Net Ownership Stake and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Net Ownership Stake (NOS), 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 NOS achieves an annualized gross (net) Sharpe ratio of 0.58 (0.52), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (24) bps/month with a t-statistic of 2.97 (3.00), 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, Asset growth) is 19 bps/month with a t-statistic of 2.58.

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 various market anomalies that appear to contradict this notion (McLean and Pontiff, 2016). While many of these anomalies are well-documented, their economic mechanisms often remain unclear, and their robustness across different methodological approaches is frequently questioned (Hou et al., 2020).

One particularly intriguing area of study involves signals related to changes in corporate ownership structure and their implications for future stock returns. While existing research has examined various aspects of ownership, including insider trading (Cohen et al., 2012) and institutional ownership changes (Gompers et al., 2003), the literature lacks a comprehensive examination of how changes in the overall net ownership stake affect future stock performance.

We propose that Net Ownership Stake (NOS) contains valuable information about future stock returns through several economic channels. First, changes in net ownership stake may signal management's private information about future firm prospects, building on theoretical frameworks of information asymmetry (Myers and Majluf, 1984). When managers increase their ownership stakes, they signal confidence in the firm's future performance.

Second, changes in ownership structure can affect agency costs and corporate governance quality (Jensen and Meckling, 1976). Higher net ownership stakes align management interests with those of shareholders, potentially leading to better decision-making and improved firm performance (Morck et al., 1988). This alignment should be particularly valuable when firms face significant growth opportunities or complex strategic decisions.

Third, ownership changes may reflect broader patterns of informed trading. Following (Glosten and Milgrom, 1985), sophisticated investors with superior information should be more likely to accumulate shares when they anticipate positive future returns. The net ownership stake measure aggregates these informed trades into a single comprehensive signal.

Our analysis reveals that Net Ownership Stake (NOS) strongly predicts future stock returns. A value-weighted long-short trading strategy based on NOS quintiles generates a monthly alpha of 24 basis points (t-statistic = 2.97) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized Sharpe ratio of 0.58 before trading costs and 0.52 after accounting for transaction costs.

The predictive power of NOS remains robust across various methodological specifications. When controlling for the six most closely related anomalies from the factor zoo, including share issuance and asset growth measures, the strategy still delivers a significant monthly alpha of 19 basis points (t-statistic = 2.58). This persistence suggests that NOS captures unique information not contained in existing signals.

Importantly, the signal's predictive power extends to large-cap stocks, where many anomalies fail to generate significant returns. Among stocks in the largest size quintile, the NOS strategy achieves a monthly return of 26 basis points (t-statistic = 2.74), indicating that the effect is not limited to small, illiquid stocks.

Our paper makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures a distinct dimension of firm behavior not previously examined in the anomalies literature. While related to existing measures like share issuance (Pontiff and Woodgate, 2008) and payout policy (Fama and French, 2001), NOS provides incremental predictive power beyond these established signals.

Second, we contribute to the literature on ownership structure and stock returns by showing that aggregate changes in ownership stake contain valuable information about future performance. This extends previous work focusing on specific types of owners, such as institutional investors (Gompers et al., 2003) or corporate insiders (Cohen et al., 2012), by providing a more comprehensive measure of ownership changes.

Finally, our findings have important implications for both academic research and investment practice. For researchers, we demonstrate the importance of considering ownership structure changes when studying return predictability. For practitioners, we document a robust signal that remains profitable after accounting for transaction costs and performs well among large-cap stocks, making it particularly valuable for institutional investors.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Net Ownership Stake. 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 CEQL for common equity. Common stock (CSTK) represents the total value of common shares issued by the company, while common equity (CEQL) reflects the total shareholders' equity excluding preferred stock and other equity items. The construction of the signal follows a change-based approach, where we calculate the difference between the current period's CSTK and its previous period's value, then scale this difference by the previous period's CEQL. This normalized change in common stock captures the relative magnitude of changes in ownership structure relative to the firm's equity base. By focusing on this relationship, the signal aims to reflect aspects of ownership dynamics and capital structure changes in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both CSTK and CEQL to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the NOS signal. Panel A plots the time-series of the mean, median, and interquartile range for NOS. On average, the cross-sectional mean (median) NOS is -0.01 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input NOS data. The signal's interquartile range spans -0.01 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the NOS signal for the CRSP universe. On average, the NOS signal is available for 6.64% of CRSP names, which on average make up 7.97% of total market capitalization.

4 Does NOS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on NOS 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 NOS portfolio and sells the low NOS 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 NOS strategy earns an average return of 0.35% per month with a t-statistic of 4.43. The annualized Sharpe ratio of the strategy is 0.58. The alphas range from 0.24% to 0.37% per month and have t-statistics exceeding 2.97 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 0.32, with a t-statistic of 5.90 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 615 stocks and an average market capitalization of at least $1,481 million.

Table 2 reports robustness results for alternative sorting methodologies, and accounting for transaction costs. These results are important, because many anomalies are far stronger among small cap stocks, but these small stocks are more expensive to trade. Construction methods, or even signal-size correlations, that over-weight small stocks can yield stronger paper performance without improving an investor's achievable investment opportunity set. Panel A reports gross returns and alphas for the long/short strategies made using various different protfolio constructions. The first row reports the average returns and the alphas for the long/short strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios. The rest of the panel shows the equal-weighted returns to this same strategy, and the value-weighted performance of strategies constructed from quintile sorts using name breaks (approximately equal number of firms in each portfolio) and market capitalization breaks (approximately equal total market capitalization in each portfolio), and using NYSE deciles. The average return is lowest for the quintile sort using cap breakpoints and value-weighted portfolios, and equals 30 bps/month with a t-statistics of 3.88. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for twenty 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 27-32bps/month. The lowest return, (27 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.43. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the NOS 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 NOS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and NOS, as well as average returns and alphas for long/short trading NOS 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 NOS strategy achieves an average return of 26 bps/month with a t-statistic of 2.74. Among these large cap stocks, the alphas for the NOS strategy relative to the five most common factor models range from 19 to 26 bps/month with t-statistics between 1.98 and 2.69.

