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Does the Seasonal Affective Disorder (SAD) Affect Analysts' Recommendations?

Evidence from the Finnish Equity Market

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ABSTRACT:

Analysts play an essential role in the stock market as information intermediaries. Prior studies about analysts have primarily concentrated on analysts' forecast accuracy and abnormal returns. The purpose of this thesis is to investigate whether seasonal affective disorder (SAD), a psychological condition that increases risk aversion and pessimism during autumn and winter seasons, affects the recommendations on Finnish analysts. Thus, SAD studies concentrate primarily on the changes in people's behavior between seasons.

Previous studies on analysts argue that while SAD should be taken into consideration, there is not a unanimous opinion on whether it has a crucial effect on analysts' forecasts. This thesis provides further evidence that seasonal affective disorder (SAD) has a significant effect on Finnish analysts' recommendations. This is done by analyzing the recommendation distributions from 2010–2018. Furthermore, this thesis examines the returns and recommendations of 55 companies from the Finnish stock market between 2010–2018. To test the statistical significance of Finnish analysts' recommendations, a regression model is run where the announcement market-adjusted return (ANNR) is tested against the firm and analyst specific controls. The SAD variable is then included in the model to test its significance on announcement day returns. Also, three subsamples are constructed to test the impact of upgrades, downgrades, and resumptions to the ANNRs.

Regression results provide evidence that SAD is a statistically significant factor. In nearly every model, the SAD variable is statistically significant. Another interesting finding is that Finnish analysts tend to issue more downgrades during the SAD season than upgrades. This might be because SAD mitigates the optimistic bias, increasing Finnish analysts' risk aversion and thus prompts them to issue more negative recommendations. Furthermore, the SAD impact was statistically more significant during winter than in fall. However, the response to downgrades is more negative during fall than in winter. This is in line with previous studies, that state that during fall the initial reaction to the seasonal change is stronger than in winter, when the amount of sunlight starts to increase (Kamstra et al., 2003). SAD's impact to analysts' forecasts is something that every investor should be aware of. Furthermore, it provides an intriguing subject to conduct future studies upon.

KEYWORDS: Seasonal affective disorder, analyst, stock recommendations

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Abbreviations

SAD	Seasonal affective disorder
EMH	Efficient markets hypothesis
CAPM	Capital asset pricing model
IBES	International Brokerage Estimate System
ANNR	Announcement market-adjusted return

1 Introduction

Professional forecasts of financial analysts play a crucial role in the capital markets by providing information to the policymakers and private economic decision-makers. In this digitalized society, investors have an ample amount of information to process, while at the same time, they are expected to make quick rational decisions to profit from their investments. Therefore, the demand for active wealth management and analysts' forecast recommendations have increased. (Foster & Warren, 2015.)

Equity analysts are entities in the stock market that issue buy, sell, or hold recommendations. They play a crucial role as an information intermediary to both fund managers and investors alike. Buy-side analysts' recommendations directly affect portfolio managers'[1] investment decisions while sell-side analysts are essential in the price discovery process. For analysts to be relevant, their forecasts need to be superior to time series forecasts and yield better measures of market earnings expectations. This questions the efficient market hypothesis, where every investor has equal knowledge and information about the capital markets. Thus, abnormal returns should not be born from individual investment decisions in the long-term. (Bradley, Clarke, Lee & Ornthanalai, 2014.)

Seasonal affective disorder (SAD) is defined as a psychological condition that increases risk aversion and pessimism in the fall and winter period. The sudden change in sunlight between seasons is believed to be the cause of this condition. The SAD theory implies that a person who is under influence of SAD is more likely to get depressed or alienated from society. This SAD effect is said to be more significant in the northern part of the globe, where winters are typically longer. However, SAD may not be adequate to explain the psychological factors behind analysts' recommendations sufficiently. Even the stock market experiences its own share of seasonal anomalies which affect the stock prices. Furthermore, the acts of terrorism and even major sports events are said to influence

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[1] Brown, Call, Clement & Sharp (2016) studied the endeavors and determinants of buy-side analysts and their recommendations.

analysts' recommendations. Nonetheless, SAD studies the individual's reaction to the changes between seasons and thus can provide an exceptional tool to determine analysts' behavior. (Kamstra, Kramer & Levi, 2003.)

1.1 Purpose of the study

The purpose of this thesis is to examine whether SAD has an impact on Finnish analysts' recommendations. This is done by examining how the recommendations behavior between Finnish analysts changes within a calendar year in Finland. The data contains recommendations and stock prices from Finnish companies listed in the Finnish stock exchange OMXH. The recommendations come in five different categories: strong buy, buy, hold, sell, and strong sell.

This thesis intends to find an answer to whether or not SAD has a crucial impact on financial analysts' stock recommendations. Kamstra et al. (2003) find that as the amount of daylight decreases, investors' propensity to trade will decrease accordingly. This might encourage analysts to issue more negative recommendations during SAD seasons and positive recommendations during non-SAD seasons when the trading frequency is expected to be higher due to investors' lower risk aversion (Kamstra et al., 2003). This is done by constructing a regression model where the company's announcement day market-adjusted return (ANNR) is the dependent variable. The main hypothesis is to find out whether SAD affects surveyed companies ANNRs. Furthermore, one of the prime interests of this thesis is to find out whether Finnish analysts are afflicted with the pessimistic bias associated with SAD. This is investigated in the second hypothesis, which examines whether the downgrades issued during SAD months affect negatively to the surveyed companies ANNRs. Also, as Kamstra et al. (2003) state, the SAD is more prominent during fall, and this assumption is investigated in the third hypothesis, which intends to find out whether downgrades issued in fall affect more negatively to the ANNRs than those issued in winter.

1.2 Contribution

The effect that SAD has on analysts' recommendations is a subject that has yet to be thoroughly studied. Most studies, such as from Kamstra et al. (2003) and Dolvin, Pyles and Wu (2009) focus on estimating the SAD's impact on analysts' forecasts and forecast revisions. However, the main contribution of this study is to examine how Finnish analysts' behavior in issuing recommendations change during the year. The main argument among the SAD studies states that during darker seasons, people tend to avoid excessive risk-taking (Kamstra et al., 2003). This approach is extended to analysts by examining the distribution of their recommendations. The purpose is to find out whether the changes between seasons and in the analysts' moods play a significant role in the Finnish equity market. This is done by scrutinizing stock recommendations issued by analysts based in Finland from 2010 to the end of 2018. This thesis contributes to the literature by being one of the first studies to scrutinize and provide information on: (i) the development of Finnish analysts' stock recommendations during the post-financial crisis era, (ii) the value of the surveilled distributions for predicting the profitability of future recommendations and lastly, (iii) the impact of SAD to the profitability of these recommendations and its predictive value. This is accomplished by constructing three subsamples depending on the recommendation typing and testing their impact on the surveyed companies' market-adjusted returns on the recommendation announcement days.

1.3 Structure of the thesis

First, this study provides a theoretical background that helps to comprehend what factors affect analysts' recommendations. Thus, the efficient market theory is presented very early on in the thesis. To sufficiently understand the impact that analysts have in the capital market, one must comprehend how analysts analyze market information.

The second part of the opening chapter presents the different stock valuation models. It is mandatory for both analysts and for investors to understand how stock are evaluated and what factors might affect their pricing. While these valuation models provide an exceptional tool for analysts to exploit, it is important essential to remember to evaluate critically what these models try to indicate.

After the literature review, the study moves on to the analysts. The third chapter presents analysts and explains how they measure market information. It also explains what factors affect analysts' recommendations. This is done by reviewing the background of the analysts. Furthermore, the chapter investigates the behavioral aspects of analysts and their effect on individual analysts' recommendations.

The fourth chapter introduces the SAD theory and seasonal anomalies that affect analysts. First, stock market anomalies are presented, which is followed by examining the SAD's impact on analysts' recommendations. The fifth chapter presents the data and methodologies used to model the empirical research conducted in this thesis. The sixth chapter presents the results from the empirical research. Afterwards, the study moves on to the last chapter of the thesis where the study concludes the main arguments that were made in the thesis and answers to the research hypotheses.

1.4 Limitations

Due to the available data, this thesis must make some exceptions. First, instead of using daily data, the monthly data is employed. This is due to the nature of the data. International Brokerage Estimate System (I/B/E/S) database presents the recommendation data as the end of the month values. As such, returns and recommendations are calculated using monthly intervals instead of daily intervals. Furthermore, the recommendation data is generic, which in a sense is not an issue. This means that the data contains the total amount of recommendations a company has received at time *t*. This, however, does not separate the origins of the recommendations i.e. which analyst issued the recommendation. As both the SAD and stock return data are adjusted to monthly intervals this might prompt reliability issues, since SAD has a different value depending on the day of the year and naturally so does stock prices. To mitigate this, a corresponding SAD value is used depending on the day of the recommendation and the same is done for the stock returns.

2 Capital markets and security pricing

To fully understand how analysts' recommendations affect stock prices one has to comprehend how the capital market works. Proper knowledge of the theory can help the market participants to execute investment decisions in practice. Thus, the reader needs to have a better comprehension of the theory behind every recommendation. The purpose of this chapter is to present the theoretical framework of the efficient market theory and the valuation models that are used to evaluate stocks.

2.1 Efficient market hypothesis

The efficient markets hypothesis (later EMH) has been the core premise of finance for nearly five decades. Eugene Fama (1970), who is held as one of the pioneers of EMH theory, defines an efficient market as one in which security prices always sufficiently reflect the available information. Thus, according to EMH, stock markets such as NASDAQ OMX Helsinki or S&P 500 are efficient. Furthermore, Fama (1970) remarks that no investor should be able to achieve excess returns of equilibrium based exclusively on information. This suggests that investor - whether a regular individual or institutional - cannot beat the market regularly. Instead, EMH suggests that investors should hold the market portfolio and subside active capital management altogether. (Shleifer, 2000: 1-5.)

EMH strongly believes that since the capital market is transparent and available to everyone, investors can and will receive every piece of information they need. Business cycle theorists have an unyielding belief that tracking the progress of several economic components over time will help interpret the evolution of the economy. Bodie, Kane & Marcus (2005: 370-378) state that any information that could affect or be used to predict stock performance should, in theory, be reflected in stock prices. However, Maurice Kendall (1953) states that there are no predictable patterns in stock prices - it seemed that they evolve indiscriminately. Furthermore, a forecast for a positive future performance leads to even more positive current performance, as market participants try to get their hands on the asset before the price hike. It is as if the stock prices moved in a random walk. (Bodie et al., 2005: 369-405.)

Fama (1995) describes random walk as a phenomenon where price changes in individual securities are independent. This suggests that a series of stock price changes have no clear memory. The prior history of given security cannot be used to predict the future in any considerable way.

Brealey, Myers & Allen (2006: 337-341) describes three forms of market efficiency. (i) the first level where, contemporary prices reflect the information contained in the history of past prices. This is defined as the weak form of market efficiency. (ii) the second level of efficiency or the so called semi-strong form of market efficiency requires that prices not only contains past information, but instead all other published information. (iii) Lastly, Brealey et al. (2006) define the third level of efficiency, the strong form of market efficiency as a form where security prices must reflect all the information that can be acquired from the market.

Figure 1. illustrates stock price reaction to new information in both efficient and in-efficient markets. In this particular case, a good news' impact is investigated to the stock price. The green line represents efficient markets and the blue line in-efficient markets response to this information. Let say that analysts predict that soon the stock price will rise from its present value. According to EMH, this will have an immediate impact on the price of this given stock, hence the upward motion of the green line. However, if the price adjustment to information is slow, like in the blue line, this is typically defined as in-efficient markets. Overreaction to this information is mainly caused by the irrational

behavior of the investors. Over time the overreaction will even out to the stock price. (Nikkinen, Rothovius & Sahlström, 2002: 80-86.)

