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Analysts' recommendations and abnormal returns in the Finnish Stock Market

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ABSTRACT:

Stock analysts are important operators in today's stock markets, and their ability to spot over- or underpriced stocks has been widely examined in academia. Analysts form their recommendations based on publicly available information. According to the semi-strong form of the Efficient Market Hypothesis following analysts should not yield abnormal returns. If abnormal returns still appear, it would indicate inefficiency in the markets. Most earlier studies have focused on the United States stock markets, which are often considered one of the most efficient in the world. This thesis examines whether abnormal returns are possible to achieve by a trading strategy following analysts' recommendations in the Finnish stock markets between 2014 and 2024.

In the thesis, six portfolios were built from OMX Helsinki stocks based on the analyst consensus recommendations they receive: three with favorable and three with unfavorable recommendations. The returns of portfolios were tested using the CAPM and the Fama–French five-factor model after transaction costs. In addition, eight industry portfolios were formed from four major industries to see if the analysts' forecasting abilities are consistent across the industries. Each industry was split into a favourable and an unfavorable portfolio.

Two of the three unfavorable portfolios produced significant negative abnormal returns, even after accounting for transaction costs. In practice, taking advantage of this result might be difficult because of the limitations of short-selling, especially for smaller firms. Portfolios formed from favorable recommendations did not yield significant positive abnormal returns. Overall, the results indicate that the Finnish stock market operates relatively efficiently. In the industry-specific analysis, analysts' forecasting ability remained generally consistent across most sectors, although some variation was still observed. The industrial sector stood out as an exception, where analyst recommendations did not perform as expected. These results suggest that analysts may have been overly optimistic in this sector, or that their forecasts were simply less accurate in a particular industry.

Research on this topic is relevant, since analysts have gained more visibility in the media and their recommendations can influence investor decisions. The results also provide insight into the efficiency of the Finnish market and the role of analysts as intermediaries of market information.

KEYWORDS: Stock recommendations, Stock analysts, Efficient Markets, Abnormal Returns

VAASAN YLIOPISTO
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TIIVISTELMÄ:

Osakeanalyytikot ovat näkyviä toimijoita nykypäivän osakemarkkinoilla. Analyytikoiden kykyä löytää yli- tai alihinnoiteltuja osakkeita sekä saavuttaa ylituottoja osakesuosituksia seuraamalla on tutkittu laajasti. Osakeanalyytikot käyttävät suoitusten muodostamiseen julkista informaatiota joten, tehokkaiden markkinoiden teorian mukaan ylituottojen saavuttaminen ei pitäisi olla mahdollista. Mikäli ylituottoja kuitenkin voidaan saavuttaa sijoitusstrategialla, joka seuraa analyytikkojen suosituksia, viittaa se mahdolliseen aukkoon markkinoiden tehokkuudessa. Suurin osa aiemmasta tutkimuksesta on keskittynyt Yhdysvaltain markkinoille, joita pidetään tehokkaimpina maailmassa. Opinnäytetyö tutkii pystyikö osakeanalyytikkojen suosituksia seuraamalla saavuttamaan epänormaaleja tuottoja Suomen osakemarkkinoilla vuosien 2014 ja 2024 välillä.

Tutkimuksessa Helsingin pörssin osakkeista muodostettiin analyytikkojen konsensussuositusten perusteella kuusi portfoliota. Potfoliot olivat kolme suosiollisen ja kolme epäsuosiollisen konsenusennusteen portfoliota. Portfolioiden tuottoja testattiin CAP-mallin ja Fama–Frenchin viiden faktorin mallin avulla. Tämän lisäksi neljän toimialan osakkeista muodostettiin kahdeksan toimialakohtaista portfoliota, jokaisesta toimialasta suosiollinen ja epäsuosiollinen portfolio. Toimiala portfolioilla pyrittiin selvittämään säilyykö analyytikkojen kykyä arvioida osakkeiden yli- ja alihinnoittelua toimialasta riippumatta.

Kaksi kolmesta epäsuotuisian suosituksen mukaan muodostetuista portfoliosta, tuotti merkitseviä negatiivisia epänormaaleja tuottoja myös kaupankäyntikulujen jälkeen. Ilmiön hyödyntäminen voi kuitenkin olla haastavaa käytännössä, sillä lyhyeksi myynti ei ole aina mahdollista, etenkään pienten yhtiöiden osalta ja lyhyeksimyynnin kulut voivat kasvaa korkeiksi. Yksikään suosiollisen ennusteen perusteella muodostetuista portfolioista ei tuottanut merkitseviä ylituottoja. Tulosten perusteella voitaneen todeta, että Suomen osakemarkkina toimii varsin tehokkaasti. Tutkittaessa analyytikkojen kykyä löytää väärin hinnoiteltuja osakkeita toimialoittain havaittiin, että heidän ennustuskykynsä säilyy pääosin toimialasta riippumatta, mutta vaihtelee hieman eri toimialojen välillä. Selvä poikkeus oli teollisuussektori, jossa analyytikoiden suositukset eivät tuottaneet odotetun kaltaisia tuloksia. Tulokset voivat johtua analyytikoiden liiallisesta optimismista tai heikommasta ennustuskyvystä toimialalla

Osakesuositukset voivat vaikuttaa sijoittajien päätöksentekoon, jonka vuoksi aiheen tutkiminen on tärkeää. Lisäksi aiheen tutkiminen tarjoaa lisätietoa Suomen osakemarkkinoiden tehokkuudesta ja analyytikkojen roolista markkinoiden informaation välittäjänä.

AVAINSANAT: Osakesuositukset, Osakeanalyytikot, Tehokkaat Markkinat, Epänormaalit tuotot

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1 Introduction

The stock analysts have been important operators in the modern stock markets for years. Institutional and individual investors try to utilize the information of the analyst's recommendations to beat the market. Capital management companies spend millions on equity research annually. In the year 2022, Investment companies spent 12 billion US dollars for sell-side and individual analysts' security research (Mayhew, 2023). On the other hand, according to semi-strong conditions of the efficient market hypothesis, the analyst's recommendations should not offer any valuable information for the making of investment decision. It is hard to believe that industry professionals would spend this money if it were useless.

Academic research agrees that stock recommendations have investment value (Stickel, 1995; Womack, 1996; Barber et al., 2001). However, it seems hard to exploit the recommendations with a trading strategy (Barber et al., 2001). Stock analyst's role has become more visible for ordinary investors also in the Finnish stock market in recent years. Despite the growing visibility of analysts in the Finnish market, little is known about the actual effectiveness of their recommendations in this context. While previous international studies have provided evidence of both short-term market reactions and long-term abnormal returns following analyst actions, the findings remain inconclusive and often limited to large and highly liquid markets such as the United States.

It is relevant to examine whether analyst consensus recommendations have predictive power for stock returns in a smaller and possibly less efficient market environment. This study focuses on the Finnish equity market and investigates whether portfolios formed according to analysts' recommendations can generate risk-adjusted excess returns. This is done by implementing a trading strategy that divides stocks into six different portfolios according to consensus recommentation they receive. Additionally, the study takes an industry-specific approach to analysts' forecasting abilities. In the four largest industries (measured by the number of companies) operating the eight industry portfolios are formed. The results can offer new information about the analysts ability to find mispriced securities across the the industries.

1.1 Purpose of the study

The thesis aims to empirically examine whether it is possible to earn abnormal returns from the Finnish stock market with a strategy that follows stock analysts' recommendations. Most of the existing study concerns the US stock market, which is generally recognized as the most efficient in the world. This thesis focuses on the Finnish stock market, which might be less efficient. The results can tell about how efficient the Finnish stock market is and do the stock analysts offer added value while making the investment decision. The results can also give some information about the analysts forecasting abilities. The main research question of the thesis is: "What is the investment value of stock recommendations in the Finnish stock markets?". Based on the literature review in chapter five, two hypotheses can be formed to answer the main research question of the thesis.

H0: A trading strategy following analysts' recommendations yields no abnormal returns.

H1: A trading strategy following analysts' recommendations yields abnormal returns consistent with the direction of the recommendation.

Additionally, the thesis provides a perspective on the stock analysts' forecasting abilities across the industries in the Finnish stock markets. The second research question of the study is: "Are the analysts' forecasting abilities consistent regardless of the industry analyzed?". Again, two hypotheses are formed:

H0: There is no difference in analysts' ability to identify mispriced securities across industries

H1: Analysts' ability to identify mispriced securities varies across industries.

1.2 Structure of the study

The thesis begins with a theoretical section that provides background on modern financial markets. Chapter two introduces the Efficient Market Hypothesis as a framework for understanding how markets operate and discusses related market anomalies and behavioral factors. Chapter three focuses on asset pricing and presents the CAPM and Fama–French factor models that are important for understanding the empirical part of the study. Chapter four reviews earlier literature on stock analysts and their forecasting abilities. Chapter five describes the data used in the analysis, while chapter six explains the research methodology. Chapter seven presents the empirical results, starting with geometric returns and moving to risk-adjusted portfolio performance. Chapter eight discusses the limitations of the study, and chapter nine concludes the thesis.

2 Efficient market hypothesis – EMH

This chapter deals with the efficient market hypothesis developed by Eugene Fama (1970). EMH sets the frame for how the modern stock market operates. Fama (1970) states that in efficient markets, prices fully reflect all the possible information at all times. Efficient markets occur when three key conditions are met: (1) There are no transaction costs, (2) All information is available to all market participants for free, and (3) The information is processed rationally.

Bodie et al. (2021, p.332) describe the working of the efficient markets. In efficient markets, when new relevant information appears, investors process the information and trade the stock. The price reaction to the new information is immediate and happens with the right magnitude. The price of the stock is set to a new fair level.

In efficient markets, the stock prices follow a random walk. Malkiel (2003, p.59) explains that in a random walk process, today's stock prices are independent of yesterday's prices. This suggests that only new information, previously unknown, influences stock prices. Because the information was unknown, the price reaction is random. Bodie et al. (2021, p.332) say that the new information must be unpredictable, otherwise it would already be reflected in stock prices.

Fama (1970) splits the market efficiency into three different stages. This is demonstrated in figure 1. In weak-form markets, the historical price data cannot forecast future price development. Technical analysis tries to use historical price and trading data to find a regularity or pattern to forecast future price development (Bodie et al., p.336-337). If market efficiency is weak, technical analysis is therefore useless.

In semi-strong form markets, all public information is reflected in the stock prices. For example, financial statements, earnings announcements, and stock splits are public information sources (Fama, 1970). Fundamental analysis utilizes public information to form the opinion that the stock’s current price is over or under its intrinsic value (Bodie et al. 2021, p.338). Semi-strong form market efficiency also includes the conditions of the weak form.

The highest form of efficiency is the strong form. In the strong form markets the stock prices reflect all the information. That means prices also include the inside information that is not public for all market participants. The strong market efficiency includes conditions of the weak and semi-strong forms (Fama, 1970).

