UNIVERSITY OF VAASA

FACULTY OF BUSINESS STUDIES

DEPARTMENT OF ACCOUNTING AND FINANCE

Vesa Ruhanen

SEASONALITY IN EPS FORECAST ERRORS IN THE FINNISH STOCK MARKET – SEASONAL AFFECTIVE DISORDER OR FUNDAMENTAL DRIVEN?

Master's Thesis in
Finance

VAASA 2017

TABLE OF CONTENTS **page**

LIST OF FIGURES page

LIST OF TABLES page

UNIVERSITY OF VAASA	
Faculty of Business Studies	
Author:	Vesa Ruhanen
Topic of the thesis:	Seasonality in EPS Forecast Errors in the Finnish Stock Market – Seasonal Affective Disorder or Fundamental Driven?
Name of the Supervisor:	Denis Davydov
Degree:	Master of Science in Economics and Business Administration
Department:	Department of Accounting and Finance
Master's Programme:	Master's Degree Programme in Finance
Year of Entering the University:	2011
Year of Completing the Thesis:	2017 **Pages: 75**

ABSTRACT

EPS forecasts are one of the most important factors affecting stock prices. Previous literature has identified seasonality in analysts' EPS forecast error. While traditional finance intends to explain the seasonality with firm fundamentals, behavioral finance emphasizes cognitive explanations. One such explanation is Seasonal Affective Disorder, according to which forecasts become more pessimistic as depression increases in the fall.

The main purpose of this thesis is to identify if SAD effect explains forecast error seasonality in EPS consensus estimates with a 1-year horizon, or if the error is explainable by traditional factors. Since previous literature combining analysts and SAD effect is based on data from the US, this thesis uses unique data from Finnish stock markets, where the effect should be theoretically stronger. Seasonality in EPS forecast error is studied with panel data consisting of 3665 common observations between 2010 and 2014. Along with SAD effect, independent variables control for firm specific fundamentals, changes in macroeconomic conditions, and analyst related factors. Regression analysis is performed for different subsamples according to firm size and forecast season. Validity of the results is verified by additional robustness tests that control for weaknesses in the methodology and possible inappropriate independent variables.

The results show general optimism, which is greater for small firms, and a seasonal pattern in forecast error. For full sample, the forecasts are 28.2% too optimistic on average. The error is the smallest in January (14.6%), peaks in March (38.2%), declines until September (21.8%), and stays flat for the year-end. Although there is weak pro SAD effect evidence, this is mitigated by robustness tests and inconsistent findings for small firms. Positive relationship is found between forecast error and previous quarter actual EPS suggesting that positive momentum decreases forecast error. Information asymmetry and analyst uncertainty about a firm's earnings, on the other hand, are negatively related to forecast error and an increase in the variables causes higher optimism. Overall, the evidence suggests that in the setup fundamentals and analyst related factors drive forecast error instead of SAD effect. Although forecast error is not fully explainable by the chosen factors, this thesis presents a clear seasonal pattern, which is stronger for small firms, which helps investors to correct the bias in estimates.

KEYWORDS: EPS forecast, forecast error, seasonal affective disorder, seasonality

1. INTRODUCTION

Stock prices are traditionally expected to reflect relevant information available of a company. Hence success in investing requires evaluation of new information, and above all it requires immediate reaction to new information (Fischer & Jordan 1991: 189). However, analyzing and collecting information requires significant amount of time. Therefore, some investors prefer buying forecasts or recommendations instead of analyzing the information themselves (De Bondt & Thaler 1990). Because of this, brokerage firms and especially their analysts have a major role in channeling firm specific information to stock markets.

New information triggers a market reaction. How the stock market reacts to the information provided by analysts depends on stock market efficiency, according to which the reaction should be immediate and of correct magnitude. For example, Womack (1996) reports that during the first three days after a new buy recommendation stock prices increase by 3.0% on average, and after a sell recommendation stock prices decrease by 4.7%. In theory, analysts should be acting rationally and provide accurate information that reflects analysts' own, truthful opinion. According to previous literature, in practice this is hardly true. Countless researchers have documented irrational behavior in analysts' forecasts such as pessimism and overreaction. These biases reduce the forecast accuracy of analysts and lead to biased market reactions.

Behavioral finance, according to which the stock markets are inefficient, intends to explain these inaccurate reactions that traditional finance has not been able to explain (Shefrin 2002: 5). Behavioral finance is constructed of 2 different sections: limits to arbitrage and psychological explanations. When considering the behavior of analysts, the main interest is on psychological biases. The decisions of stock market professionals, such as analysts, should be justified with relevant information only and should not be affected by these biases. However, previous findings suggest otherwise. One relatively new topic among the psychological biases, which might affect market participants, is *Seasonal Affective Disorder* (SAD).

SAD is a phenomenon, or a condition, reported in psychological literature arguing that environmental factors, such as sunlight hours, affect the mental well-being of individuals (Molin, Mellerup, Bolwig, Scheike & Dam 1996; Rosenthal et al. 1984). As days get shorter during fall and winter, people become more depressed, and thus are increasingly pessimistic, which leads to reduced risk taking (Dolvin, Pyles & Wu 2009). This is associated with, for example, increasing returns of risk free government treasuries during fall (Kamstra, Kramer & Levi 2015), and weaker stock market returns during fall and winter (Kamstra, Kramer & Levi 2003). This suggests that investors are prone to be affected by SAD. Thus, it is also possible that there is seasonal variation in the decision making of analysts. The interesting question is, whether the variation is explainable by changes in fundamentals, such as seasonality in earnings, or if behavioral factors are driving seasonality in forecasts.

Since stock prices reflect available information, psychological biases in analysts' forecasts will be incorporated into stock prices unless the effect is eliminated by rational market participants. However, previous literature suggests that investors are unable to identify these biases in forecasts and cannot correct them accordingly (Abarbanell & Bernard 1992; Bradshaw et al. 2006). Thus, revealing an effect of a possible psychological bias, namely SAD in this research, would help investors to adjust their return expectations correctly.

1.1. Purpose of the thesis

Given the fact that investors closely follow analysts' EPS forecasts, this research pursues to identify whether or not analysts are affected by SAD in a similar way as previous literature suggests investors to be. SAD effect on stock market returns has already been widely studied. For example, Kamstra et al. (2003) establish that there is a statistically and economically significant negative worldwide effect in stock returns during fall and winter, which seems to be the strongest in the northernmost country in the data, Sweden. However, the prevailing evidence is controversial since Kaustia & Rantapuska (2016) find little evidence that SAD affects stock returns in Finnish stock markets. The opposite findings between Finnish and Swedish stock markets are surprising since the markets and environmental conditions are rather similar.

Although analysts are a major information channel for the stock market, the effect of SAD on analysts has been left for little attention. Furthermore, previous studies concentrate purely on analysts located in the US. Dolvin et al. (2009) state that the effect of SAD is only significant for the analysts located in the northern US. Thus, whether considering the effect of SAD on different assets classes or on analysts, there is some evidence that SAD gets stronger as approaching the North Pole, but there are also country specific differences in SAD effect. Figure 1 demonstrates the differences between the latitudes of the US and Finland.

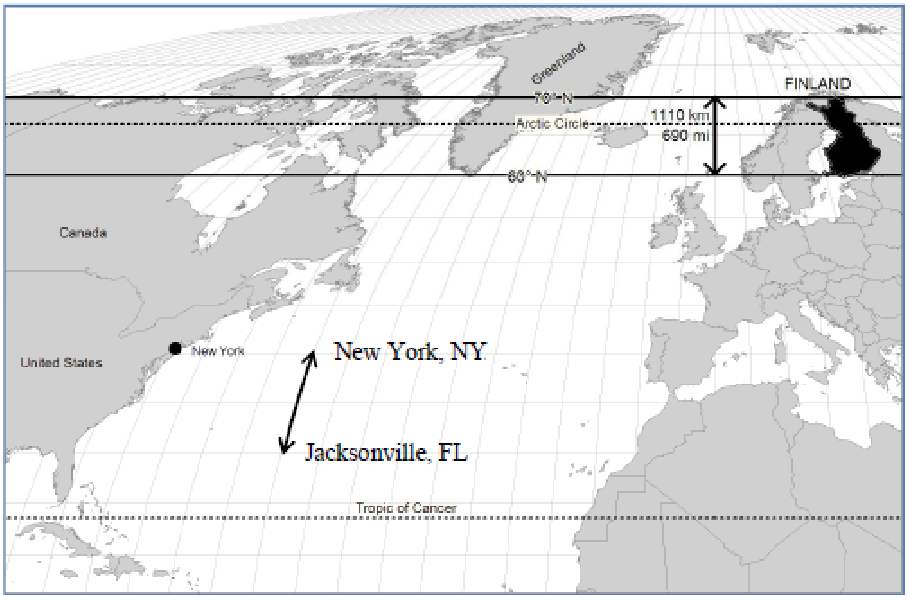


Figure 1. The location of Finland and United States. (Kaustia & Rantapuska 2016)

To the best of my knowledge, there have not been any studies about the significance of SAD effect on analysts located in the Northern Europe, where the effect should, in theory, be even more significant. In addition, the small stock markets and volatile weather conditions throughout the year provide an interesting aspect to the study. Thus, this research uses unique data from Finnish stock market analysts to test whether analysts' forecast error is seasonal, and if seasonality is explainable by fundamental factors or SAD effect.

Seasonality and the factors behind it are tested with analysts' forecast error, which is composed of consensus EPS forecasts and actual EPS between 2010 and 2014 for publicly traded Finnish companies. The use of consensus, or the average, reduces the bias of a single analyst and provides an overall view of analysts' behavior. The attributes of Finnish stock markets create an interesting environment for testing the significance of SAD. Not only are the markets located in north, but the markets are also small compared to the US. There is less information available of the firms, less analysts following the firms, and consequently the forecast accuracy is worse than in larger markets such as UK (Rothovius 2003). Therefore, it is interesting to see whether or not Finnish analysts are affected by SAD similarly as analysts located in the US.

1.2. Structure of the thesis

In brief, the research is structured as follows. After the introduction, the theoretical background and previous literature are introduced in three different chapters. The first one discusses the importance of earnings and considers the views of traditional finance, such as efficient market theory and different methods of stock valuation. The next section introduces behavioral finance and how it affects the behavior of professional analysts, giving a comprehensive view of different forms of irrational behavior.

Moving on to the next chapter, this thesis introduces broadly previous literature about the SAD effect itself, and the relationships between SAD and analysts, as well as SAD and financial markets. This fourth chapter is the last chapter focusing on previous theories and literature. As the necessary pre-knowledge has been presented, the thesis continues with the main empirical part. While the fifth chapter introduces the used data, methods and hypotheses formation, the sixth chapter focuses on empirical results. Finally, conclusions will sum up the findings and implications of the study.

.

2. EARNINGS, VALUATION AND FORECASTS – THEORETICAL BASIS

The following chapter concentrates on the views of traditional finance. Traditional finance relies on market participants' rational behavior and perfection of markets (Bruce 2010: 103). Rational behavior can simply be viewed as market participants' reasonable actions to benefit the most under his/her risk preference. In such conditions, information is used as a decision making tool. Thus, it is necessary to introduce theories such as efficient market theory. Furthermore, the chapter introduces the concept of earnings per share, how it is used in stock valuation and why earnings per share figures are emphasized heavily in the forecasting process. Since there are countless of methods to evaluate stocks and forecast future performance, this thesis will only concentrate on the ones closely related to earnings per share.

2.1. Random walk & efficient market theory

If stock prices were easy to forecast, there would not be any demand for forecasts by professional stock analysts. Fama (1965) finds that stock prices move randomly around a long-term positive trend (*random walk*). Thus, one cannot easily forecast stock price movements just with historical data of prices. According to the theory, today's rise in price does not necessarily mean a rise in price tomorrow. To put this into practical perspective, figure 2 presents daily returns for OMX Helsinki stock index between November 2014 and December 2014. The short term returns seem to move without self-evident patterns.

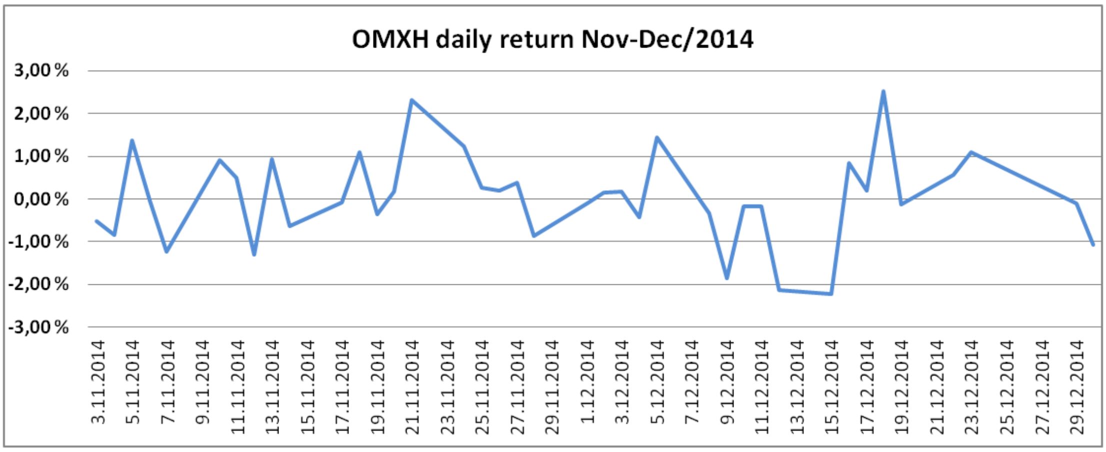


Figure 2. OMXH daily returns November-December 2014. (Data: Nasdaq 2016)

An opinion on a firm's future value is formed with the information available. Success in investing requires evaluation of new information, and above all it requires immediate reaction to the new information (Fischer & Jordan 1991: 189). New information and available information in general should directly affect stock prices. However, the availability of information depends on market efficiency – a theory, which was made popular by Fama (1970).

The efficient market theory relies on sufficient, but not necessary conditions determined by Fama (1970): *(1) there are no transaction costs related to trading (2) information is costless and available to everyone,* and *(3) everyone has an understanding of how new information affects security prices*. When considering these conditions from the perspective of analysts, if every market participant had easy, costless access to the same public information, there would be simply no need for analysts' forecasts. Thus, it seems clear that not all of the sufficient conditions hold. However, this does not directly imply that the markets are inefficient. In explanation, markets can be considered inefficient only if there are market participants that can constantly valuate assets better than the markets.

According to the efficient market theory, a simple definition for efficient markets is that the markets reflect all available information at all times (Fama 1970). However, in practice this does not necessarily hold at all times, but this does not mean that the markets could not be efficient at some level. Therefore, Fama (1970) has defined three different forms of market efficiency, which are based on what information is actually included:

1. *Weak form*
2. *Semi-strong form*
3. *Strong form*

The weak form of market efficiency reflects all information that is available from historical price data. Terms for semi-strong form are fulfilled when in addition to the terms of the weak form, stock prices reflect all publicly available information. The last form implies that stock prices reflect all information including insider information. (Fama 1970.)

Therefore, according to the weak form, technical analysis is useless: past price data cannot be used to achieve excess returns. The semi-strong form expects that new public information, such as lay-offs and earnings announcements, triggers a price reaction – and fundamental and technical analysis is useless. The strong form means that even insiders cannot earn abnormal returns. (Knüpfer & Puttonen 2012: 165.)

If stock markets actually were efficient, investors' reaction to new information would affect stock prices immediately and the reaction would have the correct magnitude. In such case, investors could not earn any abnormal returns (Fischer & Jordan 1991: 2; Grossman & Stiglitz 1980). To earn higher than average returns, investors would have to also take more risk. Instead of actively trying to beat the markets, investors would be as well off with a passive investing strategy, which is as simple as investing for example to a market index and holding on to it (Nikkinen et al. 2008: 84).

