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Signal or Noise?

The Changing Impact of Analyst Recommendations in Volatile Markets

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Abstract

This study investigates the predictive power of analyst recommendations, with particular emphasis on their effectiveness during periods of market stability compared to times of crisis. Drawing on a sample of Swedish listed companies from 2014 to 2024, we construct portfolios based on favourable (buy), neutral (hold), and unfavourable (sell) recommendations to assess whether these signals differentiate between companies with superior and inferior future performance. Our analysis covers a stable market period (2014-2019) and a crisis period (2020-2024), marked by the COVID-19 pandemic and the Russian invasion of Ukraine. We find that, under stable market conditions, favourable recommendations are associated with significantly positive abnormal returns and alpha, while neutral and unfavourable recommendations exhibit weaker and statistically insignificant performance. However, during the crisis period, the predictive power of analyst recommendations diminishes considerably. Although favourably rated stocks continue to deliver the highest raw returns, their risk-adjusted performance deteriorates, and none of the portfolios generate statistically significant abnormal returns or alpha. These findings indicate that analyst recommendations are more informative in stable environments but lose much of their effectiveness amid heightened uncertainty and macroeconomic volatility.

Keywords: analyst recommendations, portfolio performance, monthly rebalancing, abnormal returns, market efficiency, COVID-19, Russian invasion of Ukraine

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1. Introduction

Over the past decade, the ten best-performing companies on the Stockholm Stock Exchange have each experienced stock price increases exceeding 1,000%. However, it has proven difficult for retail investors to identify such top performers over the long term (Dagens PS, 2024). In financial markets saturated with information, investors frequently turn to professional analysts for guidance on capital allocation. Among the most widely followed outputs of these experts are consensus stock recommendations, which distil the collective views of analysts into simplified buy, hold, or sell signals. These recommendations are not only easily accessible but also highly influential, capable of moving markets and shaping investor sentiment. Yet, despite their popularity, a central question remains: can these recommendations reliably identify over- and underperforming stocks?

Previous research presents mixed evidence on the value of analyst recommendations. Stickel (1995) found that such recommendations could generate short-term abnormal returns, particularly around the announcement date, although the magnitude depended on factors such as analyst reputation and recommendation strength. In contrast, Altınkılıç and Hansen (2009) questioned their informational value, suggesting that observed price reactions were often driven by concurrent company announcements rather than the analysts' own insights. Barber et al. (2001) reported that while top-rated stocks produced significant gross abnormal returns, these were largely offset by transaction costs, thereby limiting their practical profitability.

Jegadeesh et al. (2004) contributed further nuance by identifying two potential mechanisms behind future returns following recommendation changes. First, analysts may interpret qualitative, firm-specific developments that are not captured by quantitative models, thereby providing genuinely new information. Second, analysts may act as opinion leaders, creating price momentum by shaping market sentiment. During crisis periods, however, these mechanisms may function differently, either becoming less effective due to heightened uncertainty and reduced predictability or losing influence as investors shift their attention to macroeconomic factors. Based on this reasoning, one might expect analysts' ability to issue profitable recommendations to weaken during crisis periods compared to more stable times. Supporting this, Barber et al. (2003) found that the accuracy of analyst recommendations declined during financial crises, such as the dot-com bubble, with the most highly recommended stocks underperforming the least favoured ones. However, to our knowledge, no study has examined whether these findings persist during the crises of the 2020s, making it particularly relevant to investigate the effectiveness of analyst recommendations in recent periods of heightened volatility.

This thesis examines the performance of analyst stock recommendations under conditions of economic instability. Specifically, we assess whether recommendations issued during recent crises, such as the COVID-19 pandemic and the Russian invasion of Ukraine, generate abnormal returns compared to those issued during a stable reference period without major disruptions. By assessing the profitability of following analyst recommendations across different market conditions, we aim to evaluate their predictive accuracy and adaptability in times of heightened uncertainty. To date, this topic has not been examined in the context of the Swedish market or in relation to these recent crisis events. Moreover, these crises differ markedly from earlier financial crises due to their non-financial origins stemming from exogenous shocks, which arguably make them more difficult for analysts to predict and respond to.

Accordingly, we aim to answer the following research questions:

1. Do investors generate excess returns by following analyst recommendations?

2. Does the ability to generate excess returns differ during periods of crisis?

To address these questions, we construct three equally-weighted portfolios that are rebalanced monthly, based on analyst consensus recommendations. Portfolio 1 contains the most favourable (buy) recommendations, while Portfolio 3 includes the least favourable (sell) recommendations. We then calculate the monthly returns of these portfolios and evaluate their performance relative to a benchmark index comprising all stocks covered by analysts. Monthly abnormal returns, defined as the difference between portfolio returns and the benchmark, are then compared across portfolios and time periods. Additionally, we apply the Fama and French (1993) three-factor model to control for common risk factors and assess whether our findings remain robust. The study examines analyst recommendations for publicly listed companies on the Stockholm Stock Exchange from January 2014 to November 2024.

Our results indicate that analyst recommendations exhibit some ability to differentiate stock performance, particularly under stable market conditions. The portfolio with the most favourable recommendations, Portfolio 1, is the only one that generates both positive and statistically significant abnormal returns and alpha during the reference period. However, during the crisis period, analysts' predictive power diminishes, as abnormal returns and alpha for all three portfolios turn negative and become statistically insignificant. These findings suggest that while analyst recommendations may provide value in stable markets, their predictive power is substantially reduced in times of market stress, underlining their conditional effectiveness depending on market context.

The remainder of this thesis is structured as follows. Section two presents the relevant theoretical frameworks and reviews previous research, followed by the proposed hypotheses. Section three describes the data used in the study and the research method employed to address our research questions. Section four presents descriptive statistics and the empirical results. In section five, we discuss and interpret our findings in relation to existing literature. Finally, section six concludes the thesis and offers suggestions for future research.

2. Literature and Theory

2.1 Market Efficiency

The Efficient Market Hypothesis (EMH), as formulated by Fama (1970), asserts that financial markets are informationally efficient, meaning that security prices at any given time fully reflect all available information. Consequently, it should not be possible to consistently achieve abnormal returns that outperform the market by relying on information already known to the public, as securities are assumed to trade at their intrinsic values.

The EMH is commonly divided into weak, semi-strong, and strong forms of efficiency. The weak form holds that prices incorporate all historical price data; the semi-strong form holds that all publicly available information is reflected in prices; and the strong form holds that prices fully reflect all public and private information (Fama, 1970).

However, historical market anomalies, including asset bubbles and market crashes, challenge the notion of complete efficiency by demonstrating that prices can deviate substantially from their fundamental values. These deviations are frequently attributed to information asymmetries, behavioural biases, market frictions, and institutional inefficiencies. Nevertheless, such disruptions are difficult to predict or systematically exploit and therefore do not necessarily contradict the long-run tendencies proposed by the EMH (Malkiel, 2003).

Despite these challenges, the concept and forms of market efficiency remain highly relevant for understanding how financial information is interpreted and acted upon. In particular, the semi-strong form has direct implications for the potential value of analyst recommendations. To better understand how prices are formed within an efficient market, it is essential to consider how stock prices are initially set and subsequently determined in the secondary market.

The initial price of a stock is determined during an initial public offering (IPO) when a company offers its shares to the public for the first time. This process involves establishing the company's valuation, determining the number of shares to be issued, and setting the offering price based on various financial and market-based metrics (Ritter, 2003). Once publicly traded, a stock's price is determined by supply and demand. This price reflects the market's perception of the company's current and future value, primarily driven by expectations of future earnings (Nasdaq, 2024).

Price movements are influenced by external factors, including macroeconomic conditions such as interest rates, inflation, unemployment, geopolitical tensions, and regulatory changes, as well as firm-specific factors such as financial performance, strategic decisions, operational developments, and sectoral trends (Chen, Roll, and Ross, 1986). These factors shape investor sentiments and expectations, which in turn affect demand and, consequently, stock prices.

Building on these insights into price movements, the Fama-French Three-Factor (FF3) Model, introduced by Fama and French (1993), represents a foundational advancement in asset pricing theory by extending traditional models such as the Capital Asset Pricing Model (CAPM). While the CAPM posits that a security's expected return is determined solely by its exposure to market risk (beta), the FF3 model incorporates two additional explanatory variables: the size factor (SMB) and the value factor (HML) (Sharpe, 1964; Fama and French, 1993). Specifically, SMB captures the historical excess returns of small-cap stocks over large-cap stocks, while HML reflects the outperformance of high book-to-market (value) stocks relative to low book-to-market (growth) stocks.

These additional factors emerged from empirical findings showing that certain stock characteristics, particularly small size and high book-to-market ratios, were consistently correlated with higher returns, even after controlling for market risk. By incorporating SMB and HML, the model enhanced the explanatory power for cross-sectional differences in equity returns and provided a more comprehensive benchmark for performance attribution in stock and fund analysis (Fama and French, 1993).

In practice, to assess a company's intrinsic value, investors rely on various valuation methods. However, such assessments can be complex, as they involve interpreting both quantitative and qualitative information under uncertainty. In this context, financial analysts play a critical role in reducing information asymmetry by analysing and communicating relevant information (Healy and Palepu, 2001). Analyst recommendations thereby facilitate more informed investment decisions. If a stock recommendation has an immediate impact on a company's stock price, it is because it reveals new information about the company, which supports the notion that pricing is influenced by perceived informational value (Asquith, Mikhail, and Au, 2005).

