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Seasonal affective disorder and investors' response to profit warnings

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ABSTRACT

A listed company must publish a profit warning if its profit or financial position differs substantially from its expected profit or financial position. I examine how seasonal affective disorder (SAD) affects investors' response to profit warnings. SAD is a medical condition that is characterized by a depressed mood during times when the amount of daylight is low.

The first part of the research examines abnormal returns caused by profit warnings. I find evidence that both positive and negative profit warnings generate significant abnormal returns on the announcement day. Moreover, investors have more difficulties to evaluate negative profit warnings than positive profit warnings. The results imply that the size, MB ratio, or analyst recommendations do not affect investors' response. However, I find differences in how investors respond to positive or negative profit warnings. Specifically, the risk of the company affects immediate response to negative profit warnings whereas the number of previous profit warnings affects post-earnings-announcement drift (PEAD) of positive profit warnings.

As the main interest of this thesis, I find that SAD affects investors' response to profit warnings. The immediate response to positive profit warnings is lower during the SAD season, which supports the hypothesis about heightened risk aversion. Moreover, the PEAD of negative profit warnings is higher during the SAD season, which also supports the SAD hypothesis. My results imply that these effects are mainly driven by the fall. Interestingly, I find that SAD does not affect the immediate response to negative profit warnings or PEAD of positive profit warnings. I suggest that these two findings are explained by the ostrich effect and negativity bias, respectively.

KEYWORDS: Profit Warning, Seasonal Affective Disorder, Behavioral Finance, Post-earnings-announcement drift

1. INTRODUCTION

A listed company must publish a profit warning if its profit or financial position differs substantially from the expected profit or financial position of the company. This ensures that investors are aware of all relevant information about the company and can make rational investment decisions. (Karjalainen, Laurila & Parkkonen 2008: 153–154.) The new information generated by the profit warning should reflect into the prices immediately and correctly to state that markets are efficient (Fama 1970).

Essentially, the market value of a share is affected by its expected return, which is estimated by various asset pricing models. The models, however, contain a lot of assumptions and estimating the correct return is difficult. The expected return can be used to calculate the abnormal return, which can be used to examine the market efficiency. If the markets are efficient, no significant abnormal returns should be observed.

However, several studies (see for example Jackson & Madura 2003a; Jackson & Madura 2003b; Bulkey & Herrarias 2005; Tucker 2007; Cox, Dayanandan & Donker 2017) show that abnormal returns are still observed several days after the profit warning. This thesis finds similar results, even though they are not as strong; abnormal returns are still observed two days after negative profit warnings. Overall, according to the efficient market hypothesis, this should not be possible.

The main interest of this thesis is to examine whether seasonal affective disorder (SAD) affects the market response to profit warnings. SAD is a medical condition that is characterized by a depressed mood during times when the amount of daylight is low (Molin, Mellerup, Bolwig, Scheike & Dam (1996); Young Meaden, Forgg, Cherin & Eastman (1997). Symptoms of SAD involve, for example, social withdrawal, decreased activity, sadness, anxiety, and increased appetite (Partonen & Lönnqvist 1998).

Because SAD causes heightened risk aversion during the fall and winter, the immediate market response to profit warnings should be lower during the SAD season. Depressed investors want to avoid risk, so they are more scared to trade with uncertain information.

However, even though the amount of daylight is low during the fall and winter, after the winter solstice, it starts to increase once again. On the other hand, after the summer solstice, the amount of daylight starts to decrease. Therefore, the post-earnings announcement drift (PEAD) should be higher during the SAD season, as investors start to see “light at the end of the tunnel.” These hypotheses are mainly supported by the findings of this study.

As SAD is highly prevailing in Northern countries **(**Magnusson 2000**)**, and Finnish listed companies seem to issue more profit warnings than other Northern countries (see Spohr 2014), it is intriguing to study these two concepts together. As there is discussion and doubts of the idea that SAD would explain the patterns in stock markets, further studies are needed to fully understand whether SAD really affects the markets or not. Because of this reason, I offer another study to this discussion. To best of my knowledge, I am the first to document the impact of SAD on profit warnings.

1.1. Profit Warning

A profit warning is a listed company’s announcement that its earnings or financial position differs substantially from its expected earnings or financial position. A profit warning is not necessarily a negative thing: a profit warning can be positive or negative. A negative profit warning means that the expected earnings or financial position of the company is worse than anticipated. Conversely, a positive profit warning means that the expected earnings or financial position of the company is better than anticipated. A profit warning must be published promptly in a situation where new information becomes apparent and when this information has a significant impact on the price of the security. (Karjalainen et al. 2008: 153–154.)

The main difference between a profit warning and a normal quarterly released earnings report is that the profit warning is announced before the earnings report and the announcement occurs unexpectedly and irregularly. Profit warnings also provide more detailed information on the company’s success as well as reasons why the company is releasing the foreknowledge. The purpose of the profit warning is to reduce the information asymmetry on the market and to ensure that investors have all relevant information in their possession. (Dayanandan et al. 2017.)

Profit warnings often cause a large change in the value of a company's share, from which both the managers and the owners would probably like to avoid. On the other hand, investors have an opportunity to generate quick profits if they succeed in defining the market reaction as unfounded. (Spohr 2014.) If SAD affects the market reaction, savvy investors could potentially use that information to generate quick profits.

1.2. Purpose of the study

The main purpose of this study is to examine whether seasonal affective disorder affects the market response to profit warnings using data from Finland during 2011–2017. The immediate reaction of the profit warnings is studied, but also PEAD is examined. Moreover, I also document whether the market response to profit warnings is delayed. Prior profit warning studies commonly examine only negative profit warnings, but I study positive profit warnings, too. This is to investigate whether the sign of the profit warning matters to SAD sufferers.

I examine six hypotheses. The first three hypotheses are formed to investigate abnormal returns that profit warnings might cause. The remaining three hypotheses are the main interest of this thesis. Specifically, I examine how SAD affects investors' response to negative and positive profit warnings. These hypotheses are explained in detail in chapter 6.2.

1.3. Intended contribution

The possible effects of seasonal affective disorder to stock markets are still studied. Some researches criticize SAD (see for example Jacobsen & Marquering (2009)) while other researches strongly support the SAD hypothesis (see for example Kamstra, Kramer & Levi (2003)). I contribute to this debate studying the SAD effect on profit warnings in Finland.

Furthermore, to best of my knowledge, I am the first to document the impact of SAD on profit warnings. I also study the market response to both negative and positive profit warnings to contribute to the profit warning literature, as prior studies are generally focused only on negative profit warnings. Moreover, if SAD causes heightened risk aversion during the fall and winter, and the immediate reaction to profit warnings is lower during the SAD season, savvy investors may benefit from this and generate quick profits. This means that profit warnings announced during the SAD season have a smaller reaction than those announced in the spring and summer. This piece of information can be used to determine if the market response is justified or not.

1.4. Structure of the thesis

The remaining of the thesis is structured as follows. In Chapter 2, actions, tasks, efficiency, asset pricing, and phenomena of financial markets are introduced. In Chapter 3, concepts of behavioral finance and seasonal affective disorder are carefully discussed. In Chapter 4, a listed company's disclosure rules are explained. Chapter 5 has two main parts. First, the prior literature of profit warnings is reviewed, and second, the prior literature of the effects of seasonal affective disorder in stock markets is discussed. Chapter 6 introduces the data used in this study and the methodology. Chapter 7 showcases the results of the study. Finally, Chapter 8 offers conclusions, discussion, and provides thoughts about possible further studies.

2. FINANCIAL MARKETS

The financial markets are traditionally divided into two sectors: the money market and the capital market. In the money market, market participants trade in the short term – in other words, with securities that have high liquidity, low risk and a maturity less than a year. Riskier securities with a maturity longer than a year are traded in the capital market. Financial instruments are generally more diverse in the capital market than in the money market. (Bodie, Kane & Marcus 2009: 23.)

The financial markets have four key functions:

1. *To allocate funds as efficiently as possible between the surplus and the deficit sector.* The financial markets are allocative efficient when investments in the surplus sector find their way into the deficit sector at the lowest possible cost and with little delay.

2. *Information transmission.* When the markets are informatively efficient, investors are up-to-date with the characteristics, return and risks of different investment objects. For example, companies must deliver their financial statements to the market on a regular basis. Therefore, a company cannot cover up, for example, weakened financial performance.

3. *Improving the liquidity.* When the financial markets are liquid, investors can realize their shares and bonds effortlessly and quickly. Liquid financial markets make it possible to invest for long-term projects as investors can realize their investment when they want to.

4. *Spread the risk.* It is not wise for an investor to invest all the wealth to one company or a bond, but to diversify the investment, for example, to several companies and thus reduce the risk.

A sound financial system ensures that capital resources can be transferred there, where they are most efficient. A functioning financial market is therefore also important from the perspective of the society. (Malkamäki & Martikainen 1990: 28–30; Knüpfer & Puttonen 2017: 53–54.)

2.1. Market efficiency

The most important task of the capital market is to allocate ownership of securities. Generally speaking, the ideal market is the one that is able to produce precise signals to allocate resources. In such markets, securities' prices include all available information. Based on this, it is possible to make investment decisions relying on the fact that the securities are correctly priced at all times. The market can be called efficient when the shares' prices include all available information on the market. (Fama 1970.)

Kendall (1953) finds in his research that it is impossible to predict future prices of shares based on a historical market data, as stock prices change randomly. This unpredictable and random variation of stock prices is called the random walk theory. Based on this theory, Kendall (1953) excogitates that the financial markets are efficient, prices reflect all available information and operate just like they should. In the literature, this idea is called the efficient market hypothesis. (Nikkinen, Rothovius & Sahlström 2002: 79–80; Bodie et al. 2005: 370–371).

Fama (1970) defines three conditions for market efficiency. Efficient markets (i) have no trading costs, (ii) all information is available for free to all market participants and (iii) all market participants agree on the impact of new information on share prices.

Along with the concept of efficient markets, informative efficiency is also usually mentioned. The markets are informatively efficient when all information is included in the share price and when the price of a share changes immediately as the new information is revealed (Bodie et al. 2005: 370–371). If investors think that the price of a share is too low taking the current level of information into account, investors will begin to buy the share, which leads to an increase of the share price. According to the efficient market hypothesis, investors can obtain excess profits only momentarily. Pricing errors disappear quickly because investors use the pricing error until the share price reaches its equilibrium once again (Copeland, Weston & Shastri 2005).

In practice, the markets have trading costs and taxes. Obtaining the information is not free either; it takes time to monitor and filter the information – time, that one could also use otherwise. However, the theory of finance is aware of this and it is important to note that the markets can function efficiently even if they are not completely perfect (Knüpfer et al. 2017: 168). As a counterargument to the efficient market hypothesis, one can propose, for example, the fact that there are numerous analysts in the markets whose job is to collect and analyze the information and use that information to find underpriced shares. If the markets were efficient, analysts' work would be completely unnecessary as prices already reflect all that information. On the other hand, one could argue that a great number of analysts are the one taking care with their actions that the markets really do reflect all information (Nikkinen ym. 2002: 82).

2.2. Three levels of market efficiency

Fama (1970) divides the market into three different categories and tests their degree of efficiency. He categorizes the efficient market hypothesis into a weak-form, a semi-strong and a strong-form markets. The grouping is based on how perfectly the information is realized in the price of a share.

When the weak-form market conditions are in question, securities' prices reflect all information that is related to the past trades. This information is derived from prices and trading volumes. Under this condition, analyzing historical information is useless as share prices change so fast that it is not possible to achieve excess returns. Furthermore, it is not possible to predict future price developments based on historical information. (Nikkinen et al. 2002: 83; Bodie ym. 2005: 371.)

In accordance with the semi-strong form, stock prices include all publicly available information. Under these terms, it is not possible to predict the future share prices, for example, on the basis of companies' earnings news or financial statements. The semi-strong form also includes the weak-form, as time series of share prices are public information. (Nikkinen et al. 2002: 83; Bodie et al. 2002: 372.)

Strong-form terms are said to be met if stock prices reflect all information related to companies. This also includes undisclosed information, i.e. insider information. According to the strong-form market efficiency, for example, decisions made by the board of directors are immediately reflected to the share price at the time of decision. This assumption is extreme and difficult to prove empirically. It is enacted in the security markets law that exploiting insider information is prohibited. (Nikkinen et al. 2002: 83; Bodie et al. 2005: 373; Knüpfer et al. 2017: 170.)

Fama's (1970) research has worked as a foundation for examining market efficiency. After his research, market efficiency has been studied a lot. Fama (1991) has later corrected his previous research by defining a new tripartition for market efficiency. According to the new grouping, the three divisions are: (i) return predictability, (ii) event studies and (iii) tests for private information.

Fama's (1991) changes relate mainly to the weak-form market efficiency conditions, as in the case of semi-strong and strong-form conditions, Fama (1991) wants to change mainly the names of the concepts and not their purpose. Testing for return predictability is added to the weak-form market efficiency, as the fluctuations in returns are no longer thought to be affected only by historical information, but also, for example, by dividends and interest rates. Because the semi-strong market efficiency is often studied using event studies, Fama (1991) considers that "event studies" as a concept describes the theory better. Event studies are used to test how quickly the market responds to an event, for example, to a publication of a company's profit warning (Nikkinen et al. 2002: 85). Similarly with the semi-strong market efficiency, Fama (1991) changes only the name of the concept "strong-form market efficiency" and keeps the theory related unchanged.

2.3. Determining the share price

Valuation models are based on calculating the present value of cash flows received by a shareholder, which is the most important task when applying valuation models. One must define a rate of return that is used to discount cash flows. The required rate of return should reflect the risk of the company. The higher risk will result in a higher rate of return. (Nikkinen et. al 2002.)

An investor receives cash flows from a share as dividends. The share price is the sum of the present value of future dividends and the price of the share at the end of the investment horizon. However, the price of a share is often determined without using the price of the share at the end of the investment horizon. This term is often omitted from the equation, since it is not sensible to use the price of the share that is to be determined, even if on a different period. The investment horizon is often considered limitless, as the principal is never returned to the investor. Essentially, the capital remains in the company forever. As the investment horizon increases, the future price of the share reduces close to a zero, and therefore is often ignored. Now, the share price can be determined solely on the basis of the present value of future dividends:

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

where P_0 = price of the share

D = dividend per share

n = the last period of the investment horizon

r = required rate of return. (Knüpfer et al. 2017: 95–96.)

Equation 1 shows only the most basic valuation model for a share. There are several other models that add more variables. One example is the model by Gordon & Shapiro (1956) which takes the annual growth rate of the dividend into account. The above model is a valuation model used to determine a company’s share price. To calculate a share price, one needs to know the correct required rate of return. There are separate models to determine the rate of return. Next, three of these models are presented briefly: CAPM, and the three-factor and the five-factor models by Fama & French (1996 & 2015).

The CAPM, *Capital Asset Pricing Model*, is a stock market equilibrium model developed by Sharpe (1964). The CAPM is considered to be perhaps the most important cornerstone of modern financial theory. The CAPM binds the expected return of the share directly to its risk: the higher the risk, the greater the return. (Nikkinen et al. 2002: 68.)

The CAPM is based on Markowitz's (1952) portfolio theory. The portfolio theory is based on an idea that diversification can be used to reduce the risk of a portfolio. In this case, the portfolio is constructed by choosing shares that do not strongly correlate with each other.

