Stock Ownership Contrast and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Stock Ownership Contrast (SOC), 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 SOC achieves an annualized gross (net) Sharpe ratio of 0.54 (0.47), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 16 (19) bps/month with a t-statistic of 2.23 (2.61), 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), Net Payout Yield, Growth in book equity, Net equity financing, Share issuance (5 year), Change in equity to assets) is 16 bps/month with a t-statistic of 2.44.

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 (Stambaugh and Yuan, 2017). While institutional ownership patterns have been shown to affect asset prices (Gompers et al., 2016), the literature has yet to fully explore how the contrast in ownership structures between connected firms might predict returns. This gap is particularly notable given the increasing sophistication of institutional investors and their ability to process complex information networks.

Prior research has established that firms' ownership structures contain valuable information about future performance (Chen et al., 2002). However, existing studies primarily focus on absolute levels of institutional ownership or changes within individual firms, rather than examining the relative differences between economically linked companies. This narrow focus potentially overlooks crucial information embedded in the broader ownership ecosystem.

We propose that the contrast in stock ownership patterns between economically connected firms contains predictive information about future returns. This hypothesis builds on two theoretical frameworks. First, the rational attention allocation theory of (Kacperczyk and Van Nieuwerburgh, 2016) suggests that sophisticated investors optimally distribute their attention across assets, implying that systematic differences in ownership between connected firms may reflect informed trading. Second, the slow information diffusion model of (Hong and Stein, 1999) predicts that complex signals combining information from multiple sources are likely to be underreacted to by the market.

The economic mechanism underlying our hypothesis operates through two channels. The first channel relates to information production - when sophisticated investors identify mispricing, they are likely to take larger positions in the more attractive firm within a connected pair (?). The second channel involves risk sharing - differences in ownership structure between connected firms may reflect sophisticated investors' superior ability to identify and price systematic risk factors (?).

This theoretical framework suggests that extreme differences in ownership structure between economically linked firms are unlikely to persist unless they reflect fundamental information about relative firm value. When sophisticated investors identify mispricing between connected firms, they should take offsetting positions that eventually eliminate uninformative ownership contrasts (?).

Our empirical analysis reveals that Stock Ownership Contrast (SOC) strongly predicts cross-sectional stock returns. A value-weighted long-short trading strategy based on SOC achieves an annualized gross Sharpe ratio of 0.54, with monthly abnormal returns of 16 basis points (t-statistic = 2.23) relative to the Fama-French five-factor model plus momentum. The predictive power of SOC remains robust after controlling for transaction costs, with the strategy delivering a net Sharpe ratio of 0.47.

Importantly, SOC's predictive ability persists among large-cap stocks, where the strategy generates monthly abnormal returns of 33 basis points (t-statistic = 3.17) in the highest size quintile. This finding suggests that the SOC effect is not merely a small-stock phenomenon and could be implemented by institutional investors. The strategy's performance remains significant even after controlling for the six most closely related anomalies, producing a monthly alpha of 16 basis points (t-statistic = 2.44).

Further analysis demonstrates that SOC's predictive power is distinct from existing anomalies. The signal's gross Sharpe ratio of 0.54 exceeds 95% of documented anomalies, while its net Sharpe ratio of 0.47 outperforms 99% of competing signals. These results indicate that SOC captures a unique dimension of mispricing not previously documented in the literature.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel predictor that captures information embedded in the relative ownership structures of connected firms, extending the work of (?) on limited attention in linked assets and (Hong and Stein, 1999) on gradual information diffusion. Second, we demonstrate that ownership contrasts contain valuable information even among large, liquid stocks, complementing research by (?) on the robustness of anomaly returns across size groups.

Methodologically, our paper advances the literature by developing a framework for measuring and testing signals based on differences in firm characteristics across economically linked firms. This approach builds on work by (?) on industry-level information processing but introduces a new dimension by focusing on ownership structure differences. Our findings suggest that examining relative characteristics between connected firms may be a fertile ground for identifying new predictors.

More broadly, our results have important implications for market efficiency and institutional investor behavior. The persistence of the SOC effect, particularly among large stocks, suggests that even sophisticated investors may face constraints or frictions that prevent them from fully arbitraging away predictable return patterns (?). These findings contribute to the ongoing debate about the role of institutional investors in price discovery and market efficiency.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Stock Ownership Contrast measure. We obtain accounting and financial data from COMPUSTAT, covering firm-level observations for publicly traded companies. To construct our signal, we use COMPUSTAT's item CSTK, which represents the carrying amount of common stock. This variable captures the book value of a company's common stock, reflecting the cumulative par or stated value of all common stock issued.construction of our signal follows a change-based approach, where we calculate the difference between the current period's CSTK and its lagged value, then scale this difference by the lagged CSTK value. This calculation can be expressed as (CSTK[t] - CSTK[t-1])/CSTK[t-1], where t represents the current period. This measure captures the relative change in common stock ownership, providing insights into changes in the firm's equity structure and potential dilution or concentration of ownership. By scaling the change by the lagged value, we ensure comparability across firms of different sizes and control for the base level of common stock. We construct this measure using end-of-fiscal-year values for CSTK to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the SOC signal. Panel A plots the time-series of the mean, median, and interquartile range for SOC. On average, the cross-sectional mean (median) SOC is -1.57 (-0.01) over the 1966 to 2023 sample, where the starting date is determined by the availability of the input SOC data. The signal's interquartile range spans -0.19 to 0.00. Panel B of Figure 1 plots the time-series of the coverage of the SOC signal for the CRSP universe. On average, the SOC signal is available for 6.58% of CRSP names, which on average make up 7.84% of total market capitalization.

