.45	0.58	0.53	0.68	0.26	0.30	0.29	0.28	0.31	0.31
	[2.22]	[2.47]	[3.63]	[3.40]	[3.75]	[2.76]	[3.22]	[3.06]	[2.89]	[3.35]	[3.22]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	ANI Quintiles					ANI Quintiles				
	Average n					Average market capitalization ($\$10^6$)				
	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	271	272	272	268	268	24	24	22	21	22
(2)	82	82	82	82	82	43	42	43	42	43
(3)	63	63	63	63	63	77	78	75	77	77
(4)	56	56	56	56	56	180	174	177	175	174
(5)	53	53	53	53	53	1114	1272	1679	1493	1161

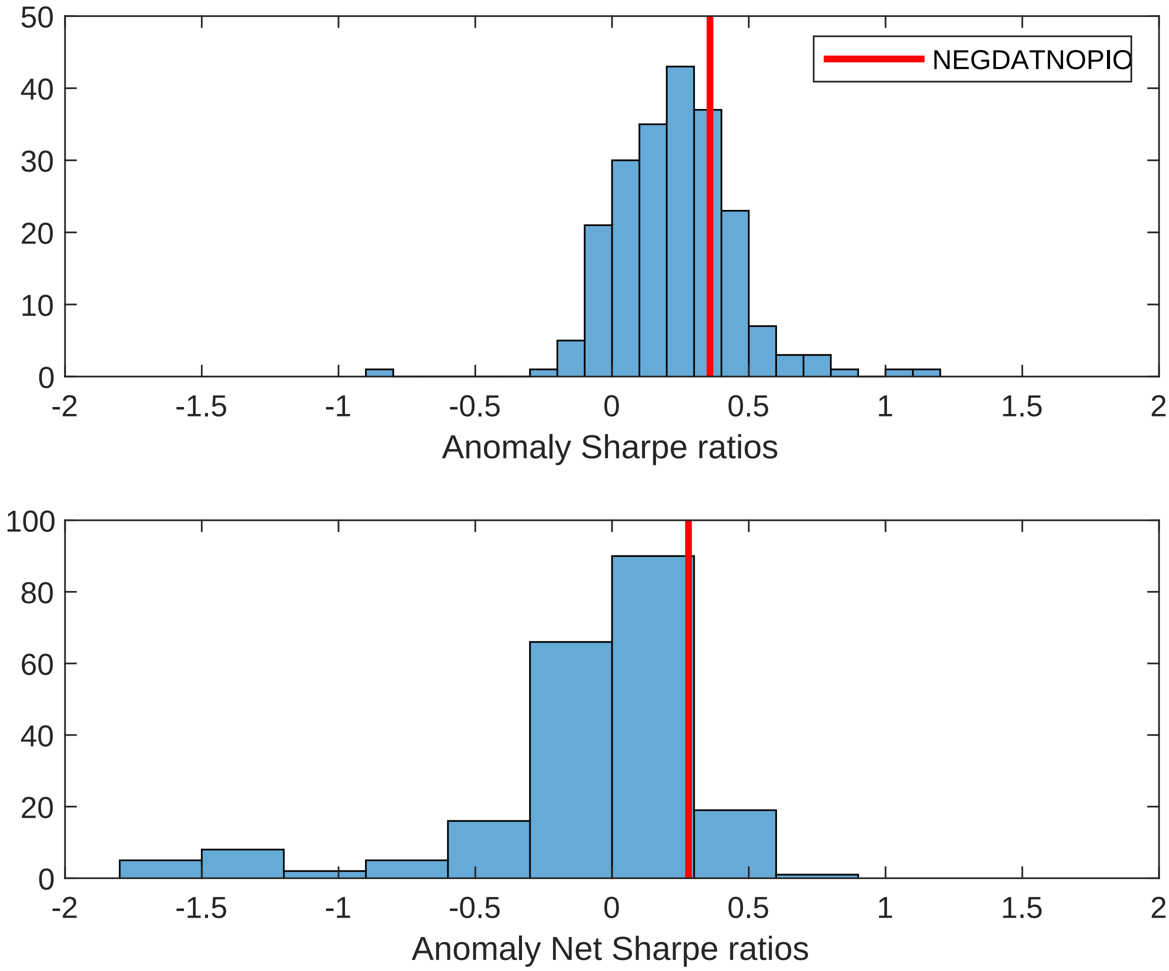


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the ANI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