The risk of a share can be divided into a non-systematic and systematic risk. Non-systematic risk refers to a firm-specific risk and systematic risk refers to market risk. Market risk consists of macroeconomic factors that affect all securities, such as interest rates and inflation. Non-systematic risk refers to, for example, the probability of an individual company being forced into a bankruptcy. With good diversification, it is possible to reduce the non-systematic risk to zero. Therefore, any remaining risk is systematic risk, as it is not possible to diversify systematic risk (Bodie et al. 2005: 283–284.) Therefore, in practice, investors expose their assets only to systematic risk, which is precisely the risk that investors demand return for. (Knüpfer et al. 2017: 153).

The CAPM has received lot of criticism mainly because of its several assumptions (see Fama & French 2004)), but even still it is widely accepted in the financial markets, and is used, for example, in brokerage firms and in real investment planning. The first criticism towards the CAPM that gained large publicity was presented by Roll (1977). He argues that it is not possible to identify the true market portfolio. Therefore, testing the CAPM is impossible. (Nikkinen et al. 2002: 75.)

The CAPM is unable to explain size and value anomalies (discussed in chapter 3.1.), which is one of the reasons it gives an incorrect estimation of stock returns. For this reason, Fama et al. (1996) present a three-factor model to explain share returns. The three-factor model by Fama et al. (1996) can be represented in the following way:

$$r_{it} = \alpha_i + \beta_{iM} R_{iM} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \varepsilon_{it}. \quad (2)$$

The first factor is the market factor R_{im}, which is the return of a stock index minus the risk-free rate. The second factor is the size factor SMB_t (Small Minus Big), which is the share returns of small companies minus the share returns of large companies. The third factor HML_t (High Minus Low) is obtained by deducting returns of companies' that have a high B/M ratio from returns of companies' that have a low B/M ratio. In the model, β_{iM}, β_{iSMB} and β_{iHML} denote the sensitivity of different portfolios.

Fama et al. (1996) find that their model manages to explain the grievances on the stock market. However, Black (1993) criticizes that when researchers browse stock return databases, they may find certain types of regularities by chance. For example, he states that the significance of the firm size effect has mainly disappeared. Nevertheless, Fama et al. (1993) believe that because the firm size effect and the B/M ratio have successfully predicted returns over several different time periods and all around the world, the use of these factors is justified.

Fama & French (2015) add two new factors, RMW_t and CMA_t, to the previous three-factor model. The five-factor model can be written in the following way:

$$r_{it} = \alpha_i + \beta_{iM}R_{iM} + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + \beta_{iRMW}RMW_t + \beta_{iCMA}CMA_t + \varepsilon_{it}. \quad (3)$$

RMW_t (robust minus weak) describes the profitability of a company. It is the difference in returns between well-diversified portfolios, where the share returns of high profitability companies is deducted from the share returns of low profitability companies. CMA_t (conservative minus aggressive) is an investment factor. Similarly, it is the difference in returns between well-diversified portfolios, where the share returns of high investment rate companies is deducted from the share returns of low investment rate companies.

Fama et al. (2015) conclude in their research that the five-factor model explains share returns better than the old three-factor model. Furthermore, they also find that in the five-factor model, $\underline{HML_t}$ appears to be unavailing, as the two new factors, RMW_t and CMA_t, absorb its effect. Thus, if an investor is interested only in explaining abnormal returns, according to Fama et al. (2015), a four-factor model where HML_t has been omitted functions just as well as the five-factor model. However, they state that the biggest problem with the five-factor model, and in fact with all pricing models, is explaining returns of small companies. The five-factor model has difficulties explaining, for example, share returns of small companies that do not generate robust profits and invest aggressively.

3. BEHAVIORAL FINANCE

Cognitive and emotional weaknesses affect all people. However, traditional finance theory ignores these cognitive biases and human emotions, as it assumes that investors act only rationally. The traditional finance theory examines how people should behave. Behavioral finance examines human errors and examines how people actually behave in a financial setting. Behavioral finance does not expect that investors behave rationally, but understands that humans are not always capable of acting rationally. Humans tend to be irrational. Behavioral finance combines psychology and finance to explain features of financial markets. (Baker & Nofsinger 2002.)

Empirical studies support the idea that investors act irrationally. Kaplanski, Levy, Veld & Veld-Merkoulova (2014) state that stock prices are correlated with several noneconomic factors. To name a few, they argue that weather conditions, season of the year and sporting events have all be found to affect stock prices.

Behavioral finance can be divided into two categories: investor psychology and limits to arbitrage. According to the efficient market theory, taking advantage of arbitrage opportunities is simple, and prices quickly revert to their fundamental values. However, behavioral finance argues that investor psychology has a significant impact on how prices are formed in the market. Furthermore, in reality, it is very hard, if not impossible, to find arbitrage opportunities that are completely riskless. (Shleifer & Summers 1990.)

According to the efficient market hypothesis, if investors make rational decisions, prices of securities are the same as their fundamental value. However, in reality, investors do not always behave rationally. Naturally, this means that prices do not always correspond the fundamental value. This mispricing opens an opportunity for rational arbitrageurs to enjoy abnormal returns. These arbitrageurs take advantage of this mispricing and according to the efficient market hypothesis, the arbitrage opportunity disappears quickly. However, behavioral finance argues that such mispricing is not easy to exploit as it may hold risks and additional costs. Therefore, the mispricing can remain unexploited. Such barriers that rational arbitrageurs face are called limits to arbitrage. (Barberis & Thaler 2003: 1054–1055.)

Limits to arbitrage can be divided into three categories (Bodie et al. 2014: 394-395):

1. *Fundamental risk.* Suppose that a share is underpriced. An investor can buy this share to capitalize the opportunity to gain profit. However, this act cannot be considered riskless, as there is no certainty that the share price would not decline even more. Another factor is the investor's investment horizon. Even though the underpricing may eventually be corrected, there is no way to know how long it will take. If the correction takes a long time, the investor may have already sold her security. This kind of risk limits the activity and efficiency of an arbitrageur.

2. *Implementation costs*. Exploiting mispricing can be difficult because of trading costs. Moreover, short selling can be impossible because of regulation, which lowers the possibilities of arbitrageurs.

3. *Model risk*. It is difficult to evaluate if one has really found a mispricing. The valuation model used to determine the mispricing can be faulty. There is always a possibility that the price is actually right. Because of this risk, arbitrageur might decide to not pursue the arbitrage opportunity any further.

There are several cognitive biases that people are affected by **(**see for example Hirshleifer 2001; Baker et al. 2002). I cover the following biases: overconfidence, belief bias, anchoring, availability bias, ostrich effect and negativity bias. These biases are chosen because investors' response to profit warnings can be influenced by these common biases.

People tend to be too overconfident about their own abilities. For example, most drivers rank themselves as better-than-average drivers. Moreover, many investors think that they can beat the market by active trading, even though many studies suggest that it is extremely hard to beat the market. Barber & Odean (2001) find that especially single men trade significantly more actively than women. The study suggests that men are more overconfident than women. (Bodie et al. 2014: 390.)

Belief bias occurs when a decision or response is made focusing on the believability of the conclusion rather than by logical validity. Prior researches about the belief bias suggest that people are more willing to accept conclusions that they believe to be true. In other words, people tend to reject any conclusions that they believe to be false. Henle & Michael (1956) illustrate the belief bias in their study by giving two syllogisms: (i) all Russians are Bolsheviks and (ii) Some Bolsheviks regiment people. There is no competent conclusion to this syllogism. However, subjects with an anti-Russian attitude might endorse the unfit conclusion that all Russians regiment people. (Evans, Newstead & Byrne 1993: 243.)

When making estimates, people tend to use starting points or initial values when adjusting the estimates. The initial value affects the final estimate even if the initial value has nothing to do with the actual topic that is being estimated. This phenomenon is called anchoring. For example, people were asked to estimate the percentage of the United Nations that were African nations. Before the estimation, the subjects spun a roulette wheel that stopped on either 10 or 65. For those subjects that spun the low value, guessed lower values than those subjects that spun the high value. Subjects who spun 10 guessed 25% and those who spun 65 guessed 45%. In another study, high-school students were asked to estimate within five seconds a numerical expression. Group one estimated the product 8*7*6*4*5*4*3*2*1 and the group two estimated the product 1*2*3*4*5*6*7*8. Because the first equation starts with higher numbers, the answer for the first equation was estimated to be higher. The median estimate for the first group was 2 250 whereas the median estimate for the second group was 512. The correct answer is 40 320. (Tversky & Kahneman 1974.)

The availability bias is a mental shortcut for people to evaluate topics or situations. People might assess the frequency of a class or the probability of an event by using information that is easy to remember. One may assess the risk of a heart attack by recalling such incidences among one’s vicinity. Furthermore, people put a higher weight for information that is more recent. (Tversky et al. 1974.)

Ostrich effect refers to a cognitive bias when people tend to ignore bad or ambiguous news. They tend to not seek for additional information and decide to “put their heads in the sand” to protect themselves from any further negative information. For example, investors are less likely to check the value of their portfolios in down markets. This is exactly what Karlsson, Loewenstein & Seppi (2009) find in their study. They find that the ostrich effect is clearly visible in the financial markets. Moreover, they argue that this kind of behavior should be observed in any situation in which people care about information and have ability to protect themselves from it. The authors illustrate this by giving an example of parents of children with chronic problems. Such parents might be prone to avoid the problem until those problems become clearly visible for other people who are not as emotionally involved.

Negativity bias means that humans tend to react more strongly to negative information than to comparably extreme positive information. Specifically, negative information is evaluated more strongly than positive information and remains in memory better (Ito, Larsen, Smith & Cacioppo 1998). Furthermore, Bargh, Chaiken, Govender & Pratto (1992) find that evaluations stored in memory become active on the mere presence or mention of the object in the environment. Therefore, combining this theory with the ostrich effect and SAD, there is a possibility that because of the depression that SAD causes, investors may temporarily ignore the negative information. However, this information is still in their subconscious, and after the depression caused by SAD decreases, investors might recall the negative profit warning, especially when the earnings announcement could act as a trigger that activates the stored memory.

3.1. Anomalies – regular deviations from market efficiency

In an efficient stock market, the best estimate of the fair value of a share is the market value and possible over or underpricings are quickly corrected to their true value. Consequently, in an efficient stock market, it is not possible for an investor to continuously achieve higher risk-adjusted returns than the market on average. (Malkamäki et al. 1990: 113.)

The underlying assumption of the efficient market is the Capital Asset Pricing model (CAPM). According to the CAP-model, stock returns are determined by the risk-free rate and the systematic risk of the share. However, in empirical studies, it has been observed that there are certain unsolved regularities that cannot be explained by systematic risk. These kinds of regular exceptional phenomena, which persist for a long time, deviate from market efficiency. These phenomena are called anomalies. (Malkamäki et al. 1990: 113; Nikkinen et al. 2002: 86.)

The existence of anomalies has challenged the efficient market hypothesis. Investors can obtain abnormal returns by utilizing anomalies, which according to the efficient market hypothesis, should not be possible. (Mehdian & Perry 2002.)

Fama & French (1996) argue that anomalies are not evidence of market inefficiency, as one of the reasons for anomalies can be the way how the risk is measured. The risk is often measured using the CAPM, which assumptions are not suitable for the actual market situation. Therefore, the CAPM fails to estimate the true risk correctly, which is why the model gives an incorrect estimate of the returns of the share. Since the CAPM fails to explain anomalies, new models have been developed to seek better explanations to anomalies, such as the previously introduced Fama & French factor models.

The problem with measuring market efficiency is the so-called joint hypothesis problem. The problem is that examining market efficiency is challenging or even impossible, because it must be tested using a pricing model. The used pricing model has to predict future returns, which must be compared to the realized returns. However, the pricing model should take all possible factors affecting the share price into account and it should explain future returns impeccably. In other words, it is difficult to prove that the used pricing model is the correct one. Consequently, anomalies can be explained because of market inefficiency, an incorrect pricing model or because of a poor estimation of the expected return. (Fama 1991.)

Numerous of anomalies are found in financial markets (see Noxy-Marx 2014). Next, few common anomalies are presented: firm size anomaly, B/M anomaly, P/E anomaly and post-earnings announcement drift (PEAD) anomaly. Previous studies have found that these anomalies affect the magnitude of the outcome of the profit warning, which is why these anomalies are important to review. In addition, Halloween effect is presented, as this can be thought to overlap with the SAD effect.

3.1.1. Firm size anomaly

Banz (1981) finds in his research that the returns of small and large companies differ. He names this phenomenon as firm size anomaly. He investigates the shares listed on the New

York Stock Exchange in 1926–1975. The shares are separated into two different portfolios based on their market value and therefore, divided into small or large companies. As a result, during this period, the average annual return of small companies was always higher than the average annual return of large companies. The difference between large and small companies' returns remains significant even if a risk-adjusted model is used. Because of this, one cannot conclude that the higher risk of small companies completely explains the firm size anomaly.

The so-called January effect is also closely related to the firm size anomaly. It has been observed, that especially in January, companies' stock returns increase more than on average. The January effect has been shown to affect particularly small companies, as the returns of small companies are at their highest specifically in January. On an annual basis, a significant portion of the firm size anomaly occurs in January. The relationship between the January effect and the firm size anomaly has been studied a lot and the results have been similar (see Watchel 1942; Rozeff & Kinney 1976; Keim 1983). Blume & Stambaugh (1983) state that, on average, the firm size anomaly originates from January alone.

The firm size anomaly is often explained by the fact that smaller companies are riskier than large companies, which is why investors demand higher return for them (Chan, Chen & Hsieh (1985). Another explanation could be institutional investors' minor interest towards small companies. In this case, there is less information available on small companies. Small companies are analyzed less than large companies and their bid-ask spread can be wide. Smaller amount of information and worse liquidity cause risks and trading costs, which requires investors to demand higher returns (Arbel & Strebel 1983; Amimud & Mendelson 1986).

Chan & Chen (1991) find that the firm size anomaly does not originate from the size of the companies itself, but from characteristics of small companies. Furthermore, they state that small companies react differently to macroeconomic information. Small companies also include so-called marginal companies, which have financial difficulties: they have been losing their market value, have weak cash flows and have lot of debt. Portfolios that are formed of small companies, include large number of such companies, which is why the higher returns of small companies could be explained by the higher level of risk.

3.1.2. B/M anomaly

Fama & French (1992) show in their research that investors can use the B/M ratio to predict future returns. The B/M ratio is the book value of a company's share divided by the market value of the company's share. If a company has a high B/M ratio, it is called a value company and, in the opposite case, a growth company. Fama et al. (1992) group companies into ten different portfolios according to their B/M ratio and study the returns of these portfolios during 1963–1990. According to their study, companies with a high B/M ratio have higher stock returns than those with a low B/M ratio. Fama et al. (1992) also investigate the causations of a B/M ratio and a company size. They find that a company's beta coefficient measured by the CAPM cannot explain returns of small companies or returns of value companies.

Instead of using the CAPM, Fama & French (1996) use their three-factor model to study the B/M anomaly. Even if the three-factor model is used, shares with a higher B/M ratio still seem to have higher returns. Kothari, Shanken & Sloan (1995) also study the B/M anomaly. However, they find that when betas are estimated on an annual basis instead of a monthly basis, shares with higher betas generate higher returns. They conclude that the significance of the B/M anomaly may be somewhat weaker than what Fama et al. (1992) document in their research.

La Porta (1996) argues that the poor ability of analysts to forecast future earnings may explain the B/M anomaly. In his research, he finds that companies that had low earnings growth forecasts actually succeeded better than companies that had high earnings growth forecasts. Therefore, analysts are said to be too pessimistic toward companies with low earnings growth prospects. Similarly, analysts appear to be too optimistic toward companies with high earnings growth prospects.

