Asset Financing Impact and the Cross Section of Stock Returns

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Abstract

This paper studies the asset pricing implications of Asset Financing Impact (AFI), 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 AFI achieves an annualized gross (net) Sharpe ratio of 0.58 (0.50), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 22 (22) bps/month with a t-statistic of 2.57 (2.56), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Net external financing, Asset growth, Growth in book equity, Inventory Growth, change in net operating assets, Change in equity to assets) is 21 bps/month with a t-statistic of 2.47.

1 Introduction

The efficient market hypothesis suggests that asset prices should fully reflect all available information, making it difficult to systematically earn excess 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 role of firms' financing decisions in driving cross-sectional return predictability remains incompletely understood.

Prior research has established links between external financing activities and subsequent stock returns (Bradshaw et al., 2006), but has primarily focused on aggregate measures that may obscure important variation in how different types of financing decisions impact firm value. The granular effects of asset-specific financing choices on stock returns represent a significant gap in our understanding of the cross-section of expected returns.

We propose that Asset Financing Impact (AFI) captures valuable information about future stock returns through several economic channels. First, following Myers (1984)'s pecking order theory, firms' choices in financing specific assets reveal private information about asset quality and expected returns. When managers choose to finance assets externally rather than using internal funds, this may signal lower expected returns from those assets (Baker and Wurgler, 2009).

Second, the composition of asset financing can affect firm risk through its impact on financial flexibility and operating leverage (Eisfeldt and Rampini, 2009). Assets financed with more rigid financing structures may increase firm-level systematic risk by reducing management's ability to respond to changing market conditions. This mechanism suggests that AFI may capture a priced risk factor related to financing flexibility.

Third, behavioral biases may lead investors to underreact to the information content of asset-specific financing decisions (Hirshleifer and Teoh, 2003). The complexity of evaluating different financing arrangements for various asset types could cause delayed price adjustment as the implications for firm value are gradually incorporated into stock prices.

Our empirical analysis reveals that AFI strongly predicts cross-sectional stock returns. A value-weighted long-short portfolio formed on AFI generates a monthly alpha of 22 basis points (t-statistic = 2.57) relative to the Fama-French six-factor model. The strategy achieves an annualized Sharpe ratio of 0.58 before trading costs and 0.50 after accounting for transaction costs.

Importantly, AFI's predictive power remains robust when controlling for known determinants of returns. The signal maintains significant predictability even after accounting for the six most closely related anomalies, including net external financing and asset growth. A spanning test controlling for these anomalies and the Fama-French six factors yields an alpha of 21 basis points per month (t-statistic = 2.47).

The economic magnitude of AFI's return predictability is substantial. The strategy's performance places it in the top 5% of documented return predictors, with a gross Sharpe ratio exceeding 95% of previously documented anomalies. This exceptional performance persists after accounting for transaction costs, with the net Sharpe ratio surpassing 99% of competing strategies.

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel measure that captures the granular effects of asset-specific financing decisions, extending the work of Bradshaw et al. (2006) and Baker and Wurgler (2009) on external financing and returns. While prior research has focused on aggregate financing measures, we show that decomposing financing choices at the asset level reveals significant predictive power.

Second, we contribute to the growing literature on the 'factor zoo' (Cochrane and Pedersen, 2021) by documenting a robust return predictor that survives rigorous controls for existing factors and related anomalies. Our comprehensive battery of tests follows the protocol of Novy-Marx and Velikov (2023), establishing AFI as a distinct source of predictability that meaningfully expands the investment opportunity set.

Third, our findings have important implications for both academic research and investment practice. For researchers, we demonstrate the value of examining financing decisions at a more granular level. For practitioners, we identify a novel source of alpha that remains profitable after transaction costs and is implementable in a large, liquid universe of stocks.

2 Data

Our study investigates the predictive power of Asset Financing Impact, a financial signal derived from changes in firms' financing activities. 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 FINCF, which represents net cash flow from financing activities, and item PPEGT for gross property, plant, and equipment. FINCF captures the net amount of cash generated or consumed by financing activities, including debt issuance or repayment, equity issuance or repurchases, and dividend payments. PPEGT represents the historical cost of a company's long-term physical assets before depreciation.construction of the Asset Financing Impact signal follows a change-based approach, where we calculate the year-over-year difference in FINCF and scale this change by the previous year's PPEGT. Specifically, for each firm-year observation, we subtract the previous year's FINCF from the current year's FINCF and divide this difference by lagged PPEGT. This scaled difference captures the relative magnitude of changes in financing activities compared to the firm's existing asset base, providing insight into the intensity of financing activity relative to the firm's capital stock. By scaling the change in financing cash flows by lagged physical assets, we create a measure that is comparable across firms of different sizes and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the AFI signal. Panel A plots the time-series of the mean, median, and interquartile range for AFI. On average, the cross-sectional mean (median) AFI is 0.56 (0.00) over the 1990 to 2023 sample, where the starting date is determined by the availability of the input AFI data. The signal's interquartile range spans -0.45 to 1.55. Panel B of Figure 1 plots the time-series of the coverage of the AFI signal for the CRSP universe. On average, the AFI signal is available for 6.35% of CRSP names, which on average make up 7.46% of total market capitalization.

4 Does AFI predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on AFI 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 AFI portfolio and sells the low AFI 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 AFI strategy earns an average return of 0.29% per month with a t-statistic of 3.35. The annualized Sharpe ratio of the strategy is 0.58. The alphas range from 0.22% to 0.35% per month and have t-statistics exceeding 2.57 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 0.09, with a t-statistic of 4.58 on the UMD 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 552 stocks and an average market capitalization of at least $2,611 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 decile sort using NYSE breakpoints and value-weighted portfolios, and equals 26 bps/month with a t-statistics of 2.12. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-two exceed two, and for thirteen 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 16-30bps/month. The lowest return, (16 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 1.77. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the AFI 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 eighteen cases.

