Growth Impact Efficiency Metric and the Cross Section of Stock Returns

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December 1, 2024

Abstract

This paper studies the asset pricing implications of Growth Impact Efficiency Metric (GIEM), 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 GIEM achieves an annualized gross (net) Sharpe ratio of 0.45 (0.40), and monthly average abnormal gross (net) return relative to the Fama and French (2015) five-factor model plus a momentum factor of 24 (21) bps/month with a t-statistic of 2.69 (2.42), respectively. Its gross monthly alpha relative to these six factors plus the six most closely related strategies from the factor zoo (Change in current operating liabilities, Total accruals, Book-to-market and accruals, Efficient frontier index, Change in Taxes, Price) is 20 bps/month with a t-statistic of 2.36.

1 Introduction

The efficient market hypothesis suggests that stock prices should reflect all publicly available information, yet decades of empirical research have documented numerous market anomalies that appear to generate persistent abnormal returns. While many of these anomalies stem from accounting-based signals, the economic mechanisms driving their predictive power often remain unclear (Harvey et al., 2016). A particularly puzzling aspect is how firms' operational efficiency metrics relate to future stock performance, as traditional accounting measures may fail to capture the dynamic nature of business growth and operational execution (Novy-Marx, 2013).

Despite extensive research on firm operating performance and stock returns, the literature has largely focused on static measures of efficiency or profitability (Fama and French, 2015). This approach overlooks how effectively companies deploy resources during periods of growth - a critical determinant of long-term value creation. The interaction between growth initiatives and operational execution efficiency represents an important but understudied dimension of firm performance that may contain valuable information for predicting future returns.

We propose that the Growth Impact Efficiency Metric (GIEM) captures how effectively firms convert growth investments into operational improvements. Building on the q-theory of investment (Cochrane and Saá-Requejo, 1992), firms with higher GIEM scores should demonstrate superior capital allocation decisions, leading to stronger future performance. This relationship emerges because GIEM identifies companies that maintain or enhance operational efficiency while pursuing growth opportunities.

The theoretical link between GIEM and expected returns can be understood through the investment-based asset pricing framework of (Zhang, 2005). When firms undertake growth initiatives, they face adjustment costs and operational challenges that can temporarily reduce efficiency. Companies with high GIEM scores navigate these challenges more successfully, indicating lower systematic risk and higher expected productivity of new investments (Li and Livdan, 2008).

We hypothesize that GIEM predicts returns because it captures information about future profitability that is not fully reflected in current market prices. This builds on evidence that markets can be slow to incorporate complex operational information (Hirshleifer and Ikenberry, 1989) and that investors may overlook the quality of growth execution when evaluating expansion initiatives (**?**).

Our empirical analysis reveals that GIEM strongly predicts cross-sectional stock returns. A value-weighted long-short portfolio strategy based on GIEM quintiles generates a monthly alpha of 24 basis points (t-statistic = 2.69) relative to the Fama-French six-factor model. The strategy's economic significance is substantial, achieving an annualized gross Sharpe ratio of 0.45, which exceeds 87% of previously documented anomalies.

Importantly, GIEM's predictive power remains robust after controlling for transaction costs. The strategy delivers a net alpha of 21 basis points per month (t-statistic = 2.42) and a net Sharpe ratio of 0.40, placing it in the top 3% of anomalies after accounting for trading frictions. This indicates that the GIEM effect represents an economically meaningful investment opportunity.

Further analysis demonstrates that GIEM's predictive ability extends across the size spectrum. Among the largest quintile of stocks, the GIEM strategy generates a monthly alpha of 35 basis points (t-statistic = 3.14), suggesting that the effect is not driven by small, illiquid stocks. Moreover, controlling for six closely related anomalies and the Fama-French factors, GIEM continues to generate a significant alpha of 20 basis points per month (t-statistic = 2.36).

Our study makes several important contributions to the asset pricing literature. First, we introduce a novel measure that bridges the gap between growth initiatives and operational execution, extending the investment-based asset pricing framework of (Zhang, 2005) and (Li and Livdan, 2008). While previous research has examined either growth or efficiency in isolation, GIEM captures their interaction, providing new insights into how operational execution quality affects expected returns.

Second, we contribute to the anomalies literature by documenting a robust return predictor that remains significant after controlling for transaction costs and other known factors. Unlike many anomalies that work primarily in small stocks (Novy-Marx and Velikov, 2016a), GIEM generates significant abnormal returns even among large-cap stocks, suggesting it captures fundamental information about firm value that is not fully reflected in market prices.

Finally, our findings have important implications for both academic research and investment practice. For researchers, we demonstrate the importance of considering operational execution quality when studying the relationship between corporate investment and stock returns. For practitioners, GIEM provides a novel tool for identifying companies that effectively execute growth initiatives, offering a new dimension for portfolio selection that is distinct from traditional value and momentum signals.

2 Data

Our study investigates the predictive power of a financial signal derived from accounting data for cross-sectional returns, focusing specifically on the Growth Impact Efficiency Metric, which is constructed as the ratio of operating activities and other to interest and related expense. 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 AOLOCH for operating activities and other, and item XINT for interest and related expense. Operating activities and other (AOLOCH) represents the net amount of cash or cash equivalents provided by or used in operating activities of the company, excluding the effects of investing and financing activities. Interest and related expense (XINT), on the other hand, represents the aggregate interest and related expense of the company, reflecting the cost of borrowed funds and similar financing charges. The construction of the signal follows a straightforward ratio format, where we divide AOLOCH by XINT for each firm in each year of our sample. This ratio captures the relationship between a firm's operating cash activities and its cost of debt financing, offering insight into how efficiently the firm generates operating cash flow relative to its interest burden. By focusing on this relationship, the signal aims to reflect aspects of operational efficiency and financial leverage in a manner that is both scalable and interpretable. We construct this ratio using end-of-fiscal-year values for both AOLOCH and XINT to ensure consistency and comparability across firms and over time.

3 Signal diagnostics

Figure 1 plots descriptive statistics for the GIEM signal. Panel A plots the time-series of the mean, median, and interquartile range for GIEM. On average, the cross-sectional mean (median) GIEM is 2.12 (-0.03) over the 1989 to 2023 sample, where the starting date is determined by the availability of the input GIEM data. The signal's interquartile range spans -1.70 to 1.48. Panel B of Figure 1 plots the time-series of the coverage of the GIEM signal for the CRSP universe. On average, the GIEM signal is available for 5.97% of CRSP names, which on average make up 7.41% of total market capitalization.

4 Does GIEM predict returns?

Table 1 reports the performance of portfolios constructed using a value-weighted, quintile sort on GIEM 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 GIEM portfolio and sells the low GIEM 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 GIEM strategy earns an average return of 0.23% per month with a t-statistic of 2.62. The annualized Sharpe ratio of the strategy is 0.45. The alphas range from 0.21% to 0.28% per month and have t-statistics exceeding 2.45 everywhere. The lowest alpha is with respect to the FF4 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 0.08, with a t-statistic of 3.91 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 537 stocks and an average market capitalization of at least $2,303 million.

