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Analysts' abnormal returns and stock specific characteristics that consciously or unconsciously impact analysts' recommendations: Evidence from Finland 1999-2014

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ABSTRACT

Analysts have become more important over the past years because the amount of information on the stock market has increased. It has led analysts to become stock market specialists and their opinions are needed. The Capital Asset Pricing model and the efficient market hypothesis cannot explain abnormal returns generated by following analysts' recommendations. Investors induce stock price reactions when analysts issue new recommendations or change existing ones, which have caused short-term and long-term abnormal returns.

Several studies have suggested that abnormal returns follow analysts' recommendations. When a new recommendation is issued, it immediately impacts the stock price. This thesis examines the phenomena through 2 distinct methods. Firstly There are three portfolios Buy, Hold and Sell constructed on the basis of analysts' recommendations, which are then benchmarked with OMXH and OMXH24 market indices and a market model regression is applied to the results. The second part examines whether stocks with the same recommendation share some specific characteristics and therefore consciously or unconsciously impact on analysts' recommendations.

This study finds indication in the Finnish stock market that it is possible to outperform the market and generate significant abnormal returns by following favourable analysts' recommendations. This study also continues the research in the area of identifying stock-specific characteristics, which consciously or unconsciously impact analysts' recommendations. Stock characteristics of liquidity, price-to-book and size are documented to have a significant impact on the analysts' recommendations in this study.

Keywords: Analyst, stock price, recommendation, abnormal returns

1. INTRODUCTION

The purpose of this thesis is to provide support from previous studies for the hypothesis that analysts' recommendations have an impact on stock returns in the Finnish stock market. Before the studies, the essential theoretical framework is demonstrated in order to provide solid basis for the reader. Previous studies concentrate mostly on the U.S markets, but there is also some evidence presented from the emerging markets and the Nordics

Lawrence D. Brown & Michael S. Rozeff (1978) defined analysts as operators who produce information and issue stock recommendations, which are used for investment decisions (whether to buy or not to buy a certain stock) on the stock market. Evli Bank analyst Mikko Ervasti (2013) defines analyst as follows: "An investment research analyst forecasts the financial future of a firm, helping investors get an understanding of future cash flows and hence the fair value of the firm's equity today". On the contrary to the previous, Eugene F. Fama (1970) presented the hypothesis about efficient markets and concluded that all available information is reflected on stock prices. Therefore it shouldn't be possible that analysts find new information about stocks. If they do, they are breaking the efficient market hypothesis.

The Capital Asset Pricing Model is generally used to calculate the stock's expected return. The model concludes that if share A generates more profit than share B, then share A must have a higher market-risk (Beta) than share B. Thus, if it is possible to achieve abnormal returns by following analysts' recommendations, they must include new information, or the risk of the stock is calculated wrong, or the whole stock is evaluated wrong. Thus, analysts' recommendations break the market efficiency and the Capital Asset pricing models' valuation. Therefore it is concluded to be an anomaly. (Sharpe 1964; Lintner 1965; Mossin 1966.)

Analysts have been researched since the 1930s. Alfred Cowles (1933) was the first one who did academic research on the subject. The research was about the analysts' capability to foretell future stock prices. However, as an anomaly the analysts' recommendations' impact on stock returns is not very commonly known. There are several studies about analysts but not the anomaly itself. The anomaly has been acknowledged for 40 years. John D. Stoffels's study in 1966 presented some facts considering analysts' recommendations to cause stock price reactions. Barber et al.

(2001) documented that it is possible to achieve abnormal returns by following the most favourable analysts' recommendations. Fariborz et al. (2009) were researching the analysts' recommendations on emerging markets (Brazil, Mexico etc.) and also suggested that abnormal returns follow recommendations. In addition, Loh and Stulz (2012) found that only 12% of the recommendations are influential and identified some of the analysts' characteristics that explain the phenomenon. One of the latest studies in relation to the abnormal returns of the analysts' recommendations is the/a research paper by Bradley et al. (2014). They document that a favourable change in an analyst's recommendation generates a return of 1,83% within 30 minutes of the issuance. In addition they conclude that the analysts are the most important source of information that is examined.

1.1. Contribution

The contribution of this thesis is to be the first one to investigate only the impact of the recommendations of the large stocks on stock returns with post-financial crisis data. In addition, this thesis continues to identify stock-specific characteristics that may consciously or unconsciously impact on the analysts' recommendations. This subject has hardly been researched at all. Finally, the previous questions are examined before and after transaction costs. The latest study that focused on analysts' recommendations impact on the Finnish stock market returns, taking transaction costs into account, was carried out in 2003 by Alexander Von Nandelstadh.

1.2. Limitations

The original data consisted of the 25 largest stocks on the Finnish stock market as of in the beginning of 2015. However, Valmet was dropped due to insufficient data availability and therefore only the 24 largest stocks are under examination. Also, only monthly data is used in this study. Analysing daily data and changes of the recommendations would be expected to increase the accuracy of the results.

Portfolio with Buy recommendations has approximately 8 times fewer stocks on monthly average compared to Hold portfolio. The Hold portfolio is the largest every month during the sample period. Another significant observation is that there are no stocks in Buy and Sell portfolios during certain months. There are a total of 46 months without Buy recommendations and a total of 9 months without Sell recommendations in the sample. For example in 2013 there are not a single stock in omxh24 with Buy recommendation. These observations suggest that analysts' recommendation may also follow the economic state and their underlying target is to perform as accurate analysis as possible and not to recommend stocks in order to increase investors willingness to trade more.

2. RESEARCH PROBLEM

This thesis aims to empirically examine whether abnormal returns were generated by analysts' recommendations of the 24 largest stocks on Finnish stock markets. From this, it can be deduced whether the analyst recommendations include beneficial information for the investors or not. This study uses the pooled consensus recommendations of all outstanding analyst recommendations for each large stock under examination. The period under investigation covers years 1999 to 2014 in order to obtain a sufficient number of observations, because the recommendations are issued and pooled monthly.

This thesis also examines whether there are some specific characteristics, which the stocks with the same recommendation share, and whether these characteristics impact the abnormal returns. In this part I aim to apply the accuracy of the analysts' recommendations to the regression model by using the mean target prices of each stock outstanding. In addition to empirical analysis, this thesis deals with the underlying reasons for the anomalies on the markets and the role of the security analysts.

This thesis aims to answer the following questions:

i) Do stocks with similar recommendations generate abnormal returns on the Finnish stock market, even after transaction costs?

ii) Do stocks with the same recommendation share similar characteristics which consciously or unconsciously impact the analysts' recommendations?

The returns of the stocks during the sample period vary greatly. In the beginning of the sample the markets underwent the so-called "dotcom" crisis that lasted until the year 2001. After the crisis period, the returns steadily grew until the year of 2008, when the global financial crisis started. However, this thesis also captures the period after the financial crisis, from 2009 to 2014, which brings a new contribution for this study.

2.1. Structure of the thesis

Before the main empirical part, this thesis broadly explains the theoretical framework behind the impact of analysts' recommendations on stock returns. The thesis begins by explaining the theory of efficient market hypothesis and how psychology may impact investors' and analysts' decision-making processes. The fourth chapter deals with stock returns. It explains the theory behind stock returns, demonstrates basic stock pricing and valuation models and how the abnormal returns are measured. It also analyses the overall performance of the Finnish stock market. The fifth chapter is all about the analysts. It first defines who the analysts are and then introduces how they valuate stocks. Analyst behaviour studies are presented towards the end of chapter. The end of chapter five introduces studies relating to analysts' recommendations' impact on stock returns. Almost all of the previous studies were conducted on the U.S. stock market with a couple of exceptions.

The Empirical part that starts in chapter 6 first describes the data and the sources and methods of collecting. The data consists of consensus recommendations of the 24 largest stocks listed on Helsinki stock exchange, OMXH index, OMXH24 index, 1-month euribor and different stock- and firm-specific figures and ratios, which are all calculated on a monthly basis. The sample period runs from 1999 to 2014. Chapter 7 deals with the portfolio construction and regression analysis, which are used as methods in this study. The stocks under examination are divided into three portfolios on the basis of analysts' consensus recommendations and the portfolios are updated every month if necessary. Portfolio returns are then benchmarked by the returns of two indices, the OMXH and the OMXH24. OMXH24 is used because it is constructed only on the basis of the 24 large stocks under examination and might thus hand out more accurate results.

After the portfolio analysis, the results of my regression analysis are presented in chapter 8. This thesis uses a market model to examine is abnormal returns generated by following the analysts' recommendations. The second empirical model is constructed on the basis of Peltoniemi (2012) in order to investigate whether there are some stock-specific characteristics that the stocks with the same recommendation share and consciously or unconsciously impact the analysts' recommendations, and thus explain the abnormal returns generated by the portfolios. Regression analysis aims to investigate and identify these characteristics and measure whether they have a statistically significant impact on the abnormal returns. Chapter 9 presents the conclusions of this thesis.

3. ARE THE MARKETS EFFICIENT?

This chapter presents the theoretical framework of the modern stock markets. The chapter deals with the efficient market hypothesis and behavioral biases to provide the reader with the needed theory in order to understand the analysts' role in the financial markets.

3.1. Efficient markets

An investment banker and a cook are walking down the street. One day they see a $50 bill lying on the ground. The Cook reaches to pick it up, when the investment banker stops him and says: "Don't bother, if it was a real $50 bill, someone would have already picked it up." This assumption that there are no free lunches supports the hypothesis of efficient markets. The story about the $50 bill gives you the impression that there is no chance that someone wouldn't have picked it up. What if there was a chance? (Findlay & Williams 2000.)

It is assumed that stock prices follow the so-called *random walk*, meaning that the consecutive price changes of stocks are independent. Prices don't follow any kind of pattern or formula, because the odds for the price change are the same time after time. There is no chance to forecast next day's stock price from the previous day's price if the markets reflect all the new available information in stock prices immediately. (Brealey, Myers & Allen 2008: 355-358.)

Fama (1970) concluded that the mission of the capital markets is to allocate money from the deficit area to the surplus area. In an ideal situation the market prices give accurate signals to investors about how to allocate their resources. Then companies and investors could trust that the market prices reflect all available information and they can make an investment decision. Efficient markets reflect all available information. (Fama 1970.)

Figure 1 demonstrates the efficient and inefficient price reactions. If a company announces bad news, the price of the stock sets immediately to the right level if the markets are efficient (green line). In inefficient markets the price reaction could be delayed or there might be overreaction. A slow price reaction (blue line) creates arbitrage opportunities. (Nikkinen et al. 2002: 81.) Overreaction (red line) is caused by investors' irrational behaviour, which is explained in next chapter *psychological aspects of the markets*. The overreaction is reversed in stock prices over time. (De Bondt and Thaler 1985.)

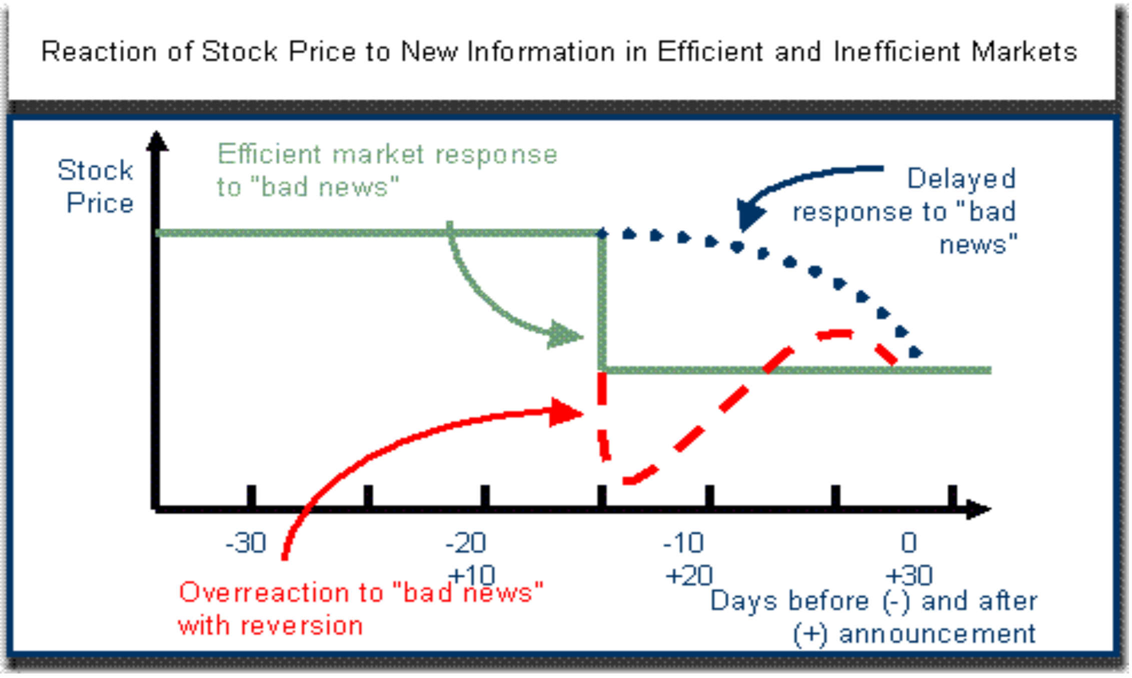

Figure 1. Reaction of stock price to new information in efficient and inefficient markets and overreaction and delayed response to bad news (Shefrin 2002; Haugen 1997: 650.)

Fama (1970) has set three conditions for the stock prices to adjust available information efficiently. (i) There are no transaction costs, (ii) Information is free and everyone can access it, and (iii) parties have the same opinion about the information's effect on present and future securities prices. The markets are efficient when they reflect all the information there is. This means that it is possible to make investment decisions based on the available information. (Fama 1970: 386-387.)

Fama (1970) also suggested that there are three levels of efficiency on the market because the markets are not perfectly efficient all of the time. Efficiency is based on availability and amount of information that is reflected to securities prices. In *weak-form efficiency* the market prices reflect only historical information and investors cannot use technical analysis for forecasting returns. If market prices reflect past and public information (profit warnings, financial statements etc.) the markets are in *semi-strong form*. In *strong-form* market prices reflect historical information, public information and private information. Private information is not public and some investors might have a monopolistic right for the information. (1970: 388)

Fama (1998) filled in his efficient market hypothesis. He stated that efficient market hypothesis applies because *anomalies* are random results on the market and there is as much overreaction as there is underreaction to new information on the market. He proposes that anomalies could be observed when markets are divided into two parts by underreaction and overreaction. One conclusion also was that long-term return anomalies are sensitive to analysing technique and they can disappear because of the changes in technique. (Fama 1988.)

Burton G. Malkiel (2003) was the first one who presented critique towards the efficient market hypothesis. He concluded that there are irrational operators on the market who cause short-term irregularities on stock prices and opportunities to predict stock prices. He also suggested that it is not possible to benefit from behavioural bias anomalies and gain excess returns even though markets are more efficient and unpredictable than other studies may suggest. Finally he states in his study that the efficient market hypothesis is going to lose its importance in 21^{st} century and many researchers will believe that stock prices are partially possible to predict. (Malkiel 2003.)

3.2. Psychological aspects of the stock market

The financial markets have been researched as long as they have existed. George C. Selden (1912) was the first study to academically represent the psychological side of the capital markets. His book was titled “Psychology of the stock market”. The roots of stock market psychology reach to 19^{th} century. In 1841, McKay’s Extraordinary Popular Delusions and The Madness Of Crowds presented the idea of fear. The book presented a chronological timeline of the panics and schemes throughout history. (Ricciardi & Simon 2000.) VIX index measures the implicit volatility of the SP500 index that has been implied to measure the investors’ fear and it is called “investor fear gauge” (Robert E. Whaley 2000.) This section examines the behavioural side of the stock market and presents studies on the matter. The purpose is to give a preliminary look for the upcoming analysts’ behavioural biases in chapter 4.

Robert J. Shiller (1981) noticed that stock prices increase relatively too high after announcements of dividend yields. Werner F. M. De Bondt and Richard Thaler (1985) concluded that returns of the stocks which have performed particularly poor (*loser stock*) in the past outstrip returns of the stocks that have performed particularly well (*winner stock*) in the past. The investors' overreaction to unexpected and dramatic events was proven to be the reason for this. Josef Lakonishok, Andrei Shleifer and Robert W. Vishny (1994) suggested that high returns of public information (accounting and price information) portfolios are consequences of investors' extrapolation of past information. Kent Daniel, David Hirshleifer and Avanidhar Subrahmanyam (1998) recognised investors' overreaction and underreaction, which are caused by investors' overconfidence. Harrison Hong and Jeremy C. Stein (1999) studied overreaction and underreaction. They recognised two investor types. One type primitively follows price trends when the other type primitively follows market news.

Behavioral finance, a new field of finance began to emerge during 1990s. It is a combination of psychology, sociology and finance. Behavioral finance investigates the cognitive factors and emotional issues that impact the investment decision-making processes of individuals, groups, and organizations. (Ricciardi & Simon 2000.)

It is assumed that anomalies are the cause of market prices varying from their true value. If the markets were efficient in a traditional finance aspect, the stock prices should be in their intrinsic value, even if there are anomalies appearing on the market. (Shefrin 2002:5) Behavioural finance argues against the claim that the stock price changes always reflect all available information and against the efficient market hypothesis. It also helps us understand phenomena in the economy, which are caused by investors' humane weaknesses in allocating resources. (Shiller 2003.)

3.2.1. Behavioral biases and market anomalies

An anomaly is a model that describes the behaviour of stock prices, which doesn't go hand in hand with the efficient market hypothesis. Alon Brav and James B. Heaton (2002) studied anomalies occuring on the financial market and analyzed two explanatory theories, investors' irrational behaviour and rational structural uncertainty. They concluded that even if investors' irrational behaviour causes anomalies, their disappearance could be dependent on rational learning, meaning that rational arbitrageurs are able to reject rational explanations for price formulas. Simply put, an anomaly is a deviation in efficiency. (Brav & Heaton 2002.)

Investors and portfolio managers actively keep their eyes and ears open. They try to know what other investors and managers are doing at all times and get tips on which stocks to buy or sell. And when things start to happen, everyone knows it and acts. This kind of behaviour is called *herding.* Herding causes problems, because it strengthens psychological biases on the market. Investors make decisions only based on the "feel" of the crowd instead of formal stock analysis. If investors happen to choose a "loser" stock, the regret they feel is lower when they know that other investors picked the same stock. (Nofsinger 2005:95.)

Investors *anchor* on their stocks, which they have recently bought. Thus, they lose opportunities to buy other, possibly better stocks. On the other hand, it is possible to anchor on one's own or others' opinions and time after time make investment decisions based on these same opinions. (Nofsinger 2005:5.)

The psychological meaning of *overconfidence* is that people overestimate their knowledge, underestimate risks and exaggerate their ability to control events. When making investment decisions, it is divided to two aspects, which are miscalibration and the better-than-average effect. Miscalibration occurs when an investor's probability distributions are too tight. The better-than-average effect means that investors have overly positive views of themselves, which are unrealistic. (Nofsinger 2005.)

The *self-attribution bias* implies that when investors make successful investment decisions they attribute their own skill but when the investment decisions are unsuccessful they blame bad luck. (Shefrin 2002:101.)

Representativeness means stereotypic judgement. In financial markets it leads to errors in investment decisions. A good, solid company is assumed to be a good investment. The company generates strong earnings, has high sales growth and quality management, but good investments are stocks that increase in price more than others. Stocks of good companies could actually be worse as investments than those of other companies. (Shefrin 2002, Solt & Statman 1989.)