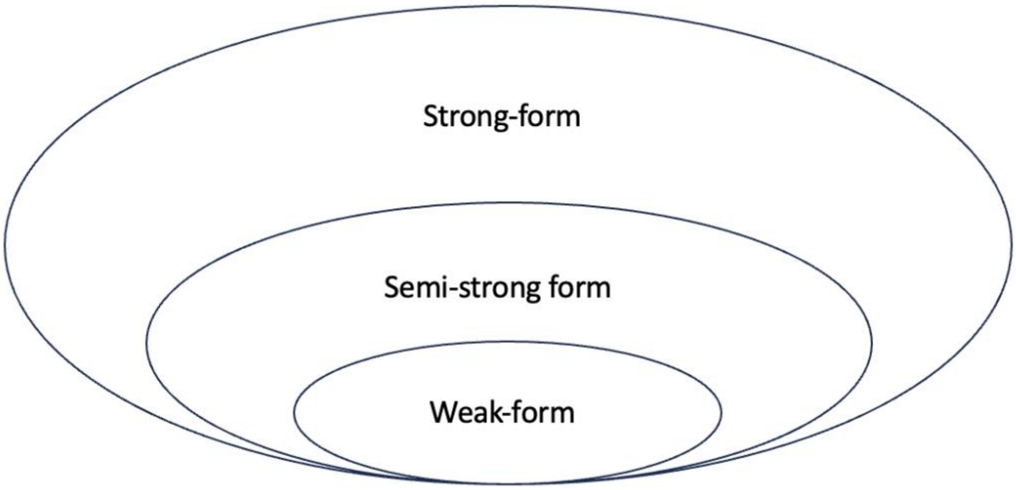

Figure 1. Forms of market efficiency

2.1 Anomalies

An anomaly refers to a pattern or event in the stock market that contradicts the efficient market hypothesis. For example, a portfolio composed of stocks with specific characteristics that yield abnormal returns may be considered a market anomaly (Bodie et al., 2021, p.349). Nikkinen et al. (2002, p.86-87) define the anomaly more simply as a deviation from the market efficiency that lasts so long that it is possible to exploit economically. Academic research has reported several possible anomalies. With anomalies, it is necessary to think whether the anomaly is real or it is the consequence of not measuring the risk properly with an asset pricing model. This sub-chapter presents the most well-known stock market anomalies that may conflict with EMH.

The price-per-earnings ratio is a commonly used valuation tool for valuing stocks among analysts (Imam et al., 2008). Basu (1977) observed that portfolios constructed from stocks with low P/E ratios tend to outperform portfolios with higher P/E ratios. The results also stand after benchmarking the results with the CAPM. It is proposed that these results are a consequence that CAPM cannot measure the risk of a company with a low P/E properly.

Banz (1981) finds that smaller firms produce significantly better risk-adjusted returns than their bigger counterparts. In the study, firms were split into different portfolios based on their market value, and the results were risk-adjusted with CAPM. Banz supposes that results indicate that there are unknown factors in stock returns that CAPM could not explain.

Fama and French (1992) observe that picking the stock with a high book-to-market ratio indicated higher stock returns. A portfolio composed of high book-to-market (B/M) stocks yielded an average monthly return 1.53% higher than that of a portfolio consisting of low B/M stocks. The paper raised serious questions about how well CAPM and beta can forecast stock returns.

Jegadeesh and Titman (1992) presented the momentum strategy. They recognized that stock price development continued with the same previously observed trend. Buying previous winner stocks and selling loser stocks outperformed the markets in 3 and 12-month holding periods. The researchers supposed that the anomaly is caused by systematically biased expectations of investors.

Market bubbles are not anomalies, yet they challenge the concept of market efficiency. According to Bodie et al. (2001, p. 357), a market bubble occurs when the prices of certain securities or entire industries deviate irrationally from their intrinsic values. While bubbles are often identifiable in hindsight, they are difficult to detect in real time.

Notable examples include the dot-com bubble of 2001 and the housing bubble of 2008, both of which had significant economic repercussions. The 2008 housing bubble triggered a global recession. Behavioral finance might offer explanations to explain the birth of market bubbles. Griffin (2021) says there was widespread fraud in the markets before the 2008 financial crisis. Fraudulent activities undermine the efficient functioning of markets, as they distort the availability of accurate information, contradicting the conditions set by Fama (1970) for market efficiency, where all available information is reflected in asset prices.

2.2 Behavioral Finance

Investors do not always act rationally. Behavioral finance is the field of finance that concentrates on investors' decision-making and psychological aspects. Behavioral biases might be the reason behind some observed anomalies and market bubbles in the financial markets (Bodie et al., 2021, p.372). Behavioral finance challenges the assumptions of the Efficient Market Hypothesis by suggesting that psychological biases can systematically affect investor and analyst decisions, leading to potential mispricing in financial markets. Stock analysts are not immune to behavioral biases while forming their recommendations.

People tend to think they are better at something than they are. This also applies to investing. The phenomenon is known as overconfidence. Overconfidence can lead to bad investment decisions and over- or under-reacting in the markets (Bodie et al., 2021, 373-374). For example, it is reported that in merger situations, overconfident CEOs are more likely to overpay for the target company (Malmendier and Tate, 2008).

Regret avoidance is a psychological phenomenon where investors feel more regret about unconventional failed investments than safer and sure investments that end badly. For example, losing with a start-up feels worse than with a blue-chip stock (Bodie et al., 2021, p. 376). De Bondt and Thaler (1987) claim that regret avoidance is the reason behind P/E and P/B anomalies.

Banerjee (1992) determines herding as people following the crowd even though their own information tells them to do otherwise. Analysts' herding behavior has been examined a lot. Banerjee (1992) presents a good example of herding: If people need to choose between two unknown restaurants, they probably choose the one with more customers dining. Chapter 4 discusses more about the herding phenomenon in the stock analysts' context.

Another bias often mentioned in analyst behavior is confirmation bias, where individuals favor information that confirms their pre-existing beliefs. This can lead analysts to underreact to new negative information about a company. Anchoring bias affects both investors and sell-side analysts, who tend to base their forecasts too heavily on reference points such as the industry median (Cen et al, 2013). This leads to overly optimistic estimates for firms with low expected earnings.

2.3 Limits of arbitrage

In efficient markets, two identical assets should have the same price. This is known as The Law of One Price (Bodie et al., 2021, p.378). Bodie et al. (2021 p.311) define arbitrage as a situation where an investor can earn riskless profit by selling the same security, trading with different prices at two different marketplaces. The investor buys the cheap security and sells the expensive one. Therefore, this position is risk-free and it is possible to implement without the investor's capital. Naturally, every rational investor wants to take this position, and trading moves the prices quickly to the right level. Vishny & Shleifer, (1997) say that arbitrage is a premise for efficient markets. This chapter presents the factors that hinder the implementation of arbitrage,

Real-world complexities can limit the use of arbitrage. Vishny & Shleifer, (1997) point out issues exploiting the arbitrage as presented in theory. Firstly, arbitrageurs tend to avoid too volatile positions, because short-term performance is important for the fund's investors. Investing in volatile securities predisposes the portfolio to price fluctuations.

The authors suppose that long-lasting mispricing in the markets is a consequence of an asset's unique risk rather than hard-to-measure macroeconomic risks. Vishny & Shleifer (1997) also outline that in reality, arbitrage is not possible without the own capital, and very often even the simplest arbitrage includes risk.

De Long et al. (1990) say that noise trading creates risks in utilizing the existing arbitrage opportunities appearing in the markets. Noise trading refers to irrational investors who are not as well-informed as professionals and can base their investing decisions on irrelevant information and rumors. Naturally, arbitrageurs want to exploit the pricing errors that noise trading creates, but their risk-taking ability is limited. Therefore, they are not always able to eliminate the arbitrage. Also, the risk arbitrageur takes can grow in a short time if the noise trader moves the price even more irrationally. In the case of noise trading, the quote of John Keynes, “The market can stay irrational longer than you can stay solvent,” fits well.

Pontiff (1996) investigates the limits of arbitrage with the closed-ended funds. Closed-end funds have proven to have a lower valuation than the assets in the fund. This can offer an arbitrage opportunity. The research presents that the pricing differences are due to the difficulty of implementing the arbitrage with low costs. Recreating the fund’s portfolio causes too many costs with, bid-ask spreads and commissions so arbitrage becomes zero profit.

3 Valuation models

This chapter concentrates on valuation models. Valuation models are important in the work of security analysts' work to find mispriced securities. In the empirical part of this thesis, the CAPM and Fama-French five-factor models are used to calculate benchmark returns of portfolios. The stock price is a consequence of many different factors. Valuation models try to determine what the fair price or expected return of the security should be.

3.1 Capital assets pricing model (CAPM)

The capital assets pricing model (CAPM) is the result of three different researchers: Sharpe (1964), Lintner (1965), and Mossin (1966). The earlier work of Markowits (1952) with the portfolio theory has also contributed significantly to the creation of the CAPM. The CAPM is the most well-known valuation model and it is said to be one of the centerpieces of modern financial theory (Bodie et al., 2021, p.275).

According to the CAPM, the expected return of the stock is dependent on the riskiness of the stock. The higher risk means the higher expected return. Traditionally the risk can be split into unique risk and systematic risk. CAPM pays attention only to systematic risk because unique risk can be eliminated with diversification. The formula of the CAPM is presented below (Bodie et al., 2021, p.282).

$$\mathrm{E}(\mathrm{r}_{\mathrm{GE}}) = \mathrm{r}_{\mathrm{f}} + \beta_{\mathrm{GE}}[\mathrm{E}(\mathrm{r}_{\mathrm{m}}) - \mathrm{r}_{\mathrm{f}}] \tag{1}$$

Where:

$\mathrm{E}(\mathrm{r}_{\mathrm{GE}})$ = Expected return of stock "GE"
r_{f} = risk – free rate
β_{GE} = Beta of stock "GE"
$E(\mathrm{r}_{\mathrm{m}})$ = Expected rate of the market portfolio

The CAPM uses market betas as a measurement of the risk. The formula for the security beta is shown below.

$$\beta_i = \frac{\mathrm{Cov}(r_{i,} r_M)}{\mathrm{Var}\ (R_m)} \tag{2}$$

$\mathrm{Cov}(r_{i,} r_M) = \text{covariance between returns of the stock and market returns}$
$\mathrm{Var}\ (R_m) = \text{variance of the market}$

The CAPM holds several background assumptions that make the model easy to question in the real world. However, CAPM is still a widely used model also among practitioners to define the cost of equity (Graham and Harvey, 2001). The background assumptions concern individual investors operating in the markets, and also the markets. The assumptions are presented below (Bodie et al., 2021, p. 276).

1. The investors are rational mean-variance optimizers.
2. Investors have the same investing horizon.
3. Investors have “homogenous expectations”. Investors have the same information about the markets and are interpreting it consistently.
4. All assets in the markets are publicly traded and available for investors in the public exchange.
5. Investors can borrow and lend at a common risk-free rate.
6. Short selling is allowed.
7. No Taxes.
8. No transaction costs.

In the CAPM, investors optimize their portfolios using Markowitz's portfolio theory (1952). Given certain inputs, investors place available risky investments on the efficient frontier, which represents the set of portfolios that offer the highest expected return for a given level of risk. On a graphical representation in figure 2, the Y-axis shows expected returns, and the X-axis represents risk, measured by the standard deviation of returns. Point P shows which portfolio offers the best risk-return trade-off (Bodie et al., 2021, p. 276-277).

