LAPPEENRANTA-LAHTI UNIVERSITY OF TECHNOLOGY LUT

School of Engineering Science

Degree Programme in Industrial Engineering and Management

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PROFITABILITY OF STOCK ANALYST RECOMMENDATIONS: CASE STUDY ON OMXH25 STOCKS

Master's thesis

Examiners: Professor Pasi Luukka

Associate Professor Sheraz Ahmed

ABSTRACT

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Profitability of stock analyst recommendations: Case study on OMXH25 stocks

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Analysts gather information from firms and create forecasts about future earnings and offer recommendations. These recommendations are absorbed by other capital market actors, such as individual investors, who then decide to follow or ignore them. For the recommendation industry to exist there should be some valuable information value in the issued recommendations which is not yet included in the stock prices. In this study three portfolios are constructed from 21 OMXH25 index listed companies based on analyst consensus recommendations from the 31.12.2013 - 31.12.2019 time period to examine whether abnormal returns could be achieved by following the recommendations. The portfolios are revised yearly according to the latest consensus recommendations collected from the financial information software Refinitv Eikon. According to the results, the best portfolio option would (surprisingly) be the one with the highest average recommendation values, namely portfolio 3.

In addition, the study explores analyst target prices to find out if they support the recommendations and how accurate the target price predictions are. The results imply that target prices are in line with recommendations and that the target prices are more accurate than the reference values. Finally, CAPM analysis is implemented to find out if the low recommendation-based investment strategy (using the I/B/E/S standardized scale from 1 to 5) has higher risk and higher expected return with respect to the market (OMXH25 and sample21) indices than the high recommendation-based investment strategy. The results from linear regression models however turn out to be statistically inaccurate and hence reliable conclusions remain uncertain.

TIIVISTELMÄ

Lappeenrannan–Lahden teknillinen yliopisto LUT
School of Engineering Science
Tuotantotalouden koulutusohjelma

Oskar Vierula

Analyytikoiden suositusten tuottavuus: Portfoliotutkimus OMXH25 indeksiin listatuista yhtiöistä

Diplomityö
2022
60 sivua, 16 kuvaa, 24 taulukkoa ja 3 liitettä
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Analyytikot keräävät tietoa firmoista ja luovat ennusteita niiden tulevista tuotoista sekä julkaisevat ennusteita. Näitä ennusteita voivat hyödyntää muut pääomamarkkinoilla toimivat osapuolet, kuten yksittäiset sijoittajat. Jotta sijoittaja olisi kuitenkin halukas maksamaan suosituksista on niiden sisällettävä informaatiota, jota markkinat eivät vielä ole hinnoitelleet osakkeisiin. Tässä tutkimuksessa selvitetään mahdollisuutta saavuttaa ylituottoa markkinaan (OMXH25) verrattuna muodostamalla kolme erilaista portfoliota 21:stä eri OMXH25 indeksissä listatusta yrityksestä perustuen analyytikoiden suosituksiin ajalta 31.12.2013-31.12.2019. portfolioita päivitetään vuosittain uusimpien Refinitiv Eikon taloustieto sovelluksesta kerättyjen konsensussuositusten mukaisesti. Tutkimuksen mukaan parhaiten kyseisellä aikavälillä suoriutui korkeita suosituksia saaneet yritykset, jotka muodostavat portfolio 3:n.

Lisäksi tutkimuksessa selvitetään tavoitehintojen ja suositusten yhteyttä sekä tavoitehintojen keskimääräistä tarkkuutta. Tulosten mukaan tavoitehinnat tukevat suositusten antamaa osta/myy informaatiota ja ne ovat tarkkuudeltaan vertailuarvoja parempia. Viimeisessä osassa tutkitaan CAP-mallia hyväksikäyttäen, mikäli I/B/E/S standardoidun skaalan (1-5) mukainen mataliin suosituksiin perustuva investointistrategia on riskisempi ja näin ollen myös korkeamman odotetun tuottoasteen omaava vaihtoehto markkinaan (OMXH25/sample21) verrattuna kuin korkeisiin suosituksiin perustuva investointistrategia. Lineaarisen regressioanalyysin tuottamat tulokset ovat kuitenkin tilastollisesti epätarkkoja eikä niiden perusteella voida antaa varmoja vastauksia eri strategioiden kannattavuudesta.

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1 INTRODUCTION

1.1 Scope and objectives

The objective of this study is to research whether an investor could earn abnormal profits by investing in OMX Helsinki 25 (OMXH25) listed companies through three different portfolios formulated according to analyst consensus recommendations. The portfolios are constructed based on a sample of 21 companies from the time period of 31.12.2013 to 31.12.2019 and revised yearly according to the latest recommendations. The first portfolio will represent seven companies with the lowest consensus recommendations (buy-oriented) in the I/B/E/S standardized 1-5 scale and the third portfolio companies with the lowest consensus recommendations. The second portfolio is formed from the remaining companies between 1-21 when using an ascending scale from low to high. The data is collected from Refinitv Eikon which is a software offering financial information for financial professionals.

The study is supported by previous academic research concerning the research topic and it is expected to share insight and reference values to the eventual results. The topic of recommendation-based investing has been broadly studied but the results depend much on how the research is carried out. In this study, the scope remains on the three portfolios and their performance with respect to the OMXH25 index during the fixed time period. The effect of limitations which are defined in section 4.5 will distort the eventual results - in reality, transaction costs and taxes would be realized every time the portfolios are updated.

In addition to the analysis of portfolio returns, the study compares whether analyst recommendations are supported by target prices and how accurate these prices tend to be. The last analysis method which is the Capital Asset Pricing Model (CAPM) focuses on examining how the market (OMXH25) affects the portfolios and whether they possess different levels of risk and expected returns.

1.2 Structure of the thesis

The paper is structured as follows: Chapter 2 describes the relevant financial theories; Chapter 3 introduces the impact of analyst recommendations using previous academic research; Chapter 4 describes research hypotheses, data collection and implemented analyses; Chapter 5 presents results obtained from the analyses; Chapter 6 concludes research findings and potential future research areas.

2 RELEVANT FINANCIAL THEORIES

This chapter focuses on describing the basic financial theory behind asset pricing through efficient market theory, the effect of diversification in portfolio risk management according to modern portfolio theory (MPT) as well as the significance of the Capital Asset Pricing Model (CAPM) in modelling the expected returns of assets.

2.1 Efficient market hypothesis

Eugene Fama (1970) describes that capital markets in an ideal state provide accurate signals to investors through pricing and that the prices of securities include at all times all available information. This sort of market is "efficient" and therefore the resource allocation is spontaneous among investors. According to Fama (1970, p. 387), three conditions should be fulfilled for capital markets to be sufficiently efficient. The conditions are: no transaction costs are collected when trading securities, all information is available for each market participant and it is free of charge, every participant in the market agrees on the impact of current information having on current prices and distributions of future security prices. In addition, Fama (1965, p. 56) points out that it is necessary to have plenty of rational participants in the market who try to maximize their profit and predict future securities prices with the same currently available relevant information.

The concept of efficient markets can further be divided into three forms, namely the weak, semi-strong, and strong. These modifications differ in the way information is presumed to be included in the stock prices. In the weak form of the efficient market hypothesis, it is supposed that future securities prices behave randomly and are not affected by past events. In the weak form, no advantage is achieved via technical analysis in future price predictions. In the semi-strong form of the efficient market hypothesis, it is supposed that securities prices respond quickly to publicly-available material information. In the semi-strong form, no advantage is achieved via fundamental or technical analysis in future price predictions but material non-public information could be of use. In the strong form, it is thought that no benefit is achieved by the investor even though he/she could be in the genesis of a new piece of information such as insider information in a public company. In the strong form of the efficient market hypothesis, it is supposed that future securities prices do not behave randomly and that they are affected by past events. (Fama 1970; Investopedia 2021a)

There is on the other hand much doubt whether real-life markets are “efficient”. Probably the first question regards the security-analysis industry and its existence - why would there be such a prospering industry in the first place if all the information was available and in fact already in the prices. A lot of research has focused on pointing out that stock recommendations have an effect on stock prices and that the adjustment of prices including all new relevant information is not immediate. Contradictory ideas to efficient market hypothesis have been suggested by Womack (1996, p. 137) who states that analysts seem to have “market timing and stock picking abilities” and Grossman and Stiglitz (1980) who propose that market prices reflect only partially all available information because those who consume resources to acquire information should receive compensation. Furthermore, Malkiel (2003, p. 80) recognizes that since there are also less rational market participants and as a consequence irregularities and identifiable patterns in pricing there will also be opportunities for short period abnormal returns.

Also, similar results supporting the value of analyst recommendations to investors and imperfect information adaptation into prices (hence indicating contradiction to EMH) have been found by among others Davies & Canes (1978), Stickel (1995) and Barber et al. (2001). There are however other challenges arising when introducing an active strategy based on analyst recommendations such as transaction costs which come into being as the portfolio is updated to comply with the latest recommendations. Yet, Barber et al. (2001, p. 562) state that in a situation where the investor is nevertheless going to make a purchase or sale of stocks (transaction takes place) it is advantageous to follow consensus recommendation ratings. More study on the effects of transaction costs in the field of recommendation-based investment strategy is conducted in section 3.5.

2.2 Modern portfolio theory

Henry Markowitz conceptualized in 1952 a theory regarding diversification, which is known today as the modern portfolio theory (MPT), based on his work implemented in the study on portfolio selection (Markowitz, 1952). Markowitz developed the theory further in 1959. The key concept in MPT is the idea of diversification by which an investor is able to find an optimal mixture of investments with high risks and high returns together with investments with low risks and low returns. The method focuses on formulating as efficient a portfolio as possible where the risks and returns of separate securities are in accordance with the level of decided risk and return expectations. This means in other words "a portfolio which gives both maximum expected return and minimum variance" (Markowitz 1952, p. 79). An essential concept of MPT is the so-called efficient frontier which is an illustration expressing the mixture of investments that will offer a maximal level of return for the minimal level of risk. An illustration of an efficient frontier can be seen below in figure 1 where the y-axis measures return and the x-axis measures risk. The investor who wants to acquire a portfolio with low risk and high return moves towards the upper left corner of figure 1. Any portfolio located on the efficient frontier will give a maximum return for the corresponding risk level while those portfolios below the efficient frontier are inefficient since they fail to maximize return given their risk.

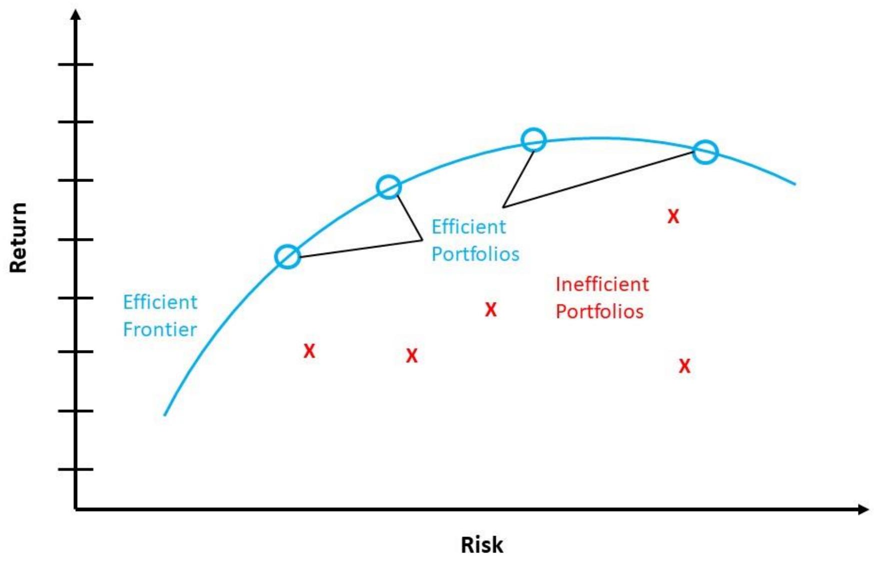

Figure 1. The efficient frontier (modified Eikelmann 2020, p.21; Investopedia 2021b)

It has been shown that there exists a somewhat optimal amount of diversification of stocks which removes most of the risk (Graham 2003, p, 114; Elton et al. 2014, p. 58-59 & 134). Even though no distinct consensus exists on the matter, it is rather widely accepted that according to the principles of MPT an optimal diversification that mitigates unsystematic risks (for example new competitors and regulations) is close to 20-30 stocks. (Investopedia 2021c) The systematic risk (such as industry risk and inflation) which cannot be removed via diversification remains naturally and is included in the total portfolio risk. (Investopedia 2021d) An illustration of how risks reduce as stocks are added to a hypothetical portfolio is shown below in figure 2.

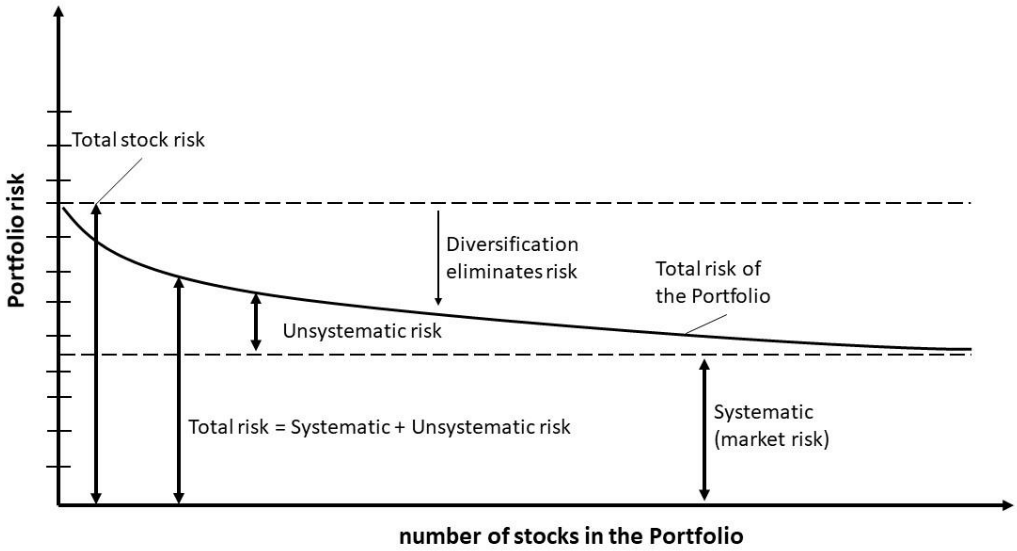

Figure 2. Effect of diversification on portfolio risk (modified from Investopedia 2021b)

More importantly however, instead of focusing excessively on the number of stocks in a portfolio the investor should ensure that the assets in a portfolio are not highly correlated with each other, as for example owing only one kind of industry increases the overall risk of the portfolio. Including for example bonds or some raw materials might be of help in decreasing the total risk. (Investopedia 2021e)

2.3 CAPM

The Capital Asset Pricing Model (CAPM) which is used to calculate the expected return of investment is a product of several economists who created the model in the 1960s. It is fundamentally based on the research done by Markowitz in the 1950s in the field of modern portfolio theory (MPT) and diversification which were introduced in the previous section 2.2. The work of Sharpe (1964) on the topic of Capital Market Line (CML) is together with the work from Markowitz (1952 & 1959) considered to be most essential in the creation of the CAPM. Treynor (1962) Lintner (1965) and Mossin (1966) published their models shortly after Sharpe (1964) and are also recognized as the developers of the CAPM.

CAPM has the following assumptions (Treynor 1962, p. 2; Eikelmann 2020, p. 19):

1. Investors are considered as risk avoiders.
2. The capital market is complete meaning no costs hinder buying and selling of securities and that singular investor decisions have an insignificant effect on prices.
3. No taxes exist.
4. Lending capital with a risk-free rate to investors is impartial and possible for everyone in the market.
5. All investors have access to all the necessary information from the market and knowledge on current price levels. They possess homogeneous expectations.
6. Portfolio theory and diversification guide investors in choosing shares. Investments are assessed against their expected value and standard deviation of return.
7. All shares can be liquidated and split into smaller parts.
8. A standard investment period is used, for instance, 1 year.

Despite its wide use, the CAPM faces much criticism for its lack to overcome and ability to fulfil real-life criteria. Many of the assumptions are questionable and there is much doubt on how well they actualize in modern financial markets. For example, investors do not necessarily have the same expectations due to differences in the amount of information and there are de facto obstacles like taxation and transaction costs in contradiction to the assumptions. Moreover, the principle of periodical investing (assumption 8 above) is often violated when discounting cash flows over several time periods. (Eikelmann 2020, p. 23-24; Dempsey 2013)

As mentioned above the CAMP is a combination of works from several economists, mostly Markowitz (1952) and Sharpe (1964). The model still serves today as one of the fundamental methods in finance. Sharpe questioned Markowitz's idea that the MPT is absolute in reflecting risks an investor faces when constructing a portfolio and hence introduced the idea of the capital market line (CML) and efficient front combined which would be known as CAPM. The idea was novel since it included the concept of systematic and hence non-diversifiable risk commonly represented by the quantity beta (β). Overall CAPM, which is used to calculate expected return of investment, includes the following components: beta of the investment (measures the movement of individual security's returns as the market swings up and down), risk-free rate (expected return from a risk-free investment) and market risk premium (difference between the expected return from a market portfolio $E(r_m)$ and the return from a risk-free asset r_f). The formula and its components together with descriptions are given below. (Brealey et al. 2016, p. 200; Eikelmann 2020, p. 19–22).

$$E(r_i) = r_f + \beta_i \, (E(r_m) - r_f) \qquad (1)$$

where

$E(r_i)$ = cost of equity capital / expected stock return

r_f = risk free interest rate

β_i = beta factor

$E(r_m)$ = return of the market portfolio

The beta factor can be calculated the following way:

$$\textit{Beta coefficient } (\beta_i) = \frac{\textit{Covariance } (r_i, r_m)}{\textit{Variance}(r_m)} \qquad (2)$$

where

r_i = *return from an individual asset*

r_m = *return from the market*

Normally when calculating CAPM the risk-free interest rate r_f is represented by a treasury Bill (T-Bill) which is a short-term (maturity of one year or less) debt obligation backed by the U.S. government. It is the least risky investment an investor can make because it doesn't react to market events and therefore has also a beta of 0 whereas a theoretical market portfolio has a beta of 1. In the Eurozone short-term Euribor (with for example three months maturity) could be used as the risk-free rate (ECB 2021). The beta factor β_i in formula 1 above instead describes how much volatility (systematic risk) particular security or portfolio has when compared to the whole market. So when summarized, the CAPM formula 1 describes the expected return of a stock/portfolio $E(r_i)$ which is the sum of the risk-free rate (r_f) and product from the multiplication of beta of the asset (β_i) times the market premium ($E(r_m) - r_f$). (Brealey et al. 2016, p. 199-201)

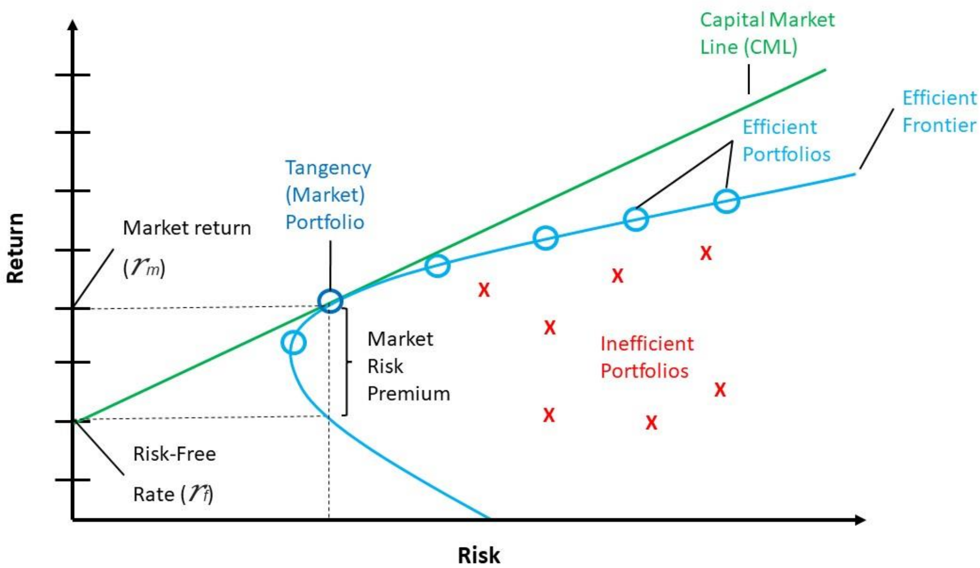

Figure 3. CAPM (modified Eikelmann 2020, p.21)

The Capital Market Line (green coloured) in figure 3 above shows all efficient investment options for all risk levels. Those portfolios which are not located on the CML are inefficient. The point in which CML and the efficient frontier join is called tangency/market portfolio and it is the most efficient portfolio with the highest profit for the corresponding risk level, namely its return to risk ratio (also known as Sharpe ratio) is the highest of all possibilities. (Eikelmann 2020, p. 20-22; Brealey et al. 2016, p. 198-199)

When using the CAPM together with ordinary least squares (OLS) it is worth testing the data and more specifically, the disturbance terms, with respect to the classical linear regression model (CLRM) assumptions. Brooks (2008) recognizes the following five assumptions:

1. The residuals should have zero mean
2. The error term has a constant variance for all x so no heteroscedasticity should exist
3. The error terms are uncorrelated with each other so no autocorrelation should exist
4. No multicollinearity ought to exist
5. The error term should be normally distributed

3 THE IMPACT OF ANALYST RECOMMENDATIONS

This chapter focuses on recognizing the role of analysts as information collectors and intermediates in the financial markets, potential risks related to the analyst recommendations, herding behaviour of financial analysts, investor behaviour with respect to issued recommendations and finally previous research findings on the profitability of recommendations and target prices.