Ball and Brown (1968) were the first ones who researched the *post-announcement-drift.* They concluded that after the earnings announcement, the cumulative abnormal returns continue increasing after good news and decreasing after bad news. George Foster, Chris Olsen and Terry Shevlin (1984) estimated that over 60 days after the earnings announcement, a long position in stocks with unexpected earnings in the highest decile and a short position in stocks in lowest decile generates 25 per cent annual abnormal return (before transaction costs).

Victor L. Bernard and Jacob K. Thomas (1989) suggested that there are two explanations to this anomaly. Firstly, it could be that when the CAP model is used to calculate abnormal returns, the model is either incomplete or misestimated and researchers have been unable to adjust raw returns to risk. The result is that abnormal returns are a fair compensation for the investor for bearing the risk, which is priced but not captured by the CAPM. Another explanation is that the response to new information is delayed. It may be caused because traders fail to assimilate available information or because certain costs exceed gains from immediate exploitation of information.

Momentum is a phenomenon where investors try to pick stocks that have outperformed other stocks in the past. The idea is to buy past "winner" stocks and short-sell past "loser" stocks. Narasimhan Jegadeesh and Sheridan Titman (1993) bought winner stocks from past 6 months and kept stocks for the next 6 months, a strategy which generated 12.01 per cent abnormal return. (Jegadeesh & Titman 1993.)

Contrarian is an investment strategy where investors buy past "loser" stocks and sell past " winner" stocks. The strategy works the other way around to momentum. There is overreaction on the market and the "winner" stocks become over-valued and "loser" stocks become under-valued. Investors benefit when stock prices balance. (Chain 1988.)

When new information about a share is announced, investors might react disproportionately, which causes share price to change dramatically, and the price doesn't immediately reflect the true value of the stock after the announcement. Shefrin (2000) concluded that investors *overreact* to negative news. De Bondt and Thaler (1985) suggested that investors overreact to bad news and good news. This then leads past "loser" stocks to become overpriced and past "winners" to become underpriced. They also argued that overreaction is based on representativeness and a "loser" portfolio outperforms the market. Shefrin (2000) suggested that this phenomenon is concentrated in the month of January.

When the stock markets increase, the investors get optimistic and assume that the markets will continue increasing in the future. When people try to predict the future, they tend to get anchored by salient past events, so they *underreact*. (Shefrin 2002.) Security prices underreact to news, for example earnings announcements. If the news are good, the stock prices continue the positive trend after the announcement, and if the news are bad, the stock prices continue decreasing. (Shleifer 2000.) When optimism reaches its highest peak, the investors' greed moves stock prices beyond their intrinsic values. In extreme cases of overreaction and underreaction, these anomalies could lead to market panics and crashes. (Shefrin 2002.)

4. STOCK RETURNS

Different factors affect stock prices. Analysts evaluate those factors and form their own opinions about the intrinsic value of stocks and thus use different valuation techniques. This chapter represents basic stock pricing and valuation models, which are generally used to evaluate stock prices and returns, to provide enough background in order to understand the analysts' methods in forming a recommendation.

4.1. Capital asset pricing model

Capital asset pricing model (CAPM) is the most commonly known model for securities pricing. William Sharpe (1964), John Lintner (1965) and Jan Moss (1966) derived the model from Harry Markowitz's portfolio theory (1952). The basic idea of the CAPM is to connect risk and return. The model ties it down that risk and return go hand in hand: the higher the risk, the higher the return. The model also points out that the only risk that affects the stock's expected return is the systematic risk (market risk) of the stock, which is measured by Beta. Because firm-specific also known as unsystematic risk can be reduced to 0 by appropriate diversification of the portfolio, only the market risk matters. (Sharpe 1964; Lintner 1965; Mossin 1966.)

The starting point of the CAPM is the equality between all of the investors. There are nine assumptions to be made that the model is being simple enough to build.
The assumptions are (Nikkinen 2002: 68-69.):

1. There are no transaction costs. It is possible to buy and sell stocks free of charge. Without this assumption the return of the stock would be dependent on whether the investor bought the stock before or after his investment decision.
2. Investment objects are divided into minimal parts.
3. There are no taxes.
4. Investors cannot influence investment object prices when they buy or sell them.
5. Investment decisions are based on portfolio theory.
6. Short-selling is allowed. Investors can sell stocks that they don't own.
7. The price for lending money is the risk-free interest.
8. Investors have homogenous expectations. Maturity of the investment is the same for everyone.

9. All of the commodities are for sale, including human capital.

All of the securities in the (hypothetical) world form *the market portfolio* (M). Investors try to create their own portfolios, which correspond to the market portfolio. The amount of individual stocks in the market portfolio is the market value of the stock divided by the market value of all the stocks in the world. **Figure 2** presents the market portfolio, which is the best efficient risk-free-return portfolio on *the capital market line* (which consists of all efficient portfolios). (Nikkinen 2002: 58-65.)

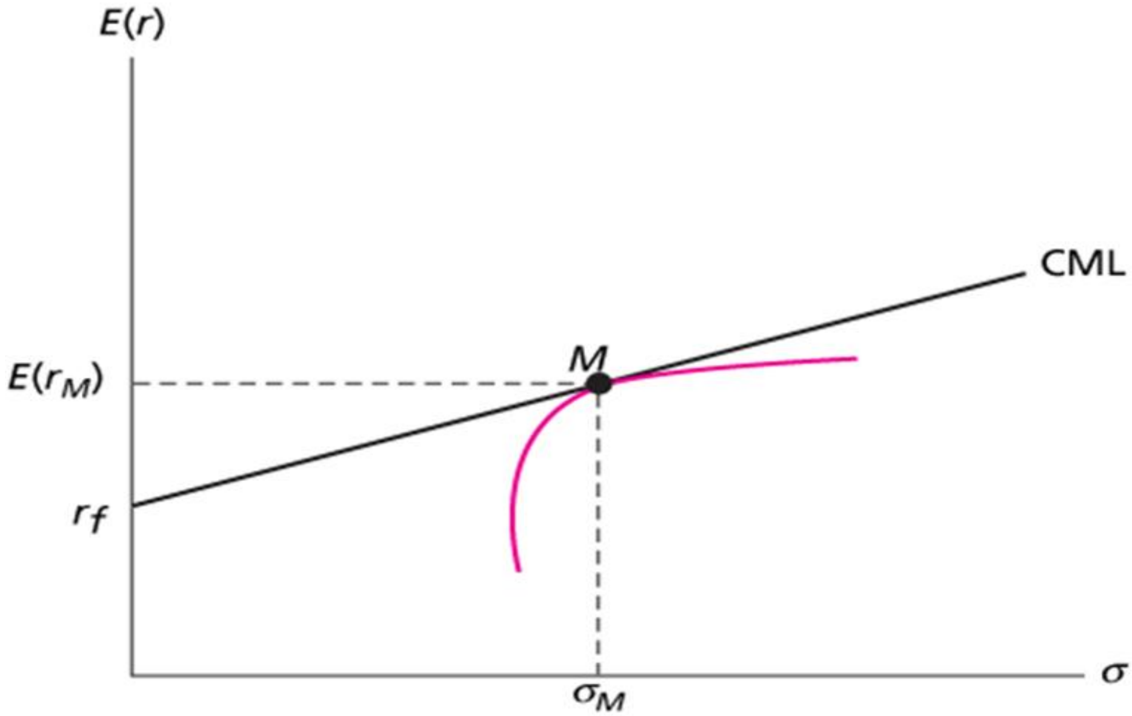

Figure 2. Capital market line and the market portfolio (Bodie et al. 2009:282.)

The CAPM determines the stock's expected return by its risk-level that is measured by *Beta*. Beta estimates the market risk of the stock and shows how much the stock returns change when the market portfolio returns change. Beta is calculated by dividing stock and market covariance by market variance.

(1) $$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)}$$

Where:

β_i	is the Beta of the stock i
$Cov(r_i, r_m)$	is covariance of stock i and market portfolio m
$Var(r_m)$	is the variance (σ^2) of the market portfolio

Beta measures the systematic risk of the stock. Systematic risk cannot be eliminated by diversification. Only company-specific risk is possible to abrogate by right diversification of stock portfolio. (Markowitz 1952.) The CAPM states that stock return exceeds risk-free return of the asset by risk premium. When market risk premium is multiplied by stock's Beta, the risk premium of the stock is obtained, and when the stock's risk premium is combined with risk-free return, the expected return of the stock is derived. Thus, the CAPM is as follows (Nikkinen et al. 2002:68-76.):

(2) $$E(r_i) = r_f + \beta_i \left[E(r_m) - r_f \right]$$

Where:

$E(r_i)$,	is the expected return of the stock.
r_f,	is the risk-free rate of interest. For example (in real world) interest rate of Finnish government bond.
β_i,	is the systematic risk of the stock.
$E(r_m)$,	is the expected return of the market.
$E(r_m) - r_f$,	is the market premium (Difference between expected return of the market and the risk-free rate).
$E(r_i) - r_f$,	is the risk premium.

Risk premium $E(r_m) - r_f$ of the market portfolio and its volatility σ_m determine the investor's individual willingness to take a risk. The equation of the CAPM forms the *security market line*, which is presented in **figure 3**. All of the correctly priced securities are on the security market line. Under the line are overvalued stocks and above the line are the undervalued stocks. The beta of the market is one. If the stock's beta is 2 its stock price deviation is twice the market's deviation. (Nikkinen 2002: 68-76.)

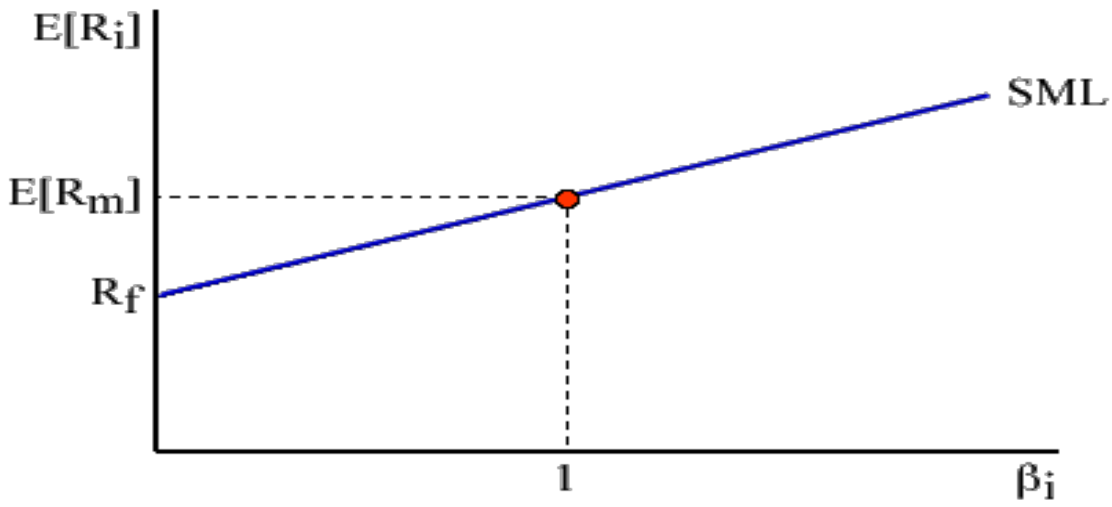

Figure 3. Security market line (Nikkinen et al. 2002: 71.)

4.1.1. Abnormal returns

Abnormal returns (AR) are returns that the CAPM cannot explain. Returns are higher than the expected returns that CAPM estimates. Thus, abnormal returns are actual realised returns minus expected returns. If the sum is positive, there are abnormal returns generated. Cumulative abnormal return (CAR) is the sum of all abnormal returns. CARs are usually calculated in days, because prior research has suggested that compounding daily abnormal returns can create a bias in the results. (Brown & Warner, 1985)

John Y. Campbell & Andrew W. Lo & Craig A. MacKinlay (1997) presented a 7-step analysis for event study evaluation. First, the event of interest and the event-test period (event window) are to be defined. The second step is to select criteria for the inclusion of given security in the study. The third step is to measure expected returns and abnormal returns. The abnormal return is the actual post-return of the security over the event window minus the expected return (CAPM) of the security. The expected return is the return that would realize if the event did not happen. (Step 4) When the performance model has been chosen, the parameters must be estimated by using a subset of the data known as the estimation window that is the period prior to the event window (the event window is not included to the estimation window, so that the event would not cause errors in the normal performance model parameter estimates). (step 5) This step determines the testing framework for abnormal returns where the null hypothesis and techniques for aggregating ARs of the stock are to be defined. In the sixth step the empirical results are presented. The seventh and the last step include interpretation and conclusions. The empirical results will demonstrate the event's impact on security prices. (Campbell, Lo & MacKinlay 1997.)

4.2. Arbitrage pricing theory

Arbitrage is a situation where it is possible to make profit without risk. It could be made by buying a security Z from market A at price x and then selling the same security to market B at a higher price y. This would not be possible if the markets were efficient. In the real world, these price variances disappear quickly between markets when investors use arbitrage opportunities. (Bodie ym. 2009: 325.)

Stephen Ross (1976) developed the *Arbitrage pricing theory* (APT). The basic assumption of the APT is that investors would want to increase their portfolios' returns if it could be done without increasing the risk. This model tries to find under-priced assets on the markets and take advantage of arbitrage. The model specifies simultaneously affecting variables (interest-rate, Gross domestic product growth, war in Iraq (an oil stock)) to the asset, which follows the equation (Nikkinen et al. 2005: 76-77; Ross 1976.):

(3) $$r_i = E(r_i) + \beta_{i1}F_1 + \beta_{i2}F_2 + \ldots + e_i$$

Where:

$B_{i1}F_1$	$B_{i2}F_2$	are prescribed factors multiplied by the per-share sensitivities.
e_i		is company-specific noise.

The basic idea is to model stock pricing without assumptions. The model presumes that the markets are not working efficiently.

4.3. Three-factor model

The arbitrage pricing model does not contain information about the amount of factors or which specific factors should be used when pricing stocks. Eugene F. Fama & Kenneth R. French (1996) concluded that a company's size and book-to-market ratio are the most important company-specific factors that impact stock returns. These factors and market risk premium form the *Three-factor model.* The model calculates stock returns and the equation is formed as below (Fama & French 1996.):

$$E(r_i) - r_f = \beta_i[E(r_M) - r_f] + s_i E(SMB) + h_i E(HML) \quad (4)$$

Where:

$\beta_i[E(r_M) - r_f]$ is the risk premium multiplied by systematic risk.

$s_i E(SMB)$ is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (SMB, small minus big) multiplied by (s_i) sensitiveness of the return to the factor (SMB).

$h_i E(HML)$ is the difference between the return on a portfolio of high book-to-market stocks and the return on portfolio of low book-to-market stocks (HML, high minus low) multiplied by (h_i) sensitiveness of the return to the factor (HML).

4.4. Valuation models

This chapter presents three essential models used generally in stock valuation.

4.4.1. Dividend discount model

The series of valuation models began when Williams (1938) introduced the dividend discount model (DDM). (Penman 1998:304.)

In the dividend discount model the value of the stock is the cash flow that a company generates in the future. Shareholders receive their part of the company's cash flow as dividends. Thus, it is possible to evaluate the stock price by discounting the future dividends by yield to present value. This model presumes that dividend flow is eternal. It does not take into account the cash flow that the company's earnings generate. For example, growth companies that do not pay dividend would be worthless if valuation was carried out applying this model. (Beneda 2003: 248.) The model is a solid tool for valuating a stock when a company has a solid history as a dividend payer. (Foerster &

Sapp 2005: 56–72.) Equation 5 presents the dividend discount model. (Barnes 2009: 29-32)

(5) $$V_o = \frac{D_1}{(1+r_e)^1} + \frac{D_2}{(1+r_e)^2} + \frac{D_3}{(1+r_e)^3} + \ldots + \frac{D_n}{(1+r_e)^n}$$

Where:

V_o	is the intrinsic value of the share now.
r_e	is the required rate of return of the shares by investors.
n	is infinity.
D_n	are the dividend payments (t = 1, 2, 3…..n years).

Another problem with the model is that it requires predicting dividend yield to infinity and predicting is difficult even just in the next few years. (Penman 1998: 304) Even slight errors in predictions cause large deviations in the results. Dividend discount models usually give unrealistic expectations of the dividend policy that a company exercises. (Dechow, Hutton & Sloan 1999: 32.)

Gordon (1962) found a model for stock evaluation that assumes the dividend yield to increase steadily in the future. The model is a good valuation tool when a mature and solid company is evaluated. It applies if the dividend is smaller than the required return of investment. Gordon growth model is presented in equation 6. (Barnes 2009: 29-32)

(6) $$P_0 = \frac{D_1}{r-g}$$

Where:

P_0,	is the stock price
D_1	is dividends at the end of first year
r,	is the required rate of return
g,	is the expected constant growth rate of the dividend

4.4.2. Discounted cash flow

Discounted cash flow (DCF) is implemented by estimating the total value of future cash flows, including inflowing and outflowing cash. Then cash flows are usually discounted using the required rate of return to present value. The aim is to estimate the total value of cash that the investment generates during the investment period. If the value of cash is higher than the cost of investment the investment is profitable. It is said that the DCF model is the most accurate model for valuating a company. One of the most commonly used DCF models is net cash flow, because it represents the cash that is possible to be distributed to equity owners without threatening or intervening with future operations. (Foerster & Sapp 2005: 48–49; Hitchner 2010:131-144.) There are two ways to estimate the net cash flow and it can be estimated to the equity shareholders and to invested capital (calculations below) (Hitchner 2010:131-133.)

Net income after tax
+ depreciation, amortization, and other non-cash changes
- incremental working capital needs
- incremental capital expenditure needs
+ new debt principal in
- repayment of debt principal
= net cash flow direct to equity

Net income after tax
+ interest expense
+ depreciation, amortization and other non-cash changes
- incremental capital expenditure needs
- incremental ”debt-free” working capital needs
= net cash flow to invested capital

Cash flow to invested capital is also known as free cash flow. Cash flow calculations preclude debt principles payment and interest expense, and thus it is a debt-free model. The method determines the value of invested capital that is typically equity, capital leases and interest-bearing debt. The invested capital method requires a suitable discount rate that as closely as possible corresponds to the cost of invested capital. Other discount rates are not applicable. (Hitchner 2010:131-133.)

When net cash flow is calculated, the present value of net cash is determined by the discount factor. Equation 7 demonstrates the discounted net cash flow model. (Hitchner 2010:131-144.)

$$PV = \frac{NCF_1}{(1+k)^1} + \frac{NCF_2}{(1+k)^2} + \ldots + \frac{NCF_n}{(1+k)^n} \tag{7}$$

Where:

NCF_n	is net cash flow (Expected future economic income in the n^{th} or last period in which an element of income is expected NCF 1, 2, etc. is the first, second and so on expected future economic income for each period before n^{th} period (or year)).
PV	is the present value of net cash flows.
k	is the discount rate.

4.4.3. Price-to-earnings ratio

Price-to-earnings ratio (P/E ratio) is the most commonly used method for evaluating stocks. (Demirakos, Strong & Walker 2004.) Francis S. Nicholson (1960) was the first one who investigated the P/E ratio. He concluded that low P/E ratio (below 10) stocks (value stocks) generated more profit than high P/E ratio (over 10) stocks (growth stocks) over time. S. Basu (1977) 17 years later investigated the same phenomenon and his findings support Nicholson's (1960) study. He also concluded that low P/E ratio stocks outperform high P/E ratio stocks.