However, the theory of market efficiency does not actually require that the market prices are constantly correct relative to the fundamental value of a stock. It only requires that the deviation from fundamental value is random, and thus cannot be forecasted (Knüpfer & Puttonen: 165). However, along with many other researchers, Grossman & Stiglitz (1980) establish that it is simply impossible that stock prices would reflect all possible information. Such long-term abnormal deviations or phenomena, which allow investors to benefit financially from them, are called anomalies (Nikkinen et al. 2008: 86). Behavioral finance is a field of finance that intends to explain these anomalies with models in which market participants are not acting rationally (Barberis & Thaler 2003). For example, Shefrin (2002) has documented that stock prices deviate from their fundamental value and the deviation is long term:

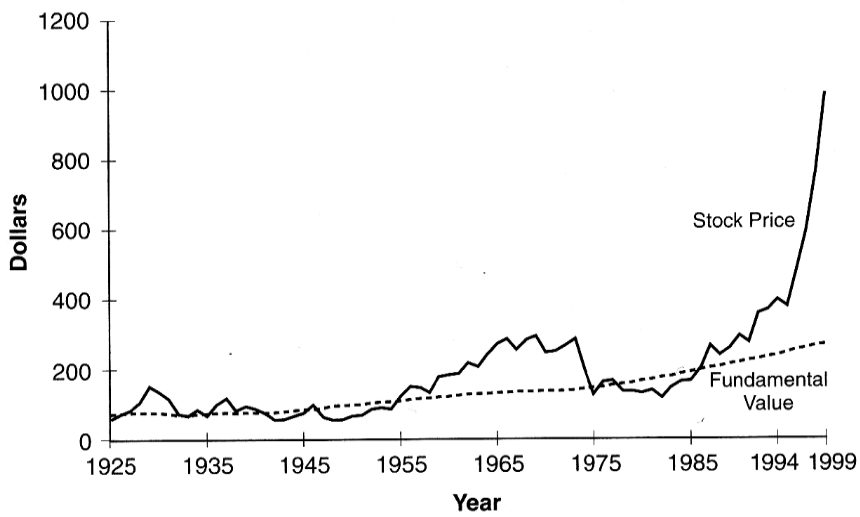


Figure 3. The relation of fundamental value and the stock prices. (Shefrin 2002: 39)

It is worth noting, though, that the 1990s deviation is due to so called Dot Com bubble. Figure 2 creates exaggerative view of irrational co-movement between market prices and fundamental value, because in fact most of the deviation reversed in the next few years:

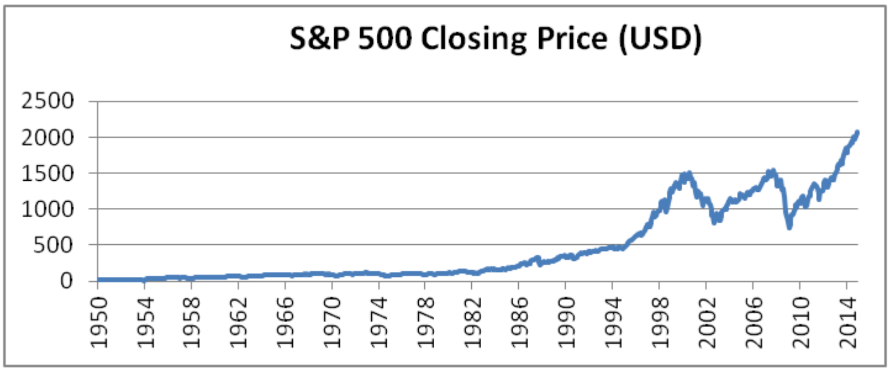


Figure 4. S&P 500 closing price. (Data: Yahoo Finance 2016)

2.2. Expected utility and prospect theory

The efficient market theory of Fama (1970) expects market participants to behave rationally; that is, to make decisions only according to the available information with no emotion involved. Understanding the expectations for an individual's rational behavior creates the basis for valuation models. Given the risky nature of investing, one needs to take into account risk when trying to simplify individuals' decision making regarding investments. Traditional expected utility theory explains how individuals and analysts should rationally make risky decisions. Von Neumann & Morgenstern (1944) state that preferences can be shown via a utility function when certain axioms of rational behavior are satisfied:

Completeness = preferences are well defined.
Transitivity = if completeness is satisfied, decisions are consistent.
Independence = if a third gamble is added to initial two, the preference order is maintained the same as when the two are presented separately of the third one.
Continuity = if there are 3 options, and an individual prefers 1 over 2, and 2 over 3, then there is a combination of 1 and 3, which is indifferent from 2.

The theory explains that individuals have certain preferences under risk. And as they follow these preferences logically and choose options with highest expected utility, decisions under risk can be expressed with a utility function.

Later such normative theories have been replaced by, for example, prospect theory by Kahneman & Tversky (1979). According to this theory, individuals make decisions by comparing gains and losses instead of the probabilities or expected outcome. Kahneman & Tversky (1979) find that individuals rather choose certain gain regardless whether utility is higher or not. Similarly, individuals seem to choose uncertain loss even though the utility might be lower (Kahneman & Tversky 1979). Thus, people are risk averse regarding gains, and risk seeking regarding losses (Kahneman & Tversky 1979). Unlike traditional expected utility theory, prospect theory states that an individual's subjective thinking affects their utility expectations. Therefore, this alternative descriptive decision making model is often viewed as a building block for psychological explanations in valuation process.

2.3. Earnings per share

Earnings per share (EPS) is a financial variable often seen in news and corporate reports, as well as in analysts' forecasts. As simple as it is, earnings is a figure that represents companies' profits, or in other words net income. While the top line of income statement, net sales, provides a quick view of a company's year to year business development, the bottom line earnings provide a measure of profitability. Thus, earnings are a more important financial measure for analysts and investors.

Since companies are of different size, the bottom line earnings of a one company might not be a meaningful measure when comparing firms. EPS figure transforms earnings into a per capita figure, which makes firms comparable with each other. Equation 1 shows how EPS is calculated (Fischer & Jordan 1991: 202-203).

$$\text{EPS} = \frac{\text{Net Income}}{\text{Average Outstanding Common Shares}} \tag{1}$$

To be precise, equation 1 presents basic EPS. In addition, companies often also report diluted EPS, which takes into account outstanding convertible bonds, warrants and stock options (Bodie et al. 2014: 704). Diluted EPS is a more cautious measure than basic EPS. When using EPS figures in investment decision making, one has to consider that there are several different EPS figures, which are not comparable with each other. In fact, there are several additional variations of the figure, such as pro-forma EPS.

EPS is often considered to be the most important factor in forecasting stock prices. For example, the long bull market between 1980 and 1999 was driven mostly by growth in earnings, declines in interest rates, and inflation (Koller, Goedhart & Wessels 2004: 9). Figure 5 provides a graphical view of how fundamental *P/E ratio* (price to earnings) compares to actual ratio:

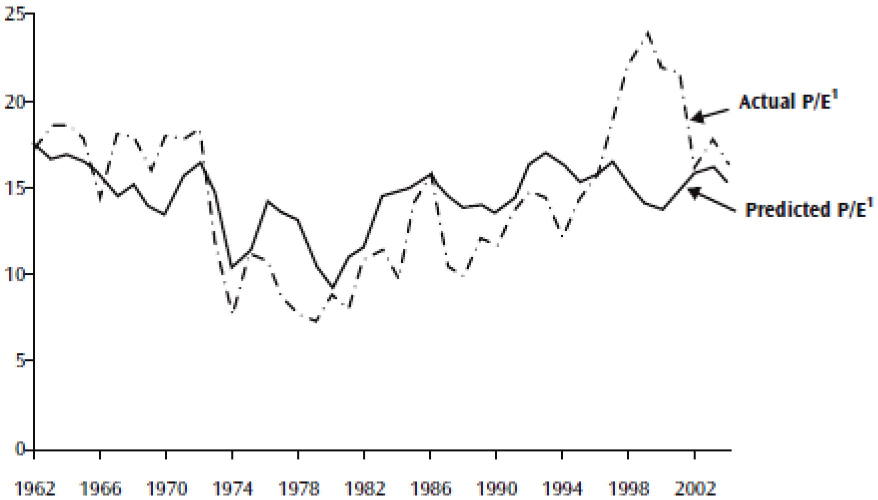


Figure 5. 1 year forward looking fundamental P/E ratio. (Koller et al. 2004: 96)

On a long term, it seems that the markets generally follow fundamentals in pricing, but there are short term (up to 2 years) deviations from the fundamental value (Koller et al. 2004: 96). Hence, stock prices are not purely random, there is fundamental reasoning behind them, which makes forecasting EPS meaningful.

However, if forecasting EPS was a simple task there would be no need for analyst recommendations. There is not one correct method for estimating the future growth in earnings. This matter will be discussed more deeply in brief. Perhaps an even more important variable for investors is the consensus forecast of EPS, which is the mean average or median of all current forecasts. One advantage of consensus forecast is that it reduces the effect of individuals' forecast errors.

2.4. Stock valuation

According to the efficient market theory, there is no simple way to pick a stock that will outperform the market. As already stated earlier, stock prices are formed based on available information. To be more specific, there are certain important factors that affect the stock prices, namely: risk, the cost of capital, dividends, future growth rate, and earnings (Elton, Gruber, Brown & Goetzmann 2011: 455). Therefore, these factors are also used in valuation and forecasting process.

Since dividends are one of the most important factors affecting stock prices, one of the most common valuation model seen in the textbooks of finance is the dividend discount model, which is composed as in equation 2. Simply, if a dividend is paid at time t+1, that is at the end of the period, the value of a common stock can be identified as follows (Elton et al. 2011: 456):

(2)
$$P_t = \frac{D_{t+1}}{(1+r)} + \frac{P_{t+1}}{(1+r)}$$

Where: P_t = the price of a stock at time t
D_{t+1} = the dividend received at the end of the period
P_{t+1} = the price of a stock at the end of the period
r = discount rate

Thus, if one was interested in determining today's reasonable price using a 2-year horizon, one would have to modify the model accordingly (Elton et al. 2011: 457):

(3)
$$P_t = \frac{D_{t+1}}{(1+r)} + \frac{D_{t+2}}{(1+r)^2} + \frac{P_{t+2}}{(1+r)^2}$$

The model can be generalized as follows (Brealey, Myers & Allen 2011: 80):

$$P_0 = \frac{D_{t+1}}{(1+k)} + \frac{D_{t+2}}{(1+k)^2} + \cdots + \frac{D_H + P_H}{(1+k)^H} \tag{4}$$

In the equation above, H denotes year. In theory, the valuation horizon could be set infinite. As approaching infinite, the value of P would diminish close to zero. Therefore, one could calculate the present value by discounting the dividends and ignoring the terminal value (Brealey et al 2011:80):

$$P_0 = \sum_{t=1}^{\infty} \frac{D_t}{(1+r)^t} \tag{5}$$

How this relates to the earnings estimates of analysts is that earnings can be used in two ways: either they can be reinvested to the business or they can be paid out to shareholders as dividends (Elton et al. 2011: 457). Thus, even though it is not visible in the equation itself, earnings play a crucial role in stock valuation and in dividend discount model. In practice, dividends are often forecasted with payout ratio, which is simple to calculate and accurate at least in the short run (Elton et al. 2011: 681). Payout ratio is calculated as in equation 6:

$$Payout\ ratio = \frac{Dividends\ per\ share}{Earnings\ per\ share} \tag{6}$$

Since firms' often pursue to increase or maintain the same level of dividend payments, when using the equation of payout ratio, the only variable needed to estimate dividends per share is forecasted EPS. In fact, since there is a tendency to maintain the level of dividends, growth in dividends per share equals the growth in earnings per share (Elton et al. 2011: 459). Thus, EPS affects both dividends and share price – factors that generate returns for investors. Consequently, EPS figures and forecasts are closely followed by market participants. However, a more sophisticated proxy would be discounting free cash flows of a firm. As a more complex method, it is, however, often ignored and EPS are considered to be a good enough measure for performance.

Furthermore, earnings are crucial for price-to-earnings multiple, which is price per share divided by earnings per share (*P/E ratio*). P/E ratio implies how much investors are willing to pay for each euro of earnings, and the ratio is used by financial analysts in valuation by comparables method. In this method analysts compare financial variables, such as P/E and M/B, of a firm with similar type of firms. (Brealey et al. 2011: 77.)

2.4.1. Measuring risk of an asset

Stocks are considered to carry a firm specific level of risk. Individuals bearing a risk also require compensation for it. The return volatility of an asset is perhaps one of the simplest, and the most common, measures of risk defined in the literature of finance. But when the investor holds a diversified portfolio, it might not be a complete measure of risk – instead one has to take into account the co-movement of the assets (Bodie et al. 2014: 10). Thus, the contribution of an asset to the volatility of a portfolio is what actually matters.

Beta of an asset, denoted as β, is the sensitivity or volatility of the asset compared to a stock market index (Bodie et al. 2014: 260). It is also commonly referred as the systematic risk factor. But foremost, beta is the security’s contribution to the volatility of a portfolio.

In the dividend discount model, risk is taken into account in the discount rate, or the required rate of return. Defining adequate discount rate is important because even a percentage point difference is large enough to cause an incorrect valuation. *Capital asset pricing model* (CAPM) predicts the relationship between the risk of an asset and the expected return of an asset, assessing the fair return for a risky asset (Bodie et al. 2014: 291). Thus, it is often used as the discount rate in dividend discount models, and in discounting methods in general. Although not completely supported by empirical evidence, it is considered accurate enough a measure for required rate of return (Bodie et al. 2014: 291). CAPM is calculated as in equation 7 (Bodie et al. 2014: 297):

$$E(r_e) = r_f + \beta_e[E(r_m) - r_f] \tag{7}$$

Where: r_f = risk free rate of return
β = sensitivity of the asset to an index
$E(r_m)$ = market rate of return

In the equation, $E(r_m)$-r_f is also known as market risk premium. In the equation risk free rate provides the baseline rate of return, which is revised upwards according to the riskiness of an asset – or more precisely according to the sensitivity of an asset to market movements. The obtained required rate of return from CAPM is commonly used as a discount rate and acts as a measure of risk in valuation with the dividend discount model.

2.5. Forecasting earnings

As previously seen, dividends could be estimated by forecasting growth in EPS. However, estimating the growth of earnings accurately can be quite complex. The methods can be divided into statistical and fundamental driven methods. In theory, one could estimate growth with a simple fundamental driven method by using *plowback ratio* and *return on equity* (ROE). The amount of re-invested earnings, plowback ratio, can be calculated as follows (Rothovius 2003):

(8) $$p = \frac{Retained\ Earnings_{t-1}}{Earnings_{t-1}}$$

Sustainable growth rate is a rate that a firm can maintain without additional external financing. Sustainable growth rate indicates that assets, earnings and dividend are all growing at the same rate denoted as g. Assuming ROE to be fixed over years, sustainable growth rate is obtained by combining ROE and plowback ratio as presented in equation 9. (Brealey et al. 2011: 748; Rothovius 2003.)

(9) $$g_t = \frac{RE_{t-1}}{E_{t-1}} x\ ROE = p\ x\ ROE$$

Where ROE is calculated as:

(10) $$ROE = \frac{Net\ income}{Average\ equity}$$

However, there are countless factors affecting earnings, which need to be taken into account. Not only does the firm specific information affect earnings, but also political decisions as well as general economic conditions. Consequently, the most accurate methods can be statistically complex. Different statistical models or time-series models that use past earnings to estimate growth are the most popular methods in practice. (Rothovius 2003.)

A naïve, as well as the simplest method would be to calculate arithmetic mean or geometric average growth from historical data, but this might not lead to meaningful estimations. Popular models are often linear or log-linear regression models, but also more complex models such as ARIMA model are used (Rothovius 2003). In short, ARIMA, or autoregressive integrated moving average, forecasts future by combining past values and past shocks with a possibility to adjust for seasonal patterns (Rothovius 2003). To put the complexity of forecasting EPS into a real world example, figure 6 presents forecasts for Metsa Group quarterly EPS with 3 different simple statistical methods: mean average, 3 period moving average, and 3 period weighted moving average. Weighted moving average has 0.7 weight for t-1, 0.2 for t-2 and 0.1 for t-3 actual EPS. Clearly, these commonly used statistical methods do not provide meaningful forecasts for EPS, which is affected by several different factors. Given the evident complexity of forecasting EPS, investors might prefer trusting analysts' EPS estimates instead of forecasting earnings themselves.

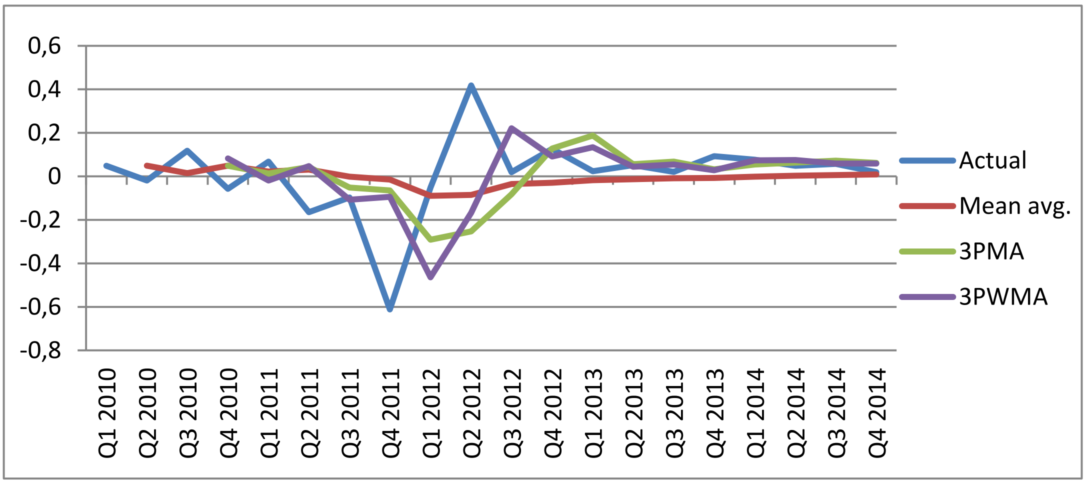


Figure 6. Actual quarterly EPS versus forecasts

3. IRRATIONAL BEHAVIOR IN FORECASTS

Behavioral finance intends to explain deviations in stock prices that the theories of traditional finance cannot explain. Built on the argument that markets are inefficient, behavioral finance explains this inefficiency with two different key aspects: limits to arbitrage and psychological biases (Barberis & Thaler 2003). When it comes to irrational behavior, there is not one correct explanation for the behavior. An example of such biased behavior is sell-side analysts' EPS forecasts being optimistic in general (e.g. Abarbanell 1991; Bradshaw et al. 2006). Optimism can be partly explained by incentive factors related to principal agency problem. However, it can also be explained by cognitive biases that not only affect investors but analysts as well (e.g. De Bondt & Thaler 1990). After first introducing the job environment of analysts, this chapter discusses these motivational and cognitive biases and introduces some of the most relevant ones from the point of view of this particular thesis, as well as the reasons behind these irrational actions.

3.1. Task of an analyst

The task of an analyst is to collect market and firm-specific information and translate the information into forecasts and stock recommendations (Shefrin 2002: 257). Analysts can be divided into 3 different segments according to who they work for: sell-side, buy-side and independent analysts, of which buy- and sell-side are the most common types. Typically, sell-side analysts work for brokerage firms while buy-side analysts are employed by, for example, pension funds (Cheng et al. 2006; Jegadeesh et al. 2004). The main difference between the two is that the recommendations by the former group are public and provide information for investors. Independent analysts, on the other hand, are self-employed, but can possibly sell recommendations to investors (Cheng et al. 2006).