Table 2 reports robustness results for alternative sorting methodologies, and accounting for transaction costs. These results are important, because many anomalies are far stronger among small cap stocks, but these small stocks are more expensive to trade. Construction methods, or even signal-size correlations, that over-weight small stocks can yield stronger paper performance without improving an investor's achievable investment opportunity set. Panel A reports gross returns and alphas for the long/short strategies made using various different protfolio constructions. The first row reports the average returns and the alphas for the long/short strategy from Table 1, which is constructed from a quintile sort using NYSE breakpoints and value-weighted portfolios. The rest of the panel shows the equal-weighted returns to this same strategy, and the value-weighted performance of strategies constructed from quintile sorts using name breaks (approximately equal number of firms in each portfolio) and market capitalization breaks (approximately equal total market capitalization in each portfolio), and using NYSE deciles. The average return is lowest for the quintile sort using NYSE breakpoints and equal-weighted portfolios, and equals 21 bps/month with a t-statistics of 3.40. Out of the twenty-five alphas reported in Panel A, the t-statistics for twenty-five exceed two, and for ten exceed three.

Panel B reports for these same strategies the average monthly net returns and the generalized net alphas of Novy-Marx and Velikov (2016b). 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 0-36bps/month. The lowest return, (0 bps/month), is achieved from the quintile sort using NYSE breakpoints and equal-weighted portfolios, and has an associated t-statistic of 0.05. Out of the twenty-five construction-methodology-factor-model pairs reported in Panel B, the GIEM trading strategy improves the achievable mean-variance efficient frontier spanned by the factor models in twenty-two cases, and significantly expands the achievable frontier in twenty cases.

Table 3 provides direct tests for the role size plays in the GIEM strategy performance. Panel A reports the average returns for the twenty-five portfolios constructed from a conditional double sort on size and GIEM, as well as average returns and alphas for long/short trading GIEM 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 GIEM strategy achieves an average return of 35 bps/month with a t-statistic of 3.14. Among these large cap stocks, the alphas for the GIEM strategy relative to the five most common factor models range from 30 to 41 bps/month with t-statistics between 2.70 and 3.55.

5 How does GIEM perform relative to the zoo?

Figure 2 puts the performance of GIEM 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 GIEM strategy falls in the distribution. The GIEM strategy's gross (net) Sharpe ratio of 0.45 (0.40) is greater than 87% (97%) 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 GIEM strategy (red line).[2] Ignoring trading costs, a \$1 invested in the GIEM strategy would have yielded \$1.31 which ranks the GIEM strategy in the top 5% across the 212 anomalies. Accounting for trading costs, a \$1 invested in the GIEM strategy would have yielded \$1.10 which ranks the GIEM strategy in the top 5% across the 212 anomalies.

Figure 4 plots percentile ranks for the 212 anomaly trading strategies in terms of gross and Novy-Marx and Velikov (2016b) 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 GIEM relative to those. Panel A shows that the

[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.

GIEM strategy gross alphas fall between the 49 and 75 percentiles across the five factor models. Panel B shows that, accounting for trading costs, a large fraction of anomalies have not improved the investment opportunity set of an investor with access to the factor models over the 198906 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 GIEM strategy has a positive net generalized alpha for five out of the five factor models. In these cases GIEM ranks between the 68 and 87 percentiles in terms of how much it could have expanded the achievable investment frontier.

6 Does GIEM 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 GIEM with 209 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 GIEM or at least to weaken the power GIEM has predicting the cross-section of returns. Figure 7 plots histograms of t-statistics for predictability tests of GIEM conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{GIEM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{GIEM} GIEM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$,

[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.

where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{GIEM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals. Then, within each quintile, we sort stocks into quintiles based on GIEM. Stocks are finally grouped into five GIEM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted GIEM trading strategies conditioned on each of the 209 filtered anomalies.

Table 4 reports Fama-MacBeth cross-sectional regressions of returns on GIEM 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 GIEM signal in these Fama-MacBeth regressions exceed 1.48, with the minimum t-statistic occurring when controlling for Book-to-market and accruals. Controlling for all six closely related anomalies, the t-statistic on GIEM is 0.42.

Similarly, Table 5 reports results from spanning tests that regress returns to the GIEM 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 GIEM strategy earns alphas that range from 18-23bps/month. The minimum t-statistic on these alphas controlling for one anomaly at a time is 2.07, which is achieved when controlling for Book-to-market and accruals. Controlling for all six closely-related anomalies and the six Fama-French factors simultaneously, the

GIEM trading strategy achieves an alpha of 20bps/month with a t-statistic of 2.36.

7 Does GIEM add relative to the whole zoo?

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

Panel A shows results using "Average rank" as the combination method. This method sorts stocks on the basis of forecast excess returns, where these are calculated on the basis of their average cross-sectional percentile rank across return predictors, and the predictors are all signed so that higher ranks are associated with higher average returns. For this method, $1 investment in the 159-anomaly combination strategy grows to $42.41, while $1 investment in the combination strategy that includes GIEM grows to $40.48.

8 Conclusion

This study provides compelling evidence for the effectiveness of the Growth Impact Efficiency Metric (GIEM) as a significant predictor of stock returns in the cross-section of equities. Our findings demonstrate that a value-weighted long/short trading strategy based on GIEM generates economically and statistically significant returns, with impressive Sharpe ratios of 0.45 and 0.40 for gross and net returns, respectively. The strategy's robustness is particularly noteworthy, maintaining sig-

[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 GIEM is available.

nificant abnormal returns even after controlling for traditional risk factors and related anomalies.

The persistence of GIEM's predictive power, evidenced by monthly alphas of 24 basis points (gross) and 21 basis points (net) relative to the Fama-French five-factor model plus momentum, suggests that this signal captures unique information not fully reflected in existing factors. Furthermore, the signal's ability to generate a significant alpha of 20 basis points monthly when controlling for six closely related strategies indicates its distinctive contribution to the cross-section of returns.

However, several limitations should be acknowledged. First, our analysis focuses on a specific time period, and the signal's effectiveness may vary across different market regimes. Second, transaction costs and market impact could affect the strategy's real-world implementation, particularly for smaller stocks or during periods of market stress.

Future research could explore several promising directions. First, investigating the interaction between GIEM and other established factors could provide insights into potential complementarities or substitution effects. Second, examining the signal's performance in international markets would test its global applicability. Finally, analyzing the underlying economic mechanisms driving GIEM's predictive power could enhance our understanding of market efficiency and asset pricing dynamics.

In conclusion, GIEM represents a valuable addition to the quantitative investor's toolkit, offering robust predictive power that survives rigorous statistical controls and practical implementation considerations.