5 How does NOS perform relative to the zoo?

Figure 2 puts the performance of NOS 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

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

ratio for the NOS strategy falls in the distribution. The NOS strategy's gross (net) Sharpe ratio of 0.58 (0.52) is greater than 95% (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 NOS strategy (red line).[2] Ignoring trading costs, a \$1 invested in the NOS strategy would have yielded \$8.82 which ranks the NOS strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the NOS strategy would have yielded \$6.61 which ranks the NOS strategy in the top 0% 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 NOS relative to those. Panel A shows that the NOS strategy gross alphas fall between the 70 and 74 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 196606 to 202306 sample. For example, 45% (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 NOS strategy has a positive net generalized alpha for five out of the five factor models. In these cases NOS ranks between the 86 and 92 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 NOS 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 NOS with 210 filtered anomaly signals.[3] Figure 6 also shows an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

A closely related anomaly is also more likely to price NOS or at least to weaken the power NOS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of NOS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{NOS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{NOS} NOS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 210 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{NOS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 210 filtered anomaly trading strategies at a time. The strategies employed in the spanning tests are constructed using quintile sorts, value-weighting, and NYSE breakpoints. Panel C plots t-statistics on the average returns to strategies constructed by conditional double sorts. In each month, we sort stocks into quintiles based one of the 210 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on NOS. Stocks are finally grouped into five NOS 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.

NOS trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on NOS 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 NOS signal in these Fama-MacBeth regressions exceed 2.78, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on NOS is 2.05.

Similarly, Table 5 reports results from spanning tests that regress returns to the NOS 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 NOS strategy earns alphas that range from 21-26bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.63, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the NOS trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.58.

7 Does NOS add relative to the whole zoo?

Finally, we can ask how much adding NOS 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 NOS 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 NOS 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 $2333.55, while $1 investment in the combination strategy that includes NOS grows to $2316.54.

8 Conclusion

This study provides compelling evidence for the predictive power of Net Ownership Stake (NOS) in forecasting cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short strategy based on NOS generates economically and statistically significant returns, with an impressive annualized Sharpe ratio of 0.58 (0.52) on a gross (net) basis. The strategy's robustness is particularly noteworthy, maintaining significant abnormal returns of 24 basis points per month even after controlling for the Fama-French five factors and momentum. Furthermore, the signal's predictive power persists when controlling for six closely related factors from the factor zoo, yielding a monthly alpha of 19 basis points with strong statistical significance.

These results have important implications for both academic research and investment practice. For academics, our findings contribute to the growing literature on return predictability and suggest that ownership structure provides valuable information about future stock performance. For practitioners, the NOS signal represents a potentially valuable tool for portfolio management, particularly given its demonstrated effectiveness after accounting for transaction costs.

However, several limitations should be noted. First, the study's findings may be sensitive to the specific time period examined. Second, the implementation of the strategy might face practical constraints in terms of liquidity and trading costs for certain stocks. Future research could explore the signal's effectiveness in international markets, investigate potential interaction effects with other established factors, and examine the underlying economic mechanisms driving the predictive power of NOS. Additionally, researchers might consider studying how the signal's effectiveness varies across different market conditions and investor sentiment regimes.