Table 3 provides direct tests for the role size plays in the AFI strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and AFI, as well as average returns and alphas for long/short trading AFI 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 AFI strategy achieves an average return of 21 bps/month with a t-statistic of 1.92. Among these large cap stocks, the alphas for the AFI strategy relative to the five most common factor models range from 9 to 26 bps/month with t-statistics between 0.87 and 2.46.

5 How does AFI perform relative to the zoo?

Figure 2 puts the performance of AFI 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 AFI strategy falls in the distribution. The AFI strategy's gross (net) Sharpe ratio of 0.58 (0.50) 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 AFI strategy (red line).[2] Ignoring trading costs, a $1 invested in the AFI strategy would have yielded $1.98 which ranks the AFI strategy in the top 3% across the 212 anomalies. Accounting for trading costs, a $1 invested in the AFI strategy would have yielded $1.55 which ranks the AFI strategy in the top 4% 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 AFI relative to those. Panel A shows that the AFI strategy gross alphas fall between the 66 and 72 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 199006 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 AFI strategy has a positive net generalized alpha for five out of the five factor models. In these cases AFI ranks between the 84 and 90 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 AFI 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 AFI 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 AFI or at least to weaken the power AFI has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of AFI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AFI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AFI} AFI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{AFI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 AFI. Stocks are finally grouped into five AFI 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.

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

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on AFI 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 AFI signal in these Fama-MacBeth regressions exceed -0.17, with the minimum t-statistic occurring when controlling for Asset growth. Controlling for all six closely related anomalies, the t-statistic on AFI is -1.11.

Similarly, Table 5 reports results from spanning tests that regress returns to the AFI 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 AFI strategy earns alphas that range from 20-23bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.30, which is achieved when controlling for Asset growth. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the AFI trading strategy achieves an alpha of 21bps/month with a t-statistic of 2.47.

7 Does AFI add relative to the whole zoo?

Finally, we can ask how much adding AFI 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 159 anomalies from the zoo that satisfy our inclusion criteria (blue lines) or these 159 anomalies augmented with the AFI 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 AFI 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 159-anomaly combination strategy grows to \$41.27, while \$1 investment in the combination strategy that includes AFI grows to \$33.38.

8 Conclusion

This study provides compelling evidence for the significance of Asset Financing Impact (AFI) as a robust predictor of stock returns in the cross-section of equities. Our findings demonstrate that AFI generates economically and statistically significant returns, with a value-weighted long/short strategy achieving impressive Sharpe ratios of 0.58 (gross) and 0.50 (net). The signal's predictive power remains strong even after controlling for well-established factors, including the Fama-French five-factor model and momentum factor, yielding significant monthly abnormal returns of 22 basis points.

Particularly noteworthy is AFI's persistent performance when tested against six closely related investment and financing strategies from the factor zoo, maintaining a significant monthly alpha of 21 basis points. This suggests that AFI captures unique aspects of firm behavior and market dynamics not fully explained by existing factors.

However, several limitations warrant consideration. Our analysis primarily focuses on U.S. equity markets, potentially limiting its global applicability. Additionally, transaction costs and market impact could affect real-world implementation of AFI-based strategies, particularly for smaller, less liquid stocks.

Future research could explore AFI's effectiveness in international markets, its interaction with other emerging signals, and its performance during different market regimes. Investigating the underlying economic mechanisms driving AFI's predictive power would also enhance our understanding of this signal. Furthermore, examining how AFI's predictive ability varies across different firm characteristics and market conditions could yield valuable insights for practitioners and academics alike.