Apart from stock recommendations (for example buy, hold and sell), analysts provide EPS-forecasts. EPS is a simple measure about a company's profit and it is closely followed by investors. An EPS-forecast represents the analyst's expectations about future earnings per share, and is often considered to be one of the most important factors in forecasting future stock price. Forecasts are based on information that is gathered from different sources, such as annual reports. The information can be further divided into firm specific, industry related, and macroeconomic information (Fischer & Jordan 1991). General market characteristics can explain up to 50% of stock prices (King 1966; Fischer

& Jordan 1991). The meaningfulness of gathering and analyzing information depends on three different factors: market efficiency, the price of collecting the information, and the quality of the information (Grossman & Stiglitz 1980). Clearly, if all market participants had equally easy access to information, there would be no incentive to gather it. Since the latter does not hold in practice, by using resources to collect and analyze information one can possibly find over- or undervalued stocks (Grossman & Stiglitz 1980). This creates the basis for the occupation of financial analysts, which is summarized in figure 7:

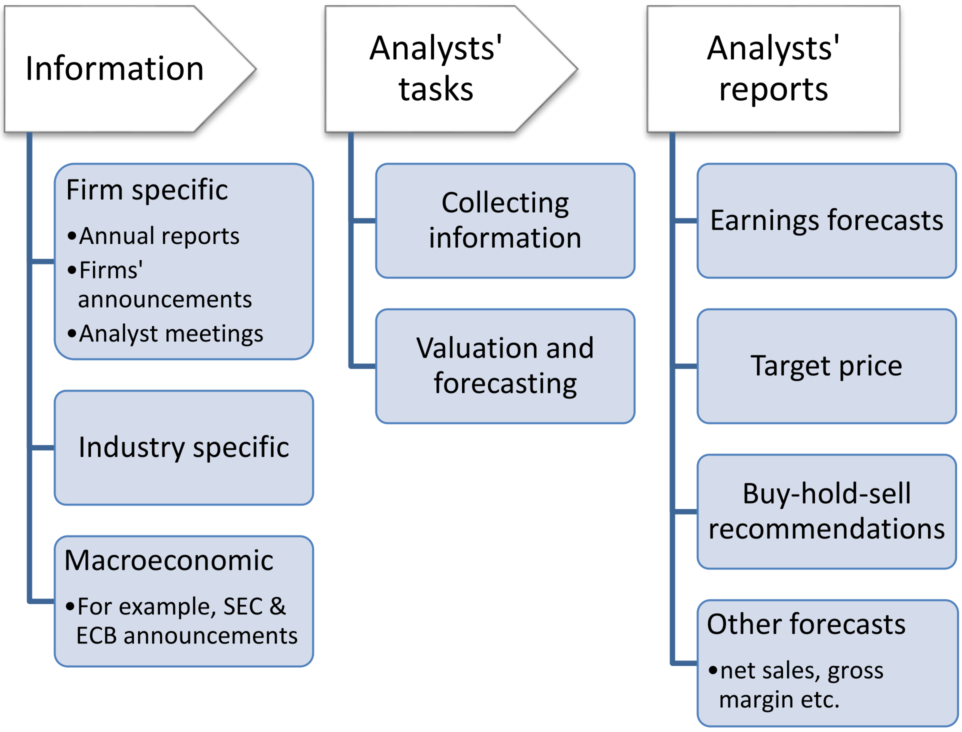


Figure 7. Job environment of an analyst

3.2. Principal agency problem

The global financial crisis started a broad conversation about incentive structures of financial institutions, including brokerage firms'. Given that arguably the main task of sell-side analysts is to release forecasts that encourage investing decisions, it is important to introduce the concept of principal agency problem.

The principal-agent problem refers to a relation of two parties, a principal and an agent. The principal authorizes the agent to act on behalf of the principal. Agency costs arise when the interests of the two are in conflict and one has to pay the price. (Jensen & Meckling 1976.)

The task of an analyst is to create rational forecasts that encourage investors to trade. What benefits the investor the most is an accurate, unbiased forecast. With such forecast, the investor could maximize his/her risk-adjusted returns. Analysts, on the other hand, may have several incentives to release a forecast that necessarily does not fully reflect their own rational opinion. Some literature suggests that analysts prefer optimistic forecasts, since they have a greater trade generation attribution than pessimistic forecasts (e.g. Jackson 2005; Trueman 1994). Another explanation found in previous literature is that optimistic forecasts are preferred to maintain the relationship with the evaluated firm (e.g. Michaely & Womack 1999). Whatever the reason is, it is clear that there is a conflict of interest between analysts and investors and investors bear the agency costs.

Like any other firm, brokerage firms pursue to maximize their profitability. Thus, it can be argued that the compensation of analysts depends on their contribution to the target. Indeed, the compensation is mainly determined by two factors: the usefulness of the analyst for the brokerage firm, and the reputation of the analyst (Michaely & Womack 1999). Naturally, reputation depends on previous forecast accuracy. Jackson (2005) sums up that because of the conflict of interests, sell-side analysts face a decision between two different options:

1. Either sell-side analysts could publish their own truthful opinions, which would potentially increases their reputation. Consequently, the benefit of such recommendation or forecast would be realized in long a long period of time.
2. Or, the analyst could choose to present a biased opinion to enhance the brokerage actions of his employer. Over a short term, analyst would benefit from increased bonuses.

In essence, analysts face a decision between pleasing their employer and increasing their reputation. Even before the global financial crisis, a settlement about a separation between research and the investment-banking department was made in the US to mitigate this problem, but without much success (Jackson 2005).

3.3. Irrational behavior in analysts' forecasts.

As stock market professionals, analysts are expected to act rationally. In explanation, investors expect EPS-forecasts to be unbiased, and thus the recommendations should provide valid information about a company. However, it is important to note that public recommendations of sell-side analysts encourage investors to trade, which generates trading commissions for brokerage firm. These commissions are, in fact, perhaps one of the most important factors in the brokerage firm's profits.

The previously discussed conflict of interest actualizes for example by preferring glamour stocks over value stocks in sell-side analyst recommendations. Such stocks are, for example, stocks with positive momentum, large volume of trade, and attractive growth opportunities. What unites these stocks is that they clearly attract investors and are often expensive. (Jegadeesh et al. 2004.)

However, conflict of interest is not the only reason explaining biased forecasts. For example, optimism remains even if investment-banking affiliations are eliminated (Jackson 2005). Thus, previous literature agrees that sell-side analysts not only have financial incentives to intentionally publish forecasts that do not represent their honest opinion but also suffer from psychological behavioral biases. The literature about analysts' irrational behavior is extensive, but this thesis only introduces the most important ones that are considered to be related to SAD effect. These biases are optimism, pessimism, overreaction and underreaction.

3.3.1. Optimism and pessimism

In brief, optimism can be defined as positive thinking, and accordingly pessimism as negative thinking. Analysts' forecasts are based on information. Therefore in this context, irrational optimism (pessimism) can be seen as releasing optimistic (pessimistic) forecasts that cannot be explained by any available information. Previous literature does not provide a clear agreement on whether analysts are actually optimistic or pessimistic. SAD on the other hand, intends to explain seasonality in optimism and pessimism, and suggests that individuals become more pessimistic during fall. If irrational pessimistic and optimistic behavior occurs, forecasts are biased, misleading, and not driven by fundamentals.

De Bondt & Thaler (1990) suggest that analysts tend to prefer optimistic forecasts. More precisely, they find that on average the actual EPS is only 65% of the forecasted value. In addition, the original forecasts seem to be revised downwards between April and December (De Bondt & Thaler 1990). Although this can be explained by mean reversion after initial overreaction and optimism, the seasonal time pattern is similar as in SAD effect. Similarly to De Bondt & Thaler (1990), Butler & Lang (1991) find that on average 76.5% of forecasts made by analysts are too optimistic implying that analysts constantly overestimate a firm's capability to produce earnings. Complementing findings about optimism have been made by Womack (1996) and Jackson (2005), among others.

Optimism is highly related to principal agency problem. The following statement by De Bondt & Thaler (1990) summarizes well one reason behind optimism: "Every customer is potentially interested in a buy recommendation, while only current stockholders are interested in sell recommendations." Thus, optimistic forecasts create more trade than pessimistic ones (e.g. Trueman 1994; Womack 1996; Jackson 2005). However, the principal agency problem cannot be viewed as the only reason for the biased behavior, because individuals with no financial incentives are also shown to be optimistic (De Bondt & Thaler 1990; Jackson 2005). Hence, cognitive biases seem to be relevant as well.

But are optimistic forecasts actually irrational – how does one determine rationality? Analysts not only collect information from public news, but they also rely heavily on analyst meetings that are organized by companies. These meetings create the basis for analysts' informational superiority. Unfavorable forecasts could compromise this information channel. Indeed, Lim (2001) finds that analysts rationally provide optimistic forecasts to balance between access to information and forecasting bias (similar findings by e.g. Pratt 1993). In addition, Michaely & Womack (1999) find that with favorable recommendations, analysts maintain good relationship with companies whose IPO has been managed by the brokerage firm. But in the end, rational or not, optimistic forecasts are possibly costly for investors who are unable to fully identify the bias in the forecasts and correct them accordingly (Abarbanell & Bernard 1992; Bradshaw et al. 2006).

Contradictory to many studies, Ciccone (2005) suggests that optimism among analysts has been decreasing and transformed to pessimism in the very beginning of the 21st century. In more detail, analysts seem to be pessimistic about profit firms and optimistic about loss firms (Ciccone 2005). Pessimism is found to enhance the accuracy of forecasts (e.g. Butler & Lang 1991; Ciccone 2005). Later studies, on the other hand, suggest seasonal differences in optimism and pessimism. For example, Dolvin et al. (2009)

suggest that analysts are optimistic overall, but approaching the end of the year analysts become less optimistic and forecasts become more accurate.

3.3.2. Overreaction and underreaction

Analysts' overreaction can be simply defined as reacting too strongly to new information. In the case of underreaction, the reaction is too small. In terms of overreaction, EPS forecasts would be revised excessively after a surprise in the reported earnings. For example, De Bondt & Thaler (1990) conclude that analysts overreact to good news.

However, the majority of previous literature prefer the view that analysts actually underreact instead overreacting. For example, Abarbanell & Bernard (1992) find that analysts tend to underreact to a recent earnings announcement. Similarly Zhang (2006) states that when new information becomes available about earnings, analysts do not revise their forecasts sufficiently: the revisions are too small, indicating underreaction in analysts' decision making. There is also some evidence that the reaction actually varies depending on the content of the announcement. If the announcement contains negative (positive) information, analysts underreact (overreact) (Easterwood & Nutt 1999).

Figure 8 provides a real world example of analysts' incorrect reactions. The interim reports of Plexus Corporation were positive surprises as they were able to beat analyst EPS forecasts consecutively five times. After the first positive report, analysts clearly did not revise their expectations sufficiently and underreacted. In addition to the forecast error pattern, the figure showcases a phenomenon known as post earnings announcement drift (*PEA drift*). After earnings announcements, investors' reaction causes the stock price to climb to an excessive price, which partially reverts. (Shefrin 2002.)

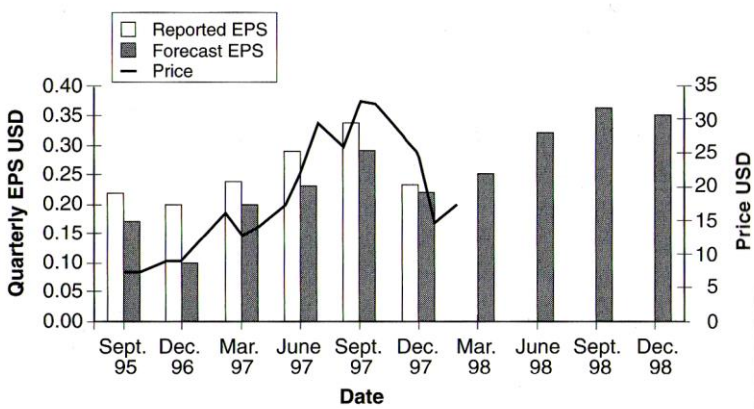


Figure 8. Quarterly EPS forecast of Plexus Corp. and the reported EPS. (Shefrin 2002)

Overall, there is more evidence in favor of underreaction. In fact, this is understandable as overreacting could harm analysts' reputation much more than underreacting. Such reactions would deviate from consensus, and are most likely intentionally avoided by analysts in similar manner as Womack (1996) finds that sell recommendations are. Whether or not analysts are optimistic or pessimistic, overreact or underreact, in the sense of traditional finance these are just random deviations from rational decisions and fundamental values. But from the point of view of behavioralists, these are persistent predictable patterns. In terms of seasonal patterns, behavioralists expect forecasts to be less optimistic (pessimistic) during fall. As for seasonality in forecast error, figure 8 shows no clear accuracy improvement during the third quarter, but the deviation between reported and forecasted EPS clearly diminishes in December.

3.4. Analysts' forecast accuracy

Sell-side analysts, who face the principal agency problem, are documented to be affected by several forms of irrational behavior. Irrational behavior has an influence on forecasts, and thus might weaken the forecast accuracy of an analyst. Hence there is a wide debate on whether the forecasts are useful or not. Butler & Lang (1991) find that on average 76.5% of forecasts over-estimate earnings on a 4 year data period. The data consists of large firms and active analysts, and thus the results should not be driven by lack of available information. Furthermore, De Bondt & Thaler (1990) find that the forecast error increases alongside with the time period. On a one year forecasting period, the announced EPS is only 65% of the forecasted one (De Bondt & Thaler 1990). Analysts also seem to herd, which makes EPS forecasts from different analysts homogeneous at the same time weakening forecasting accuracy (O'Brien 1988).

Although earnings forecasts of analysts are somewhat inaccurate, they outperform time series models on a forecasting period shorter than one year. However, in the beginning of the fiscal year neither of the above mentioned do better than a random walk prediction of no change. When the number of analysts following a firm is small, better forecasting results are obtained by the combination of time series and analysts' EPS forecasts. (Conroy & Harris 1987.)

A similar finding about EPS forecasts outperforming time series models has been made by O'Brien (1988). Short period forecast accuracy could be related to analysts having easy access to firm specific information. Indeed, Fried & Givoly (1982) relate previously mentioned superiority to analysts having a more comprehensive set of information than is included in historical data.

Documented optimism, herding and forecasts being only slightly better than time series models make the forecasting accuracy of analysts debatable. In addition to behavioral biases, there are several factors affecting analysts' forecasting accuracy, which can be divided into firm specific and analyst related factors. The two most dominant firm specific factors are firm size and analyst coverage. Grossman & Stiglitz (1980) suggest that stock prices reflect more information when the number of individuals gathering information increases. Thus, analyst coverage increases available information and improves market efficiency (Nikkinen et al. 2008: 82). Simultaneously, information uncertainty decreases. There is also a positive relationship between firm size and analyst coverage, and a negative relationship between firm size and forecast error (Bhuskan 1989). The greater information uncertainty the greater will be the forecast errors, and the effect is documented to be stronger after bad news (Zhang 2006). Another important firm characteristic is prior earnings performance (Lim 2001).

An example of individual-related factors is analysts' experience. Clement (1999) states that analysts' EPS forecasts tend to become more accurate as forecasting experience increases. Furthermore, analysts working for smaller firms have 7.7% larger average forecast error than analysts working for large firms (Clement 1999). Forecast accuracy also improves when an analyst concentrates on a smaller selection of firms (Clement 1999).

An interesting question is whether forecast error actually makes forecasts useless. EPS forecasts are one important factor determining stock price and one of the factors driving stock recommendations published by analysts. Both Womack (1996) and Barber, Lehavy, McNichols & Trueman (2001) find that analyst recommendations create abnormal returns when rebalanced daily. However, for an individual investor the abnormal returns might not be achievable due to high trading costs related to the significant trading volume. On the other hand, Bradshaw (2004) finds no evidence for abnormal returns being generated with stock recommendations. Figure 9 shows the finding of Shefrin (2002: 73) implying that analysts' recommendations outperform S&P 500, even when adjusted for trading commissions.

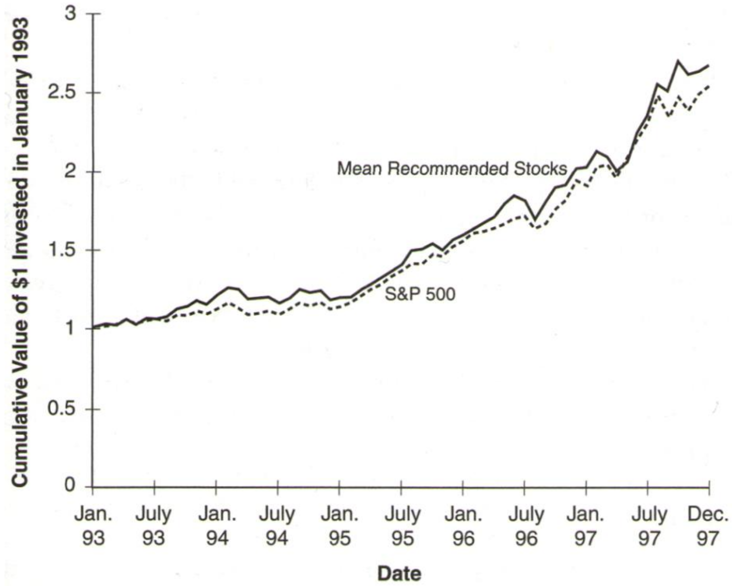


Figure 9. Portfolio returns generated by analyst recommendations. (Shefrin 2002: 73)

Clearly, there is mixed evidence about the usefulness of analysts' forecasts and recommendations. However, the EPS forecasts are only one source of information available to investors. A rational investor more than likely forms his/her own opinion about firms' future – at least an experienced one would. Thus, instead of arguing whether forecasts and recommendations can generate excess returns, one should question whether or not they consist of useful information. The field of finance develops constantly and so does the forecast accuracy of analysts. Ciccone (2005) finds that between 1990 and 2001 analysts' forecast dispersion and error steadily decreases, while optimism also decreases. However, at the same time earnings guidance and earnings management has been increasing. One well known example of earnings management is Microsoft.

