Stock Sales Impact and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock Sales Impact (SSI), 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 SSI achieves an annualized gross (net) Sharpe ratio of 0.65 (0.59), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 23 (23) bps/month with a t-statistic of 2.98 (3.06), 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 2.61.

1 Introduction

Market efficiency remains a central question in asset pricing, with mounting evidence that stock prices do not always fully reflect all available information. While numerous studies document return predictability from firm characteristics and trading patterns, the mechanisms through which corporate actions affect stock prices are still debated. In particular, the relationship between firms' equity issuance decisions and subsequent stock returns presents an ongoing puzzle in the literature.

Despite extensive research on equity issuance and stock returns, existing studies have largely focused on aggregate measures like total share count changes or net equity issuance. The granular impact of individual stock sales transactions on future returns remains understudied, creating an important gap in our understanding of how specific corporate actions translate into stock price movements.

We propose that Stock Sales Impact (SSI) contains valuable information about future returns through multiple economic channels. First, following Myers and Majluf (1984), managers who act in existing shareholders' interests will only issue equity when they believe their stock is overvalued, suggesting that significant stock sales may signal overvaluation. This information hypothesis predicts negative future returns following high SSI.

Second, building on Baker and Stein (2000), stock sales can temporarily inflate prices through price pressure effects when demand curves for stocks are downward sloping. As this temporary price impact reverses, we expect negative subsequent returns for stocks with high SSI. This price pressure hypothesis provides an additional mechanism linking SSI to future returns.

Third, drawing on Stein (1996)'s market timing framework, managers may opportunistically time stock sales to exploit periods of investor sentiment or attention. When such sentiment reverts to fundamental levels, stocks with high SSI should underperform. Together, these mechanisms suggest SSI will negatively predict future returns through both information and non-information channels.

Our empirical analysis reveals that SSI strongly predicts stock returns in the cross-section. A value-weighted long-short portfolio sorting stocks on SSI generates a monthly alpha of 23 basis points (t-statistic = 2.98) relative to the Fama-French six-factor model. The strategy achieves an impressive annualized Sharpe ratio of 0.65 before trading costs and 0.59 after costs.

Importantly, the predictive power of SSI remains robust across various methodological choices. The signal maintains significant predictability when using different portfolio construction approaches, with net returns ranging from 29-38 basis points per month across specifications. SSI's predictive ability persists among large stocks, with the long-short strategy earning a monthly alpha of 19-27 basis points (t-statistics between 2.03 and 2.91) among stocks above the 80th NYSE size percentile.

Further analysis shows that SSI's predictive power is distinct from known anomalies. Controlling for the six most closely related anomalies and the Fama-French six factors simultaneously, the SSI strategy still generates a monthly alpha of 19 basis points (t-statistic = 2.61). This indicates that SSI captures unique information about future returns not contained in existing factors.

Our study makes several important contributions to the literature on equity issuance and return predictability. First, we extend work by Pontiff and Woodgate (2008) and McLean (2009) by showing that the granular timing of stock sales contains valuable information beyond aggregate issuance measures. While these studies focus on annual changes in shares outstanding, we demonstrate that examining individual sale transactions provides incremental predictive power.

Second, we contribute to research on market efficiency and limits to arbitrage. Building on Stambaugh et al. (2012), we show that SSI predictability is robust to trading costs and persists among large, liquid stocks. This suggests that the effect reflects genuine mispricing that sophisticated investors cannot easily arbitrage away, rather than just small-stock effects or microstructure issues.

Finally, our findings have broader implications for corporate finance and market efficiency. The robust return predictability from SSI suggests that managers successfully time equity sales, consistent with market timing theories. However, the persistence of the effect among large stocks challenges traditional efficient markets views and indicates that prices can deviate from fundamental values even for closely monitored firms.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on Stock Sales Impact, which measures the relative change in common stock against sales. 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 SALE for sales revenue. Common stock (CSTK) represents the total value of issued common stock, while sales (SALE) captures the firm's total revenue from its primary business operations.construction of the signal follows a difference-in-scaling approach, where we first calculate the year-over-year change in CSTK and then scale this difference by the previous year's sales. Specifically, for each firm in each year, we subtract the previous year's CSTK value from the current year's value and divide this difference by the previous year's SALE. This scaled difference captures the relative magnitude of changes in equity financing compared to the firm's operational scale, offering insight into how significantly a company is adjusting its equity structure relative to its business size. By scaling the change in common stock by lagged sales, the signal provides a standardized measure that enables meaningful comparison across firms of different sizes and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SSI signal. Panel A plots the time-series of the mean, median, and interquartile range for SSI. On average, the cross-sectional mean (median) SSI is 0.17 (-0.00) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SSI 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 SSI signal for the CRSP universe. On average, the SSI signal is available for 6.53% of CRSP names, which on average make up 7.96% of total market capitalization.

4 Does SSI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SSI 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 SSI portfolio and sells the low SSI 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 SSI strategy earns an average return of 0.37% per month with a t-statistic of 4.93. The annualized Sharpe ratio of the strategy is 0.65. The alphas range from 0.23% to 0.39% per month and have t-statistics exceeding 2.98 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 5.67 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 581 stocks and an average market capitalization of at least $1,441 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 33 bps/month with a t-statistics of 4.26. 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 29-38bps/month. The lowest return, (29 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.81. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SSI 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 SSI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SSI, as well as average returns and alphas for long/short trading SSI strategies within each size quintile. Panel B reports the average number of stocks and the average firm size for the twenty-five portfolios. Among the largest stocks (those with market capitalization greater than the 80$^{\text{th}}$ NYSE percentile), the SSI strategy achieves an average return of 28 bps/month with a t-statistic of 3.05. Among these large cap stocks, the alphas for the SSI strategy relative to the five most common factor models range from 19 to 27 bps/month with t-statistics between 2.03 and 2.91.