The Capital Market Line (CML) is a specific line that is tangent to the efficient frontier at the market portfolio, which consists of all risky assets in the market, weighted by their market value (Figure 3). This line represents the best possible combination of risk and return available to investors, achieved by mixing the market portfolio with a risk-free asset. The market portfolio is unique in that it maximizes the Sharpe ratio, representing the best risk-adjusted return (Bodie et al., 2021, p. 276-277).

The CML is a type of Capital Allocation Line (CAL), but it is distinguished because it uses the market portfolio as the risky component. The CML represents the optimal trade-off between risk and return for all investors, assuming homogeneous expectations, publicly traded assets, and common investment horizons (Bodie et al., 2021, p. 276-277).

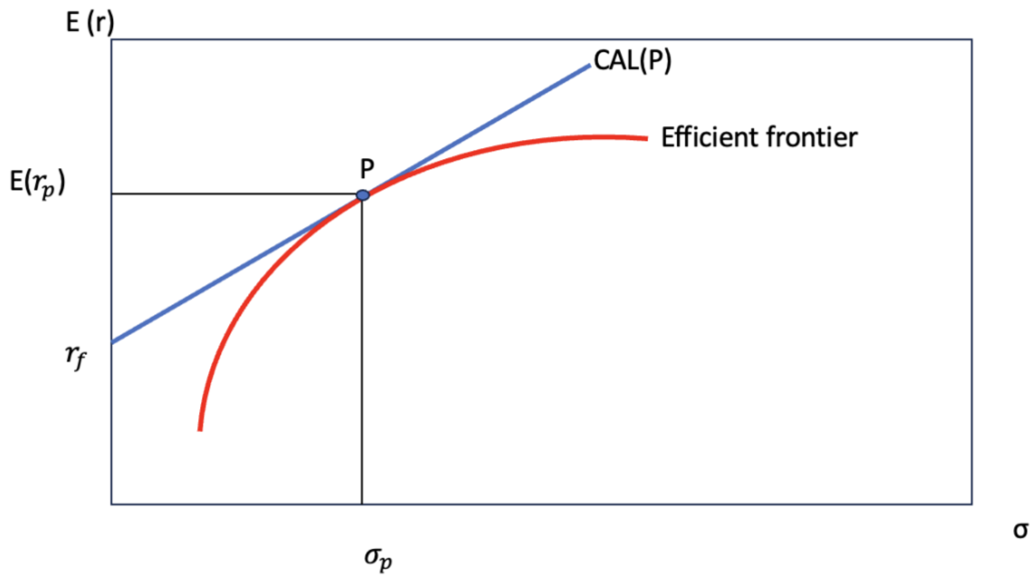

Figure 2. The efficient frontier of risky assets and the optimal CAL. (Bodie et al., 2021, p. 277)

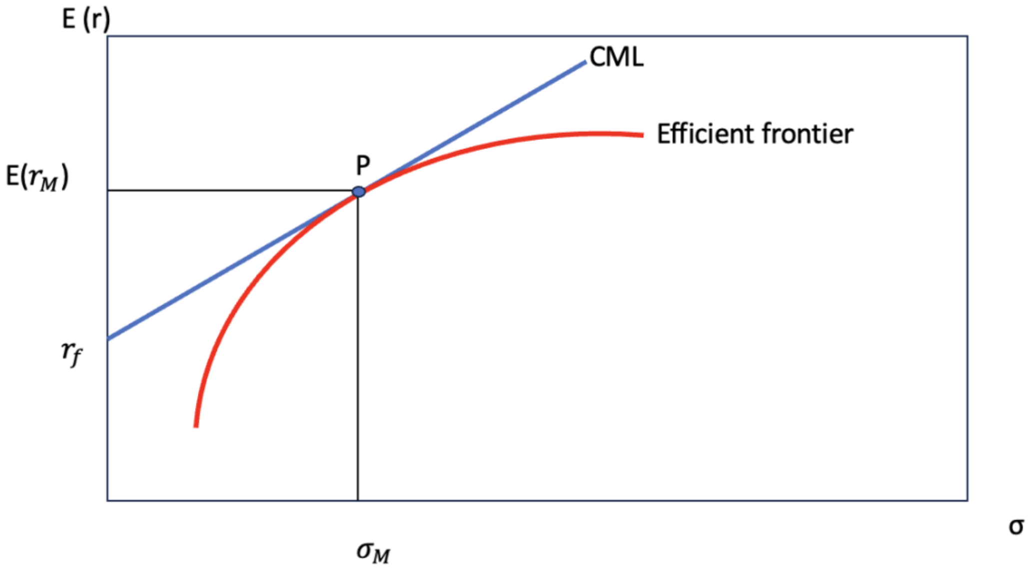

Figure 3. The efficient frontier and the capital market line. (Bodie et al 2021, p.277).

3.1.1 Abnormal returns

Abnormal returns are the difference between the benchmark returns and the observed returns. The simplest benchmark can be the broad market index like the S&P500. Asset pricing models such as the CAPM and the Fama-French Five-Factor model provide benchmarks that account for the riskiness of stocks, making them more academically accepted measures for benchmark returns (Bodie et al. 2021, p.342).

When estimating stocks' expected returns with CAPM stocks can be placed on the security market line (SML). The X-axis holds the betas (a measure of risk) and the Y-axis holds the expected returns. The beta of the market is one. Based on the beta, every stock gets the expected return. If the stock's returns exceed the benchmark that is known as a positive alpha. Figure 4 shows a visual representation of stock with positive alpha. According to CAPM stock with 1,2 beta should give the expected return of 15,6%. Because the actual return is 17% the alpha of stock is 17% -15,6%= 1,4% (Bodie et al. 2021, p.284).

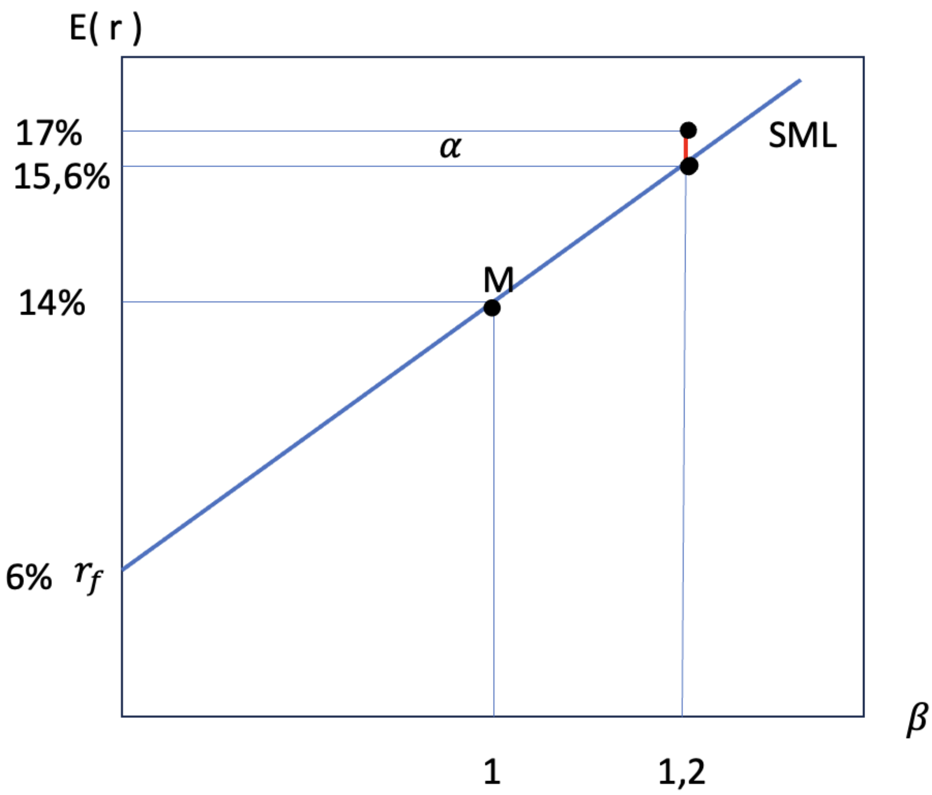

Figure 4. Security market line and the stock with positive alpha.

3.2 Arbitrage pricing model

The concept of arbitrage is presented carefully in chapter 2.3. Stephen Ross (1976) introduced the Arbitrage Pricing Theory. The APT model has three background assumptions: (1) Security returns can be described with a factor model, (2) there are enough investment possibilities that the unique risk can be diversified away, (3) if arbitrage opportunities rise the investors will exploit them and arbitrage will vanish. Like the CAPM, the APT predicts the security market line, and risk and return are positively correlated. The APT is a multifactor model, which means that the expected returns are dependent on chosen variables that are thought to affect stock returns. Since unique risk can be diversified away (condition 2), APT focuses on macroeconomic factors that affect systematic risk. For example, there can be for the GDP-, oil price- or interest factor. However, the ATP's factors are not strictly determined. (Bodie et al. p.308-311)

$$R_t = \alpha + b_1(r_{factor1}) + b_2(r_{factor2}) + \cdots + e \qquad (3)$$

Where:

$\alpha =$	constant for an asset
$b_1 =$	Stock's sensitivity to factor 1
$b_2 =$	Stock's sensitivity to factor 2
$e =$	Assest's idiosyncratic risk
$R_t =$	Return of the stock

3.3 Fama-French Five Factor Model

The Fama-French Five Factor model is the application of CAPM. In the CAPM the market risk measured with the stock's beta is the only source of the risk. The Fama-French factor model concentrates on company characteristics that have proven to be additional sources of risk. Fama and French (1993) developed the three-factor model to better describe the expected stock returns. The launch of this development started with the observation that CAPM could not fully identify a stock's riskiness. The three-factor model recognizes the small-firm effect and high book-to-market ratio as an additional source of risk. Size- and value factors are responding to these sources of risk. Like the previously presented APT model, the F-F 3 model is a factor model but its factors are strictly determined.

The construction of these factors is based on portfolio-sorting procedures. Stocks are typically sorted annually into portfolios according to their market capitalization and book-to-market ratio. The average returns of these portfolios are then used to calculate factor-mimicking portfolios—such as SMB and HML—that represent the excess returns attributable to size and value characteristics (Fama and French, 1993; Fama and French, 2015). In this way, the Fama–French factors are empirically derived measures of systematic risk, not theoretical constructs.

In 2015, Fama and French expanded their model by introducing two additional factors: profitability and investment. Since then, this expanded model has been referred to as the Fama-French Five-Factor Model. The model is presented below.

$$R_t = \alpha_i + \beta_{im}R_{Mt} + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + e_{it} \quad (4)$$

Where:

β_x = Beta for the particular factor
R_{Mt} = Expected return of the market
SMB_t = Small minus big, size factor
HML_t = High minus low, value factor
RMW_t = Robust minus weak, profitability factor
CMA_t = Conservative minus agressive, Investment factor
e_{it} = Assest's idiosyncratic risk
α_i = constant for asset

3.4 Carthart four-factor model

In 1997, Mark Carhart added the momentum factor to the Fama-French Three-Factor Model, known as Winners Minus Losers (WML). This factor, inspired by Jegadeesh and Titman's 1992 findings, captures the tendency of stocks to continue their past performance trends. It measures the difference in returns between stocks that have performed well (winners) and those that have performed poorly (losers) over the past 12 months, adding a dimension of risk and return analysis not covered by the original model. The formula is similar to that presented in formula Z but the factors are market-factor, SMB, HML, and WML.