Until 1997 Microsoft had beaten analysts' quarterly EPS estimates 41 times out of 42 since its IPO. Forecast error was not large enough to make analysts unhappy of their performance but kept investors happy because of the positive earnings surprises, which lead to stock price increasing steadily. Analysts rely heavily on information provided by a firm. By providing extra cautious estimates, Microsoft was able to control analysts EPS forecasts. (Fox & Rao 1997.)

Such earnings guidance improves analysts' forecast accuracy and is likely to cause decrease in optimism (increase in pessimism). Although it could be the case, the steady improvement in analysts' forecasting accuracy does not seem to be fully explained by increased earnings management and guidance conducted by firms. However, it seems that analysts have had an increasing tendency to forecast more loss firms than before the 21st century – and even more accurately than before. More precisely, for unprofitable firms the error has decreased by half from 1990 to 2001, while for profitable firms the decrease was about 25%. Thus, the forecast accuracy difference between profitable and unprofitable firms has diminished significantly. One possible explanation for the improved accuracy is better availability of information due to the revolution of World Wide Web. (Ciccone 2005.)

To conclude, profitable firms with good earlier earnings performance and less uncertainty are much easier to forecast than small firms. This explains analysts' tendency to prefer profitable firms in forecasts.

4. SEASONAL AFFECTIVE DISORDER

Seasonal affective disorder is a phenomenon documented by research in psychology. According to SAD, which was first noted by Rosenthal et al. (1984), people become more depressed during fall and winter. Rosenthal et al. (1984) report a strong relationship between changes in day length, daylight and depression. Moreover, the further north the test subjects lived, the more severe was the depression and the earlier it started (Rosenthal et al. 1984). The mental effect itself seems plausible. For example Google Trends search for the word “depression” shows a clear seasonal pattern, which bottoms during summer and increases rapidly from the beginning of September:

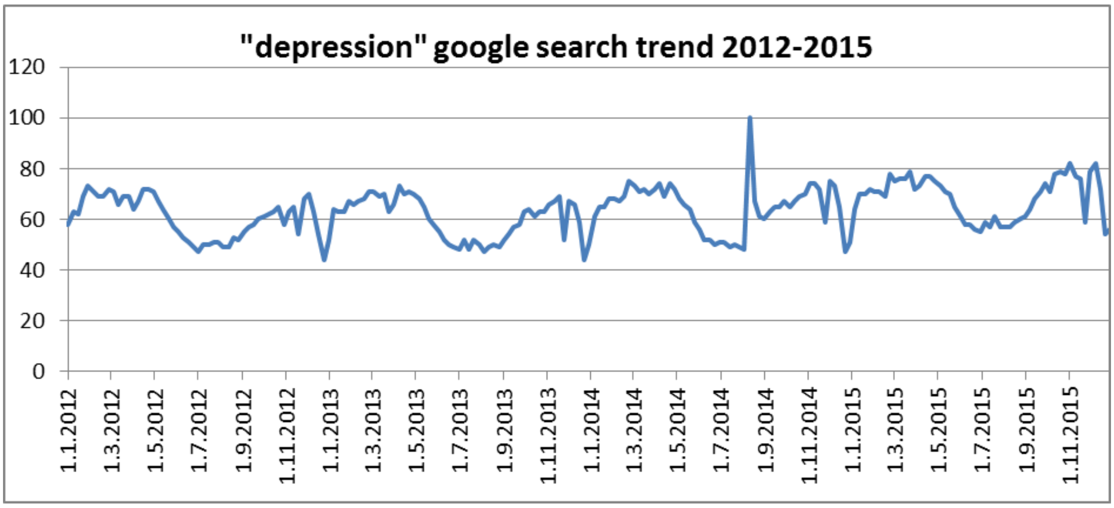


Figure 10. Seasonality in google search for “depression”. (Data: Google Trends 2016)

In addition to minutes of sun time and the length of a day, Molin et al (1996) report a significant relationship between temperature and depression. However, cloudiness and rainfall do not seem to cause seasonal depression (Molin et al. 1996). Due to the mentioned correlation with the length of a day, one would expect the effects of SAD to be greater in Finland, where the shortest day during winter is less than 6 hours in Helsinki. This chapter consists of two parts. The first part discusses the effects of SAD on financial markets in general, while the second part investigates the possible influence of SAD effect on a specific group: stock market analysts.

4.1. Seasonal affective disorder and financial markets

It is common knowledge that during particular months stock returns are significantly higher than on average. These calendar effects, for example January effect, are consistent in time, and thus widely studied. January effect can be explained by investors selling their stocks at the end of the year because of tax planning reasons. This might be a reason explaining lower stock returns as approaching year end. However, another explanation for the realized weaker stock returns during fall and winter months might be provided by SAD.

The interest in the relationship between SAD effect and stock returns started increasing during the 21st century. For example, Kamstra et al. (2003) study the relationship between stock returns and SAD in different latitudes. After taking into account Monday effect, tax-loss selling effect, there still exists strong evidence that investors are more risk averse during fall (Kamstra et al. 2003). In result, there is a negative relationship between fall months and stock returns. Furthermore, in the northern countries, where the seasonal differences in daylight are larger, SAD effect seems to be stronger (Kamstra et al. 2003). To present the effect in numbers, Kamstra et al. (2003) use a neutral allocation portfolio, which allocates half of the portfolio on Australian stocks and the other half on Swedish stocks. The returns for such portfolio are 13.2 % in their dataset. However, if the portfolio is allocated 100% according to SAD effect twice a year at fall and spring, the returns would be 21.1% (Kamstra et al. 2003). Thus, the effect of SAD seems to be economically meaningful.

As people become more risk averse, they shift their portfolios towards less risky assets, such as government bonds. The seasonal pattern of this is documented by Kamstra, Kramer & Levi (2011) who find that U.S. Treasury Securities, which are often considered to be risk free assets, have a strong return correlation with SAD months. Consistent with the SAD related findings by Kamstra et al. (2003), Kamstra et al. (2015) suggest that U.S. Treasury Securities earn higher returns during SAD season, and thus investors have a tendency to prefer bonds over equity during fall because there is less risk incorporated.

Consistent with psychological studies showing that extraordinary weather changes affect an individual's behavior, Cao & Wei (2005) show an inverse relationship between stock market prices and temperature. Cao & Wei (2005) document a return pattern of lower returns during summer and fall, which is similar with SAD related studies. These patterns are not driven by individuals' acts to maximize utility, which should drive investment decisions. Understandably, there are also studies questioning the credibility of SAD. Jacobsen & Marquering (2008) note that both Cao & Wei (2005) and Kamstra et al. (2003) actually agree on the same seasonal phenomena – just the explanation is different. This raises the questions if the findings in previous literature are driven by a shared seasonal factor or unsound evidence.

A puzzling difference in the studies of Cao & Wei (2005) and Kamstra et al. (2003) is that the latter finds no significant effect from temperature. This might be because of the simultaneous use of control variables for SAD and temperature, which possibly causes multicollinearity problem. Interestingly although both studies use daily data, neither of them tests for heteroscedasticity, which often occurs in noisy daily data. In addition the studies disregard January and Halloween effect, which can partly affect the seasonal pattern. (Jacobsen & Marquering 2008.)

After controlling for the mentioned issues, Jacobsen & Marquering (2008) conclude that there is a seasonal pattern in stock returns, but the evidence is not robust enough to determine one correct explanation for this. Similarly Novy-marx (2014) shows the easiness of replicating the previous results of correlation between weather and stock returns and suggests that the results are more likely due to weaknesses in the traditional econometric methods than in the forecasting power of weather. Furthermore, similarly with Jacobsen & Marquering (2008), Kelly & Meschke (2010) suggest that the pro SAD evidence of Kamstra et al. (2003) arises from overlapping dummy variables. In explanation multicollinearity seems to be one possible explanation for the results in their study.

As it seems, several studies suggest that the evidence in favor of SAD is weakened by, for example, problems in data as well as weaknesses in the used methodology. The conclusion of the critique seems to be that there are seasonal patterns in different financial assets, but so far there is no conclusive evidence for the reasoning behind it. Hence according to these findings, a simple dummy variable for this effect should be as effective control variable as daylight or any other SAD related factor.

From the perspective of this particular thesis, evidence from the Finnish markets is most valuable and interesting. In a recent study, Kaustia & Rantapuska (2016) examine the effect on Finnish stock markets. Although some evidence suggests that the length of the day is partly related to trading volume, overall a little evidence is found to support the hypothesis that SAD effect is significant in Finnish stock markets as there is no increase in sell orders. Also, there is some evidence that precipitation is negatively related to stock returns. On the other hand, sunniness and temperature are not statistically significant. Overall, the weather conditions do not seem meaningful variables as the predictive power from all mood variables combined is extremely small. Instead, trading activity seems to follow more closely seasonal vacation patterns. (Kaustia & Rantapuska 2016.)

The findings of Kaustia & Rantapuska (2016) raise doubts on the significance of SAD effect on decision making of individuals and professional analysts operating on the Finnish stock markets. One possible explanation for the findings could be that the weather in Finland is rather volatile throughout the whole year, which might result in the depression effect of SAD being less significant. However, this does not explain the opposite findings between Finnish and Swedish markets.

4.2. Seasonal affective disorder and analysts' forecasts

There seems to be some evidence that individual investors' financial decisions vary seasonally. However, in the past the effect of behavioral biases on stock market professionals has often been denied, after all they are considered to represent the so-called smart money side of the markets. Although the SAD effect itself is a relatively old phenomenon, there is very little evidence of the possible effects on stock market analysts. Surprisingly, there seems to be very few published researches on this particular topic, and the most cited ones are by Lo & Wu (2010) and Dolvin et al. (2009).

Complementary evidence that professionals are also affected by SAD can be found from underpricing of initial public offerings (IPOs). In brief, IPO of a firm is underpriced when the initial offer price is significantly lower than the closing price on the very first trading day (Dolvin & Pyles 2007). Dolvin & Pyles (2007) find that IPOs issued during SAD months, and especially in winter months, tend to have higher upward adjustment on the first trading date, and thus appear to be underpriced. Dolvin & Pyles (2007) suggest that this happens because issuers are forced to reduce offer prices to encourage risk-averse investors to invest. Thus, the results suggest that investors are affected by SAD. However, the research does not address the possibility that the professionals of the underwriting firm could be affected by SAD, which would explain the increasing underpricing during fall and winter.

Dolvin et al. (2009) study the errors in annual EPS forecasts relative to actual earnings in US stock markets between 1998 and 2004. They find evidence consistent with previous literature that analysts' forecasts continuously overestimate EPS. However, during the considered time period forecast errors seem to be significantly smaller during fall and winter. In explanation, analysts seem to become more pessimistic during the time period considered to be related to SAD. Although the forecasts remain optimistic, they do become more accurate. These results remain the same in both univariate and multivariate tests. Using a subsample of analysts located in northern and southern states reveals that the effect is stronger in the northern states. In fact, the results suggest that there is no significant SAD effect among analysts located in southern states. (Dolvin et al. 2009.)

Dolvin et al. (2009) divided the sample into Non SAD and SAD, in which SAD sample consists forecasts released between September 21 and March 20. In the two different samples they use a dummy variable "FALL" as an explanatory variable, which takes the value of 1 if the forecast is released during September 21 and December 20. They also have a separate control variable SAD, which takes a value of:

$$\begin{cases} H_t - 12, & \text{when trading days are in the fall and winter} \\ 0 & \text{otherwise} \end{cases}$$

Where H_t represents the length of night on a trading day, and 12 is the average number of night hours during the whole year. The strength of this variable for measuring the effect of SAD is that it captures the psychological and medical symptoms of the effect of the length of the day previously reported in psychological literature (e.g. Rosenthal et al. 1984).

In terms of explanatory power, a questionable characteristic of SAD effect is that it is only relevant during fall and winter. And since many firms have their fiscal years ending at the end of December, the forecasts are expected to become more accurate as more information becomes available towards the year end. However, Dolvin et al. (2009) solve this issue by dividing their sample into subsamples consisting of different fiscal years revealing that SAD effect remains significant.

A similar finding to Dolvin et al. (2009) is made by Lo & Wu (2010). In addition to forecast errors, Lo & Wu (2010) use average downward revisions as an indicator for SAD during time period 1980-2006. The method they use is a bit different approach than the one used by Dolvin et al. (2009). Lo & Wu (2010) do not divide their sample into subsamples according to SAD season. Instead they run a regression, where the dependent variable is forecast revisions and they control for revisions done between non-fall and fall, between fall and fall, and between fall and non-fall.

Since the control variable that captures forecast revisions done during fall is significantly negative, analysts seem to become more pessimistic during SAD months. Consistent with findings of Dolvin et al (2009) the results of analysts becoming more accurate during fall are partly driven by the decreasing time remaining to earnings announcement (Lo & Wu 2010). However, after controlling for this effect by identifying the fiscal years of firms, SAD effect remains significant.

Interestingly, Lo & Wu (2010) find that although analysts' forecasts become more accurate, investors do not change their expectations accordingly. Thus, investors seem to suffer significantly more from SAD than analysts. Lo & Wu (2010) also note that the returns for firms with no revisions are more negative than returns for firms with revisions. Therefore it seems that pessimistic analysts actually help to reduce investors' biased reaction during SAD season (Lo & Wu 2010).

The amount of existing literature combining the two topics, namely analysts and SAD, is very limited, and thus there is no criticism against the two presented articles. However, one can always question whether the seasonal differences in forecast accuracy are due to SAD effect or if they are plainly explainable by rational stock market characteristics, such as year-end accruals. Or could it be a reversal effect of another bias? Interestingly, as early as in the '90s De Bondt & Thaler (1990) found that two-year EPS forecasts made in April were reversed on average by 38% before December. For one year forecasts the reversal is 18% (De Bondt & Thaler 1990). It is clear that the pattern is roughly the same but the explanation is the reversal of overly optimistic forecasts. Similar interpretation has been made by Chopra (1998) who finds that initial forecast overestimates earnings by 11% and is revised to only 1% overestimation in December due to the forecast period becoming shorter and shorter. In addition, business cycles seem to cause seasonal overestimation (Chopra 1998).

The seasonality in forecast error can also arise from seasonal earnings. Figure 11 presents the average quarterly reported EPS for Finnish publicly listed firms between 2010 and 2014. Evidently, on average there are large seasonal differences between the quarters. The weakest earnings are historically recorded in the first quarter, which can cause forecast reversals towards year-end if not taken into account initially.

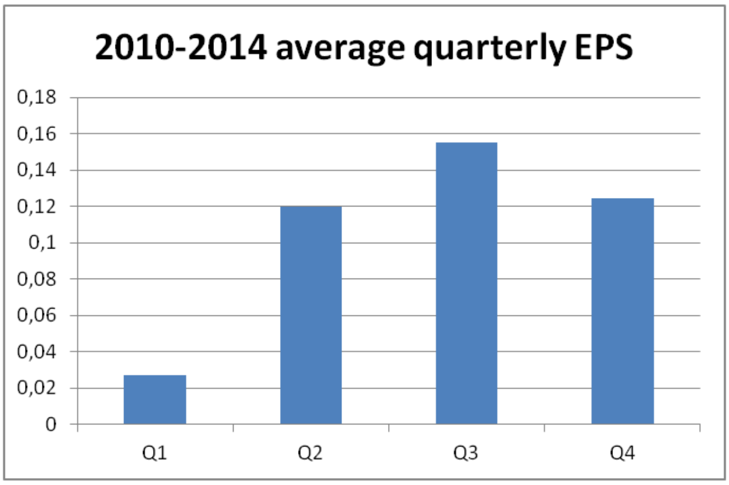


Figure 11. Average quarterly EPS in Finland between 2010 and 2014

Evidently, the findings of both Dolvin et al. (2009) and Lo & Wu (2010) should not be accepted without critical consideration. There are some similar seasonal patterns in quarterly earnings, and other fundamental reasoning that can cause possible seasonality in forecast error. Without ruling out all other possible explanations, it cannot be interpreted that the less optimistic forecasts during fall and early winter are solely due to SAD effect.

5. DATA, METHODOLOGY AND HYPOTHESES

To investigate the possible effects of SAD on analysts, regression analysis is performed with data consisting of various control variables. Different variables are chosen according to their acknowledged explanatory power in academic literature. Not only are the previous findings taken into account in variable selection but also in the methodology, which pursues to account for some of the criticism presented in previous literature. This chapter gives a detailed view of the used data, the assumptions behind the hypotheses, and of the chosen methodology.

5.1. Data description

In addition to stock recommendations (e.g. buy, hold, and sell), analysts publish forecasts about companies' future fundamentals. One of these is EPS forecast, which is directly expected to affect a firm's stock price (Fischer & Jordan 1991: 243). Because EPS figures are closely followed by investors, this research uses EPS forecasts as an indicator of analysts' opinions. EPS forecasts, the actual EPS, forecast standard deviations, and the number of forecasts are obtained from ThomsonReuters database, which reports consensus estimates from I/B/E/S. Consensus EPS figures are used, since the main interest is to identify a common behavior pattern among sell-side analysts. EPS observations are followed through time to identify whether or not there is any evidence of seasonal variation in forecasts.