5 How does SSI perform relative to the zoo?

Figure 2 puts the performance of SSI 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 SSI strategy falls in the distribution. The SSI strategy's gross (net) Sharpe ratio of 0.65 (0.59) is greater than 97% (99%) of anomaly Sharpe ratios, respectively.

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

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 SSI strategy (red line).[2] Ignoring trading costs, a \$1 invested in the SSI strategy would have yielded \$10.52 which ranks the SSI strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the SSI strategy would have yielded \$8.01 which ranks the SSI 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 SSI relative to those. Panel A shows that the SSI strategy gross alphas fall between the 70 and 75 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 SSI strategy has a positive net generalized alpha for five out of the five factor models. In these cases SSI ranks between the 87 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does SSI 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 predic-

[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.

tive 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 SSI 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 SSI or at least to weaken the power SSI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of SSI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SSI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SSI} SSI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SSI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SSI. Stocks are finally grouped into five SSI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SSI trading strategies conditioned on each of the 210 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SSI 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

[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.

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 SSI signal in these Fama-MacBeth regressions exceed 3.35, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SSI is 3.02.

Similarly, Table 5 reports results from spanning tests that regress returns to the SSI 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 SSI strategy earns alphas that range from 20-25bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.65, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SSI trading strategy achieves an alpha of 19bps/month with a t-statistic of 2.61.

7 Does SSI add relative to the whole zoo?

Finally, we can ask how much adding SSI 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 SSI 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

[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 SSI is available.

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 SSI grows to \$2252.33.

8 Conclusion

This study provides compelling evidence for the significance of Stock Sales Impact (SSI) as a robust predictor of cross-sectional stock returns. Our findings demonstrate that SSI-based trading strategies yield impressive results, with value-weighted long/short portfolios achieving annualized Sharpe ratios of 0.65 (gross) and 0.59 (net). The signal's predictive power remains strong even after controlling for established factors, generating significant monthly abnormal returns of 23 basis points relative to the Fama-French five-factor model plus momentum.

Particularly noteworthy is the signal's persistence when tested against closely related strategies from the factor zoo, maintaining a significant monthly alpha of 19 basis points. These results suggest that SSI captures unique information about future stock returns that is not fully explained by existing factors or related anomalies.

From a practical perspective, our findings have important implications for investment professionals and portfolio managers. The robust performance of SSI-based strategies, even after accounting for transaction costs, indicates its potential value in real-world applications. However, practitioners should consider the implementation challenges and capacity constraints that may affect the strategy's scalability.

While our results are promising, several limitations warrant mention. Future research could explore the signal's performance across different market regimes, international markets, and asset classes. Additionally, investigating the underlying economic mechanisms driving the SSI effect could provide valuable insights. Further studies might also examine potential interactions between SSI and other established market anomalies to develop more comprehensive investment strategies.

In conclusion, SSI represents a valuable addition to the arsenal of return predictors, offering both statistical and economic significance in forecasting cross-sectional stock returns. Its robustness to various controls and net profitability make it particularly relevant for practical applications in investment management.