3.5 Discounted cash-flow model

Valuation models are based on the time value of the money. The euro today is more valuable than the euro tomorrow. The future cash flows, dividends, or earnings are moved to the present-day discounting with the opportunity cost of capital (Nikkinen et al. p.148-155; Brealey et al. 2023 p.90-91).

According to Imam et al. (2008), the discounted cash-flow model is the most used valuation method among security analysts in the UK. That is why it is presented in this thesis. However, the principle and basic present value formula remain the same when discounting dividends or earnings.

Free cash flow can be calculated for the whole firm or just for the equity. Weighted average cost of capital (WACC) is usually a discounting factor when calculating the firm's value. When calculating the value of equity, the cost of equity is used as a discount factor. Present value calculations commonly include a terminal value to simplify the valuation process by approximating the value of all future cash flows beyond a certain point, thereby avoiding the need to estimate cash flows into perpetuity (Bodie et al. 2021, p.596-597).

The free-cash-flow of the firm (*FCFF*) and the Free-cash-flow of the equity (*FCFE*)(Bodie et al. 2021, p.297):

$$\mathrm{FCFF} = \mathrm{EBIT}(1 - \mathrm{t_c}) + \mathrm{Depreciation} - \mathrm{Capital\ expenditure} - \mathrm{Increase\ in\ NWC} \tag{5}$$

Where:

EBIT = Earning before interests
$\mathrm{t_c}$ = The corporate tax rate
NWC = Net working capital

$$\mathrm{FCFE} = \mathrm{FCFF} - \text{Interest expenses} * (1 - \mathrm{t_c}) + \text{Increase in net dept}$$

Present value formula:

$$\mathrm{PV} = \sum \frac{\mathrm{FCF_n}}{(1+\mathrm{r})^{\mathrm{n}}} \tag{6}$$

Where:

FCF = Free-cash-flow of the firm or the equity

R = Discounting factor, Opportunity cost of the capital (WACC or cost of equity)

Constant growth formula:

$$\mathrm{V_T} = \frac{\mathrm{FCF_{t+1}}}{\mathrm{r-g}} \tag{7}$$

Where:

$\mathrm{V_T}$= Terminal value

R= Discount factor

G= Estimated constant growth per year

3.6 Price per earnings ratio

The price-per-earnings (P/E) ratio is still a commonly used valuation method, especially together or to supplement the results of DCF analysis (Imam et al. 2008). The P/E ratio is calculated by dividing the stock market price by the earnings per share from the income statement. The P/E ratio can be thought of as a payback time. The ratio tells how many years it takes to fill the current price of the stock if the earnings remain the same (Nikkinen et al, 2002, p.144-145).

The P/E ratio is influenced by a company's growth expectations and risk. Higher growth expectations lead to a higher present value of discounted future earnings, resulting in a higher P/E ratio. Conversely, if two stocks have similar growth expectations, the riskier stock will have a lower P/E ratio because investors demand a higher rate of return, which lowers the stock's present value and P/E ratio. The P/E ratio is particularly useful for comparing stock valuations within the same industry (Nikkinen et al, 2002, p.144-145).

4 Literature review stock analysts and stock recommendations

This chapter focuses on the stock analysts. The chapter answers the question: who are the stock analysts and who are they working for? The chapter also presents evidence as to why the analysts' objectivity can be questioned. Lastly, the chapter gathers a literature review of previous studies concerning the analysts' ability to earn abnormal returns for the investors.

4.1 Who are the stock analysts?

Stock analysts can be divided into two groups based on their employers. The first group is sell-side analysts. They usually work in the research department of the brokerage houses. Sell-side analysts analyze company and industry information to form earnings forecasts and stock recommendations. This information is produced for the brokers of the company and the buy-side clients, such as hedge, mutual, and pension funds (buy-side). The earnings forecasts and recommendations are also available publicly for all market participants (Cheng et al., 2006, p.51-52; Hong et al., 2000, p.122).

The other type of stock analyst is the buy-side analyst. They work for asset management companies, producing information exclusively for the money managers to back up investment decisions. Unlike sell-side analysts' recommendations, buy-side analysts' information is not public. Naturally, most of the academic research concentrates on sell-side analysts because the recommendations are public (Cheng et al. 2006, p.52). This thesis focuses on the recommendations of sell-side analysts.

Michaely and Womack (1999) describe the sell-side analysts' employers more precisely. Usually, stock analysts work in Investment banks. Traditionally, the sources of income in investment banking are divided into corporate finance, brokerage services, and proprietary trading. Analysts work in the brokerage department's equity research.

4.2 Methods analysts use

Fundamental analysis utilizes public information to find if the stock is fairly priced (Bodie et al. 2021, p.338). Bhagwat and Liu (2020, p.59-60) say that the information analysts use is mostly public but also marginally private. Information is gathered from, for example, earnings announcements, financial statements, conference calls, and private interviews with the management. Previously mentioned sources include mostly “hard” and quantitative information but also “soft” sources are used in modern security analysis. One example is analyzing the tone of the news concerning the company. Womack (1996) says that although research is made with factual sources it still has an evaluative and predictive nature.

Imam et al. (2008) investigated which methods analysts use to form the recommendations. The DCF model and P/E-ratio seem to be the most used valuation methods among the stock analysts. EV/EBITDA was the third most popular option to valuate companies. Usually, analysts use more than one valuation tool in their valuation process. The combination of DCF and P/E was the most popular. DCF model and P/E ratio are presented more carefully in chapter three.

The result of a sell-side analyst’s work is a stock recommendation, or earnings forecast for their clients and also all the market participants. The stock recommendation is usually presented on a five-stage scale: strong sell, sell, hold, buy, strong buy.

4.3 Objectivity compromised

Through the field academic research has proven that stock analysts’ recommendations are positively biased (Bodie et al. 2021, p.358). For example, Womack (1996) reported that there were seven buy recommendations to one sell recommendation. The reasons for this phenomenon might be found in the incentives and behavioral aspects that analysts face in their daily work. Also, the interest of the bank affects to analysts’ behavior can affect analysts’ objectivity.

Michaely and Womack (1999) reported that investment banks simultaneously underwrite the Initial Public Offer (IPO) and giving recommendations for the company tends to be more inaccurate than analysts in not underwrite banks. The authors suggest that the results are due to a possible conflict of interest between the security research in brokerage services and the corporate finance department. The interest of the corporate finance department is to sell all the issued shares at the best possible price. On the other hand security research needs to produce accurate and rightly timed information for bank's clients. Rosenbaum et al. (2001) say that IPO business is one of the most important sources of cash flow in investment banks. Therefore, it would be beneficial for the bank to give favorable recommendations for the IPO stock.

Hong and Kubik (2003) investigate if the analysts are rewarded for accuracy or optimism. They find that bit of both. Investment banking has a hierarchy where certain banks like JPMorgan Chase, Goldman Sachs, and Morgan Stanley are top of the pyramid and regional banks are on the lower tier. Authors find out that accurate analysts are more likely to move to the top tier. On the other hand, analysts were also rewarded for their optimism. The author suggests that the second observation is due to investment banks promoting stocks generally to generate brokerage business and lure corporate finance clients. It seems that Hong and Kubik's suggestion hit the target because in 2003 Wall Street investment banks faced record-high fines (1,4 billion US dollars) due to generating corporate finance business with favorable stock recommendations for potential corporate finance clients (Ulick, 2003).

4.4 Can analysts' recommendations create abnormal returns?

The research about analysts' forecasting ability starts with Cowles's (1933) study: "Can stock market forecasters forecast?". Over the 4 and a half years period neither fire insurance companies, financial service companies or financial publications did not succeed in winning the performance of average common stock. The financial service companies lost 1,43% per annum and fire insurance companies by 1,20% to the market index. Financial publications lost by 4% to the randomly selected portfolio.

Stickel (1995) researched the investment value of stock recommendations and what factors affect the influence of stock recommendations. The newly published buy recommendations create a 1,16% price increase in an 11-day event window. Sell recommendations cause a -1,28% decline in stock price. The recommendation was given on the sixth day. The author reminds readers that the stock price is under the influence of different factors like earnings announcements and revisions of earnings forecasts, so the results can be misleading. Stickel reports that the large size of the brokerage house and analyst’s II All-American status (reputational factor) improved the influence of recommendations. The recommendation changes concerning smaller companies have a greater impact on the stock price.

Womack (1996) finds evidence that analysts’ recommendations have investment value. Like Stickel (1995) the study is an event study where the price development of the stock is followed in different time windows. The study pays attention only to the recommendation changes when stock is added or removed to/from the most extreme category (strong buy or strong sell). In the three-day window, from the published recommendation, the returns are the largest in the same direction as analysts have forecasted. If the recommendation is changed, the six-month development is significantly different from zero to the direction analysts have forecasted. Abnormal returns seem to appear during the first month if the stock is added to the buy category. In the case of a sell recommendation, the negative abnormal return appears during six months. Womack reports asymmetrical distribution between the appearance of buy and sell recommendations with a 7:1 ratio. Also, the price reactions were asymmetric, the new sell recommendation created a significantly larger price drift. Womack repeats the observation of Stickel (1995) that the influence of recommendation on stocks with small market capitalization is greater.

Previous research by Stickel (1995) and Womack (1996) indicated that there could be an anomaly in the markets concerning the stock analysts. Barber et al. (2001) create an investment strategy based on analysts' recommendations that could exploit the possibly existing anomaly. Stocks are divided into five different portfolios based on their consensus recommendation. Portfolios are balanced after each day if the consensus recommendation of the single stock has changed. Over the research period 1986-1996, the most favorable portfolio (strong buy) succeeded in earning 4,13% abnormal returns, and the least favorable portfolio (strong sell) -4,91% before transaction costs. The research used the Carhart 4-factor model to determine the normal returns. They notice that the abnormal returns shrink quickly if the portfolios are not balanced regularly. However, implementing the strategy required heavy trading. After the trading costs any of the portfolios do not succeed in earning abnormal returns. The authors suggest that the results indicate the market does not meet the semi-strong form of efficiency before accounting for transaction costs. Figure 5 shows the annualized gross returns of different portfolios and how portfolios have performed compared to the market. The figure shows that analysts have forecasting abilities, even though the profit melts after transaction costs.