4 Does SOC predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on SOC 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 SOC portfolio and sells the low SOC 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 SOC strategy earns an average return of 0.35% per month with a t-statistic of 4.06. The annualized Sharpe ratio of the strategy is 0.54. The alphas range from 0.16% to 0.45% per month and have t-statistics exceeding 2.23 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 0.50, with a t-statistic of 10.40 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 527 stocks and an average market capitalization of at least $1,297 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 35 bps/month with a t-statistics of 4.06. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-four exceed two, and for nineteen 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 31-40bps/month. The lowest return, (31 bps/month), is achieved from the quintile sort using NYSE breakpoints and value-weighted portfolios, and has an associated t-statistic of 3.57. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the SOC 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 SOC strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and SOC, as well as average returns and alphas for long/short trading SOC 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 SOC strategy achieves an average return of 33 bps/month with a t-statistic of 3.17. Among these large cap stocks, the alphas for the SOC strategy relative to the five most common factor models range from 9 to 43 bps/month with t-statistics between 0.95 and 4.22.

5 How does SOC perform relative to the zoo?

Figure 2 puts the performance of SOC 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 SOC strategy falls in the distribution. The SOC strategy's gross (net) Sharpe ratio of 0.54 (0.47) 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 SOC strategy (red line).[2] Ignoring trading costs, a $1 invested in the SOC strategy would have yielded $8.87 which ranks the SOC strategy in the top 1% across the 212 anomalies. Accounting for trading costs, a $1 invested in the SOC strategy would have yielded $6.39 which ranks the SOC strategy in the top 0% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms

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

[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.

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 SOC relative to those. Panel A shows that the SOC strategy gross alphas fall between the 61 and 79 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 SOC strategy has a positive net generalized alpha for five out of the five factor models. In these cases SOC ranks between the 83 and 91 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does SOC 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 SOC 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 SOC or at least to weaken the power SOC has predicting the cross-section of returns. Figure 7 plots histograms

[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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on SOC 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 SOC signal in these Fama-MacBeth regressions exceed 5.41, with the minimum t-statistic occurring when controlling for Net Payout Yield. Controlling for all six closely related anomalies, the t-statistic on SOC is 1.50.

Similarly, Table 5 reports results from spanning tests that regress returns to the SOC 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 SOC strategy earns alphas that range from 14-21bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.97, which is achieved when controlling for Net Payout Yield. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the SOC trading strategy achieves an alpha of 16bps/month with a t-statistic of 2.44.

7 Does SOC add relative to the whole zoo?

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

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 155-anomaly combination strategy grows to $2333.55, while $1 investment in the combination strategy that includes SOC grows to $2158.80.

8 Conclusion

This study provides compelling evidence for the effectiveness of Stock Ownership Contrast (SOC) as a significant predictor of cross-sectional stock returns. Our findings demonstrate that a value-weighted long/short strategy based on SOC generates economically and statistically significant returns, with impressive Sharpe ratios of

[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 SOC is available.

0.54 and 0.47 for gross and net returns, respectively. The strategy's robustness is particularly noteworthy, as it maintains significant abnormal returns even after controlling for the Fama-French five factors, momentum, and six closely related anomalies from the factor zoo.

The persistence of the SOC signal's predictive power, evidenced by monthly alphas of 16-19 basis points with strong statistical significance, suggests that this metric captures unique information about future stock returns that is not fully reflected in existing factors. These results have important implications for both academic research and practical investment management, offering a potentially valuable tool for portfolio construction and risk management.

However, several limitations should be noted. First, our analysis focuses on U.S. equity markets, and the signal's effectiveness in international markets remains to be tested. Second, transaction costs and market impact could affect the strategy's real-world implementation, particularly for smaller stocks or during periods of market stress.

Future research could explore the underlying economic mechanisms driving the SOC effect, its interaction with other market anomalies, and its performance across different market regimes. Additionally, investigating the signal's effectiveness in international markets and alternative asset classes could provide valuable insights into its broader applicability. Finally, examining the impact of different market microstructure elements and implementation constraints would enhance our understanding of the strategy's practical utility.