3.1 The role of analysts in the market

The role of analysts in recognizing abnormity and patterns from historical information is recognized by many researchers arguing that since analysts are able to acquire their living from making recommendations and future predictions on companies' abilities to succeed/fail, then there must be some value, relying simply on pure logic, for the investor from the predictions in the first place. (Grossman and Stiglitz 1980, p. 393; Womack 1996, p. 138) Analysts globally produce forecasts on corporate earnings, analyze individual companies as well as focus on specific industries and sectors. On top of the aforementioned activities and many others, they also offer stock recommendations and target prices which are the focus of this study. Several studies have pointed out that analysts generate valuable information which enhances market efficiency via more precise valuation of companies. (Schipper 1991; Brown 2000)

The efficient market hypothesis (EMH) and its statement of full information existence in share prices can be seen principally controversial in the field of analysts as their work is constructed around finding inefficiencies in information flows and pointing out market anomalies which consequently may pose opportunities for abnormal returns through buying and selling. There is considerable evidence supporting that such opportunities exist (Brown 2000, p. 69-87).

As mentioned earlier the analysts gather information from firms and create forecasts about future earnings and offer recommendations. These recommendations are then absorbed by other capital market actors, such as individual investors, who then decide to follow or ignore them according to their own perceptions. The analysts are often specialized in some particular sector and further on some group of companies of which they have explicit knowledge (via communication with company managers) leading to predominance when compared to individual investors. Even though the information could be accessible for an individual investor he/she could be willing to rely on an analyst to search the relevant information and provide the resulting recommendation. (Eikelmann 2020 p. 54–55; SEC 2010)

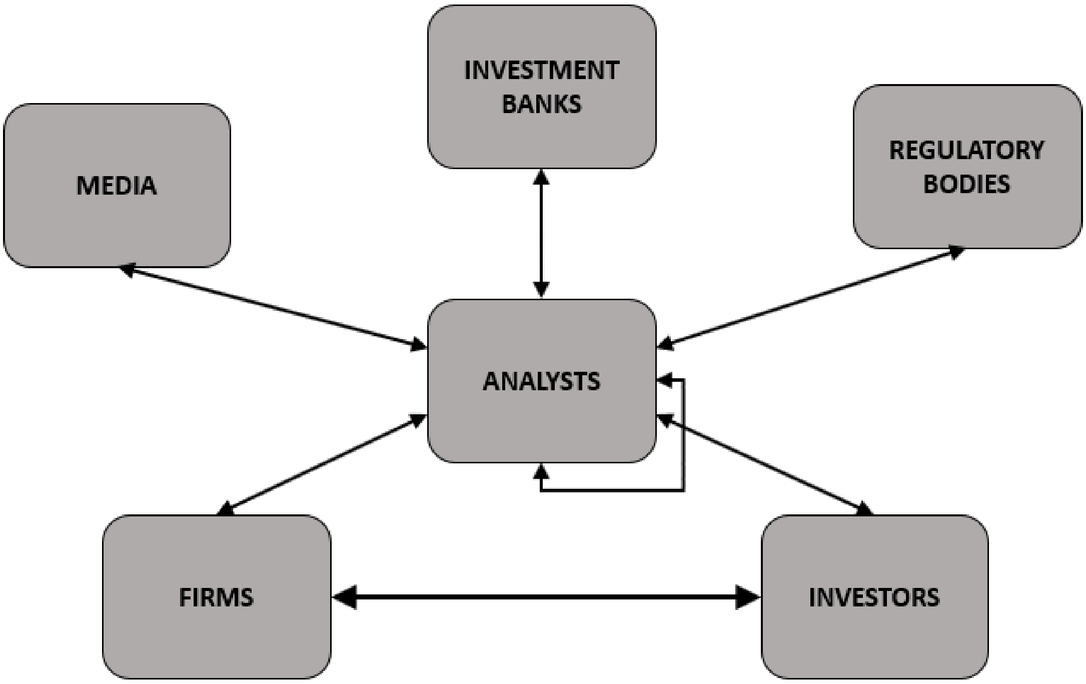

Figure 4. Analysts' role in the context of stakeholders and operational information flows between the actors (modified Brauer & Wiersema 2018 p. 220)

On top of individual investors, analysts provide information to other stakeholders as well. In figure 4 above are shown important parties to analysts who are at the centre of information flow between firms and investors (as a whole). The relevant stakeholders to analysts are among others media, investment banks, regulatory bodies, firms and other investors. Analysts are understood as information intermediaries between the stakeholders and as monitoring actors in the financial markets. (Brauer & Wiersema 2018)

3.2 Risks related to analyst recommendations

While an analyst strives to stay objective and neutral when making his/her work and offering recommendations to investors there are some potential conflicts of interest that may occur. There are for instance situations where the same firm in which the analyst works may be underwriting securities of companies that the analyst makes analysis of. Moreover, the analyst oneself could own these stocks he/she makes analysis of either directly or indirectly. To avoid this the investor should not simply rely on analyst recommendation but in fact, have some view of his/her own by reading the annual reports for example to get a general understanding of the company in question. Future prospects are especially important in the case of the so-called initial public offerings (IPOs) where there is only minimal historical information available. (Michaely & Womack 1999, p. 683; SEC 2010; Dechow et al. 2000, p. 27-28)

The traditional conception of analysts being simply rational actors who process financial information and provide earnings forecasts without delay and precisely is however under dispute. Easterwood and Nutt (1999, p. 1796) state that there is much evidence supporting the fact that analysts intentionally and systematically underreact and overreact to new information. Explanations for such behaviour could be derived from a systematic proclivity for biased information interpretation or due to a disposition to interpret information in an optimistic manner. According to Lin & McNichols (1998 p.124-125), an analyst’s tendency to behave excessively optimistically when issuing growth forecasts and recommendations to affiliated companies could reside from the desire to preserve client relations. Furthermore, they found that there is an inducement for companies to select investment banks where the analysts make more propitious forecasts. Similar situations in which analysts are under external pressure were found by Barniv et al. (2009, p. 1036) according to whom conflicts inside brokerage firms took place when analysts who worked in the research department providing stock recommendations were expected to produce favourable forecasts in favour of the investment banking department. However, Morgan & Stocken (2003, p.199) conclude in their study using US stock market data that all analysts seem to issue more favourable (buy) than unfavourable (sell) recommendations, no matter if the analyst’s incentives align with those of the investor’s or not. The situation of buy-oriented recommendations exceeding sell-oriented ones was also found earlier by Womack (1996, p. 139) in the US stock markets and later by Easton & Sommers (2007, p. 986-987) but also outside of US markets - for example recently by Lien et al. (2020,

p. 797) in Taiwanese stock markets (TWSE) and Brycz et al. (2021, p. 3672-3673) in Polish stock markets (WSE).

Lin & Wu (2019, p. 9-10) recognized in their study the risk related to investment banks recommendation and their trading patterns. In their study on Taiwanese stock markets, they found out that investment banks bought, via their proprietary trading division, the same recommended stocks of which they had made recommendations before releasing the strong buy recommendations to the public. During the process, due to increased investor interest and thanks to a strong stock recommendation, the price of the stock would go up and consequently profit the investment bank at the expense of investors.

Findings from Dechow et al. (2000, p. 27-28) imply that there exists a relation between excess optimism with long-term earnings growth forecast and weak performance of the corresponding stock price. In addition, they notice that these affiliated analysts are also "particularly active in promoting these overly optimistic forecasts." The topic of optimism among analysts was also addressed by Lim (2001, p. 383-384) who found in his research that less experienced analysts make more optimistic forecasts. The emerging error in forecasts appears to be greater in environments where information uncertainty is more frequent and where analysts rely more on the management as the information source.

Jackson (2005, p.706) found in his research that analysts do however suffer from making incorrect predictions via reputation decay. His main findings are that analysts with strong reputations generate great trading volume in the future, reputation grows relative to prediction accuracy and optimistic predictions produce greater trading volume. Actions that build up an analyst's reputation can nevertheless deteriorate if the analyst opportunistically exploits investor beliefs in search of short-term gains. Indeed, the main problem for analysts according to Jackson (2005) is whether to preserve reputation in the eyes of investors by making realistic and accurate predictions or to make short term profit through increased trading enabled by optimism bias.

Motivation for optimistic forecasting among analysts does according to Hong & Kubik (2003, p. 342-346) also correlate with career prospects. They conclude that brokerage firms have along with accuracy encouraged their analysts to give optimistic prospects for companies in order to promote the underwriting of their stocks and to establish greater trading commissions. Analysts who analysed the companies of which their brokerage firm had underwritten stocks and had been optimistic in their views appeared to manage their careers as well as those analysts whose record was based on accuracy and more realistic views. Interestingly Hong et al. (2000, p. 143) also noticed that more inexperienced analysts' herd more than the older, experienced counterparts and that their forecasts stand closer to the consensus forecast. This risk-avoiding behaviour has according to Hong et al. (2000, p. 143) to do with the fact that younger analysts are not willing to take too big risks since inaccurate forecasts have a negative effect on their career outcomes.

Barniv et al. (2009, p. 1036) express in their study the importance of regulative measures in helping to decrease the gap between analyst produced forecasts and published recommendations. According to SEC (2010), multiple actions have been made in the fields of relationships & communication, compensation and disclosures for example to mitigate motivation for corruptive behaviour among analysts and their stakeholders. It could be concluded that the gain achieved from optimistic forecasting remains even though it has been in the focus of regulative actions and strengthened ruling. More on the nature of analyst herding behaviour and its risks are addressed in the next section 3.3.

The risks related to target prices commonly follow the same pattern as recommendations and hence suffer from the same risks related to overoptimism. Namely, (Bradshaw et al. 2012, p. 953) found in their study on 12-month forward-looking target price forecasts that they are on average overoptimistic and inaccurate. As Arand & Kerl (2015, p. 47) conclude there appears to be a positive association between analysts' optimistic target prices and the relations he/she/firm has with the subject company. They state even having seen some evidence of underperformance in stocks that have been favoured by affiliated analysts with conflicts of interest. Many of the reasons behind such optimistic predictions are shown to be of the same origin as discussed above.

3.3 Herding of analysts in forecasting

The phenomenon of the so-called herding behavior in economic activities has been proven by many researchers (Hong et al. 2000, p. 143; Trueman 1994. p.115; Scharfstein & Stein 1990, p.477-478; Grinblatt et al. 1995, p. 1104). The rational herding of analysts has been shown to be true (Lee & Lee 2015, p. 65; Chen & Jiang 2006, p. 349-350) the action in which analysts intentionally decide to herd with one another instead of publishing forecasts that deviate from the consensus estimate and consequently risk their future reputation. The chance of analysts publishing biased estimates is however influenced by their capabilities to process information which in turn depends on the experience of the analyst. A young and inexperienced analyst who lacks the abilities and relationships of the older and experienced one might with good reason decide to follow the consensus estimate in order to reduce the reputation risk. This herding behaviour could be a dominating factor even in cases when an analyst possesses relevant and crucial private information which could produce different results than those of the consensus forecast (Trueman 1994, p. 115; Welch 2000, p. 393-394).

Brown et al. (2014, p. 19) found in their research on mutual funds herding behaviour that career-concerned managers tend to comply more with analyst recommendations and that they tend to herd more when receiving negative stock information since the risks of reputation loss and lawsuits are bigger when holding these losing stocks. According to the study mutual funds seem to follow the consensus recommendations both in buying and selling but they react more aggressively to recommendation downgrades due to the aforementioned reputational and legal threats. Similar results of herding in case of negative and positive information are achieved by Blasco et al. (2018, p. 5506-5507), Jegadeesh & Kim (2010, p. 931) and Lin (2018. p. 104).

Graham (1999, p. 238) emphasized the following four incentives which he believed would influence the chance of an analyst to ignore his/her private information and instead copy the actions of a market leader:

1. Grows according to his/her initial reputation (protect initial reputation instead of risking it)
2. Decreases according to his/her abilities (the more skills the less the need)
3. Grows the more the prior public info is in line with market leader’s actions
4. Grows depending on how well the informative signals correlate

Clement & Tse (2005, p. 308-310) describe the relationship between analyst characteristics and herding behaviour as complicated. They state that bold forecasts are produced by analysts (not so liable to mimic others) who

1. so far possess a history of accurate forecasts
2. work for large brokerage firms,
3. actively engage themselves in forecasting
4. possess universal knowledge instead of company-specific expertise

In addition, Clement & Tse (2005, p. 308-310) point out the fact that on average daring forecasts happen to be more accurate than the common herding forecasts which accordingly indicates that bold analysts' forecasts seem to contain the more of the analysts' relevant private information than those of the herding analysts' forecasts.

According to several researchers (Xu et al. 2017, p. 311-342; Lux 1995 p. 883-894; Kindleberger & Aliber 2005) the phenomenon of herding does entail risks that may have severe consequences, the worst of which is the stock market crash. Xu et al. (2017) state in their study on Chinese equity markets that there is a positive correlation between analyst herding and a company's crash risk. In addition, they found herding having a delaying effect on negative news passage in the market. It has been shown that herding takes place in situations when information uncertainty is greater and in risky times especially among those analysts who have less experience and who less actively update their recommendations (Lin 2018, p. 104). To summarize, the herding behaviour of which analysts are part of might lead to investors (as well as analysts) ignoring the fundamentals of investing and by this way absorbing them into the enthusiastic and optimistic coloured cycle of financial bubble which eventually could result in a market crash.

3.4 Investor behaviour with respect to recommendations

Individuals are known to make decisions based on historical events, their own personal beliefs and preferences, using quantitative as well as qualitative methods. The research on investor behaviour is a combination of studies focused on psychology and microeconomics (individuals and groups) and macroeconomics (governments, markets etc.). (Ricciardi & Baker 2014, p. 7) This chapter addresses the question of how investors react to analyst recommendations.

Studies done on how investors react to analyst recommendations show evidence that investors react to analyst recommendations both in upgrades and downgrades and that there is a post-earnings announcement drift element in stock prices (meaning markets do not necessarily absorb all information contained in analyst recommendations immediately and hence inefficiency exists) which influences how well an investor can profit from analyst recommendations. (Barber et al. 2001, p. 561-562; Womack 1996, p. 138; Stickel 1995, p. 35-36)

Welagedara et al. (2017, p. 223) find that investors might behave irrationally as they react to new information released in the form of analyst recommendations. According to their study investors linger when facing recommendation upgrades and overreact when facing downgrades. In their opinion, such irrationality may be caused by psychological distortions like opposition to regret or disposition effect. Also, Nofsinger (2018, p. 90) points out how harmful the disposition effect is; to escape regret and search for pride, investors typically sell their winning stocks too early and keep their losing stocks too long. This kind of behaviour leads to poor investment performance due to large tax payments and weak stock returns. On the other hand, Loh (2010, p. 1249) states in his study that the drift effect in stock prices is due to investor inattention and that it simultaneously poses opportunities for profits among those investors who are aware of such inattention.

A difference between the behaviour of small and large investors on stock recommendations is acknowledged by many researchers. Below are given factors combining the common features characterizing these two investor groups according to several researchers. (Malmendier & Shanthikumar 2007; Mikhail et al. 2007, Lee 1992; De Franco et al. 2007; Lien et al. 2020; Nofsinger 2018).

1. Small investors are not as good at processing analyst information comprehensively as large investors and tend to obey recommendations literally (observes only recommendation score 1-5). A strong bull market and high stock returns might cause major overconfidence among small investors.
2. Small investors tend to purchase more stocks after recommendation revision in both cases upgrades and downgrades as larger investors seem to sell in case of downgrades.
3. Large investors appear to make more profit in both (downgrades/sells and upgrades/buys) revision cases.
4. Small investors make negative profit after downgrade revision and trivial profit after upgrade revision.

Differences to the features provided above exist however as Hsieh & Lee (2021, p. 24-25) describe in their study on investors trading responses in the Taiwanese stock markets. According to them, there is a difference in how institutional investors use information in Taiwan and the US, namely large investors seem to use all available information in the US but in Taiwan, large investors seem to react mostly to the recommendations (target price used for supporting decision making) part while ignoring the earnings forecasts part of the analyst report. The reason for such ignorance of information (which would be considered crucial in more efficient markets) is in their opinion the result of a large number of uninformed investors in the Taiwanese market.

The findings of Wiersema & Zhang (2011, p. 1178-1179) indicate that not only investors follow the analyst recommendations but also company boards who decide the firm's CEO and his/her dismissals. According to their research, the board will more likely dismiss the CEO in the case when analyst recommendations on the company's stock are negative and when the board assumes that these analyst recommendations are thought to affect the investors (firm's stock owners) decisions.

Linking the topics of investor behaviour regarding stock recommendations and herding discussed earlier in section 3.3, Lien et al. (2020, p. 797- 798) noticed in their study using Taiwanese stock data that, on average, institutional investors focus more strongly on a few specific stocks than individual investors who conversely distribute their choices more broadly on several stocks. Additionally, they find that investment trusts are the kind of investors who are most certain to show signs of herding due to reputational risks.

3.5 The findings of previous studies regarding the relationship of abnormal returns with analyst recommendations and target prices

In the previous chapters there has been discussion on how the analysts serve investors by giving recommendations and by providing target prices for future expectations as well as risks related to analyst recommendations, herding and investor behaviour. In this chapter, a closer look is done at relevant previous studies implemented in the field of how investor returns and analyst recommendations are related and how large the potential benefits are.

Studies on how useful analyst recommendations are have a long history, some of which are done as early as in the 1930s (Cowles 1933). Stickel (1995) found by studying Wall Street brokerage house analysts’ recommendations and New York Stock Exchange (NYSE) stock prices in the United States that on short term buy recommendations were accompanied by an average 1.16% price growth and sell recommendation by -1.28% price decrease inside a time window of 11 business days (5 days before and 5 after). However, the obtained results were considered rather ambiguous since the change in prices could have resulted from several factors such as the magnitude of recommendation change, namely a large change in recommendation scale (for example from “hold” to “strong-buy”) would cause more notable price changes than adjustments of one level (or example from “hold” to “buy”). Also, other factors like the size of the brokerage house, analyst reputation and supporting information sources such as reminiscent earnings forecast revision were seen to have an effect on the price changes.

A similar relation between price change of a stock and revision change in the recommendation of the same stock was noticed by Elton et al. (1986) who stated that it is worth mimicking from brokerage houses which stocks to buy and sell but even more important to react on the changes in recommendations or in other words update one's own holdings according to the newest revisions from analysts. Furthermore, Elton (1986) stated it was possible to acquire 4.5% more return by purchasing stocks with “buy” recommendations instead of stocks with ”sell” recommendations. Womack (1996) was of the same opinion, underlining the fact that stock prices change not only because an individual recommendation changes but because of revision changes per se. He found that the post recommendation drift in stock prices is parallel to analyst forecasts and most intensive after three days from the recommendation with (size-adjusted mean) values +3% for added-to-buy recommendations and -4.7% for added-to-sell recommendations.

The drift effect in stock prices following the recommendation release was also recorded by Ryan & Taffler (2006) in their study using data from the United Kingdom stock market. They noticed that the price changes are quick and notable in both new buys and new sells, however, the reaction is larger in the case of new sells than in new buy recommendations. According to the study an investor could make on average, in the same month when the recommendation changes, abnormal returns of the following size: +2.06% for new buy (upward) recommendations and -3.3% for new sell (downward) recommendations. Likewise, Chang & Chan (2008) find the same mechanics to be true (similar to Womack (1996) and Ryan & Taffler (2006)) in their study on recommendations for stocks listed in the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and National Association of Securities Dealers Automated Quotation (NASDAQ). They observe the following average cumulative market-adjusted returns using the three-day event window: 7.8% for downward stock recommendation revisions and 3.04% for upward stock recommendation revisions.

Barber et al. (2001) state that by acquiring stocks (forming a portfolio) with the best favourable consensus recommendation an investor could achieve on average annually 4.13% in abnormal gross returns and similarly a portfolio consisting of the stocks with the least favourable recommendations would yield on average annually -4.91% in abnormal gross return. Furthermore, Barber et al. (2001) point out that if the portfolios are updated on a daily basis according to the latest analyst recommendations (buy stocks with high recommendations and sell away the least recommended) would result in even higher returns.

Despite these multiple pieces of research that indicate possibilities for abnormal returns inside a specific timeframe often reaching from a few days up to 12 months, there is also much evidence of the triviality stigmatizing the strategy of recommendation-based investing. In other words, there seems to be proof implying that the markets nowadays, at least in highly developed countries, are efficient and that new information quickly gets recorded into current stock prices.

For example, a study from Souček & Wasserek (2014) using German stock data (DAX 30) accepts the existence of a post-recommendation stock price drift (six months for upgrades and three months for downgrades) but nevertheless achieving relevant abnormal returns an (individual) investor would have to engage into active trading at the same day time the recommendations are given (often on daily bases) which after transaction costs would probably not fit most of the individual investors.

Moulya & Mallikarjunappa (2020) state in their study, carried out using data from the Indian stock markets (Nifty 50 stocks), that day-traders could not earn any abnormal returns by following analyst recommendations on a daily basis (even though some price drift was identified). The preceding fact serves as an empirical implication and is in favour of the realization of the efficient market hypothesis (EMH), at least on day-trading, in the Indian stock market.

In the academic field, research has also been conducted focusing on the question of whether local analysts perform better than foreign analysts in predicting company prospects and producing recommendations based on these findings. Results from previous studies show evidence that analysts with a geographically shorter distance to the companies which are analyzed have information benefits over other (foreign) analysts and by utilizing this advantage they make more accurate forecasts. (Malloy 2005; Bae et al. 2008) In the light of these facts Hendricks et al. (2010) state in their study, using German stock data (DAX 30), that although German bank recommendations have better predictive power when it comes to daily stock returns in comparison with foreign counterparts it would not be possible to obtain any significant abnormal return by an (individual) investor due to the efficiency of information assimilation in the market.