2.2 Security Analyst Recommendations

2.2.1 The Role and Impact of Security Analysts and Recommendations

The value and impact of stock recommendations issued by security analysts have long attracted interest from both academia and the financial community. Extensive prior research presents conflicting evidence, thereby contributing to the ongoing debate on whether such recommendations can generate returns exceeding a relevant benchmark (Stickel, 1995; Barber et al., 2001; Altınkılıç and Hansen, 2009). The inconsistencies observed in the existing literature are likely attributable to differences in geographical scope, sample periods, and methodologies used to model expected returns. These factors may lead to materially different results, as noted in the aforementioned studies. This debate is closely connected to theoretical notions of market efficiency and the extent to which analyst input can be seen as informative or redundant.

According to the EMH, analyst recommendations should not generate excess returns, particularly under the semi-strong form, as the underlying information is assumed to be already reflected in prices (Fama, 1970). However, the distinction between unprocessed public information and the analytical evaluations produced by analysts raises the question of whether interpretation and synthesis alone constitute value creation. This ambiguity suggests that analysts could, in fact, contribute valuable information to the investment process, particularly in contexts where they possess superior analytical frameworks or access to corporate management and investor networks, thereby challenging the weaker forms of market efficiency.

Equity research analysts issue stock recommendations as part of broader research reports, which often include target prices, earnings forecasts, and qualitative assessments of company prospects. Such recommendations are based on a combination of fundamental analysis, financial modelling, and sector-specific expertise. Recommendations are commonly expressed as buy, hold, or sell, and are disseminated through investment banks, brokerage platforms, or financial media. Institutional investors often receive more timely or comprehensive access, whereas retail investors typically rely on public disclosures (Brauer and Wiersema, 2018). While the impact of such recommendations varies, their potential to influence investor behaviour may be particularly pronounced during periods of heightened market uncertainty.

Although research on analyst performance can be traced back to Cowles (1933), more recent studies offer a nuanced understanding, particularly regarding the effectiveness of buy and sell recommendations.

2.2.2 Research on Buy and Sell Recommendations

Stickel (1995) examined the impact of buy and sell recommendations on US stock prices between 1988 and 1991, drawing on a sample comprising 55% buy, 12% sell, and the remainder hold recommendations. This distribution reflects a broader market tendency to favour buy over sell recommendations. He found that brokerage house recommendations significantly affected prices in both the short and long term, with abnormal returns primarily concentrated around announcement dates. However, he noted that such findings could be misleading, as price reactions depend on several factors, including recommendation strength, the magnitude of the change, analyst reputation, brokerage and company size, and contemporaneous earnings forecast revisions. While most of these effects were temporary, only recommendation strength, company size, and forecast revisions appeared to have lasting informational effects on the market. Importantly, Stickel did not incorporate transaction costs into his analysis, which could substantially reduce or even offset the reported abnormal returns. He further showed that more informative recommendations, which incorporate multiple reinforcing factors, resulted in significantly higher abnormal returns.

In contrast, Altınkılıç and Hansen (2009) questioned the informational value of analyst recommendations, arguing that observed price reactions often reflected firm-specific announcements rather than material information generated by the analyst. They demonstrated that recommendations were frequently issued in close proximity to events such as earnings releases, creating a contamination effect when measuring abnormal returns, as the market reaction reflects both the recommendation and the underlying event. This suggests that analysts often “piggyback” on recently disclosed information, using it to time their revisions and enhance their perceived stock-picking ability rather than contribute genuinely new information. Once the influence of preceding news was accounted for, short-term market reactions became statistically insignificant, indicating that recommendation revisions were uninformative.

Despite concerns about the informational content of recommendations, other researchers have examined whether such recommendations can nonetheless be used to construct profitable trading strategies. Barber et al. (2001) investigated whether investors could achieve abnormal returns by engaging in daily rebalancing and trading based on public consensus analyst recommendations between 1986 and 1996. They found that portfolios based on the most and least favourable recommendations delivered significant annual abnormal gross returns, even after controlling for size and book-to-market effects. A trading strategy involving long positions in favourably rated stocks and short positions in unfavourably rated ones resulted in even greater abnormal returns. These gains, however, were largely offset by substantial transaction costs, including bid-ask spreads and commissions resulting from frequent trading, ultimately leaving no reliably positive net returns. Notably, less frequent rebalancing, such as weekly or monthly reallocation, reduced turnover and thus transaction costs, but also diminished gross returns, particularly for highly rated stocks, as the strategy became less responsive to changes in recommendations. Furthermore, the study underscored analysts' persistent reluctance to issue negative recommendations, with approximately 47% classified as buy and only around 6% as sell. This tendency may reflect a preference, particularly among analysts at large institutions, to discontinue coverage of underperforming companies rather than risk future investment banking relationships by issuing negative ratings. While the gross returns suggested semi-strong market inefficiencies, the authors concluded that net profitability was ultimately eroded by substantial trading frictions.

Building on these insights, Jegadeesh et al. (2004) shifted the focus to whether analyst recommendations provide incremental investment value beyond established return predictors, using US data from 1985 to 1998. The authors found that analysts systematically favoured "glamour stocks", characterised by high growth, momentum, and trading volume, while neglecting value stocks, despite the historical tendency of the latter to outperform. After controlling for twelve quantitative signals, including momentum, valuation, growth, and volume, the absolute level of consensus recommendations exhibited limited predictive power. By contrast, changes in recommendations emerged as more robust predictors of future returns, as these revisions appeared to convey information not already captured by known signals.

These findings led the authors to propose two potential explanations: (i) analysts may provide insights orthogonal to existing quantitative indicators, potentially by interpreting firm-specific developments; or (ii) analysts may function as opinion leaders whose recommendation changes influence market prices, thereby generating self-reinforcing price momentum. Moreover, the study highlighted how structural biases, driven by analysts' economic incentives, ultimately undermined the objectivity and long-term informational value of their recommendations.

2.2.3 Crisis Effects on Markets and Analyst Recommendations

Beyond the general dynamics of buy and sell recommendations, market conditions have been shown to significantly affect their accuracy and effectiveness. Barber et al. (2003) found that during the dot-com bubble and the subsequent downturn in the early 2000s, highly rated stocks underperformed, in contrast to their strong performance during the bullish late 1990s. Interestingly, stocks with the lowest recommendations generated positive abnormal returns during the downturn, suggesting a reversal in the predictive value of analyst recommendations under crisis conditions. This shift reflected broader underperformance among analysts, driven by delayed model adjustments and a continued preference for small-cap growth stocks, despite their substantial losses during the market correction.

During stable economic periods such as 2014 to 2019, analysts have typically relied on historical financial data and economic trends to make relatively accurate forecasts. However, in times of crisis, characterised by inflationary shocks and geopolitical tensions, as observed between 2020 and 2024, sudden macroeconomic disruptions have challenged the reliability of traditional valuation models. In this context, Hwang and Salmon (2004) examined the Russian and Asian crises of the late 1990s and observed pronounced herding behaviour in the South Korean and US markets. This further complicated analysts' forecasting efforts and contributed to increased market volatility. In contrast, Yarovaya, Matkovskyy, and Jalan (2021) investigated the impact of "black swan" events on cryptocurrency markets and found no increase in herding behaviour during the COVID-19 pandemic, suggesting that the dynamics of herding may vary considerably across asset classes.

Analyst activity and the quality of financial forecasts have also been influenced by uncertainty in the corporate environment. Bilinski (2023) reported that analysts increased both their research output and the number of forecast revisions in response to the COVID-19 pandemic, compared to the pre-pandemic period. Zhang et al. (2022) further noted that analysts became increasingly distracted by rapid market changes, which led to a decrease in both the dispersion of forecasts and the number of earnings estimates issued. Supporting this, Yukselturk and Tucker (2015) analysed narrative sentiment in UK analyst reports during the Global Financial Crisis from 2006 to 2010. Their findings indicated that the influence of thematic sentiment on stock recommendations and target prices varied across pre-crisis, crisis, and post-crisis periods. Prior to the crisis, negative sentiments regarding macroeconomic and regulatory conditions were strongly associated with analysts' outputs, a relationship that diminished during the crisis but re-emerged afterward. Sentiment related to growth showed only a weak positive effect before the crisis and disappeared thereafter, while sentiment regarding financial performance became a significant positive driver following the crisis. These results suggest that analysts adopted a "back to basics" approach in the aftermath of the crisis, placing renewed emphasis on financial fundamentals in their assessments.

In addition to analyst behaviour, Sun (2021) evaluated the performance of the Fama-French Five-Factor (FF5) Model across US industry portfolios before and after the onset of the COVID-19 pandemic. The study found that the model's explanatory power improved during the early phase of the pandemic, implying that it captured cross-industry return variations more effectively under heightened volatility. However, the increase in unexplained variation pointed to the emergence of new risk factors not incorporated in traditional asset pricing models.

Similarly, Harjoto and Rossi (2023) assessed the impact of the COVID-19 pandemic declaration on emerging equity markets, comparing them to developed markets. Their analysis of cumulative abnormal returns revealed that emerging markets experienced a more severe negative reaction, particularly among small-cap and growth stocks. Sectoral variation was also observed, with healthcare and telecommunications proving more resilient, while financial and energy sectors were disproportionately affected. Notably, both developed and emerging markets were found to recover more rapidly from the COVID-19 shock than from the 2008 Global Financial Crisis, underscoring differences in investor responses and market dynamics across crises.

Finally, Yousaf, Patel, and Yarovaya (2022) investigated the financial market impact of the Russia-Ukraine conflict across G20 nations. Their findings indicated significant negative abnormal returns in both European and Asian stock markets following the outbreak of the conflict. Similarly, Ahmed et al. (2023) found that European stock markets experienced significant negative abnormal returns on the event day, with adverse effects persisting in the subsequent days. The severity of these effects varied across industries, countries, and company sizes, with sectors such as consumer staples, financials, and utilities among the most impacted. These results highlight that even traditionally defensive sectors were not immune to geopolitical shocks, underscoring the need to account for geopolitical risk in investment decisions and portfolio management strategies.