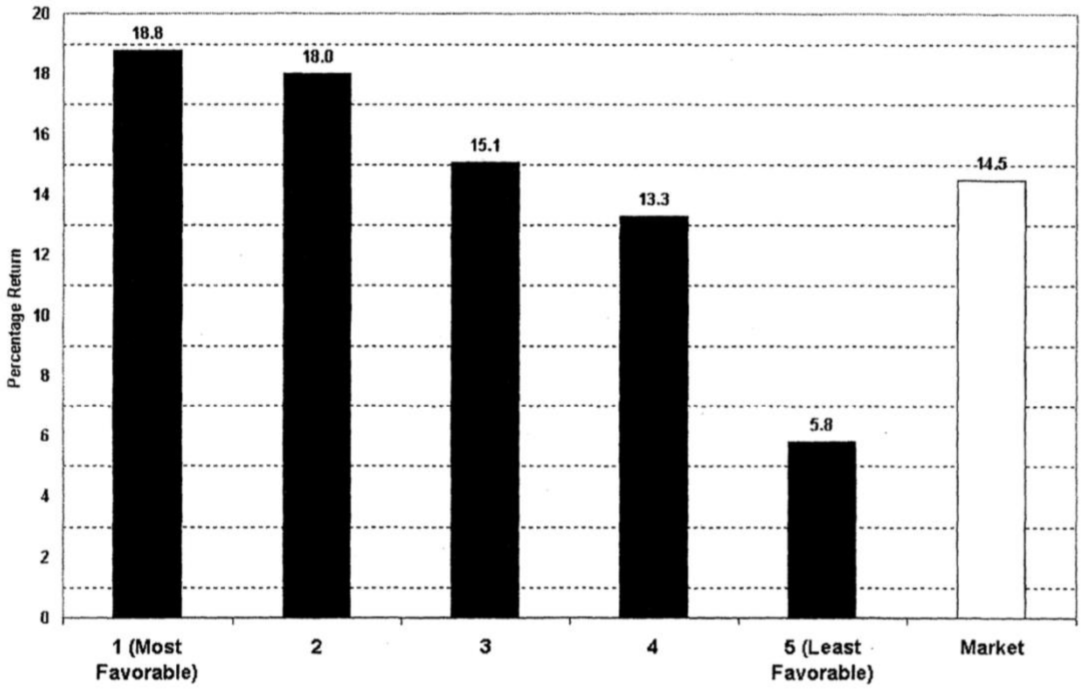

Figure 5. The annualized gross returns of consensus portfolios. Barber et al. (2001).

Park & Park (2019) repeated the research of Barber et al. (2001) between the years 2001-2016 with US stocks. Unlike Barber et al. (2001), Park & Park (2019) succeed in finding abnormal returns even after the transaction costs. The strategy that short-sells the portfolio “strong-sell” and buys the portfolio “strong buy” earned annual abnormal returns of 4,7%-5,8% benchmarked with the Carthart 4-factor model. The most significant difference between Barbert et al. (2001) and Park & Park (2019) is the calculation of the transaction costs. Barber et al. (2001) used 1,31% fixed costs from the value of the trade. Park & Park (2019) calculated the transaction costs as presented in Holden (2009). This approach makes the transaction costs significantly lower. Also, the researchers note that generally, the transaction costs have decreased notably from the 90’s.

5 Data

This chapter presents the descriptive statistics of the consensus recommendations during the sample period. The timeframe of the study spans 11 years, from January 1, 2014, to December 31, 2024. The data are obtained from Datastream and include consensus recommendation data, return indices of stocks listed on the OMX Helsinki Exchange (OMXH), and the number of analysts covering each company.

To evaluate normal returns using the Fama–French five-factor model, the study employs the European factor data provided by Kenneth R. French's data library. The OMX Helsinki Return Index (OMXHGI) is applied as the market proxy in the CAPM, as it captures the total return of the Finnish equity market and does not distinguish between large-, mid-, and small-cap segments, thereby providing the broadest representation of the market.

The three-month Euribor, obtained from the Bank of Finland, serves as the proxy for the risk-free rate in the CAPM estimations. This measure reflects the short-term, euro-denominated risk-free rate available to Finnish investors and aligns with standard practice in empirical asset pricing.

The original dataset includes 594 securities. After removing the companies with dual listing, companies with no consensus recommendation, and other data with errors, the sample ended up being 215 companies. All of those companies had at least one stock analyst giving a recommendation at some point between 2014 and 2024.

Consensus recommendations are expressed on a numerical scale from 1 to 5, with the following classifications: 1,0–1,49 = Strong Buy, 1,5–2,49 = Buy, 2,5–3,49 = Hold, 3,5–4,49 = Sell, and 4.5–5.0 = Strong Sell. The recommendations are reported with two decimal places of precision. Extreme ratings in the "Strong Buy" and "Sell" categories are rare. Table 1 shows the distribution of analysts' consensus recommendations between the recommendation classes. Table 1 presents that recommendations are asymmetrically distributed, and the category buy is the most common. This indicates that analysts tend to be rather optimistic than pessimistic also in the Finnish markets.

Table 1. The average number of companies in each consensus recommendation category from year to year.

	Strong Buy	Buy	Hold	Sell	Strong Sell
2014	0,21	26,17	39,11	11,93	0,81
2015	1,00	34,85	33,30	10,98	0,00
2016	0,83	41,83	34,03	11,69	0,00
2017	0,37	39,78	37,30	13,91	0,58
2018	1,17	48,48	30,35	14,36	0,00
2019	0,12	47,94	31,79	20,13	0,00
2020	0,98	44,02	30,33	26,00	0,12
2021	0,52	57,65	29,33	19,18	0,21
2022	3,17	59,10	26,68	29,28	0,00
2023	3,05	66,17	23,40	28,97	0,08
2024	2,20	65,68	24,31	30,09	0,00
2014-2014	1,24	48,33	30,90	19,68	0,16

At the beginning of the sample period, the average number of analyst recommendations per company was 8,5 with a median of 6. By the end of 2024, this figure had decreased to an average of 4,2 recommendations per firm and a median of 2. Although the number of individual recommendations has declined, the overall analyst coverage of the Finnish market has remained relatively stable. In 2014, consensus recommendations were available for 86 out of 117 listed companies (73.5% coverage). By the end of 2024, the number of covered firms had increased to 159, while the total number of listed companies on the Main Market and First North was 215 companies (74.6% coverage). These figures are based on DataStream data. MiFID II regulation, which came into effect in 2018, can explain the decreased number of individual recommendations given. As Lang et al. (2024) present, MiFID II did not lead to a significant overall decline in analyst coverage, although research intensity decreased mainly for large firms, while research quality remained stable or slightly improved.

6 Methodology

To form sufficient portfolios, the low number of extreme consensus recommendations poses a challenge: how to construct portfolios with a sufficient number of stocks in each. Table 1 shows that for many years, there have been hardly any stocks in the most extreme recommendation categories. To address this, all available consensus recommendations are divided into four quartiles daily. The quartiles form the four portfolios: Strong buy (Q1), Buy (Q2), Sell (Q3), and Strong sell (Q4). Portfolios are formed as follows: Strong buy $1 < CR \leq Q_1$, Buy $Q_1 < CR \leq Q_2$, Sell $Q_2 < CR \leq Q_3$, and lastly Strong sell $Q_3 < CR \leq 5$. where Q_i denotes the consensus recommendation score, and CR represents the respective quartile thresholds. Portfolios are rebalanced and quartiles are updated daily basis.

As the literature review shows, the abnormal returns most likely appear from the most extreme categories. This quartile-based approach necessarily broadens those categories to ensure a sufficient number of stocks in each portfolio. This may reduce the potential to fully capture the abnormal returns of only the most extreme recommendations. However, the strength of the chosen methodology lies in its mathematically grounded and transparent portfolio formation process. The quartile division is based on formal percentile rules rather than arbitrary cut-offs. Ensuring that portfolio construction is systematic, replicable, and free from subjective bias. To further test the robustness of the results, “extreme” portfolios are also constructed, consisting of the Top 10% and Bottom 10% of all available consensus recommendations each day. These additional portfolios help evaluate whether abnormal returns are indeed concentrated in the tails of the recommendation distribution.

Additionally, eight industry portfolios are constructed based on the industries with the largest number of companies that have a consensus recommendation during the sample period. In the OMX Helsinki, the ICB industries with the highest company counts over the sample period were: Industrials (56), Consumer Discretionary (36), Technology (28), and Financial Services (20). Each industry portfolio is formed using the median consensus recommendation, dividing the stocks into two groups: buy and sell. Unlike the quartile portfolios discussed earlier, the consensus recommendations of companies are compared only with firms within the same industry. This relative approach is essential to ensure that each portfolio contains a sufficient number of stocks for meaningful analysis. Portfolios are rebalanced quartiles are updated daily based on the updated consensus recommendation scores.

Portfolio returns are calculated on a daily basis and subsequently aggregated to monthly frequency. Each portfolio is equally weighted, and daily portfolio returns are computed using formula 8. To align the data with the benchmark frequency required for regression analysis, the daily returns are geometrically compounded into monthly returns, as illustrated in formula 9.

Portfolio's daily return formula:

$$\mathrm{R_t} = \frac{1}{\mathrm{N_t}}\sum\nolimits_{\mathrm{i}} \mathrm{r_{i,t}} \tag{8}$$

Where:

$\mathrm{R_t}$ = Portfolio's return at the moment t
$\mathrm{r_{i,t}}$ = The return of a stock at the moment t
N = Number of stocks at the moment t

Daily returns to monthly returns formula:

$$R_t = \prod\nolimits_{d=1}^{D_t} \left(1 + r_{d,t}\right) - 1 \tag{9}$$

Where:
$\mathrm{r_{d,t}}$ = Daily return of a stock at the moment t
$\mathrm{D_t}$ = Number of trading days in month t

For performance evaluation, the thesis employs the CAPM and the Fama–French five-factor model as benchmarks for normal returns. These models allow for assessing the abnormal performance (alpha) of the constructed portfolios relative to standard risk factors.

In the CAPM framework, the OMX Helsinki Gross Index (OMXHGI) is applied as the market benchmark to represent the overall Finnish equity market. The OMXHGI includes both price changes and reinvested dividends, providing a measure of total market performance. It is therefore considered a suitable proxy for market returns in the Finnish context, as it reflects the full return investors could realize from holding a broad, diversified Finnish equity portfolio. Furthermore, using a domestic, dividend-adjusted index ensures that the estimated market beta captures local market dynamics more accurately than broader regional or global indices.

In addition to the single-factor CAPM, the Fama–French five-factor model is employed to control for multiple systematic risk sources that have been shown to explain the cross-section of expected stock returns. The model expands on the traditional market factor by incorporating size (SMB), value (HML), profitability (RMW), and investment (CMA) factors.

As the literature review shows, the transaction costs can be the crucial factor in determining whether abnormal returns are found or not. The performance of the portfolio is tested with the transaction costs. Transaction costs are incorporated using a simple approach based on the number of trades executed to form the portfolio and the total number of trading months in the sample. The cost per trade was assumed to be 0,6%. This is the lowest retail brokerage fee level offered by two Finnish major brokers, Osuuspankki and Nordnet (2025). Implementing the chosen strategy requires intensive trading, so the lowest transaction fee level is justified. The formula 8 shows how the transaction costs are calculated.

$$\text{TC/month} = \frac{\text{Number of trades}}{\text{Number of Months}} \times \text{Cost per Trade} \quad (10)$$

7 Results

This chapter presents the empirical results of the study and evaluates how the constructed portfolios have performed during the sample period. The analysis focuses on assessing whether it is possible to earn abnormal returns in the Finnish market. At the beginning of the study, two hypotheses were formed:

H0: A trading strategy following analysts' recommendations yields no abnormal returns.

H1: A trading strategy following analysts' recommendations yields abnormal returns consistent with the direction of the recommendation.

Additionally, the industry portfolios were formed. By constructing industry portfolios, the thesis can achieve a broader perception of stock analysts' forecasting abilities. This approach can offer preliminary results on whether analyst recommendations carry similar informational value in all industries or whether certain sectors are more prone to mispricing than others. Two hypotheses were formed:

H0: There is no difference in analysts' ability to identify mispriced securities across industries

H1: Analysts' ability to identify mispriced securities varies across industries.