3.1.3. P/E anomaly

The P/E ratio is a key figure where a company's share price is divided by the company's earnings per share from last year (Bodie et al. 2005: 47). Basu (1977) finds that shares with a low P/E ratio are more profitable than shares with a high P/E ratio. Furthermore, the result does not change even if a risk-adjusted model is used. Booth, Martikainen, Perttunen & Yli-Olli (1994) investigate the P/E anomaly during 1976–1986 both on the U.S. and the Finnish market. These markets differ considerably in terms of size, for example. Although the markets are very different, the P/E anomaly is observed on both markets: shares with a low P/E ratio generate better returns than shares with a high P/E ratio.

Analyzing and calculation the P/E ratio is extremely easy, which makes it strange that using such a simple method could be used to earn abnormal returns. One explanation to the P/E anomaly could be that the market equilibrium model does not measure the risk correctly. If two companies have the same expected earnings, but the other company is riskier, its share price is lower and, by definition, its P/E ratio is also lower. The higher risk is reflected as a higher expected return. (Bodie et al. 2005: 389.)

3.1.4. Post-earnings-announcement drift

The basic assumption of the efficient market hypothesis is that all new information is immediately reflected to the price of a share (Bodie et al. 2005: 392). Ball & Brown (1968) find in their research that stock prices continue to develop in the direction of an earnings surprise for several days after the publication of the surprise. In the case of a negative earnings surprise, share prices continued to decline after the publication of the result. In the case of a positive earnings surprise, share prices continued to increase after the publication of the result. This phenomenon is called post-earnings announcement drift (PEAD). Many other scholars have also observed the same phenomenon (see Foster, Olsen & Shevlin 1984 Bernard & Thomas 1989; Kim & Kim 2003; Sadka 2006).

Foster et al. (1984) find a clear evidence supporting PEAD phenomenon. They divide companies into ten portfolios according to the magnitude of the earnings surprise. They find that share prices continued to develop parallel to the earnings surprise. The more positive (negative) the surprise is, the more positive (negative) the post-announcement abnormal returns are. Bernard et al. (1989) argue that the explanation of the phenomenon may be the incorrect assumptions of the CAPM. They state that trading costs have a significant impact and investors are not able to absorb new information properly.

Kim et al. (2003) construct a four-factor model, which they use to explain PEAD. They add a fourth factor, unexpected earnings surprise, to the Fama & French three-factor model. Using this model, with the exception of the first two days after the earnings announcement, the cumulative returns of 60 days after the announcement are no longer statistically significant. Their model explains PEAD better than the Fama & French three-factor model, which still shows statistically significant results after 60 days of the announcement. As a conclusion, PEAD reported in prior studies may be due to an incorrect model and a failure of measuring risk. Also Sadka (2006) argues that PEAD is due to an unsuccessful measurement of risk. According to him, liquidity risk affects PEAD and pricing models should include a component that takes this risk into consideration.

3.1.5. Halloween effect

Halloween effect (also Halloween indicator) is presumable originally inherited from a saying "Sell in May and go away." Bouman & Jacobsen (2002) are the first to document significant results of this anomaly, which states that stock returns are lower during May through September than during the rest of the year. They examine 37 different countries and find that in 36 of them, the returns are higher from November through April than during the rest of the year. The results are robust even if risk, measured by the standard deviation, is taken into consideration. The standard deviation of the two different periods is fairly constant and does not differ significantly between the two periods.

Bouman et al. (2002) try explaining the anomaly with several different hypothesis. They examine if interest rates, trading volume, the size of the agricultural sector, vacations, news, January effect or data mining could explain the phenomenon. However, the only significant explanatory factor is found to be vacations, and more precisely the length and the timing of the vacations and their impact on trading activity. Interestingly, at least according to the efficient market hypothesis, this kind of behavior should be easily exploited by arbitrageurs. Therefore, if this is taken as the explanation, this kind of anomaly should not persist in long-term.

Jacobsen & Zhang (2012) study the Halloween effect in 108 different stock markets around the world. They find that the returns are higher during November–April than during May–October in 81 countries. The difference of these returns is statistically significant in 35 countries, where conversely two of the countries have higher returns during May–October. According to their research, there is no evidence that the Halloween effect has weakened in the recent years. On the contrary, it seems like the anomaly has strengthened. However, Dichtl & Drobetz (2014) challenge prior studies by examining the recent studies using data-snooping resistant simulations. As a result, they state that Halloween effect has decreased or completely vanished during the recent years and that the Sell in May strategy has never offered statistically significant higher returns than the traditional buy-and-hold strategy.

3.2. Risk Aversion

Risk aversion measures the amount of uncertainty that a human is willing to take. Risk averse investors do not want to invest on portfolios that have fair risk-return profile or worse. Instead, they consider risk-free or speculative prospects with positive risk premiums. Assume that an investor can assign a utility score to different portfolios according to their expected return and risk. Those portfolios with more attractive risk-return profiles have higher values of utility. The utility function can be expressed in the following way:

$$U = E(r) - 0{,}5A\sigma^2 \; . \tag{4}$$

The utility value is denoted by U and A is an index of the investor's risk aversion. As the equation shows, higher expected returns enhance the utility and higher amount of risk diminishes the utility. (Bodie et al. 2014: 170.)

The level of risk aversion of individual investors can be estimated by different questionnaires. Moreover, researchers track behaviour of groups of individuals to determine average levels of risk aversion. (Bodie et al. 2014: 174.)

However, as the above model focuses only on asset risk and return, behavioral finance focuses as well on affect. This means that investors may have “good” or “bad” feelings that affect their choices in the financial markets. For example, companies that have good reputation for socially responsible policies can have higher affect in public perception. Investors’ feelings can drive up prices of these stocks. (Bodie et al. 2014: 393.)

Prospect theory, which originated from the study of Kahneman & Tversky (1979), challenge the conventional thought about rational risk-averse investors. Figure 1 shows the conventional utility function of a risk-averse investor. As can be seen, higher wealth leads to higher utility, but at a diminishing rate. A loss of 1 000 euros reduces the utility more than a gain of 1 000 euros increases it. Hence, investors are keen to reject those risky prospects that do not offer risk premiums. (Bodie et al. 2014: 393.)

Figure 2 illustrates the utility function under prospect theory. As can be seen, the utility no longer depends on the amount of wealth, but on changes in it from current levels. On the left side of the figure the curve is convex rather than concave. Several conventional utility functions predicate that investors may become less risk averse as wealth increases. However, as can be seen from the figure, the function re-centers on current wealth. This means that such decreases in risk aversion are ruled out. Furthermore, the figure shows that because of the convex curvature to the left of the origin, investors tend to become more risk seeking rather than risk averse when it comes to losses. For example, Coval & Shumway (2005) find that traders in the T-bond futures contract market appear to be highly loss-averse. If traders lost money during morning sessions, they assume significantly higher risk in afternoon sessions. (Bodie et al. 2014: 393.)

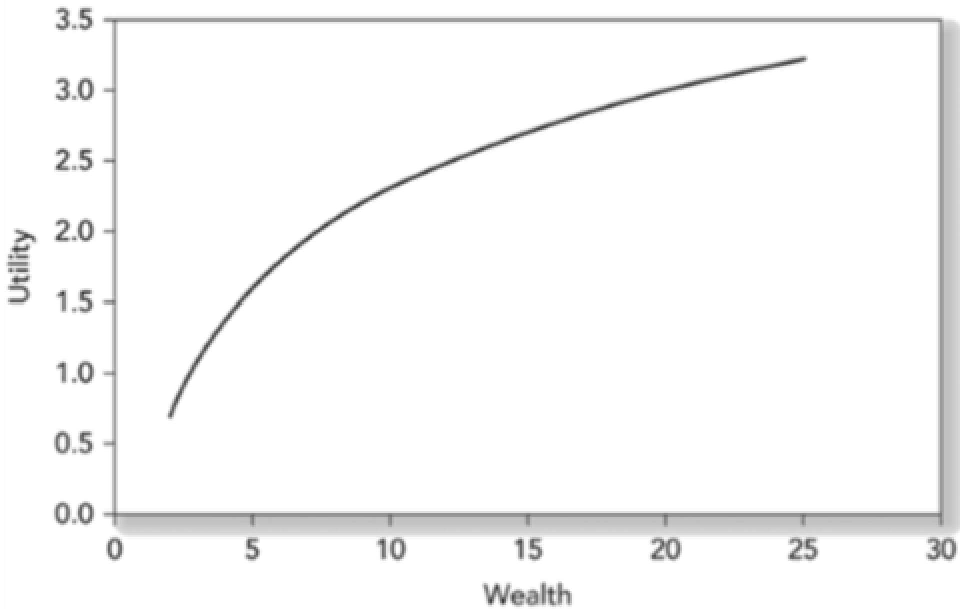

Figure 1. Conventional utility function (Bodie et al. 2014: 393).

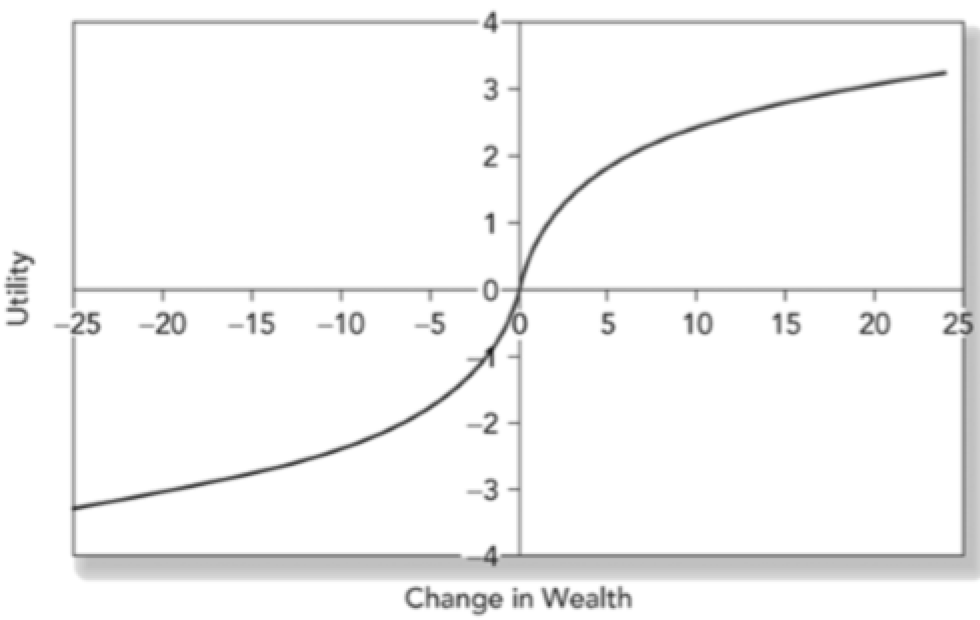

Figure 2. Utility function under prospect theory (Bodie et al. 2014: 393).

3.3. Seasonal Affective Disorder

Seasonal affective disorder (SAD) is related to the changing of the seasons (Rosenthal, Sack, Gillin, Lewy, Goodwin, Davenport & Wehr (1984). Specifically, SAD is a medical condition that is characterized by a depressed mood during times when the amount of daylight is low. In other words, as Molin, Mellerup, Bolwig, Scheike & Dam (1996) and Young Meaden, Forgg, Cherin & Eastman (1997) report in their studies, this kind of seasonal depression is increased when hours of daylight are declining. Rosenthal (1998) and Kamstra, Kramer, Levi & Wermers (2017) find evidence that even those people who are not affected by SAD might be affected by “winter blues”, which can cause milder mood changes.

SAD causes several symptoms, such as social withdrawal, decreased activity, sadness, anxiety, lowered sex-drive, poor quality of sleep, and increased appetite and weight gain. As the amount of daylight starts to increase after the winter solstice, SAD sufferers cognitive functions start to improve. Moreover, light therapy has been documented as a practical treatment for SAD, which supports the hypothesis that the decreasing amount of daylight is the main driver of SAD. (Partonen & Lönnqvist 1998.)

Magnusson (2000) reviews 20 retrospective studies about SAD and reports that the prevalence of SAD has been reported to be from 0% to 9,7%. The review suggests that SAD is more prevalent at the higher northern latitudes, but also that the prevalence of SAD varies across different ethnic groups. However, Magnusson (2000) states that all things considered, SAD seems to be a relatively common disorder. Interestingly, even though SAD is reported to be more prevalent at northern latitudes, which is also strongly suggested by Dowling & Lucey (2008), Iceland seems to be an outlier. Magnusson & Stefansson (1993) study the SAD in Iceland and find that Icelanders seem to be not affected by it. Cott & Hibbeln (2001) suggest that the large consumption of fish compared to other Nordic countries could be one explanation. They argue that acids that fish contain, such as Omega 3, decrease the amount of depression. Naturally, this would decrease the amount of depression caused by SAD, too.

As SAD causes depression, it also affects emotions and moods of people, and therefore, it affects decision making of people, too. Wright & Bower (1992) report that those who are in good mood tend to make more optimistic decisions. Furthermore, those people evaluate their surroundings more positively. For example, they tend to have a higher level of life satisfaction, and they also tend to view past events, other people, and consumer products more positively. Furthermore, people who are in bad moods find negative information more available or salient (Forgas & Bower (1987).

Schwarz (1990) and Sinclair & Mark (1995) document that people in bad moods are more engaged in detailed analytical activity, whereas people in good moods do not process information as critically. Furthermore, Mackie & Worth (1991) find that those in good moods are more receptive not only to weak arguments, but strong ones as well. However, Isen (2000) reminds that the interpretation of the results of such studies examining psychological effects can be difficult and complex.

Psychologist have been documenting correlation between sunshine and behavior for decades (Hirshleifer & Shumway 2003). For example, correlation between lack of sunshine and depression has been documented by Eagles (1994). Moreover, Tietjen & Kripke (1994) show in their research that lack of sunshine is also linked to suicides. Hirshleifer et al. (2003) conclude that most evidence suggests that people feel better when they are exposed to sunshine.

According to prior studies (see Molin et al. 1996; Schwarz et al. 1983; Young et al. 1997), SAD rises individuals' risk aversion when the amount of daylight is at its lowest, i.e. during the fall and winter. Moreover, Kramer & Weber (2012) find evidence that the depression associated with SAD affects risk aversion of investors. The authors use a survey with real financial payoffs to find that as the level of depression of SAD sufferers increases, choices that contain less risk are more frequently chosen.

Naturally, the medical literature has also been interested in explaining if depression causes heightened risk aversion among investors. Grable & Roszkowski (2008) conclude that there are two competing theories that explain how mood affects investors' risk aversion. These are the affect infusion model (AIM) and the mood maintenance hypothesis (MMH). The affect infusion model is supported by, for example, Forgas (1995), Smoski, Lynch, Rosenthal, Cheavens, Chapman & Krishnan (2008) and Kamstra et al. (2012). Forgas (1995) finds that negative mood leads to a heightened risk aversion and positive mood decreases it. Specifically, he finds that those in good moods are more probable to focus on positive environmental cues. On the other hand, those in bad moods tend to focus on negative incidents. Smoski et al. (2008) find that depressed individuals are less likely to participate in risky gambles.

Isen, Nygren & Ashby (1998) and Isen & Patrick (1983) suggest that the MMH theory is the correct theory. According to the MMH theory, people in positive mood are less willing to take risks because they want to preserve their current state. On the contrary, those who are depressed might want to take additional risks in hope that their current state would become more positive.