2.3 Hypotheses

This thesis aims to evaluate the accuracy of stock recommendations across different market conditions by comparing their effectiveness during a relatively stable period (2014-2019) with that observed in a more volatile and crisis-prone period (2020-2024). By analysing recommendation performance in these contrasting environments, our study seeks to contribute to the broader literature on the reliability of financial analysis and its implications for investors.

Based on previous research in this area, we propose the following hypotheses:

H1: Stocks with favourable (unfavourable) consensus recommendations are expected to outperform (underperform) their benchmark and generate positive (negative) abnormal returns over the reference period (2014-2019).

H2: During the crisis period (2020-2024), stocks with favourable (unfavourable) consensus recommendations are expected to underperform (outperform) relative to the reference period.

3. Method

3.1 Sample and Data Selection

This study uses data from two separate datasets. Firstly, we use the Institutional Brokers' Estimate System (IBES) to collect analyst recommendations for companies listed on the Stockholm Stock Exchange, covering those listed on both Nasdaq Stockholm and First North. The analyst recommendations from IBES are given on a rating from 1 to 5, with 1 being the most highly recommended stocks and 5 the least recommended, as shown in Table 1. We use the consensus recommendation for each company, which is calculated as the average of all individual analyst recommendations.

Table 1: Analyst consensus recommendations collected from IBES

Value	Meaning
1.00 - 1.49	Strong buy
1.50 - 2.49	Buy
2.50 - 3.49	Hold
3.50 - 4.49	Underperform
4.50 - 5.00	Sell

Secondly, we retrieve monthly data from Compustat - Capital IQ on the stock closing prices, shares outstanding, and book value of equity, all reported in the local currency, SEK. We also use the Swedish Riksbank Repo Rate as a proxy for the risk-free rate. For the book-to-market ratio, we use both market value and book value of equity. The market value for each company is computed by multiplying the closing stock price with the number of shares outstanding for each period.

This study covers public companies and analyst recommendations on the Stockholm Stock Exchange between January 2014 and November 2024. We divide the sample into two distinct periods. The reference period (January 2014 - December 2019) is selected to provide a baseline of market behaviour under relatively stable economic conditions. In contrast, the crisis period (January 2020 - November 2024) captures the effects of extraordinary market disruptions, including the COVID-19 pandemic and the wartime period. This division enables meaningful comparisons between stable and volatile market environments.

To construct our sample, we first identify all public companies that are listed on the Stockholm Stock Exchange at any point between 2014 and 2024. This includes companies listed throughout the entire period, as well as those listed or delisted during the timeframe, resulting in an initial pool of 898 individual companies. Next, we exclude 552 companies due to either (i) a lack of analyst coverage on IBES during our study period or (ii) missing data on stock prices, shares outstanding, or book value of equity, thereby reducing the sample to 346 companies. We then remove 3 companies that exhibit clear outliers in the dataset before finalising the sample. Our final sample thus comprises 343 individual companies, from which we collect a total of 25,498 analyst recommendations.

3.2 Research Design

To determine whether investors can earn abnormal returns from following analyst recommendations, we first construct portfolios based on the consensus recommendations, which refer to the average recommendation, for all stocks covered by at least one analyst. The average recommendation for company *i* on date $t-1$, denoted $\hat{A}_{t-1}$, is calculated by summing the individual recommendations A_{t-1} made by n_{t-1} analysts who have outstanding recommendations for the company during that month, and dividing the total by n_{t-1} (Barber et al., 2001):

$$\hat{A}_{t-1} = 1/n_{t-1} \times \sum^{nt-1}{}_{i=1} A_{t-1} \quad (1)$$

We use equally-weighted portfolios to ensure that each stock contributes equally to portfolio returns, regardless of company size. This approach is particularly relevant given the diverse composition of our sample, which includes both small- and large-cap companies. A value-weighted portfolio could obscure the predictive power of analyst recommendations for smaller companies. Since larger companies receive more weight in such portfolios, and because markets are generally more efficient for these companies, this may bias the results against finding evidence of abnormal returns (Barber et al., 2001). This supports our choice of using equally-weighted portfolios, as they are more likely to capture effects that may be present among smaller, less efficiently priced stocks. Prior research applies both equally-weighted and value-weighted portfolios, with the choice often varying depending on sample composition and research focus. One limitation of using equally-weighted portfolios is that they tend to result in higher turnover and transaction costs, while also increasing exposure to illiquid stocks, particularly smaller companies that are less frequently traded (Battaglia and Leal, 2017).

We group all stocks into three equally-weighted portfolios based on average analyst recommendations: buy, hold, and sell, following the classification presented in Table 2. The first portfolio comprises the most highly recommended stocks (strong buy and buy), the second includes stocks with hold recommendations, and the third contains the least favourably recommended stocks (underperform and sell). We construct only three portfolios, broadly following Barber et al. (2001), but with adjustments to better reflect the structure of analyst recommendations on the Swedish stock market, where recommendations are issued at three levels (buy, hold, and sell), and to ensure clear cutoffs that fairly represent the distribution of recommendations across companies (Stickel, 1995; Barber et al., 2001). Although sell recommendations are relatively infrequent, we maintain them as a distinct category, unlike Barber et al. (2001), to preserve their potential informational value.

Table 2: Portfolio classification based on the average of analyst recommendations

Portfolio	**Limits for Consensus Recommendations (CONREC)**
1 (Buy)	1.00 ≤ CONREC ≤ 2.50
2 (Hold)	2.50 < CONREC ≤ 3.50
3 (Sell)	3.50 < CONREC ≤ 5.00

Note: CONREC denotes the consensus recommendation, based on the average of analyst recommendations, as shown in Table 1 in section *3.1 Sample and Data Selection*.

We rebalance the portfolios monthly, primarily due to data availability, as analyst recommendations from the IBES database for the Swedish market are made available only monthly. If a stock's consensus recommendation changes during the month, we reassign it to the appropriate portfolio at the beginning of the following month. This rebalancing frequency better reflects the behaviour of passive retail investors, who, unlike institutional investors, typically adjust their portfolios less frequently due to delayed access to updated recommendations or the impracticality of daily rebalancing (Kirilova, 2021). Monthly rebalancing may influence our results, as established by Barber et al. (2001), who found that less frequent rebalancing leads to lower abnormal returns, particularly for highly recommended stocks, where timely reactions are crucial to capture the price drift following recommendation changes, and delays can result in holding downgraded stocks during periods of adverse price movements. After assigning stocks to portfolios, we calculate the monthly equally-weighted return for each portfolio. If a new analyst initiates coverage of a stock mid-month, the stock is added to the relevant portfolio at the beginning of the next month.

Portfolio Returns

For each period in our sample, we calculate the equally-weighted monthly return for portfolio *p*, as given by the equation below:

$$R_{pm} = 1/n \times \sum_{i=1}^{n} R_{im} \tag{2}$$

where:

- R_{pm} = return of portfolio p in month m
- n = total number of stocks in portfolio p
- R_{im} = return of stock i in month m

Benchmark Returns

To evaluate each portfolio's performance over the sample period, we compare portfolio returns to a benchmark. We construct this benchmark index using all the stocks included in our study. Since the benchmark covers a large share of the total market value, it serves as a reasonable proxy for the overall market performance. The monthly return of the index is calculated according to the following equation:

$$R_{bm} = 1/n \times \sum_{i=1}^{n} R_{im} \tag{3}$$

where:

- R_{bm} = return of index b in month m
- n = total number of stocks in the index
- R_{im} = return of stock i in month m

Evaluation of Performance

To determine whether profitable investment strategies based on analyst recommendations exist, we calculate returns adjusted for the benchmark index, thereby obtaining the abnormal returns by subtracting the monthly return of the benchmark from the return of each portfolio.

This adjustment isolates the portfolios' performance relative to the overall market as represented by our constructed benchmark:

$$AR_{pm} = R_{pm} - R_{bm} \tag{4}$$

where:

- AR_{pm} = abnormal returns from portfolio p in month m
- R_{pm} = return of portfolio p in month m
- R_{bm} = return of index b in month m

We then compute the average monthly abnormal return for each portfolio during each period by summing all abnormal return observations for portfolio p during the relevant period and dividing the total by the number of observations.

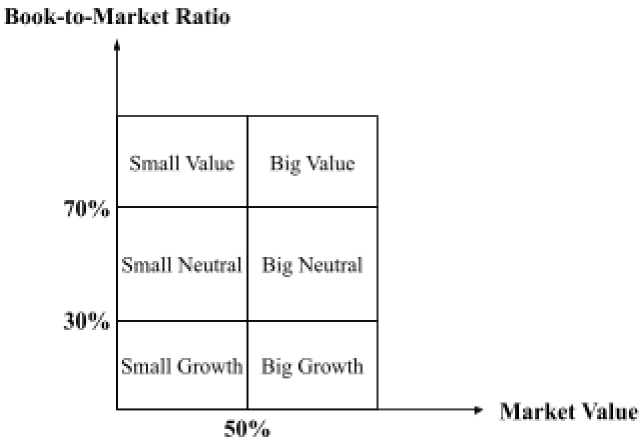
3.3 Robustness Testing

Fama-French Three-Factor Model

To further evaluate the portfolio's performance and control for additional systematic risk factors, we employ the FF3 model. In particular, we construct the two additional factors, SMB (Small Minus Big) and HML (High Minus Low), which capture size and value effects, respectively (Fama and French, 1993). All factor calculations and portfolio sorts are conducted monthly, following the standard approach of sorting stocks to ensure that the resulting portfolios reflect the intended exposures to the underlying size and value risk factors.

