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EVIDENCE OF A COMPLEMENTARY RELATIONSHIP BETWEEN FUNDAMENTAL AND TECHNICAL ANALYSIS IN THE FINNISH STOCK MARKET

Master's Thesis
Master's Degree Programme in Finance

VAASA 2019

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UNIVERSITY OF VAASA

Faculty of Business Studies

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Title of the Thesis:	Evidence of a complementary relationship between fundamental and technical analysis in the Finnish stock market
Name of the Supervisor:	Timo Rothovius
Degree:	Master of Science in Economics and Business Administration
Department:	School of Accounting and Finance
Master's Programme:	Master's Degree Programme in Finance
Year of Entering the University:	2014
Year of Completing the Thesis:	2019 **Number of pages: 85**

ABSTRACT

Through modern history, market participants have continuously aspired to find means to predict future prices for profit opportunities. Considering the classic theory of market efficiency, this should not be possible. However, there are versatile and extensive body of literature presenting highly significant results of models predicting future prices or stock returns.

Two often competing methods to strive for abnormal returns have been noticed by the academic community: technical and fundamental analysis. These methods of analyzing securities are often seen as separate and examined in isolation of each other. This stems from their entirely differing point of views. A technical analyst studies pricing information alone while a fundamental analyst attempts to determine the true value of a stock based on their financial statements and forecasts on the future. However, several recent studies have found that there is value in combining the methods to benefit from their complementary relationship rather than considering them as substitutes.

In this thesis, I study this proposed complementary relationship in Finland by following the methodology introduced in the study of Bettman, Sault & Shultz (2009). The explanatory power of fundamental and technical models is first examined in isolation and finally alongside by integrating the models to create a hybrid model of explaining stock prices of Finnish firms with technical and fundamental factors. Based on the results found in this thesis, fundamental factors seem to possess greater ability to predict and explain future prices than technical factors in the Finnish market during the sample period from 2000 to 2018. Through the examination of the evolution of adjusted R^2, Akaike Information Criterion and log likelihood values, it is evident from the data that there is value in considering technical and fundamental analysis as complementary rather than competing models of analyzing securities.

KEYWORDS: Fundamental analysis, Technical analysis, Momentum, Tobin's Q, Accruals

1. INTRODUCTION

Capital markets bear both the possibility of rising quickly to wealth and on the other hand the risk of losing it all. The act of selling and buying securities has persisted to be a significant object of interest to researchers around the world through all modern history. Naturally, humans are continuously striving to find new ways of choosing the right stocks and recognizing the right timing for their transactions. (Edwards & Magee 1992: 3.)

This continuing journey to prosperity has been highlighted by two major ways of analyzing securities. Bettman et al. (2009) remark that a rational investor uses technical analysis and fundamental analysis while searching for investment objectives. While technical analysis is an analyzation method that studies price changes themselves, fundamental analysis looks to find reasons behind those changes (Ylä-Kauttu 1989: 7). Fundamental analysis studies mainly financial statements of the companies in question. Additionally, fundamental analyst takes the company's dividend history, sales data and market environment into account. With the general view created from this information, a fundamental analyst aims to determine the growth potential of the company's yield and stock price. (Siegel, Shim, Qureshi & Brauchler 2000: 106.) In contrast, technical analysis is based purely on market information, mainly market prices and trading volume. With the analysis, the technical analyst is looking to achieve profits by recognizing patterns in the price paths as early as possible. (Edwards & Magee 2001: 4).

Even though academics have treated technical analysis with great skepticism, the practitioners have taken the investing methods of technical analysis to wide use. For example, brokerage firms, fund managers and institutional investors utilize technical trading rules in their actions. (Lento & Gradojevic 2007: 13.)

The research of explaining equity prices has long been divided into these two often competing ways of predicting future returns. Even though the actors of fundamental and technical analysis have agreed upon the general nature of factors that are important in explaining equity prices, the identification of specific value generating variables remains an ongoing debate. (Bettman et al. 2009.)

Graham & Dodd (1934) wrote one of the first papers regarding the importance of fundamental factors in share valuation. Since then, further studies, namely Gordon & Shapiro (1956) have expanded the literature around the relationship between share prices and fundamental factors providing a basis for future researchers. In the context of this thesis, the most significant extension to Gordon & Shapiro's (1956) paper is written by Ohlson (1995). He created a model that expresses price as a linear function of book value per share, earnings per share and a vector of other relevant value information. There exists a consensus that his model of a Residual Income Valuation Model is a foundational work of fundamental valuation. (Bettman et al. 2009.)

In addition to these, one of the most influential papers of fundamental analysis was written by Abarbanell & Bushee (1997). In their paper, they study whether current changes in fundamental signals are a major driver in providing information about following variations in earnings. Additionally, they solidify a benchmark for estimating how efficiently analysts use fundamental signals. They argue that predicting accounting earnings, instead of explaining security returns, should be the main concern of fundamental analysis. Abarbanell & Bushee (1997) state, based on relations between individual signals examined and future earnings changes, that there is an economic justification to rely on many, but not all, of the 12 fundamental signals originally identified by Lev & Thiagarajan (1993) when estimating future firm performance.

As well as with fundamental analysis, the ability of technical trading methods to explain stock prices and returns has long fascinated practitioners and academics. The use of past prices to predict future movements dates to a series of editorials published by Charles Dow in the Wall Street Journal between 1900 and 1902. These editorials created a foundation for further research into the ability of technical analysis to explain asset prices. (Bettman et al. 2009.)

From a wide set of different technical analysis methods over the years, momentum has emerged as probably one of the most studied and most successful ones. The foundational paper for momentum was written by Jegadeesh & Titman (1993), and the method has been used widely ever since. They generate in total of 32 portfolio strategies of stocks based on their returns over the past 1 to 4 quarters. The paper uses NYSE and AMEX stock data from 1965-1989. The authors rank the stocks in the portfolios by recent performance and divide them into deciles. The decile of best performers is the "winners" and the decile for poorest performers is the "losers". Jegadeesh & Titman (1993) find out that, over 3-to-12-month holding periods, strategies, which sell stocks that have performed poorly in the past and buy stocks that have performed well in the past, generate significant positive returns.

In practice, the methods of technical and fundamental analysis are often used together. Allen & Taylor (1992) note that around 90 per cent of foreign exchange dealers use both technical and fundamental analysis. Also, Lui & Mole (1998) research this subject by conducting a questionnaire in the Hong Kong market. They were provided a member list of the Hong Kong Forex Association. The list contained names of 812 finance professionals to whom the authors sent the completed questionnaires. Lui & Mole (1998) find out that, out of 153 respondents who answered, over 85% rely both on technical analysis and fundamental analysis as a means of predicting future price movements. Further, Oberlechner (2001) studies this matter with a data from a set of European trading centers (Frankfurt, London, Vienna and Zurich). He also finds out that foreign exchange dealers do not see these two types of analyses as mutually exclusive. A majority of foreign exchange traders seem to use a balanced mix of both forecasting approaches. Oberlechner (2001) also finds out that technical analysis is seen as more important on shorter forecasting horizons while fundamental analysis is more important for most market participants on longer forecasting horizons. Kumar, Mohapatra & Sandhu (2013) discovered similar results of relying technical or fundamental factors depending on the investment horizon. They conducted their questionnaire in the Indian stock market.

Prior to this thesis, fairly few studies have been published about valuation models combining technical and fundamental analysis. Bettman et al. (2009) study this matter in the

U.S. market using data from 1983-2002. They create a valuation model that integrates both analyzation methods and recognizes their potential as complements. First, they create a regression model for fundamental analysis using book value per share, earnings per share and forecasted earnings per share as main explanatory variables. Second, they introduce a model with components of technical analysis. In this second regression model, the returns are explained by momentum variables and lagged price. Finally, they combine the models to form a hybrid model to explain stock returns. The authors find out that the hybrid model has the highest adjusted R^2 while all coefficients remain highly significant.

1.1. Purpose of the study

The main purpose of this study is to find out whether there is a complementary relationship between technical and fundamental analysis in Finland. The methods are often seen as separate, and I am aspiring to find out whether they should rather be considered as ways of analyzing securities that supplement each other and should be used together. As a matter of fact, they are widely used together in practice by market professionals as noted in the previous chapter. However, the body of literature about combination models is almost inexistent. The purpose is thus to build on the literature of uniting these analyzation methods and the awareness of not thinking at them as substitutes.

This purpose is pursued by studying technical methods alongside with a fundamental model of price explained by ratios of profitability, value and accrual earnings. The performance of the created models is then evaluated in contrast to each other to find out what are the drivers of prices here in Finland. The research methodology for this thesis follows closely the framework outlined in the study by Bettman et al. (2009). However, there are two explaining variables added to the fundamental model and thus to the final hybrid model. These added variables are backed with proof of significance from previous studies conducted on fundamental analysis and make for an intriguing basis to conduct a study in a marketplace where this has not yet been tested.

However, there are also other drivers of motivation and reasons to conduct this thesis. First, the sample studied in this thesis covers 20 previous years of data from Finnish listed companies. Thus, the sample period contains a notable period of recent macroeconomic history with including major events such as the dot-com bubble and the financial crisis. Bettman et al. (2009) use a sample from the U.S. ranging from 1983 to 2002. Thus, this serves also as an out-of-sample test for it since Bettman et al. (2009) use an entirely different market in a differing time period. Also, it is interesting to find out whether Finland's, as being the market studied, results and significant building blocks of prices differ from the results from studies conducted elsewhere.

1.2. Research hypotheses

This thesis is following closely the research paper by Bettman et al. (2009) and I attempt to replicate a tuned version of their study in the Finnish market. Thus, the main research question and hypothesis is constructed based on their findings. As outlined in the final paragraph of the introduction, they found a complementary relationship between technical analysis and fundamental analysis by studying the measures of explanatory power of their proposed models.

Thus, the research question of this thesis is as follows: *Does a combined model of fundamental and technical factors explain stock prices better than using the analysis methods as separate models?*

From the research question above, the main hypothesis of this thesis is derived:

H_1: *The explaining power of the combined model is greater than that of the separate models. Adjusted R^2 of the combined model > Adjusted R^2 of either of the separate models.*

Also, as Bettman et al. (2009) discover that in their sample from the U.S. technical analysis seemed to explain prices better than the fundamental model, I assume similar results from Finland. Consequently, a second hypothesis is formed:

H_2: *The explaining power of the technical model is greater than that of the fundamental model. Adjusted R^2 of the technical model > Adjusted R^2 of the fundamental model.*

As I attempt to build on the paper by Bettman et al. (2009), I include two additional variables to the equity valuation exercises. First, an accruals variable is added as it has been found to have a significant negative relationship with prices (e.g. Sloan 1996; Richardson, Sloan, Soliman & Tuna 2005; Bartram & Grinblatt 2018). Based on these studies, a third hypothesis is formed:

H_3: *Accruals has a significant negative relationship with stock prices. The coefficient of the accruals variable is negative and significant.*

Second, a variable denoting Tobin's Q is included in the valuation models as recent studies by Wang (2013; 2015) have found it to have a significant positive relationship with prices. Based on this, I assume similar results and form the final hypothesis.

H_4: *Tobin's Q has a significant positive relationship with stock prices. The coefficient of the Tobin's Q variable is positive and significant.*

This chapter presented the major hypothesis of the thesis along with supporting hypotheses derived from the results of earlier studies. Next, the structure of the thesis is summarized.

1.3. Structure of the thesis

This thesis is divided into 8 major chapters. In the introduction, I outline the issues revolving the subjects of this thesis. The first major chapter after the introduction presents previous studies that address fundamental and technical analysis. The literature review is divided into four subchapters to first cover technical analysis, momentum and fundamental analysis literature separately and ending in presenting combination studies similar in nature as this thesis. After covering previous literature, the thesis moves to addressing the foundational theory of stock market efficiency. This is done to illustrate the nature of the relationship both analysis methods have with a building block theory of economics. Also, the mathematics behind Fama's (1970) efficient market models is presented.

After illustrating the background behind this study, I move to the main subjects of the thesis. First in line is technical analysis and its' basic assumptions, critique and a few of its' most important methods relevant to this thesis. The methods section ends on momentum since it represents technical analysis with lagged price in the main regression of the thesis. Next up is the other main subject of the thesis: fundamental analysis. This chapter explains the basics of fundamental analysis and covers the usual ways to conduct fundamental analysis and the variables used to explain stock prices in the regression models.

After the theory section, I outline the mechanics behind the empirical part of this master's thesis. This is started with presenting the data and methodology used. Finally, the last two chapters of the thesis discuss the results from the main regressions conducted and the conclusions drawn on the basis of the results.

2. LITERATURE REVIEW

There persists an on-going debate among researchers on whether it is more useful to base equity valuation on prices rather than fundamentals to understand the dynamics behind stock price movements. These two longstanding approaches to value stocks are called fundamental and technical analysis. (Hong & Wu 2016.) The next subchapters cover literature of these approaches first separately and then together by presenting results of studies attempting to combine them.

2.1. Technical analysis

Researchers have studied extensively the profitability of different technical trading techniques. One of the most significant and quoted studies concerning technical analysis is executed by Brock, Lakonishok & LeBaron (1992). (Lento & Gradojevic 2007: 13.) They studied the profitability of moving averages and support and resistance levels with the Dow Jones Index in the years of 1897—1986. The material was studied using a total of 26 different methods and the results strongly support the operability of buy and sell signals provided by the technical strategies. The study showed that the profits following buy signals were larger than the profits following sell signals. Furthermore, the volatility of the profits following buy signals was significantly smaller than normal.