P/E ratio indicates how the market rates the company and its future earnings. The higher the P/E ratio is, the more eager investors are to pay for the company's future earnings. P/E ratios vary within industries. Thus it is stated that P/E ratios between companies should be compared within industry and not over the industry. P/E ratio calculates how many years it takes for the company to pay back the invested money for a share. Equation 8 demonstrates the P/E ratio. (Barnes 2009: 26-29.)

$$\text{P/E ratio} = \frac{P}{EPS} \tag{8}$$

Where:

P	is market price of the stock.
EPS	is earnings per share.

4.5. Stock returns in Finland

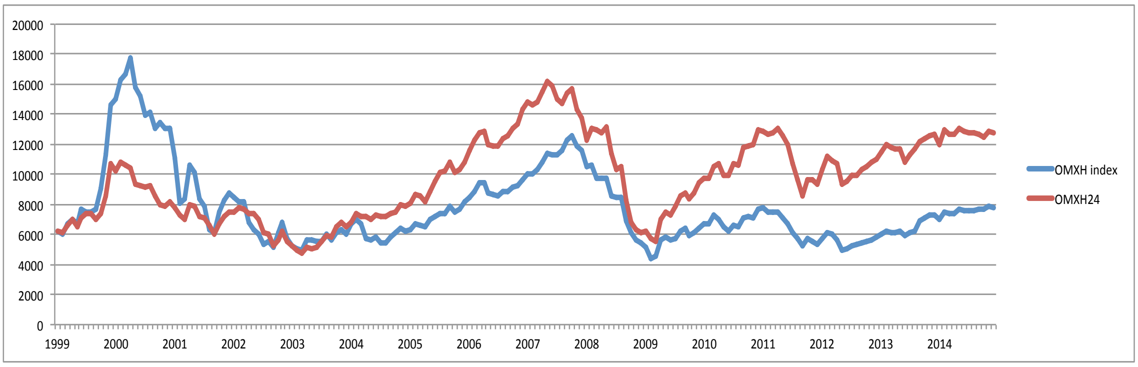

Figure 4. Development of OMXH and OMXH24

Figure 4 represents the stock prices of OMXH and the OMXH24 indexes. It can be noted that the stock market in Finland develops in cycles. There ha been peaks in 2000, 2007-2008 and 2011.

Figure 5. Annual returns of OMXH and OMXH24

The **figure 5** Illustrates the annual returns of OMXH and OMXH24. The returns have been the highest during the dotcom bubble in 1999 and 2009 just prior the GFC. The average annual returns for the period of OMXH and OMXH 24 are 6% and 12% respectively. The large-cap stocks have a much higher returns compared to the overall average. This may be explained by that the larger companies also do business globally and therefore are more resilient during economic downturns.

5. ANALYSTS' LITERATURE REVIEW

For years, researchers have been interested in whether analysts are able to affect stock returns with their recommendations. If they are, they break the efficient market hypothesis. When testing the *strong form* of the efficient markets, it is researched whether some investors or groups have monopolistic rights to private information, which might impact stock prices. (Fama 1970.) The difference between public and private information is hard to define and analysts use both. They obtain private information by visiting companies, having special relationships to companies and personnel or conducting their own views ("private insight") from public information. (Dimson & Marsh 1984: 1258) This chapter presents the analysts' role in the capital markets, their valuation methods, forecasting accuracy, behavioral biases and previous studies related to their recommendations' impact on stock returns.

5.1. Who are the analysts?

Why do the brokerage houses spend money on stock analysis? The analysts' stock valuation is based on information and generally used valuation models. The efficient market hypothesis concludes that it shouldn't be possible to find new information about a stock because the stock prices should reflect all available information (Fama 1970). Despite the efficient market hypothesis, brokerage houses spend hundreds of millions of dollars every year to analyse stocks in order to prove to investors that some stocks are better (worse) than others. (Womack 1996:138.) Because operators on the capital market are paying for the recommendations and forecasts, which the analysts produce, the information is concluded to be valuable for investors. (Brown & Rozeff 1978.) The critical questions answered in this chapter are how the analysts manage to create investment value with their opinions, and how their recommendations impact on stock returns.

Analysts are operators on the financial market who produce new information for investors. They are responsible for almost all of the new research done on the capital markets. In the produced information analysts try to forecast what is going to happen on the markets in the future. Companies' earnings forecasts, reports on specific companies, and sector and industry analysis are examples of the information the analysts produce. Based on these future forecasts, analysts make stock recommendations. Usually there are five levels of stock recommendations, which are *Sell, Underperform, Hold, Buy* and *Strong Buy*. In addition to recommendations, the analysts give target prices on specific stocks. The target price duration is generally 12 months, but it could also be 1, 3, 6 or 24 months. (Dimson & Marsh 1984: 1257.)

Analysts' recommendation levels indicate their own opinion about the firm's value. Recommendations express their expectations about the stock's near-term (usually 12 months) return performance. High recommendations (Buy, Strong Buy) indicate that the stock is undervalued on the market and the expected return of the stock is higher compared to other stocks. Low recommendations (Sell, Underperform) suggest that the stock is overvalued and future earnings will be lower compared to other stocks. (Jegadeesh, Kim, Krische & Lee 2004.)

Analysts generally concentrate on one industry and make recommendations within the industry on approximately 20 stocks. The amount of economical information has increased during past years. This has forced analysts to become so-called specialists in relatively small areas on the stock market, thus covering only a small segment of the stock market. (Nandelstadh 2003: 1.)

Hemang Desai (2000) concluded that analysts who are able to create solid personal relationships to their clients are highly valued. On the other hand, he suggested that if analysts' forecasts are continuously wrong, they are never seen as "good" analysts. Therefore their recommendations cannot be used for investment decisions. There are two different analyst types operating on the market: buy-side analysts and sell-side analysts. Buy-side analysts work for asset management companies and make internal recommendations and forecasts exclusively to money managers. There is little research done on buy-side analysts. (Yingmei, Liu, & Qian 2006.) Sell-side analysts are employed by brokerage firms and provide research for the firm's brokers and clients. The public also have access to their earnings forecasts and stock recommendations. Therefore it is suggested that sell-side analysts' research has investment value. (Elton, Gruber and Grossman 1986, Stickel 1995, Womack 1996, Barber Lehavy, McNichols and Trueman 2001 and Li 2005.) This thesis deals only with sell-side analysts' recommendations.

Analysts produce earnings forecasts, target price forecasts, stock recommendations and qualitative reports of companies' prospects (3.1). Analysts also develop expertise (3.2) and in order to produce recommendations and future forecasts they analyze information from different sources, for example earnings and other information from SEC filings (proxy statements, periodic financial reports, industry and macroeconomic conditions along with management communications and other information). Investors then use the information that analysts produce to make trading decisions that affect market prices (3.3). If the capital markets are efficient, the market prices should immediately reflect all of the information. If not, the inefficiencies create analyst forecast errors and changes in stock prices that can be predicted (3.4). The analysts' decision process and research output depend on regulatory and institutional factors that vary over time and across countries (3.5). Analysts' economic incentives and behavioural biases must also be taken into account (3.6). At last, the research design issues that constrain the researcher's ability to observe the forces that ultimately drive market prices are created by the limitations associated with archival databases, econometric tools, and mathematical models (3.7). (Ramnath & Rock & Shane 2008.) **Figure 6** demonstrates the analysts' decision process and their research output.

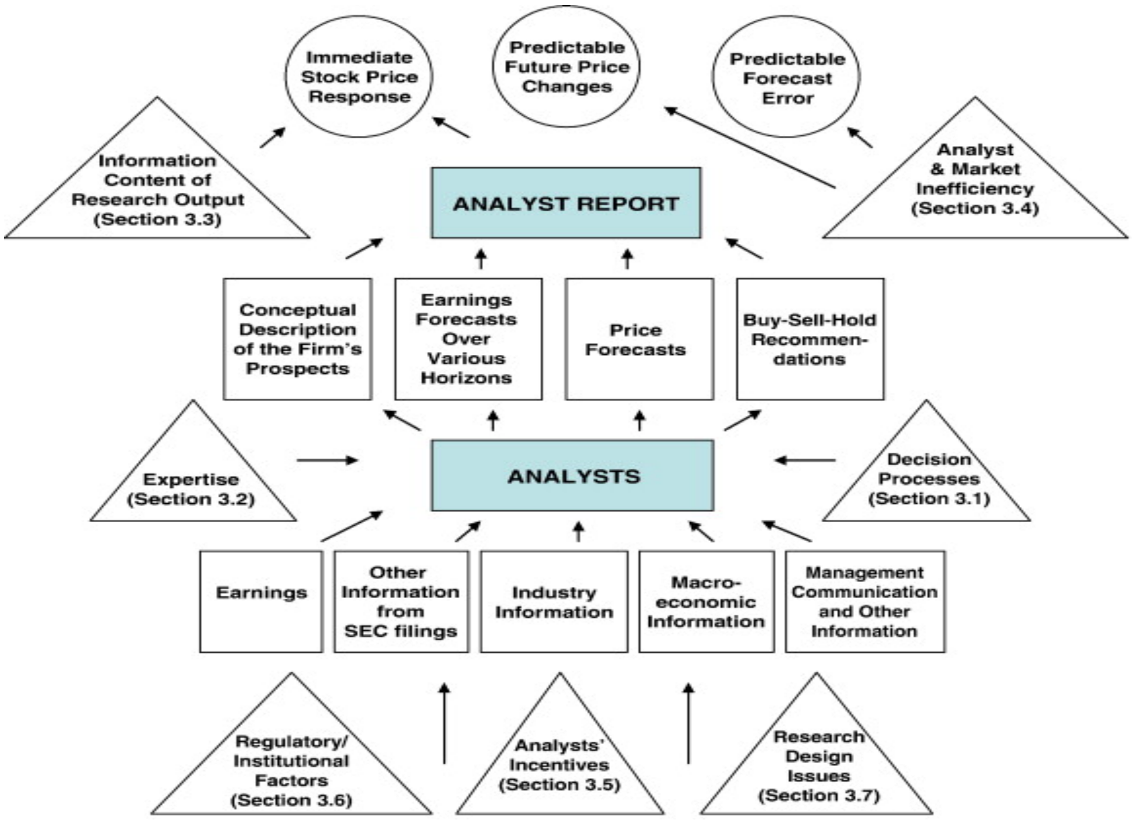

Figure 6. Analysts' decision making processes and research output (Ramnath & Rock & Shane 2008.)

5.2. How do the analysts forecast?

"Virtually all Wall Street (sell-side) analysts take an industry perspective in coming up with the valuations, including earnings estimates and recommendations, which they provide to investors." (Bodi & Womack 2006.)

Analysts use different stock valuation models in order to evaluate and determine the stock price. By this evaluation they are able to give stock recommendations. Most commonly used evaluation model for stock valuation among analysts was the Price-to-earnings ratio (P/E). It was also concluded that other approaches are important as well, for example the dividend yield. (Arnold & Moizer 1984.)

Richard G. Barker (1999) documented that the P/E ratio dominates dividend yield as a valuation model used by analysts for companies in the services, industrials and consumer goods stock market sectors, but the dividend yield dominates financials and utilities sectors. It was concluded that services, industrials and consumer goods stocks are "P/E valued" and financials and utilities stocks are "yield valued". This research suggests that the analysts choose their valuation models by the stock market sector, which they are analysing. (Barker 1999.)

Efthimios G. Demirakos, Norman C. Strong & Martin Walker (2004) researched the analysts' valuation methods. Their study material was obtained from 104 analysts' reports from international investment banks. Stock sectors analysed in reports were beverages, electronics and pharmaceuticals. Their study concluded that analysts use comparative valuation more in the beverages sector than in electronics or pharmaceuticals sectors. Analysts also use the P/E model or an explicit multi-period Discounted-Cash-Flow model (DCF) as their main valuation model, but there were no analysts who used the price to cash flow as main valuation model. A limited group of analysts who construct explicit multi-period valuation models used a comparative model as their dominant valuation model. It was also concluded, like earlier in Barker's (1999) research, that the analysts tailor their valuation models for the specific stock market sector, which they are analysing. (Demirakos, Strong & Walker 2004.)

Nancy L. Beneda's (2003) research suggests that analysts should pay more attention to the operative efficiency of a company in their valuations. Today, valuation is too strongly based on earnings and thus the use of free cash flows is recommended and justified. (Beneda 2003: 249-250.)

One of the most recent studies on analysts' valuation methods was conducted by Shamed Imam, Richard Barker and Colin Clubb (2008). They examined UK investment analysts' use of valuation models. Their study data came from interviews of 35 sell-side analysts from 10 leading investment banks, who provided 98 equity research reports for FTSE-100 companies, and 7 buy-side analysts from 3 asset management firms. They found that discounted cash flow (DCF) and other more complex models have become significantly more important than previous studies have suggested. They also suggest that "unsophisticated" valuation multiples, in particular the price-to-earnings ratio (P/E), have remained important. The technical applicability of DCF is rather limited, which causes analysts to rely on valuation multiples and their own subjective judgement. Consequently, the analysts rely on DCF on rare occasions when determining target prices and stock recommendations. Finally, it was concluded that the analysts' actual use of valuation models requires them to understand social and economic context and motivations, although the literature concentrates on technical merits of alternative valuation models. (Imam, Barker & Clubb 2008.)

Imam, Barker & Clubb (2008) also made a survey for 35 sell-side analysts to find out which valuation model they would prefer. Their survey suggests that the P/E and DCF models dominate. The economic value added (EVA) and the dividend discount model (DDM) were rated to be less important. Unsophisticated and accruals-based models were ranked important if they involved cash flow or earnings - if not, they were not relevant tools for analysts. In the other panel, Imam et al. (2008) collected the valuation models, which were used in equity reports (98 reports). They found that DCF was used in 49 reports out of 98. P/E was used in 45 and EV/EBITDA in 25. Results support the findings in research interviews.

5.3. Can the analysts forecast?

Alfred Cowles (1993) was the first one who studied the analysts' ability to forecast and the impact of their recommendations on stock returns. He concluded that the analysts' forecasting ability is poor and there is no impact on stock prices caused by their recommendations. John Cragg & Burton G. Malkiel (1968) concluded that analyst forecasts are not more accurate than the time series models and that BJ models produce more accurate forecasts than martingale and submartingale models. They also suggested that Value Line Investment Survey makes more accurate forecasts than the BJ and naive time series models. However, Brown & Rozeff (1978) studied the fact that brokerage houses are spending millions of dollars every year on stock analysis. They presumed that analysts must have superior capability to forecast returns. Their research indicate that analysts produce more accurate forecasts than time series models. (Brown & Rozeff 1978.)

Sanford Grossman and Joseph Stiglitz (1980) concluded that market prices do not reflect all of the information there is. If they did, the data gatherers couldn't get enough compensation for their expensive business. Money for data gathering comes from underwriting fees, trading profits, and commissions from securities trading. Therefore the brokerage company should be paid only if the expected return from the investment advice is worth as much as for the cost of the advice. A logical source of value for investors could be excess stock returns which are caused by the analysts' changes in stock recommendations. (Grossman & Stiglitz 1980.)

Many studies have been made about the analysts' capability to forecast, the accuracy of their forecasts and the value of their investment information. For example, Hemang Desai and Prem C. Jain (1995) analysed Barron's Roundtable recommendations for 24 years and received a result which concluded that investors do not benefit from analysts' advise. Michael B. Clement (1999) researched the reasons for the accuracy differences between different analysts' earnings forecasts. He used the I/B/E/S (Institutional brokers' estimate system) detail history database for his research and concluded that forecast accuracy is positively associated with the analysts' experience and the size of their employer. Experience here refers to surrogate for the analysts' ability and skill, and employer size refers to a surrogate for resources available. Forecast accuracy is negatively associated with the number of companies and industries followed by the analysts, which refers to task complexity. The results suggest that the characteristics of the analysts may explain the differences in the forecasting accuracy. (Clement 1999.)

Kent L. Womack (1996) concluded that the analysts' forecasting ability is based on the right timing and short-term stock picks when giving buy recommendations. Forecasting ability in Sell recommendations is based on right timing, short-term stock picks, and the right choice of industry. The Sell recommendations were much more accurate than buy recommendations. (Womack 1996.)

It is also relevant to ask, whose information should be trusted. There are huge differences between analysts. Age was found to be one factor. Harrison Hong, Jeffrey D. Kubik, and Amit Solomon (2000) argued in their research that older analysts were more accurate than younger ones in their forecasts. This supports Clements' (1999) research, which concluded that analysts experience affects the forecasting accuracy. Also, if the analysts' forecast accuracy was good in the past, it would positively affect their forecasting abilities in the future, findings are supported by Clement and Senyo Y. Tse (2005). They also argued that forecast frequency positively affected analysts' forecasting abilities.

Narasimhan Jegadeesh, Joonghyuk Kim, Susan D. Krische & Charles M. C. Lee (2004) noticed that quarterly change in consensus recommendations is a reliable return forecaster. Their research clarifies that the explanatory power of the change in analysts' consensus recommendation is stronger than that of the level of the recommendation. Changes in recommendations during the previous quarter explained the future returns, when used separately or in conjunction with other predictive signals. This research suggests that the return-relevant information contained in analyst recommendation changes does not correlate with other information. One explanation for this is that the recommendation change contains qualitative information (for example managerial abilities, strategic alliances, intangible assets, or other growth opportunities) that other signals do not. (Jegadeesh, Kim, Krische & Lee 2004.)

5.4. Analysts' behaviour studies

De bondt and Thaler (1990) suggest in their research that analyst forecasts are too optimistic and extreme, especially if the forecasts are made 2 years in the future. Therefore, they concluded that the markets are not rational. Jeffrey S. Abarbanell and Victor L. Bernard (1992) found that the reason for analyst forecasting errors is that analysts do not fully process the latest changes in earnings per share. They conclude that security analysts are more likely to underreact than overreact to news.

There had been concerns in financial press that a professional relationship between an analyst and an underwriting company creates overly optimistic investment recommendations. For example analysts from Morgan Stanley have stated that the bankers in Morgan Stanley have pressured them to alter negative research reports on the stocks of the firm's corporate clients, especially those for which it did stock underwriting deals. (Siconolfi 1992.) Hsiou-Wei Lina and Maureen F. McNichols's (1998) research compared earnings forecasts and recommendations from underwriter analysts, co-underwriter analysts and unaffiliated analysts. They concluded that underwriter and co-underwriter analysts' earnings forecasts and recommendations are more favourable than those of unaffiliated analysts but generally their near-term growth forecasts are not. Their findings also state that there are no differences in post-announcement returns associated with underwriter and unaffiliated analysts' recommendations. This indicates that it does not matter whether investors follow recommendations of affiliated or unaffiliated analysts. A significant difference was found in the *Hold* recommendation, which was interpreted as a more negative signal if the recommendation came from an underwriter rather than an unaffiliated analyst. (Lina & McNichols's 1998.)