To construct these factors, we independently sort all stocks into six portfolios based on two dimensions: size (market value) and value (book-to-market ratio). First, we classify the companies as either small or big based on whether their market value is below or above the median. Second, we group them into value, neutral, or growth categories based on the 30th and 70th percentiles of the book-to-market distribution. This double sorting results in six equally-weighted portfolios: small value, small neutral, small growth, big value, big neutral, and big growth. See Figure 1 for a visual representation of the portfolio construction.

Figure 1: Construction of six portfolios based on market value and book-to-market ratio



Note: Portfolios are constructed by independently sorting stocks into terciles based on the book-to-market ratio (30th and 70th percentiles) and into two groups based on market value (median split at 50%).

We calculate the SMB factor as the average return of the three small-stock portfolios minus the average return of the three big-stock portfolios, as follows:

$$SMB = \tfrac{1}{3} \times (Small\ Value + Small\ Neutral + Small\ Growth) - \tfrac{1}{3} \times (Big\ Value + Big\ Neutral + Big\ Growth) \quad (5)$$

Similarly, we derive the HML factor by comparing returns across value and growth portfolios. Specifically, we calculate HML as the average return of the two high book-to-market portfolios minus the average return of the two low book-to-market portfolios, as follows:

$$HML = \tfrac{1}{2} \times (Small\ Value + Big\ Value) - \tfrac{1}{2} \times (Small\ Growth + Big\ Growth) \quad (6)$$

Additional Robustness Tests

To assess the consistency of our findings, we conduct hypothesis tests comparing the monthly abnormal returns and alphas across portfolios within each time period. The objective is to evaluate whether there are statistically significant differences in performance among the portfolios during either the crisis or reference period. The null hypothesis in these tests assumes equal returns across portfolios. Accordingly, two-tailed tests are applied, based on monthly average abnormal returns and alphas for each respective period.

Additionally, we test for potential differences in the accuracy of analyst recommendations across company sizes. We split the sample into two subsamples based on company size, classifying companies as either small or large depending on whether their market value falls below or above the median. This allows us to evaluate whether analysts are more accurate in predicting returns for large-cap compared to small-cap companies.

3.4 Hypotheses Testing

We base our statistical tests on the two hypotheses outlined in Section *2.3 Hypotheses*. To evaluate whether Portfolio 1 outperforms the market during the reference period, we test the null hypothesis that the abnormal return (alpha) is less than or equal to zero. This allows us to test against the alternative hypothesis that abnormal return (alpha) is greater than zero, indicating outperformance. A similar logic is applied to Portfolio 3, but with reversed signs, where we test whether performance is significantly worse than the market. For Portfolio 2, the null hypothesis assumes returns equal to the benchmark index, as we are interested in whether the mid-range portfolio performs significantly differently from the benchmark.

In the context of the crisis period, we aim to examine whether analysts can generate abnormal returns (alpha) that significantly deviate from zero, in either direction. Accordingly, for all portfolios during this period, the null hypothesis states that returns are equal to the benchmark index. Given that our sample consists of more than 30 observations, we apply the Central Limit Theorem (CLT) to justify the use of parametric tests.

To assess whether the abnormal returns of each portfolio during the reference period align with findings from prior research, we conduct the hypothesis tests summarised in Table 3, in accordance with our first hypothesis. These average abnormal returns are calculated using data exclusively from Period 1.

Table 3: Hypotheses tested on abnormal returns in the reference period (Period 1)

Portfolio	Null Hypothesis (H_0)	Alternative Hypothesis (H_1)
1	H_0: $\mu_{AR,1} \leq 0$	H_1: $\mu_{AR,1} > 0$
2	H_0: $\mu_{AR,1} = 0$	H_1: $\mu_{AR,1} \neq 0$
3	H_0: $\mu_{AR,1} \geq 0$	H_1: $\mu_{AR,1} < 0$

Note: $\mu_{AR,1}$ denotes the mean abnormal return during the reference period.

Before we evaluate whether the abnormal returns observed during the crisis period support our second hypothesis, we conduct the statistical test summarised in Table 4 to examine the presence of abnormal returns in either direction across all three portfolios. In this case, the average abnormal return is calculated using data from Period 2.

Table 4: Hypotheses tested on abnormal returns in the crisis period (Period 2)

Portfolio	H_0	H_1
1-3	H_0: $\mu_{AR,2} = 0$	H_1: $\mu_{AR,2} \neq 0$

Note: $\mu_{AR,2}$ denotes the mean abnormal return during the crisis period.

To examine whether the abnormal returns of portfolios differ between the periods and align with our second hypothesis, we conduct the hypothesis tests summarised in Table 5.

Table 5: Hypotheses tested on differences in abnormal returns between the crisis and reference periods

Portfolio	H_0	H_1
1	H_0: $\mu_{AR,2} - \mu_{AR,1} \geq 0$	H_1: $\mu_{AR,2} - \mu_{AR,1} < 0$
2	H_0: $\mu_{AR,2} = \mu_{AR,1}$	H_1: $\mu_{AR,2} \neq \mu_{AR,1}$
3	H_0: $\mu_{AR,2} - \mu_{AR,1} \leq 0$	H_1: $\mu_{AR,2} - \mu_{AR,1} > 0$

Note: $\mu_{AR,2} - \mu_{AR,1}$ denotes the difference in mean abnormal returns between the crisis and reference periods.

In addition to the hypothesis tests described above, we extend our analysis by running regressions using the FF3 model, which also provides the basis for subsequent hypothesis testing. This allows us to control for other known risk factors and isolate the alpha component driven by size and value effects. We estimate the following regression equation for both the reference period and the crisis period:

$$R_{pm} - R_{fm} = \alpha_p + \beta_p \times (R_{bm} - R_{fm}) + s_p \times SMB_m + h_p \times HML_m + \varepsilon_{pm} \quad (7)$$

where:

- R_{fm} = risk-free return in month m
- α_p = alpha of portfolio p
- β_p = benchmark beta of portfolio p
- s_p = SMB beta of portfolio p
- SMB_m = SMB factor in month m
- h_p = HML beta of portfolio p
- HML_m = HML factor in month m
- ε_{pm} = the error term of portfolio p in month m

To assess whether the alphas of the portfolios estimated from the FF3 model during the reference period align with previous research, we conduct the hypothesis tests summarised in Table 6, in accordance with our first hypothesis, using data from Period 1.

Table 6: Hypotheses tested on alpha in the reference period

Portfolio	$\mathbf{H_0}$	$\mathbf{H_1}$
1	H_0: $\alpha_1 \leq 0$	H_1: $\alpha_1 > 0$
2	H_0: $\alpha_1 = 0$	H_1: $\alpha_1 \neq 0$
3	H_0: $\alpha_1 \geq 0$	H_1: $\alpha_1 < 0$

Note: α_1 denotes the alpha during the reference period.

We also test for the existence of any alphas, in either direction, for all three portfolios during the crisis period by conducting the statistical test summarised in Table 7, using data from Period 2.

Table 7: Hypotheses tested on alpha in the crisis period

Portfolio	$\mathbf{H_0}$	$\mathbf{H_1}$
1-3	H_0: $\alpha_2 = 0$	H_1: $\alpha_2 \neq 0$

Note: α_2 denotes the alpha during the crisis period.

Finally, we test whether the alphas of the different portfolios differ between the reference period and the crisis period, in accordance with our second hypothesis, by conducting the hypothesis tests summarised in Table 8.

Table 8: Hypotheses tested on differences in alpha between the crisis and reference periods

Portfolio	$\mathbf{H_0}$	$\mathbf{H_1}$
1	H_0: $\alpha_2 - \alpha_1 \geq 0$	H_1: $\alpha_2 - \alpha_1 < 0$
2	H_0: $\alpha_2 = \alpha_1$	H_1: $\alpha_2 \neq \alpha_1$
3	H_0: $\alpha_2 - \alpha_1 \leq 0$	H_1: $\alpha_2 - \alpha_1 > 0$

Note: $\alpha_2 - \alpha_1$ denotes the difference in alpha between the crisis and reference periods.

4. Findings and Analysis

4.1 Descriptive Statistics

In the following section, we present a description of our data and a summary of the results.

4.1.1 Portfolio Characteristics

Portfolio Composition Over Time

Table 9 presents the average number of companies in each portfolio and offers insight into the distribution of analyst sentiment across the market. Portfolio 1, which comprises those with the most favourable analyst recommendations, consistently contains the largest number of companies throughout the sample period. The average rose from 81 companies in 2014, reaching a maximum of 147 in 2022, before declining slightly to 121 by 2024. This growth suggests that an increasing number of companies began receiving optimistic analyst coverage over time, potentially reflecting heightened market optimism or an expansion of analyst coverage focused on well-regarded companies.

Table 9: Average monthly number of companies per portfolio for the full sample period, reference period (Period 1), and crisis period (Period 2)

Date	Portfolio 1	Portfolio 2	Portfolio 3
2014	81	68	7
2015	97	64	7
2016	105	70	10
2017	113	82	10
2018	143	60	11
2019	129	64	16
2020	138	58	12
2021	142	57	7
2022	147	56	6
2023	125	61	7
2024	121	60	7
Total	**122**	**64**	**9**
Period 1	111	68	10
Period 2	135	58	8

Note: Portfolios are constructed based on analyst consensus recommendations.

In contrast, Portfolio 3, which includes companies with the least favourable recommendations, remains much smaller, averaging only nine companies across the entire period. This aligns with prior research, such as Barber et al. (2001), and reflects a consistent pattern in analyst behaviour: negative recommendations are rare. Across several years, Portfolio 3 includes fewer than ten companies, with the count falling as low as six in 2022. Portfolio 2, capturing companies with neutral recommendations, remains relatively stable, with an average of 64 companies across the period.