A prominent debilitating factor when measuring the profits achieved by exploiting analyst recommendations is the existence of transaction costs. It is important to realize that the transaction costs are not similar to large institutional investors and small individual investors and normally smaller investors are obligated to pay larger costs when trading (Keim 1997). In many studies, it is shown that the effect of transaction costs is crucial when considering the conditions in which an (individual) investor has to operate. Simply put, the more trading is needed in order to produce abnormal returns (which is vital in most of the modern-day markets) the more transaction costs are created making many recommendation-based active strategies inefficient. (Davis & Canes 1978, p. 55; Barber et al. 2001, p. 562; He et al. 2013, p. 468; Boudt et al. 2015 p. 711; Glezakos & Merika 2011, p. 109; Cai & Xu 2011, p. 75)

Analyst target prices are also known to affect direct market reactions and changes in stock prices alone and along with recommendations and earnings forecasts (Feldman et al. 2012; Brav & Lehavy 2003; Kanne et al. 2012). Kanne et al. (2012, p. 426) pointed out that investors should be careful in investing decisions when recommendations and target prices have great differences in their message about the particular company's prospects. In other words, when the two indicators point in opposite directions there is a great risk the decision to buy or sell a stock goes wrong. They add that target prices could be useful in a situation where the investor is nevertheless going to trade stocks, much like Barber et al. (2001, p. 562) stated concerning analyst recommendations, it could serve as additional support for decision making. According to Brav & Lehavy (2003, p.1963-1964), the one year ahead predicted target prices were on average 28 percent higher than current market prices (using US stocks and the NYSE/AMEX/Nasdaq value-weighted market index). Bradshaw (2002, p. 39-40) finds in his study that favourable recommendations (buy-oriented) tend to go along with higher target prices (compared to present prices) and that analysts use target prices to empower their recommendations. Similarly, Zhou (2013, p. 11) finds in his study using stocks listed in NYSE, AMEX and Nasdaq from 2000 to 2009 that there is a positive association between more favourable stock recommendations and the higher difference between the ratio of target price to price and the benchmark return (the higher the risk the more favourable the recommendation).

Specific evidence of how inaccurate the stock recommendations in the Finnish stock market have been during the analyzed time period (31.12.2013-31.12.2020) can also be found from a Finnish business newspaper Kauppalehti (2020 & 2021). Findings show that many stocks listed in the OMXH25 which have acquired “buy” recommendations from analysts have been beaten during 2016-2021 by the OMXH25 index while those stocks with “sell” have been able to beat the index. For example, Nokia which has mainly been classified as “buy” stock has underachieved its recommendations constantly whereas Elisa classified as “sell” stock has outweighed the index in many years. According to Kauppalehti, the recommendations are always eventually simply opinions and therefore expected to be false sometimes. Also analyst recommendations are known, on average, to be over optimistic. What is important is to focus on the explanations given by the analyst and utilize them in support of the individual investment decisions (Kauppalehti 2019, 2020 & 2021)**.** Summarized, it could be said that combining both analyst consensus recommendation and target price are of use when creating portfolios with advantageous risk/return ratios. This fact was recognized also by Huang et al. (2009) in their study on stocks listed on NYSE, AMEX and NASDAQ indices.

3.6 Target price accuracy

A target price released by an analyst is a mixture of multiple forecasts: large scale fundamental analysis such as firms cash flow analysis and industry prospects in terms of growth, competition, regulation etc., but also technical analysis focusing on recognizing trends from the stocks historical data such as trading activity, price movement and volume. (Asquith et al. 2005, p. 276; Investopedia 2021f)

In this section, a short overview is carried out on the existing academic literature concerning target price accuracy. The findings serve as a background for result interpretation in section 5.2. It is worth noticing that target prices are in this study compared to the eventual stock prices at the end of the 12- month long time period and not any possible time slot inside the 12-month long time window. Table 1 in the following two pages concludes the values and relevant information from previous studies.

Research info	Market and analysis period	Research method	Values (compared wrt. results in section 5.2)
Bradshaw et al. (2012)	US firms, from January 2000 to December 2009. Data is from Center for Research in Security Prices (CRSP).	Analysts' target prices are met or beaten by realized market prices at the end of a 12 month period so TPMETEND is P12>=TP. The absolute average difference between the target price and the actual stock price at the end of the 12-month forecast horizon, P12, scaled by the stock price at the TP issue date Ps. This "aTPE" is calculated as aTPE = abs((P12-TP)/Ps).	TPMETEND is 38%. Average absolute forecast error (aka. aTPE) is 45%.
Bonini, et al. 2010	Italy, Milan Stock Exchange, from January 1, 2000 to December 31, 2006.	Number of forecasts met or exceeded by the stock price at the end of the forecast window. TPMETEND P12>=TP	TPMETEND is 20%.
Bilinski et al. 2013	International study. Target prices for firms domiciled in 16 countries, From 2002 to July 1, 2009. US data from CRSP and non-U.S data from Datastream.	The absolute difference between the target price and the actual stock price at the end of the 12-month forecast horizon (aka. aTPE), P12, scaled by the stock price at the TP issue date Ps. Calculated as aTPE = abs ((P12-TP)/Ps).	Average aTPE(%) of 16 countries is 44.70%. aTPE(%) for Finland is 44.10%.

Table 1. Relevant target price reference values

Research info	**Market and analysis period**	**Research method**	**Values (compared wrt. results in section 5.2)**
Investopedia 2021f	-	The overall accuracy of target prices reaching from 12 to 18 months forward.	Close to 30%.
Erkilet et al. 2021	Germany (DAX30 companies), January 2014 and June 2017.	Calculated as the absolute difference between the target price forecast and the stock price at the end of the 12-month forecast horizon, scaled by the stock price at the end of the 12-month forecast horizon. TPE (aka. aTPE) calculated as |(TP-P12)/P12|.	The total sample has a mean target price error ("aTPE") of 0.20-0.22 depending on the valuation approach.
Cheng et al. 2019	Taiwan stock market, January 2007 to December 2016. Data from the Taiwan Economic Journal (TEJ) database.	The second measure, TP_end, is the absolute difference between the target price and the actual price at the end of the 12-month forecast horizon (aka. aTPE), scaled by the actual price at the end of the forecast horizon. TP_end (aTPE) is calculated as |(TP-P12)/P12|.	On average, the forecast error is 49% at the end of the period.
Almeida & Gaspar. 2021	50 European large capitalization companies which have stayed longest in the Eurostoxx index. From 2004 to 2019.	Panel data regressions. "To what extent analysts' target prices (TP) forecast futures prices (FP) and compare their forecasting performance to that of using simple capitalisations of current market prices—capitalised prices (CP)."	"Bloomberg's consensus 12-month target prices are not accurate forecasts for future markets prices."

Table 1. Relevant target price reference values continued

In addition to the results discussed above Asquith et al. (2005, p. 276) state that “analysts might be more likely to issue highly favourable recommendations due to concerns over personal compensation, relationships with the analyzed firms’ management, or their own firm’s underwriting business. Price targets can be either a way for analysts to ameliorate the effects of overly optimistic reports or a part of the sales hype used to peddle stocks”. These statements reflect much of the same challenges covered in sections 3.2 and 3.3 and remind of Bradshaw's (2002, p. 39) remark on how target prices are used to justify published recommendations.

4 RESEARCH HYPOTHESES, DATA COLLECTION AND ANALYSES

The figure 5 below illustrates the process implemented in the following three chapters 4, 5 and 6. Let us start by defining the hypotheses and subsequently move to the conclusions through five different phases.

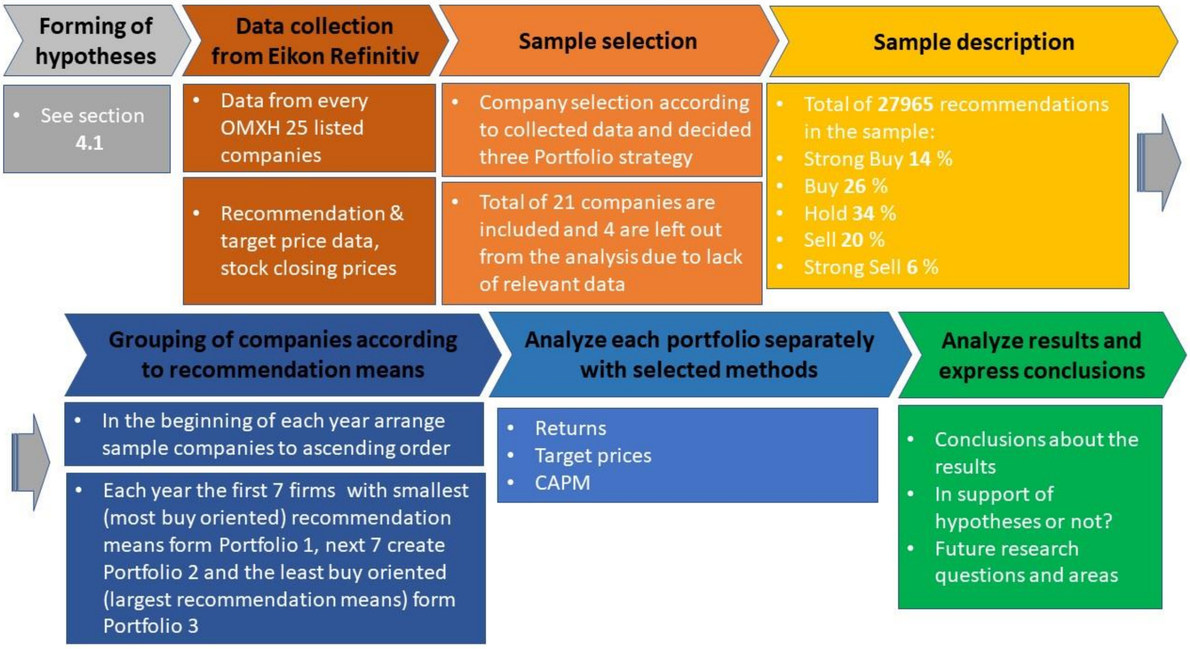

Figure 5. Research process by stages

4.1 Research hypothesis

Analysts issue recommendations for investors based on future prospects of companies. In order to exist, the industry has to create some additional value for the investors in the form of informative predictions. This study focuses on analyzing whether an investor could profit from following analyst recommendations issued on selected 21 companies listed in the OMX Helsinki 25 index (OMXH25). The companies are analyzed by constructing three portfolios from them based on the average consensus recommendations and then updating the portfolios every year according to the latest recommendations. In this way, the portfolios will have different features as some include more buy-oriented stocks and some more sell-oriented ones. Based on this idea the first hypothesis is as follows:

Hypothesis 1: Analyst recommendation-based investment strategy generates abnormal returns.

Analysts also provide other prediction measures than recommendations. In addition to earnings forecasts, one of the qualitative indicators is the target price which is commonly regarded as a useful measure since it is continuous and easily comparable. In the light of these points and the opportunity to include target prices in the original data sample the second hypothesis is the following:

Hypothesis 2: Analyst target prices endorse consensus recommendations and provide useful information to investors

By constructing portfolios after distinct recommendations, it would be interesting to find out how market fluctuations affect them and whether the buy-oriented portfolio behaves differently in contrast to the sell-oriented portfolio. This means our third and last hypothesis is the following:

Hypothesis 3: Low recommendation-based investment strategy has higher risk and higher expected return with respect to OMXH25 index than a high recommendation-based investment strategy

4.2 Research data and sample selection

The data examined in this research is acquired via Refinitv Eikon which is a software offering financial information for financial professionals. The data collected from Refinitiv Eikon is I/B/E/S (Institutional Brokers' Estimate System) standardized meaning that the analysts' ratings are converted to a five-point (1-5) scale system in case a different recommendation scale is used by the analyzing institution/contributor. The recommendation mean which is the most relevant parameter in this study is calculated by multiplying the I/B/E/S standardized (scale from 1 to 5) recommendation value with the amount of that particular recommendation (Strong Buy/Buy/Hold/Sell/Strong Sell) and then dividing the total sum with the amount of all recommendations. The recommendation data was collected between the period of 31.12.2013 and 31.12.2019 and the target price data between the period 31.12.2013 and 31.12.2020. The following records shown in table 2 below were collected from Refinitiv Eikon:

Number Of Strong Buy Number Of Buy Number Of Hold Number Of Sell Number Of Strong Sell Number Of No Opinion Number Of Recommendations in Total Recommendation Mean (1-5)	Price Target – Mean (1-5) Price Target - Number of Estimates Price Target - Number of Included Estimates Stock Closing Price

Table 2. Collected data from Refinitiv Eikon

Below in table 3 is shown the common recommendation scale and the corresponding I/B/E/S values.

Recommendation	Strong Buy	Buy	Hold	Sell	Strong Sell
I/B/E/S scale	1	2	3	4	5

Table 3. The Refinitiv I/B/E/S standardized scale

Out of the 25 companies listed in the OMXH index 21 were selected to be included in the study. Reasons behind the rejection of the 4 companies (see table 4 below) were solely due to the lack of relevant data from the aforementioned time period of 31.12.2013 to 31.12.2020 either in terms of the number of recommendations given by analysts or shortage of data during the decided analysis period. Also, the number of portfolios was fixed to 3 making it practical to use 7 companies per portfolio.

Included	**Excluded (due to)**
WRT1V UPM TYRES TIETO STERV SAMPO OUT1V ORNBV NOKIA NESTE NDAFI MOCORP METSB KNEBV KESKOB KEMIRA KCRA HUH1V FORTUM ELISA CGCBV	VALMT (No data available from 2013) TELIA1 (Only from 2 to 4 recommendations available per month throughout the time period) QTCOM (Data becomes available after 30.4.2016 and still has only from 1 to 4 recommendations available per month throughout the time period) KOJAMO (Data becomes available only after 30.6.2018)

Table 4. Included and excluded sample companies

4.3 Sample description

The sample dataset collected from Refinitiv Eikon includes recommendations on every company starting from 31.12.2013 and ending on 31.12.2019. As can be seen from table 5 below, during this period there are overall 2381 recommendations given for the selected 21 OMXH25 listed companies. The amount of “No opinion” recommendations has been zero during the analyzed time period for all selected companies**.**

Year	Strong Buy	Buy	Hold	Sell	Strong Sell	No Opinion	Total
2019	46	79	116	57	21	0	319
2018	73	91	93	40	13	0	310
2017	46	93	114	56	22	0	331
2016	44	88	118	77	23	0	350
2015	49	92	115	73	14	0	343
2014	44	89	123	72	23	0	351
2013	32	77	143	97	28	0	377
Total	334	609	822	472	144	Total #	2381

Table 5. Distribution of recommendations during the time period 2013-2019

Strong Buy (1)	Buy (2)	Hold (3)	Sell (4)	Strong Sell (5)
14 %	26 %	35 %	20 %	6 %
Buy oriented			Sell oriented	
40 %			26 %	

Table 6. Total of Buy and Sell-oriented recommendations during the time period 2013-2019

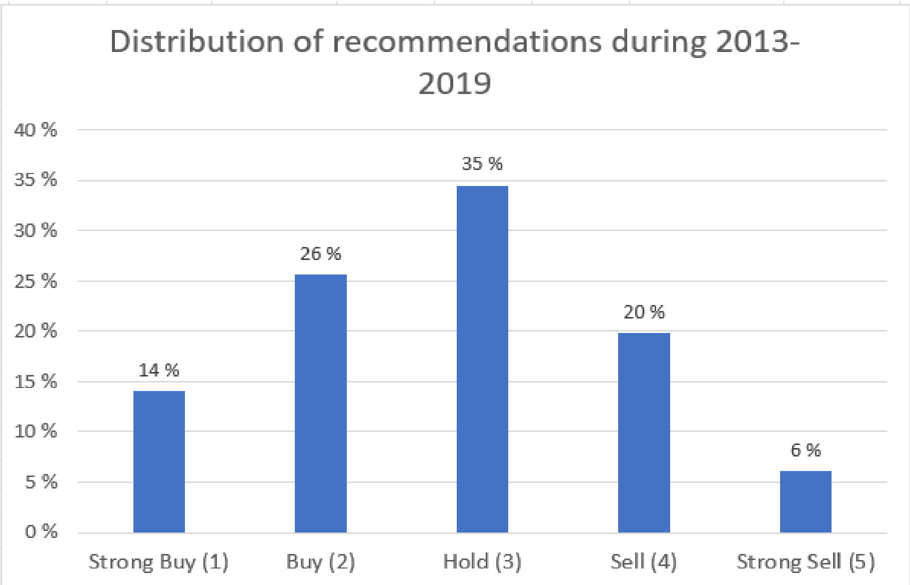

Figure 6. Distribution of recommendations during the whole 2013-2019 time period

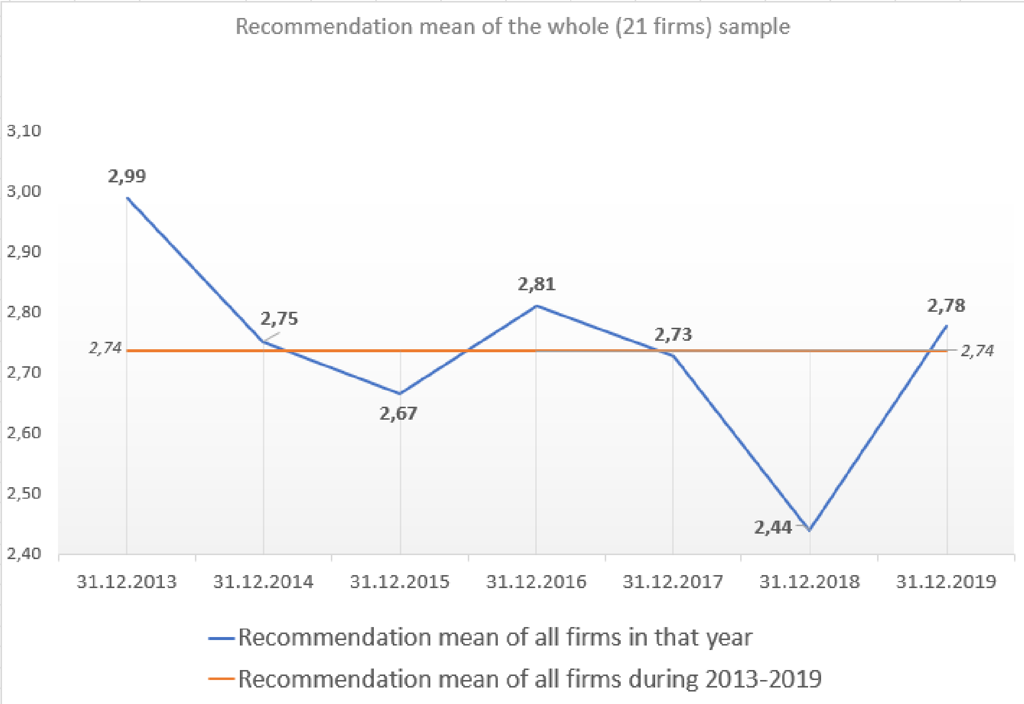

Figure 7. Recommendation mean of the total sample using I/B/E/S 5-point scale during the 2013-2019 analysis period

It is noticed from figure 7 above that the total recommendation mean of the whole sample during the analysis period is 2.74 (scale of 1-5) meaning it is a bit more buy-oriented than sell-oriented.

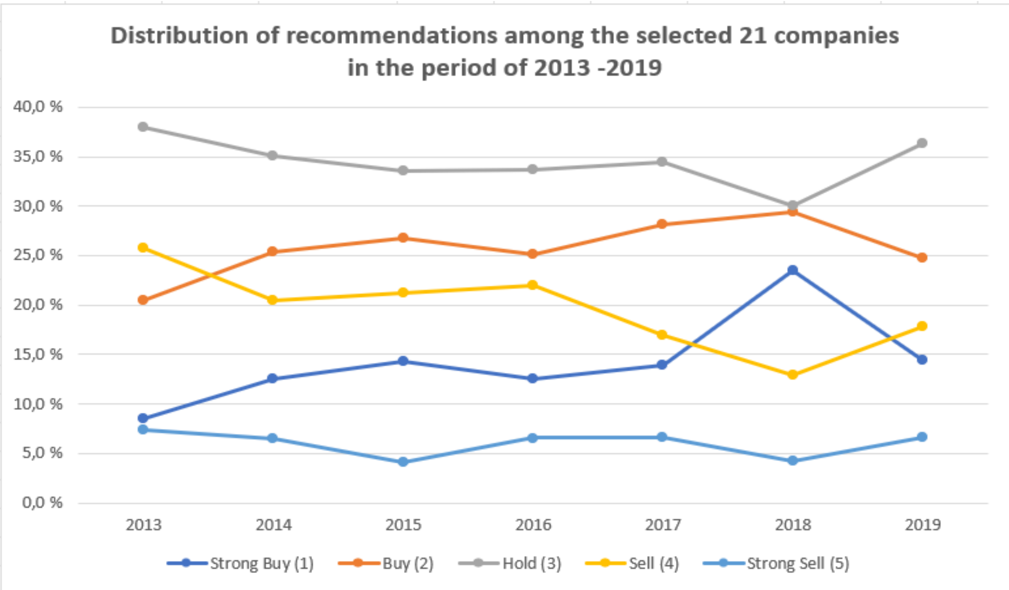

Figure 8. Weight of each recommendation level with respect to the total recommendation mass (that year) during the analyzed time period 2013-2019

Figure 8 above shows that the strongest recommendations have without the exception of years 2018 and 2019 always been the smallest contributors to the total of recommendations each year. “Hold” has been the most common recommendation to be given for the companies during the whole time period of 2013-2019 with a total number of 822.

It is noticed from figure 6 and table 6 that there are clearly more buy than sell-oriented recommendations, namely “Strong Buy” (334) and “Buy” (609) add to 943 (40% wrt. total recommendations) whereas “Strong Sell” (144) and “Sell” (472) add to 616 (26% wrt. total recommendations). There are in other words 327 (14% in total) more buy-oriented recommendations than those with either “Sell” or “Strong sell”. The notion of buy-oriented recommendations outweighing the sell-oriented recommendations have been noticed many times in previous studies as well (for example Womack 1996 p. 139; Morgan & Stocken 2003 p. 199; Lien et al. 2020, p. 797) and the academic literature related to overoptimism was discussed also in detail in section 3.2. In the light of these aforementioned findings, slight similarities of recommendation optimism could be seen in this data sample.

In table 7 below are presented the company-specific recommendations for each firm during 2013-2019 and in the last row the total average values. Below table 7 is shown table 8 which shows company weights in the OMXH25 -index based on information acquired from Nasdaq (2021) using values from 1st of June 2021. By applying them to the whole analysis period from 2013 to 2019 it becomes possible to acquire some approximation for recommendation division among the stocks according to their weight in the OMXH25 -index. Table 8 indicates that the top 10 companies in our sample of 21 companies sum up to around 77% of the real OMXH25 -index and have a recommendation average value of 2,76. The remaining 11 companies sum up to around 18% and have a recommendation average of 2,72. In other words, when roughly 95% of the OMXH25 -index is observed (ignoring the remaining 5% from excluded companies) it is noticed that, using the I/B/E/S five-point (1-5) scale, the recommendation mean is below 3, namely 2,74. There seems not to be more favourable recommendations for the most weighted companies with respect to those with minor weight.

	WRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBV
31.12.2013	2,70	2,94	2,89	3,00	2,81	2,95	3,69	3,58	2,73	3,60	2,17	3,50	2,73	3,15	2,60	2,86	3,06	2,50	3,20	3,24	2,88
31.12.2014	2,71	2,94	3,10	2,77	2,44	2,68	2,16	3,82	2,82	3,42	2,00	3,20	2,13	3,09	2,50	2,73	2,93	2,13	3,21	3,00	2,00
31.12.2015	3,05	2,76	3,33	2,64	2,61	2,80	2,47	3,80	2,21	2,44	2,00	2,57	2,33	3,20	2,25	2,50	2,50	2,25	2,93	3,32	2,00
31.12.2016	2,90	2,82	2,73	2,75	2,28	2,83	2,52	3,75	2,20	3,39	2,00	3,27	2,30	3,23	2,89	3,11	2,82	2,00	3,66	2,88	2,70
31.12.2017	2,95	2,67	2,74	2,92	2,67	2,65	2,25	3,00	2,14	3,21	2,75	3,00	2,56	3,11	2,44	3,00	2,15	2,57	2,96	3,38	2,17
31.12.2018	1,89	1,93	2,20	2,90	1,87	2,28	2,39	2,13	1,96	2,80	2,38	2,64	2,38	3,00	3,38	2,88	1,83	2,00	2,95	3,25	2,20
31.12.2019	2,89	2,38	3,00	2,82	2,56	2,19	3,05	4,00	2,24	2,30	2,13	1,70	3,33	3,54	3,38	3,25	2,50	2,38	2,67	3,90	2,10
Total average	2,73	2,64	2,86	2,83	2,46	2,63	2,65	3,44	2,33	3,02	2,20	2,84	2,54	3,19	2,78	2,90	2,54	2,26	3,08	3,28	2,29

Table 7. Company specific recommendation averages from 2013-2019

Company	Recommendation mean	Share in OMXH25 -index
NESTE	3,02	10,57 %
NOKIA	2,33	10,51 %
NDAFI	2,20	10,11 %
KNEBV	3,19	9,89 %
SAMPO	2,63	9,53 %
UPM	2,64	8,34 %
FORTUM	3,08	5,30 %
STERV	2,46	4,63 %
KESKOB	2,78	4,03 %
ELISA	3,28	3,79 %
MOCORP	2,84	3,63 %
WRT1V	2,73	2,66 %
TYRES	2,86	2,20 %
ORNBV	3,44	1,92 %
HUH1V	2,26	1,92 %
KCRA	2,54	1,27 %
TIETO	2,83	1,17 %
CGCBV	2,29	0,97 %
METSB	2,54	0,87 %
OUT1V	2,65	0,80 %
KEMIRA	2,90	0,76 %
VALMT	not analysed	2,5 %
KOJAMO	not analysed	1,7 %
TELIA1	not analysed	0,3 %
QTCOM	not analysed	not available
	Top 10's recommendation mean	Top 10's share from OMXH25
	2,76	76,7 %
	Remaining 11's rec. mean	Remaining 11's share from OMXH25
	2,72	18,17 %
		Excluded share from OMXH25
		4,45 %

Table 8. Sample companies' recommendation means from 2013-2019 and weights in OMXH25 in 1st of June 2021 (Nasdaq 2021)

4.4 Portfolio formulation and research methods

The formulation of the three portfolios and necessary calculations are described by using the phases described below. Necessary data processing, calculations and visualizations were actualized by using MATLAB and Microsoft Excel.

1. Each year, starting on 31.12.2013 and ending in 31.12.2020, the 21 companies listed in table 4 are divided into three groups, namely portfolios 1,2 and 3.
    a. This is done according to their calculated recommendation mean, in other words, all the companies are arranged into ascending order by their recommendation mean values and then the first (lowest recommendation mean) seven (1-7) companies constitute the portfolio 1, the next seven companies the portfolio 2 (8-14) and the remaining (15-21) seven portfolio 3. As the years change the portfolios get updated according to the latest recommendation mean values. Each yearly ranking of the companies and portfolio combinations are provided in appendix 1.

b. Once the membership of the companies in each portfolio at all times is known the analysis for each separate portfolio is implemented by using the raw returns, target prices and CAPM.

2. Once the membership of the companies in each portfolio at all times is known an analysis of raw returns is implemented. For raw returns: the one-year return of a company in a portfolio is calculated as the result of the stock price at the end of the year reduced by the stock price at the beginning of the year and then divided by the stock price at the beginning of the year. The yearly return of a whole portfolio is acquired by summing all the returns from the member companies in that portfolio from the specific year.

3. This third phase is the target price analysis part and has a total of four phases. In the terminology notice the following: "**Ps"** means current stock price, "**P12"** means the actual stock price at the end of the 12-month forecast-horizon or sometimes addressed simply as "future price" and lastly target price abbreviated as "**TP**".

   a. Find out the distribution of upwardly oriented and downwardly oriented target prices among the portfolios.
   b. Compare issued target prices (TP) and realized prices from the future to find out the potential associations between recommendations (buy vs. sell) and target prices.
   c. Target prices (TP), current stock prices (Ps) and actualized prices in one year away from the moment of target price release (P12) are measured to recognize their prediction abilities and possible similarities with stock recommendations. This first accuracy measure finds out how well the current price (Ps) and expected price (TP) align with future price (P12) and current price (TP). In other words, the following is done: count the cases when a Ps has been expected to go up/down (TP>Ps or TP<Ps) and compare that to the actual development P12>=Ps or P12<Ps. If both expected and actualized development are of the same direction, either both positive or both negative the prediction is considered successful. In other cases, it has been unsuccessful. This measure gives no attention to the magnitude of the price development.

d. Calculate the mean absolute percentage error (MAPE) for each portfolio in two ways:

1. The absolute difference between the target price and the actual stock price at the end of the 12-month forecast horizon P12, scaled by the actual stock price at the end of the 12-month forecast horizon P12. In the results section 5.2 it is measured against the "aTPE" reference values described in section 3.6 in table 1.

$$MAPE_1 = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{F_i - P12_i}{P12_i} \right| \tag{3}$$

where

F_i is the forecasted target price (TP)
$P12_i$ is the actual stock price at the end of the 12-month forecast horizon
n is the total number of observations

2. The absolute difference between the target price and the actual stock price at the end of the 12-month forecast horizon P12, scaled by the stock price at the TP issue date Ps. The formula is given below. In the results section 5.2 it is measured against the "aTPE" reference values described in section 3.6 in table 1.

$$MAPE_2 = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{F_i - P12_i}{Ps_i} \right| \tag{4}$$

where

F_i is the forecasted target price (TP)
$P12_i$ is the actual stock price at the end of the 12-month forecast horizon
Ps_i is the actual stock price at the target price issue date
n is the total number of observations

4. Next the processes for CAPM analysis and CLRM assumption testing are described. With the CAPM it is studied how the sample company returns vary with their level of market risk. By finding out the beta coefficients it would be possible to observe how the three different portfolios react to an increase (decrease) in the market return. The three portfolios are structured based on the issued analyst recommendations (as described in phase 1 described above) and these company specific CAPM values will eventually serve as attributes to the overall portfolio performances.

    a. In the CAPM short-term Euribor of three months is used as the risk-free rate and the linear regression model is taught by using monthly prices (compared to recommendation and target price analyses which use yearly 31.12.xxxx prices). The details are as follows:

       1. Linear regression models are created for each company (21) by using the company excess returns and two index returns: OMXH25 and “sample21” excess returns. The “sample21” index consists of average excess returns taken from all of the selected 21 companies from 2014-2020. The fitting of a model is done using 84 observations (7 years * 12 months) for x (OMXH25/sample21) and y (selected company). The following information for each company is acquired and analysed by using Matlab's fitlm function: alphas, betas, the p-values for beta, the p-value for alphas, adjusted R-squared. The Matlab function fitlm uses the ordinary least squares (OLS) method for estimating the unknown parameters in the linear regression model.

       2. Portfolio values are calculated according to the company specific values acquired from the previous phase.

    b. In addition, the Classical Linear Regression Model (CLRM) assumptions, which were addressed in section 2.3, are tested in Matlab by using the following methods:

       1st assumption: Calculate mean of residuals
       2nd assumption: White test
       3rd assumption: Durbin-Watson test
       4th assumption: Condition number test
       5th assumption: Jarque–Bera test

4.5 Limitations of the study

This study focuses on analyst recommendations and target prices while earnings forecasts are left out. Therefore, potential information on the selected 21 OMXH25 listed companies is left out which could in a broader study be useful. Also, the recommendation sample data is collected from only one source, namely Refinitiv Eikon, which is considered as a limiting factor.

The recommendation research is done using recommendations starting from 31.12.2013 and ending 31.12.2019. The recommendations issued in 31.12.2013 serve as the structure for 2014 portfolios and in a similar manner recommendations issued in 31.12.2014 serve as a structure for 2015 portfolios and so on. As said the last analysed year is 2020 which is based on recommendations given on 31.12.2019.

When counting the results for the 21 firms, annual dividends are not taken into account and the focus remains only on price development. In a broader study, dividends would be included on top of the price increase/decrease (sum x multiplied by the number of shares) to find out the raw returns. In addition, the portfolio weights are divided equally among the firms, namely 14,3% (1/7) for each firm in a portfolio. This means that the OMXH25-index will yield different returns for two reasons: the lack of four companies (see table 4) and distinct weighting between the portfolios and actual OMXH25 weighting. In this study, the OMXH25 company weighting system (see example weighting from Nasdaq, 2021) is not used but instead, every company is evenly regarded in the portfolios.

The recommendations given for the sample data are prioritized, in other words, the portfolios are structured according to the recommendation and not for example both recommendations and target prices. Also, target price measurement is limited to studying the difference between current (t) prices and one-year future prices (t + 1 year). Since the analysis window of target prices is defined differently in financial literature and this study focuses only narrowly on target prices and their relevance in investment strategy, future research could focus on studying price development inside the one-year time-window, for example, t + 3 months, t + 6 months and so on.

The drift-effect (see theory in sections 3.4 and 3.5) is not studied and therefore the short-term trading aspect is left unstudied. More studies should be carried out to find potential short-term patterns (less than one year) in company/portfolio returns.

Transaction costs are not taken into account in this study, something which has in previous studies (for example Barber et al. 2001, p. 562; He et al. 2013, p. 467-468) proven to be crucial in mitigating the total abnormal returns of recommendation-based investing portfolios with minor rebalancing (which is the case in this study). In real life, transaction costs are realised/paid to brokers (especially in individual investing) every time the investor either sells or buys stocks and therefore the executed portfolio management strategy (passive vs. active and long term vs. short-term) plays an essential role in how large abnormal returns (with respect to markets) an investor is able to achieve. On top of the transaction costs also taxes would decrease the potential abnormal returns of a portfolio when it is updated.

5 RESULTS

In this chapter results are presented through three different perspectives as described in section 4.4, namely via portfolio returns, from the standpoint of target prices as well as information from the CAP model. As described in the first phase in section 4.4, after the division of companies into three portfolios is done every year, a more precise portfolio specific analysis is implemented.

This section addresses phase 1 from Section 4.4 where the three portfolios are constructed based on analyst recommendations. When studying the average recommendation values for all portfolios, which are given below in table 9, it is clear that portfolio 1 is the most buy/upwardly oriented with an average value of **2,24** from the whole analysis period. Portfolio 2 has the total average recommendation value of **2,71** and portfolio 3 has an average of **3,26** from the years of 2013-2019. Note in table 9 in the "Company" column that the recommendation is given 31.12 each year and the following year is based on the recommendations given on that day. For example, recommendations issued for portfolio 1 on 31.12.2013 form the actual portfolio 1 in the year 2014.

PORTFOLIO 1 (1-7)																						
Company	WRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBV	Average yearly recommendation
Recommendation values in 31.12.2013	2,7				2,8				2,7		2,2		2,7		2,6			2,5				2,61
Recommendation values in 31.12.2014					2,4		2,2				2,0		2,1		2,5			2,1			2,0	2,19
Recommendation values in 31.12.2015									2,2	2,4	2,0		2,3		2,3			2,3			2,0	2,21
Recommendation values in 31.12.2016					2,3		2,5		2,2		2,0		2,3					2,0			2,7	2,29
Recommendation values in 31.12.2017							2,3		2,1				2,6		2,4		2,2	2,6			2,2	2,33
Recommendation values in 31.12.2018	1,9	1,9			1,9			2,1	2,0								1,8	2,0				1,95
Recommendation values in 31.12.2019						2,2			2,2	2,3	2,1	1,7						2,4			2,1	2,15
																						2,24

PORTFOLIO 2 (8-14)																						
Company	WRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBV	Average yearly recommendation
Recommendation values in 31.12.2013		2,94	2,89	3,00		2,95										2,86	3,06				2,88	2,94
Recommendation values in 31.12.2014	2,7	2,9		2,8		2,7			2,8							2,7	2,9					2,80
Recommendation values in 31.12.2015		2,76		2,64	2,61		2,47					2,57				2,50	2,50					2,58
Recommendation values in 31.12.2016		2,82	2,73	2,75		2,83									2,89		2,82			2,88		2,82
Recommendation values in 31.12.2017	2,95	2,67	2,74	2,92	2,67	2,65					2,75											2,76
Recommendation values in 31.12.2018			2,20			2,28	2,39				2,38	2,64	2,38								2,20	2,35
Recommendation values in 31.12.2019	2,89	2,38	3,00	2,82	2,56												2,50		2,67			2,69
																						2,71

PORTFOLIO 3 (15-21)																						
Company	WRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBV	Average yearly recommendation
Recommendation values in 31.12.2013							3,69	3,58		3,60		3,50		3,15					3,20	3,24		3,42
Recommendation values in 31.12.2014			3,10					3,82		3,42		3,20		3,09					3,21	3,00		3,26
Recommendation values in 31.12.2015	3,05		3,33			2,80		3,80						3,20					2,93	3,32		3,20
Recommendation values in 31.12.2016	2,90							3,75		3,39		3,27		3,23		3,11			3,66			3,33
Recommendation values in 31.12.2017								3,00		3,21		3,00		3,11		3,00			2,96	3,38		3,09
Recommendation values in 31.12.2018				2,90						2,80				3,00	3,38	2,88			2,95	3,25		3,02
Recommendation values in 31.12.2019							3,05	4,00					3,33	3,54	3,38	3,25				3,90		3,49
																						3,26

Table 9. Recommendation values used for each portfolio during the analysis period 2014-2020

The number of times each firm has been in one of the portfolios is shown in table 10 below. As can be noticed, some companies have been in the same portfolio every year during the 2014-2020 time period, for example, HUH1V (Huhtamäki Oyj) and KNEBV (Kone Oyj). On the other hand, some of the sample companies have been classified diversely between the portfolios, such as OUT1V (Outokumpu Oyj) and WRT1V (Wärtsilä Oyj Abp).

Portfolio 1 companies	Number of times	Portfolio 2 companies	Number of times	Portfolio 3 companies	Number of times
HUH1V	7	UPM	6	KNEBV	7
NOKIA	6	TIETO	6	ORNBV	6
NDAFI	5	TYRES	5	FORTUM	6
METSB	5	SAMPO	5	ELISA	6
CGCBV	5	KCRA	5	NESTE	5
STERV	4	WRT1V	3	MOCORP	4
KESKOB	4	STERV	3	KEMIRA	4
OUT1V	3	KEMIRA	3	WRT1V	2
WRT1V	2	OUT1V	2	TYRES	2
NESTE	2	NDAFI	2	OUT1V	2
KCRA	2	MOCORP	2	KESKOB	2
UPM	1	CGCBV	2	TIETO	1
SAMPO	1	NOKIA	1	SAMPO	1
ORNBV	1	METSB	1	METSB	1
MOCORP	1	KESKOB	1	UPM	0
TYRES	0	FORTUM	1	STERV	0
TIETO	0	ELISA	1	NOKIA	0
KNEBV	0	ORNBV	0	NDAFI	0
KEMIRA	0	NESTE	0	KCRA	0
FORTUM	0	KNEBV	0	HUH1V	0
ELISA	0	HUH1V	0	CGCBV	0

Table 10. Division of the 21 sample companies among portfolios during the analysis period

5.1 Portfolio returns

This section addresses phase 2 from Section 4.4 where the portfolio returns are analyzed. The annual return of an individual company is acquired by comparing the stock price of the previous year's last day (t-1), for example, 31.12.2013, to the stock price of the current year's last day (t) for example 31.12.2014. The annual return of a portfolio is the sum of all included companies' annual returns.

Table 11 below describes the division of sample companies among the portfolios during the analysis period 2013 - 2020 and their contribution to the total returns during the years. In addition, table 12 summarizes the results of all portfolios 1,2 and 3 as well as shows the reference results from the alternative OMXH25 stock market index. The same information given in table 12 is also illustrated in figure 9 in order to offer a better understanding of the performance of different portfolio options on a yearly basis.

PORTFOLIO 1																						
Year	VRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBY	Average yearly return
2014	4 %				2 %				18 %		-1 %		42 %		13 %			17 %				13 %
2015					13 %		-43 %				5 %		58 %		7 %			53 %			35 %	18 %
2016									-29 %	32 %	5 %		-1 %		47 %			5 %			24 %	12 %
2017					29 %		-9 %		-15 %		-5 %		5 %					-1 %			10 %	2 %
2018							-59 %		29 %				-28 %		4 %		-31 %	-23 %			-43 %	-22 %
2019	-29 %	40 %			29 %			36 %	-34 %								4 %	53 %				14 %
2020						-11 %			-4 %	91 %	-8 %	42 %						2 %			12 %	18 %
Average return of the firm in the time period	-13 %	40 %			18 %	-11 %	-37 %	36 %	-6 %	61 %	-1 %	42 %	15 %		18 %		-14 %	15 %			8 %	8 %

PORTFOLIO 2																						
Year	VRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBY	Average yearly return
2014		11 %	-42 %	31 %		9 %										-19 %	-8 %				-6 %	-3 %
2015	14 %	27 %		15 %		21 %			1 %							10 %	-4 %					12 %
2016		35 %		5 %	22 %		211 %					47 %				11 %	48 %					54 %
2017		11 %	7 %	0 %		8 %									-5 %		13 %			6 %		6 %
2018	-21 %	-15 %	-29 %	-9 %	-24 %	-16 %					-28 %											-20 %
2019			-4 %			3 %	-12 %				0 %	87 %	21 %								13 %	15 %
2020	-17 %	-1 %	12 %	-3 %	21 %												8 %		-10 %			1 %
Average return of the firm in the time period	-8 %	11 %	-11 %	6 %	6 %	5 %	100 %		1 %		-14 %	67 %	21 %		-5 %	1 %	11 %		-10 %	6 %	4 %	9 %

PORTFOLIO 3																						
Year	VRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBY	Average yearly return
2014							34 %	26 %		40 %		-42 %		15 %					8 %	17 %		14 %
2015			63 %					24 %		38 %		-22 %		4 %					-23 %	54 %		20 %
2016	1 %		7 %			-9 %		32 %						9 %					5 %	-11 %		5 %
2017	23 %							-27 %		46 %		42 %		5 %		-5 %			13 %			14 %
2018								-3 %		26 %		-57 %		-7 %		-14 %			16 %	10 %		-4 %
2019				18 %						38 %				40 %	34 %	35 %			15 %	37 %		31 %
2020							15 %	-9 %					47 %	14 %	33 %	-2 %				-9 %		13 %
Average return of the firm in the time period	12 %		35 %	18 %		-9 %	24 %	7 %		38 %		-20 %	47 %	11 %	34 %	3 %			6 %	16 %		13 %

Table 11. Company and portfolio returns from 2014 - 2020

Year	OMXH25	Portfolio 1	Portfolio 2	Portfolio 3	All 21 firms
2013	0 %	0 %	0 %	0 %	0 %
2014	5 %	13 %	-3 %	14 %	8 %
2015	12 %	18 %	12 %	20 %	17 %
2016	10 %	12 %	54 %	5 %	24 %
2017	6 %	2 %	6 %	14 %	7 %
2018	-6 %	-22 %	-20 %	-4 %	-15 %
2019	15 %	14 %	15 %	31 %	20 %
2020	9 %	18 %	1 %	13 %	11 %
Time period average	7,3 %	8,0 %	9,2 %	13,1 %	10,1 %

Table 12. Portfolio and OMX25 -index returns from 2014 - 2020

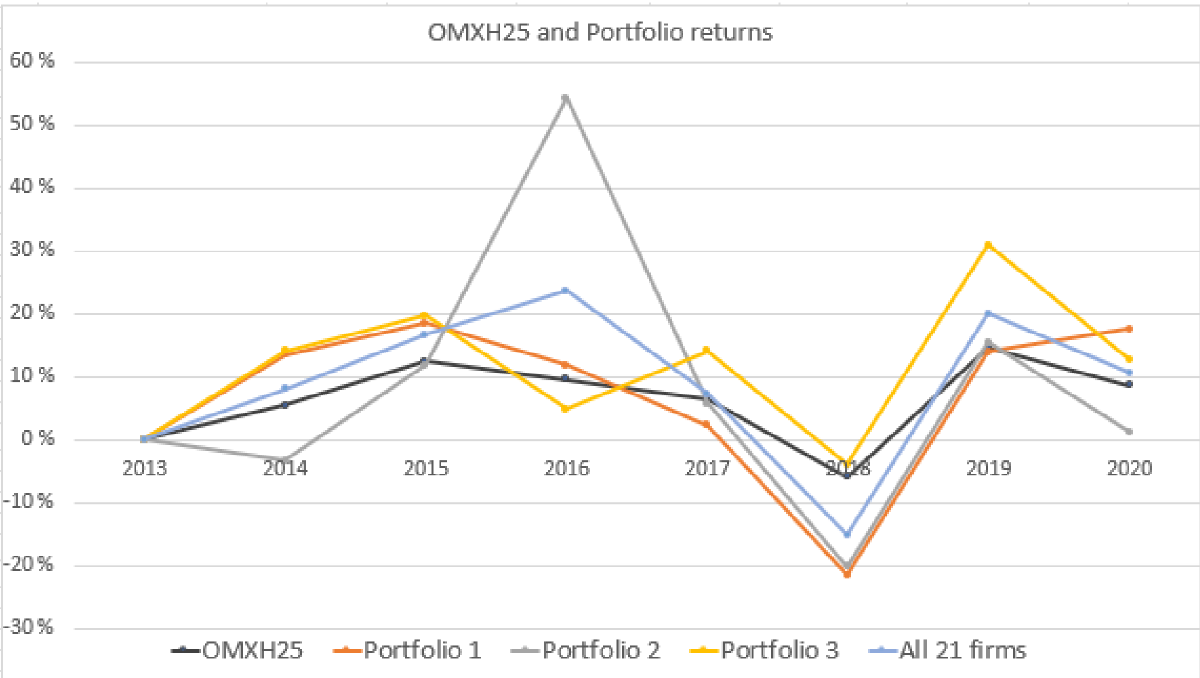

Figure 9. Portfolio and OMX25 -index returns from 2014 - 2020

It is noticed from table 12 that best returns are achieved by portfolio 3 (13,1%) then by portfolio 2 (9,2%) and lastly by portfolio 1 (8,0%). In other words, those companies with relatively highest recommendations, that is to say, those with most sell/downward-oriented recommendations (see table 9) which form portfolio 3 (all-time average is 3,26), seem to produce the best returns out of the three possible portfolio options. Portfolio 1 which has the all-time average of 2,24, and hence represents the most buy/upward-oriented option, has instead the poorest return rate with only 8% growth during the analysis period. The whole sample of 21 companies has a return of 10.1% from the 2014-2020 time period.

