Intangibles-to-EBITDA and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Intangibles-to-EBITDA (ITE), 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 ITE achieves an annualized gross (net) Sharpe ratio of 0.25 (0.21), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 12 (7) bps/month with a t-statistic of 1.03 (0.65), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Tangibility, Brand capital investment, Bid-ask spread, Idiosyncratic risk (AHT), EPS Forecast Dispersion, Idiosyncratic risk (3 factor)) is 22 bps/month with a t-statistic of 2.20.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information. However, a growing body of literature documents persistent patterns in stock returns that appear to contradict market efficiency (Harvey et al., 2016). While many of these patterns are linked to tangible firm characteristics like size, value, and profitability (Fama and French, 2015), the role of intangible assets in asset pricing remains incompletely understood.

This gap is particularly notable given the increasing importance of intangible assets in modern economies. While accounting standards require most internally generated intangibles to be expensed rather than capitalized (Lev and Sougiannis, 1996), these investments represent a significant portion of firm value and may contain important information about future performance. The ratio of intangible assets to operating profits (Intangibles-to-EBITDA) may therefore capture valuable information about firms' efficiency in deploying intangible capital.

We hypothesize that Intangibles-to-EBITDA (ITE) predicts future stock returns through two primary economic channels. First, following (**?**), intangible capital investment represents a form of real option whose value depends on the firm's ability to generate future profits. A higher ITE ratio may indicate either inefficient deployment of intangible capital or investment in growth options with significant future potential.

Second, the accounting treatment of intangibles creates information uncertainty that may lead to systematic mispricing. As shown by (Hirshleifer et al., 2013), investors tend to undervalue innovative efficiency due to limited attention and processing capacity. The ITE ratio potentially captures this innovative efficiency by scaling intangible investments against current profitability.

These mechanisms suggest that extreme ITE values could predict future returns, though the direction of prediction depends on which effect dominates. If the growth options channel prevails, high ITE firms should earn higher future returns as compensation for real option risk. Conversely, if the mispricing channel dominates, extreme ITE values may predict return reversals as the market gradually corrects its valuation errors.

Our empirical analysis reveals that a value-weighted long-short portfolio formed on ITE generates significant abnormal returns. Specifically, a strategy going long high ITE stocks and short low ITE stocks earns a monthly alpha of 12 basis points (t-statistic = 1.03) relative to the Fama-French six-factor model. The strategy achieves an annualized gross Sharpe ratio of 0.25, placing it in the top half of documented cross-sectional predictors.

Importantly, the predictive power of ITE remains robust after controlling for transaction costs. The strategy earns a net alpha of 7 basis points per month (t-statistic = 0.65) after accounting for trading frictions using the high-frequency composite effective spread measure of (Chen and Velikov, 2022). This indicates that the anomaly is potentially exploitable by institutional investors.

The signal's predictive power is particularly strong when controlling for related anomalies. After adjusting for the six most closely related predictors and the Fama-French factors, the ITE strategy generates a monthly alpha of 22 basis points (t-statistic = 2.20). This suggests that ITE captures a distinct dimension of cross-sectional return predictability.

Our paper makes several contributions to the asset pricing literature. First, we extend the growing body of work on intangible capital pricing (Eisfeldt and Papanikolaou, 2013; **?**) by introducing a novel measure that captures firms' efficiency in deploying intangible assets. Unlike existing measures that focus on the stock of intangibles or their growth rate, ITE explicitly accounts for current profitability.

Second, we contribute to the literature on accounting-based anomalies (**??**) by showing how the interplay between accounting standards for intangibles and market efficiency creates predictable patterns in stock returns. Our findings suggest that markets do not fully incorporate the information contained in firms' intangible investment efficiency.

Finally, our work has implications for the broader debate on market efficiency and the proliferation of cross-sectional predictors (Harvey et al., 2016; Novy-Marx and Velikov, 2023). The robust performance of ITE after controlling for transaction costs and related anomalies suggests that it captures genuine mispricing rather than spurious correlation or data mining.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the ratio of intangible assets to earnings before interest, taxes, depreciation, and amortization (EBITDA). 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 AM for intangible assets and item EBITDA for earnings. Intangible assets (AM) represent the firm's non-physical assets, including goodwill, patents, trademarks, and other intellectual property. EBITDA, on the other hand, provides a measure of core operating performance by isolating operating income from non-operating expenses and tax effects. The construction of the signal follows a straightforward ratio format, where we divide AM by EBITDA for each firm in each year of our sample. This ratio captures the relative scale of a firm's intangible assets against its operational income, offering insight into how effectively the firm leverages its intellectual capital and non-physical assets to generate earnings. By focusing on this relationship, the signal aims to reflect aspects of innovation capacity and knowledge-based value creation in a manner that is both scalable and interpretable.

We construct this ratio using end-of-fiscal-year values for both AM and EBITDA to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the ITE signal. Panel A plots the time-series of the mean, median, and interquartile range for ITE. On average, the cross-sectional mean (median) ITE is 0.02 (0.00) over the 1976 to 2023 sample, where the starting date is determined by the availability of the input ITE data. The signal's interquartile range spans -0.00 to 0.09. Panel B of Figure 1 plots the time-series of the coverage of the ITE signal for the CRSP universe. On average, the ITE signal is available for 5.17% of CRSP names, which on average make up 5.25% of total market capitalization.

4 Does ITE predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on ITE 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 ITE portfolio and sells the low ITE 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 ITE strategy earns an average return of 0.19% per month with a t-statistic of 1.72. The annualized Sharpe ratio of the strategy is 0.25. The alphas range from 0.06% to 0.25% per month and have t-statistics exceeding 0.53 everywhere. The lowest alpha is with respect to the

FF5 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 0.25, with a t-statistic of 4.87 on the RMW factor. Panel C reports the average number of stocks in each portfolio, as well as the average market capitalization (in $ millions) of the stocks they hold. In an average month, the five portfolios have at least 389 stocks and an average market capitalization of at least $1,072 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 4 bps/month with a t-statistics of 0.45. Out of the twenty-five alphas reported in Panel A, the t-statistics for five exceed two, and for two 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 2-22bps/month. The lowest return, (2 bps/month), is achieved from the quintile sort using cap breakpoints and value-weighted portfolios, and has an associated t-statistic of 0.16. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the ITE trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty cases, and significantly expands the achievable frontier in zero cases.