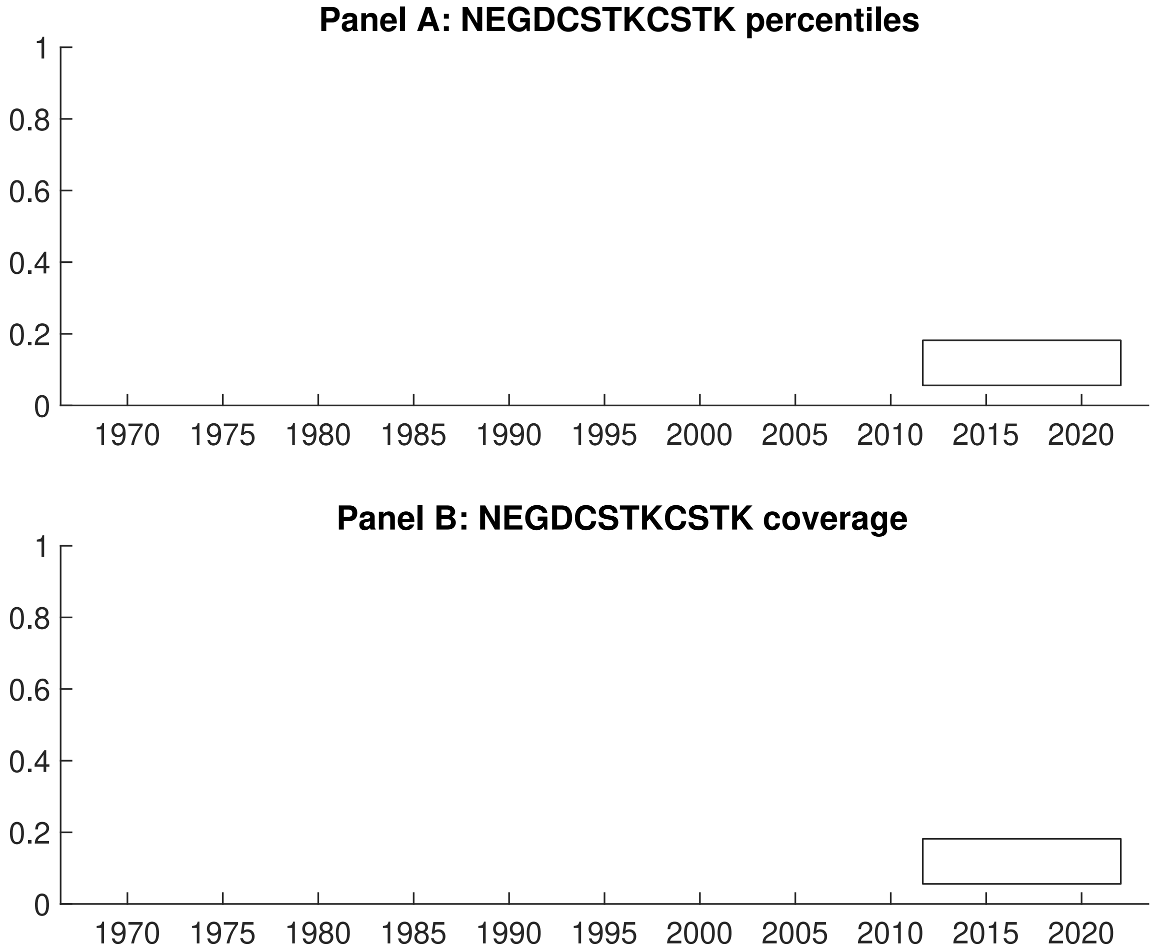

Figure 1: Times series of SOC percentiles and coverage.
This figure plots descriptive statistics for SOC. Panel A shows cross-sectional percentiles of SOC over the sample. Panel B plots the monthly coverage of SOC relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on SOC. 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 SOC-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.41	0.61	0.62	0.64	0.76	0.35
	[2.07]	[3.38]	[3.64]	[3.86]	[4.53]	[4.06]
α_{CAPM}	-0.22	0.04	0.09	0.12	0.24	0.45
	[-4.33]	[0.89]	[1.78]	[2.57]	[4.94]	[5.55]
α_{FF3}	-0.18	0.04	0.05	0.08	0.19	0.37
	[-3.75]	[0.99]	[1.06]	[1.81]	[4.16]	[4.84]
α_{FF4}	-0.14	0.05	0.04	0.04	0.17	0.30
	[-2.82]	[1.09]	[0.77]	[1.05]	[3.66]	[3.98]
α_{FF5}	-0.10	0.05	-0.06	-0.02	0.09	0.20
	[-2.22]	[1.16]	[-1.32]	[-0.54]	[2.10]	[2.72]
α_{FF6}	-0.08	0.06	-0.06	-0.04	0.08	0.16
	[-1.64]	[1.24]	[-1.35]	[-0.95]	[1.91]	[2.23]
Panel B: Fama and French (2018) 6-factor model loadings for SOC-sorted portfolios						
β_{MKT}	1.04	0.99	0.98	1.00	0.99	-0.05
	[94.83]	[89.13]	[86.76]	[102.30]	[95.18]	[-3.12]
β_{SMB}	0.04	0.04	0.05	-0.09	-0.01	-0.06
	[2.79]	[2.63]	[2.94]	[-6.47]	[-0.79]	[-2.28]
β_{HML}	0.01	-0.04	0.03	0.07	0.06	0.05
	[0.42]	[-2.04]	[1.57]	[3.83]	[3.11]	[1.63]
β_{RMW}	-0.01	-0.04	0.23	0.12	0.12	0.14
	[-0.56]	[-1.77]	[10.35]	[6.21]	[6.16]	[4.12]
β_{CMA}	-0.30	0.03	0.15	0.22	0.21	0.50
	[-9.51]	[1.00]	[4.58]	[8.05]	[6.98]	[10.40]
β_{UMD}	-0.04	-0.01	0.00	0.03	0.01	0.05
	[-3.90]	[-0.64]	[0.30]	[2.72]	[1.12]	[3.20]
Panel C: Average number of firms (n) and market capitalization (me)						
n	881	692	527	695	770	
me ($\$10^6$)	1862	1297	1819	2163	2391	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the SOC 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	0.45	0.37	0.30	0.20	0.16
			[4.06]	[5.55]	[4.84]	[3.98]	[2.72]	[2.23]
Quintile	NYSE	EW	0.61	0.73	0.63	0.50	0.44	0.35
			[7.28]	[9.72]	[9.40]	[7.94]	[7.07]	[5.97]
Quintile	Name	VW	0.36	0.46	0.38	0.31	0.21	0.17
			[4.08]	[5.52]	[4.80]	[3.90]	[2.76]	[2.22]
Quintile	Cap	VW	0.39	0.50	0.41	0.32	0.20	0.15
			[4.00]	[5.35]	[4.65]	[3.64]	[2.39]	[1.77]
Decile	NYSE	VW	0.45	0.55	0.45	0.38	0.33	0.29
			[4.26]	[5.38]	[4.60]	[3.89]	[3.45]	[3.02]
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	0.42	0.34	0.31	0.20	0.19
			[3.57]	[5.09]	[4.51]	[4.08]	[2.83]	[2.61]
Quintile	NYSE	EW	0.39	0.51	0.41	0.35	0.22	0.19
			[4.43]	[6.21]	[5.68]	[5.01]	[3.32]	[2.87]
Quintile	Name	VW	0.32	0.43	0.35	0.31	0.22	0.20
			[3.59]	[5.09]	[4.49]	[4.04]	[2.89]	[2.64]
Quintile	Cap	VW	0.35	0.47	0.39	0.34	0.22	0.19
			[3.59]	[5.00]	[4.42]	[3.92]	[2.66]	[2.35]
Decile	NYSE	VW	0.40	0.51	0.42	0.38	0.32	0.31
			[3.79]	[4.94]	[4.29]	[3.94]	[3.35]	[3.18]