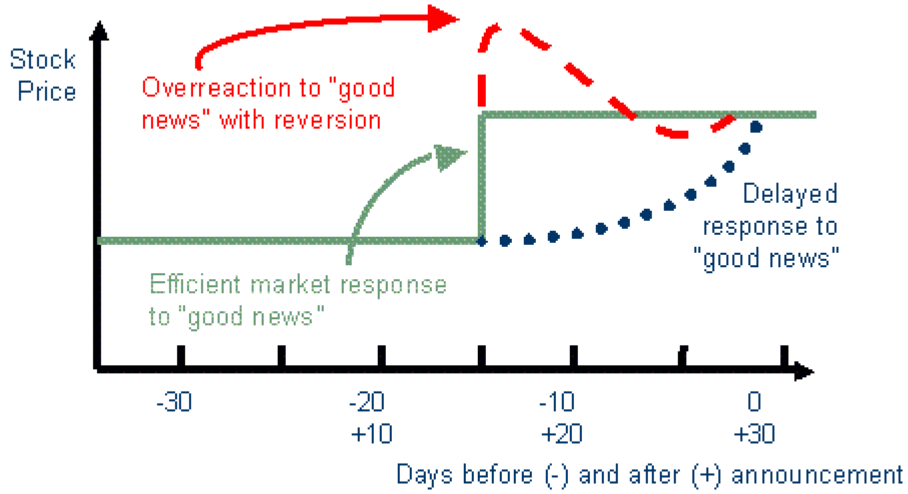

Figure 1. New information's impact on the stock price on efficient and inefficient markets (Haugen, 1997: 650.)

Shleifer (2000: 2-28) argues that the primary theoretical case for the EMH culminates in three arguments. The first one being that investors are assumed to be rational and value assets rationally. Secondly, if some investors are not rational, their trades are random and thus cancel each other out without affecting prices. And lastly, if investors are irrational in similar ways, they are met in the market by rational arbitrageurs who will eliminate their influence on prices.

Arbitrageurs are participants on the market who make use of arbitrage. Arbitrage, as defined by Bodie et al. (2005: 343-344) is "the exploitation of security mispricing in such a way that risk-free profits can be earned." Furthermore, to profit from this disparity in prices the transaction involves simultaneous purchase and sale of similar assets.

2.2 Behavioral finance and heuristic biases

Psychologists have discovered two significant facts about the financial markets. Firstly, fear and greed are not the primary emotions that define risk-taking behavior but instead fear and hope as psychologist Lola Lopes noted in 1987 (Lopes 1987). Secondly, all types of financial practitioners make the same mistakes repeatedly. To better comprehend the psychological aspects of stock markets and investor behavior, economic researchers have created an application to study these concepts further. This application is known as behavioral finance. Shefrin (2002: 3-12) states that if financial advisers recognize their own and others' mistakes, then they will be more effective at providing help to other investors because they have a better grasp of investor psychology. One investor's downfall can mean others fortune. The main argument that Shefrin (2002) tries to make is that any financial practitioner is prone to commit psychological errors. Sufficient knowledge of behavioral finance can help investors recognize the mistakes of others as well as their own.

As stated in the previous chapter, for the EMH to hold, certain conditions regarding information and investor behavior must be met. However, Shiller's (1981) study on stock market volatility proves that stock prices are far more volatile than could be justified. Shiller estimated the net present values of stocks using a constant discount rate with some specific assumptions about the stock's dividend processes. Shiller's findings have helped to point out the way to an entirely new area of research. The purpose of this chapter is to present the most common behavioral biases.

2.2.1 Representativeness

Arguably one of the most defining principles affecting financial decisions is known as *representativeness*. Shefrin (2002: 14-18) defines that representativeness refers to judgments based on and reliance on stereotypes.

Shleifer (2000: 127-129) states that a crucial example of the representative heuristic is when people think that they can see patterns in entirely sporadic sequences. This form of the representativeness heuristic is suggestive of the overreaction phenomenon described in figure 2. Analysts under the representativeness heuristic might disregard the fact that a history of excessively high earnings growth is unlikely to repeat itself, thus overvalue the company, and become disappointed in the future when the forecasted earnings growth fails to come to fruition.

The winner-loser effect documented in figure 2 can be used to illustrate the representativeness bias. De Bondt and Thaler (1985) compared two separate portfolios: extreme losers and winners. They found out that stocks that have been extreme past losers in the preceding three years fared much better than extreme past winners over the following three years. One explanation for this phenomenon, like De Bondt and Thaler (1985) stated, was that stock prices have a tendency to overreact – extreme losers become too undervalued whereas the extreme winners become too expensive and thus yield lower subsequent returns as shown in the figure.

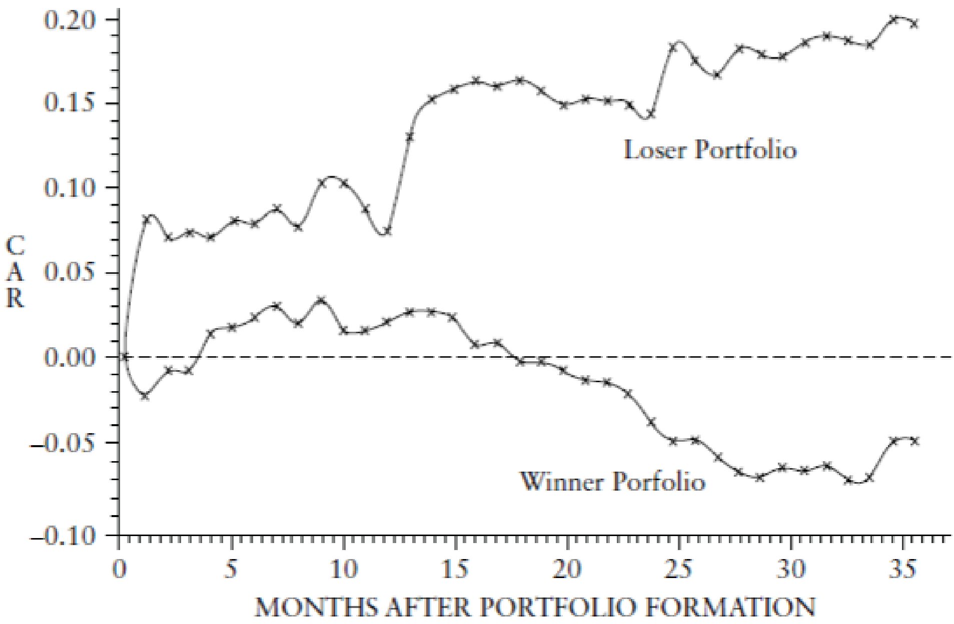

Figure 2. Cumulative average returns for winner and loser portfolios (De Bondt & Thaler, 1985.)

2.2.2 Anchoring

Psychological studies of forecast behavior point out that predictions by individual market participants are prone to systematic biases, which may induce predictable and significant forecast errors. One extensively documented form of these systematic biases is anchoring. Campbell and Sharpe (2009) define anchoring as a bias where investors choose forecasts that are too close i.e. anchored, to some readily observable prior or arbitrary point of departure. This kind of behavior yields in estimations that underweight new information. Furthermore, anchoring bias can increase predictable forecast errors.

Sherfin (2002) states that depending on the information available for analysts play a crucial role in their forecasts. Some might have a hard time to assimilate new information to their forecast and make proper adjustments while other fail to notice prior information after receiving new. Sherfin (2002) further explains that most people – analysts included - tend to react too conservatively to new information. He believes this is because people get anchored in the initial information and cannot adjust properly to the new information.

2.2.3 Herding

For self-preservation, people have adopted a social behavior that prompts us to interact in a crowd. That is something that is hardwired to the primitive part of our brains. Researchers Jane Cote and Debra Sanders (1997) defined herding as a behavior that occurs when individuals use consensus opinion to adjust their own beliefs. However, this kind of behavior can be hazardous in financial situations. If investors want to maximize the profit from their investments, they should be the first one to act. If they decide to "go with the flow", they are too late. However, there is overabundance of information accessible to investors. Some investors may not have enough resources to analyze all the required information. Instead, they place their trust in entities who are specialized at scrutinizing information, like financial analysts for example. (Durand, Limkriangkrai & Fung, 2014.)

Herding behavior is something that we humans have developed throughout our history of evolution. It has been one of the key factors that enabled us to become what we are today. However, in financial decisions herding bias can cause more harm than good. At worst, herding bias can exaggerate the total impact that information can cause to the stock prices. (Durand, Limkriangkrai & Fung, 2014.)

2.3 Valuation models

Previous chapters have focused on the efficient market hypothesis. However, in volatile markets such as the stock markets, there can be scenarios where an incident cannot be reconciled with the EMH. Bodie et al. (2005: 281-302) define these as the efficient market anomalies. The main difficulty lies in the portfolio risk, which needs to be adjusted to evaluate the success of an investment strategy. One answer to this dilemma is the capital asset pricing model (later CAPM).

2.3.1 Capital asset pricing model

CAPM is arguably one of the most well-known models for asset pricing. It was cultivated from the research by William Sharpe, John Litner, and Jan Mossin. CAPM is a tool to measure risk. The premise behind the model is that risk and return should go hand in hand – the more risk investor decides to bear, the higher the expected return should also be. Furthermore, the model determines market risk as a systematic risk, which is the only risk that affects the securities expected return. The stock-specific risk is measured by beta which varies depending on how volatile the company i.e. the stock itself is. (Sharpe 1964; Litner 1965; Mossin, 1966.)

One of the main appeals of the CAPM is that it aims to make every investor equal. For this to happen, the model makes several assumptions about the investor behavior and even the market itself. The list can vary depending on the literature, but according to Bodie et al. (2005: 282-284) the main assumptions are:

1. There are plenty of investors on the market, and their wealth is small compared to the market capitalization.
2. Every investor has the same holding period.
3. Investments are limited to publicly traded financial assets.
4. There are no taxes and transaction costs.
5. All investors are rational market participants.
6. Everyone investigates securities in the same way and share the same economic view.

According to CAPM, beta variable measures the degree to which returns on the security and the market move in unison. In other words, the risk premium on individual securities are relative to the risk premium on the market portfolio, and the beta coefficient of the asset is proportional to the market portfolio. Bodie et al. (2005: 283-284) define beta as

(1) $$\beta_i = \frac{Cov(r_i\ , r_{M)}}{\sigma_M^2}$$

Where:

β_i	is the beta of an individual security.
$Cov(r_i\ , r_{M)}$	is the covariance between stock i and market portfolio M.
σ_M^2	is the variance of market portfolio M.

Nikkinen et al. (2002: 68-75) point out that beta estimates the systematic risk of the individual security. Even with diversification, investors cannot fathom to eliminate the systematic risk. However, when investors have diversified their portfolio, they have mitigated their stock-specific risk. In other words, the systematic market risk is the only risk that they hold in their diversified portfolio. The expected return on stock exceeds the return of risk-free asset by the risk premium. The risk premium is defined as the product of stock-specific beta multiplied by market risk premium:

(2) $$E(r_i) = r_f + \beta_i\, [E(r_M) - r_f]$$

Where:

$E(r_i)$	is the expected return of the stock.
r_f	is the expected return on the risk-free asset
β_i	is the beta for stock i.
$E(r_M)$	is the expected return of the market.
$E(r_i) - r_f$	is the risk premium.
$E(r_M) - r_f$	is the market risk premium.

2.3.2 Stock returns

CAPM is one of many models that offers to estimate the expected return of the stock. Bodie et al. (2005: 318-326) state that macroeconomic forces or anomalies that impacts the entire stock market should also be taken into consideration when evaluating the expected returns of the stock. These events are unexpected and can have either positive or negative influence on the stock prices. However, firm-specific factors should also be evaluated. Bodie et al. (2005) describe that these firm-specific events could be for instance new inventions of the death of key employee. Equation 3. further demonstrates this effect:

(3) $$r_i = E(r_i) + m_i + e_i$$

Where:

r_i	is the expected return on stock i.
$E(r_i)$	is the expected return on the asset at the beginning of the holding period.
m_i	measures the impact of an unanticipated macroeconomic event.
e_i	is the impact of an unanticipated corporate specific event.

It is important to realize, that both m_i and e_i represents the impact of unanticipated events. Thus, their expected values by definition should be zero on average. Bodie et al. (2005: 319-320) also mention that we should recognize the fact that different companies react differently to the macroeconomic events. This can be further explained by the *index model*:

(4) $$R_i = \alpha_i + \beta_i R_M + e_i$$

Where:

R_i	is the excess returns of stock i.
α_i	is the stock's expected return if the market stays neutral.