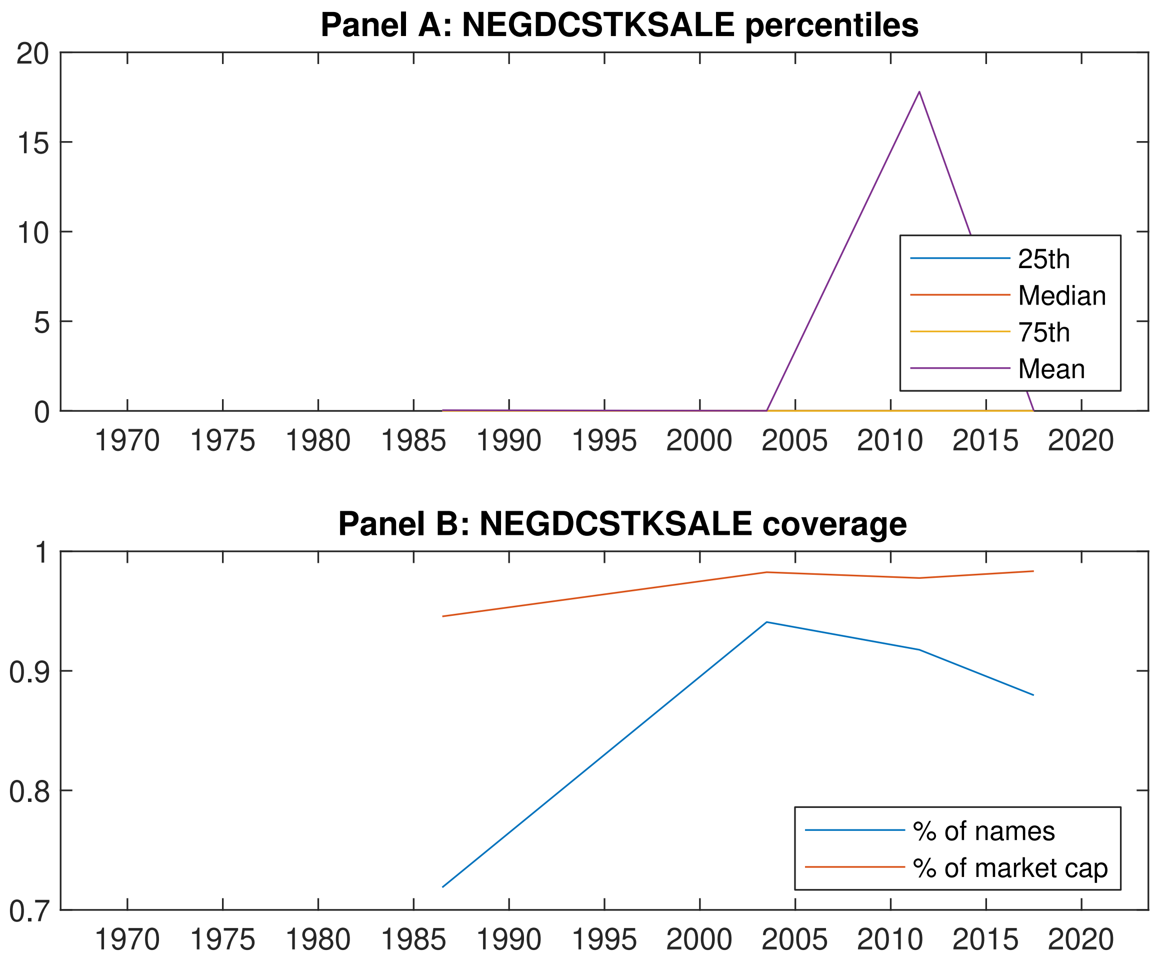

Figure 1: Times series of SSI percentiles and coverage.
This figure plots descriptive statistics for SSI. Panel A shows cross-sectional percentiles of SSI over the sample. Panel B plots the monthly coverage of SSI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SSI. 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 SSI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.40	0.55	0.64	0.69	0.77	0.37
	[2.27]	[2.87]	[3.35]	[4.08]	[4.55]	[4.93]
α_{CAPM}	-0.15	-0.06	0.04	0.16	0.24	0.39
	[-2.90]	[-1.24]	[0.78]	[3.41]	[5.08]	[5.10]
α_{FF3}	-0.16	-0.04	0.06	0.12	0.19	0.35
	[-3.13]	[-0.87]	[1.07]	[2.86]	[4.35]	[4.62]
α_{FF4}	-0.13	-0.01	0.08	0.09	0.17	0.31
	[-2.64]	[-0.28]	[1.50]	[1.98]	[3.84]	[4.00]
α_{FF5}	-0.16	0.02	0.08	0.02	0.09	0.25
	[-3.08]	[0.40]	[1.51]	[0.59]	[2.20]	[3.33]
α_{FF6}	-0.14	0.04	0.10	0.00	0.09	0.23
	[-2.72]	[0.76]	[1.80]	[0.07]	[2.01]	[2.98]
Panel B: Fama and French (2018) 6-factor model loadings for SSI-sorted portfolios						
β_{MKT}	0.96	1.04	1.03	1.00	0.99	0.03
	[78.69]	[94.15]	[79.63]	[99.51]	[96.98]	[1.44]
β_{SMB}	-0.05	0.02	0.05	-0.06	-0.02	0.03
	[-2.92]	[1.38]	[2.66]	[-4.41]	[-1.29]	[1.26]
β_{HML}	0.07	-0.02	-0.02	0.05	0.05	-0.02
	[2.87]	[-0.74]	[-0.99]	[2.39]	[2.57]	[-0.49]
β_{RMW}	0.06	-0.08	0.00	0.13	0.13	0.07
	[2.33]	[-3.61]	[0.17]	[6.61]	[6.33]	[2.00]
β_{CMA}	-0.07	-0.11	-0.09	0.20	0.22	0.29
	[-2.03]	[-3.68]	[-2.58]	[7.16]	[7.58]	[5.67]
β_{UMD}	-0.03	-0.03	-0.03	0.03	0.01	0.04
	[-2.25]	[-2.40]	[-2.02]	[3.46]	[1.12]	[2.17]
Panel C: Average number of firms (n) and market capitalization (me)						
n	806	695	581	693	768	
me ($\$10^6$)	1796	1441	1992	2250	2438	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the SSI 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	0.37	0.39	0.35	0.31	0.25	0.23
			[4.93]	[5.10]	[4.62]	[4.00]	[3.33]	[2.98]
Quintile	NYSE	EW	0.57	0.64	0.56	0.49	0.40	0.36
			[8.47]	[9.79]	[9.23]	[8.14]	[7.06]	[6.32]
Quintile	Name	VW	0.36	0.37	0.35	0.31	0.27	0.25
			[4.90]	[4.96]	[4.60]	[4.12]	[3.57]	[3.31]
Quintile	Cap	VW	0.33	0.33	0.31	0.26	0.24	0.21
			[4.26]	[4.23]	[3.92]	[3.30]	[3.07]	[2.68]
Decile	NYSE	VW	0.37	0.36	0.32	0.26	0.27	0.23
			[4.08]	[3.93]	[3.50]	[2.82]	[2.87]	[2.42]
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	0.34	0.36	0.32	0.30	0.24	0.23
			[4.45]	[4.67]	[4.26]	[3.95]	[3.24]	[3.06]
Quintile	NYSE	EW	0.38	0.44	0.36	0.32	0.19	0.18
			[5.06]	[5.98]	[5.33]	[4.87]	[3.06]	[2.86]
Quintile	Name	VW	0.33	0.34	0.32	0.30	0.26	0.25
			[4.41]	[4.56]	[4.25]	[4.02]	[3.46]	[3.31]
Quintile	Cap	VW	0.29	0.30	0.28	0.25	0.23	0.21
			[3.81]	[3.85]	[3.57]	[3.25]	[2.96]	[2.74]
Decile	NYSE	VW	0.33	0.33	0.29	0.26	0.25	0.23
			[3.64]	[3.54]	[3.18]	[2.84]	[2.68]	[2.46]