Table 3: Conditional sort on size and SOC

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

		SOC Quintiles					SOC Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.26	0.78	0.88	0.95	0.95	0.70	0.82	0.74	0.63	0.53	0.46
		[0.89]	[2.92]	[3.58]	[3.81]	[4.03]	[6.79]	[8.40]	[8.27]	[7.14]	[6.31]	[5.51]
	(2)	0.46	0.73	0.85	0.88	0.94	0.48	0.60	0.46	0.40	0.29	0.25
		[1.76]	[3.01]	[3.64]	[4.02]	[4.23]	[4.49]	[5.85]	[5.09]	[4.40]	[3.21]	[2.83]
	(3)	0.44	0.71	0.86	0.77	0.94	0.50	0.60	0.50	0.44	0.37	0.33
		[1.83]	[3.18]	[4.00]	[3.81]	[4.63]	[4.99]	[6.37]	[5.77]	[5.08]	[4.25]	[3.84]
	(4)	0.42	0.68	0.79	0.78	0.80	0.39	0.50	0.36	0.29	0.10	0.07
		[1.87]	[3.26]	[3.91]	[4.06]	[4.27]	[3.76]	[5.10]	[4.30]	[3.41]	[1.35]	[0.88]
	(5)	0.39	0.55	0.52	0.55	0.72	0.33	0.43	0.33	0.24	0.14	0.09
		[1.94]	[3.15]	[3.04]	[3.26]	[4.29]	[3.17]	[4.22]	[3.38]	[2.50]	[1.47]	[0.95]

Panel B: Portfolio average number of firms and market capitalization

		SOC Quintiles Average n					SOC Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	392	394	394	391	392	34	36	37	28	29
	(2)	111	111	111	111	111	56	57	57	55	57
	(3)	81	80	80	80	81	95	96	97	99	99
	(4)	67	67	67	68	68	199	202	209	211	213
	(5)	62	61	61	61	61	1329	1348	1647	1514	1730

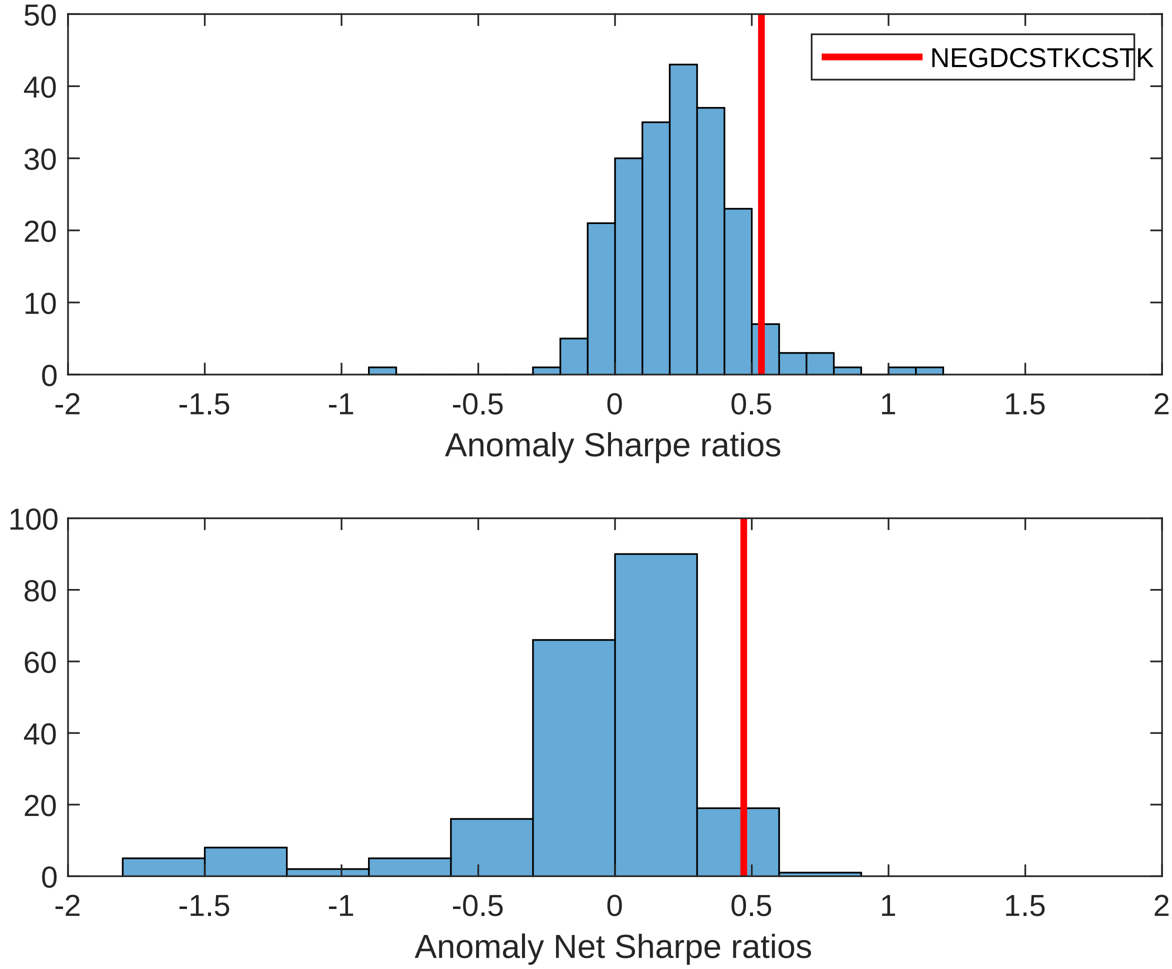

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the SOC with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