The focus will be on Finnish companies that are traded in the Helsinki Stock Exchange. The fact that large companies are followed by both Finnish and foreign analysts, including all firms from the OMX Helsinki Index means that foreign analysts will be included in the dataset, which could possibly weaken the local effects. In order to bypass this issue, one would have to identify the firms that are only followed by Finnish analysts. Unfortunately due to data restrictions, it is not possible to identify individual analysts. Assumably, firms followed by purely Finnish analysts are small firms that are included in OMX Helsinki mid and small cap indexes. In addition, if there is a very small amount of monthly EPS forecast observations, it is highly unlikely that the analysts are foreign. Since Finnish firms are rather small, the number of active foreign analysts is likely to be low as well. Thus, it is unlikely that foreign analysts would mitigate the local effects.

The data consists of monthly observations between fiscal years 2010 and 2014. All firms are included in the sample, no matter if their fiscal year is precisely from the first of January to the end of December or not. The starting point of the sample period is chosen accordingly to exclude the global financial crisis from the sample. The chosen time period also differs from the previous literature, which has concentrated purely on pre-crisis observations. This period is particularly interesting because of the prevailing market conditions, which are presented in figure 12.

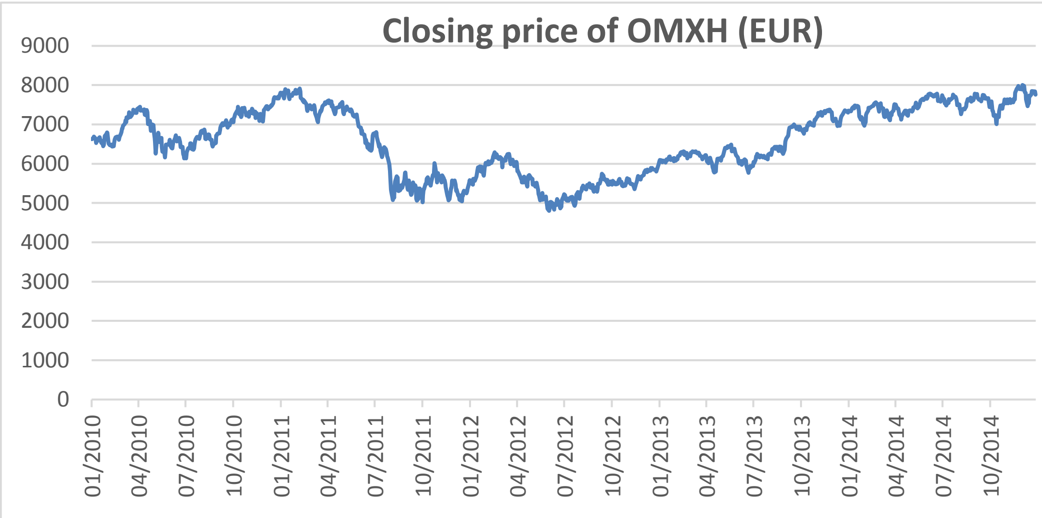


Figure 12. Closing prices of OMX Helsinki Index 2010-2014. (Data: Nasdaq 2016)

The global financial crisis transformed financial markets. As visible in figure 12, the markets have been volatile and have experienced several smaller downfalls and reversals after the crisis. During a time period like this, one would expect analysts to publish extra cautious forecasts. Alternatively, analysts might be more concerned about their careers and prefer sale generating forecasts. In addition, from the first quarter of 2012, the market has been increasing steadily, which adds an interesting momentum factor in the forecasting process. Thus, the time period is extremely interesting, yet challenging, as the market is seeking its path.

To extend the number of observations, even large firms will be included in the dataset. However, obtaining a wide selection of observations is not the only reason to include large firms. This also makes it possible to examine whether the findings are consistent for small firms. Anomalies are often stronger or sometimes only relevant for small firms.

Therefore, any anomaly like SAD effect should also be visible in a sample consisting of purely small firms, and the effects are likely to be stronger.

In the previous research, it has often been the practice to exclude consensus recommendations that are based on a single forecast. This is understandable since the consensus is precisely used to eliminate the bias of individual analysts. Since standard deviation in forecasts cannot be calculated without multiple observations, consensus forecasts with only one observation are excluded from the dataset. Naturally, using a common sample restricts the observations even further. Due to the above mentioned reasons and the decision to remove outliers from the sample, the final common sample consists of 3665 observations. The detection of outliers is discussed more thoroughly in section 6.1.

5.2. Hypotheses formation

Motivated by the findings of Lo & Wu (2010) and Dolvin et al. (2009), this thesis investigates whether there is to be found significant seasonal variation in the EPS forecasts for Finnish firms, and if this can be explained by SAD effect after controlling for various factors. Overall, there are three alternative hypotheses in this thesis. The first hypothesis follows the finding of Rothovius (2003) that Finnish analysts are generally optimistic:

> *H_{01}: There is no bias in analysts' forecasts.*
> *H_1: Analysts' forecasts overestimate EPS and are generally optimistic.*

If there is an upward bias in analysts' forecasts, forecasts should in theory become more accurate during the SAD months, because according to the theory of SAD, individuals become more pessimistic during the SAD months. Respectively, if analysts are pessimistic in general, forecast error should increase during the SAD season. Thus, the second hypothesis is constructed to identify whether or not analysts are affected by SAD:

> *H_{02}: SAD effect has no effect on analysts.*
> *H_2: SAD effect makes forecasts more accurate (inaccurate) if analysts are optimistic (pessimistic).*

The third hypothesis tests the importance of the findings by determining if the results are driven by small firm effects.

H_{03}: Small firm size does not strengthen SAD effect
H_3: SAD effect is stronger for small firms

Accepting the null hypothesis for the third hypothesis indicates that the effect is not more meaningful for small firms as many other anomalies are. If, however, there is no evidence of a significant SAD effect for small firms and SAD effect is significant for the full sample, the robustness of the evidence needs to be considered carefully.

5.3. Methodology

Using the available data from analysts' EPS forecasts, the research investigates whether seasonality in analysts' forecasts is caused by SAD or driven by fundamental reasons. For this purpose the research uses forecast error as an indicator for changes in analysts' forecasting ability. Forecast error is calculated as in equation 11:

$$(11) \qquad FE = \frac{Reported\ actual\ earnings - Forecasted\ earnings}{Reported\ actual\ earnings} * 100$$

FE denotes percentage error and is a more meaningful variable than just the difference between actual earnings and forecasted earnings. A negative coefficient of FE suggests that the actual earnings fall short of the forecasts, meaning that the forecasts are optimistic. The included control variables for the multivariate tests can be divided into three groups: firm specific characteristics, general market conditions, and analyst related variables. The used firm specific characteristics are log of B/M ratio and log of total asset, as well as momentum. B/M is the ratio of book value to market value, and controls for analysts' tendency to favor glamour stocks over value (Jegadeesh et al. 2004). Log of total assets is a measure for firm size, which should be negatively correlated with forecast error and contributes to smaller information uncertainty (Bhuskan 1989; Grossman & Stiglitz 1980). From here on, these variables are named as log(BM) and log(TA). Both variables are reported values from previous fiscal year end.

In addition, a momentum factor is included to control for the possibility that a firm's past performance affects analysts' forecasts. Denoted as MOM, the variable is the latest quarter's EPS. Although MOM already captures some market specific factors, an additional market factor is included. OMXH Index returns are used to capture overall market movements. After all, stock markets are expected to move according to firm and market fundamentals. The variable is denoted as OMXH1.

The analyst related variables are as follows: number of forecasts and standard deviation in forecasts. The more analysts are following a firm the more information is generated to markets. Thus, there is less information asymmetry on the markets (Grossman & Stiglitz 1980). For example, Zhang (2006) suggest that analyst forecasts tend to be positively upward biased whenever there is more uncertainty. The number of analysts' estimates, log(NEST), is used as a control variable for this. Standard deviation in analysts' forecasts, on the other hand, is used as a control variable because it captures the uncertainty among analysts about firms' earnings. From here on, standard deviation is referred to log(STDDEV).

STDDEV, NEST, TA and B/M are all transformed into log values as all of these consist of positive values. The distributions are characterized by a long right tail, and with the log transformation the distributions become closer to normal distributions. However, the transformation is a trade-off between normal distribution and easiness of interpretation.

In order to identify SAD effect, several additional control variables are introduced. Following the findings of Kaustia & Rantapuska (2016), the focus will not be on any other environmental related factor than the main variable, denoted as SAD from here on. The SAD variable is constructed similarly as in Dolvin et al (2009) and Kamstra et al (2003). Variable SAD is a binary variable, which either takes a value of H_t -12 or 0. In which H_t is the difference between sunset and sunrise:

$$\begin{cases} H_t - 12, & \text{When trading days are in the fall and winter} \\ 0, & \text{Otherwise} \end{cases}$$

Essentially the SAD variable shows the increase in time without daylight (or increase in the length of night). Unfortunately, there is no freely, easily available data about daylight hours in Finland. However, the hours can be calculated manually. The calculation is done similarly as in Kamstra et al. (2003) and Forsythe et al. (1995). First of all, the sun's declination angle is needed to calculate the time without daylight (Kamstra et al. 2003):

$$\text{(12)} \qquad \text{declination angle} = 0.4102 * \sin[\left(\frac{2\pi}{365}\right) * (julian_t - 80.25)]$$

$Julian_t$ is a factor ranging between 1 and 365 and represents the number of the day in the year. From here SAD variable can be completed by calculating H_t for each day as follows. (Kamstra et al. 2003.)

$$\text{(13)} \qquad H_t = 24 - 7.72 * arccos[-\tan\left(\frac{2\pi\delta}{360}\right) * \tan(declination)$$

Appendix 1 provides an illustrative graph of the formed SAD variable. As an alternative seasonal factor, the length of the day, or hours of daylight, (DAYLENGTH) is used as a robustness check in case that SAD is not a suitable variable. Coefficient of SAD should be positive since forecast error is expected to become more pessimistic as the amount of time without daylight increases. DAYLENGTH on the other hand should have an inverse relation with FE. Following Jacobsen & Marquering (2008) critique that a simple dummy variable is able to explain the seasonality effect around fall as well as any other behavioral explanation, SAD is replaced with a simple dummy variable: SADSEASON. The variable takes the value of 1 between September and February, and 0 otherwise. If Jacobsen & Marquering (2008) critique is valid, there should not be much difference between the explanatory power of SAD, DAYLENGTH and SADSEASON. Consequently, concluding that SAD effect is the reason behind seasonality would be challenging.

When it comes to the significance of anomalies, they are often relevant only for small firms. However, forecast error itself is also expected to be larger for small firms because information is not as easily available. In Helsinki stock exchange, a firm belongs to a certain index according to its market value:

Small cap – market value less than 150 million
Mid cap – market value more than 150 million but less than 1 billion
Large cap – market value more than 1 billion

In this thesis, the market values used for determining correct index are end of the year values. Since Finnish stock markets are dominated by small and mid cap firms, it could well be that forecast error is partly caused by information limitations related to small firms. Thus, it is necessary to use a dummy variable SMALL to control for small firm effect. This is also essential for testing H_{03}.

This thesis benefits a lot from the use of subsamples. Firstly, the research provides descriptive statistics for the whole sample. Furthermore, the data is divided into two subsamples: Forecasts prevalent in September-February and in March-August. This allows the seasonal comparison of forecast error. The regressions are also repeated with these subsamples as a robustness check.

To avoid the possibility of overlapping variables, SADSEASON, DAYLENGTH and SAD control variables are not used simultaneously. Instead the regression is repeated with the different variables as a robustness test. Furthermore to access the robustness of the results, the data is tested for heteroscedasticity, multicollinearity and serial correlation. Some variables suffer from multicollinearity problem and cannot be used simultaneously (see section 6.1. for more thorough discussion). The OLS (or Panel Least Squares) regressions are done in several steps, but the final regression is carried out with following two equations:

$$FE = \alpha + \beta_1 log(BM) + \beta_2 log(STDDEV) + \beta_3\, log(NEST) + \beta_4 OMXH1 + \beta_5 MOM \\ + \ \beta_6 SAD + error$$

$$FE = \alpha + \beta_1 \log(BM) + \beta_2 \log(STDDEV) + \beta_3 \mathrm{OMXH1} + \beta_4 MOM + \ \beta_5 SAD \\ + \beta_6 SMALL + error$$

These multivariate tests pursue to identify if seasonality in EPS forecast is explainable by analyst related, macroeconomic and firm fundamental factors, or if there is additional explanatory power in SAD effect. Differently than in the previous literature studying stock returns, it is not necessary to address other seasonal patterns such as January and Halloween effect because these should not affect analysts. Since uncertainty increases in time, old unrevised forecasts could cause excessive forecast error. However, due to data restrictions, this cannot be controlled for because the data does not consist of details about individual forecasts.

6. EMPIRICAL RESULTS

This chapter is fully dedicated to empirical hypotheses testing. Firstly, general hypotheses discussion is carried out by using descriptive statistics. Later on the hypotheses are tested with the regressions introduced in the former chapter. Multivariate tests are performed to evaluate the possible effect of SAD when controlling for firm characteristics, analyst related factors, and general market conditions. To ease the interpretation of the results in this chapter, the following table summarizes the used variables:

VARIABLE	EXPLANATION
FE	Forecast error in percentages
SAD	Seasonal control variable for SAD effect, binary variable taking into account the time without daylight
SADSEASON	Dummy variable for forecasts between September and February
LOG(BM)	Book to market ratio, captures the effect of glamour/value stocks
LOG(TA)	Total assets, captures possible size effect
MOM	Momentum factor, controls for the effect of last reported quarterly EPS
OMXH1	Market returns, controls for general market movements
LOG(NEST)	Number of EPS forecast estimates, controls for information asymmetry
LOG(STDDEV)	Standard deviation in EPS forecasts. Controls for uncertainty among analysts
SMALL	Dummy variable for small firms
DAYLENGTH	Alternative variable for SAD. Observations are monthly daylight averages.

Table 1. Variable descriptions

6.1. Descriptive statistics

If we assumed consistently with H1 forecasts to be optimistic and naïvely assumed forecast error to be fully correlated to day length, the forecasting accuracy should start increasing from July onwards simultaneously with the length of the day decreasing. However, if there is any evidence supporting SAD effect, this would most likely take place between September and December. If any of the alternative hypotheses were to be accepted, assumingly there would already be some supporting evidence in the descriptive statistics of the sample.

For the raw uncommon sample, FE is very large, even exceptionally large at -179%. The median, however, is only -16.4%. By its characteristics, mean is much more volatile to outliers, which leads to the question if some of the forecasts are very old or if there are other data related issues. In this case, mean would not be a meaningful estimation of average. Further studying of the distribution of FE in figure 13 reveals a large negative skewness and an extreme deviation in observations, which causes distribution to have a long left tail. In more detail, the descriptive statistics for this raw data state a skewness of -19.8. These descriptive statistics are provided in Appendix 2.

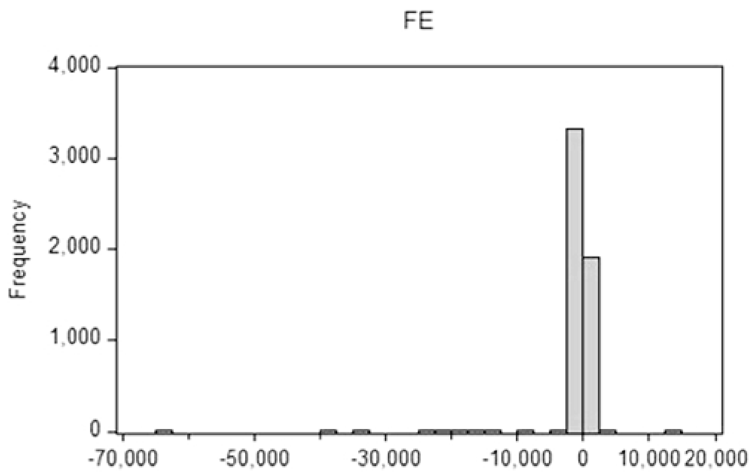


Figure 13. Full sample distribution of FE observations

The values on x-axis are percentage forecast errors. Clearly some of the values appear to be outliers. Since they are mostly on the negative side, FE will be excessively optimistic. However, even small changes in the dataset can lead to large changes in the results. Thus, no data point should be excluded without valid statistical justification. There are several different ways to detect outliers, but here outliers are calculated using boxplot interquartile ranges (IQR). Upper and lower fences are calculated as follows (Frigge, Hoaglin & Iglewicz 1987):

Upper fence = Quartile 3+1.5 x (Quartile 3-Quartile 1)
Lower fence = Quartile 1-1.5 x (Quartile 3-Quartile 1)

Based on the calculation, FE values above 159.55% or below -241.1% are outliers. As a result from outlier detections the common sample is reduced to 3665 observations. In addition, mean FE is reduced to -28.18%, which is a much more realistic value than what was observed in the raw data. Also, skewness is reduced to -1.02 and the median is much closer to the mean at -9.09%. Although there is a large impact on the data, the deletion of outliers seems justified by both common sense and statistics.

Figure 14 combines two graphs: periodical mean average for the length of the day, and periodical mean average for FE between 2010 and 2014. At the latitude of 60°N for Helsinki, the maximum error of the daylight calculation is expected to be less than 7 minutes (Forsythe et al. 1995).