When dividing the data into the reference period (Period 1) and the crisis period (Period 2), certain structural shifts become evident. The average number of companies in Portfolio 1 increases from 111 in Period 1 to 135 in Period 2, supporting the notion of growing analyst optimism or a concentration of coverage in higher-rated companies. Meanwhile, Portfolio 3 experiences a slight decline in average company count, suggesting either a narrowing group of poorly rated companies or a reduced willingness among analysts to issue strong negative signals to the market.

Return Volatility and Distribution Characteristics

Table 10 presents the standard deviation, kurtosis, and skewness of monthly raw returns for each portfolio across both subperiods. A key finding is the clear increase in overall market volatility between the reference period (Period 1) and the crisis period (Period 2). The average standard deviation across all portfolios rises from 4.15% to 7.30%, consistent with the typical surge in volatility observed during turbulent market environments.

Table 10: Standard deviation, kurtosis, and skewness of equally-weighted raw portfolio returns during the reference period and the crisis period

		Standard Deviation	**Kurtosis**	**Skewness**
Period 1	Portfolio 1	4.25%	0.32	0.43
	Portfolio 2	3.75%	−0.71	0.06
	Portfolio 3	5.83%	0.25	−0.24
	Total	**4.15%**	**−0.05**	**0.26**
Period 2	Portfolio 1	7.54%	1.12	0.27
	Portfolio 2	6.63%	−0.21	−0.09
	Portfolio 3	8.19%	−0.15	−0.23
	Total	**7.30%**	**0.69**	**0.15**

Note: The “Total” row reports the mean value across the three portfolios for each period, providing a summary measure of the overall behaviour of the portfolios.

Portfolio-level patterns align with expectations regarding the risk-return trade-off and analyst recommendations. Portfolio 3 consistently exhibits the highest standard deviation in both periods, increasing from 5.83% in Period 1 to 8.19% in Period 2, underscoring the elevated risk profile of companies with unfavourable analyst coverage. Conversely, Portfolio 2 demonstrates the lowest volatility, reinforcing its intermediate risk-return positioning. The standard deviation of Portfolio 1 also rises markedly, from 4.25% to 7.54%, in line with the broader market trend, but remains lower than that of Portfolio 3.

The shape of the return distributions offers further insight. All portfolios exhibit relatively low kurtosis in both periods, although there is a general increase during Period 2. Portfolio 1 experiences the most notable rise in kurtosis, from 0.32 to 1.12, indicating a growing likelihood of extreme returns or fatter tails during the crisis. This may reflect greater dispersion in returns among companies with positive buy recommendations under conditions of heightened uncertainty. In contrast, Portfolios 2 and 3 exhibit slightly negative kurtosis in the crisis period (−0.21 and −0.15, respectively), suggesting thinner tails relative to a normal distribution. However, the magnitude of change was small, indicating limited impact on the overall distribution.

Skewness patterns also evolve across periods. Portfolio 1 maintains a consistently positive skew in both timeframes, 0.43 in Period 1 and 0.27 in Period 2, indicating a tendency towards frequent small losses offset by occasional large gains. This distributional profile may offer upside potential while still maintaining relative stability, a trait that could make Portfolio 1 attractive under both stable and volatile market conditions. Meanwhile, Portfolios 2 and 3 shifts from near-symmetric or slightly skewed distributions in Period 1 to more pronounced negative skewness in Period 2 (−0.09 and −0.23, respectively), suggesting an increase in likelihood of extreme negative returns during the crisis, particularly for Portfolio 3.

Overall, these findings highlight distinct risk-return characteristics across the portfolios. Portfolio 1 demonstrates a relatively favourable distribution, characterised by moderate volatility, positive skewness, and a manageable increase in kurtosis during periods of turbulence. This suggests a comparatively stable performance profile with upside potential. In contrast, Portfolio 3 exhibits a riskier profile, marked by persistently high volatility, increasingly negative skewness, and unstable tail behaviour during market stress. These distributional characteristics are not merely descriptive but play an essential role in evaluating whether potential returns are being pursued at the cost of increased downside risk. As such, they are central to assessing the performance and resilience of each portfolio under varying market conditions. The full monthly return series for all portfolios are provided in Appendix 1, Diagram 1-3.

Coverage and Market Representation

Analyst coverage of the market, measured by the proportion of listed companies included in the portfolios, declines steadily over the sample period. In 2014, 53.2% of listed companies are covered by analysts, but this figure drops to just 26.0% by 2024 (see Table 11). This sharp decline may reflect changes in market structure, increasing costs of coverage, or heightened information asymmetry for smaller or less visible companies. Notably, during this period, the total number of listed companies on the Nasdaq Stock Exchange, which typically includes larger companies, increases by approximately 43%, while the number of companies listed on First North, which tends to consist of smaller companies less frequently covered by analysts, increases by over 270% (SCB, 2024).

Table 11: Analyst coverage on the Stockholm Stock Exchange, including number of listed and covered companies and proportion of total market value covered

			Covered Companies	
Date	**Number of Listed Companies**	**Number of Covered Companies**	**% of Listed Companies**	**% of Market Value**
2014	365	194	53.2%	85.4%
2015	413	205	49.6%	86.2%
2016	467	229	49.0%	85.5%
2017	522	245	46.9%	85.9%
2018	601	262	43.6%	81.5%
2019	609	244	40.1%	77.4%
2020	646	233	36.1%	75.7%
2021	669	257	38.4%	83.0%
2022	786	223	28.4%	81.9%
2023	796	209	26.3%	84.0%
2024	778	202	26.0%	83.2%
Total	**629**	**228**	**39.8%**	**82.7%**

Note: Covered companies are those with at least one analyst recommendation. Column (4) reports the percentage of listed companies covered; column (5) reports the percentage of total market value covered.

Despite the decline in company coverage in absolute terms, the proportion of market value represented by covered companies remained consistently high, exceeding 75% in all years. This suggests that analysts primarily concentrate their attention on larger, more influential companies, ensuring that the portfolios continue to represent a substantial share of total market value even as the breadth of coverage narrows.

Analyst Consensus Recommendations

Table 12 presents the average consensus recommendations across the sample period and indicates a stable yet slightly optimistic analyst outlook. The overall average recommendation declines from 2.52 in 2014 to 2.35 in 2024, suggesting a modest improvement in analyst sentiment over time as well as a shift from neutral hold recommendations on average to buy recommendations. Portfolio 1 consistently includes stocks with highly favourable ratings, averaging 1.96, while the average rating for Portfolio 3 holds an average above 4.00 in most years, indicating consistently pessimistic analyst views.

Table 12: Average and median consensus recommendations for the full sample and by portfolio

Date	Average	Median	Portfolio 1	Portfolio 2	Portfolio 3
2014	2.25	2.50	2.02	2.97	4.06
2015	2.47	2.50	2.02	2.96	4.05
2016	2.47	2.50	2.04	2.92	3.99
2017	2.48	2.50	1.98	2.97	4.14
2018	2.29	2.17	1.88	2.95	4.04
2019	2.39	2.33	1.92	2.95	4.04
2020	2.33	2.25	1.92	2.95	4.01
2021	2.26	2.17	1.92	2.89	3.90
2022	2.24	2.15	1.93	2.88	4.01
2023	2.33	2.31	1.95	2.90	4.24
2024	2.35	2.33	1.97	2.91	4.04
Total	**2.37**	**2.33**	**1.96**	**2.93**	**4.05**

Note: Portfolio values represent average consensus recommendations.

Importantly, the relative distance between portfolios remains stable, reinforcing the robustness of the ranking methodology. Portfolio 2 holds an average rating of 2.93 throughout the sample period, providing a midpoint between the optimistic and pessimistic ends of the spectrum. This internal consistency strengthens the credibility of the portfolio formation process.

Book-to-Market Ratios

The average book-to-market (B/M) ratios, reported in Table 13, serve as a proxy for company valuation and help distinguish between value and growth stocks. Overall, the B/M ratio is highest for Portfolio 3, averaging 0.67, while Portfolios 1 and 2 are relatively similar, with average B/M ratios of 0.59 and 0.54, respectively. This pattern suggests that analysts exhibit a preference for growth stocks, defined as those with relatively low B/M ratios, over value stocks, which are characterised by relatively high B/M ratios (Barber et al. 2001).

Table 13: Average book-to-market ratios by portfolio over the sample period

Date	Portfolio 1	Portfolio 2	Portfolio 3
2014	0.71	0.78	0.46
2015	0.49	0.47	0.61
2016	0.50	0.51	2.14
2017	0.48	0.44	0.57
2018	0.49	0.47	0.56
2019	0.50	0.48	0.58
2020	0.58	0.47	0.43
2021	0.39	0.43	0.55
2022	0.55	0.57	0.67
2023	1.20	0.72	0.85
2024	0.61	0.61	0.97
Total	**0.59**	**0.54**	**0.76**

4.1.2 Portfolio Performance

Average Raw Returns

Table 14 provides descriptive statistics for the three portfolios constructed based on analyst consensus recommendations. Examining the average raw returns, we observe a clear difference in performance across the portfolios over the entire sample period. The results indicate that the average raw return remains positive for all three portfolios during both Period 1 and Period 2, with Portfolio 1 consistently achieving the highest average raw returns, Portfolio 3 the lowest, and Portfolio 2 remains in between.

Notably, while Portfolios 1 and 2 show a decrease in average raw returns from Period 1 to Period 2, Portfolio 3 exhibits the opposite trend, with an increase during the same time. This suggests that, over longer periods, analysts' favourable and unfavourable stock recommendations can effectively differentiate between the best- and worst-performing companies, as presented in Appendix 2, Diagram 4. However, although the difference in average raw returns between the portfolios is pronounced during Period 1, Portfolios 1 and 2 perform quite similarly in Period 2, with Portfolio 3 remaining the weakest performer (see Appendix 2, Diagrams 5-6).