At first, general statistics and geometric returns of portfolios formed are reported. The first sub-chapter provides an indication of performance differences between portfolios formed based on analyst recommendations. The raw returns are then complemented with risk-adjusted performance measures derived from the CAPM and the Fama–French five-factor model to examine whether the portfolios succeeded in producing abnormal returns or not.

7.1 Geometric returns

Totally six portfolios were formed: quartile portfolios Q1-Q4 and “extreme” portfolios, Top 10% and Bottom 10%. Figure 6 presents the annualized geometric returns of portfolios. During the examined period, the OMXH return index yielded 6,90% annual return. Measuring with raw returns, the best performing portfolio was the strong buy portfolio Q1 (7,23%), making it the only portfolio able to outperform the OMXH return index. A bit surprisingly, the Top 10% portfolio (5,88%) failed to outperform the Q1 portfolio. The Fama-French five-factor regression in Chapter 7.3 might offer some answers for this observation. The last favorable portfolio Q2 yielded 2,26% per annum. The results suggest that stocks receiving the most favorable consensus recommendations tend to outperform the broader Finnish equity market, even after accounting for transaction costs measured with the geometric returns.

The performance of portfolios with unfavorable recommendations is also in line with stock analysts’ recommendations. The bottom 10% portfolio gave strongly negative -11,52% annualized geometric returns, and the strong sell Q4 portfolio yielded -6,65%. Lastly, the sell portfolio Q3 yielded -2,67%. Overall, the geometric returns of portfolios are consistent with the stock analyst’s recommendation, which can imply that analysts have forecasting abilities. The results are consistent with the findings of the literature review (Womack, 1996; Stickel, 1995), suggesting that analysts’ recommendations tend to have greater market impact on the unfavorable side of the field and that extreme recommendations contain more informational value for investment decisions.

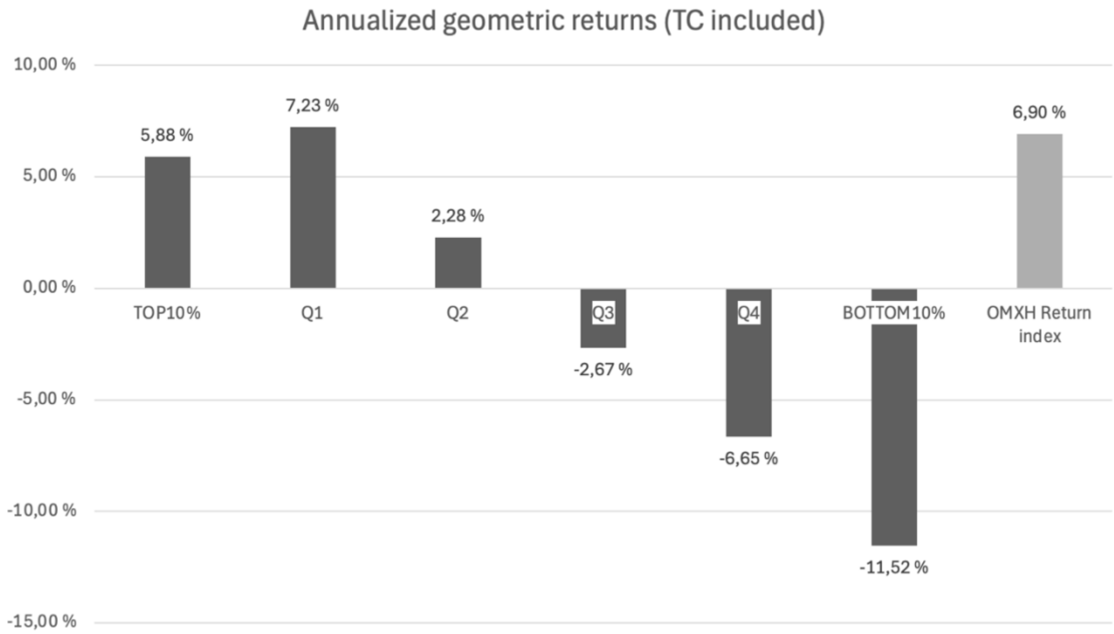

Figure 6. Annualized geometric returns of quartile portfolios.

Figure 7 presents the cumulative returns of portfolios and the benchmark index OMXH gross index. The cumulative return analysis reveals a clear monotonic relationship between analyst consensus recommendations and subsequent portfolio performance. The portfolios based on the most favorable recommendations, strong buy Q1, and the Top 10% consistently outperform the OMX Helsinki Gross Index. The post-COVID recovery, which began in the middle of 2021, is strongest for the most favorable portfolios. Interestingly, the Q1 stays above the Top 10% during the whole sample period, even though the Q1 holds a significantly larger number of stocks. The possible explanation for this observation might be that Top 10% portfolio may capture the most extreme recommendations, but it is also more exposed to idiosyncratic risk and individual stock volatility, which leads to Q1 outperformance.

Portfolios formed from the least favorable recommendations, strong sell Q4, and the Bottom 10%, show clear and persistent underperformance. The performance gap between these extremes widens throughout the sample period, suggesting that analyst recommendations carry predictive power regarding future stock returns. Importantly, these results remain robust even after accounting for transaction costs, indicating that the observed abnormal returns are not merely theoretical but potentially economically exploitable. For the least favourably recommended portfolios Q4 and the bottom10%, the COVID recovery era increased the return, but the effect was significantly more diluted than for any other portfolio constructed.

Tables 2 and 3 present the monthly averages of the number of stocks included in each portfolio, along with the daily transaction costs and the number of trades required to implement them. These descriptive statistics provide an overview of how portfolio size evolves over time. The quartile-based portfolio construction ensures that the number of firms in either the favorable (buy) or unfavorable (sell) portfolios does not directly depend on overall market sentiment. As a result, each portfolio remains sufficiently diversified throughout the entire sample period, minimizing concentration risk even during periods of high volatility.

The quartile-based approach can, however, lead to situations where the middle-quartile portfolios (Q2 and Q3) become temporarily empty when the distribution of analyst recommendations becomes polarized. This occurs in the Q2 portfolio around mid-2023, when no firms fell within that quartile’s recommendation range for several months. Consequently, the sample period for the Q2 portfolio was cut mid-2023 to maintain data consistency and avoid including empty months that harm regression analysis.

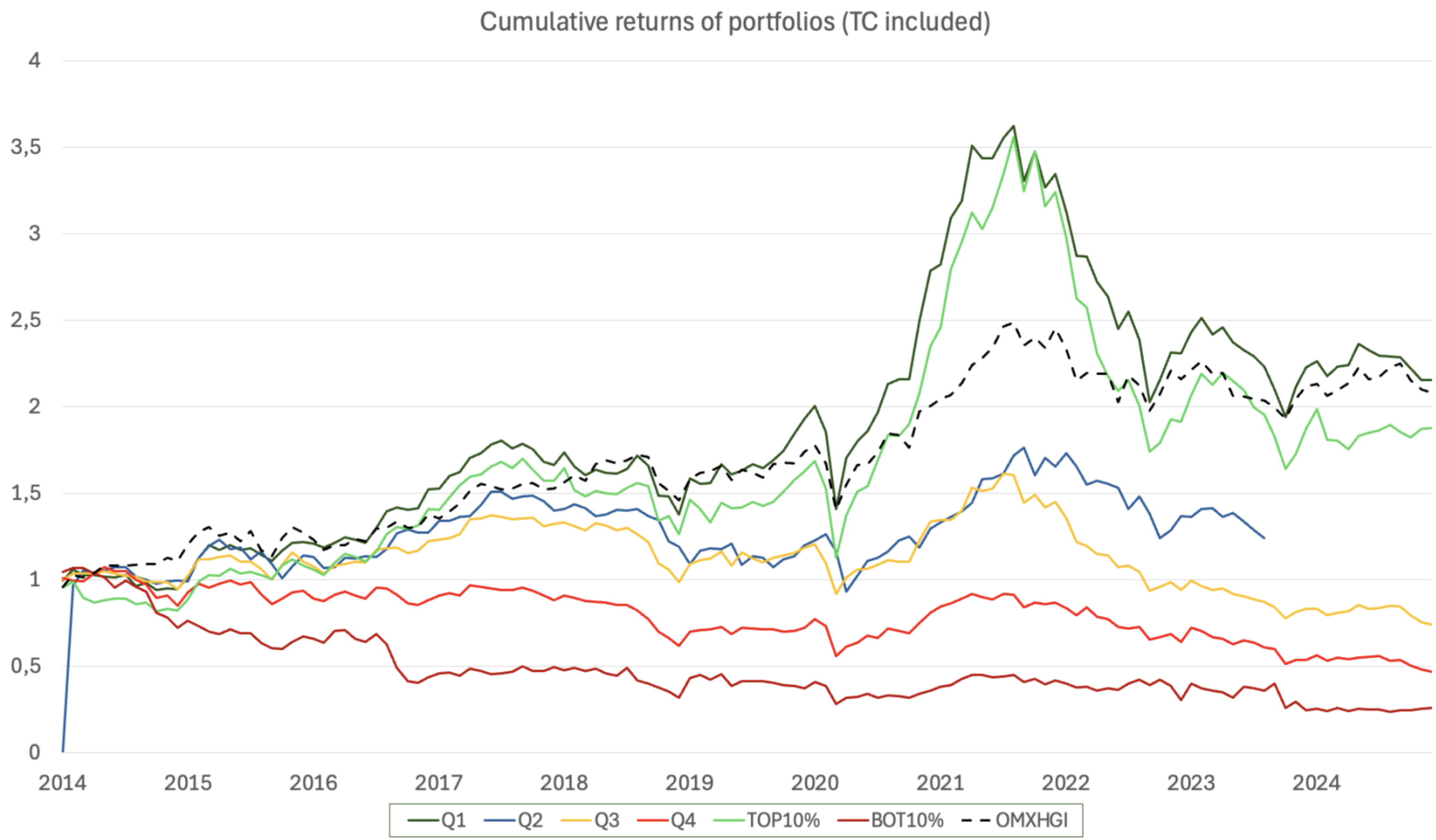

Figure 7. Cumulative returns of quartile, top 10% and bottom 10% portfolios.

Table 2. Average number of stocks in portfolios year to year.

The table shows the average number of stocks in each portfolio, month by month, and the average number of stocks for the whole sample period. The number of trades to implement the portfolio and the daily transaction costs are also reported.

	Q1 Strong Buy	**Q2 Buy**	**Q3 Sell**	**Q4 Strong Sell**	**Top10%**	**Bottom10%**
2014	13	21	22	25	6	7
2015	32	18	24	32	9	7
2016	37	17	26	37	11	8
2017	32	24	27	32	9	5
2018	41	21	30	41	11	4
2019	41	25	33	41	12	6
2020	40	26	34	40	12	7
2021	52	18	34	52	13	9
2022	59	25	35	59	15	6
2023	66	19	41	66	15	9
2024	69	14	41	69	13	9
Average	**44**	**21**	**32**	**45**	**11**	**7**
N trades	1542	1646	1929	1235	793	334
TC/day	0,0070	0,0006	0,0088	0,0056	0,0036	0,0015

Table 3. Average number of stocks in industry portfolios

The table shows the average number of stocks in each industry portfolio, month by month, and the average number of stocks for the whole sample period. The number of trades to implement the portfolio and the daily transaction costs are also reported.

