Abnormal Returns and Risk Adjusted Performance of Analyst-Driven Portfolios: Evidence from Swedish Equity Research

Can portfolios built of recommendations from Swedish equity analysts systematically exceed the return of the benchmark index, and do these portfolios produce statistically significant alpha in addition to known risk factors?

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Abstract

This thesis investigates whether portfolios constructed from over 8000 recommendations from analyst companies operating in Sweden (2019-2024), outperform their benchmarks and generate abnormal returns in excess of common risk factors. Four of the six analyst-driven portfolios outperformed their respective indices in cumulative returns, but factor model explained most of the excess performance. Notably, Redeye's and Inderes' portfolios provided a statistically significant alpha even after market, size, value, and momentum factors were controlled for, suggesting genuine informational value. The findings suggest the reality of the fact that while most analyst recommendations reflect factor exposures, some contain unique skill or insight, underlining that selective use of analyst research can provide long-term abnormal returns in the Swedish market.

Keywords: Analyst Recommendations, Fama-French Model, Abnormal Returns, Alpha, Market Efficiency.

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Introduction

Financial markets are influenced by the constant flow of information and market participants' perception of it. Among the most prominent intermediaries in this process are equity analysts, whose recommendations and estimation values can influence investor decision, guide trading behaviour and establish market sentiment (Barth & Hutton, 2003). In the Swedish stock market, reports by analysts are a pillar in the investment landscape, yet their predictive ability, biases and relative value remain less studied compared to larger and better studied markets such as the United States. The question of whether analyst recommendations do indeed convey accurate, value relevant information or merely reflect prevailing market trends has significant implications for capital allocation efficiency, investor policy, and market integrity. However, recent evidence suggests that analyst forecasts often contain a good amount of noise, which can capture overoptimism, herding as well as poor information efficiency in certain environments (de Silva & Thesmar, 2023).

Previous literature has confirmed that analyst recommendation profitability and informativeness vary across markets, time and reporting formats. Jegadeesh et al. (2004) and Asquith et al. (2005) studies indicate that the explanatory ability of analyst output is typically dependent on recommendations revision, qualitative quality of supporting explanations, and the overall market environment. Azevado and Müller (2024) demonstrated how suggestions are particularly insightful in certain non-American markets, and Guedj and Bouchaud (2005) and Kadan et al. (2020) showed biases, herding, and benchmark specifications can significantly influence recommendations performance. However, there is not up-to-date evidence that has examined such issues in the Swedish market, particularly in the public equity recommendations format, in which analysts provide fair value ranges rather than definite buy, hold, or sell recommendations. This reporting difference alters the way that recommendations must be interpreted and translated into investment strategies, necessitating a distinct signal extraction procedure.

The objective of this thesis is to study whether analyst recommendations by the Swedish analyst companies can be used to create abnormal returns in a systematic manner. The research question guiding the study is: "*Can portfolios built of recommendations from Swedish equity analysts systematically exceed the return of the benchmark index, and do these portfolios produce statistically significant alpha in addition to known risk factors?*". The used data is collected by publicly available analyst recommendations by six different companies. The data are reports that are openly available from the analysts' own sites, with full transparency and reproducibility. By the Efficient Market Hypothesis (Fama, 1970) (even in its weak form), such publicly available information must already be incorporated to market prices and therefore have no return opportunity to exploit Testing whether these signals generate abnormal returns, two hypotheses are formulated:

H1: Portfolios constructed based on Swedish equity analysts' recommendations outperform the benchmark index

H2: Alpha of portfolios based on Swedish equity research analysts' recommendations is significant even after adjusting for systematic risk factors.

The results show that, although some analyst companies recommendations are linked to beating the index portfolios and having a positive statistically significant alpha, others perform worse than their index and show no evidence of statistically significant alpha. The findings are consistent with global evidence on heterogeneity among analysts' performance and the role of structural biases. Swedish evidence from this research both confirms and modifies previous research.

This research contributes to the previous literature in three ways. It extends empirical research on analyst recommendations to the Swedish stock market and operational players such as the underlying analyst companies. Second, it develops and applies a systematic approach to obtaining actionable investment insight from fair-value range-based valuations that can be extended to other markets that might use the same reporting conventions. Third, putting the Swedish findings into the international evidence. The conclusion drawn is that selective use of analyst recommendations in Sweden, focusing on the most precise valuations can yield abnormal returns, although these opportunities are unevenly distributed and highly sensitive to methodological choices.

1. Theoretical Framework

1.1. Market Theories

The theoretical starting point of this study is to focus on the question of whether analysts' recommendations can systematically generate abnormal returns for investors. If an investor were to build a portfolio solely based on analysts' recommendations, the significance of using this must be assessed within the framework of market efficiency, information symmetry, behavioural dynamics and trading friction factors.

The Efficient Markets Hypothesis (EMH) remains one of the most fundamental theories of price formation in finance. The EMH, formed by Fama (1970), proposes that financial markets are information-efficient and that asset prices reflect all available information at any given time. According to the semi-strong form of EMH, which is appropriate for this study, it is argued that prices immediately adapt to public information, including analysts' recommendations, making it impossible for investors to consistently earn abnormal returns based on such data (Fama, 1970). If the market were indeed semi-strong efficient, building a portfolio based solely on published analyst reports would not be able to generate better returns than what is expected from risk exposure. However, deviations in EMH theory have been documented in the market. Empirical evidence suggests that the market does not always process information perfectly or immediately. Jegadeesh and Titman (1993), have shown that certain public signals, including analyst recommendations, can lead to sustained returns, especially in the short term. These findings indicate that market participants may underreact to the information, leading to delayed price changes and short-term opportunities for investors acting quickly on analysts' recommendations.

To ascertain whether these excess returns constitute a genuine alpha or merely compensation for systematic risk, asset pricing theories must be employed. One of the best ways which have been utilized in this regard is the Fama-French three-factor-model, which extends the capital asset pricing model (CAPM) by adding two more explanatory factors: size (SMB - small minus big) and value (HML - high minus low) (Fama and French, 1993). The model considers the performance of the tendency of value and small-cap stocks to outperform large and growth cap stocks' returns, qualities that can be incorporated into portfolios made of analysts' recommendations.

EMH and factor models focus on rational pricing models, but behavioural economics presents psychologically sound explanations for why investors might react to analysts' recommendations in a predictable way. This can be explained, for example, by herd behaviour, as investors follow others, which reinforces the impact of widely followed analyst reports (Banerjee, 1992). According to Harris and Guerel (1986), institutional investors and retail investors can react in the same way to significant information signals, which contributes to the creation of short-term price pressures that are not related to fundamentals. In this framework, analysts' recommendations can act as catalysts for consideration, which in turn contribute to temporarily shifting demand and raising prices.

Grossman and Stiglitz (1980) argue that if the market were fully efficient, there would be no incentive for data collection, which again suggests that a certain degree of inefficiency must exist to reward those who obtain or interpret information. According to information asymmetry theory, analysts' recommendations can thus narrow the information gap between companies and investors, especially in the case of small companies and under-tracked stocks (Akerlof, 1970). Analysts act as informed intermediaries, thus play a valuable role in transforming complex economic data for investing audiences. However, analysts' recommendations contain information, practical limitations may prevent investors from taking full advantage of them. Shleifer and Vishny (1997) emphasise the limits of arbitrage and the fact that trading costs, short selling restrictions and market effects can prevent pricing errors from being corrected. For example, the commonly used 1% trading fee on transactions per trade. If trading is based on analysts' advice, the returns would have to exceed the threshold significantly to be worthwhile. This is especially important in the markets like Sweden, where liquidity is limited but execution costs are high.

The strategy used challenges assumptions about market efficiency, tests the explanatory power of asset pricing patterns, leverages behavioural cues and potential information asymmetries, and must be weighed against real-world frictions and structural constraints. Together, these theoretical pillars support the framework of this study, guide the interpretation of observed deviations, and place the strategy on the broader landscape of finance.

1.2. Previous Empirical Research

Empirical research on analysts' stock recommendations has expanded significantly in recent decades, especially as data has become available on a global scale and more accurate. Central to this literature is the question of whether analysts' recommendations can systematically generate excess returns when considered in active portfolio strategies.

Azevedo and Müller (2024) conducted one of the most comprehensive studies of analyst recommendations in a global sense by analysing monthly observations from more than 3.8 million companies in 45 different countries. The findings of the study showed that analysts' recommendations strongly predict abnormal returns outside the U.S. and especially informative ones in less developed and smaller markets. The study also specifically found that analysts tend to give more favourable recommendations for underpriced stocks. This suggests that analysts are mitigating, rather than exacerbating, pricing errors in international markets, which supports the informative value of their guidance.

At the investor level, the dynamics vary significantly. In their study, Kong et al. (2021) used detailed account-by-account trading data from the Shanghai Stock Exchange to distinguish between institutional and retail investor reactions to analysts' recommendations. It turned out that institutional investors reacted to the "Buy" and "Strong Buy" recommendations by increasing their position while avoiding or selling stocks marked "Hold" or "Sell". The study also incorporated analysts' buy-side influence into their trading strategies, resulting in statistically significant abnormal returns. On the other hand, individual investors usually reacted contrarily and often made suboptimal decisions. Such findings strengthen the argument on how different classes of investors react to analyst recommendations, especially in information asymmetry and behavioural bias environments.

Han et al. (2021) present evidence of portfolio building, in which stock prices initially moved in the direction of analysts' target prices but later drifted in the opposite direction. The study's findings were in the United States with data from 1999 to 2020, revealing that a long-short strategy based on analysts' target price revisions could generate a monthly return of 0.75%. This was due to corrections of pricing errors and changes in discount rates over time. This, in turn, suggested that the initial optimism of analysts could temporarily mislead the market valuation. On the coverage side, Cevheroğlu-Acar et al. (2022) examined the "coverage premium" and found that stocks that were not tracked by analysts consistently returned higher risk-adjusted returns than stocks with high tracking coverage. The study was conducted in twenty countries with a zero-cost strategy of buying under-covered stocks and selling high-coverage stocks, yielding a monthly alpha of 0.34%. This contributes to the hypothesis that the scarcity of information creates inefficiency in valuation, which in turn can benefit from knowledge-based trading.

Casey (2013) has shown in research that changes in the recommendations of independent research companies are significantly less informative than changes in investment bank analysts. Although the study considered differences in resources and analyst experience, increases and decreases in independent analyst recommendations yielded lower abnormal returns. Later, Buslepp, Casey, and Huston (2023) expanded on this research by examining the impact of the Global Research Analyst Settlement, which would be intended to promote unbiased and independent research. The study found that while the goal was to reduce conflicts of interest, the resulting independent research was often of lower quality and more predictable in terms of future returns.

There are also biases of sentiment and ownership in the literature. Chan et al. (2018) found that analysts who own stocks in the companies they follow gave more informative and accurate recommendations. On the other hand, these analysts were also more likely to give optimistic forecasts, and the research also found that more than half of them sold their holdings while maintaining a "Buy" recommendation. In a European study, del Río, Ferrer, and López-Arceiz (2024) investigated the impact of opinion on the predictive power of analysts' recommendations, especially in companies with high ESG reports. The study found that high ESG reporting increased optimism in the eyes of analysts but did not improve the accuracy of buyers' recommendations. Conversely, the study showed that informational signals were clearly more accurate in sell stock recommendations for firms with negative ESG reports.

In addition to these findings, research also has examined how differences in analyst outputs and report contents affect investment value. Jegadeesh et al. (2004) found that while consensus recommendations by sell-side houses tends to concentrate on glamorous stocks and perform below par, revision in consensus recommendations are strong predictor of future returns, suggesting the usefulness of revision-based strategies. Asquith et al. (2005) also showed that price target revisions and the written case credibility provide distinct market signals, often stronger than the label of recommendation standing alone, a discovery especially relevant to markets like Sweden, where fair value ranges dominate explicit buy/sell ratings.

Behavioural biases in analyst reports have also been extensively reported. Over-optimism and herding by analysts were shown by Guedj and Bouchard (2005) to be present, with accuracy at times being little better than a simple no change model. Such behaviour can lead to correlated sector-level forecasting errors and thus lower diversification benefits in analysts-based portfolios.

Difference in the method brokerages determine their benchmarks could also explain difference in performance. Kadan et al. (2020) found that a “buy” recommendation can be outperformance related to an industry index buy one firm, or relative to the market by another, with important consequences for recommendation dissemination and market reaction.

Lastly, response biases to past returns have also been reported. Jung et al. (2015) find that analysts react more forcefully to very negative stock returns (“losers”) than to very positive ones (“winners”), reducing forecast accuracy. The asymmetry persisted following regulatory reforms like the Global Settlement, implying structural behavioural patterns that can influence analyst performance over time and regimes.

Taken together, these studies provide strong empirical support for the view that analysts' recommendations can form the basis for profitable investment strategies, especially when portfolios are formed dynamically and aligned to the investor’s capability and market climate. The research also highlights that the quality of recommendations varies by source, optimism biases are present, and signal efficacy can be highly contingent upon the nature of the investors as well as the context in which the market functions. These findings form the basis for research on how to use analysts' recommendations as a portfolio building strategy in the Swedish stock market.

2. Data and Methodology

2.1. Sample and Data Selection

This research examines the return on investment activities of portfolios built based on Swedish equity analyst recommendations. The data for the research consists of six independent equity research companies providing publicly accessible in-depth stock reports: Mangold, Redeye, Carnegie, Analyst Group, Aktiespararna and Inderes. From the forementioned companies, Inderes' main market is Finland, but they have an increasing amount of coverage and operations in Sweden, and their analyses are available from both markets, which justifies their inclusion in the research. These six analyst companies were chosen as they make their recommendations publicly accessible through their website with full transparency and reproducibility of the dataset. On the other hand, there were institutions such as Nordea, SEB, ABG Sundal Collier, Handelsbanken and Swedbank that were left out of the sample because their equity research reports and recommendations are not released publicly. Large investment banks being excluded might weight the data on small- and mid-cap stocks, as independent analyst companies typically have these types of companies as their customers (Kirk, 2011).

Each analyst company is treated as an independent unit of analysis, and six separate portfolios are built to examine analyst company-specific forecast accuracy and performance dynamics. Inclusion in the dataset required the published recommendation to be supported by a full stock research report. Short updates, comment snippets or investment blog posts were omitted. This ensures the integrity and depth of the underlying signal. It's important to note that stock coverage doesn't have to overlap between different companies; Each analyst company can focus on a unique market segment (e.g., small caps, growth companies), reflecting the diversity of real-world research priorities and customer base since the benchmark is going to be the index formulated from the companies under coverage.

The research period is from 1st of January 2019 to 31st of December 2024, which is the period most analyst companies in the sample had data available. The years used for analyst companies are started from the first full year, where recommendations are available. 8482 recommendations were collected directly from the analyst companies' website to ensure consistency, transparency, and replicability. Manual collection process was necessary, because the complete dataset was not in a similar format in the major financial databases, so public releases served as the basis for the research, except from Inderes, who gave recommendations from their data-archives. While manually collecting reports can introduce small non-systematic errors (e.g., dates, fair-value ranges, missed updates), in the traditional errors-in -variables model, such noise primarily attenuates estimated relations (zero bias) rather than creating spurious performance (Abel, 2018). Daily stock data was collected through Capital IQ to ensure the quality and reliability of the data.