Average Abnormal Returns

The average abnormal returns for each portfolio, which measure the individual performance relative to the benchmark index, are summarised in Table 14. The results indicate that the monthly average abnormal return is positive and significant for Portfolio 1 during Period 1. However, in Period 2, Portfolio 1 records a negative average abnormal return, which is no longer statistically significant. Both Portfolios 2 and 3 exhibit no significant average abnormal returns at conventional significance levels during either period. Although the results are not statistically significant, the estimates for Portfolios 2 and 3 remain consistently negative across both periods.

Table 14: Monthly portfolio performance based on analyst consensus recommendations, reporting average raw and abnormal returns, FF3 factor coefficients, alpha intercept and, R^2 values

			Fama-French Factors				
	Average Raw Return	**Average Abnormal Return**	**$R_m - R_f$**	**SMB**	**HML**	**Alpha Intercept**	**R^2**
Portfolio 1							
Period 1	1.459%	0.076%*	0.383***	−0.032	−0.114***	0.998%**	0.285
		(**1.949**)	(**5.119**)	(−0.679)	(**−3.170**)	(**2.084**)	
Period 2	0.675%	−2.179%	0.757***	−0.008	−0.295***	−0.314%	0.605
		(−0.855)	(**9.079**)	(−0.051)	(**−2.749**)	(−0.045)	
Portfolio 2							
Period 1	0.905%	−0.478%	0.349***	−0.058	−0.082**	0.453%	0.302
		(−1.092)	(**5.415**)	(−1.440)	(**−2.644**)	(1.109)	
Period 2	0.629%	−2.225%	0.682***	−0.312**	−0.060	−0.625%	0.644
		(−1.073)	(**9.887**)	(**−2.374**)	(−0.679)	(−1.077)	
Portfolio 3							
Period 1	0.011%	−1.372%	0.413***	−0.033	−0.100*	−0.628%	0.180
		(−0.880)	(**3.765**)	(−0.478)	(**−1.902**)	(−0.904)	
Period 2	0.137%	−2.718%	0.668***	−0.169	−0.159	−0.716%	0.455
		(−1.073)	(**6.370**)	(−0.844)	(−1.180)	(−0.812)	

Note: The hypotheses tested in this table are shown in Tables 3-4 and 6-7, in section *3.4 Hypotheses Testing*. Reported coefficients are estimated using the FF3 model. $R_m - R_f$ denotes the excess market return. T-statistics are shown in parentheses. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Difference in Abnormal Returns and Alphas Across Periods

The differences in average abnormal returns and alphas for each portfolio between Period 1 and Period 2 are reported in Table 15. Portfolio 1 shows a significant and negative difference for both abnormal return and alpha, suggesting that it performs significantly better in Period 1 in comparison to period 2. However, there are no significant differences in either abnormal returns or alphas for Portfolios 2 and 3, where both are negative.

Table 15: Differences in average monthly abnormal returns and alphas between the crisis and reference periods by portfolio

Portfolio	**Difference in Average Abnormal Return ($\mu_{AR,2} - \mu_{AR,1}$)**	**Difference in Alpha ($\alpha_2 - \alpha_1$)**
Portfolio 1	−2.255%**	−1.302%*
	(**−2.532**)	(**−1.942**)
Portfolio 2	−1.747%	−1.078%
	(−1.465)	(−0.824)
Portfolio 3	−1.346%	−0.088%
	(−1.039)	(−1.192)

Note: The hypotheses tested in this table are shown in Tables 5 and 8, in section *3.4 Hypotheses Testing*. T-statistics are shown in parentheses. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

4.1.3 Robustness Check

Fama-French Three-Factor Model

Table 14 summarises the results when controlling for known risk factors using the FF3 model, and these findings are broadly consistent with the patterns observed in previous sections.

Under the FF3 model, we find a positive and significant alpha only for Portfolio 1 during Period 1. Portfolios 2 and 3 exhibit positive and negative alphas, respectively, but neither is statistically significant. In Period 2, all portfolios show insignificant negative alphas.

Across both periods, the market risk factor is positive and significant for all three portfolios, suggesting that their returns tend to move with the overall market and that this is one of the primary determinants of performance. The HML factor is statistically significant for Portfolio 1 in both periods and for Portfolio 2 during Period 1, consistent with Barber et al. (2001). A likely explanation we propose is that these portfolios may include companies with low book-to-market ratios. Additionally, the HML factor is insignificant for Portfolio 3 during Period 2, although significant in Period 1. The SMB factor is significant only for Portfolio 2 in Period 2, while it remains insignificant for the other portfolios across all periods.

Finally, the R^2-values for the portfolios under the FF3 model are all lower in Period 1 than in Period 2, consistent with Sun (2021). This suggests that the model explains a larger share of return variation during the more turbulent crisis period, potentially reflecting stronger common factor effects under conditions of market stress.

Difference in Abnormal Returns and Alphas Between Portfolios Within Periods

In addition, we conduct hypothesis tests to compare the monthly average abnormal returns and alphas between portfolios within each period, as presented in Appendix 3, Table 16. The objective is to assess whether statistically significant performance differences exist among the portfolios during either the reference or the crisis period. We find that the overall magnitude of the return difference decreases during Period 2 compared to Period 1. In terms of abnormal returns, Portfolio 1 performs significantly better than Portfolios 2 and 3 during period 1, but neither differences in abnormal returns are significant during Period 2. For alphas, Portfolio 1 only significantly outperforms Portfolio 3 during Period 1, while all differences in alphas are insignificant for Period 2.

Difference in Portfolio Performance based on Company Size

We also conduct a robustness check to see if the accuracy of analyst recommendations differ depending on the size of the company, as presented in Appendix 4, Table 17-18. The results show that, similar to our main test, presented in Table 14, there is a significant positive abnormal return and alpha present for Portfolio 1 during Period 1. However, this is only significant for small companies, defined as those with a market value below the median, while large companies, defined as those with a market value above the median, show no significant abnormal returns or alphas for any portfolios during either period. These results suggest that analyst recommendations may be more informative or impactful for smaller companies, possibly due to greater information asymmetry, and that larger companies might generally be more efficiently priced (Barber et al, 2001). These findings also support our earlier results, indicating that this effect is likely driven by smaller companies.

4.2 Results of Hypotheses

Based on the hypotheses testing results presented in Tables 14 and 15, we conclude that the answer concerning our hypotheses is inconclusive. Regarding our first hypothesis, while stocks with favourable consensus recommendations (Portfolio 1) exhibit statistically significant abnormal returns and a positive alpha, the same is not true for the least favourable stocks (Portfolio 3), which do not exhibit any significant abnormal returns and negative alpha. These findings suggest that analyst recommendations have some predictive power during stable market conditions, but this ability is not consistent across all portfolios. Hence, Hypothesis 1 is partially supported.

Regarding our second hypothesis, the results clearly support the view that analyst recommendations lose predictive power in times of market stress. The significant outperformance of Portfolio 1 in Period 1 disappears in Period 2, and the differences in both abnormal returns and alphas between the two periods are significantly negative. While Portfolio 3 continues to underperform, its results remain statistically insignificant. These findings suggest that analyst recommendations become less informative during periods of heightened uncertainty. However, since we cannot establish consistent significance across all measures, partial support is found for Hypothesis 2.

5. Discussion

5.1 Research Question and Main Findings

In this thesis, we examine whether analyst consensus recommendations can effectively differentiate between the future performance of companies' stocks, with a particular focus on whether their predictive power is preserved during a period of market crisis. More specifically, we analyse how portfolios constructed based on favourable (Portfolio 1), neutral (Portfolio 2), and unfavourable (Portfolio 3) consensus recommendations perform across two distinct periods: one representing a stable market environment and the other a period of crisis. Performance is assessed in terms of both raw and abnormal returns.

During the reference period, we find that favourable analyst recommendations produce statistically and economically significant returns. Portfolio 1 not only generates the highest raw return but also produces a significantly positive abnormal return and alpha. Neutral recommendations result in moderate performance, while unfavourable recommendations underperform across all metrics. These findings indicate that analysts demonstrate a reasonable ability to identify underperforming companies in a stable market environment.

In contrast, the results differ substantially during the crisis period. Although Portfolio 1 continues to produce the highest raw return, its abnormal return and alpha become negative and statistically insignificant. Portfolio 2 shows relatively better performance than expected, displaying greater resilience compared to the reference period. Most importantly, Portfolio 3 continues to generate the lowest returns. However, the performance gap between portfolios appears to narrow, and the abnormal returns of all three portfolios are no longer statistically significant.

Overall, we conclude that the profitability of following analyst recommendations declines during periods of heightened market uncertainty. The findings from the crisis period indicate a reduced ability of analysts to consistently identify outperforming stocks. Although favourable recommendations still perform best in terms of raw returns, their relative advantage diminishes significantly after adjusting for risk. Furthermore, the narrowing performance differences between portfolios point to greater difficulty in distinguishing strong from weak stocks during crises, possibly due to increased market-wide uncertainty and noise.

Our results support the notion that analyst recommendations are more informative during stable periods and that their value diminishes in turbulent times. This has clear implications for investors, as the reliability of analyst consensus as a trading signal appears to be conditional on market context, and caution should therefore be exercised when applying these recommendations during financial distress.

5.2 Comparison with Previous Research

The main findings of this study broadly align with and extend prior research on the role of analyst recommendations in market pricing, particularly in relation to market efficiency and changing macroeconomic environments. Consistent with Barber et al. (2001), we find that during the stable reference period (2014-2019), Portfolio 1, which includes stocks with the most favourable consensus recommendations (strong buy and buy), delivers statistically significant positive abnormal returns and alpha. This suggests that, even under the semi-strong form of the EMH (Fama, 1970), such recommendations may reflect incremental information not fully incorporated into prices at the time of issuance, which is also in line with the notion of analysts acting as interpreters of complex or underappreciated public information (Healy and Palepu, 2001; Asquith, Mikhail, and Au, 2005).