β_i is the stock specific beta.

R_M is the excess returns of risk-free asset M.

e_i is the measurement of unexpected events to stock i.

The index model defines two sources of risk that security *i* might possess. Market or *systematic risk* R_M , which is the assets vulnerability to macroeconomic events that affect the stock market as a whole. And secondly, the *stock specific risk* e_i, which is the factor that measures the unexpected events that are relevant to the security. (Bodie et al., 2005: 319-321.)

For analysts and investors to estimate the risk in their portfolio, it is fundamental for them to understand the concept of standard deviation and variance. Variance can be described as volatility while risk can be defined as the deviation from the expected return. Standard deviation σ measures the deviation from the expected return thus demonstrating the risk that the investor has to bear. Standard deviation is also the square root of the variance. Since e_i is asset specific, the correlation between the components R_M and e_i is zero. Thus, according to Bodie et al. (2005) the variance of the rate of return on asset *i* is the sum of the common and firm specific variances. This can be calculated from the formula (5): (Bodie et al., 2005: 320-322; Nikkinen et al., 31-35.)

(5) $$\sigma_i^2 = \beta_i^2 \sigma_M^2 + \sigma^2(e_i)$$

Where:

σ_i^2 is the variance of the security i

$\beta_i^2 \sigma_M^2$ is the product of stock specific beta and market portfolios variance.

$\sigma^2(e_i)$ is the product of variance and unexpected events of stock i.

3 Analysing the analysts

In this society, filled with information, it can be quite demanding to keep up with every bit of information that one can obtain from their environment. The same dilemma applies to the stock market. As markets grow, investors are expected to know more external factors that could affect their portfolios. Furthermore, information can be quite expensive to process. This is one of the main reasons why analysts and brokerage firms have gained popularity – these entities are responsible for a significant share of the initial studies carried out about the stock market. They assess the market information and then issue either forecasts or recommendations. Their findings are then enforced by essentially all active fund managers. Thus, it is not surprising that most funds and investors rely almost entirely on such exogenous information. The purpose of this chapter is to describe who the analysts are, illustrate their prediction models and exhibit how their forecasts may affect stock equity. (Dimson & Marsh, 1984.)

3.1 Characteristics of analysts and their recommendations

Analysts are generally divided into two groups: *buy-side* and *sell-side* analysts. Both analyst groups play a crucial role in the capital market as intermediaries to provide information. The information that the analysts provide about financial markets can be used/sold in two way, directly or indirectly. Sell-side analysts sell their information directly while buy-side analysts indirectly. The individual impact of buy-side analysts and sell-side analysts depends on the type of analysis these entities produce. *Public investment signals* are more reflected to the stock prices than the *private investment signals.* However, investor's reaction to private investment signals are exceptionally stronger compared to the public signals[2]. Since the private investment signal is less disclosed in

[2] According to Frey & Herbst (2014), for the public investment signal to have any investment value, the signal needs to be imperfectly observable.

the stock prices, investor’s response to these signals should be stronger. (Frey & Herbst, 2014.)

Buy-side analysts’ recommendations impact directly on the investment decisions of portfolio managers. These analysts typically work for an investment bank or firm and carry out their research exclusively for the company that employs them. Compared to the sell-side analysts, buy-side analysts’ reliance on financial statement is in much more pivotal role. Interestingly, buy-side analysts receive compensation from their forecasts and recommendations. Naturally, this might raise a question about the ethicality behind their recommendations. This is due to the financial incentive they can receive from the company that these buy-side analysts are employed to. (Brown, Call, Clement & Sharp, 2016.)

Stefan Frey and Patrick Herbst (2014) investigate the trading behavior of fund managers. Their results support the belief that buy-side analysts’ have a remarkable effect on the trading behavior of fund managers. They also prove that buy-side analysts’ recommendation upgrades yield positive abnormal returns while downgrades negative abnormal returns. As a result, fund managers respond more firmly to the changes in buy-side analysts’ recommendations. However, Frey and Herbst remind that because of the private nature of buy-side recommendations, the stock prices might not mirror all of the information. Thus, they believe that it is more profitable for the investors to react to the private information.

One of the primary purposes of sell-side analysts is to endorse securities to investors. It is extremely argued assumption that funds and fund managers rely extensively on buy-side recommendations compared to the sell-side recommendations. Although, sell-side analysts’ analysis concentrates more on small stocks or significant forecast errors and dispersions, compared to buy-side analysis which is more focused on big corporations. However, studies have showed that sell-side analysts can offer profitable recommendations, and thus sell-side analysts' portfolios can perform profitably[3]. Furthermore, researchers Hobbs and Singh (2015) point out that the buy-side analysts follow sell-side analysts' recommendations. Why is it then that fund managers tend to favor buy-side recommendations? One possible answer is that the sell recommendations can more likely affect negatively to the stock prices and the image of the company. Thus, the stock recommendations from sell-side analysts can be questionable to include. (Hobbs & Singh, 2015.)

Hong, Kubik and Solomon (2000) find that sell-side analysts follow companies in specific industries and generate information, such as stock recommendations and earnings forecasts to their clients. Furthermore, Hong et al. (2000) reiterate that sell-side analysts' clients consist mostly of buy-side analysts and institutional investors. Their primary way to accrue income comes from compensation. These can include fees from the trading volume the sell-side analysts generate to their clients or from the investment banking business that they offer to their client corporations.

3.2 Forecasting process

Foster (1986: 262-264) classifies four forecasting models used by financial analysts. The *Mechanical* approach requires that the data inputs are combined in a predetermined way such that the same estimate will always be made. In a *non-mechanical* approach, the investigated data and the forecast has no clear connection. For instance, an emotional or a judgmental factor may be incorporated into the analyst's recommendation. A *univariate* approach is described as an approach where analyst analyzes only a single variable, and in the *multivariate* approach, the analyst investigates with multiple variables. However, Foster points out that these approaches can go hand in hand. For instance, there can be a combination of mechanical and multivariate approaches. In fact, an

[3] Hobbs & Singh (2015) studied the discrepancies between buy-side and sell-side analysts. Their finding suggests that from 1994 to 2009, sell-side analysts' portfolios performed profitably on average. For further literature, see Hobbs, Jeffrey & Singh, Vivek (2015). A Comparison of Buy-Side and Sell-Side Analysts.

example of this is a regression model that estimates the earnings of a company by forecasts of at least two independent variables.

Ramnath, Rock, and Shane (2008) define the factors that affect analyst's forecasts and the impact of analysts' forecasts. This is illustrated in figure 3. As analysts scrutinize information from numerous sources, such as from firm's financial statements or industry forecasts, their competence will increase. They make use of information from these sources to produce recommendations and investors make their investment decisions from the reports that analysts generate. If the stock market works efficiently, this information is directly reflected in the stock prices. However, Ramnath et al. (2008) state that the inefficiency that occurs in the capital market and between analysts can create predictable forecast errors and security price changes. Also, the external factors such as regulations and the available data processing tools affect how analysts form their forecasts. Regulations set a standard at how analysts should issue their forecasts. Furthermore, regulations can differ significantly between countries. Also, the tools that an analyst has access to limits the possibilities that the analyst can scrutinize the available information. Naturally, the individual analyst's incentives and behavioral biases affect how he or she observes information.

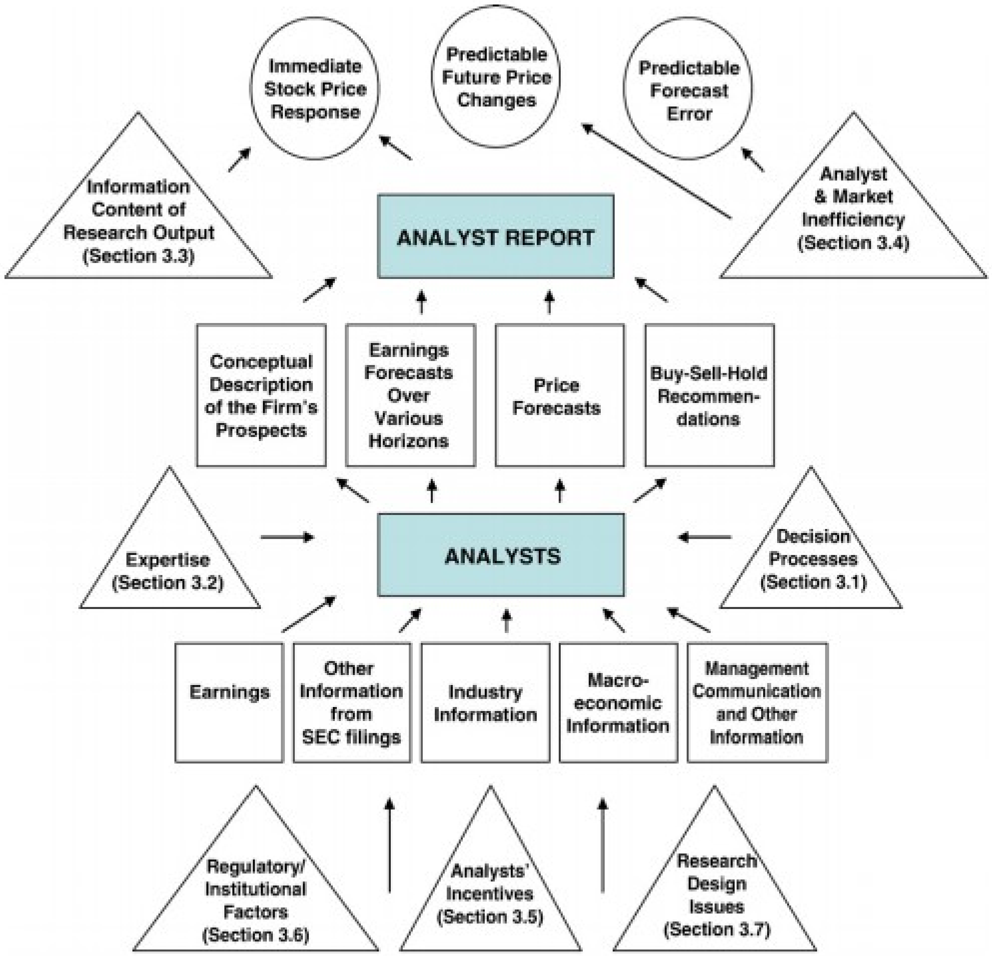

Figure 3. Analysts' forecast process (Ramnath, Rock & Shane, 2008.)

3.3 Analysts' behavioral biases

Institutional factors and regulations play a pivotal role on how analysts produce their recommendations (Ramnath et al. 2008). Analysts are human like every one of us, and they too are prone to subdue to the behavioral biases. However, unlike us, they are expected to issue rational and accurate recommendations. Hong et al. (2000) review in their research about analysts' career concerns. They find that herding among analysts could be intentional. This is thought to derive from the career pressure analysts face. Hong et al. (2000) reiterate that young analysts have a danger to get fired for issuing divergent forecasts from the consensus. Instead, it might be better for them to comply with the consensus opinion.

Ivo Welch (2000) states that during a positive economic period, analysts collective herding towards consensus is especially stronger than in a downward trend. He warns that there also possess the danger. Upswings in the economy can warp the perceived information, making them more “fragile”. In other words, the consensus has a significant influence on individual analysts forecast recommendations when economic expectations are positive. Thus, for example new information from the news have much more substantial impact during bull than in bear market.

Easterwood and Nutt (1999) argue that analysts are systematically optimistic to the new information. Analysts tend to underestimate bad news while overreact to positive earnings news. This systematic behavior is also called as optimism bias. Easterwood and Nutt (1999) point out two reasons for analyst’s optimistic bias. Firstly, analyst have financial incentives to offer the stocks of their brokerage firms. Secondly, analysts need to get close with corporate executives. For this to happen, analysts might have to issue positive forecasts for the company.

Andrew Jackson (2005) studied career laddering and analyst reputation. Jackson found a negative correlation between analysts’ short-term financial incentives and building a reputation by providing honest forecasts. He conducted his investigation by investigating analyst optimism. According to Jackson (2005), the more trading volume an analyst can bring to the company, the more optimistic the analyst’s behavior is. However, Jackson notes that analysts do have the incentive to accumulate commissions for the cost of their reputation. Since analysts’ commissions are based on how much their recommendations can generate trade, it creates the financial incentives to adjust their behavior towards exciting the company. Jackson (2005) believes this is clearly linked to analysts’ optimism bias. However, Jackson does remind that if analysts’ issue dubious recommendations their reputation will falter. Thus, analysts who care for their careers should avoid submitting to their urges.