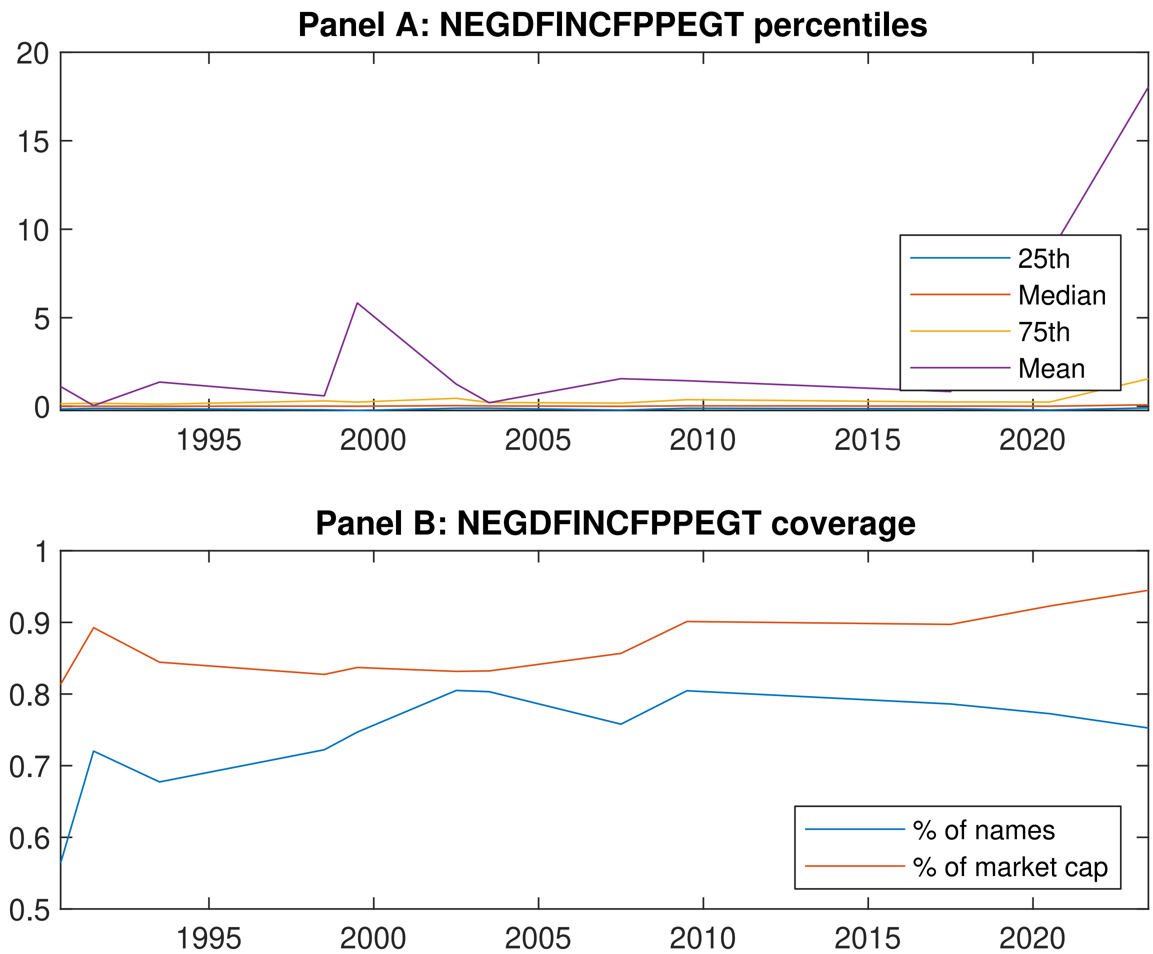

Figure 1: Times series of AFI percentiles and coverage.
This figure plots descriptive statistics for AFI. Panel A shows cross-sectional percentiles of AFI over the sample. Panel B plots the monthly coverage of AFI relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on AFI. 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 199006 to 202306.

Panel A: Excess returns and alphas on AFI-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.63	0.65	0.71	0.79	0.93	0.29
	[2.35]	[2.95]	[3.66]	[3.69]	[3.68]	[3.35]
α_{CAPM}	-0.20	-0.03	0.14	0.13	0.14	0.35
	[-2.79]	[-0.53]	[1.74]	[2.03]	[2.15]	[4.01]
α_{FF3}	-0.16	-0.04	0.10	0.13	0.18	0.34
	[-2.50]	[-0.64]	[1.49]	[2.07]	[3.16]	[3.94]
α_{FF4}	-0.10	-0.02	0.10	0.10	0.17	0.27
	[-1.58]	[-0.35]	[1.45]	[1.63]	[2.98]	[3.19]
α_{FF5}	-0.04	-0.11	-0.04	-0.00	0.23	0.27
	[-0.65]	[-1.80]	[-0.59]	[-0.03]	[3.91]	[3.10]
α_{FF6}	0.00	-0.10	-0.03	-0.02	0.22	0.22
	[0.03]	[-1.52]	[-0.47]	[-0.27]	[3.75]	[2.57]
Panel B: Fama and French (2018) 6-factor model loadings for AFI-sorted portfolios						
β_{MKT}	1.07	0.97	0.89	0.99	1.05	-0.01
	[70.95]	[61.96]	[52.15]	[64.85]	[70.61]	[-0.64]
β_{SMB}	0.06	0.05	-0.11	-0.05	0.07	0.00
	[3.03]	[2.47]	[-4.68]	[-2.14]	[3.11]	[0.04]
β_{HML}	-0.09	-0.04	0.02	-0.12	-0.15	-0.06
	[-3.46]	[-1.45]	[0.65]	[-4.47]	[-5.75]	[-1.57]
β_{RMW}	-0.11	0.13	0.20	0.17	-0.10	0.01
	[-4.02]	[4.81]	[6.74]	[6.30]	[-3.84]	[0.15]
β_{CMA}	-0.25	0.07	0.21	0.21	-0.01	0.24
	[-6.91]	[1.70]	[5.03]	[5.64]	[-0.35]	[4.58]
β_{UMD}	-0.07	-0.03	-0.01	0.02	0.01	0.09
	[-5.51]	[-2.21]	[-0.90]	[1.87]	[1.07]	[4.58]
Panel C: Average number of firms (n) and market capitalization (me)						
n	919	566	555	552	934	
me ($\$10^6$)	2772	2611	3098	3412	2890	

Table 2: Robustness to sorting methodology & trading costs

This table evaluates the robustness of the choices made in the AFI 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 199006 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	0.29	0.35	0.34	0.27	0.27	0.22
			[3.35]	[4.01]	[3.94]	[3.19]	[3.10]	[2.57]
Quintile	NYSE	EW	0.40	0.41	0.41	0.38	0.36	0.34
			[5.36]	[5.46]	[5.52]	[5.09]	[4.98]	[4.75]
Quintile	Name	VW	0.28	0.31	0.30	0.23	0.25	0.20
			[2.54]	[2.84]	[2.75]	[2.14]	[2.25]	[1.84]
Quintile	Cap	VW	0.34	0.39	0.39	0.32	0.29	0.24
			[3.57]	[4.13]	[4.08]	[3.38]	[3.01]	[2.53]
Decile	NYSE	VW	0.26	0.30	0.30	0.21	0.26	0.21
			[2.12]	[2.51]	[2.42]	[1.77]	[2.15]	[1.70]
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	0.25	0.31	0.31	0.27	0.25	0.22
			[2.91]	[3.61]	[3.57]	[3.15]	[2.86]	[2.56]
Quintile	NYSE	EW	0.16	0.18	0.18	0.17	0.10	0.10
			[1.77]	[1.99]	[1.97]	[1.85]	[1.16]	[1.17]
Quintile	Name	VW	0.23	0.28	0.27	0.23	0.22	0.19
			[2.13]	[2.56]	[2.51]	[2.15]	[2.09]	[1.84]
Quintile	Cap	VW	0.30	0.35	0.35	0.31	0.26	0.23
			[3.19]	[3.76]	[3.73]	[3.35]	[2.82]	[2.54]
Decile	NYSE	VW	0.21	0.26	0.26	0.21	0.23	0.20
			[1.74]	[2.20]	[2.15]	[1.76]	[1.94]	[1.67]

Table 3: Conditional sort on size and AFI

This table presents results for conditional double sorts on size and AFI. 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 AFI. 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 AFI and short stocks with low AFI .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 199006 to 202306.