In the case of SAD, Kramer et al. (2012) argue that AIM explains the phenomenon better because an individual is in relatively persistent negative mood state. They also argue that MMH is more related to a behavior of an individual that is affected by more temporarily induced mood state. This thinking is supported by studies of Pietromonaco & Rook (1987), Smoski et al. (2008) and Raghunathan & Pham (1999). Pietromonaco et al. (1987) find evidence that depression is linked with heightened risk aversion, whereas Raghunathan et al. (1999) find that those individuals who are suffering from a temporary sadness are more willing to take part in riskier gambles.

Taking all this into consideration, the SAD hypothesis is that because sunlight affects the mood positively, the decreasing amount of daylight causes increased levels of depression and bad mood. As documented by Molin et al. (1996) and Young et al. (1997), this leads to a heightened risk aversion during the SAD season, i.e. during the fall and winter. This heightened risk aversion is thought to affect the financial markets. Given the link between depression and risk-taking, investors may be averse to buy upon good news and sell upon bad news, as hypothesized by Lin (2015). In the case of profit warnings, this would lead to a smaller magnitude of immediate response and a subsequent larger PEAD during SAD months. Prior studies about how SAD affects financial markets are reviewed in chapter 5.4.

4. LISTED COMPANY’S DISCLOSURE OBLIGATION

The purpose of the disclosure obligation is to ensure that investors have the correct and sufficient information on companies’ situations. For example, listed company’s disclosure obligation requires companies to report regularly on their financial development and on any surprising changes in their business or profitability. Due to the disclosure obligation, investors can rely on market functioning rationally and that capital is allocated to the most profitable targets. Securities market control is based on the idea that every investor has perfect information on companies, markets and prevailing prices. Furthermore, the disclosure obligation makes information more symmetric for market participants. Naturally, company executives are more aware of the situation of their company than investors are, but the disclosure obligation ensures that this insider information also transpires to investors’ knowledge. (Huovinen 2004: 3–5.)

Traditionally, the disclosure obligation is divided into a periodic disclosure obligation and into an ongoing disclosure obligation. The periodic disclosure obligation states that companies must report about their financial development. Companies must regularly publish, for example, a quarterly report, a management interim report, a financial statement bulletin, a financial report, an annual report and an annual summary. (Leppiniemi 2009: 126.)

The ongoing disclosure obligation means that a company has a continuous obligation to immediately publish all relevant information that may have an impact on the value of its share. Companies disclose such information by publishing an announcement, which is sent to the market operator and to the media at the same time. Particular caution must be exercised if a company’s securities are quoted in market places in several countries. The new information must be reported simultaneously to all market places. In general, companies do not announce new information when the company’s shares are traded in one market place while another market place is still closed. (Leppiniemi 2009: 126–127.)

When information that has a significant impact on the share price arises, a company must publish a stock exchange announcement. Such situations include, for example, acquisitions,

acquisitions of own shares or a weakened financial performance, in which case the company should announce a profit warning. (Leppiniemi 2009: 126–127.)

When a company is considering publishing a stock exchange announcement, the company must think about the relevance of the information and its potential effects on the value of a share from an investor’s point of view. The relevance of the information is always company-specific, and it can be influenced by the company’s internal changes and by changes in the external operational environment. Overall, if a company has handled its disclosure obligation in a satisfying manner, a publishing of the financial statement or a quarterly report should not result in a significant change in the company’s share price. (Mars, Virtanen & Virtanen 2000: 70–73; Leppiniemi 2009: 127.)

5. PREVIOUS STUDIES

This chapter has three main parts. First, Kothari's (2001) study of earnings response coefficient (ERC) is briefly reviewed to offer basic knowledge about earnings surprises. Even though profit warnings are generally examined using abnormal returns, the review of Kothari's (2001) study on ERC is relevant, because, in the end, a profit warning is just an extreme case of earnings report. Second, prior studies about companies' motives to announce profit warnings are examined. Third, prior studies on the markets' reactions to profit warnings are presented. Finally, previous studies on SAD's impacts on the stock market are reviewed in detail.

If a company has taken care of the requirements of its on-going disclosure obligation in a satisfying manner, neither the financial statement nor the interim report should cause a significant change in the company's share price. However, if they do cause a significant change in the share price, one can state that there is some information that has not been immediately reflected into the price of the share. In this case, the markets are not efficient.

In a similar way, according to the efficient market hypothesis, a profit warning should not result in a significant change in the share price. As a concept, an earnings report is close to a profit warning. The most significant difference between the two is that the earnings report is published on a regular basis. On the announcement date, whether it is a profit warning or an earnings report, the price of the share should not experience a significant change.

It is essential to review the fundamentals of profit warnings in detail to get a comprehensive understanding of the phenomenon. In order to examine the effect of SAD on profit warnings, first, one must understand the motives for publishing a profit warning and what kind of reactions can result from the publication of the profit warning. A review of prior studies also offers a good foundation for the research section of the thesis. In the research section, in chapter 7, I investigate whether the publication of a profit warning causes abnormal returns in Finland during 2011–2017. Furthermore, the main interest in this thesis is to examine how SAD affects those abnormal returns. The relation between SAD and profit warnings has not been previously studied, which is the reason I review prior studies about the impacts of SAD on quarterly earnings reports and the stock market in general.

5.1. Earnings response coefficient

Kothari (2001) examines how much the price of a share changes when the earnings of a company are announced. This change is measured by the earnings response coefficient (ERC). In order to estimate the magnitude of this coefficient, one must choose a valuation model, predict future revenues, and determine the discount rate. To predict future revenues, financial statements of the company are often used. The magnitude of the coefficient is influenced in particular by four factors: persistence, risk, growth opportunities, and interest rate. Persistence means that the greater the expectation of the future earnings of the market is, the greater the coefficient is (Kormendi & Lipe 1987; Easton & Zmijewski (1989). Easton et al. (1989) state that risk, in this context, refers to a systematic risk and it has a negative effect on ERC; the higher the risk, the higher the interest rate and thus the smaller discounted value.

Collins & Kothari (1989) explain that growth opportunities refer either to ongoing projects or future projects that are expected to yield higher return than their risk-adjusted rate of return suggests. However, this is not a proof of market inefficiency, as this only means that the company has extra pricing power, for example, because of a monopoly position. Obviously, growth opportunities affect the coefficient positively. Collins et al. (1989) continue that interest rate refers to the risk-free rate, which affects the coefficient negatively. Naturally, the higher risk-free rate increases the discount rate and thus reduces the magnitude of the coefficient.

ERC has been found to be empirically too small; the share price changes less than valuation models estimate. This can be explained by at least four different hypotheses. The first hypothesis is that the estimation of the result, and in particular the assessment of the "surprise" part of earnings report or profit warning, is difficult. Second, the market inefficiency can be considered. If the market is not able to interpret the earnings surprise correctly, the coefficient is smaller than it should be. It has been observed that the markets underreact to earnings surprises and the new information is gradually reflected into the price of the share. One example of this could be the previously demonstrated post-earnings-announcement drift anomaly. (Kothari 2001.)

The third reason why ERC is observed to be too small, can be explained by inadequate GAAP. This may result in a so called “low quality” earnings that are poorly correlated with the return of the share. In other words, there is a chance that the reported earnings by companies are not completely substantial. As the fourth hypothesis, one can consider so-called temporary earnings. This means, for example, that companies may have large one-off transactions. Such actions have an impact on the company’s book values, which can make it difficult to evaluate ERC. (Kothari 2001.)

ERC can be used for examining a profit warning, but when the impact of a profit warning on the company’s share is considered, the abnormal return of the share is often examined instead. This relationship between the share return and the profit warning is more generally studied using the event study methodology. The event study methodology is presented in chapter 6.3.1.

5.2. Issuing of a voluntary profit warning

Skinner (1994) points out in his research that a negative profit warning will cause a stronger reaction to the share price than a positive profit warning. He is particularly interested in why companies voluntarily publish negative or positive profit warnings. Skinner (1994) states that companies publish negative profit warnings to avoid possible legal costs. If a company reveals an extremely negative earnings report, there is a possibility that the company will be prosecuted because it has not published a profit warning. On the other hand, if a company reveals a particularly positive earnings report, no one is prosecuting the company even if it did not announce a profit warning.

The reasons for publishing a positive or a negative profit warning can be quite different. The most important reason for publishing a negative profit warning is to avoid possible litigation.

A company may also publish a negative profit warning because, for example, it tries to improve its relations with the investors or because it tries to maintain its reputation. On the other hand, companies may publish positive profit warnings because they want to stand out from competitors. (Skinner 1994.)

Skinner (1997) continues his earlier research and finds evidence that companies voluntarily publish unfavorable earnings announcements much more often than any other kind of earnings announcements. Moreover, he finds more evidence that potential legal costs affect the most on the decision of publishing a profit warning. He finds in his research that companies are more likely to publish a profit warning when there is a high chance of prosecution. Skinner (1997) finds that if a company has an ongoing lawsuit in the quarter, it is more likely to announce a profit warning. However, he notes that this evidence is inconsistent with the hypothesis that publishing a profit warning could avoid possible litigation.

Kaznik & Lev (1995) investigate publications of voluntary profit warnings and the market reaction to these publications. They observe companies that released unexpected profits on the earnings announcement day. Kaznik et al. (1995) monitor the communication of these companies from the last 60 days before the announcement day. They find that about half of the companies do not warn about the profits in advance. Less than ten percent of the companies warn about the weakened performance by publishing quantitative information. The more negative the profit warning is, the more likely the company is to publish a profit warning and also provide more accurate quantitative information about its performance. In addition, Kasznik et al. (1995) find that a negative profit warning is more likely to be published than a positive profit warning.

According to Kasznik et al. (1995), companies that publish a profit warning experience a greater reaction to their market value than those companies that decide to wait for the official earnings report date. Because of this reaction, Kasznik et al. (1995) rationalize the decision of companies to leave the profit warning unpublished. They find that companies publish profit warnings when the change in the performance is caused by permanent factors. If the negative performance is due to a random one-off factor, for example, a factor that affects only one quarter, the odds are that the company is not going to publish a profit warning. Kothari, Shu & Wysocki (2009) also state that companies are reluctant to voluntarily publish negative information in advance. However, companies are generally happy to publish positive information beforehand.

When it comes to issuing a profit warning, Kasznik et al. (1995) also report industry-specific differences. Especially high technology companies are more likely to publish negative profit warnings. High-tech companies are often riskier than other companies, which makes them more vulnerable to legal proceedings. This may be an explanation of why high-tech companies are publishing profit warnings more frequently. Regulated industries, such as the banking sector, publish profit warnings less frequently on average. One possible explanation for this is, for example, that such industries report about their performance and operations more than once in a quarter. Therefore, the information is not as unevenly distributed as in other industries.

Kasznik et al. (1995) argue that a corporate structure also has an impact on how likely it is for a company to publish a profit warning. Issuance of negative profit warnings is affected by company size, previous forecasts, and if the company is operating in a high-tech industry. Issuance of a positive profit warning is not affected by the high-tech sector, but similar to a negative profit warning, it is affected by company size and previous forecasts. Large companies issue more profit warnings than small companies. One reason for this may be that large companies are more exposed to litigation than small companies.

Soffer, Thiagarajan & Walther (2000) find that there are differences in how companies announce negative and positive profit warnings. When a company issues a negative profit warning, it publishes it with all possible information and leaves nothing untold. In the case of a positive profit warning, companies publish only a part of all possible information; some parts of the information are left for the official earnings report day. Soffer et al. (2000) note that the market seems to be more interested in the official earnings report. The pre-announced information does not seem to be as interesting as the official report. Because of this, companies publish all the negative information before the official day and only a portion of the positive information. Companies are trying to control the change in the share price which is caused by the publication. However, the study states that the market seems to underreact to profit warnings, as the outcome of the official earnings report still significantly affects the share prices.

Dayanandan, Donker & Karahan (2017) investigate the effect of issuing a profit warning on market liquidity. They discover that a company's decision to issue a negative profit warning strengthens its liquidity after the announcement day. The negative profit warning reduces the uneven distribution of information, reduces the bid-ask-spread and increases the trading volume of the share. Therefore, it is possible to reduce the cost of capital by issuing a profit warning. If the economy is on a boom, issuing a profit warning will cause a bigger reaction to the share price. The study shows that although the reactions caused by a negative profit warning are generally negative, the company may experience a significant improvement in its liquidity when it issues the negative profit warning.

Francoeur (2008) suggests that the management can decide to issue a profit warning for its own interest. The more the management owns the company's shares, the less eager it is to issue a negative profit warning, as it would also cause a decrease in the value of their own investment. Francoeur (2008) also states that the management may issue a negative profit warning if it feels that the company's share is too overvalued. If the management believes that analysts' forecasts for the company are too optimistic, the management may issue a profit warning to curb this overvaluation. However, Francoeur (2008) states that if it is the market that has overestimated the share price, the management will not do anything about the situation.

5.3. Markets' reaction to profit warnings

Jackson & Madura (2003a.) investigate the effect of negative profit warnings on the share return. They conclude that issuance of a negative profit warning causes a significant negative reaction to the return of the share. The abnormal return is found to be -10,75 percent on the announcement day. The study also reveals that the date of the announcement does not affect the abnormal return. It does not matter if a company announces the profit warning more than one month before the official earnings report day or if it announces it less than one month before the official day. In both situations, the statistical impact on the share return is the same. However, smaller companies experience a larger reaction to their share price on the profit warning day than large companies. Smaller companies are followed less, which makes their announcements more surprising.

Although the biggest reaction occurs on the day when the profit warning is announced, Jackson et al. (2003a.) find that the price of the share begins adjusting already five days before the announcement day. This may be due to a leak of insider information to the public or to the fact that the market has been able to predict the deteriorating situation, for example on the basis of the economic situation. Jackson et al. (2003a.) also argue that even though the return of the share experiences a major reaction on the day of the profit warning, the market still underreacts to it. Abnormal returns are generated even five days after the profit warning. During the period of five days before the profit warning and five days after the profit warning, the cumulative abnormal return is -21,69 percent. However, overall, the markets may overreact to profit warnings, as positive abnormal returns occur on days 11–60 after the profit warning.

In their other study, Jackson & Madura (2003b.) investigate foreign shares listed in the United States, and how profit warnings affect such shares. Likewise, foreign companies also experience negative share returns on the day of the profit warning. On the profit warning day, the abnormal return is -6,47 percent. However, the cumulative abnormal return 10 days before the profit warning is found to be -4,61 percent. Jackson et al. (2003b.) argue that because of this, the markets are inefficient and insider information has been exploited by selling the shares in advance.

Kasznik et al. (1995) state that the markets punish companies for openness. Tucker (2007) finds results that strengthen this claim. Companies that decide to publish a profit warning experience a greater shock to their share return than companies that decide to wait for the official earnings report day. These findings hold even between companies with a similar risk profile. However, Tucker (2007) reminds that companies which publish a profit warning have more negative information to offer to the market than those companies which wait for the official day. Share returns are found to be 10,1 percent lower on average for those companies that publish a profit warning. However, Tucker (2007) finds evidence that, after all, the markets do not punish more companies that announce a profit warning; when the research period is increased to three months, the difference in share returns disappears.

Xu (2008) also investigates differences between companies that decide to issue a profit warning and companies that decide to wait for the official earnings report day. He also finds that the markets punish more those companies that issue profit warnings. However, Xu's (2008) results do not provide evidence that the markets would overreact to profit warnings. When companies that publish profit warnings are compared to companies that do not publish them, it is noticed that during several different longer time periods, abnormal returns of these companies are not significantly different.