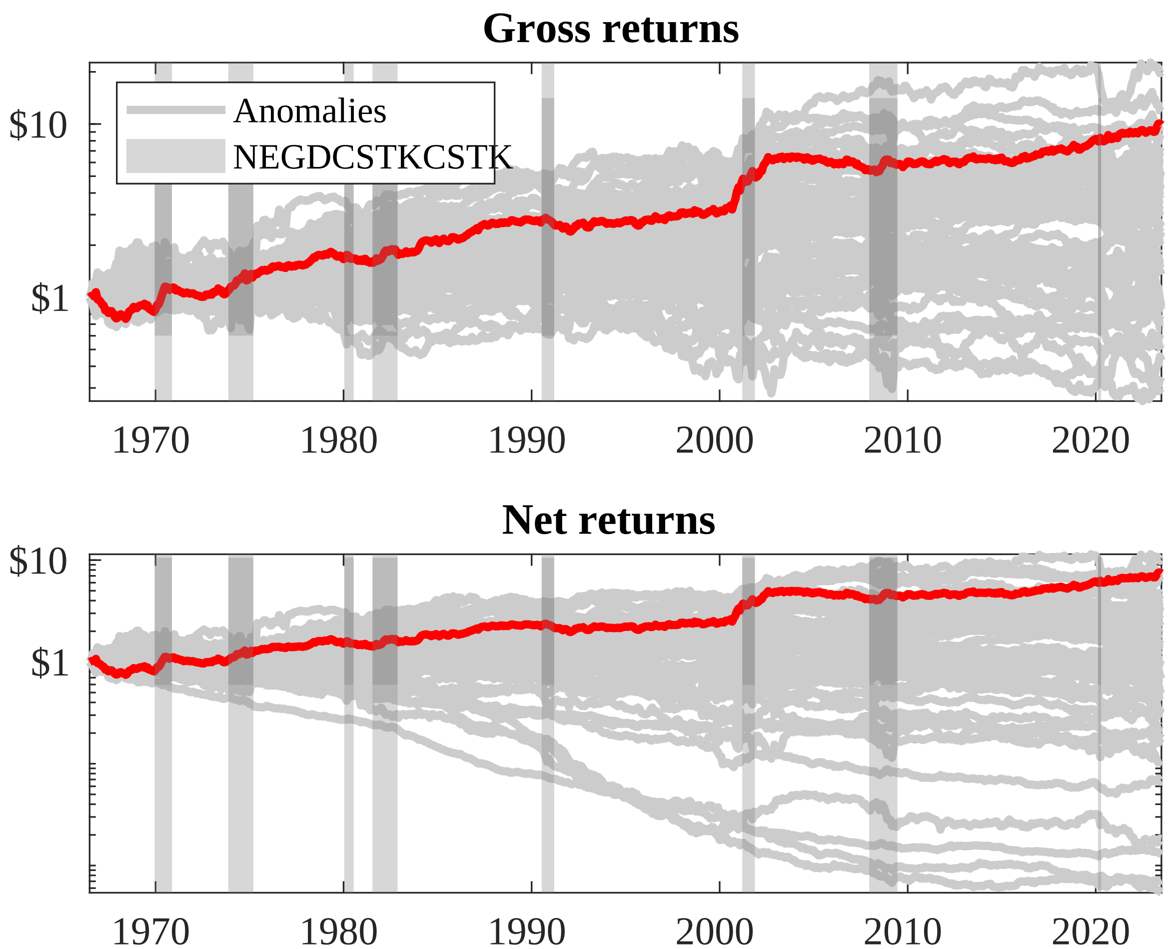

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the SOC trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