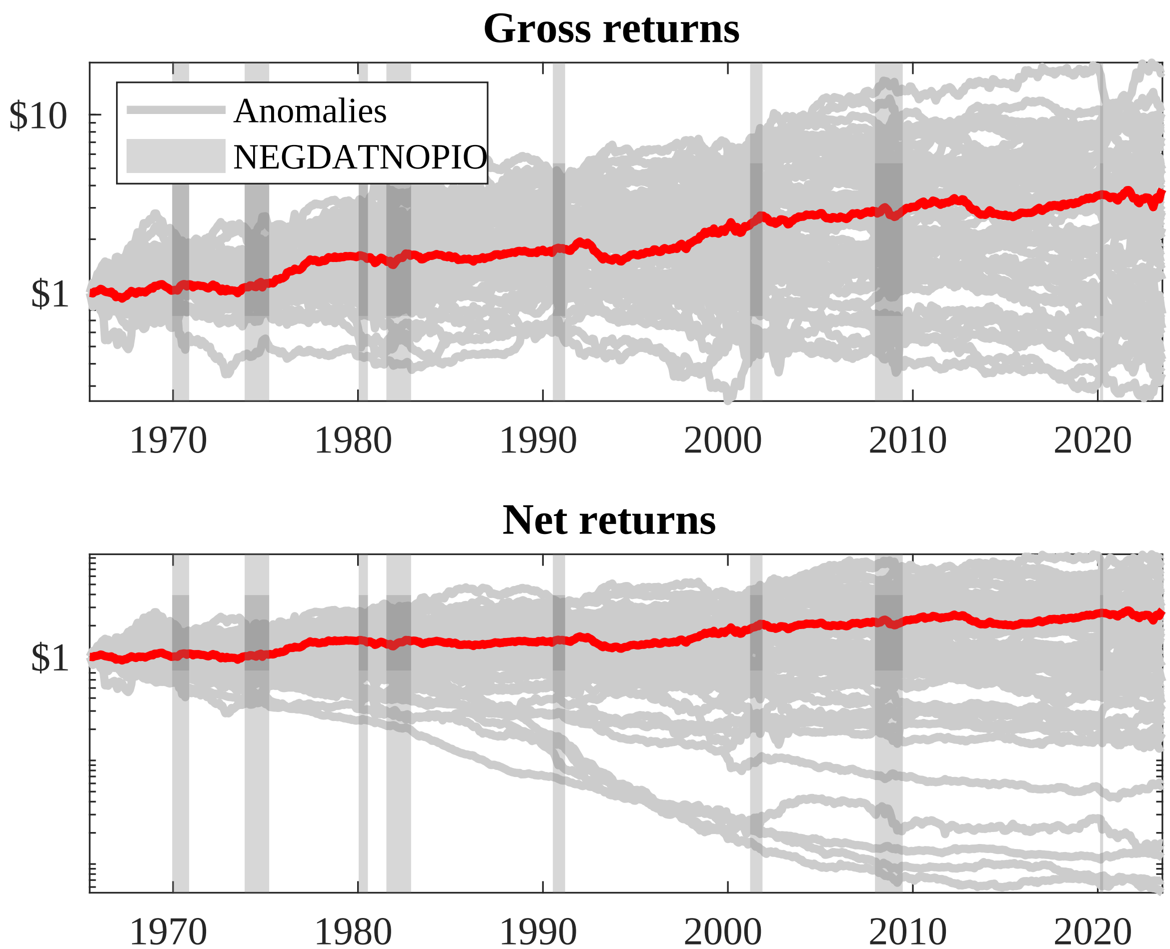


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the ANI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