Table 3: Conditional sort on size and SSI

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

	SSI Quintiles					SSI Strategies					
Size quintiles	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.37	0.75	0.91	0.98	0.97	0.60	0.67	0.60	0.55	0.45	0.42
	[1.38]	[2.82]	[3.54]	[3.83]	[4.09]	[7.38]	[8.31]	[8.00]	[7.28]	[6.21]	[5.77]
(2)	0.50	0.76	0.82	0.87	0.96	0.46	0.51	0.42	0.39	0.31	0.29
	[2.12]	[3.14]	[3.40]	[3.81]	[4.32]	[5.29]	[5.98]	[5.18]	[4.67]	[3.72]	[3.46]
(3)	0.51	0.67	0.83	0.80	0.94	0.43	0.46	0.41	0.40	0.31	0.31
	[2.44]	[2.96]	[3.62]	[3.77]	[4.65]	[5.62]	[5.96]	[5.40]	[5.16]	[4.06]	[4.02]
(4)	0.45	0.63	0.81	0.81	0.80	0.35	0.38	0.31	0.29	0.11	0.11
	[2.31]	[2.96]	[3.77]	[4.05]	[4.25]	[4.30]	[4.63]	[3.98]	[3.63]	[1.50]	[1.48]
(5)	0.43	0.48	0.53	0.54	0.71	0.28	0.27	0.26	0.21	0.22	0.19
	[2.55]	[2.57]	[2.85]	[3.13]	[4.24]	[3.05]	[2.91]	[2.76]	[2.27]	[2.36]	[2.03]

Panel B: Portfolio average number of firms and market capitalization

	SSI Quintiles					SSI Quintiles				
	Average n					Average market capitalization ($\$10^6$)				
Size quintiles	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	388	389	388	386	387	32	34	39	29	29
(2)	111	111	110	110	110	56	57	57	55	56
(3)	81	80	81	80	81	97	96	98	99	100
(4)	68	68	68	68	68	203	207	211	215	217
(5)	62	62	62	62	62	1394	1424	1738	1608	1766

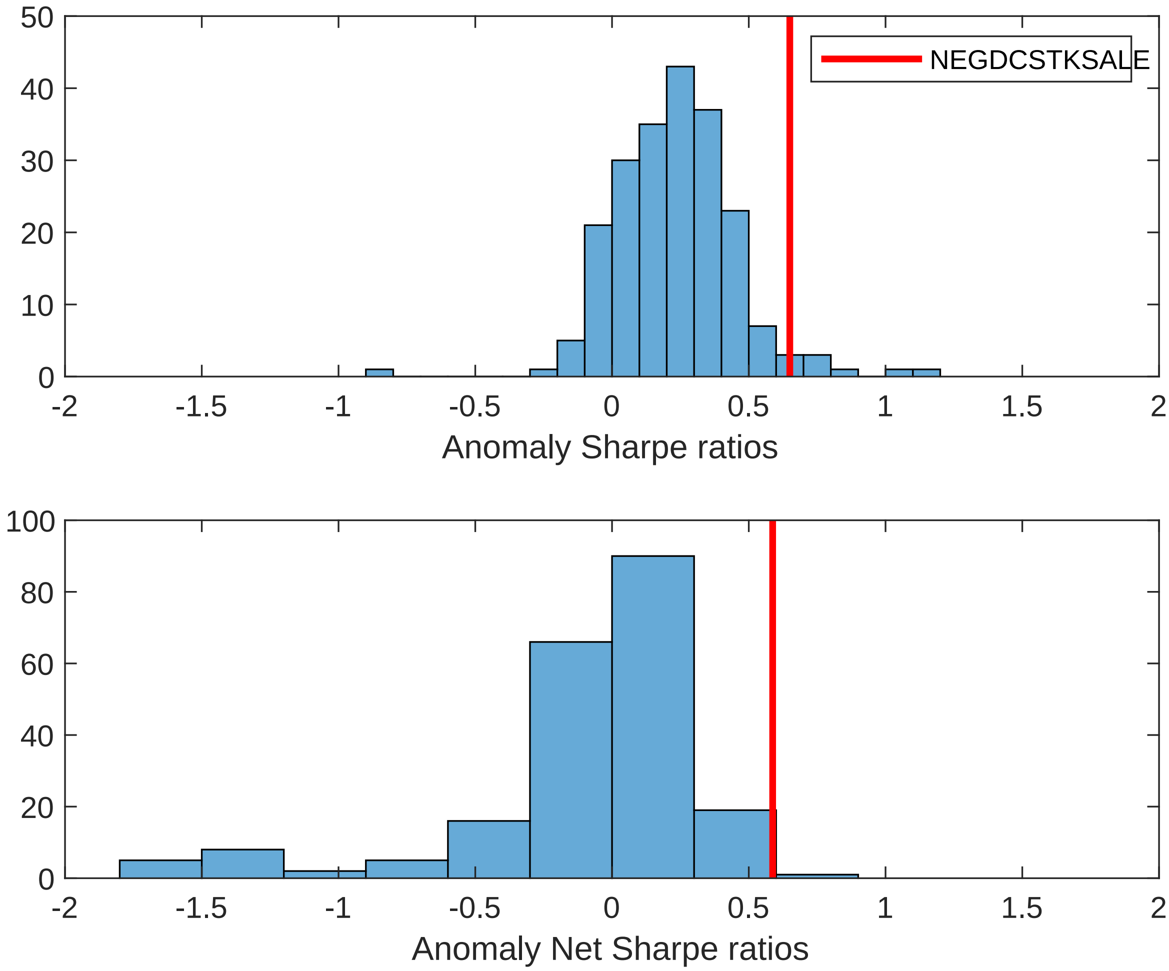

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SSI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