	Industrials Buy	Industrials Sell	Consumer Disc. Buy	Consumer Disc. Sell	Technology Buy	Technology Sell	Financials Buy	Financials sell
2014	13	12	7	7	7	6	3	3
2015	14	12	8	7	9	9	5	3
2016	16	15	9	8	9	8	6	3
2017	18	16	10	8	9	8	5	5
2018	19	17	12	8	9	7	8	5
2019	23	19	11	9	10	7	8	7
2020	21	20	12	10	10	8	8	7
2021	22	20	13	12	11	9	8	7
2022	25	24	15	13	15	11	9	8
2023	28	25	14	14	15	10	9	7
2024	27	24	14	13	13	11	8	8
Average	**21**	**19**	**11**	**10**	**10**	**9**	**7**	**6**
N trades	606	615	313	297	316	316	219	313
TC/day	0,0028	0,0028	0,0014	0,0014	0,0014	0,0014	0,0009	0,0014

Figure 8 presents the annualized geometric results for industry portfolios. Consumer Discretionary Buy (14,24%), Technology Buy (14,16%), and Financials Buy (13,15%) were the strongest portfolios outperforming the OMXH return index. Industrials were the worst-performing sector during the sample period. Again, analysts' consensus recommendations are in line with portfolio returns.

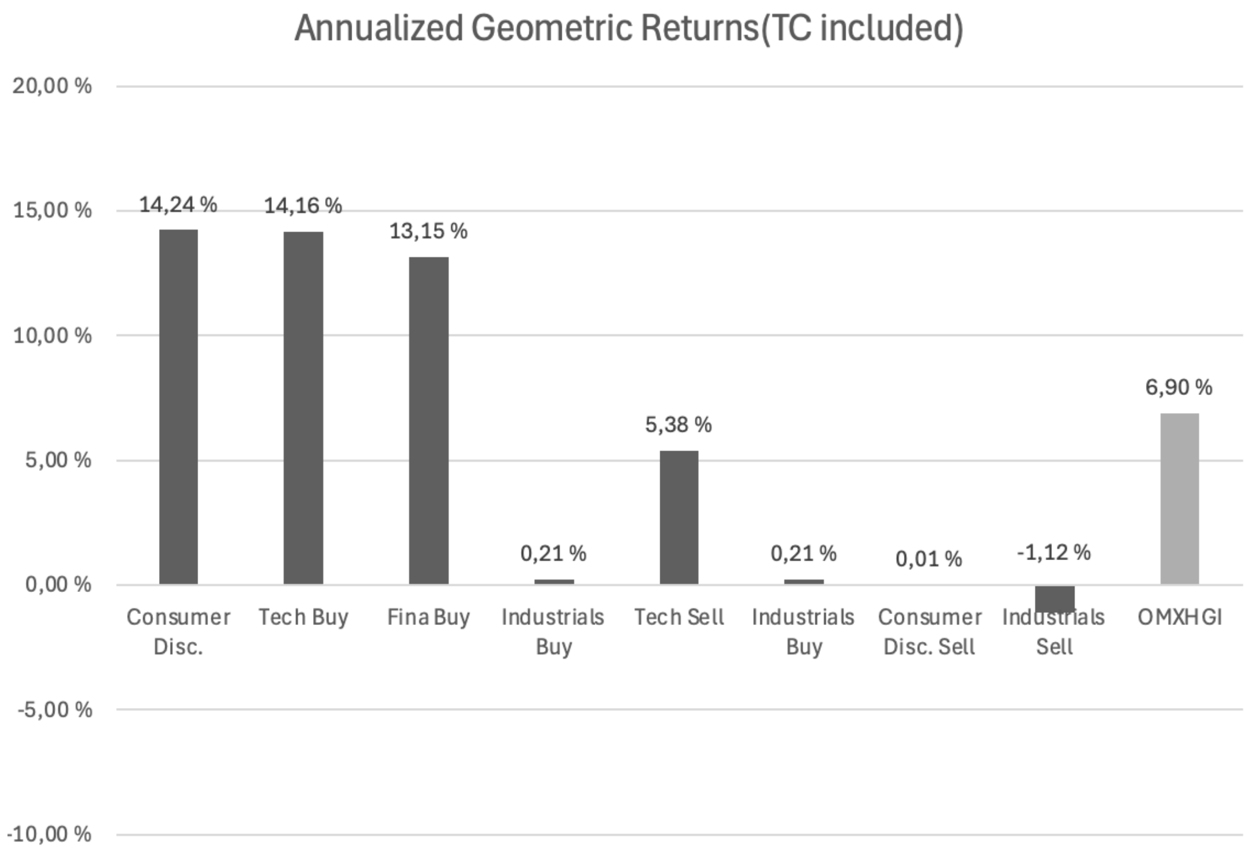

Figure 8. Annualized geometric returns of industry portfolios

7.2 Risk-adjusted returns quartile, top 10% and bottom 10 %portfolios

The performance of portfolios is tested with traditional CAPM and the Fama-French Five-Factor model. The results are shown in table 4. After risk-adjusting portfolio returns with the CAPM, none of the favorable portfolios, Q1, Q2, or Top 10% generate a statistically significant positive alpha. Although the Strong Buy Q1 portfolio produces the highest geometric return, its alpha becomes statistically insignificant once market risk is taken into account. This indicates that the superior raw performance of Q1 is largely attributable to systematic risk exposure rather than genuine abnormal returns. The buy portfolio Q2, in contrast, underperforms its expected CAPM benchmark, yielding a negative alpha that is statistically significant at the 5% level. In the case of Q2, the portfolio occasionally contained very few stocks when the market segment shifted, as the distribution of consensus recommendations became uneven around the median threshold. This structural imbalance has likely affected the performance of Q2. This observation decreases the reliability of Q2 portfolios' results. However, this finding suggests that analyst recommendations tend to cluster around specific levels rather than being symmetrically distributed, which is an informative finding in itself.

When risk-adjusted using the Fama–French five-factor model, the results remain broadly consistent. Both the Q1 and Top 10% portfolios continue to show positive but statistically insignificant alphas, while the Q2 portfolio again produces a significantly negative alpha. The size factor (SMB) is positive and statistically significant for both the Q1 and Top 10% portfolios, suggesting a mild small-firm bias. This small-cap exposure likely contributes to their higher raw returns, as smaller firms are generally associated with higher risk premiums. In chapter 7 top 10% portfolio's weaker performance against the Q1 raises questions. Although the Top 10% portfolio includes the most optimistic analyst recommendations, it fails to produce a significant positive alpha. This likely reflects both higher volatility and transaction costs, as well as analysts' inherent optimism bias. The most extreme buy recommendations may stem from overconfidence or conflicts of interest rather than superior information. In contrast, the broader Q1 portfolio benefits from greater diversification and less bias, resulting in more consistent, economically meaningful performance. Overall, the findings suggest that analysts' strongest buy signals should be interpreted cautiously, as excessive optimism can offset genuine stock-picking ability.

On the unfavorable side of the recommendation spectrum, the sell Q3 and strong sell Q4 portfolios generated significantly negative alphas of –0.7% and –1.1% per month, respectively, according to the CAPM. These results are highly significant at the 1% level. The Bottom 10% portfolio also exhibited a negative alpha, although only significant at the 10% level. The results remain consistent under the Fama–French five-factor regression, where the Q3 (–0.6%) and Q4 (–0.8%) portfolios again produced negative alphas. In the FF5 model, the Bottom 10% portfolio showed the most negative alpha (–1.1%), though the result was statistically insignificant. Interestingly, portfolios with more pessimistic consensus recommendations not only deliver lower returns but also display systematically lower market betas, suggesting that analysts' bearish sentiment is related to both lower expected returns and reduced risk exposure of the underlying companies. Probably the unfavorable portfolios contain mature companies with low expected growth opportunities.

The standard market model explains the performance of the constructed portfolios relatively well, as the adjusted R^2 values are fairly high, ranging from 0,70 to 0,58. The Bottom 10% portfolio is the only exception, with the market factor explaining only about 22% of its return variation. Interestingly, the beta of this portfolio remains close to one, indicating that it still tends to move in line with the overall market. There are several possible explanations for this pattern. First, investors may react strongly to new negative consensus recommendations, leading to short-term price drifts that reduce the explanatory power of the market model. Second, the portfolio likely includes firms whose company-specific characteristics introduce additional idiosyncratic risk. This interpretation is reasonable, as the Bottom 10% portfolio most likely consists of financially distressed or otherwise problematic firms whose returns are driven more by firm-specific shocks than by general market movements.

Table 4. Geometric returns of portfolios and the results of the CAPM and FF5 regression.

This table reports geometric portfolio returns and the results of the CAPM and Fama–French five-factor regressions for portfolios formed by analyst consensus recommendation: “strong buy” $1 < \mathrm{CR} \leq \mathrm{Q}_1$, “buy” $\mathrm{Q}_1 < \mathrm{CR} \leq \mathrm{Q}_2$, “sell” $\mathrm{Q}_2 < \mathrm{CR} \leq \mathrm{Q}_3$, and lastly “strong sell” $\mathrm{Q}_3 < \mathrm{CR} \leq 5$. Where Q_i denotes the daily quartile thresholds of the consensus recommendation distribution. Top 10%- and bottom 10%-portfolios comprise stocks that receive the CR above and below the relative limit. Reported coefficients are monthly estimates with transaction costs included. t-statistics are shown in parentheses. Statistical significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% significance levels, respectively.

	Q1 Strong buy	Q2 Buy	Q3 Sell	Q4 Strong Sell	Top 10%	Bottom 10%
Geometric monthly average return	0,0058	0,0019	-0,0023	-0,0057	0,0048	-0,0101
Intercept (Alpha Monthly)	0,0008 (0,2860)	-0,0043** (-1,9882)	-0,0076*** (-3,8388)	-0,0107*** (-3,5898)	0,0002 (0,0415)	-0,0125* (-1,8135)
Mkt-RF (Beta)	1,1003*** (17,5662)	1,0366*** (21,7327)	0,9594*** (21,8453)	0,9008*** (13,5799)	1,1215*** (13,6975)	0,9681*** (6,3221)
Adj. R^2	0,7013	0,8052	0,7843	0,5834	0,5876	0,2293
Intercept (Alfa monthly)	0,0024 (0,8260)	-0,0890*** (-7,8733)	-0,0059** (-2,4841)	-0,0087*** (-2,7461)	0,0021 (0,5660)	-0,0114 (-1,6085)
Mkt-RF	0,8159*** (11,7300)	0,0048* (1,7549)	0,7528*** (13,1500)	0,6827*** (8,9370)	0,8602*** (9,5441)	0,8120*** (0,1705)
SMB	0,9915*** (5,4106)	0,0210*** (2,8831)	0,4281*** (2,8385)	0,5232** (2,5995)	1,0328*** (4,3496)	0,0335 (0,0746)
HML	0,1101 (0,5469)	0,0107 (1,2653)	-0,0265 (-0,1600)	0,1400 (0,6332)	-0,1454 (-0,5577)	0,5120 (1,0373)
RMW	0,2006 (0,7170)	0,0243** (2,1335)	0,4056* (1,7615)	0,2196 (0,7146)	-0,0277 (-0,0764)	0,4275 (0,6230)
CMA	-0,3356 (-1,0427)	-0,0063 (-0,4818)	0,0760 (0,2869)	-0,0951 (-0,2689)	-0,2538 (-0,6084)	-0,3833 (-0,4855)
Adj. R^2	0,6660	0,1542	0,6530	0,4868	0,5566	0,1907

7.3 Risk-adjusted returns industry portfolios

In this chapter, the performance of the industry portfolios is evaluated using CAPM and the Fama-French Five Factor model. The performance of industry portfolios is presented in table 5. The alphas obtained from the CAPM and Fama–French five-factor regressions should not be interpreted as absolute abnormal returns, since the portfolios are formed within a single industry and are evaluated relative to market-wide risk factors. Instead, the alpha values still reflect the extent to which analyst consensus recommendations can identify mispriced stocks within each industry after controlling for common risk exposures. A positive and statistically significant alpha, therefore, indicates that analysts' buy recommendations generate returns above those implied by the portfolio's systematic risk profile, suggesting genuine stock-picking ability rather than exposure to known risk factors.