Table 1. Total Amount of Stocks Used and Followed by the Analyst Companies, Total Amount of Equity Reports Used. Observed by 6.7.2025.

Analyst Companies	**Used stocks**	**Stocks followed**	**Analyst Companies**	**Equity Reports**
Analyst Group	118	365	Analyst Group	630
Aktiespararna	46	55	Aktiespararna	459
Carnegie	65	80	Carnegie	1166
Mangold	21	32	Mangold	121
Redeye	107	126	Redeye	1686
Inderes	180	227	Inderes	5470
Total				8482

To preserve the quality of information, stock data were removed from the research period if they were removed from the stock market during the time or if the data was missing from other unknown reasons. Removal of stocks may introduce survivorship bias. This is a common limitation in the analyst studies (Barber et al., 2001), and, in the absence of systematic correlation on between delisting's and recommendation category, is not likely to significantly alter findings.

2.2. Portfolio Formation Methodology

In this research, investment portfolios are built based on equity research reports published by six Swedish analyst companies: Mangold, Redeye, Carnegie, Analyst Group, Aktiespararna and Inderes. Based on the recommendations of each analyst company, a separate portfolio is built that reflects the behaviour of an investor who follows one house of analysts exclusively. The key objective is to assess whether recommendation-based strategies can generate permanent, risk-adjusted abnormal returns.

While some companies use explicit Buy, Hold, or Sell markups, most Swedish analysts' offer fair value ranges (later FVR) as the primary valuation outcome. To convert them into structured and tradable recommendations, each range was divided into quartiles and compared to the price on the stock's publication date. The logic follows a structured transformation process:

- If the stock price is in the 1st quartile of the FVR, or below the lower bound, it is classified as Buy.
- If the stock price falls in the 2nd or 3rd quartile of the FVR, it is classified as Hold.
- If the stock price is in the 4th quartile, or above the upper bound, it is classified as Sell.

This method ensures consistency in the interpretation of signals across different valuation styles and recent research confirms that sell-side analyst reports retain investment value, particularly when their recommendations are converted into systematic portfolio strategies, but excess return size varies according to market context and firm coverage characteristics (Lv, 2025). Using alternative methods such as terciles would reduce the ability to distinguish neutral recommendations, since the middle category would be very broad and could blur valuation variation in analyst conviction. Furthermore, quartiles are robust to asymmetries in distributions: whether ranges are broad or narrow, quartiles can be applied in the same way, whereas other partitions may give too much influence on extreme values. The use of quartiles as a statistical construct is supported by Agarwal (2006), who emphasizes their usefulness in dividing distributions into relevant, comparable parts without relying on assumptions about distribution. This approach is particularly appropriate when recommendations are made at intervals rather than as separate points, as fair value estimates are inherently subject to uncertainty. If a FVR is not provided, but such as target price is, the target price has been used as the break-even point.

The interpretation of the Hold covering the middle two quartiles reflects a greater level of ambiguity or neutrality. This reflects the logic of Cowen and Ellison (2008). They point out that estimates expressed as variations close to natural or statistical limits often involve greater uncertainty and that the centre of the range is not always an informative predictor. In contrast, Buy and Sell recommendations, which are issued when the price falls to quarter 1 or 4 or even outside the boundaries, represent confidence in a stronger direction. Thus, the quartile system captures both the confidence gradient of the recommendation and the uncertainty inherent in the fair value analysis.

It is acknowledged that observations near the break-even points may not perfectly capture the analyst's intent. The most valuable aspect is to have the quartiles to harmonize heterogeneous report formats. This is consistent with evidence that brokers use different benchmarks and that the selection of benchmark affects the distribution of recommendations, price reaction and investment value, so researchers should account for benchmark when comparing analysts' output (Kadel et al., 2020).

To provide transparency about the characteristics of the fair value ranges across different analyst companies, descriptive statistics of widths of FVR are presented in Table 2. The values highlight differences in range widths, which may influence levels of price variability across quartile breakpoints. It is noticeable, that Mangold and Inderes uses only single target prices, so FVR statistics are not available.

Table 2. Descriptive Statistics of Fair Value Ranges

Analyst Companies	**Mean FVR Width (%)**	**Median FVR Width (%)**	**Min Width (%)**	**Max Width (%)**
Aktiespararna	29.4	24.2	0.8	149.6
Analyst Group	104.7	104.5	-90.9	192.4
Carnegie	13.7	7.7	0.0	90.1
Mangold	-	-	-	-
Redeye	121.3	124.8	54.5	200
Inderes	-	-	-	-

More updates and tighter ranges can imply higher accuracy valuations and higher confidence, while wider ranges or fewer updates can imply higher uncertainty. Prior research has shown that analysts who have more accurate target valuations and update more frequently make timelier and more accurate recommendations (Jegadeesh et al., 2004). Since update activity and valuation might also impact portfolio outcomes, Table 3. combines average frequency of updates, median days to update and mean percentage deviation between FVR midpoints and latest market prices. Mangolds and Inderes' mean observed bias is calculated as the distance of price to the target price.

Table 3. Descriptive Statistics of Recommendation Updates and Observed Bias

Analyst Companies	Average Update Frequency (per year)	Median Days Between Updates	Observed Bias (mean % above market price)
Aktiespararna	91	88	58
Analyst Group	89	91	128
Carnegie	266	58	55
Mangold	30	103	151
Redeye	228	90	122
Inderes	960	42	19

Recommendations are implemented in portfolios on the same trading day that they are published, since the reports are usually published before the market opens. If the report is published in the market after hours, it will be implemented straight in the next day. Each recommendation will remain active for a maximum of 12 months, unless a new report is issued for the same stock earlier. When a new recommendation is published, it replaces the previous one. For stocks that have had a valid recommendation from middle of the first year of data, the recommendation is set to start at the beginning of the next year to include only full years in the research.

Position management is guided by both time and price movements. If a buy position (Q1 or below the range) moves to the 4th quartile, the position will be closed. Conversely, if a sell position (Q4 or above the range) moves to the 1st quartile, it will also exit. If the price is in Q2 or Q3 at the time of the recommendation, the position will be held until a new recommendation is issued or the 12-month period ends. This rule reflects a dynamic response to changes in valuation while ensuring that minor fluctuations don't trigger unnecessary trades. As the purpose of the study is to study long-term portfolios, the study applies a method in which the stock must be 3 days above/under the recommendation, depending on whether it is a Buy or Sell recommendation.

The 3-day buffer rule is not volatility adjusted and can lead to early exits in volatile stocks. However, such fixed-duration mechanisms are common in portfolio and risk management studies. Glasserman and Wu (2017) mention the concept "margin period of risk", which is a predefined number of days during which a position can be closed. This works just like a buffer, which is not typically volatility adjusted. They further note that fixed buffer durations can overestimate or underestimate true risk depending on conditions of volatility but remain prevalent to reduce noise in the short run and avoid overreactions to short run price changes. That suggests, although not ideally aligned with volatility, a fixed buffer is a prevalent technique choice and should not consistently bias findings in favour of or against any form of recommendation. While alternative thresholds could be tested, the current choice strikes a balance between responsiveness and reliability, and testing further variations falls outside the scope.

The portfolios are rebalanced daily and include any new changes or changes to the recommendations. Each position is weighted according to the strengths of the recommendations:

Buy = +2

Hold = +1

Sell = -2 (Short position)

The structure of this allows stronger views to carry more weight. Daily portfolio values are normalized to ensure that returns are comparable over time, between different analyst companies.

Inderes uses Buy, Accumulate, Hold, Reduce and Sell in its recommendations. The recommendations have been changed in the research with an emphasis on weights: Buy +2, Accumulate +1, Hold +1, Reduce (no weight) and Sell -2 (short position), which is in line with Inderes' own portfolio construction techniques from similar research. Otherwise, the portfolio construction and updating works in the same way as with other companies.

2.3. Factor Model Implementation

The Fama-French Three-Factor model is used to assess whether the portfolios made by Swedish equity analysts' stock recommendations generate statistically significant abnormal returns on a risk-adjusted basis.

Given the data from the study and the general nature of the Swedish stock market, where a significant proportion of covered stocks are small and mid-cap and many of them have value characteristics, this framework is highly relevant (OECD, 2025). Also, analysts' recommendations are seen as fundamental analysis and long-term valuation values rather than short-term technical price momentum (Bradshaw, 2011). Incorporating size and value guarantee that abnormal returns due to recommendations are not merely compensation for such risk premia.

The Fama-French three-factor model is expressed by the following regression:

$$\left(R_{pt} - R_{ft}\right) = \alpha_p + \beta_{pM}\left(R_{Mt} - R_{ft}\right) + \beta_{pSMB} \cdot SMB_t + \beta_{pHML} \cdot HML_t + \varepsilon_{pt}$$

Where:

- R_{pt} = Return of the portfolio ρ at time τ
- R_{ft} = Risk-free rate at time τ
- R_{Mt} = Market return at time τ
- SMB_t = Return difference between small-cap and large-cap stocks at time τ
- HML_t = Return difference between high book-to-market (value) and low book-to-market (growth) stocks at the time τ
- α_p = Portfolio alpha (risk-adjusted excess return)
- β_{pM}, β_{pSMB}, β_{pHML} = Factor ladings (sensitives)

And,

ε_{pt} = Idiosyncratic error term

In this setup, alpha (α_p) represents the portion of portfolio returns that cannot be explained by the effects of the market, size, or value factors. Factor returns (market, SMB and HML) are taken from the AQR Capital Management, which includes the data for Fama-French regression models for the Swedish equity market.

The choice of the above model is supported by the literature of Gupta and Shrivastava (2021), which points out that the Fama-French Three-Factor Model is the extension of CAPM with size and value factors, thereby capturing the long-term outperformance of small-cap and high book-to-market companies. As a significant part of the Swedish stock market consist of such stocks, and as the study focuses on fundamental, long term investment approaches rather than short-term momentum effects, the model gives both empirical applicability and theoretical coherence.

It should be noted that in the stocks covered by Inderes, Swedish stocks are a minority, and Finnish stocks are a majority, so AQR data from Finnish factors is used for Inderes to obtain a more accurate and legitimate result

3. Analysis and Discussion

3.1. Portfolio Performance

This section presents and evaluates the annual performance of portfolios formed from the dataset of analyst companies' stock recommendations over the period 2019 and 2024. The model of the research does not consider transaction costs, bid-ask price differences, short selling restrictions or market effects that have an impact on practical implementation. The results are compared to indices consisting of the same stocks of each analyst company followed with the 1x holding weight. The focus is on annual returns, cumulative total returns, and compound annual growth (later CAGR), which allows for a comparative assessment of both absolute and relative performance. On Table 4. negative values are presented in brackets and the index related to analyst company on the right side of the respective company.

Table 4. Portfolio Performances Through 2019-2024, CAGR and Difference Between Portfolios and Indices.

Year	**Aktiespararna**	**Index**	**Analyst Group**	**Index**	**Carnegie**	**Index**	**Mangold**	**Index**	**Redeye**	**Index**	**Inderes**	**Index**
2019			35.1%	38.4%					24.6%	24.8%	30.9%	36.0%
2020	107.9%	60.2%	69.2%	57.7%					94.2%	80.8%	35.8%	31.7%
2021	36.7%	35.5%	73.7%	41.0%	59.2%	47.9%	(15.4%)	(23.7%)	19.6%	13.8%	35.9%	24.2%
2022	(13.9%)	(31.5%)	(45.7%)	(38.2%)	(32.9%)	(28.6%)	(47.3%)	(53.8%)	(21.7%)	(32.3%)	(22.4%)	(27.8%)
2023	4.0%	2.9%	(20.2%)	(9.2%)	(14.2%)	(1.8%)	(11.1%)	(28.2%)	3.0%	5.0%	2.0%	(5.4%)
2024	(4.1%)	(3.2%)	(19.1%)	(9.0%)	(12.1%)	7.5%	(44.5%)	(37.1%)	1.4%	2.94%	2.7%	(0.6%)
CAGR	20.4%	9.5%	6.9%	9.4%	(4.5%)	3.8%	(30.9%)	(36.0%)	17.7%	13.5%	12.9%	8.3%
Total	153.3%	57.2%	49.4%	71.2%	(16.7%)	16.2%	(77.2%)	(83.2%)	165.2%	113.5%	107.53%	61.35%
Difference	96.1%		(21.8%)		(32.9%)		6.0%		51.7%		46.18%	

Table 4 presents return on the recommendation portfolios and the benchmark indices. Of the six portfolios, the portfolios built based on Aktiespararna, Redeye and Inderes recommendations stood out with long-term returns. Aktiespararna’s portfolio achieved a cumulative return of 153.3% for the period in research, which is equivalent to a compounding growth rate of 20.4% per annum and beats its own benchmark index well. Based on this, it can be said that Aktiespararna consistently added value to investment decisions, especially during the strong market years of 2020 and 2021.

Redeye’s portfolio had a total return of 165.2%, with annual growth rate of 17.7%, versus the annual growth rate of 13.5% for the index. Recommendation strategy showed strong upside potential in bull markets, especially in 2020, when the return was 94.2%, and in 2021, when the portfolio returned 19.6%. However, the strategy showed relative flexibility in the weakest years such as 2023 and 2024, when returns remained marginally positive at 3% and 1.4%, and in 2024.

In contrast, portfolios built based on Carnegie's and Mangold’s recommendations performed significantly worse both in absolute and relative terms. After a strong start and a year in 2019 when the Carnegie portfolio returned 59.2%, the portfolio failed to recover from consecutive years of losses and ended up with a negative performance overall. However, of all the portfolios, Mangold was the weakest and consistently showed negative returns throughout the period under review. With a cumulative loss of -30.9% and a clear downward trend from 2021, culminating in a steep decline of -77.2% overall. However, it should be noted that Mangold's benchmark index performed even worse at -83.2%, highlighting the broader negative sentiment in the stocks the analyst company tracks. On a positive note, Mangold won its own benchmark index.

The results of Analyst Group's portfolio were mixed. Although the portfolio in 2020 & 2021 saw strong returns of 69.2% and 73.7%, there was a sharp decline towards the end of the monitoring period. Especially in 2023 and 2024, when the declines were -45.7% and -20.2% respectively. Over the entire investigation period, the portfolio's annual growth rate was 6.9%, which was below its benchmark index of 9.4%. This means Analyst Group had some short-term successes, but these were not lasting.

Inderes' portfolio generated a total return of 107.53% during the period and a CAGR of 12.9% compared to 8.3% in comparison. The strategy delivered strong 30.9% returns in 2019, 35.8% in 2020 and 35.9% in 2021, which had a significant impact on the long-term growth of the portfolio. Although the return for 2022 (-22.4%) was negative, it won the index. However, returns moderated in the last years of the period in 2023 (2.0%) and 2024 (2.7%), suggesting increased market challenges or more cautious recommendation practices.

Table 5. also shows that Aktiespararna, Redeye and Inderes achieved significantly better Sharpe Ratios (0.597; 0.730 and 0.61 respectively) and their portfolios generated stronger excess return per risk unit. The Sharpe Ratio is a key metric for risk-adjusted performance and is calculated as trade off where higher value indicates that returns are not just results of high risk, but result from genuine informational value (Sharpe, 1994). In contrast, the negative Sharpe Ratios for Carnegie and Mangold reflect that their returns were not sufficient compensation for the risk they experienced.