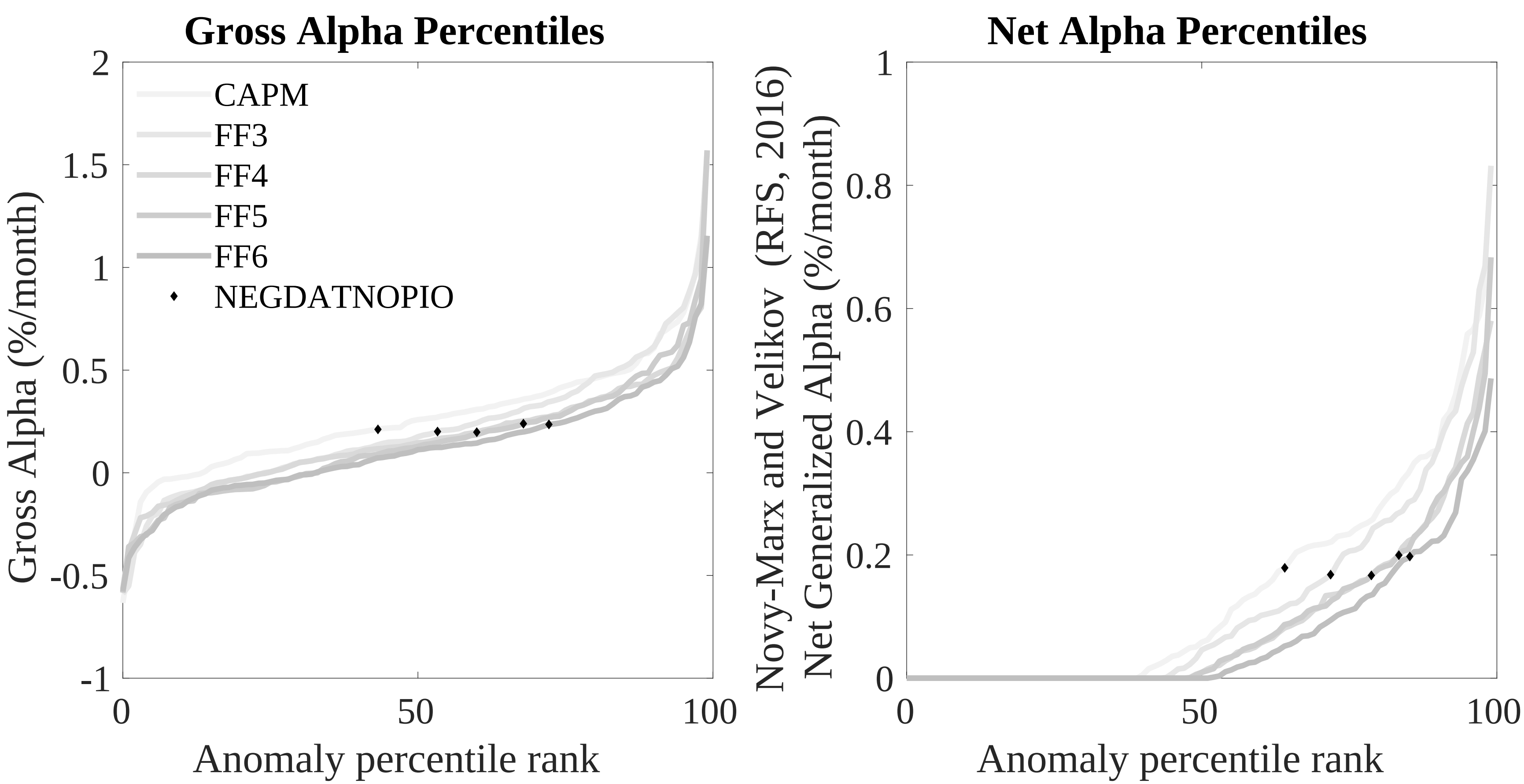
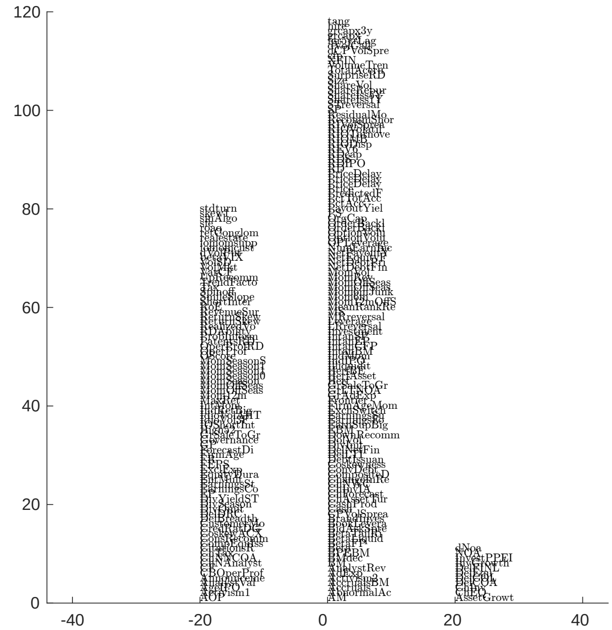
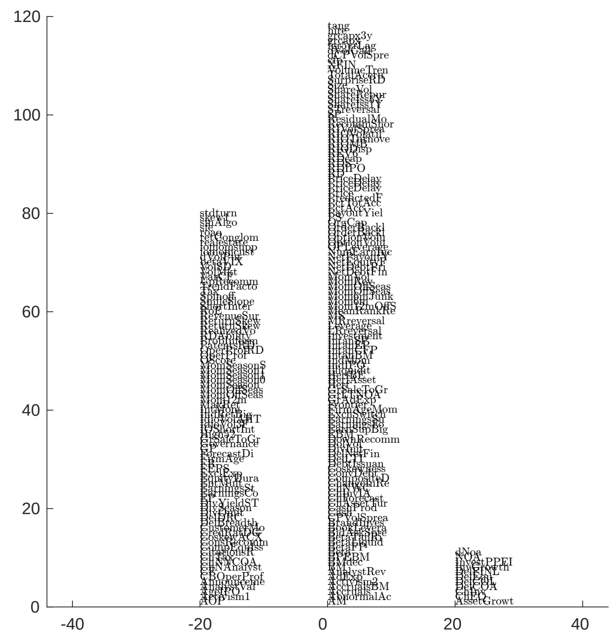