Tawatnuntachai & Yaman (2007) study what kind of a reaction issuing a profit warning causes to the company's share price and enterprise value. Similar to other studies, they also find that a negative profit warning causes a strong negative reaction to the share price. Furthermore, companies that warn about the deteriorating performance in advance experience a stronger reaction than those companies that do not warn in advance. However, according to the study, this difference does not mean market overreaction. Although the price of the share falls fiercely, there are no significant differences between the two choices when enterprise value or operational performance are considered. Whether the company issues a profit warning or waits for the earnings report day, in the long run, there are no significant differences observed in the returns of the shares either.

Tawatnuntachai et al. (2007) argue that the strong reaction in the share price on the day of the profit warning is not a sign of overreaction, but rather a sign of investors' change of perception of the company's long-term performance. Therefore, the authors conclude that the decision of issuing a profit warning is irrelevant to the share return in the long run.

Bulkey & Herrerias (2005) distribute negative profit warnings to qualitative and quantitative profit warnings. A qualitative profit warning refers to an announcement where the company bluntly states that earnings forecasts will not be reached. A quantitative profit warning means more accurate information about the company's earnings and often the company provides corrections to earlier forecasts. Both types yield negative abnormal returns, but qualitative profit warnings cause much greater reaction than quantitative profit warnings. Qualitative profit warnings result in a 9,6 percent negative cumulative abnormal return over a three-month period, whereas quantitative profit warnings yield only a -2,2 percent cumulative abnormal return. It can be concluded that the market responds more strongly to vague information.

Quantitative and qualitative profit warnings are observed to affect share returns of small companies significantly more strongly than large companies. Furthermore, growth companies are found to respond slightly more to profit warnings than value companies, but this difference is not statistically significant. According to the study, the market is underreacting to profit warnings, as abnormal returns also occur several days after the profit warning. (Bulkey et al. 2005.)

Cox, Dayanandan & Donker (2016) study how a company's decision to issue a profit warning affects other companies in the same industry that do not publish any foreknowledges. They find that profit warnings in the same industry also affect those companies that do not issue profit warnings. The profit warning is considered to bring more information to the market about the whole industry, which also affects the returns of the shares of other companies in the same industry. How strongly the companies that do not issue profit warnings are affected by those companies' decisions that do announce profit warnings, is depended on the general economic situation. The effect on other companies is positively correlated with the general economic situation; during a boom the effect is larger and during a contraction the effect is smaller. In addition, Cox et al. (2016) find that domestic companies experience a greater movement in the share return than international companies.

Using the Fama & French three-factor model, Cox, Dayanandan, Donker & Nofsinger (2017) investigate U.S. listed companies that have issued profit warnings during 1995–2012. They find that a negative profit warning causes a -13,38 percent abnormal return on the day of announcement. Furthermore, the cumulative abnormal return 30 days before the announcement day is -5,27 percent. On this basis, they interpret that insider information has leaked to the market or the market has anticipated the profit warning. The market has begun to adjust to the situation even before the publication of profit warning. However, the market does not adjust strongly enough, as on the announcement day, the return of the share still experiences a strong reaction.

Cox et al. (2017) also find that the markets punish companies for their openness. Issuance of a profit warning results in a higher negative abnormal return when compared to a situation where the company waits for the official earnings report day. Companies that do not publish profit warnings experience only an abnormal return of -1,17 percent on the earnings report date.

Cox et al. (2017) continue their research by examining whether the general economic situation has any effect on the reaction caused by a profit warning. They find that if the economy is in recession, profit warnings do not cause as strong reactions as in boom. If the economy is in recession, bad news are not as surprising, which means that the price of the share will not fluctuate so strongly.

Cox et al. (2017) argue that companies have an opportunity to disclose the negative information prematurely or to wait for the earnings report day. They note that even though a disclosure of negative information in advance may be justifiable for example due to legal obligations, it is worth considering the significant negative reaction to the company's share price. According to their research, when the economy is in recession, the markets do not respond as strongly to profit warnings. Therefore, it may be more profitable to issue a profit warning when the economy is in recession.

Spohr (2014) investigates profit warnings in different Nordic countries; Finland, Sweden, Denmark and Iceland in 2005–2011. First, he finds that the data set is clearly skewed towards Finland, as over 70 percent of all profit warnings are from Finland. Alves, Pope & Young (2009) also find that Finnish companies tend to issue profit warnings more frequently than other European companies. Spohr (2014) finds that on the day of the profit warning, the abnormal return for positive warnings is 4,8% and for negative ones it is -6,1 percent. Interestingly, abnormal returns continue to be significant four days after the profit warning. However, this is true only for negative warnings, as the abnormal return from positive profit warnings is significant only on the announcement day. Spohr (2014) also finds evidence that the market response is bigger if the warning is issued by a high-risk company and if the issuance comes as a surprise to the market.

5.4. Seasonal Affective Disorder and financial markets

Kamstra et al. (2003) are the first to document the relation between SAD and stock returns. Before this study, the closely related literature is by Saunders (1993), who examines the effect of sunshine on stock markets. As the amount of sunshine is factored by the amount of cloud cover and number of hours of daylight, Saunders (1993) uses these to find a positive correlation between the amount of sunshine and stock returns. Later, Hirshleifer & Shumway (2003) provide more evidence from 26 different stock markets and find results similar to Saunders' (1993) study.

Kamstra et al. (2003) investigate four stock indexes in the U.S. and eight indexes from all over the world, including northern markets in Sweden and southern markets in Australia. Just by looking at the average returns, the conclusion is clear for all the indexes; returns are low in early autumn and at their lowest in September. Autumn is followed by higher returns as days begin to lengthen. To capture the SAD effect from this finding, Kamstra et al. (2003) use standard approximations from spherical trigonometry. This methodology is presented in chapter 6.3.2. SAD is found to be statistically significant in all studied countries. Furthermore, the farther away the county is from the equator, the stronger and more significant the SAD variable is. They are also able to find that investors try to avoid risky investments during the fall. Consistent with the SAD-induced seasonal pattern in returns, investors are found to resume their risky holdings in the winter. In other words, when the amount of daylight is decreasing, investors become more risk averse. When the amount of daylight starts to increase towards the winter, investors start to see "light at the end of the tunnel" and they become less risk averse, i.e. they resume their risky investments.

Using these findings, Kamstra et al. (2003) illustrate a trading strategy that could have been used during 1980–2010. They compare two different portfolios: a neutral portfolio and a

SAD portfolio. The neutral portfolio consists of 50/50 allocation between the Swedish index and the Australian index. The SAD portfolio is formed by reallocating 100 percent of the portfolio between the Swedish and Australian index. The investor puts her money in the Swedish market during the Northern Hemisphere's fall and winter and shifts the investment to Australian markets during the Southern Hemisphere's fall and winter. Using this strategy, the investor gains 7,9 percent higher return compared to the first strategy.

Kaplanski, Levy, Veld & Veld-Merkoulova (2015) conduct a survey in Netherlands and study approximately 5 000 households. Their analyses are based on 1 465 questionnaires done by individual investors. They find that positive investor sentiment is positively correlated with higher expected returns and lower expected risk. Moreover, they find that SAD also affects return expectations, as SAD is found to be correlated with mood. They conclude that SAD is an important factor in forming subjective expectations. Consistent with prior studies, Kaplanski et al. (2015) find that SAD sufferers have low expected returns in autumn.

Garret, Kamstra & Kramer (2005) use a conditional version of the CAPM to capture the effect of SAD. Their model allows the price of risk to vary over time. Using a daily and monthly market data from several countries: the U.S., Japan, the UK, Sweden, New Zealand and Australia, they are able to detect the SAD effect. Furthermore, they state that their model is able to capture the SAD effect completely. They conclude their study stating that SAD might be a natural coincidence of changes in risk aversion over time.

Kamstra, Kramer & Levi (2015) study U.S. Treasuries and try to find if more evidence supporting SAD could be found. Naturally, if investors indeed approach less risky assets in autumn, because of heightened risk aversion, U.S. Treasuries would be a clear choice, as they are generally thought to be the risk-free asset. Kamstra et al. (2015) study seasonal changes in the returns of U.S. Treasuries. They find that monthly returns are approximately 80 basis points higher in October than in April. They elaborate that this difference is economically and statistically highly significant. They control for various factors, for example, macroeconomic cycles, employment turnover, stock market volatility, FOMC announcement cycle and the Fama-French momentum factors, and find that none of these are able to explain a notable proportion of the seasonality in returns. The only model that explains this is the model that has a proxy for seasonal variation in risk aversion. This model explains over 60 percent of the swing in returns.

Dolvin, Pyles & Wu (2009) study effects of SAD to stock market analysts. Optimism and pessimism of analysts' estimates is widely studied subject. However, the conclusion can be viewed as controversial, even though the analysts' bias is widely accepted in the literature. Some studies (see, for example, Brown & Rozeff 1978; Lim 2001; Hilary & Menzly 2005) state that analysts are too optimistic in their estimates whereas some studies (see, for example, Brown 2001; Matsumoto 2002; Richardson, Teoh & Wysocki 2004) find increasing pessimism. Dolvin et al. (2009) find evidence that analysts' degree of pessimism increases during fall and winter. The results are especially strong for states located in the North where SAD is found to be more prevailing. They suggest that the increased pessimism caused by SAD, offsets the existing positive bias. So, as a result, they conclude that SAD makes analyst estimates more accurate as a whole.

Dolvin & Pyles (2007) investigate if SAD affects pricings of initial public offerings (IPOs). The authors collect data of issued IPOs during 1986–2000. They find evidence that companies that decide to go public in the fall and winter, must offer their shares at a lower price. The reason for this is that as investors are affected by SAD, their risk aversion is increased and demand is lowered. Therefore, companies must offer their shares at a lower price to induce investors. However, even though they expect to find an asymmetric effect around the winter solstice, they are not able to find any evidence of this. In other words, they are not able to prove that underpricing is more prevalent during the fall months than during the winter months. However, they do find evidence that offer price revisions are increased especially during the winter months. This is consistent with the SAD hypothesis; investors' emotions are becoming more positive, as days begin to lengthen.

Kliger, Gurevich & Haim (2012) challenge the efficient market theory on chronological grounds. As the efficient market theory states that investors act rationally, Kliger et al. (2012) also find that SAD affects pricings of IPOs. The authors investigate the short and the long-run performance of IPOs. In the short run, IPOs issued during shortening days (depressive days) generated less returns than IPOs issued during lengthening days (cheerful days). This is consistent with the study of Dolvin et al. (2007). When returns are examined in the long-run (1.5–3 years), the authors find that excess returns of IPOs issued during the cheerful days revert to the grand mean of returns of IPOs. Nevertheless, the initial difference in returns between IPOs issued during the cheerful and depressive days is 5–10 percent of the offering. If the company is publicly less exposed, this difference increases as high as up to 15–25 percent.

Dolvin & Fernhaber (2014) continue the investigation of IPOs and SAD. Similarly to prior studies, they find that SAD affects pricings of IPOs. More importantly, they find evidence that especially younger companies are affected by SAD. This finding is consistent with the study of Kliger et al. (2012), as one can interpret younger companies as publicly less exposed. Even though Dolvin et al. (2014) find that SAD influences IPO underpricing, they state that using a high-quality underwriter or changing the share retention decision can be used to reduce the causation.

Kamstra et al. (2017) find evidence of seasonality in investors' risk aversion. They investigate the money flow between mutual fund categories and find that investors prefer same mutual funds in autumn and risky funds in spring. The authors document that this finding is correlated with seasonality in investors' risk aversion, which is affected by SAD.

Kaustia & Rantapuska (2015) challenge the prior literature that claims that weather and length of day affects stock returns. They study these factors in Finland, which should offer a great opportunity to study this causality, as weather and length of day have significant variation in Finland. The authors have massive data set of account level stock trading data from January 1995 through November 2002. Their final data includes 1,2 million individual investors, 45 000 institutions and 13 million trades. The authors cannot find any statistical significance of sunniness or temperature, but find that precipitation is economically and statistically highly significant. Furthermore, they find little evidence that SAD affects to tendency to buy versus sell. However, they find that SAD might have a positive effect on the volume of trade.

Kaustia et al. (2015) state that they do not find any clear seasonal patterns that are originated from environmental mood variables. However, they do find a pattern that seems to correlate with holiday seasons. They find that investors trade less during the holiday season and tend to sell their investments prior the holiday. They argue that vacation-related consumption could be a lucid explanation to this. This finding is consistent with the Halloween effect.

Lin (2015) studies the effects of SAD on quarterly earnings announcements in the U.S. markets. Lin (2015) documents evidence that during the SAD months, the immediate reaction to earnings announcements is lower. Furthermore, PEAD is found to be higher during the SAD months. This is explained by the fact that due to an increased risk aversion, investors tend to react slowly. The immediate reaction is asymmetric; in the fall, the SAD effect is stronger than in winter. Interestingly, Lin (2015) does not find evidence that this kind of asymmetry prevails in the case of PEAD. She also reports differences in positive and negative earnings announcements. SAD is found to have an immediate influence on positive earnings announcements, but in the case of negative earnings, there is no statistically significant difference in returns between the SAD season and other seasons.

Lin (2015) argues that the direction of earnings announcements is important. The immediate reaction to positive earnings announcements is smaller during the SAD seasons, as investors are more risk averse. However, she does not find evidence that SAD affects the immediate reaction to negative earnings announcements. She argues that this is due to the ostrich effect. The ostrich effect is a human tendency to pretend that negative or uncomfortable information does not exist. Lin (2015) argues that during the SAD season, people are more likely to alleviate cognitive dissonance by actively avoiding information that could increase the dissonance.

Lin (2015) also investigates abnormal trading volumes and finds that the three-day abnormal volume is lower in the fall for positive earnings announcements. Investors are found to be more risk averse and less willing to trade even when positive information is released. When the daylight starts to increase, trading volumes also increase. The SAD effect is asymmetric; investors trade less in the fall than in the winter. Lin (2015) notes that these findings hold only when positive earnings announcements are considered. The same argument for the ostrich effect is given. Moreover, she finds that the SAD effect is more prevailing in stocks that investors are more interested in. This kind of salience is proxied by firm size, age, turnover and number of analyst recommendations.

Even though several studies have found SAD affecting financial markets, there are also researchers who criticize these studies. The main point of critique is that even if a seasonal effect is documented, it does not necessarily mean that the effect is caused by SAD.

Kelly & Meschke (2010) extend and replicate the study of Kamstra et al. (2003). They show that the SAD hypothesis is not supported by psychological or econometric literature. They state that SAD does not affect stock returns. They argue that that the SAD effect is only a "turn-of-year" effect. Furthermore, they claim that the SAD model has econometric problems in it; according to their study, the SAD model mechanically induces the statistical significance of the SAD variable. Kelly et al. (2010) conclude that the medical or psychological evidence is not sufficient to state the causation between the SAD effect and investor sentiment.

Because of the accusations of Kelly et al. (2010), Kamstra, Kramer & Levi (2012) re-examine the causation of the SAD effect and stock returns. Kamstra et al. (2012) shred the study of Kelly et al. (2010), stating that they misinterpret their empirical results, ignore several coefficient-estimates that clearly support the SAD hypothesis, and in the end, only interrupt legitimate scientific research. According to Kelly et al. (2010), the SAD effect is no different from a "turn-of-year" effect. Kamstra et al. (2012) remind that the original study of Kamstra et al. (2003) specifically controls for such "turn-of-year" effects. Furthermore, as Kamstra et al. (2012) study the data of Kelly et al. (2009), they find statistically significant results that clearly support the SAD hypothesis. Lastly, Kamstra et al. (2012) state that Kelly et al. (2010) misrepresent the finance, psychology and medical literatures, choosing selective quotes that can easily misguide readers.