Table 5. Annualized Sharpe Ratios for Analyst Companies Portfolios

Company	Aktiesprarna	Analyst G.	Carnegie	Mangold	Redeye	Inderes
Sharpe Ratio	0.597	0.310	-0.282	-0.877	0.730	0.61

The findings support the H1 hypothesis, according to which portfolios built based on Swedish analyst companies perform better than the benchmark index. Of the six companies examined, four portfolios (Aktiespararna, Mangold, Redeye and Inderes) showed better performance relative to their own benchmark indices and annual growth rate. With four out of six portfolios performing better, we can accept hypothesis H1 in the context and scope of this study.

From a practical point of view, the results also highlight the variations in quality and forecasts between companies. Carnegie's weaker returns and the volatility observed in Analyst Group's returns indicate that not all recommendations are equally practical and reliable. Even if hypothesis H1 is accepted, its validity depends on the choice of the analyst company, and investors should not treat analysts' signals as homogeneous.

The dispersion in earnings support the empirical verification of single analyst firms and continuous monitoring. In conclusion, although analyst recommendations are valuable instrument in the Swedish stock market, their success is dependent upon the quality, methodology, and consistency of the recommender.

3.2. Factor Model

To examine whether excess returns of analyst companies-based portfolios would be explained by known systematic risk sources, the Fama-French Three-Factor model is applied. According to the EMF, risk and reward should move together and any abnormal return over the long run should be attributed to compensation for holding priced risk factors. In this framework, the portfolio returns are broken down in exposures to market risk premium, MRP (Market Risk Premium, which is $MKT - Rf$), size factors (SMB) and value factors (HML).

Alpha (α) captures the risk-adjusted portion of return not explained by these risk factors. A large alpha indicates that the analysts can provide information or expertise that isn't yet fully embedded in market prices and hence bring additional value to investors. A small alpha would indicate that returns are significantly driven by exposures to systematic risk and not by separable analyst opinion.

It is important to note that the reported alpha levels in this research are gross of all trading, costs, taxes and implementation frictions. These are frictionless trading returns under the assumption. So even if statistically significant alphas may indicate informational value, economic payoffs to investors would indeed be lower when realistic costs are incorporated. Table 6. summarizes the results of regression analysis of portfolios based on analysts' recommendations.

Table 6. Fama-French Three-Factor Model Monthly Results

Companies	α_p	**t-stat** α_p	MRP	**t-stat** MRP	SMB	**t-stat** SMB	HML	**t-stat** HML	R^2	**Adj.** R^2	**F-stat**	**N**
Aktiespararna	0.023	1.851***	0.540	3.157*	1.001	2.544**	-0.343	-0.764	0.261	0.221	6.587*	60
Analyst Group	0.006	0.963	0.663	6.980*	0.718	3.446*	0.113	0.455	0.478	0.455	20.76*	72
Carnegie	0.003	0.598	0.561	6.847*	0.686	3.821*	-0.041	-0.188	0.595	0.567	21.56*	48
Mangold	-0.022	-1.464	0.825	3.798*	0.486	1.021	0.088	0.153	0.278	0.229	5.650*	48
Redeye	0.015	3.499*	0.666	11.062*	0.902	6.830*	-0.172	-1.097	0.728	0.716	60.75*	72
Inderes	0.008	3.007*	0.774	14.940*	0.499	5.189*	0.124	1.449	0.821	0.812	100.6*	72

Significant at 1% (*), 5% (**), 10% (***)

The monthly alpha of Aktiespararna's portfolio is positive at 0.023 and statistically significant at the 10% level. This suggests weak but meaningful evidence of abnormal returns outside of systematic risk. However, the portfolio is heavily burdened by a market risk premium (MRP = 0.540) and a size factor (SMB = 1.001), suggesting strong exposure to small-cap stocks and moderate correlation with market movements. A negative and unmitigated HML load (HML = -0.343) reflects an increase in the price of growth stocks. The model explains a reasonable share of the return variation and R^2 is 0.261.

Analyst Group alpha is positive, but statistically not significant, 0.006 per month. Although the portfolio shows significant exposure to risk factors MRP (0.663) and SMB (0.718), its alpha does not support the existence of a return. A relatively high R^2 of 0.478 indicates that the factors explain most of the return variation in the portfolio. This is in line with earlier studies (Barber e al., 2001; Azevedo & Müller, 2024), which show that in markets with high concentrations of small- and mid-cap stocks, the majority of portfolio perfromance is driven by factor exposure rather than single analyst skill.

The alpha of Carnegie's portfolio is insignificant and statistically also insignificant 0.003 per month. The portfolio has a significant statistical exposure to the market MRP (0.561) and a size SMB (0.686), while the HML load is close to zero and not a significant -0.041. Model's R^2 has a stable value of 0.567, which shows strong explanatory power but does not provide evidence of risk-weighted overperformance.

An interesting finding is that the alpha of the Mangold portfolio is negative and statistically insignificant -0.022. This means, performance is due to the factor exposures of the portfolio rather than idiosyncratic analyst skill. The portfolio has a large and significant exposure to a market factor (MRP = 0.825) and a positive but insignificant load of 0.586 for SMB. The HML load is small and insignificant 0.088. At R^2 0.278, the model explains only a modest part of the yield variation, and the results do not reveal the existence of significant abnormal returns, which is consistent with prior findings with Swedish small- and mid-cap stocks which exhibit substantial idiosyncratic volatility (Azevedo & Müller, 2023).

Redeye has a statistically significant alpha at the 1% level. The alpha is 0.015 per month and significant at the 1% level. This strongly supports the existence of abnormal returns that are not due to exposure to normal risk factors. The portfolio is also statistically significantly burdened in relation to the market (MRP = 0.666) and size (SMB = 0.902). HML with a negative but insignificant load of -0.172. The R^2 model has a strong coefficient of 0.728, indicating that factor exposures explain most of the variation in returns, but the statistically significant alpha suggests that Redeye's recommendations provide real informational value.

Similar to Redeye, Inderes' portfolio yielded a statistically significant alpha of 0.008 at the 1% level, indicating strong outperformance in addition to the systematic risk factors. The portfolio showed significant exposure to market (MRP = 0.774) and size factors (SMB = 0.499), while value exposure was negligible. With adjusted R^2 of 0.812, the model explains the variation in returns very well. The results highlighted Inderes' strong and consistent performance in relation to risk.

The results obtained provide limited but meaningful support for hypothesis H2. Of the six portfolios, only Redeye and Inderes shows statistically significant alpha at the 1% level, while Aktiespararna shows a weaker marginally significant alpha at the 10% level. Analyst Group, Carnegie and Mangold do not generate significant abnormal returns when the impact of market, size and value factors is controlled. Hypothesis H2 cannot be accepted in its general form. However, we accept the H2 hypothesis with limited or conditional consideration and acknowledge that certain companies, such as Redeye and Inderes, shows statistically significant alpha after considering systematic risk. The results suggest that while some analysts' recommendations contain value-related information that is not covered by standard risk models, this is not a universal feature in all companies. Alpha's appearance seems to be very analyst company-specific.

3.3. Robustness Check

Four-Factor model is used to check the robustness of findings of the Fama-French Three-Factor Model and check whether alpha is being influenced by the momentum factor. The fourth factor is momentum factor (UMD – Up Minus Down), which captures the empirical pattern of past performing stocks to keep on performing better than their benchmarks in the short term (Jegadeesh & Titman, 1993; Carhart, 1997). Although momentum is technically distinguished by Fama and French as priced risk factor, it is generally added to empirical asset pricing to capture return patterns related to liquidity frictions, short-selling constraints, and investor sentiment.

The UMD series is taken from AQR's publicly available factory library that is widely used in academic research due to its transparent construction methodology, stable market coverage, and regular updates. Using AQR's Swedish UMD factor (Finnish for Inderes) ensures methodological consistency with prior factors, research and eliminates the need for additional in-house factor construction.

Adding a momentum is particularly appropriate in this research, as the Swedish stock market includes a lot of these stocks (OECD, 2025). Pope et al. (2019) state that momentum effects in the Nordic market are typically weaker and transitory, particularly when trade frictions and market microstructure are considered. If significant alpha observed during the Three-Factor Model has been driven by momentum exposure, it should reduce after adding UMD. If alpha continues to be significant, this will reinforce the argument that analysts' recommendations have informative valuation beyond known return regularities.

The four-factor regression results are presented in Table 7. The addition of the UMD factor does not greatly alter the general conclusion of the Three-Factor Model, but it does add support to the robustness of the interpretation of results.

Table 7. Four-Factor Model Monthly Results

Companies	α_p	**t-stat** α_p	MRP	**t-stat** MRP	SMB	**t-stat** SMB	HML	**t-stat** HML	UMD	**t-stat** UMD	R^2	**Adj.** R^2	**F-stat**
Aktiespararna	0.025	1.871***	0.525	2.971*	0.982	2.454*	-0.386	-0.828	-0.124	-0.379	0.263	0.209	4.900*
Analyst Group	0.008	1.129	0.645	6.516*	0.709	3.383*	0.064	0.249	-0.130	-0.715	0.482	0.451	15.58*
Carnegie	0.002	0.353	0.581	6.796*	0.716	3.903*	0.029	0.126	0.115	0.856	0.602	0.565	16.25*
Mangold	-0.020	-1.240	0.785	3.449*	0.428	0.876	-0.050	-0.080	-0.227	-0.632	0.285	0.218	4.279*
Redeye	0.016	3.532*	0.655	10.442*	0.896	6.749*	-0.201	-1.235	-0.793	-0.687	0.730	0.714	45.33*
Inderes	0.009	3.097*	0.774	14.901*	0.505	5.217*	0.119	1.385	-0.065	-0.776	0.822	0.811	75.17*

Significant at 1% (*), 5% (**), 10% (***)

After the regression, Aktiespararna's alpha remains positive at 0.025 monthly and is statistically significant at the 10% level. Although the alpha is slightly stronger than in the three-factor model, the change is minimal and shows that momentum does not essentially explain the perceived return. The portfolio is significant statistically to size factors but not to market factors. The UMD load is negative -0.124 and statistically insignificant, confirming that the alpha of the portfolio is not driven by recent gain-and-loser effects. R^2 0.263 and adjusted R^2 0.209 are consistent with previous results.

The monthly alpha of the Redeye portfolio is still a statistically significant 0.016 at the 1% level. This result confirms that Redeye's recommendations produce genuine abnormal returns, even after considering the momentum. The portfolio is also significant statistically to market factor (MRP = 0.655) and size factor (SMB = 0.896) at the 1% level. The UMD coefficient is negative and statistically insignificant. This indicates that momentum is not a significant explanatory factor for Redeye's returns. The R^2 remains high at 0.730, suggesting a strong model fit.

Analyst Group alpha is still irrelevant. Market, size and value explain a large part of the fluctuation in returns. The UMD multiplier is insignificant in the portfolio. These results suggest that returns are mainly explained by systemic risks and not by the information content of the recommendations. Again, Carnegie's portfolio does not have a significant alpha. Exposure to market and size factors are still significant, while value and momentum factors are not. The UMD factor is positive 0.115, but statistically insignificant. The model explains a large part of the yield variation (R^2 = 0.602), which contributes to the conclusions that Carnegie's recommendations do not lead to abnormal returns after the risk adjustment. Mangold portfolio continues to generate negative and insignificant alpha, which is in line with the result of the three-factor model. The model shows statistically significant market exposure (MRP = 0.785) at the 1% level, but not significantly at SMB, HML or UMD. The momentum factor UMD is negative -0.227, but it doesn't matter. A modest R^2 of 0.285 does not indicate evidence of alpha or strong exposure to systematic momentum effects.

Inderes' alpha rises slightly but remains almost the same at the 1% significance level and ends to 0.009 per month. The addition of the momentum factor has a minimal effect, and the explanatory power of the model remains exceptionally high with an Adjusted R^2 of 0.811, suggesting that Inderes' alpha is not driven by momentum, but by exposure to other systematic risk factors. The uniformly high explanatory power of both models further strengthens confidence in the effectiveness of the strategy.

The results obtained from the four-factor model confirm the validity of the observations. The inclusion of the momentum factor does not materially affect the statistical significance of alpha, especially in the case of Redeye and Inderes, which continues to generate strong statistically significant abnormal returns. It is important to note that the UMD factor is statistically insignificant in all portfolios and therefore does not contribute to the explanation This adds credibility to the interpretation that certain analysts' recommendations provide unique and value adding information rather than merely repeating recent price trends.

In summary, the robustness check supports the conditional acceptance of Hypothesis H2 and supports the interpretation that at least some companies produce statistically significant alpha after controlling risk and momentum factors.

Conclusion

Evidence from this research indicates that portfolios built from Swedish analyst companies' recommendations do not consistently outperform the benchmark indices once market, size and value factors are controlled for. Alphas were small, and when they were large, they were either positive or negative, indicating that performance is very different between analyst companies rather than following a common pattern. On the signal level, portfolios built from analyst companies recommendations performed better than hold indices on average, but the magnitude and stability of this advantage varied by providers, so company-specific research styles matter.

Placed in the context of the prior evidence, results partly confirm findings that analyst-based strategies can earn abnormal returns (Azevedo and Müller (2024), while showing a narrower analyst company specific effect than commonly reported in the previous studies. Like the results of Jegadeesh et al., (2004), dispersion in precision and timeliness appears to be important. Analyst companies that issue tighter valuation ranges and update more frequently (as indicated in Table 2. and Table 3.) seems to exhibit more stronger risk-adjusted performances (Redeye & Inderes) except Carnegie, although these correlations should be interpreted as suggestive, not causal. On the data sample, having a tight update frequency seems to help outcomes on the portfolio returns.

Recent empirical work puts these patterns into context. De Silva and Thesmar (2023) documented rising forecast noise and bias with horizon, which helps explain why not all analyst companies turn the same sets of information into the same performance. Lv (2025) found that process-oriented, formal sell-side products retain investment value, which might explain relatively better performance among analyst companies other than Mangold, which had smallest update frequency.

This study opens several doors for future research. The incorporation of transaction costs and liquidity frictions would enable more realistic testing of recommendation-based strategies. Extending the data to include investment bank analysts or cross-country comparison across the Nordic markets could confirm the generality of the findings. Future studies can also explore analyst heterogeneity more deeply, by breaking down sector concentration, update frequency, or the language of research reports. Finally, the combination of analyst recommendations with machine learning or other data sources such as sentiment indicators or ESG signals may reveal new dimensions of predictive information.

The contribution of this study lies in providing systematic, multi analyst companies comparison of Swedish analyst companies recommendations based on a factor-adjusted method, in a long-term, fundamental-based, small- and mid-cap dominated market. The results show that analyst recommendations can deliver value but are highly context-dependent and relying on the provider.