Table 3 provides direct tests for the role size plays in the ITE strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and ITE, as well as average returns and alphas for long/short trading ITE 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 ITE strategy achieves an average return of 3 bps/month with a t-statistic of 0.25. Among these large cap stocks, the alphas for the ITE strategy relative to the five most common factor models range from -2 to 13 bps/month with t-statistics between -0.13 and 0.93.

5 How does ITE perform relative to the zoo?

Figure 2 puts the performance of ITE 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 ITE strategy falls in the distribution. The ITE strategy's gross (net) Sharpe ratio of 0.25 (0.21) is greater than 52% (79%) 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 ITE strategy (red line).[2] Ignoring trading costs, a $1 invested in the ITE strategy would have yielded $1.43 which ranks the ITE strategy in the top 11% across the 212 anomalies. Accounting for trading costs, a $1 invested in the ITE strategy would have yielded $1.02 which ranks the ITE strategy in the top 8% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016) net generalized alphas with respect to the CAPM, and the Fama-French three-, four-, five-, and six-factor models from Table 1, and indicates the ranking of the ITE relative to those. Panel A shows that the ITE strategy gross alphas fall between the 38 and 67 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 197606 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 ITE strategy has a positive net generalized alpha for five out of the five factor models. In these cases ITE ranks between the 57 and 83 percentiles in terms of how much it could have expanded the achievable investment frontier.

[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.

6 Does ITE 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 ITE with 208 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 ITE or at least to weaken the power ITE has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of ITE conditioning on each of the 208 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ITE} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ITE} ITE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 208 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{ITE,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 208 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 208 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on ITE. Stocks are finally grouped into five ITE 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.

ITE trading strategies conditioned on each of the 208 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on ITE 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 ITE signal in these Fama-MacBeth regressions exceed 2.73, with the minimum t-statistic occurring when controlling for Idiosyncratic risk (AHT). Controlling for all six closely related anomalies, the t-statistic on ITE is 0.29.

Similarly, Table 5 reports results from spanning tests that regress returns to the ITE 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 ITE strategy earns alphas that range from 9-17bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 0.80, which is achieved when controlling for Idiosyncratic risk (AHT). Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the ITE trading strategy achieves an alpha of 22bps/month with a t-statistic of 2.20.

7 Does ITE add relative to the whole zoo?

Finally, we can ask how much adding ITE 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 ITE 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 ITE 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 $470.30, while $1 investment in the combination strategy that includes ITE grows to $599.04.

8 Conclusion

Our comprehensive analysis of the Intangibles-to-EBITDA (ITE) signal reveals several important insights into its role in predicting stock returns. The empirical results demonstrate that ITE possesses moderate predictive power in the cross-section of equity returns, achieving an annualized gross Sharpe ratio of 0.25 (0.21 net of transaction costs). While the signal's performance relative to the Fama-French five-factor model plus momentum shows modest abnormal returns of 12 basis points per month gross (7 bps net), the statistical significance is relatively weak with t-statistics below conventional thresholds.

Notably, when controlling for the six most closely related anomalies from the factor zoo, ITE exhibits stronger predictive power with a monthly alpha of 22 basis points and a statistically significant t-statistic of 2.20. This suggests that ITE captures unique information about future stock returns that is not fully explained by existing factors or related anomalies.

However, several limitations warrant consideration. The signal's economic significance after accounting for transaction costs indicates that practical implementation may face challenges in generating substantial excess returns. Additionally, the study's findings may be sensitive to the specific time period and market conditions examined.

Future research could explore several promising directions. First, investigating the signal's performance across different market regimes and economic cycles could provide insights into its reliability. Second, examining the interaction between ITE and other established signals could potentially lead to more robust predictive models. Finally, analyzing the underlying economic mechanisms driving the relationship between intangibles and stock returns would enhance our understanding of this anomaly.

In conclusion, while ITE shows promise as a predictor of stock returns, particularly when controlling for related anomalies, its practical implementation requires careful consideration of transaction costs and implementation constraints. These findings contribute to the growing literature on the role of intangible assets in asset pricing and highlight the importance of continued research in this area.