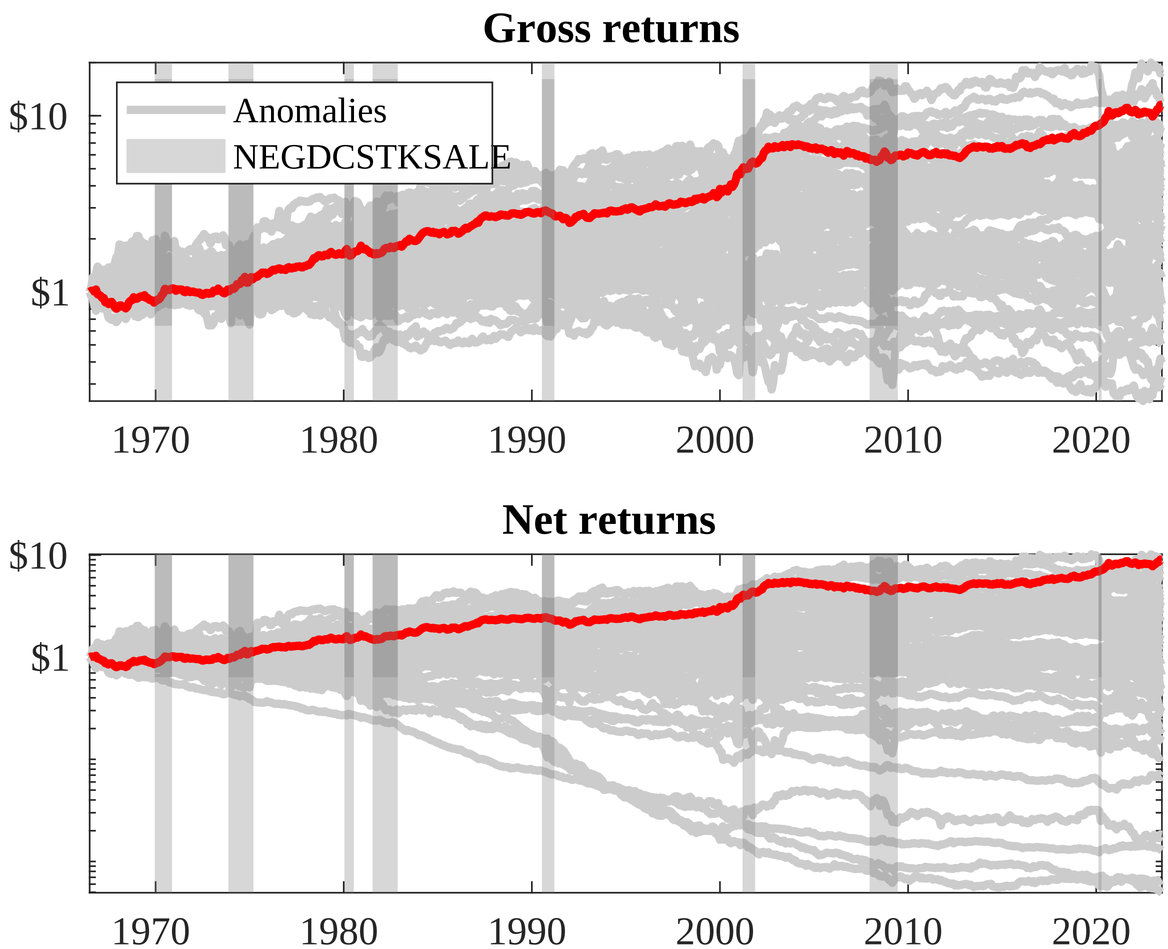

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SSI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