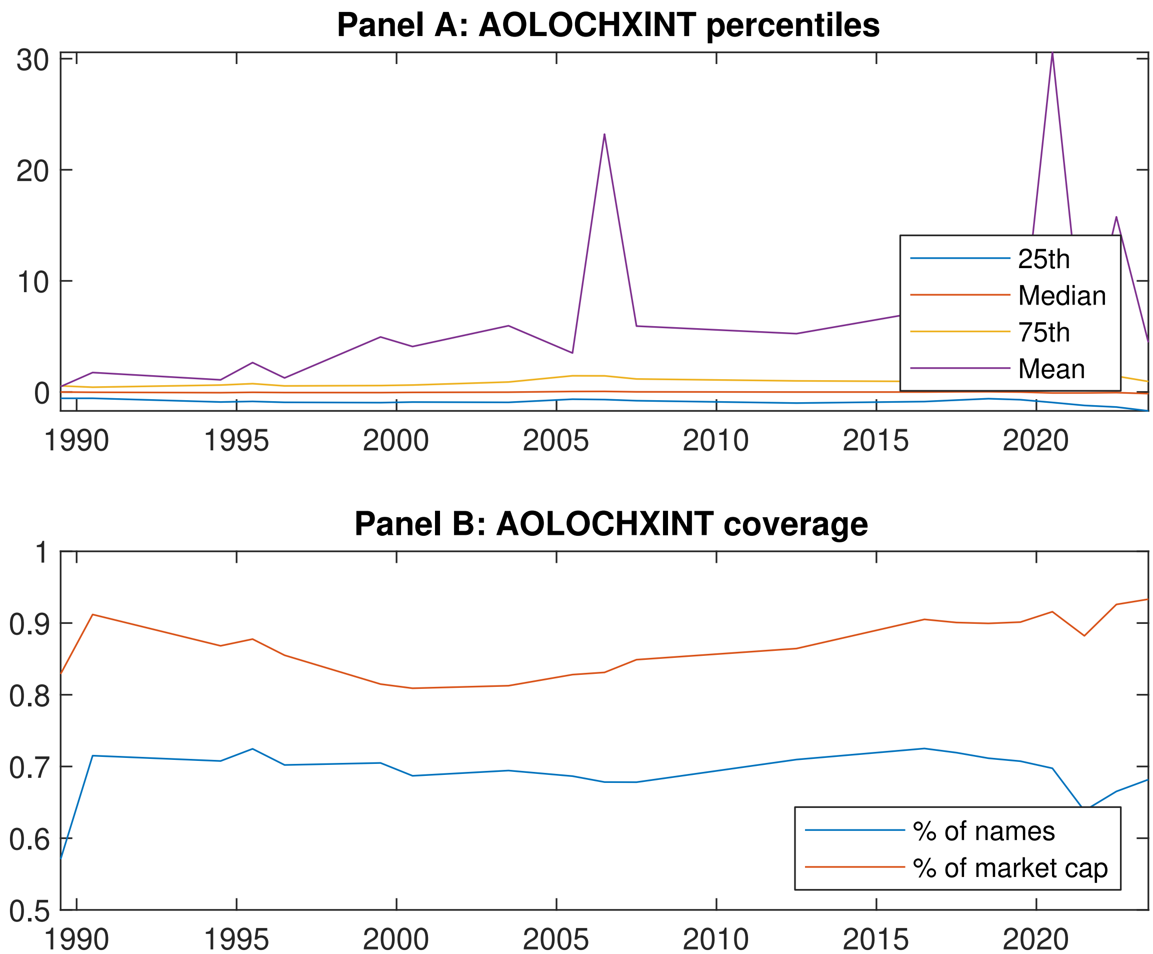


Figure 1: Times series of GIEM percentiles and coverage.
This figure plots descriptive statistics for GIEM. Panel A shows cross-sectional percentiles of GIEM over the sample. Panel B plots the monthly coverage of GIEM relative to the universe of CRSP stocks with available market capitalizations.

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

This table reports average excess returns and alphas for portfolios sorted on GIEM. 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 198906 to 202306.

Panel A: Excess returns and alphas on GIEM-sorted portfolios						
	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.62	0.69	0.66	0.70	0.84	0.23
	[2.64]	[3.20]	[3.30]	[3.29]	[3.71]	[2.62]
α_{CAPM}	-0.12	0.02	0.06	0.04	0.13	0.25
	[-2.01]	[0.37]	[0.78]	[0.64]	[2.30]	[2.82]
α_{FF3}	-0.11	-0.00	0.02	0.02	0.15	0.26
	[-1.84]	[-0.05]	[0.29]	[0.35]	[3.03]	[3.03]
α_{FF4}	-0.07	-0.00	0.02	0.03	0.14	0.21
	[-1.18]	[-0.02]	[0.35]	[0.47]	[2.78]	[2.45]
α_{FF5}	-0.09	-0.11	-0.15	-0.08	0.19	0.28
	[-1.53]	[-1.72]	[-2.39]	[-1.45]	[3.61]	[3.16]
α_{FF6}	-0.06	-0.10	-0.14	-0.07	0.18	0.24
	[-1.02]	[-1.56]	[-2.17]	[-1.24]	[3.36]	[2.69]
Panel B: Fama and French (2018) 6-factor model loadings for GIEM-sorted portfolios						
β_{MKT}	1.01	0.99	0.93	0.99	1.00	-0.02
	[68.85]	[63.44]	[59.43]	[67.63]	[77.17]	[-0.87]
β_{SMB}	0.01	0.01	-0.02	-0.04	-0.05	-0.06
	[0.57]	[0.56]	[-0.71]	[-1.93]	[-2.47]	[-1.85]
β_{HML}	-0.09	0.03	0.04	-0.01	-0.08	0.01
	[-3.61]	[0.99]	[1.61]	[-0.36]	[-3.77]	[0.21]
β_{RMW}	-0.05	0.13	0.27	0.17	-0.02	0.02
	[-1.79]	[4.47]	[9.47]	[6.41]	[-1.00]	[0.62]
β_{CMA}	0.06	0.20	0.21	0.13	-0.11	-0.17
	[1.76]	[5.20]	[5.33]	[3.52]	[-3.40]	[-3.22]
β_{UMD}	-0.05	-0.02	-0.02	-0.02	0.02	0.08
	[-4.20]	[-1.12]	[-1.62]	[-1.56]	[1.79]	[3.91]
Panel C: Average number of firms (n) and market capitalization (me)						
n	857	579	537	587	808	
me ($\$10^6$)	2781	2303	2311	2867	4024	