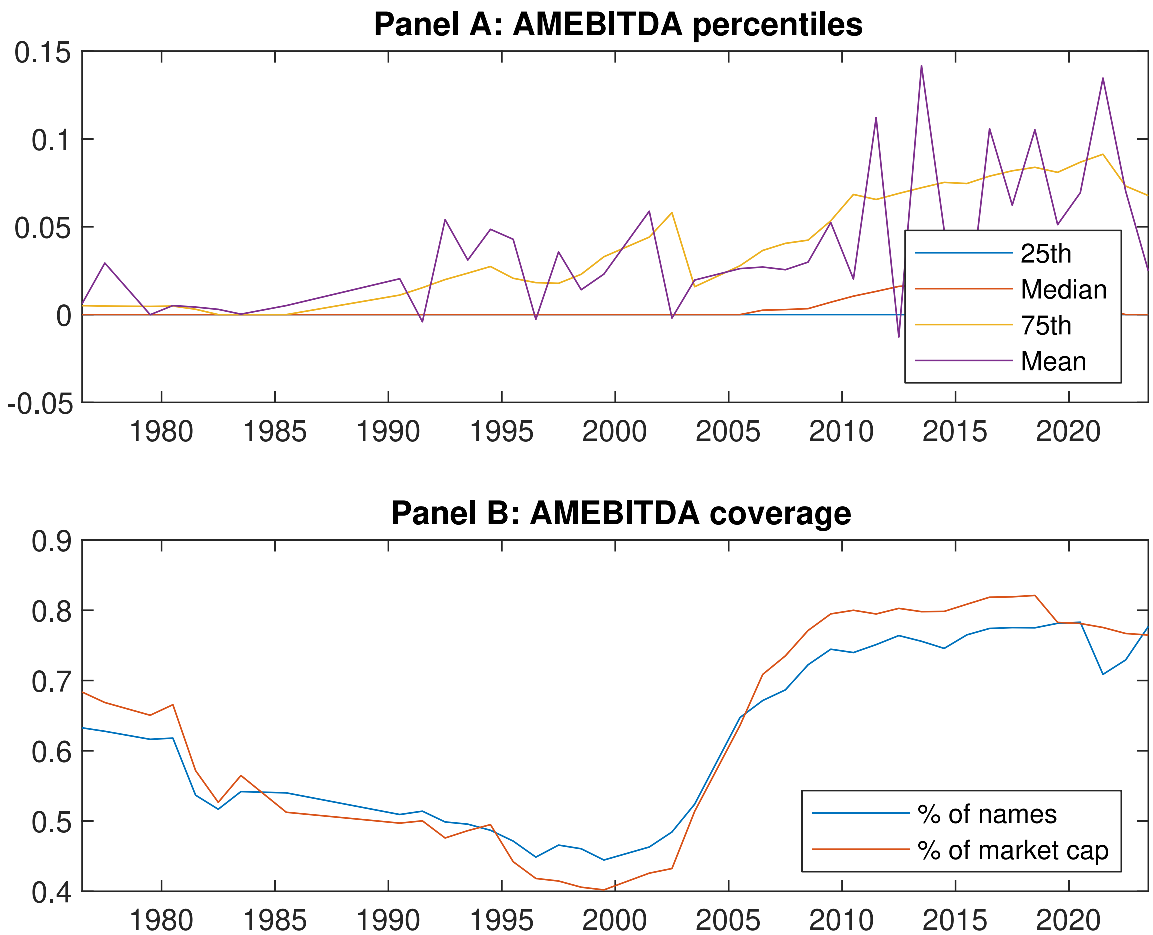

Figure 1: Times series of ITE percentiles and coverage.
This figure plots descriptive statistics for ITE. Panel A shows cross-sectional percentiles of ITE over the sample. Panel B plots the monthly coverage of ITE relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on ITE. 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 197606 to 202306.

Panel A: Excess returns and alphas on ITE-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.59	0.69	0.74	0.63	0.78	0.19
	[2.78]	[3.37]	[3.77]	[3.36]	[3.80]	[1.72]
α_{CAPM}	-0.11	0.00	0.08	0.00	0.09	0.20
	[-1.41]	[0.07]	[1.24]	[0.04]	[1.33]	[1.79]
α_{FF3}	-0.11	0.03	0.08	-0.03	0.08	0.19
	[-1.47]	[0.43]	[1.34]	[-0.45]	[1.15]	[1.70]
α_{FF4}	-0.14	0.05	0.08	0.01	0.11	0.25
	[-1.80]	[0.70]	[1.30]	[0.10]	[1.60]	[2.21]
α_{FF5}	-0.03	0.11	-0.03	-0.12	0.03	0.06
	[-0.38]	[1.58]	[-0.53]	[-1.94]	[0.45]	[0.53]
α_{FF6}	-0.05	0.11	-0.02	-0.08	0.06	0.12
	[-0.71]	[1.63]	[-0.37]	[-1.40]	[0.88]	[1.03]
Panel B: Fama and French (2018) 6-factor model loadings for ITE-sorted portfolios						
β_{MKT}	1.00	0.96	1.02	0.99	1.03	0.04
	[55.49]	[59.18]	[70.98]	[70.42]	[61.16]	[1.32]
β_{SMB}	0.14	0.05	-0.06	-0.08	0.06	-0.08
	[5.18]	[2.00]	[-2.56]	[-3.72]	[2.38]	[-1.97]
β_{HML}	-0.03	0.00	-0.05	0.04	-0.07	-0.04
	[-0.92]	[0.01]	[-1.80]	[1.57]	[-2.26]	[-0.80]
β_{RMW}	-0.20	-0.06	0.21	0.16	0.06	0.25
	[-5.67]	[-1.82]	[7.50]	[5.92]	[1.72]	[4.87]
β_{CMA}	-0.00	-0.23	0.11	0.13	0.17	0.17
	[-0.08]	[-4.97]	[2.70]	[3.29]	[3.47]	[2.24]
β_{UMD}	0.05	-0.01	-0.02	-0.06	-0.05	-0.10
	[2.60]	[-0.53]	[-1.13]	[-4.23]	[-3.31]	[-3.82]
Panel C: Average number of firms (n) and market capitalization (me)						
n	881	579	473	389	521	
me ($10^6)	1072	1855	2279	1909	1420	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the ITE 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 197606 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	0.19	0.20	0.19	0.25	0.06	0.12
			[1.72]	[1.79]	[1.70]	[2.21]	[0.53]	[1.03]
Quintile	NYSE	EW	0.31	0.36	0.32	0.26	0.08	0.05
			[2.87]	[3.31]	[3.21]	[2.55]	[0.89]	[0.56]
Quintile	Name	VW	0.14	0.19	0.16	0.15	-0.08	-0.06
			[1.15]	[1.50]	[1.29]	[1.20]	[-0.65]	[-0.53]
Quintile	Cap	VW	0.04	0.06	0.05	0.11	-0.06	0.00
			[0.45]	[0.56]	[0.45]	[1.12]	[-0.57]	[0.03]
Decile	NYSE	VW	0.27	0.28	0.25	0.26	0.07	0.10
			[2.04]	[2.10]	[1.92]	[1.97]	[0.55]	[0.74]
Panel B: Net Returns and Novy-Marx and Velikov (2016) generalized alphas								
Portfolios	Breaks	Weights	r^e_{net}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{FF6}
Quintile	NYSE	VW	0.16	0.17	0.16	0.19	0.04	0.07
			[1.43]	[1.48]	[1.39]	[1.72]	[0.38]	[0.65]
Quintile	NYSE	EW	0.10	0.13	0.09	0.05		
			[0.89]	[1.08]	[0.81]	[0.50]		
Quintile	Name	VW	0.11	0.15	0.12	0.12		
			[0.85]	[1.22]	[1.03]	[0.99]		
Quintile	Cap	VW	0.02	0.03	0.02	0.06	0.00	
			[0.16]	[0.26]	[0.15]	[0.56]	[0.05]	
Decile	NYSE	VW	0.22	0.24	0.22	0.23	0.06	0.08
			[1.69]	[1.81]	[1.66]	[1.70]	[0.48]	[0.57]