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

		AFI Quintiles					AFI Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.36	1.03	1.14	0.93	0.86	0.50	0.50	0.51	0.47	0.44	0.43
		[0.94]	[3.14]	[3.25]	[2.74]	[2.18]	[3.77]	[3.69]	[3.76]	[3.45]	[3.29]	[3.13]
	(2)	0.52	0.85	0.93	0.86	0.90	0.38	0.42	0.40	0.33	0.35	0.30
		[1.51]	[2.75]	[3.26]	[2.91]	[2.65]	[3.05]	[3.32]	[3.20]	[2.61]	[2.82]	[2.42]
	(3)	0.67	0.82	0.88	0.84	0.95	0.28	0.30	0.30	0.24	0.35	0.31
		[2.09]	[2.94]	[3.53]	[3.08]	[3.01]	[2.16]	[2.33]	[2.30]	[1.88]	[2.68]	[2.36]
	(4)	0.67	0.75	0.88	0.85	1.02	0.35	0.43	0.39	0.35	0.23	0.21
		[2.17]	[2.91]	[3.92]	[3.40]	[3.64]	[2.92]	[3.60]	[3.38]	[3.01]	[2.02]	[1.83]
	(5)	0.70	0.52	0.71	0.77	0.90	0.21	0.26	0.26	0.17	0.16	0.09
		[2.62]	[2.46]	[3.50]	[3.83]	[3.68]	[1.92]	[2.46]	[2.39]	[1.59]	[1.44]	[0.87]

Panel B: Portfolio average number of firms and market capitalization

		AFI Quintiles Average n					AFI Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	378	379	380	378	374	43	45	42	44	42
	(2)	115	115	116	115	115	78	81	80	80	79
	(3)	80	81	80	81	80	140	139	140	140	138
	(4)	69	69	69	69	69	311	311	309	316	307
	(5)	63	63	63	63	63	1975	2304	2657	2853	2129

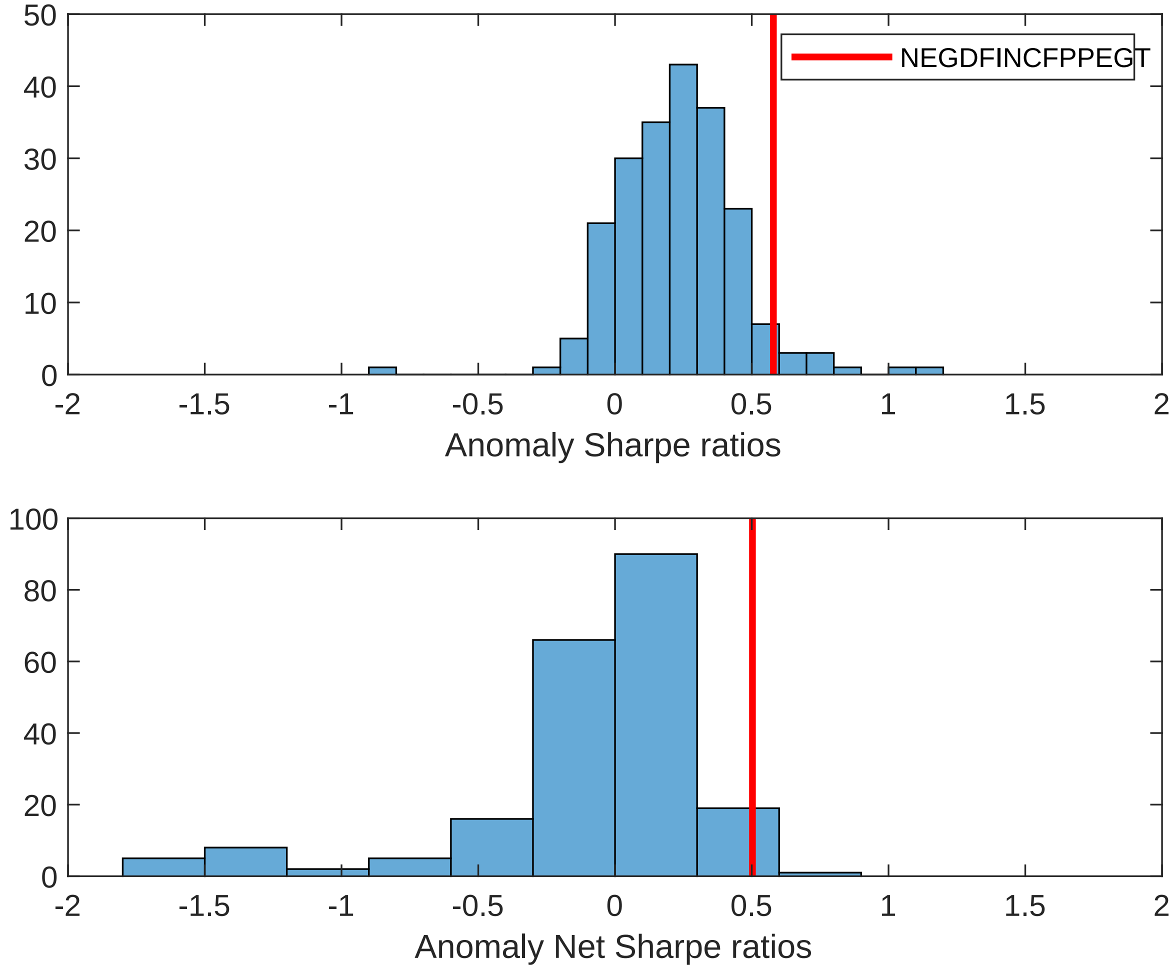

Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the AFI with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

