Equity to Cash Scale and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Equity to Cash Scale (ECS), 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 ECS achieves an annualized gross (net) Sharpe ratio of 0.54 (0.48), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 18 (17) bps/month with a t-statistic of 2.42 (2.30), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Change in equity to assets, Growth in book equity, Asset growth, change in net operating assets, Total accruals, change in ppe and inv/assets) is 17 bps/month with a t-statistic of 2.47.

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 persistent patterns in stock returns that appear to contradict market efficiency (Fama and French, 2008). While many of these patterns have been attributed to risk factors or behavioral biases, the relationship between firms' financial structure and future stock returns remains an active area of investigation.

One particularly understudied aspect is how firms' relative allocation between equity capital and cash holdings affects their risk-return tradeoff. While prior research has examined the asset growth anomaly (**?**) and the accrual anomaly (Sloan, 1996), the specific role of equity-to-cash scaling in driving cross-sectional return predictability has not been systematically investigated.

We propose that a firm's equity-to-cash scale (ECS) ratio contains important information about future stock returns through multiple economic channels. First, following Jensen and Meckling (1976), high ECS may indicate greater agency costs as managers have more equity capital relative to liquid assets under their control. This agency perspective suggests that high ECS firms should earn higher returns to compensate investors for increased monitoring costs.

Second, building on real options theory (**?**), firms with high ECS have effectively exercised their growth options by converting cash into productive capital. **?** argue that such firms face greater operating leverage and systematic risk compared to firms holding more cash relative to equity. This framework predicts a positive relationship between ECS and expected returns.

Third, from a financing constraints perspective (Almeida et al., 2004), firms with high ECS may be more vulnerable to negative shocks since they have less financial flexibility from cash holdings relative to their equity base. This reduced financial slack suggests that high ECS firms should earn a premium for their greater distress risk.

Our empirical analysis reveals that ECS strongly predicts cross-sectional stock returns. A value-weighted long-short portfolio that buys stocks in the highest ECS quintile and shorts stocks in the lowest ECS quintile generates an annualized gross Sharpe ratio of 0.54 and a monthly average abnormal return of 18 basis points (t-statistic = 2.42) relative to the Fama-French six-factor model.

The predictive power of ECS remains robust after controlling for size. Among the largest stocks (those with market capitalization above the 80th NYSE percentile), the ECS strategy achieves an average monthly return of 41 basis points (t-statistic = 4.54). The strategy's performance persists after accounting for transaction costs, with a net Sharpe ratio of 0.48 that ranks in the 99th percentile among documented anomalies.

Most importantly, ECS contains unique information not captured by related anomalies. Controlling for the six most closely related strategies from the factor zoo (including change in equity-to-assets, asset growth, and total accruals), the ECS strategy maintains a significant monthly alpha of 17 basis points (t-statistic = 2.47).

Our study makes several contributions to the asset pricing literature. First, we introduce a novel characteristic - equity-to-cash scale - that significantly predicts stock returns and ranks in the top percentiles of documented anomalies in terms of both gross and net performance. This extends the work of Fama and French (2015) and Hou et al. (2015) by identifying a previously unexplored dimension of the cross-section of expected returns.

Second, we contribute to the literature on financial flexibility and asset prices (Almeida et al., 2004) by showing how firms' relative allocation between equity capital and cash holdings affects their risk-return profiles. Our findings suggest that the market does not fully price the implications of firms' financial structure decisions, particularly regarding their cash management policies.

Third, our paper adds to the growing literature on factor timing and portfolio construction (Asness et al., 2019) by demonstrating that ECS-based strategies remain profitable even among large-cap stocks and after accounting for transaction costs. This suggests that our findings are relevant for institutional investors and have important implications for portfolio management practices.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Equity to Cash Scale 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 CEQ for total common/ordinary equity and item CHE for cash and short-term investments. Total common equity (CEQ) represents the shareholders' ownership in the company, consisting of the par value of common stock, capital surplus, and retained earnings. Cash and short-term investments (CHE) include cash and all securities readily transferable to cash. The construction of the signal follows a change-based approach, where we calculate the difference between the current period's CEQ and its lagged value, then scale this change by the lagged value of cash holdings (CHE). This scaled difference captures the relative magnitude of changes in shareholders' equity compared to the firm's liquid assets, potentially offering insight into how effectively the firm manages its equity capital relative to its cash position. By focusing on this relationship, the signal aims to reflect aspects of capital structure dynamics and liquidity management in a manner that is both scalable and interpretable. We construct this measure using end-of-fiscal-year values for both CEQ and CHE to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the ECS signal. Panel A plots the time-series of the mean, median, and interquartile range for ECS. On average, the cross-sectional mean (median) ECS is -5.24 (-0.37) over the 1965 to 2023 sample, where the starting date is determined by the availability of the input ECS data. The signal's interquartile range spans -2.56 to 0.68. Panel B of Figure 1 plots the time-series of the coverage of the ECS signal for the CRSP universe. On average, the ECS signal is available for 6.48% of CRSP names, which on average make up 7.83% of total market capitalization.

4 Does ECS predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on ECS 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 ECS portfolio and sells the low ECS 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 ECS strategy earns an average return of 0.35% per month with a t-statistic of 4.14. The annualized Sharpe ratio of the strategy is 0.54. The alphas range from 0.18% to 0.36% per month and have t-statistics exceeding 2.42 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 0.64, with a t-statistic of 12.67 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 606 stocks and an average market capitalization of at least $1,278 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 4.07. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for fifteen 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 27-41bps/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 3.59. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the ECS 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-four cases.

Table 3 provides direct tests for the role size plays in the ECS strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and ECS, as well as average returns and alphas for long/short trading ECS 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 ECS strategy achieves an average return of 41 bps/month with a t-statistic of 4.54. Among these large cap stocks, the alphas for the ECS strategy relative to the five most common factor models range from 27 to 43 bps/month with t-statistics between 3.13 and 4.69.