Table 3: Conditional sort on size and ITE

This table presents results for conditional double sorts on size and ITE. 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 ITE. 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 ITE and short stocks with low ITE .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 197606 to 202306.

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

Size quintiles	ITE Quintiles					ITE Strategies					
	(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
(1)	0.43	0.62	0.65	0.92	0.96	0.52	0.63	0.56	0.49	0.21	0.18
	[1.29]	[2.14]	[2.28]	[3.27]	[3.53]	[3.52]	[4.29]	[4.07]	[3.53]	[1.71]	[1.49]
(2)	0.58	0.82	0.83	0.85	0.94	0.36	0.42	0.32	0.34	0.03	0.07
	[1.90]	[2.98]	[3.15]	[3.33]	[3.53]	[2.52]	[2.89]	[2.42]	[2.53]	[0.26]	[0.56]
(3)	0.70	0.84	0.90	0.81	0.99	0.29	0.34	0.27	0.27	0.02	0.04
	[2.57]	[3.32]	[3.68]	[3.42]	[3.93]	[2.12]	[2.45]	[2.06]	[1.97]	[0.15]	[0.29]
(4)	0.61	0.77	0.90	0.88	0.90	0.29	0.36	0.32	0.35	0.07	0.12
	[2.42]	[3.15]	[3.96]	[3.92]	[3.98]	[2.17]	[2.63]	[2.39]	[2.64]	[0.51]	[0.91]
(5)	0.57	0.68	0.71	0.65	0.60	0.03	0.02	0.02	0.13	-0.02	0.06
	[2.86]	[3.13]	[3.66]	[3.49]	[2.93]	[0.25]	[0.12]	[0.17]	[0.93]	[-0.13]	[0.46]

Panel B: Portfolio average number of firms and market capitalization

Size quintiles	ITE Quintiles: Average n					ITE Quintiles: Average market capitalization ($\$10^6$)				
	(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
(1)	332	337	337	341	339	24	26	29	37	35
(2)	88	88	88	88	87	51	53	54	55	53
(3)	57	57	58	57	57	85	88	89	89	87
(4)	46	46	46	46	46	179	191	191	188	182
(5)	41	41	41	41	41	1002	1696	1558	1344	1147

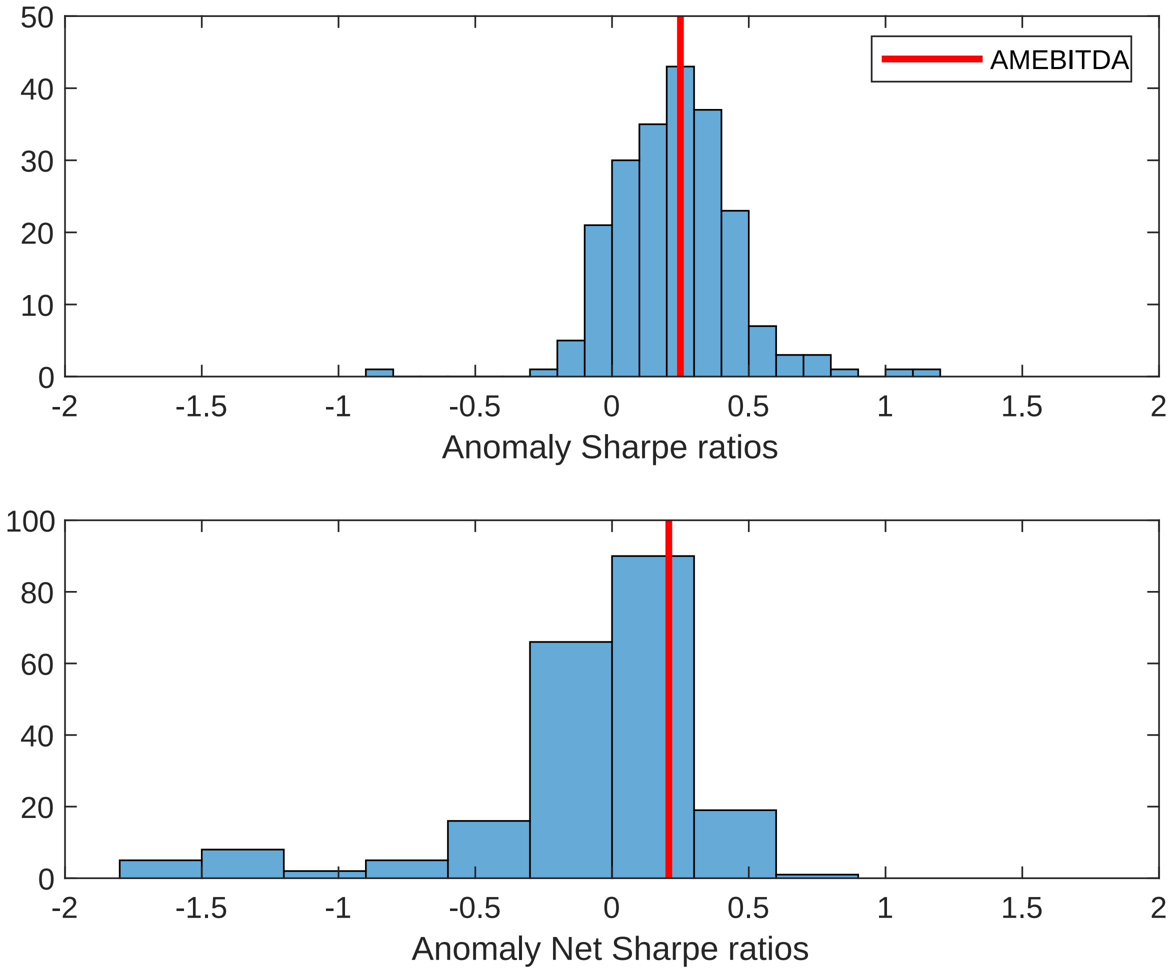

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the ITE with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