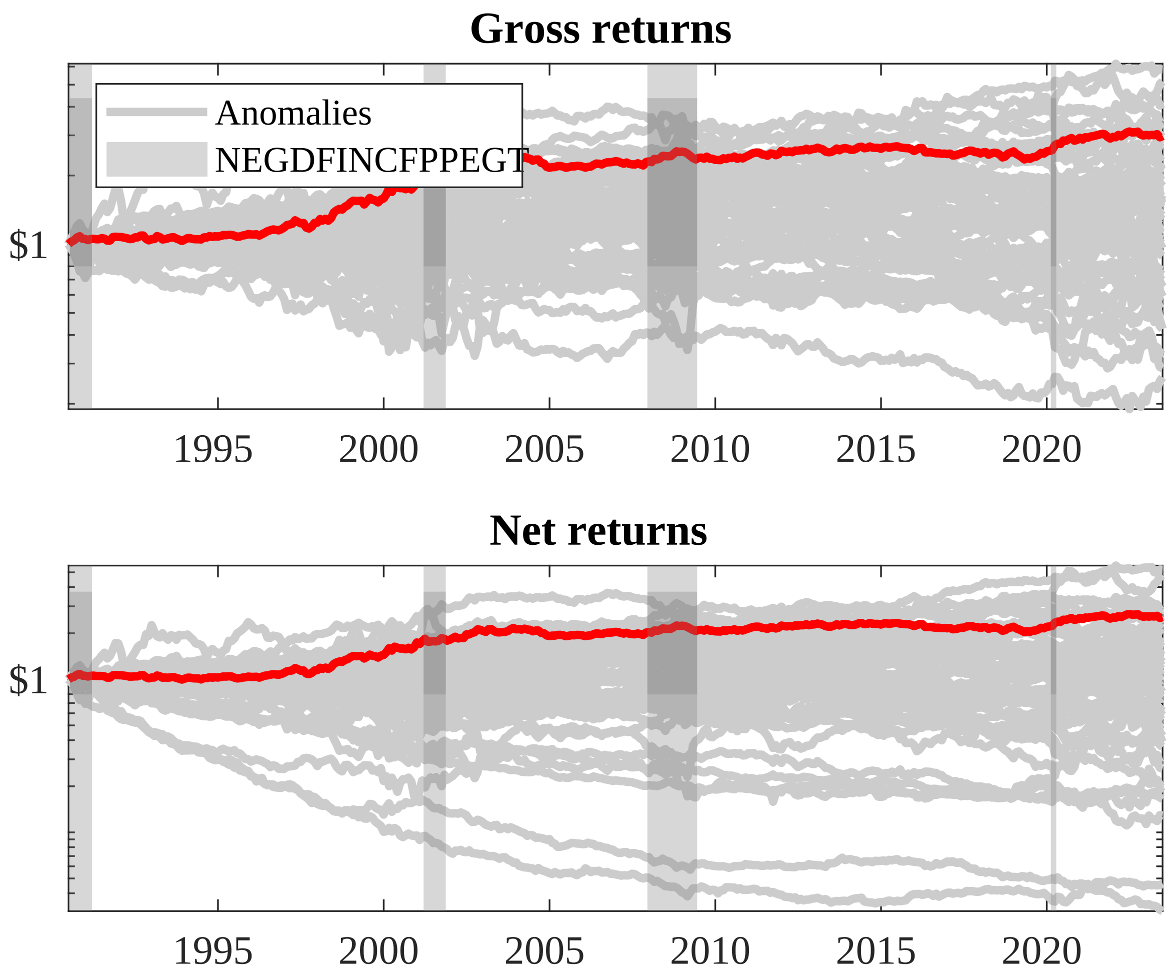

Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the AFI trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