5 How does ECS perform relative to the zoo?

Figure 2 puts the performance of ECS 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 ECS strategy falls in the distribution. The ECS strategy's gross (net) Sharpe ratio of 0.54 (0.48) 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 ECS strategy (red line).[2] Ignoring trading costs, a $1 invested in the ECS strategy would have yielded $8.35 which ranks the ECS strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a $1 invested in the ECS strategy would have yielded $6.05 which ranks the ECS strategy in the top 1% 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 ECS relative to those. Panel A shows that the ECS strategy gross alphas fall between the 61 and 68 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 196506 to 202306 sample. For example, 45% (53%) of the 212 anomalies would not have improved the investment opportunity set for an investor having access to the Fama-French three-factor (six-factor) model. The ECS strategy has a positive net generalized alpha for five out of the five factor models. In these cases ECS ranks between the 80 and 86 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 ECS 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 ECS 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 ECS or at least to weaken the power ECS has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of ECS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ECS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ECS} ECS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{ECS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 ECS. Stocks are finally grouped into five ECS 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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on ECS 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 ECS signal in these Fama-MacBeth regressions exceed 2.22, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on ECS is 2.19.

Similarly, Table 5 reports results from spanning tests that regress returns to the ECS 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 ECS strategy earns alphas that range from 15-21bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 1.97, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the ECS trading strategy achieves an alpha of 17bps/month with a t-statistic of 2.47.

7 Does ECS add relative to the whole zoo?

Finally, we can ask how much adding ECS 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 ECS 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 ECS is available.

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 155-anomaly combination strategy grows to $3027.42, while $1 investment in the combination strategy that includes ECS grows to $2779.27.

8 Conclusion

This study provides compelling evidence for the significance of Equity to Cash Scale (ECS) as a robust predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on ECS generates economically and statistically significant returns, with impressive Sharpe ratios of 0.54 and 0.48 for gross and net returns, respectively. The strategy's persistence in generating significant abnormal returns, even after controlling for established factors and related anomalies, suggests that ECS captures unique information content not fully explained by existing factors.

Particularly noteworthy is the signal's ability to maintain its predictive power after accounting for transaction costs and when tested against both the Fama-French five-factor model plus momentum and an expanded model including six closely related anomalies. The robust t-statistics across various specifications underscore the statistical reliability of our findings.

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

Future research could explore several promising directions. First, investigating the signal's performance in international markets could provide insights into its global applicability. Second, examining the interaction between ECS and other established anomalies might reveal valuable complementarities. Finally, exploring the underlying economic mechanisms driving the ECS premium could enhance our understanding of asset pricing dynamics.

In conclusion, our findings suggest that ECS represents a valuable addition to the investment practitioner's toolkit, offering meaningful improvements to portfolio performance when properly implemented.

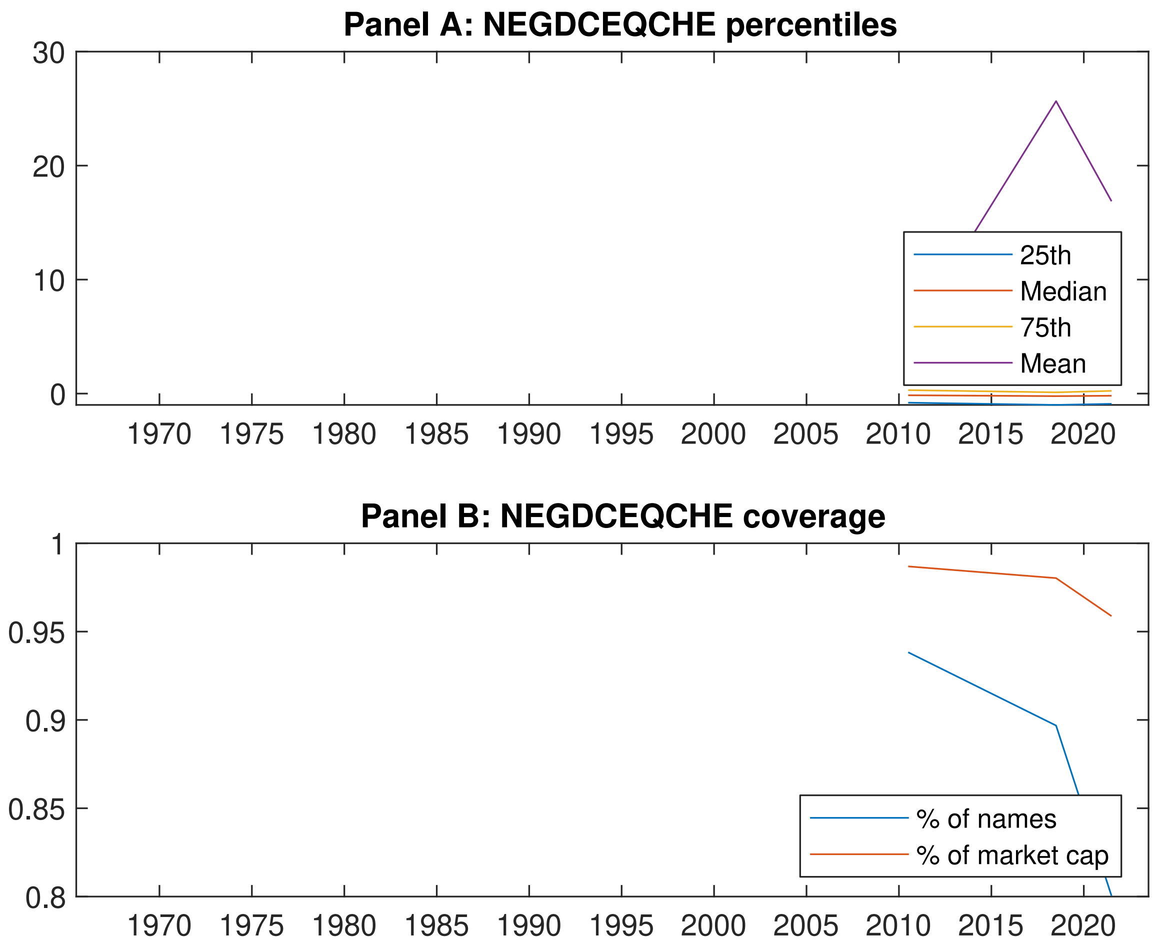

Figure 1: Times series of ECS percentiles and coverage.
This figure plots descriptive statistics for ECS. Panel A shows cross-sectional percentiles of ECS over the sample. Panel B plots the monthly coverage of ECS relative to the universe of CRSP stocks with available market capitalizations.