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the ANI trading strategy alphas (diamonds). The strategies are constructed using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



Panel A: Pearson



Panel B: Spearman

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

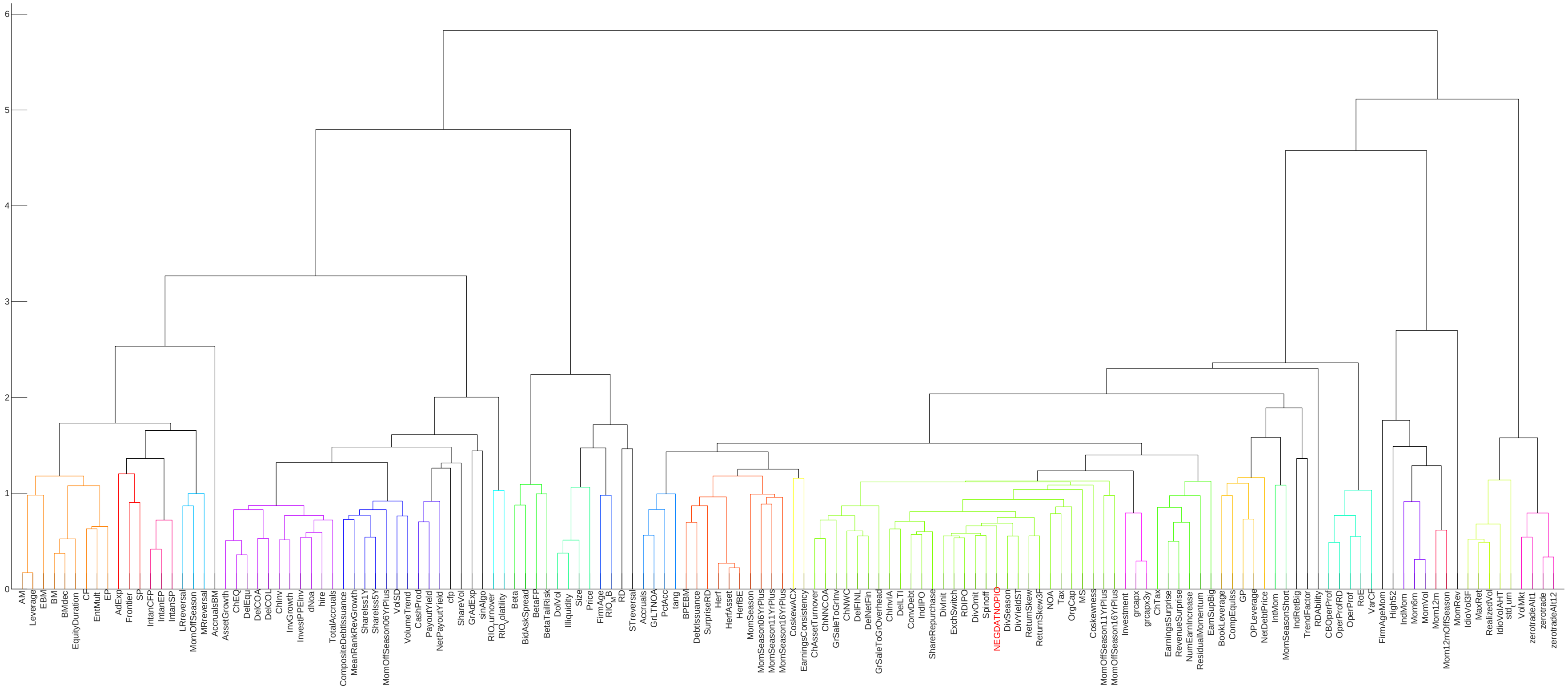


Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

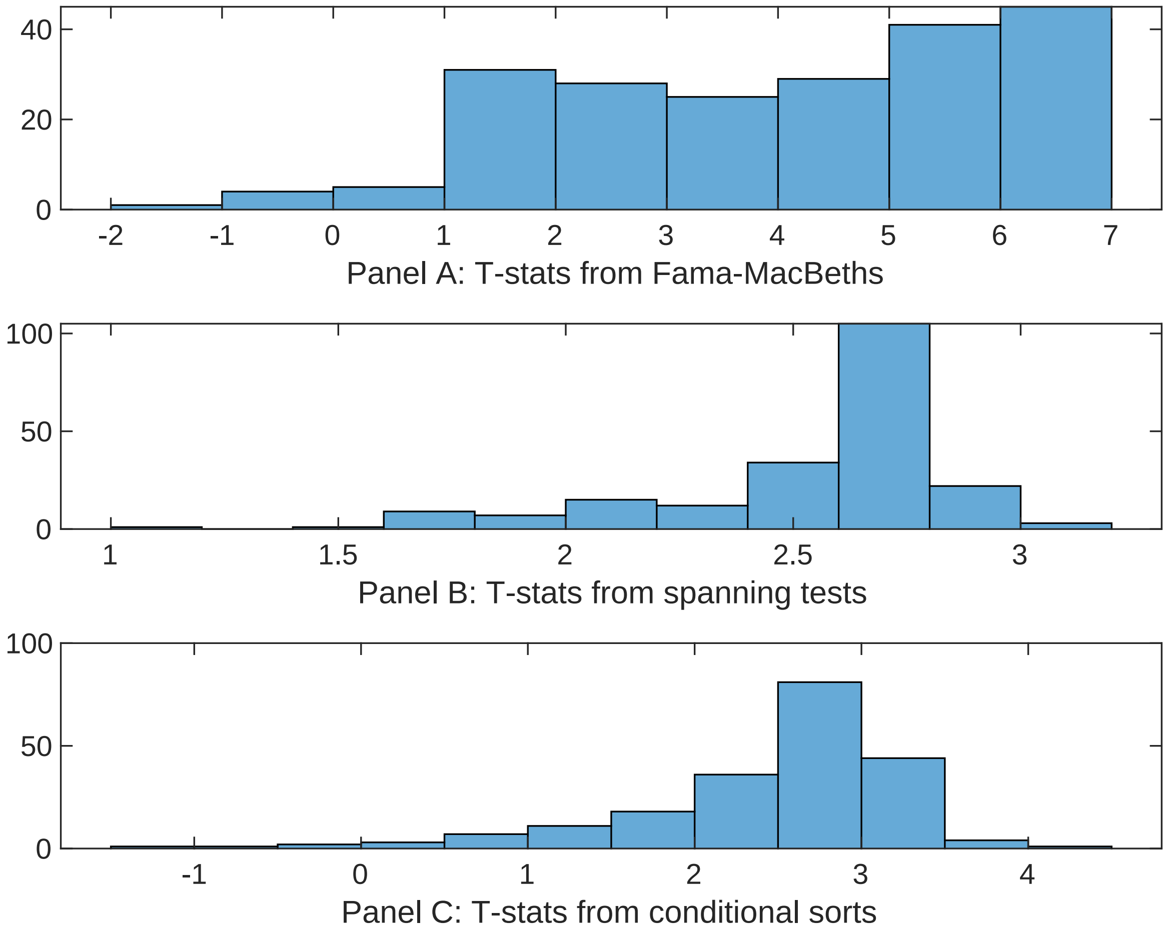


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of ANI conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ANI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ANI} ANI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{ANI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 ANI. Stocks are finally grouped into five ANI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted ANI 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 ANI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{ANI} ANI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Growth in book equity, Inventory Growth, net income / book equity, Growth in long term operating assets, Accruals, Change in net financial assets. 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	0.12	0.12	0.12	0.12	0.12	0.17