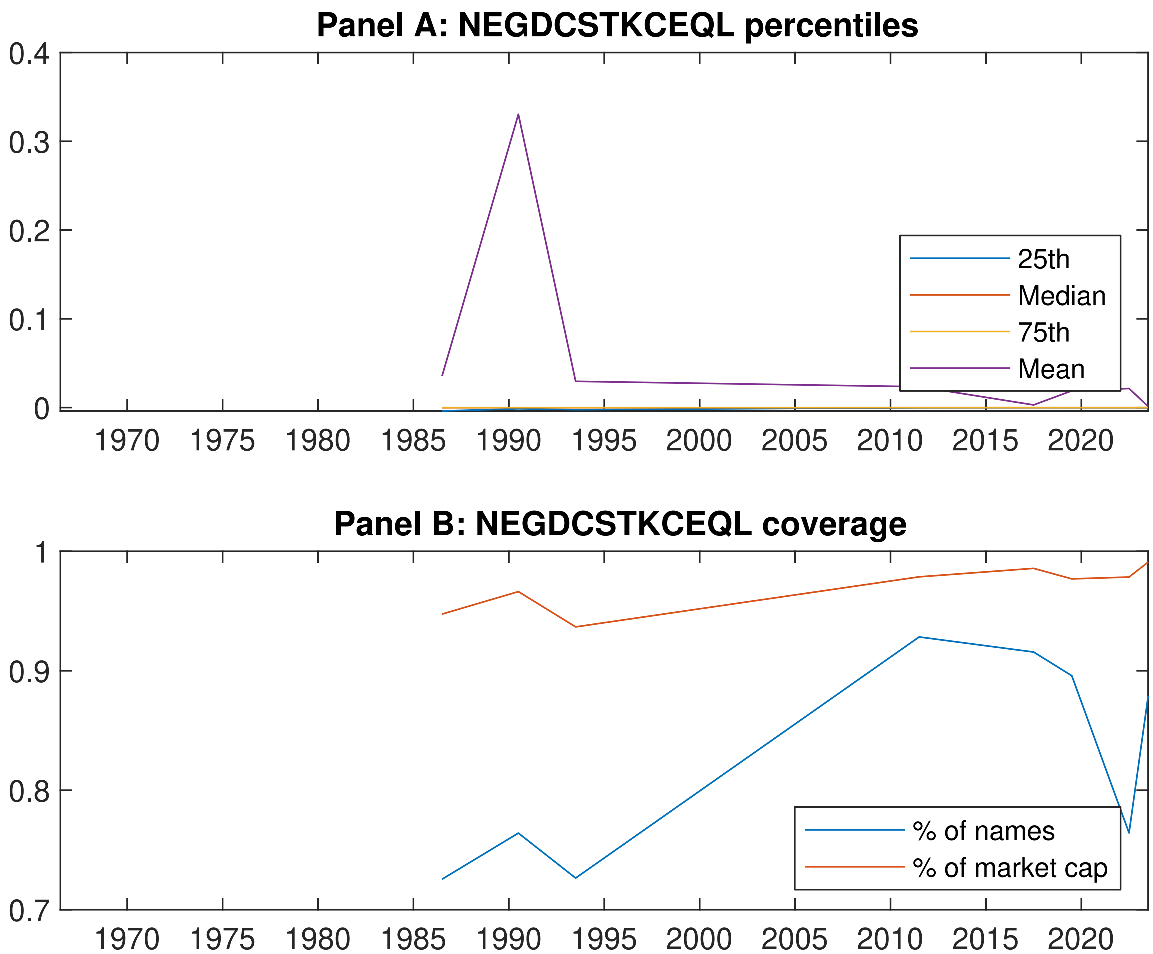


Figure 1: Times series of NOS percentiles and coverage.
This figure plots descriptive statistics for NOS. Panel A shows cross-sectional percentiles of NOS over the sample. Panel B plots the monthly coverage of NOS relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on NOS. 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 NOS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.42	0.49	0.68	0.66	0.77	0.35
	[2.35]	[2.55]	[3.62]	[3.88]	[4.51]	[4.43]
α_{CAPM}	-0.13	-0.12	0.09	0.13	0.23	0.37
	[-2.51]	[-2.55]	[1.80]	[2.65]	[4.95]	[4.64]
α_{FF3}	-0.14	-0.10	0.11	0.09	0.19	0.33
	[-2.70]	[-2.29]	[2.25]	[2.08]	[4.17]	[4.17]
α_{FF4}	-0.12	-0.07	0.12	0.05	0.17	0.29
	[-2.24]	[-1.63]	[2.53]	[1.14]	[3.75]	[3.63]
α_{FF5}	-0.16	-0.04	0.14	0.01	0.10	0.26
	[-3.05]	[-0.97]	[2.80]	[0.12]	[2.24]	[3.29]
α_{FF6}	-0.14	-0.03	0.15	-0.02	0.09	0.24
	[-2.68]	[-0.55]	[2.98]	[-0.48]	[2.11]	[2.97]
Panel B: Fama and French (2018) 6-factor model loadings for NOS-sorted portfolios						
β_{MKT}	0.97	1.03	1.01	1.01	0.99	0.02
	[76.68]	[94.09]	[85.68]	[96.35]	[94.16]	[0.87]
β_{SMB}	-0.02	0.02	0.04	-0.08	0.00	0.02
	[-1.07]	[0.96]	[2.13]	[-5.09]	[0.02]	[0.73]
β_{HML}	0.07	-0.01	-0.07	0.06	0.05	-0.03
	[3.03]	[-0.54]	[-3.07]	[3.09]	[2.24]	[-0.79]
β_{RMW}	0.13	-0.09	-0.07	0.11	0.11	-0.02
	[5.18]	[-4.37]	[-2.84]	[5.54]	[5.36]	[-0.50]
β_{CMA}	-0.11	-0.09	-0.01	0.17	0.21	0.32
	[-2.92]	[-3.00]	[-0.38]	[5.78]	[7.08]	[5.90]
β_{UMD}	-0.03	-0.03	-0.02	0.04	0.01	0.04
	[-2.28]	[-2.74]	[-1.45]	[4.01]	[0.67]	[1.90]
Panel C: Average number of firms (n) and market capitalization (me)						
n	748	724	615	715	793	
me ($\$10^6$)	1739	1481	2083	2278	2350	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the NOS 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	0.35	0.37	0.33	0.29	0.26	0.24
			[4.43]	[4.64]	[4.17]	[3.63]	[3.29]	[2.97]
Quintile	NYSE	EW	0.48	0.52	0.47	0.42	0.38	0.35
			[8.49]	[9.61]	[8.97]	[8.00]	[7.31]	[6.69]
Quintile	Name	VW	0.34	0.36	0.32	0.29	0.25	0.24
			[4.35]	[4.51]	[4.07]	[3.61]	[3.20]	[2.96]
Quintile	Cap	VW	0.30	0.31	0.28	0.24	0.25	0.22
			[3.88]	[3.93]	[3.61]	[3.03]	[3.21]	[2.81]
Decile	NYSE	VW	0.36	0.36	0.31	0.27	0.29	0.26
			[4.02]	[3.96]	[3.43]	[2.98]	[3.17]	[2.87]
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	0.31	0.34	0.30	0.28	0.25	0.24
			[3.96]	[4.22]	[3.82]	[3.56]	[3.17]	[3.00]
Quintile	NYSE	EW	0.27	0.32	0.27	0.24	0.16	0.15
			[4.30]	[5.05]	[4.41]	[4.03]	[2.78]	[2.59]
Quintile	Name	VW	0.30	0.32	0.29	0.28	0.24	0.23
			[3.87]	[4.09]	[3.71]	[3.49]	[3.10]	[2.96]
Quintile	Cap	VW	0.27	0.28	0.26	0.23	0.24	0.22
			[3.43]	[3.55]	[3.27]	[2.97]	[3.07]	[2.85]
Decile	NYSE	VW	0.32	0.32	0.28	0.26	0.26	0.25
			[3.55]	[3.53]	[3.08]	[2.86]	[2.88]	[2.76]