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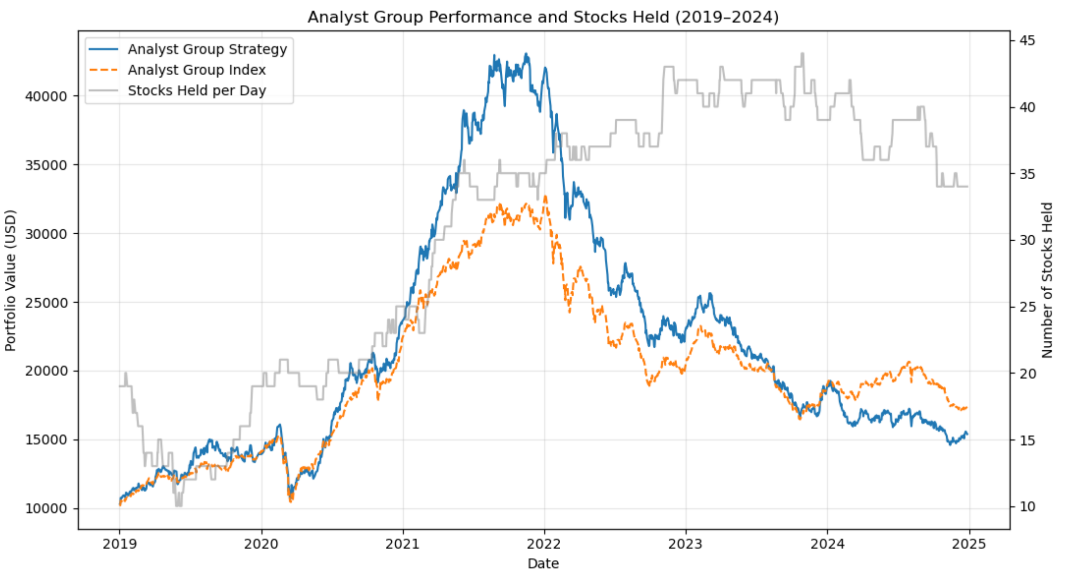

Figure 1. Analyst Group Performance and Stocks Held (2019-2024)

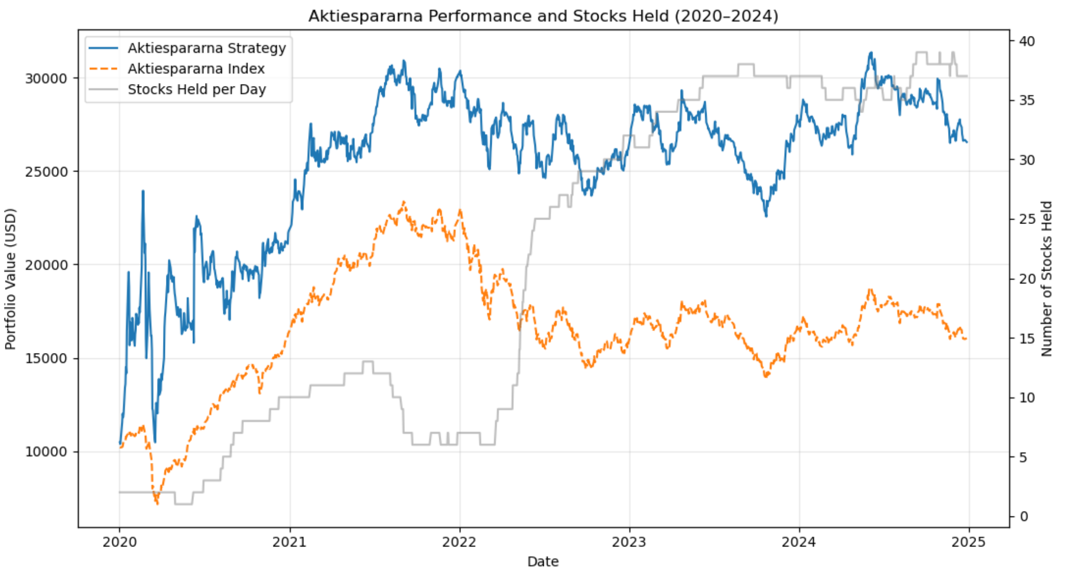

Figure 2. Aktiespararna Performance and Stocks Hels (2020-2024)

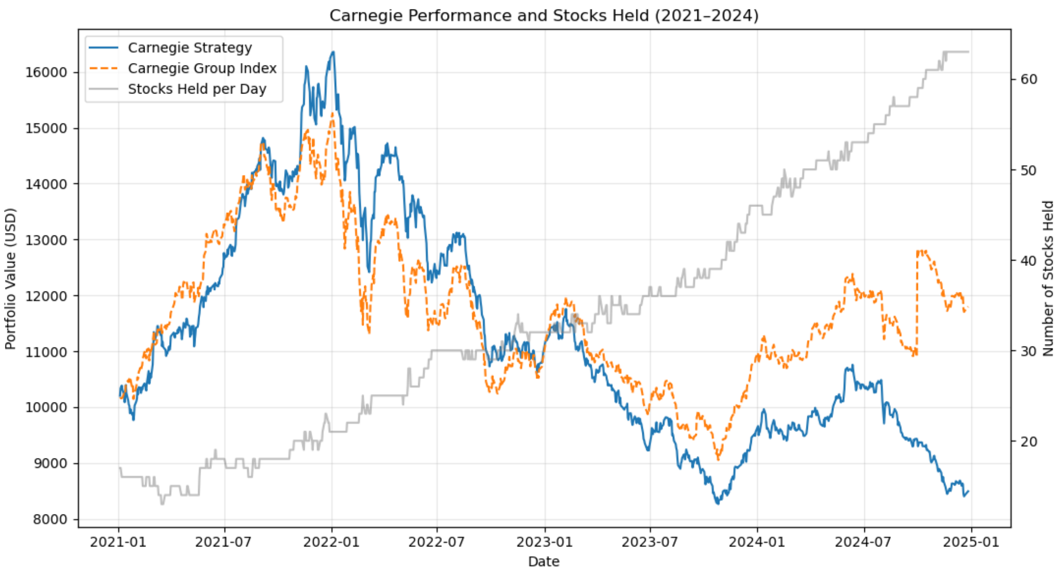

Figure 3. Carnegie Performance and Stocks Held (2021-2024)

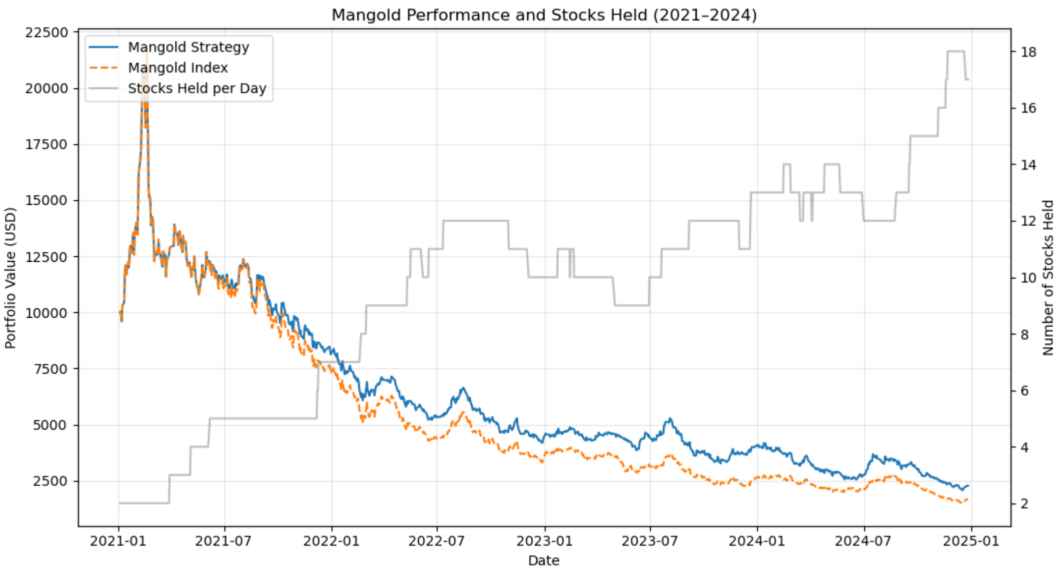

Figure 4. Mangold Performance and Stocks Held (2021-2024)

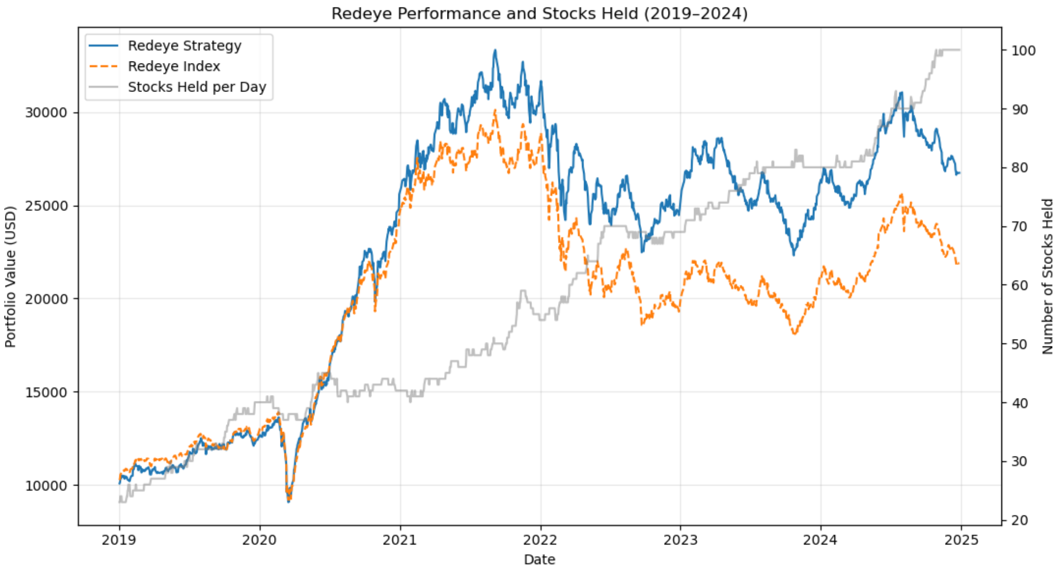

Figure 5. Redeye Performance and Stocks Held (2019-2024)

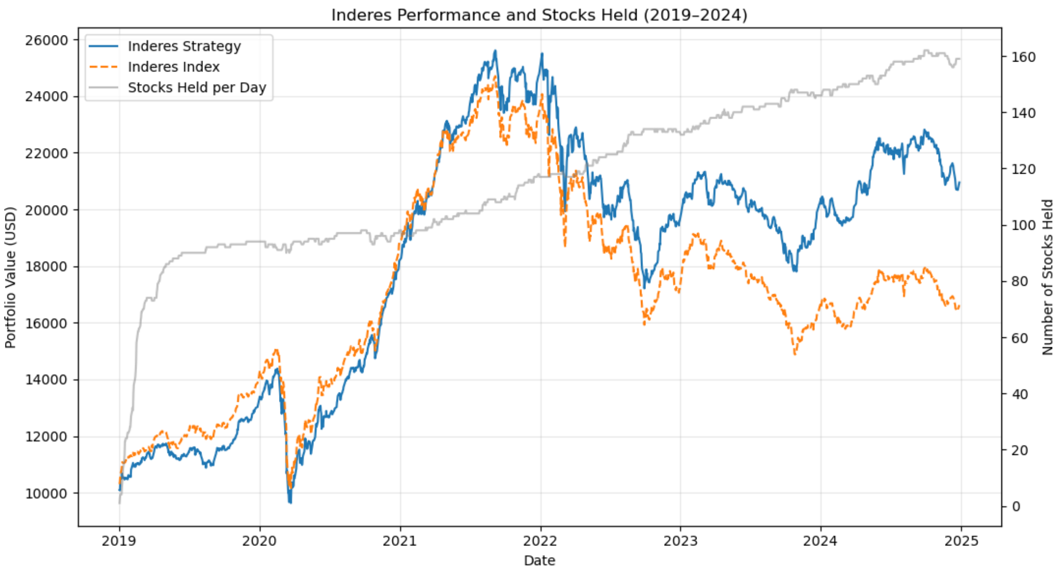

Figure 6. Inderes Performance and Stocks Held (2019-2024)

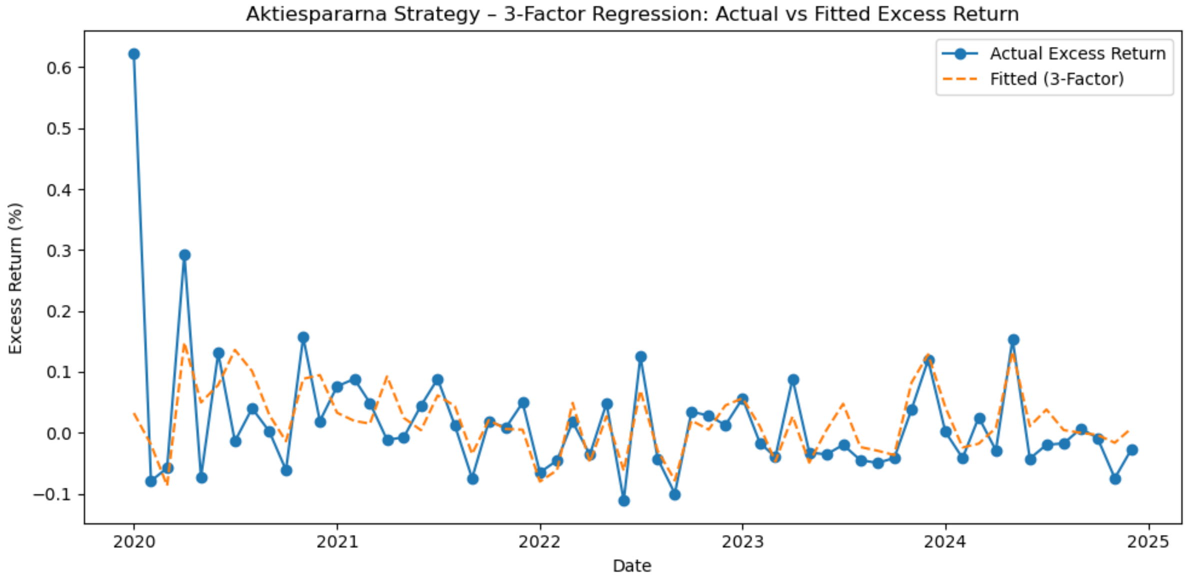

Figure 7. Aktiespararna - Three-Factor Regression: Actual vs Fitted Excess Return