Bessembinder & Chan (1995) perform an out-of-sample test for the paper presented above by testing the same trading rules in the Asian markets. They find similar results of predictive power of the rules in Japan, Hong Kong, South Korea, Malaysia, Thailand and Taiwan. This supports reasoning on information inefficiency in the Asian markets during the sample period of 1975 to 1989.

However, there exists almost an equal amount of studies concluding that technical trading rules cannot predict future prices. Allen & Karjalainen (1999) use a genetic algorithm to learn technical trading rules for the S&P 500 index. As their data, they use daily prices from 1928 to 1995. They find that, after transaction costs, the rules generated do not earn persistent excess returns over a simple buy-and-hold strategy in the out-of-sample test periods. The diminishing performance of the trading rules after transaction costs has been also documented by for example, Bessembinder & Chan (1998) and Ready (2002). In addition with the effect of transaction costs, data-snooping has been a debated issue revolving the research of technical trading rules. The apparent positive performance of trading rules has been critically tested through the years for the effect of data-snooping.

Data snooping occurs when a given data set is used more than once for purposes of inference or model selection. This might lead to satisfactory results being simply lucky accidents rather than results of a working model. Sullivan, Timmermann & White (1999) present a test statistic that portray the significance of the best-performing model after accounting for data-snooping. They test the results of Brock et al. (1992) and find that the results are indeed robust after accounting for data-snooping. However, they find that the performance does not continue in an out-of-sample experiment covering the following years of 1987-1996.

Bajgrowicz & Scaillet (2012) perform a similar test using daily prices of the Dow Jones Industrial Average index from 1897 to 2011. They approach the issue with a new approach to data snooping called false discovery rate (FDR). The paper presents results that an investor would have never been able to select the future best-performing rules beforehand. Additionally, even in-sample, the profitability is entirely offset by introducing moderate transaction costs.

As the main technical trading rule used in the empirical part of this thesis is momentum, the next subchapter of the literature review is focused entirely on the momentum phenomenon.

2.2. Momentum

The substantial research documenting the apparent abnormal returns to momentum strategies present a severe challenge to existing asset pricing models. Momentum effect is rather simple: stocks whose returns in previous months place them in the top/bottom decile of prior return performance seem to outperform/underperform other stocks in the following months. (Grundy & Martin 2001.)

Cross-sectional momentum analysis has been studied in various markets. Rouwenhorst (1997) found evidence that momentum strategies were profitable for equities in European markets and (1999) that the effect is present among stocks listed on emerging stock markets. Liu, Strong & Xu (1999) also showed that there is a momentum effect present in UK stocks while controlling for systematic risk, size, price, book-to-market ratio and cash earnings-to-price ratio. Chan, Hameed & Tong (2000) on turn studied a sample of 23 countries using a weighted relative strength strategy (WRSS), that is a strategy of buying stocks in proportion to their returns over the ranking period. Their study confirmed the findings of Rouwenhorst (1999) that momentum strategies seem to be profitable in global equity markets.

Momentum has also been studied through what is called industry momentum. Moskowitz & Grinblatt (1999) argue that this industry effect of momentum accounts for much of the individual stock momentum anomaly. These individual stock momentum profits diminish significantly when controlled for industry momentum. Industry portfolios exhibit significant momentum effect even after controlling for size, book-to-market, individual stock momentum, the cross-sectional dispersion in mean returns and possible microstructure effects. Moskowitz & Grinblatt (1999) form 20 industry portfolios and assign monthly ranks for them. Three of the best performed industry portfolios (previous six-month returns) are then bought and the three worst performed are shorted. These returns are found to be significantly greater than traditional individual stock momentum.

The source of momentum profits has been also proposed to be explained by factor models. Grundy & Martin (2001) discovered that momentum strategies that base their winner or loser specifications on stock-specific return components are even more profitable than strategies based on total returns. They also found that 95% of winner or loser return variability can be explained by factor models. However, they show that the profitability cannot be explained by neither the three factors of Fama & French (1996), cross-sectional variability of average returns or exposure to industry factors. The profitability seems to reflect momentum in stock-specific component of returns.

In contrast to traditional cross-sectional momentum analysis, another feature of momentum has been discovered in recent years – time series momentum. Moskowitz, Ooi & Pedersen (2012) shed light to this aspect of momentum in their novel paper of testing the strategy across asset classes. They find persistence of past in returns for one to 12 months. This effect reverses over longer horizons that is in line with the theories of momentum based on initial under-reaction and delayed over-reaction. They discover that even though the time series momentum effect is correlated with traditional cross-sectional momentum, the cross-sectional momentum doesn't subsume the effect. Time series momentum strategy delivers substantial alpha unexplained by standard asset pricing factors.

So, can the strategy be applied in real life with actual market frictions? The persistence of momentum profits has been also tested after transaction costs. Korajczyk & Sadka (2004) use intraday data to test the returns after proportional and non-proportional trading costs. Proportional costs are calculated by dividing the difference between transaction price and the bid/ask midpoint by the bid-ask midpoint. Non-proportional trading costs are calculated two ways and they constitute the price impact costs that increase by portfolio size. They find that a few of the momentum strategies constructed earn significant abnormal returns in relation to a conditional approach of the Fama and French (1993) three-factor asset pricing model. These strategies remain profitable after proportional trading costs. After this, they derive break-even fund sizes after which the profits diminish.

There are both upsides and downsides in momentum analysis. The upside is that momentum seems to work better than fundamental analysis on a shorter time horizon partly because of the slow incorporation of news into stock prices. However, as a downside, momentum does not have a theoretical basis and is mainly influenced by crowd behavior.

Also, it has no forward-looking aspect since it only uses historical prices. (Hong & Wu 2016).

2.3. Fundamental analysis

A large body of research has shown that fundamental signals derived from public financial statements have predictive power of future abnormal returns. Ou & Penman (1989) discover that a trading strategy based on a wide set of financial ratios generates notable size-adjusted returns. Likewise, Abarbanell & Bushee (1998) provide evidence of significant excess returns produced by a trading strategy based on fundamental signals that applies an investment strategy presented first by Lev and Thiagarajan (1993) on an eight to twelve-month period. Piotroski (2001) on the other hand, applies this trading strategy to firms with high book-to-market ratios discovering annual market-adjusted returns of 23%. Mohanram (2005) applies fundamental analysis-based strategy to growth firms yielding similar results of large abnormal returns.

There is still an ongoing discussion about the sources of these abnormal returns. The most straightforward explanation is that the market underreacts to information in financial statements. An alternate explanation is that fundamental signals express an unknown component of systematic risk that is rightly included into stock prices. (Mohanram 2005.)

There also exists a paper by Beneish, Lee and Tarpley (2001), who test whether market information and fundamentals could be valuable in predicting companies extreme short-term market performance. They use eight fundamental variables to test three-month return predictabilities. After they choose the possible extreme performances based on market signals, firm age, size and price to sales -ratio, the authors evaluate their market performance using fundamental signals. Beneish et al. (2001) find that only three of eight fundamental signals used are relevant for future stock return prediction: earnings surprises, capital expenditures and accruals.

Xue & Zhang (2011) examine whether institutional investors trade on these fundamental signals and what are the implications of institutional investors' trading for stock valuation. They find that institutional investors systematically trade on fundamental signals thus providing evidence that market underreaction to financial statement information is a more likely explanation for the abnormal returns related to fundamental signals.

There are also studies about the declining value-relevance of historical cost financial statements like earnings and book values over time, because of the changes in the economy. By these changes, they mean the shift from an industrialized economy to a high-tech, service-orientated economy. Lev and Zarowin (1999) and Ramesh and Thiagarajan (1995) provide support to these claims by reporting a decline in the value-relevance of earnings over time. Likewise, Amir and Lev (1996) find similar results of irrelevancy of book values, earnings and cash flows while valuing firms in the intangible-intensive mobile phone industry.

Collins, Maydew and Weiss (1997) however claim, that the same factors that contribute to this loss of value-relevance of earnings might in turn cause an increase in the value-relevance of book values. This claim is based on studies suggesting that book values are more important than earnings when earnings are negative or contain nonrecurring items. What can be deduced from this, is that the value-relevance of earnings and book values tend to move inversely to one another. Nevertheless, Collins et al. (1997) find that the combined value-relevance of book values and earnings have not declined during the period of 1957 to 1997.

Ohlson (1995) provided a valuation framework expressing prices as a function of both earnings and book value of equity. Even though, to some extent, acting as substitutes, earnings and book values function also as complements by providing explanatory power incremental to one another. Hence, both valuation items are represented in this thesis as variables explaining prices.

However, it is important to note that these two variables are not the only ones explaining market prices. Ohlson (1995) and Felthman & Ohlson (1995) address that so-called "other information” also affects value. This aspect represents the idea that forecasting future accounting data depends on information beyond current known accounting data. Ohlson (1995) introduces analysts’ earnings expectations that can be understood to be the variable for “other information”. In addition to forecasted future earnings, accruals and Tobin’s Q are also viewed in this thesis as supporting components of prices.

Penman & Sougiannis (1998) study how results of different valuation methods of fundamental analysis differ used practically over finite one-, two-, five- or eight-year time horizons and particularly, whether forecasting accounting earnings work better on finite horizons than forecasting cash flows. They conclude that valuations based on estimating GAAP (Generally Accepted Accounting Principles) accrual earnings and book values (Residual Income Model, RIM) have practical advantages over forecasting dividends (Dividend Discount Model, DDM) and cash flows (Discounted Cash Flow Model, DCFM). These basics of these models are outlined in a later chapter in this thesis since they make for the major part of the valuation methods used in fundamental analysis to derive the intrinsic value of a firm.

Chung & Kim (2001) study the usefulness of a structured financial statement analysis as the basis of investment decisions with a straightforward approach. They create their own firm valuation model of fundamental variables (ability to generate cash flows, growth potential and risk) to derive a firm’s intrinsic value. This value is then compared with the actual market price to examine deviations between them. Thusly, they find out which stocks are undervalued or overvalued. Undervalued (overvalued) stocks are then assigned to the long (short) position that are then held for various holding periods to examine their profitability. Their model generates significant positive returns that support their hypothesis of constructing a profitable trading strategy based only on a structured financial statement analysis.

Similarly, Ou & Penman (1989) predicted signs of one-year ahead earnings development by taking a long (short) position in companies’ stocks which one-year ahead earnings are estimated to increase (decrease). Additionally, Holthausen & Larcker (1992) propose a strategy where a long (short) position is taken in stocks which consecutive annual returns are expected to be positive (negative). Ragab & Omran (2006) also study changes in earnings and their ability to predict stock returns. They find that, at least in the Egyptian stock market, no significant relationship exists between earnings changes and stock returns. However, they find that earnings levels are significantly associated with prices and thus conclude that accounting information is still value relevant in the Egyptian equity market.

Frankel & Lee (1998) estimate intrinsic value of a firm using I/B/E/S consensus forecasts of future earnings and a residual income model to examine its usefulness in predicting cross-sectional stock returns in the U.S. They find that the resulting ratio of value-to-price is a reliable predictor of cross-sectional returns, especially for longer time horizons.

Recently, Bartram & Grinblatt (2018) have tested the ability of fundamental analysis to explain prices by virtually all its most recently reported balance sheet, income statement and cash flow statement items. By identifying peer-implied values from these linear functions they study the profitability of buying undervalued and selling overvalued stocks, measured by percentage deviations of actual market capitalizations. In their regressions, they also include accruals and momentum as in this thesis. Their method generated abnormal returns of 4% to 10% per year implying that market prices do not fully reflect accounting data. They conclude their paper by claiming that fundamental analysis works, and the abnormal returns are not due to an omitted risk factor.

2.4. Combination models

As technical analysis focuses on stock’s own historical prices and returns, it provides meaningful information not provided by the items in the balance sheet nor the financial statement. The past prices might indicate the psychology of the market and the sentiment of the market participants better than the fundamentals. Thus, past historical price information should be useful with fundamentals on explaining stock price movements. (Hong & Wu 2016.)

Hong & Wu (2016) performed a similar study to this thesis by investigating whether including past stock returns could enhance the performance of fundamental analysis in explaining stock price movements. They use a sample of U.S. stocks over the period from 1999 to 2012. Additionally, their study also investigates whether market uncertainty affects the relative importance of past returns and fundamentals. They find that fundamental information is most important in explaining stock price movements in small firms, which have greater information asymmetry, and in times where market uncertainty is high (f.e. during the Financial Crisis of 2007-2008). Momentum however is at its best during stable and good times. Hong & Wu (2016) find out that combining fundamental analysis with momentum analysis has substantial benefits on explanatory power of stock price movements.

The four-factor model of Carhart (1997) can also be viewed as an example of the complementary nature of fundamental and technical analysis by adding momentum as a part of the asset pricing model created by Fama & French (1993). Carhart (1997) documented that momentum is significant in explaining mutual fund performance along with the three-factor model that depends on the market risk premium and fundamental information of the firm: market capitalization and book-to-market ratio.