However, it is important to emphasise that Portfolios 2 and 3, based on hold and sell recommendations respectively, do not generate statistically significant abnormal returns or alphas. This asymmetry aligns with prior research. For instance, both Stickel (1995) and Barber et al. (2001) noted that while buy recommendations tend to be more informative, sell recommendations were both more rare and in certain conditions also less impactful, partly due to reputational and commercial pressures that discourage negative ratings. Portfolio 3, in particular, consists of very few companies, with an average of 10 and 8 stocks during the reference and crisis period, respectively, which may reduce the generalisability of those results due to the possibility that they represent either outliers or highly specific firm characteristics or events. The weak performance of Portfolio 2 may reflect an ambiguous positioning effect, comprising companies that analysts hesitate to downgrade despite negative signals or instances where weak buy recommendations are effectively treated as holds, further diluting the predictive value of this category.

During the crisis period (2020-2024), the performance of recommendation-based portfolios deteriorates considerably. Abnormal returns and alphas across all three portfolios becomes statistically insignificant, in line with findings from Barber et al. (2003) during the dot-com bubble and Hwang and Salmon (2004), who highlighted how elevated uncertainty and herding behavior reduced analysts' ability to differentiate company fundamentals from broader market noise. Similar to previous research, we note an increase in the raw return from Portfolio 3 during the crisis period. However, we do not see the least favourable stocks outperforming the most favourable ones, either on abnormal or raw returns, in contrast to Barber et al. (2003). This could support the research results of Bilinski (2023) and Zhang et al. (2022) that documented how the COVID-19 crisis led to more reactive, less precise analyst output, since rapidly changing market conditions and external, non-financial shocks disrupted traditional valuation methods.

During the crisis period, our findings suggest that analysts may temporarily shift focus from firm-specific fundamentals to thematic or macroeconomic narratives, only returning to fundamentals once volatility and uncertainties reduce. Similarly to Yukselturk and Tucker (2015), this is supported by the observed reduction in forecast dispersion and diminished market impact of recommendations during the crisis years in our sample.

Another possible explanation for the reduced performance during crises is offered by Altınkılıç and Hansen (2009), who argued that stock price reactions around recommendation dates may stem from concurrent firm-specific announcements, rather than the signals given by analyst recommendations themselves. Given our monthly rebalancing frequency, important price relevant developments between rebalancing points may have gone uncaptured especially during periods of rapid information flow. This practical constraint could have limited the responsiveness of our strategy to real-time market dynamics, similarly to the diminishing abnormal returns found by Barber et al. (2001) when going from daily rebalancing to weekly or monthly rebalancing.

From a retail investor perspective, our findings reinforce the idea, consistent with Barber et al. (2003), that analyst recommendations can be a useful input during normal market conditions but may lose effectiveness during times of elevated uncertainty. Moreover, the use of monthly portfolio rebalancing introduces a methodological limitation in volatile environments, as recommendations may lag behind rapidly evolving market conditions. Accordingly, investors could benefit from combining analyst insights with more frequent monitoring and broader market signals, especially during turbulent periods. Furthermore, an important implication of our results is that, for retail investors, it may not be worthwhile to follow analyst recommendations on a monthly basis, as this strategy fails to generate significant abnormal returns. To potentially capitalise on analyst input, investors would need access to more frequent recommendations and adjust their portfolios accordingly, ideally on a daily basis. However, this strategy is likely impractical due to limited access to timely information and the inherent difficulties associated with daily rebalancing (Kirilova, 2021).

It is also important to note that, similarly to Stickel (1995), this study does not account for transaction costs, which can substantially eliminate any abnormal returns, especially with more frequent rebalancing as demonstrated by Barber et al. (2001). This is particularly relevant for retail investors who face higher commissions, wider bid-ask spreads and lower liquidity. As such, while gross returns in some cases could suggest semi-strong inefficiencies, the net returns might be less compelling after accounting for trading costs.

6. Conclusion

6.1 Concluding Remarks

The objective of this study is to investigate the predictive value of analyst consensus recommendations, with a particular focus on their effectiveness during periods of financial stability compared to periods of market crisis on the Swedish stock market. Specifically, we examine whether these recommendations can systematically differentiate between stocks with superior and inferior future returns.

Our analysis identifies several key insights. First, during the stable reference period (2014-2019), favourable recommendations are associated with significantly positive monthly abnormal returns and alpha, suggesting that analyst consensus reflects valuable information not yet fully incorporated into stock prices. In contrast, stocks with neutral and unfavourable recommendations generate weaker and statistically insignificant results. These findings affirm prior research that highlights the value of analyst input under normal market conditions, especially in the context of semi-strong market efficiency.

However, during the crisis period (2020-2024), the predictive power of analyst recommendations weakens considerably. Although favourably rated stocks continue to exhibit the highest raw returns, their risk-adjusted performance deteriorates and all portfolios exhibit statistical insignificance in terms of abnormal returns and alpha. These results suggest that during times of elevated uncertainty, the ability of analysts to discern firm-specific fundamentals might be impaired, likely due to an increase in market volatility, information noise, and the prevalence of macroeconomic narratives. These results indicate that it might not be profitable to follow monthly analyst recommendations on the Swedish stock market.

In conclusion, this study reinforces the notion that the value of analyst recommendations is not constant but conditional, strongest during stable periods and diminishing during financial stress. These findings have important implications for investors and researchers alike, emphasising the need to contextualise analyst signals within prevailing market environments when using them for investment decision-making or empirical analysis.

6.2 Limitations of the Study

There are certain limitations in our study that may affect the interpretation and generalisability of our findings and should therefore be acknowledged.

First, we approximate the market portfolio using an index constructed solely from the stocks included in our sample. Since the index incorporates only companies covered by analysts, we exclude companies without coverage. As a result, our proxy for the market portfolio may not fully reflect the broader market, introducing potential bias if the covered stocks differ systematically from the full market. However, the companies in our sample represent a substantial share of the total market value of the Nasdaq and First North Stock Exchanges, suggesting that any bias arising from this limitation is likely to be minimal. Similarly, we construct the SMB and HML factors for FF3 using only the companies included in our sample, since there is no available data on the FF3-factors during the entire sample period in the Swedish market.

Second, the data used is limited to a monthly frequency from the database, in terms of recommendation updates. This restriction may hinder the ability to capture short-term market reactions and changes in analyst sentiment, as firm-specific or macroeconomic developments occurring between rebalancing dates could go unnoticed. This could potentially underestimate the true responsiveness and relevance of recommendations, particularly during periods of heightened volatility.

Third, while our study relies on a large and diverse set of analyst recommendations, not all companies with such recommendations are consistently included in the database. This incomplete coverage may skew the results if the omitted companies systematically differ in terms of size, liquidity, or analyst coverage.

6.3 Suggestions for Future Research

Building on the findings and limitations of our study, several avenues for future research emerge. One direction would be to investigate whether more frequent portfolio rebalancing, using daily or weekly data, similar to Barber et al. (2001), on the Swedish market could improve the responsiveness and performance of recommendation-based strategies, especially during periods of heightened market volatility. Such an approach would allow for a more precise capture of short-term market reactions to analyst updates, and may provide insights into the timing and durability of recommendation effects.

Another valuable avenue for extension is to account explicitly for transaction costs, liquidity constraints, and bid-ask spreads. While our analysis demonstrates the gross return differences between portfolios, incorporating these real-world frictions could significantly alter the net profitability and practical viability of implementing such strategies, particularly for retail investors and during volatile periods when trading costs may spike.

Furthermore, future studies could expand the geographic scope by conducting cross-country comparisons across the Nordic region. Examining whether the predictive power of analyst recommendations holds similarly in markets like Denmark, Norway, and Finland could reveal useful insights about the influence of market structure, regulatory environments, or cultural factors on analyst behaviour and investor responses.

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8. Appendix

Appendix 1: Portfolio return scatterplots for the full sample, reference, and crisis periods

Diagram 1: Monthly equally-weighted returns for all three portfolios over the full sample period, January 1, 2014, to November 30, 2024

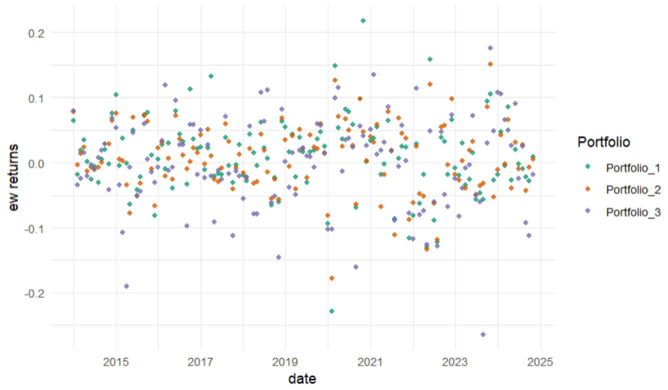


Diagram 2: Monthly equally-weighted returns for all three portfolios during the reference period (Period 1), January 1, 2014, to December 31, 2019

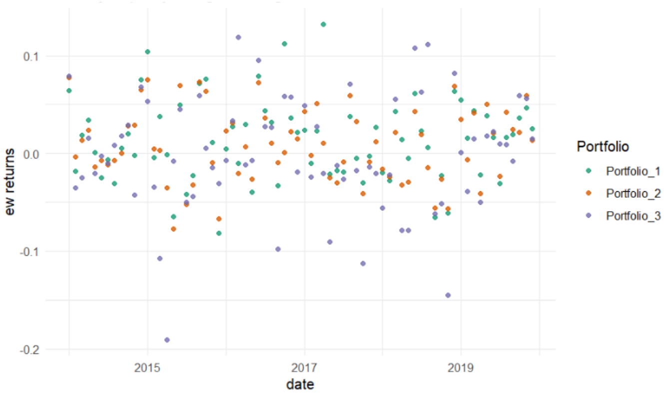
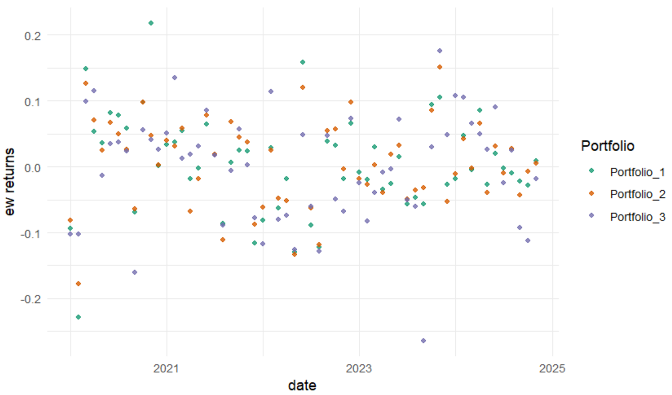


Diagram 3: Monthly equally-weighted returns for all three portfolios during the crisis period (Period 2), January 1, 2020, to November 30, 2024



Note (for Diagram 1-3): Logarithmic returns.