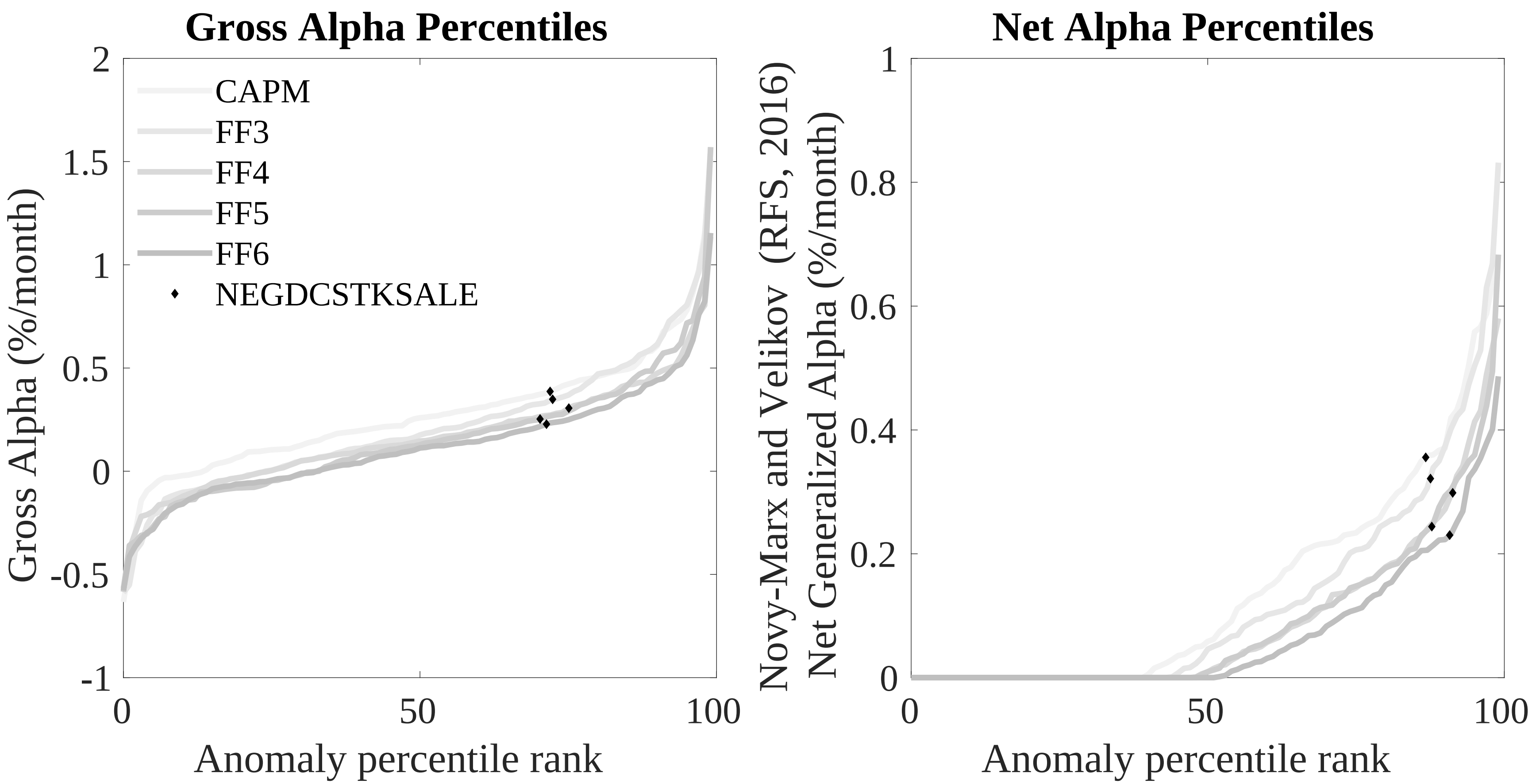

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SSI trading strategy alphas (diamonds). The strategies are constructed using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

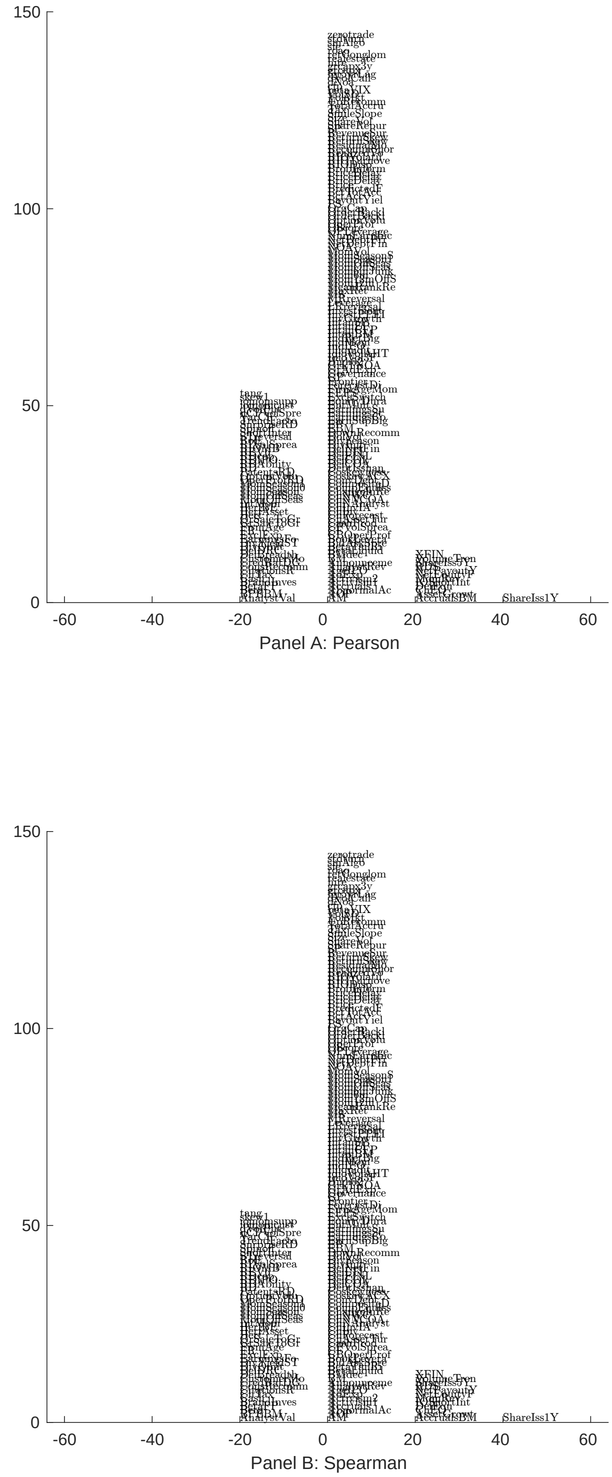

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with SSI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