Amini, Rahnama & Alinezhad (2015) take on a different approach by studying stock returns gained using a trading strategy based on picking the stocks with fundamental analysis and then timing the transactions using technical analysis. From their results, they find significant possibilities for abnormal returns combining these approaches of stock valuation. Eiamkanitchat, Moontuy & Ramingwong (2016) also approach the issue similarly by seeing it as an opportunity for stock filtration and abnormal results through the proper timing of buying and selling via technical analysis. Their study also presents promising results of profit opportunities created by a combination approach.

Asness, Moskowitz & Pedersen (2013) study the profitability of value and momentum strategies across eight diverse markets and asset classes. They find significant profit opportunities in combining these two approaches. Value strategy can be stated simply as buying value stocks, stocks with high book-to-market ratios, and shorting stocks with low book-to-market ratios, which are usually labeled as growth stocks. The basis of their momentum strategy is the same as the one in this thesis. Companies are ranked by their cumulative returns over the past 12-month period, excluding the most previous month. Using these ranks, the top decile stocks are then bought, and bottom decile stocks shorted. These strategies are then rebalanced monthly. After each month, a new portfolio is constructed in the basis of these trading rules. Asness et al. (2013) find that even though value and momentum strategies perform well on their own, the returns are even greater when the strategies are combined. They discover that this is due to negative correlation between the strategies.

3. HYPOTHESIS OF MARKET EFFICIENCY

The market is full of various kinds of information. By using market information investors strive to attain higher returns than market participants in general. This target is pursued in multiple ways like using technical or fundamental analysis. (Bettman et al. 2009.) The performance of these two methods studied in this thesis wind up tightly with the building block theory of hypothesis of market efficiency by Eugene F. Fama (1970). The concept of market efficiency assumes that prices reflect all relevant available information instantaneously (Copeland & Weston 1988: 331).

Fama (1970: 387) introduces three conditions needed to achieve market efficiency:

1. No transaction costs for trading securities.
2. All information is available for everyone in the market free of charge.
3. Participants in the market approve the influence of currently available information on current and future prices of assets.

The efficient market hypothesis is linked with the idea of a "random walk". Random walk is a term loosely used in the finance literature standing for a price series where all consecutive price changes represent random individual departures from former prices. The logic of this is that if the information flows perfectly and information is instantly reflected in stock prices, then price changes of tomorrow must reflect only tomorrow's news and thus it will be independent from today's price movements. As news is by definition unpredictable, price changes must be unpredictable and random. The result derived from this is that prices fully reflect all known information. (Bodie, Kane & Marcus 2009: 334; Malkiel 2003.)

This assumption of market efficiency means that nobody can systematically earn excess returns using any available information. Thus, neither technical analysis, which is the study of past prices to predict future prices by time series analyzation, nor fundamental analysis, which is the analysis of financial information to help investors select mispriced stocks, should be able to help investors earn higher returns than those that could be earned by holding a portfolio of randomly selected stocks - at least not with corresponding rise in risk. (Malkiel 2003; Nikkinen, Rothovius & Sahlström 2002: 82-85).

As is known by every investor, these conditions defined above are still not fully observed in the market almost fifty years since their creation. There are transaction costs, investors are rarely rational and the information available is only available to a certain number of investors. However, it is fortunate to note that the conditions need not to be met perfectly to form efficient markets. The critique against efficient market hypothesis often base its trust on the valuation errors that are evident in the markets. Nevertheless, even though during the Internet bubble, as an example, most of the prices were surely not rational and perfect but from that fact alone one cannot automatically deduct that the markets are in-efficient. (Malkiel 2003; Copeland, Weston & Shastri 2005: 354-355.)

Fama has divided in his compilation of the theory of market efficiency into three different categories: weak, semi-strong and strong, which approach market efficiency from the perspective of how much information is available to the market and how it reflects on stock prices. (1970: 387). However, Fama (1970) reminds his followers that the situation where prices reflect all available information is considered as an extreme null hypothesis that is not even expected to be perfectly true or at least not at all times.

Weak form efficiency is the critical one to technical analysis, one of the two main issues studied in this thesis. Weak form efficiency asserts that prices reflect all price, trading volume and other market-generated information included in earlier trades. Since technical analysis studies benefitting from using information gathered from earlier price changes, for technical analysis or any trading rule to produce any excess returns the weak terms of market efficiency cannot be at effect. (Copeland & Weston 1988: 332.) According to market efficiency, even at its' weak form, not much can be achieved by basing trades on past market data. If such data could ever produce reliable signals of future performance, investors would have already learned to exploit these signals. Thus, the signals would lose their value after they become widely known. (Bodie et al. 2009: 338.)

Semi-strong efficiency means that the prices of assets reflect all publicly available information. Therefore, no investor can achieve excess returns using any public knowledge. The public knowledge means for example financial statements, news, dividends, new products or profit predictions. (Copeland & Weston 1988: 332.) Hence, it also means fundamental ratios, which are derived from financial statements, should not predict future performance. Thus, the semi-strong terms are critical to fundamental analysis, which is the second part of this thesis. This form also covers the weak form hypothesis since all information included in it is public information (Edwards & Magee 1992: 3).

Despite the difference of fundamental analysis and technical analysis, as illustrated earlier in this thesis, they are often used together. Usually, in practice, fundamental analysis is used to pick companies to invest in and then technical analysis is used to time the buy or sell transactions. (Ylä-Kauttu 1989: 7—8; Siegel et al. 2000: 106).

Finally, *strong form efficiency* stands for a situation where prices include all public as well as unpublished information relevant to a company. This indicates that even insider information is always reflected in prices. (Copeland & Weston 1988: 332.) The strong form efficiency covers also both the weak and semi-strong forms of the efficient market hypothesis. The strong form presents a world with perfect markets where all information is free and available to everyone simultaneously. This kind of extreme interpretation of market efficiency leads to a situation where excess returns are impossible to achieve. However, it is important to note that the thought of market efficiency is always a simplification of reality. (Leppiniemi 2009: 110).

Nevertheless, one thing that all efficient market hypothesis versions have in common is that they assert that prices should reflect available information. Whatever is available is not always all that is. Prices are not expected to be always right. The hypothesis only states that at a given time, using currently available information, one cannot be sure whether today's prices will prove to be right or wrong in the future. However, if market participants are rational, prices should be correct on average. (Bodie et al. 2009: 338.)

Consequently, it can be understood from the efficient market hypothesis that both technical analysis and fundamental analysis should not be in any way effective. However, as can be seen in history, they can be significantly successful at times. (see f.e. Brock et al. 1992; Jegadeesh & Titman 1993; Bessembinder & Chan 1995; Abarbanell & Bushee 1998; Hong & Wu 2016) In this thesis, fundamental ratios are used with a technical analysis method momentum to explain future prices. So, past pricing and public information, deemed unusable to explain future prices by the efficient market hypothesis, are tested whether they can do just that in a complementary fashion.

3.1. Efficient market models

According to Fama (1970), the claim that efficient markets fully reflects available information is so generalized that it contains no empirically testable content. To get the model testable, price formation should be covered more closely. Also, it should be defined what is meant by markets fully reflecting the prices. Fama (1970) introduces three different models to empirically test market efficiency in his paper. First, a fair game model that is based on expected returns. Second, a submartingale model which uses market information and finally, a random walk model that is based on independent price movements.

The first model to be considered is the fair game model. In the context of this model Fama (1970) depicts the stock market with two parameters: risk and expected return. According to Fama (1970) the expected return of a security is actually a function of its' own risk. Actually, different theories differ mainly on how to define risk. All models that fall to the category of "fair game models" can be written in a mathematical notation as follows:

(1) $E(\tilde{p}\_(j,\ \ t+1) \dashv|\ \Phi\_t) = [1 + E(\tilde{r}\_(j,\ \ t+1) \dashv|\ \Phi\_t)]p\_jt$, where

E is the expected return, p_{jt} is the price of the security j at time t and $p_{j,\ \ t+1}$ its' price at time t+1. $r_{j,\ \ t+1}$ is the percent return of a time period, which can be calculated from the following equation: $\frac{(p_{j,\ t+1} - p_{jt})}{p_{jt}}$. The symbol ϕ_t represents the information that is assumed to be fully reflected in the price at time t.

Next, Fama (1970) illustrates the relation between actual and expected returns with the following formulas (2) and (3):

(2) $$x_{j,\ t+1} = p_{j,\ t+1} - E(p_{j,\ t+1} \mid \Phi_t)$$

(3) $$E(\tilde{x}_{j,\ t+1} \mid \Phi_t) = 0,$$

which means, by definition, that the sequence $x_{j,\ t+1}$ is in a fair game relation in respect to the information Φ_t available at time t. In these formulas, $x_{j,\ t+1}$ illustrates excess returns. These equations also show that the expected value $E(\tilde{x}_{j,\ t+1} \mid \Phi_t)$ of the excess return $x_{j,\ t+1}$ is zero. Therefore, every investor has an equal position in relation to information.

The next model Fama (1970) presents in his foundational paper is the submartingale model. He states that the price series' follow a submartingale model with respect to the corresponding information series. This means that the expected value of the next periods price, which is based on the information available, is equal to or greater than the current price. This can be illustrated with a following formula:

(4) $$E(\tilde{p}_{j,\ t+1} \mid \Phi_t) \geq p_{jt}.$$

This equation holds an important assumption concerning the efficient market hypothesis. It implies that based only on the information Φ_t, mechanical trading rules cannot be applied for excess returns during the period in future in question. (Fama 1970.)

Third, and the last, of Fama's (1970) models for efficient models is the random walk that was mentioned in the earlier chapters. The hypothesis for this model practically means that because market information immediately reflects to prices, the followed price changes can only be the consequences of unexpected future events and thus independent from previous price development. This means that any information affecting prices of assets should already be reflected on the prices of those assets. (Gerritsen 2016: 180; Malkiel 2003.) The random walk model to empirically test market efficiency is based on two previous hypotheses. The first states that consecutive price changes are independent. The second one claims that the probability distributions of subsequent price changes are identical. Fama (1970) combines these hypotheses as notated in the following equation:

(5) $$f(r\_(j,\ t+1) ┤|\ \Phi\_t) = f(r\_(j,\ t+1))$$

This equation states that the conditional and marginal probability distributions of an independent random variable are identical. Also, it can be derived from this that the whole probability distribution is independent of available information. The equation (5) can also be presented with the expected value. Then, it means that the mean of the probability distribution of the term $r_{j,\ t+1}$ is independent of available information Φ_t at time t. Eugene Fama considers that the model of a random walk is an extension of the fair game model where random walk is just a better and more detailed expression of the economic state in the markets. (Fama 1970.)

4. TECHNICAL ANALYSIS

Technical analysts base their activities on the belief that, in contrary to weak-form efficiency described earlier in the thesis, information contained in past prices is not entirely incorporated in the current price. Technical analysis is one of the most used and most popular tools for investors on the financial markets. It is often used as an umbrella term when discussed about various analyzation techniques used in trading. Technical analysis is simply the study of the advancement of price and trade volume and the use of this information to predict future prices. The analysts are trying to search for mispriced securities to which all the information has not yet reached.

The other main purpose of technical analysis, other than finding mispriced securities, is spotting recurrent and predictable patterns in prices. As it can be learned from the following chapter, technical analysts try to find these trends on the market that are created by investor's opinions about the economic, political and psychological universe. This study of price patterns and trends is often done with graphs. The practitioners of technical analysis believe that changes in supply and demand can be observed by exploring only charts which represent market activity. This is utilized in the simplest form by identifying an upward trend before it starts. (Antoniou, Ergul, Holmes & Priestley 1997; Brock et al. 1992; Edwards & Magee 1992: 4.)

The practitioners of technical analysis are sometimes called "chartists". The history of technical analysis is defined by the amount of broad critique it has overgone by the academic community. The background of the critique lies in the subjective character of technical analysis. (Lo, Mamaysky & Wang 2000.) The only thing researchers seem to agree about the profitability of technical analysis is that it works better on emerging less efficient markets. (see e.g. Bessembinder & Chan 1995; Hsu & Kuan 2005)

To a lot of people, technical analysis is the original form of investment analysis. Technical analysis dates to the 19th century. In the United States, the use of technical regularities to find patterns from the stock prices is probably as old as the stock market itself. The analyzation method was in broad usage before the era of comprehensive and pervasive public information. The era of public information enabled the bloom of fundamental analysis. (Brock et al. 1992: 1731.)

There is a considerable amount of different methods used in technical analysis alternating from very simple ones to highly complicated methods. The tools of technical analysis are nowadays broadly available to investors and many investing firms offer functions of technical analysis to their customers (Gerritsen 2016: 179).

According to Cheung & Wong (2000), depending of the investing horizon, 12,8—40,8% of exchange rate investors in Hong Kong, Tokyo and Singapore use technical indicators as the basis of their trading. In addition to this, Allen's & Taylor's (1992) research indicates that approximately 90% of the brokers in London use technical analysis as the primary or secondary source of information. 60% of these brokers thought that technical analysis is at least as important as fundamental analysis. Hoffmann, Shefrin & Pennings (2010) have similar findings about the importance of technical analysis. They have found that most private investors use technical analysis instead of fundamental analysis.