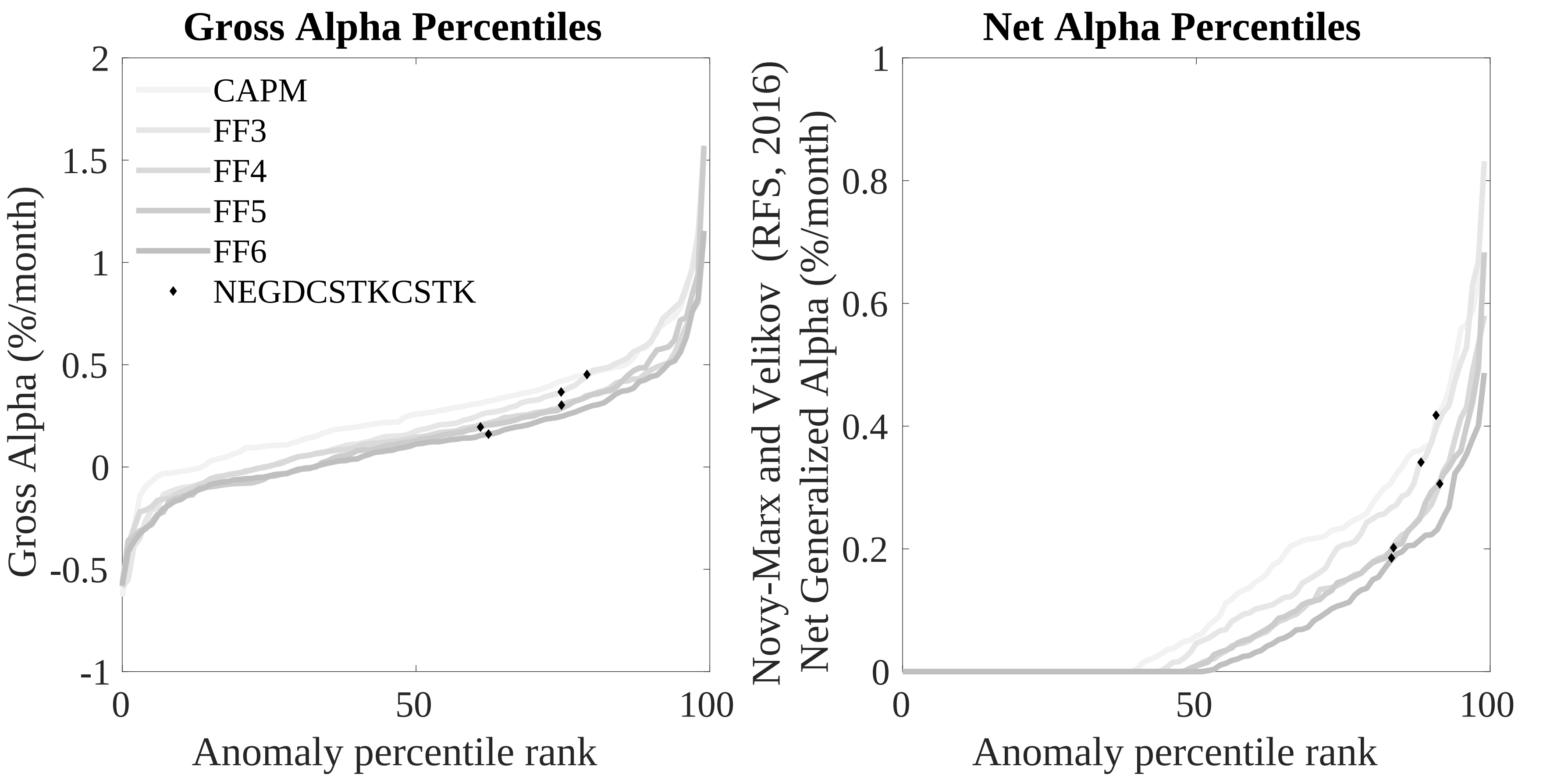

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the SOC trading strategy alphas (diamonds). The strategies are constructed using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

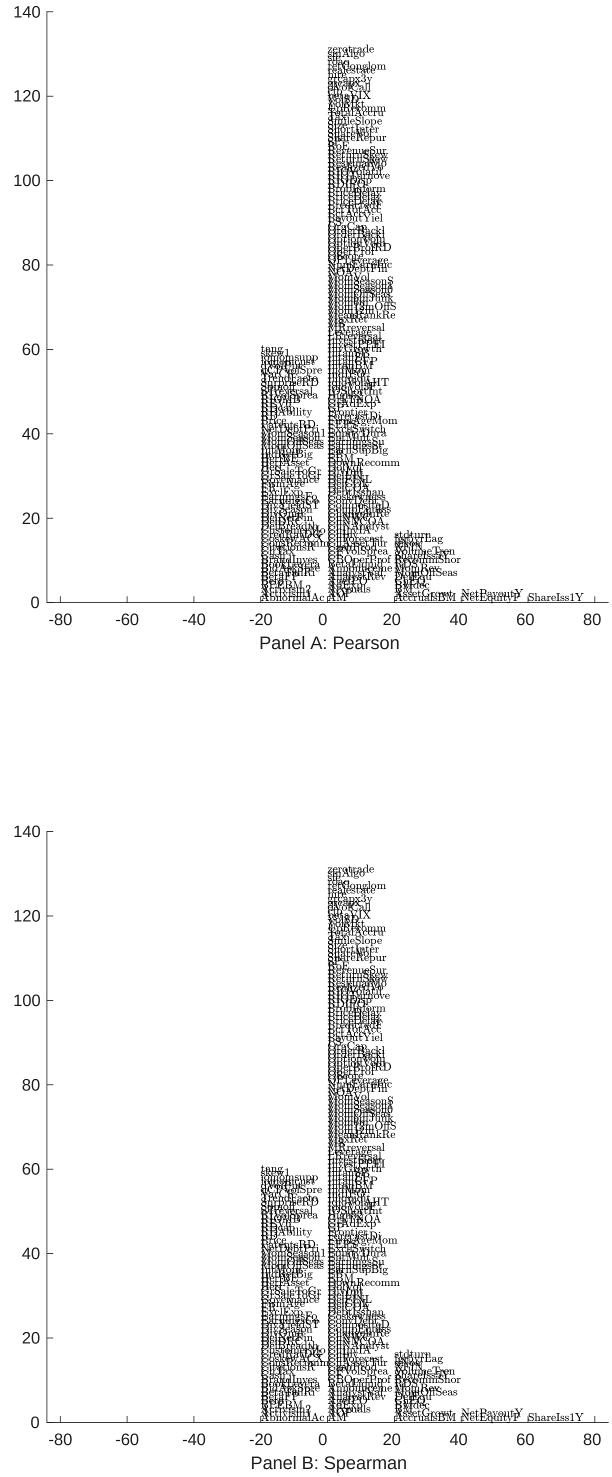

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with SOC. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