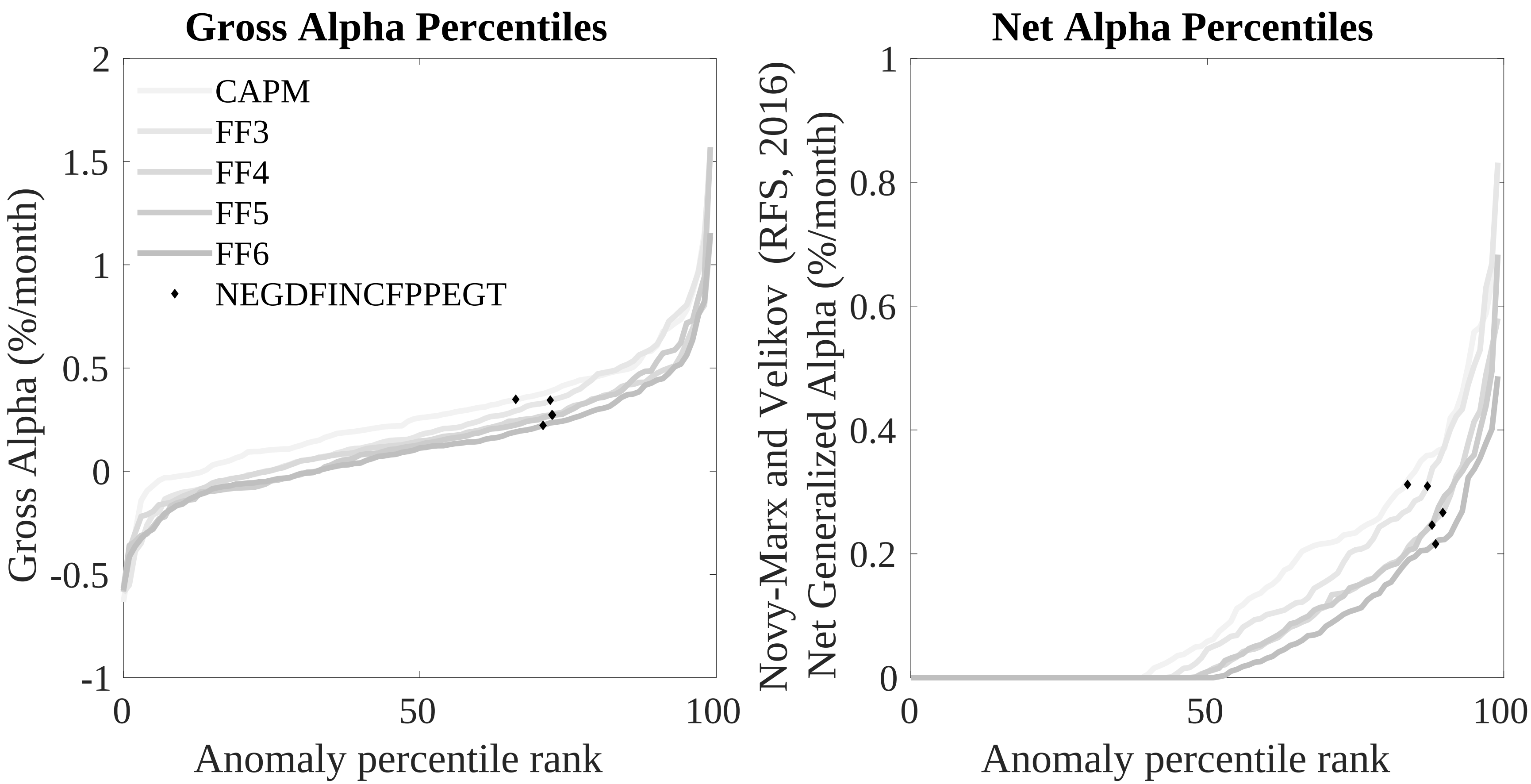

Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the AFI trading strategy alphas (diamonds). The strategies are constructed using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

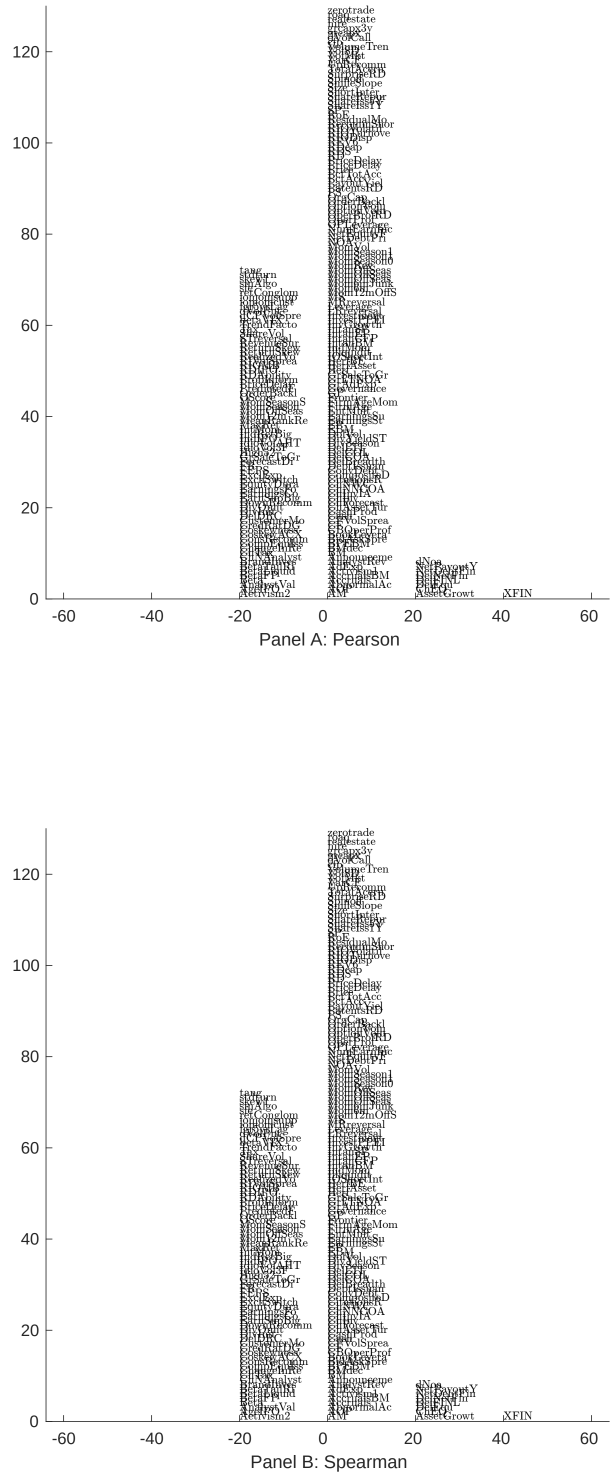

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 210 filtered anomaly signals with AFI. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