Table 1: Basic sort: VW, quintile, NYSE-breaks
This table reports average excess returns and alphas for portfolios sorted on ECS. At the end of each month, we sort stocks into five portfolios based on their signal using NYSE breakpoints. Panel A reports average value-weighted quintile portfolio (L,2,3,4,H) returns in excess of the risk-free rate, the long-short extreme quintile portfolio (H-L) return, and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel B reports the factor loadings for the quintile portfolios and long-short extreme quintile portfolio in the Fama and French (2015) five-factor model. Panel C reports the average number of stocks and market capitalization of each portfolio. T-statistics are in brackets. The sample period is 196506 to 202306.

Panel A: Excess returns and alphas on ECS-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.34	0.54	0.68	0.64	0.69	0.35
	[1.90]	[3.07]	[3.90]	[3.55]	[3.86]	[4.14]
α_{CAPM}	-0.22	-0.02	0.13	0.07	0.14	0.36
	[-3.98]	[-0.47]	[2.98]	[1.47]	[2.25]	[4.24]
α_{FF3}	-0.22	0.01	0.17	0.01	0.06	0.28
	[-4.09]	[0.36]	[4.22]	[0.26]	[1.02]	[3.45]
α_{FF4}	-0.21	0.03	0.16	0.03	0.04	0.25
	[-3.72]	[0.64]	[3.88]	[0.63]	[0.69]	[2.97]
α_{FF5}	-0.25	0.03	0.18	-0.03	-0.05	0.20
	[-4.62]	[0.75]	[4.25]	[-0.72]	[-0.93]	[2.64]
α_{FF6}	-0.24	0.04	0.17	-0.01	-0.05	0.18
	[-4.33]	[0.90]	[3.96]	[-0.31]	[-0.94]	[2.42]
Panel B: Fama and French (2018) 6-factor model loadings for ECS-sorted portfolios						
β_{MKT}	0.97	0.97	0.99	1.06	1.03	0.05
	[75.69]	[100.68]	[98.96]	[100.29]	[79.05]	[3.06]
β_{SMB}	0.06	-0.04	-0.10	-0.06	0.10	0.05
	[3.04]	[-2.53]	[-7.08]	[-3.85]	[5.59]	[1.87]
β_{HML}	0.07	-0.01	-0.07	0.13	-0.02	-0.09
	[3.02]	[-0.68]	[-3.63]	[6.63]	[-0.74]	[-2.70]
β_{RMW}	0.17	0.05	-0.01	0.06	0.03	-0.14
	[6.64]	[2.81]	[-0.70]	[3.06]	[1.09]	[-3.97]
β_{CMA}	-0.16	-0.16	-0.02	0.11	0.48	0.64
	[-4.40]	[-5.86]	[-0.81]	[3.69]	[13.12]	[12.67]
β_{UMD}	-0.02	-0.01	0.01	-0.03	0.00	0.02
	[-1.52]	[-0.99]	[1.51]	[-2.55]	[0.12]	[1.17]
Panel C: Average number of firms (n) and market capitalization (me)						
n	631	606	681	790	804	
me ($\$10^6$)	1348	2023	2596	2516	1278	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the ECS strategy construction methodology. In each panel, the first row shows results from a quintile, value-weighted sort using NYSE break points as employed in Table 1. Each of the subsequent rows deviates in one of the three choices at a time, and the choices are specified in the first three columns. For each strategy construction methodology, the table reports average excess returns and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, Fama and French (2015) five-factor model, and the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor following Fama and French (2018). Panel A reports average returns and alphas with no adjustment for trading costs. Panel B reports net average returns and Novy-Marx and Velikov (2016) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 196506 to 202306.

Panel A: Gross Returns and Alphas								
Portfolios	Breaks	Weights	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Quintile	NYSE	VW	0.35	0.36	0.28	0.25	0.20	0.18
			[4.14]	[4.24]	[3.45]	[2.97]	[2.64]	[2.42]
Quintile	NYSE	EW	0.51	0.51	0.42	0.44	0.51	0.52
			[4.79]	[4.70]	[4.19]	[4.31]	[5.69]	[5.84]
Quintile	Name	VW	0.34	0.36	0.27	0.23	0.16	0.15
			[3.95]	[4.12]	[3.20]	[2.77]	[2.20]	[2.05]
Quintile	Cap	VW	0.30	0.32	0.27	0.26	0.19	0.19
			[4.07]	[4.31]	[3.68]	[3.45]	[2.86]	[2.89]
Decile	NYSE	VW	0.47	0.49	0.38	0.33	0.24	0.22
			[4.33]	[4.52]	[3.64]	[3.16]	[2.49]	[2.29]
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	0.32	0.25	0.23	0.18	0.17
			[3.64]	[3.69]	[3.03]	[2.78]	[2.46]	[2.30]
Quintile	NYSE	EW	0.29	0.30	0.22	0.24	0.26	0.28
			[2.62]	[2.62]	[2.07]	[2.23]	[2.83]	[2.98]
Quintile	Name	VW	0.30	0.31	0.23	0.21	0.15	0.14
			[3.44]	[3.54]	[2.76]	[2.54]	[2.01]	[1.89]
Quintile	Cap	VW	0.27	0.29	0.24	0.24	0.18	0.18
			[3.59]	[3.84]	[3.30]	[3.20]	[2.77]	[2.74]
Decile	NYSE	VW	0.41	0.44	0.34	0.32	0.23	0.21
			[3.83]	[3.98]	[3.25]	[3.01]	[2.36]	[2.24]

Table 3: Conditional sort on size and ECS

This table presents results for conditional double sorts on size and ECS. 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 ECS. 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 ECS and short stocks with low ECS .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 196506 to 202306.