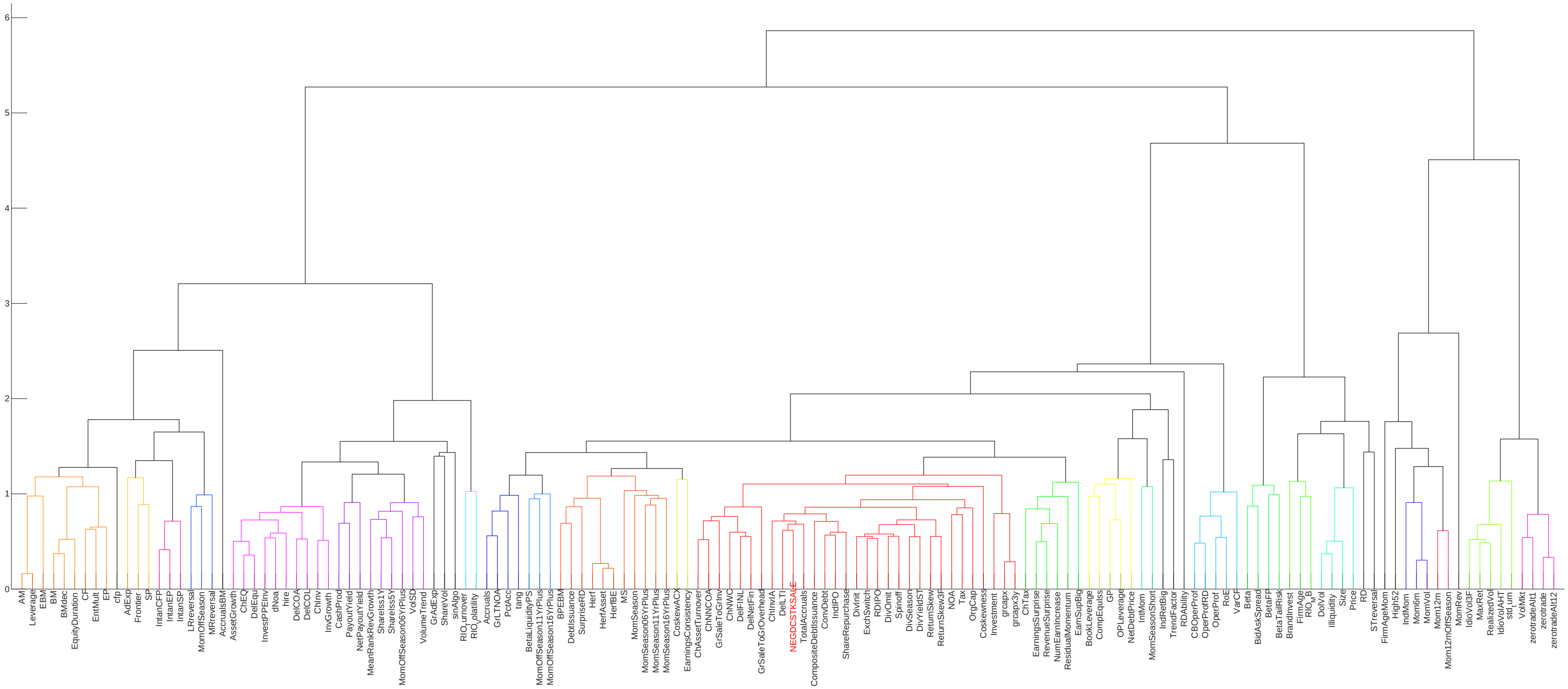

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

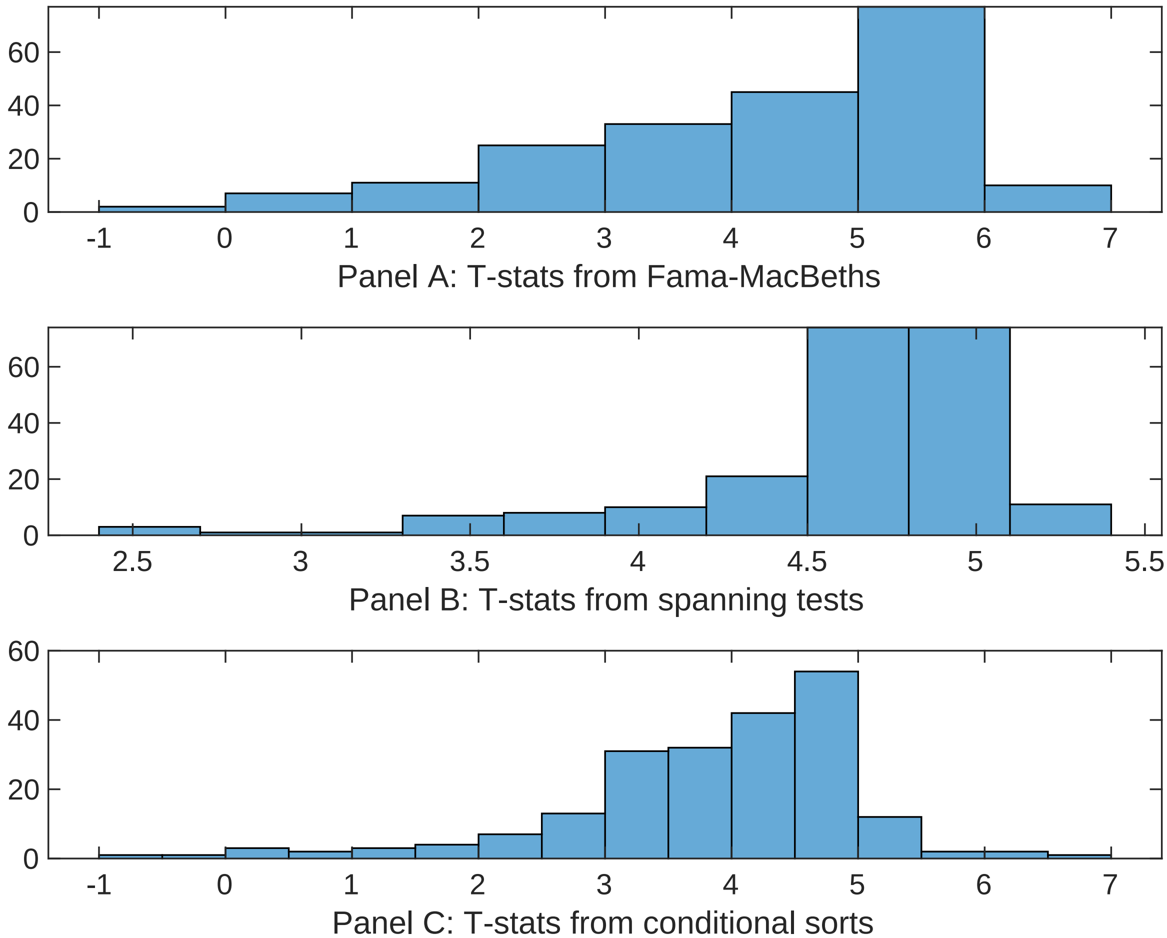

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SSI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SSI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SSI} SSI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SSI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SSI. Stocks are finally grouped into five SSI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SSI 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 SSI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SSI} SSI_{i,t} + \sum_{k=1}^{s} ix \beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. 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	0.18	0.12	0.13	0.13	0.14	0.13
	[5.73]	[7.40]	[5.26]	[6.09]	[5.67]	[6.12]	[5.28]
SSI	0.38	0.34	0.28	0.35	0.37	0.30	0.26
	[5.37]	[4.70]	[3.35]	[4.43]	[5.16]	[4.23]	[3.02]
Anomaly 1	0.24						0.90
	[5.38]						[2.15]
Anomaly 2		0.49					-0.22
		[4.35]					[-0.15]
Anomaly 3			0.27				0.22
			[2.36]				[2.03]
Anomaly 4				0.38			0.40
				[4.43]			[0.45]
Anomaly 5					0.15		-0.11
					[4.13]		[-0.20]
Anomaly 6						0.10	0.68
						[8.64]	[6.48]
