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Stock Analysts' Recommendations: Abnormal Returns and the Role of Analyst Coverage and Marketplace

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TIIVISTELMÄ:

Tämän tutkielman tarkoituksena on tutkia osakeanalyytikoiden suositusten arvoa sijoittajille tarkastelemalla, kuinka konsensussuositusten noudattaminen vaikuttaa osaketuottoihin Suomessa. Lisäksi tutkitaan analyytikoiden määrän ja markkinapaikan vaikutuksia tuottoihin. Suositusten vaikutusta tuottoihin tutkitaan useilla eri menetelmillä: laskemalla salkkujen geometriset keskiarvotuotot, raakatuotot ja markkinakorjatut tuotot sekä johtamalla salkkujen epänormaalit tuotot kolmen eri regression avulla.

Tutkielman aineisto koostuu päivittäisistä osake- ja markkinatuotoista, analyytikoiden konsensussuosituksista, Fama-French riskifaktoreista sekä yhtiöitä seuraavien osakeanalyytikoiden määrästä ja markkinapaikkatiedoista. Riskittömänä korkona käytetään Suomen valtion kymmenen vuoden viitelainan korkoa. Tutkimusperiodi on 2010–2022 lukuun ottamatta viimeisen empiirisen osan lyhennettyä, viiden vuoden periodia. Kolmentoista vuoden aikavälillä tutkimuksessa on mukana yhteensä 224 listattua yhtiötä Helsingin pörssistä. Osakkeet jaetaan aluksi neljään salkkuun saamiensa konsensussuositusten perusteella. Toisessa vaiheessa salkkujen tuottojen kestävyyttä testataan ottamalla huomioon myös kaupankäyntikustannukset. Lopuksi yhtiötä seuraavien analyytikoiden määrän ja markkinapaikan vaikutuksia tuottoihin tutkitaan jakamalla alkuperäiset salkut kahtia näiden ominaisuuksien perusteella.

Kaksi enimmäistä tutkielmassa asetettua hypoteesia saavat tukea empiirisistä tuloksista. Vuosittaiset geometriset keskiarvotuotot laskevat joka askeleella siirryttäessä parhaimman konsensussuosituksen salkusta kohti huonointa. Lisäksi kaksi parasta salkkua tuottavat tilastollisesti merkitseviä positiivisia ylituottoja käytetystä metodista riippumatta, kun taas huonoin salkku tuottaa tilastollisesti merkitsemättömiä negatiivisia epänormaaleja tuottoja. Tulokset säilyvät samankaltaisina kaupankäyntikustannusten huomioon ottamisen jälkeenkin. Analyytikoiden määrän tutkiminen osoittaa kuitenkin vähäisen seurannan osakkeista koostuvien salkkujen ennustavan tulevia tuottoja parhaiten. Parhaimmat tuotot ovat salkulla, jolla on paras konsensussuositus ja alhainen analyytikoiden määrä, kun taas huonoiten pärjää huonoimman konsensussuosituksen ja alhaisen analyytikoiden määrän salkku. Tämä on linjassa tutkielman toisen hypoteesin kanssa. Kolmas hypoteesi hylätään, sillä markkinapaikalla ei näytä olevan ennustevoimaa tulevien tuottojen suhteen.

Empiiriset tulokset liittyvät myös laajempaan keskusteluun markkinoiden tehokkuudesta. Monet akateemiset tutkimukset osoittavat markkinoiden tehokkuuden parantuneen 2000-luvulla alentuneiden transaktiokustannusten ja teknologian kehittymisen myötä. Tämä tutkielma ei hylkää tehokkaiden markkinoiden hypoteesia, mutta osoittaa ylituottojen tienaamisen olevan yhä mahdollista ainakin Helsingin pörssin kaltaisella pienellä reunamarkkinalla.

AVAINSANAT: Osakesuositukset, Osakeanalyytikot, Epänormaalit tuotot, Markkinoiden tehokkuus, Helsingin pörssi

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1 Introduction

Brokerage houses use a lot of money to hire good stock analysts. According to Engelberg et al. (2020), financial companies spend over 4 billion dollars annually on their sell-side research including recommendations, forecasts, and target prices. Analysts usually work long hours creating their reports and the media reports on the recommendations given by well-known analysts. As a result, stock recommendations are noticed by many different market participants.

Rational investors should use stock recommendations to support their investment decisions only if they can benefit from recommendations in terms of better returns. According to Barber et al. (2001), both brokerage houses and investors believe that it is possible to achieve abnormal returns by following stock analyses, but it should be impossible in the long run if the market is efficient in a semi-strong form. This conflict is a motivation to investigate the impact of analysts' recommendations on stock returns and test the validity of the efficient market hypothesis. On the one hand, analysts should be experts in their field, and consensus recommendations represent their collective, average view of the specific company. If they cannot beat the market, it is good evidence favoring the efficient market hypothesis (Malkiel, 2003). On the other hand, rejecting the null hypothesis would contradict the efficient market hypothesis and could indicate the real economic value of the stock analysts' recommendations. Hence, investors could create a profitable investment strategy based on stock recommendations since the data is relatively easily accessible also for retail investors.

There are mixed research results regarding the value of stock recommendations. Malkiel (2003) states evidence favoring market experts' superior returns is negligible. In contrast, post-revision return drift indicates that recommendation revisions can predict long-term returns (Altınkılıç et al., 2016). This debate about market efficiency among researchers has continued for a long time. However, recent studies by Guo et al. (2020) and Altınkılıç et al. (2016) show that recommendations have become less valuable in the post-2000 era. This can indicate that stock markets have become more efficient in recent years.

Analysts usually analyze companies' financial numbers in-depth and have meetings with the top managers. Their reports and recommendations can be valuable for investors who do not have the time or skills to evaluate firms. Moreover, retail investors rarely can meet and discuss with the companies' managers. Hence, analysts have an important role in reducing information asymmetry in the stock markets. However, active trading and portfolio rebalancing based on recommendations is a costly strategy despite decreased trading costs.

1.1 Purpose and contribution of this study

The purpose of this paper is to study how analysts' recommendations affect stock returns. More specifically, this research gathers evidence on whether it is possible to earn positive abnormal returns by following analysts' recommendations. In addition, it examines what is the role of analyst coverage and the marketplace and how they influence the relationship between recommendations and returns.

This paper studies the impact of analysts' recommendations on stock returns in Finland by examining consensus recommendations and stock returns during 13 years between 2010-2022. Abnormal returns are investigated with different models by allocating Finnish companies into four portfolios based on their consensus recommendations. A robustness check is provided by considering the impact of trading fees. Finally, to study the impact of analyst coverage and the marketplace, the original portfolios are split into two based on these characteristics.

Other relevant studies in this field consider mostly the U.S. or other considerable international markets. Therefore, this paper contributes to the existing literature by researching a smaller stock exchange in Finland. The reaction to analysts' recommendations can be different due to smaller market caps, lower trading volumes, and less interest from institutional and international investors. There can also be more inefficiencies, especially for less followed small stocks listed on the First North marketplace. Moreover, many companies are followed by only a few analysts and only the most important companies have high analyst coverage. An expert's new insight about a specific firm gets a lot of attention if there are only a few analysts following the company in a small market and hence the impact of analyst coverage can be different compared to the U.S.

Most studies allocate stocks into portfolios based on the absolute consensus recommendation levels. This paper contributes to existing research by examining how better recommendations perform compared to less favorable ones, regardless of the absolute recommendation levels. This is done by ranking stocks based on their consensus recommendations and allocating them into relatively similar-sized portfolios based on their ranking. This also eliminates the issue found in many studies, where the results depend on the placement of boundaries that separate the portfolios.

A relatively recent and long research period provides information about the impacts of many international changes and events affecting stock markets for 13 years. For instance, the research period includes the European debt crisis, the COVID-19 pandemic, the energy crisis due to the Russian invasion of Ukraine, increased inflation, a historically rapid rise in interest rates from negative to positive, and tightened regulation of stock markets.

1.2 Hypotheses

This study examines the relationship between consensus stock recommendations and returns in Finland. It also focuses on the impact of analyst coverage and marketplace and studies whether they can have an impact on returns. Consequently, the empirical part of this study covers three separate parts, and hypotheses are derived for all of them. The development of hypotheses is based on existing research and empirical evidence. The hypotheses development is presented below.

First, the value of a recommendation-based strategy is examined. The well-known efficient market hypothesis states that stock prices should reflect all available information and its semi-strong form incorporates publicly available information, including stock recommendations. However, Barber et al. (2001) find that a recommendation-based strategy leads to significant long-term abnormal returns with daily portfolio rebalancing and argue that the market is inefficient in a semi-strong form. Moreover, Womack (1996) reports significant price reactions after recommendation announcements lasting for the following months and defends the ability of analysts to pick stocks and time the market. Recent empirical results by Palmon et al. (2020) also indicate significant abnormal returns at least in a short event window. Generally, it can be argued that even short-term abnormal returns are sufficient to create a profitable long-term portfolio since the portfolio is rebalanced daily in this research. Furthermore, all these research samples presented above cover U.S. stocks, and it is consistent to assume the same strategy can also work in a smaller and less efficient Finnish stock market. Thus, the first hypothesis (in alternate form) is as follows:

H_1: It is possible to earn positive abnormal returns by following stock recommendations.

Second, this research examines how analyst coverage influences the relationship between stock recommendations and returns. The idea behind the second hypothesis is motivated by the additional information provided by analysts. The more analysts are following a particular company, the more market participants have information and different perspectives to evaluate this firm. It is therefore reasonable to expect that investors can price the company more accurately leading to lower pricing errors and fewer excess return opportunities. Recent empirical results also support this inference chain. Li (2020) shows analyst coverage has a negative causal effect on misvaluation meaning that companies followed by many analysts are less mispriced. Recommendation changes also have a more significant impact if the firm has fewer analysts following (Loh & Stulz, 2018). It can be argued that investors benefit more from stock recommendations when there is less market information available. Hence, the second hypothesis (in alternate form) is the following:

H_2: Analysts' recommendations have better predictive power regarding stock returns if fewer analysts follow the company.

Third, this study explores how the marketplace influences the relationship between stock recommendations and returns. A company can be listed on First North Growth Market Finland or the official list of Nasdaq Helsinki. The First North marketplace typically includes newer, smaller, less liquid, and growing stocks. The First North marketplace also has lighter regulations and requirements. For instance, compliance with international IFRS rules is not required for stocks listed on the First North. It can be assumed that there is less information available regarding First North stocks and they get less attention from institutional and international investors. This can lead to higher pricing errors providing more opportunities to achieve abnormal returns. Limited information sources regarding these stocks also highlight the importance of information produced by stock analysts. Therefore, the third hypothesis (in alternate form) is the following:

H_3: Analysts' recommendations have better predictive power regarding stock returns if the company is listed on the First North marketplace.

1.3 Structure of this study

A theory about market efficiency follows the introduction section. It covers the efficient market hypothesis and a random walk as well as limits to arbitrage and anomalies. The asset pricing is considered in the third section including the concept of abnormal returns and all the asset pricing models used in the empirical part of this study. It also presents the criticisms leveled at the traditional asset pricing models. After that, there is a theory regarding stock analysts, recommendations, and their role in the market. The fifth chapter covers a literature review and presents evidence for and against abnormal returns caused by stock recommendations. It also presents elements that can affect returns when following stock recommendations.

Section 6 starts the empirical part of this paper. It describes the data, methodology, and descriptive statistics. It also shows how portfolios are created. The next chapter includes the characteristics and performance of the portfolios, and it illustrates how trading fees, analyst coverage, and the marketplace affect returns. Section 8 outlines the potential limitations that this research may have. Finally, section 9 concludes the main findings of this paper and proposes ideas for future research.

2 Market efficiency

Market efficiency has been an extensively researched topic over decades. According to Fama (1970), efficient market prices completely reflect information available in the market. To test this, the price formation, risk, and price equilibrium must be defined precisely (Fama, 1970). Nevertheless, many anomalies seem to be exceptions to the efficient markets. Researchers debate whether these anomalies exist or are abnormal returns only risk premiums resulting from the greater risk that a particular asset pricing model does not consider (Shleifer & Vishny, 1997). If this is the case, it should be possible to explain anomalies by improving the asset pricing models (Shleifer & Vishny, 1997).