Table 3: Conditional sort on size and NOS

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

		NOS Quintiles					NOS Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.45	0.65	0.87	0.92	0.92	0.47	0.50	0.47	0.43	0.40	0.37
		[1.75]	[2.45]	[3.35]	[3.65]	[3.77]	[6.94]	[7.45]	[7.11]	[6.40]	[5.90]	[5.45]
	(2)	0.56	0.66	0.85	0.88	0.91	0.35	0.39	0.33	0.29	0.29	0.26
		[2.38]	[2.73]	[3.50]	[3.86]	[4.03]	[4.36]	[4.77]	[4.17]	[3.62]	[3.53]	[3.18]
	(3)	0.54	0.67	0.75	0.82	0.95	0.41	0.42	0.39	0.39	0.36	0.36
		[2.58]	[2.95]	[3.26]	[3.88]	[4.62]	[5.71]	[5.76]	[5.38]	[5.21]	[4.83]	[4.77]
	(4)	0.50	0.63	0.75	0.82	0.77	0.27	0.29	0.23	0.21	0.11	0.11
		[2.54]	[3.00]	[3.55]	[4.14]	[4.04]	[3.57]	[3.82]	[3.18]	[2.89]	[1.54]	[1.48]
	(5)	0.45	0.46	0.51	0.54	0.71	0.26	0.26	0.23	0.19	0.23	0.21
		[2.62]	[2.46]	[2.80]	[3.13]	[4.22]	[2.74]	[2.69]	[2.43]	[1.98]	[2.43]	[2.10]

Panel B: Portfolio average number of firms and market capitalization

		NOS Quintiles Average n					NOS Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	397	397	397	394	393	32	34	41	29	30
	(2)	112	112	111	111	111	57	57	57	57	57
	(3)	82	81	81	80	81	99	96	98	100	100
	(4)	68	68	68	68	68	206	204	212	216	217
	(5)	62	62	62	62	62	1422	1428	1722	1615	1743

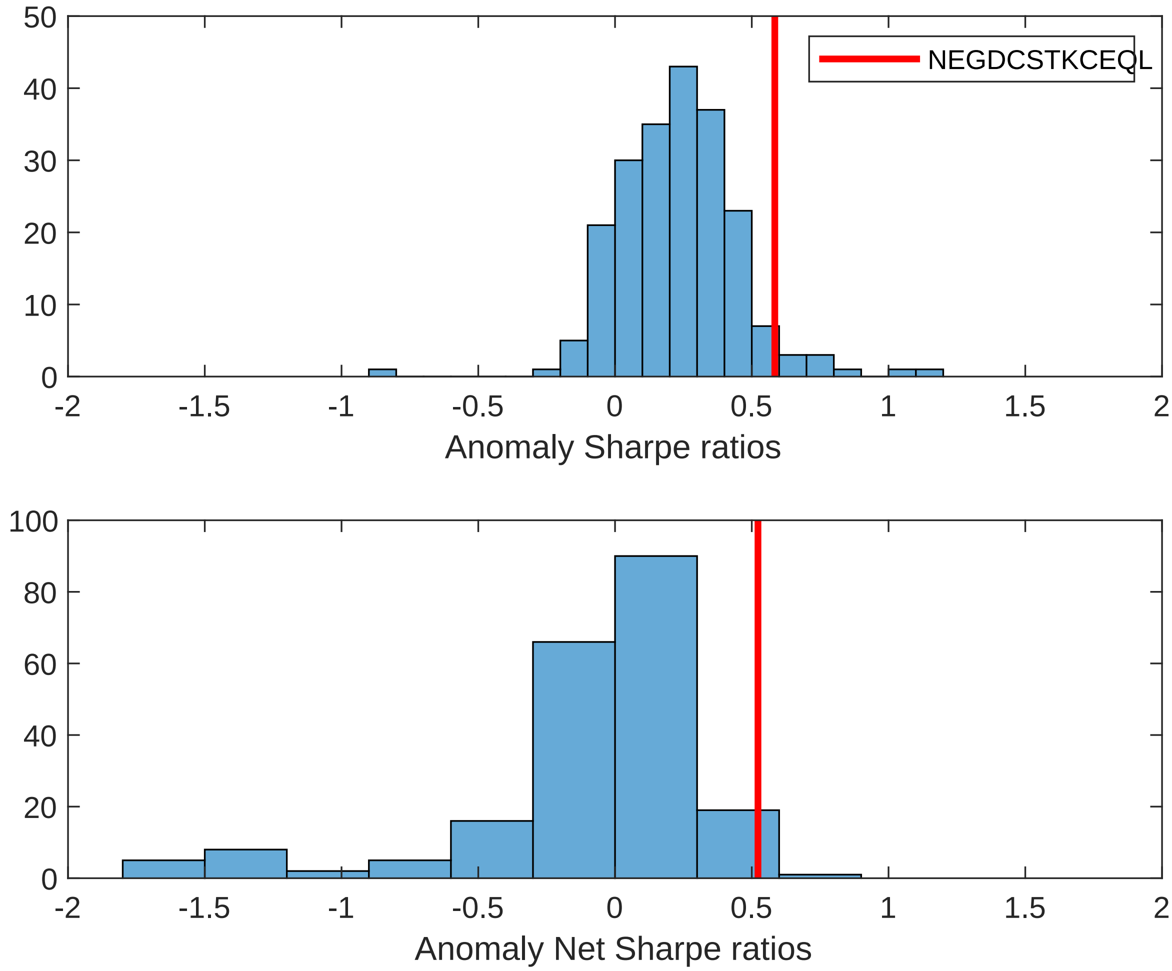


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the NOS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