Furthermore, Jackson (2005) states that investors are more likely to follow the recommendations issued by well-known analysts. Jackson (2005) finds that forecasts made by All-American analysts, who are among the best ranked analysts in the U.S., issue, on average, the most accurate forecasts. Jackson continues that his research proves that All-American analysts could accumulate more excess returns to their respective brokerage firms. The interesting finding here is that the more renowned the analyst is, the more financial utility that analyst can gain. Jackson's (2005) outcome implies that in the long run it might be more profitable for the analysts to be honest and accurate rather than pursuing short-term benefits.

Lang and Lundholm (1996) investigated analyst behavior and the corporate disclosure. They find that firms that disclose their company-related information are more likely to be followed by analysts. Furthermore, they state that as firms publish more of their company-related information, the more analysts they will attract. When the disclosure of company-specific information is extensive, the discrepancies between analysts' recommendations are caused by the differences in non-company-specific information.

3.4 Analyst forecast accuracy

It might not be a simple task to form a cohesive investment decision and make a profit out of it. One concern may arise from the fact that there is so much information available about the capital markets. However, market participants can utilize different forecasts, such as univariate time series forecasts or recommendations made by analysts. Univariate time series forecasts assist in measuring the earnings expectations by the best available forecasts. Besides past earnings, these univariate time series forecasts disregard any other possible time series. Thus, they do not produce the most accurate forecasts. When comparing univariate time series forecasts to analysts' forecasts, analysts' forecasts employ more data, and thus they should be superior to them. Furthermore, analysts' forecasts measure more effectively market earnings expectations than time series models. (Brown & Rozeff, 1978.)

Hilary and Hsu (2013) review the analysts forecast consistency and find that analysts who consistently make forecast errors affect greatly to the stock prices. They state three reasons for this. First, analysts who consistently issue accurate recommendations are less likely to get fired and thus are more probable to be promoted to top tier analysts. Secondly, to increase their consistency, analysts purposely issue biased forecasts. Lastly, the institutional investors' presence affects how analysts produce their forecasts.

Stickel (1992) reiterates that on average, All-American analysts can produce more accurate recommendations than any other analysts. Furthermore, most recommendations from the market are most probably issued by All-American analysts. Stickel's findings suggest that recommendations issued by All-American analysts' affect stock prices more than recommendations issued by other analysts as well. Their forecasts differ significantly from the consensus making them less predictable too. Stickel's study further support the assumption that All-American analysts are the most effective analysts in the field.

4 The impact of seasonal factors on analysts

Seasonal affective disorder (SAD) and the stock market anomalies and their impact on security analysts are in the focal point in this chapter. It also presents the current literature of SAD's impact on analysts' recommendations.

4.1 Seasonal affective disorder and the capital markets

> "And God said, Let there be light; and there was light. And God saw that the light was good." (Genesis 1:3.)

Above phrase from the Bible is something that most Scandinavians can agree to - at least after the winter. One way to examine the effect of deprivation of light in people is through SAD. Kamstra et al. (2003) define SAD as a psychological condition that heightens depression and pessimism during fall and winter periods. The sudden change and the lack of sunlight is believed to be the root cause of this phenomenon. Besides the sudden increase in depression and risk aversion, other known SAD symptoms include increase in difficulties while concentrating, sleep debt, decrease in sexual activity and possibly alienation from society. Kamstra et al. (2003) state in their study that there is an unmistakable connection between risk aversion and depression. When the days get shorter, the depression in people tends to rise. Furthermore, as humans get more depressed their susceptibility to anxiety and other negative emotions starts to increase. This can reduce their willingness to bear any unnecessary risk taking. In addition, if this were to be extended to the capital markets, it would suggest that investors risk tolerance starts to decrease as the SAD season commences. According to Kamstra et al. (2003) this is apparent in the capital market as lower returns, especially during fall. Because of this, during autumn SAD-influenced investor's start to reassess their portfolios and invest into more secure assets.

Kamstra et al. (2003) remind that the SAD anomaly does not derive from the changes that happen to the length of the day between different seasons. Instead, they propose that the SAD is caused by the actual length of the day. Therefore, the anomaly is much prominent during fall than in winter. A study conducted by Kelly and Meschke (2010) support this hypothesis. In their research, they constructed regression models of SAD and stock returns. They find that compared to fall periods, SAD-influenced investors mood recovers in winter and as a result, they start to put more weight on stocks. This naturally has a positive impact which boosts the stock prices. This is illustrated in figure 4. Kelly and Meschke (2010) also investigate the monthly returns of different market indices in 1933-2008. They find that during winter the average yield in stocks are much higher compared to yield in fall. Their findings support the argument of seasonal patterns in stock returns.

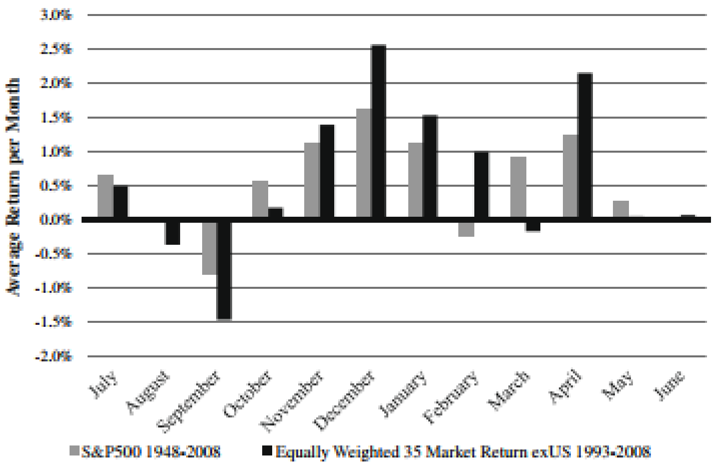

Figure 4. Average monthly stock returns (Kelly & Meschke, 2010.)

However, Kelly and Meschke (2010) state in their study that investors could, at least in theory, take advantage of seasonal anomalies in stock returns. Although this would require these anomalies to be predictable. Their finding is relevant because it challenges the concept of efficient market hypothesis. If the seasonality in stock returns were predictable, it would offer an exploit to be used to the rational investors for extensive financial gains. However, they emphasize that not every investor is rational, and it is crucial that these anomalies need to be foreseeable.

While SAD primarily examines how the lack of light and the length of the day affect human behavior, the research problem can also be turned upside down. Instead, one could investigate how the abundance of light affect people. And this is exactly what researchers Hirshleifer and Shumway (2003) did. They examine the effect of morning sunshine on stock returns across 26 different countries. They find that people tend to assess their future more optimistically when they are in a good mood. Furthermore, depending on the impact that the environment has on its people, it can have a considerable impact on how people evaluate their decisions. According to Hirshleifer and Shumway (2003), sunshine has a significant effect on investors. They find that during sunny days stock prices seemed to hike while on dark and gloomy days stocks seemed to take a dip. Symeonidis, Daskalakis and Markellos (2010) backs this argument in their study and find that during sunny days when people are more optimistic, they tend to execute long positions, generating higher returns.

Kaustia and Rantapuska (2016) examine the impact of mood on trading behavior. They conducted their research in Finland, where seasonal variations are remarkable. They find that during Finnish holiday seasons, such as summer and winter vacations, trading frequency seems to increase. They infer that this is due to families increased need of consumption during said periods. However, it is important to note that compared to the international standards, in Finland vacations are moderately long. Although their analysis on Finnish stock market does not give much support for the SAD hypothesis, they do find clear seasonal trading indications.

Goetzmann and Zhu (2005) provide another interesting finding. They conducted their research by studying the impact of sunny and cloudy weather on trading behavior in five major US cities. They find that during cloudy days spreads in New York Stock Exchange (NYSE) tend to widen. They believe that the weather anomaly is more probable in market specialists rather than in individual investors. Furthermore, their finding suggest that weather conditions have significant impact on liquidity and volatility in the capital markets. However, Loughran and Schultz (2004) believe that it is unlikely that esteemed investors would be influenced by factors such as weather. But they do concur that there is minor evidence of weather anomaly in NYSE stocks. Furthermore, Levy and Galili's (2008) research support the weather anomaly hypothesis. They find that especially young male investors with low income, had a tendency to position themselves as net buyers on cloudy days. They argue that this might derive from possible gambling behavior that may occur within this segment.

Symeonidis et al. (2010) believe that the weather affects the market participant's cognitive behavior. They claim that the changes in stock market volatility could be the cause of weather-related shifts and its impact on information that these participants consume. Also, they state that while evaluating stocks, social interaction between humans plays a pivotal role. Thus, it might be that during warm and sunny weather market participants are more likely to interact with each other, increasing the commonly shared information and thus volatility.

4.2 SAD's impact on analysts' recommendations

Ronald Doeswijk (2008) finds seasonal patterns in analysts' behavior. His reseach implies that during winter season analysts twelve-month forward expected earnings growth rate increases while in summer period they decrease. Doeswijk (2008) points out that this finding on analysts is in line with the seasonal cycles in the stock market. He suggests that this might be because analysts may take into consideration earlier stock price performances into their revisions. Doeswijk (2008) also finds that analysts react slowly to new information and incorporate it into their forecasts. The is illustrated in figure 5.

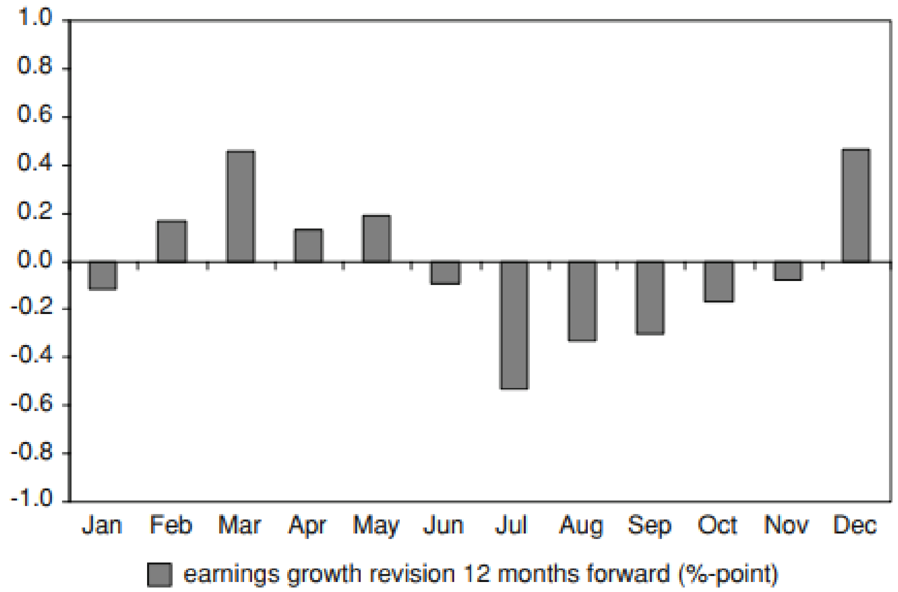

Figure 5. Analysts' earnings growth revisions (Ronald Q. Doeswijk, 2008.)

Dolvin, Pyles and Wu (2009) study the SAD's impact on analysts' recommendations. They conducted their research by reviewing empirically the analysts forecast errors during 1998-2004. Their finding suggests that SAD is both statistically and economically significant factor in analyst recommendation behavior. They find that in the US forecasts made by the analysts during fall and winter months were more pessimistic compared to those made during non-SAD months. Their results indicate systematic measurement errors for analyst's one-year ahead forecasts during SAD months. They were less optimistic and more pessimistic than the optimistic bias would suggest. However, they reiterate that the difference is even more apparent in analysts based in the northern part of the US.