2.1 Efficient market hypothesis

Fama (1970) presents the efficient market hypothesis, which states that stock prices should reflect all available information. The efficient market hypothesis has three forms: weak, semi-strong, and strong. These three levels are presented in more detail below.

In the weak form, only historical data, such as past trading volumes and price trends, are considered (Fama, 1970). When the market is efficient in a weak form it is not possible to achieve positive abnormal returns through technical analysis or forecasting stock prices based on historical trends (Fama, 1970).

According to Fama (1970), the semi-strong form covers historical data and publicly available information, including financial statements, dividend policies, and analyst recommendations. This implies that exploiting stock recommendations, technical analysis, or fundamental analysis should not generate abnormal returns in semi-strong form efficient markets.

Fama (1970) shows that the strong form covers all information from the weak and semi-strong forms and all other information that is relevant to the price formation process, such as insider information. Thus, even insider trading is unable to earn abnormal returns in a strong-form efficient market (Fama, 1970).

Fama (1998) notes that the market underreacts and overreacts but these nonrational reactions balance each other out and are randomly distributed. This observation highlights the validity of the efficient market hypothesis, as the expected value of excess returns is zero (Fama, 1998). Fama (1998) also shows that long-term abnormal returns often disappear when adjusting the research methodology, potentially due to poor asset pricing models.

2.2 Random walk

The random walk theory shows that movements in stock prices are unpredictable and random (Fama, 1995). Therefore, variations in stock prices should be independent of one another. According to Fama (1995), share prices do not have a memory. Hence, technical analysis does not provide additional value because past price changes do not have an impact on how prices will develop in the future. This supports a weak-form version of the efficient market hypothesis.

According to the random walk hypothesis, stock prices provide a reliable assessment of a company's fundamental value (Fama, 1995). If investors do not have new information or an improved idea of how this information affects the firm and its future, fundamental analysis does not add value (Fama, 1995).

2.3 Limits to arbitrage

Arbitrage is defined as the simultaneous purchasing and selling of identical securities at different prices (Lamont & Thaler, 2003). According to this definition, the strategy does not contain risk or require own capital (Shleifer & Vishny, 1997). Arbitrage is an important concept since many finance theories and asset pricing models have assumptions regarding arbitrage. For example, the law of one price says that the same goods must have the same price (Lamont & Thaler, 2003). However, the law of one price does not always hold. Exceptions to this law may result for example from trading costs, trade barriers, or uncompetitive markets (Lamont & Thaler, 2003). Shleifer and Vishny (1997) argue that exploiting market mispricing supports market efficiency. Arbitrage is, therefore, an essential element of efficient markets.

A few elements limit arbitrageurs to return prices to their equilibriums (Shleifer & Vishny, 1997). According to Shleifer and Vishny (1997), almost none of the arbitrage opportunities are risk-free and they usually need capital. Arbitrageurs do not utilize arbitrage if the risks and costs are higher than the benefits. Therefore, performance-based arbitrage cannot fully remove market mispricing, particularly in volatile market conditions (Shleifer & Vishny, 1997). Three main risks limiting arbitrage are presented below.

Most of the arbitrage circumstances include fundamental risk (Shleifer & Vishny, 1997). Arbitrageurs cannot be sure whether their opinion of the security's fundamental value is correct. Also, mispricing can last a long period and investors may not want to take the risk that their positions cannot be closed when needed. Shleifer and Vishny (1997) argue that arbitrage opportunities are profitable in most cases but not every time and this is the fundamental risk that limits arbitrage.

Implementation risk is particularly related to trading costs and short-selling restrictions. Transaction costs and short-selling commissions reduce profits when trying to benefit from arbitrage opportunities (Pontiff, 1996). Hence, costs can be higher than mispricing. Pontiff (1996) shows that high arbitrage costs are positively correlated with price deviations from their fundamental values. He also states that arbitrage does not return prices to equilibrium as effectively when interests are high. Moreover, bid-ask spreads can be seen as transaction costs to the arbitrageurs, and therefore illiquid securities with high bid-ask spreads are more vulnerable to mispricing (Pontiff, 1996). Illiquidity can also lead to a situation where arbitrage does not pay off because there are not enough securities to be traded.

Noise trader risk refers to the situation where mispricing does not disappear or even deepens in the short run (Shleifer & Vishny, 1997). Rational arbitrageurs may not be able to eliminate mispricing caused by irrational noise traders. Long-lasting mispricing can force investors to liquidate their positions early and therefore suffer sizeable losses (Shleifer & Vishny, 1997). For example, reputation risks caused by poor short-term performance and arbitrage funds' trading restrictions can lead to forced liquidation due to noise risk (Shleifer & Vishny, 1997). Shleifer and Vishny (1997) note that new and young arbitrageurs are sensitive to past returns and they cannot exploit arbitrage opportunities during great mispricing because they do not have equal amounts of funds compared to older and more reputable arbitrageurs.

2.4 Anomalies

Finance research recognizes many exceptions of efficient markets, called anomalies, where a specific strategy has produced higher returns than expected based on its systematic risk (Shleifer & Vishny, 1997). Thus, anomalies contradict the efficient market hypothesis by achieving consistent excess returns, not reflecting available information, and not following a random walk.

According to Boubaker et al. (2021), many of the identified anomalies cannot be captured by the capital asset pricing model. Thus, they generate statistically significant alphas when measured by CAPM. To mention a few of these CAPM anomalies, Fama and French (1993) note that firm size and average returns have a negative relation. In addition, they show that value stocks with high book-to-market ratios tend to have higher average returns. According to Fama and French (2015), firms with robust profitability and conservative investment strategies outperform their opposites. Past winners with price momentum also tend to generate higher average returns than past losers (Fama & French, 2016).

According to Hou et al. (2020), most of the anomalies cannot be replicated since they do not pass statistical tests. Depending on the test and t-cutoff, 65%-82% of the anomalies are rejected. Furthermore, the economic significance of replicated anomalies is smaller than identified earlier. Hou et al. (2020) highlight p-hacking concerns by saying that researchers occasionally tend to customize samples and tests to get significant results. This leads to false anomalies that cannot be found subsequently. They argue that more than previously thought, markets are more efficient. This is consistent with the findings of Altınkılıç et al. (2016) showing that market efficiency has improved because of declining transaction costs. Cederburg and O'Doherty (2015) also show that firm-level anomalies apply essentially for small stocks and tend to disappear after being documented for the first time. However, they verify that multiple firm-level CAPM anomalies exist and even more advanced multifactor models cannot explain them. Therefore, the conclusions of this section can be summarised as follows: it seems that anomalies still exist but their magnitude has decreased and market efficiency has increased.

3 Asset pricing

Existing literature suggests many different asset pricing models. These models can be used to calculate expected returns and abnormal returns can also be identified if the models cannot fully explain returns. There are pricing models for many securities, but this study focuses on models that are suitable for pricing stocks. This section also discusses the criticisms leveled at these models.

3.1 Abnormal returns

According to Jacobsen (1988), the abnormal return can be defined as the actual return minus the competitive return. The competitive return is dependent on the opportunity cost and risk of other investments (Jacobsen, 1988). Since the competitive return is only able to maintain the current capital investment, it is not an approved method in the case of stock investment. Consequently, Jacobsen (1988) and Eberhart et al. (2004) describe abnormal returns as the difference between actual and expected returns.

Actual return is relatively easy to define and calculate. Instead, there are many methods to calculate the expected return. One common concept to these models is risk. Sharpe (1964) notes that higher risk should yield higher expected returns and investors can improve expected returns only by increasing the risk level. What is considered to be a risk depends on the model. On the one hand, the return on the market portfolio can be seen as a benchmark for the portfolio's expected return under examination. Sharpe (1964) argues that expected return and systematic risk have a positive relation and thus market risk is the only risk factor included in the capital asset pricing model. On the other hand, multifactor models cover more risk factors. For example, the latest six-factor model by Fama and French (2018) has five factors in addition to market risk. It is important to use several methods when measuring a portfolio’s abnormal performance to ensure the robustness of the results.

3.2 Market-adjusted returns

The simplest method to test a portfolio’s performance is market-adjusted returns. The idea is to test portfolio performance against the market portfolio. It is easy to use since the only data needed is market returns and the model does not require estimating regressions alpha or the exposures against risk factors. Barber et al. (2001) calculate market-adjusted returns with the following formula.

$$MAR_{it} = R_{it} - R_{mt} \tag{1}$$

Where,

MAR_{it} = Market-adjusted return on portfolio i for period t
R_{it} = Return on portfolio i for period t
R_{mt} = Return on market portfolio m for period t

It can be argued that positive market-adjusted returns can be described by risk factors such as market, size, or value factors (Barber et al., 2001). Therefore, the market-adjusted model is indicative but too simple to measure the statistical or economic significance of the abnormal returns.

3.3 Capital asset pricing model

Capital asset pricing model (CAPM) is one of the well-known asset pricing models and it can be used to price securities. The portfolio theory by Markowitz (1952) contributed to the development of CAPM. It assumes that rational investors want to optimize their portfolios by choosing the optimal relationship between risk and return (Markowitz, 1952). Rational investors always choose a portfolio with lower risk when the expected return is the same, and conversely, they choose a portfolio with higher expected returns when the risk is the same. This idea is also used to price securities with CAPM.

The capital asset pricing model is based on studies by Sharpe (1964), Litner (1965), and Mossin (1966). According to Sharpe (1964), security's expected return is affected by the risk-free rate, the expected return of the market portfolio, and the security's beta. Beta describes the systematic risk of a security. According to Sharpe (1964), the expected return and systematic risk have a positive relationship and thus CAPM states that increasing beta (risk) leads to higher expected returns. The capital asset pricing model can be written as an equation below (Barber et al., 2001).

$$R_{it} - R_{Ft} = a_i + b_i(R_{mt} - R_{Ft}) + e_{it} \tag{2}$$

Where,

R_{it} = Return on portfolio i for period t

R_{Ft} = Risk-free rate for period t

a_i= Intercept

b_i= Beta

R_{mt}= Return on market portfolio m for period t

$R_{mt} - R_{Ft}$= Market factor (market return over the risk-free rate)

e_{it}= Error term of the regression

The capital asset pricing model is popular in finance but performs poorly in empirical tests (Fama & French, 2004). This can result from invalid tests or unrealistic and simplifying assumptions behind the model that do not work in the real world (Fama & French, 2004). Fama and French (2004) argue that average returns and market beta have a positive relation but it is flatter than CAPM predicts. Consequently, CAPM estimates too low expected returns for low beta stocks and too high expected returns for high beta stocks. Cederburg and O'Doherty (2015) note that CAPM cannot describe the cross-sectional variation of average stock returns potentially because of omitted risk factors. Despite empirical failings of the capital asset pricing model, the importance of CAPM anomalies is overemphasized and its performance is competitive compared to multifactor models (Cederburg & O'Doherty, 2015).