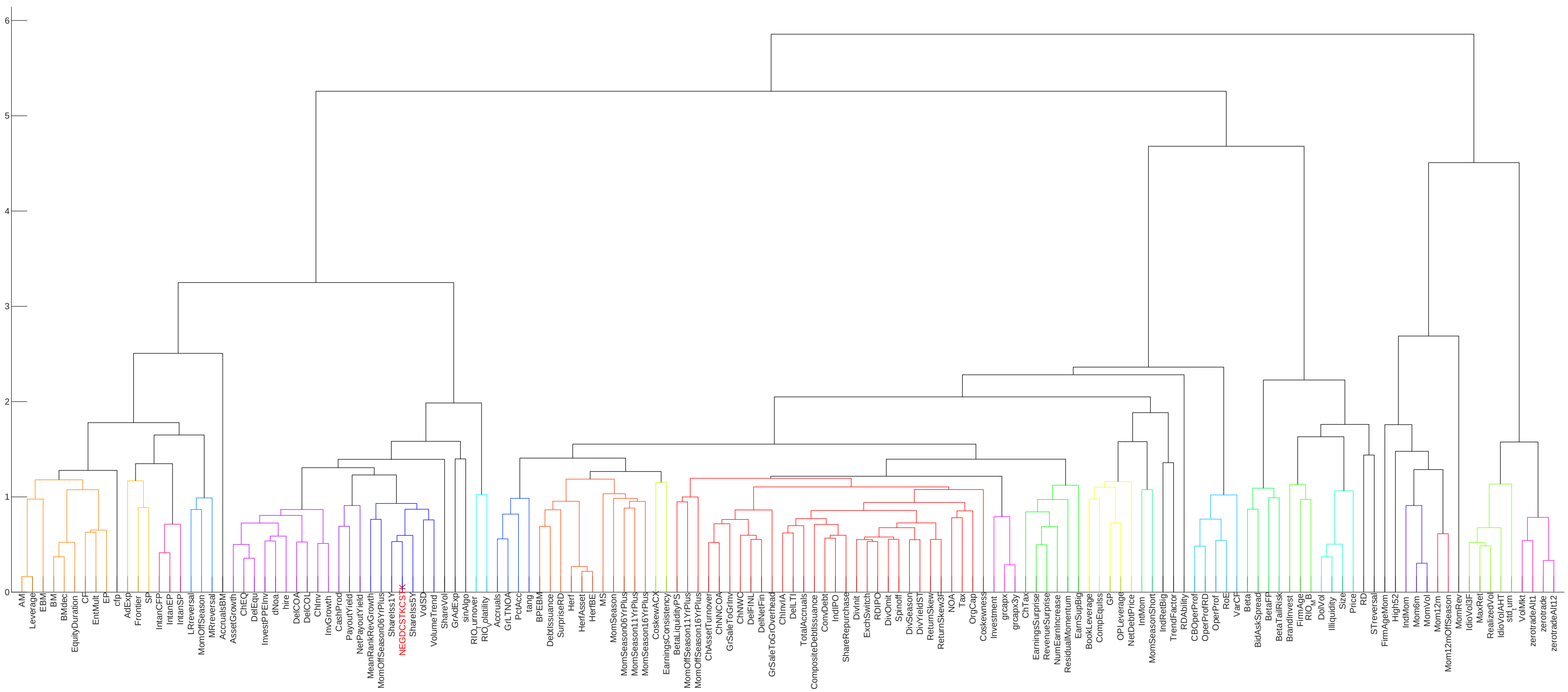

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

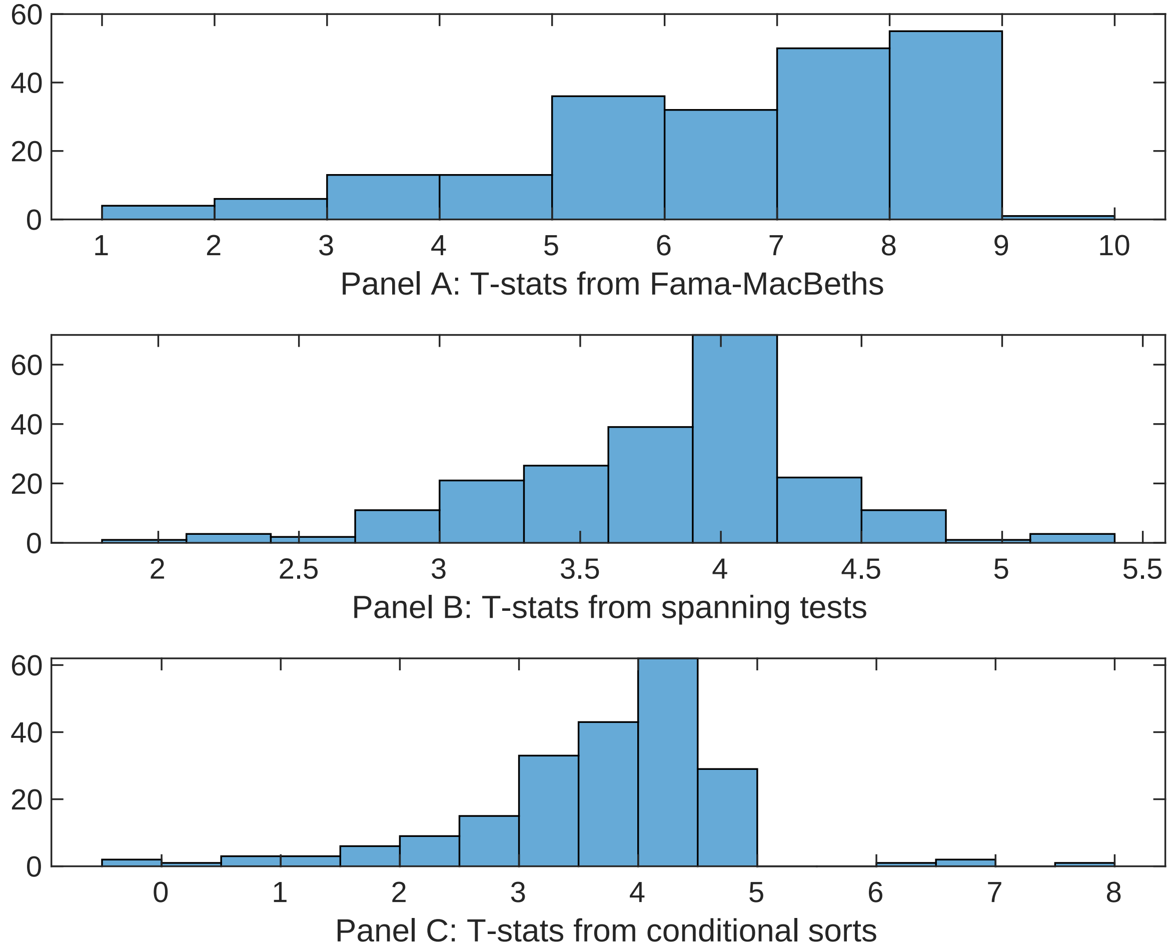

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of SOC conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{SOC} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{SOC} SOC_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{SOC,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 SOC. Stocks are finally grouped into five SOC portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted SOC 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 SOC. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{SOC} SOC_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Share issuance (1 year), Net Payout Yield, Growth in book equity, Net equity financing, Share issuance (5 year), Change in equity to 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 196606 to 202306.

Intercept	0.13	0.12	0.17	0.13	0.13	0.13	0.15
	[5.82]	[5.42]	[7.03]	[5.54]	[6.12]	[5.75]	[5.32]
SOC	0.67	0.43	0.53	0.60	0.49	0.61	0.13
	[7.86]	[5.41]	[6.32]	[6.94]	[6.29]	[7.19]	[1.50]
Anomaly 1	0.16						1.00
	[3.67]						[2.22]
Anomaly 2		0.25					0.18
		[2.27]					[3.69]
Anomaly 3			0.41				0.14
			[3.95]				[0.81]
Anomaly 4				0.12			-0.86
				[2.00]			[-1.05]
Anomaly 5					0.30		0.11
					[3.50]		[1.11]
Anomaly 6						0.12	0.39
						[3.60]	[0.62]
# months	679	679	684	618	679	684	611
$\bar{R}^2(\%)$	0	1	0	1	0	1	0

Table 5: Spanning tests controlling for most closely related anomalies