Table 2: Robustness to sorting methodology & trading costs
This table evaluates the robustness of the choices made in the GIEM 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 (2016b) generalized alphas as prescribed by Detzel et al. (2022). T-statistics are in brackets. The sample period is 198906 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	0.23	0.25	0.26	0.21	0.28	0.24
			[2.62]	[2.82]	[3.03]	[2.45]	[3.16]	[2.69]
Quintile	NYSE	EW	0.21	0.23	0.23	0.17	0.22	0.16
			[3.40]	[3.68]	[3.80]	[2.82]	[3.43]	[2.71]
Quintile	Name	VW	0.28	0.30	0.32	0.24	0.29	0.23
			[2.73]	[2.88]	[3.07]	[2.30]	[2.73]	[2.15]
Quintile	Cap	VW	0.29	0.29	0.31	0.25	0.36	0.31
			[2.91]	[2.95]	[3.19]	[2.58]	[3.58]	[3.07]
Decile	NYSE	VW	0.38	0.39	0.42	0.29	0.42	0.31
			[2.82]	[2.87]	[3.10]	[2.20]	[2.95]	[2.27]
Panel B: Net Returns and Novy-Marx and Velikov (2016b) generalized alphas								
Portfolios	Breaks	Weights	r^e_{net}	α^*_{CAPM}	α^*_{FF3}	α^*_{FF4}	α^*_{FF5}	α^*_{FF6}
Quintile	NYSE	VW	0.20	0.21	0.22	0.19	0.24	0.21
			[2.36]	[2.42]	[2.57]	[2.23]	[2.69]	[2.42]
Quintile	NYSE	EW	0.00	0.01	0.01			
			[0.05]	[0.18]	[0.19]			
Quintile	Name	VW	0.26	0.27	0.28	0.23	0.26	0.22
			[2.49]	[2.57]	[2.71]	[2.25]	[2.46]	[2.11]
Quintile	Cap	VW	0.26	0.26	0.28	0.24	0.32	0.28
			[2.69]	[2.60]	[2.79]	[2.43]	[3.13]	[2.84]
Decile	NYSE	VW	0.36	0.36	0.38	0.30	0.38	0.31
			[2.62]	[2.61]	[2.79]	[2.25]	[2.69]	[2.29]

Table 3: Conditional sort on size and GIEM

This table presents results for conditional double sorts on size and GIEM. 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 GIEM. 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 GIEM and short stocks with low GIEM .Panel B documents the average number of firms and the average firm size for each portfolio. The sample period is 198906 to 202306.

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

		GIEM Quintiles					GIEM Strategies					
		(L)	(2)	(3)	(4)	(H)	r^e	α_{CAPM}	α_{FF3}	α_{FF4}	α_{FF5}	α_{FF6}
Size quintiles	(1)	0.55	0.81	0.70	0.80	0.79	0.24	0.22	0.20	0.19	0.23	0.21
		[1.59]	[2.36]	[1.85]	[2.33]	[2.27]	[2.40]	[2.17]	[2.03]	[1.85]	[2.20]	[2.03]
	(2)	0.69	0.75	0.82	0.74	0.77	0.07	0.11	0.14	0.08	0.12	0.08
		[2.17]	[2.46]	[2.72]	[2.53]	[2.41]	[0.64]	[1.00]	[1.21]	[0.75]	[1.05]	[0.69]
	(3)	0.73	0.70	0.79	0.82	0.85	0.12	0.11	0.13	0.07	0.25	0.19
		[2.57]	[2.54]	[2.85]	[3.02]	[2.94]	[1.07]	[0.96]	[1.21]	[0.64]	[2.23]	[1.74]
	(4)	0.80	0.70	0.70	0.81	0.92	0.11	0.10	0.13	0.08	0.20	0.15
		[2.93]	[2.85]	[2.89]	[3.34]	[3.29]	[1.21]	[1.05]	[1.43]	[0.88]	[2.11]	[1.64]
	(5)	0.59	0.66	0.65	0.65	0.94	0.35	0.35	0.37	0.30	0.41	0.35
		[2.58]	[3.27]	[3.21]	[3.09]	[4.09]	[3.14]	[3.11]	[3.31]	[2.70]	[3.55]	[3.05]

Panel B: Portfolio average number of firms and market capitalization

		GIEM Quintiles Average n					GIEM Quintiles Average market capitalization ($\$10^6$)				
		(L)	(2)	(3)	(4)	(H)	(L)	(2)	(3)	(4)	(H)
Size quintiles	(1)	356	355	352	353	355	37	39	39	38	39
	(2)	111	111	111	111	111	72	74	74	75	75
	(3)	78	78	78	78	78	130	132	133	132	133
	(4)	68	68	68	68	68	291	299	296	305	300
	(5)	62	62	62	62	62	2387	1924	2029	2415	2817