# months	679	684	679	679	684	684	679
$\bar{R}^2(\%)$	0	0	1	0	1	0	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the SSI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SSI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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	0.20	0.23	0.22	0.20	0.25	0.23	0.19
	[2.78]	[3.10]	[2.95]	[2.65]	[3.25]	[3.04]	[2.61]
Anomaly 1	26.55						17.59
	[7.00]						[4.02]
Anomaly 2		34.83					38.43
		[8.57]					[6.50]
Anomaly 3			14.51				2.48
			[4.96]				[0.75]
Anomaly 4				15.06			2.06
				[3.81]			[0.49]
Anomaly 5					19.22		-9.82
					[4.80]		[-1.78]
Anomaly 6						4.53	-16.60
						[0.90]	[-3.18]
mkt	4.82	3.89	5.18	4.86	2.44	2.76	6.18
	[2.76]	[2.25]	[2.86]	[2.65]	[1.37]	[1.53]	[3.49]
smb	4.91	2.35	6.62	3.00	3.22	3.12	5.25
	[1.95]	[0.94]	[2.55]	[1.16]	[1.25]	[1.17]	[2.04]
hml	-4.39	-5.41	-6.49	-5.10	-3.76	-1.46	-7.65
	[-1.29]	[-1.61]	[-1.78]	[-1.39]	[-1.08]	[-0.42]	[-2.15]
rmw	-1.83	8.58	-1.24	4.09	8.66	6.67	0.61
	[-0.51]	[2.55]	[-0.32]	[1.15]	[2.48]	[1.89]	[0.15]
cma	16.17	-5.89	18.54	24.56	8.67	23.18	10.61
	[3.02]	[-0.93]	[3.33]	[4.64]	[1.32]	[2.90]	[1.38]
umd	3.72	3.54	5.29	4.17	4.49	4.02	2.69
	[2.17]	[2.08]	[3.01]	[2.37]	[2.53]	[2.22]	[1.58]
# months	680	684	680	680	684	684	680
$\bar{R}^2(\%)$	15	17	12	11	11	8	21

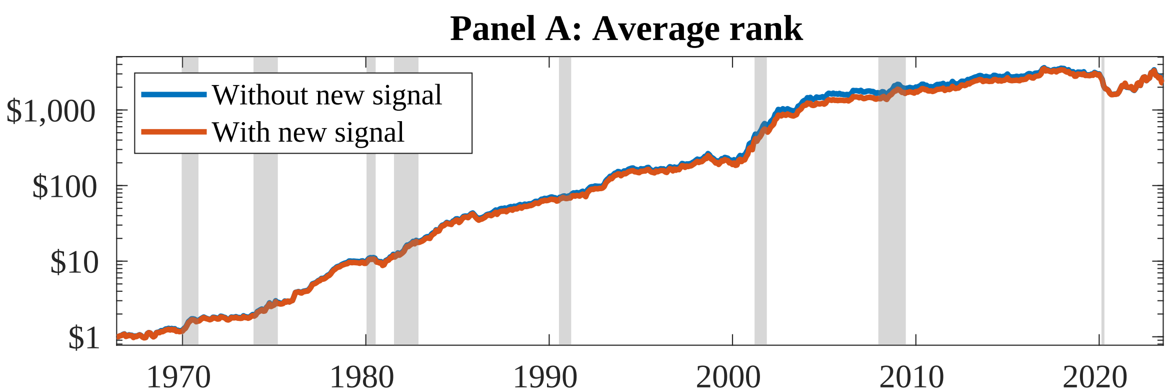

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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