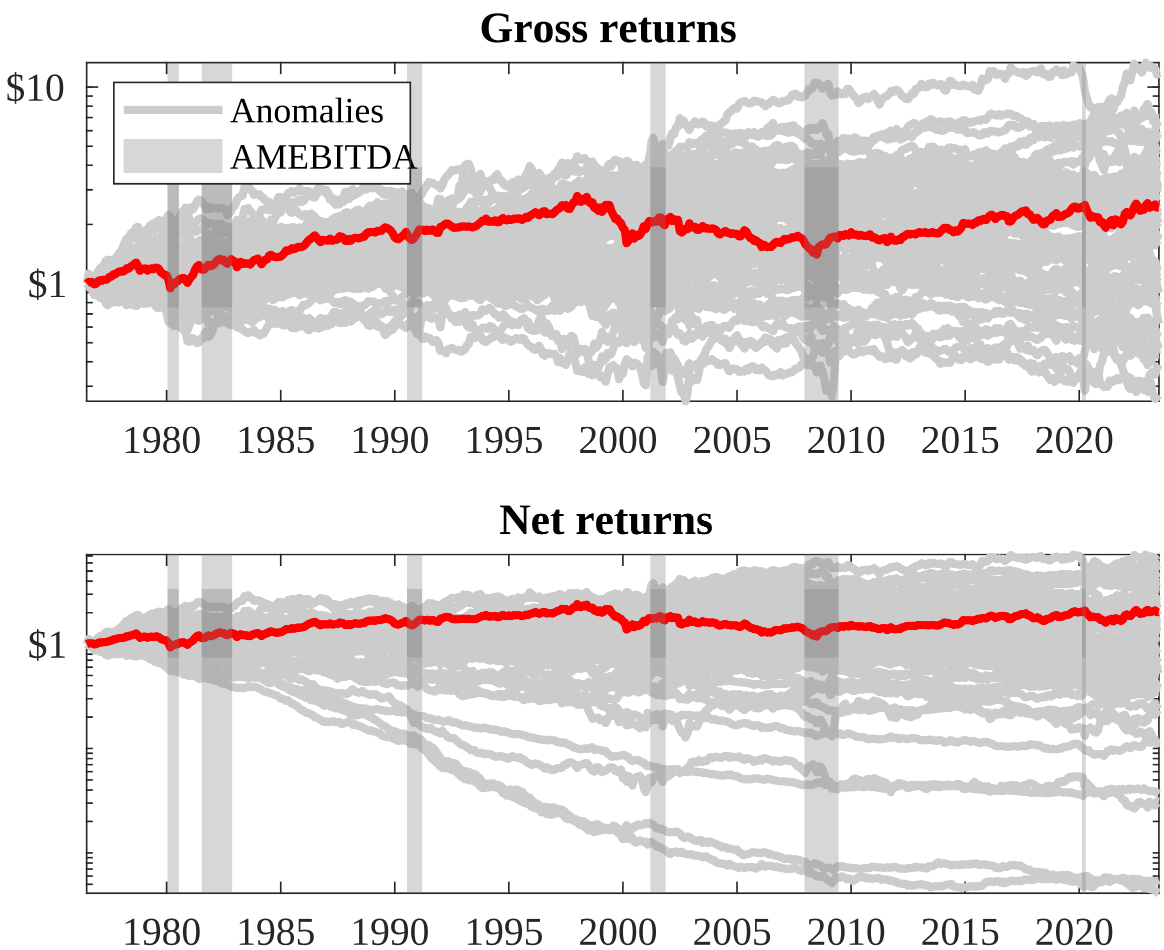

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the ITE trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