In table 12 and figure 9 also OMXH25 index returns are provided for the sake of reference, however it is worth noticing that the portfolios and the OMX25 index are differently structured in terms of weights and firm content - the overall point is only to give insight how the recommendation-based portfolio investment strategy approach performs with respect to the general OMXH25 index (market). As can be seen portfolio 3 is able to beat the overall sample returns from the time period as portfolios 1 and 2 remain below the average value. Interestingly it seems also that by investing evenly on the selected sample companies (instead of OMXH25 standard weighting) an investor would have achieved better returns than the OMXH25 index.

Figure 9 shows that the returns of different investment options seem to behave rather homogeneously - the ups and downs in returns happen pretty much at the same time. Portfolio 2, however, has a notable increase in 2015 when its returns grow over 40% but then again, the returns decrease over 40% the next year in 2016.

5.2 Target price results

This section describes the results from the target price analysis part of the study. In the study the target prices were collected according to the recommendation-based portfolios (as described in phases 1 and 3 in section 4.4). Three pieces of price data were needed in yearly calculations: current price of the stock (at time **t**), issued target price for the stock (at time **t**), the current price of the stock after one year (**t** + 1 year). With this information, the performance of different portfolios could be studied by measuring the accuracy of the target price forecasts and comparing the association between issued stock recommendations and target prices. In other words, it was interesting to find out whether the recommendations and target prices convey the same information of buying or selling.

In the first phase 3a from Section 4.4 the orientations of the target prices are analyzed. Table 13 below shows the results from the target price analysis in which current prices and future target prices are compared. The first row in table 13 describes how many stocks in each portfolio have had optimistic (upward-oriented) prices compared to the current price and the second row how many of the issued target prices have been negative (downward-oriented). The next two rows express the same information as the two first but in percentage form. Below table 13, in figure 10 these ratios are additionally illustrated.

	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	TOTAL AVERAGE
Positiv target price compared to current price	42	36	19	97
Negative target price compared to current price	7	13	30	50
Ratio of positive (updward) target prices	86 %	73 %	39 %	66 %
Ratio of negative (downward) target prices	14 %	27 %	61 %	34 %

Table 13. Comparison of current prices and target prices among portfolios

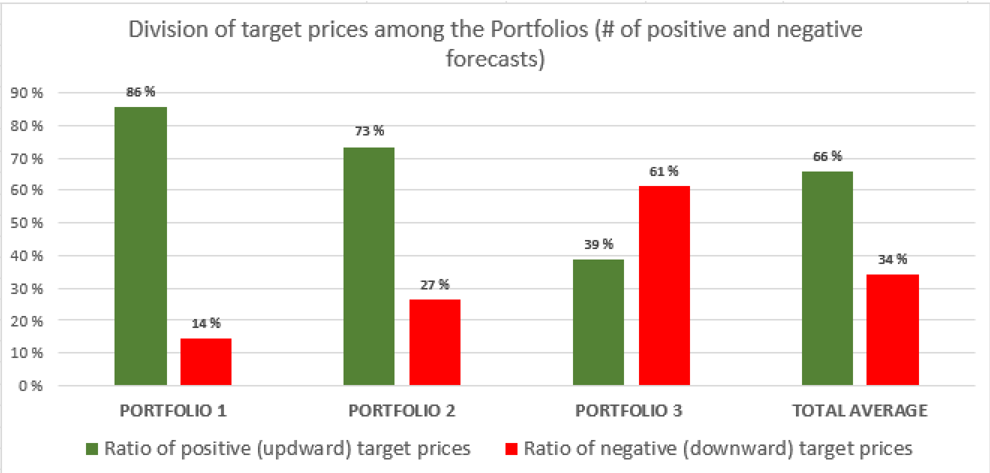

Figure 10. Number of positive and negative target prices during 2014-2020

In figure 10 above where current stock prices are compared to issued target prices, it is noticed that portfolio 1 has the largest ratio of positive (optimistic) target prices (86%) out of the three portfolios. Following the same logic, portfolio 2 has the second largest (73%) amount of positive target price forecasts and finally portfolio 3 with a ratio of 39%. It is clear that portfolio 1 is the most buy-oriented option whereas portfolio 3 is the most sell-oriented one. In addition, figure 11 below shows how large these target prices have been with respect to current prices when the target prices have been issued. Similarly with the number of positive target prices, portfolio 1 has also the largest differences between forecasted target prices and current stock prices with an average value of 11.9% from the analysis period. Portfolio 2 has the second largest with 10.0% and portfolio 3 has -2.1%.

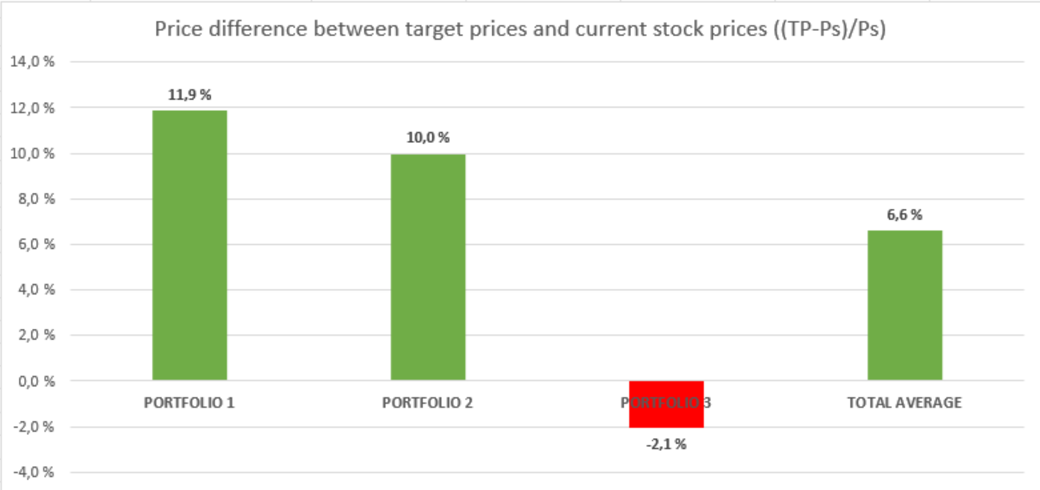

Figure 11. Averages from 2014-2020 describing the magnitude of target prices with respect to current prices

In the two figures 12 and 13 below are illustrated the yearly average ((Yearly TP-Ps)/Ps) -ratios of the portfolios and yearly max. ((TP-Ps)/Ps) values. As can be seen from figure 12 the average (TP-Ps)/Ps ratio has always been lowest and more often negative for portfolio 3. Portfolios 1 and 2 however experience continuously positive ratios. In figure 13 are shown the yearly maximum (TP-Ps)/Ps ratios for each portfolio. The all-time high is from portfolio 2 with a value of over 60%.

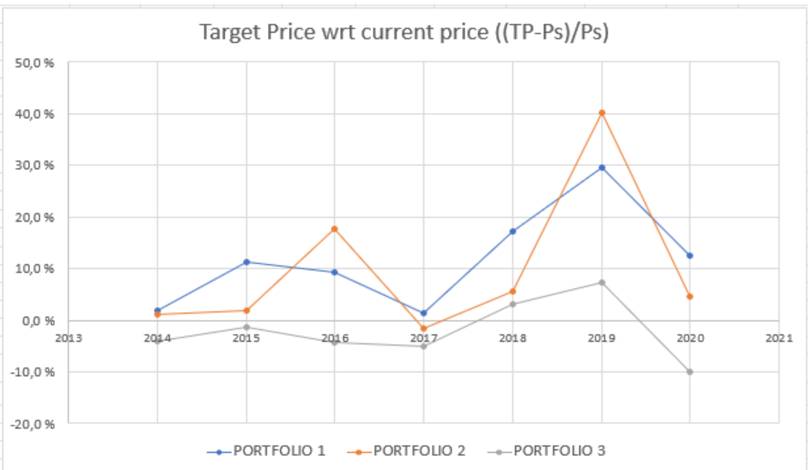

Figure 12. Yearly average ((Yearly TP-Ps)/Ps) -ratios of the portfolios

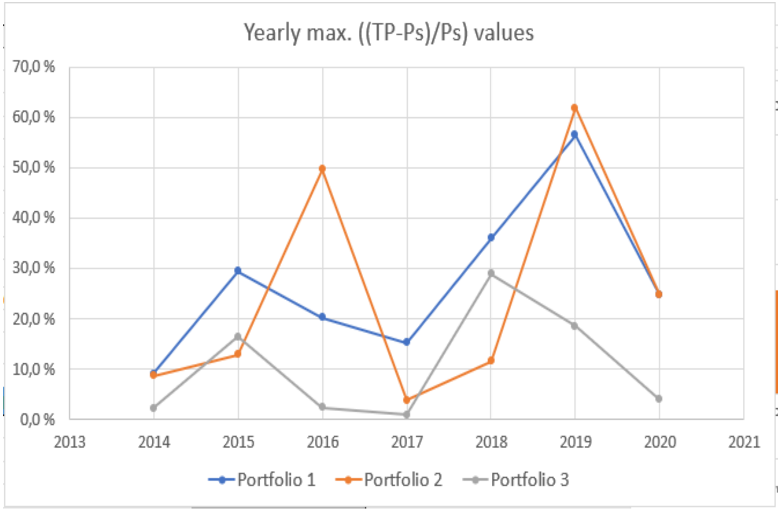

Figure 13. Yearly max. ((TP-Ps)/Ps) values

When looking at table 14 it is noticed notice that there seems to be a clear association between low recommendations (buy-oriented) and more frequent and higher target prices. Low recommendation portfolio 1 gets more (row 2) and higher (row 3 and 4) upward target prices with respect to current prices, while portfolio 3 with more sell-oriented recommendations gets fewer upward target prices (row 2) and lower (row 3 and 4) target prices. These results resonate well with the logic of target price and recommendation association recognized in academic literature (Bradshaw 2002; Zhou 2013) and there seems to be no contradiction in the essence of the information of the two indicators.

		PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3
1	Total average recommendation value between 2014 - 2020	2,24	2,71	3,26
2	Ratio of positive (updward) target prices	86 %	73 %	39 %
3	Average from Portfolio's target prices wrt. current prices ((TP-Ps)/Ps)	11,9 %	10,0 %	-2,1 %
4	Average from yearly max. ((TP-Ps)/Ps) values	27,3 %	24,7 %	10,4 %

Table 14. Association table of recommendations and target prices during 2014-2020

In this part, corresponding to phase 3b from Section 4.4, target prices and actual prices one year later from the issuing date (t+1) were compared. In table 15 below, the first two rows show for each portfolio, how many target price predictions ended up being positive and negative. In other words, a positive case is when the actual stock price after a year from the publishing date (t+1) is higher than the issued target price one year ago (t) - considered as “a happy surprise”. Similarly, a negative case happens when the future price (t+1) is lower than the predicted target price (t) - considered as “a negative surprise”. The ratios (percentage form) given in rows three and four are also illustrated in figure 14 below table 15. The last row describes how large the price difference ((TP-P12)/P12) was during the 2014-2020 analysis period when comparing the issued target prices (t) and realized prices after a year from the publishing date (t+1). In case the difference is zero it can be concluded that the target price was precise and no upwardly or downwardly error exists.

	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	TOTAL AVERAGE
# of times when P12 >= TP	23	22	37	82
# of times when P12 < TP	26	27	12	65
Ratio for # of times when P12 >= TP	47 %	45 %	76 %	56 %
Ratio for # of times when P12 < TP	53 %	55 %	24 %	44 %
Magnitude of price difference (P12-TP)/TP	-1,74 %	-0,47 %	16,48 %	4,76 %

Table 15. Comparison of issued TPs and actual stock prices one year from TP -release (P12) during 2014 - 2020

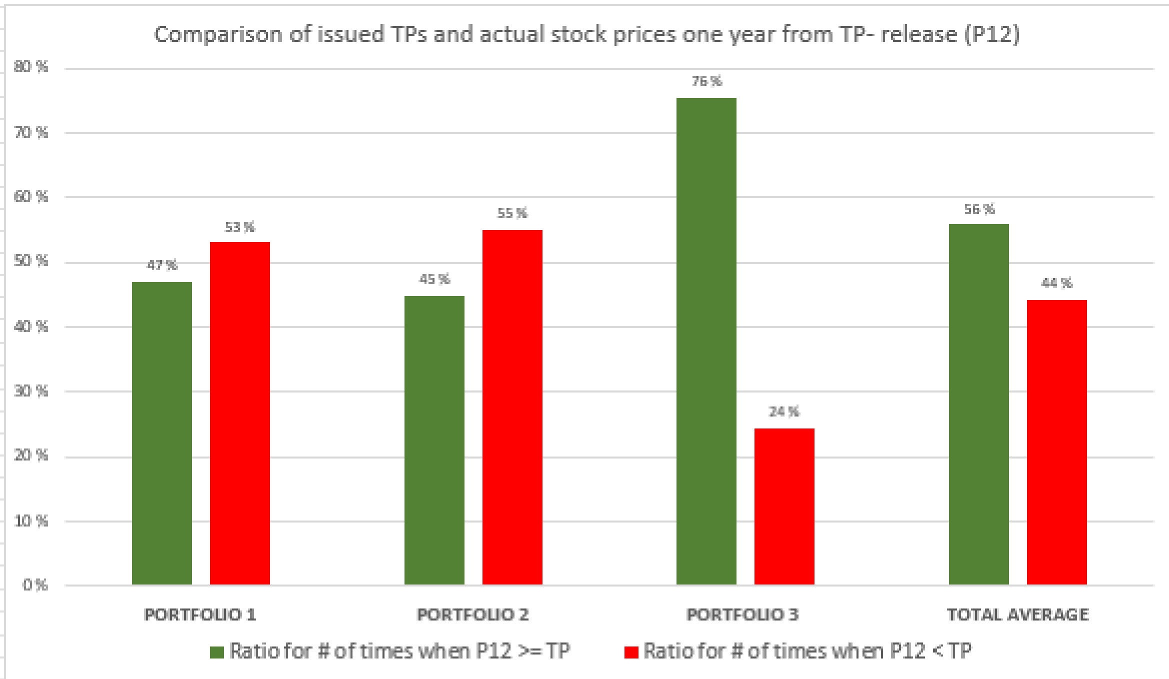

Figure 14. Comparison of issued TPs and actual stock prices one year from TP- release (P12) during 2014 - 2020

As can be seen, for both portfolio 1 and 2 the overall development has been rather close to zero (-1.74% and -0.47%) which means there is not much error between the target prices and actual realized prices during the analysis period. For portfolio 1 the price difference is -1.74% so the issued target prices have been a bit upwardly biased compared to actual realized prices after 12 months. For portfolio 3 on the other hand, the target prices have been quite too reserved when compared to the eventual stock prices - it has also continuously been able to beat the issued target prices as can be seen from figure 15 below. This "surprise" seems to support the results acquired in section 5.1 where the sell-oriented recommendation portfolio 3 nevertheless achieved the best returns and managed to beat the analyst expectations. It's also worth noticing that even though the average (P12-TP)/TP ratios given in row 4 in table 15 above seem for portfolio 1 and 2's part to average close to zero there was a significant dip that took place between 2017 and 2018 (see figure 15 below).

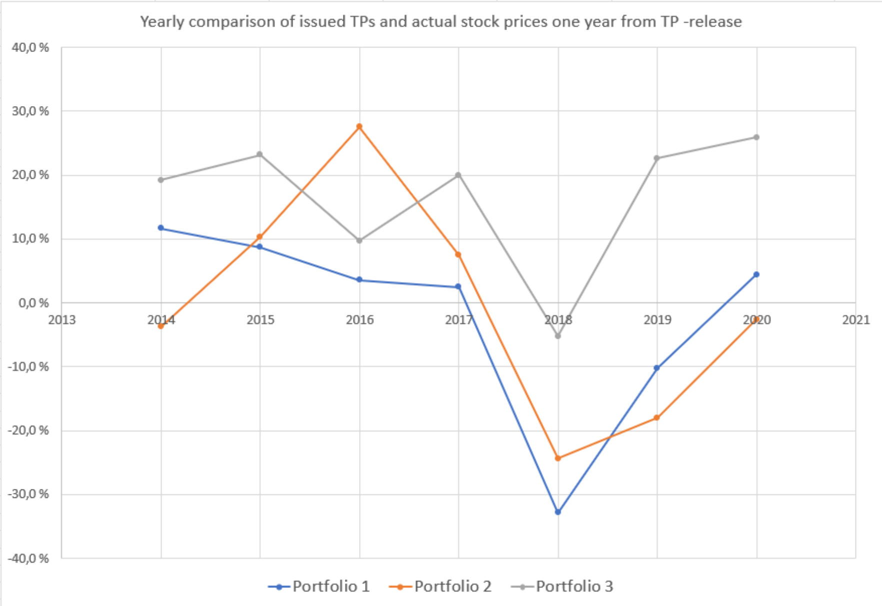

Figure 15 Yearly accuracy of target prices wrt. realized prices one year from TP-release

In phase 3c from Section 4.4, the expected and actualized development of stock prices were observed. This next accuracy measure is the result of correct predictions/failed predictions as explained in phase 3c. As can be seen in table 16 below, the ability to predict price development direction (upwards vs. downwards) is rather hard - on average the analysts were able to tell the direction of stock prices in about half of the cases. The accuracy on the yearly level is also shown in figure 16 below. As can be seen, portfolio accuracies tend to move around the 50% line at all times.

	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	TOTAL AVERAGE
Accuracy of expected and real price development	53 %	45 %	47 %	48 %

Table 16. Accuracy of expected price development with respect to the realized outcome

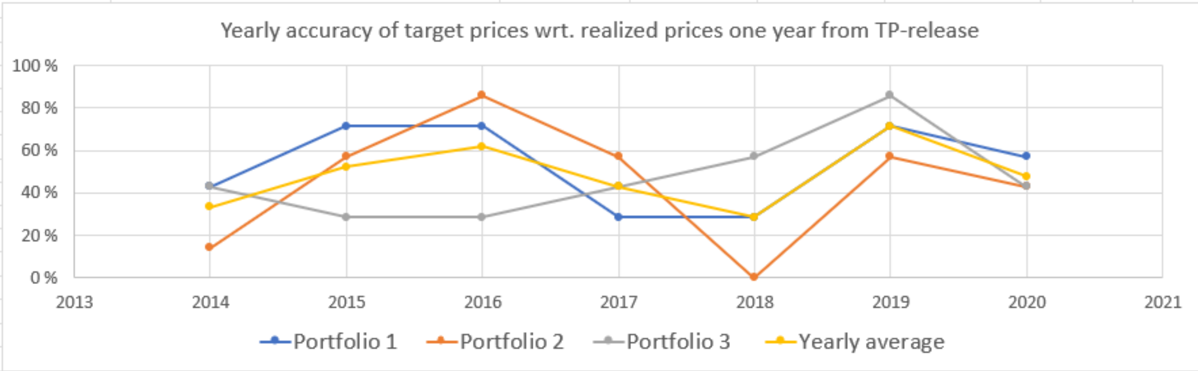

Figure 16. Accuracy of expected and actualized development of stock prices

In addition to the accuracy measure defined in phase 3c, portfolio accuracies were tested by using two different mean absolute percentage error (MAPE) formulas for each portfolio as described in phase 3d from Section 4.4. The first one (MAPE1) considered two price values: the target price (TP) and the actual stock price at the end of the 12-month forecast horizon P12. The second one (MAPE2) was calculated based on three price values: the target price (TP) and the actual stock price at the end of the 12-month forecast horizon P12 and the stock price at the TP issue date Ps. The results are given in table 17 below.

	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	TOTAL AVERAGE
MAPE using TP and P12	30 %	20 %	23 %	24 %
MAPE using TP,P12 and current P	26 %	21 %	25 %	24 %

Table 17. Mean absolute percentage error values from 2014-2020

When summarizing all the relevant accuracy measures the following table 18 is acquired.

		PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	TOTAL AVERAGE
1.	Total average recommendation value between 2014 - 2020	2,24	2,71	3,26	2,74
2.	Ratio of positive (updward) target prices	86 %	73 %	39 %	66 %
3.	Ratio of negative (downward) target prices	14 %	27 %	61 %	34 %
4.	Average from Portfolio's target prices wrt. current prices ((TP-Ps)/Ps)	11,9 %	10,0 %	-2,1 %	6,6 %
5.	Ratio for # of times when P12 >= TP	47 %	45 %	76 %	56 %
6.	Ratio for # of times when P12 < TP	53 %	55 %	24 %	44 %
7.	Magnitude of price difference (P12-TP)/TP	-1,7 %	-0,5 %	16,5 %	4,8 %
8.	Accuracy of expected and real price development	53 %	45 %	47 %	48 %
9.	MAPE using TP and P12	30 %	20 %	23 %	24 %
10.	MAPE using TP,P12 and current P	26 %	21 %	25 %	24 %

Table 18. Summary table of target prices (section 5.2)

The following notions are made based on the results of table 18:

1. From rows 1, 2 and 3 it becomes clear that the low recommendation values are more often accompanied by positive/upward target prices. In addition, these target prices are more optimistic when compared to stocks with high recommendations (sell-oriented) as can be seen from row 4. On average the 21 sample stocks selected from the OMXH25 list possess more optimistic target prices during the analysis period of 2014-2020.

2. When comparing rows 2 and 5 they seem to behave inversely proportionally - in other words when the ratio of positive target prices (TP) grows the cases when future actual price P12 manages to beat or be equal with target prices seems to drop. Portfolio 1 with 86% upwardly target prices has a ratio of 47% for P12>=TP whereas portfolio 3 has only 39% upwardly target prices and yet has been equal or beaten the target prices 76% of times. Portfolio 2 behaves quite similarly as portfolio 1. So the relatively low recommendation mean portfolio 1 which has supporting buy-oriented target prices only manages to beat or reach the target prices (P12>=TP) in 47% of the cases, while the relatively high recommendation mean portfolio 3 with sell-oriented target prices manages to beat the target prices in the future (P12>=TP) in 76% of the cases even though it is, according to analyst recommendations and target prices, expected to go downwards.

3. Row 4 in table 18 relates to the abovementioned observation - the magnitude of expected target prices with respect to current prices have been largest for portfolio 1 with a value of 11,9% and lowest for portfolio 3 with a value of -2.1% but when looking at the realized development that has taken place after the target price (TP) release it is noticed by looking at row 7 that the price development has been in fact lowest or portfolio 1 with a value of -1.7% and largest for portfolio 3 with a value 16.5%. This means the expectations of analysts target prices and actual prices have moved in exactly opposite directions.

When projecting these results to previous studies on target prices (see section 3.5) and target price accuracy (see section 3.6) the following similarities are noticed:

1. Recommendations and target prices move in the same direction and convey similar buy/sell messages so the concern of Kanne et al. (2012, p.426) about opposite indications is not present in this sample. In fact, the results support the findings of previous studies from Bradshaw (2002) and Zhou (2013) which point out that favourable recommendations (buy-oriented) tend to go along with higher target prices (compared to present prices).

2. Portfolio 1 (buy-oriented) is associated with overoptimism when comparing expectations and realized returns - rows 4 and 7 show how expectation and reality have moved in opposite directions. This phenomenon is in line with previous findings (Dechow et al. 2000; Bradshaw et al. 2012)

3. Target prices are on average 6.6% higher than the current stock prices which supports the findings of Brav and Lehavy (2003) but with a lower magnitude (they recorded +28%).

4. Times, when target prices are met or beaten by realized market prices at the end of a 12 month period (P12 >= TP), had the average value of 56%. A similar test (see table 1) from Bradshaw et al. (2012) documented 38% when using US firms from 2000 to 2009 and 20% from Bonini et al. (2010) when using Italian firms from 2000 to 2006. This means that either the target prices in this study have better predicting ability or that analysts have made too optimistic forecasts in the reference studies.

5. MAPE calculated as |(P12-TP)/Ps| and |(P12-TP)/P12| give both averages of 24%. These values are low with respect to the (aTPE) reference values of Bradshaw et al. (2012) who recorded a value of 45%, Bilinski et al. (2013) with the value of 44.10% for Finland (44.70% with 16 countries) and Cheng et al. (2019) with a value of 49% when using Taiwanese data. The closest reference value is from Erkilet et al. (2021), with an average of 20-22% when using DAX30 companies. Both MAPE values are however below the academic average of 30% (Investopedia 2021f). Overall, it could be concluded that the accuracy of the target prices is sufficient when compared to previous studies.

5.3 CAPM results

This section describes the results from the CAPM analysis and addresses the fourth phase in section 4.4. The CAPM is used to find out how the portfolios differ in performance: alphas describe how well the portfolios have performed (the larger the better) when compared to the OMXH25 and sample21 benchmark indices and beta tells how volatile (low value means lower risk and high vice versa) a portfolio has been when compared to the market, that is to say, the OMXH25 and sample21 indices. The coefficients (alpha and beta) of the CAMP model are obtained by using ordinary linear regression model (OLS). In the section, first, the key values from CAPM analysis are presented (phase 4a) and then the results from the CLRM assumptions testing (phase 4b). A more detailed view of company specific CAPM values are given in appendices 2 and 3.

	With respect to OMXH25				With respect to sample (selected 21 firms) index		
Alpha	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	Alpha	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3
2014	0,000	-0,002	0,006	2014	-0,001	-0,004	0,004
2015	0,002	-0,003	0,006	2015	0,000	-0,005	0,004
2016	0,004	0,000	0,000	2016	0,003	-0,003	-0,001
2017	-0,001	0,002	0,003	2017	-0,003	0,001	0,001
2018	0,001	-0,003	0,006	2018	-0,001	-0,004	0,004
2019	0,000	-0,002	0,007	2019	-0,002	-0,005	0,006
2020	0,001	-0,001	0,005	2020	-0,001	-0,003	0,003
Total mean	0,001	-0,001	0,005	Total mean	-0,001	-0,003	0,003

Table 19. Average portfolio alphas

	With respect to OMXH25				With respect to sample (selected 21 firms) index		
Beta	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	Beta	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3
2014	1,082	1,209	1,026	2014	0,935	1,094	0,961
2015	1,284	1,129	0,903	2015	1,207	0,966	0,817
2016	1,132	1,399	0,786	2016	0,994	1,326	0,670
2017	1,350	0,912	1,055	2017	1,230	0,811	0,950
2018	1,274	1,095	0,947	2018	1,181	0,949	0,860
2019	1,139	1,349	0,829	2019	0,992	1,281	0,716
2020	1,237	1,170	0,909	2020	1,098	1,028	0,864
Total mean	1,214	1,181	0,922	Total mean	1,091	1,065	0,834

Table 20. Average portfolio betas

	With respect to OMXH25				With respect to sample (selected 21 firms) index		
p-value alpha	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	p-value alpha	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3
2014	0,290	0,528	0,478	2014	0,390	0,440	0,410
2015	0,464	0,424	0,407	2015	0,471	0,406	0,364
2016	0,271	0,705	0,319	2016	0,288	0,644	0,309
2017	0,489	0,389	0,418	2017	0,502	0,383	0,356
2018	0,495	0,400	0,401	2018	0,434	0,463	0,344
2019	0,440	0,535	0,320	2019	0,515	0,401	0,324
2020	0,375	0,547	0,374	2020	0,311	0,569	0,362
Total mean	0,403	0,504	0,388	Total mean	0,416	0,472	0,353

Table 21. Average alpha p-values

	With respect to OMXH25				With respect to sample (selected 21 firms) index		
p-value beta	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	p-value beta	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3
2014	1,11E-04	1,16E-07	1,61E-02	2014	9,66E-05	6,57E-08	2,39E-02
2015	1,12E-04	6,25E-08	1,61E-02	2015	6,32E-05	3,34E-05	2,39E-02
2016	1,11E-04	3,16E-07	1,61E-02	2016	9,66E-05	1,14E-09	2,39E-02
2017	3,57E-07	1,60E-02	1,47E-04	2017	3,34E-05	2,39E-02	5,53E-05
2018	1,12E-04	1,16E-07	1,61E-02	2018	9,66E-05	6,93E-08	2,39E-02
2019	1,47E-04	4,31E-07	1,60E-02	2019	8,86E-05	6,68E-08	2,39E-02
2020	8,52E-08	1,16E-07	1,62E-02	2020	3,34E-05	6,93E-08	2,40E-02
Total mean	8,49E-05	2,29E-03	1,38E-02	Total mean	7,26E-05	3,42E-03	2,05E-02

Table 22. Average beta p-values

	With respect to OMXH25				With respect to sample (selected 21 firms) index		
Adjusted R-squared	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3	Adjusted R-squared	PORTFOLIO 1	PORTFOLIO 2	PORTFOLIO 3
2014	0,371	0,461	0,248	2014	0,368	0,483	0,265
2015	0,387	0,442	0,251	2015	0,433	0,428	0,255
2016	0,358	0,417	0,305	2016	0,367	0,466	0,283
2017	0,407	0,338	0,335	2017	0,435	0,342	0,339
2018	0,340	0,453	0,287	2018	0,379	0,440	0,297
2019	0,380	0,392	0,309	2019	0,381	0,433	0,302
2020	0,414	0,428	0,237	2020	0,417	0,426	0,272
Total mean	0,380	0,419	0,282	Total mean	0,397	0,431	0,288

Table 23. Average adjusted R-squared

First of all, it is noticed from table 21 that the p-values for alpha are in every time period over 0.1 significance level, meaning that the alpha findings in table 19 are not statistically significant and there is not enough evidence that the portfolios could beat the OMXH25 or sample21 indices and yield excess return. It could be speculated that since portfolio 3 has an average alpha of 0.005/0.003 and relatively lowest alpha p-value it could be the best option to produce abnormal returns even though they are rather trivial. Nevertheless, there is not enough evidence for this conclusion.

When looking at table 20 which shows average beta values for the portfolios it is noticed that portfolio 1 has the highest average beta value of 1.214/1.091 and portfolio 3 has the lowest average value of 0.922/0.834. In other words, it seems that portfolio 1 with lower recommendation (buy-oriented) companies is riskier than the relatively more sell-oriented portfolio 3 which is more risk-averse according to beta. As portfolio 1's beta is over 1 it means it is more volatile than the market (OMXH25) and has also potential for higher returns. The case is the opposite for portfolio 3 where there is less risk and in theory smaller chances for profit. Portfolio 2 has a beta value of 1.181/1.065 which is closer to portfolio 1's value than portfolio 3's meaning it is theoretically the second riskiest option. The average p-values for beta are shown in table 22 and are regarded as significant with the 5% significance level.

Table 23 shows that portfolio 2 has the highest adjusted R-squared value of 0.419/0.431 and portfolio 3 the lowest of 0.282/0.288. This means that portfolio 2 is most affected by the

OMXH25/sample21 index while portfolio 3 is the least. Portfolio 1 has an adjusted R-square value of 0.380/0.397. It could be concluded that as portfolio 3 has the lowest adjusted R-squared value it correlates least with the benchmark OMXH25/sample21 -index concerning excess returns. When summarized the adjusted R-square values indicate a low correlation between the OMXH25/sample21 indices and constructed portfolios and hence the selected benchmark indices are only partially able to explain movements in them. Consequently, the observed beta values become also unreliable.

The resulting values from CLRM assumptions testing (phase 4b from Section 4.4) are summarized below.

With respect OMXH25 index																						
FIRM	WRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBV	TOTALS
Assumption 1 (Mean of residuals)	-3E-19	2E-18	1E-18	-3E-18	0E+00	2E-19	3E-18	-2E-18	2E-18	-9E-18	2E-18	5E-18	1E-18	-2E-18	-2E-18	3E-18	4E-18	5E-19	2E-18	-5E-18	2E-19	2E-19
Assumption 2 (Heteroscedacity test (p-value of <= to 0.05 means heteroscedacity exists))	0,05	0,13	0,18	0,01	0,76	0,00	0,95	0,72	0,46	0,26	0,17	0,94	0,00	0,00	0,39	0,53	0,00	0,35	0,08	0,03	0,66	7
Assumption 3 (Autocorrelation test) (d < 2 indicates positive serial correlation)	0,432	0,464	0,724	0,214	0,602	0,352	0,396	0,518	0,772	0,685	0,141	0,189	0,191	0,486	0,187	0,043	0,008	0,917	0,990	0,114	0,114	0,406543806
Assumption 4 (Multicollinearity test for OMXH25)																						5,8454
Assumption 5 (Normality test (if 0 then is normal))	0	0	1	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	1	0	6
With respect to sample (selected 21 firms) index																						
FIRM	WRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBV	TOTALS
Assumption 1 (Mean of residuals)	2E-18	2E-18	4E-18	-2E-20	2E-18	3E-18	4E-18	-5E-18	7E-18	-6E-18	2E-18	5E-18	5E-18	7E-19	3E-19	6E-18	6E-18	9E-19	2E-18	-3E-18	2E-18	2E-18
Assumption 2 (Heteroscedacity test (p-value of <= to 0.05 means heteroscedacity exists))	0,02	0,13	0,02	0,01	0,71	0,00	0,76	0,63	0,66	0,11	0,47	0,38	0,00	0,00	0,57	0,69	0,01	0,85	0,02	0,23	0,85	8
Assumption 3 (Autocorrelation test) (d < 2 indicates positive serial correlation)	0,375	0,287	0,727	0,271	0,445	0,318	0,440	0,473	0,624	0,549	0,219	0,114	0,082	0,337	0,091	0,026	0,018	0,988	0,543	0,105	0,195	0,344177467
Assumption 4 (Multicollinearity test for OMXH25)																						4,441
Assumption 5 (Normality test (if 0 then is normal))	0	0	1	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	1	0	6

Table 24. CLRM assumption testing results

Table 24 shows that the 1st assumption (mean of residuals) is practically zero at all times during the analysed period and so fulfils the assumption. The assumption 2 (heteroscedasticity using White test) results however imply there are seven firms that exhibit heteroscedasticity, namely WRT1V, TIETO, SAMPO, METSB, KNEBV, KCRA and ELISA when using OMXH25 index as reference. With sample21 as reference, also TYRES and FORTUM show heteroscedasticity but ELISA not. This heteroscedasticity reduces the precision of the estimates - an alternative estimation method that takes this into account could be used, for example, generalised least squares (GLS), but in this study, this violation of assumption 2 is ignored.

The assumption 3 (autocorrelation using Durbin-Watson test) results show the d-values for each company and as can be seen the values are all below 2, including the overall average. This indicates a positive serial correlation and since other assumptions are also violated it is clear that the OLS is no longer the Best Linear Unbiased Estimator (BLUE). This means it will provide unreliable predictions.

Assumption 4 (multicollinearity) shows a result of 5.85/4,44 when using the Condition number test on the OMXH25/sample21 index data. This result is not assumed to be a problem as the threshold value for severe multicollinearity is 30 or more as suggested by Belsley et al. (1991).

Assumption 5 (normality using Jarque–Bera test) implies there are a total of six companies of which the data is not normally distributed, namely TYRES, SAMPO, OUT1V, NOKIA, NESTE and ELISA. However, because the sample size is small it is justifiable to say that the normality test may not have sufficient power to detect a significant departure from normality, even if it is present. It is nevertheless decided to ignore this assumption in order to make the sample sizes sufficiently large and hence encompassing for subsequent analysis. Alternative models based on daily data could make the normality violations disappear, but this is not in the scope of this study and consequently, other assumption violations could arise making any further analysis trivial.

To summarize, it is noticed that many of the linear regression models fitted the data poorly and the assumptions are violated to the degree that the OLS is not BLUE. It seems that the OMXH25/sample21 benchmark index can not reliably explain the returns of the portfolios. To make the CAMP more reliable some of the sample companies ought to be removed (for example SAMPO and ELISA), alternative estimation methods (GLS) could be used, and sample size should be augmented if possible.

6 CONCLUSIONS

Analysts release stock recommendations continuously on several markets around the world and investment strategies based on them have been broadly studied. As the markets should be effective according to the efficient market hypothesis, possibilities for abnormal returns ought to be limited. Previous studies have shown that abnormal returns are possible in markets where information spreads relatively slowly to prices and where analysts can take advantage of this. However, strategies relying on stock recommendations all tend to face the same challenges which are large amounts of trading and consequently major transaction costs. Multiple studies recognize the fact that abnormal returns are achievable but invariably involve active trading, often on a daily basis and only for a certain time period. The existence of price drift effect after recommendation release, which was not in the scope of this study, is commonly acknowledged and proven to yield abnormal returns. Nevertheless, this strategy will due to continuous transaction costs mean that the remaining return decreases to trivial levels making these active strategies inefficient for at least to individual investors. The role of an analyst involves after all many other aspects than only recommendation composing - they serve as monitors and information intermediators among shareholders and are therefore considered as essential actors in the financial markets. Referring to the hypotheses formulated in section 4.1 and observations made in chapter 5 the following answers were found.

Hypothesis 1: Analyst recommendation-based investment strategy generates abnormal returns.

With the limitations defined in 4.5 and in force, it is observed that all the three portfolios with selected 21 companies manage to yield better returns than the OMXH25 index. The best performance is perceived from portfolio 3 which was constructed at all times from the highest consensus recommendations signifying it was the most sell-oriented option. With the prevalent set-up (sample, weights and limitations) it managed to beat the OMXH25 index in return with about 5.8% during the analysis period. On the contrary, portfolio 1 performed the worst in the group even though the consensus recommendations were of the lowest type, that is to say, the most buy-oriented ones in every situation. With the prevalent setup, it only managed to beat the OMXH25 index in return with about 0.7% during the analysis period. Portfolio 2 beat the OMXH25 index in return with 1.9%. On the other hand, returns of all 21 sample companies also show that by investing evenly on the selected sample companies (instead of OMXH25 standard weighting) an investor would have achieved better returns than the OMXH25 index. As mentioned, these results do not take into account transaction costs or dividends. Also the OMXH -index as a benchmark is only directional as the weighting and company configuration is different. It is concluded that by following analyst (buy/sell) recommendations an investor would have beaten the index with any portfolio, but the highest returns would have been achieved by investing according to portfolio 3, that is to say to the companies with sell-oriented recommendations.

Hypothesis 2: Analyst target prices endorse consensus recommendations and provide useful information to investors

Target price and recommendation observations show that low recommendations (buy-oriented portfolio 1) are accompanied more often (86%) with positive target prices and that these prices are also higher (target price wrt. current price) than those associated with high recommendations (sell-oriented portfolio 3). With sell-oriented recommendations, the target prices are more often downwards (61%). In conclusion, it is found that the target prices move in the same direction together with analyst recommendations.

In addition, it was found that the target price predictions failed mostly in the case of buy-oriented portfolio 1 and surprised by overachieving in the case of sell-oriented portfolio 3. This development is in line with the findings addressing the first hypotheses. When measuring the accuracy for only price development direction up/down (magnitude considered irrelevant) it was found that the prediction was in 48% of the cases correct so in roughly half of the predictions analysts were able to tell whether a stock price would go up/down. In total, it was found that the prediction accuracy of the target prices in the sample is on average better than the average found in academic research.

Overall the sample observation shows that there are more buy-oriented samples (40%) than sell-oriented samples (26%), and that the overall sample recommendation mean is 2.74 meaning our sample is a bit optimistic and more buy-oriented in both recommendations and target prices.

Hypothesis 3: Low recommendation-based investment strategy has higher risk and higher expected return with respect to OMXH25 index than high recommendation-based investment strategy

Results from CAPM show that low recommendations (buy-oriented portfolio 1) have a higher beta average (1.21/1.09) meaning they are more volatile than the market (OMXH25/sample21) and possess more risk and consequently potential for higher returns than the high recommendations (sell-oriented portfolio 2) which have a lower beta average (0.92/0.83). The alpha values, which measure anomalies among the portfolios and could reveal possible underpricing among them, do not have enough statistical proof to be considered significant and therefore offer no support for possible abnormal returns among the portfolios.

The adjusted R-square values indicate a low correlation between the OMXH25/sample21 index and constructed portfolios and hence the selected benchmark indices are only partially able to explain movements in them. As a consequence of low correlation, the observed beta values become more unreliable. Violations of CLRM assumptions also support the fact that the CAPM analysis is not accurate. In conclusion, it is observed that the findings using CAPM are unreliable when using the selected sample and OMXH25/sample21 as the benchmark index.

Eventually, with the limitations in force, it is found that by investing conversely to analyst recommendations (by using portfolio 3) concerning 21 selected companies from the OMXH25 list, an investor would have experienced the best abnormal returns of +5.8% during the years 2014-2020. However, transaction costs and taxes would reduce the overall returns to some point which remains unstudied. Some weak evidence also shows that the high recommendation (sell-oriented portfolio 3) based investment strategy would be more risk-averse (with respect to OMXH25/sample21 indices) when compared to the low recommendation based (buy-oriented portfolio 1) strategy. Further research should focus on analyzing the companies which most often acquire low recommendations to possibly find out some similarities in the reasoning of favourable recommendations. In the same manner, companies that are most often associated with high recommendations should be analyzed.

As mentioned multiple times, future research should focus on investigating whether recommendation-based investment strategies are profitable when considering the transaction costs and taxes which are realized when updating the portfolios. Results would be even more realistic if dividends could be considered along with appreciation in the price. Another strongly influential factor is the application of weights - this study did not mimic the actual weights used in the OMXH25 index but instead treated every company evenly.

Moreover, it would be interesting to define alternative investment strategies based on both analyst recommendations and target prices and potentially even by including earnings forecasts in the analysis. In addition, Potential abnormal returns among the portfolios could be studied from several distinct perspectives such as including different durations of time windows when analyzing prices, more intense portfolio updates and usage of revisions as well as potentially profitable post recommendation price drifts.

REFERENCES

Almeida, J. & Gaspar, R. M. 2021. Accuracy of European Stock Target Prices. Journal of risk and financial management. Vol.14 (9), p. 443.

Arand, D., & Kerl, A. 2015. Sell-side analyst research and reported conflicts of interest. Europen Financial Management. Vol. 21, p. 20-51.

Asquith, P., Mikhail, M.B. & Au, A.S. 2005. Information content of equity analyst reports. Journal of financial economics. Vol.75 (2), p. 245-282.

Bae, K-H., Stulz, R.M. & Tan, H. 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. Journal of financial economics. Vol. 88 (3), p. 581-606.

Barber, B., Lehavy, R., McNichols, M., Trueman, B. 2001. Can Investors Profit from The Prophets? Security Analyst Recommendations and Stock Returns. Journal of Finance. Vol. 56 (2), p. 531-563.