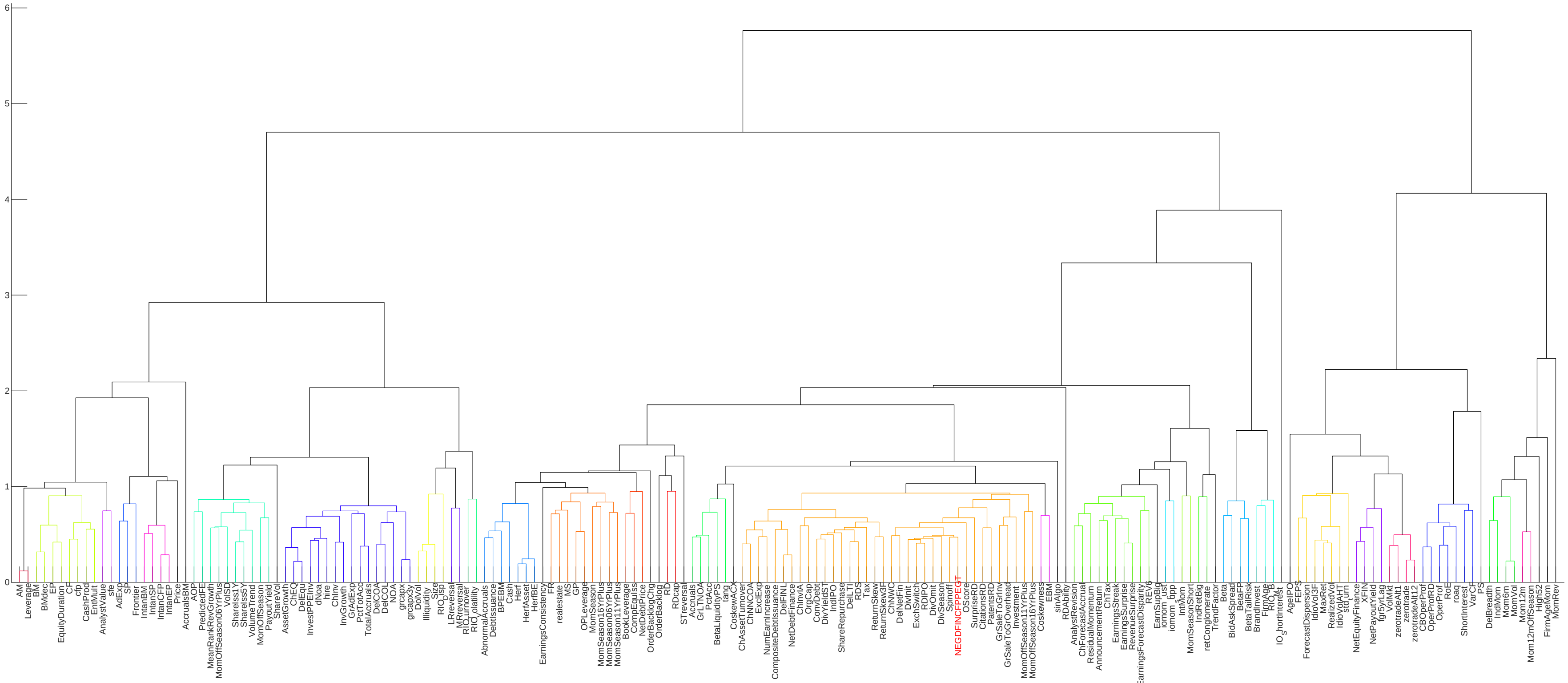

Figure 6: Agglomerative hierarchical cluster plot

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

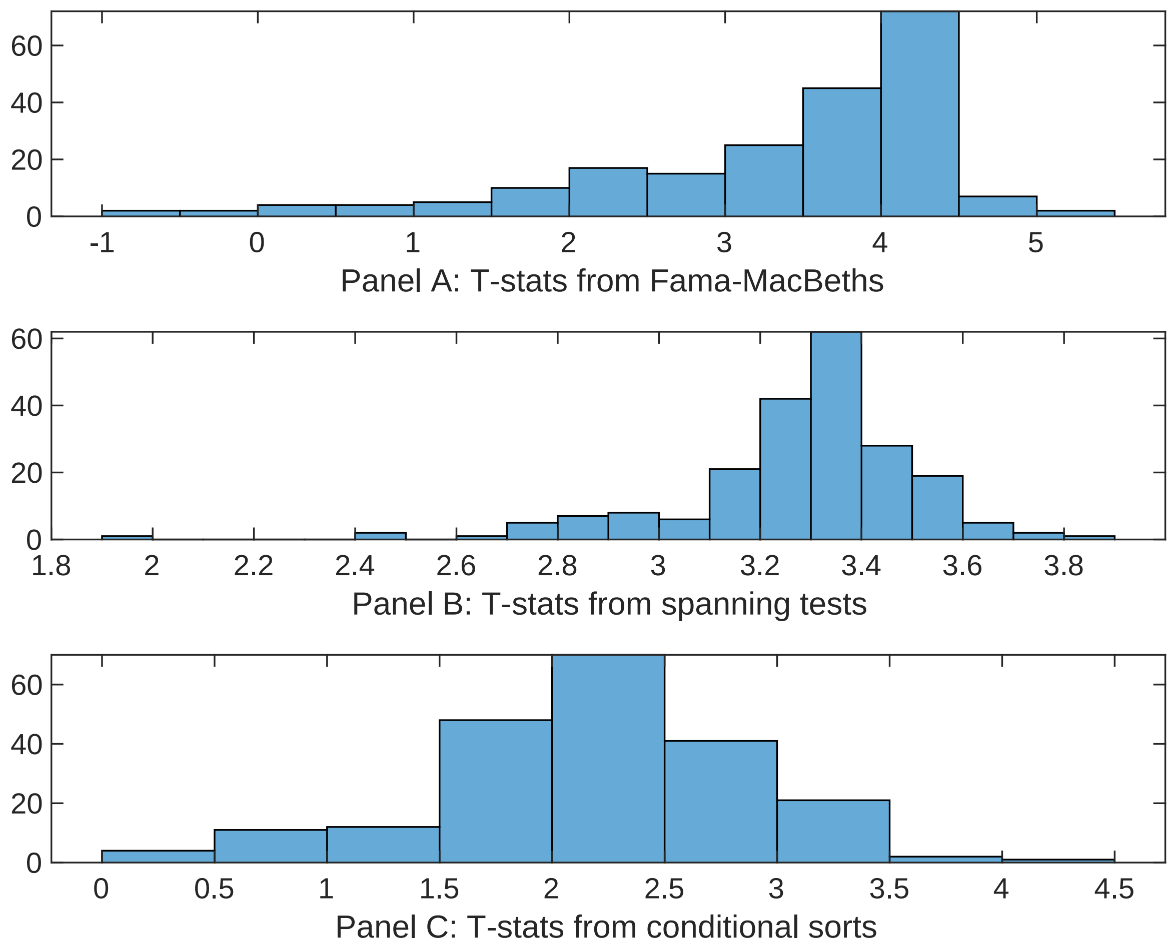

Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of AFI conditioning on each of the 210 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{AFI} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{AFI} AFI_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, 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: $r_{AFI,t} = \alpha + \beta r_{X,t} + \epsilon_t$, 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 AFI. Stocks are finally grouped into five AFI portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted AFI 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 AFI. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{AFI} AFI_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Net external financing, Asset growth, Growth in book equity, Inventory Growth, change in net operating assets, 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 199006 to 202306.

Intercept	0.13	0.13	0.18	0.12	0.13	0.12	0.14
	[4.37]	[4.31]	[5.73]	[3.93]	[4.16]	[3.95]	[4.95]
AFI	0.13	-0.17	0.15	0.52	0.22	0.20	-0.16
	[0.11]	[-0.17]	[1.64]	[4.16]	[2.37]	[2.16]	[-1.11]
Anomaly 1	0.19						0.18
	[4.53]						[3.53]
Anomaly 2		0.95					0.11
		[7.83]					[0.61]
Anomaly 3			0.50				0.62
			[6.71]				[0.57]
Anomaly 4				0.33			0.34
				[5.16]			[0.49]
Anomaly 5					0.12		0.61
					[7.98]		[2.85]
Anomaly 6						0.15	0.35
						[4.99]	[0.72]