Appendix 2: Cumulative portfolio return diagrams for the full sample, reference, and crisis periods

Diagram 4: Cumulative monthly equally-weighted returns for all three portfolios over the full sample period, January 1, 2014, to November 30, 2024

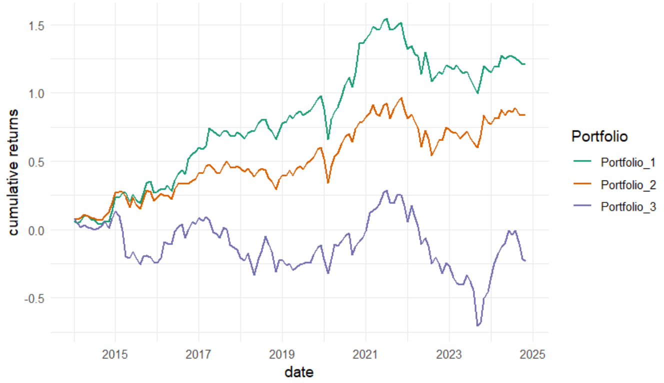


Diagram 5: Cumulative monthly equally-weighted returns for all three portfolios during the reference period (Period 1), January 1, 2014, to December 31, 2019

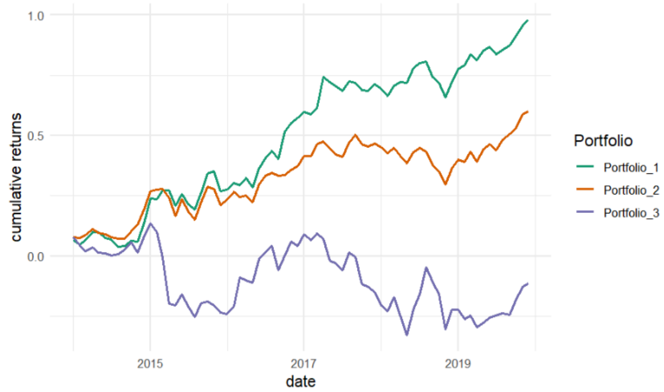
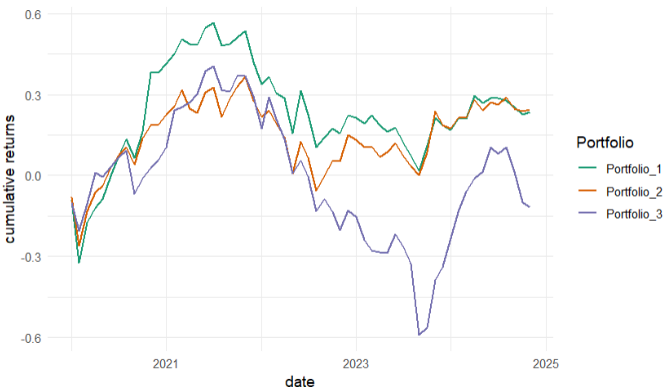


Diagram 6: Cumulative monthly equally-weighted returns for all three portfolios during the crisis period (Period 2), January 1, 2020, to November 30, 2024



Note (for Diagram 4-6): Logarithmic returns.

Appendix 3: Differences in abnormal returns and alphas between portfolios

Table 16: Differences in average monthly abnormal returns (AR) and alphas (α) between portfolio pairs (row minus column), reported for Period 1 and Period 2

Difference in Abnormal Returns in Period 1

Portfolio	1	2	3
1		0.554%*	1.448%**
		(**1.771**)	(**2.447**)
2	−0.554%*		0.894%
	(**−1.771**)		(1.683)
3	−1.448%**	−0.894%	
	(**−2.447**)	(−1.683)	

Difference in Abnormal Returns in Period 2

Portfolio	1	2	3
1		0.046%	0.539%
		(0.102)	(0.638)
2	−0.046%		0.493%
	(−0.102)		(0.650)
3	−0.539%	−0.493%	
	(−0.638)	(−0.650)	

Difference in Alphas in Period 1

Portfolio	1	2	3
1		0.535%	1.616%*
		(0.854)	(**1.922**)
2	−0.535%		1.081%
	(−0.854)		(1.342)
3	−1.616%*	−1.081%	
	(**−1.922**)	(−1.342)	

Difference in Alphas in Period 2

Portfolio	1	2	3
1		0.311%	0.402%
		(0.652)	(0.608)
2	−0.311%		0.091%
	(−0.652)		(0.087)
3	−0.402%	−0.091%	
	(−0.608)	(−0.087)	

Note: Significance levels refer to hypothesis tests where the null hypothesis states that abnormal returns or alphas are equal across portfolios. T-statistics are shown in parentheses. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Appendix 4: Portfolio performance based on company size

Table 17: Monthly portfolio performance based on analyst consensus recommendations of companies with the highest 50% market value, reporting average raw and abnormal returns, FF3 factor coefficients, alpha intercept and, R^2 values

	Average Raw Return	Average Abnormal Return	Fama-French Factors				R^2
			$R_m - R_f$	SMB	HML	Alpha Intercept	
Portfolio 1							
Period 1	1.121%	-0.262% (1.151)	0.414*** (**6.253**)	−0.083** (**−2.012**)	−0.110*** (**−3.357**)	0.511% (0.419)	0.366
Period 2	0.414%	−2.440% (−1.124)	0.731*** (**11.014**)	−0.416*** (**−3.291**)	−0.010 (−0.122)	−0.731% (−1.432)	0.696
Portfolio 2							
Period 1	0.158%	−1.225% (−0.809)	-0.137 (-1.182)	−0.246*** (**−3.432**)	−0.099* (**−1.798**)	0.857% (1.087)	0.195
Period 2	0.337%	−2.517% (−1.400)	0.671*** (**10.124**)	−0.432*** (**−3.425**)	0.023 (0.275)	−1.081% (−1.557)	0.674
Portfolio 3							
Period 1	0.112%	−1.494% (−1.005)	0.425*** (**3.610**)	−0.061 (−0.827)	−0.075 (−1.330)	−0.781% (−1.049)	0.170
Period 2	1.169%	−1.686% (−1.191)	0.746*** (**6.002**)	−0.817 (−3.486)	0.249 (1.581)	−1.027% (−0.480)	0.448

Table 18: Monthly portfolio performance based on analyst consensus recommendations of companies with the lowest 50% market value, reporting average raw and abnormal returns, FF3 factor coefficients, alpha intercept and, R^2 values

	Average Raw Return	Average Abnormal Return	Fama-French Factors				R^2
			$R_m - R_f$	SMB	HML	Alpha Intercept	
Portfolio 1							
Period 1	1.933%	0.550%* (**1.834**)	0.351** (**2.880**)	−0.007 (−0.093)	−0.125* (**−2.131**)	1.462%* (**1.896**)	0.122
Period 2	1.367%	−1.487% (−0.452)	0.808*** (**5.966**)	0.600** (**2.326**)	−0.723*** (**−4.152**)	−1.116% (−0.980)	0.454
Portfolio 2							
Period 1	-0.305%	−1.688% (−0.392)	-0.093 (-0.669)	−0.259*** (**-3.026**)	−0.139** (**−2.101**)	0.603% (0.638)	0.172
Period 2	1.561%	−1.293% (−0.279)	0.763*** (**5.798**)	0.041 (0.165)	−0.324 * (**−1.913**)	0.549% (0.496)	0.385
Portfolio 3							
Period 1	-0.971%	−2.354% (−1.212)	0.839*** (**3.155**)	−0.040 (−0.372)	−0.238** (**−2.504**)	−1.530% (−1.480)	0.151
Period 2	-2.787%	−5.642% (−0.411)	0.876*** (**4.166**)	0.311 (0.773)	−0.564 (−2.078)	−0.688% (−0.382)	0.279

Note (for Table 17-18): The hypotheses tested in this table are shown in Tables 3-4 and 6-7, in section *3.4 Hypotheses Testing*. Reported coefficients are estimated using the FF3 model. $R_m−R_f$ denotes the excess market return. T-statistics are shown in parentheses. Significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Appendix 5: The use of generative AI

For this thesis, we utilised generative artificial intelligence (AI) through ChatGPT. It was primarily applied in the coding process in RStudio, including troubleshooting and formatting, and was also used to confirm our existing understanding of certain sources. Additionally, it supported text refinement, revision, and proofreading, offering suggestions to improve language and clarity. Overall, the use of AI enhanced the efficiency of the process.

Nonetheless, given the risks associated with accuracy, all outputs were critically reviewed, and only credible, verified sources were relied upon.