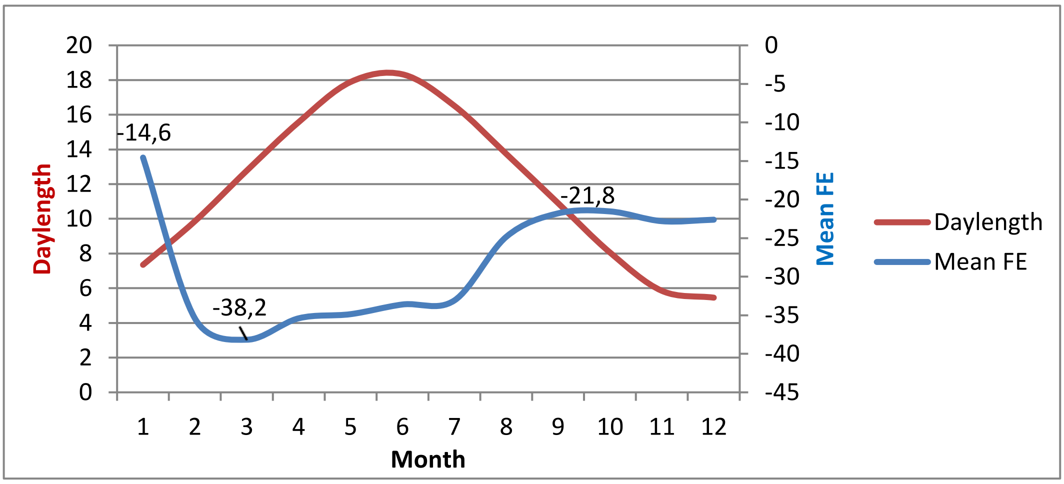


Figure 14. Co-movement of mean FE and length of the day 2010-2014

Clearly, the variation in length of the day in Finland is quite substantial. More precisely, the maximum day length is 18.5 hours and the minimum is 5.3 hours. If the length of the day figures had an effect on analysts, one would assume the effect to be strong in an environment similar to this. Indeed, in figure 14 there seems to be some similar seasonal patterns between mean average FE and the length of the day. The highest mean forecast error is -38.17% in March and improves steadily until September (-21.80%). However, FE stays flat the end of the year and is smallest surprisingly during January (-14.55). These finding do not fully fit the pattern of SAD. MOM and mean FE also have similar seasonal patterns:

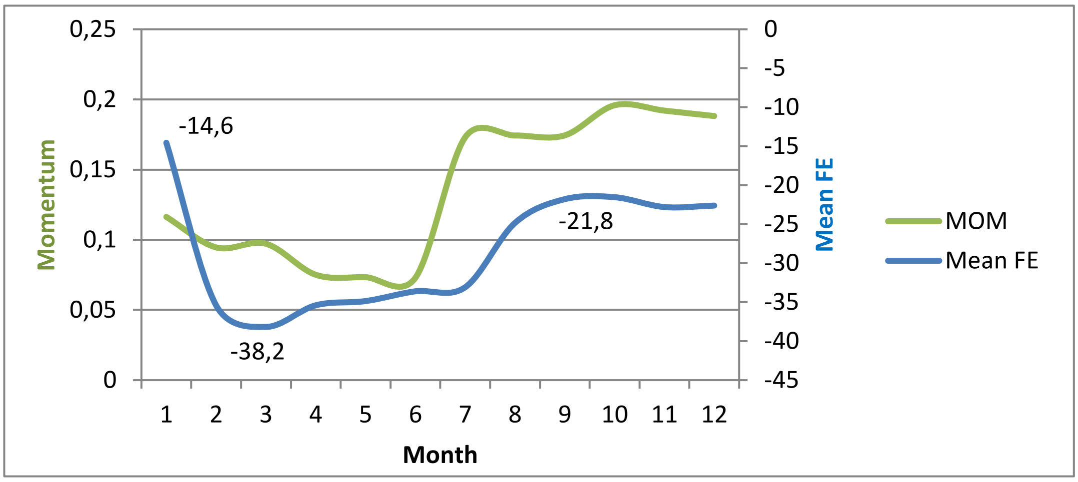


Figure 15. Co-movement of mean momentum and mean FE

Co-movement in figure 14 and 15 suggests that previous bad performance would cause higher forecast error, and decreasing day length would reduce forecast error. However, co-movement or correlation does not necessarily mean causality. The correlations between dependent and independent variables for the common sample are low and barely significant, which is possibly caused by the large number of observations. MOM has the highest correlation with FE (0.19).

	FE	*Log (STDDEV)*	*Log (NEST)*	*SAD*	*MOM*	*OMXH1*	*FALL*	*log(MB)*	*log(TA)*	*SMALL*
FE	1,00									
log(STDDEV)	-0,05	1,00								
log(NEST)	0,05	0,36	1,00							
SAD	0,08	-0,07	-0,01	1,00						
MOM	0,19	0,07	0,14	0,08	1,00					
OMXH1	0,04	-0,02	-0,01	0,23	0,04	1,00				
FALL	0,06	-0,04	-0,01	0,39	0,08	0,20	1,00			
log(MB)	0,04	-0,18	0,08	-0,01	0,19	-0,04	0,00	1,00		
log(TA)	0,06	0,44	0,76	0,01	0,12	0,03	0,01	-0,36	1,00	
SMALL	-0,04	-0,28	-0,60	-0,01	-0,13	-0,02	-0,01	-0,05	-0,66	1,00

Table 2. Correlation matrix for full common sample

The correlations between independent variables suggest the possibility of multicollinearity problem, especially between log(TA) and other variables. Therefore, log(TA) is excluded from the regressions. This is not expected to affect the interpretation of seasonality in FE since log(TA) observations are year-end values. Nevertheless, log(TA) will be presented in descriptive statistics as it expresses information of firm sizes in this particular market. In addition, there is an expected positive correlation between SMALL and log(NEST). More detailed descriptive statistics for the sample between time period 2010 and 2014, which consists of 3665 common observations, are provided in Table 3:

Descriptive statistics
Common Sample

	FE	*log(STDDEV)*	*log(NEST)*	*SAD*	*MOM*	*OMXH1*	*log(MB)*	*log(TA)*
Mean	-28,18	-1,25	0,89	2,06	0,14	0,00	-0,18	2,89
Median	-9,09	-1,22	0,90	1,00	0,11	0,00	-0,16	2,98
Std. Dev	63,83	0,40	0,33	2,49	0,35	0,05	0,36	0,71
Minimum	-238,46	-2,00	0,30	0,00	-4,12	-0,12	-1,68	1,02
Maximum	158,62	0,15	1,70	6,57	3,58	0,10	0,62	4,57
Kurtosis	1,22	-0,23	-0,86	-1,11	30,62	-0,39	1,14	-0,67
Skewness	-1,02	-0,07	-0,17	0,72	-1,28	-0,06	-0,59	0,11
Observations	3665	3665	3665	3665	3665	3665	3665	3665

Table 3. Descriptive Statistics after removing outliers.

Since the mean average for FE in the 3665 observations is negative, actual earnings seems to fall short from forecasts. Thus, the descriptive statistics of the whole common sample indicate that forecasts are upward biased and forecasts are too optimistic in general. This is consistent with alternative H1. The mean for number of estimates, log(NEST), is relatively low at 0.89 due to the small size of financial markets in Finland. As a clarification, this translates to mean of 8 estimates. Thus, individual forecasts have higher weight in the consensus forecasts, and the error might be larger in comparison to other markets. As the data is only slightly skewed (-1.0) mean is used as the main measure for average. Mean FE is -28.2% for the full common sample and median is -9.1%. If we compare the mean FE (-28.2%) to the findings of Dolvin et al. (2009), the pattern is similar: in their sample, the mean average of forecast error is about -19.6%. In explanation, forecasts overestimate the earnings by 19.6%. As expected, the forecast error seems to be larger in Finland probably due to smaller firm size and smaller amount of estimates.

Descriptive statistics for the whole sample do not provide any information regarding possible seasonality in forecasting accuracy. Thus for further investigation, the observations are divided into two subsamples according to month. Table 4 provides the sample for forecasts between September and February, and table 5 presents March-August sample.

Descriptive statistics
September-February

	FE	*log(STDDEV)*	*log(NEST)*	*SAD*	*MOM*	*OMXH1*	*log(MB)*	*log(TA)*
Mean	-23,08	-1,27	0,88	4,11	0,16	0,02	-0,18	2,89
Median	-6,58	-1,30	0,90	4,62	0,13	0,02	-0,16	2,98
Std. Dev	61,49	0,40	0,33	1,98	0,37	0,05	0,36	0,71
Minimum	-238,46	-2,00	0,30	1,00	-4,12	-0,09	-1,68	1,34
Maximum	158,62	0,12	1,69	6,57	3,58	0,10	0,62	4,57
Kurtosis	1,71	-0,05	-0,83	-1,36	30,59	-0,46	1,22	-0,67
Skewness	-1,09	0,08	-0,17	-0,25	-0,67	-0,18	-0,62	0,12
Observations	1836	1836	1836	1836	1836	1836	1836	1836

Table 4. Descriptive statistics for subsample September-February

Descriptive statistics
March-August

	FE	*log(STDDEV)*	*log(NEST)*	*SAD*	*MOM*	*OMXH1*	*log(MB)*	*log(TA)*
Mean	-33,30	-1,23	0,89	0,00	0,11	-0,01	-0,18	2,88
Median	-14,09	-1,22	0,90	0,00	0,10	-0,01	-0,16	2,98
Std. Dev	65,71	0,39	0,33	0,00	0,33	0,05	0,35	0,71
Minimum	-238,46	-2,00	0,30	0,00	-4,12	-0,12	-1,68	1,02
Maximum	158,62	0,15	1,70	0,00	2,46	0,09	0,62	4,57
Kurtosis	0,83	-0,35	-0,88	NA	29,61	-0,18	1,06	-0,67
Skewness	-0,95	-0,22	-0,17	NA	-2,27	0,03	-0,56	0,11
Observations	1829	1829	1829	1829	1829	1829	1829	1829

Table 5. Descriptive statistics for subsample March-August

Consistent with the second alternative hypothesis, forecast error seems to be smaller in the sample representing the SAD season than in the non-SAD sample. Mean FE in the SAD season subsample is -23.1% while between March-August the mean is -33.3%. The difference seems quite remarkable. A similar pattern is also visible in median FE. These figures are also very much in line with the findings of Dolvin et al. (2009), who find -25.2% average outside and -12.5% during the SAD season. On the other hand, Lo & Wu (2010) do not find as large a difference: four quarters ahead consensus forecasts are 10% more pessimistic during fall (Lo & Wu 2010). However, the findings of Lo & Wu (2010) are possibly more realistic as the use of 4 quarter ahead approach decreases the year end effect.

Interestingly, there is only a small change in log(NEST) and number of sample observations in the two samples. There are also only minor changes in log(STDDEV), as well as in the standard deviation of FE. If analysts were systematically affected by SAD, one could expect standard deviations to decrease during SAD period as analysts should according to SAD theory become more pessimistic, and simultaneously forecasts should become more accurate. This does not seem to be the case.

Furthermore, there are seasonal changes in the fundamental variables MOM and OMXH1. Mean average MOM for September-February is 0.16€ and for March-August 0.11€. The difference of 0.05€ can be considered economically meaningful when considering EPS. In addition, the mean average values for OMXH1 subsamples are 0.02 (returns of 2%) and -0.01. Thus, the overall market conditions are worse for the March-August sample. Hence, short term momentum is negative and market conditions are worse – both of which are important factors affecting forecast error (e.g. Lim 2001). To analyze the seasonality more carefully, descriptive statistics are further divided into four seasons:

Panel A	Spring sample							
	FE	*log(STDDEV)*	*log(NEST)*	*SAD*	*MOM*	*OMXH1*	*log(MB)*	*log(TA)*
Mean	-36,16	-1,21	0,90	0,00	0,08	-0,02	-0,18	2,88
Median	-17,41	-1,15	0,95	0,00	0,09	-0,01	-0,16	2,98
Std. Dev	67,30	0,39	0,33	0,00	0,35	0,05	0,35	0,71
Kurtosis	0,53	-0,32	-0,89	NA	37,94	0,36	0,67	-0,68
Skewness	-0,82	-0,23	-0,19	NA	-4,19	0,18	-0,42	0,12
Panel B	**Summer sample**							
Mean	-30,52	-1,24	0,88	0,00	0,14	-0,01	-0,18	2,88
Median	-12,21	-1,22	0,90	0,00	0,10	-0,01	-0,15	2,98
Std. Dev	64,03	0,39	0,33	0,00	0,31	0,04	0,36	0,72
Kurtosis	1,21	-0,38	-0,87	NA	14,51	-1,12	1,39	-0,66
Skewness	-1,09	-0,21	-0,15	NA	0,42	-0,13	-0,68	0,10
Panel C	**Fall sample**							
Mean	-22,04	-1,27	0,88	3,74	0,19	0,02	-0,18	2,90
Median	-6,47	-1,22	0,90	3,94	0,14	0,02	-0,16	2,98
Std. Dev	56,97	0,39	0,33	2,07	0,35	0,05	0,36	0,71
Kurtosis	2,73	-0,02	-0,86	-1,50	26,33	-0,02	1,41	-0,68
Skewness	-1,34	0,04	-0,13	-0,16	1,99	-0,32	-0,69	0,12
Panel D	**Winter Sample**							
Mean	-24,13	-1,27	0,89	4,50	0,13	0,02	-0,18	2,89
Median	-6,86	-1,30	0,90	4,62	0,12	0,02	-0,16	2,98
Std. Dev	65,79	0,40	0,32	1,81	0,40	0,04	0,36	0,70
Kurtosis	0,99	-0,08	-0,79	-1,49	31,87	-1,28	1,02	-0,67
Skewness	-0,90	0,12	-0,21	-0,22	-2,46	0,03	-0,55	0,12

Table 6. Seasonal descriptive statistics

Panel A is for March-May, panel B for June-August, panel C for September-November, and finally panel D is for December-February. Evidently there is a similar pattern as found in previous tables. Interestingly, there is no significant difference between means of FE for the winter and fall samples, although the MOM varies quite substantially. In the fall sample, there is a steep increase in positive momentum, which presumably contributes to the decrease in forecast error.

According to descriptive statistics analysts seem to be optimistic in general as proposed in alternative H_1. Thus, H_{01} is rejected and H_1 is accepted. However, the evidence supporting SAD is not so clear although the forecast error is much smaller during fall and winter. Although there is some evidence for the SAD effect, there are also similar seasonal patterns in fundamental variables. Hence, the descriptive statistics alone cannot identify the main driver of seasonality in forecast error. One fact that should be taken into account before making any conclusions is that forecast accuracy is expected to be lower in the beginning of the fiscal year due to uncertainty in earnings. This relation between the length of the forecasting period and forecast error has been documented, for example, by De Bondt & Thaler (1990). However, figures 14 and 15 showcased that the FE is actually the lowest in January (-14.55%), and gets worse steeply until March. Thus, several different firm specific and environmental factors need be taken into account and more detailed regression analysis is needed before H_{02} and H_{03} can be either accepted or rejected.

6.2. Panel Least Squares estimation

To determine if fundamentals drive seasonality in forecast error or if SAD effect has any explanatory power, Panel Least Squares regression described in the previous chapter is performed for the common sample. Serial correlation and heteroscedasticity could cause biased hypothesis testing. Heteroscedasticity means that standard deviations of a variable are not constant over time, which is one of the basic assumptions of OLS. Serial correlation, on the other hand, implies that the variable is correlated with itself over time intervals. In essence, if there is heteroscedasticity and (or) serial correlation, the standard errors are not fully efficient in OLS regression (Brooks 2008: 135). These two do not rule out each other. In fact, serial correlation possibly causes heteroscedasticity tests to be biased. Hence, it is meaningful to address any serial correlation issues first.

In panel data regression, one way to identify serial correlation is to examine Durbin-Watson statistic. Durbin-Watson should be about 2 if there is no serial correlation, whereas 0 indicates perfect positive serial correlation (Brooks 2008: 147). In this particular case, the values are around 0.3. Consequently, there is positive serial correlation in the data and p-values are therefore smaller than robust p-values (Brooks 2008: 150). However, serial correlation often appears in panel data and therefore it is left unadjusted here. If one wanted to adjust for it, there are several different methods for overcoming this issue, such as lagged variables and differencing.

White heteroscedasticity test is unfortunately not available for panel data due to software related restrictions. However it is available for unstructured data. White heteroscedasticity test reveals that the hypothesis of homoscedasticity must be rejected. Therefore each of the estimations provide heteroscedasticity consistent, White adjusted standard errors and covariance. This adjustment does not affect coefficients, but it affects standard errors, t-statistics and p-values – and thus possibly causes differences in statistical significance of variables. Since detected serial correlation and the use of unstructured data for the test could cause the heteroscedasticity test to be biased, unadjusted regressions are performed as a robustness check in table 9.

It is also essential to control for multicollinearity. Multicollinearity refers to a correlation between two explanatory variables (Brooks 2008: 170). When the variables suffer from multicollinearity, a model can be sensitive to even small changes. Some of the earlier studies regarding SAD effect and financial markets have not controlled for this nor for heteroscedasticity. The correlation matrix in table 2 shows that log(TA) could cause a multicollinearity problem and the variable is, therefore, excluded from regressions.

Table 7 provides regressions for the full common sample with White corrected standard errors and covariances. The regression is repeated adding one variable at a time. This allows to track the changes in R-squared and the significance of variables. As expected from the correlations, log(NEST) and SMALL suffer from multicollinearity. Therefore, models 6 and 7 include all other variables and one of the latter at a time. Model 8 also includes fixed cross-section firm effects to the regression. Hausman test was used to determine whether fixed or random effect model should be used. Since the p-value of the test is significant, the fixed effect model is appropriate.