# months	396	396	396	396	396	396	396
$\bar{R}^2$(%)	1	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 AFI trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{AFI} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 Net external financing, Asset growth, Growth in book equity, Inventory Growth, change in net operating assets, 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 199006 to 202306.

Intercept	0.20	0.23	0.22	0.23	0.21	0.22	0.21
	[2.30]	[2.67]	[2.50]	[2.65]	[2.43]	[2.55]	[2.47]
Anomaly 1	14.88						10.83
	[3.55]						[2.50]
Anomaly 2		17.66					11.26
		[3.45]					[1.71]
Anomaly 3			9.65				8.79
			[2.06]				[1.12]
Anomaly 4				10.60			8.66
				[3.46]			[2.66]
Anomaly 5					9.83		0.41
					[2.04]		[0.08]
Anomaly 6						7.14	-10.96
						[1.46]	[-1.32]
mkt	0.11	-1.60	-1.63	-2.04	-2.27	-1.85	-0.05
	[0.05]	[-0.75]	[-0.76]	[-0.96]	[-1.06]	[-0.85]	[-0.02]
smb	4.70	-1.26	-0.72	0.96	0.14	-0.10	2.97
	[1.43]	[-0.42]	[-0.24]	[0.32]	[0.05]	[-0.03]	[0.88]
hml	-4.64	-8.14	-7.35	-7.35	-7.57	-7.24	-6.53
	[-1.27]	[-2.24]	[-2.01]	[-2.04]	[-2.06]	[-1.97]	[-1.78]
rmw	-7.53	2.34	1.28	3.40	2.01	2.02	-4.03
	[-1.65]	[0.62]	[0.33]	[0.89]	[0.53]	[0.53]	[-0.86]
cma	14.35	2.85	15.11	15.24	16.69	16.82	-1.13
	[2.44]	[0.35]	[2.21]	[2.62]	[2.61]	[2.31]	[-0.13]
umd	8.07	9.18	8.23	7.75	8.17	8.46	7.90
	[4.39]	[4.95]	[4.43]	[4.20]	[4.39]	[4.54]	[4.22]
# months	396	396	396	396	396	396	396
$\bar{R}^2(\%)$	17	16	15	16	15	14	19

Panel A: Average rank

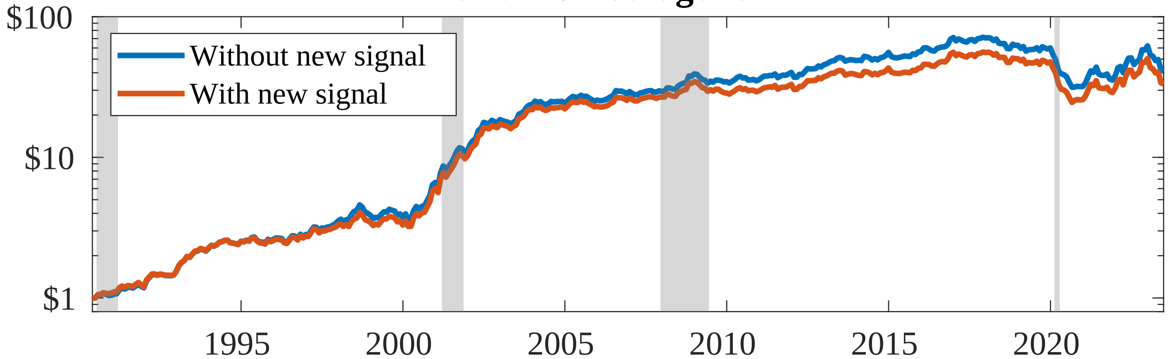

Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines indicate combination trading strategies that utilize the 159 anomalies as well as AFI. Panel A shows results using "Average rank" as the combination method. See Section 7 for details on the combination methods.

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