3.4 Fama-French factor models

Fama and French (1992) reject the capital asset pricing model and state that it does not explain average returns during the last 50 years. Fama and French (1993) note that small firms tend to generate higher average returns than big companies. In addition, the book-to-market ratio and average returns have a positive relationship showing that value stocks outperform their opposites. Therefore, they extend the capital asset pricing model by including size and value factors in addition to the market factor presented by CAPM. Fama and French (1993) show three-factor model has a regression intercept close to zero indicating good explanatory power of the model in terms of a cross-section of the average returns. The three-factor model can be written with the following equation (Fama & French, 2015).

$$R_{it} - R_{Ft} = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + e_{it} \quad (3)$$

Where,

R_{it} = Return on portfolio i for period t

R_{Ft} = Risk-free rate for period t

a_i = Intercept

Mkt_t = Market factor (market return over the risk-free rate)

SMB_t = Size factor (small minus big)

HML_t = Value factor (high minus low)

e_{it} = Error term of the regression

Fama and French (2015) observe that the three-factor model cannot explain average returns' variation resulting from profitability and investment factors. They show the model including these factors outperforms the original three-factor model in explaining average stock returns and reducing pricing error. Consequently, they add profitability and investment factors to their five-factor model. The five-factor model can be presented as the formula below (Fama & French, 2015).

$$R_{it} - R_{Ft} = a_i + b_iMkt_t + s_iSMB_t + h_iHML_t + r_i\mathrm{RMW}_t + c_i\mathrm{CMA}_t + e_{it} \quad (4)$$

Where,

RMW_t = Profitability factor (robust minus weak)

CMA_t = Investment factor (conservative minus aggressive)

According to Fama and French (2016), models without a momentum factor do not perform well in their tests. Furthermore, the six-factor model adding momentum to the five-factor model is the winning combination of factors when comparing the performance of the models (Fama & French, 2018). Grobys and Kolari (2022) also note the six-factor model outperforms other models. The six-factor model is presented below (Fama & French, 2018).

$$R_{it} - R_{Ft} = a_i + b_iMkt_t + s_iSMB_t + h_iHML_t + r_i\mathrm{RMW}_t + c_i\mathrm{CMA}_t + m_i\mathrm{UMD}_t + e_{it} \quad (5)$$

Where,

UMD_t = Momentum factor (up minus down)

Cederburg and O'Doherty (2015) present evidence against the performance of multifactor models. They argue that multifactor models are unable to resolve the majority of CAPM anomalies. Multifactor models improve CAPM only by explaining anomalies directly related to factors included in the model, otherwise, their added performance is negligible (Cederburg & O'Doherty, 2015). This is consistent with the findings of Grobys and Kolari (2022) showing that the three-factor model does not perform better than the capital asset pricing model in Japan, Europe, and the U.S. even though Fama and French (1993) rejected CAPM and argued that the performance of the three-factor model is superior compared to CAPM. According to Grobys and Kolari (2022), findings in favor of the three-factor model are specific to time and sample.

3.5 Criticism of the asset pricing models

Explaining expected returns by adding factors to asset pricing models is also subject to criticism. Harvey et al. (2016) raise concerns regarding data mining problems in asset pricing tests. They present a multiple testing framework where a new factor is accepted when a t-statistic is over 3,0. They argue that using a t-statistic of 2,0 as a statistical significance cutoff is not reasonable and even their 3,0 cutoff can be too low. Depending on their test's adjustments, 27%-53% of 296 factors seem to be wrong findings. Hence, hundreds of factors are suggested to explain returns but most of these findings are not real (Harvey et al., 2016).

Fama and French (2018) also warn of data dredging when adding more factors to asset pricing models. They argue that including empirically significant factors in models without a theoretical basis leads to a long list of unreliable factors. This is an interesting concern since Fama and French have added five factors to the capital asset pricing model between 1993-2018. However, Fama and French (2018) motivate the addition of these factors for example with the dividend discount model theory.

According to Grobys (2021), empirical finance uses mainly t-statistics to test results' validity. He notes that existing variances of variances for the model variables are required to get statistically reliable results with t-statistics. However, Grobys (2021) studies the S&P 500 index among other assets and shows that there are no existing variances of variances since the power law exponents are less than 3. Thus, t-statistics are sample-dependent, and correlation-based estimates such as CAPM and Fama-French factor model point estimates, are uninformative (Grobys, 2021). Even Fama (1963) states in his early study that infinite variance leads to misleading results when using statistical methods such as least-squares regressions. However, he uses OLS regressions in his later studies.

Correlation-based methods are suitable for Gaussian distributions. However, the KS test p-value of 0,5830 for the S&P 500 index indicates a power law distribution rather than a normal distribution (Grobys, 2021). This is supported by the fact that variance processes of the S&P 500 are strongly fat-tailed meaning extreme observations have a more sizeable role in distribution (Grobys, 2021). Grobys (2021) finally argues that traditional asset pricing methods do not perform well because their assumptions contradict the nature of financial markets.

4 Analysts and stock recommendations as part of the stock market

This chapter covers research reports, the translation process of converting forecasts into recommendations, analysts' role in reducing information asymmetry, and on the other hand, elements that can affect the reliability of forecasts and recommendations.

4.1 Research reports

Analysts investigate different firms and convey their findings to investors through research reports. Mao et al. (2019) argue analysts usually prepare and publish reports to express their opinions on the companies they follow. According to Miwa (2022), reports include both quantitative outputs (recommendations, target prices, earnings forecasts) and textual outputs (comments related to a firm's performance, strategy, and risk). Quantitative outputs are easier to follow but Miwa (2022) also remarks that textual tones have predictive power regarding future earnings and sales forecast revisions. Thus, investors should analyze the full report to exploit it maximally. The content of the financial analyst research report is illustrated in figure 1.

Figure 1. Content of the financial analyst research report (Miwa, 2022).

Huang et al. (2014) also recognize the value of qualitative outputs. They show that research reports' text sections can predict earnings development in the following five years. Investors' reactions are stronger to negative text and hence analysts have a great role in communicating negative news (Huang et al., 2014). Furthermore, they argue that reports' text sections are more valuable for investors when they do not only focus on financial factors but also consider other elements such as CSR issues and client satisfaction. Research reports' non-financial topics are important since they can be difficult to process and managers are often not eager to disclose this information (Huang et al., 2014). Therefore, investors may trust more analysts' opinions.

4.2 Translation process

Corredor et al. (2019) state that first analysts make their earnings forecasts and then translate them into recommendations. Investor sentiment impairs this translation process for stocks that are highly sensitive to sentiment. Hence, there can be a skew between forecasts and recommendations if the translation process is not fully effective (Corredor et al., 2019). Corredor et al. (2019) also argue that optimism is cognitively driven and has a more significant impact on recommendations than on forecasts. This finding together with the results of Miwa (2022), highlighting the importance of textual outputs and tones, encourages one to read the whole research paper as quantitative and qualitative outputs seem to complement each other but on their own can give a distorted picture of the company.

Ertimur et al. (2007) study the translation process by researching the relationship between good earnings forecasts and the profitability of recommendations. The more accurate the analysts, the more profitable the recommendations (Ertimur et al., 2007). The translation process from accurate forecasts to profitable recommendations is undermined by the conflicting incentives from the investment banking world. For instance, accurate forecasts translate into profitable buy recommendations only if the analyst is unaffiliated. Regulation changes seem to improve this translation process (Ertimur et al., 2007).

4.3 Information asymmetry

Analysts analyze publicly available information such as financial statements and profit warnings. Their work also includes private meetings with firms (Cai & Qi, 2021). Retail investors are inherently disadvantaged compared to large institutional investors and analysts, who have more private information. Not every retail investor has the opportunity for private visits with firm managers; thus, they must be satisfied with information published by firms. However, analysts can reduce this information asymmetry by conveying their information and opinions to the market.

Cai and Qi (2021) show that analysts' private meetings and discussions with the company can lead to more accurate short-term earnings forecasts. This finding indicates that private meetings with managers can be seen as an information channel for analysts which helps to create better reports and forecasts (Cai & Qi, 2021). Retail investors also benefit from more accurate forecasts and reduced information asymmetry.

Analysts’ research has an impact on market efficiency. Analysts and their reports benefit the entire market by decreasing information asymmetry (Li, 2020). Li (2020) argues that there is a negative relation between analyst coverage and stock misvaluation meaning firms are less mispriced if there are numerous analysts following them. This shows that information asymmetry leads to higher misvaluation, and analysts can alleviate this problem.

4.4 Factors mitigating the reliability of analysts' outputs

Analysts should be experts in their field and may have more information compared to retail investors. However, it is important to notice that analysts make mistakes and recommendations are not always accurate. For example, misleading recommendations can be due to economic incentives, judgment errors, or psychology-based behavior. Biased forecasts and recommendations are not valuable for market participants and investors should not follow analyses if they are misleading. Unreliable outputs also undermine confidence in the analysts’ analyses, exacerbate market mispricing, and reduce the possibility of earning especially long-term abnormal returns by following analysts’ analyses.

Analysts are susceptible to similar behavioral biases as normal retail investors. Jegadeesh and Kim (2010) show that stock analysts have herding tendencies. Herding behavior is a more significant problem when downgrading recommendations. Therefore, it seems that being different from others is more difficult when giving negative recommendations. Moreover, analysts working for reputable brokerage houses herd more than others. Jegadeesh and Kim (2010) find, however, that markets can consider analysts’ herding tendencies and therefore should not cause pricing errors.

Another example of analysts' behavioral biases is overconfidence. Bosquet et al. (2015) find that this behavioral bias occurs together with strategic incentives. They argue that analysts rely too heavily on private information and overestimate earnings forecasts.

However, there is a statistically significant difference between genders: men overweight private information but women are more rational (Bosquet et al., 2015).

Guo et al. (2020) note that biased recommendations analysts give may increase mispricing. They argue that analysts give better recommendations for overvalued stocks, and this is more common during high-sentiment periods. This is explained by analysts' behavioral biases, not economic or other incentives. Analysts' behavioral biases cause market friction, which undermines market efficiency. Jegadeesh et al. (2004) find similar evidence that analysts often give favorable recommendations for stocks with good previous performance. Thus, stock recommendations correlate with momentum and abnormal returns may not be due to stock recommendations but to momentum strategy (Jegadeesh et al., 2004).

Incentive structures also guide analysts' actions. Libby et al. (2008) argue that it is more difficult for sell-side analysts to convey negative opinions on quantitative parts due to different incentives. Quantitative parts are often viewed as final outputs, yet negative news can also be conveyed through text sections. Libby et al. (2008) find patterns where analysts' forecasts are optimistic at the beginning of the quarter and pessimistic at the end of the quarter. These patterns are also confirmed by Bosquet et al. (2015). The patterns are greater when analysts have a good relationship with managers and less significant when analysts do not have to maintain good client relationships and the only target is to create accurate forecasts. Analysts know that these forecast patterns exist and they trust that it will improve their client relationships in the future (Libby et al., 2008). Biased forecasts are not only a problem for inexperienced and young analysts but also experienced analysts' earnings forecasts can be based on history and guidance from management.

Lin and McNichols (1998) also study client relationships and affiliated analysts. They find that unaffiliated analysts tend to give lower recommendations than affiliated ones. Affiliated analysts avoid giving sell recommendations because it can harm customer relationships. This evidence indicates that finding connections between analysts and recommended firms and being skeptical about affiliated analysts can pay off.

Womack (1996) states that a wrong sell recommendation is worse for analysts' reputation than a wrong buy recommendation. Sell recommendation is more radical and investors notice it easier. Moreover, Irvine (2004) argues that favorable recommendations lead to higher trading activity and hence higher trading commissions than sell recommendations. Therefore, analysts have an incentive to give buy recommendations to avoid reputation risk and increase trading commissions. On the one hand, these findings support the idea that analysts give less frequently sell recommendations than buy recommendations. On the other hand, if a sell recommendation is given there is probably a good reason for it, and it can be valuable information for investors.

Findings presented in this section indicate that analysts can improve or reduce market efficiency depending on the reliability of their outputs. At least buy recommendations must be questioned since they are less risky for analysts' reputations and customer relationships. The sell recommendation, however, can contain valuable information or at least the risk that the sell recommendation is biased seems to be lower. This is probably one reason investors consider sell recommendations more radical: unfavorable recommendations cause stronger and longer price reactions than buy recommendations (Womack, 1996).

5 Literature review

Existing literature has no unequivocal consensus on whether stock recommendations can generate positive abnormal returns and there is evidence for and against their usefulness. Thus, both perspectives are presented separately in this literature review to create a complete overview of the topic. Results of previous studies can vary, for instance, due to different research samples, periods, or research methods. This literature review also addresses elements that influence whether abnormal returns are temporary or permanent.

5.1 Evidence for abnormal returns

Barber and Loeffler (1993) examine stock recommendations published in the Dartboard column. The Dartboard column is published monthly in the Wall Street Journal. Four analysts each recommend one stock, which is compared with randomly selected shares. Barber and Loeffler (1993) have a sample period between 1988-1990. They find that stocks picked by analysts yield an average abnormal return of 4% two days after recommendation and half of it disappears in 25 days. Barber and Loeffler (1993) argue that excess returns on recommendation announcements result from both purchasing pressure (the price pressure hypothesis) and valuable information included in recommendations (the information hypothesis).