This table presents spanning tests results of regressing returns to the SOC trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{SOC} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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), Net Payout Yield, Growth in book equity, Net equity financing, Share issuance (5 year), Change in equity to 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 196606 to 202306.

Intercept	0.14	0.17	0.16	0.21	0.14	0.19	0.16
	[2.21]	[2.54]	[2.40]	[2.88]	[1.97]	[2.66]	[2.44]
Anomaly 1	39.51						23.55
	[11.76]						[5.67]
Anomaly 2		23.38					9.17
		[8.83]					[2.70]
Anomaly 3			39.68				26.84
			[10.62]				[5.03]
Anomaly 4				23.07			0.49
				[7.04]			[0.13]
Anomaly 5					21.48		3.91
					[5.87]		[1.04]
Anomaly 6						25.99	-7.44
						[7.01]	[-1.47]
mkt	-2.52	-1.73	-3.85	-1.63	-2.57	-5.56	-0.56
	[-1.63]	[-1.06]	[-2.43]	[-0.93]	[-1.52]	[-3.37]	[-0.34]
smb	-3.33	-0.51	-6.69	6.40	-6.10	-5.77	-0.47
	[-1.50]	[-0.21]	[-2.91]	[2.30]	[-2.54]	[-2.41]	[-0.18]
hml	1.75	-2.14	1.18	4.93	0.99	2.54	-2.45
	[0.58]	[-0.65]	[0.38]	[1.56]	[0.29]	[0.79]	[-0.78]
rmw	-0.24	-0.40	15.44	4.03	8.77	15.95	3.03
	[-0.07]	[-0.11]	[5.00]	[1.06]	[2.66]	[4.93]	[0.81]
cma	28.37	30.43	10.37	25.97	41.22	22.70	1.25
	[5.99]	[6.03]	[1.78]	[4.97]	[8.40]	[3.74]	[0.22]
umd	5.10	7.56	5.02	5.88	5.77	6.24	6.01
	[3.35]	[4.75]	[3.20]	[3.58]	[3.54]	[3.80]	[4.01]
# months	680	680	684	618	680	684	614
$\bar{R}^2$(%)	50	46	47	40	42	42	51

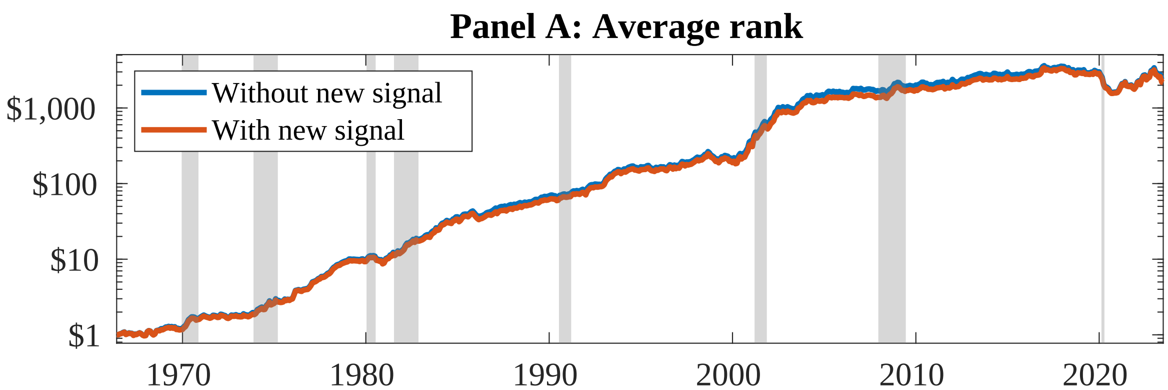

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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