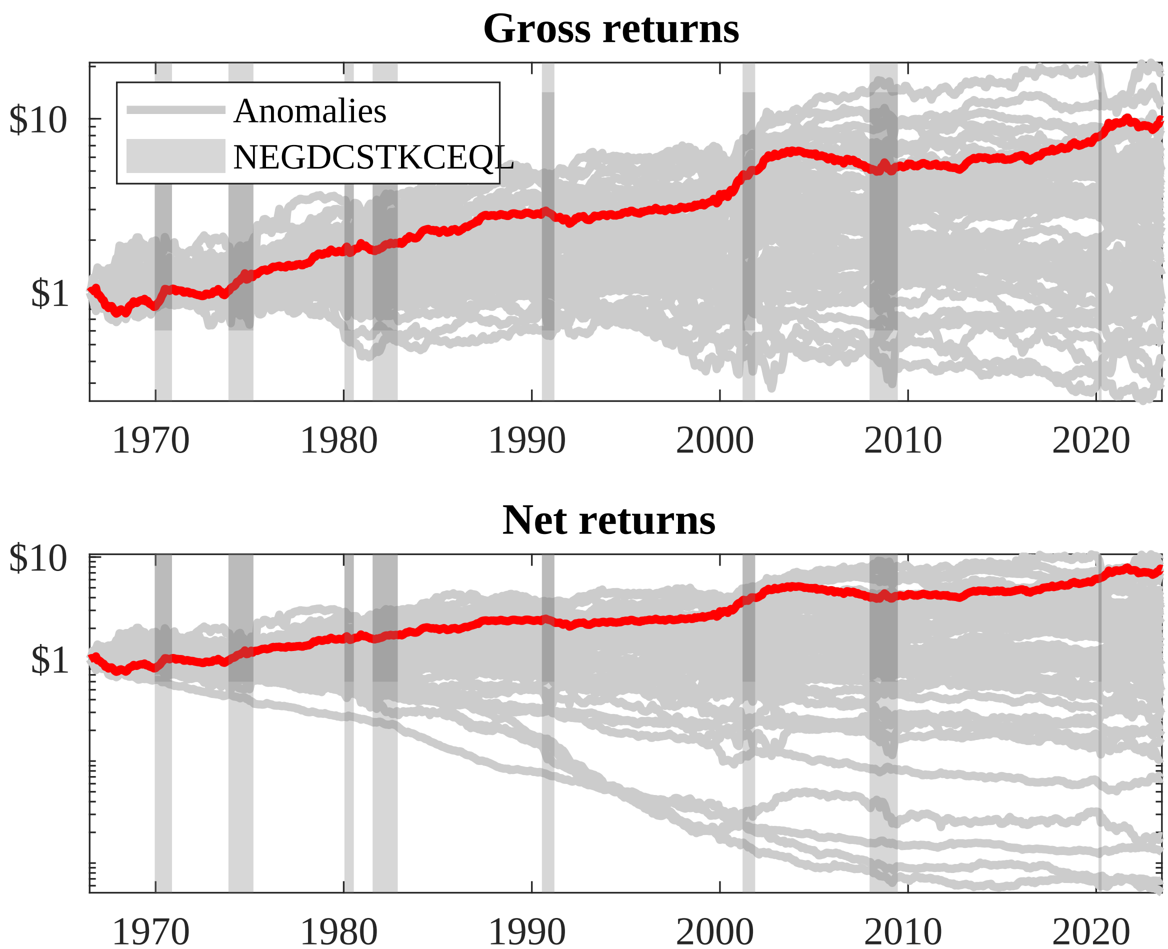


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the NOS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