John C. Easterwood and Stacey R. Nutt (1999) researched *overreaction* and *underreaction* among analysts. They assumed that if analysts systematically underreact to news, they act irrationally or continuously misinterpret the news. Misinterpretation also suggests that the analysts overreact to news. On the other hand, their continuous optimism implies that they underreact to negative earnings news and overreact to positive news. They found evidence of underreaction and overreaction in the capital market. Evidence was also found from analysts not being irrational and not revising their forecasts enough when the forecast news is negative. When the forecast news is positive, they increase their forecasts too much. (Eastwood & Nutt 1999.)

Francis Kim Hansog and Christos Pantzalis (2003) researched analyst *herding* between years 1980 and 1998. They concluded that the more diversified the company the analysts are analysing is, the more herding among analysts will occur. They also concluded that the harder the analysing job is, the more herding there is among analysts. Herding decreases the market value of the company evaluated. (Hansog & Pantzalis 2003.) Rick A. Cooper & Theodore E. Day & Craig M. Lewis. (2001) investigated the timing between analysts who herd and those who do not. They suggested that the lead analysts issue the most informative forecasts when forecast accuracy, stock price response or abnormal trading volume is used to identify informative forecasts. They also suggest that analysts who know they are not such good forecasters have a tendency to follow the forecasts of lead analysts. (Cooper, Day & Lewis 2001)

Douglas E. Stevens & Arlington W. Williams. (2004) found evidence in their research that suggests analysts to *anchor* to their own forecasts when they actually should revise them. Ling Cen, Gilles Hilary and John K. C. Wei (2013) concluded that analysts use the industry median forecast as an anchor. They implemented the study by interviewing six security analysts to find out, which valuation tools they would use to forecast earnings per share. Thus the amount of stocks of a company within an industry determines the factors for analysts' forecasts.

5.5. Analysts' recommendations and stock returns

Alfred Cowles (1933) made the first research about analysts. 45 professional agencies attempted to forecast the future movement of the stock market. The first part of the research dealt with the attempts of 20 fire insurance companies from year 1928 to 1931 and 16 financial services companies between years 1928 to 1932. They tried to foretell which stocks turn out to be the most profitable. The second part tested the foretelling skills of 24 financial publications. They attempted to forecast the future course of the stock market.

How did they manage? The first part's success was poor; only six of 16 financial services were successful. The average annual effective rate of all the services was -1.43 per cent. Only 6 out of the 20 fire insurance companies succeeded in foretelling. The average annual effective rate of the 20 fire insurance companies was -4.72 per cent. Return of the selected stocks was only 1.20 per cent. The foretelling success of the 24 financial publications was weak as well; only one third was successful. The research concludes that the analysts' forecasting skills were not trustworthy between years 1928-1932 and their recommendations didn't have significant effects on stock returns. (Cowles 1933.)

John D. Stoffels (1966) studied the short-term effect of analyst recommendations on stock prices and stock returns. He presumed in his research that Buy recommendations made by investment advisory service have an effect on the demand of individual stocks. It was also concluded that only the retail investors were responsible for the increase in demand of individual stocks. Professional and institutional investors wouldn't buy the stock just because of the analyst recommendations. They might get interested in the recommended stock but they would make more research and valuations about the stock before buying it. (Stoffels 1966.)

Stoffels (1966) concluded in his research that analyst recommendations have a positive effect on stock price for three or four days after the recommendation is published. In some cases the effect lasted even ten or eleven days from the announcement. There are many explanations for this phenomenon: for example, the investors' underlying confidence in the investment advisory service and enthusiasm to be in the market, which leads them to accept any recommendation just because they want to be in the game. Another explanation is that an investor is already interested in a certain stock and has valuated it. When an analyst makes a recommendation on the stock, it strengthens the investor's view and the stock is bought. (Stoffels 1966:85-86.)

Kent L. Womack (1996) studied the effects of the analysts' Buy and Sell recommendations on stock returns. Recommendations for his study were gathered from security analysts at major U.S. brokerage firms. Womack (1996) concluded that stock returns follow *post-announcement drift (post-recommendation stock price drift* in this case*)*. When an analyst publishes a buy recommendation, the stock immediately begins to generate abnormal returns and continues to increase to a level where the stock price is equal to the new information, which the recommendation included. The reaction is the same, but in the opposite direction, if it is a Sell recommendation that the analyst issues. (Womack 1996:138.)

Womack (1996) concluded the stock price reaction to be permanent and not quickly mean-reverting. This conclusion is the opposite of the one arrived at by Brad M. Barber & Douglas Loeffler (1993). Abnormal returns generated by Buy recommendations realized in one month (+2.4 per cent) but Sell recommendations returns realized in six months after recommendations were given (-9.1 per cent). Womack also stated that price-reactions in Sell recommendations were stronger than in buy recommendations. This all means that the investors *underreact* to the information when a new recommendation is given and that is the reason stocks continue to generate abnormal returns for several days after the announcement. Womack also found out that analysts issue Buy recommendations seven times more than Sell recommendations. Findings imply that the analysts are reluctant to give Sell recommendations. The reason for this is the cost of issuing recommendations; it is cheaper to make a Buy recommendation. (Womack 1996: 138.)

The consensus recommendation is formed by gathering all the recommendations (Buy, Sell, Hold) there are to a whole, and by identifying the main points of the recommendations. The recommendations are ranked from number 1 to 5 to correspond to the recommendation. Numbering technique of consensus recommendation is demonstrated below.

Sell (Strong Sell) = 5

Underperform (Sell) (4)
Hold = 3
Buy (2)
Strong Buy = 1

From the table we can calculate the consensus recommendation. If there are 3**Sell* + 4**Hold* + 3**Strong Buy,* the consensus recommendation would be (3*5+4*3+3*1) /10 = ***3* = *Hold***. The result is rounded to the closest integer, which means that the result only can be 1, 2, 3, 4 or 5. (Jegadeesh, Kim, Krische & Lee 2004: 1089-1093.)

Jegadeesh et al. (2004) researched the effect of analyst consensus recommendations on stock returns. Targets of the research were new and existing recommendations. They concluded that sell-side firms' analysts prefer so-called "glamour" stocks in their recommendations. Glamour stocks have positive momentum, high growth, high volume, and they are relatively expensive (High P/E). Recommended stocks correlate positively with momentum but negatively with contrarian. They also concluded that the recommendations add value only to value (low P/E) and positive momentum stocks. Among recommended glamour stocks, higher consensus recommendations are associated with worse future returns. One reason to this phenomenon could be that positive analyst recommendations might just help delay the eventual decrease of glamour stock price to the right fundamental price. (Jegadeesh, Kim, Krische & Lee 2004.)

One of the latest studies related to analyst recommendations' effect on stock returns is Moshirian, Ng & Wu's research on emerging markets. The research contained recommendation data, stock return data and accounting data from thirteen emerging countries from 1996 to 2005. They examined post-recommendation Buy and Hold abnormal returns. They concluded that (see Womack 1996 p. 34) recommended stocks reacted significantly and immediately when the recommendation was issued. Reaction continued for the next couple of days after the announcement. Observations were the same, whether there was a new recommendation issued or if there was a change in recommendation. Researchers presented some facts implying that investors could benefit from reacting immediately to the analyst recommendations and obtain abnormal returns. Abnormal returns in the emerging markets are generated because of the asymmetries in information. (Moshirian, Ng & Wu 2009: 82.)

Previously presented results were compared to same studies, which were made in G7-countires. The post-recommendation abnormal returns in emerging market countries were higher than in G7-countries. Therefore investors require higher risk-premium on emerging markets because they suffer from abnormal expenses, which are explained by information availability problems, liquidity problems and risks in the investors' safety. In emerging countries much more Buy recommendations than Sell recommendations were given. (Moshirian, Ng & Wu 2009.)

Moshirian et al. (2009) identified the Market-to-book (M/B) ratio to be the most important indicator in valuating stock recommendations. The higher the M/B ratio, the more valuable the recommendation is. The post-recommendation Buy-and-Hold abnormal returns correlate positively with the M/B ratio. It was also concluded that the analysts prefer positive momentum stocks in their recommendations. Researchers point out the fact that common factors in emerging markets such as law, transparency of the markets, economic development and the protection of the investors could affect the analysts' recommendations.

Roger K. Loh and René M. Stulz (2011) investigated when the changes in analyst recommendations are influential. They concluded that in *I/B/E/S, only 10 per cent of the recommendation changes are influential and 25 per cent of the analysts never make an impact to stock prices with their recommendations. They also concluded that a large impact causes a paradigm shift after a recommendation is issued. Investors might change their evaluation of a firm because of a change in recommendation. The study suggests that the influential recommendation change is more likely to come from analysts with larger leader-follower ratios, large brokers, away-from-consensus revisions, issued contemporaneously with earnings forecasts, and more experienced analysts. (Loh & Stulz 2011.)

*The I/B/E/S (International Brokers' estimate system) is a database of analyst earnings estimates. The database began to collect estimates in 1976 and ever since it has been used as a tool for researchers as they have tried to prove that it might be possible to gain abnorml returns by following analysts' forecast changes. Today the database is owned by Thomson Reuters. (Thomson Reuters 2013.)

5.5.1. Factors that impact stock price reaction

Scott E. Stickel (1995) made a function model about the impact analyst recommendations have on stock prices. He presented that the price reaction that followed the new analyst recommendation could be formed to a function. The function consists of the reputation of the analyst, the marketing ability of the brokerage house, the strength of the recommendation, differences in the information environments of the companies recommended, simultaneously issued earnings forecast revisions, and the magnitude of the change in recommendation. Functions are introduced more closely below.

The better the analyst's reputation is, the stronger the impact is on stock prices. To measure *the reputation of the analyst,* Stickel (1995) used Institutional Investor (II)'s All America Research Team list, where the analysts were ranked. The more the analysts received votes from treasurers, the better their rank was. Stickel's (1995) hypothesis assumed that the effect of the Buy or Sell recommendation given by an analyst on the All-America Research Team list was stronger than one given by an analyst not on the list. (Stickel 1995: 29.)

The marketing ability of the brokerage house means that the bigger the brokerage house is, the more sales persons they have. This implies that they also have a better marketing ability and they are able to assure investors of their superior stock recommendations. Now investors trust their recommendations and when they change their recommendation, the effect on stock prices is stronger. (Stickel 1995: 29.)

The strength of the recommendation means that is the underlying recommendation *Underperform* or *Sell* for example, where Sell is the stronger recommendation. *Underperform* means that the stock is slightly overpriced and *Sell* implies that the stock is strongly overpriced. Therefore, if an analyst gives an *Underperform* recommendation, the effect on stock price is not as strong as if the recommendation was *Sell.* If an analyst issues a *Strong Buy* recommendation, the effect on stock price is stronger than if the analyst gives a *Buy* recommendation. (Stickel 1995: 28.)

Differences in the information environments of the companies recommended affects the price reaction considering the fourth hypothesis that the smaller companies have bigger price reaction in *Buy* and *Sell* recommendations than bigger companies. It was concluded that the information is less relatively gathered and processed from small companies than big companies. Therefore new single information about small companies has a stronger effect on stock price. (Stickel 1995: 29.)

Stickel (1995: 30) found out from previous research that *simultaneously issued earnings forecast revisions* and stock recommendations both affect stock prices. For example, if there is a *Buy* recommendation given for a Nokia share, the recommendation causes a price reaction, but if there is a simultaneously issued positive earnings forecast revision on Nokia, it causes the price reaction to be stronger. This stated that if there is a positive recommendation standing but not a simultaneously positive (for example, negative) earnings forecast, the effect on stock prices is not as strong as if a positive earnings forecast was issued. (Stickel 1995: 30.)

The magnitude of the change in recommendation is measured in recommendation levels. When a stock's recommendation changes from *Sell* to *Buy*, the magnitude of the change in recommendation is 3 levels and if the change from *Underperform* to *Hold*, the change would only be one level. Stickel (1995) concluded that the three-level (*Sell*→*Buy*) "jump" has a stronger impact on stock price than a one-level (*Underperform*→*Hold*) "jump". (Stickel 1995: 28)

Stickel (1995) then concluded that the strength of the recommendation, marketing ability of the brokerage house and simultaneously issued earnings forecast revisions are related to permanent stock price change. These permanent changes are called *information effects*. In turn, the magnitude of the change in recommendation, the marketing ability of the brokerage house and the reputation of the analyst seem to only influence temporary price reactions.

5.5.2. Value Line studies

Value Line is one of the largest independent financial research companies in the world. It collects data and analyses approximately 8,000 stocks, 15,000 mutual funds, 80,000 options and other securities. The company has almost 80 years of experience in tracking, analysing and ranking securities. They publish a great deal of studies and reports but the most commonly known study is The Value Line investment survey, published weekly. It is a wide source of information and recommendations on approximately 1,700 stocks in 98 industries, the stock market and the economy. The basic idea of the survey is that it ranks the stocks by performance from 1 (the best) to 5 (the worst). Rank 1 stocks are expected to perform the best and rank 5 the worst in the next 12 months. There have been made multiple researches on The Value Line Investment Survey stock returns. (Value Line 2013.

Stickel (1985) investigated the stock's change in ranking on The Value Line Investment Survey and how it affects stock prices. He concluded that the change in ranking affects stock prices but the strength of the price reaction depends on the type of the change. Ranking change from rank 2 to rank 1 has the largest price reaction. A cross-sectional analysis finds that small-cap stocks have a stronger price reaction to the rank change than large-cap stocks. This finding supports theories on the frequency of report arrival and precision of information. A speed of adjustment test suggests that the prices of the securities adjust to the rank change information over a multiple-day period (see Womack 1996 p. 34). (Stickel 1985.)

James Choi (2000) researched the information produced by Value Line Investment Survey rankings and the performance of the stocks presented in the Survey from 1965 to 1996. He used time series and regression analyses and compared the rankings to benchmark portfolios corresponding to their size, book-to-market, and momentum characteristics. He found evidence that the Survey's recommendations, especially stocks ranked number 1 or 2, do perform better than the market. On the other hand, when he reduced the transaction costs from stock returns, it was doubtful whether there were any abnormal returns generated from the recommendations. The success of rank 1 and 2 stocks was caused by market friction, which prevents pricing errors to ameliorate. This conclusion suggests that small firms have the most market friction and that is why they realize a great amount of abnormal returns. Value Line Investment Survey's recommendations were not able to help investors to gain significant abnormal returns from large company stocks. (Choi 2000.)

5.5.3. Dartboard studies

The Wall Street Journal's "Dartboard" column, published monthly since 1988, contains stock recommendations from four analysts chosen by the paper. The recommended stocks are then compared to randomly picked stocks. Barber and Loeffler (1993) were the first ones to make research from Dartboard column's data to measure stock returns and trading volume behaviour from October 1988 to October 1990. They had two hypotheses to test. The first one was the *price pressure hypothesis*, which assumed that a Buy recommendation of a stock creates a temporary buy pressure among naive investors. This buy pressure then generates observed abnormal returns. Secondly, their *information hypothesis* assumed that analyst recommendations reveal new information about stocks and therefore the abnormal returns following recommendations suggest that the stocks should be re-evaluated.

Barber and Loeffler (1993) concluded that recommended stocks generated approximately 4.06 per cent abnormal return in two days post-recommendation (the day when a new recommendation was issued and the next trading day after the recommendation). Randomly picked stocks did not show any signs of excess returns in the same period. They also noticed that the price pressure of the recommended stocks reversed between second and the 25th day from the recommendation. During that time the stocks generated negative abnormal return of 2.08 per cent, while the randomly picked stocks generated none. (Barber & Loeffler 1993.)

This research suggested that stocks with the highest trading volumes on the day the recommendations were issued have the largest positive price reaction and later the strongest price decrease. This observation is in line with the price pressure hypothesis. Considering all the observations, Barber and Loeffler (1993) concluded that a certain type of investor buys stocks, which are recommended by analysts. This buy pressure leads to temporary increase in stock prices. Only a part of the stock's price increase is permanent, which suggests that the analyst recommendations do contain some new information. (Barber & Loeffler 1993.)

Bing Liang (1999) studied the "Dartboard" column's recommendations' impact on stock prices and whether the impact was short-term or long-term from January 1990 to September 1994. The data consisted of 208 buy recommendations and 8 Sell recommendations. The performance of these 216 stocks was then compared to that of 201 randomly picked ones. Market return was calculated using the daily stock prices announced by the Center for Research in Security Prices. Stock returns were followed over a six-month period. His research showed 3.52 per cent abnormal return 2 days after the recommendation was issued. Expert analysts with previous success in stock recommendations generated 5.34 per cent abnormal returns in the same period.

His study suggests that naive investors rely on successful and experienced analysts in their investment decisions. His findings support the price pressure hypothesis. Liang (1999) concluded that the price reaction is reversed between the second and the 15th trading day (see Barber & Loeffler 1993). He found that in a six-month period the cumulative abnormal returns were approximately 23.8 per cent. Finally, Liang (1999) suggests that there is information leakage on the market because just before the day the new recommendation is issued, the abnormal returns, cumulative abnormal returns and trading volumes are all positive.

5.5.4. Analyst recommendations investment strategies

Brad Barber, Reuven Lehavy, Maureen McNichols, Brett Trueman (2001) documented that buying (short-selling) stocks with the most (least) favourable analysts' consensus recommendations, combined with daily portfolio management and immediate response to recommendation changes generate over 4 per cent annual abnormal returns. Returns diminish with less frequent portfolio management and slow reaction to recommendation changes. The abnormal returns remain significant for the least favourably recommended stocks. They also documented that to execute analyzed strategies efficiently the recommended stocks in portfolio must have high trading volumes. (Barber, Lehavy, McNichols & Trueman 2001.)

There were two portfolios formed from analyst consensus recommendations. The first portfolio contained the most favourably recommended stocks and the second one contained the least favourable recommended stocks. When analysts changed their recommendations or issued new recommendations, the consensus recommendation of the stock was re-calculated and the stock was transferred to another portfolio if was necessary. The re-balancing of the portfolios was done in the end of each trading day. The most favourably recommended stock portfolio's return was 18.8 per cent and the least favourably recommended was 5.78 per cent. Capital balanced market portfolio made a total return of 14.5 per cent in the same period. Therefore the most favourably recommended stocks generated total of 4.17 per cent gross abnormal return when market risk, stock sizes, book-to-market ratio and price momentum were taken in concern. The effect was pronounced in small firms. (Barber, Lehavy, McNichols & Trueman 2001.)

Leslie Boni and Kent Womack (2006) investigated the analysts' ability to take industry into consideration in (Buy and Sell) stock recommendations. They concluded that analysts' ability to rank stocks within the industry creates value. Investment strategy that is based on industry improves the return-to-risk ratio significantly and diminishes the reversal of the stock price when comparing to portfolios, which do not exploit industry-based strategies. Investment strategy is implemented by buying stocks with buy recommendation and short-selling stocks with Sell recommendation within the same industry. This strategy generates approximately 1.23 per cent monthly return, which is 30 per cent more than strategies without exploiting the industry factor. Even after Fama & French (1996) risk-adjusted factors (Excess returns divided by returns' volatility) the abnormal returns monthly were 0.49 per cent. Returns were almost double compared to a portfolio that did not benefit from the industry-based strategy. (Bodi & Womack 2006.)

5.6. Summary of the literature review

Fama (1998) presented overreaction to be reason for unexplained stock price changes and the reverse of price changes over time. Barber & Loeffler (1993) and Liang (1999) study supports Fama's hypothesis. However, there also is evidence of permanent price changes caused by analyst recommendations, presented by Womack (1996) and Stickel (1995).