Panel A: portfolio average returns and time-series regression results

		ECS Quintiles					ECS Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.52	0.79	0.96	0.98	0.73	0.21	0.16	0.06	0.02	0.13	0.09
		[2.04]	[3.26]	[4.21]	[3.64]	[2.36]	[1.43]	[1.07]	[0.45]	[0.13]	[0.92]	[0.68]
	(2)	0.63	0.73	0.84	0.93	0.89	0.27	0.29	0.21	0.21	0.32	0.31
		[2.55]	[3.08]	[3.68]	[4.26]	[3.61]	[2.58]	[2.74]	[2.05]	[2.00]	[3.38]	[3.31]
	(3)	0.59	0.76	0.79	0.92	0.83	0.24	0.26	0.19	0.16	0.27	0.25
		[2.62]	[3.47]	[3.71]	[4.38]	[3.75]	[2.27]	[2.35]	[1.73]	[1.44]	[2.75]	[2.49]
	(4)	0.49	0.69	0.77	0.84	0.81	0.32	0.29	0.19	0.22	0.14	0.17
		[2.47]	[3.39]	[3.77]	[4.23]	[3.91]	[3.59]	[3.25]	[2.26]	[2.59]	[1.63]	[2.07]
	(5)	0.28	0.57	0.60	0.55	0.70	0.41	0.43	0.38	0.36	0.28	0.27
		[1.64]	[3.33]	[3.40]	[2.98]	[4.19]	[4.54]	[4.69]	[4.16]	[3.86]	[3.18]	[3.13]

Panel B: Portfolio average number of firms and market capitalization

		ECS Quintiles Average n					ECS Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	393	393	393	387	371	37	38	35	30	24
	(2)	109	110	109	109	109	56	57	56	56	55
	(3)	79	79	79	79	79	97	96	98	97	97
	(4)	66	66	66	66	66	206	205	211	205	209
	(5)	61	61	61	61	61	1144	1571	1820	1782	1480

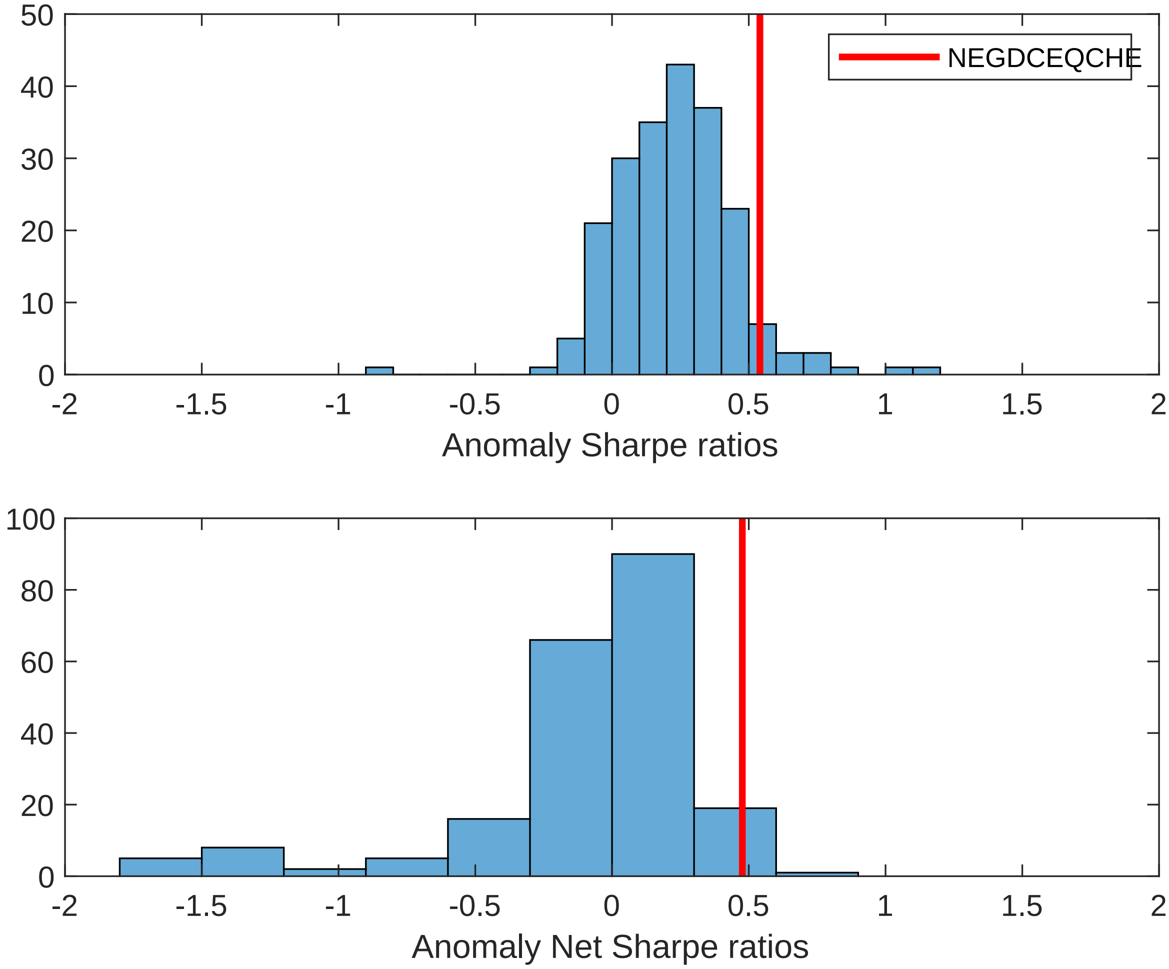

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the ECS with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