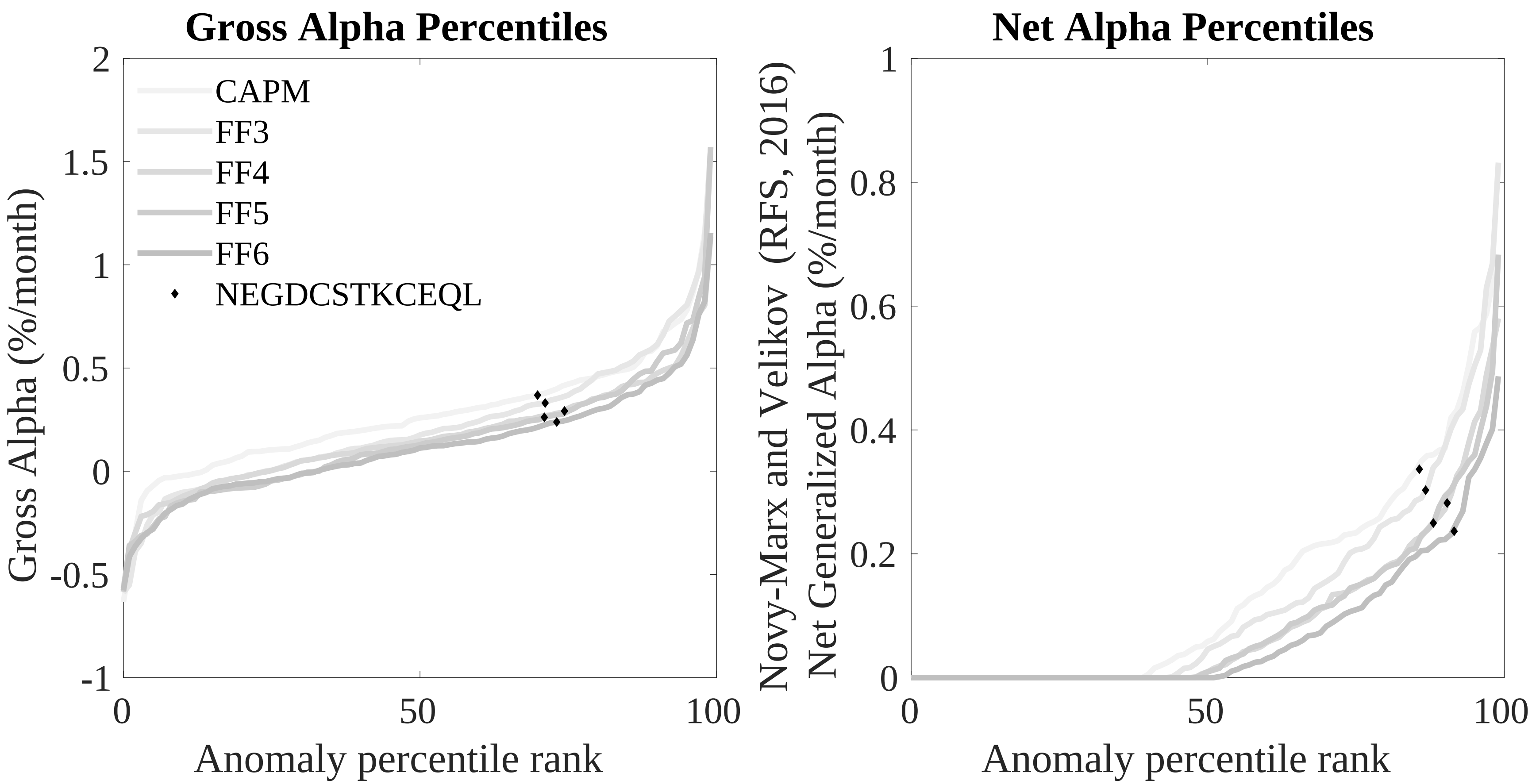
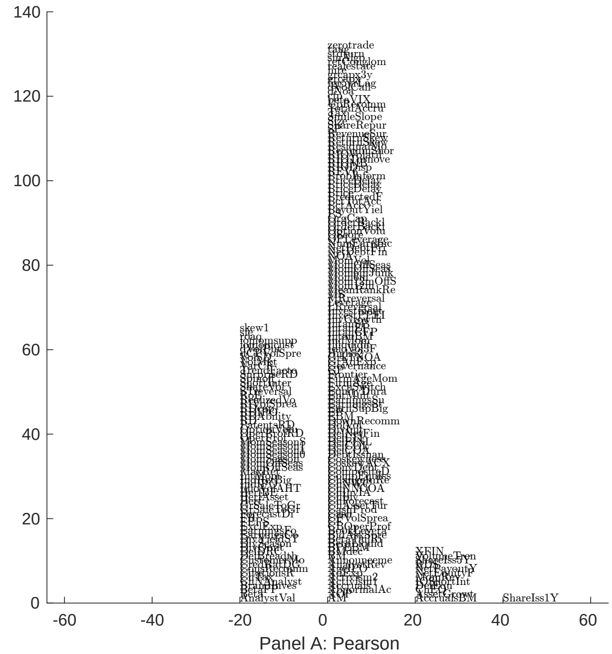


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the NOS trading strategy alphas (diamonds). The strategies are constructed using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



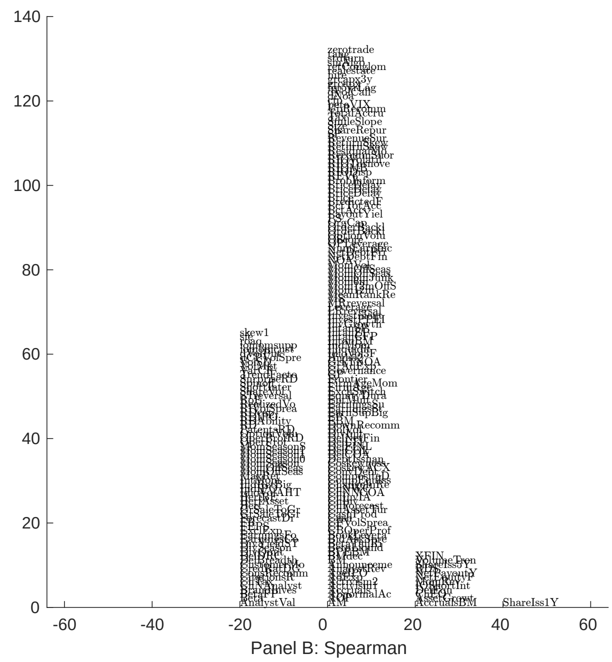


Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with NOS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