4.1. Assumptions

Academics perceive technical analysis with skepticism because it is thought to break the profound idea of rationality of capital markets (Gehrig & Menkhoff 2006: 327). Technical analysis is based on three major basic assumptions:

> *The market discounts all information affecting it*. According to this first assumption, the price reflects the fundamental, political, psychological as well as every other type of possible information. Therefore, market behavior is the basis of technical analysis. It follows that if all information affecting the prices is already in the prices, it must be that the prices are the only thing to

keep track of. Thus, when the price is rising it can be assumed that the company's fundaments are also increasing.

The prices move in trends. In technical analysis, trends mean a kind of development patterns. They can be perceived as different directions the price curve is moving towards. The most important thing is to pick up the trends as early as possible. Thus, the trades can be done to follow the trend. For example, in the case of a rising trend, an investor should note the trend early on and buy the stock cheap and ride the trend until it shows signs of turning around. When there is a sign of trend reversal the stock should be sold as close to the peak price as possible. (Ylä-Kauttu 1989: 8-9; Murphy 1999: 3-4.)

History repeats itself. Humans have a tendency to act the same way in similar circumstances. When the price is decreasing rapidly investors tend to sell almost at any price possible. However, when prices start to rise quickly investors attempt to profit from the situation by buying at almost any price given. (Ylä-Kauttu 1989: 9.)

The roots of modern technical analysis stem from the Dow Theory which was developed by Charles H. Dow. Dow is thought to be the father of modern technical analysis. His research of the price changes of securities gave rise to a completely new way of analyzing the capital markets known today as technical analysis. (Achelis 2001: 1; Ylä-Kauttu 1989: 11).

4.2. The Dow Theory

Charles H. Dow published the outlines of his theory in the Wall Street Journal (WSJ) from 1900 to 1902. Hamilton (1922), who was the follower of Dow as the editor of WSJ, then gathered and combined Dow's theories of market movements in his book *The Stock Market Barometer*. Although Dow invented all the basic theorems behind the theory, Hamilton's contribution to the Dow Theory is considered as crucial (Brown, Goetzmann & Kumar 1998). After this, in 1932, Robert Rhea constructed the theory into theorems in his book called *Dow Theory* (Pring 2002: 36-37).

All three of the basic principles presented in the previous subchapter are either directly or indirectly traced to the Dow theories (Achelis 2001: 7). Originally, the Dow theories were created to be used in industrial and railroad indices but today the use of the principles is extended to consider the stock market in general. The main idea in the Dow Theory revolves around trends. It identifies three different types of trends called *primary trend*, *secondary trend* and *tertiary trend*.

Primary trends, better known as bull or bear markets, are long-term movements of prices. This kind of a trend can last from several months to even years. Secondary trends, on the other hand, are shorter-term price deviations from the underlying primary trend. A secondary trend is thought to last from several days to even a month until the price corrects itself from the deviation. Finally, tertiary trends are considered as fluctuations of an independent trading day. They offer only little noteworthiness in comparison to the bigger picture. (Brown et al. 1998; Bodie, Kane & Marcus 2005: 373-374.) The main trends are illustrated in the simplified figure below. Tertiary trends can be perceived as short-term fluctuations inside the primary and secondary trends.

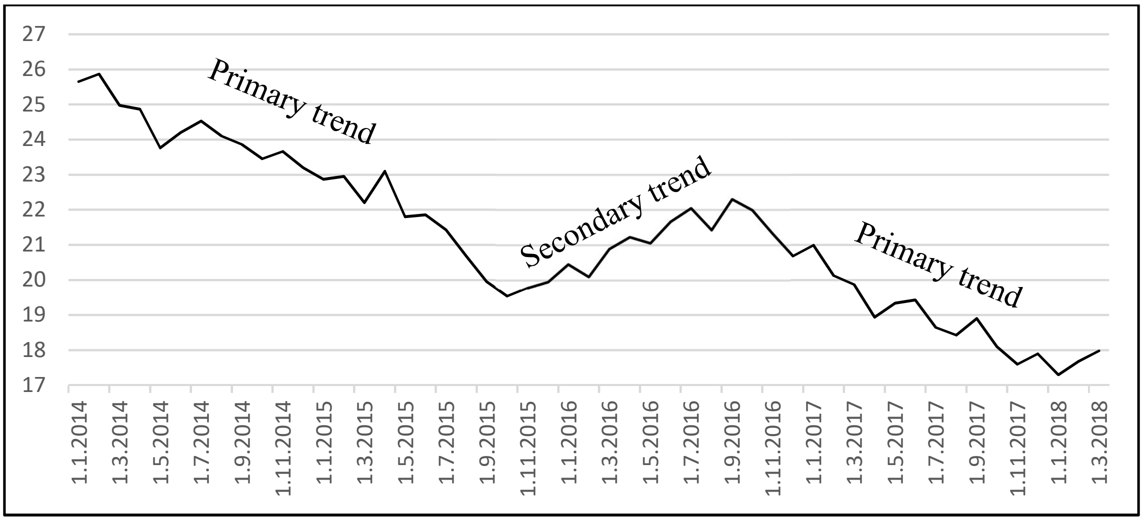

Figure 1. Primary and secondary trends.

The primary trend is relatively easy to identify. The lowest price paid for the security on a certain time period is thought to be the start of the trend while the highest price paid for it on that same period is then considered to be the end. Secondary trend can be expressed in a similar way but only the time period is shorter than in a primary trend. (Bodie et al. 2005: 374.)

A concept that is tightly wound with trends is called *resistance areas*. A resistance area is created when an asset hits its peak price and then declines. This signifies an area where the selling pressure overruns the buying interest. The area is tested when the price starts going up again and nears the same peak again. If it rises past the previous peak, it is likely to keep on rising and continue the rising trend. However, if the price does not reach the previous peak but instead goes back to a lower level, then it might indicate a reversal of the trend and a start of a possible downward trend. Here, investor expectations have changed and there has been shift in demand. The resistance areas could be tested for several times until one can identify what the following trend will be. (Siegel et al. 2000: 269, 278; Ylä-Kauttu 1989: 15; Hsu, Taylor & Wang 2016: 33.)

4.3. Critique of technical analysis

Three basic critiques towards technical analysis and the answers to them by Murphy (1999: 16-21.) are outlined in this chapter. One of these is a phenomenon called self-fulfilling prophecy. The second one critiques the assumption that future price changes could be forecasted from past movements. The third one is based on the random walk theory.

The self-fulfilling prophecy critique is based on two observations. During recent years the methods of technical analysis have become so common that investors are well aware of them and often act according to their signals. This creates a self-fulfilling prophecy as the trading volume significantly increases as favorable patterns emerge. The second observation is about the subjectivity of price patterns, which are just in the eyes of the perceiver. (Murphy 1999: 16-21.) Moreover, there are technical rules that do not need a human opinion about the markets and price movements. These kinds of strategies are made easier by computers (Levy 1966: 88).

However, Murphy (1999: 16-17.) states that these observations actually cancel out each other. If the patterns are subjective, how could everyone perceive the same pattern at the same time and thus create a self-fulfilling prophecy. These two points can't be presented at the same time. It is true that some methods of technical analysis are highly subjective and often embody elements of doubt and disagreement. Even though everyone interpreted the pattern the same way, they wouldn't enter the market homogenously and simultaneously. Some would try to anticipate the signals and others would act only after seeing a sure thing. Some would do short-term investments and others think about longer horizons. Murphy (1999: 17.) also proposes that the self-fulfilling prophecy is self-repairing. When the investors rely strongly on patterns, their collective action would start affecting the market or distort it. If this happened, the investors would stop using the methods or alter their strategies.

The second critique is using information of past price changes to forecast future changes. The theory of statistics is based upon two types of statistic information: descriptive and inductive. Descriptive statistic information refers to the graphic presentation of data on f.e. graphs. Inductive statistics, on the other hand, refers to generalizations and analyzes that is grounded on collected data. Analyzing price information is a part of time-series analysis, that is specifically focused on studying past information. So, Murphy (1999: 19.) states that forecasting future price changes based on past price information lies on solid ground of statistical theory. Future can't be forecasted on any other way than projecting past experiences to the future.

The random walk theory is the basis of the third critique. As presented earlier in this thesis, according to the theory, price changes are independent and random and thus aren't reliable for projecting future movements. What follows from the random walk theory is that the buy and hold strategy is the best chance of beating the market. It is intuitive to think that the market holds a touch of unpredictability, but it doesn't feel natural to think that all price changes are random. (Murphy 1999: 19.) As his opposition, Murphy (1999: 20.) presents different trendlines and -patterns. How do these exist if price changes should be random?

In addition to these addressed by Murphy (1999), Detry & Gregoire (2001: 3) present a noteworthy critique of technical analysis that is directed to searching for regularities from data sets. It is called data mining or data snooping. An issue shortly grasped in the literature review section. The critique is based on that if hundreds of researches look for patterns in the same data, it is highly probable that they will find at least one even though it was completely random. Therefore, the most known and successful studies have been tried to replicate with different data sets to minimize this kind of distortion of data. Yen & Hsu (2010: 128) go as far as stating that the success of technical analysis might result from this data snooping bias.

For example, Hsu & Kuan (2005) study the effects of this phenomena to technical analysis by using different tests that correct the distortions. The researchers end up on the realization that even though there are distortions, profitable strategies were perceived on young markets. In older markets, these biases weren't perceivable anymore. This might result from the fact that younger markets tend to fulfill the terms of market efficiency incompletely and the reflecting of information to prices as well as market liquidity is still on a lower level compared to the older markets. (Hsu & Kuan 2005.)

4.4. Methods

There are two kinds of ways to conduct technical analysis. The first one is to use qualitative or subjective methods, which are based mainly on analyzing graphs and the inductive depictions made from patterned behavior. Therefore, a conclusion derived from subjective methods reflects the private interpretations of an analyst who is applying them, and it can thusly deviate greatly from another analysts' interpretations from the same market data.

The second one is objective or quantitative technical analysis which uses quantitative tools, where transaction signals are derived from time series data using quantitative analysis. The signals are thus unambiguous so testing and evaluating them by simulations on historical data is possible. This is called back-testing, which is a repeatable experiment allowing profitability claims to be tested and refuted with statistical evidence. The two ways are often used to support each other. (Aronson 2007: 15-16; Menkhoff & Taylor 2007: 4; Hsu et al. 2016: 5.) In this thesis, three of the most used technical analysis tools are presented. One of them, momentum, is used in the empirical part representing technical analysis along with lagged price in explaining stock prices.

4.4.1. Moving average

A majority of the methods of objective technical analysis is based on using moving averages to profit on trends. Moving average is intended to separate significant trends from insignificant ones and to smoothen insignificant price fluctuations by averaging the price information. However, the moving average line lags market action. Therefore, it is called a trend following indicator. (Menkhoff & Taylor 2007: 4-6.)

Moving average can be calculated with different time-frames. The shorter ones are more sensitive to market action. The most used ones are 50-day and 200-day moving averages. Usually a moving average is calculated with closing prices. Metghalchi, Chang & Garza-Gomez (2012) studied the profitability of technical analysis in the Taiwan stock market using 9 different indicators. The authors found that from all of the indicators, the 50-day moving average yielded the best results.

The practitioners of this method can use one or several averages at the same time to generate trade signals. The moving averages are plotted on the price chart along with the actual price information and their relative movements are observed. A signal to buy is created when the closing price of the asset rises above the moving average line. On the contrary, a sell signal is generated when the closing price decreases below the moving average. It is important to note that using shorter timespans and thus more sensitive averages produces more signals and the possibility of false signals is significantly higher. On the other hand, the signals are generated earlier than the longer averages.

The longer averages tend to work better on continuing trends while the shorter ones are more usable when the trend is about to reverse. Thus, the most effective way of using moving averages is to use a shorter and a longer average at the same time. This is called the double crossover method, where trading signals are generated by the crossing of these two moving average lines. This lags the market more than the use of a single average but creates less false signals. (Murphy 1999: 195-203; Edwards, Magee & Bassetti 2007: 644-649.)

A simple moving average can be calculated in the following way:

(6) $$SMA_t = \frac{1}{n} \sum_{i=1}^{n} P_i,$$

where SMA_t = simple moving average in period t

P = closing price of security i

n = number of periods

The simple moving average is often criticized because it gives equal weights to every single days' price. This is thought to cause possible distortions because of extreme price changes. Consequently, an exponential moving average has been invented that weighs recent price data heavier than those further in the past. Many practitioners of technical analysis find this version as more accurate than the simple moving average. (Siegel et al. 2000: 196.)

The exponential moving average can be presented in a following way:

(7) $$EMA_t = EMA_{t-1} + SF * (C_t - EMA_{t-1}),$$

where EMA_t = exponential moving average in period t

SF = smoothing factor based on $\frac{2}{n+1}$, n = days

C_t = closing price

4.4.2. Relative Strength Index

The Relative Strength Index (RSI) is the most common indicator to predict a reversal of a trend. This indicator was created by an American called J. Welles Wilder during the latter part of the 1970's. It measures the relative strength of a single asset to itself by comparing the closing prices of the asset as follows (Siegel et al. 2000: 234; Rosillo, de la Fuente & Brugos 2013.):

(8) $$RSI_t = 100 - \left(\frac{100}{1+RS}\right)$$

$$RS = \frac{AG}{AL},$$

where RSI_t = relative strength index at time t

RS = relative strength

AG = average upward price change

AL = average downward price change

The oscillator ranges from 0 to 100 which makes the values easy to compare to each other. Wilder (1978: 68) set the most used timespan (14-day time period) and signal levels (30 and 70) in his foundational book of RSI. A value of 100 practically means that there have been only positive price changes and a value 0 on the contrary means that only negative price changes have been observed. (Nor & Wickremasinghe 2014; Wong, Manzur & Chew 2003.)