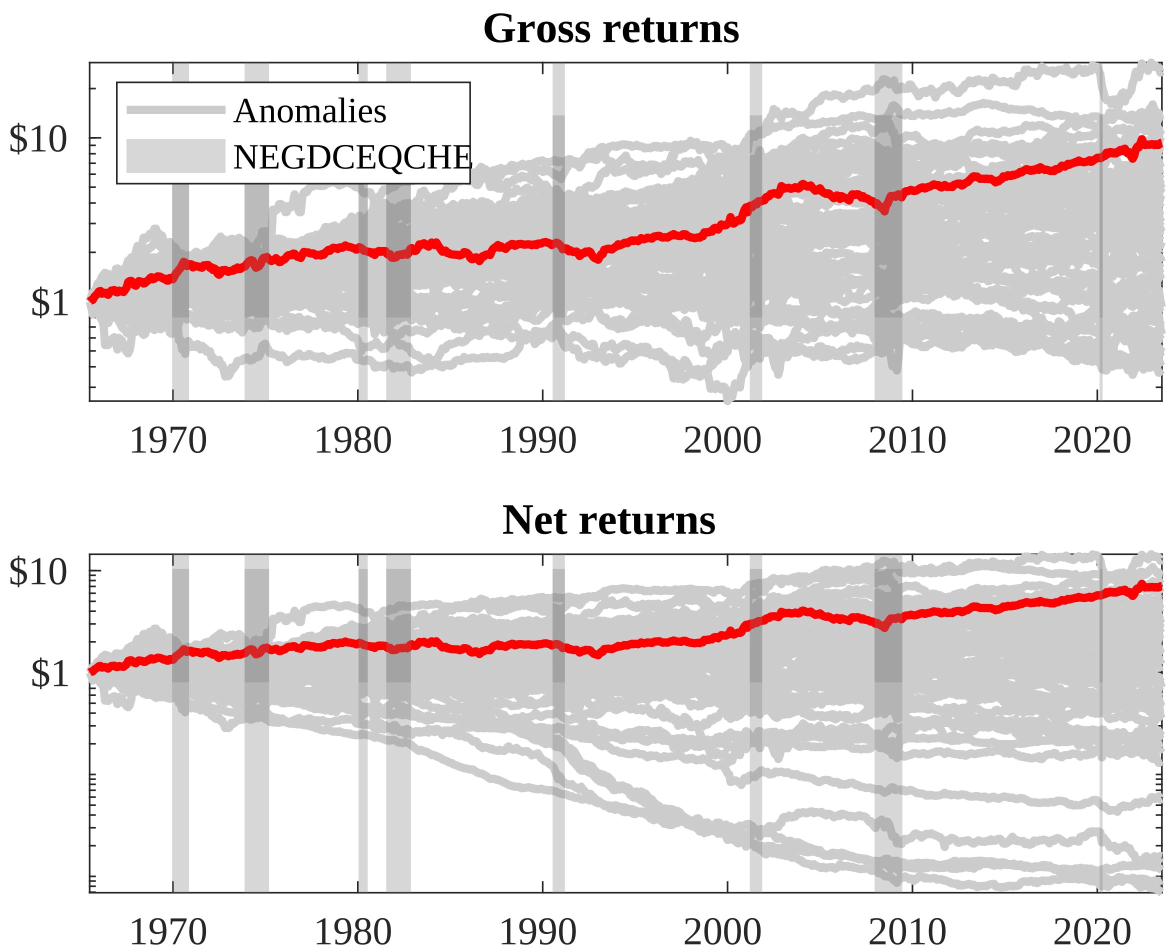

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the ECS trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