Overall, Value Line studies suggest that it is not possible to benefit from analyst recommendations. On the contrary, Dartboard studies suggest that significant abnormal returns are generated, but it is controversial whether the price reaction is reversed over time. Stickel (1985) concluded that there is a pattern determining whether the price reaction is permanent or temporary.

Barber et al. (2001) and Bodi & Womack (2006) studies indicate that it is possible to make money by fixedly following analyst consensus recommendations and their recommendations within industry. They documented evidence of abnormal returns generated.

There is prior evidence that analyst recommendations impact stock returns. It remains unclear whether the impact is permanent or temporary. However, there is indication that there is a price reaction and that analyst recommendations generate abnormal returns. Studies suggest that it is an anomaly that follows the so-called post-recommendation drift. Studies imply that the reason for the anomaly is underreaction to positive recommendations, overreaction to negative recommendations and the investors' delayed response to recommendations. There are also studies that simply conclude that analysts are superior forecasters and able to beat the market.

6. DATA

6.1. Sources and methods of collecting

The analyst recommendations that are used in this thesis are provided by Thomson Reuters database. The recommendations are gathered from 1999 to the end of 2014. This study is utilized on the basis of analysts' consensus recommendations and mean of target prices. Consensus recommendation is the recommendation mean of all of the outstanding recommendations from distinct banks or brokerage houses. The recommendation scale is as follows 1= Strong Buy, 2= Buy, 3= Hold, 4= Sell and 5= Strong Sell. Mean target price is the mean of all of the outstanding target prices there is for a certain stock given by analysts 12 months into the future.

This study covers 24 of the largest firms that are listed in the Helsinki stock exchange. The original data consisted of 25 of the largest companies, however, Valmet was dropped from the sample due to insufficient data from the past 15-year period compared to the others. Thus it could bias the sample. The below **table 1** presents the 24-largest companies which are under examination in this thesis.

Amer Sports	Konecranes	Outotec
Cargotec	Metso	Sampo A
Elisa	Neste Oil	Stora Enso
Fortum	Nokia	Teliasonera
Huhtamäki	Nokian Renkaat	Tieto Oyj
Kemira	Nordea Bank FDR	UPM-Kymmene
Kesko B	Orion B	Wärtsilä
Kone B	Outokumpu	YIT

Table 1. OMXH24 stocks

7. METHODOLOGY, APPROACH & MODEL

This study concentrates on examining is it possible to obtain statistically significant abnormal returns by following analyst recommendations of the 24 largest Finnish stocks on the Finnish stock market. This is investigated by constructing three portfolios Buy, Hold and Sell on the basis of analysts' recommendations, which are then updated monthly and benchmarked with OMXH and OMXH24 indices. The OMXH24 index is constructed by holding all of the 24 stocks in the "OMXH24" portfolio. The second object of examination is the shared characteristics of the stocks with the same recommendation to find whether these characteristics consciously or unconsciously impact analysts' recommendations. These characteristics are investigated with a regression analysis that consists of certain stock- and firm-specific figures and ratios. The basic regression model is constructed on the basis of Peltoniemi (2012).

7.1. Portfolio construction

In this study, the impact of analyst recommendations on stock returns is measured by long-term stock returns. On the basis of analysts' consensus recommendations, three distinct portfolios are constructed. The first portfolio "Buy" includes stocks, which have achieved a Strong Buy or Buy recommendation by receiving a consensus recommendation of $\overline{A}_{it} \leq 2$. The second portfolio includes stocks, which have received a Hold recommendation and a consensus recommendation equivalent to $2 < \overline{A}_{it} \leq 3$. The third portfolio holds stocks that have received a recommendation of Sell or Strong Sell with a consensus recommendation that is $\overline{A}_{it} > 3$. See Barber et al. (2001).

The consensus recommendations are available only on a monthly basis and thus a stock is added or kept in, or removed from the portfolio in the beginning of each month. Portfolios are brought up to date monthly if necessary, and the number of transactions are calculated for each month for every portfolio. The transaction costs are calculated on the basis of transactions made per portfolio. This study uses Nordea's quoted transaction costs in the beginning of 2015 for trades over 2500€, that is, 0,06% per trade. The consensus recommendation is illustrated mathematically below in **equation 9.**

(9) $$\overline{A}_{it} = \frac{1}{n_{it}} \sum_{j=1}^{n_{it}} A_{ijt}$$

Where $\overline{A}_{it}$ is the average of recommendations for a stock i at time t, n_{it} is the number of recommendations for stock i at time t and A_{ijt} is an individual recommendation for stock i at time t.

The returns of the portfolios are calculated monthly on the basis of the monthly cumulative returns of the stocks that are in each portfolio. **Equation 10** below presents how the monthly return of a portfolio is calculated mathematically.

(10) $$R_{pt} = \frac{1}{n}\sum_{i=1}^{n} Rit$$

Where R_{pt} is the monthly return of portfolio p, Rit is the monthly t return of a stock i and n is the number of stocks in the portfolio.

The returns of each portfolio (Buy, Hold and Sell) are benchmarked to the returns of the markets (OMXH and OMXH24). Thus, the return of the market R_{mt} is subtracted from the return of each portfolio R_{pt}. This gives out the abnormal return. This is demonstrated in **equation 11.**

(11) $$AR_{pt} = R_{pt} - R_{mt}$$

The statistical significance of the returns is examined with Jensen's alpha and market-model derived from CAPM. The returns of the portfolios and the returns of the market are then placed in the market-model regression after subtracting the risk-free interest rate (in this study, 1-month Euribor) from the returns of portfolios and return of the market that is. The significance of the results is examined by the p-values and t-statistics. Where the t-value of 2 implies significance at the level of 5%. The regression model is presented in **equation 12.**

(12) $$(R_{pt} - R_f) = \alpha + \beta(R_{mt} - R_f)$$

Where R_{pt} is the return of the portfolio, R_f is the risk-free rate that in this study is the 1-month Euribor, α is the intercept and illustrates the abnormal return, β is the beta of the portfolio and R_{mt} is the return of the market.

7.2. Characteristics of stocks with the same consensus recommendation

In the second part of the empirical research, stock-specific characteristics are examined with regression analysis. More specifically, this examination aims to determine, whether stocks with the same consensus recommendation share some characteristics and what these characteristics are. In addition the outlying interest is that do these characteristics consciously or unconsciously impact the analysts' recommendations. A basic model is applied on the basis of Peltoniemi (2012) and then 3 more models are applied by adding important factors to the regression model.

Examination is carried out with the data gathered from 1999-2014. The dependent variable in the regression is the abnormal return AR_{pt} . The independent variables that are in the basic model that is presented in **equation 13** are stock specific return on invested capital (ROIC), liquidity of each stock (LIQ), logarithm of market capitalization of each stock (LOGMCAP) and P/B ratio (PTB). This original regression is constructed on the basis of Peltoniemi (2012) because it has gathered the most basic stock-specific characteristics. In this thesis the model is extrapolated and examined with additional variables. The other regression models are constructed on the basis of the basic model by adding one other variable to each model to examine is there other stock specific characteristics that may increase the explanation for the abnormal returns.

(13) $$AR_{pt} = \beta_0 + \beta_1 ROIC_i + \beta_2 LIQ_i + \beta_3 LOGMCAP_i + \beta_4 PTB_i + \varepsilon_{it}$$

Where $ROIC_i$ is the return of invested capital of firm i, LIQ_i is the firm's cash and equivalents divided by the total amount of the firm i's current assets, $LOGMCAP_i$ is the natural logarithm of the market value of firm i and PTB_i is the market value of the firm divided by the book value of the firm.

ROIC describes the performance of the firm i and implicates how well a company generates cash flow in relation to invested capital. LIQ illustrates the financial distress of a company, thus if the figure diminishes or is small firm i experiences a shortfall in cash. Also the stock market capitalization was chosen to the regression in order to measure if the size of the company has an impact on the abnormal returns, and to find out whether the analysts prefer to pick large or very large companies.

The LOGMCAP describes the market capitalization of the stock and aims to identify, does the size of the company impact the abnormal returns in terms of information asymmetry and market liquidity. The P/B ratio describes the ratio between the stock's market price and its book value. On the basis of this, stocks are divided into growth stocks and value stocks. Growth stocks usually have a high P/B-ratio (over 1) because they are expected to experience large growth in the future. Value stocks are expected to pay dividends evenly and are expected to create moderate but certain value through profit. Value stocks usually have lower P/B ratio (under 1) than growth stocks. This coefficient indicates what kind of recommendations analysts prefer to issue for value and growth stocks.

(14)
$$AR_{pt} = \beta_0 + \beta_1 ROIC_i + \beta_2 LIQ_i + \beta_3 LOGMCAP_i + \beta_4 PTB_i + \beta_5 GFCDUMMY_i + \varepsilon_{it}$$

Equation 14 illustrates the regression model with GFCDUMMY. Where $GFCDUMMY_i$ is added in order to investigate the regression with the data that is considered as the post financial crisis period. The dummy achieves the value of 0 1999-2008 and a value of 1 from 2009 to 2014.

(15)
$$AR_{pt} = \beta_0 + \beta_1 ROIC_i + \beta_2 LIQ_i + \beta_3 LOGMCAP_i + \beta_4 PTB_i + \beta_5 ACCURACY_i + \varepsilon_{it}$$

Equation 15 represents the regression model where $ACCURACY_i$ is added to find out whether there is an impact also on the analysts' accuracy on the recommended stocks. The accuracy is calculated by subtracting the analysts' 12-month forecasted price at time t from the actual stock price at time t+12-months and then dividing the value by the actual share price at time t+12 months. Thus the absolute value of the figures is used in the regression. This regression is applied in order to investigate do the analysts' accuracy have impact on the abnormal returns and do they for example issue similar recommendations on some stocks on the basis of their past accuracy. This variable was added on the basis of Clement and Senyo Y. Tse (2005) findings that analysts past accuracy impacts their recommendations.

(16)
$$AR_{pt} = \beta_0 + \beta_1 ROIC_i + \beta_2 LIQ_i + \beta_3 LOGMCAP_i + \beta_4 PTB_i + \beta_5 LOGTURNOVER_i + \varepsilon_{it}$$

Above is the **equation 16**, where $LOGTURNOVER_i$ the natural logarithm of the trading volume of the stock is added to the basic regression model in order to research whether the trading volume impacts the abnormal returns of the portfolios. This variable is based on Barber & Loeffler's (1993) and Barber et al. (2001) findings, which indicate that the impact is only perceived on stocks with the highest trading volumes. Turnover (LOGTURNOVER) measures how traded the stock is on the market and indicates the trading volume of a stock. Thus, it gives information about what kinds of recommendations analysts issue in terms of stock liquidity, in this case, whether they prefer stocks with high or medium liquidity. All of the coefficients are calculated on monthly basis.

8. RESULTS

This part deals with the empirical part of the thesis. There are two hypotheses constructed, which are tested and analysed statistically and empirically in this part. The first hypothesis examines that are the analyst recommendations beneficial in order to achieve statistically significant abnormal returns on the stock market before and after transaction costs by following the recommendations of the largest stocks in the Finnish stock market. This phenomenon is measured by the performance of three distinct portfolios. Thus, if the constructed portfolios generate statistically significant abnormal returns, it can be concluded that analyst recommendations include new information that the stock prices has not yet captured. Thus, it is possible to employ investment strategy in order to follow new information of the analysts in order to achieve abnormal returns. Results indicate whether it is possible to generate positive or negative abnormal returns by following analyst recommendations and to find out are the results statistically significant.

H1: By following analysts' recommendations it is not possible to achieve statistically significant abnormal returns.

The second hypothesis deals with stock characteristics and examines do the stocks with the same recommendation share some specific characteristics. In addition do these stock specific characteristics consciously or unconsciously impact the analysts' recommendations. Four distinct models are constructed in order to examine these impacts. The variables (characteristics) are aggregated in regression as monthly average of each portfolio. These averages are then used as explanatory variables in the regression in order to explain the abnormal returns of these portfolios. Thus, if one or more of these coefficients are statistically significant it can be deduced that this or these characteristics impact consciously or unconsciously on the construction process of analysts' recommendations. Then certain kind of stock returns can be expected on the basis of these characteristics.

H2: Stocks with the same consensus recommendation do not have similar stock specific characteristics with each other.

8.1. The portfolios are constructed on the basis of the analysts' consensus recommendations

This part presents the construction of the portfolios and their performance. The descriptive statistics of the portfolios are presented in **table 2**.

As mentioned in the limitations section, it is notable when comparing the portfolios with each other that portfolios with Buy recommendation have approximately 8 times fewer stocks on monthly average compared to hold-portfolios. The Buy portfolio remains the smallest for the whole period with the largest portfolio containing 6 stocks in September 2004 and on average they are 2 times smaller than Sell portfolio. The Largest Sell portfolio contained 13 stocks in March 2014 and the largest hold-portfolio contained 22 stocks in May 2008. The Hold portfolio is the largest every month during the sample period. Another significant observation is that there are no stocks in Buy and Sell portfolios during certain months. There are a total of 46 months without Buy recommendations and a total of 9 months without Sell recommendations in the sample. For example in 2013 there are not a single stock in omxh24 with buy recommendation. **Table 2** represents the annual average of monthly consensus recommendations and the total annual recommendations outstanding for each portfolio.

Year	Buy annual nro of recomm	Buy average of monthly recomm	Hold annual nro of recomm	Hold average of monthly recomm	Sell annual nro of recomm	Sell average of monthly recomm	Total
1999	25	2,08	169	14,08	21	1,75	215
2000	37	3,08	161	13,42	23	1,92	221
2001	38	3,17	176	14,67	14	1,17	228
2002	26	2,17	184	15,33	18	1,50	228
2003	15	1,25	174	14,50	40	3,33	229
2004	35	2,92	186	15,50	24	2,00	245
2005	22	1,83	203	16,92	41	3,42	266
2006	**46**	**3,83**	196	16,33	36	3,00	278
2007	25	2,08	209	17,42	54	4,50	**288**
2008	32	2,67	**235**	**19,58**	21	1,75	**288**
2009	9	0,75	193	16,08	86	7,17	**288**
2010	10	0,83	213	17,75	65	5,42	**288**
2011	33	2,75	201	16,75	54	4,50	**288**
2012	7	0,58	217	18,08	64	5,33	**288**
2013	0	0,00	189	15,75	99	8,25	**288**
2014	14	1,17	167	13,92	**107**	**8,92**	**288**
Total	374	1,95	3073	16,01	767	3,99	4214

Table 2. The annual average of monthly consensus recommendations and the total annual recommendations outstanding for each portfolio

The stock market cycles should also be taken into account when examining the given data set of the analysts' recommendations. In 2001-2002 the dotcom bubble caused a stock crash. As illustrated by **table 2** the number of buy recommendations decrease from 2001 to 2003 from 38 to 15. At the same time the number of Sell recommendations increase from 14 to 40. Hold portfolio remains almost unchanged.

The second significant phenomenon on the market was the global financial crisis. It was triggered by subprime loans in the United States that caused stock market crash in 2008-2009. In 2009 there were only approximately 0,75 Buy recommendations in each month and 9 for the whole year. The monthly average for Sell recommendations was 7,17 and there were 86 Sell recommendations outstanding. Also, Hold recommendations were the highest in 2008 for the whole sample period 1999-2014. On monthly average there were 19,58 stocks in the Hold portfolio and the total outstanding recommendations in 2008 were 235. This might indicate that also analysts foreshadow the financial crisis. The Buy recommendations were the highest in 2006 prior the global financial crisis with a total of 46 Buy recommendations outstanding.

However, the most interesting period is the European debt crisis during 2011-2013, which seems to have had a large impact to the year 2013. During that year there were zero stocks with Buy recommendation. However, there were a total of 99 stocks with Sell recommendation and 8,25 stocks on monthly average in Sell portfolio. Overall there was the smallest number of recommendations in 1999 with a total number of 215 and the largest amount of recommendation each year after 2007 totalling an amunt of 288.

Table 3 illustrates the standard deviation of the size of the portfolios in terms of recommendations. The standard deviation of the Hold portfolio is the largest with STD of 1,42, meaning that it experienced the largest changes in size compared to the other 2 portfolios. However the standard deviation of the Hold portfolio is only 0,37 stocks higher than buy-portfolio's and 0,14 stocks higher than Sell portfolio's. Thus, none of the portfolios experienced significantly higher volatility compared with each other. Buy portfolio experienced the largest STD of 2,1 in 2004 Hold portfolio in 2007 with STD of 1,98 and Sell portfolio in 2014 with STD of 2,43. The period after the European debt crisis might explain the large STD of the Sell portfolio in 2014.

Year	Buy annual std of the recomm	Hold annual std of the recomm	Sell annual std of the recomm
1999	1,38	1,61	0,92
2000	1,11	1,32	0,95
2001	0,69	1,37	0,80
2002	0,99	1,11	0,65
2003	0,92	0,96	1,31
2004	**2,10**	1,12	1,96
2005	1,21	1,80	1,71
2006	1,46	1,89	1,15
2007	0,64	**1,98**	1,89
2008	1,37	1,61	1,09
2009	0,60	1,66	1,46
2010	0,99	1,09	0,95
2011	1,30	1,23	1,04
2012	0,95	1,38	1,37
2013	0,00	0,83	0,83
2014	1,07	1,80	**2,43**
Average	1,05	1,42	1,28

Table 3. Annual standard deviation of the number of stocks in each portfolio

Table 4 below illustrates the annual returns of the constructed portfolios and the markets OMXH and OMXH24. OMXH24 is formed from all of the stocks under examination in this study. The list of the picked stocks was represented in the data part of this study.

Year	Buy monthly average	Hold monthly average	Sell monthly average	OMXH	OMXH24
1999	**64,63%**	37,38%	27,59%	**106,16%**	43,74%
2000	-6,94%	-8,82%	0,01%	-9,13%	-2,32%
2001	16,43%	10,35%	-24,86%	-23,10%	8,47%
2002	20,78%	-13,80%	-5,50%	-35,92%	-11,34%
2003	53,77%	22,58%	27,09%	7,10%	24,84%
2004	35,54%	23,10%	17,60%	6,07%	24,39%
2005	46,06%	33,03%	17,70%	28,15%	31,75%
2006	30,70%	30,17%	39,54%	17,31%	32,04%
2007	-1,97%	8,02%	-31,32%	19,46%	1,50%
2008	-93,27%	-67,22%	-81,23%	-71,57%	-67,89%
2009	18,18%	**54,80%**	**60,09%**	22,12%	**56,76%**
2010	11,23%	39,54%	18,78%	18,96%	33,68%
2011	-35,68%	-25,62%	-18,51%	-33,97%	-26,72%
2012	25,55%	17,41%	18,55%	9,64%	18,38%
2013	0,00%	24,90%	3,32%	24,43%	17,29%
2014	-5,00%	-2,21%	4,95%	6,11%	2,16%
Total	179,99%	183,60%	73,83%	91,82%	186,73%
Annual average	11,25%	11,47%	4,61%	5,74%	11,67%
monthly average	1,23%	0,96%	0,40%	0,48%	0,97%
Std	36,43%	28,99%	31,87%	37,13%	29,06%
return-to-risk	4,94	6,33	2,32	2,47	6,43

Table 4. Annual market and portfolio returns

It is notable that the highest and the lowest returns of each portfolio came from either during the dotcom bubble or during the GFC. Also in 2008 during the GFC the buy portfolio had the worst success by yielding the highest negative return during that time. All portfolios and the markets yielded a negative return in 2008 and also in 2011 during the European debt crisis.