Barniv, R., Hope, O-K., Myring, M.J & Thomas, W.B. 2009. Do Analysts Practice What They Preach and Should Investors Listen? Effects of Recent Regulations. The Accounting review. Vol. 55 (3), p. 1015-1039.

Belsley, D. 1991. Conditioning Diagnostics: Collinearity and Weak Data in Regression. New York: Wiley.

Bilinski, P., Lyssimachou, D., & Walker, M. 2013. Target Price Accuracy: International Evidence. The Accounting review. Vol.88 (3), p .825-851.

Blasco, N., Corredor, P. & Ferrer, E. 2018. Analysts herding: when does sentiment matter? Applied economics. Vol.50 (51), p. 5495-5509.

Bonini, S., Zanetti, L., Bianchini, R. & Salvi, A. 2010. Target Price Accuracy in Equity Research. Journal of business finance & accounting. Vol.37 (9-10), p. 1177-1217.

Boudt, K., de Goeij, P., Thewissen, J., Van Campenhout, G. & Wyatt, A. 2015. Analysts' forecast error: a robust prediction model and its short-term trading profitability. Accounting and finance (Parkville). Vol. 55 (3), p. 683-715.

Bradshaw, M. 2002. The use of target prices to justify sell-side analysts’stock recommendations. Accounting Horizons. Vol. 16, p. 27–41.

Bradshaw, M.T., Brown, L.D. & Huang, K. 2012. Do sell-side analysts exhibit differential target price forecasting ability? Review of accounting studies. Vol. 18 (4), p. 930-955.

Brauer, M. & Wiersema, M. 2018. Analyzing Analyst Research: A Review of Past Coverage and Recommendations for Future Research. Journal of management. Vol.44 (1), p. 218-248.

Brav, A. & Lehavy, R. 2003. An Empirical Analysis of Analysts' Target Prices: Short-term Informativeness and Long-term Dynamics. The Journal of finance (New York). Vol.58 (5), p. 1933-1967.

Brealey R. A., Myers S.C. & Allen F. 2016. Principles of Corporate Finance. McGraw-Hill Education. 12th ed. p. 198-201.

Brooks, C. 2008. Introductory econometrics for finance. 2nd edition. Cambridge: Cambridge University Press. p. 43-44.

Brown, L.D. 2000. I/BIEIS Research Bibliography. UMI Company. 6th ed. p. 1-183.

Brown, N.C., Wei, K.D. & Wermers, R. 2014. Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices. Management science. Vol. 60 (1), p. 1-20.

Brycz, B., Dudycz, T. & Włodarczyk, K. 2021. Are Analysts Really Optimistic in Their Stock Recommendations? The Case of the Polish Capital Market. Emerging markets finance & trade. Vol.57 (13), p. 3649-3676.

Cai, F. & Xu, L. 2011. Will Investors Profit By Following The Stock Recommendations Published In Barrons? Journal of business & economics research. Vol.4 (3), p. 69-80.

Chang, Y. & Chan, C. 2008. Financial analysts' stock recommendation revisions and stock price changes. Applied Financial Economics. Vol. 18 (4), p. 309-325.

Chen, Q., & Jiang, W. 2006. Analysts' weighting of private and public information. Review of Financial Studies. Vol. 19, p. 319–355.

Cheng, L-Y., Su, Y-C., Yan, Z. & Zhao, Y. 2019. Corporate governance and target price accuracy. International review of financial analysis. Vol.64, p. 93-101.

Clement, M.B., Tse, S.Y. 2005. Financial Analyst Characteristics and Herding Behavior in Forecasting. Journal of Finance. Vol. 60 (1), p. 307-341.

Davies, P.L & Canes, M. 1978. Stock Prices and the Publication of Second-Hand Information: Introduction. The Journal of business. Vol.51 (1), p. 43-56.

Dechow, P.M., Hutton, A.P & Sloan, R.G. 2000. The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings. Contemporary accounting research. Vol.17 (1), p. 1-32.

De Franco, G., Lu, H., Vasvari, F.P. 2007. Wealth transfer effects of analysts' misleading behavior. J. Account. Res. Vol. 45 (1), p. 71–110.

Dempsey, M. 2013. The Capital Asset Pricing Model (CAPM): The History of a Failed Revolutionary Idea in Finance? Vol.49 (S1), p. 7-23.

Easton, P.D & Sommers, G.A 2007. Effect of Analysts' Optimism on Estimates of the Expected Rate of Return Implied by Earnings Forecasts. Journal of accounting research. Vol.45 (5), p. 983-1015.

Eikelmann, N. 2020. Value Based Performance Measures: Theoretical Evaluation and Empirical Analysis of Their Application and Value Relevance on a European Level. Wiesbaden: Springer Vieweg. p. 19-55.

Elton, E. J., Gruber, M. J. & Grossman, S. 1986. Discrete Expectational Data and Portfolio Performance. Journal of Finance. Vol. 41(3), p. 699-713.

Elton, E.J., Gruber, M.J., Brown, S.J., Goetzmann, W.N. 2014, Modern portfolio theory and investment analysis. 9th ed. Wiley.

Erkilet, G., Janke, G. & Kasperzak, R. 2021. How valuation approach choice affects financial analysts' target price accuracy. Journal of Business Economics. Springer. p. 1-39.

European Central Bank. 2021. Working group on euro risk-free rates. [WWW-document].[Accessed 2.12.2021]
Available from: https://www.ecb.europa.eu/paym/interest_rate_benchmarks/WG_euro_risk-free_rates/html/index.en.html

Fama, E. F., 1965. Random Walks in Stock Market Prices. Financial Analysts Journal. Vol. 21 (1), p. 55-59.

Fama, E. 1970. Efficient capital markets: A review of theory and empirical work. The Journal of Finance. Vol. 25 (2), p. 383-387.

Feldman, R., Livnat, J. & Zhang, Y. 2012. Analysts' Earnings Forecast, Recommendation, and Target Price Revisions. Journal of portfolio management. Vol.38 (3), p. 120-132.

Glezakos, M. & Merika, A. 2011. The Impact Of Analysts‟ Recommendations: Evidence From The Athens Stock Exchange. Journal of applied business research. Vol.23 (2).

Graham, B. (revised Zweig, J.) 2003 (original 1949). The intelligent investor. HarperBusiness Essentials. 4th ed.

Grinblatt, M., Titman, S., Wermers, R. 1995. Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior. American Economic Review. Vol. 85 (5), p. 1088-1105.

Grossman, S.J. & Stiglitz, J.E. 1980, On the impossibility of informationally efficient markets. American Economic Review. Vol. 70 (3), p. 393-408.

He, P.W., Grant, A. & Fabre, J. 2013. Economic value of analyst recommendations in Australia: an application of the Black-Litterman asset allocation model. Accounting and finance (Parkville). Vol. 53 (2), p. 441-470.

Hendricks, T., Kempa, B. & Pierdzioch, C. 2010. Do local analysts have an informational advantage in forecasting stock returns? Evidence from the German DAX30. Financial markets and portfolio management. Vol. 24 (2), p. 137-158.

Hong, H., Jeffrey D. K. & Amit S. 2000. Security analysts' career concerns and herding of earnings forecasts. RAND Journal of Economics. Vol. 31, p. 121-143.

Hong, H., Kubik, J.D. 2003. Analyzing The Analysts: Career Concerns and Biased Earnings. Journal of Finance. Vol. 58 (1), p. 313-351.

Hsieh, W.G. & Lee, C-S. 2021. Who reacts to what information in securities analyst reports? Direct evidence from the investor trade imbalance. Pacific-Basin finance journal. Vol. 65, p. 1-26.

Huang, J., Mujtaba Mian, G & Sankaraguruswamy, S. 2009. The value of combining the information content of analyst recommendations and target prices. Journal of financial markets (Amsterdam, Netherlands). Vol.12 (4), p. 754-777.

Investopedia. 2021a. Efficient Market Hypothesis (EMH). [WWW-document].[Accessed 2.12.2021]
Available from: https://www.investopedia.com/terms/e/efficientmarkethypothesis.asp

Investopedia. 2021b. Modern Portfolio Theory: Why It's Still Hip. [WWW-document].[Accessed 2.12.2021]
Available from: https://www.investopedia.com/managing-wealth/modern-portfolio-theory-why-its-still-hip/

Investopedia. 2021c. Signs of Overdiversification. [WWW-document].[Accessed 2.12.2021]
Available from: https://www.investopedia.com/articles/financial-theory/11/signs-of-over-diversification.asp

Investopedia. 2021d. The Dangers of Over-Diversifying Your Portfolio. [WWW-document].[Accessed 2.12.2021]
Available from: https://www.investopedia.com/investing/dangers-over-diversifying-your-portfolio/#citation-1

Investopedia. 2021e. Why Market Correlation Matters. [WWW-document].[Accessed 2.12.2021]
Available from: https://www.investopedia.com/articles/financial-advisors/022516/4-reasons-why-market-correlation-matters.asp

Investopedia. 2021f. Price Target. [WWW-document].[Accessed 2.12.2021]
Available from: https://www.investopedia.com/terms/p/pricetarget.asp

Jackson, A.R. 2005. Trade generation, Reputation, and Sell-Side Analysts. Journal of Finance. Vol. 60 (2), p. 673-717.

Jegadeesh, N. & Kim, W. 2010. Do analysts herd? An analysis of recommendations and market reactions. Review of Financial Studies. Vol. 23 (2), p. 901–937.

Kanne, S., Klobucnik, J., Kreutzmann, D. & Sievers, S. 2012. To buy or not to buy? The value of contradictory analyst signals. Financial markets and portfolio management. Vol.26 (4), p. 405-428.

Kauppalehti. 2019. Osta, pidä, vähennä – mitä analyytikoiden sijoitussuositukset tarkoittavat ja miksi niitä kohtaan pitää olla kriittinen: Kokosimme ohjeet. [WWW-document].[Accessed 2.12.2021]
Available from:
https://www.kauppalehti.fi/uutiset/osta-pida-vahenna-mita-analyytikoiden-sijoitussuositukset-tarkoittavat-ja-miksi-niita-kohtaan-pitaa-olla-kriittinen-kokosimme-ohjeet/e3a5c793-c821-450b-81c9-9b6d865ce990

Kauppalehti. 2020. Kannattaako sijoittajan seurata analyytikoiden suosituksia? – Näissä pörssin suuryhtiöissä tavoitehinnat pahiten pielessä. [WWW-document].[Accessed 2.12.2021]
Available from:
https://www.kauppalehti.fi/uutiset/kannattaako-sijoittajan-seurata-analyytikoiden-suosituksia-naissa-porssin-suuryhtioissa-tavoitehinnat-pahiten-pielessa/3da1f582-27b7-4d58-8779-2266baea3a06

Kauppalehti. 2021. Tässä ovat analyytikoiden ikisuosikit ja -inhokit Helsingin pörssistä – Analyytikoiden hyljeksimilläkin osakkeilla on päässyt hyviin tuottoihin [WWW-document].[Accessed 2.12.2021] Available from: https://www-kauppalehti-fi.ezproxy.cc.lut.fi/uutiset/tassa-ovat-analyytikoiden-ikisuosikit-ja-inhokit-helsingin-porssista-analyytikoiden-hyljeksimillakin-osakkeilla-on-paassyt-hyviin-tuottoihin/b83c1c3b-9c83-47d7-9241-4b4b6ebc34ca

Keim, D.B & Madhavan, A. 1997. Transactions costs and investment style: an inter-exchange analysis of institutional equity trades. Journal of financial economics. Vol.46 (3), p. 265-292.

Kindleberger, C.P. & Aliber, R. 2005. Manias, Panics, and Crashes: A History of Financial Crises. Wiley. p. 38-63

Lee, C. 1992. Earnings news and small traders: An intraday analysis. Journal of Accounting and Economics. Vol. 15 (2-3), p. 265–302.

Lee, C.F. & Lee, J.C. 2015. Handbook of Financial Econometrics and Statistics. New York, NY: Springer New York.

Lien, D., Hung, P-H. & Chen, L-W. 2020. Analyst Recommendations, Herding Intensity, and Trading Performance. Asia-Pacific Journal of Financial Studies. Vol. 49(5), p. 772-802.

Lim, T. 2001. Rationality and Analysts' Forecast Bias. Journal of Finance. Vol. 56 (1), p. 369-385.

Lin, H., McNichols, M.F. 1998. Underwriting Relationships, Analysts' Earnings Forecasts and Investment Recommendations. Journal of Accounting and Economics. Vol. 25 (1), p. 101-127.

Lin, M-C. 2018. The impact of aggregate uncertainty on herding in analysts' stock recommendations. International review of financial analysis. Vol. 57, p. 90-105.

Lin, M-C. & Wu, Y-Z. 2019. Interest conflicts, stock recommendations and investor attention. International review of financial analysis. Vol. 65, p. 1-10.

Lintner, J. 1965. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. The Review of Economics and Statistics. Vol. 47 (1), p. 13-37.

Loh, R.K. 2010. Investor Inattention and the Underreaction to Stock Recommendations. Financial management. Vol. 39 (3), p. 1223-1252.

Lux, T. 1995. Herd Behaviour, Bubbles and Crashes.The Economic journal (London). Vol. 105 (431), p. 881-896.

Markowitz, H. 1952. Portfolio selection. Journal of Finance. Vol. 7 (1), p. 77- 91.

Markowitz, H.M. 1959. Portfolio Selection: Efficient Diversification of Investments. New York: John Wiley & Sons.

Malloy, C.J. 2005. The Geography of Equity Analysis. Journal of Finance. Vol. 60 (2), p. 719-755.

Malkiel, B. 2003 The efficient market hypothesis and its critics. The Journal of Economic Perspectives. Vol. 17 (1), p. 59-82.

Malmendier, U. & Shanthikumar, D. 2007. Are small investors naive about incentives? Journal of financial economics. Vol 85 (2), p. 457-489.

Michaely, R. & Womack, K.L. 1999. Conflict of Interest and The Credibility of Underwriter Analyst Recommendations. Review of Financial Studies, Vol. 12 (4), p. 653-686.

Mikhail, M.B., Walther, B.R. & Willis, R.H. 2007. When Security Analysts Talk, Who Listens? The Accounting review. Vol.82 (5), p. 1227-1253.

Morgan, J. & Stocken, P.C. 2003. An Analysis of Stock Recommendations. The Rand journal of economics. Vol.34 (1), p. 183-203.

Mossin, J. 1966. Equilibrium in a Capital Asset Market. Econometrica Vol 34 (4), p. 768–783.

Moulya, V. H. & Mallikarjunappa, T. 2020. Does an Analyst's Stock Recommendation cause Anomalous Price Drift? A Study of the Indian Stock Market. South Asian journal of management. Vol.27 (1), p. 150-167.

Nasdaq. 2021. OMX Helsinki 25 weights in trade date 1.6.2021. [WWW-document].[Accessed 2.12.2021] Available from:
https://www.nasdaq.com/docs/2021/06/02/omxh25.pdf

Nofsinger, J. 2018. The psychology of investing. 6 ed. Routledge, New York. p. 44-90.

Ricciardi, V. & Baker, H. 2014. Investor behavior: the psychology of financial planning and investing. John Wiley & Sons Inc, New Jersey.

Ryan, P. & Taffler, R. J. 2006. Do brokerage houses add value? The market impact of UK sell-side analyst recommendation changes. The British Accounting Review. Vol 38(4), p. 371-386.

Scharfstein, D.S & Stein, J.C. 1990. Herd Behavior and Investment. American Economic Review. Vol, 80, p. 465-479.

Schipper, K. 1991. Analysts' forecasts. Accounting Horizons. Vol 5, p. 105-121.

SEC (U.S. Securities and Exchange Commission). 2010. Analyzing Analyst Recommendations. [WWW-document].[Accessed 13.12.2021] Available from: https://www.sec.gov/tm/reportspubs/investor-publications/investorpubsanalystshtm.html

Sharpe, W. F. 1964. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. The Journal of Finance. Vol 19 (3), p. 425–442.

Stickel, S.E. 1995. The Anatomy of The Performance of Buy and Sell Recommendations. Financial Analysts Journal, Vol. 51, No. 5, p. 25-39.

Treynor, J.L. 1962. Toward a Theory of Market Value of Risky Assets. [WWW-document].[Accessed 9.12.2021] Available from SSRN: https://ssrn.com/abstract=628187

Trueman, B. 1994. Analyst Forecasts and Herding Behavior, Review of Financial Studies. Vol. 7, p. 97-124.

Welagedara, V., Deb, S.S. & Singh, H. 2017. Investor attention, analyst recommendation revisions, and stock prices. Pacific-Basin finance journal. Vol.45, p. 211-223.

Welch, Ivo. 2000. Herding among security analysts. Journal of financial economics. Vol. 58 (3), p. 369-396.

Wiersema, M.F., Zhang, Y. 2011.CEO Dismissal: The role of investment analysts. Strategic management journal. Vol.32 (11), p. 1161-1182

Womack, K.L. 1996. Do Brokerage Analysts’ Recommendations Have Investment Value? Journal of Finance. Vol. 51, No. 1, p. 137-167.

Xu, N., Jiang, X., Chan, K.C & Wu, S. 2017. Analyst Herding and Stock Price Crash Risk: Evidence from China. Journal of international financial management & accounting. Vol.28 (3), p. 308-348.

Zhou, J. 2013. Analysts’ Target Prices and Stock Recommendations. Accounting and Finance Research. Vol. 2 (1), p. 1-18.

APPENDICES

Appendix. 1 All portfolio combinations during the time period of 31.12.2013 - 31.12.2019

PORTFOLIO 1 (1-7)

Company	WRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBV
Recommendation values in 31.12.2013	2,7				2,8				2,7		2,2		2,7		2,6			2,5			
Position in Portfolio distribution	4				7				6		1		5		3			2			
Recommendation values in 31.12.2014					2,4		2,2				2,0		2,1		2,5			2,1			2,0
Position in Portfolio distribution					6		5				2		4		7			4			2
Recommendation values in 31.12.2015									2,2	2,4	2,0		2,3		2,3			2,3			2,0
Position in Portfolio distribution									3	7	2		6		5			5			2
Recommendation values in 31.12.2016					2,3		2,5		2,2		2,0		2,3					2,0			2,7
Position in Portfolio distribution					4		6		3		2		5					2			7
Recommendation values in 31.12.2017							2,3		2,1				2,6		2,4		2,2	2,6			2,2
Position in Portfolio distribution							4		1				6		5		2	7			3
Recommendation values in 31.12.2018	1,9	1,9			1,9			2,1	2,0								1,8	2,0			
Position in Portfolio distribution	3	4			2			7	5								1	6			
Recommendation values in 31.12.2019						2,2			2,2	2,3	2,1	1,7						2,4			2,1
Position in Portfolio distribution						4			5	6	3	1						7			2

PORTFOLIO 2 (8-14)

Company	WRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBV
Recommendation values in 31.12.2013		2,94	2,89	3,00		2,95										2,86	3,06				2,88
Position in Portfolio distribution		11	10	13		12										8	14				9
Recommendation values in 31.12.2014	2,7	2,9		2,8		2,7			2,8							2,7	2,9				
Position in Portfolio distribution	9	14		11		8			12							10	13				
Recommendation values in 31.12.2015		2,76		2,64	2,61		2,47					2,57				2,50	2,50				
Position in Portfolio distribution		14		13	12		8					11				10	10				
Recommendation values in 31.12.2016		2,82	2,73	2,75		2,83									2,89		2,82			2,88	
Position in Portfolio distribution		11	8	9		12									14		10			13	
Recommendation values in 31.12.2017	2,95	2,67	2,74	2,92	2,67	2,65					2,75										
Position in Portfolio distribution	14	10	11	13	10	8					12										
Recommendation values in 31.12.2018			2,20			2,28	2,39				2,38	2,64	2,38								2,20
Position in Portfolio distribution			9			10	13				12	14	12								9
Recommendation values in 31.12.2019	2,89	2,38	3,00	2,82	2,56												2,50		2,67		
Position in Portfolio distribution	13	8	14	12	10												9		11		

PORTFOLIO 3 (15-21)

Company	WRT1V	UPM	TYRES	TIETO	STERV	SAMPO	OUT1V	ORNBV	NOKIA	NESTE	NDAFI	MOCORP	METSB	KNEBV	KESKOB	KEMIRA	KCRA	HUH1V	FORTUM	ELISA	CGCBV
Recommendation values in 31.12.2013							3,69	3,58		3,60		3,50		3,15					3,20	3,24	
Position in Portfolio distribution							21	19		20		18		15					16	17	
Recommendation values in 31.12.2014			3,10					3,82		3,42		3,20		3,09					3,21	3,00	
Position in Portfolio distribution			17					21		20		18		16					19	15	
Recommendation values in 31.12.2015	3,05		3,33			2,80		3,80						3,20					2,93	3,32	
Position in Portfolio distribution	17		20			15		21						18					16	19	
Recommendation values in 31.12.2016	2,90							3,75		3,39		3,27		3,23		3,11			3,66		
Position in Portfolio distribution	15							21		19		18		17		16			20		
Recommendation values in 31.12.2017								3,00		3,21		3,00		3,11		3,00			2,96	3,38	
Position in Portfolio distribution								18		20		18		19		18			15	21	
Recommendation values in 31.12.2018				2,90						2,80				3,00	3,38	2,88			2,95	3,25	
Position in Portfolio distribution				17						15				19	21	16			18	20	
Recommendation values in 31.12.2019							3,05	4,00					3,33	3,54	3,38	3,25				3,90	
Position in Portfolio distribution							15	21					17	19	18	16				20	

Appendix 2. CAPM values when using OMXH25 index

PORTFOLIO 1

Alpha								
2014	-0,008	0,003	-0,009	-0,009	0,008	0,012	0,005	0,000
2015	0,003	-0,001	-0,009	0,008	0,012	0,005	-0,003	0,002
2016	-0,009	0,026	-0,009	0,008	0,012	0,005	-0,003	0,004
2017	0,003	-0,001	-0,009	-0,009	0,008	0,005	-0,003	-0,001
2018	-0,001	-0,009	0,008	0,012	-0,003	0,005	-0,003	0,001
2019	-0,008	0,005	0,003	0,007	-0,009	-0,003	0,005	0,000
2020	-0,005	-0,009	0,026	-0,009	0,000	0,005	-0,003	0,001
						Total mean		0,001