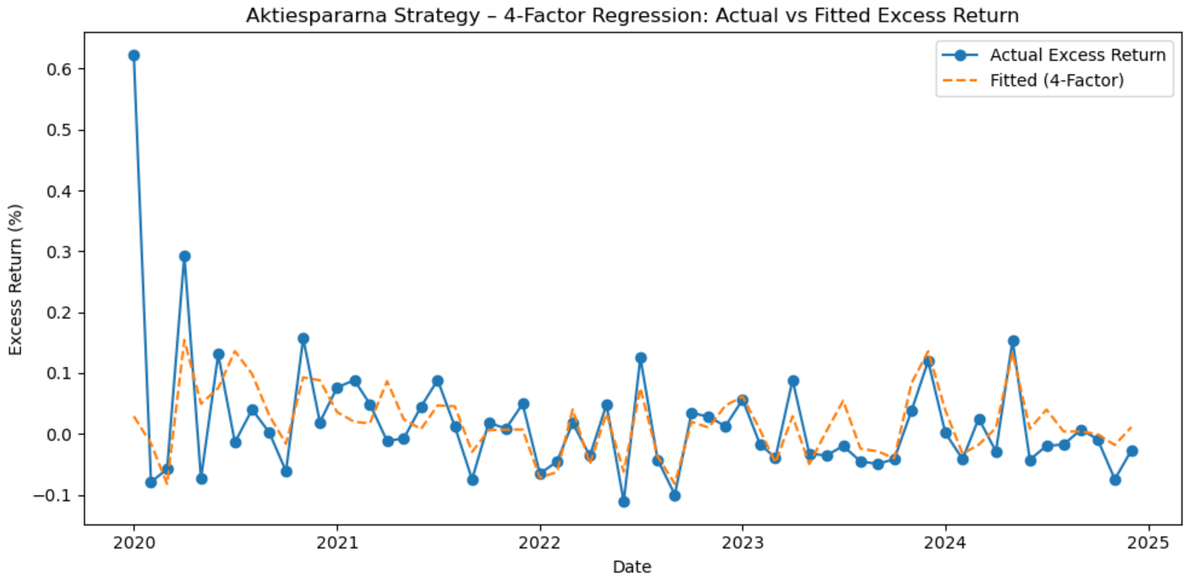

Figure 8. Aktiespararna - Four-Factor Regression: Actual vs Fitted Excess Return

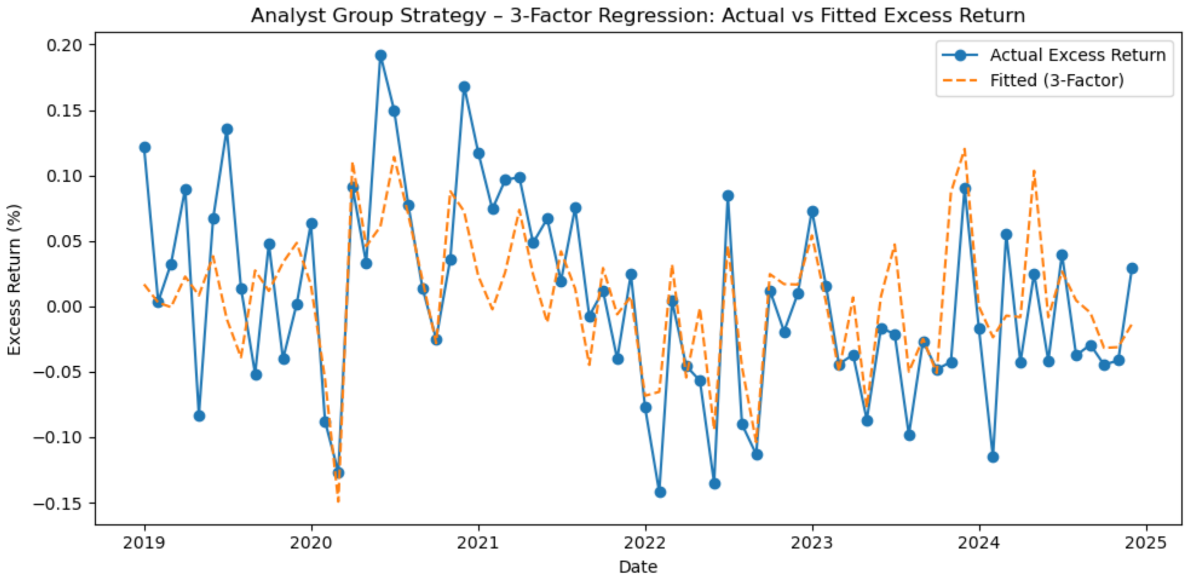

Figure 9. Analyst Group - Three-Factor Regression: Actual vs Fitted Excess Return

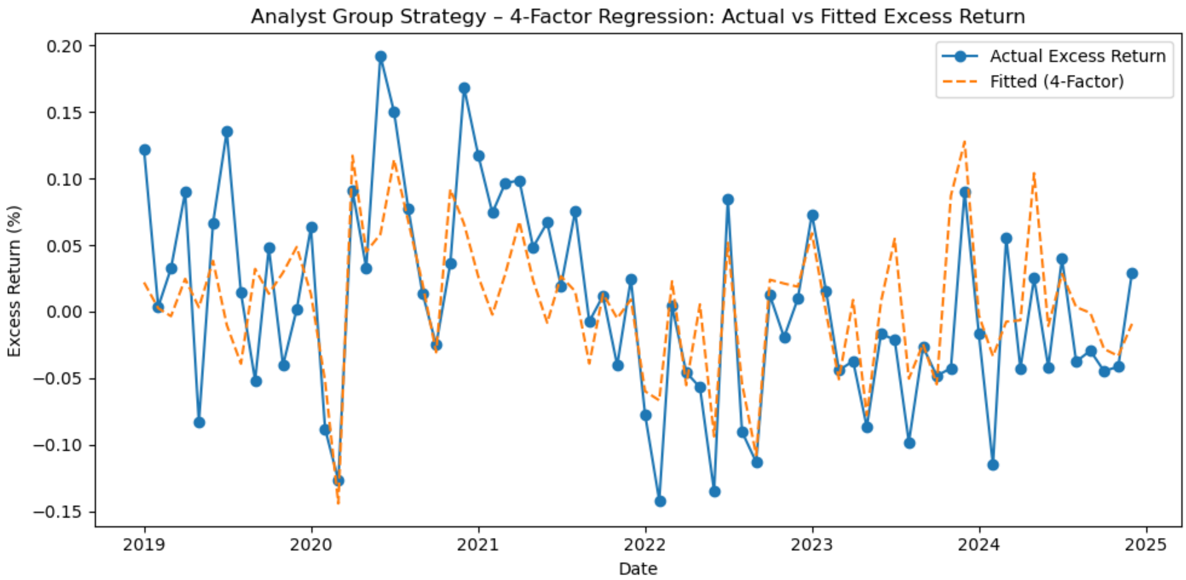

Figure 10. Analyst Group - Four-Factor Regression: Actual vs Fitted Excess Return