Values over 70 are usually thought of as overbought as values under 30 are thought as oversold. In these areas, the upper and lower bound, the signals of RSI are the most significant. The levels or bounds chosen are used to produce buy and sell signals. Wong et al. (2003) present four different ways of interpreting RSI signals: *Touch*, *Peak*, *Retracement* and *50 Crossover*. *Touch* means that a buy (sell) signal is created when the RSI line touches the defined lower (upper) bound. *Peak* means that signals are created when a reversal is observed on the oversold or overbought zone. For example, when RSI is above the upper bound and turns downward, a signal to sell is created. Similarly, in the *retracement* method, a signal is created in the same way but not until the RSI line falls back to the upper bound and crosses it. The *50 crossover* method generates signals when the RSI crosses a line set in the middle (50). (Wong et al. 2003.)

4.4.3. Momentum

Momentum, which is often described as the continuation of the direction of prior stock returns, was first documented by Jegadeesh and Titman (1993) and since then few market anomalies have received as much attention in empirical research than the momentum effect. Behind momentum is a simple idea of buying prior winners and selling short prior losers. Jegadeesh and Titman (1993) discover that previous winners in the US stock market outperform previous losers by as much as 1,49% per month.

Still on this day, after more than two decades from its initial discovery, reports about the profitability of momentum trading strategies keep on coming up on an ongoing basis. Since the first version by Jegadeesh and Titman (1993) the strategies of momentum have been altered and tested in many different forms. F.e. Novy-Marx (2012) argue that in fact strategies based on intermediate past performance (12-7 months) yield significantly higher returns than those that are based on recent past performance (6-2 months). However, Gong, Liu & Liu (2015) find that there is no significant difference between the predictability of stock performance in the intermediate past and the recent past. They dictate this by excluding two months (2nd and the 12th) from the construction of momentum strategies in the US and 26 other major international markets.

Various theories have been proposed as the explanation to momentum returns. In addition with industry (as introduced in the literature review chapter), size has also been introduced as the driver of these returns. Hong, Lim & Stein (2000) find that once they move from the smallest stocks, the profitability of momentum strategies sharply decline. They also discover that momentum works better on stocks with less analyst coverage. The researchers base their study on a simple hypothesis: If momentum comes from gradual information outflow, then there should be stronger momentum in stocks to which information gets out more slowly. The results support this hypothesis.

The profitability of these strategies has also been tested on various markets (see Rouwenhorst 1997; Liu et al. 1999; Chan et al. 1999). The impressive excess returns of momentum and its negative relation to other risk factors make it look like a free lunch for investors, but the successful performance of momentum comes with occasional crashers. In 1943, the winners-minus-losers strategy generated a -91,59% return in just two months. In 2009, the crash was the magnitude of -73,42% in only three months. These sudden crashes take decades to recover from and even the large returns of these strategies do not compensate a reasonably risk averse investor. These two most expressive momentum crashes happened as the markets were rebounding from large previous declines.

Barroso & Santa-Clara (2015) as well as Grundy and Martin (2001) deem this as the result of time-varying systematic risk of the momentum strategy. This follows from the following phenomena: as the strategy ranks stocks by their returns over a formation period, during good times the well-performed stocks tend to be high-beta stocks and losers low-beta stocks. So, because the momentum strategy shorts losers to buy winners, it has by construction a significant time-varying beta: positive after bull markets and negative after bear markets. However, Barroso & Santa-Clara (2015) find that this risk is highly predictable and can be managed to eliminate the exposure to crashes.

There have been mixed results of the relationship between momentum returns and macroeconomic risk. Griffin, Ji & Martin (2003) research internationally, covering 40 countries, whether momentum profits could be explained by macroeconomic risk. They find that momentum profits have weak co-movement across countries. This indicates that if the momentum is driven by risk, the risk is majorly country-specific. Griffin et al. (2003) test momentum profits in different economic states classified by GDP growth and aggregate stock market movements. They find generally positive profits in all macroeconomic states. Thus, there is no evidence that macroeconomic risk variables explain momentum.

On the contrary, momentum profits are globally economically large in both good and bad states of the economy.

Min & Kim (2016) on the other hand argue that the momentum strategy is related to economic distress risk. From 1954 to 2005 during bad times the mean monthly momentum profit is -1,90% while in good times momentum strategy generates a mean monthly profit of +2,09%. Furthermore, momentum strategies display a countercyclical pattern of risk, that means that the payoffs of the strategy tend to positively covary with macroeconomic conditions. From their findings, they conclude that time variation in momentum strategy is linked to variations in macroeconomic risk.

Grobys (2014) also study the effect of macroeconomic state on global momentum profits. Across the overall sample of 1998 to 2013 there persisted positive returns on momentum strategies, but statistically significant negative returns during recessions, which were studied using a recession dummy. This is majorly driven by the financial crisis of 12/2007 to 6/2009. Daniel & Moskowitz (2013) state that these "momentum crashes" can be seen as a result of up- and down-beta differentials of loser portfolios in bear markets.

5. FUNDAMENTAL ANALYSIS

Fundamental analysis differs from technical analysis in the fact that it studies the reasons behind price changes as technical analysis focuses on the data of price changes alone (Ylä-Kauttu 1989: 7). Fundamental analyst attempts to determine the true value of the stock prices of firms based on information from their financial statements and forecasts on the future, namely earnings and dividend prospects, expectations of future interest rates and the firms risk valuations. Usually, by conducting a discounted cash flow analysis, the analyst tries to determine whether the value of all the payments received during a lifespan of the stock will exceed the current price. If this derived intrinsic value of the stock is greater than the current price, a fundamental analyst would recommend buying the stock. (Bodie, Kane & Marcus 2014: 356.)

The analysis is executed in hope to find value in firms that other investors haven't found yet. The analysts work towards this goal mainly by studying past earnings of the firms and examining their balance sheets. This is sometimes supplemented with the evaluation of the quality of the firm's management and the industry's outlook. This macroeconomic and industry outlook might be, for some firms, more important than the relative performance of the firm within its industry. A great emphasis is laid on the future growth potential of the analyzed firm. (Bodie, Kane & Marcus 2010: 356, 557; Siegel et al. 2000: 106.)

Fundamental analysis in in direct contradiction with the hypothesis of efficient markets, which is one of the base theories in economics, and especially the case of semi-strong efficiency. The hypothesis states that regarding semi-strong efficiency, no investor can generate abnormal results using public information (Copeland & Weston 1988: 332). At least the analysts' results are not supposed to be likely to be going to be significantly more accurate than those made by rival investors. So, what can be done is to identify the firms that are better than anyone else thinks they are. It doesn't benefit the analyst to find firms that are in good shape if the market also knows they are good. Naturally, if the knowledge is already out there, the profits are not as high. Still, fundamental analysis is not merely about finding well-run firms as there can be significant potential found in poorly run firms that are not as bad as their stock prices suggest. (Bodie et al. 2014: 356.)

5.1. Stock valuation models

To estimate intrinsic values of shares, fundamental analysis literature has seen four different major types of models. These are introduced in the next subchapters. The fundamental model that is used in this thesis can be understood as a multiple depending model based on ratios of accounting information. All of the following models use information of current and future earnings of the companies studied to evaluate their fair or intrinsic value and then compare that with the market value to determine possible investing opportunities. The intrinsic value represents the present value of all cash payments per share to the stockholder.

Since a company's value is mainly based on its ability to produce cash flows and correspondingly the uncertainty of those cash flows, in addition with the most important principle of modern finance being "any asset value equal to the present value of all expected cash flows discounted at the required return" and given the complexity and importance of stock valuation, a various techniques have arisen. (Wafi, Hassan & Mabrouk 2015.)

5.1.1. Dividend Discount Models (DDM)

The dividend discount model is based on a basic assumption of a stock's value being determined by discounting the expected future cash flows of a firm. Thus, the fair value of the stock is determined by the present values of future dividends that are expected to be generated as a result of owning the stock in question. Therefore, the general model for DDM can be constructed as follows:

(9) $$V_0 = \sum_{t=1}^{t=\infty} \frac{D_t}{1+k},$$

where V_0 is the value of a stock,

D is the expected dividend per share,

k is the required rate of return of the stock.

This model works based on the following assumptions:

- The company continues to operate to infinity
- The distribution policy of dividends of a company is fixed for predicting continuity of cash flows
- The required rate of return k remains constant
- The market works as is assumed in the theory of market efficiency. (Wafi et al. 2015.)

In addition to the plain dividend discount model, a constant-growth DDM (also known as the Gordon model after Myron J. Gordon who made this model popular) has also been introduced to making DDM practical since usually dividends are trending upward. From this assumption, a following model has been created:

(10) $$V_0 = \frac{D_1}{k-g},$$

where g is the growth rate. As can be perceived from this formula, the constant-growth DDM is only valid when the growth rate g is less than the required rate of return k. If the growth rate was indeed higher, the value of the stock would be infinite. The constant-growth DDM implies that the value of a stock will rise if it will give higher dividends per share, if the rate of k is lowered or if the expected growth rate of dividends rises. Since the constant-growth DDM assumes constant dividend growth rate, other versions have arisen such as the multistage versions of DDM. (Bodie et al. 2009: 574-576.)

The DDM model has also received critique since it is extremely hard to predict future dividends. As even short-term future dividends are hard to predict, estimations of dividends from now to infinity are impossible to achieve. Also, since companies can – at least temporarily – reduce dividends or stop the distribution of them altogether, an alternative model, a free cash flow model, has been created. (Wafi et al. 2015.)

5.1.2. Models which depend on multiples

These models see a company's value through market-based ratios called multiples. Multiples that calculate equity values are more widely used and the most common ratio used in this category is the earning multiplier model calculated by the price to earnings ratio (P/E ratio). This is also the simplest form of a multiplier model and can be calculated by dividing the market price of a stock (P) by the earnings (E) per share of the company. The main assumption in the P/E ratio is that companies make profits. Losses cannot be applied to this model.

The multiplier models continue to be used widely since they are easy to apply and can be applied to value almost anything. On the other hand, they have also been characterized as less accurate and less objective as f.e. the DDM model. (Wafi et al. 2015.)

Book value per share, earnings per share and forecasted earnings per share are these so-called market-based ratios that show the value placed on the company by the shareholders. The value of a firm is equal to the market capitalization of the firm. This in turn is equal to the number of shares outstanding times the price per share. (McGowan 2014: 53.)

Here are the equations for these ratios that are used in the empirical part of this thesis:

(11) $$Earnings\ per\ share = \frac{Net\ income}{Number\ of\ shares\ outstandin}$$

(12) $$Book\ value\ per\ share = \frac{Owne\ \ 's\ equity}{Number\ of\ shares\ outstanding}$$

Even though previous studies have found that price is highly dependent on book value per share, using book values also has some limitations. As opposed to market values representing current values of assets and liabilities, book values reflect only their original costs. In addition with focusing on the balance sheet items, for a better estimate of a firm's value, an analyst must turn towards expected future cash flows. (Bodie et al. 2009: 571.)

(13) $$Forecasted\ earnings\ per\ share = \frac{Analysts\ forecasts\ of\ future\ income}{Number\ of\ share\ \ outstanding}$$

These are the three variables used in the study of combining technical and fundamental analysis by Bettman et al. (2009). It is the base study that this thesis is following and recreating in the Finnish stock market with a few modifications like Tobin's Q and the accrual anomaly aspect which are presented after fundamental stock valuation models.

5.1.3. Discounted Cash Flow Models (DCFM)

Free cash flow approach is an alternative to the dividend discount model. It values a firm based on its' cash flow available to the firm or its equity holders net of capital expenditure. This approach is particularly useful for firms that do not pay dividends. These models calculate free cash flow (FCF) as follows (Bodie et al. 2009: 595-596.):

(14) $$FCF = EBIT * (1 - Tax\ Rate) + Depreciation - Change\ in\ Working\ Capital - Capital\ Expenditure$$

To get firm value (F_t) from this, the net present value of free cash flow is calculated using an appropriate discount rate. The discount rate usually used is the weighted average cost of capital (WACC) that is calculated as follows:

(15) $$WACC = \frac{E}{E+D} * Cost\ of\ Equity + \frac{D}{E+D} * Cost\ of\ Debt * (1 - Tax\ Rate),$$

where E is the market value of the firm's equity and D is the market value of the firm's debt. When the weighted average cost of capital is calculated, the firm value can be calculated as follows:

(16) $$Firm\ Value_t = \sum_{t=1}^{T} \frac{FCF_t}{(1-WACC)^t} + \frac{V_t}{(1-WAC\ \ )^t}$$

where

(17) $$V_t = \frac{FCF_t+1}{WACC},$$

in this equation, g is the growth rate. From this a value of equity can be reached by a following calculation:

(18) $$Value\ of\ Equity = Firm\ Value + Excess\ Cash - Outstanding\ Debt + Value\ Investment$$

From this a fair value per share can be calculated by dividing the value of equity by the number of shares outstanding. (Bodie et al. 2009: 595-596; Wafi et al. 2015.)