Stickel (1995) studies buy and sell recommendations from Wall Street brokerage houses between 1988-1991. He reports that buy recommendations cause on average a 1,16% price increase and sell recommendations a -1,28% price decrease during the following 11 trading days. Recommendations therefore seem to have predictive power regarding future returns. However, these results are unreliable because abnormal returns can be caused by earnings announcements and forecast revisions (Stickel, 1995).

Womack (1996) analyzes recommendation changes of the top 14 U.S. brokerage firms between 1989 and 1991. He shows that recommendations instantly cause significant price reactions after the announcement and last for the following months. Moreover, he finds distinctions between buy and sell recommendations. Buy recommendations cause average size-adjusted returns of 2,4% during the first month after the announcement. Sell recommendations generate on average -9,1% post-event drift within the next six months. Therefore, the effects caused by sell recommendations are stronger and longer compared to buy recommendations (Womack, 1996). Womack (1996) argues that analysts seem to be able to pick stocks and time the market successfully.

Liang (1999) finds a meaningful 2-day announcement effect of 3,52% for recommended stocks in the Dartboard column between 1990 and 1994. However, he does not find evidence in favor of the information hypothesis since excess returns disappear after 15 days (Liang, 1999). There is a positive correlation between analysts' past track record and the magnitude of the announcement effect and recommended stocks have higher trading volumes compared to others (Liang, 1999). Liang (1999) argues that these findings are in line with the price pressure hypothesis and short-term abnormal returns are due to purchasing pressure from naïve investors.

Barber et al. (2001) examine consensus recommendations in the U.S. between 1986-1996. Their evidence shows that stocks with the highest consensus recommendations earn 4,13% and stocks with the worst consensus recommendations produce -4,91% annual abnormal returns after controlling the market, size, value, and momentum factors. The long-short strategy generates 0,75% excess returns per month. This requires daily portfolio rebalancing and rapid reactions to recommendation revisions since slow reactions lead to lower returns. Barber et al. (2001) argue that the market is inefficient in semi-strong form. Nonetheless, they note that daily trading causes higher transaction costs and after controlling increased costs, abnormal returns do not differ significantly from zero (Barber et al., 2001). These findings indicate that stock recommendations are valuable even in the long run but are difficult to exploit in practice.

Jegadeesh et al. (2004) examine strategies based on stock recommendations. They analyze stock recommendations from 1985 to 1998. According to Jegadeesh et al. (2004), a strategy where stocks in the highest consensus recommendation quintile are bought and stocks in the lowest quintile are sold generates 2,3% market-adjusted returns within the next six months. Moreover, stocks with buy recommendations tend to outperform stocks with sell recommendations on average. Jegadeesh et al. (2004) also document that recommendation revisions have greater predictive power than recommendations' absolute level.

Palmon et al. (2020) examine bold recommendations covering U.S. firms from 1992 to 2015. They define bold as a recommendation differing significantly from the consensus. They find that bold buy recommendations cause 1,48% and sell recommendations -3,14% cumulative abnormal returns in (0, +4) event window. Both buy and sell recommendations seem to generate short-term abnormal returns, and bold recommendations cause stronger reactions in both cases (Palmon et al., 2020). Palmon et al. (2020) also report significant positive CARs for both bold and nonbold buy recommendations over the (0, +180) window. Sell recommendations cause insignificant negative returns with the same window.

To conclude this section, prior research seems to have strong evidence in favor of at least short-term abnormal returns caused by stock recommendations. It depends on the research whether the recommendations only cause short-term price reactions because of naive investors or whether they contain valuable additional information in the long term.

5.2 Evidence against abnormal returns

Bradshaw (2004) examines analysts' earnings forecasts and valuation models behind stock recommendations. He argues that recommendations should be based on earnings forecasts since forecasts are connected to stock value and recommendations reflect experts' insights of firms' value compared to their price. He finds analysts' recommendations do not correlate with present value models but are often based on heuristic valuation models, such as the price-earnings-to-growth model. Hence, Bradshaw (2004) notes that these recommendations are less valuable for buy-and-hold investors than present value calculations. He argues stock recommendations alone do not provide superior long-term returns since analysts' views can bias recommendations. Thus, it is more important to focus on valuation models and earnings forecasts behind the recommendations (Bradshaw, 2004).

Barniv et al. (2010) argue that analysts should estimate firms' present values from expected future earnings and then include earnings forecasts in residual income valuation models. After the calculations, analysts should compare the residual income value to the stock price and give a recommendation accordingly. Nevertheless, they find that analysts' recommendations correlate positively with valuation heuristics and are therefore negatively related to future stock returns. Hence, analysts do not tend to follow their forecasts when giving stock recommendations. Barniv et al. (2010) argue that recommendations are not motivated by the mispricing of stocks but by economic incentives. The biased behavior of stock analysts questions their value and benefit to investors since it can cause significant financial losses to investors and give misleading information to market participants.

Altınkılıç et al. (2016) investigate post-revision returns drift (PRD). PRD is based on the observation that recommendation upgrades predict positive and downgrades negative long-term returns. Altınkılıç et al. (2016) notice that between 2003 and 2010 PRD does not differ significantly from zero. This is an important finding because it indicates how security markets and analysts' roles have changed. After declining transaction costs and the generalization of supercomputers market efficiency has improved (Altınkılıç et al., 2016). Today, analysts do not produce new valuable information for the market and recommendations do not provide investors with significant opportunities to achieve abnormal returns in the long run (Altınkılıç et al., 2016).

Guo et al. (2020) examine stock recommendation changes and strategies that are founded upon these updates. They measure alphas with the Fama-French three-factor model. Their results show that a strategy where stocks with upgraded recommendations are bought, and downgraded stocks are sold short, does not provide statistically meaningful alpha in 2001-2014. In contrast, the same strategy generates 68 basis points monthly alpha between 1993 and 2000. They also find that recommendation levels do not contain valuable information for investors and are more uninformative compared to recommendation revisions. These findings support evidence of Altınkılıç et al. (2016) about improved market efficiency.

Engelberg et al. (2020) have a slightly different approach to investigating analysts' performance. They use 125 anomalies that predict future stock returns and create anomaly variables by sorting stocks by anomaly characteristics. They also create extreme quintiles for each anomaly strategy defined as "longs" and "shorts". Engelberg et al. (2020) find that longs generate 16% and shorts 9% annual returns and returns increase linearly from shorts to longs. Nevertheless, analysts give an average recommendation of 3,75 for longs and 3,74 for shorts even though there is a significant difference in realized returns of shorts and longs. Engelberg et al. (2020) argue analysts are not able to give better recommendations for stocks that generate higher returns in the future and recommendations can even increase anomaly mispricing.

Concluding this section, it seems to be difficult to earn long-term abnormal returns by following stock recommendations. Market efficiency has improved due to declined costs, supercomputers, and active algorithmic trading and it is more difficult to exploit experts' recommendations in a meaningful way (Altınkılıç et al., 2016). However, most of these studies are based on U.S. data and do not provide information on whether the same applies to smaller and less efficient markets.

5.3 Elements affecting returns

The magnitude and longevity of abnormal returns caused by stock recommendations are not constant but are affected by many factors. According to Stickel (1995), six factors influence whether abnormal performance caused by recommendations is temporary or permanent and these elements are presented below.

Stickel (1995) mentions three factors that tend to cause only temporary price reactions due to the price pressure effect. The first factor is analysts' reputation. Stickel (1995) argues that analysts with good reputations have a greater impact on stock prices since investors seem to rely more on reputable analysts. The second factor affecting returns is the magnitude of the recommendation revision. For example, revisions skipping a rank from hold to strong sell cause greater price reactions than revisions from hold to sell. The third factor is defined as the size of a brokerage house. Stickel (1995) shows that recommendations given by large brokerage firms have a greater impact on the prices than those given by smaller brokerage houses. He argues that larger firms have a better ability to market their recommendations and therefore price pressure is greater.

Stickel (1995) also notices three factors that permanently impact returns due to the information effect. The first factor is firm size. It means that analysts' recommendations have a greater impact on small firms' prices compared to larger firms. This effect is explained by limited information sources regarding small firms and thus individual recommendations have a significant influence on prices. The second factor is defined as the strength of the recommendation. The recommendation downgrades to strong sell or sell have a greater influence on prices than downgrades to hold. In addition, recommendation upgrades to a strong buy have a greater impact on prices than upgrades to buy. Finally, the third factor is related to earnings forecast changes. Stickel (1995) argues that the price reactions caused by stock recommendations are greater if there are simultaneous earnings forecast revisions.

Other studies support the findings of Stickel (1995). For example, Liang (1999) notices analysts' reputations have an impact on price reactions. He argues that investors trust more recommendations given by reputable analysts and thus price pressure is greater. Moreover, Stickel (1992) finds similar evidence regarding the relationship between price reactions, analysts' reputations, and their performance. He compares the performance of Institutional Investor All-American Research Team analysts to other analysts' performance. Hence, the All-American Research Team position indicates a good reputation in his study. Stickel (1992) argues that reputable analysts have superior performance and have a greater impact on prices than others.

Lin and McNichols (1998) show that hold recommendations given by affiliated analysts generate more negative returns than those given by unaffiliated ones. They argue that investors assume that affiliated analysts give a hold recommendation, even if a sell is more justified. However, there is no difference in investors' reactions in the case of strong buy and buy recommendations. Sorescu and Subrahmanyam (2006) observe that large recommendation revisions cause negative abnormal returns if the analyst is inexperienced or works for an investment bank with a poor reputation. Thus, the reputation of analysts and brokerage firms along with the size of broker companies affect abnormal returns after the announcement date.

Kim et al. (2021) study how firm-level sentiment periods affect investors' reactions to recommendation revisions. They find that domestic investors react less to recommendation downgrades during optimistic sentiment and reactions to upgrades are more moderate during low sentiment periods. In contrast, sentiment periods do not affect foreign investors' reactions due to less biased trading decisions (Kim et al., 2021). They also show that the sentiment effect can explain investors' asymmetric reactions to recommendation revisions. For instance, reactions caused by recommendation downgrades last longer than those caused by upgrades. Overall, sentiment periods seem to affect investors' overconfidence, and stock market reactions to recommendation changes also depend on market sentiment (Kim et al., 2021).

To summarize this section, market reactions to stock analysts' recommendations depend on many elements. The characteristics of the recommended firm and brokerage house influence the market reaction. Also, an analyst's experience, reputation, and affiliations can change the magnitude of price reaction. Finally, the strength of the recommendation and market sentiment have an impact. The market's reaction to individual recommendation revision appears to be difficult to predict, as many elements can strengthen and weaken the reaction at the same time.

6 Data and methodology

Before documenting the empirical results in section 7, this section presents the data and descriptive statistics of analysts' recommendations. The portfolio creation process and empirical methods are also explained.

6.1 Data and descriptive statistics

The sample period of this study is 13 years from the beginning of January 2010 to the end of December 2022, except section 7.4 having a period of 2018-20022 due to the limited number of First North stocks having consensus recommendations. The sample includes stocks listed in Nasdaq Helsinki and Nasdaq First North Growth Market Finland marketplaces. All stocks for which return, consensus recommendation, analyst coverage, and marketplace data are available are included in the sample. After removing stocks with no data available, the sample includes 224 firms in total. All data is collected from Datastream except the Fama-French factors collected from Kenneth R. French's Data Library.

The OMX Helsinki total return index is used as a proxy for market return in this paper because it is a broad index having, for example, similar country and political risk as stocks included in portfolios under research. Stock and index returns are total returns to avoid the problem that price reactions after dividend payments can harm the results. The risk-free rate is the Finnish 10-year government bond yield. At the lowest trading level of Osuuspankki (2024) and Nordnet (2024), the trading fee is 0,2% and therefore it is used to test the robustness of the results.

Table 1 shows the descriptive statistics of this study. The number of covered firms increases from 114 to 176 during the research period. The mean and median of the consensus recommendations do not appear to be radical on average, as extreme recommendations balance each other out, and the average consensus tends to settle in the middle of the scale. However, the average consensus has slightly improved during the sample period. An interesting observation is the decreasing number of analysts per firm. While in 2010 the number is clearly over 8, in 2022 it is under 4. Both the numerator and denominator explain this: the number of analysts has decreased while the number of firms covered has increased. Lang et al. (2023) note that after the Markets in Financial Instruments Directive (MiFID) II entered into force in the EU in 2018 the number of sell-side analysts decreased significantly. Tighter regulation to protect investors may be one reason for the decline in the number of analysts.