The findings from Dolvin et al. (2009) research signify that SAD has an effective impact on analyst's recommendations and behavior. Their results indicate that analyst located in the northern part of the US issue more pessimistic forecasts on average compared to those in the southern states. Dolvin et al. (2009) state, that if companies win analysts' estimates by even 1 cent, they are content. However, according to their findings, the SAD factors impact around 0.54-1.40 cents to analysts' estimates. The effect is remarkable. Furthermore, this result supports the SAD hypothesis that people are relatively less pessimistic in winter than in fall. Nearing the year-end, analysts seem to make more optimistic recommendations compared to autumn.

SAD is known to affect people's cognition by increasing risk aversion and pessimism. When this is extended to analysts, the effect of SAD on analysts would determine their willingness to accept excessive risk taking. However, studies have emphasized that because of the optimistic bias, analysts issue more optimistic recommendations (Brown 1997; Matsumoto 2002). One argument of SAD's impact on analysts' recommendations is that it mitigates the effect of the optimistic bias in analysts' recommendations, making them more accurate. (Dolvin, Pyles & Wu, 2009.)

4.3 Other seasonal anomalies in the stock market

As stated previously, the ongoing season affect how a person perceives and utilizes information. It is thought, that during warm summer days people are more likely to be hopeful and optimistic for their future (Hirshleifer & Shumway 2003). Whereas, during fall and winter seasons people are more liable to depression and pessimism (Kamstra et al., 2003). To make things even more complicated, the stock markets itself has its share of seasonal anomalies. Although SAD emphasizes the lack of sunlight's effect on people, it is essential to comprehend stock market anomalies. They are not necessarily the cause of SAD or vice versa, but they all affect the market participants. (Jacobsen & Visaltanachoti, 2009.)

There are anomalies in stock markets that are more fixated on a specific calendar date or month. An example of former would be the Monday effect and the January effect for latter. January effect is a stock market anomaly, where the average returns in January far exceed those in the subsequent months. The anomaly is more substantial in small value companies compared to large corporations. There has not been unanimous answer for the anomaly, but one prominent argument revolves around taxes. Investors gain more cash at the end of the year either by bonuses or tax loss selling. The increase in the stock prices of small firms can be explained by the increased demand of their stock at the turn of the year. (Seyhun, 1988.)

However, Sias and Starks (1997) point out that the window dressing that professional investors may exercise has a respectable impact on January effect. Window dressing can be defined as a strategy where fund managers or professional investors sell badly fared investments from their portfolio and in return buy stock that have performed well. Sias and Starks (1997) state that window dressing derives from the pressure that institutional investors confronts. At the end of each year, their proficiency is evaluated by the annual performance of their managed portfolio. Thus, they have an incentive to sell bad investments and buy winners to their portfolio before the annual evaluation on year-end.

Another variation of January effect is the Other January Effect. Marshall and Visaltanachoti (2010) define the Other January Effect as an anomaly which suggests that positive, or negative, returns in January can predict the returns in the subsequent months. The theory defines that if a company accumulated positive returns in January, that company should, on average, yield positive returns during the rest of the year. The Other January effect offers an exceptional tool for investors if this argument holds. Marshall and Visaltanachoti (2010) reiterate that the Other January Effect should not be used as evidence against the efficient market theory since the risk-adjusted excess returns are not statistically or economically different from buy-and-hold returns. However, they find that the returns from the remaining 11 months after positive January are larger than after negative January.

Monday effect is another calendar date anomaly in the capital markets. Many studies find that stock returns are negative on average on Mondays (Ariel, 1987; Lakonishok &

Smidt, 1988). The Monday effect is not just an anomaly occurring in one specific stock market either. Instead, it takes place in other stock markets and between different types of securities as well. In addition, the Monday effect appears to be the most eminent in the last two weeks of the month. One explanation to the Monday effect is the correlation between the returns on Monday and Friday. The returns on last two Mondays of the month are positively correlated with Friday, which interestingly is the prior trading day. Thus, the returns on Friday can foretell the returns of the next trading day, Monday. (Wang, Li & Erickson, 1997.)

Lakonishok and Maberly (1990) find that compared to other days of the week, the trading frequency in NYSE on Monday is much lower. They suggest this is due to the lack of institutional investors activity on Monday. Furthermore, they continue that individual investors seem to favor sell transaction over buy transactions on Monday. Lakonishok and Maberly (1990) believe their finding could help to depict both the Monday and weekend effects. Furthermore, Flannery and Protopapadakis (1988) find that similar securities performed significantly differently depending on the season. They conducted their research by scrutinizing different Treasury bonds and stock indices. They believe that market-specific or institutional components cannot by themselves describe seasonality in the stock market.

Another remarkable seasonal anomaly in the stock market is the Halloween effect. It is defined as a stock market anomaly, where stock returns during summer period are superior to those in winter months. Furthermore, the infamous saying “Sell in May and go away” is derived from this anomaly. Bouman and Jacobsen (2002) conducted their study on 37 different countries and discovered that the Sell in May effect is present in 36 of those countries. They find five characteristics that make the anomaly stunning. First, the anomaly is not solely present in the developed markets, but it also exists in the emerging markets as well. Secondly, unlike other anomalies, the Halloween effect has not disappeared after its discovery. Thirdly, Bouman and Jacobsen (2002) find the Sell in May strategy outperformed all the other portfolios in most of the sample countries. The fourth finding is that compared to the January or the Monday effect, the Halloween effect cannot be described plainly by analyzing the data. Furthermore, they argue that the anomaly is more like an inherited habit than another calendar anomaly. They conclude by saying that the Halloween effect is not a sector-specific anomaly or a derivation of January effect. Instead, they propose that the anomaly has a connection to the timing and the length of summer holidays and its influence on investors trading behavior.

5 Data and methodology

This chapter presents the data and methodology used in this thesis. Furthermore, the research hypotheses are introduced in this chapter as well. First, this chapter presents the utilized data, which consists of analyst recommendations based in Finland during 2010–2018. Afterwards, the main hypotheses and methodology are presented at the end of this chapter.

5.1 Data description

This thesis employs data which is collected from the Institutional Brokers Estimate System (later I/B/E/S) Forecast database. The data consist of analysts' stock recommendations and stock prices from the Finnish stock exchange (OMXH) from 01/2010 to 12/2018. A stock and its recommendations are included only if the corresponding company has received recommendations for the whole observation period. Thus, corporations that have been removed/moved off from the OMXH or have not gotten any recommendations during the observed period or if they have been sold, have been excluded. After conducting this screening, 55 companies met these requirements. The list of observed companies can be found at the appendix section at the end of this thesis. Overall, there were 64422 stock recommendations issued within this period.

The database also provides information regarding analysts forecast estimates. As a matter of fact, most papers on SAD studies such as Kamstra et al (2003), Dolvin, Pyles and Wu (2009) and Lo and Wu (2018) concentrate on analysts' forecast estimates and forecast revisions. However, the focus on this thesis is on stock recommendations and their distribution within the fiscal year. Furthermore, the thesis examines whether there remains a connection between the distribution of analysts' stock recommendations and the future profitability of their recommendations. According to Barber et al. (2006), a relation should exist as long as: (1) recommendations issued by the analysts have investment value, (2) the implicit information in analysts' recommendations is not immediately assimilated into market prices, and (3) the recommendations classification criteria differ across analysts.

The stock recommendations are presented as a percentage unit during a specific period. Moreover, they are calculated at the end of a month from the number of total recommendations for a specific stock, for example a buy recommendations proportion is derived from the equation:

$$REC\ BUY\ \% = \frac{NO.OF\ REC\ BUY}{NO.OF\ RECOMMENDATIONS}\ x\ 100$$

where,

REC BUY %	is the percentage proportion of buy recommendations from the total recommendations issued for a company at the end of a specific month
NO. OF REC BUY	is the number of buy recommendations issued for a company at the end of a specific month
NO. OF RECOMMENDATIONS	is the total number of recommendations issued for a company at the end of a specific month

The same application is extended to calculate the percentage proportion of strong buy, hold, sell and strong sell recommendations.

5.2 Hypotheses

The main premise of interest in this thesis is to examine how the recommendations, issued by Finnish analysts, have changed between seasons. This is done by documenting the distributions of analysts' recommendations within 2010–2018, to see whether there have been any significant trends. To test the statistical significance, an ordinary least squares (later OLS) regression is run, where the announcement day market adjusted return (ANNR) is compared to the control variables, such as firm-specific controls and SAD variables. Later on, the stocks will be distributed into three subsamples depending on the recommendation type and whether the firm has received an upgrade, downgrade, or resumption. This allows to scrutinize whether recommendation distributions can predict profitability. And furthermore, it is interesting to see whether SAD variables have significance to the excess returns of the surveyed stocks. (Barber et al. 2006.)

Thus, the first regression hypothesis is:

H_1: SAD does affect the ANNRs of the surveyed stocks, which have received a recommendation from Finnish analysts

Furthermore, as analysts are associated with the optimism bias, the SAD should make them less optimistic during SAD months (Easterwood and Nutt, 1999). This should affect also to the companies ANNRs and thus the second hypothesis is:

H_2: Downgrades during SAD months have a negative effect to the surveyed stocks ANNRs

Kamstra et al. (2003) state that the change in daylight is more notable during fall than in winter. To examine this, the third hypothesis intends to find out whether the change in ANNRs are more effective during fall than in winter months.

H_3: The impact of SAD is more negative to the surveyed stocks ANNRs during fall period than in winter period

5.3 Methodology

In this section the study presents the principal methodologies which are used to empirically scrutinize the data. To determine whether the analysts' recommendations have an impact to the stock prices, the stock returns are used as the dependent variable. The monthly stock returns are obtained from monthly stock prices which are gathered from I/B/E/S database. To obtain the monthly stock returns, the logarithmic difference is employed to calculate the monthly stock returns:

(6) $$R_{it} = \ln(P_{it}) - \ln(P_{it-1})$$

where,

R_{it}	is the monthly stock return
$\ln(P_{it})$	is the natural logarithmic of a stock's price at the end of the month
$\ln(P_{it-1})$	is the natural logarithmic of a stock's price at the end of the t-1 month

5.3.1 Calculating the Seasonal Affective Disorder

Kamstra et al. (2003) examine the seasonal patterns in the stock markets. They constructed a measure for SAD based on normalized hours of night. This value, H_t , can be acquired by using standard approximations from spherical trigonometry. Thus, to derive a value for hour of night at latitude δ Kamstra et al. (2003) employ the sun's declination angle, λ_t , to the equation:

(7) $$\lambda_t = 0{,}4102 * \sin\left[\left(\frac{2\pi}{365}\right)(julian_t - 80{,}25)\right]$$

where $julian_t$ is represented as the number of the day in the year and is defined as a variable that ranges from 1 to 365. On 1st of January its value is 1, and on 2nd of January 2, and so on. From this assumption we can acquire the number of hours of night H_t as:

$$(8) \qquad H_t = 24 - 7{,}72 * \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan(\lambda_t)\right]$$

where arccos is defined as the arc cosine. Moreover, according to Kamstra et al. (2003) the value for latitude δ for Helsinki is 60,19.

Finally, after acquiring H_t Kamstra et al. (2003) construct SAD measure SAD_t as following:

$$(9) \qquad SAD_t = \begin{cases} H_t - 12 \; for\ trading\ days\ in\ the\ fall\ and\ winter \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases}$$

Furthermore, this thesis aims to study the seasonal variations within the SAD period. Lin (2015) did exactly this by constructing two dummy variables. $Fall_t$ variable is equal to one if the recommendation is announced in the fall period and 0 otherwise, while $Winter_t$ is equal to one if the recommendation has been announced in the winter and 0 otherwise.