Jacobsen & Marquering (2008) also challenge the study by Kamstra et al. (2003). They do find strong evidence of seasonality in stock returns, but state that the evidence to conclude that SAD is the reason for this, is not sufficient. The authors argue that other variables with a seasonal pattern can be used to explain the change in returns in the fall and the winter. For example, the Halloween indicator seems to explain these returns better than the SAD variable. The main argument is that Kamstra et al. (2003) cannot conclude that the SAD effect is responsible for the change in investors' risk aversion. Moreover, as there is also contrary evidence that people in good moods become more risk averse and people in sad moods become less risk averse (see Parker & Tavassoli 2000), Jacobsen et al. (2008) argue that the evidence supporting the SAD hypothesis is not adequate.

Jacobsen et al. (2008) argue that there is no reason for complex trigonometry to calculate the SAD variable, as a simple seasonal dummy variable would be a better choice. Kamstra, Kramer & Levi (2009) publish a comment for study of Jacobsen et al. (2008). Kamstra et al. (2009) state that there are several methodological problems in the study of Jacobsen et al. (2008). Kamstra et al. (2009) are not able to replicate the findings of Jacobsen et al. (2008), and note that there are misspecifications in their econometric model. However, even though Kamstra et al. (2009) agree that SAD might not be an explanation for all variation in equity markets, they state that the economically and statistically significant results of the original study by Kamstra et al. (2003) still hold.

Jacobsen & Marquering (2009) response to the comment by Kamstra et al. (2009). They note that Kamstra et al. (2009) miss the main point of their paper; that several things are correlated with the well-known summer-winter pattern in stock returns and it is difficult to recognize what exactly is causing this pattern. Jacobsen et al. (2009) claim that the evidence of Kamstra et al. (2009) is not convincing and that they just assume that it is the SAD causing the pattern. Jacobsen et al. (2009) show that they can explain the pattern by ice cream consumption or airline travel. Therefore, Jacobsen et al. (2009) conclude that there is not enough evidence to state that the SAD effect is influencing stock returns. Because of these controversial thoughts, a further investigation of the SAD effect is needed.

6. DATA AND METHODOLOGY

The used data, research hypotheses, and methodology are presented in this chapter. Briefly, the data consists of Finnish stock return data of companies who have issued profit warnings during 2011–2017 and the actual profit warnings announcements. In addition, several control variables are used in the regression analysis. The research hypotheses are presented at the end of this chapter. Lastly, in chapter 6.3., the methodology used to study these hypotheses is presented.

6.1. Data description

This study uses profit warnings issued by Finnish companies during the period 2011 to 2017. Profit warnings are gathered by hand from NASDAQ OMX Central Storage Facility (CSF) using several different keywords, for example, announce, outlook, profit warning, guidance, change and profit. Using these and other keywords, approximately 9 800 announcements were reviewed, and finally 354 profit warnings were selected.

An announcement is defined as a profit warning, if certain qualities are fulfilled. First of all, the announcement must report about a significant change in the company's expected earnings or financial performance. Moreover, the announcement must be a separate stock exchange announcement. Any foreknowledge given in an interim report, financial statement, or with any other significant event, has not been included as a profit warning. If a company issues an announcement about changing its long-term strategy or updates its long-term financial goals, such announcements are not included as profit warnings. Announcement about nonrecurring items can be defined as a profit warning only if the company clearly states that these items will affect its earlier guidance. If a company issues an announcement where it states that the company maintains its guidance despite difficult financial times, I have not included such announcements as profit warnings. Any announcement about change in equity or share issues are not taken into account.

It is worth noting that it is not always distinct if an announcement is a profit warning or not. When choosing if an announcement can be included in the material, it is often required to check the company's earlier announcements about its earlier guidance. Moreover, some profit warnings are omitted from the material because of lack of trading or lack of return data**.** Shares that constantly trade at less than 1 euro are omitted from the material. It is notable that in Finnish stock market several companies with a share value of less than 1 euro have issued especially negative profit warnings. The final number of profit warnings used in the study is 286. These profit warnings are listed in Appendix 1.

The data consists of 102 positive profit warnings and 184 negative profit warnings. Figure 3 shows how negative and positive profit warnings are scattered around the year. Most of the profit warnings are announced in October and January. One explanation for the high number of warnings in October can be that announcement of Q3 earnings reports is close. In January, the financial statements or Q4 earnings reports are usually disclosed. The lowest amount of warnings is in May. Once again, the cycle of quarters can explain this. Most of the profit warnings regarding Q1 earnings report are already announced in April.

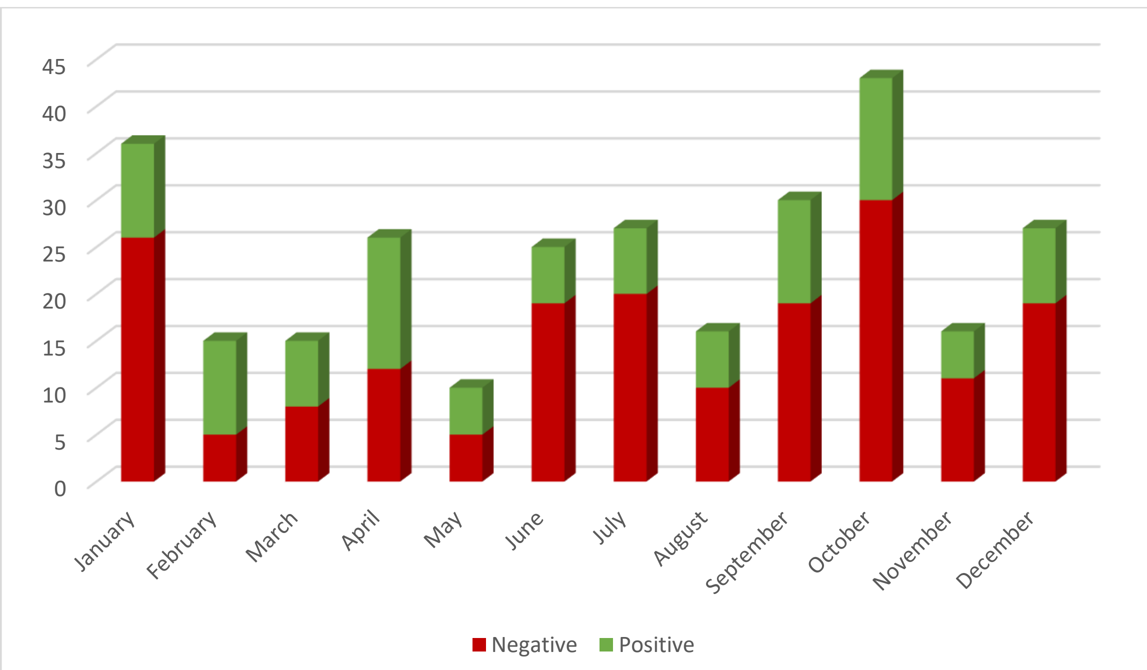

Figure 3. Positive and negative profit warnings on a monthly basis.

Table 1 shows the distribution of negative and positive profit warnings used in the study in more detail. Over 50 percent of the profit warnings are announced during the SAD season, i.e. during the fall and winter. Furthermore, there are more profit warnings announced in the fall than during the winter. If investors' risk aversion is heightened during the SAD season, it might be beneficial for companies to announce their negative profit warnings especially in the fall and positive profit warnings during the spring and summer.

Table 1. Distribution of positive and negative profit warnings to SAD season, non-SAD season, Fall, non-Fall and Winter.

Panel A: SAD and non-SAD			
	SAD	**Non-SAD**	**Total**
Negative	101	83	**184**
Positive	53	49	**102**
Total	**154**	**132**	**286**
Panel B: Fall and non-Fall			
	Fall	**Non-Fall**	**Total**
Negative	64	120	**184**
Positive	25	77	**102**
Total	**89**	**197**	**286**
Panel C: Fall and Winter			
	Fall	**Winter**	**Total**
Negative	64	37	**101**
Positive	25	28	**53**
Total	**89**	**65**	**154**

Daily stock return data and control variables for regressions are obtained from Datastream and EPS estimates from I/B/E/S. Figure 4 shows how indexes OMXH and OMXHCAP have developed during 2010–2017. OMXH indicates the overall performance of all shares listed in the stock exchange. OMXHCAP also indicates the overall performance of all shares listed in the stock exchange, but one stock cannot have a weight more than ten percent. For example, during the best days of Nokia Plc, OMXH was strongly correlated with the development of Nokia Plc's share price. This is the main reason why OMXHCAP is used as the reference index in this study. Moreover, the use of value-weighted index is common in prior literature. The used index is a return index, i.e. it includes dividends.

Figure 4. Returns of OMXH and OMXHCAP return indexes during 2010–2017.

Kamstra et al. (2003) assume in their study that winter solstice takes place on the 21st of December and summer solstice on the 21st of June. They also note that the actual timing can vary by a couple of days. Kamstra et al. (2003) and Lin (2015) define fall as 21st of September to 20th of December and winter as 21st of December to 21st of March. I also follow these definitions in my study.

6.2. Hypotheses

The main part of interest of this thesis is to examine the possible effects of SAD to profit warnings. However, also market reactions to profit warnings are examined. The reason for this is to provide a deeper understanding of profit warnings. Tests related to profit warnings can be seen as a supplemental information about the phenomenon. However, reviewing the market reaction to profit warnings helps to understand the magnitude of the event, but also how long it takes for markets to react. Furthermore, if the abnormal returns are found to be insignificant, one can argue that it is unreasonable to test how SAD affects the immediate reaction to profit warnings. A brief analysis of the abnormal returns also reinforces the descriptive statistics.

As profit warning offers new information for the market and can happen unexpectedly, I expect to see abnormal returns on the day of the profit warning. This leads to the first hypothesis:

H1: *An announcement of profit warning generates abnormal returns on the day of the announcement.*

Jackson et al. (2003a.) find that abnormal returns are generated even before the profit warning. This means that the market anticipates the profit warning. To examine this possibility, I investigate the second hypothesis.

H2: *The market anticipates the profit warning and abnormal returns are generated a few days before the announcement.*

Jackson et al. (2003a.) also find that abnormal returns are generated even five days after the profit warning. This suggests that the market has difficulties in determining the magnitude of the profit warning. Because of this reason, I examine the third hypothesis.

H3: *Abnormal returns continue generating after the announcement, as the market cannot assimilate the information quickly enough.*

Because SAD sufferers' risk aversion increases during the SAD season, they tend to be more careful about their investment decisions. This should lead to a smaller immediate reaction to profit warnings during the SAD season. Reviewing the results of Lin (2015), I expect to find a significantly smaller immediate reaction to positive profit warnings in the fall. However, because of the ostrich effect, I do not expect to find a significant difference when negative profit warnings are examined. The ostrich effect refers to investors' tendency to avoid bad news. To avoid an exposure to bad news, investors pretend that the news do not exist. Prior studies have used the ostrich effect as an explanation for such results. For example, Galai & Sade (2006) explain differences in returns in the fixed income market with the ostrich effect. Moreover, Karlsson et al. (2009) also find evidence supporting the ostrich effect. As profit warnings are very similar to earnings announcements, I expect to find results similar to Lin (2015). This leads to the fourth hypothesis.

H4: *Because of seasonal affective disorder, the immediate reaction to positive profit warnings is smaller during the SAD season, but there is no significant difference for negative profit warnings between SAD and non-SAD seasons.*

According to Kamstra et al. (2003), investors who are affected by SAD can behave differently in the fall months versus the winter months. Even though the amount of daylight is low in the winter, its length is increasing. As the amount of daylight starts to increase after the winter solstice, investors' risk aversion should start to decrease, i.e. investors are more willing to take risks and trade more. Therefore, the PEAD should be larger during the SAD season than during the non-SAD season, when the amount of daylight might be decreasing. Furthermore, as the amount of daylight increases towards the spring, the PEAD should be higher during the winter than during the fall. This conjecture signifies an asymmetric effect in SAD. I examine these possibilities with the following hypotheses:

H5: *Because of seasonal affective disorder, the PEAD is larger during the SAD season.*

H6: SAD has an asymmetric effect, which leads to a smaller immediate reaction to profit warnings in the fall and higher magnitude of PEAD in the winter.

6.3. Methodology

Methodology, i.e. methods used to study hypotheses, are presented in this chapter. First, it is examined if profit warnings generate abnormal returns around the announcement day. After examining the abnormal returns, it is studied if the SAD effect affects those returns.

Daily returns of shares are calculated in the following way:

$$R_{it} = \ln(P_{it}) - \ln(P_{it-1}) \tag{5}$$

where R_{it} = return of a share on day t

$\ln(P_{it})$ = natural logarithm of a share's closing price

$\ln(P_{it-1})$ = natural logarithm of a share's closing price on day t-1.

When calculating daily returns of the index, R is the return of the index and P is the closing price of the index.

The rest of the chapter is formed in the following way. First, the event study methodology which is used to study abnormal returns of profit warnings is presented. Second, the methodology to study the SAD effect, the so-called sine wave measure, is presented. Lastly, regression equations used in this study are discussed in detail.

6.3.1. Event study methodology

Event studies are used to measure the impact of various market incidents. In this study, event study methodology is used to measure the impact of profit warnings to companies' stock prices. The method is based on the assumptions that markets function rationally, and the information is correctly and instantly reflected to the prices. Event studies are a common approach to examine abnormal returns. (MacKinlay 1997.)

To conduct an event study, first it is needed to specify the event that is to be examined. Next, one must specify the period over which the security prices of the firms involved in the event will be examined. This time interval is called an event window. It is common to determine the event window to begin already before the realization of the studied event and to continue after the event. This way it is possible to detect the price movements before and after the event. Therefore, it allows a possibility to observe how quickly markets react. To calculate abnormal returns, an estimation period must be specified. To make sure that the event does not affect expected returns, it is essential that estimation period does not overlap with the event window. (MacKinlay 1997.)

Figure 5 summarizes the event study methodology and shows the estimation period and estimation window used in this study.

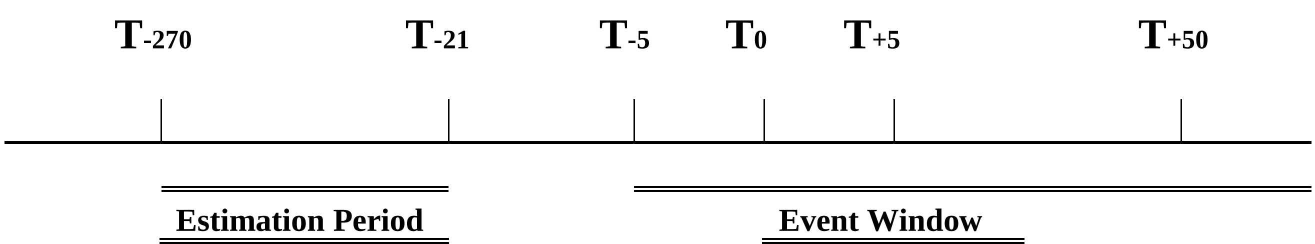

Figure 5. Event windows and estimation period used in the study.

T_0 denotes the announcement day of the profit warning. Following Lin (2015), the estimation period is one-year period from date -270 to -21. This study uses a few different event windows between days -5 and +50 to study the evolution of abnormal returns around the profit warning day. Even though the main interest is in the SAD effect, it is essential to understand how prices behave around profit warnings. Event windows (-1, +1) and (+2, +50) are used to study the SAD effect. The three-day window measures the SAD effects on immediate response to profit warnings and the longer event window measure the SAD effects on the PEAD. Because of data, program and labor limitations, I use event window (+2, +50) instead of (+2, +61) that Lin (2015) uses. However, referring to findings of Bernard et al. (1989), it is unlikely that the absent 11 days are highly relevant, especially when explaining the relation between SAD and PEAD.