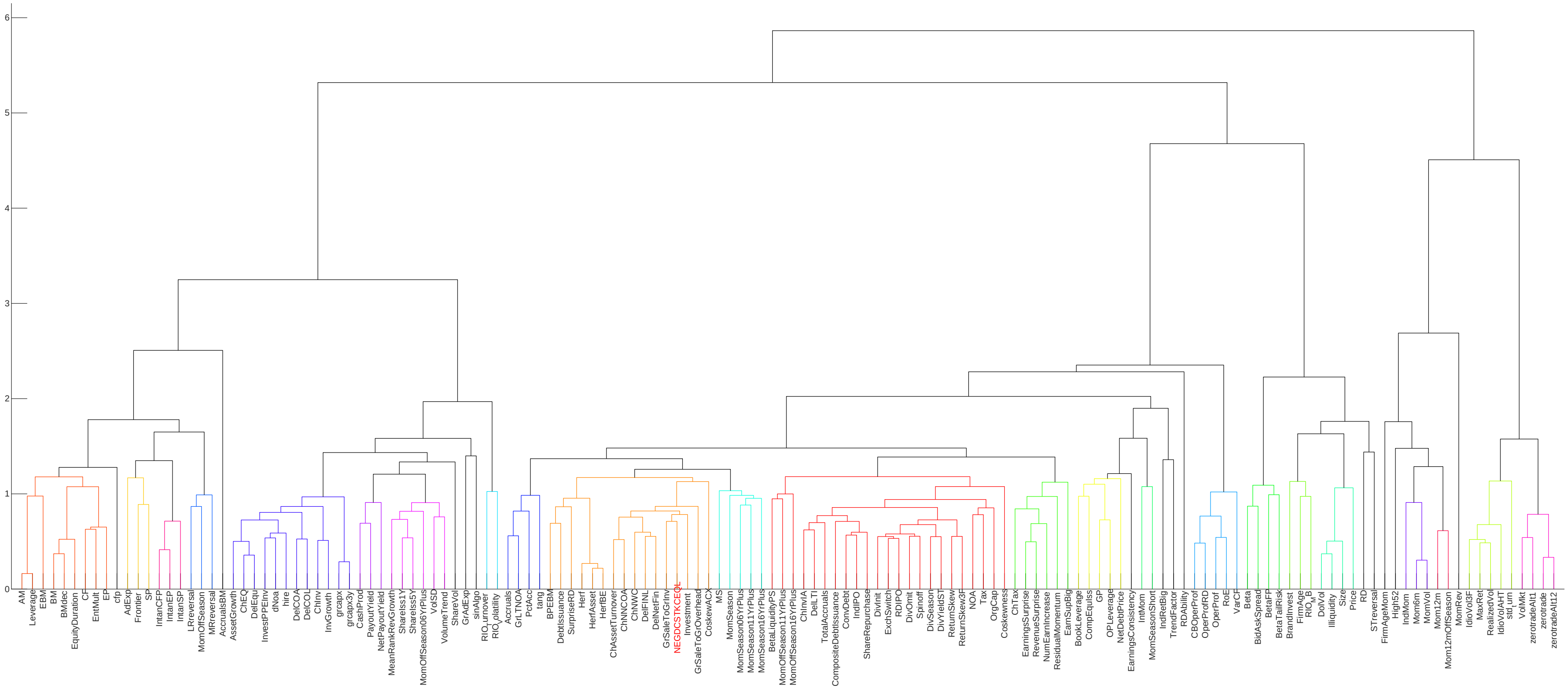


Figure 6: Agglomerative hierarchical cluster plot

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

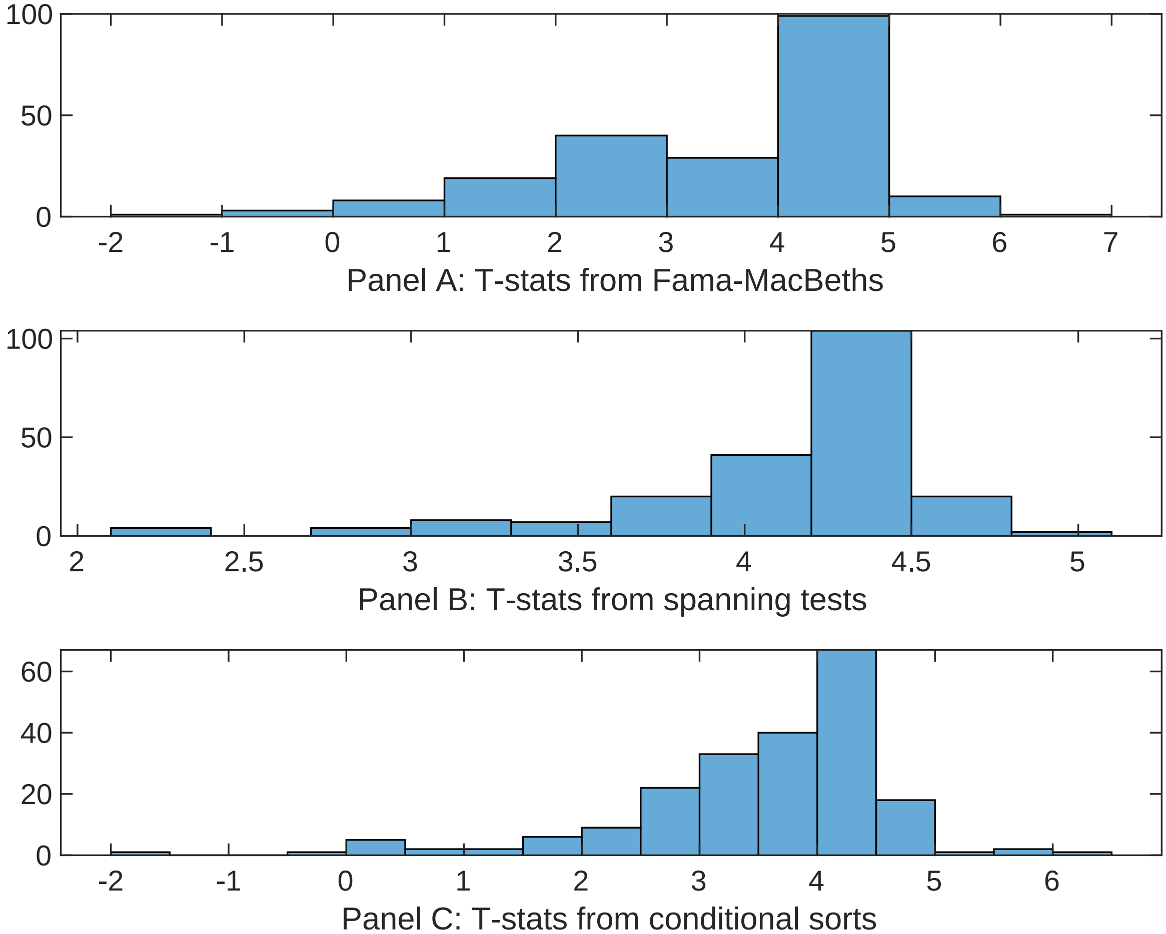


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of NOS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{NOS} from Fama-MacBeth regressions of the form $r_{i,t}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

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

This table presents Fama-MacBeth results of returns on NOS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{NOS} NOS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Growth in book equity, Net Payout Yield, Share issuance (5 year), Change in equity to assets, Asset growth. 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	0.17	0.12	0.13	0.12	0.13	0.13
	[5.65]	[7.20]	[5.24]	[6.02]	[5.56]	[6.03]	[5.13]
NOS	0.21	0.19	0.17	0.21	0.19	0.15	0.12
	[4.16]	[4.13]	[2.78]	[4.06]	[3.81]	[3.02]	[2.05]
Anomaly 1	0.27						0.97
	[5.93]						[2.41]
Anomaly 2		0.46					-0.30
		[4.22]					[-0.19]
Anomaly 3			0.27				0.23
			[2.42]				[2.11]
Anomaly 4				0.37			0.34
				[4.33]			[0.37]
Anomaly 5					0.14		-0.11
					[4.11]		[-0.19]
Anomaly 6						0.10	0.68
						[8.81]	[6.48]