Across the examined industries, buy-rated portfolios generally exhibit positive and statistically significant alphas, suggesting that analyst recommendations contain valuable information for stock selection. The strongest evidence of within-sector stock-picking ability is observed in the technology, financials, and consumer discretionary sectors, where buy-rated stocks generate monthly risk-adjusted excess returns of approximately 0,6–0,7% under both the CAPM and FF-5 models. In contrast, the industrials sector shows negative alphas, indicating that analysts' buy recommendations in this segment do not lead to superior performance. Vice versa, the results might indicate the analyst being overly optimistic about the industry sector. Overall, the results imply that analysts are able to identify undervalued stocks in most of the analyzed sectors, generating genuine intra-industry abnormal returns beyond those explained by common risk factors.

Across industries, the sell-rated portfolios generally exhibit weak or insignificant alphas close to zero, indicating that analysts' negative recommendations seldom lead to substantial abnormal underperformance once common risk factors are accounted for.

In the technology, industrials, and financial sectors, sell portfolios show no statistically significant excess returns, suggesting that analysts' sell signals in these industries have limited predictive power. However, the consumer discretionary sector stands out with a strongly negative and statistically significant alpha, implying that analysts are particularly effective at identifying overvalued firms within this industry. The reason for this sector-specific skill is not entirely clear, but one plausible explanation lies in the heterogeneous nature of the consumer discretionary industry, which includes firms from very different subsectors such as media, retail, automotive, and leisure. The diversity of business models may create larger valuation disparities, making mispricing easier to detect and increasing the predictive value of analysts' sell recommendations in this segment. Moreover, macroeconomic conditions, such as the overall state of the Finnish economy, can quickly be reflected in consumer behavior. Analysts might be able to recognize this and incorporate it into their recommendations.

Higher R^2 values in sectors such as technology and consumer discretionary imply that market and common risk factors play a relatively larger role in explaining returns, whereas lower values in the industrials sector suggest that other, industry-specific or idiosyncratic factors may have a greater influence on the expected returns. However, R^2 are substantially lower than in quartile quartile-based approach, which is expected when portfolios do not have diversification across the sectors.

In summary, analyst recommendations appear to add value primarily through their buy signals in selected sectors, while sell signals generally offer limited predictive power except in the consumer discretionary industry. These results suggest that analyst forecasts can serve as an effective tool for sector-specific stock selection rather than as a universal signal across all industries.

Table 5. Industry portfolios CAPM and FF5 results.

The table reports geometric average portfolio returns and the results of the CAPM and Fama–French five-factor regressions for portfolios formed based on analyst consensus recommendations. Within each industry, firms are divided into two groups using the industry median recommendation to form buy and sell portfolios. Reported coefficients are monthly estimates that include transaction costs. t-statistics are shown in parentheses. Statistical significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% significance levels, respectively.

	Tech Buy	**Industrials Buy**	**Financials Buy**	**Consumer Dis. Buy**	**Tech Sell**	**Industrials Sell**	**Financials Sell**	**Consumer Dis. Sell**
Geometric monthly average return	0,1416	0,0021	0,1315	0,1424	0,0538	-0,0112	0,0420	0,0001
Intercept (Alfa Monthly)	0,0065* (1,6762)	-0,0049*** (-4,0073)	0,0054* (1,7307)	0,0064* (1,8080)	-0,0002 (-0,0575)	-0,0057 (-1,6546	-0,0015 (0,6606)	-0,0050*** (-4,2297)
Mkt-RF (Beta)	1,0971*** (12,8502)	0,1332*** (4,9604)	0,8409*** (12,1395)	1,1234*** (14,2465)	0,9946*** (11,0983)	0,9589*** (12,4714)	0,8501*** (11,4648)	0,1407*** (5,3298)
Adj. R^2	0,5561	0,1527	0,5277	0,6066	0,4826	0,5412	0,4989	0,1730
Intercept (Alfa Monthly)	0,0072* (1,8777)	-0,0012*** (-5,5208)	0,0073*** (2,5382)	0,0073** (2,0891)	0,0006 (0,1452)	-0,0035 (-0,9722	0,0018 (0,5076)	-0,1367** (-9,4324)
Mkt-RF	0,7925*** (8,6487)	-0,0033 (-0,6324)	0,6146*** (8,8725)	0,6146*** (10,6813)	0,6906*** (7,1541)	0,8151*** (9,3819)	0,5546*** (6,4196)	0,0066*** (1,9045)
SMB	1,0819*** (4,4817)	0,0387*** (2,8035)	0,7864*** (4,3091)	0,7864*** (4,4201)	1,0552*** (4,1490)	0,3480 (1,5206)	0,4265* (1,8739)	0,0329*** (3,5834)
HML	0,1679 (0,6333)	0,0171 (1,1290)	0,4925** (2,4572)	0,4925 (1,4409)	0,1267 (0,4536)	-0,0835 (-0,3321)	-0,0319 (-0,1277)	0,0134 (1,3298)
RMW	0,7145* (1,9386)	0,0581*** (2,7571)	0,2387 (0,8568)	0,7684* (1,9787)	-0,0124 (-0,0354)	-0,0124 (-0,0354)	-0,4708 (-1,3549)	0,0376 (2,6808)
CMA	-0,2796 (-0,6594)	-0,2796 (-0,6594)	-0,2581 (-0,8051)	-0,2581 (-1,5503)	-0,2521 (-0,5644)	0,0024 (0,0060)	-0,5506 (-1,3773)	-0,0012 (-0,0726)
Adj. R^2	0,5342	0,0789	0,5650	0,5650	0,4561	0,4742	0,3630	0,1606

8 Limitations of the study

Although several unfavorable portfolios show significant negative alpha, exploiting this possible anomaly might be challenging in practice. In this study, all sizes of firms constructed the portfolios. FF-5 regression shows, many of the portfolios have a size-factor as a significant factor affecting returns, meaning that. Short-selling is only possible for a limited number of stocks in the Finnish trading platforms. For example, Nordnet (2025) offers a short-selling opportunity for 53 stocks when 182 stocks are listed in the main list, and First-North (Nasdaq, 2025). This limits the possibilities to exploit the possible anomaly.

Another uncertainty factor is related to the transaction costs ; do the transaction costs used really reflect reality? With large data sets, it is not possible to take into account every detail and need to settle for a compromise. This study does not involve short-selling portfolios, but it seems that exploiting inefficiency needs short-selling. Muravyev et al, (2022) present in their study that the costs of short-selling crumble the abnormal returns from anomalies.

European Fama-French factors are not perfect for modeling returns in the Finnish markets, which can be observed from the lower R^2 values compared to the CAPM. However, the portfolios with significant alphas were the same no matter which model was used. The choice of risk-free rate and market benchmark could also lead to slightly different results. However, these uncertainties are always present when modeling expected returns.

Taxation also limits the practical exploitation of potential abnormal returns. In Finland, capital gains are taxed while losses are only partly deductible, and dividends are also subject to taxation. Even though the book-entry system (arvo-osuustili) enables transparency and efficiency, it ensures full reporting of transactions to tax authorities, leaving little room for tax optimization (Vero.fi, 2025). These features further reduce the after-tax profitability of active and short-selling strategies.

9 Conclusions

The results of the study indicate that analysts are relatively skilled at finding overpriced stocks, also in the Finnish stock markets. The first research question was: “What is the investment value of stock recommendations in the Finnish stock markets?”. In the case of these Q3 and Q4 portfolios, the null hypothesis can be rejected, cause portfolios created significant negative alpha. For the favorable portfolios and the bottom 10% portfolio, the null hypothesis still stands. Portfolios did not succeed in creating positive (negative) significant alpha. This implies that the Finnish stock market operates efficiently. As discussed in chapter 8 the utilizing the negative abnormal returns is difficult in practice because of the limitations and costs of short-selling. The anomaly might be there where it cannot be exploited.

Surprisingly, the extreme portfolios’ top and bottom 10% do not yield statistically significant positive or negative alphas, even though they should, in theory, contain the most “mispriced” stocks according to analyst consensus recommendations. The underperformance of the top 10% portfolio relative to the broader strong buy Q1 portfolio can be explained by the Q1’s better diversification and the presence of analysts’ optimism bias, which does not translate into realized excess returns. For the Bottom 10% portfolio, the absence of significant abnormal returns can be attributed to the factor model’s ability to account for the associated risk exposures. This implies that the low returns are largely justified by systematic risk rather than mispricing.

Formed industry portfolios offered insights into analysts’ forecasting ability, industry-specifically. The industry-level analysis shows that analysts’ forecasting ability varies across sectors. Buy recommendations generate significant positive alphas in the technology, financials, and consumer discretionary industries, indicating genuine stock-picking skill within these sectors. In contrast, negative alphas in the industrials sector suggest limited forecasting accuracy or excessive optimism. Sell recommendations generally lack predictive power, except in the consumer discretionary sector, where analysts appear adept at identifying overvalued firms. Overall, the findings imply that analyst performance is sector-dependent, and their recommendations add value mainly through industry-specific insights rather than universal market signals.

During the writing of this thesis, several potential areas for future research emerged. This study provides some evidence of analysts' ability to identify mispriced stocks within individual industries. However, much remains to be explored regarding analysts' forecasting accuracy from an industry-specific perspective. Since the industry analysis was not the primary focus of this thesis, alternative methodologies could be better suited to examine this aspect in greater depth. Moreover, only the four largest industries (measured by the number of firms) were included in the analysis, leaving many sectors and related issues unaddressed.

The data revealed that firms remaining for an extended period in the "unfavorable" portfolios tend to disappear from the sample over time. This likely reflects cases of bankruptcy, delisting, or mergers. Consequently, an interesting avenue for future research would be to investigate whether analysts' recommendations could serve as a form of early-warning indicator of financial distress, similar to models such as the Z-score. Such an approach could reveal whether analysts incorporate distress risk into their recommendations before it becomes evident in financial statements.

Lastly, the implementation of the MiFID II regulation in 2018 has transformed the field of equity research by separating research services from brokerage activities and giving rise to independent analyst firms. Future research could examine the objectivity and potential biases of this new class of independent analysts, particularly in comparison with traditional sell-side research providers.

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