Even though the usage of the method is not clear at all in practice and actually it is not that widely used by researchers and practitioners, it is one of the most important valuation models. It captures all the elements that affect firm value in a comprehensive way. (Penman 1992)

5.1.4. Residual Income Valuation Model (RI)

Existing literature has generally provided support to this model and seen it as an alternative to the DCF models. The classical residual income formula calculates intrinsic value of a company from forecasted earnings along with book values (Penman & Sougiannis 1998).

Thus, equity value can be split into two components – an accounting measure of capital invested (book value) and a measure of the present value of future residual income, which is defined as the present value of the future cash flows that are not captured by the book value. Thus, a firm's value is its book value if the firm doesn't create or lose value relative to their accounting-based shareholders' equity. The stock's fundamental value can be derived in this model with a following formula:

(19) $$V_t = B_t + \sum_{i=1}^{\infty} \frac{E_t[NI_{t+1} - (r_e B_{t+1-i})]}{(1+r_e)^i}$$

(20) $$B_t + \sum_{i=1}^{\infty} \frac{E_t[(ROE_{t+1} - r_e) B_{t+1-i}]}{(1+r_e)^i},$$

where B_t is the book value at time t, $E_t[.]$ is expectation that is based on information available at time t. NI_{t+1} is the Net Income for period $t+i$, r_e is the cost of equity capital and ROE_{t+1} is the after-tax return on book equity for period $t+i$. (Frankel & Lee 1998.)

5.2.Accrual anomaly

A major limitation of using cash-flows to measure firm performance is that the present timing and matching problems cause it to be very noisy. To overcome these issues, it Is common to use accounting accruals to intertemporally smooth earnings. These accruals are then used to divorce the timing of cash-flows from their accounting recognition. Accruals can be divided to non-discretionary and discretionary accruals. These discretionary accruals are the portion of accruals that are managed by firms. Thus, they may sometimes be influenced by diverse earnings management purposes and result in a statistical anomaly worth noticing. (Calmès, Cormier, Racicot & Théoret 2013.)

The accrual anomaly suggests that firms with high reported accruals in a reported period tend to have abnormally low future earnings and stock returns. On the other hand, firms with low reported accruals tend to generate abnormally high future earnings and returns. This phenomenon was first documented by Sloan (1996). He hypothesizes in his original paper that this follows from investors naively fixating on bottom line income and not understanding that earnings are composed of both operating cash flows and non-cash elements (accruals). Investors also often don't get that the cash flow and accrual components of earnings have different abilities to predict future earnings.

Sloan (1996) defines these accruals by using changes in parts of the balance sheet, and measures accruals as changes in non-cash working capital minus depreciation expense scaled by average total assets. This is defined accurately as follows:

(21) $$Accruals = [(\Delta CurrentAssets - \Delta Cash) - (\Delta CurrentLiabilities - \Delta ShortTermDebt - \Delta TaxesPayable) - Depreciation] / AverageTotalAssets$$

Richardson et al. (2005) introduce a more general definition of accruals. They separate operating from financing activities and reshape the standard balance sheet identity of assets equal to liabilities plus book value of equity. Moreover, assets (A) and liabilities (L) both have an operating (O) component (OA & OL) and financing (F) component (FA & FL). By rearranging the basic accounting identity, they obtain the following:

(22) $$NOA = NFO + B,$$

which recognizes that net operating assets (operating assets minus operating liabilities) are equal to net financial obligations (short-term debt plus long-term debt minus financial assets) plus book value of equity. The same relation holds also for changes:

(23) $$\Delta \mathrm{NOA} = \Delta \mathrm{NFO} + \Delta \mathrm{B},$$

where the left-hand side is the broad measure of accruals. This measure captures both the current accruals defined in the original work of Sloan (1996) such as changes in inventory, accounts receivables and accounts payable, but also non-current accruals like intangibles, property, plant and equipment and deferred employment obligations.

Accrual anomaly hypotheses are based on the idea that certain components of income are expected to be less long-term. Researchers have indeed generally found that various accrual elements are less persistent than the cash flow element. The most challenging aspect of accounting anomaly and fundamental analysis literature is that the hypothesis development of return forecasting uses the evidence from the earnings forecasting hypotheses and then combines it with additional claims about capital market imperfections that can support stock prices that do not completely enclose information in an appropriate manner. The research has generally found that the accrual component of earnings is negatively associated with future returns. (Richardson, Tuna & Wysocki 2010.)

Kothari, Loutskina & Nikolaev (2007) discover that overvalued firms have incentives to stay overvalued while undervalued firms have no incentives to continue being undervalued. These incentives establish an asymmetric relation between measures of accruals and past and future returns. Kothari et al. (2007) argue that this relation is more consistent with an agency theory of overvalued equity rather than the naive investor fixation on bottom line income explanation by Sloan (1996) for the accrual anomaly. Richardson et al. (2010) summarize from the research revolving accrual anomaly that the primary explanation for the negative relation between accruals and future stock returns seems to be that capital market participants fail to correctly use accrual information in their forecasts of future earnings.

5.3. Tobin's Q

Brainard and Tobin (1968) and Tobin (1969) defined this ratio to be used to measure the firm's incentive to invest in capital. This ratio has become known as average q or Tobin's Q, sometimes also called as the shadow price of capital. It can be understood simply as the ratio of market value of existing capital to its replacement cost. This average Q is sometimes simplified and measured by market-to-book ratio that is expressed as the ratio between market value of equity and the book value of equity. Market-to-book ratio measures the ratio of present value of all expected cash flows from current assets and the future investment opportunities to the accumulated value generated from existing assets. (Pietrovito 2016.)

The usual formula for Tobin's Q is the asset's market value divided by the asset's replacement cost. As Chung & Pruitt (1994) revised the formula:

(24) $$(Market\ value\ of\ equity + Book\ value\ of\ liabilites)/ (Book\ value\ of\ total\ assets)$$

The advantages of calculating Tobin's Q as denoted above is that it reduces differences in accounting methods adopted by different companies (Wang 2015). However, Tobin's Q has been also calculated in different ways. McNichols, Rajan & Reichelstein (2014) measure Tobin's Q as the market-to-book ratio divided by a conservatism correction factor they create to illustrate the unconditional accounting conservatism. The conservatism factor is calculated as the replacement value of a firm's assets in relation to the book value of assets. They find that this resulting Q has a greater explanatory power in predicting future investments than the usual market-to-book ratio.

Additionally, Wang (2015) denotes that Tobin's Q is commonly used as an approach for intellectual capital valuation. He includes Tobin's Q as a variable in Ohlson's (1995) equity valuation model along with book value per share and earnings per share in a similar fashion as in this thesis. He finds that the Q ratio is in fact significantly positively related to the current price by modelling these variables along with various interaction variables of Tobin's Q with different characteristics of the firms' corporate governance to the stock price of a firm. Wang (2015) measures all the variables, dependent and independent at the end of the fiscal year. This differs from this study as it doesn't have the forward-looking aspect that this thesis includes. Additionally, Tobin's Q has also been found to have a positive relationship with firm value in an earlier paper of Wang (2013).

6. DATA AND METHODOLOGY

In this chapter, the data and methodology are presented and explained in depth. The research design follows closely that of Bettman et al. (2009). However, there are explaining variables added that previous studies have found significant and relevant. (see Sloan 1996; Bartram & Grinblatt 2018; Richardson, Sloan, Soliman and Tuna 2001; Wang 2015.) Also, as Bettman et al. (2009) construct their data as a pooled cross-sectional sample, this thesis bases empirical testing on panel data from a smaller market of Finland.

6.1. Data

The data for this thesis is collected from two different databases. The study incorporates both fundamental variables drawn from accounting information and a technical variable, momentum, which is constructed from price data. These variables are then modelled with monthly prices.

The accounting data is constructed from quarterly reports. This is handled by reflecting the quarterly data to the following months leading to the next quarter. Thus, the accounting data is estimated to have predictive power since the accounting ratios are known at the time of modelling. The accounting values are regressed against prices at the next month to grasp their integration to prices. Prices, momentum dummies and forecasted earnings per share values are monthly data while accrual, earnings per share, book value per share and Tobin's Q are constructed using quarterly balance sheet items and then extended to represent the following quarter.

The data for this thesis amounts to unbalanced panel of 115 active listed companies in OMX Helsinki over the time period of 1998-2018. Even though the raw data is from that time period, for the final sample, the sample narrows by two years to reach from 2000 to 2018. This is in majority due to the formation of the momentum variables. The data set is a so-called microeconomic panel data containing companies from only one economy. The structure allows to account for unobservable firm-specific fixed effects to eliminate some of the bias due to omitted variables. Also, using panel data implies an increase in the variability of data. By using White period covariance method, a portion of the following omitted variable bias can be eliminated.

The sample of companies represents the whole universe of listed companies in Finland since it contains firms of all sizes and maturities. Firms from the financial sector are excluded from the sample as in Bettman et al. (2009). If all the firms of the sample were active during the whole sample period, they would add up to 28 865 firm-month observations. However, since the sample is created from the whole universe of Finnish listed companies, from which data was available, it is obvious that a majority of the companies were not around at the starting period (12/1997) of the sample. Thus, actual monthly pricing data from the sample period amounts to 21 660 firm-month observations. Figure 2. below illustrates the average monthly prices of the companies during the sample period to grasp the big picture developments in the Finnish stock market. What first stands out is the “Dot-com bubble” that happened at the turn of the millennium. The financial crisis can be also observed from the following figure.

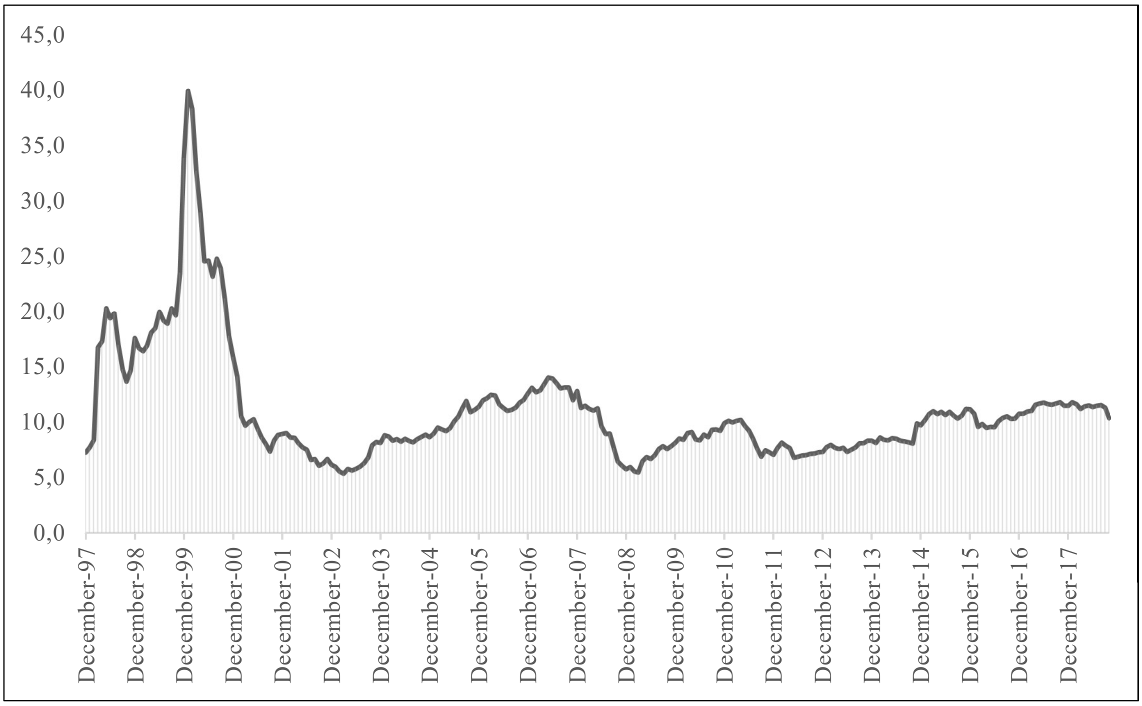

Figure 2. Average monthly prices of the companies during the sample period.

The forecasted earnings per share variable is calculated using consensus (mean) estimates drawn from the I/B/E/S database. These are monthly estimates reflecting the forthcoming year on the viewpoint of the month at time t. The variable used in the regression is then leaded forward a month (t+1) as in Bettman et al. (2009) since the estimates are published usually at the middle of the month, so their effect is assumed to have fully integrated to prices at the end of the month.

Book value per share, earnings per share, Tobin's Q and accrual variables are calculated using quarterly accounting information from Thomson Reuters/Datastream -database. The value of the quarter is then used as the values for the months of the following quarter.

The return information used to calculate the momentum dummy variables are calculated from price data (without dividends) following the definition of Chen, Da & Zhao (2013):

(25) $$\Delta P_t = \frac{P_t - P_{t-1}}{P_{t-1}},$$

where ΔP_t is the monthly stock return. Since the availability of data varied between different variables, a relatively low amount of observations can be utilized in the final regression (10 594). The descriptive statistics of the variables can be seen in the following Table 1.

Table 1. Descriptive statistics.