Table 1. Descriptive statistics of stock analysts' recommendations.

This table provides descriptive statistics regarding the stock recommendations. The number of firms covered includes all the firms having a minimum of one recommendation during the year. Consensus recommendation provides information about the mean and median of all the consensus recommendations given during the year. The scale for consensus recommendation is from 1 (the best) to 5 (the worst). The last two columns show the mean and median of the daily "number of analysts / firms covered" ratio.

Year	Number of firms covered	Consensus recommendation		Number of analysts per firm	
		Mean	Median	Mean	Median
2010	114	2,90	2,80	8,39	8,50
2011	120	2,89	2,75	8,38	8,30
2012	117	2,80	2,70	8,52	8,72
2013	97	2,87	2,81	8,63	8,64
2014	99	2,79	2,80	7,36	7,37
2015	108	2,66	2,56	6,75	6,65
2016	123	2,64	2,50	6,33	6,31
2017	127	2,73	2,64	6,02	6,12
2018	138	2,61	2,50	5,28	5,28
2019	142	2,77	2,55	4,73	4,76
2020	141	2,82	2,67	4,55	4,52
2021	154	2,65	2,35	4,44	4,36
2022	176	2,61	2,40	3,97	3,94
Average	127	2,75	2,62	6,41	6,42

6.2 Creation of portfolios

Consensus recommendations have a scale from 1 (the best) to 5 (the worst). Stocks are ranked based on their consensus recommendations daily and recommendation quartiles,

Q_n, are calculated. Stocks are then allocated into four portfolios based on consensus recommendations, CRs, as follows: 1,0≤ CR <Q_1: Strong Buy, Q_1≤ CR <Q_2: Buy, Q_2≤ CR <Q_3: Sell, and Q_3≤ CR ≤5,0: Strong Sell. Q_1 indicates the value of the first quartile, Q_2 is the value of the second quartile (median), and Q3 is the value of the third one. Consensus recommendations 1 and 5 are the minimum and maximum values, respectively. Due to the limited number of First North stocks having consensus recommendations, the buy and sell portfolios are combined into one hold portfolio in section 7.4 as follows: 1,0≤ CR ≤Q_1: Strong Buy, Q_1< CR <Q_3: Hold, and Q_3≤ CR ≤5,0: Strong Sell. The long-short portfolio takes a long position on strong buy and a short position on strong sell. All the portfolios are equal-weighted for better diversification benefits as portfolios are diversified across a broader range of stocks and sectors. Moreover, the risk of overweighing big and overvalued stocks is smaller. The Fama-French size factor captures the effect of a possible increasing size risk.

To test the impact of analyst coverage, all four portfolios are split into two. First, the mean analyst coverage of each portfolio is calculated daily. Then each portfolio is split into two based on analyst coverages, ACs, as follows: 1≤ AC < MEAN: Low Coverage and MEAN ≤ AC ≤ MAX: High Coverage. This portfolio allocation leads to eight sub-portfolios in total. To test the impact of the marketplace, all three portfolios are split into two based on the marketplaces of the stocks, leading to six sub-portfolios.

Portfolios are not created solely based on their absolute consensus recommendation or analyst coverage. Instead, stocks are ranked and evaluated in relation to each other. There are a couple of reasons for this. First, the recommendation distribution is not normally distributed but asymmetric as strong sell recommendations in particular seem to be rare. In addition, strong buy and strong sell consensus recommendations are often given when only one analyst is following the firm. Consensus in the middle of the scale is more common in the case of high analyst coverage. Thus, eight different portfolios cannot be built reasonably if only absolute levels are considered.

The second reason is related to seasonality and market sentiment. Strong sell and sell recommendations tend to be less frequent during positive market sentiment whereas recommendations become more negative during the downturn. Comparing recommendations to each other keeps the portfolios relatively the same size through different market conditions. It allows one to compare whether favorable recommendations can beat less favorable recommendations regardless of the market sentiment.

6.3 Empirical methods

Testing and verifying the abnormal performance of a strategy requires several models. This study uses a combination of simple, traditional, and widely used methods together with more complex models. First, annualized geometric means returns, monthly raw returns, and monthly market-adjusted returns are calculated. Second, three different regressions are used: 1) Capital asset pricing model, 2) Fama-French three-factor model, and 3) Fama-French five-factor model. The regressions consider different factors that have been noticed to affect returns. This ensures that possible excess returns are not caused by omitted risk factors but by a real additional value of stock recommendations. The idea is to test whether statistically significant regression alphas can be found after controlling portfolios' exposures to different risk factors.

Daily stock and index returns are compounded into monthly returns to better outline excess portfolio returns. Also, monthly Fama-French European factors are used because they are not provided separately for Finland or Nordics. Daily returns are compounded over n trading days into monthly returns with the following formula below.

$$R_{\text{monthly}} = \prod_{i=1}^{n}(1 + R_{\text{daily i}}) - 1 \qquad (6)$$

First, annualized geometric mean returns and monthly raw returns are calculated. The idea is to outline the differences in portfolio returns. Second, monthly market-adjusted returns are calculated with the formula presented in equation 1 of section 3.2. In this method, portfolio returns are compared with market returns by subtracting monthly market returns from monthly portfolio returns. OMX Helsinki total return index is used as a proxy for market return. However, this method does not include any risk factors and is thus a poor model for controlling different risks of portfolios.

The first regression used in this study is a simple and traditional capital asset pricing model explained in equation 2 of section 3.3. Beta illustrates the portfolios' exposure to systematic risk. The idea behind the capital asset pricing model is that increasing beta is expected to lead to higher expected returns. The selection of this model is justified by the findings of Grobys and Kolari (2022) showing that the performance of CAPM is equally good as the Fama-French three-factor model in their European sample. The performance of factor models seems to depend on the sample and period and hence it is necessary to use CAPM since it has been noticed to perform better with European stocks. Nevertheless, one can argue excess returns measured by CAPM are due to additional risk factors such as size risk. Therefore, Fama-French multifactor models are needed to solve this problem.

The second regression used is the Fama-French three-factor model described in equation 3 of chapter 3.4. It adds two more factors, size and value, to better explain portfolio returns. The reason behind this is that CAPM cannot take into account higher returns of small and value stocks. Fama and French (1993) document that this model has a regression intercept close to zero reflecting that it explains returns well enough. It is, however, an old model, and therefore a more recent method is also used.

The last regression is the Fama-French five-factor model presented in more detail in equation 4 of section 3.4. In addition to market, size, and value factors it includes also profitability and investment factors. Fama and French (2015) argue firms with robust profitability and conservative investment strategies outperform their opposites and therefore they must be included in the model. The Fama-French five-factor model is the latest and most complex model used in this research. Moreover, it provides the most information on the characteristics of portfolios by describing how the portfolios correlate with five different risk factors.

It is assumed that calculating raw and market-adjusted portfolio returns and estimating regression alphas with three models is sufficient to describe differences in portfolio returns and explain return fluctuations resulting from risk factors. Consequently, the value of the recommendations can be reliably tested.

7 Results

This chapter provides the empirical results of this study. First, portfolios' characteristics are described by explaining how they correlate with different risk factors. Portfolios' performance is presented by calculating annualized geometric mean returns and then deriving three regression alphas reflecting abnormal returns. These results are tested by considering also trading fees. Finally, the impact of analyst coverage and the marketplace on portfolio returns is presented.

7.1 Characteristics and performance of the portfolios

Characteristics of recommendation-based portfolios are presented in table 2. It shows the average number of companies, average consensus recommendations, and average number of analysts per firm for all portfolios. Ranking stocks based on their consensus recommendations and allocating them into portfolios makes the portfolios relatively the same size. In particular, strong buy and strong sell portfolios become more sizeable. Not surprisingly, the average consensus recommendation increases towards five when moving from strong buy to strong sell. As discussed in section 6.2, strong buy and strong sell consensus recommendations are more often given when only one analyst is following the firm, and thus the average number of analysts per firm for these portfolios is significantly lower. For the middle two portfolios, this number is on average about twice as high compared to strong buy and strong sell portfolios.

Table 2 shows that market risk factor is significant for all portfolios and size and investment factors are also significant in most cases. It can be seen that all the portfolios comove with the market portfolio but excess returns due to market risk premium generally decrease when moving from strong buy to strong sell. Moreover, all but the long-short portfolio seem to invest in small stocks because the point estimates against the SMB factors are positive and statistically highly significant. Most of the portfolios also have a significant and negative correlation with the CMA factor meaning portfolios invest in firms that have an aggressive investment structure. Value and profitability factors are not statistically significant for most portfolios. Adjusted R^2 indicates that the five-factor model best explains the returns on the sell portfolio.

Table 2. Characteristics of recommendation-based portfolios.

This table presents the characteristics of five recommendation-based portfolios. Stocks are allocated into portfolios based on consensus recommendations, CRs, and recommendation quartiles, Q_n, as follows: $1{,}0 \leq CR < Q_1$: Strong Buy, $Q_1 \leq CR < Q_2$: Buy, $Q_2 \leq CR < Q_3$: Sell, and $Q_3 \leq CR \leq 5{,}0$: Strong Sell. The long-short portfolio takes a long position on strong buy and a short position on strong sell. The number of companies, consensus recommendation, and number of analysts per firm columns are daily averages. The following five columns show the point estimates from the Fama-French five-factor model and the adjusted R2 is also provided. T-statistics are shown in parentheses below the coefficients. *, **, and *** illustrate statistical significance at 10%, 5%, and 1% levels, respectively.

Portfolio	Number of companies	Consensus recommendation	Number of analysts per firm	Point estimates for the Fama-French five-factor model					Adjusted R^2
				MRF	SMB	HML	RMW	CMA	
Strong Buy	21	1,64	4,81	0,924***	0,767***	0,156	-0,332	-0,614**	0,742
				(16,161)	(5,085)	(0,877)	(-1,308)	(-2,420)	
Buy	35	2,30	7,54	0,871***	0,511***	0,307*	0,070	-0,462**	0,743
				(16,776)	(3,734)	(1,898)	(0,302)	(-2,002)	
Sell	29	2,89	9,07	0,889***	0,281***	0,063	-0,200	-0,423**	0,824
				(22,330)	(2,674)	(0,506)	(-1,132)	(-2,393)	
Strong Sell	31	3,90	4,46	0,730***	0,512***	0,334**	-0,022	-0,378	0,670
				(13,515)	(3,598)	(1,987)	(-0,092)	(-1,575)	
Long-Short	NA	NA	NA	0,310***	0,282	-0,323	-0,748**	0,147	0,167
				(4,389)	(1,510)	(-1,464)	(-2,384)	(0,468)	

Figure 2 provides the annualized geometric mean returns for the four recommendation-based portfolios and the market portfolio. It shows that the strong buy portfolio earns a relatively high geometric mean return of 17,91% per year. The buy portfolio has a geometric mean return close to strong buy but returns decrease significantly when moving to portfolios including stocks with the least favorable recommendations. The difference between the strong buy and strong sell is 14,74 percentage points in favor of the strong buy. Interestingly, all the portfolios have positive annual geometric mean returns and only the strong sell has lower returns than the market.