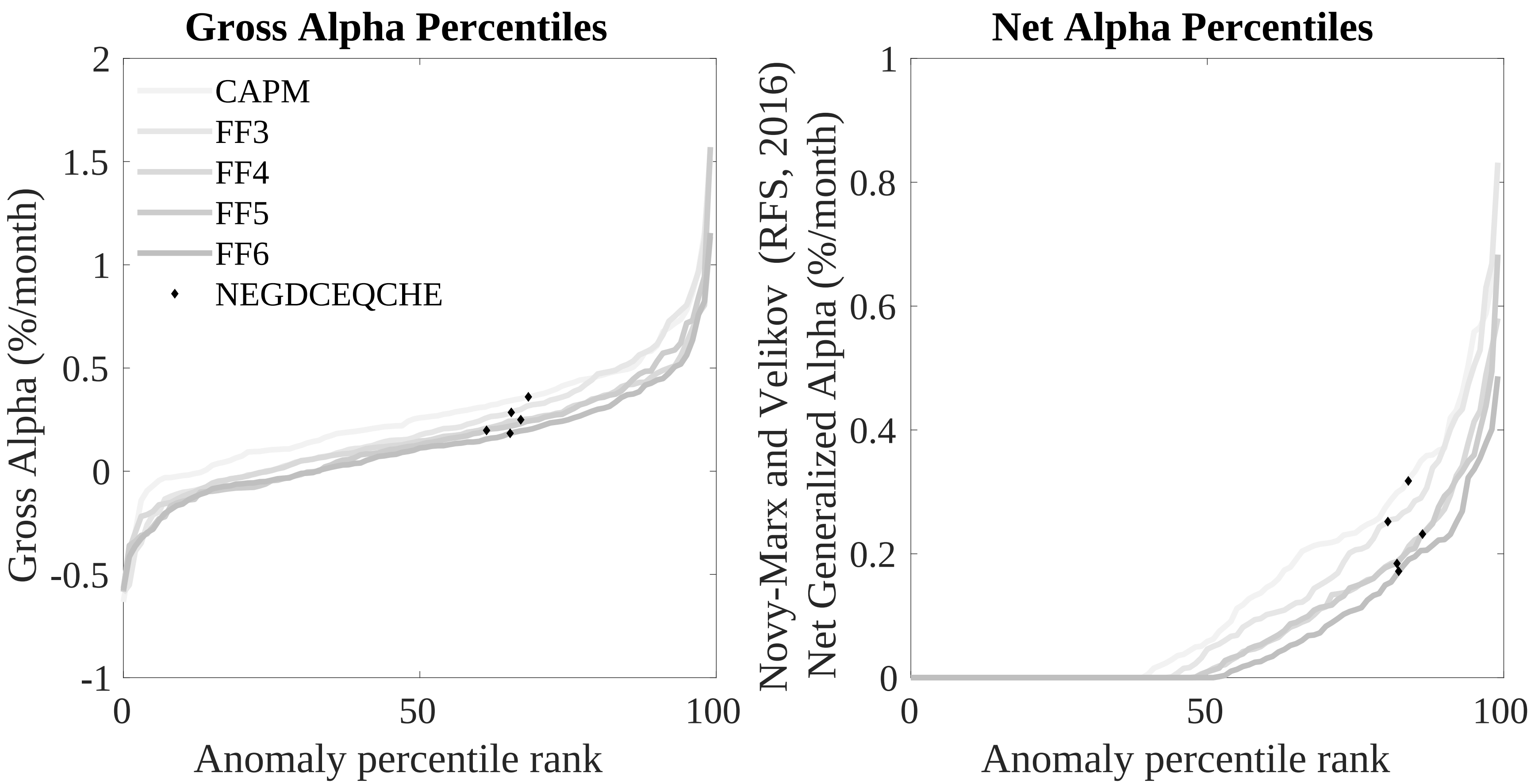

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the ECS trading strategy alphas (diamonds). The strategies are constructed using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

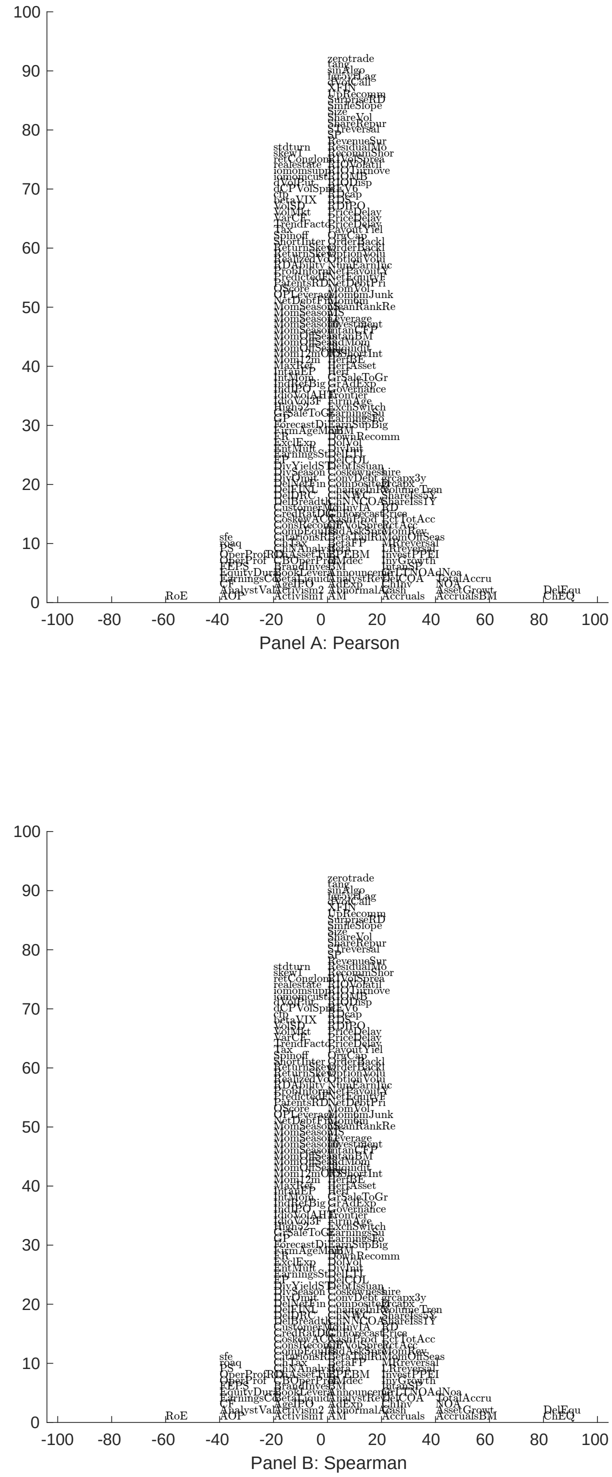

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with ECS. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