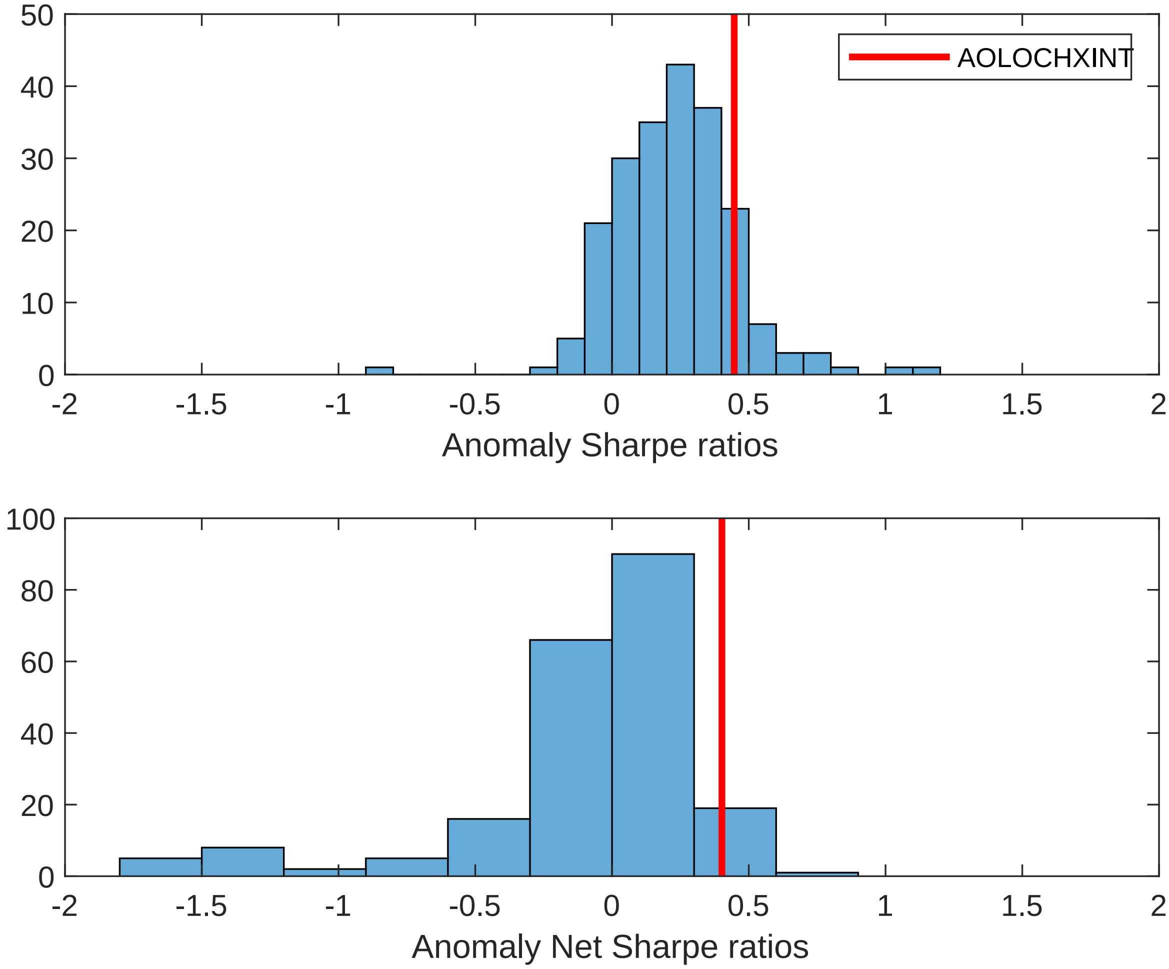


Figure 2: Distribution of Sharpe ratios.
This figure plots a histogram of Sharpe ratios for 212 anomalies, and compares the Sharpe ratio of the GIEM with them (red vertical line). Panel A plots results for gross Sharpe ratios. Panel B plots results for net Sharpe ratios.

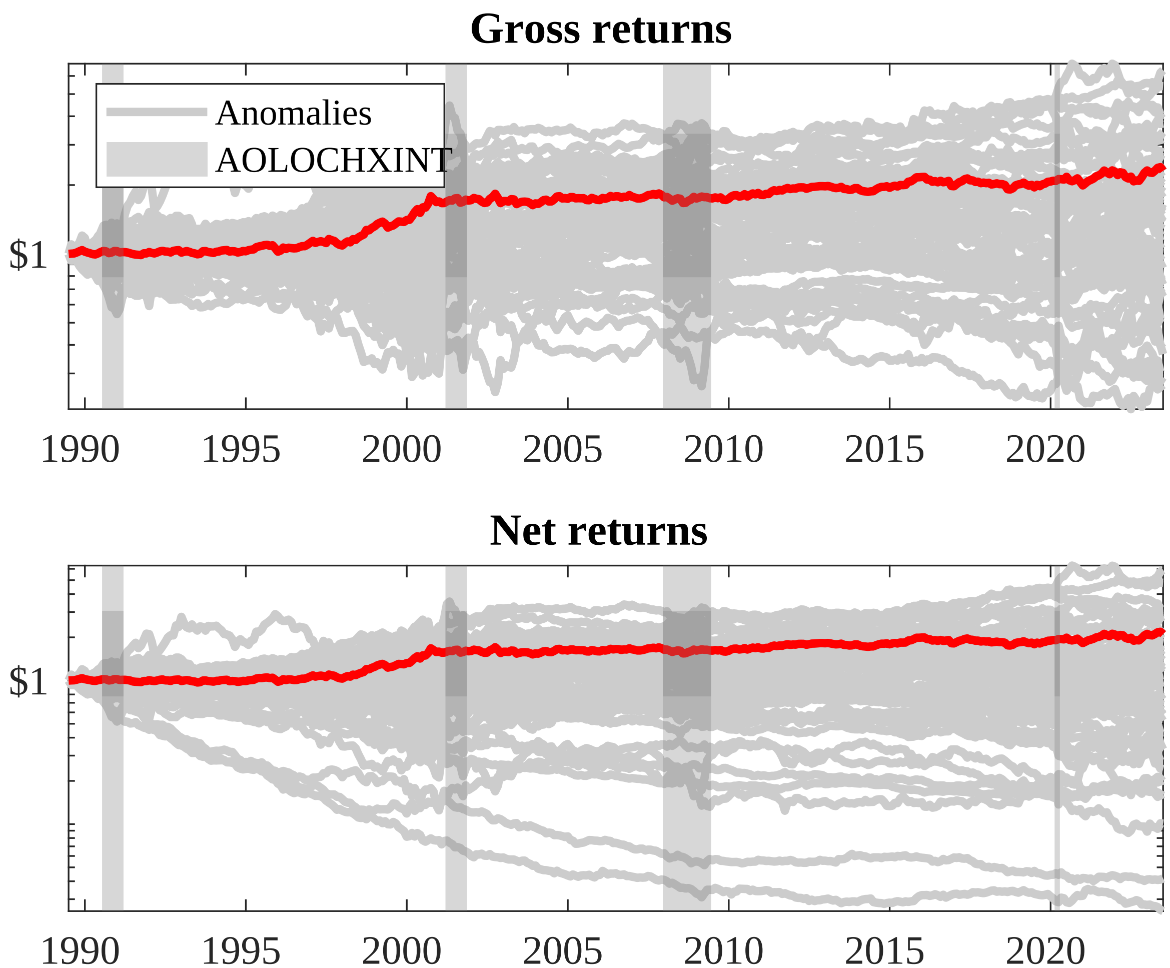


Figure 3: Dollar invested.
This figure plots the growth of a $1 invested in 212 anomaly trading strategies (gray lines), and compares those with the GIEM trading strategy (red line). The strategies are constructed using value-weighted quintile sorts using NYSE breakpoints. Panel A plots results for gross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