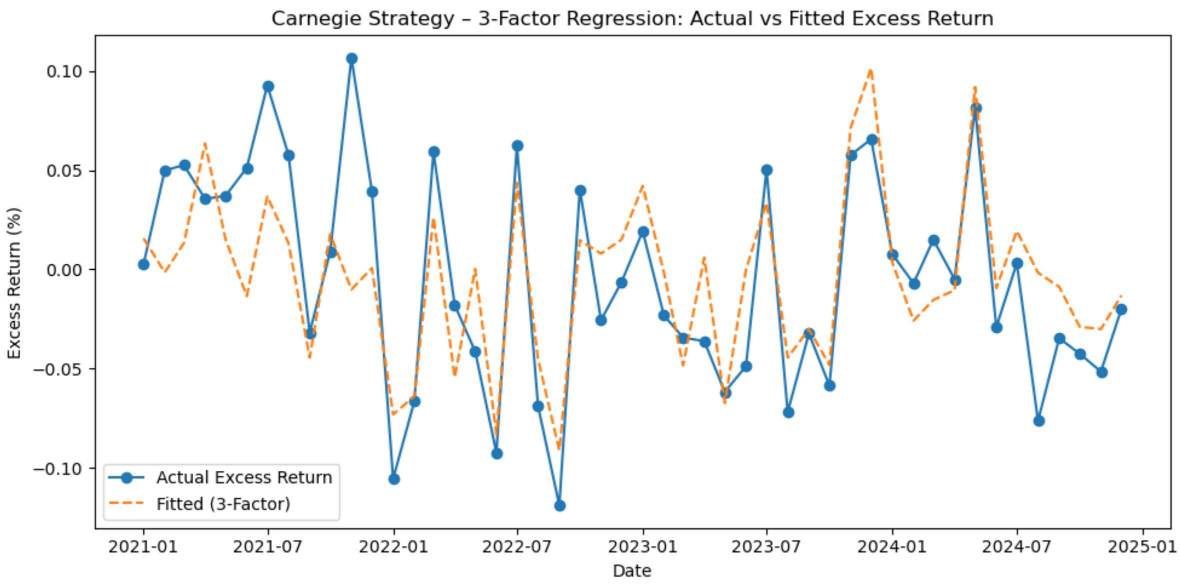

Figure 11. Carnegie - Three-Factor Regression: Actual vs Fitted Excess Return

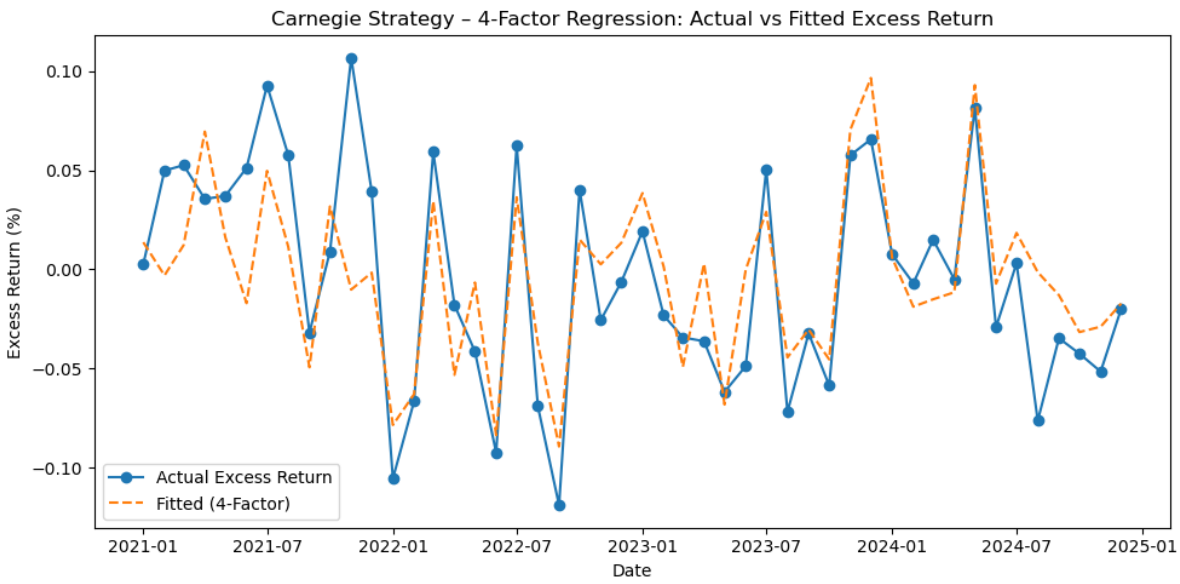

Figure 12. Carnegie - Four-Factor Regression: Actual vs Fitted Excess Return

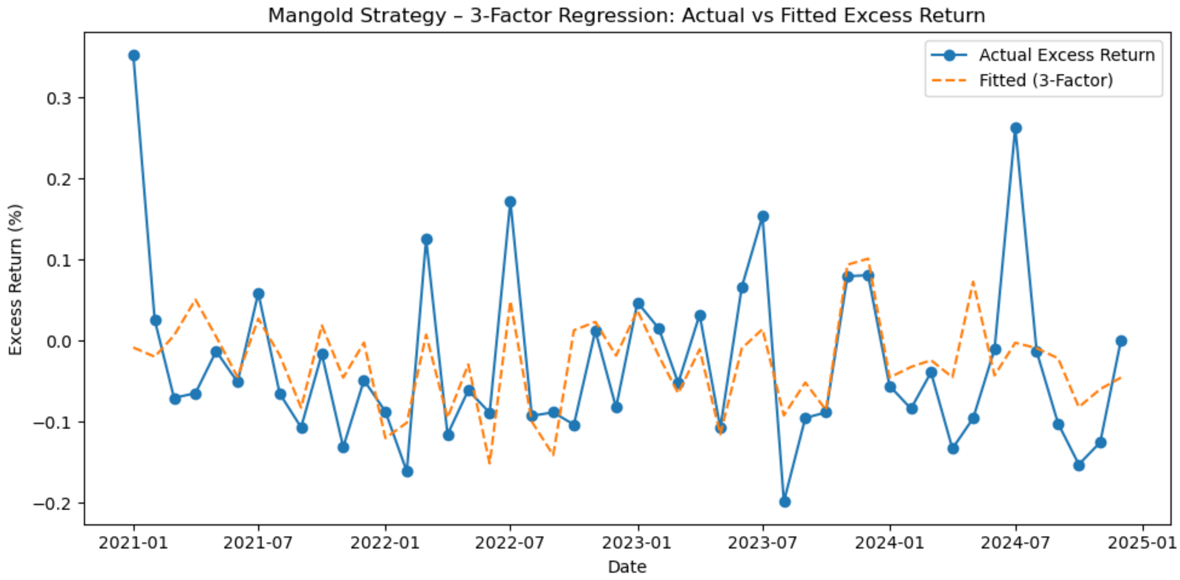

Figure 13. Mangold - Three-Factor Regression: Actual vs Fitted Excess Return

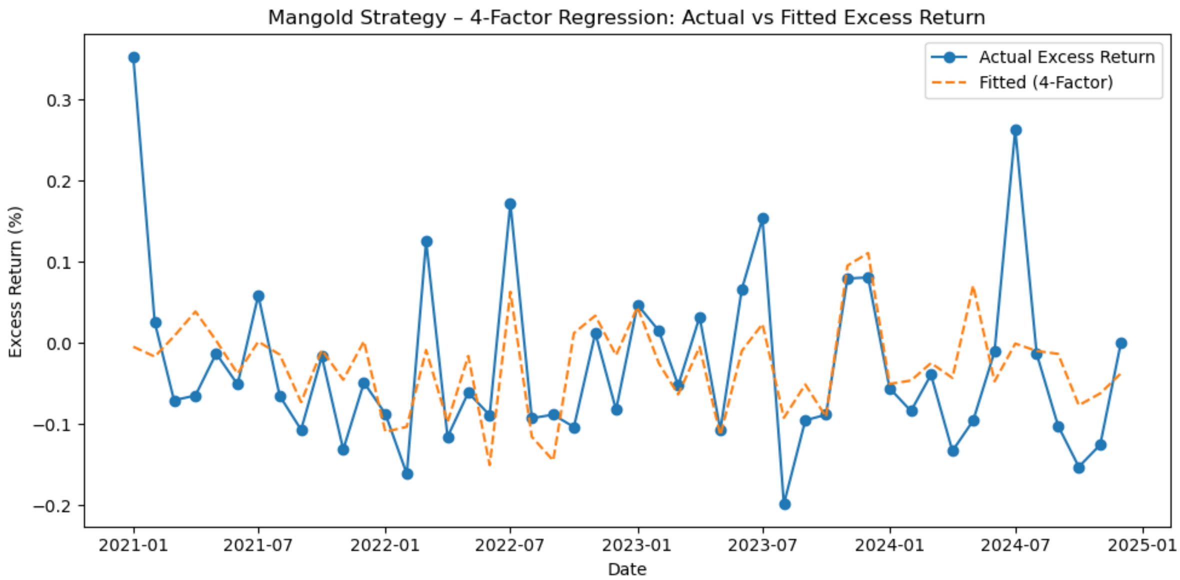

Figure 14. Mangold - Four-Factor Regression: Actual vs Fitted Excess Return

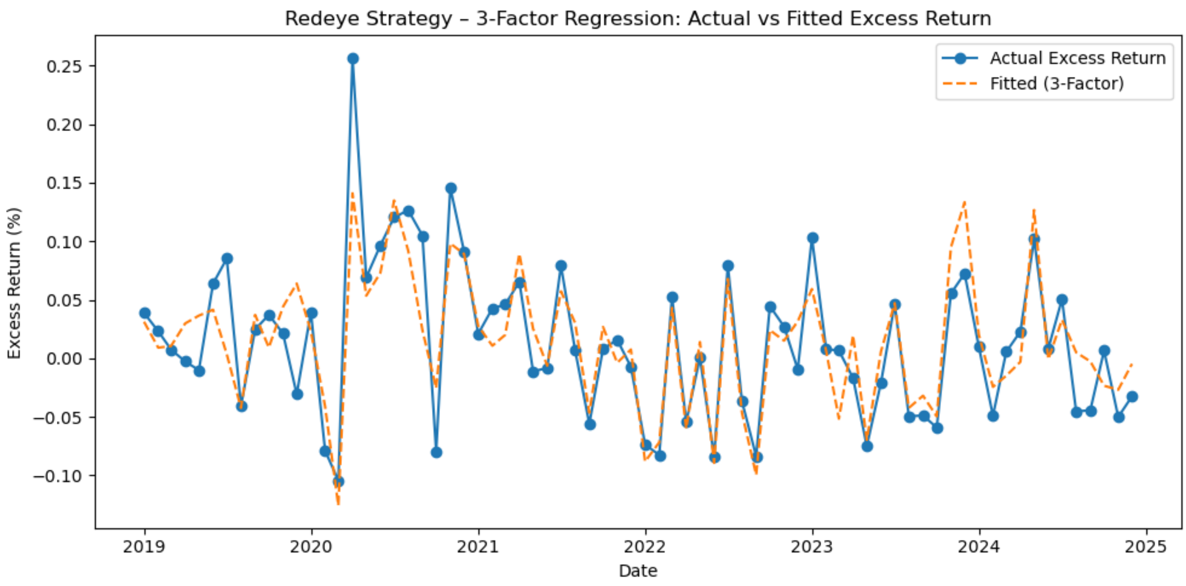

Figure 15. Redeye - Three-Factor Regression: Actual vs Fitted Excess Return

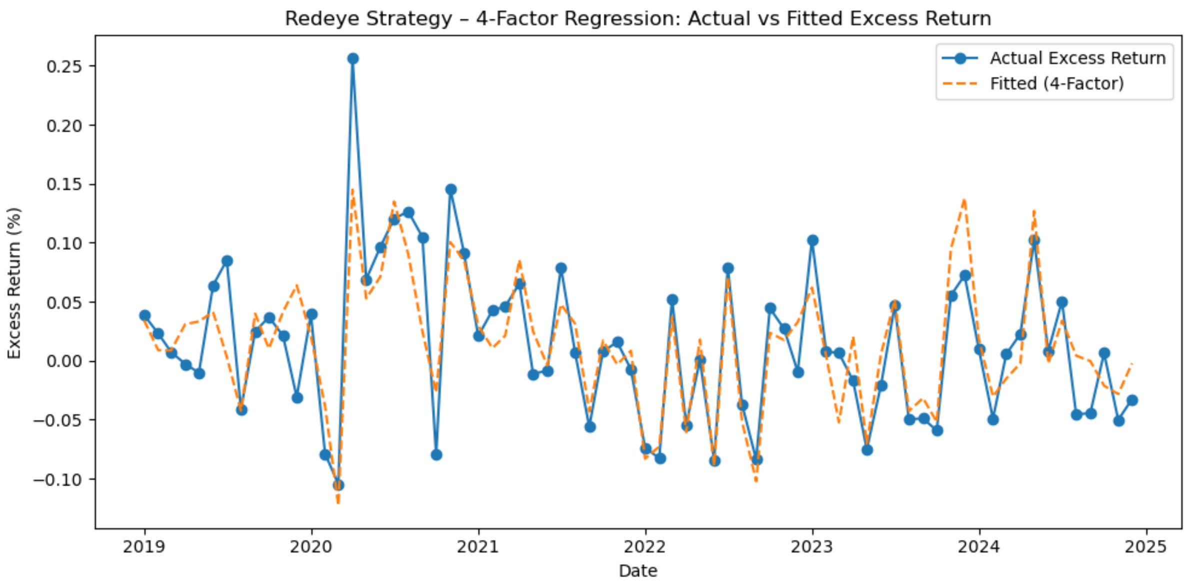

Figure 16. Redeye - Four-Factor Regression: Actual vs Fitted Excess Return

Figure 17. Inderes - Three-Factor Regression: Actual vs Fitted Excess Return

Figure 18. Inderes – Four-Factor Regression: Actual vs Fitted Excess Returns

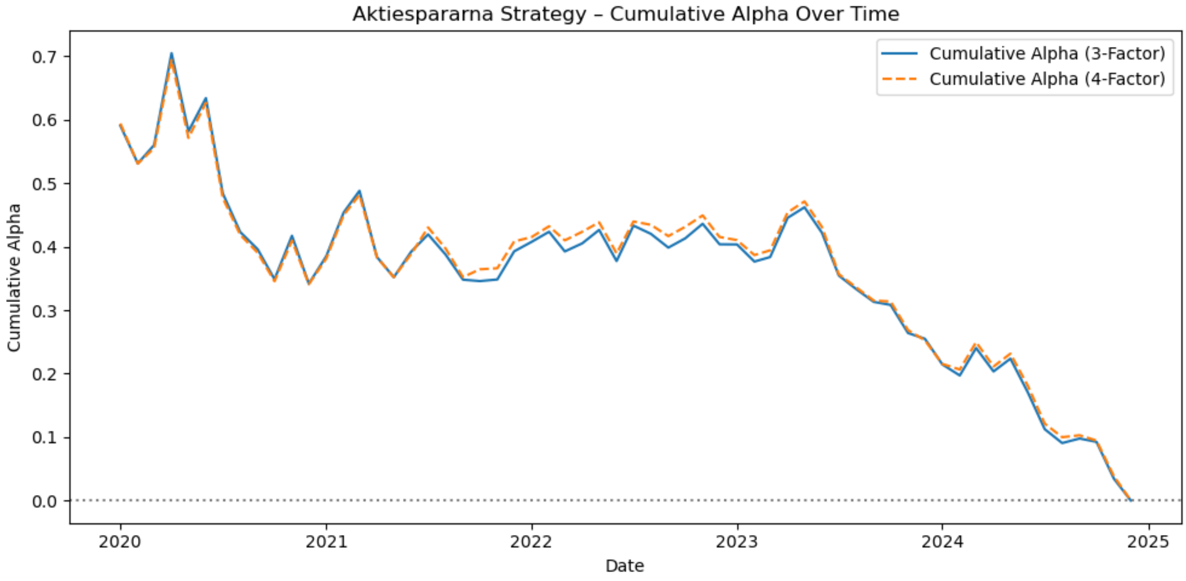

Figure 19. Aktiespararna - Cumulative Alpha Over Time

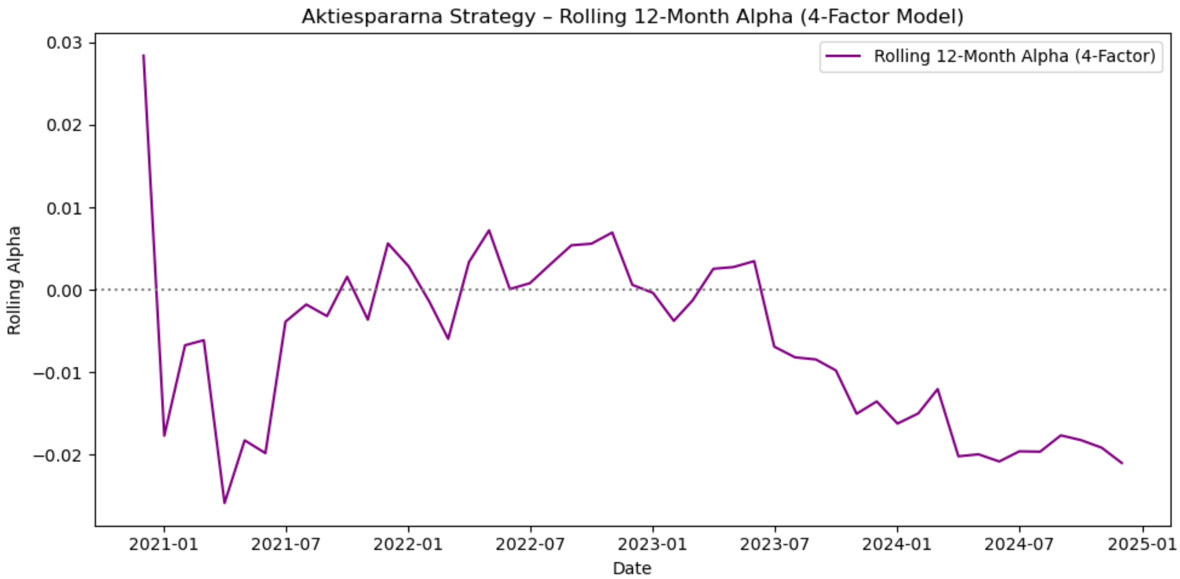

Figure 20. Aktiespararna - Rolling 12-Month Four-Factor Alpha

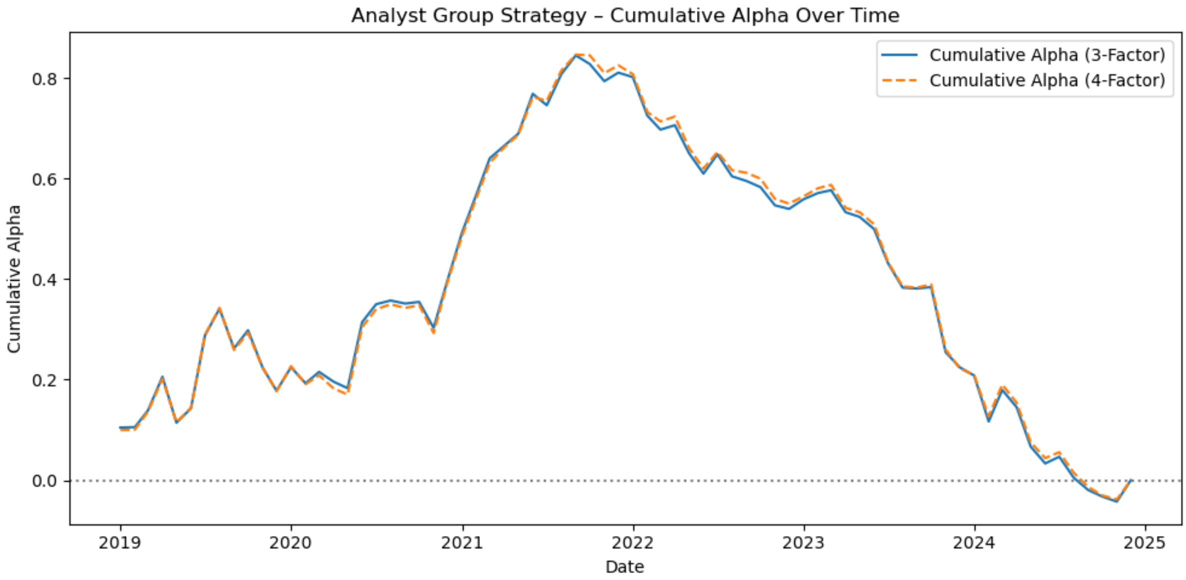

Figure 21. Analyst Group - Cumulative Alpha Over Time

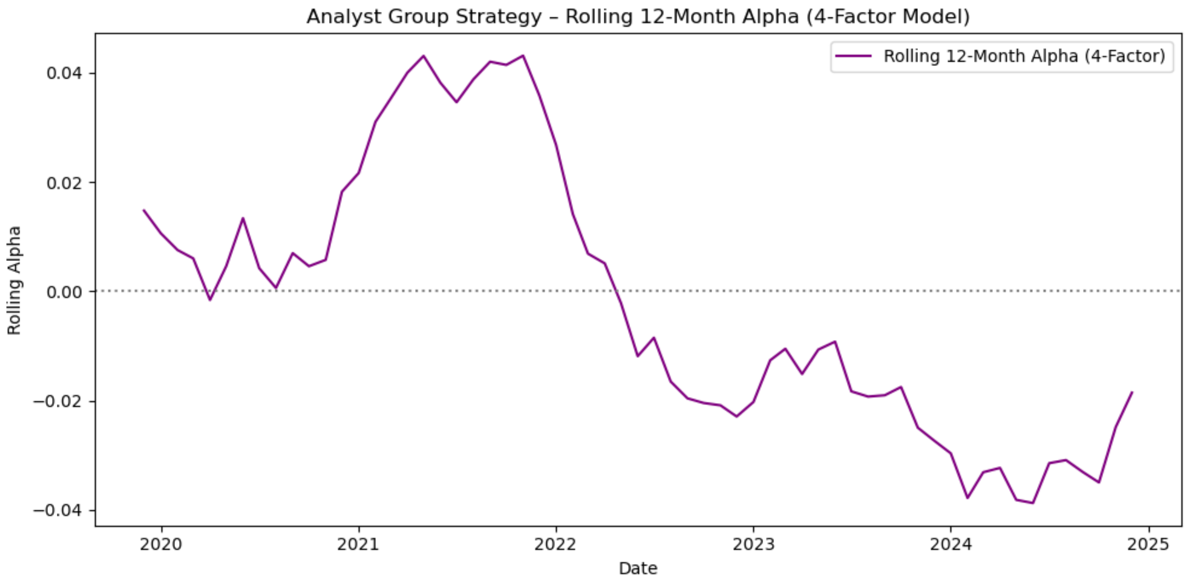

Figure 22. Analyst Group Rolling 12-Month Four-Factor Alpha

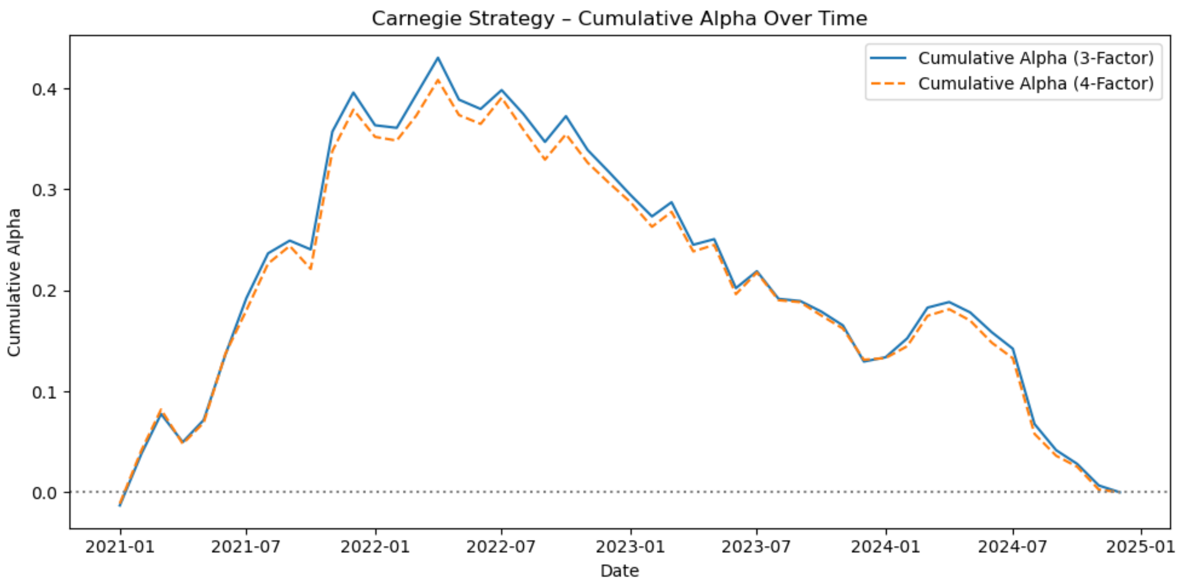

Figure 23. Carnegie Cumulative Alpha Over Time

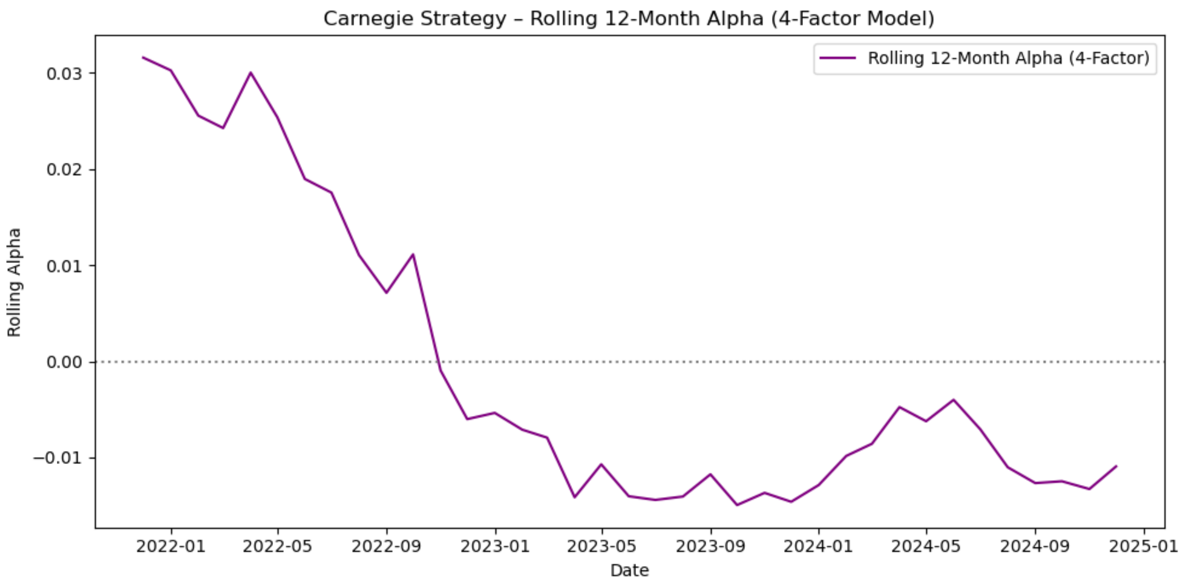

Figure 24. Carnegie Rolling 12-Month Four-Factor Alpha

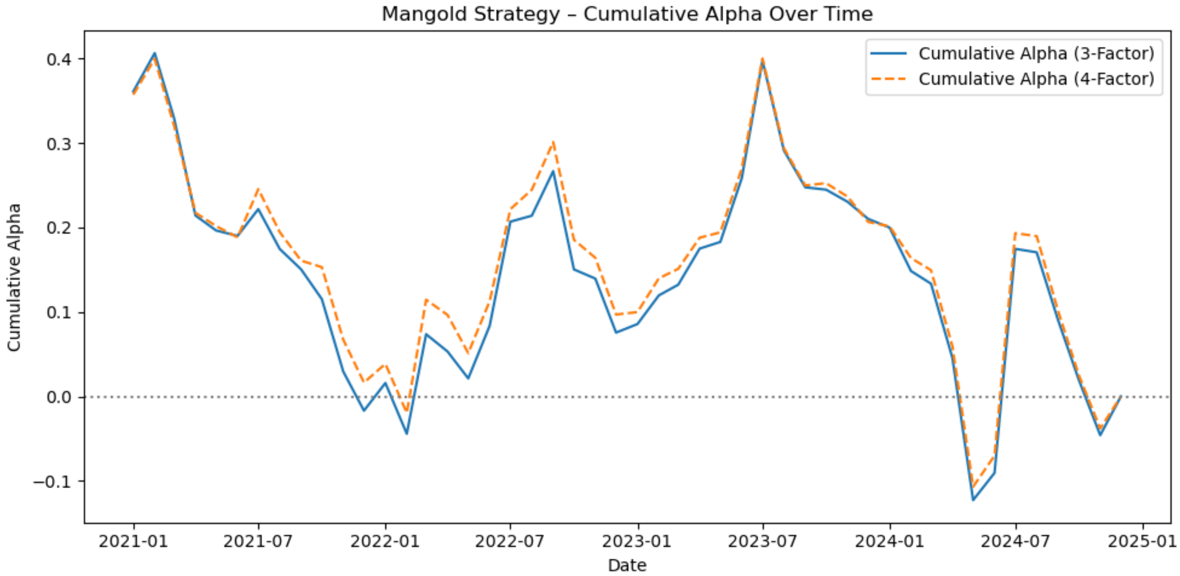

Figure 25. Mangold Cumulative Alpha Over Time

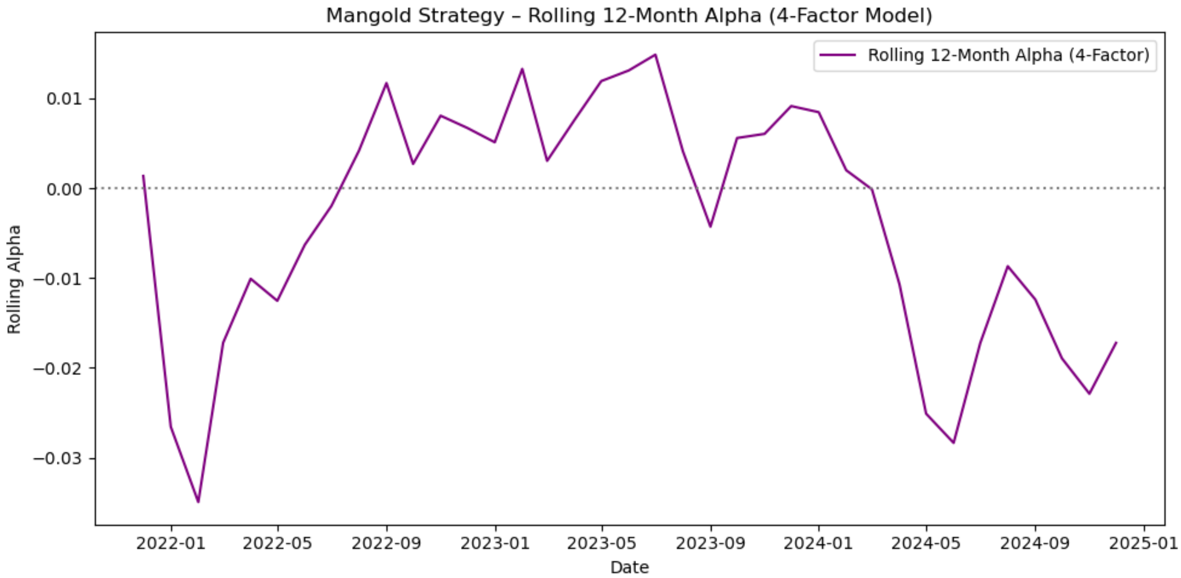

Figure 26. Mangold Rolling 12-Month Four-Factor Alpha

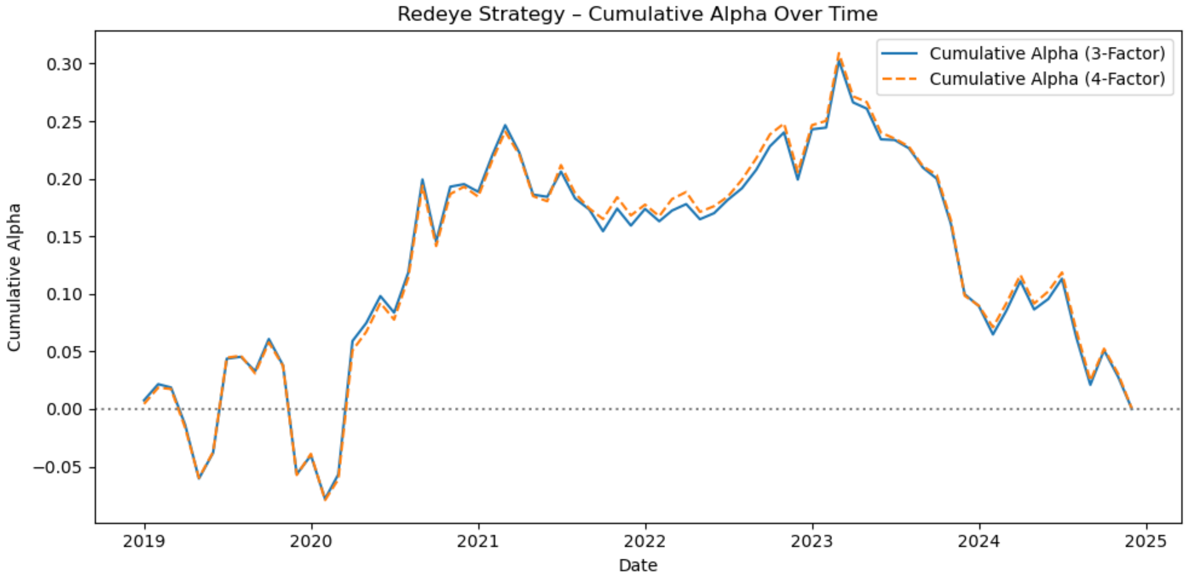

Figure 27. Redeye Cumulative Alpha Over Time

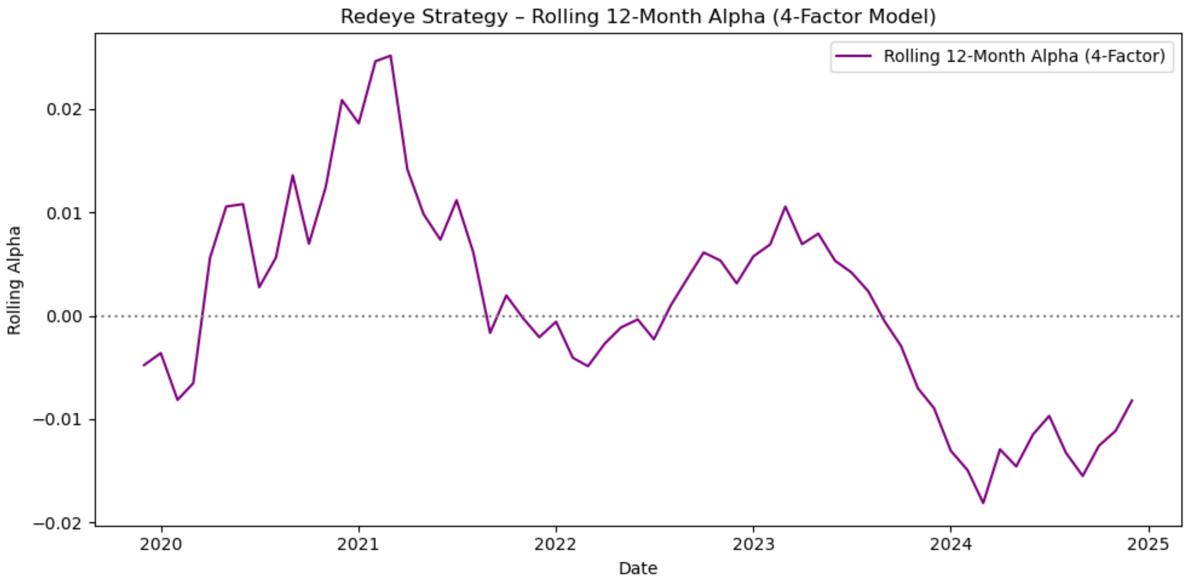

Figure 28. Redeye Rolling 12-Month Four-Factor Alpha

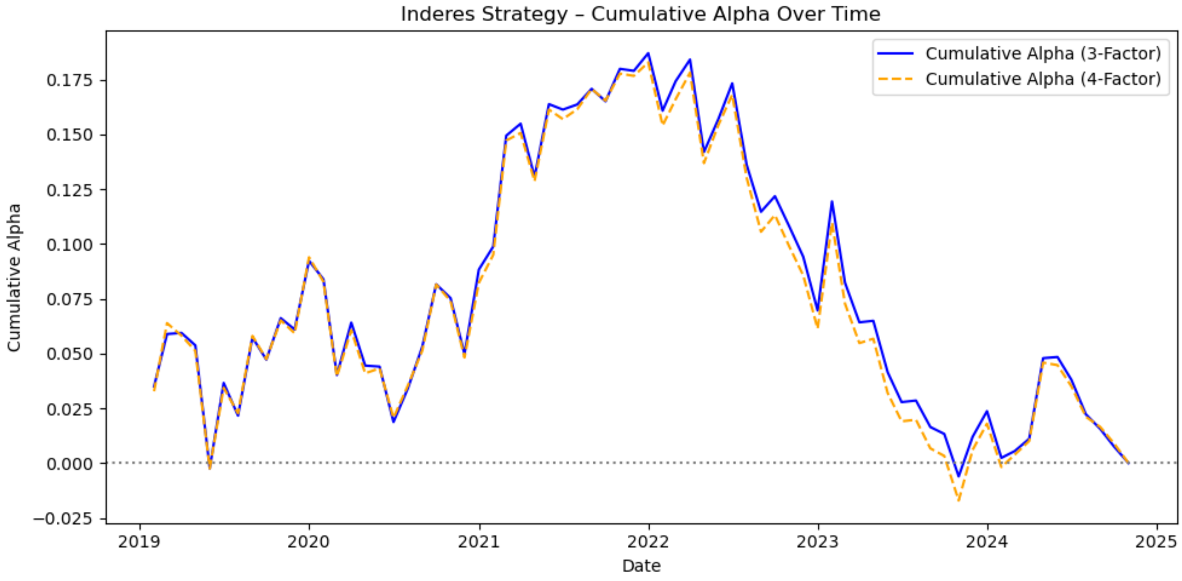

Figure 29. Inderes Cumulative Alpha Over Time

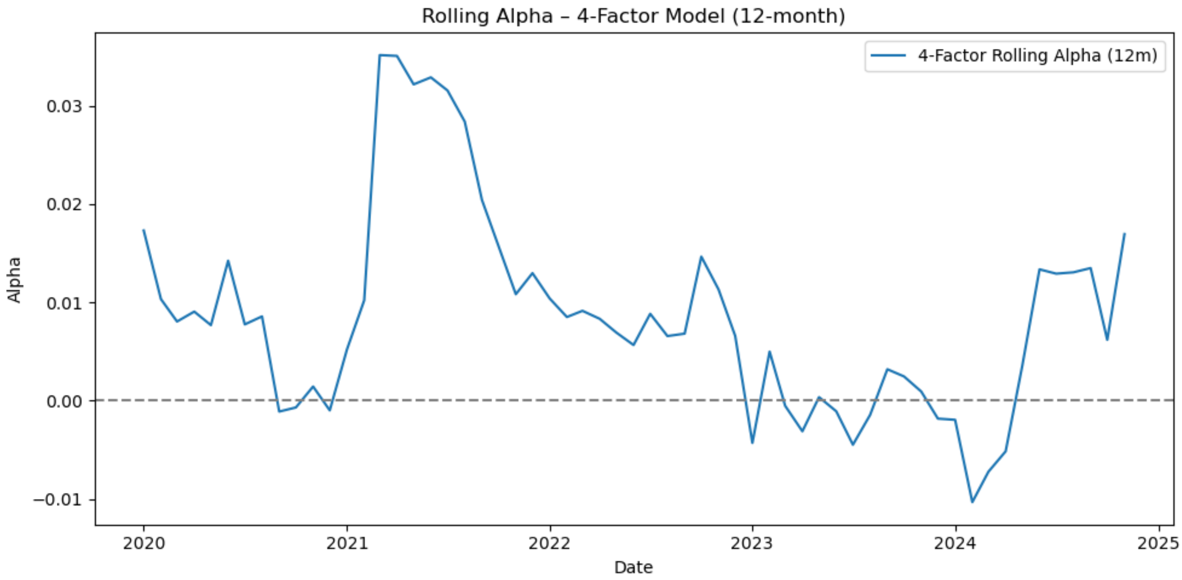

Figure 30. Inderes Rolling 12-Month Four-Factor Alpha

Aktiespararna – 3-Factor Regression Summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Excess_Return   R-squared:                       0.261
Model:                            OLS   Adj. R-squared:                  0.221
Method:                 Least Squares   F-statistic:                     6.587
Date:                Mon, 04 Aug 2025   Prob (F-statistic):           0.000683
Time:                        11:33:27   Log-Likelihood:                 58.521
No. Observations:                  60   AIC:                            -109.0
Df Residuals:                      56   BIC:                            -100.7
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0232      0.013      1.851      0.069      -0.002       0.048
Mkt-RF         0.5399      0.171      3.157      0.003       0.197       0.882
SMB            1.0011      0.393      2.544      0.014       0.213       1.789
HML           -0.3430      0.449     -0.764      0.448      -1.242       0.556
==============================================================================
Omnibus:                       93.014   Durbin-Watson:                   1.517
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1976.318
Skew:                           4.434   Prob(JB):                         0.00
Kurtosis:                      29.681   Cond. No.                         38.7
==============================================================================
```

Table 1. Aktiespararna - Three-Factor OLS-Regression Summary

Aktiespararna – 4-Factor Regression Summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Excess_Return   R-squared:                       0.263
Model:                            OLS   Adj. R-squared:                  0.209
Method:                 Least Squares   F-statistic:                     4.900
Date:                Mon, 04 Aug 2025   Prob (F-statistic):            0.00188
Time:                        11:33:27   Log-Likelihood:                 58.600
No. Observations:                  60   AIC:                            -107.2
Df Residuals:                      55   BIC:                            -96.73
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0246      0.013      1.871      0.067      -0.002       0.051
Mkt-RF         0.5250      0.177      2.971      0.004       0.171       0.879
SMB            0.9815      0.400      2.454      0.017       0.180       1.783
HML           -0.3861      0.467     -0.828      0.411      -1.321       0.549
UMD           -0.1240      0.327     -0.379      0.706      -0.780       0.532
==============================================================================
Omnibus:                       94.385   Durbin-Watson:                   1.508
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2090.209
Skew:                           4.521   Prob(JB):                         0.00
Kurtosis:                      30.465   Cond. No.                         39.9
==============================================================================
```

Table 2. Aktiespararna - Four-Factor OLS-Regression Summary

Analyst Group – 3-Factor Regression Summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Excess_Return   R-squared:                       0.478
Model:                            OLS   Adj. R-squared:                  0.455
Method:                 Least Squares   F-statistic:                     20.76
Date:                Mon, 04 Aug 2025   Prob (F-statistic):           1.17e-09
Time:                        11:25:25   Log-Likelihood:                 108.95
No. Observations:                  72   AIC:                            -209.9
Df Residuals:                      68   BIC:                            -200.8
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0064      0.007      0.963      0.339      -0.007       0.020
Mkt-RF         0.6634      0.095      6.980      0.000       0.474       0.853
SMB            0.7177      0.208      3.446      0.001       0.302       1.133
HML            0.1125      0.247      0.455      0.650      -0.381       0.606