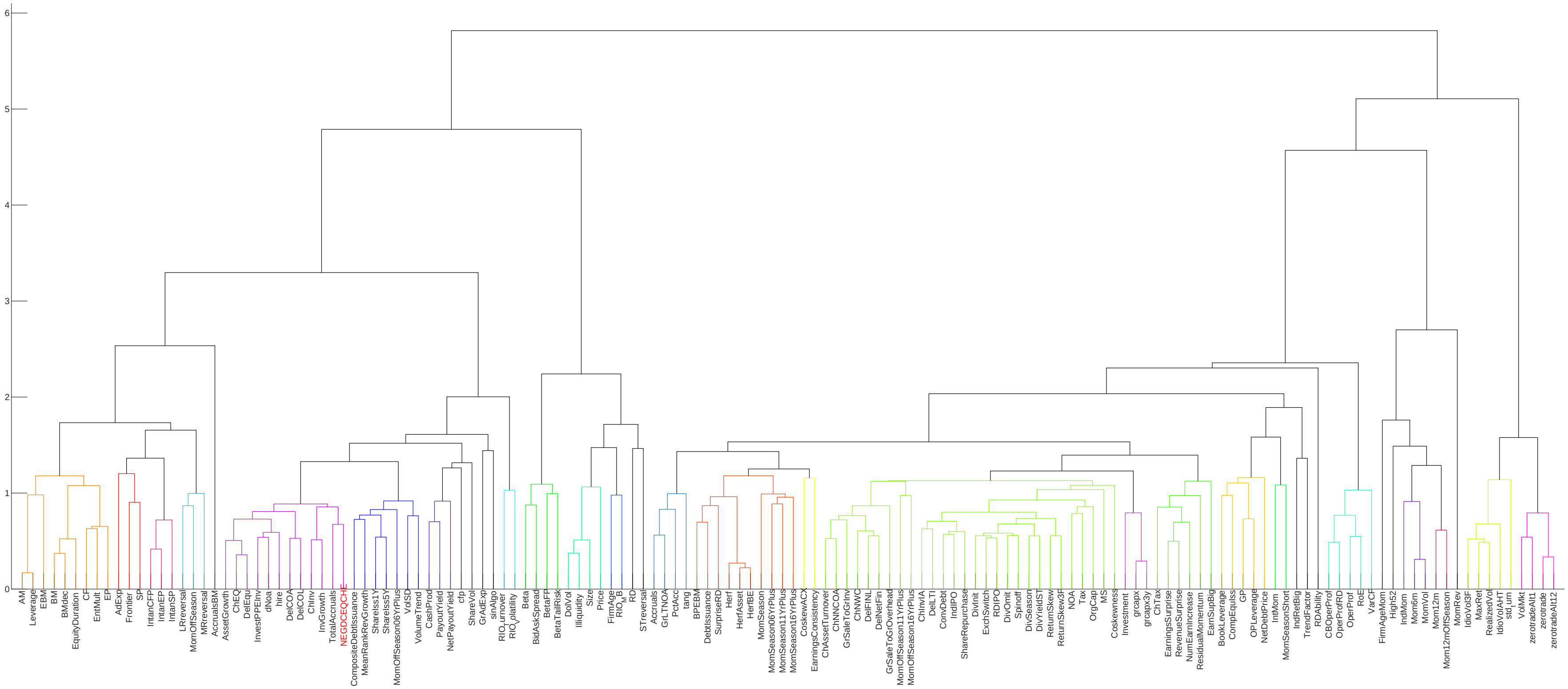

Figure 6: Agglomerative hierarchical cluster plot
This figure plots an agglomerative hierarchical cluster plot using Ward's minimum method and a maximum of 10 clusters.