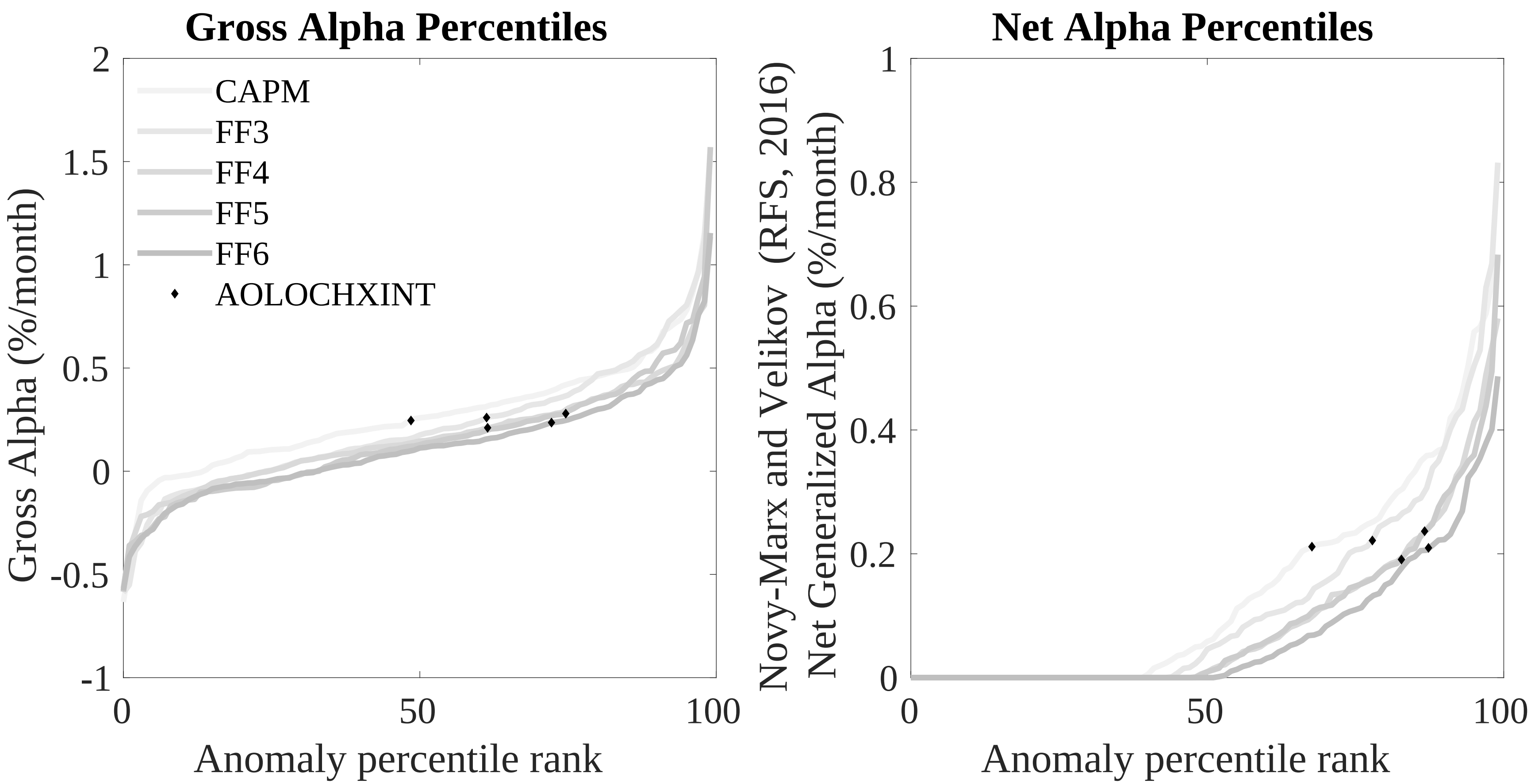
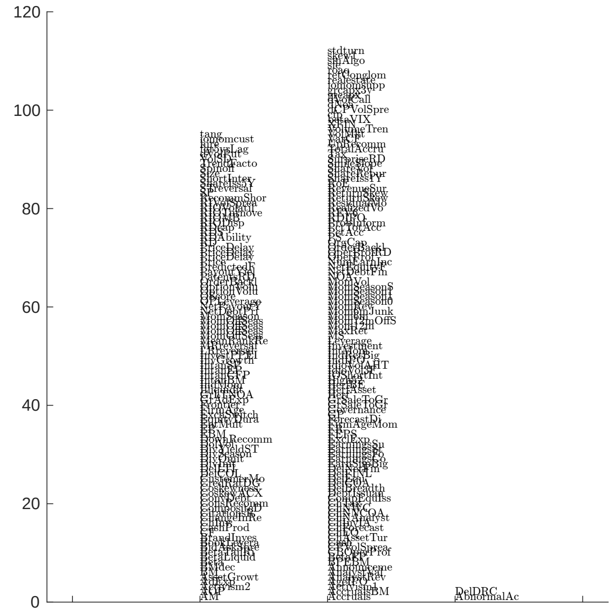
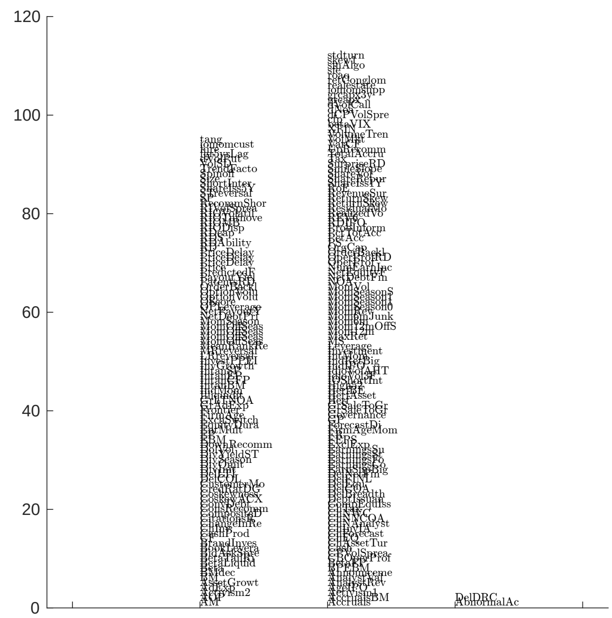


Figure 4: Gross and generalized net alpha percentiles of anomalies relative to factor models
This figure plots the percentile ranks for 212 anomaly trading strategies in terms of alphas (solid lines), and compares those with the GIEM trading strategy alphas (diamonds). The strategies are constructed 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 (2016b) net generalized alphas.



Panel A: Pearson



Panel B: Spearman

Figure 5: Distribution of correlations.
This figure plots a name histogram of correlations of 209 filtered anomaly signals with GIEM. The correlations are pooled. Panel A plots Pearson correlations, while Panel B plots Spearman rank correlations.