==============================================================================
Omnibus:                        2.206   Durbin-Watson:                   1.666
Prob(Omnibus):                  0.332   Jarque-Bera (JB):                1.654
Skew:                           0.362   Prob(JB):                        0.437
Kurtosis:                       3.164   Cond. No.                         39.1
==============================================================================
```

Table 3. Analyst Group - Three-Factor OLS-Regression Summary

Analyst Group – 4-Factor Regression Summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Excess_Return   R-squared:                       0.482
Model:                            OLS   Adj. R-squared:                  0.451
Method:                 Least Squares   F-statistic:                     15.58
Date:                Mon, 04 Aug 2025   Prob (F-statistic):           4.63e-09
Time:                        11:25:26   Log-Likelihood:                 109.22
No. Observations:                  72   AIC:                            -208.4
Df Residuals:                      67   BIC:                            -197.1
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0079      0.007      1.129      0.263      -0.006       0.022
Mkt-RF         0.6447      0.099      6.516      0.000       0.447       0.842
SMB            0.7086      0.209      3.383      0.001       0.291       1.127
HML            0.0640      0.257      0.249      0.804      -0.449       0.578
UMD           -0.1302      0.182     -0.715      0.477      -0.493       0.233
==============================================================================
Omnibus:                        2.344   Durbin-Watson:                   1.629
Prob(Omnibus):                  0.310   Jarque-Bera (JB):                1.744
Skew:                           0.368   Prob(JB):                        0.418
Kurtosis:                       3.201   Cond. No.                         41.5
==============================================================================
```

Table 4. Analyst Group - Four-Factor OLS-Regression Summary

Carnegie – 3-Factor Regression Summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Excess_Return   R-squared:                       0.595
Model:                            OLS   Adj. R-squared:                  0.567
Method:                 Least Squares   F-statistic:                     21.56
Date:                Mon, 04 Aug 2025   Prob (F-statistic):           9.69e-09
Time:                        11:37:22   Log-Likelihood:                 93.791
No. Observations:                  48   AIC:                            -179.6
Df Residuals:                      44   BIC:                            -172.1
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0034      0.006      0.598      0.553      -0.008       0.015
Mkt-RF         0.5605      0.082      6.847      0.000       0.396       0.726
SMB            0.6858      0.179      3.821      0.000       0.324       1.047
HML           -0.0406      0.216     -0.188      0.852      -0.476       0.395
==============================================================================
Omnibus:                        9.165   Durbin-Watson:                   1.528
Prob(Omnibus):                  0.010   Jarque-Bera (JB):                8.692
Skew:                           0.822   Prob(JB):                       0.0130
Kurtosis:                       4.283   Cond. No.                         43.2
==============================================================================
```

Table 5. Carnegie - Three-Factor OLS-Regression Summary

Carnegie – 4-Factor Regression Summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Excess_Return   R-squared:                       0.602
Model:                            OLS   Adj. R-squared:                  0.565
Method:                 Least Squares   F-statistic:                     16.25
Date:                Mon, 04 Aug 2025   Prob (F-statistic):           3.51e-08
Time:                        11:37:22   Log-Likelihood:                 94.197
No. Observations:                  48   AIC:                            -178.4
Df Residuals:                      43   BIC:                            -169.0
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0021      0.006      0.353      0.726      -0.010       0.014
Mkt-RF         0.5808      0.085      6.796      0.000       0.408       0.753
SMB            0.7155      0.183      3.903      0.000       0.346       1.085
HML            0.0292      0.232      0.126      0.900      -0.438       0.496
UMD            0.1153      0.135      0.856      0.397      -0.156       0.387
==============================================================================
Omnibus:                        9.871   Durbin-Watson:                   1.676
Prob(Omnibus):                  0.007   Jarque-Bera (JB):                9.713
Skew:                           0.853   Prob(JB):                      0.00778
Kurtosis:                       4.396   Cond. No.                         46.7
==============================================================================
```

Table 6. Carnegie - Four-Factor OLS-Regression Summary

Mangold – 3-Factor Regression Summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Excess_Return   R-squared:                       0.278
Model:                            OLS   Adj. R-squared:                  0.229
Method:                 Least Squares   F-statistic:                     5.650
Date:                Mon, 04 Aug 2025   Prob (F-statistic):            0.00230
Time:                        11:40:39   Log-Likelihood:                 46.959
No. Observations:                  48   AIC:                            -85.92
Df Residuals:                      44   BIC:                            -78.43
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0221      0.015     -1.464      0.150      -0.053       0.008
Mkt-RF         0.8249      0.217      3.798      0.000       0.387       1.263