5.3.2 OLS regression

After calculating SAD_t, an OLS regression is employed. This thesis utilizes a similar research approach as Barber et al. (2006), where they examine the investment banks' stock recommendation distributions in the US. However, the notable differences here besides the data sample is that this thesis examines the SAD and its effect to the announcement day market-adjusted returns. The OLS formula is as follows:

$$(10) \qquad ANNR_i = \alpha + \beta_1 SAD_t + \beta_2 MB_{it} + \beta_3 Beta_{it} + \beta_4 RecCons_{it} + \beta_5 ALLREC_{it} + \beta_6 RECUP_{it} + \beta_7 RECDOWN_{it} + \varepsilon$$

$ANNR_i$ is the announcement day market-adjusted return of stock *i* (the stock's announcement day return minus the return of OMXHCAP value-weighted market index). As stated previously, SAD_t gains a different value depending on the day of the year i.e. on the day of the announcement. Several control variables are included to the OLS regression to control cross-sectional differences. After the SAD variable, firm-specific control variables are introduced. Most notably the size, which is measured by the company's market-to-book, and volatility, beta, are included to the model. Size is an important variable and known to affect analysts' recommendations (Dolvin et al., 2009). After firm-specific controls, analyst-specific control variables are included to the model. Most notably the consensus recommendation rating and the total outstanding recommendations for the company are added. Barber at al. (2001) state that it is important to control consensus rating, since it can influence the way investors react to analyst recommendations. Better overall rating, the more moderately investors react to negative information about the company and so forth. Furthermore, Barber et al. (2006) use total outstanding recommendations in their model to examine how the amount of issued analyst recommendations affect the market-adjusted returns. The more recommendations a company has received, the more endorsed the company is (Barber et al. 2006).

MB_{it} is the stock's market to book ratio the day before the recommendation, $Beta_{it}$ is individual company's beta, $RecCons_{it}$ is the analysts' consensus recommendation for the stock *i* during time *t* (it can have value from 1 to 5 depending on the consensus recommendation, where 1 = strong buy and 5 = strong sell), $ALLREC_{it}$ is the number of outstanding recommendation for stock *i* at time *t*. The last two control variables, $RECUP_{it}$ and $RECDOWN_{it}$, are dummy variables taking the value of 1 if the stock has received an upgrade or downgrade at time *t* and 0 otherwise. Furthermore, regressions using only one of these dummy variables with other control variables are constructed depending on the portfolio i.e. if the stock has received an upgrade to the buy recommendation, the upgrade dummy variable takes the value of one. Afterwards, the recommendations are pooled into three subsamples: (1) upgrades to strong buy or buy, (2) downgrades to either hold, sell or strong sell, (3) resumptions of coverage i.e. when the company has not received an upgrade nor a downgrade. Thus, three separate regression models are run depending on the subsample. Below is an example of subsample (1):

$$(11)\quad ANNR_i = \alpha + \beta_1 SAD_t + \beta_2 MB_{it} + \beta_3 Beta_{it} + \beta_4 RecCons_{it} + \beta_5 ALLREC_{it} + \beta_6 RECUP_{it} + \varepsilon$$

For subsamples (2) and (3), the regression model is modified so that the $RECUP_{it}$ control variable is changed to $RECDOWN_{it}$ or $RESUMPTION_{it}$ respectively. $RESUMPTION_{it}$ is a dummy variable just like $RECUP_{it}$ and $RECDOWN_{it}$, gaining the value of 1 if the company has not received an upgrade nor a downgrade at time t and 0 otherwise.

Finally, this thesis intends to examine the seasonal differences in subsamples within the SAD period. To achieve this, two dummy variables are added into the equation 11. This is done by following Lin's (2015) example. Below is the regression model for the upgrade subsample.

$$(12)\quad ANNR_i = \alpha + \beta_1 Fall_t * SAD_t + \beta_2 Winter_t * SAD_t + \beta_3 MB_{it} + \beta_4 Beta_{it} + \beta_5 RecCons_{it} + \beta_6 ALLREC_{it} + \beta_7 RECUP_{it} + \varepsilon$$

Again, for subsamples (2) and (3), the regression model is otherwise identical to equation (12), except the $RECUP_{it}$ control variable is exchanged to $RECDOWN_{it}$ or $RESUMPTION_{it}$ respectively.

6 Empirical research

This chapter presents the results of the empirical research. The main interest is to see whether there are any seasonal patterns in analyst's recommendation behavior in Finland. Then an OLS regression, which was presented in last chapter, will be run to analyze the statistical significance of the hypotheses.

Table 1 presents data on Finnish analysts' stock recommendations and distributions between strong buy, buy, hold, sell and strong sell recommendations from 2010–2018. The values represent the end of the year value i.e. at the end of 2010, "buy" recommendations were issued 3002 times in total.

Table 1. Descriptive statistics on the distribution of analysts' recommendations

Year	Strong buy	Buy	Hold	Sell	Strong sell	Total
2010	926	3002	1981	2146	281	8356
2011	894	3199	2296	2052	342	8783
2012	1002	2654	2409	1803	276	8144
2013	743	2143	2349	1838	463	7535
2014	754	1981	1881	1541	484	6641
2015	956	1927	1806	1387	342	6417
2016	913	2013	1741	1516	303	6486
2017	632	1903	2158	1218	334	6245
2018	839	1866	1865	997	248	5815
Total	7658	20708	18487	14498	3071	64422
Total (%)	11,89 %	32,14 %	28,70 %	22,50 %	4,77 %	100 %

Buy ratings have been by far the most prominent recommendation rating within analysts based in Finland. Figure 8 illustrates both the evolution of analysts' recommendations distribution and evolution of the Finnish equity market OMXH during 2010–2018. Later in the regressions, OMXHCAP which is the value-weighted index, is used as the reference index. The main reason being that in a value-weighted index, such as in OMXHCAP, a firm cannot have a weight over ten percent to the market, thus mitigating possible correlation biases. Furthermore, dividends are also included in the OMXHCAP, and in literature the use of value-weighted indices are more common.

In figure 8 both “BUY” and “SELL” lines include also strong buy and strong sell recommendations. The proportions (%) of recommendations are on the left-hand side and the OMXH on the right-hand side. The figure indicates that the Finnish analysts have had an optimistic expectation for the future, hence such a strong consensus towards buy recommendations. Within nine years only for three months (10/2013–11/2013 and 01/2014) has buy recommendation not been the most issued recommendation. It has risen from 40 % to over 50 % by the end of 2018. On the other hand, after 2010, sell recommendations have been the least issued recommendation type. While both buy recommendations and the OMXH has increased during 2010–2018 period, sell recommendations have decreased from almost 40 % to below 20 %. Interestingly both sell and hold recommendations follow an eerily similar distribution path. Another interesting finding is that the total amount of issued recommendations have steadily decreased within this eight-year time period from 8356 at 2010 to 5816 on 2018.

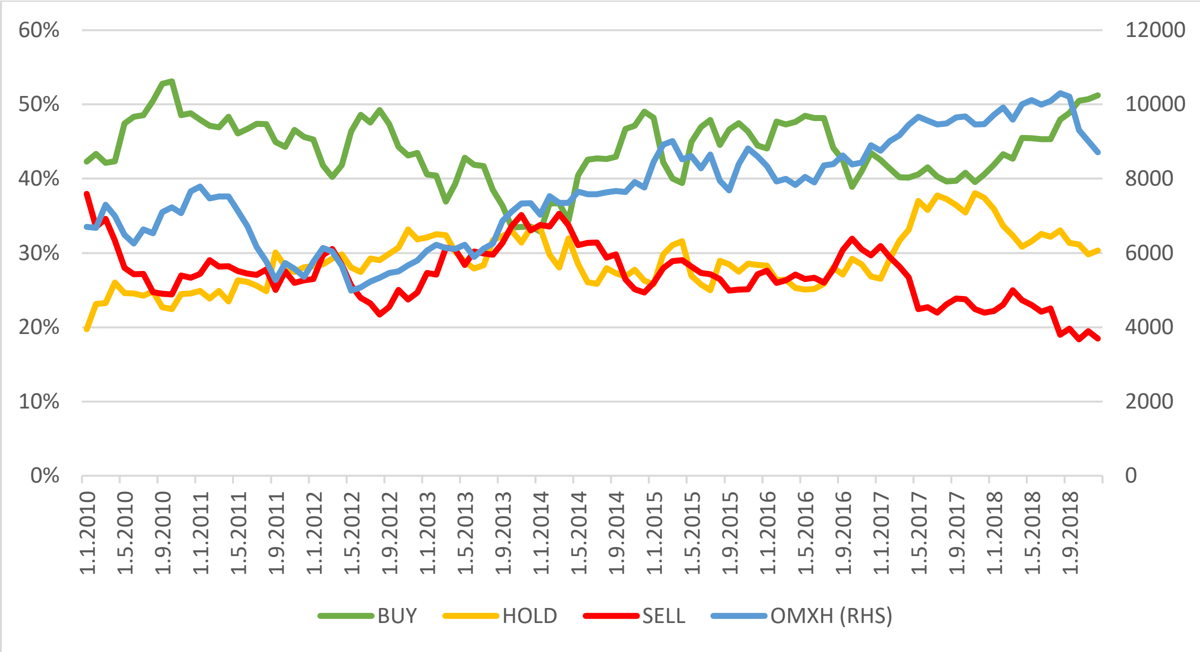

Figure 6. The distribution of analysts' stock recommendations in Finland during 01/2010–12/2018

Table 2 illustrates the recommendation distributions during SAD and non-SAD months. As can be seen, regardless of the recommendation type or year, recommendations issued by Finnish analysts during SAD months exceed those that are issued during non-SAD season i.e. non fall or winter periods. The largest gap between these two seasons is in buy recommendations (3272 recommendations) and smallest in strong sell (620). Besides sell recommendations, the other recommendations have not experienced such fluctuations during SAD months. However, sell recommendations have more than halved from 1287 to 555 recommendations. Similar finding is apparent in non-SAD months as well, where sell recommendations have decreased from 860 to 442 recommendations. Overall, as seen previously in table 1, the total amount of recommendations has steadily decreased from 2010 to 2018. Another notable trend is that Finnish analysts tend to issue more recommendations during SAD seasons.

Table 2. The distribution of analysts' recommendations during SAD seasons

Year	Strong Buy	Buy	Hold	Sell	Strong Sell	Total
2010	512	1774	1111	1287	169	4854
2011	509	1836	1360	1180	191	5075
2012	553	1553	1456	1082	181	4826
2013	413	1197	1430	1076	295	4410
2014	460	1159	1108	894	267	3888
2015	552	1144	1073	796	200	3766
2016	515	1133	1041	892	203	3784
2017	366	1110	1210	751	189	3626
2018	501	1084	1083	555	151	3374
Total	4380	11990	10874	8514	1846	37603

Recommendation distribution during non-SAD months

Year	Strong Buy	Buy	Hold	Sell	Strong Sell	Total
2010	414	1247	869	860	111	3502
2011	386	1363	937	871	151	3708
2012	449	1101	953	721	95	3318
2013	329	946	919	762	168	3125
2014	294	822	773	647	217	2753
2015	403	783	733	591	142	2651
2016	398	880	700	625	100	2702
2017	266	793	948	467	145	2619
2018	339	782	782	442	97	2441
Total	3279	8718	7613	5984	1226	26819

Table 3 presents the descriptive statistics regarding analysts' stock recommendation upgrades and downgrades. The "Upgrade" and "Downgrade" columns display the total upgrades to either sell, hold, buy or strong buy recommendations and total downgrades to buy, hold, sell or strong sell at the end of that specific year. The columns "SAD" and "Non-SAD" represents the value of upgrades and downgrades respectively during each SAD and non-SAD month. Interestingly, it seems that Finnish analysts tend to issue both upgrades and downgrades more frequently during SAD months than on non-SAD months. Overall, from 2010 to 2018, Finnish analysts issued over 1500 upgrades during SAD months while almost 1400 upgrades during non-SAD months. More apparent difference can be seen on downgrades. The difference between SAD and non-SAD downgrades are almost 600 downgrades. The findings suggest that during SAD months, analysts are more pessimistic and issue more downgrades to either buy, hold, sell, or strong sell. Furthermore, while OMXH rose from 6000 to over 10000 points during this time frame, it is interesting to witness more downgrades than upgrades. However, most of those downgrades have been issued during 2011–2013, which incidentally is during the European debt crisis.

Table 3. The distribution of analysts' upgrades and downgrades during non-SAD and SAD seasons

Year	Upgrade	SAD	Non-SAD	Downgrade	SAD	Non-SAD
2010	365	163	202	364	217	147
2011	442	226	216	435	267	168
2012	368	155	213	426	265	161
2013	322	161	161	427	289	138
2014	349	203	146	255	141	114
2015	286	131	155	307	218	89
2016	238	152	86	283	157	126
2017	248	152	96	238	142	96
2018	284	165	119	192	112	80
Total	2902	1508	1394	2927	1808	1119

6.1 Regression analysis

This chapter presents the results of the OLS regression analysis. The regression analysis measures whether the announcement day market-adjusted returns, and the control variables that were introduced in the previous chapter, are statistically significant. The aim is to investigate whether seasonality play any role in the stock returns and, is this an occurrence that investors should be concerned with.