Even though the hold-portfolio yielded the highest cumulative and average returns during the sample period it did not offer the highest returns every year. Buy portfolio offered the highest annual returns in 1999, 2001, 2002, 2003, 2004, 2005 and 2012. However the Sell portfolio offered the highest annual returns of the portfolios in 2000, 2006, 2009, 2011 and 2014. Also, none of the portfolios won the market in 1999 and 2007. It is quite interesting because both of those periods are a year prior to dotcom and subprime crisis. This might indicate that analysts tend to loose creditability on the edge of crisis periods.

In addition in 2014 buy-portfolio offered the worst return with -5%, hold-portfolio - 2,21% and surprisingly the Sell portfolio yielded a return of 4,95%. This might indicate of huge undervaluation of stocks that had received a Sell recommendation during European financial crisis and in 2014 they increased to their fundamental value. It might also be so that analysts can't forecast the right stocks to buy and Sell. The **figure 7** represents the annual returns graphically.

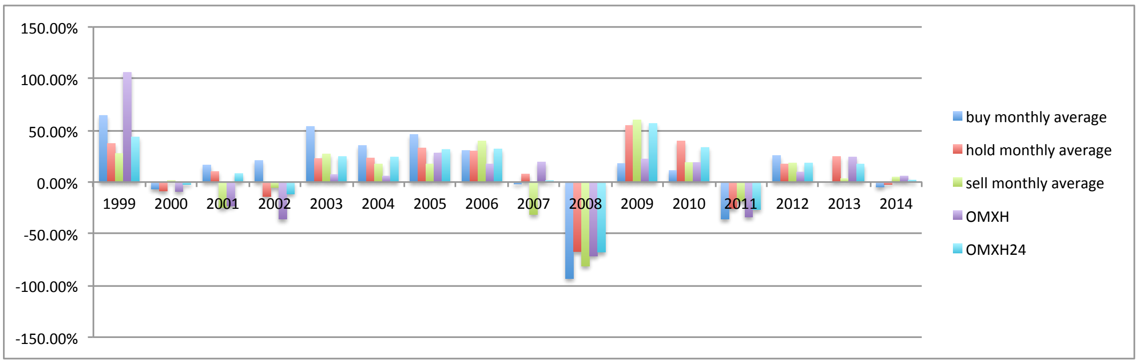

Figure 7. Annual market and portfolio returns

Buy portfolio has the highest standard deviation of 38,20% and the market has just a little less 36,43%. Hold portfolio has the lowest standard deviation 28,99% of the portfolios, however, OMXH24 has 29,06%. The OMXH24 index offered the highest return in terms of risk level and achieved the highest return-to-risk ratio 6,43 (total cumulative return/standard deviation). However, the Hold portfolio offered the second highest return-to-risk ratio of 6,33 that was also the highest out of the three portfolios. Surprisingly, the OMXH offered the second lowest return-to-risk ratio 2,47 making it the least attractive investment. Finally, the Sell portfolio had a return-to-risk ratio of only 2,32 and a total 15-year return of 73,83% making it the only portfolio that did not outperform the OMXH. **Table 5** illustrates the returns of each portfolio and key ratios after adjusting for trading costs.

Year	Buy-tc monthly average	Hold-tc monthly average	Sell-tc monthly average	OMXH	OMXH24
1999	**63,85%**	35,64%	27,29%	**106,16%**	43,74%
2000	-7,36%	-9,84%	-0,47%	-9,13%	-2,32%
2001	16,19%	9,69%	-25,34%	-23,10%	8,47%
2002	20,30%	-14,76%	-5,98%	-35,92%	-11,34%
2003	53,29%	21,68%	26,55%	7,10%	24,84%
2004	34,82%	21,72%	16,88%	6,07%	24,39%
2005	45,40%	31,05%	16,38%	28,15%	31,75%
2006	29,80%	28,19%	38,40%	17,31%	32,04%
2007	-2,63%	5,92%	-32,76%	19,46%	1,50%
2008	-94,11%	-69,20%	-82,31%	-71,57%	-67,89%
2009	17,94%	**52,94%**	**58,47%**	22,12%	**56,76%**
2010	10,87%	37,98%	17,58%	18,96%	33,68%
2011	-36,88%	-27,48%	-19,29%	-33,97%	-26,72%
2012	25,13%	15,91%	17,47%	9,64%	18,38%
2013	0,00%	23,58%	2,06%	24,43%	17,29%
2014	-5,42%	-3,83%	3,69%	6,11%	2,16%
Total	171,17%	159,18%	58,65%	91,82%	186,73%
Annual average	10,70%	9,95%	3,67%	5,74%	11,67%
monthly average	0,89%	0,83%	0,31%	0,48%	0,97%
Std	36,49%	28,99%	31,83%	37,13%	29,06%
return-to-risk	4,69	5,49	1,84	2,47	6,43

Table 5. Portfolio returns post trading costs

In **table 6** is presented the difference between each portfolio and two market benchmarks OMXH and OMXH24, which are calculated on monthly basis. The buy-portfolio has outperformed the OMXH during 8 years out of 15 and OMXH24 in 7 years. However the hold-portfolio outperformed the market OMXH24 during 7 years and OMXH during 13 years. Sell portfolio outperformed OMXH and OMXH24 during 8 years. We find that buy –and hold-portfolios did beat the OMXH index, however when benchmarked with OMXH24 the results change and only none of the portfolios outperformed the OMXH24-index. Hold –and Sell portfolios yielded their highest annual abnormal returns in 2001 and buy-portfolio in 2002 when benchmarked with OMXH. The post Tech bubble period would explain why the highest abnormal returns are concentrated in 2001-2002. However when benchmarked with OMXH24 the buy-portfolio yields the highest return also in 2002, hold-portfolio in 2013 and Sell portfolio in 2011. On average the hold-portfolio had the highest absolute average return monthly and annually out of the three portfolios. All of the portfolios performed poorly and yielded a negative return from the 15-year period when benchmarked with omxh24.

Year	Buy-omxh	Hold-omxh	Sell-omxh	Buy-omxh24	Hold-omxh24	Sell-omxh24
1999	-41,53%	-68,78%	-78,57%	20,88%	-6,37%	-16,16%
2000	2,19%	0,31%	9,14%	-4,62%	-6,50%	2,33%
2001	39,53%	**33,45%**	-1,75%	7,96%	1,87%	-33,33%
2002	**56,70%**	22,12%	30,42%	**32,12%**	-2,46%	5,84%
2003	46,67%	15,48%	19,99%	28,93%	-2,25%	2,26%
2004	29,47%	17,02%	11,53%	11,15%	-1,29%	-6,79%
2005	17,91%	4,88%	-10,45%	14,31%	1,28%	-14,05%
2006	13,39%	12,86%	22,23%	-1,34%	-1,87%	7,50%
2007	-21,43%	-11,44%	-50,77%	-3,48%	6,52%	-32,82%
2008	-21,70%	4,35%	-9,65%	-25,38%	0,67%	-13,33%
2009	-3,94%	32,68%	**37,97%**	-38,59%	-1,96%	3,33%
2010	-7,72%	20,58%	-0,17%	-22,45%	5,86%	-14,89%
2011	-1,71%	8,35%	15,46%	-8,96%	1,10%	**8,21%**
2012	15,91%	7,77%	8,91%	7,17%	-0,97%	0,17%
2013	-24,43%	0,46%	-21,11%	-17,29%	**7,61%**	-13,96%
2014	-11,11%	-8,32%	-1,16%	-7,16%	-4,37%	2,79%
Total	88,17%	91,78%	-17,99%	-6,73%	-3,13%	-112,90%
Annual average	5,51%	5,74%	-1,12%	-0,42%	-0,20%	-7,06%
monthly average	0,46%	0,48%	-0,09%	-0,04%	-0,02%	-0,59%
Std	26,87%	22,87%	28,70%	19,12%	4,06%	12,94%
return-to-risk	3,28	4,01	-0,63	-0,35	-0,77	-8,73

Table 6. Annual abnormal returns of the portfolios

Year	Buy-tc-omxh	Hold-tc-omxh	Sell-tc-omxh	Buy-tc-omxh24	Hold-tc-omxh24	Sell-tc-omxh24
1999	-42,31%	-70,52%	-78,87%	20,10%	-8,11%	-16,46%
2000	1,77%	-0,71%	8,66%	-5,04%	-7,52%	1,85%
2001	39,29%	**32,79%**	-2,23%	7,72%	1,21%	-33,81%
2002	**56,22%**	21,16%	29,94%	**31,64%**	-3,42%	5,36%
2003	46,19%	14,58%	19,45%	28,45%	-3,15%	1,72%
2004	28,75%	15,64%	10,81%	10,43%	-2,67%	-7,51%
2005	17,25%	2,90%	-11,77%	13,65%	-0,70%	-15,37%
2006	12,49%	10,88%	21,09%	-2,24%	-3,85%	6,36%
2007	-22,09%	-13,54%	-52,21%	-4,14%	4,42%	-34,26%
2008	-22,54%	2,37%	-10,73%	-26,22%	-1,31%	-14,41%
2009	-4,18%	30,82%	**36,35%**	-38,83%	-3,82%	1,71%
2010	-8,08%	19,02%	-1,37%	-22,81%	4,30%	-16,09%
2011	-2,91%	6,49%	14,68%	-10,16%	-0,76%	**7,43%**
2012	15,49%	6,27%	7,83%	6,75%	-2,47%	-0,91%
2013	-24,43%	-0,86%	-22,37%	-17,29%	**6,29%**	-15,22%
2014	-11,53%	-9,94%	-2,42%	-7,58%	-5,99%	1,53%
Total	79,35%	67,36%	-33,17%	-15,55%	-27,55%	-128,08%
Annual average	4,96%	4,21%	-2,07%	-0,97%	-1,72%	-8,00%
Monthly average	0,41%	0,35%	-0,17%	-0,08%	-0,14%	-0,67%
Std	26,90%	23,02%	28,67%	19,08%	4,01%	12,97%
Return-to-risk	2,95	2,93	-1,16	-0,82	-6,88	-9,88

Table 7. Annual abnormal returns of portfolios when transaction costs taken into consideration

Table 7 Illustrates the abnormal returns of the portfolios after subtracting transaction costs from the portfolios returns and then the market returns were subtracted. Transaction costs are determined by first calculating the total monthly trades executed by each portfolio. Then I have used Nordea's trading costs for over 2500€ trades in the Nordics that were 0,06% for one trade. Thus, after calculating the monthly trades the trading costs are multiplied by the number of trades executed in that month and subtracted from the monthly portfolio returns.

The long-short portfolio was built based by allocating stocks with buy recommendation to be bought and stocks with Sell recommendation to be short sold. This means that if stocks with buy recommendation has a positive return the portfolio returns would increase and if Sell side has a negative return it also increases the overall portfolio return because I have shorted the stocks. This study does not take dividends, short-interest rebate nor other costs associated with short Selling into account. Only transaction costs are examined.

The below **table 8** shows that by holding stocks with buy recommendation and short Selling stocks with sel recommendation does not yield a higher return compared to buy and hold portfolios. However the long-short portfolio does exceed the returns of the Sell portfolio. It is also notable that the total transaction costs for the period stand at 24% that is high relative to other portfolios. The hedge portfolio also performs the best during the dotcom bubble in 1999-2001. On the other hand the performance is very poor during the GFC in 2009-2011.

Year	Long on Buy, short on Sell	Long on Buy, short on Sell - tc
1999	**41,54%**	**40,46%**
2000	-1,47%	-2,37%
2001	24,73%	24,01%
2002	18,68%	17,72%
2003	-14,02%	-15,04%
2004	19,51%	18,07%
2005	14,47%	12,49%
2006	0,78%	-1,26%
2007	17,48%	15,38%
2008	15,76%	13,84%
2009	-54,02%	-55,88%
2010	-14,70%	-16,26%
2011	-7,77%	-9,75%
2012	-7,07%	-8,57%
2013	-3,32%	-4,58%
2014	-7,22%	-8,90%
Total	43,36%	19,36%
Annual average	2,71%	1,21%
Monthly average	0,23%	0,10%
Std	21,24%	40,46%
Return-to-risk	2,04	0,48

Table 8. Hedge portfolio, long on Buy - short on Sell

Table 9 demonstrates the total annual trading costs experienced by each portfolio in order to follow recommendations. Buy-portfolio experienced the highest trading costs in 2011 with 1,20% while annual average being 0,55% and monthly average 0,05%. Hold portfolio experienced its top trading costs in 2007 being 2,10%, having an annual and monthly average of 1,53% and 0,13% respectively. Sell portfolio had the highest trading costs 1,62% in 2009 with annual average of 0,95% and monthly average of 0,10%. Global financial crisis would explain the high recommendation changes in 2009 thus causing large trading costs for Sell portfolio. I find the trading costs to remain at a low level, however, the Nordea's quoted trading prices might bias the trading costs because those costs were pobably much higher prior to the GFC.

Year	Buy	Hold	Sell	Long-Short
1999	0,78%	1,74%	0,30%	1,08%
2000	0,42%	1,02%	0,48%	0,90%
2001	0,24%	0,66%	0,48%	0,72%
2002	0,48%	0,96%	0,48%	0,96%
2003	0,48%	0,90%	0,54%	1,02%
2004	0,72%	1,38%	0,72%	1,44%
2005	0,66%	1,98%	1,32%	1,98%
2006	0,90%	1,98%	1,14%	2,04%
2007	0,66%	**2,10%**	1,44%	**2,10%**
2008	0,84%	1,98%	1,08%	1,92%
2009	0,24%	1,86%	**1,62%**	1,86%
2010	0,36%	1,56%	1,20%	1,56%
2011	**1,20%**	1,86%	0,78%	1,98%
2012	0,42%	1,50%	1,08%	1,50%
2013	0,00%	1,32%	1,26%	1,26%
2014	0,42%	1,62%	1,26%	1,68%
Total	8,82%	24,42%	15,18%	24,00%
Annual average	0,55%	1,53%	0,95%	1,50%
monthly average	0,05%	0,13%	0,10%	0,12%
Std	0,29%	0,43%	0,39%	0,45%

Table 9. Total annual trading cost of each portfolio

8.1.1. Regression analysis

The first empirical part identifies whether the abnormal returns of the portfolios are statistically significant or not. After the portfolio returns are cleared out, it is investigated are the portfolio returns random or is there a pattern how the returns are achieved. The portfolio returns are then regressed by using the **market-model** in order to investigate the statistical significance of the Jensen's alphas. The statistical significance is measured on 1%, 5% and 10% levels respectively. The regression results are presented in **tables 10** and **11.** In **table 10** OMXH and in **table 11** OMXH24 is used as benchmark.

Market-model	Intercept	OMXH	R^2	D-W
Buy	0,465***	0,531***	0,324	1,644
t-statistic	8,472	9,537		
Hold	0,402***	0,595***	0,578	1,520
t-statistic	11,053	16,134		
Sell	0,596***	0,392***	0,177	1,790
t-statistic	9,881	6,402		
	Significance level at	*10%	**5%	***1%

Table 10. Portfolios regressed on OMXH

Market-model	Intercept	OMXH24	R^2	D-W
Buy	0,166***	0,831***	0,469	1,786
t-statistic	2,617	12,983		
Hold	0,000	1,000***	0,965	1,954
t-statistic	-0,029	72,384		
Sell	0,079	0,914***	0,571	2,050
t-statistic	1,390	15,897		
	Significance level at	*10%	**5%	***1%

Table 11. Portfolios regressed on OMXH24

What is notable from the results when regressed on OMXH is that the alphas are all significant on 1%-level. Thus, implicating the results to be highly statistically significant. Thus meaning that the hypothesis (i) is rejected on the basis of all three portfolios when examining the alphas prior to subtracting trading costs. The intercept of Buy portfolio is 0,4655 and achieving an R-squared of 0,324. I find the results convincing on the part of Buy portfolio. The results on Hold portfolio are similar to Buy portfolio. The alpha is 0,402 and R-squared 0,578 implicating even stronger results than Buy portfolio. However Sell portfolio has the alpha of 0,596 and R-squared of 0,177. Low R-squared compared to others implicate that the model does not explain the returns that well. Durbin-Watson statistics implicate low autocorrelation levels by achieving values ranging from 1,52 to 1,79.

When the portfolios are regressed on OMXH24 only the Buy portfolio now remains significant on 1%-level with alpha of 0,166 and an increased R-squared of 0,469 compared to the previous results. The Hold and Sell portfolios are not statistically significant, however the R-squared of hold-portfolio has increased from 0,578 to 0,965 and Sell portfolio from 0,177 to 0,571. Meaning that the model now explains the alphas very well. Durbin-Watson statistics has also increased close to 2 indicating low autocorrelation levels.

Tables 12 and **13** illustrate the market-model regression results after subtracting transaction costs from monthly returns. As described by the tables, the results remain exactly the same. Thus, the hypothesis (i) is rejected even after trading costs. Results give a strong indication of the fact that it is possible to beat the market and achieve statistically significant abnormal returns by following the recommendations of large stocks.

Market-model	Intercept	OMXH	R^2	D-W
Buy	0,464***	0,532***	0,324	1,650
t-statistic	8,472	9,547		
Hold	0,401***	0,595***	0,577	1,521
t-statistic	11,017	16,101		
Sell	0,596***	0,392***	0,177	1,794
t-statistic	9,871	6,392		
Significance level at		*10%	**5%	***1%

Table 12. Portfolios regressed on OMXH after transaction costs

Market-model	Intercept	OMXH24	R^2	D-W
Buy	0,165**	0,832***	0,470	1,788
t-statistic	2,599	12,983		
Hold	-0,002	-0,125	0,965	1,960
t-statistic	-0,125	72,311		
Sell	0,079	0,913***	0,570	2,051
t-statistic	1,390	15,856		
Significance level at		*10%	**5%	***1%

Table 13. Portfolios regressed on OMXH24 after transaction costs

8.2. Stock characteristics of stocks within the same recommendation group, which may consciously or unconsciously impact analysts' recommendations

The second empirical part tries to assess whether the stocks with the same recommendation share some stock specific characteristics. Which is also the second hypothesis of this study H:2. This analysis is based on the fact that analysts' issue consciously or unconsciously similar recommendations for the stocks with the same kind of stock specific characteristics. Hence, these stock specific characteristics may hold information, which explain the abnormal returns generated by the portfolios. In addition, these characteristics may be applied in forecasting the performance of stocks with specific characteristics. Portfolios average key ratios are presented in **table 14**.

Coefficients	Buy	Hold	Sell
ROIC	14,440	11,959	11,294
LIQ	15,859	18,612	19,056
LOGMCAP	3,660	3,828	3,392
PTB	3,083	2,219	2,149
GFCdummy	2009-2014	2009-2014	2009-2014
ACCURACY	0,363	0,405	0,404
LOGTURNOVER	4,316	4,594	4,150

Table 14. Portfolios' average key ratios of the coefficients 1999-2014

Table 15 presents the results of the paired two sample of means t-test. 83% of the key-ratio differences between portfolios are highly significant indicating strong support on behalf of the coefficients. PTB (price-to-book) coefficient has the weakest significance between the portfolios, whereas turnover has the highest.