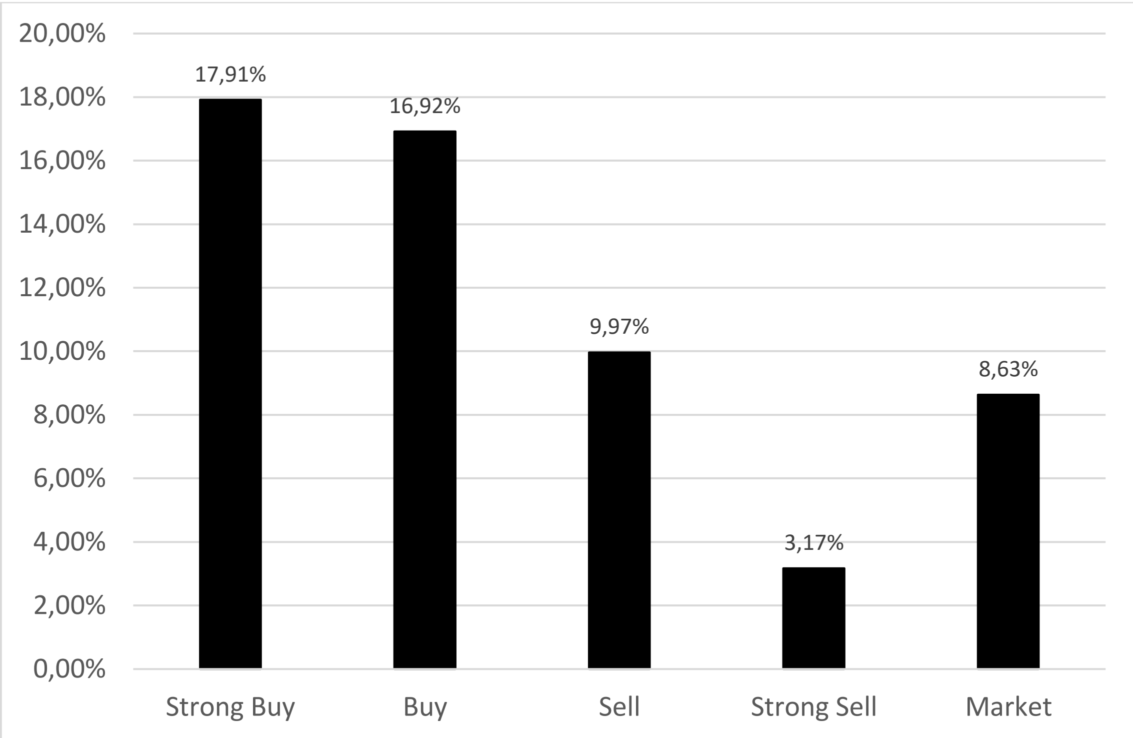

Figure 2. Annualized geometric mean returns 2010-2022.

The results from figure 2 are not evidence of the absolute superiority of high-recommended stocks but give the motivation to continue to investigate returns. If all portfolios had the same geometric mean returns, it could indicate that it would not be possible to earn abnormal returns with a strategy based on consensus recommendations. However, the notable difference in favor of strong buy and buy portfolios rationalizes a closer examination of returns using factor models.

Monthly portfolio returns are presented in table 3. The monthly mean raw return is 1,55% for strong buy and it decreases step by step when moving towards less favorable recommendations being only 0,37% for strong sell. However, all the portfolios have positive monthly raw returns on average. These results are in line with the results in figure 2 suggesting that consensus recommendations could have explanatory power in terms of portfolio returns.

Estimated regression intercepts from the capital asset pricing model and Fama-French factor models show that these regressions cannot fully explain the returns of strong buy, buy, and long-short portfolios. Strong buy and buy portfolios have positive excess returns that are highly significant at the 1% level regardless of the model. However, strong buy outperforms buy portfolio across all models. Long-short portfolio also has positive abnormal returns being significant at 1% or 5% level depending on the model. The intercepts are slightly positive for the sell portfolio and slightly negative for the strong sell portfolio, but they are insignificant and thus not statistically different from zero.

To interpret the results of table 3, stocks having consensus recommendations better than the median outperform the stocks with least favorable recommendations. The differences in raw, market-adjusted, and abnormal returns between strong buy and strong sell are great in all models. Nevertheless, sell and strong sell portfolios do not earn statistically significant negative abnormal returns in any model. This is in line with Palmon et al. (2020) finding significant positive abnormal returns due to buy recommendations but only insignificant negative abnormal returns generated by sell recommendations in their longer research period of 180 days. The best recommendations thus provide more valuable information for investors. This contradicts Womack (1996) arguing the effects caused by sell recommendations are stronger and longer compared to buy recommendations.

Table 3. Portfolios' performance 2010-2022.

This table presents the monthly returns of five recommendation-based portfolios in decimal form. Stocks are allocated into portfolios based on consensus recommendations, CRs, and recommendation quartiles, Q_n, as follows: 1,0≤ CR <Q_1: Strong Buy, Q_1≤ CR <Q_2: Buy, Q_2≤ CR <Q_3: Sell, and Q_3≤ CR ≤5,0: Strong Sell. The long-short portfolio takes a long position on strong buy and a short position on strong sell. The mean return is the average monthly raw return, and the mean market-adjusted return is the average from the monthly raw returns minus the monthly OMX Helsinki total return index. Estimated regression intercepts present monthly abnormal returns from three different models. T-statistics are shown in parentheses below the coefficients. *, **, and *** illustrate statistical significance at 10%, 5%, and 1% levels, respectively.

Portfolio	Mean return	Mean market-adjusted return	Estimated regression intercepts		
			CAPM	Fama-French three-factor model	Fama-French five-factor model
Strong Buy	0,0155	0,0075	0,0074***	0,0069***	0,0076***
			(2,707)	(2,726)	(2,932)
Buy	0,0145	0,0065	0,0068***	0,0066***	0,0062***
			(2,892)	(2,914)	(2,655)
Sell	0,0091	0,0011	0,0015	0,0011	0,0017
			(0,823)	(0,650)	(0,919)
Strong Sell	0,0037	-0,0043	-0,0032	-0,0032	-0,0033
			(-1,304)	(-1,363)	(-1,343)
Long-Short	0,0114	0,0034	0,0073**	0,0073**	0,0093***
			(2,365)	(2,344)	(2,913)

In conclusion, based on the various methods employed in this section, stocks with favorable consensus recommendations consistently earn relatively high returns, regardless of the chosen method. The conclusion also does not depend on whether the returns of top portfolios are compared with the worst portfolios or the overall market portfolio. On the other hand, investing in sell or strong sell portfolios does not seem to have a particularly detrimental impact on investors' wealth, although investing in the strong buy portfolio yields significantly better returns over time. The results in this section are inconsistent with the efficient market hypothesis, as stocks in strong buy, buy, and long-short portfolios do not seem to reflect all publicly available information in the market. The results are therefore in line with the first hypothesis.

7.2 Trading fees

Portfolio returns presented above do not consider the impact of trading fees. However, trading fees must be paid when stocks are bought or sold. On the one hand, active daily portfolio rebalancing increases costs significantly. On the other hand, fees and costs related to stock trading have decreased in the post-2000 era. This chapter serves as a robustness test of the impact of trading fees. Chapter 7.1 provides evidence that a recommendation-based strategy can earn abnormal returns in theory. The results of this section, however, are closer to reality.

The trading fee used in this study is 0,2%. It is the highest trading fee of the lowest trading level for both Osuuspankki (2024) and Nordnet (2024). Active trading could also lead to lower trading fees but using the highest fee provides a safety margin for the research. Possible fixed monthly costs, taxes, liquidity premiums, or market impact costs are not taken into account. From this perspective, this robustness test works best if an investor is using a relatively new Finnish equity savings account. According to the Finnish Tax Administration (2024), trading stocks within an equity savings account is possible without tax consequences. Dividends are also tax-free inside the account and can be reinvested without having to pay taxes in between. Hence, compound interest works better leading to higher returns over time. For example, previously mentioned major Finnish brokers Nordnet (2024) and Osuuspankki (2024) do not have opening, monthly, or storage fees for the equity savings account. Nordnet (2024) provides this benefit for all clients and Osuuspankki (2024) for their owner-customers.

There are also limitations on the equity savings account that are not considered in this study. For example, a maximum of 100 000 euros can be deposited into the equity savings account (Finnish Tax Administration, 2024). After withdrawing money from the account, the tax rate on capital income is 30% up to 30 000 euros and 34% for the part over it (Finnish Tax Administration, 2024).

Figure 3 shows the annualized geometric mean returns for all portfolios after considering the 0,2% trading fee. The portfolio returns decrease at every level when moving from strong buy to strong sell. The buy portfolio is again relatively close to the strong buy and the drop in returns is the greatest when moving to sell and strong sell. However, even the strong sell portfolio return is not negative. Especially, the strong buy portfolio’s trading fee-adjusted return seems to be high compared to the market or other portfolios.

The results of figure 3 give motivation for further research. Using the capital asset pricing model and Fama-French regressions on trading fee-adjusted returns provides evidence on whether the positive abnormal returns of strong buy and buy portfolios remain significant and whether the abnormal returns of sell and strong sell portfolios turn negative and statistically significant.

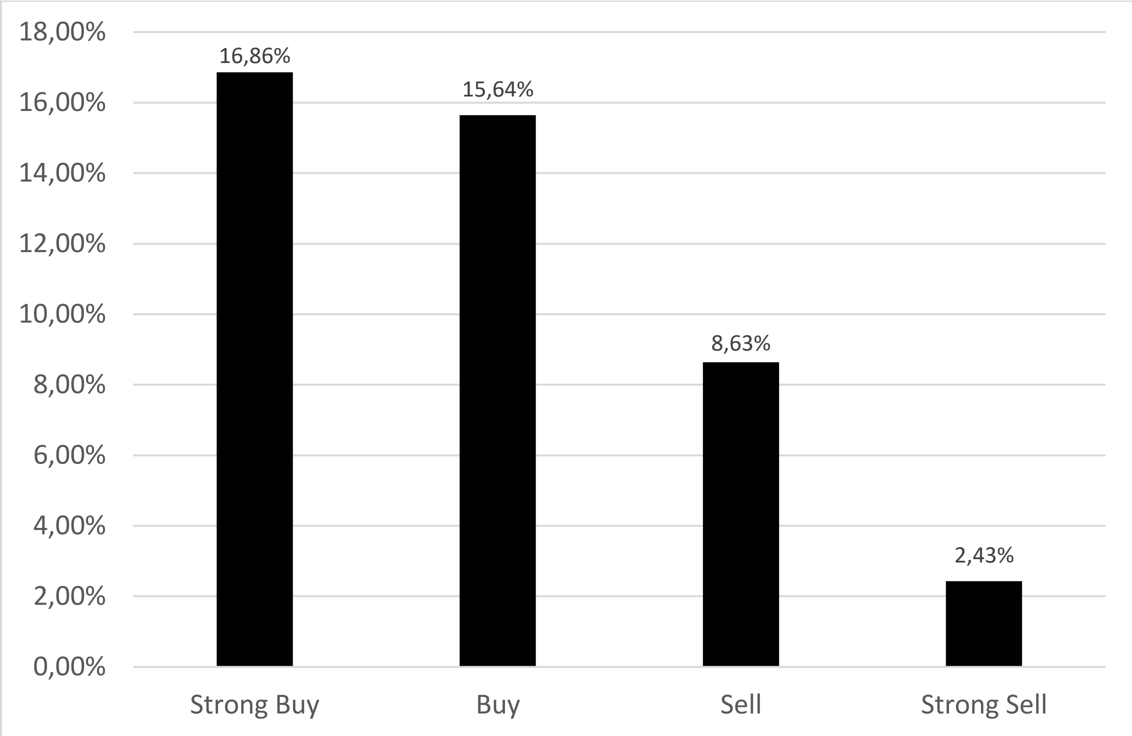

Figure 3. Trading fee-adjusted annualized geometric mean returns 2010-2022.

Table 4 illustrates the monthly trading fee-adjusted portfolio returns for all four portfolios. It can be seen that strong buy and buy portfolios earn positive abnormal returns across all three regressions. The strong buy has a monthly abnormal return between 0,6-0,7% and the buy portfolio 0,5-0,6% depending on the model. All these excess returns are statistically significant, at least at the 5% level. Abnormal returns decrease at every level with the strong sell portfolio having the lowest abnormal returns. It generates insignificant negative abnormal returns although they are close to the 10% significance level.

Table 4. Trading fee-adjusted portfolios' performance 2010-2022.

This table presents the monthly returns of four trading fee-adjusted recommendation-based portfolios in decimal form. The trading fee used is 0,2%. Stocks are allocated into portfolios based on consensus recommendations, CRs, and recommendation quartiles, Q_n, as follows: 1,0≤ CR <Q_1: Strong Buy, Q_1≤ CR <Q_2: Buy, Q_2≤ CR <Q_3: Sell, and Q_3≤ CR ≤5,0: Strong Sell. The mean return is the average monthly raw return, and the mean market-adjusted return is the average from the monthly raw returns minus the monthly OMX Helsinki total return index. Estimated regression intercepts present monthly abnormal returns from three different models. T-statistics are shown in parentheses below the coefficients. *, **, and *** illustrate statistical significance at 10%, 5%, and 1% levels, respectively.