PORTFOLIO 2

Alpha								
2014	0,005	-0,005	0,001	-0,005	-0,004	-0,003	-0,003	-0,002
2015	-0,008	0,005	0,001	-0,005	-0,009	-0,004	-0,003	-0,003
2016	0,005	0,001	0,003	-0,001	0,000	-0,004	-0,003	0,000
2017	0,005	-0,005	0,001	-0,005	0,012	-0,003	0,010	0,002
2018	-0,008	0,005	-0,005	0,001	0,003	-0,005	-0,009	-0,003
2019	-0,005	-0,005	-0,001	-0,009	0,000	0,008	-0,003	-0,002
2020	-0,008	0,005	-0,005	0,001	0,003	-0,003	-0,003	-0,001
						Total mean		-0,001

PORTFOLIO 3

Alpha								
2014	-5E-04	7E-03	3E-02	-4E-04	6E-03	-3E-03	1E-02	0,006
2015	-5E-03	7E-03	3E-02	-4E-04	6E-03	-3E-03	1E-02	0,006
2016	-8E-03	-5E-03	-5E-03	7E-03	6E-03	-3E-03	1E-02	0,000
2017	-8E-03	7E-03	3E-02	-4E-04	6E-03	-4E-03	-3E-03	0,003
2018	7E-03	3E-02	-4E-04	6E-03	-4E-03	-3E-03	1E-02	0,006
2019	1E-03	3E-02	6E-03	1E-02	-4E-03	-3E-03	1E-02	0,007
2020	-5E-04	7E-03	8E-03	6E-03	1E-02	-4E-03	1E-02	0,005
						Total mean		0,005

PORTFOLIO 1

Beta								
2014	0,955	1,470	1,038	1,104	1,372	0,579	1,054	1,08
2015	1,470	1,728	1,104	1,372	0,579	1,054	1,682	1,28
2016	1,038	1,095	1,104	1,372	0,579	1,054	1,682	1,13
2017	1,470	1,728	1,038	1,104	1,372	1,054	1,682	1,35
2018	1,728	1,038	1,372	0,579	1,469	1,054	1,682	1,27
2019	0,955	1,267	1,470	0,719	1,038	1,469	1,054	1,14
2020	1,003	1,038	1,095	1,104	1,686	1,054	1,682	1,24
						Total mean		1,21

PORTFOLIO 2

Beta								
2014	1,267	0,868	1,000	1,003	1,174	1,469	1,682	1,21
2015	0,955	1,267	1,000	1,003	1,038	1,174	1,469	1,13
2016	1,267	1,000	1,470	1,728	1,686	1,174	1,469	1,40
2017	1,267	0,868	1,000	1,003	0,579	1,469	0,198	0,91
2018	0,955	1,267	0,868	1,000	1,470	1,003	1,104	1,10
2019	0,868	1,003	1,728	1,104	1,686	1,372	1,682	1,35
2020	0,955	1,267	0,868	1,000	1,470	1,469	1,162	1,17
						Total mean		1,18

PORTFOLIO 3

Beta								
2014	1,728	0,719	1,095	1,686	0,596	1,162	0,198	1,03
2015	0,868	0,719	1,095	1,686	0,596	1,162	0,198	0,90
2016	0,955	0,868	1,003	0,719	0,596	1,162	0,198	0,79
2017	0,955	0,719	1,095	1,686	0,596	1,174	1,162	1,06
2018	0,719	1,095	1,686	0,596	1,174	1,162	0,198	0,95
2019	1,000	1,095	0,596	0,579	1,174	1,162	0,198	0,83
2020	1,728	0,719	1,372	0,596	0,579	1,174	0,198	0,91
						Total mean		0,92

PORTFOLIO 1

p-value alpha								
2014	0,1873	0,6520	0,2751	0,1157	0,3210	0,1008	0,3767	0,290
2015	0,6520	0,9731	0,1157	0,3210	0,1008	0,3767	0,7090	0,464
2016	0,2751	0,0011	0,1157	0,3210	0,1008	0,3767	0,7090	0,271
2017	0,6520	0,9731	0,2751	0,1157	0,3210	0,3767	0,7090	0,489
2018	0,9731	0,2751	0,3210	0,1008	0,7084	0,3767	0,7090	0,495
2019	0,1873	0,3894	0,6520	0,4930	0,2751	0,7084	0,3767	0,440
2020	0,1723	0,2751	0,0011	0,1157	0,9740	0,3767	0,7090	0,375
						Total mean		0,403

PORTFOLIO 2

p-value alpha								
2014	0,389	0,479	0,802	0,172	0,437	0,708	0,709	0,528
2015	0,187	0,389	0,802	0,172	0,275	0,437	0,708	0,424
2016	0,389	0,802	0,652	0,973	0,974	0,437	0,708	0,705
2017	0,389	0,479	0,802	0,172	0,101	0,708	0,070	0,389
2018	0,187	0,389	0,479	0,802	0,652	0,172	0,116	0,400
2019	0,479	0,172	0,973	0,116	0,974	0,321	0,709	0,535
2020	0,187	0,389	0,479	0,802	0,652	0,708	0,611	0,547
						Total mean		0,504

PORTFOLIO 3

p-value alpha								
2014	0,973	0,493	0,001	0,974	0,220	0,611	0,070	0,478
2015	0,479	0,493	0,001	0,974	0,220	0,611	0,070	0,407
2016	0,187	0,479	0,172	0,493	0,220	0,611	0,070	0,319
2017	0,187	0,493	0,001	0,974	0,220	0,437	0,611	0,418
2018	0,493	0,001	0,974	0,220	0,437	0,611	0,070	0,401
2019	0,802	0,001	0,220	0,101	0,437	0,611	0,070	0,320
2020	0,973	0,493	0,321	0,220	0,101	0,437	0,070	0,374
						Total mean		0,388

PORTFOLIO 1

p-value beta								
2014	1,2E-09	3,6E-16	4,36E-07	5,12E-13	1,17E-10	0,0007799	1,86E-12	1,1E-04
2015	3,6E-16	2,06E-06	5,12E-13	1,17E-10	0,00078	1,858E-12	3,46E-14	1,1E-04
2016	4,4E-07	1,19E-08	5,12E-13	1,17E-10	0,00078	1,858E-12	3,46E-14	1,1E-04
2017	3,6E-16	2,06E-06	4,36E-07	5,12E-13	1,17E-10	1,858E-12	3,46E-14	3,6E-07
2018	2,1E-06	4,36E-07	1,17E-10	0,00078	9,23E-12	1,858E-12	3,46E-14	1,1E-04
2019	1,2E-09	4,07E-14	3,6E-16	0,001031	4,36E-07	9,232E-12	1,86E-12	1,5E-04
2020	2,4E-19	4,36E-07	1,19E-08	5,12E-13	1,48E-07	1,858E-12	3,46E-14	8,5E-08
						Total mean		8,5E-05

PORTFOLIO 2

p-value beta								
2014	4,1E-14	8E-07	1E-11	2E-19	3E-14	9E-12	3,46E-14	1,2E-07
2015	1,2E-09	4E-14	1E-11	2E-19	4E-07	3E-14	9,23E-12	6,2E-08
2016	4,1E-14	1E-11	4E-16	2E-06	1E-07	3E-14	9,23E-12	3,2E-07
2017	4,1E-14	8E-07	1E-11	2E-19	0,0008	9E-12	1,11E-01	1,6E-02
2018	1,2E-09	4E-14	8E-07	1E-11	4E-16	2E-19	5,12E-13	1,2E-07
2019	8,1E-07	2E-19	2E-06	5E-13	1E-07	1E-10	3,46E-14	4,3E-07
2020	1,2E-09	4E-14	8E-07	1E-11	4E-16	9E-12	8,36E-14	1,2E-07
						Total mean		2,3E-03

PORTFOLIO 3

p-value beta								
2014	2,1E-06	0,0010314	1E-08	1E-07	1E-07	8E-14	1,11E-01	1,6E-02
2015	8,1E-07	0,0010314	1E-08	1E-07	1E-07	8E-14	1,11E-01	1,6E-02
2016	1,2E-09	8,091E-07	2E-19	0,001	1E-07	8E-14	1,11E-01	1,6E-02
2017	1,2E-09	0,0010314	1E-08	1E-07	1E-07	3E-14	8,36E-14	1,5E-04
2018	1,0E-03	1,187E-08	1E-07	1E-07	3E-14	8E-14	1,11E-01	1,6E-02
2019	1,0E-11	1,187E-08	1E-07	0,0008	3E-14	8E-14	1,11E-01	1,6E-02
2020	2,1E-06	0,0010314	1E-10	1E-07	0,0008	3E-14	0,1115	1,6E-02
						Total mean		1,4E-02

PORTFOLIO 1

Adjusted R-squared								
2014	0,357	0,552	0,260	0,466	0,392	0,119	0,449	0,371
2015	0,552	0,232	0,466	0,392	0,119	0,449	0,500	0,387
2016	0,260	0,321	0,466	0,392	0,119	0,449	0,500	0,358
2017	0,552	0,232	0,260	0,466	0,392	0,449	0,500	0,407
2018	0,232	0,260	0,392	0,119	0,428	0,449	0,500	0,340
2019	0,357	0,498	0,552	0,113	0,260	0,428	0,449	0,380
2020	0,625	0,260	0,321	0,466	0,279	0,449	0,500	0,414
						Total mean		0,380

PORTFOLIO 2

Adjusted R-squared								
2014	0,498	0,249	0,426	0,625	0,503	0,428	0,500	0,461
2015	0,357	0,498	0,426	0,625	0,260	0,503	0,428	0,442
2016	0,498	0,426	0,552	0,232	0,279	0,503	0,428	0,417
2017	0,498	0,249	0,426	0,625	0,119	0,428	0,019	0,338
2018	0,357	0,498	0,249	0,426	0,552	0,625	0,466	0,453
2019	0,249	0,625	0,232	0,466	0,279	0,392	0,500	0,392
2020	0,357	0,498	0,249	0,426	0,552	0,428	0,489	0,428
						Total mean		0,419

PORTFOLIO 3

Adjusted R-squared								
2014	0,232	0,113	0,321	0,279	0,284	0,489	0,019	0,248
2015	0,249	0,113	0,321	0,279	0,284	0,489	0,019	0,251
2016	0,357	0,249	0,625	0,113	0,284	0,489	0,019	0,305
2017	0,357	0,113	0,321	0,279	0,284	0,503	0,489	0,335
2018	0,113	0,321	0,279	0,284	0,503	0,489	0,019	0,287
2019	0,426	0,321	0,284	0,119	0,503	0,489	0,019	0,309
2020	0,232	0,113	0,392	0,284	0,119	0,503	0,019	0,237
						Total mean		0,282

Appendix 3. CAPM values when using sample21 index

PORTFOLIO 1								
Alpha								
2014	-0,009	0,000	-0,009	-0,011	0,005	0,011	0,003	-0,001
2015	0,000	-0,006	-0,011	0,005	0,011	0,003	-0,007	0,000
2016	-0,009	0,025	-0,011	0,005	0,011	0,003	-0,007	0,003
2017	0,000	-0,006	-0,009	-0,011	0,005	0,003	-0,007	-0,003
2018	-0,006	-0,009	0,005	0,011	-0,006	0,003	-0,007	-0,001
2019	-0,009	0,004	0,000	0,005	-0,009	-0,006	0,003	-0,002
2020	-0,006	-0,009	0,025	-0,011	-0,005	0,003	-0,007	-0,001
						Total mean		-0,001

PORTFOLIO 2								
Alpha								
2014	0,004	-0,007	0,000	-0,006	-0,007	-0,006	-0,007	-0,004
2015	-0,009	0,004	0,000	-0,006	-0,009	-0,007	-0,006	-0,005
2016	0,004	0,000	0,000	-0,006	-0,005	-0,007	-0,006	-0,003
2017	0,004	-0,007	0,000	-0,006	0,011	-0,006	0,010	0,001
2018	-0,009	0,004	-0,007	0,000	0,000	-0,006	-0,011	-0,004
2019	-0,007	-0,006	-0,006	-0,011	-0,005	0,005	-0,007	-0,005
2020	-0,009	0,004	-0,007	0,000	0,000	-0,006	-0,004	-0,003
						Total mean		-0,003

PORTFOLIO 3								
Alpha								
2014	-6E-03	5E-03	3E-02	-5E-03	5E-03	-4E-03	1E-02	0,004
2015	-7E-03	5E-03	3E-02	-5E-03	5E-03	-4E-03	1E-02	0,004
2016	-9E-03	-7E-03	-6E-03	5E-03	5E-03	-4E-03	1E-02	-0,001
2017	-9E-03	5E-03	3E-02	-5E-03	5E-03	-7E-03	-4E-03	0,001
2018	5E-03	3E-02	-5E-03	5E-03	-7E-03	-4E-03	1E-02	0,004
2019	3E-05	3E-02	5E-03	1E-02	-7E-03	-4E-03	1E-02	0,006
2020	-6E-03	5E-03	5E-03	5E-03	1E-02	-7E-03	1E-02	0,003
						Total mean		0,003

PORTFOLIO 1								
Beta								
2014	0,780	1,318	0,686	0,957	1,304	0,529	0,970	0,93
2015	1,318	1,786	0,957	1,304	0,529	0,970	1,587	1,21
2016	0,686	0,926	0,957	1,304	0,529	0,970	1,587	0,99
2017	1,318	1,786	0,686	0,957	1,304	0,970	1,587	1,23
2018	1,786	0,686	1,304	0,529	1,405	0,970	1,587	1,18
2019	0,780	1,110	1,318	0,677	0,686	1,405	0,970	0,99
2020	0,837	0,686	0,926	0,957	1,721	0,970	1,587	1,10
						Total mean		1,09

PORTFOLIO 2								
Beta								
2014	1,110	0,776	0,867	0,837	1,076	1,405	1,587	1,09
2015	0,780	1,110	0,867	0,837	0,686	1,076	1,405	0,97
2016	1,110	0,867	1,318	1,786	1,721	1,076	1,405	1,33
2017	1,110	0,776	0,867	0,837	0,529	1,405	0,151	0,81
2018	0,780	1,110	0,776	0,867	1,318	0,837	0,957	0,95
2019	0,776	0,837	1,786	0,957	1,721	1,304	1,587	1,28
2020	0,780	1,110	0,776	0,867	1,318	1,405	0,939	1,03
						Total mean		1,06

PORTFOLIO 3								
Beta								
2014	1,786	0,677	0,926	1,721	0,527	0,939	0,151	0,96
2015	0,776	0,677	0,926	1,721	0,527	0,939	0,151	0,82
2016	0,780	0,776	0,837	0,677	0,527	0,939	0,151	0,67
2017	0,780	0,677	0,926	1,721	0,527	1,076	0,939	0,95
2018	0,677	0,926	1,721	0,527	1,076	0,939	0,151	0,86
2019	0,867	0,926	0,527	0,529	1,076	0,939	0,151	0,72
2020	1,786	0,677	1,304	0,527	0,529	1,076	0,151	0,86
						Total mean		0,83

PORTFOLIO 1								
p-value alpha								
2014	0,1622	0,9409	0,3441	0,0711	0,5024	0,1330	0,5785	0,390
2015	0,9409	0,6921	0,0711	0,5024	0,1330	0,5785	0,3815	0,471
2016	0,3441	0,0023	0,0711	0,5024	0,1330	0,5785	0,3815	0,288
2017	0,9409	0,6921	0,3441	0,0711	0,5024	0,5785	0,3815	0,502
2018	0,6921	0,3441	0,5024	0,1330	0,4067	0,5785	0,3815	0,434
2019	0,1622	0,5778	0,9409	0,5972	0,3441	0,4067	0,5785	0,515
2020	0,1283	0,3441	0,0023	0,0711	0,6685	0,5785	0,3815	0,311
						Total mean		0,416

PORTFOLIO 2								
p-value alpha								
2014	0,578	0,366	0,996	0,128	0,225	0,407	0,382	0,440
2015	0,162	0,578	0,996	0,128	0,344	0,225	0,407	0,406
2016	0,578	0,996	0,941	0,692	0,668	0,225	0,407	0,644
2017	0,578	0,366	0,996	0,128	0,133	0,407	0,075	0,383
2018	0,162	0,578	0,366	0,996	0,941	0,128	0,071	0,463
2019	0,366	0,128	0,692	0,071	0,668	0,502	0,382	0,401
2020	0,162	0,578	0,366	0,996	0,941	0,407	0,531	0,569
						Total mean		0,472

PORTFOLIO 3								
p-value alpha								
2014	0,692	0,597	0,002	0,668	0,306	0,531	0,075	0,410
2015	0,366	0,597	0,002	0,668	0,306	0,531	0,075	0,364
2016	0,162	0,366	0,128	0,597	0,306	0,531	0,075	0,309
2017	0,162	0,597	0,002	0,668	0,306	0,225	0,531	0,356
2018	0,597	0,002	0,668	0,306	0,225	0,531	0,075	0,344
2019	0,996	0,002	0,306	0,133	0,225	0,531	0,075	0,324
2020	0,692	0,597	0,502	0,306	0,133	0,225	0,075	0,362
						Total mean		0,353

PORTFOLIO 1								
p-value beta								
2014	2,51E-08	3,23E-17	0,000234	1,16E-12	6,48E-13	0,0004424	4,56E-14	9,7E-05
2015	3,23E-17	7,76E-09	1,16E-12	6,48E-13	0,000442	4,5562E-14	2,23E-17	6,3E-05
2016	0,000234	4,8E-08	1,16E-12	6,48E-13	0,000442	4,5562E-14	2,23E-17	9,7E-05
2017	3,23E-17	7,76E-09	0,000234	1,16E-12	6,48E-13	4,5562E-14	2,23E-17	3,3E-05
2018	7,76E-09	0,000234	6,48E-13	0,000442	1,25E-14	4,5562E-14	2,23E-17	9,7E-05
2019	2,51E-08	4,05E-14	3,23E-17	0,000387	0,000234	1,2505E-14	4,56E-14	8,9E-05
2020	1,07E-16	0,000234	4,8E-08	1,16E-12	2,25E-10	4,5562E-14	2,23E-17	3,3E-05
						Total mean		7,3E-05

PORTFOLIO 2								
p-value beta								
2014	4,1E-14	5E-07	2E-11	1E-16	4E-16	1E-14	2,23E-17	6,6E-08
2015	2,5E-08	4E-14	2E-11	1E-16	0,0002	4E-16	1,25E-14	3,3E-05
2016	4,1E-14	2E-11	3E-17	8E-09	2E-10	4E-16	1,25E-14	1,1E-09
2017	4,1E-14	5E-07	2E-11	1E-16	0,0004	1E-14	1,67E-01	2,4E-02
2018	2,5E-08	4E-14	5E-07	2E-11	3E-17	1E-16	1,16E-12	6,9E-08
2019	4,6E-07	1E-16	8E-09	1E-12	2E-10	6E-13	2,23E-17	6,7E-08
2020	2,5E-08	4E-14	5E-07	2E-11	3E-17	1E-14	2,53E-11	6,9E-08
						Total mean		3,4E-03

PORTFOLIO 3								
p-value beta								
2014	7,8E-09	0,0003868	5E-08	2E-10	7E-08	3E-11	1,67E-01	2,4E-02
2015	4,6E-07	0,0003868	5E-08	2E-10	7E-08	3E-11	1,67E-01	2,4E-02
2016	2,5E-08	4,598E-07	1E-16	0,0004	7E-08	3E-11	1,67E-01	2,4E-02
2017	2,5E-08	0,0003868	5E-08	2E-10	7E-08	4E-16	2,53E-11	5,5E-05
2018	3,9E-04	4,796E-08	2E-10	7E-08	4E-16	3E-11	1,67E-01	2,4E-02
2019	2,1E-11	4,796E-08	7E-08	0,0004	4E-16	3E-11	1,67E-01	2,4E-02
2020	7,8E-09	0,0003868	6E-13	7E-08	0,0004	4E-16	0,16684	2,4E-02
						Total mean		2,0E-02

PORTFOLIO 1								
Adjusted R-squared								
2014	0,308	0,577	0,143	0,455	0,463	0,130	0,496	0,368
2015	0,577	0,328	0,455	0,463	0,130	0,496	0,581	0,433
2016	0,143	0,298	0,455	0,463	0,130	0,496	0,581	0,367
2017	0,577	0,328	0,143	0,455	0,463	0,496	0,581	0,435
2018	0,328	0,143	0,463	0,130	0,512	0,496	0,581	0,379
2019	0,308	0,498	0,577	0,133	0,143	0,512	0,496	0,381
2020	0,565	0,143	0,298	0,455	0,382	0,496	0,581	0,417
						Total mean		0,397

PORTFOLIO 2								
Adjusted R-squared								
2014	0,498	0,259	0,416	0,565	0,551	0,512	0,581	0,483
2015	0,308	0,498	0,416	0,565	0,143	0,551	0,512	0,428
2016	0,498	0,416	0,577	0,328	0,382	0,551	0,512	0,466
2017	0,498	0,259	0,416	0,565	0,130	0,512	0,011	0,342
2018	0,308	0,498	0,259	0,416	0,577	0,565	0,455	0,440
2019	0,259	0,565	0,328	0,455	0,382	0,463	0,581	0,433
2020	0,308	0,498	0,259	0,416	0,577	0,512	0,414	0,426
						Total mean		0,431

PORTFOLIO 3								
Adjusted R-squared								
2014	0,328	0,133	0,298	0,382	0,290	0,414	0,011	0,265
2015	0,259	0,133	0,298	0,382	0,290	0,414	0,011	0,255
2016	0,308	0,259	0,565	0,133	0,290	0,414	0,011	0,283
2017	0,308	0,133	0,298	0,382	0,290	0,551	0,414	0,339
2018	0,133	0,298	0,382	0,290	0,551	0,414	0,011	0,297
2019	0,416	0,298	0,290	0,130	0,551	0,414	0,011	0,302
2020	0,328	0,133	0,463	0,290	0,130	0,551	0,011	0,272
						Total mean		0,288