Abnormal returns (ARs) and cumulative abnormal returns (CARs) are defined using the event study methodology. There are several options to calculate abnormal returns (MacKinlay 1997). I follow Lin (2015) and use the market model to estimate the abnormal returns. Abnormal returns are defined as the difference between the realized return and the expected return:

(6) $$AR_{it} = R_{it} - E(r_{it}).$$

The market model is defined as

(7) $$E(R_{it}) = \alpha_i + \beta_i R_{mt} ,$$

where $E(R_{it})$ = expected return of a share on day t

α_i = estimated constant

β_i = estimated market beta for a share

R_{mt} = market return on day t.

The market model assumes a linear relationship between the stock return and the market return. In this study, the market return is given by the OMXHCAP index. When the expected return is calculated, the abnormal return can be calculated as it is shown in Equation 6. (MacKinaly 1997.)

When the daily returns of a share from a certain period are summed together, one achieves the cumulative abnormal return. This can be expressed in the following way:

(8) $$CAR_i(t_1 t_0) = \sum_{T_0}^{T_1} AR_t.$$

Daily average abnormal return (AAR) and cumulative average abnormal return (CAAR) are simply achieved by taking the arithmetic mean of all abnormal returns or all cumulative abnormal returns of the observations. The statistical significance of AARs and CAARs are studied using the two-sided t-test. The abnormal returns are expected to be normally distributed.

6.3.2. Measuring Seasonal Affective Disorder

SAD is linked to the daylight in the sense of length of day. Length of day is depended on season and latitude. According to prior studies (see Molin et al. 1996; Schwarz et al. 1983; Young et al. 1997**)**, SAD rises an individual's risk aversion when the daylight is at its lowest, i.e. during the fall and winter.

Following Kamstra et al. (2003), SAD is measured based on the number hours between sunset and sunrise. As SAD is prevalent only during the fall and winter, the SAD variable has values different from zero only during the fall and winter. To obtain values for the SAD variable, standard approximations from spherical trigonometry are needed. This method is called the sine wave measure.

As Kamstra et al. (2003) demonstrate, the first step is to define $julian_t$ as number of the day in the year. This variable takes values ranging from 1 to 365 and to 366 in a leap year. Meaning, the value for January 1st is 1, for January 2nd 2, and so on. Next, the sun's declination angle λ_t is calculated:

(9) $$\lambda_t = 0{,}4102 * \sin[(\frac{2\pi}{360})(julian_t - 80{,}25)]\ .$$

After the declination angle of the sun has been calculated, the number of hours of night in the Northern Hemisphere is obtained by

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

where arccos is the arc cosine and δ is the latitude, which is 60.19 in Helsinki. (Kamstra et al. 2003.)

After calculating H_t, I then deduct 12 from it to obtain the length of night that is relative to the annual average length of night. Furthermore, following Kamstra et al. (2003), the SAD variable is specified only for trading days in the fall and winter:

$$SAD_t = \begin{cases} H_t - 12, \text{for trading days in the fall and winter} \\ 0, \text{ otherwise} \end{cases} \quad (11)$$

To examine the asymmetry explained with the Hypothesis 6, I follow Lin (2015) and generate two dummy variables, $Fall_t$, which is equal to one if the profit warning is announced in the fall, and $Winter_t$, which equals one if the profit warning is announced in the winter.

Figure 6 illustrates the daily SAD measure around the year. The day of the winter solstice has the highest SAD value, as it is the shortest day of the year. After that, daylight starts to increase, and SAD sufferers start to recover. This means a lower value for the SAD variable. After September equinox, days start to shorten, and the SAD variable starts to have higher values. In other words, the SAD measure is negatively correlated with the amount of daylight.

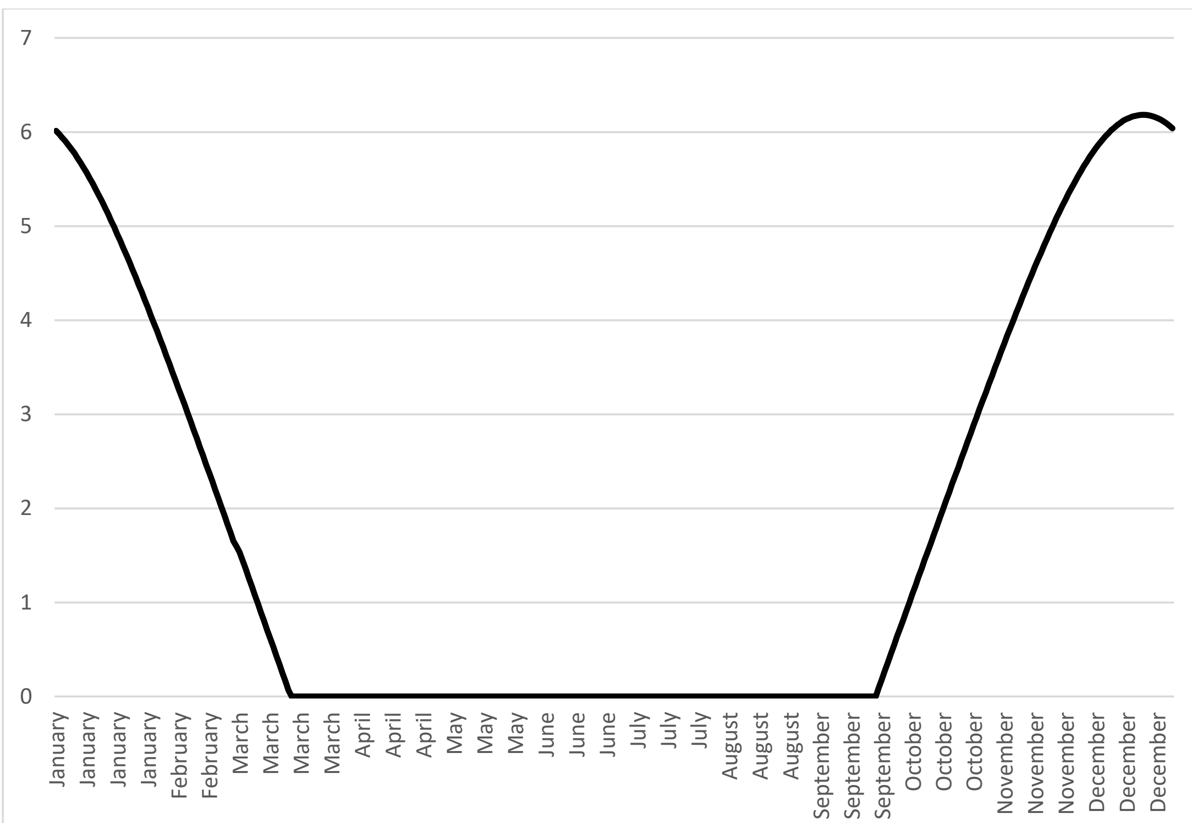

Figure 6. Daily SAD measure around the year.

Finally, the regression equation is defined in the following way:

$$(12) \qquad CAR_{it}(-1,+1) = \beta_0 + \beta_1 Fall_t * SAD_t + \beta_2 Winter_t * SAD_t + \beta_3 Size_{it} + \beta_4 MB_{it} + \beta_5 Beta_{it} + \beta_6 Rec_i + \beta_7 EP_i + \beta_8 MultiW_i + \varepsilon.$$

$CAR_{it}(-1, +1)$ is the cumulative abnormal return over the three-day window centered on the profit warning date. When examining PEAD and the SAD effect, the dependent variable is changed to $CAR_{it}(+2, +50)$. In addition, I also estimate the regression model with only SAD_t and the controls, i.e. without the fall and winter dummy variables to examine the SAD effect as a whole. To control for cross-sectional differences, several control variables are added to the equation. These variables are known to influence investors' response to earnings surprises. Specifically, it is important to control for size (see, Hong, Lim & Teoh 2000) and market to book ratio (see, Hirshleifer, Lim & Teoh 2009).

$Size_{it}$ is log of market capitalization of equity the day before the profit warning, MB_{it} is market to book ratio the day before the profit warning, $Beta_{it}$ is the beta from the market model, Rec_i is the consensus analyst recommendation on a scale from 1 to 5 (1 = strong buy and 5 = strong sell), EP_i is the earnings-to-price multiple where the earnings is the consensus EPS estimate for the current financial year while price is the share price one day before the profit warning, and $MultiW_i$ is a dummy variable with a value of 1 if the company has three or more profit warnings with the same sign during the observation period. I include the final four variables to follow findings of Spohr (2014).

However, previous studies do not use that many independent variables when explaining abnormal returns of profit warnings. For example, Jackson et al. (2003a) use only the size variable and two different dummy variables that equal one when the company cites reduced revenue as the source of their profit warning and if the decline in earnings is expected to be major. Some studies, see for example Bartov, Radhakrishnan & Krinsky (2000), control for analyst coverage. However, as Hong et al. (2000) show, analyst coverage is strongly correlated with firm size. Therefore, I control for size taking log of market capitalization of equity the day before the profit warning, as it is already highly correlated with analyst coverage. However, analyst recommendations may have a significant impact on the abnormal returns. Because of this, following Spohr (2014), I add analyst recommendations and EPS estimates as controlling variables. Furthermore, Chruch & Donker (2010) report that companies that announce profit warnings frequently have smaller responses to their warnings. For this reason, I also include the dummy variable $MultiW_i$.

Firm size is generally thought to be important to control for, as Jackson et al. (2003) and Church et al. (2010) show, the response decreases with the size of the company. However, Jackson et al. (2007) find that firm size nor analyst coverage have any impact. Bulkey et al. (2005) show that the market to book ratio does not have any significant impact on profit warnings, whereas Hirshleifer et al. (2009) show that it does affect investors' response to earnings surprises. Because of this contradictory, I use several of these variables as control variables. Naturally, this also allows me to examine the contradictory of prior studies. However, the main interest is in the SAD variable. In other words, I include various control variables and examine if SAD variable is still significant even when several company specifications are controlled for.

7. EMPIRICAL RESULTS

This chapter reports the empirical results of the thesis. Negative and positive profit warnings are examined as separate portfolios; a negative portfolio and a positive portfolio. The chapter is formed according to the following. First, descriptive statistics for the entire sample are presented to provide general knowledge about the used data. Second, the results about market reactions to profit warnings are provided showing the AARs and CAARs, and their significance levels. Third, effects of SAD to profit warnings are examined on univariate level. Lastly, results of the regression analysis are discussed.

Table 2 shows the descriptive statistics for the entire sample. CAR(+1, +1) is three-day cumulative abnormal return around profit warning day (in percent) and CAR(+2, +50) is cumulative abnormal return over the window period between 2 days and 50 days after the profit warning day (in percent). Size, MB, Beta, Rec and EP are as defined in the earlier chapter. N is the number of observations and Stdev is the standard deviation. Min and Max are the smallest and highest values in the sample, respectively.

Table 2. Summary statistics.

Variables	*N*	*Mean*	*Stdev*	*Median*	*Min*	*Max*
CAR(-1, +1)	286	-0,011	0,082	-0,006	-0,278	0,376
CAR(+2, +50)	286	-0,014	0,124	-0,011	-0,396	0,320
Size	286	5,406	1,794	5,478	1,428	9,979
MB	286	2,030	1,669	1,460	-2,280	10,320
Beta	286	0,588	0,435	0,460	-0,192	2,271
Rec	286	2,450	1,273	2,610	1,000	5,000
EP	286	6,134	13,589	1,418	-33,589	88,070

The reason for negative means and medians for CARs might be because of higher number of negative profit warnings in the sample.

7.1. Market reaction to profit warnings

Table 3 reports the AARs from the 11-day period. Specifically, Panel A shows the results of the negative portfolio and Panel B the results of the positive portfolio. Negative profit warning causes, on average, -3,7% abnormal return on the day of the announcement, which is also statistically highly significant. Furthermore, statistically significant abnormal returns occur also a day after the announcement and even a day after that. This implies that the market cannot assimilate all the information immediately and shows an underreaction by the market. If the market was efficient, abnormal returns should not occur after the announcement. This lagged reaction by the market is evidence against the efficient market hypothesis. As the returns continue being negative on the days one and two, it seems that the immediate reaction on the announcement day is not large enough. According to the efficient market hypothesis, all the information should be reflected into the prices immediately and correctly. Therefore, the immediate reaction should be higher and abnormal returns should not be statistically different from zero after the announcement.

Positive profit warnings generate, on average, 5,4% abnormal return on the day of the announcement. Furthermore, the immediate reaction is more in line with the efficient market hypothesis, as there are no statistically significant abnormal returns on the days 1 and 2. However, on the days 3 and 4, there are abnormal returns that are statistically significant at 10% level. Even though this significance is not the highest, it does raise interest. On the day 3, the return is -0,39%, but on the following day it is 0,41%, which means that the cumulative price movement of these days is close to zero. The negative return on day 3 indicates that the market thinks that there might have been an overreaction. However, this thought is quickly buried, as on the next day the market concludes that the previous drop in price was not justifiable. However, in the end, the statistical significance of these returns is not high enough to make distinct conclusions.

Table 3. Market response to negative and positive profit warnings. The table shows abnormal returns five days prior profit warnings and five days after. Day 0 represents the day of an announcement. ***, ** and * represent statistically significant at the 1%, 5% and 10% levels, respectively.

Panel A: Negative profit warnings

Day	AAR	t-value
-5	0,0005	0,33
-4	0,0012	1,13
-3	-0,0002	-0,12
-2	0,0002	0,14
-1	-0,0013	-0,73
0	-0,0368	-9,01***
1	-0,0106	-4,33***
2	-0,004	-2,16**
3	-0,0012	-0,59
4	0,0004	0,20
5	0,0009	0,52

Panel B: Positive profit warnings

Day	AAR	t-value
-5	0,0009	0,57
-4	0,0002	0,14
-3	0,0011	0,72
-2	0,0005	0,33
-1	0,0006	0,31
0	0,0535	10,95***
1	0,0038	1,48
2	0,0001	0,10
3	-0,0039	-1,92*
4	0,0041	1,95*
5	0,0018	0,66

To summarize Table 3, negative and positive profit warnings generate statistically significant abnormal returns on the day of the announcement. There is an underreaction to be seen in the case of negative profit warnings, as abnormal returns are generated even after the announcement. This is not true in the case of the positive portfolio, even though there is some trading to be observed on the days 3 and 4. Contradictory to prior studies, the immediate reaction to positive profit warnings is higher. Spohr (2014) reports similar results that negative profit warnings cause abnormal returns even after the announcement day, but positive profit warnings do not. This indicates that the markets have difficulties to process negative information. This makes sense as negative news cause more uncertainty. Anyway, several prior studies about profit warnings tend to examine only negative profit warnings (Spohr 2014). So, there might not be enough studies about differences between positive and negative profit warnings.

Table 3 supports Hypotheses 1 and 3, but not Hypothesis 2. As the abnormal returns are highly statistically significant on the announcement day, in both cases of negative and positive profit warnings, Hypothesis 1 can be accepted. Negative profit warnings show results that support Hypothesis 3, but positive profit warnings do not. Therefore, this hypothesis can be accepted partially, as the market is not able to assimilate the negative information quickly enough. On the contrary, the market absorbs the information from positive profit warning effectively. Therefore, these results suggest that the sign of the profit warning matters whether the market is able to react efficiently. Hypothesis 2 is not supported by these results. This means that the market does not anticipate the profit warning, as the study of Jackson et al. (2003a.) suggests. This finding supports the efficient market theory, whereas accepting Hypothesis 3, does not.