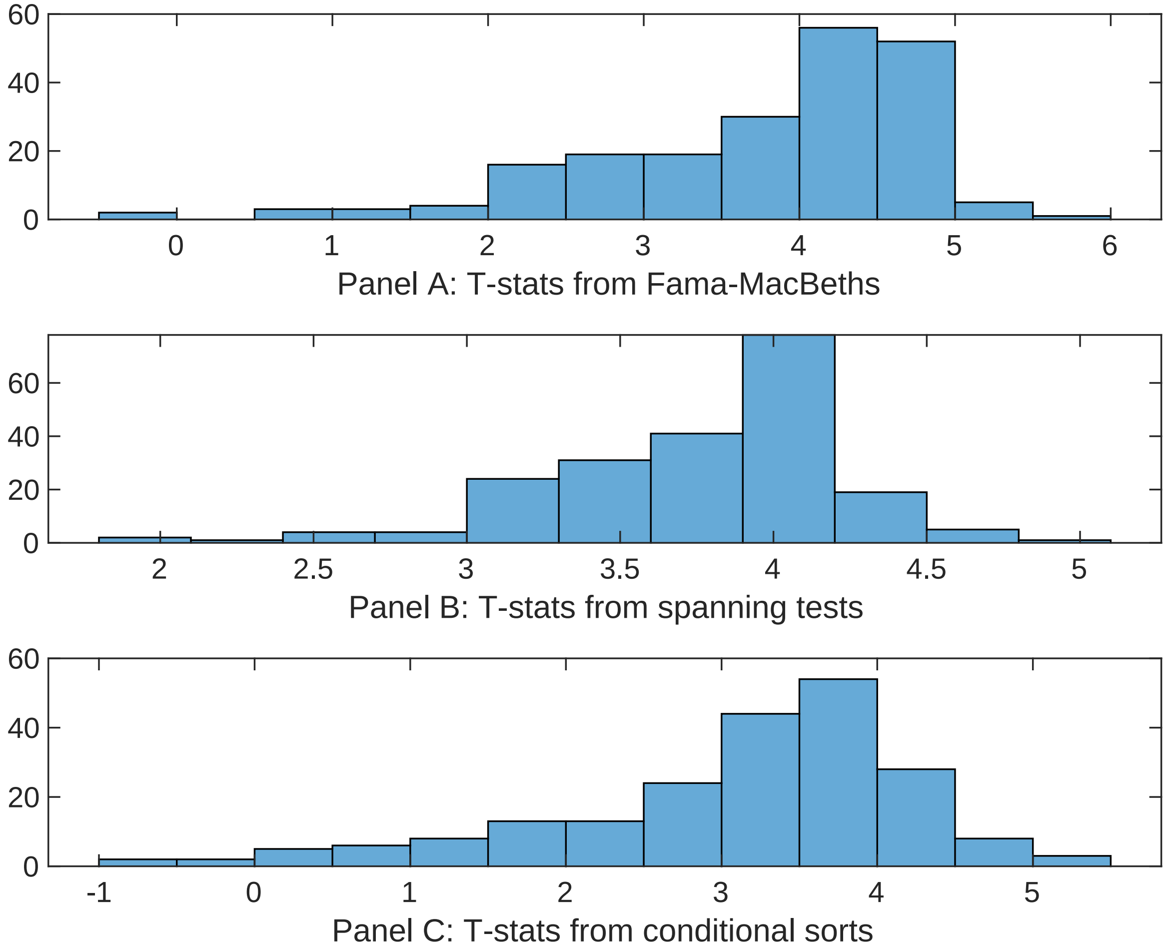

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of ECS conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ECS} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ECS} ECS_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{ECS,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 ECS. Stocks are finally grouped into five ECS portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted ECS 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 ECS. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{ECS} ECS_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in equity to assets, Growth in book equity, Asset growth, change in net operating assets, Total accruals, change in ppe and inv/assets. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196506 to 202306.

Intercept	0.13	0.18	0.14	0.13	0.12	0.14	0.13
	[5.68]	[7.45]	[6.15]	[5.99]	[5.43]	[5.97]	[6.23]
ECS	0.13	0.15	0.10	0.13	0.25	0.15	0.98
	[2.66]	[3.34]	[2.22]	[2.50]	[4.38]	[3.04]	[2.19]
Anomaly 1	0.14						0.68
	[4.10]						[1.20]
Anomaly 2		0.46					-0.92
		[4.35]					[-0.66]
Anomaly 3			0.10				0.32
			[9.67]				[1.86]
Anomaly 4				0.13			0.60
				[10.19]			[3.04]
Anomaly 5					0.37		-0.30
					[1.94]		[-1.36]
Anomaly 6						0.16	0.52
						[8.56]	[2.29]
# months	696	696	696	696	696	696	696
$\bar{R}^2(\%)$	0	0	0	0	0	0	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the ECS trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{ECS} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Change in equity to assets, Growth in book equity, Asset growth, change in net operating assets, Total accruals, change in ppe and inv/assets. These anomalies were picked as those with the highest combined rank where the ranks are based on the absolute value of the Spearman correlations in Panel B of Figure 5 and the R^2 from the spanning tests in Figure 7, Panel B. The sample period is 196506 to 202306.

Intercept	0.21	0.17	0.19	0.15	0.17	0.17	0.17
	[2.94]	[2.38]	[2.53]	[1.97]	[2.20]	[2.31]	[2.47]
Anomaly 1	42.98						24.55
	[11.59]						[4.42]
Anomaly 2		46.53					30.62
		[12.06]					[5.50]
Anomaly 3			22.82				-8.74
			[4.63]				[-1.64]
Anomaly 4				20.05			10.73
				[4.58]			[2.27]
Anomaly 5					13.76		-6.23
					[3.84]		[-1.65]
Anomaly 6						13.81	3.48
						[3.84]	[0.97]
mkt	4.95	7.13	5.71	5.66	5.21	5.29	6.32
	[3.00]	[4.34]	[3.21]	[3.18]	[2.91]	[2.96]	[3.87]
smb	4.27	3.38	2.95	5.53	4.99	4.69	4.49
	[1.79]	[1.42]	[1.13]	[2.15]	[1.93]	[1.81]	[1.88]
hml	-15.14	-15.25	-10.46	-11.05	-9.30	-11.01	-17.44
	[-4.72]	[-4.79]	[-3.06]	[-3.22]	[-2.71]	[-3.19]	[-5.50]
rmw	-9.70	-11.47	-14.23	-13.52	-11.87	-13.94	-10.47
	[-2.99]	[-3.58]	[-4.10]	[-3.89]	[-3.36]	[-4.00]	[-3.27]
cma	20.17	18.86	36.99	49.54	57.42	54.22	12.23
	[3.33]	[3.14]	[4.72]	[8.21]	[10.62]	[9.42]	[1.65]
umd	3.47	1.57	2.97	1.61	2.48	2.02	1.76
	[2.12]	[0.97]	[1.68]	[0.92]	[1.41]	[1.15]	[1.08]
# months	696	696	696	696	696	696	696
$\bar{R}^2$(%)	40	40	30	30	29	29	42

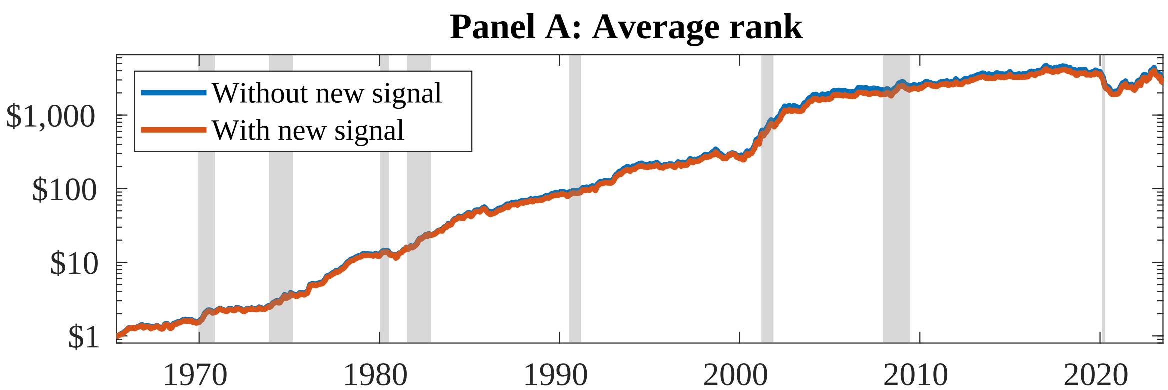

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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