Portfolio	Mean return	Mean market-adjusted return	Estimated regression intercepts		
			CAPM	Fama-French three-factor model	Fama-French five-factor model
Strong Buy	0,0147	0,0068	0,0067**	0,0061**	0,0068***
			(2,433)	(2,427)	(2,636)
Buy	0,0136	0,0056	0,0059**	0,0057**	0,0053**
			(2,499)	(2,503)	(2,260)
Sell	0,0080	0,0001	0,0005	0,0001	0,0007
			(0,252)	(0,066)	(0,363)
Strong Sell	0,0031	-0,0049	-0,0038	-0,0038	-0,0039
			(-1,548)	(-1,619)	(-1,582)

Results from figure 3 and table 4 indicate that a recommendation-based strategy can earn statistically significant positive abnormal returns and thus investors can benefit from consensus recommendations even after controlling trading fees. This is also in line with the first hypothesis of this study. Positive abnormal returns are possible mainly because of the low trading costs that brokers have today. It may not be possible to benefit from this strategy if costs were significantly higher, as they were in the last century. Moreover, this study examines only Finnish stocks and does not provide evidence for other countries.

7.3 Analyst coverage

This section is related to the second hypothesis of this study and examines the impact of analyst coverage on portfolio returns. As argued in section 1.2, the more analysts follow and analyze a company, the more information market participants have on which to base their decisions. It can therefore be assumed that investors can price the company more accurately, leading to lower pricing errors. Also, if only a few analysts follow the company, the recommendation revision of one analyst gets more attention in the market. Hence, the second hypothesis assumes that analysts' recommendations have better predictive power regarding stock returns if fewer analysts follow the company. This means that portfolios with low analyst coverage earn more if the recommendations are favorable and less if the recommendations are unfavorable, compared to corresponding portfolios with high analyst coverage.

Figure 4 provides annualized geometric mean returns for eight sub-portfolios which are built by splitting the original four portfolios into two based on the analyst coverage. These results seem to be in line with the second hypothesis. On the one hand, strong buy and buy portfolio returns are notably higher if the analyst coverage is low. On the other hand, sell and strong sell portfolios have significantly lower returns if the analyst coverage is low. The difference between the two sub-portfolios is greater for strong buy and strong sell portfolios while the difference is less significant for the middle two portfolios.

The original strong buy portfolio has an annualized geometric mean return of 17,91%. Interestingly, this return is mainly due to low analyst coverage stocks. The strong buy high portfolio has lower returns compared to the original buy, sell, and market portfolios. Respectively, the strong sell low portfolio has only a slightly positive mean return and its return is significantly lower than the return on the strong sell high portfolio. Results show that consensus recommendation is not the only element affecting returns but analyst coverage also has an impact on returns. Choosing only strong buy stocks with high analyst coverage does not seem to be a particularly profitable strategy. The great difference of 22,71 percentage points between strong buy low and strong sell low portfolios would cause a remarkable difference in returns over time.

The difference between sub-portfolio returns is less significant for buy and sell portfolios compared to strong buy and strong sell. One reason could be that the analyst coverage of buy and sell portfolios is generally higher compared to strong buy and strong sell. For example, buy and sell portfolios rarely have only one analyst following a company while it is more common for strong buy and strong sell. This is because, in many cases, several analysts do not fully agree on the recommendation of a stock. Several differing recommendations balance each other out leading to a consensus in the middle of the scale. If only one analyst follows the company and he or she gives a strong buy or strong sell recommendation, it is automatically also the consensus recommendation. It could be that these stocks with only one analyst are the best return predictors within portfolios.

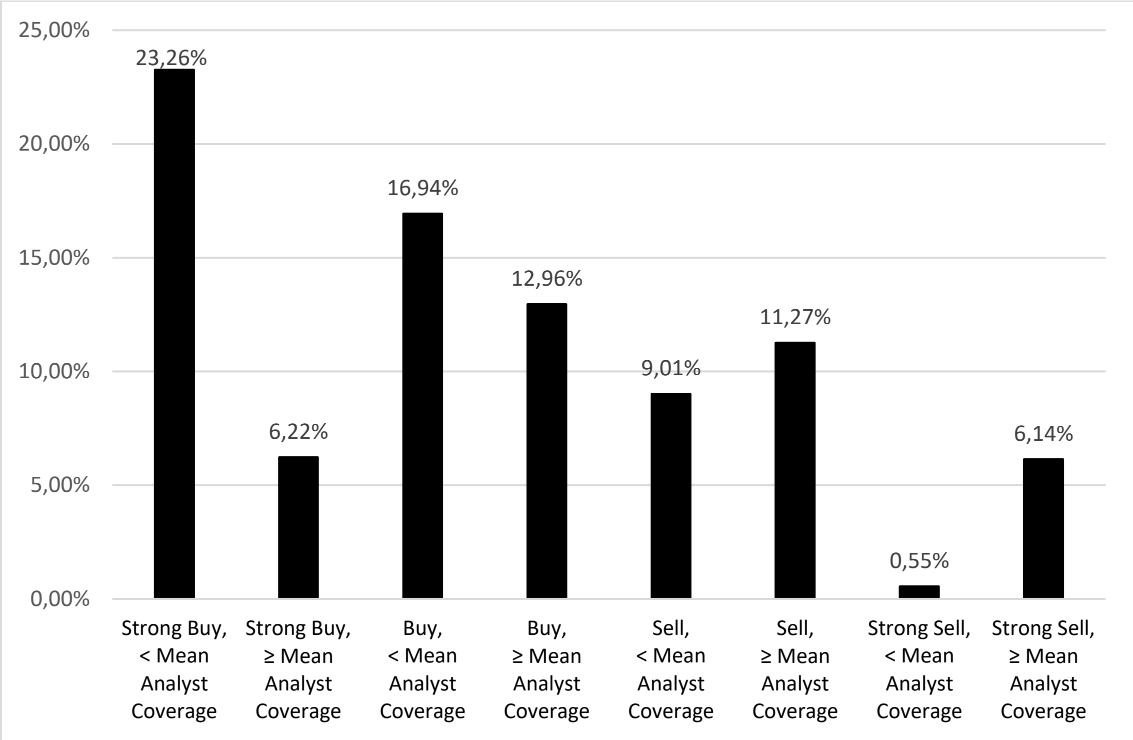

Figure 4. Annualized geometric mean returns by analyst coverage 2010-2022.

One can argue that the market, size, value, profitability, or investment factors can explain the patterns in the annualized geometric mean returns. The results from table 5 show that the return patterns are not caused by these factors. After controlling for risk factors, the results are still in line with figure 4.

Strong buy low and buy low portfolios earn the highest raw and market-adjusted returns on average compared to others. The same portfolios earn highly significant positive excess returns while the abnormal returns of the corresponding portfolios with high analyst coverage do not differ statistically from zero. In fact, the strong buy high portfolio produces insignificant negative abnormal returns. This supports the finding from figure 4 that high returns of original strong buy and buy portfolios are mainly caused by stocks with low analyst coverage. Neither the sell high nor the strong sell high portfolio returns are statistically significant. The strong sell low portfolio, however, generates significant negative abnormal returns at the 10% level.

If low analyst coverage portfolios are compared together, the value of recommendations seems to remain: abnormal returns decrease monotonically when moving from strong buy to strong sell. Instead, in the case of high coverage portfolios, strong buy underperforms compared to buy and sell portfolios across all models. It also loses against strong sell with two models. All high coverage portfolio returns are insignificant. Therefore, the entire value of recommendations disappears when changing from low to high coverage stocks. This supports the finding of Li (2020) showing that analyst coverage has a negative causal effect on misvaluation. Among high coverage portfolios, the buy portfolio has the highest returns and is closest to the significance cutoff. This supports the findings from figure 4.

Table 5. Portfolios' performance by analyst coverage 2010-2022.

This table presents the monthly returns of eight recommendation-based portfolios by analyst coverage in decimals. Stocks are allocated into portfolios based on consensus recommendations, CRs, and recommendation quartiles, Q_n, as follows: 1,0≤ CR <Q_1: Strong Buy, Q_1≤ CR <Q_2: Buy, Q_2≤ CR <Q_3: Sell, and Q_3≤ CR ≤5,0: Strong Sell. Then, portfolios are split into two based on analyst coverages, ACs, as follows: 1≤ AC < MEAN: Low Coverage and MEAN ≤ AC ≤ MAX: High Coverage. The mean return is the average monthly raw return, and the mean market-adjusted return is the average from the monthly raw returns minus the monthly OMX Helsinki total return index. Estimated regression intercepts present monthly abnormal returns from three different models. T-statistics are shown in parentheses below the coefficients. *, **, and *** illustrate statistical significance at 10%, 5%, and 1% levels, respectively.

Portfolio	Mean return	Mean market-adjusted return	Estimated regression intercepts		
			CAPM	Fama-French three-factor model	Fama-French five-factor model
Strong Buy, < Mean Analyst Coverage	0,0193	0,0114	0,0115*** (3,609)	0,0108*** (3,688)	0,0114*** (3,768)
Strong Buy, ≥ Mean Analyst Coverage	0,0073	-0,0007	-0,0013 (-0,375)	-0,0016 (-0,483)	-0,0010 (-0,287)
Buy, < Mean Analyst Coverage	0,0145	0,0066	0,0068*** (2,752)	0,0065*** (2,851)	0,0063*** (2,639)
Buy, ≥ Mean Analyst Coverage	0,0121	0,0041	0,0045 (1,252)	0,0045 (1,231)	0,0040 (1,038)
Sell, < Mean Analyst Coverage	0,0084	0,0004	0,0012 (0,483)	0,0006 (0,248)	0,0011 (0,485)
Sell, ≥ Mean Analyst Coverage	0,0103	0,0023	0,0021 (1,125)	0,0023 (1,189)	0,0027 (1,343)
Strong Sell, < Mean Analyst Coverage	0,0018	-0,0062	-0,0051* (-1,706)	-0,0050* (-1,762)	-0,0047 (-1,579)
Strong Sell, ≥ Mean Analyst Coverage	0,0064	-0,0016	-0,0005 (-0,173)	-0,0007 (-0,213)	-0,0021 (-0,651)

To summarize this section, the value of recommendations depends considerably on analyst coverage. The high returns of original strong buy and buy portfolios are mainly generated by stocks with low analyst coverage. Moreover, strong sell low stocks perform poorly, producing significant negative abnormal returns at the 10% level. Therefore, the second hypothesis seems to hold since analysts' recommendations have better predictive power regarding stock returns if fewer analysts follow the company. Stocks with low analyst coverage get more market attention when their consensus recommendation changes and investors have less information about these stocks. Hence, low analyst coverage stocks react more in the recommendation's direction.

7.4 Results by the marketplace

This section is related to the third hypothesis of this study and examines the impact of the marketplace on portfolio returns. A company can be listed on First North Growth Market Finland or the official list of Nasdaq Helsinki. As argued in section 1.2, less information is available regarding First North stocks and they get less attention from institutional and international investors. This can lead to higher pricing errors providing more opportunities to achieve abnormal returns. Hence, the third hypothesis assumes that analysts' recommendations have better predictive power regarding stock returns if the company is listed on the First North marketplace. This means that First North portfolios earn more if the recommendations are favorable and less if the recommendations are unfavorable, compared to corresponding portfolios with the official list's stocks.

Due to the limited number of First North stocks having consensus recommendations, the sample period is shortened to five years from 2018 to 2022. The buy and sell portfolios are also combined into one hold portfolio so that the shares can be allocated into portfolios reasonably. Thus, the main portfolios of interest are strong buy and strong sell. This chapter studies whether First North's strong buy stocks earn more and strong sell stocks less compared to the official list's shares, as hypothesized in section 1.2. Because of different sample periods, returns are not comparable to previous parts but studying the differences resulting from marketplaces is possible.