	[7.00]	[5.52]	[5.29]	[5.29]	[5.14]	[5.45]	[8.41]
ANI	0.30	0.29	0.39	0.36	0.31	0.31	0.21
	[4.93]	[4.60]	[6.21]	[5.66]	[5.02]	[4.84]	[3.56]
Anomaly 1	0.44						0.38
	[3.98]						[3.59]
Anomaly 2		0.33					0.14
		[6.54]					[2.73]
Anomaly 3			-0.11				0.77
			[-0.59]				[0.30]
Anomaly 4				0.67			0.47
				[2.70]			[0.20]
Anomaly 5					0.16		0.55
					[5.17]		[1.59]
Anomaly 6						0.92	0.79
						[6.14]	[5.03]
# months	696	696	696	696	696	696	696
$\bar{R}^2$(%)	0	0	0	0	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the ANI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{ANI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Inventory Growth, net income / book equity, Growth in long term operating assets, Accruals, Change in net financial assets. 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	0.24	0.23	0.25	0.24	0.22	0.21	0.16
	[3.27]	[3.00]	[3.31]	[3.12]	[2.92]	[2.75]	[2.18]
Anomaly 1	13.79						18.07
	[3.31]						[4.07]
Anomaly 2		11.66					6.44
		[3.08]					[1.69]
Anomaly 3			-5.39				-2.31
			[-1.30]				[-0.55]
Anomaly 4				8.87			6.99
				[2.54]			[1.60]
Anomaly 5					8.55		1.45
					[2.80]		[0.37]
Anomaly 6						13.89	19.38
						[3.68]	[4.69]
mkt	-2.23	-2.39	-3.45	-1.94	-2.05	-2.51	-1.35
	[-1.26]	[-1.35]	[-1.84]	[-1.08]	[-1.15]	[-1.42]	[-0.72]
smb	0.97	2.93	-0.17	3.13	3.17	2.57	4.01
	[0.38]	[1.13]	[-0.06]	[1.18]	[1.21]	[1.00]	[1.35]
hml	-2.55	-1.63	-1.40	-0.38	0.95	-0.81	-3.04
	[-0.74]	[-0.48]	[-0.41]	[-0.11]	[0.27]	[-0.24]	[-0.88]
rmw	-15.05	-13.70	-10.79	-13.18	-12.83	-13.85	-6.13
	[-4.35]	[-3.89]	[-2.07]	[-3.64]	[-3.54]	[-3.97]	[-1.19]
cma	-6.89	-0.91	5.49	4.29	4.06	9.36	-14.55
	[-1.06]	[-0.16]	[1.07]	[0.84]	[0.80]	[1.85]	[-2.20]
umd	0.60	0.04	0.92	0.97	0.04	0.39	-0.19
	[0.35]	[0.02]	[0.52]	[0.55]	[0.02]	[0.22]	[-0.11]
# months	696	696	696	696	696	696	696
$\bar{R}^2$(%)	5	5	4	4	5	5	9

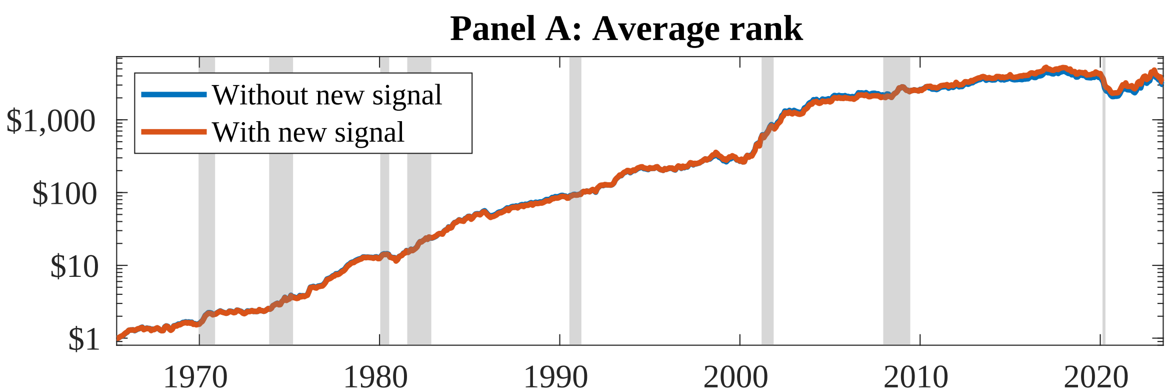


Figure 8: Combination strategy performance
This figure plots the growth of a \$1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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