Coefficient	Buy-hold	Buy-sell	Hold-sell
ACCURACY	-7,082***	-3,951***	0,718
LIQ	-6,536***	-5,308***	1,759**
LOGMCAP	-10,508***	-7,028***	4,017***
ROIC	-2,065**	0,317	2,611***
PTB	0,526	1,306*	2,643***
LOGTURNOVER	-9,561***	-4,23***	7,977***
Significance level at	*10%	**5%	***1%

Table 15. T-test results of paired two sample for means for the differences between the portfolios' (Buy, Hold and Sell) key ratios

8.2.1. Regression analysis

There are some irregularities within the coefficients due to the fact that there are some specific months when there are no stocks in Buy and Sell portfolios. There are 46 months without stocks in Buy portfolio and 9 months without stocks in Sell portfolio during 1999-2014. However, these irregularities are not constant expect during year 2013 in the case of Buy portfolio and thus do not significantly impact the results.

The averages of the coefficients in **table 14** were calculated for the portfolios each month. ROIC is the return on invested capital, LIQ that is the cash and cash equivalents divided by current assets, LOGMCAP is the natural logarithm of the market capitalization, PTB that is the market price of the stock divided by the book-value of the stock, GFCDUMMY measures if there is an impact of the financial cycle on the coefficients and GFCDUMMY receives a value of 0 1999-2008 and a value of 1 in 2009-2014, ACCURACY is the actual share price at time t+12 months divided by analyst forecast at time t divided by the actual share price at time t+12 months, thus the coefficient is lagged by 12 month in order to examine whether the accuracy of the forecast impacted in the past and finally the natural logarithm of the turnover that is the trading volume of the stock on the market. It is notable from the table that all of the coefficients are quite close to each other, especially the logarithm of market capitalization, accuracy and turnover. Buy portfolio has the largest ROIC and PTB. However, Sell portfolio has the highest LIQ on average.

The **table 16** illustrates the regression results of the 4 different models when the portfolio abnormal returns are regressed on OMXH. Results in **table 16** suggest poor statistical significance. Only the Sell portfolio achieved a price-to-book ratio on 10% statistical significance level when ACCURACY was added to the basic model. The -0,015 coefficient implicates that an increase in price-to-book ratio has a negative impact on the abnormal returns of the stocks, which have received a recommendation of Sell. The Sell portfolio had the lowest average of price-to-book ratio out of the three portfolios during the period of 1999-2014. Also, the R-squared is the highest in the model with ACCURACY. The Buy portfolio achieved the highest R-squared of 0,111. Durbin-Watson is also the highest on average when ACCURACY is added to the model. Durbin-Watson varies between 1,462 and 2,135 across models and portfolios.

Table 17 illustrates the results after adjusting portfolio returns with OMXH24. The results change when adjusting with OMXH24. However, the results of the Buy portfolio remain exactly the same. Only the intercept achieves a 10% significance level when ACCURACY is added to the model. The Hold portfolio, on the other hand, achieves completely different results. The intercepts are statistically significant on 5%-level in every model expect when ACCURACY is added. The logarithm of market capitalization is also statistically significant on 10%-level in every model expect when ACCURACY is added. The coefficient varies from 0,004 to 0,006, implicating that the size of the stocks that achieved a Hold recommendation has a positive impact on the abnormal returns of these stocks. The Hold portfolio had the largest average market capitalization out of the three portfolios during 1999-2014.

Coefficients	Buy-omxh	Buy-omxh	Buy-omxh	Buy-omxh	Hold-omxh	Hold-omxh	Hold-omxh	Hold-omxh	Sell-omxh	Sell-omxh	Sell-omxh	Sell-omxh
Intercept	0,040	0,047	0,16**	0,108	-0,094	-0,102	0,303	-0,092	-0,033	-0,014	0,028	-0,034
t-statistic	0,882	1,001	2,331	1,402	-1,128	-1,151	1,795	-1,094	-0,601	-0,228	0,568	-0,568
ROIC	0,000	-0,001	-0,001	0,000	0,001	0,001	-0,001	0,001	0,000	0,000	0,001	0,001
t-statistic	-0,079	-0,578	-0,424	0,113	0,619	0,657	-0,716	0,550	0,445	0,490	0,597	0,440
LIQ	0,000	0,000	0,001	0,000	0,000	0,000	-0,001	0,000	0,000	0,000	0,001	0,000
t-statistic	-0,618	0,082	1,546	-0,359	0,156	-0,128	-0,713	0,168	0,170	-0,110	0,989	0,167
MCAP	0,002	-0,002	-0,013	0,004	0,015	0,016	-0,032	0,012	0,005	0,003	-0,001	0,005
t-statistic	-0,397	-0,325	-1,599	0,441	1,336	1,320	-1,571	0,743	0,615	0,333	-0,192	0,499
PTB	-0,001	-0,001	-0,013	-0,001	-0,023	-0,023	0,007	-0,022	-0,007	-0,008	-0,015*	-0,007
t-statistic	-0,344	-0,327	-0,853	-0,322	-1,655	-1,661	0,593	-1,538	-0,897	-0,934	-1,941	-0,849
GFCdummy		-0,021				0,004				0,011		
t-statistic		-0,789				0,263				0,623		
ACCURACY			-0,016				-0,001				-0,015	
t-statistic			-0,771				-0,117				-1,499	
LOGTURNOVER				-0,013				0,002				0,000
t-statistic				-1,092				0,289				0,015
R squared	0,002	0,021	0,111	0,025	0,022	0,023	0,049	0,023	0,006	0,009	0,064	0,006
Durbin-Watson	1,828	1,839	1,809	1,878	1,448	1,450	1,927	1,450	1,462	1,467	2,135	1,462

Significance level at *10% **5% ***1%

Table 16. Regression results of each model after adjusting portfolio returns with OMXH

Coefficients	Buy-omxh24	Buy-omxh24	Buy-omxh24	Buy-omxh24	Hold-omxh24	Hold-omxh24	Hold-omxh24	Hold-omxh24	Sell-omxh24	Sell-omxh24	Sell-omxh24	Sell-omxh24
Intercept	0,042	0,045	0,1*	0,061	-0,039**	-0,043**	-0,075	-0,041**	-0,057*	-0,065*	-0,035	-0,050
t-statistic	1,228	1,285	1,802	1,039	-2,100	-2,190	-1,267	-2,169	-1,700	-1,688	-1,005	-1,406
ROIC	0,000	0,000	0,001	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
t-statistic	0,026	-0,280	0,351	0,094	0,625	0,737	0,957	0,780	0,059	0,027	-0,233	-0,031
LIQ	0,000	0,000	0,001	-0,001	0,000	0,000	0,001**	0,000	0,001	0,001	0,001	0,001
t-statistic	-1,220	-0,584	1,065	-1,098	0,844	0,043	2,050	0,806	0,684	0,795	1,211	0,728
MCAP	-0,005	-0,004	-0,008	-0,003	0,004	0,0049*	0,007	0,006*	0,007	0,008	0,004	0,008
t-statistic	-1,006	-0,958	-1,205	-0,478	1,662*	1,772	1,009	1,789	1,318	1,370	0,914	1,391
PTB	0,003	0,003	-0,016	0,003	-0,002	-0,002	-0,002	-0,003	-0,005	-0,005	-0,006	-0,004
t-statistic	0,988	0,994	-1,277	0,992	-0,668	0,488	-0,529	-0,852	1,002	-0,970	-1,134	-0,766
GFCdummy		-0,009				0,002				-0,005		
t-statistic		-0,457				0,633				-0,416		
ACCURACY			-0,012				-0,001				-0,010	
t-statistic			-0,736				-0,427				-1,431	
LOGTURNOVER				-0,003				-0,002				-0,002
t-statistic				-0,391				-0,866				-0,539
R squared	0,036	0,038	0,078	0,037	0,032	0,034	0,043	0,036	0,020	0,021	0,058	0,022
Durbin-Watson	1,848	1,856	1.591	1,865	1,994	1,998	2,146	1,992	1,960	1,960	2,072	1,960

Significance level at *10% **5% ***1%

Table 17. Regression results of each model after adjusting portfolio returns with OMXH24

It is interesting that when the ACCURACY coefficient is added to the basic model (**table 17**), the Hold portfolio has statistically significant LIQ on 5%-level. The coefficient is 0,001, implicating that the LIQUIDITY ratio has a positive impact on the returns of the stocks in the Hold portfolio. It is notable that in the case of each portfolio, the R-squared is the highest when ACCURACY is added to the basic model, achieving the highest R-squared of 0,078 in the Buy portfolio. The Durbin-Watson statistic reaches values from 1,591 to 2,146 across the portfolios, implicating a low level of autocorrelation in the regressions. Sell portfolios do not offer any statistically significant results. This might be due to the high negative abnormal returns.

Overall, the results when adjusting with OMXH suggest that price-to-book ratio has a negative impact on the stocks, which have received a recommendation of Sell. This indicates that an increase in price-to-book ratio has a negative impact on returns of stocks in the Sell portfolio. This follows from the fact that value stocks are seen more favourable in terms of long-term returns than growth stocks. However, the results remain on 10%-statistical significance level.

When adjusting with OMXH24 the results indicate that an increase in market capitalization of stocks in the Hold portfolio has a positive impact on the returns of those stocks. An increase in market value can be seen as a positive indicator of future growth, or at least investors expect growth. The results also remain on 10% statistical significance level. When ACCURACY is added to the model, the LIQ coefficient achieves the only statistical significance level of 5% in the Hold portfolio. The coefficient suggests that an increase in liquidity has a positive impact on stock returns in the Hold portfolio. However, the coefficient is quite small at 0,001, suggesting only a marginal impact.

8.2.2. Transaction costs

Tables 18 and 19 represent the regression results for each model after adjusting the portfolio returns with transaction costs. Results after adjusting with OMXH presented in **table 18** seem interesting because now the price-to-book coefficient is statistically significant on 10%-level in the Hold portfolio's basic model and when GFCDUMMY is added. In addition, the coefficient is statistically significant on 10%-level in the Sell portfolio when ACCURACY is added to the model. This corresponds to the results achieved also before trading costs in **table 16**. The coefficients received a value of -0,023 in the basic model and when GFCDUMMY was added. This suggests that price-to-book ratio has a negative impact on the stock returns of the Hold portfolio. The Hold portfolio has the second-highest monthly average of price-to-book ratio, and the Sell portfolio the lowest monthly average. What is significant is that the results remain exactly the same when GFCDUMMY is added. This fact implicates that the periods of financial crisis, any other crisis, and stock cycles seem to have no impact on the results. Again, the portfolios with the ACCURACY coefficient achieve the highest R-squared, meaning that the data best fits this model when compared with the others. Durbin-Watson varies from 1,449 to 2,129, implicating a low amount of autocorrelation.

Coefficients	Buy-tc-omxh	Buy-tc-omxh	Buy-tc-omxh	Buy-tc-omxh	hold-tc-omxh	hold-tc-omxh	hold-tc-omxh	Hold-tc-omxh	Sell-tc-omxh	Sell-tc-omxh	Sell-tc-omxh	Sell-tc-omxh
intercept	0,040	0,047	0,159**	0,109	-0,097	-0,104	0,299***	-0,095	-0,033	-0,014	0,027	-0,033
t-statistic	0,878	1,004	2,333	1,418	-1,159	-1,178	1,775	-1,128	-0,591	-0,221	0,554	-0,557
ROIC	0,000	-0,001	-0,001	0,000	0,001	0,001	-0,001	0,001	0,000	0,001	0,001	0,001
t-statistic	-0,086	-0,589	-0,412	0,110	0,586	0,624	-0,774	0,524	0,441	0,486	0,581	0,435
LIQ	0,000	0,000	0,001	0,000	0,000	0,000	-0,001	0,000	0,000	0,000	0,001	0,000
t-statistic	-0,619	0,088	1,556	-0,355	0,113	-0,146	-0,727	0,124	0,173	-0,109	0,996	0,171
MCAP	-0,002	-0,002	-0,013	0,004	0,015	0,017	-0,032	0,012	0,005	0,003	-0,001	0,005
t-statistic	-0,405	-0,332	-1,605	0,450	1,364	1,343	-1,555	0,783	0,598	0,318	-0,198	0,488
PTB	-0,001	-0,001	-0,014	-0,001	-0,023***	-0,023***	0,007	-0,022	-0,007	-0,008	-0,015***	-0,007
t-statistic	-0,333	-0,316	-0,873	-0,310	-1,653	-1,658	0,600	-1,542	-0,913	-0,950	-1,937	-0,863
GFCdummy		-0,021				0,004				0,011		
t-statistic		-0,799				0,255				0,619		
ACCURACY			-0,016				-0,001				-0,015	
t-statistic			-0,781				-0,110				-1,483	
LOGTURNOVER				-0,013				0,002				0,000
t-statistic				-1,114				0,260				0,010
R squared	0,017	0,021	0,112	0,025	0,023	0,023	0,050	0,023	0,006	0,009	0,063	0,006
Durbin-Watson	1,827	1,838	1,809	1,878	1,449	1,451	1,928	1,451	1,463	1,467	2,129	1,463

Significance lev ***10% **5% *1%

Table 18. Regression results of each model after transaction costs and adjusting portfolio returns with OMXH

After adjusting with trading costs and OMXH24 in **table 19,** the results remain very close to **table 18,** prior to adjusting with trading costs. Only the Hold portfolio now holds some statistical significance on every model, and the coefficients also remain almost exactly the same. Market Capitalization achieves a 10% statistical significance level in three out of four models with the coefficient ranging from 0,005 to 0,007, a change of 0,0001 from the results without trading costs. The results are in line with the previous finding prior to trading costs. In addition, when ACCURACY is added to the model, it again achieves the highest R-squared in each portfolio, and now also the LIQ factor is statistically significant on 5%-level with a coefficient of 0,001. This again indicates that liquidity positively impacts the abnormal returns of the Hold portfolio stocks.

Coefficients	Buy-tc-omxh24	Buy-tc-omxh24	Buy-tc-omxh24	Buy-tc-omxh24	hold-tc-omxh24	hold-tc-omxh24	hold-tc-omxh24	hold-tc-omxh24	Sell-tc-omxh24	Sell-tc-omxh24	Sell-tc-omxh24	Sell-tc-omxh24
intercept	0,042	0,045	0,100***	0,062	-0,042**	-0,046**	-0,079	-0,044**	-0,056***	-0,064***	-0,035	-0,050
t-statistic	1,223	1,284	1,805	1,060	-2,241	-2,313	-1,346	-2,324	-1,680	-1,672	-1,019	-1,385
ROIC	0,000	0,000	0,001	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
t-statistic	0,017	0,296	0,367	0,090	0,481	0,589	0,806	0,663	0,053	0,021	-0,253	-0,038
LIQ	-0,001	0,000	0,001	-0,001	0,000	0,000	0,001**	0,000	0,000	0,001	0,001	0,001
t-statistic	-1,222	-0,577	1,077	-1,094	0,654	-0,125	2,033	0,611	0,688	0,801	1,218	0,732
MCAP	-0,005	-0,004	-0,008	-0,003	0,005***	0,005***	0,008	0,007***	0,007	0,007	0,004	0,008
t-statistic	-1,016	-0,968	-1,211	-0,467	1,792	1,876	1,074	1,972	1,287	1,348	0,901	1,369
PTB	0,003	0,003	-0,017	0,003	-0,002	-0,002	-0,002	-0,003	-0,005	-0,005	-0,006	-0,004
t-statistic	1,003	1,010	-1,302	1,009	-0,666	-0,691	-0,519	-0,880	-1,028	-0,995	-1,129	-0,788
GFCdummy		-0,009				0,002				-0,005		
t-statistic		-0,470				0,602				-0,421		
ACCURACY			-0,012				-0,001				-0,010	
t-statistic			-0,749				-0,429				-1,407	
LOGTURNOVER				-0,004				-0,002				-0,002
t-statistic				-0,420				-0,994				-0,544
R squared	0,037	0,039	0,080	0,038	0,003	0,034	0,004	0,037	0,019	0,020	0,057	0,021
Durbin-Watson	1,848	1,857	1,589	1,866	1,997	2,001	2,165	1,998	1,960	1,958	2,062	1,958

Significance level at ***10% **5% *1%

Table 19. Regression results of each model after transaction costs and adjusting portfolio returns with OMXH24

As an overall summary of the results, only size, P/B and liquidity seem to have any statistically significant impact on the abnormal returns of the portfolios. However, the statistical significance is concentrated on the returns of the Hold portfolio, which also has the highest amount of observations compared to Buy and Sell portfolios. Therefore it is possible to achieve more accurate results with more detailed or larger amount of data.

The R-squared also remains at a low level across the portfolios, achieving its highest value of 0,112 in the Buy portfolio when returns are adjusted with OMXH24 and ACCURACY is added to the basic model. The model has the highest explanatory value out of the models, which implicates that ACCURACY coefficient could be essential to the model. Also, the idea of these regressions was to find new variables to the model of Peltoniemi (2012) in order to identify factors that explain the abnormal returns of the portfolios that are constructed out of the large listed stocks on the basis of analysts' recommendations. In addition, the new aspect was to examine whether transaction costs have any impact in this case. Results suggest that when the portfolio returns were adjusted with OMXH, there was only one P/B coefficient in the Sell portfolio with statistical significance on 10%, suggesting that PTB has a negative impact on abnormal returns. However, after adjusting with trading costs, the results of the Hold portfolio also suggested price-to-book to impact the abnormal returns negatively.

More research on the area of abnormal returns generated by the portfolios is needed with wider and more accurate data, probably from other countries, in order to achieve more accurate results. This also continued the new area of research, how stock specific characteristics could explain the abnormal returns, which was started by Peltoniemi (2012). Results are promising and further research is suggested in this field.

9. CONCLUSIONS

The purpose of this study was to examine two phenomena related to analysts' recommendations. Firstly, I investigated whether it is possible to achieve statistically significant abnormal returns by following analysts' recommendations of large stocks and hence break the efficient market hypothesis. Secondly, this study tried to determine whether the stocks with similar recommendations share some stock-or firm-specific characteristics, which impact the abnormal returns of the portfolios and thus consciously or unconsciously impact analysts' recommendations. As for the data, this study employs the 24 largest stocks listed in OMXH. The OMXH24 index is constructed on the basis of the returns of the 24 largest Finnish stocks as of beginning of 2015. A 1-month Euribor is used as the risk-free rate. The analysts' consensus recommendations and target prices are also employed in this study. All of the data is collected from the Thomson Reuters database between 1999 and 2014. The hypotheses are the following:

H1: *By following analyst recommendations it is not possible to achieve statistically significant abnormal returns before and after transaction costs*

H2: *Stocks with the same consensus recommendations do not have similar stock-specific characteristics with each other before or after taking transaction costs into consideration*

The abnormal returns were examined by constructing three portfolios Buy, Hold and Sell on the basis of analysts' consensus recommendations. While Buy is the most favourable portfolio, Hold is somewhat neutral and Sell is the least favourable. The monthly abnormal and the risk-free return adjusted abnormal returns (Jensen's alphas) were calculated for the portfolios. The statistical significance was tested with the market-model regression that is based on CAPM. OMXH and OMXH24 were used as the market return and a 1-month Euribor as the risk-free return.