The first row of each variable reports the coefficient for the variable. In addition, t-statistics are presented in brackets. Significance levels reported with stars are as follows:

P-value < 0.05 (5% level) *
P-value < 0.01 (1% level) **
P-value < 0.001 (0.1% level) ***

Dependent variable = FE

White standard errors & covariances

	1	2	3	4	5	6	7	8
C	-26,79***	-35,22***	-53,53***	-53,15***	-58,10***	-59,94***	-48,03***	-48,86***
	(-15,09)	(-6,41)	(-7,83)	(-7,88)	(-8,56)	(-8,63)	(-8,14)	(-6,13)
log(MB)	7,65**	6,31*	4,36	4,73	-1,88	-1,57	-0,93	-19,56*
	(2,59)	(2,35)	(1,60)	(1,72)	(-0,69)	(-0,57)	(-0,34)	(-1,96)
log(STDDEV)		-6,55	-11,05**	-10,51**	-12,79***	-12,03**	-10,62**	-2,24
		(-1,83)	(-2,99)	(-2,91)	(-3,40)	(-3,27)	(-3,08)	(-0,41)
log(NEST)			13,88***	13,78***	10,00***	9,88***		
			(5,62)	(5,57)	(4,11)	(4,17)		
OMXH1				51,80	39,63	21,95	20,53	12,75
				(1,56)	(1,17)	(0,59)	(0,54)	(0,33)
MOM					33,96***	33,14***	33,39***	11,39**
					(8,38)	(8,22)	(8,38)	(2,86)
SAD						1,51*	1,57*	2,06**
						(2,55)	(2,51)	(3,29)
SMALL							-5,60*	38,25***
							(-2,27)	(3,39)
Cross section fixed effects								Yes
Observations	3665	3665	3665	3665	3665	3665	3665	3665
R-squared	0,002	0,004	0,008	0,01	0,042	0,046	0,045	0,318
Adjusted R-squar.	0,002	0,003	0,007	0,009	0,041	0,044	0,043	0,300
Mean FE	-28,16	-28,16	-28,16	-28,16	-28,16	-28,16	-28,16	-28,16
Durbin-Watson	0,256	0,256	0,259	0,260	0,290	0,285	0,284	0,373

Table 7. Panel least square regression for full common sample.

Overall, there is very little evidence that log(MB) would have a significant effect on FE, since the variable is only meaningful in fixed effect model when combined with other variables. Log(STDDEV) and log(NEST) seem to affect FE throughout the models. Out of the two, log(NEST) is statistically the more significant factor. Surprisingly, model 4 shows that OMXH1 does not have any statistically significant effect on FE, and the same notation can be made from the other models as well. Thus, the performance of OMXH index cannot explain forecast error. MOM, however, is significant at 0.1% level throughout models 5-7. There is also evidence that SAD and SMALL have a significant effect on forecast error, although only at the significance level of 5% in models 6-7.

If we concentrate on models 6-7 with all variables, of fundamental variables only MOM seems to be statistically significant. Of the analyst related factors, measure of information asymmetry (log(NEST)) is significant at 0.1% level and analyst uncertainty (log(STDDEV)) at 1% level. In model 6, the coefficients of log(NEST) and log(STDDEV) are 9.88 and -12.03, respectively. Therefore, it seems that both fundamental reasons and analyst related variables drive forecast error. The signs of the coefficients for MOM and SAD are as expected: positive momentum decreases forecast error and increase in SAD increases pessimism. However, throughout the models the coefficient of SAD is small, varying between 1.51 and 1.57 in models 6 and 7. If we compare SAD to coefficients of MOM, which is above 33 in the two models, the variable does not seem as economically meaningful as MOM – nor the other significant variables. R-squared peaks at 0.046 (4.6%) in model 6, which is not particularly impressive. However, the R-squared is in line with earlier studies: for example the highest adjusted R-squared that Dolvin et al. (2009) report is 0.0306.

Including fixed effects causes large changes in the variables. The most notable changes are that log(MB) becomes statistically significant (5% level), log(STDDEV) insignificant and SMALL highly significant. Both MOM and SAD are statistically significant at 1% level. Although not reported here, even if the regressions were executed with only log(MB) and fixed effects, the R-squared would be close to 0.30. This raises some doubts regarding applicability of fixed effect panel regression. However, in the fixed effect model, two variables behave consistently with the other models: MOM and SAD.

Table 7 provides some evidence that SAD effect may affect forecast error, but the effect is rather weak. To identify if the significance of variables becomes stronger when the sample consists of small firms, the regressions is executed purely on firms with market value less than 150 million euros. The sample size is 829 observations, which corresponds to roughly 23% of the full sample. Before discussing the results of the regression more thoroughly, it is worth noting that mean FE is -33.2%, which is 5 percentage points higher than in the full common sample. Therefore, in line with for example Bhuskan (1989), smaller firms with greater information uncertainty have higher forecast error. Interestingly, the seasonality pattern for FE is quite different in the last quarter for small firms: instead of being flat from September onwards, forecast accuracy decreases steeply.

Similarly as in the full sample, FE bottoms in January (12.9%), and optimism increases to 49.5% in March. Evidently, the earnings of small firms are much more volatile, which causes larger variation in forecast error during a year. Figure 16 illustrates seasonality of both MOM and FE for small firms, and table 8 provides the regression analysis.

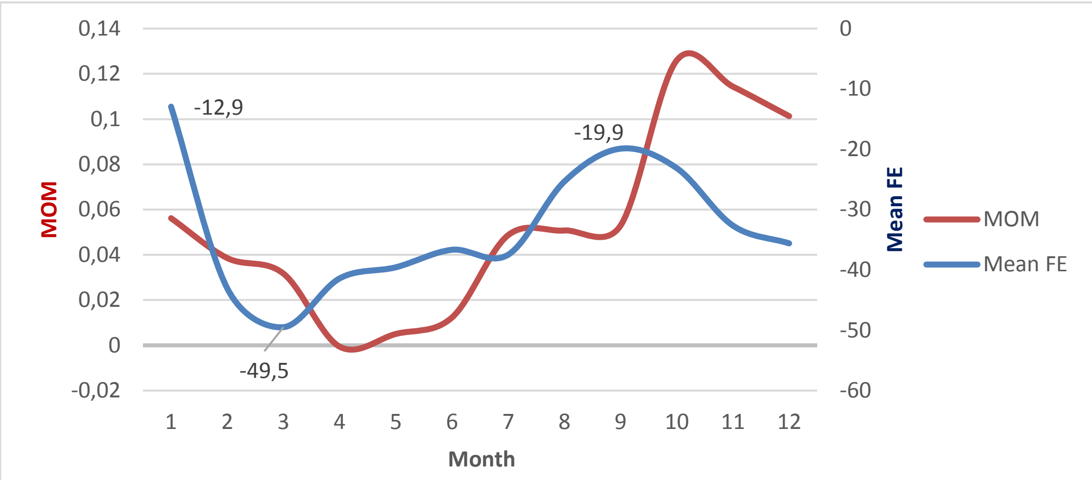


Figure 16. Seasonality of FE and MOM for small firms

Dependent variable = FE
Small firms, White standard errors & covariances

	1	2	3	4	5	6
C	-32,46***	-6,34	-23,16	-23,18	-32,35	-34,10
	(-10,15)	(-0,48)	(-1,39)	(-1,40)	(-1,69)	(-1,76)
log(MB)	3,45	10,08	8,64	8,68	3,83	4,27
	(0,30)	(0,87)	(0,76)	(0,76)	(0,33)	(0,37)
Log(STDDEV)		17,04*	15,25	15,25	11,53	11,70
		(2,00)	(1,74)	(1,73)	(1,16)	(1,17)
log(NEST)			26,60*	26,65*	27,68*	27,31*
			(2,17)	(2,18)	(2,28)	(2,26)
OMXH1				3,94	-8,57	-21,34
				(0,08)	(-0,17)	(-0,40)
MOM					41,66*	39,50*
					(2,40)	(2,25)
SAD						1,19
						(1,07)
Observations	829	829	829	829	829	829
R-squared	0,000	0,009	0,013	0,014	0,027	0,028
Adjusted R-squar.	0,000	0,006	0,010	0,009	0,021	0,021
Mean FE	-33,21	-33,21	-33,21	-33,21	-33,21	-33,21
Durbin-Watson	0,357	0,363	0,365	0,365	0,380	0,375

Table 8. Regressions for small firms

It is clear that none of the models work particularly well for small firms as the significance of variables diminishes and R-squared figures are low. This is explained by the characteristics of chosen variables. Especially log(NEST) and log(STDDEV) are problematic for small firms. As there is less trading with stocks of small firms, analysts have less incentive to follow these firms. Consequently, the number of estimates decreases, and at the same time variation in forecasts is likely to decrease. As variation in independent variables diminishes, the variables become presumably less significant. Fixed effect model is not reported as all of the variables were insignificant.

Nevertheless, there are similarities with the full sample regressions. In the model with all variables, only MOM and log(NEST) are significant, but only at 5% level. In all of the models, MOM seems to be the dominant variable according to coefficients (39.5). In the full sample regression, SMALL was only significant at 5% level, but evidently firm size affects forecast error. The weak significance is possibly explainable by the fact that the observations for firm size are t-1 year-end values. Regarding the small firms sample, SAD on the other hand is not significant at all. In general, anomalies are expected to become more meaningful or even to be meaningful only for small firms. The evidence of the regressions in table 8 cannot support this claim. Therefore H_{03} is accepted.

6.3. Robustness tests

Table 9 provides robustness tests for the regression results. First of all, since there is serial correlation in the data, and hence the heteroscedasticity test could be invalid, models 1 and 2 provide regressions without White adjustment for the two most comprehensive regressions in table 7. In explanation, these regressions include all main variables. Dolvin et al (2009) use similar SAD variable as used in this thesis. In fact, the same control variable has been used in several studies that report significant SAD effect (e.g. Kamstra et al. 2003). Nor Dolvin et al (2009) or Kamstra et al (2003) discuss the possibility that a simple dummy variable could be used to control for the effect around fall and winter. To exclude the possibility of an inappropriate variable, the regressions are executed with two alternative variables: the length of the day (DAYLENGTH), and the dummy variable for SAD season (SADSEASON).

Dependent variable = FE

Robustness check

	1	2	3	4	5	6
C	-59,94***	-48,03***	-35,06***	-35,06***	-49,02***	-49,02***
	(-10,33)	(-12,74)	(-5,32)	(-7,11)	(-8,02)	(-12,83)
log(MB)	-1,57	-0,93	-0,99	-0,99	-1,05	-1,05
	(-0,51)	(-0,31)	-0,36	(-0,33)	(-0,39)	(-0,35)
Log(STDDEV)	-12,04***	-10,62***	-10,76**	-10,76***	-10,81**	-10,81***
	(-4,17)	(-3,81)	(-3,11)	(-3,85)	(-3,12)	(-3,88)
log(NEST)	9,88**					
	(2,88)					
OMXH1	21,95	20,53	12,23	12,23	11,52	11,52
	(1,00)	(0,94)	(0,33)	(0,54)	(0,28)	(0,51)
MOM	33,14***	33,39***	33,36***	33,36***	33,50***	33,50***
	(10,97)	(11,05)	(8,49)	(11,04)	(8,48)	(11,09)
SAD	1,50***	1,51***				
	(3,52)	(-3,51)				
SMALL		-5,60*	-5,71*	-5,71*	-5,71*	-5,71*
		(-2,16)	(-2,31)	(-2,20)	(-2,31)	(-2,20)
DAYLENGTH			-0,84*	-0,84***		
			(-2,39)	(-3,40)		
SADSEASON					7,71*	7,71***
					(2,00)	(3,50)
Covariance method	Unadjusted	Unadjusted	White	Unadjusted	White	Unadjusted
Observations	3664	3664	3664	3664	3664	3664
R-squared	0,046	0,045	0,045	0,045	0,045	0,045
Adjusted R-squared	0,044	0,043	0,043	0,043	0,055	0,043
Mean FE	-28,16	-28,16	-28,16	-28,16	-28,16	-28,16
Durbin-Watson	0,285	0,284	0,285	0,285	0,288	0,289

Table 9. Robustness tests

As expected, the t-statistics in models 1 and 2 are higher than in Table 7. With this change, SAD becomes highly statistically significant. Other than this, there are only minor changes in the other variables; MOM, log(NEST) and log(STDDEV) remain statistically significant at either 1% or 0.1% level.

Replacing SAD variable with DAYLENGTH shows very little difference in the variables, other than the smaller coefficient for DAYLENGTH. The variables have different signs because SAD essentially measures increase in the length of night rather than decrease in the length of day. Secondly, simple dummy variable SADSEASON is tested for capturing the same effect. SADSEASON takes value 1 if the month is September-February, and 0 otherwise. Surprisingly, the t-statistics for regressions 5 and 6 are virtually the same as for regressions with SAD or DAYLENGTH. However, the coefficient for SADSEASON is 7.71, which is much higher than the comparable coefficient for SAD (1.51). Thus, it seems that a simple dummy variable can capture the forecast error effect during SAD season equally well, if not even more efficiently than more sophisticated explanatory variables. Consequently, since a simple dummy variable leads to a similar results as a more complex SAD variable, it is challenging to conclude that the results would be driven by SAD effect.

To check that this conclusion is, indeed, valid, the regression is further divided into two subsamples: September-February and March-August. The results are provided in table 10:

Dependent variable = FE		
	September-February	March-August
C	-39,98***	-69,77**
	(-4,24)	(-2,95)
log(MB)	-0,14	-3,63
	(-0,35)	(-0,93)
Log(STDDEV)	-10,63*	-13,31*
	(-2,17)	(-2,37)
log(NEST)	6,85*	12,34***
	(2,16)	(3,54)
OMXH1	8,50	23,90
	(0,21)	(0,36)
MOM	26,63***	41,73***
	(6,13)	(5,74)
DAYLENGTH	-0,90	0,26
	(-0,94)	(0,21)
Covariance method	White	White
Observations	1835	1829
R-squared	0,032	0,05
Adjusted R-squared	0,028	0,047
Mean FE	-23,03	-33,30
Durbin-Watson stat	0,552	0,289

Table 10. Regressions for subsamples September-February, and March-August.

When divided into subsamples, DAYLENGTH is not statistically significant in either of the regressions. The t-statistics are very small (less than 1.00), and although not reported in the table, reporting unadjusted covariances and t-statistics does not change these results. Given the results from all of the regressions, H_{02} is accepted, meaning that the decreasing amount of daylight does not seem to be the reason behind seasonality in forecast error. Instead, table 10 verifies that the seasonality is mostly explainable by analyst uncertainty about earnings, information asymmetry and momentum.

6.4. Discussion of the limitations

Overall, the results are in line with the previous literature discussing separately seasonal affective disorder in the Finnish stock markets, and analysts' forecast error. According to the findings in descriptive statistics, H_{01} was rejected and alternative hypothesis H_1 was accepted. Analysts on the Finnish markets seem to be optimistic in general. H_{02} and H_{03}, on the other hand, are accepted even though there is some weak pro SAD effect evidence in table 7. Further regressions for small firms and robustness tests, however, show insignificant SAD variable in the former and controversial findings for the alternative control variables in the latter. There is clear seasonality in forecast error, which is partly due to momentum, analysts' uncertainty about earnings, and information asymmetry. There is also certain pattern around fall and winter months, but this is more efficiently explained by a dummy variable rather than daylight related factors.

There are some factors that could influence the results. Firstly, observations for log(MB) are year-end values and do not capture seasonality. Therefore, log(MB) could incorrectly appear statistically insignificant in this thesis. In addition, there are some multicollinearity problems with log(NEST) and SMALL, which prevents the simultaneous use of both variables. Consequently, the effect of information asymmetry is not fully captured. An efficient variable for this would be the number of analysts providing forecasts.

The second topic is the chosen methodology. First of all, serial correlation is left uncontrolled. Since positive serial correlation was detected, the estimates appear more precise than they really are, meaning that the p-values are smaller than they should be. Consequently, controlling for serial correlation should not affect the interpretation of the evidence of SAD effect. In fact, the evidence against SAD effect would presumably become even stronger.

Deleting data points as outliers can be viewed controversial as it can cause significant changes in the results. Furthermore, different methods lead to different number of outliers. Lo & Wu (2010) winsorize 1% and 99 % EPS forecasts, whereas Dolvin et al. (2009) use several different excluding criteria, and yet both find a significant SAD effect. In this thesis there is some evidence that SAD is weakly statistically significant, but given that there is no difference between a simple dummy variable and a more sophisticated variable, it cannot be concluded that SAD effect decreases forecast error during fall and winter. Overall, the results suggest that there is a clear seasonal pattern in forecast error, but the evidence found is simply too weak to support the argument that increasing pessimism during fall and winter is due to SAD effect.

Furthermore, Lim (2001) identifies a possible I/B/E/S data related factor causing upward biased EPS forecasts: While I/B/E/S forecasts exclude special items, the treatment is not consistent in the reported earnings. These special items are items such as restructuring expenses and characterized by large one-time write offs happening most frequently in the fourth quarter (Lim 2001). However, after controlling for this problem in the data, Lim (2001) states that this alone cannot explain optimism in forecasts. Therefore, it is unlikely that this would be the only reason behind the optimism observed in this thesis.

7. CONCLUSIONS

Companies are under pressure to beat analysts' EPS estimates. Since EPS is one of the most important factors affecting stock prices, missing analyst estimates almost certainly results in sudden decline in the market value of a company. At the same time, a publicly listed company's main purpose is to maximize shareholders' value. Consequently, there has been increasing interest to meet estimates with, for example, earnings guidance (Ciccone 2005). However, reaching estimates can be challenging if the estimates themselves are inaccurate. Moreover, it certainly does not help that investors often cannot correct the bias (Bradshaw et al. 2006).

Forecasting EPS is challenging. Growth depends not only on a firm's fundamentals but also on general macroeconomic conditions and political aspects (Rothovius 2003). Therefore, a minor forecast error is acceptable. However, analysts have a tendency to prefer optimistic forecasts (e.g. Jackson 2005), and case by case react too mildly or too drastically to news (e.g. Zhang 2006; Easterwood & Nutt 1999). Sell-side analysts have incentives to prefer trade generating forecasts, but also suffer from cognitive biases. Dolvin et al (2009) suggest that analysts suffer from Season Affective Disorder, according to which individuals become pessimistic and depressed during fall when the hours of daylight decrease. If this was valid, analysts' forecast error would be the most optimistic during spring and summer, and accuracy would improve from September onwards.