# months	679	684	679	679	684	684	679
$\bar{R}^2$(%)	0	0	1	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 NOS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{NOS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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, Asset growth. 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	0.21	0.24	0.23	0.21	0.26	0.24	0.19
	[2.76]	[3.09]	[2.92]	[2.63]	[3.23]	[3.02]	[2.58]
Anomaly 1	28.01						19.48
	[7.06]						[4.26]
Anomaly 2		36.38					40.53
		[8.53]					[6.56]
Anomaly 3			14.85				2.31
			[4.85]				[0.67]
Anomaly 4				14.47			0.53
				[3.49]			[0.12]
Anomaly 5					19.97		-10.13
					[4.76]		[-1.75]
Anomaly 6						3.92	-18.44
						[0.74]	[-3.38]
mkt	4.03	2.99	4.35	3.91	1.47	1.80	5.29
	[2.21]	[1.65]	[2.29]	[2.04]	[0.79]	[0.95]	[2.85]
smb	3.71	1.02	5.45	1.82	1.93	1.90	4.28
	[1.41]	[0.39]	[2.00]	[0.67]	[0.71]	[0.68]	[1.59]
hml	-5.76	-6.77	-7.77	-6.05	-5.03	-2.61	-8.66
	[-1.61]	[-1.93]	[-2.04]	[-1.57]	[-1.38]	[-0.71]	[-2.33]
rmw	-11.03	-0.16	-10.14	-4.49	-0.09	-2.16	-8.22
	[-2.92]	[-0.05]	[-2.52]	[-1.20]	[-0.02]	[-0.58]	[-1.99]
cma	18.24	-4.79	21.10	27.64	10.53	26.56	13.66
	[3.26]	[-0.72]	[3.61]	[4.98]	[1.53]	[3.17]	[1.70]
umd	3.40	3.23	5.03	3.88	4.21	3.69	2.26
	[1.89]	[1.80]	[2.73]	[2.11]	[2.27]	[1.95]	[1.27]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	16	17	12	11	11	8	22

Panel A: Average rank

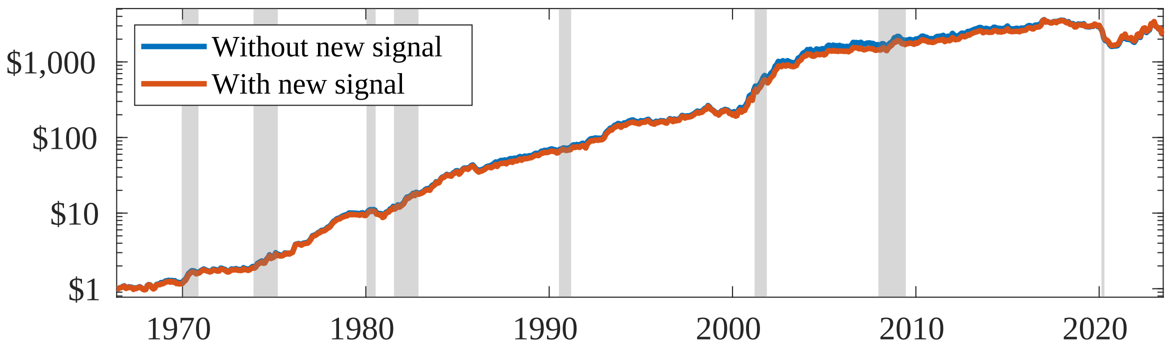


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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