Variable	Mean	Median	Minimum	Maximum	Standard deviation	Observations
P_{t+1}	10.877	6.0000	0.0240	1423.42	30.584	21660
P_{t-5}	10.851	6.0000	0.0240	1423.42	30.898	21133
EPS_t	0.0491	0.0745	-85.67	130.000	2.8088	16631
$FEPS_{t+1}$	0.5873	0.4700	-63.30	16.9800	1.6451	17032
$BVPS_t$	5.5234	3.3250	-34.26	438.840	10.694	16403
Tobin's Q_t	1.7203	1.3946	0.4262	22.9368	1.2452	16599
$Accruals_t$	0.0337	0.0059	-24.00	31.0189	1.0367	13065

As having used time series data in this analysis, I perform unit root testing for both common and individual roots to allay possible concerns of non-stationary price process. Common unit root testing is performed using Levin, Lin & Chun -test that rejects the price series having a common unit root. Individual unit root process is tested using Fisher test with similar results. Both conclude that price is indeed a stationary process.

6.2. Methodology

First what is examined in this thesis, is the ability of fundamental and technical methods to explain share prices in isolation. The regression models presented and tested are simple OLS regression models. The complementary nature of technical and fundamental analysis is then studied examining the adjusted R^2, Akaike Information Criterion and log likelihood values of the models.

The following table includes definitions of all the variables used in Models (1) to (7). Specifically, it details the way variables are calculated as well as providing information on the source of variable constituents. Datastream stands for Datastream of Thomson Reuters, and the numbers in the parenthesis depict the data identifiers in the database.

Table 2. Variable definition and measurement.

Variable	Definition	Data source
P_{t+1}	The firm's end-of-month share price in the month forecast earnings are announced for the coming fiscal year.	Datastream
P_{t-5}	The firm's end-of-month share price six months before P_{t+1}.	Datastream
$BVPS_t$	The book value of the firm's equity (#03501) scaled by shares outstanding (#05192). This ratio is calculated from quarterly reports and the values are used for the coming months until the next report.	Datastream
EPS_t	The basic earnings per share calculated as the net income of the firm after preferred dividends (#01706) scaled by shares outstanding (#05192).	Datastream
$FEPS_{t+1}$	The consensus forecast earnings per share for the firm. These are gathered monthly and they forecast the values on the forthcoming fiscal year.	I/B/E/S

Tobin's Q_t	The q-ratio of the firm. Calculated by subtracting the book value of equity (#03501) from the sum of market capitalization of the firm (#08001) and total assets (#02999) and then dividing the result by the total assets of the firm (#02999).	Datastream
$Accruals_t$	The accruals are calculated by the change in net operating assets, where net operating assets are derived by subtracting the operating liabilities from operating assets. Here, operating assets are calculated by subtracting cash and short-term investments (#02001) from the total assets of the firm (#02999). Operating liabilities are calculated subtracting total debt (#03255), common equity (#03501), preferred stock (#03451) and minority interest (#01501) from the total assets of the firm (#02999).	Datastream
D_{Up}	A dummy variable equal to 1 if the stocks cumulative return in the prior 12-month period (excluding the most recent month) placed it in the highest performance decile, and 0 otherwise.	Datastream
D_{Down}	A dummy variable equal to 1 if the stocks cumulative return in the prior 12-month period (excluding the most recent month) placed it in the lowest performance decile, and 0 otherwise.	Datastream

What can be observed below in Table 3 are the correlations between different variables used in this thesis excluding dummy variables of momentum.

Table 3. Correlation matrices.

	P_{t+1}	P_{t-5}	EPS_t	$FEPS_{t+1}$	$BVPS_t$	Q_t	Acc_t
P_{t+1}	1.0000						
P_{t-5}	0.9296	1.0000					
EPS_t	0.2315	0.1391	1.0000				
$FEPS_{t+1}$	0.5729	0.5152	0.5438	1.0000			
$BVPS_t$	0.6251	0.6562	0.0779	0.3259	1.0000		
Q_t	0.1940	0.1713	0.0614	0.0850	-0.2132	1.0000	
Acc_t	-0.0140	-0.0152	-0.0037	-0.0178	-0.0090	0.0273	1.0000

The matrix shows interesting relationships in line with those found in Bettman et al. (2009). To allay concerns of a correlation structure affecting the reporter results, the regressions used in this thesis are conducted using heteroscedasticity and autocorrelation consistent standard errors by using White-period covariance method and cross section fixed effects. The results are thus robust to time-serial correlation and missing regressors.

Forecasted earnings per share seem to have stronger correlation with price and the book value per share than the earnings per share variable. As Zhang (2005) states, book-to-market ratio corresponds naturally with the inverse of Tobin's Q, so there exists also a negative relation between book value per share and Tobin's Q.

Tobin's Q is also positively correlated with accruals in contrast to other variables. The magnitude of the correlation is also greater than with any other variable. This supports the finding of Calmès et al. (2013) that Tobin's Q has a very significant positive impact on non-discretionary accruals. Calmès et al. (2013) study whether accruals could be partly affected by Tobin's Q by using it as one of the explanatory variables to constitute firms' accruals in one of their models. What can also be perceived from the correlation matrix is that there is a negative relation between accruals and next month's price. This supports previous studies of accruals (e.g. Sloan 1996). Self-evident relation observable from the matrix is that contemporaneous are highly correlated with past prices.

Previous studies have found that price is highly dependent on book value per share. Two reasons have been seen to affect this dependence. The first being drawn from the clean surplus valuation framework used by Ohlson (1995). He addresses that book value per share represents the resources a firm has that can be transformed to future earnings. The second argument proposes that book value per share positively relates to price as it represents the liquidation or adaptation value of the firm's assets. (Bettman et al. 2009) This is why the first model explains prices by book value alone:

Model (1) with only book value per share:

(26) $$P_{t+1} = \alpha + \beta_1 Book\ value\ per\ share_t$$

For the second model, I construct a two-factor model similar to that of Collins et al. (1997) and Bettman et al. (2009) that relates price to earnings per share and book value per share.

Model (2) with earnings per share:

(27) $$P_{t+1} = \alpha + \beta_1 BVPS_t + \beta_2 Earnings\ per\ share_t$$

However, in previous literature, a model that utilizes analysts' forecasts has found to be better at explaining stock prices (see Ng, Solnik, Wu and Zhang 2013; Chen et al. 2013). This may emerge from the fact that investors overweight information in analysts' forecasts and underweight the information in current earnings and the book value (Dechow, Hutton & Sloan 1999).

Thus, analysts' forecasts are added to the third model as the forecasted future earnings variable.

Model (3) with fundamental factors including analyst's forecasts:

(28) $$P_{t+1} = \alpha + \beta_1 BVPS_t + \beta_2 EPS_t + \beta_3 Forecasted\ earnings\ per\ share_{t+1}$$

After this, the accrual variable is added to the model that is included in this thesis because of its' previous success at explaining stock returns (see 5.2. Accrual anomaly). Since there were limited amount of data of income taxes payable by the firms in the sample, two ways of constructing the accrual variable was decided to implement. The first variable of accruals was calculated using the equation by Sloan (1996):

(29) $$Accruals = [(\Delta CurrentAssets - \Delta Cash) - (\Delta CurrentLiabilities - \Delta ShortTermDebt - \Delta TaxesPayable) - Depreciation] / AverageTotalAssets$$

After it was evident that this equation generated limited amount of results, the second variation of calculating the accrual variable was tested. This one was created by Richardson et al. (2001):

$$(30) \qquad \frac{NOA_t - NOA_{t-1}}{NOA_{t-1}},$$

where

$$(31) \qquad NOA_t = (TotalAssets - Cash\&ShortTermInvestments) - (TotalAssets - TotalDebt - CommonEquity - PreferredEquity - MinorityInterest)$$

This one generated more data because of availability of certain data and thus is the accrual variable that is presented in the empirical results.

Model (4) with accrual variable:

$$(32) \qquad P_{t+1} = \alpha + \beta_1 BVPS_t + \beta_2 EPS_t + \beta_3 FEPS_{t+1} + \beta_4 Accruals_t$$

Tobin's Q's are also calculated of the sample and tested whether it yields similar results as in the study by Wang (2015). Tobin's Q illustrates the ratio of the market value of existing capital to its replacement cost. I calculate Q as denoted in the paper by Pietrovito (2016):

$$(33) \qquad (MarketCapitalization + TotalAssets - CommonEquity)/TotalAssets$$

Model (5) with Tobin's Q:

$$(34) \qquad P_{t+1} = \alpha + \beta_1 BVPS_t + \beta_2 EPS_t + \beta_3 FEPS_{t+1} + \beta_4 Accruals_t + \beta_5 Q_t$$

Next a technical model, following Bettman et al. (2009), with momentum and past price is tested in isolation. I use a similar time frame of that of Bettman et al. (2009) for the past price variable for comparability purposes. Past prices are included since researchers of technical analysis have agreed upon their ability to forecast future returns (see e.g. Lo & MacKinlay 1998, 1999). The momentum variable is calculated assigning dummy variables that were constructed using a cumulative return of previous 12-months. The cumulative returns were then compared to other firms in the sample and assigned percentage ranks. Dummy variable D_{Up} is then assigned a value of 1 if, at that month, the cumulative return is in the top 10% of all the firms in the sample and a value of 0 if not. The variable D_{Down} is constructed correspondingly gaining a value of 1 if the cumulative return is in the bottom 10% of the sample and 0 otherwise. The dependent price variable is then lagged forward a month. This achieves a similar effect of excluding the previous month from calculation as in the paper by Bartram & Grinblatt (2018). The momentum dummies are calculated monthly.

Model (6) of technical factors with momentum and past price:

(35) $$P_{t+1} = \alpha + P_{t-5} + \beta_6 D_{Up} + \beta_7 D_{Down}$$

Finally, the technical model (5) and the fundamental model (6) are merged to form a hybrid model to explain a firms' share price.

Model (7) with fundamental variables and momentum:

(36) $$P_{t+1} = \alpha + \beta_1 BVPS_t + \beta_2 Q_t + \beta_3 EPS_t + \beta_4 FEPS_{t+1} + \beta_5 Acc_t + P_{t-5} + \beta_5 D_{Up} + \beta_6 D_{Down}$$

The empirical results of these models of explaining contemporaneous prices with fundamental and technical factors are presented and evaluated in depth in the following chapter.

7. EMPIRICAL RESULTS

Before considering whether fundamental and technical analyses complement each other in the context of share valuation, I examine the explanatory power of the methods in isolation. First up are fundamental models.

Table 4. Regression results of Models (1) to (5) with fundamental factors.

	(1)	(2)	(3)	(4)	(5)
Intercept	6.8450	6.5680	3.3865	3.6627	-0.9956
	(5.3718***)	(5.0850***)	(6.2756***)	(4.7105***)	(-0.4762)
BVPS	0.6287	0.6877	1.1413	0.8847	0.9477
	(2.6857***)	(2.8785***)	(10.4630***)	(8.5833***)	(9.3127***)
EPS		-0.7458	-1.1486	0.3416	0.3491
		(-1.9436*)	(-0.9454)	(0.4188)	(0.4594)
$FEPS_{t+1}$			2.2860	3.9159	3.4046
			(2.0699**)	(3.6435***)	(3.3578***)
Accruals				-0.0834	-0.1395
				(-1.1550)	(-1.8660*)
Tobin's Q					2.7207
					(2.3712**)
Sample	15 905	15 890	13 084	10 803	10 645
Firm-fixed effects	YES	YES	YES	YES	YES
Adjusted R^2	0.5889	0.5985	0.7088	0.7465	0.7900
AIC	6.8812	6.8583	6.5855	6.2553	6.0706
F-statistic	199**	205***	272***	313***	390***
Log likelihood	-54 607	-54 372	-42 965	-33 685	-32 207

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively. t-statistics are included in the parenthesis and they are heteroscedasticity and autocorrelation consistent.

Model (1) presented in Table 4 illustrates that price is highly positively dependent on a firms' book value per share. This finding is in line with previous studies ranging from the clean surplus valuation framework advanced by Ohlson (1995) to the base study of this thesis by Bettman et al. (2009). The high significance of book value per share also persists through all the models implicating applicability of predicting future prices. This finding provides contrasting evidence in relation with a branch of past literature reporting a declining value-relevance of book values and earnings (Amir & Lev 1996; Lev & Zarowin 1999; Ramesh and Thiagarajan 1995). This first model with only book value per share is already highly statistically significant and possesses an adjusted R^2 of 58.89 per cent. The second model includes earnings per share variable to the equation. Interestingly, the coefficient is negative until the introduction of accruals in Model (4). Thus, considering these results, there seems to be a negative relationship between price and earnings per share. This feels highly illogical and sheds misbelief. Also, it is naturally in contradiction with existing literature (see e.g. Dechow et al. 1999; Ely & Waymire 1999; Bettman et al. 2009). In earlier studies, price has been seen to be highly positively dependent on current earnings per share.