Figure 5 provides annualized geometric mean returns for six sub-portfolios which are built by splitting three recommendation-based portfolios into two based on the marketplace. This figure does not reflect return patterns as assumed. First North's strong sell stocks seem to have lower returns and better predicting returns than corresponding stocks on the official list. However, the same does not apply to the strong buy stocks: the official list's stocks have higher returns meaning that they better predict future returns. Interestingly, hold portfolios have completely different returns, with First North's hold stocks having the poorest performance of all.

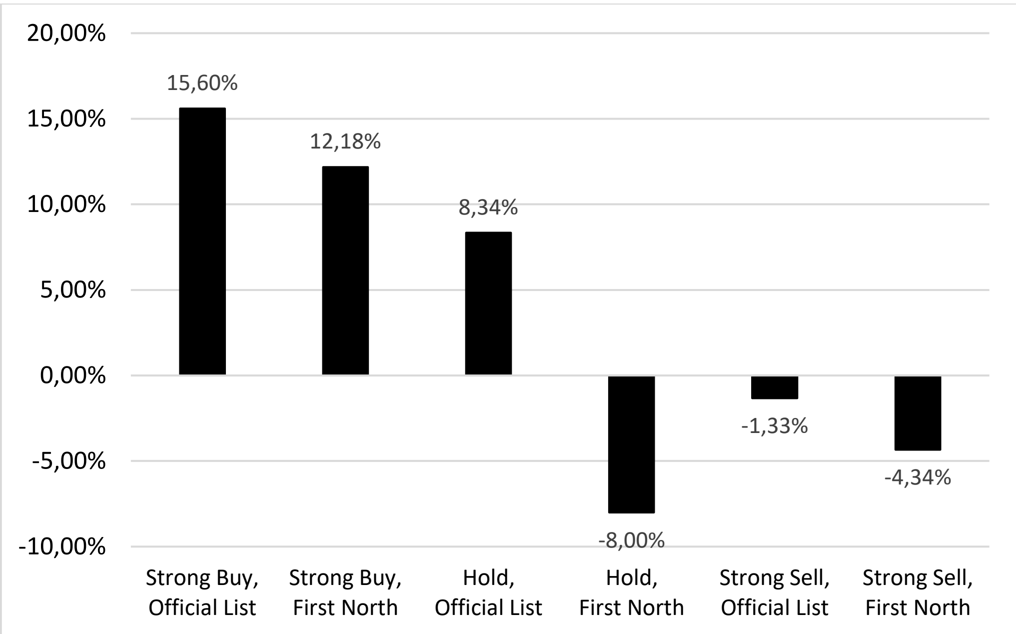

Figure 5. Annualized geometric mean returns by marketplace 2018-2022.

Although annual returns do not provide clear insight into how the marketplace predicts returns within recommendation-based portfolios, regression analysis is done to confirm the results from figure 5. Table 6 shows monthly returns for the same portfolios and results are in line with figure 5: return patterns cannot be found between the official list and First North. All but the official list's strong buy stocks generate insignificant abnormal returns across all models and the marketplace does not have predicting power regarding stock returns. Therefore, the third alternative hypothesis cannot be accepted.

Table 6. Portfolios' performance by marketplace 2018-2022.

This table presents the monthly returns of six recommendation-based portfolios by marketplace in decimal form. Stocks are allocated into portfolios based on consensus recommendations, CRs, and recommendation quartiles, Q_n, as follows: 1,0≤ CR ≤Q_1: Strong Buy, Q_1< CR <Q_3: Hold, and Q_3≤ CR ≤5,0: Strong Sell. The mean return is the average monthly raw return and the mean market-adjusted return is the average from the monthly raw returns minus the monthly OMX Helsinki total return index. Estimated regression intercepts present monthly abnormal returns from three different models. T-statistics are shown in parentheses below the coefficients. *, **, and *** illustrate statistical significance at 10%, 5%, and 1% levels, respectively.

Portfolio	Mean return	Mean market-adjusted return	Estimated regression intercepts		
			CAPM	Fama-French three-factor model	Fama-French five-factor model
Strong Buy, Official List	0,0145	0,0075	0,0058	0,0082**	0,0065
			(1,362)	(2,154)	(1,668)
Strong Buy, First North	0,0126	0,0056	0,0058	0,0067	0,0070
			(0,740)	(0,839)	(0,848)
Hold, Official List	0,0083	0,0013	0,0008	0,0016	0,0007
			(0,293)	(0,583)	(0,252)
Hold, First North	-0,0019	-0,0089	-0,0089	-0,0091	-0,0075
			(-0,757)	(-0,772)	(-0,621)
Strong Sell, Official List	0,0002	-0,0068	-0,0053	-0,0046	-0,0049
			(-1,332)	(-1,130)	(-1,149)
Strong Sell, First North	-0,0003	-0,0073	-0,0081	-0,0063	-0,0033
			(-0,963)	(-0,738)	(-0,373)

8 Limitations of this study

The main results of this study are significant in both economic and statistical terms and are consistent with the first two hypotheses. However, it is important to note the factors that may limit the reliability and generalizability of the results. This chapter critically assesses the factors affecting the results and focuses on potential issues.

Despite the relatively long sample period of this thesis, the market in general has performed well during this period. The annualized geometric mean return of OMX Helsinki total return index is 8,63%. Especially, between the European debt crisis and the Covid-19 pandemic the market has been bullish in Finland. This may make it easier to predict future stock returns. According to Statistics Finland (2024) and the Bank of Finland (2024), the inflation and Finnish government bond yields have been close to zero or even negative at the same time. This uncommon phenomenon covers a great part of the research period and may affect the results. Moreover, due to the shorter sample period in section 7.4, these results cannot be compared to other sections.

The results depend on the chosen methods and factors used. This study uses the OMX Helsinki total return index as a proxy for market return and the Finnish 10-year government bond yield as a proxy for the risk-free rate. Nevertheless, a different choice could justifiably be made, and this could affect the results. However, the effect is not assumed to be significant or to change the direction of the results. Academic research knows many methods for examining abnormal returns. This study uses the capital asset pricing model, the Fama-French three-factor model, and the Fama-French five-factor model. Other factor models with different risk factors could also be used. Correlation-based asset pricing methods are subject to limitations, and they are discussed more closely in section 3.5. Choosing different research methods could affect results although they are robust and consistent across models used in this thesis.

One limitation relates to exploiting recommendation-based strategy in reality. The long-short strategy is particularly difficult to implement in practice. For example, Osuuspankki

(2024) allows to sell short only 25 shares. This list typically includes the biggest and most liquid stocks. Thus, exploiting the long-short strategy and benefiting from its abnormal returns is impossible for retail investors in practice. On the other hand, a simple buying strategy also generates statistically significant excess returns.

The last limitation is related to elements that this research does not take into account. For example, fixed monthly costs, taxes, liquidity premiums, or market impact costs are not considered because of the difficulty of assessing their real level and impact. Especially, taxes and liquidity premiums exist in the real world and have an impact on returns. The equity savings account enables tax-free trading inside the account but only up to 100 000 euros and does not remove the problem of less liquid stocks. The problem of hidden costs is tried to minimize by using the brokers' highest trading fee although active trading would probably justify lower fees. Results remain significant also after considering trading fees in robustness check.

9 Conclusions

This thesis first presents the theoretical background and relevant literature related to the topic. The theoretical background considers market efficiency, asset pricing, and analysts’ role in the market. The literature review covers older well-known articles and recent papers that better reflect today's changed world. The empirical part investigates the impact of analysts’ recommendations on stock returns in Finland over 13 years from 2010 to 2022. The reliability and sensitivity of the results are tested with a robustness check considering the effect of trading fees. In addition, the impact of analyst coverage and the marketplace on portfolio performance is examined to better explain which stocks perform best inside the portfolios.

Stocks are allocated into the following four portfolios based on their consensus recommendations: strong buy, buy, sell, and strong sell. The results of these four portfolios show the value of stock recommendations for investors. Geometric mean returns decrease step by step when moving from strong buy to strong sell. Estimated regression intercepts support this finding. The strong buy portfolio earns about 0,7-0,8% and the buy portfolio 0,6-0,7% positive monthly abnormal returns depending on the model. Excess returns are highly significant at the 1% level. The long-short strategy also produces statistically significant abnormal returns of 0,7-0,9% a month. The bottom two portfolios do not generate significant abnormal returns, but the strong sell portfolio has insignificant negative excess returns.

The positive abnormal returns of the top two portfolios remain after the robustness test. Trading fees reduce returns but do not remove all excess returns. The strong buy portfolio still generates a statistically significant monthly abnormal return of 0,6-0,7% and the corresponding excess return for the buy portfolio is 0,5-0,6% per month. The negative abnormal returns of the strong sell portfolio are close to the 10% significance level but again slightly insignificant.

Examining the effect of analyst coverage shows that consensus recommendations alone do not contain all relevant information. It is, however, important to also consider analyst coverage to benefit maximally from recommendations. When creating eight sub-portfolios by splitting the original four portfolios into two based on analyst coverage, it seems that strong buy stocks with low analyst coverage outperform other portfolios while the strong buy high portfolio earns insignificant negative abnormal returns and cannot compete against the original buy and sell portfolios. Instead, the strong sell low portfolio generates about -0,5% negative monthly abnormal return being significant at the 10% level. Thus, the high returns of the original top two portfolios are mainly resulting from stocks that have low analyst coverage. Respectively, the strong sell high stocks seem to balance the lower returns of strong sell low stocks in the original strong sell portfolio.

A positive observation from investors' perspective is that while favorable recommendations offer the potential for higher returns, even strong sell stocks are not entirely catastrophic for investors' wealth. Annualized mean returns are slightly positive also for the worst portfolios and only strong sell low stocks produce statistically significant negative abnormal returns. The difference in returns between strong buy and strong sell portfolios is nevertheless economically significant.

The first two hypotheses of this paper assume that it is possible to earn positive abnormal returns by following stock recommendations and recommendations have better predictive power regarding returns if fewer analysts follow the company. The third one hypothesizes that recommendations have better predictive power regarding returns if the stock is listed on the First North marketplace. The empirical part shows that stocks with good consensus recommendations outperform others in terms of annual returns and it seems that market, size, value, profitability, or investment factors cannot explain the patterns in stock returns. In addition, low analyst coverage stocks better predict future returns in the direction of the recommendation. The findings therefore allow the first two null hypotheses to be rejected and alternative hypotheses to be accepted.

However, the marketplace does not seem to have predicting power regarding returns, and thus the third alternative hypothesis cannot be accepted.

The results also relate to the broader debate on market efficiency. Barber et al. (2001) argue that the market is inefficient in semi-strong form because their recommendation-based strategy earns positive abnormal returns over a long sample period. This study does not reject the efficient market hypothesis but shows that profitable strategies can be built even if market efficiency has improved in the ongoing century as Altınkılıç et al. (2016) and Guo et al. (2020) argue. However, trading fees reduce abnormal returns and active trading is a time-consuming strategy for retail investors.

This study proposes a few ideas for future research. First, sentiment periods could be considered when examining the impact of stock recommendations on returns. For instance, whether sell (buy) recommendations generate more negative (positive) returns during the low (high) market sentiment period compared to other periods. This would test how market efficiency varies between positive and negative market sentiment.

The second idea is to do sector-specific analysis related to stock recommendations. Most of the studies provide general results regarding stock recommendations without focusing on how the value of recommendations varies across different sectors. Focusing on the different industries could enhance the practical applicability of recommendations and provide economic benefits for investors. For example, optimizing portfolios by weighing sectors where recommendations best predict returns could improve portfolio performance.

Third, studying more closely the relationship between stock analysts and corporate environmental, social, and governance (ESG) performance would provide a more accurate picture of how sustainability factors are considered in analysts' research reports and recommendations. Moreover, it could be examined whether analyst coverage affects companies' ESG performance. It can be assumed that there would be greater pressure to perform well on ESG-related questions if more analysts followed and monitored the company. Sustainability factors are important for consumers, investors, and other stakeholders. Sustainability reporting will also have a more notable role in the future. Consequently, the complete neglect of sustainability factors related to environmental, social, and governance does not bode well for the company's long-term performance. ESG-related studies should follow this development because of sustainability-related elements' great and growing role.

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