The purpose of this thesis was to expand understanding of seasonality in analysts' EPS forecasts by identifying if SAD effect actually affects analysts or if seasonality is explainable by firm fundamentals. In the 3665 observations between 2010 and 2014, analyst forecast error is about 28% optimistic on average. There is also a clear seasonal pattern in the error, which at first glance is partly in line with SAD theory. The surprising finding is that January is the most accurate month with about 15% too optimistic forecast. The error peaks in March (38%) and declines steadily until September and stays flat for the year-end, while SAD theory expects forecasting accuracy to improve especially from September onwards.

One could argue that forecasting accuracy will always be better during the fourth fiscal quarter due to more information becoming available to the public. However, the information flow should never stop. In fact, this can be viewed to be in conflict with PLCs disclosure obligations. According to Security Market Act, publicly listed companies are obligated to disclose all information that affects the market value of the company (Finnish Financial Supervisory Authority 2016). Publicly traded companies need to publish information regularly in the form of interim reports, but also constantly disclose news that will affect market value of the company (Finnish Financial Supervisory Authority 2016). The regulation is formatted so that the regular disclosure obligation provides information of a company's future outlook, while the annual report provides more comprehensive discussion of the future. On the other hand, it is clear that the further in the future one is forecasting, the more uncertainty is involved.

Descriptive statistics provide evidence of minor seasonal changes in the number of estimates and standard deviation of forecasts. More substantial seasonality is visible in momentum factor and SAD. Regressions results suggest that the increase in previous quarter EPS, or positive momentum improves forecast accuracy. There is only a little evidence in favor of SAD and even then offset by the fact that a simple dummy variable can control for the same effect as well if not even better as daylight based variables. In addition to momentum, increase in analyst uncertainty about earnings causes higher forecast and higher optimism, while an increasing amount of information, or decreasing information asymmetry, improves the accuracy. Therefore, fundamentals and analyst related factors seem to be driving forecast error and causing seasonality instead of SAD effect.

It is also evident that small firms have higher forecast error. To be exact, average forecast error is 33% optimistic for small firms, which is 5 percentage points higher than average for the full common sample. The seasonal variation in forecast accuracy between months is much higher, which is explainable by volatile earnings. Also, there is less information available about small firms and therefore more uncertainty about firms' earnings. In addition, fewer analysts are interested in following these firms, which is most likely to be related to less trading activity around these stocks.

This thesis has identified a seasonal pattern in EPS forecast error, which is partly explained by fundamentals, uncertainty among analysts and information asymmetry regarding the firms. The seasonal forecast error pattern in the Finnish stock market does not fully fit the theory of SAD effect, and is better to be explained by a dummy variable. Thus, the finding of Kaustia & Rantapuska (2016) about Finnish stock market returns not being affected by SAD also applies to stock market analysts.

Several questions about analysts' optimism in EPS forecasts remain open for future research. Firstly, it is unclear why January is the most accurate forecast month. It is unlikely that this would be due to SAD effect as there is no pessimism effect between September and December. Secondly, it is surprising that the forecast accuracy does not improve after September – it even deteriorates for small firms. This could be due to analysts rationally providing optimistic forecasts to balance between access to information and forecasting bias (Lim 2001), financial incentives to provide optimistic forecasts, or cognitive bias other than SAD effect. Clearly, further research is needed to understand seasonality in analyst forecast error. The methodology used in this thesis is not by any means perfect. As discussed in section 6.4, the treatment of outliers, heteroscedasticity and serial correlation can affect the results. One option to improve this research would be to use Robust Least Squares estimation instead of OLS or Panel Least Squares in order to handle outliers differently.

Although many reasons behind seasonality in EPS forecast error still remain open, this thesis provides beneficial information for investors that follow analysts' forecasts. There is clear seasonal optimism in EPS forecasts, which is greater for small firms. Due to the optimism in estimations, investors should correct the bias according to the different seasonal levels of optimism found in this thesis.

REFERENCES

Abarbanell, Jeffery S. (1991). Do Analysts' Earnings Forecasts Incorporate Information in Prior Stock Price Changes? *Journal of Accounting and Economics* 14:2, 147-165.

Abarbanell, Jeffery S. & Victor L. Bernard (1992). Tests of Analysts’ Overreaction/ Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior. *The Journal of Finance* 47:3, 1181-1207.

Barber, Brad, Reuven Lehavy, Maureen McNichols & Brett Trueman (2001). Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns. *The Journal of Finance* 56:2, 531-563

Barberis, Nicholas & Richard Thaler (2003). A Survey of Behavioral Finance. *Handbook of the Economics of Finance* 1, 1053-1128.

Bhuskan, Ravi (1989). Firm Characteristics and Analyst Following. *Journal of Accounting and Economics* 11:2, 255-274.

Bodie, Zvi, Kane Alex & Alan J. Marcus (2014). *Investments*. 10th edition. New York: McGraw-Hill Education. 1080p. ISBN: 978-0-07-786167-4.

Bradshaw, Mark T. (2004). How Do Analysts Use Their Earnings Forecasts in Generating Stock Recommendations? *The Accounting Review* 79:1, 25-50.

Bradshaw, Mark T., Scott A. Richardson & Richard G. Sloan (2006). The Relation between Corporate Financing Activities, Analysts’ Forecasts and Stock Returns. *Journal of Accounting and Economics* 42:1, 53-85.

Brealey, Richard A., Stewart C. Myers & Franklin Allen (2011). *Principles of Corporate Finance*. 10th edition. New York: McGraw-Hill/Irwin. 875 p. ISBN: 978-0-07-353073-4.

Brooks, Chris (2008). *Introductory Econometrics for Finance*. 2nd edition. Cambridge: Cambridge University Press. 648 p. ISBN: 978-0-521-87306-2.

Bruce, Brian (2010). *Handbook of Behavioral Finance*. Cheltenham: Edward Elgar Publishing Limited. 1st edition. 436 p. ISBN: 978-1-84844-651-9.

Butler, Kirt C. & Larry H.P. Lang (1991). The Forecast Accuracy of Individual Analysts: Evidence of Systematic Optimism and Pessimism. *Journal of Accounting and Research* 29:1, 150-156.

Cao, Melanie & Jason Wei (2005). Stock Market Returns: a Note on Temperature Anomaly. *Journal of Banking and Finance* 29:6, 1559-1573.

Ciccone, Stephen J. (2005). Trends in Analyst Earnings Forecast Properties. *International Review of Financial Analysis* 14:1, 1-22.

Clement, Michael B. (1999). Analyst Forecast Accuracy: Do Ability, Resources and Complexity Matter? *Journal of Accounting and Economics* 27:3, 285–303.

Cheng, Yingmei, Mark H. Liu, & Jun Qian (2006). Buy-Side Analysts, Sell-Side Analysts, and Investment Decisions of Money Managers. *Journal of Financial and Quantitative Analysis* 41:1, 51-83.

Chopra, Vijay K. (1998). Why So Much Error in Analysts' Earnings Forecasts. *Financial Analysts Journal* 54:6, 35-42.

Conroy, Robert & Robert Harris (1987). Consensus Forecasts of Corporate Earnings: Analysts' Forecasts and Time Series Methods. *Management Science* 33:6, 725-738.

De Bondt, Werner F.M. & Richard H. Thaler (1990). Do Security Analysts Overreact? *The American Economic Review* 80:2, 52-57.

Dolvin, Steven D. & Mark. K. Pyles (2007). Seasonal Affective Disorder and the Pricing of IPOs. *Review of Accounting and Finance* 6:2, 214-228.

Dolvin, Steven D., Mark K. Pyles & Qun Wu (2009). Analysts Get SAD Too: The Effects of Seasonal Affective Disorder on Stock Analysts' Earnings Estimates. *The Journal of Behavioral Finance* 10:4, 214-225.

Easterwood, John C. & Stacey R. Nutt (2009). Inefficiency in Analysts' Earnings Forecast/Systematic Misreaction or Systematic Optimism? *The Journal of Finance* 54:5, 1777-1797.

Elton, Edwin J., Martin J. Gruber, Stephen J. Brown & Willian N. Goetzmann (2011). *Modern Portfolio Theory and Investment Analysis.* 8th edition. New York: John Wiley & Sons. 727 p. ISBN 978-0-470-50584-7.

Fama, Eugene F. (1965). The Behavior of Stock Market Prices. *Journal of Business* 38:1, 34–105.

Fama, Eugene F. (1970) Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance* 25:2, 383-417.

Finnish Financial Supervisory Authority (2016). Disclosure obligations [Online]. Available from World Wide Web: <URL:http://www.finanssivalvonta.fi/en/Listed_companies/Disclosure_obligation/Pages/Default.aspx >.

Fisher, Donald E. & Ronald J. Jordan (1991). *Security Analysis and Portfolio Management*. 5th edition. New Jersey: Prentice-Hall Inc. 768 p. ISBN: 0-13-798455-3.

Forsythe, William C., Edward J. Rykiel Jr., Randal S. Stahl, Hsin-I Wu & Robert M. Schoolfield (1995). A Model Comparison for Daylength as a Function of Latitude and Day of Year. *Ecological Modelling* 80, 87-95.

Fox & Rao (1997). Learn to Play the Earnings Game (And Wall Street Will Love You). *Fortune* 135:6, 76-79.

Fried Dov & Dan Givoly (1982). Financial Analysts' Forecasts of Earnings: A Better Surrogate for Market Expectations. *Journal of Accounting and Economics* 4:2, 85-107.

Fricke, Michael, David C. Hoaglin & Boris Iglewicz (1987). Some Implementation of the Boxplots. *Statistical Computing* 43:1, 50-54.

Google Trends (2016). Depression [Online]. Available from World Wide Web: <URL: https://www.google.com/trends/explore?q=depression>.

Grossman, Sanford, & Joseph Stiglitz (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review* 70:3, 393-408.

Jacobsen, Ben & Wessel Marquering (2008). Is It the Weather? *Journal of Banking & Finance* 32:4, 526-540.

Jackson, Andrew R. (2005). Trade Generation, Reputation, and Sell-Side Analysts. *The Journal of Finance* 60:2, 673-717.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische & Charles M.C. Lee (2004). Analyzing the Analysts: When Do Recommendations Add Value? *The Journal of Finance* 59:3, 1084–1124.

Jensen, Michael C. & William H. Meckling (1976). Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of Financial Economics* 3:4, 305-360.

Kahneman, Daniel & Amos Tversky (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica: Journal of Econometric Society* 47, 263−291.

Kamstra, Mark J., Lisa A. Kramer & Maurice D. Levi (2003). Winter Blues: A SAD Stock Market Cycle. *The American Economic Review* 93:1, 324-343.

Kamstra, Mark J., Lisa A. Kramer & Maurice D. Levi (2015). Seasonal Variation in Treasury Returns. *Critical Finance Review* 4, 45-115.

Kaustia, Markku & Elias H. Rantapuska (2016). Does Mood Affect Trading Behavior? *Journal of Financial Markets* 29, 1-26.

Kelly, Patrick J. & Felix Meschke (2010). Sentiment and Stock Returns: the SAD Anomaly Revisited. *Journal of Banking and Finance* 34:6, 1308-1326.

Knüpfer, Samuli & Vesa Puttonen (2012). *Moderni Rahoitus.* 6th edition. Helsinki: Sanoma Pro Oy. 244 p. ISBN 978-952-63-0842-5.

King, Benjamin F. (1966). Market and Industry Factors in Stock Price Behavior. *The Journal of Business* 39:1, 139-190.

Koller, Tim, Marc Goedhart & David Wessels (2004). *Measuring and Managing the Value of Companies.* 4th edition. New Jersey: John Wiley & Sons. 767 p. ISBN-10 0-471-70221-8.

Lim, Terence (2001). Rationality and Analyst' Forecast Bias. *The Journal of Finance* 56:1, 369-385.

Lo, Kin & Serena S. Wu (2010). The Impact of Seasonal Affective Disorder on Financial Analysts and Equity Market Returns [Online]. *SSRN* 1-34. Available from World Wide Web: <URL: https://ssrn.com/abstract=1321808 >.

Michaely Roni & Kent L. Womack (1999). Conflict of Interests and the Credibility of Underwriter Analyst recommendations. *Review of Financial Studies* 12:4, 653-686.

Molin, Jeanne, Erling Mellerup, Tom Bolwig, Thomas Scheike & Henrik Dam (1996). The Influence of Climate on Development of Winter Depression. *Journal of Affective Disorders* 37:2-3, 151-155.

Nasdaq (2016). OMX Helsinki PI [Online]. Available from World Wide Web: <URL: http://www.nasdaqomxnordic.com/index/index_info?Instrument=FI0008900006>.

Nikkinen, Jussi, Timo Rothovius & Petri Sahlström (2008). *Arvopaperisijoittaminen*. 1st–3rd edition. Helsinki: WSOY. 244 p. ISBN 978-951-0-26627-4.

Novy-Marx, Robert (2014). Predicting Anomaly Performance with Politics, the Weather, Global Warming, Sunspots, and the Stars. *Journal of Financial Economics* 112:2, 137-146.

O'Brien, Patricia C. (1988). Analysts' Forecasts as Earnings Expectations. *Journal of Accounting and Economics* 10:1, 53-83.

Pratt, Tom (1993). Wall Street's Four-letter Word. *Investment Dealers Digest* 59:13, 18-22.

Rosenthal, Norman E., David A. Sack, Christian J. Gillin, Alfred J. Lewy, Frederick K. Goodwin, Yoland Davensport, Peter S. Mueller, David A. Newsome & Thomas A. Wehr (1984). A Description of the Syndrome and Preliminary Findings with Light Therapy. *Arch Gen Psychiatry* 41:1, 72-80.

Rothovius, Timo (2003). Empirical Evidence on Earnings and Analysts` Earnings Forecasts. *Vaasa: Vaasa University Press*. 1-170.

Shefrin, Hersh (2002). *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing.* 1st edition. New York: Oxford University Press Inc. 368p. ISBN: 978-0-19-516121-2.

Trueman, Brett (1994). Analyst Forecasts and Herding Behavior. *Review of Financial studies* 7:1, 97-124.

Von Neumann, John & Oskar Morgenstern (1944). Theory of Games and Economic Behavior. *Princeton University Press*. 1-45.

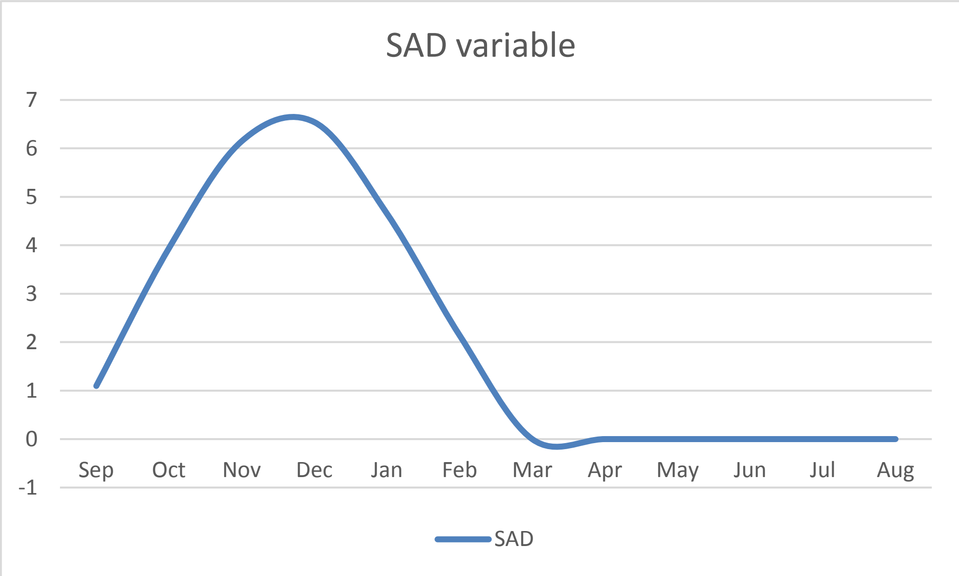
Womack, Kent L. (1996). Do Brokerage Analysts' Recommendations Have Investment Value? *The Journal of Finance* 51:1, 137-167.

Yahoo Finance (2016). S&P 500 [Online]. Available from World Wide Web: <URL: https://finance.yahoo.com/quote/%5EGSPC?ltr=1>.

Zhang, X. Frank (2006). Information Uncertainty and Analyst Forecast Behavior. *Contemporary Accounting Research* 23:2, 565-590.

APPENDICES

Appendix 1. SAD variable that takes value of 0 between March and August and monthly increase in length of night between September and February.



Appendix 2. Descriptive statistics for raw data, uncommon sample.

Descriptive statistics
Uncommon raw data

	FE	*log(STDDEV)*	*log(NEST)*	*SAD*	*MOM*	*OMXH1*	*log(MB)*	*log(TA)*
Mean	-179,14	-1,25	0,72	2,13	0,10	0,00	-0,21	2,70
Median	-16,37	-1,22	0,78	1,00	0,07	0,00	-0,19	2,69
Std. Dev	1806,33	0,40	0,45	2,52	0,34	0,05	0,36	0,81
Minimum	-62900,00	-2,00	0,00	-1,00	-4,12	-0,12	-1,68	0,78
Maximum	13700,00	0,15	1,70	6,57	3,58	0,10	0,90	4,57
Kurtosis	487,17	-0,22	-1,05	-1,18	32,82	-0,30	1,13	-0,73
Skewness	-19,78	-0,06	-0,25	0,68	-0,94	-0,09	-0,48	0,15
Observations	5342	4222	5283	5342	5202	5260	5244	5244