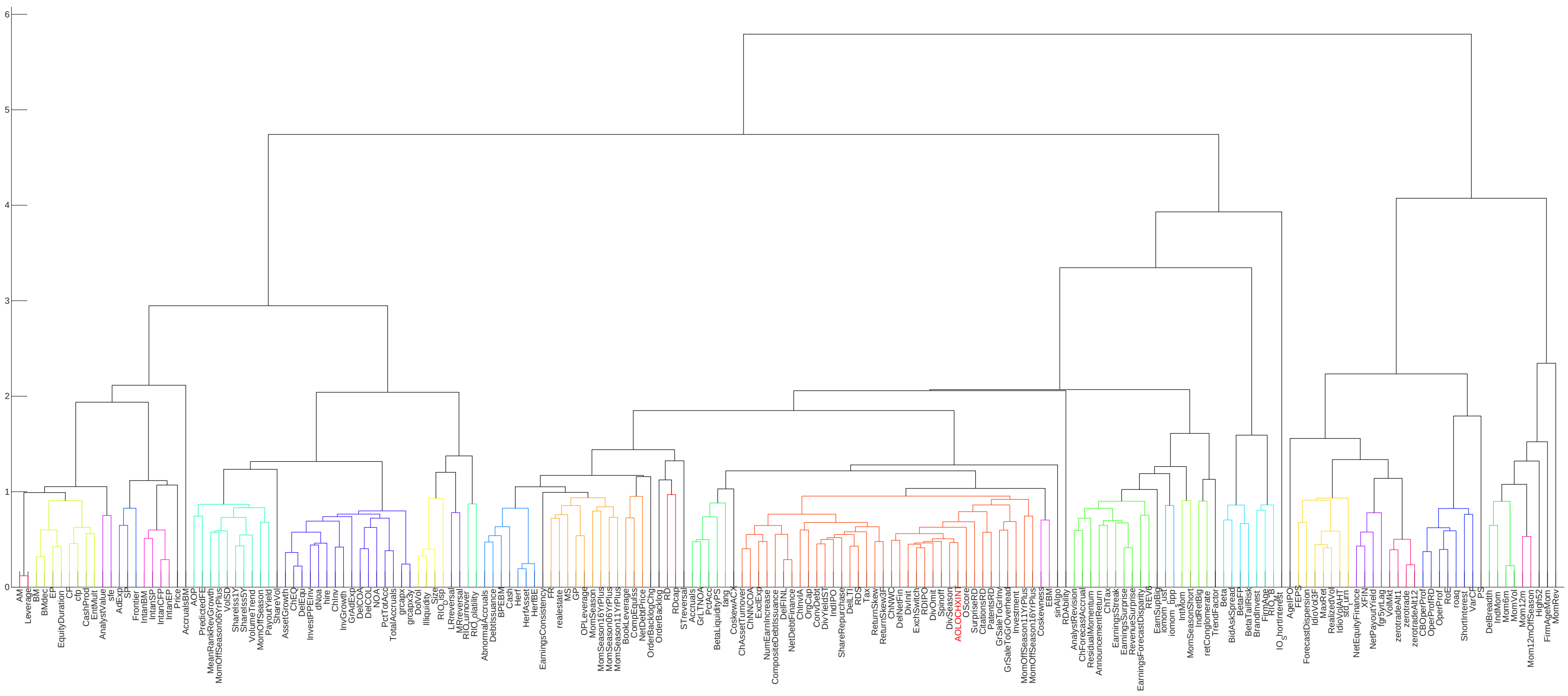


Figure 6: Agglomerative hierarchical cluster plot

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

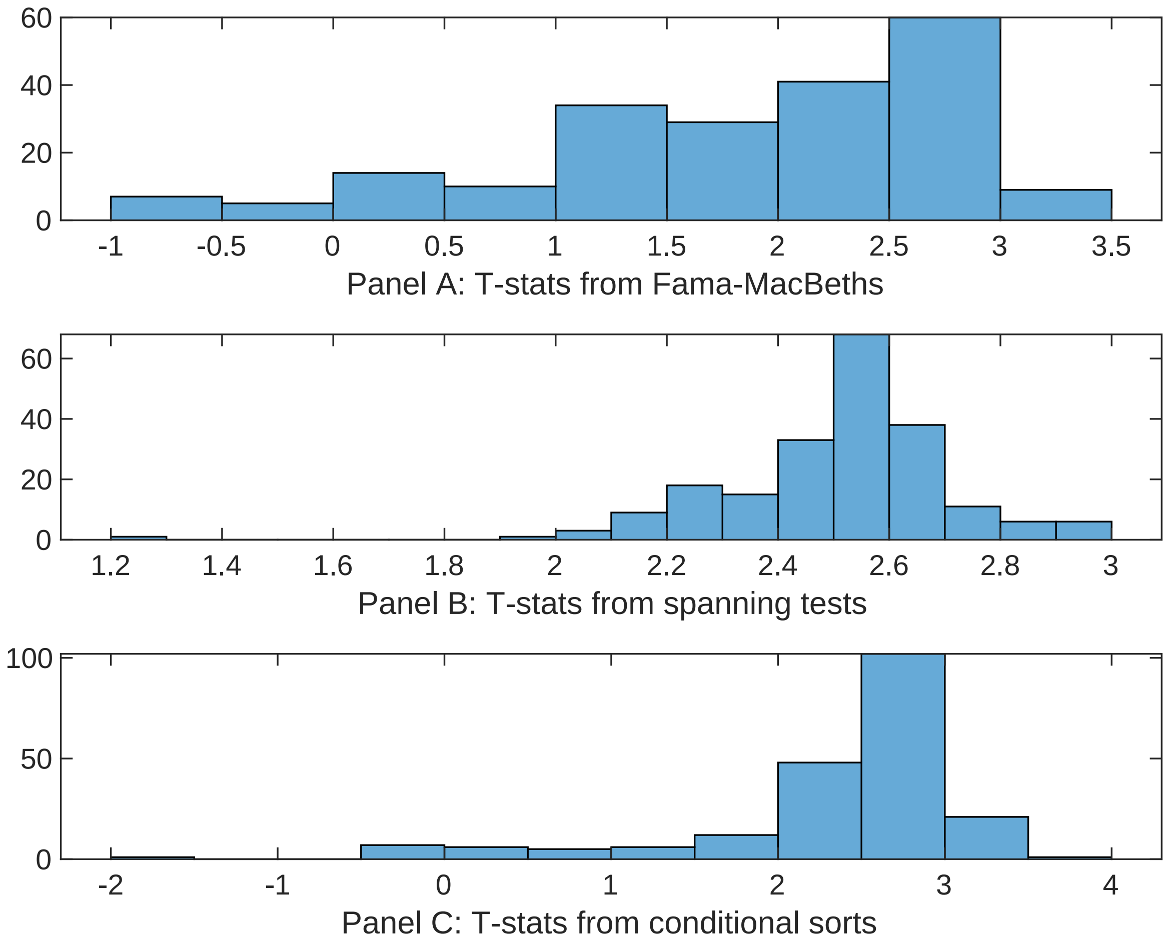


Figure 7: Distribution of t-stats on conditioning strategies
This figure plots histograms of t-statistics for predictability tests of GIEM conditioning on each of the 209 filtered anomaly signals one at a time. Panel A reports t-statistics on β_{GIEM} from Fama-MacBeth regressions of the form $r_{i,t} = \alpha + \beta_{GIEM} GIEM_{i,t} + \beta_X X_{i,t} + \epsilon_{i,t}$, where X stands for one of the 209 filtered anomaly signals at a time. Panel B plots t-statistics on α from spanning tests of the form: $r_{GIEM,t} = \alpha + \beta r_{X,t} + \epsilon_t$, where $r_{X,t}$ stands for the returns to one of the 209 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 209 filtered anomaly signals at a time. Then, within each quintile, we sort stocks into quintiles based on GIEM. Stocks are finally grouped into five GIEM portfolios by combining stocks within each anomaly sorting portfolio. The panel plots the t-statistics on the average returns of these conditional double-sorted GIEM trading strategies conditioned on each of the 209 filtered anomalies.