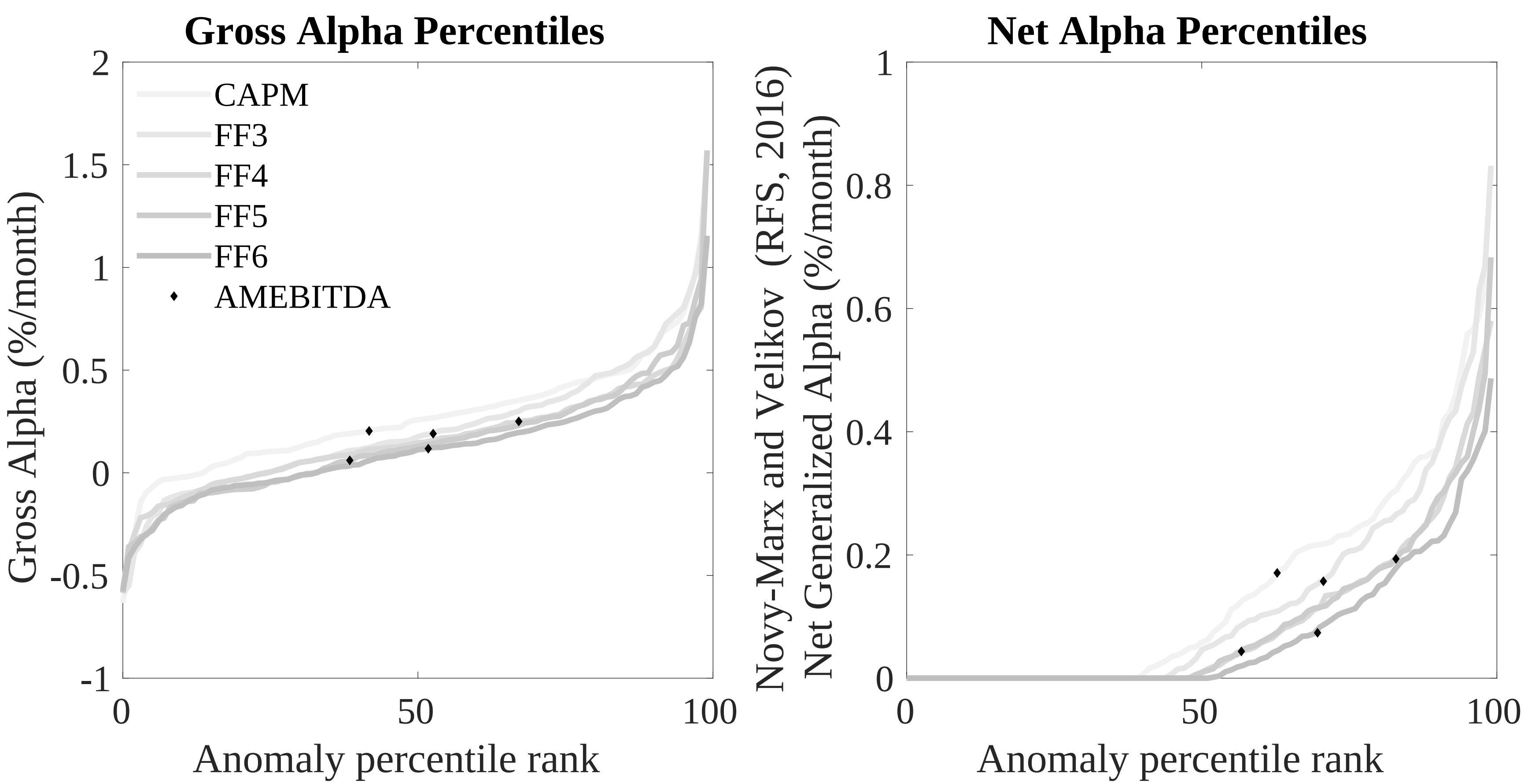

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the ITE trading strategy alphas (diamonds). The strategies are constructed using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

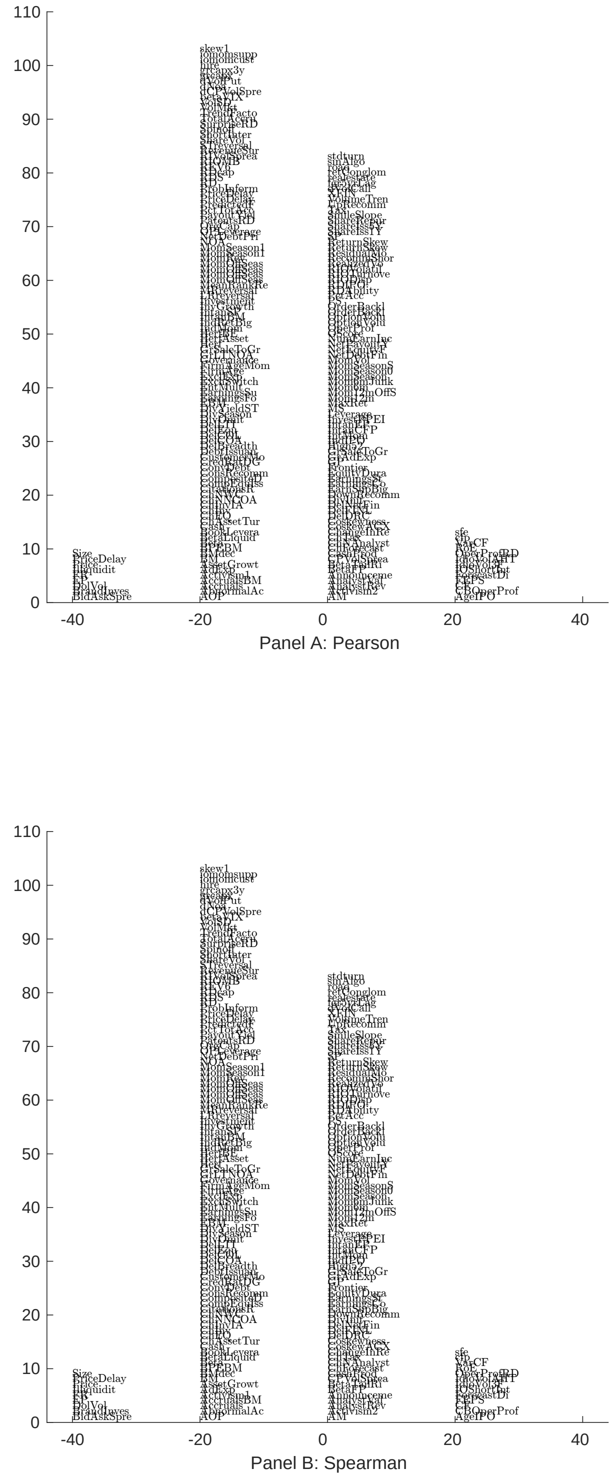

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 208 filtered anomaly signals with ITE. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