Table 4 reports the results of the first OLS regression where the dependent variable in each seven (7) regressions is the recommendation announcement day market-adjusted return for stock *i*. Almost every control variable besides beta and total recommendations are statistically significant, and in most cases at the 1 % significance level. Most notably the statistical significance of SAD variable increases as more controls are added. The intercept term, or alpha, interestingly changes depending on the model. First it is negative, while only firm specific controls are included into the regression model, such as MB and beta. However, as analyst specific variables, like consensus recommendations and total outstanding recommendations, are added, the intercept becomes positive. RecCons coefficient term is naturally negative since higher value indicates worse rating. Furthermore, the coefficient on upgrade is positive, meaning if the stock has received an upgrade, it yields a positive reaction to the ANNR. The coefficient on the downgrade variable is negative, which implies that if the company has received a downgrade, it affects negatively to the ANNR's. These findings are quite logical. The coefficient in the SAD is positive, and it is statistically significant at 1 % level in every model besides in model (7), where it is 5 % significant. This would imply that after the winter solstice, when the duration of daylight increases, both analysts and investors alike, who are suffering from the SAD, begin to recuperate, which leads to higher ANNRs during the SAD season. The results in table 4 suggest that SAD affects the ANNRs of the surveyed companies and thus provides support that the first hypothesis holds true.

Table 4. The results of the OLS regression.
The ANNR is the dependent variable and the independent/control variables are visible on the first column. The t-values are shown in the square brackets.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0,0022	-0,0101	-0,0128	0,0177	0,0176	0,0148	0,0131
	[-1,71]*	[-5,27]***	[-3,87]***	[3,03]***	[3,02]***	[2,53]**	[2,23]**
SAD	0,0012	0,0012	0,0012	0,0012	0,0011	0,0012	0,0012
	[2,85]***	[2,84]***	[2,84]***	[2,83]***	[2,83]***	[2,99]***	[3,13]**
MB		0,0035	0,0036	0,0039	0,0039	0,0039	0,0039
		[5,57]***	[5,65]***	[6,11]***	[6,10]***	[6,10]***	[6,02]***
Beta			0,0025	0,0012	0,0017	0,0010	0,0017
			[0,99]	[0,48]	[0,62]	[0,39]	[0,65]
RecCons				-0,0108	-0,0108	-0,0101	-0,0092
				[-6,31]***	[-6,27]***	[-5,83]***	[-5,33]***
All Rec					-0,0000	-0,0002	-0,0000
					[-0,46]	[-1,58]	[-0,26]
RECUP						0,0093	0,0095
						[4,16]***	[4,25]***
RECDOWN							-0,0103
							[-4,52]***
R-Square	0,0369	0,0809	0,0819	0,1154	0,1156	0,1159	0,1401

* indicates statistical significance at the 10 % level
** indicates statistical significance at the 5 % level
*** indicates statistical significance at the 1 % level

Tables 5 and 6 present the results of the three subsamples: (1) upgrades to strong buy and buy, (2) downgrades to hold, sell or strong sell, and (3) resumption with a strong buy, buy, hold, sell, or strong sell. The results of the first two subsamples are illustrated in table 5 while the third in table 6. Again, the SAD variable is statistically significant in every model, and the same conclusion from the previous regression results can be derived here in upgrades and downgrades as well. As SAD sufferers start to recover from the year-end, it has a positive effect and in turn ANNRs start to go up. These findings also support the second hypothesis since the downgrade variable is statistically significant in all three models and the coefficients are all negative. The results are somewhat in line with the first regression as well; MB is statistically significant, and the coefficient is positive. Thus, companies that have high MB ratio tends to have higher ANNRs. However, the beta variable becomes statistically significant at 10 % level in models 4 and 5. The coefficient is positive, therefore surveyed companies with higher beta yielded more ANNR. Interestingly, in the models 2 and 5, the total recommendation variable is statistically significant at 10 % level. The coefficient is negative in the model 2, which suggests that as the number of analysts buy recommendations increases, the less ANNR that company accumulates. The opposite is true in model 5, which captures the ANNRs in downgrades to strong sell. This would imply that the more recommendations a company, that has received a downgrade to strong sell, has, the more ANNR is earned. One thing to bear in mind is, that even though a company might have received a downgrade from one analyst, others might have resumed their coverage. Thus, the more recommendations that individual company has, the more likely it is that specific company might have either a positive or negative recommendation(s) outstanding.

Table 5. Regression results of subsample (1) and (2)
This table reports the regression results of ANNR on seasonal affective disorder, market to book, consensus recommendation value, recommendations outstanding on the stock, upgrades, and downgrades. Regressions (1) and (2) are upgrades to strong buy and buy respectively, while (3)-(5) are downgrades to hold, sell and strong sell. The t-values are shown in the square brackets.

Variable	(1)	(2)	(3)	(4)	(5)
Intercept	0,01040	0,0087	0,0014	-0,0067	-0,0040
	[2,00]**	[1,39]	[0,23]	[-1,11]	[-1,01]
SAD	0,0018	0,0027	0,0026	0,0025	0,0007
	[4,92]***	[6,14]***	[6,01]***	[5,90]***	[2,66]***
MB	0,0029	0,0039	0,0040	0,0034	0,0017
	[4,93]***	[5,71]***	[5,92]***	[5,60]***	[3,83]***
Beta	0,0013	0,0019	0,0035	0,0062	0,0041
	[0,54]	[0,64]	[1,22]	[2,17]**	[2,22]**
RecCons	-0,0059	-0,0060	-0,0049	-0,0031	-0,0016
	[-3,79]***	[-3,29]***	[-2,76]***	[-1,71]*	[-1,34]
All REC	-0,0001	-0,0002	0,0001	0,0002	0,0001
	[-1,03]	[-1,77]*	[1,06]	[1,45]	[1,86]*
RECUP	0,0010	0,0033			
	[0,51]	[1,37]			
RECDOWN			-0,0088	-0,0103	-0,0041
			[-3,72]***	[-4,36]***	[-2,63]**
R-Square	0,1015	0,1169	0,1245	0,1229	0,0798

* indicates statistical significance at the 10 % level
** indicates statistical significance at the 5 % level
*** indicates statistical significance at the 1 % level

Table 6 reports regression results from subsample (3), where the condition was that a company has not received either an upgrade or a downgrade at time *t*. Again, the results are in line with the previous regressions. SAD and MB variables are 1 % significant in every model. The consensus recommendation variable is 1 % statistically significant in models 1 to 3, while 5 % significant in model 4. The resumption variable is statistically significant at 5 % level in models 2 (buy) and 3 (hold), and 4 (sell). This indicates that the covered firms that have received an initiation from analysts with a buy, hold or sell, have generated positive ANNR during 2010–2018. The coefficient is highest in buy recommendation (model 2) and lowest in sell recommendation type (model 4). This is logical, as the more positive rating the more positive response from the investors.

Table 6. Regression results of subsample (3)
Regression (1) stands for strong buy, (2) buy, (3) hold, (4) sell, and (5) strong sell. The t-values are shown in the square brackets.

	(1)	(2)	(3)	(4)	(5)
Intercept	0,0090	0,0060	-0,0008	-0,0088	-0,0047
	[1,66]*	[0,92]	[-0,13]	[-1,39]	[-1,13]
SAD	0,0018	0,0026	0,0025	0,0024	0,0007
	[4,89]***	[6,06]***	[5,87]***	[5,74]***	[2,57]***
MB	0,0029	0,0040	0,0041	0,0039	0,0017
	[4,93]***	[5,72]***	[6,00]***	[5,70]***	[3,88]***
Beta	0,0016	0,0025	0,0032	0,0059	0,0040
	[0,65]	[0,86]	[1,14]	[2,06]**	[2,14]**
RecCons	-0,0059	-0,0063	-0,0056	-0,0039	-0,0019
	[-3,86]***	[-3,45]***	[-3,16]***	[-2,18]**	[-1,62]
All REC	-0,0000	-0,0001	0,0000	0,0001	0,0001
	[-0,50]	[-0,72]	[0,63]	[0,85]	[1,43]
RESUMPTION	0,0022	0,0046	0,0045	0,0044	0,0016
	[1,14]	[2,03]**	[2,07]**	[2,10]**	[1,11]
R-Square	0,1023	0,1185	0,1180	0,1126	0,0736

* indicates statistical significance at the 10 % level
** indicates statistical significance at the 5 % level
*** indicates statistical significance at the 1 % level

Table 7 reports regression results where SAD variable has been split into two dummies: fall and winter dummy variables. They take the value of one depending on the SAD season: if the season is fall, the fall dummy is equal to one and 0 otherwise. And during winter period, the winter dummy is equal to one and so on. The variable is then multiplied by the value of SAD variable. Table 7 presents regression results from upgrades and downgrades in fall and winter periods, thus providing findings for subsamples (1) and (2). Models 1 and 2 represents subsample (1) i.e. upgrades to strong buy and buy respectively. Models 3-5 illustrates the results for subsample (2); downgrades to hold, sell and strong sell. The results suggest that the SAD effect is statistically most prominent during the winter season since the winter dummy is statistically significant in every model besides in model 5 (strong sell). Downgrade variable is statistically significant with negative coefficients, which suggests that when a company receives a downgrade it has a diminishing effect to the company's announcement day market-adjusted returns. Furthermore, it seems that investors response to downgrades are more negative during fall than in winter, hence the Fall coefficient being mostly negative and lower than the Winter coefficient. Fall variable is only positive in model 1 (strong buy), which is the most optimistic recommendation type. This is in line with Kamstra et al. (2003), because the sudden decrease in daylight during fall season affect more negatively to people than in winter, when the amount of daylight starts to ramp up again. This finding supports the third hypothesis, reinforcing the assumption that the SAD's impact is more negative during fall. Interestingly, the amount of outstanding recommendations is statistically significant at 10 % level only on upgrades to buy (2) and downgrades to strong sell (5) models. The coefficient is negative in the former and positive in the latter. This suggests that during SAD months, companies that have received a lot of recommendations from Finnish analysts tend to have smaller ANNRs if they have received an upgrade to buy. The opposite is true when companies have received a downgrade to strong sell.

Table 7. Regression test on upgrades and downgrades using fall and winter dummies
Regressions (1) and (2) are upgrades to strong buy and buy respectively, while (3)-(5) are downgrades to hold, sell and strong sell. The t-values are shown in the square brackets.

	(1)	(2)	(3)	(4)	(5)
Intercept	0,0123	0,0119	0,0047	-0,0032	-0,0030
	[2,36]**	[1,90]*	[0,77]	[-0,52]	[-0,76]
Fall	0,0001	-0,0005	-0,0002	-0,0006	0,0000
	[0,37]	[-1,05]	[-0,50]	[-1,31]	[0,05]
Winter	0,0015	0,0031	0,0026	0,0029	0,0005
	[3,21]***	[5,58]***	[4,81]***	[5,29]***	[1,45]
MB	0,0029	0,0040	0,0040	0,0038	0,0017
	[4,93]***	[5,72]***	[5,94]***	[5,63]***	[3,83]***
Beta	0,0013	0,0019	0,0034	0,0061	0,0041
	[0,55]	[0,65]	[1,21]	[2,16]**	[2,22]**
RecCons	-0,0059	-0,0062	-0,0052	-0,0033	-0,0016
	[-3,82]***	[-3,36]***	[-2,88]***	[-1,86]*	[-1,37]
All REC	-0,0001	-0,0003	0,0001	0,0002	0,0002
	[-1,08]	[-1,90]*	[0,88]	[1,25]	[1,80]*
RECUP	0,0012	0,0039			
	[0,61]	[1,62]			
RECDOWN			-0,0078	-0,0092	-0,0039
			[-3,27]***	[-3,86]***	[-2,48]**
R-Square	0,0917	0,1130	0,1168	0,1184	0,0748

* indicates statistical significance at the 10 % level
** indicates statistical significance at the 5 % level
*** indicates statistical significance at the 1 % level

The results from table 8 supports the finding that the SAD effect is more prominent during winter season. This is apparent even in the resumption subsample (3). Again, the Winter variable is statistically significant at 1 % level in every model except in model 5. The coefficient in the Fall variable is negative in models 2-5, suggesting that investors initial reaction to resumptions are mostly negative during SAD months. However, this finding is not statistically significant. Interestingly, the amount of recommendations a surveyed company has received does not seem to be statistically significant in subsample (3). Furthermore, the market-to-book ratio is statistically significant at 1 % level in every model here as well. Beta variable is statistically significant at 5 % level only in models 4 (sell) and 5 (strong sell). Thus, the individual company's volatility should be taken into consideration even if analysts have resumed their recommendations at sell or strong sell. However, while having a positive coefficient, the resumption variable is not statistically significant. This is interesting, since in table 6, the resumption variable was statistically significant in buy, hold, and sell regressions. This might derive from the fact that both Fall and Winter dummies are included into the regressions. Table 9 illustrates the findings when these dummies have been separated into their own regressions. Interestingly, now the resumption variable is again statistically significant in models 2-4. Furthermore, the results suggest that for the resumption subsample, the fall season is much more statistically significant period, because the resumption variable has higher t-values in the fall than in the winter regression model.