Table 4: Fama-MacBeths controlling for most closely related anomalies
This table presents Fama-MacBeth results of returns on GIEM. and the six most closely related anomalies. The regressions take the following form: $r_{i,t} = \alpha + \beta_{GIEM} GIEM_{i,t} + \sum_{k=1}^{s} ix\beta_{X_k} X_{i,t}^{k} + \epsilon_{i,t}$. The six most closely related anomalies, X, are Change in current operating liabilities, Total accruals, Book-to-market and accruals, Efficient frontier index, Change in Taxes, Price. 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 198906 to 202306.

Intercept	0.11	0.11	0.66	0.12	0.11	0.11	0.24
	[3.87]	[3.78]	[1.81]	[3.84]	[3.83]	[2.95]	[3.38]
GIEM	0.32	0.22	0.77	0.30	0.26	0.33	0.29
	[2.79]	[1.90]	[1.48]	[2.08]	[2.29]	[3.02]	[0.42]
Anomaly 1	0.20						0.99
	[4.72]						[0.58]
Anomaly 2		0.55					0.67
		[1.87]					[1.04]
Anomaly 3			0.15				-0.25
			[5.00]				[-3.25]
Anomaly 4				0.50			0.20
				[4.89]			[6.40]
Anomaly 5					0.13		0.20
					[4.69]		[2.25]
Anomaly 6						0.54	-0.75
						[1.00]	[-0.80]
# months	408	408	403	403	408	408	267
$\bar{R}^2(\%)$	0	0	1	1	0	1	0

Table 5: Spanning tests controlling for most closely related anomalies

This table presents spanning tests results of regressing returns to the GIEM trading strategy on trading strategies exploiting the six most closely related anomalies. The regressions take the following form: $r_t^{GIEM} = \alpha + \sum_{k=1}^{6} \beta_{X_k} r_t^{X_k} + \sum_{j=1}^{6} \beta_{f_j} r_t^{f_j} + \epsilon_t$, 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 current operating liabilities, Total accruals, Book-to-market and accruals, Efficient frontier index, Change in Taxes, Price. 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 198906 to 202306.

Intercept	0.18	0.23	0.23	0.23	0.23	0.23	0.20
	[2.07]	[2.59]	[2.63]	[2.61]	[2.72]	[2.56]	[2.36]
Anomaly 1	-13.43						-9.45
	[-3.29]						[-2.17]
Anomaly 2		-11.38					-3.91
		[-2.71]					[-0.87]
Anomaly 3			-1.21				-1.64
			[-1.02]				[-1.38]
Anomaly 4				-0.98			0.37
				[-0.37]			[0.13]
Anomaly 5					16.07		14.28
					[4.56]		[3.91]
Anomaly 6						-0.07	-0.18
						[-0.02]	[-0.05]
mkt	-1.17	-1.32	-1.10	-1.41	-3.00	-1.37	-2.12
	[-0.54]	[-0.61]	[-0.50]	[-0.65]	[-1.39]	[-0.61]	[-0.95]
smb	-6.71	-6.01	-4.22	-4.22	-5.59	-5.29	-5.48
	[-2.16]	[-1.94]	[-1.34]	[-1.26]	[-1.84]	[-1.22]	[-1.31]
hml	7.28	-0.16	2.68	2.22	3.48	0.86	9.25
	[1.74]	[-0.04]	[0.69]	[0.56]	[0.94]	[0.23]	[2.05]
rmw	2.36	-0.31	1.79	2.21	2.10	2.13	0.87
	[0.61]	[-0.08]	[0.45]	[0.56]	[0.55]	[0.47]	[0.19]
cma	-9.85	-8.94	-17.85	-18.48	-15.83	-16.97	-8.37
	[-1.70]	[-1.45]	[-3.22]	[-3.35]	[-2.98]	[-3.10]	[-1.33]
umd	6.88	6.48	6.67	7.02	3.52	7.56	1.89
	[3.61]	[3.33]	[3.10]	[2.69]	[1.70]	[2.60]	[0.60]
# months	408	408	404	404	408	408	404
$\bar{R}^2(\%)$	10	9	8	8	12	8	13

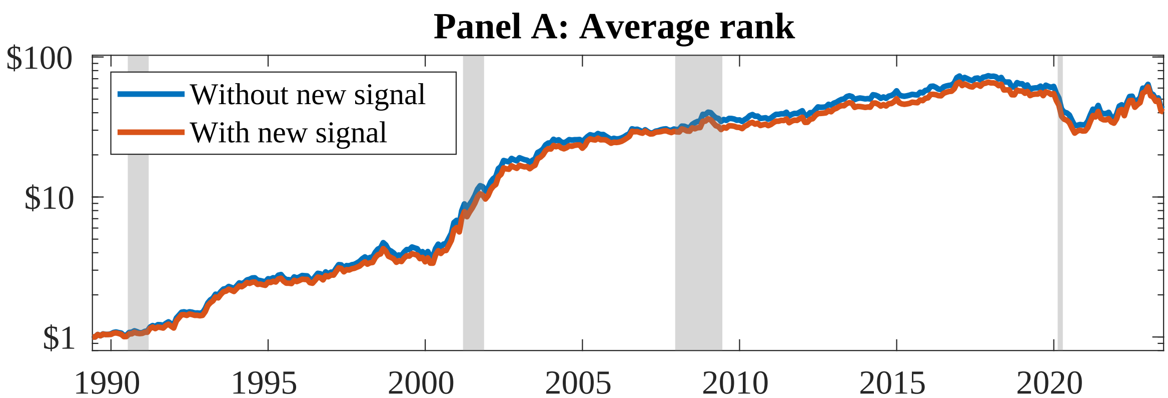


Figure 8: Combination strategy performance
This figure plots the growth of a $1 invested in trading strategies that combine multiple anomalies following Chen and Velikov (2022). In all panels, the blue solid lines indicate combination trading strategies that utilize 159 anomalies. The red solid lines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

References

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Chen, A. and Velikov, M. (2022). Zeroing in on the expected returns of anomalies. *Journal of Financial and Quantitative Analysis*, Forthcoming.

Chen, A. Y. and Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2):207–264.

Cochrane, J. H. and Saá-Requejo, J. (1992). The q theory of investment. *Journal of Finance*, 47(2):425–465.

Detzel, A., Novy-Marx, R., and Velikov, M. (2022). Model comparison with transaction costs. *Journal of Finance, Forthcoming.*

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2):234–252.

Harvey, C. R., Liu, Y., and Zhu, H. (2016). ... and the cross-section of expected returns. *Review of Financial Studies*, 29(1):5–68.

Hirshleifer, D. and Ikenberry, D. L. (1989). Investor psychology and security market under- and overreactions. *Journal of Finance*, 44(6):1789–1805.

Li, E. X. and Livdan, D. (2008). Investment and expected returns. *Review of Financial Studies*, 21(5):2141–2178.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1):1–28.

Novy-Marx, R. and Velikov, M. (2016a). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2016b). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, 29(1):104–147.

Novy-Marx, R. and Velikov, M. (2023). Assaying anomalies. *Working paper.*

Zhang, L. (2005). The value premium. *Journal of Finance*, 60(1):67–103.