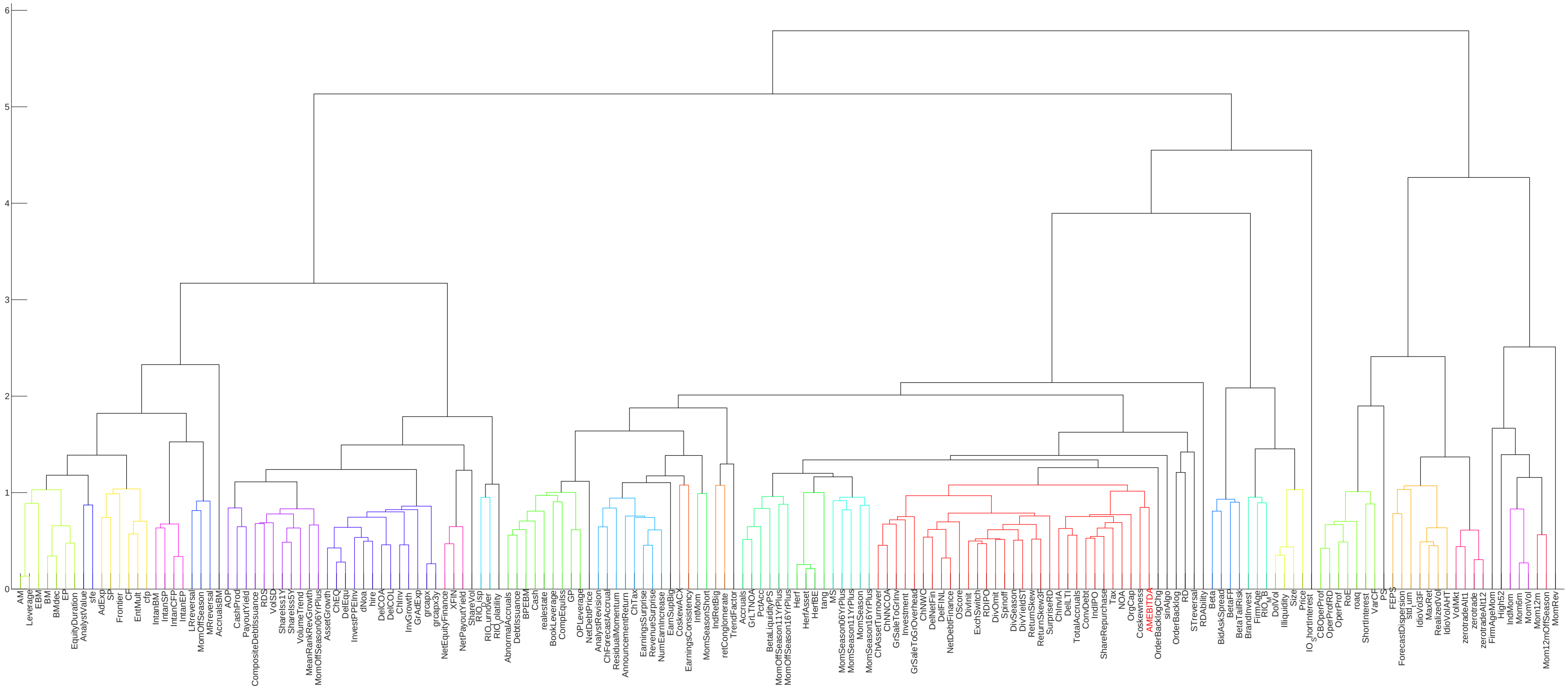

Figure 6: Agglomerative hierarchical cluster plot

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

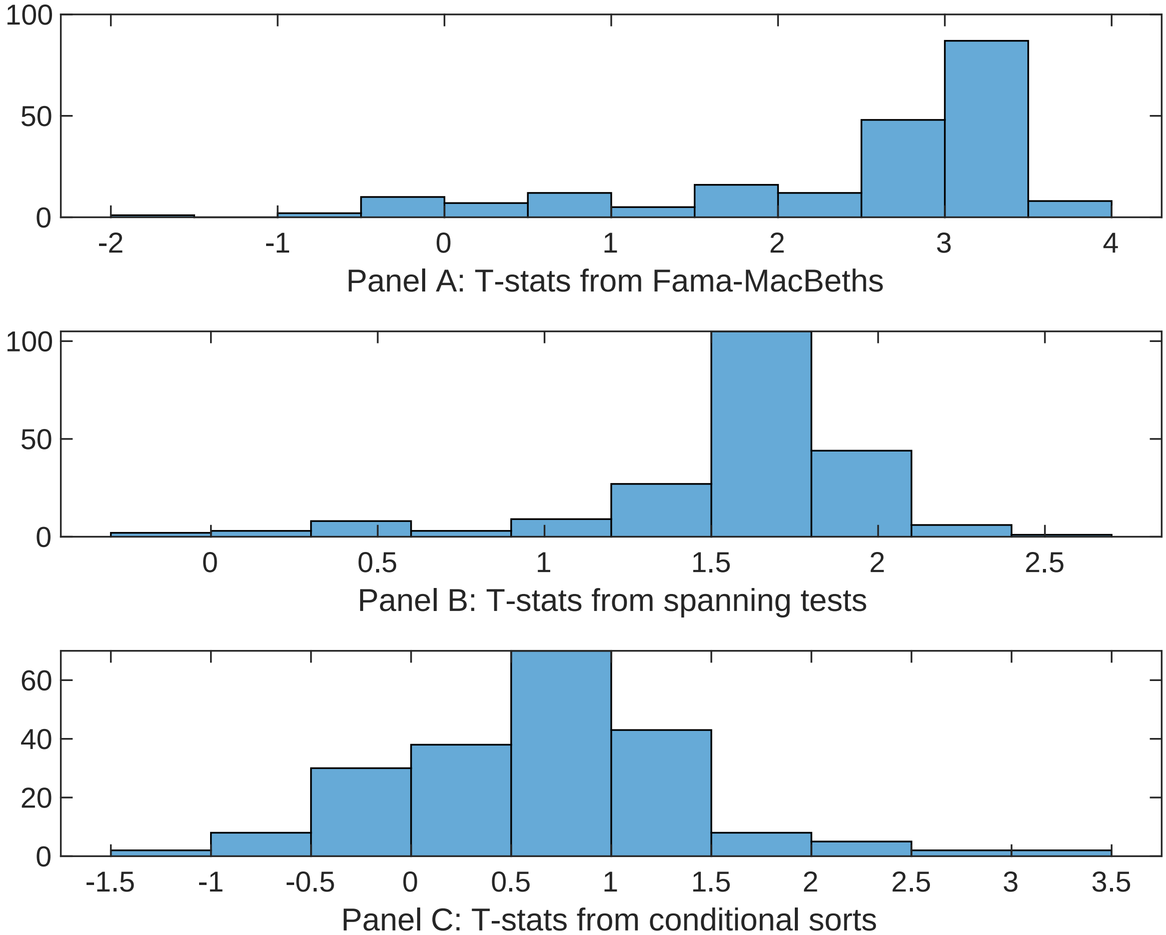

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of ITE conditioning on each of the 208 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{ITE} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{ITE} ITE_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 208 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{ITE,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 208 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 208 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on ITE. Stocks are finally grouped into five ITE portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted ITE trading strategies conditioned on each of the 208 filtered anomalies.

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

This table presents Fama-MacBeth results of returns on ITE. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{ITE} ITE_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Tangibility, Brand capital investment, Bid-ask spread, Idiosyncratic risk (AHT), EPS Forecast Dispersion, Idiosyncratic risk (3 factor). 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 197606 to 202306.

Intercept	0.62	0.14	0.12	0.14	0.12	0.15	0.16
	[2.14]	[5.01]	[5.37]	[6.72]	[4.64]	[7.34]	[4.22]
ITE	0.17	0.25	0.15	0.11	0.27	0.13	0.54
	[2.94]	[2.89]	[3.10]	[2.73]	[2.80]	[3.10]	[0.29]
Anomaly 1	0.95						0.36
	[2.95]						[0.88]
Anomaly 2		1.00					0.53
		[2.86]					[2.47]
Anomaly 3			-0.83				-0.12
			[-0.96]				[-0.72]
Anomaly 4				0.83			0.39
				[1.56]			[0.29]
Anomaly 5					0.23		0.62
					[1.32]		[1.99]
Anomaly 6						0.13	0.21