The total cumulative returns of the portfolios differed greatly from the cumulative market return of the OMXH, however, they were closer to the cumulative return of OMXH24. The cumulative returns from 1999 to 2014 were somewhat loyal to the recommendations. The abnormal returns of Buy and Hold portfolios were 88,17% and 91,78% respectively and the total return of the Sell portfolio remained at -17,99% when adjusted with OMXH. When results are adjusted with the OMXH24 index, the returns were -6,73%, -3,13% and -112,90%, respectively. The setup changes after transaction costs were taken into consideration when the Buy portfolio yielded the highest abnormal return of 79,35%. The Hold portfolio yielded 67,36% and the Sell portfolio -33,17% when adjusted with OMXH. However, the results change when benchmarked with OMXH24 - the results were -15,55%, -27,55% and -128,08% respectively. It can be concluded that trading costs seem to play a significant role in terms of cumulative abnormal returns of the portfolios. However, by following the Buy and Hold recommendations, it is possible to beat the market by almost 80%, even after trading costs. When following Buy recommendations, and by 67% when following Hold recommendations. Also a long-short portfolio was constructed which yielded a total cumulative 15-year return of 43,46% and only 19,36% after transaction costs. When adjusted with OMXH and OMXH24 the abnormal returns before transaction costs were the worst out of all portfolios when benchmarked with OMXH -48,36% and with OMXH24 -143,27%. After transaction costs the returns drop significantly to -72,46% when benchmarked with OMXH and -167,37% when benchmarked with OMXH24.

My regression analysis supports the previous findings by yielding significant alphas for every portfolio when the portfolios are regressed on OMXH. The alphas remained positive and statistically significant at 1%-level even after adjusting for trading costs. The only curious thing was that the Sell portfolio yielded a positive and significant alpha, but the R-squared was only 17%, approximately half of the R-squared of the Buy portfolio and one third of the Hold portfolio. This indicates that the model did not explain the abnormal returns particularly well. The alpha of the Buy portfolio was 0,465. On the basis of my findings the first hypothesis H:1 is rejected in the case of Buy and Hold portfolios. It can be concluded that it is possible to generate statistically significant abnormal returns by following analysts' recommendations of large stocks in the Finnish stock market which have received a recommendation of Buy or Hold. Also the Sell portfolio yielded a positive alpha of 0,596, but the R-squared was very small compared to other portfolios, which raises some red flags.

Only the Buy portfolio remained statistically significant before and after trading costs, when the portfolios were regressed on OMXH24. The Buy portfolio thus yields statistically significant alpha on 1%-level, confirming the previous results. The R-squared also experiences a strong increase during this examination and the alphas of Hold and Sell portfolios were negative and insignificant after trading costs. On the basis of this regression analysis the H1 is rejected in the case of the Buy portfolio only.

There are two possible explanations for the results. The first possibility is that the analysts' recommendations do break the efficient market hypothesis and their recommendations do include new information, which is released to the market when the recommendation is issued. The second explanation is that the Finnish stock market may not operate as efficiently as it could. More research on the subject is needed, however, my results suggest that it is possible to beat the market by following analysts' Buy recommendations of large stocks in the Finnish stock market. These results are in line with previous findings on the field by Barber et al. (2001), Nandelstadh (2003), Bodi & Womack (2006), Fariborz et al. (2009) and Bradley et al. (2014). Peltoniemi (2012) was not able to identify statistically significant alpha in his study. However, this is the first study that has achieved statistically significant alphas with large stocks and post-financial crisis data on the Finnish stock markets. This study could also be carried out, by adding another controlling variable to the market model. In addition, examining the returns and recommendations with three and/or four factor model could also give interesting results. I suggest that more research on this field should be conducted.

The second hypothesis examined the firm- and stock-specific characteristics of the stocks with the same recommendation. The dependent variables were the abnormal returns of each portfolio Buy, Hold and Sell. Abnormal returns were calculated by subtracting OMXH and OMXH24 from the portfolio returns before and after transaction costs. OMXH24 was used in order to examine how well the characteristics explain abnormal returns generated from an index that includes only the large stocks that are under examination in this study. The independent variables in the basic regression model were ROIC, LIQ, the natural logarithm of market capitalization and price-to-book ratio. The basic model was constructed by Peltoniemi (2012). He was the first one to examine the factors that may explain the abnormal returns generated by following analysts' recommendations. Three more variables were then separately added to the model in order to examine if these variables increase the explanatory power of the model. These added variables were GFCDUMMY, ACCURACY and natural logarithm of TURNOVER.

When the abnormal returns were examined by subtracting OMXH from the portfolio returns, there was only one statistically significant coefficient on 10%-level that was the price-to-book ratio in the Sell portfolio. However, when the abnormal returns were examined by using OMXH24 as the market return, the results showed 4 statistically significant coefficients only in the Hold portfolio. The basic model and the model with GFCDUMMY and LOGTURNOVER implicate that the market capitalization has a positive impact on the returns of the portfolios on 10%-level of statistical significance. However when ACCURACY is added to the basic model, the results indicate that LIQ impacts the returns of the Hold portfolio. The result shows a statistical significance on 5%-level.

When trading costs were taken into account, the results surprisingly changed when abnormal returns were calculated by applying OMXH market return. The results then showed three significant factors that have an impact on portfolio returns. The basic model showed that price-to-book impacts the returns of the Hold portfolio negatively on 10%-level of significance. In addition, when GFCDUMMY is added to the model the results remain exactly the same as when examining the price-to-book coefficient. However, the negative impact of price-to-book ratio (at 10%-level of significance) on returns of the Sell portfolio remains when compared to the results prior to the subtraction of transaction costs. Results after adjusting with transaction costs, when calculating abnormal returns using OMXH24 as the market benchmark, remain exactly the same.

What is notable about the difference between the models is that the model that included ACCURACY as an independent variable offered the only result on 5%-level of significance and the highest R-squared that indicates an increase in how well the data fits the model. The different results before and after transaction costs implicate that transaction costs actually impact the explanatory variables of the constructed models. These results may open a new area of research, which identifies the stock or-firm specific characteristics, which explain the abnormal returns generated by the analysts' recommendations. The results might be more accurate with a larger and more detailed data set. This thesis gives implications for further research.

The insufficient data on consensus recommendations on other than large stocks reduced the accuracy of this thesis and therefore only the large stocks were examined. This thesis uses only monthly consensus recommendations and therefore also monthly data on OMXH and OMXH24. The research on the stock-specific characteristics is a continuation from the study of Peltoniemi (2012) and thus I have separately added three more variables to the Peltoniemi's basic model. Results indicate that adding ACCURACY only yields that LIQ positively impacts the returns of the Hold portfolio on 5%-level of significance. Thus, more research is needed in this area. It is possible to add even more variables to the regression models and to use daily data in order to identify the true drivers of the abnormal returns, to find the stock and firm specific characteristics which impact consciously or unconsciously on analysts' recommendations and to achieve more accurate results.

In addition the analysts' behavioural biases, which were presented in chapter 3.1 should be researched. For example do analysts herd when their forecasting task is harder, or if there are many other recommendations on the same stock do analysts prefer to follow the recommendations of the other analysts. This area should also be appointed in the future studies because it may offer some explanations why it is possible to generate abnormal returns by following analysts' recommendations. Also it is in great interest how stock and firm-specific characteristics may impact on the abnormal returns and therefore consciously or unconsciously analysts' recommendations.

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INTERVIEWS

Mikko Ervasti, *Evli Bank Analyst*: 12th of December 2013, Helsinki.

APPENDICES

Appendix 1. Evli Bank analyst report of Elisa, stock recommendation and target price

EVLI

ELISA

Telecommunication services/Finland, October 18, 2013
Spot comment

Subscriber adds weak, cost cuts help

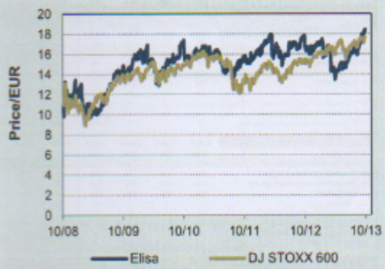
Elisa's profitability was a positive surprise as accelerated efficiency measures had a quick effect. The newly announced headcount reductions are also likely to boost margins in the short term, mainly in 1H 2014E. Although ARPU development is stabilizing, subscriber additions in mobile raise concerns. In our view, shares are fully valued with limited changes to operational forecasts. We keep our "Reduce" recommendation with EUR 18.7 (18.5) target price.

Mobile subscriber additions hitting the wall
Consumer Finland mobile subscriptions declined -1% YoY and -0.3% QoQ. This kind of a decline was a surprise to us, as solid presence by Elisa in the marketplace with its Saunalahti brand despite competition was supposed to help grow subscribers in Q3. Fortunately for Elisa, Finnish consumer ARPU increased QoQ. We expect flat YoY revenues in Finnish mobile in Q4, Consumer segment sales being driven down -2% YoY purely by Estonian ARPU decrease.

Margins set to expand slightly
Q3 delivered a positive margin surprise, helped by accelerated efficiency measures in the company without headcount reductions. Pending outsourcing and redundancies are set to boost short term clean EBITDA margins further. We forecast 32.5% in 4Q13E (31.3% a year ago) and improvement to 33.1% in 2014E. EBIT margins are seen more or less flat YoY due to higher depreciation.

Fully valued – "Reduce" reiterated
We keep our "Reduce" recommendation with limited upside for the shares. Peer multiples expansion on FCF and profit metrics have lifted Elisa shares and keeping fair value close to EUR 20 level, but DCF suggests there is clear downside. As a result of our equally-weighted DCF, P/FCF and EV/EBITDA valuation components, we make a slight adjustment to target price, now at EUR 18.7 (18.5). Dividend yield 7% could attract buyers towards year-end, however.

Rating — REDUCE



Share price, EUR (Last trading day's closing price)	18.40
Target price, EUR	18.7
Latest change in recommendation	04-Jul-13
Latest report on company	17-Oct-13
No. of shares outstanding, '000's	157,005
No. of shares fully diluted, '000's	157,005
Market cap, EURm	2,889
Free float, %	80.0
Exchange rate EUR/USD	1.310
Reuters code	ELI1V.HE
Bloomberg code	ELI1V FH
GICS Industry code	50101020
Next interim report	
Web site	www.elisa.com
Analyst	Mikko Ervasti
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BUY ACCUMULATE REDUCE SELL

KEY FIGURES

	Sales EURm	EBIT EURm	EBIT %	Ptx profit EURm	EPS EUR	P/E (x)	EV/Sales (x)	P/CF (x)	EV/EBIT (x)	DPS EUR
2011	1,530	296	19.3%	266	1.30	12.0	2.1	6.0	10.9	1.30
2012	1,554	299	19.2%	272	1.35	12.4	2.2	7.0	11.6	1.30
2013E	1,547	291	18.8%	268	1.29	14.2	2.5	6.7	13.1	1.30
2014E	1,541	291	18.9%	269	1.29	14.3	2.5	6.7	13.0	1.29
2015E	1,595	302	19.0%	279	1.35	13.7	2.4	6.8	12.5	1.35

Market cap, EURm	2,889	BV per share 2013E, EUR	5.4	CAGR EPS 2012-15, %	-0.2
Net debt 2013E, EURm	909	Price/book 2013E	3.4	CAGR sales 2012-15, %	0.9
Enterprise value, EURm	3,806	Dividend yield 2013E, %	7.1	ROE 2013E, %	24.0
Total assets 2013E, EURm	2,071	Tax rate 2013E, %	24.0	ROCE 2013E, %	16.9
Goodwill 2013E, EURm	797	Equity ratio 2013E, %	41.1	PEG, P/E 13/CAGR	5.5

All the important disclosures can be found on the last pages of this report.

Appendix 2. Regression results

Dependent Variable: BUY_RF
Method: Least Squares
Date: 04/17/15 Time: 14:37
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.465196	0.054906	8.472629	0.0000
OMXH_RF	0.531151	0.055696	9.536657	0.0000

R-squared	0.323718	Mean dependent var	0.987006
Adjusted R-squared	0.320158	S.D. dependent var	0.076599
S.E. of regression	0.063158	Akaike info criterion	-2.675994
Sum squared resid	0.757896	Schwarz criterion	-2.642061
Log likelihood	258.8954	Hannan-Quinn criter.	-2.662251
F-statistic	90.94783	Durbin-Watson stat	1.644256
Prob(F-statistic)	0.000000		

Dependent Variable: BUY_RF
Method: Least Squares
Date: 04/17/15 Time: 14:38
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.166075	0.063455	2.617225	0.0096
OMXH24_RF	0.831443	0.064137	12.96357	0.0000

R-squared	0.469354	Mean dependent var	0.987006
Adjusted R-squared	0.466561	S.D. dependent var	0.076599
S.E. of regression	0.055946	Akaike info criterion	-2.918509
Sum squared resid	0.594685	Schwarz criterion	-2.884577
Log likelihood	282.1769	Hannan-Quinn criter.	-2.904766
F-statistic	168.0543	Durbin-Watson stat	1.785683
Prob(F-statistic)	0.000000		

Dependent Variable: BUY_TC_RF

Method: Least Squares
Date: 04/17/15 Time: 14:39
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.464285	0.054894	8.457864	0.0000
OMXH_RF	0.531611	0.055684	9.546992	0.0000

R-squared	0.324192	Mean dependent var	0.986547
Adjusted R-squared	0.320635	S.D. dependent var	0.076609
S.E. of regression	0.063144	Akaike info criterion	-2.676428
Sum squared resid	0.757567	Schwarz criterion	-2.642496
Log likelihood	258.9371	Hannan-Quinn criter.	-2.662685
F-statistic	91.14506	Durbin-Watson stat	1.645029
Prob(F-statistic)	0.000000		

Dependent Variable: BUY_TC_RF
Method: Least Squares
Date: 04/17/15 Time: 14:39
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.164852	0.063418	2.599444	0.0101
OMXH24_RF	0.832216	0.064100	12.98303	0.0000

R-squared	0.470101	Mean dependent var	0.986547
Adjusted R-squared	0.467312	S.D. dependent var	0.076609
S.E. of regression	0.055914	Akaike info criterion	-2.919650
Sum squared resid	0.594006	Schwarz criterion	-2.885718
Log likelihood	282.2864	Hannan-Quinn criter.	-2.905908
F-statistic	168.5591	Durbin-Watson stat	1.788011
Prob(F-statistic)	0.000000		

Dependent Variable: HOLD_RF
Method: Least Squares
Date: 04/17/15 Time: 14:41
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.402178	0.036386	11.05309	0.0000
OMXH_RF	0.595488	0.036910	16.13370	0.0000

R-squared	0.578055	Mean dependent var	0.987194
Adjusted R-squared	0.575835	S.D. dependent var	0.064265
S.E. of regression	0.041855	Akaike info criterion	-3.498858
Sum squared resid	0.332847	Schwarz criterion	-3.464926
Log likelihood	337.8904	Hannan-Quinn criter.	-3.485116

F-statistic	260.2961	Durbin-Watson stat	1.523122
Prob(F-statistic)	0.000000		

Dependent Variable: HOLD_RF
Method: Least Squares
Date: 04/17/15 Time: 14:41
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000392	0.013671	-0.028651	0.9772
OMXH24_RF	1.000232	0.013818	72.38358	0.0000

R-squared	0.965005	Mean dependent var	0.987194
Adjusted R-squared	0.964821	S.D. dependent var	0.064265
S.E. of regression	0.012054	Akaike info criterion	-5.988534
Sum squared resid	0.027605	Schwarz criterion	-5.954601
Log likelihood	576.8992	Hannan-Quinn criter.	-5.974791
F-statistic	5239.382	Durbin-Watson stat	1.953806
Prob(F-statistic)	0.000000		

Dependent Variable: HOLD_TC_RF
Method: Least Squares
Date: 04/17/15 Time: 14:42
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.401367	0.036432	11.01678	0.0000
OMXH_RF	0.595019	0.036957	16.10050	0.0000

R-squared	0.577050	Mean dependent var	0.985922
Adjusted R-squared	0.574824	S.D. dependent var	0.064271
S.E. of regression	0.041908	Akaike info criterion	-3.496314
Sum squared resid	0.333695	Schwarz criterion	-3.462382
Log likelihood	337.6462	Hannan-Quinn criter.	-3.482571
F-statistic	259.2260	Durbin-Watson stat	1.521468
Prob(F-statistic)	0.000000		

Dependent Variable: HOLD_TC_RF
Method: Least Squares
Date: 04/17/15 Time: 14:43
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001710	0.013686	-0.124960	0.9007
OMXH24_RF	1.000279	0.013833	72.31096	0.0000

R-squared	0.964937	Mean dependent var	0.985922
Adjusted R-squared	0.964753	S.D. dependent var	0.064271
S.E. of regression	0.012066	Akaike info criterion	-5.986432
Sum squared resid	0.027663	Schwarz criterion	-5.952499
Log likelihood	576.6974	Hannan-Quinn criter.	-5.972689
F-statistic	5228.875	Durbin-Watson stat	1.960281
Prob(F-statistic)	0.000000		

Dependent Variable: SELL_RF
Method: Least Squares
Date: 04/17/15 Time: 14:52
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.596414	0.060358	9.881224	0.0000
OMXH_RF	0.391956	0.061227	6.401720	0.0000

R-squared	0.177425	Mean dependent var	0.981477
Adjusted R-squared	0.173096	S.D. dependent var	0.076352
S.E. of regression	0.069430	Akaike info criterion	-2.486634
Sum squared resid	0.915900	Schwarz criterion	-2.452701
Log likelihood	240.7168	Hannan-Quinn criter.	-2.472891
F-statistic	40.98202	Durbin-Watson stat	1.792207
Prob(F-statistic)	0.000000		

Dependent Variable: SELL_RF
Method: Least Squares
Date: 04/17/15 Time: 14:53
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.079062	0.056881	1.389957	0.1662
OMXH24_RF	0.913970	0.057493	15.89709	0.0000

R-squared	0.570832	Mean dependent var	0.981477
Adjusted R-squared	0.568574	S.D. dependent var	0.076352
S.E. of regression	0.050150	Akaike info criterion	-3.137226
Sum squared resid	0.477858	Schwarz criterion	-3.103293
Log likelihood	303.1737	Hannan-Quinn criter.	-3.123483
F-statistic	252.7175	Durbin-Watson stat	2.049584
Prob(F-statistic)	0.000000		

Dependent Variable: SELL_TC_RF
Method: Least Squares
Date: 04/17/15 Time: 14:53
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.596057	0.060385	9.870872	0.0000
OMXH_RF	0.391514	0.061254	6.391629	0.0000

R-squared	0.176965	Mean dependent var	0.980686
Adjusted R-squared	0.172633	S.D. dependent var	0.076365
S.E. of regression	0.069461	Akaike info criterion	-2.485734
Sum squared resid	0.916724	Schwarz criterion	-2.451801
Log likelihood	240.6304	Hannan-Quinn criter.	-2.471991
F-statistic	40.85292	Durbin-Watson stat	1.794103
Prob(F-statistic)	0.000000		

Dependent Variable: SELL_TC_RF
Method: Least Squares
Date: 04/17/15 Time: 14:53
Sample: 1999M01 2014M12
Included observations: 192

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.079113	0.056974	1.388578	0.1666
OMXH24_RF	0.913118	0.057587	15.85634	0.0000

R-squared	0.569574	Mean dependent var	0.980686
Adjusted R-squared	0.567309	S.D. dependent var	0.076365
S.E. of regression	0.050232	Akaike info criterion	-3.133957
Sum squared resid	0.479423	Schwarz criterion	-3.100025
Log likelihood	302.8599	Hannan-Quinn criter.	-3.120214
F-statistic	251.4234	Durbin-Watson stat	2.050870
Prob(F-statistic)	0.000000		