Model (3) yields, by including forecasted earnings per share, results similar with previous studies of Bettman et al. (2009) and Dechow et al. (1999) that current earnings seem to become insignificant after the introduction of these analysts forecasts of future earnings. Dechow et al. (1999) argue that forecast earnings per share subsume current earnings figures as well as offers incremental information about the ongoing value of the firm. After this inclusion of forecasts, in all the fundamental models, the earnings per share variable seems to be insignificant. This suggests that, at least in this sample of Finnish companies, forecasted earnings seem to be more significant constitutes of future prices compared to current earnings. The insignificance of current earnings also supports the claim of declining value-relevance of earnings through time (Amir & Lev 1996; Lev & Zarowin 1999; Ramesh & Thiagarajan 1995). Collins et al. (1997) claim, that the same factors that contribute to this loss of value-relevance of earnings might in turn cause an increase in the value-relevance of book values. This inverse relationship between the value-relevance of book values and earnings is evident in these results from Finnish companies.

As Ohlson (1995) and Felthman & Ohlson (1995) address, the so-called “other information” affects the contemporaneous stock price. The forecasted earnings per share is significant in all of the models and in contrast to the inclusion of earnings per share measure not increasing the explanatory power of the model in a notable way, the forecast earnings per share increases the Adjusted R^2 of the Model (3) by over 10 per cent to 70.88 per cent.

In Model (4), the accruals variable is included in the equation. As illustrated in the earlier chapters, and especially in chapter 5.2. Accrual anomaly, accruals have been noted to have a negative relationship with profitability. This relationship, first documented by Sloan (1996), can be observed from Table 4 even though the variable is not significant in Model (4). It becomes significant at the 10% level after the introduction of Tobin’s Q. The inclusion of accruals also subsumes information in prices since the explanatory power is increased by 4%. Information about the values behind the accrual variable were not available for a substantial amount of the companies, so the sample decreases by over 2 000 after the inclusion of accruals. A notable change in relation to other variables in the fundamental models is that by including accruals, forecast earnings per share variable coefficient doubles in size and the significance increases significantly to being significant at the 1% level.

Finally, Model (5) includes Tobin’s Q to the equation alongside with the other fundamental constitutes of price. The coefficient is positive and statistically significant indicating that Tobin’s Q provides information not included in the book value per share. This is in line with the study of Wang (2015). Including Q causes the intercept to turn non-significant while increasing the adjusted R^2 substantially to 79 per cent. As mentioned earlier in this thesis, the final model, fundamental as well as hybrid, is modelled using relatively limited amount of observations. This results from scarce availability of comprehensive data for the sample firms. Relatively high number of firms have also been publicly listed for only several years. However, the explanatory power of the fundamental model is extremely high – 79 per cent. This can be partly affected by the limited number of observations. Additionally, the other measures indicating goodness of fit of the model are changing to the right direction as new variables are introduced in the model. Akaike Information

Criterion (AIC) is decreasing and Log likelihood is increasing with the inclusion of explanatory variables.

Comparing to the results in Bettman et al. (2009), in their study, the explanatory power of the fundamental model is 42.9 per cent. However, there are several differences in this study and in theirs. First, I included additional variables of Tobin's Q and accruals in my fundamental model. Second, their sample consists of U.S. firms amounting to a larger sample of 33 952 observations. As they are using U.S. companies, naturally they have a larger universe of companies to build their sample from. Third, they drop firms with negative book values per share. Fourth, I do not adjust values for capitalization changes. Last, Bettman et al. (2009) use diluted versions of earnings per share and book value per share variables. Thus, my sample is more of a raw sample comprising of all the available companies listed in Finland.

Table 5. Regression results of Model (6) with technical factors.

	(6)
Intercept	2.4873
	(17.1597***)
P_{t-5}	0.7592
	(80.4471***)
D_{Up}	3.2608
	(1.3774)
D_{Down}	-3.3531
	(-1.9867**)
Sample	20624
Firm-fixed effects	YES
Adjusted R^2	0.6765
AIC	8.4973
F-statistic	370***
Log likelihood	-87 506

** and *** indicate statistical significance at the 5 and 1 per cent levels, respectively. T-statistics are included in the parenthesis and they are heteroscedasticity and autocorrelation consistent.

Next, in examining the ability of technical analysis to explain future price, I consider the results of fitting Model (6) that are illustrated above in Table 5. Results indicate that contemporaneous price consists to great extent of lagged price as is intuitive and found also in Bettman et al. (2009). However, the momentum variables seem to not have as significant effect on price as assumed on the basis of previous studies (see e.g. Bartram & Grinblatt 2018; Hong & Wu 2016).

The price of companies, whose cumulative return of past 12-month period, excluding the most recent month, has placed them in the top performance decile, cannot be said to have significantly increased in price a month after the formation of the dummy variable. Even though the coefficient is large and positive, the t-statistic is only 1.38 and thus not significant. However, negative performance of the companies ranked similarly in the bottom decile seem to enjoy negative performance in the month of modelling price. Yet, the coefficient is significant only at the 5% level.

Concluding, the momentum effect, with performance calculated similarly to Bartram & Grinblatt (2018), but formed with dummy variables, seem to not have a very strong effect in the prices of the sample consisting of Finnish listed companies. Bettman et al. (2009), who studied firms in the U.S., found a strong connection between contemporaneous prices and momentum dummies. However, the dummies were calculated differently by the ranking done 6 months before modelling and the formation period being performance of the 6 months before that. Thus, they had a longer period between forming the dummies and modelling price. As I used two months (a month before formation and a month after) for detecting the momentum effect, Bettman et al. (2009) went with 6 months.

Nevertheless, the overall technical model is highly significant and holding an adjusted R^2 of 67.65 per cent. Moreover, an interesting contrast to the study of Bettman et al. (2009), as they found that technical analysis seemed to explain asset prices better in isolation than fundamental analysis, I found the exact opposite results. In Finland, fundamental analysis seems to possess greater ability to explain prices than technical analysis when examining the analyzation methods individually. However, both models are highly significant and possess extremely high values of adjusted R^2.

The previous discussion provides evidence on the ability of both technical and fundamental analysis to explain contemporaneous prices in isolation, but it however does not say anything about the complementary nature of the studied methods. This issue is handled next in the following Table 6.

Table 6. Regression results of the hybrid Model (7) along with Models (1) to (5) with fundamental factors.

	(1)	(2)	(3)	(4)	(5)	(7)
Intercept	6.85	6.57	3.39	3.66	-1.00	-0.26
	(5.37***)	(5.09***)	(6.28***)	(4.71***)	(-0.48)	(-0.35)
BPVS	0.63	0.69	1.14	0.88	0.95	0.21
	(2.69***)	(2.88***)	(10.46***)	(8.58***)	(9.31***)	(4.21***)
EPS		-0.75	-1.15	0.34	0.35	1.18
		(-1.94*)	(-0.95)	(0.42)	(0.46)	(3.14***)
$FEPS_{t+1}$			2.29	3.92	3.40	1.21
			(2.07**)	(3.64***)	(3.36***)	(2.00**)
Accruals				-0.08	-0.14	-0.04
				(-1.16)	(-1.87*)	(-1.72*)
Tobin's Q					2.72	0.92
					(2.37**)	(2.20**)
P_{t-5}						0.71
						(12.33***)
D_{Up}						1.096
						(4.20***)
D_{Down}						-0.52
						(1.56)
Sample	15 905	15 890	13 084	10 803	10 645	10 594
Firm-fixed effects	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.5889	0.5985	0.7088	0.7465	0.7900	0.8920
AIC	6.8812	6.8583	6.5855	6.2553	6.0706	5.4091
F-statistic	199**	205***	272***	313***	390***	834***
Log likelihood	-54 607	-54 372	-42 965	-33 685	-32 207	-28 546

*, ** and *** indicate statistical significance at the 10, 5 and 1 per cent levels, respectively. T-statistics are included in the parenthesis and they are heteroscedasticity and autocorrelation consistent.

I provide evidence of a complementary relationship by merging Models (5) and (6) to create the final hybrid Model (7). The results of this are presented above. The final combined model is formulated with 10 594 observations.

Results reveal the significance of both types of analysis in explaining share price. Moreover, consistent with the findings of Bettman et al. (2009) and the existing literature (see e.g. Collins et al. 1997), book value per share is consistently a significant and a positive estimator of prices. On the other hand, the results of earnings per share are somewhat different as in aforementioned studies. In Model (7), the earnings per share variable is highly significant and positive as found in Bettman et al. (2009) and Collins et al. (1997). However, before fitting technical and fundamental models to make for the hybrid model, earnings per share does not serve as a significant estimator of share prices. Additionally, the coefficient is even negative and not significant in Model (2) and (3) providing mixed results of significance of the ratio in Finland from 2000 to 2018.

Like book value per share, Tobin's Q also serves consistently as a positive explanator of share price even in the presence of technical factors. Forecasted earnings per share however loses some of its' significance and magnitude as technical factors are included in modelling. Accruals, the other self-included variable besides Tobin's Q, retains its' slight significance on explaining prices as the variable is significant only at the 10% level. The intercept is not statistically significant in Model (7) indicating goodness of fit and that the variables used to explain future prices subsume a good part of the information affecting them.

The only explanatory variable holding no statistical significance is the momentum D_{Down} dummy. This is an interesting result since when examining technical factors in isolation, the D_{Down} dummy of persisting negative performance of companies ranked in the bottom decile on the ground of past 12-month cumulative return and excluding the most prior month was significant. The significance did not persist in the presence of fundamental factors. Additionally, the dummy variable of momentum indicating persisting positive performance of companies ranked similarly in the top decile turned highly significant as the technical and fundamental factors were merged to form Model (7).

The t-statistic of lagged price also decreased considerably as the models were merged and is significantly lower (12.33) than in the base study of Bettman et al. (2009) where the value was 45.12. This might serve as further evidence on the lower explanatory power of the technical factors in relation to fundamental factors in Finland from 2000 to 2018 compared to their sample of U.S. companies from 1983 to 2002.

However, as technical factors are introduced and fitted to the fundamental model, the explanatory power of the model increases to an extremely high value of adjusted R^2 of 89 per cent. The explanatory power of Models (1) to (7) is comprehensively evaluated, following Bettman et al. (2009), considering also AIC values as well as the adjusted R^2 measure. Even though the response variable in all models is the same and therefore the comparison of their adjusted R^2 values is necessary and meaningful, this measure is insufficient as it does not alone adequately consider entropy and goodness-of-fit. The AIC estimates have been noted to be a more suitable method to measure goodness-of-fit in large samples. Thus, the AIC values are also undertaken and compared through the examination of different models. As can be seen from Table 6. the Akaike Information Criterion (AIC) also significantly decreases and Log likelihood increases supporting the hypothesis of complementary relationship of fundamental and technical analysis.

As a notable limitation to the study, likelihood-ratio testing comparing the models to each other, like Bettman et al. (2009), cannot be performed since this omitted variable test requires that there is the same amount of observations in the test equations (Eviews 2019). Thus, further evidence on the improvement of the statistical significance of fitting fundamental and technical models cannot be provided.

8. CONCLUSIONS

Academic literature puts a lot of effort in determining the ability of two often competing methods of fundamental and technical analyses to explain or value stock prices. The literature often sees them as separate and examines them in isolation of each other. However, several recent studies have studied their complementary relationship in stock valuation efforts. In this thesis, I tackled this issue with a sample of Finnish companies from 2000 to 2018 by following the methodology introduced in the study of Bettman et al. (2009). However, I include two additional fundamental variables of accruals and Tobin's q to the examination. Along with these inclusions, I propose an integrated model of fundamental and technical factors for stock valuation.

Concerning individual explanatory variables, this study presents evidence of persisting value-relevance of book values and forecasts of future earnings, while reporting mixed results of the relevance of current earnings. Both added variables, accruals and Tobin's Q, yielded results as hypothesized based on previous studies. However, their significance was not as prominent as in earlier papers. Also, the momentum effect seems to not be as strong in Finland as found in previous studies from the U.S. (Bettman et al. 2009; Hong & Wu 2016; Bartram & Grinblatt 2018). In a similar study of a combination model of fundamental and technical factors, Hong & Wu (2016) propose that momentum seems to be at its best during stable and good times. As the sample used in this thesis is from 2000 to 2018, a time period not characterized by stability since it includes events like the dot-com bubble and the financial crisis, the instability could affect the significance of the momentum effect.

The hypothesis that technical analysis explains prices better than fundamental analysis, is rejected since the fundamental model has superior explanatory power in relation to the technical model when they are tested in isolation. This is an interesting finding and could be due to the effect documented by Hong & Wu (2016) that fundamental information is most important in explaining stock price movements in small firms, which have greater information asymmetry. The Finnish market consists to a large extent of small and medium sized firms.

As the main hypothesis of this thesis is that there exists a complementary relationship between fundamental and technical analysis in Finland, I illustrate this by showing that the combination model has superior explanatory power in relation to the either one of the analyzation methods examined in isolation. This hybrid model of both fundamental and technical factors sees significant increases in adjusted R^2 values and considerable drops in corresponding AIC figures. This main finding of the thesis is important in bridging the gap in the literature of fundamental and technical analysis. The results of combination benefits are in line with previous studies of Bettman et al. (2009) and Hong & Wu (2016).

For future research, to overcome the limitation of not being able to perform likelihood-ratio testing to provide support to the goodness-of-fit of the combined model, one could test this framework with a larger Nordic data. With a bigger sample, this issue could be overcome by comprehensive data availability for a sufficient number of firms. Additionally, the literature around using fundamental analysis as means for stock filtration and technical analysis for transaction timing to reach for abnormal returns is frankly limited and should be studied to a greater extent.

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