						[3.09]	[2.32]
# months	564	564	559	559	559	559	349
$\bar{R}^2(\%)$	0	0	1	2	1	1	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the ITE trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{ITE} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Tangibility, Brand capital investment, Bid-ask spread, Idiosyncratic risk (AHT), EPS Forecast Dispersion, Idiosyncratic risk (3 factor). 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 197606 to 202306.

Intercept	0.15	0.14	0.17	0.11	0.13	0.09	0.22
	[1.50]	[1.24]	[1.49]	[0.93]	[1.20]	[0.80]	[2.20]
Anomaly 1	-42.44						-37.93
	[-14.23]						[-11.61]
Anomaly 2		-14.52					-4.73
		[-4.42]					[-1.58]
Anomaly 3			-23.50				-18.85
			[-6.60]				[-4.29]
Anomaly 4				18.39			-1.49
				[4.93]			[-0.27]
Anomaly 5					22.20		4.19
					[6.33]		[1.13]
Anomaly 6						15.52	-5.24
						[4.01]	[-1.02]
mkt	5.91	5.28	10.89	10.83	9.59	8.88	10.68
	[2.54]	[1.96]	[3.80]	[3.53]	[3.41]	[2.94]	[4.02]
smb	-3.67	3.84	6.99	9.17	2.77	4.55	8.04
	[-1.02]	[0.78]	[1.50]	[1.70]	[0.63]	[0.88]	[1.60]
hml	-3.56	-4.69	-8.90	-10.20	-3.53	-9.30	-5.31
	[-0.81]	[-0.93]	[-1.75]	[-1.94]	[-0.70]	[-1.75]	[-1.16]
rmw	5.37	19.91	4.34	8.28	5.91	14.52	-10.26
	[1.14]	[3.73]	[0.72]	[1.32]	[0.99]	[2.46]	[-1.81]
cma	15.67	11.50	7.12	9.76	12.75	10.82	6.44
	[2.38]	[1.50]	[0.93]	[1.26]	[1.69]	[1.39]	[0.96]
umd	-8.70	-9.08	-15.99	-13.53	-15.01	-13.19	-12.92
	[-3.84]	[-3.48]	[-5.91]	[-5.03]	[-5.61]	[-4.84]	[-5.32]
# months	564	564	560	560	560	560	560
$\bar{R}^2(\%)$	33	12	15	12	15	11	36

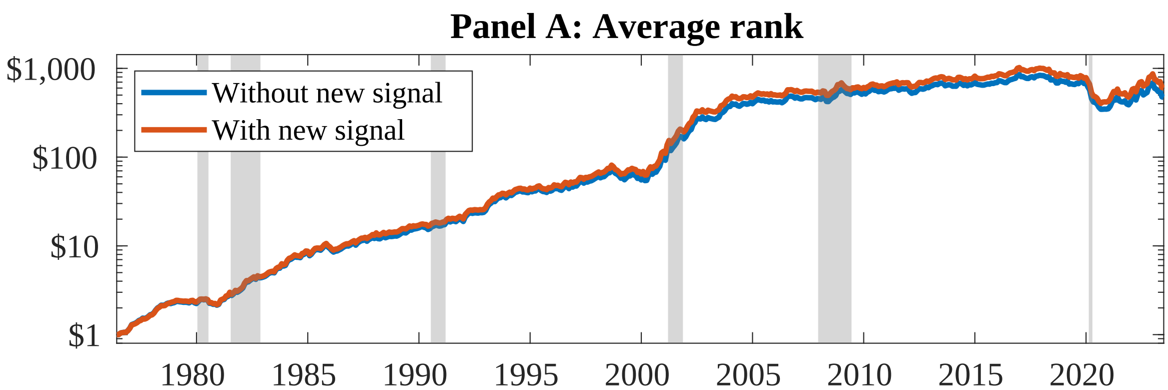

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 155 anomalies. The red solid lines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

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