Table 8. Regression results on resumptions using fall and winter dummies
Regression (1) stands for strong buy, (2) buy, (3) hold, (4) sell, and (5) strong sell. The t-values are shown in the square brackets.

	(1)	(2)	(3)	(4)	(5)
Intercept	0,0113	0,0102	0,0030	-0,0045	-0,0035
	[2,10]**	[1,57]	[0,47]	[-0,72]	[-0,86]
Fall	0,0002	-0,0004	-0,0003	-0,0007	-0,0000
	[0,43]	[-0,92]	[-0,60]	[-1,45]	[-0,04]
Winter	0,0014	0,0029	0,0026	0,0029	0,0005
	[3,05]***	[5,26]***	[4,82]***	[5,33]***	[1,50]
MB	0,0029	0,0040	0,0041	0,0039	0,0017
	[4,93]***	[5,73]***	[6,01]***	[5,71]***	[3,89]***
Beta	0,0016	0,0025	0,0032	0,0058	0,0040
	[0,64]	[0,84]	[1,13]	[2,04]**	[2,14]**
RecCons	-0,0059	-0,0065	-0,0058	-0,0041	-0,0019
	[-3,90]***	[-3,54]***	[-3,24]***	[-2,28]**	[-1,64]
All REC	-0,0000	-0,0001	0,0000	0,0000	0,0001
	[-0,61]	[-0,93]	[0,44]	[0,62]	[1,37]
RESUMPTION	0,0017	0,0035	0,0036	0,0035	0,0014
	[0,89]	[1,53]	[1,62]	[1,58]	[0,98]
R-Square	0,0921	0,1128	0,1109	0,1093	0,0688

* indicates statistical significance at the 10 % level
** indicates statistical significance at the 5 % level
*** indicates statistical significance at the 1 % level

Table 9. Regression test results on resumptions using fall dummy

Regression (1) stands for strong buy, (2) buy, (3) hold, (4) sell, and (5) strong sell. The t-values are shown in the square brackets.

	(1)	(2)	(3)	(4)	(5)
Intercept	0,0114	0,0104	0,0032	-0,0043	-0,0035
	[2,11]**	[1,60]	[0,50]	[-0,69]	[-0,85]
Fall	0,0006	0,0004	0,0005	0,0020	0,0001
	[1,62]	[1,00]	[1,18]	[0,47]	[0,52]
MB	0,0029	0,0040	0,0041	0,0039	0,0017
	[4,92]***	[5,71]***	[5,99]***	[5,69]***	[3,89]***
Beta	0,0016	0,0026	0,0033	0,0059	0,0040
	[0,66]	[0,88]	[1,16]	[2,08]**	[2,15]**
RecCons	-0,0059	-0,0063	-0,0056	-0,0039	-0,0019
	[-3,84]***	[-3,43]***	[-3,15]***	[-2,18]**	[-1,62]
All REC	-0,0000	-0,0001	0,0000	0,0001	0,0001
	[-0,48]	[-0,71]	[0,64]	[0,84]	[1,44]
RESUMPTION	0,0023	0,0049	0,0048	0,0048	0,0017
	[1,23]	[2,13]**	[2,16]**	[2,18]**	[1,16]
R-Square	0,0832	0,0901	0,0918	0,0850	0,0660

Regression results on resumptions using winter dummy

Regression (1) stands for strong buy, (2) buy, (3) hold, (4) sell, and (5) strong sell. The t-values are shown in the square brackets.

	(1)	(2)	(3)	(4)	(5)
Intercept	0,0116	0,0095	0,0026	-0,0055	-0,0036
	[2,16]**	[1,48]	[0,41]	[-0,88]	[-0,87]
Winter	0,0015	0,0028	0,0025	0,0027	0,0005
	[3,43]***	[5,27]***	[4,92]***	[5,15]***	[1,58]
MB	0,0029	0,0039	0,0041	0,0039	0,0017
	[4,94]***	[5,73]***	[6,01]***	[5,70]***	[3,89]***

Beta	00016	0,0024	0,0032	0,0058	0,0040
	[0,64]	[0,84]	[1,13]	[2,04]	[2,14]**
RecCons	-0,0060	-0,0064	-0,0058	-0,0040	-0,0019
	[-3,91]***	[-3,52]***	[-3,23]***	[-2,25]**	[-1,64]
All REC	-0,0000	-0,0001	0,0000	0,0000	0,0001
	[-0,63]	[-0,90]	[0,46]	[0,67]	[1,37]
RESUMPTION	0,0017	0,0036	0,0036	0,0037	0,0014
	[0,87]	[1,59]	[1,65]*	[1,66]*	[0,99]
R-Square	0,0919	0,1121	0,1107	0,1078	0,0688

* indicates statistical significance at the 10 % level
** indicates statistical significance at the 5 % level
*** indicates statistical significance at the 1 % level

Overall, the empirical research gives evidence that SAD has statistical significance to the surveyed companies market-adjusted returns by increasing the company's announcement day market adjusted returns as we move on from fall period to the winter period. Hence, the positive seasonal effect to the ANNRs is more prominent during winter season than in fall. Thus, the first hypothesis holds, and the results suggest that SAD does affect companies' announcement day market-adjusted returns. As for the second hypothesis, the downgrades are statistically significant in every model. Furthermore, downgrades had a diminishing effect to the surveyed companies' ANNRs. In addition, downgrades are statistically significant in subsample (2) i.e. when a surveyed company received a downgrade. Thus, the second hypothesis holds true. The third hypothesis also holds true, since in every model, the fall coefficient was lower than that of winters. Furthermore, the coefficient for the winter variable was statistically significant in every model, while the opposite was true for the fall variable.

Interestingly, while in the overall sample (table 4) the upgrade variable was statistically significant, it was not in any model when the subsamples were introduced. The overall sample did not include any subsamples, nor did it have Fall and Winter dummies. Thus, no clear conclusions can be made of the statistical significance of upgrades to the surveyed companies ANNRs.

Nonetheless the regression results provided interesting findings. MB ratio was statistically significant in every model, implying that the size of the company is positively correlated with the announcement day returns. Beta, on the other hand, was not statistically significant until the subsamples were introduced. Thus, the volatility of the company should be considered when the company receives either an upgrade, downgrade, or resumption. Furthermore, the alphas in strong buy samples were in every model statistically significant. Whether the company had received an upgrade or a resumption with a strong buy, the surveyed companies generated positive alphas. The consensus analyst rating was mostly statistically significant, which roughly means that a company with a strong sell consensus rating typically accumulates less ANNR than a company which has a strong buy recommendation – which makes sense. Surprisingly, the total recommendations did not play that much importance to the ANNRs. This thesis employed generic data from the recommendations issued by the Finnish analysts, where the total outstanding recommendations for a stock *i* at a time *t* was given. Another interesting topic for further studies would be to analyze individual analysts' recommendation behavior and how their recommendation pattern changes depending on the season.

7 Conclusions

The purpose of this study was to examine the effect of SAD on Finnish analysts' recommendations. The study presented important literature and theoretical background about analysts and the factors that can affect their recommendations and behavior. Like the rest of us, analysts too are human and prone to the same behavioral biases. The most prominent bias being the optimistic bias, which affects analyst's capability to incorporate new information. (Ramnath, Rock & Shane 2008.)

The main argument behind SAD hypothesis is that people tend to be more risk averse during autumn and winter periods. The lack of sunlight is thought to be the cause of this, and it is believed to increase pessimism and depression. In addition, weather and even a person's mood affects how people react to new information. Thus, it is not too far 'fetched to state that cold and dark weather will influence negatively on people, making them more likely to feel negative emotions. (Kamstra et al. 2003.)

This thesis offers further support to SAD studies, showing that during 2010-2018, SAD was both economically and statistically significant in explaining the market-adjusted returns of companies that had received a recommendation from the Finnish analysts. More specifically, the SAD effect of the surveyed companies was statistically more significant during winter period i.e. from December to March. However, the initial response to downgrades during fall season was higher than those issued in winter. This is in line with previous studies with Kamstra et al. (2003), where they state that the SAD effect is more dominant during autumn months.

This thesis employed an OLS regression model, where the announcement day market-adjusted return was the independent variable. Furthermore, firm specific controls like size and volatility with analyst specific control were added to study the impact of SAD to the surveyed companies ANNR. SAD was statistically significant at 5 % level when all the control variables were included. Furthermore, four subsamples were constructed to study the impact of upgrades, downgrades, and resumptions to the ANNRs. Again, SAD was statistically significant in every model.

Another interesting finding was that Finnish analysts tend to issue more recommendations during SAD months, where the buy recommendation is the most common recommendation. The Finnish stock market has experienced consistent upside trend within the surveyed eight-year timeframe. Thus, it is not surprising to see an optimistic recommendation, such as the buy recommendation, as the most common one.

Furthermore, this thesis showed that Finnish analysts issue more downgrades during SAD months than upgrades. One could argue this is due to SAD mitigating the optimistic bias, by increasing analysts' risk aversion, and thus prompting them to issue less optimistic recommendations. This is a finding that should be further investigated. Barber et al. (2006) study similar phenomenon with the US analysts and stocks. By incorporating their model with Finnish analysts' upgrades and downgrades and constructing portfolios depending on the recommendations should yield interesting results. In addition, as suggested earlier, another interesting topic to research is how the behavior of individual analysts changes during different seasons. This would allow different controls to be added to the regression model, such as the prestige of the analyst and its effect to his/her recommendation forecasts.

This thesis provided further support to studies about SAD and its impact on analysts. As stated, the results imply that SAD affects Finnish analysts, and the Finnish financial market as well. When evaluating stocks or recommendations issued by Finnish analysts, investors in Finland should consider seasonality. To conclude, the impact that external factors, such as the weather and the circumstances of analysts' living conditions, have on analysts' behavior is intriguing and deserve further research.

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Appendices

List of companies

AKTIA BANK A
ALMA MEDIA
AMER SPORTS
APETIT
ASPO
ATRIA 'A'
BASWARE
BITTIUM
CAPMAN 'B'
CARGOTEC 'B'
CITYCON
CRAMO
DIGIA
ELISA
ETTEPLAN
FINNAIR
FISKARS 'A'
FORTUM
F-SECURE
HKSCAN A
HUHTAMAKI
KEMIRA
KESKO B
KONE 'B'
KONECRANES
LASSILA & TIKANOJA
MARIMEKKO
METSA BOARD B
METSO
NESTE
NOKIA
NOKIAN RENKAAT
NORDEA BANK
OLVI A
ORIOLA B
ORION B
OUTOKUMPU 'A'
OUTOTEC
PONSSE
POYRY
RAISIO
RAMIRENT
RAPALA VMC
SAMPO 'A'
SANOMA
SRV YHTIOT
STOCKMANN B
STORA ENSO R
TELESTE
TIETO OYJ
UPM-KYMMENE
UPONOR
VAISALA A
WARTSILA
YIT