SMB            0.4861      0.476      1.021      0.313      -0.473       1.446
HML            0.0877      0.573      0.153      0.879      -1.068       1.243
==============================================================================
Omnibus:                       28.433   Durbin-Watson:                   1.407
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               61.577
Skew:                           1.667   Prob(JB):                     4.25e-14
Kurtosis:                       7.436   Cond. No.                         43.2
==============================================================================
```

Table 7. Mangold - Three-Factor OLS-Regression Summary

Mangold – 4-Factor Regression Summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Excess_Return   R-squared:                       0.285
Model:                            OLS   Adj. R-squared:                  0.218
Method:                 Least Squares   F-statistic:                     4.279
Date:                Mon, 04 Aug 2025   Prob (F-statistic):            0.00529
Time:                        11:40:40   Log-Likelihood:                 47.181
No. Observations:                  48   AIC:                            -84.36
Df Residuals:                      43   BIC:                            -75.01
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0195      0.016     -1.240      0.222      -0.051       0.012
Mkt-RF         0.7850      0.228      3.449      0.001       0.326       1.244
SMB            0.4277      0.488      0.876      0.386      -0.557       1.412
HML           -0.0496      0.617     -0.080      0.936      -1.293       1.194
UMD           -0.2268      0.359     -0.632      0.531      -0.950       0.497
==============================================================================
Omnibus:                       27.737   Durbin-Watson:                   1.416
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               58.192
Skew:                           1.640   Prob(JB):                     2.31e-13
Kurtosis:                       7.282   Cond. No.                         46.7
==============================================================================
```

Table 8. Mangold - Four-Factor OLS-Regression Summary

Redeye – 3-Factor Regression Summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Excess_Return   R-squared:                       0.728
Model:                            OLS   Adj. R-squared:                  0.716
Method:                 Least Squares   F-statistic:                     60.75
Date:                Mon, 04 Aug 2025   Prob (F-statistic):           3.28e-19
Time:                        11:43:42   Log-Likelihood:                 141.80
No. Observations:                  72   AIC:                            -275.6
Df Residuals:                      68   BIC:                            -266.5
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0147      0.004      3.499      0.001       0.006       0.023
Mkt-RF         0.6662      0.060     11.062      0.000       0.546       0.786
SMB            0.9015      0.132      6.830      0.000       0.638       1.165
HML           -0.1718      0.157     -1.097      0.277      -0.484       0.141
==============================================================================
Omnibus:                        7.990   Durbin-Watson:                   1.983
Prob(Omnibus):                  0.018   Jarque-Bera (JB):                9.887
Skew:                           0.462   Prob(JB):                      0.00713
Kurtosis:                       4.563   Cond. No.                         39.1
==============================================================================
```

Table 9. Redeye - Three-Factor OLS-Regression Summary

Redeye – 4-Factor Regression Summary

OLS Regression Results

Dep. Variable:	Excess_Return	R-squared:	0.730
Model:	OLS	Adj. R-squared:	0.714
Method:	Least Squares	F-statistic:	45.33
Date:	Mon, 04 Aug 2025	Prob (F-statistic):	2.22e-18
Time:	11:43:43	Log-Likelihood:	142.05
No. Observations:	72	AIC:	-274.1
Df Residuals:	67	BIC:	-262.7
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0156	0.004	3.532	0.001	0.007	0.024
Mkt-RF	0.6548	0.063	10.442	0.000	0.530	0.780
SMB	0.8959	0.133	6.749	0.000	0.631	1.161
HML	-0.2013	0.163	-1.235	0.221	-0.527	0.124
UMD	-0.0793	0.115	-0.687	0.494	-0.310	0.151

Omnibus:	6.565	Durbin-Watson:	1.971
Prob(Omnibus):	0.038	Jarque-Bera (JB):	7.632
Skew:	0.385	Prob(JB):	0.0220
Kurtosis:	4.397	Cond. No.	41.5

Table 10. Redeye - Four-Factor OLS-Regression Summary

3-Factor Regression Summary

OLS Regression Results

Dep. Variable:	Excess_Return	R-squared:	0.821
Model:	OLS	Adj. R-squared:	0.812
Method:	Least Squares	F-statistic:	100.6
Date:	Thu, 21 Aug 2025	Prob (F-statistic):	1.42e-24
Time:	12:59:38	Log-Likelihood:	165.89
No. Observations:	70	AIC:	-323.8
Df Residuals:	66	BIC:	-314.8
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0084	0.003	3.007	0.004	0.003	0.014
Mkt-RF	0.7740	0.052	14.940	0.000	0.671	0.877
SMB	0.4991	0.096	5.189	0.000	0.307	0.691
HML	0.1242	0.086	1.449	0.152	-0.047	0.295

Omnibus:	0.145	Durbin-Watson:	2.382
Prob(Omnibus):	0.930	Jarque-Bera (JB):	0.290
Skew:	0.092	Prob(JB):	0.865
Kurtosis:	2.745	Cond. No.	36.1

Table 11. Inderes - Three-Factor OLS-Regression Summary

4-Factor Regression Summary

OLS Regression Results

Dep. Variable:	Excess_Return	R-squared:	0.822
Model:	OLS	Adj. R-squared:	0.811
Method:	Least Squares	F-statistic:	75.17
Date:	Thu, 21 Aug 2025	Prob (F-statistic):	1.15e-23
Time:	12:59:39	Log-Likelihood:	166.21
No. Observations:	70	AIC:	-322.4
Df Residuals:	65	BIC:	-311.2
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0090	0.003	3.097	0.003	0.003	0.015
Mkt-RF	0.7744	0.052	14.901	0.000	0.671	0.878
SMB	0.5049	0.097	5.217	0.000	0.312	0.698
HML	0.1194	0.086	1.385	0.171	-0.053	0.292
UMD	-0.0651	0.084	-0.776	0.440	-0.233	0.102

Omnibus:	0.306	Durbin-Watson:	2.350
Prob(Omnibus):	0.858	Jarque-Bera (JB):	0.477
Skew:	0.112	Prob(JB):	0.788
Kurtosis:	2.663	Cond. No.	36.6

Table 12. Inderes - Four-Factor OLS-Regression Summary