Table 4 shows the cumulative average abnormal return from different event windows. Similar to Table 3, this table reports results of negative and positive profit warnings separately; Panel A shows the results of the negative portfolio and Panel B shows the results of the positive portfolio.

Results of Table 4 strengthen the findings from Table 3. As it can be seen, the CAAR prior the profit warning is not statistically significant. The immediate reaction, CAAR(-1, +1), is statistically highly significant in both portfolios, as Table 3 suggests. Moreover, earlier findings gain support, as in the case of the negative portfolio, the CAAR(+1, +5) is statistically significant, but in the case of the positive portfolio, it is not. CAAR(-5, +5) is statistically significant in both portfolios, which highlights the effect of the profit warning announcement. Combining the findings from Table 3 and Table 4, Hypotheses 1 and 3 can be accepted, but Hypothesis 2 needs to be rejected.

Table 4. Cumulative abnormal returns of positive and negative profit warnings. The table shows various CAARs around the profit warning; showing cumulative average abnormal returns prior profit warnings, around the announcement day, and the PEAD. ***, ** and * represent statistically significant at the 1%, 5% and 10% levels, respectively.

Panel A: Negative profit warnings

	Return	**t-value**
CAAR(-5, -2)	0,0017	0,29
CAAR(-1, +1)	-0,0487	-9,97***
CAAR(-5, +5)	-0,0508	-7,94***
CAAR(+1, +5)	-0,0144	-4,00***
CAAR(+6, +11)	-0,0052	-1,48
CAAR (+6, +50)	-0,0153	-1,71

Panel B: Positive profit warnings

	Return	**t-value**
CAAR(-5, -2)	0,0027	0,31
CAAR(-1, +1)	0,0579	9,66***
CAAR(-5, +5)	0,0627	8,67***
CAAR(+1, +5)	0,0058	1,09
CAAR(+6, +11)	0,0043	0,98
CAAR (+6, +50)	-0,0055	-0,51

7.2. SAD and investors’ response to profit warnings

As the used data is now described in detail, I move to examine the primary hypotheses of the study – does SAD affect the market response to profit warnings. Once again, I examine negative and positive profit warnings separately. Table 5 reports the univariate analyses showing the results for immediate reaction (-1, +1) and PEAD (+2, +50). Specifically, Panel A compares the mean returns of profit warnings announced during the SAD season, i.e. the fall and winter, against profit warnings announced during the spring and summer. Following (Lin 2015), I also divide the sample to test for differences between the fall season and non-fall season (Panel B). To examine Hypothesis 6, I also compare the returns between the fall and winter (Panel C).

Reviewing the results of the immediate reaction first, as Table 5 Panel A shows, there is a highly statistically significant difference in the immediate reaction of positive profit warnings between the SAD season and non-SAD season. This finding supports the hypothesis that SAD causes heightened risk aversion and investors do not react as strongly to positive news during the SAD season. However, there is no difference in the case of negative profit warnings. These two findings are consistent with the study of Lin (2015). Lin (2015) proposes that the reason for insignificant difference in negative profit warnings is due to the ostrich effect, i.e. investors pretend that the negative news do not exist. Following Lin (2015), I follow this explanation as well. Panel B strengthens the SAD hypothesis, as returns in the fall are lower than during the rest of the year. Similarly, the difference is not significant in the case of the negative portfolio.

Because the amount of daylight is increasing towards the spring, the PEAD should be higher during the SAD season versus the non-SAD season. As Panel A shows, this is indeed the case with the negative portfolio. However, there is no difference with positive profit warnings. Once again, Panel B strengthens this finding. However, Lin (2015) finds that the difference is significant also in the case of positive earnings announcements. This is another piece of evidence that negative and positive warnings might be treated differently. Moreover, the market might treat profit warnings and earnings announcements differently, and that can be an explanation for different results from Lin (2015).

Table 5. Univariate analyses: SAD effects on immediate response to positive and negative profit warnings and PEAD. The table shows three-day cumulative abnormal returns around profit warnings (CAR(-1, +1)) and the PEAD (CAR(+2, +50)) upon positive and negative profit warnings. Panel A compares the difference between SAD season and non-SAD season. Panel B is the difference between Fall and non-Fall season, and Panel C reports the difference between Fall and Winter. ***, ** and * represent statistically significant at the 1%, 5%, and 10% levels, respectively.

Panel A: SAD and non-SAD

	Average	SAD	Non-SAD	Diff	t-value
CAR(-1, +1)					
Positive	0,0579	0,0419	0,0752	-0,0333	-2,87***
Negative	-0,0487	-0,0407	-0,0539	0,0132	1,36
CAR(+2, +50)					
Positive	-0,0035	0,0048	-0,0126	0,0174	0,81
Negative	-0,0191	-0,0006	-0,0418	0,0412	2,05**

Panel B: Fall and non-Fall

	Average	Fall	Non-Fall	Diff	t-value
CAR(-1, +1)					
Positive	0,0579	0,0324	0,0662	-0,0338	-2,48***
Negative	-0,0487	-0,0381	-0,0512	0,0131	1,29
CAR(+2, +50)					
Positive	-0,0035	-0,0206	0,0020	-0,0226	-0,91
Negative	-0,0191	0,0062	-0,0327	0,0389	2,07**

Panel C: Fall and Winter

	Average	Fall	Winter	Diff	t-value
CAR(-1, +1)					
Positive	0,0579	0,0324	0,0504	-0,018	-1,70*
Negative	-0,0487	-0,0381	-0,0452	0,0071	0,58
CAR(+2, +50)					
Positive	-0,0035	-0,0206	0,0275	-0,0481	-1,53
Negative	-0,0191	0,0062	-0,0123	0,0185	0,87

Panel C examines Hypothesis 6; whether SAD has an asymmetric effect. The immediate reaction should be lower during the fall than winter and PEAD should be higher in the winter.

The only difference that is statistically significant is the immediate reaction to positive profit warnings, which is statistically significant at 10% level. Lin (2015) reports that there are no significant differences in the case of negative profit warnings. I observe the same. However, Lin (2015) finds that PEAD in the positive portfolio is statistically significant. As it can be seen, my t-value is only -1,53, which is not significant, but close being significant at 10%. However, the actual difference in returns is still almost 5%, which is economically highly significant. Nevertheless, the statistical evidence is low, and even though it might be because of the small sample size, Hypothesis 6 does not gain support.

Table 5 provides support for Hypothesis 4. Hypothesis 5 has only partial support, as the PEAD is larger during the SAD season, but only in the case of the negative portfolio. Hypothesis 6 has only weak support, as the results show only very low statistical significance.

Clearly, there are signs of a seasonal pattern. However, further multivariate analysis is needed before any conclusions can be made. Even if there seems to be a seasonal pattern, there is no evidence that SAD creates or affects this pattern. Because of this, as stated earlier, I control for cross-sectional differences and create a SAD variable to capture the SAD effect. If the SAD variable is found to be significant, there is a strong support for the SAD hypothesis, that is, SAD causes heightened risk aversion and affects the market reaction to profit warnings.

Tables 6 and 7 show the regression results for immediate reaction to negative profit warnings. As expected, the SAD effect is not statistically significant. Dividing the SAD effect to fall and winter does not change the outcome. This finding can be explained by the ostrich effect suggested by Lin (2015). Table 6 and 7 show that the beta variable is statistically significant at 5% level and close being statistically significant at 1% level. This means that the riskier the firm is, the stronger the immediate response to the profit warning is. This finding is in line with the results of Spohr (2014). All other explanatory variables are statistically insignificant, which suggests that the size, MB ratio, analyst recommendations, EPS estimates or frequent warnings of a company, do not explain the immediate reaction to negative profit warnings. Size is statistically significant at 10% level, but this significance is very weak, and drops significantly after controlling for analyst recommendation.

Table 6. Regression tests of the SAD effect on immediate reaction to negative profit warnings. ***, ** and * represent statistically significant at the 1%, 5%, and 10% levels, respectively.

CAR (-1, +1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0,0531 -[8,07]***	-0,0509 [-3,05]***	-0,0500 [-2,97]***	-0,0601 [-3,52]***	-0,0665 [-3,47]***	-0,0596 [-3,03]***	-0,0622 [-3,02]***
SAD	0,0019 [0,99]	0,0002 [0,99]	0,0019 [0,99]	0,0020 [1,05]	0,0020 [1,04]	0,0020 [1,09]	0,0022 [1,15]
Size		-0,0004 [-0,13]	0,0000 [-0,02]	0,0063 [1,64]*	0,0058 [1,50]	0,0041 [1,00]	0,0040 [0,98]
MB			-0,0014 [-0,46]	-0,0020 [-0,67]	-0,0018 [-0,60]	-0,0030 [-0,98]	-0,0031 [-1,00]
Beta				-0,0362 [-2,42]**	-0,0351 [-2,34]**	-0,0339 [-2,25]**	-0,0337 [-2,24]**
Rec					0,0028 [0,70]	0,0032 [0,79]	0,0032 [0,79]
EP						0,0006 [1,46]	0,0006 [1,51]
MultiW							0,0044 [0,43]
R-Square	0,0055	0,0056	0,0067	0,0382	0,0408	0,0523	0,0534

Table 7. Regression tests of SAD effects on immediate reaction to negative profit warnings. ***, ** and * represent statistically significant at the 1%, 5%, and 10% levels, respectively.

CAR (-1, +1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0,0527 -[8,05]***	-0,0508 [-3,03]***	-0,0499 [-2,95]***	-0,0607 [-3,52]***	-0,0672 [-3,47]***	-0,0602 [-3,02]***	-0,0631 [-3,02]***
SAD*Fall	0,0021 [0,92]	0,0021 [0,90]	0,0021 [0,89]	0,0023 [0,99]	0,0024 [1,04]	0,0024 [1,05]	0,0027 [1,12]
SAD*Winter	0,0013 [0,52]	0,0013 [0,52]	0,0013 [0,53]	0,0015 [0,60]	0,0013 [0,52]	0,0015 [0,60]	0,0016 [0,65]
Size		-0,0003 [-0,12]	0,0000 [-0,01]	0,0064 [1,66]*	0,0059 [1,51]	0,0041 [1,02]	0,0041 [1,00]
MB			-0,0014 [-0,46]	-0,0020 [-0,66]	-0,0017 [-0,59]	-0,0030 [-0,97]	-0,0031 [-0,99]
Beta				-0,0364 [2,43]**	-0,0353 [-2,34]**	-0,0341 [-2,26]**	-0,0340 [-2,25]**
Rec					0,0030 [0,75]	0,0034 [0,83]	0,0034 [0,83]
EP						0,0006 [1,45]	0,0006 [1,51]
MultiW							0,0047 [0,46]
R-Square	0,0050	0,0051	0,0063	0,0382	0,0412	0,0526	0,0537

Tables 8 and 9 report the regression results for negative profit warnings using CAR(+2, +50) as the dependent variable to measure the PEAD. This time, the SAD variable is statistically significant at 10% level in every model and at 5% level in model 3. In other models, the corresponding p-values are close to 5%, ranging from 5,6% to 6%. As the coefficients are positive, this suggests that as the amount of daylight starts to increase after the winter solstice, SAD sufferers begin to heal, and this leads to a higher PEAD during the SAD season. As Table 9 shows, the winter variable is not statistically significant, but the fall variable is. This implies that the SAD effect is driven mainly by the fall. There is also some significance for the MB ratio, even though this significance drops from the 10% level after controlling for EPS estimates. Even though the statistical significance is low, there is some evidence that companies with high MB ratios have lower PEAD. The beta variable is not significant like it was in Tables 6 and 7, which implies that the risk of the company only affects the immediate reaction and not the PEAD. All other explanatory variables are statistically insignificant.

Table 8. Regression tests of the SAD effect on post-earnings announcement drifts of negative profit warnings. ***, ** and * represent statistically significant at the 1%, 5% and 10% levels, respectively.

CAR (+2, +50)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0,0386 -[2,72]***	-0,0537 [-1,61]	-0,0473 [-1,42]	-0,0361 [-1,05]	-0,040 [-1,02]	-0,03912 [-0,97]	-0,0385 [-0,92]
SAD	0,0077 [1,86]*	0,0078 [1,88]*	0,0051 [1,97]**	0,00781 [1,90]*	0,0079 [1,91]*	0,0079 [1,90]*	0,0078 [1,88]*
Size		0,0027 [0,50]	0,0081 [0,93]	-0,0013 [-0,17]	-0,0016 [-0,20]	-0,0018 [-0,22]	-0,0017 [-0,21]
MB			-0,0102 [-1,77]*	-0,0096 [-1,66]*	-0,0095 [-1,63]*	-0,0097 [-1,59]	-0,0096 [-1,58]
Beta				0,0365 [1,23]	0,0371 [1,24]	0,0372 [1,24]	0,0372 [1,24]
Rec					0,0017 [0,21]	0,0018 [0,22]	0,0017 [0,22]
EP						0,0000 [0,08]	0,0000 [0,07]
MultiW							-0,0012 [-0,05]
R-Square	0,0188	0,0202	0,0370	0,0451	0,0454	0,0454	0,0454

Table 9. Regression tests of SAD effects on post-earnings announcement drifts of negative profit warnings. ***, ** and * represent statistically significant at the 1%, 5% and 10% levels, respectively.

CAR (+2, +50)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0,0368 -[2,73]***	-0,0518 [-1,58]	-0,0454 [-1,38]	-0,0342 [-1,01]	-0,0369 [-0,96]	-0,0356 [-0,90]	-0,0360 [-0,87]
SAD*Fall	0,0077 [1,86]*	0,0078 [1,88]*	0,0080 [1,94]*	0,0078 [1,90]*	0,0079 [1,90]*	0,0079 [1,89]*	0,0079 [1,87]*
SAD*Winter	0,0075 [1,01]	0,0074 [1,01]	0,0082 [1,11]	0,0078 [1,06]	0,0077 [1,04]	0,0077 [1,04]	0,0078 [1,04]
Size		0,0027 [0,50]	0,0051 [0,93]	-0,0014 [-0,19]	-0,0016 [-0,21]	-0,0019 [-0,24]	-0,0019 [-0,24]
MB			-0,0103 [-1,77]*	-0,0096 [-1,66]*	-0,0096 [-1,63]*	-0,0098 [-1,60]	-0,0098 [-1,59]
Beta				0,0372 [1,26]	0,0377 [1,26]	0,0379 [1,26]	0,0379 [1,26]
Rec					0,0012 [0,15]	0,0013 [0,16]	0,00130 [0,16]
EP						0,0000 [0,12]	0,0001 [0,13]
MultiW							0,0007 [0,03]
R-Square	0,0199	0,0212	0,0380	0,0465	0,0466	0,0467	0,0467

Tables 10 and 11 show the regression results for immediate reaction to positive profit warnings. Using SAD as the only explanatory variable in Table 10, the variable is significant at 10% level, but in models 2, 3, 4 and 5 the SAD variable becomes insignificant. However, in models 6 and 7 the SAD variable becomes significant again at 10% level. A closer investigation in Table 11 shows that the fall variable is significant in every model, being significant at 5% level in models 1, 6 and 7, and close being significant at 5% in other models. This implies that the SAD effect is driven by the fall, as the winter variable is not significant. As in Tables 6 and 7, size becomes significant at 10% level after adding the beta variable. However, size becomes insignificant when Rec is added. Other variables are insignificant.

Table 10. Regression tests of the SAD effect on immediate reaction to positive profit warnings. ***, ** and * represent statistically significant at the 1%, 5%, and 10% levels, respectively.

CAR (-1, +1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0,0665 [8,67]***	0,0907 [4,88]***	0,0906 [4,85]***	0,0992 [5,11]***	0,0995 [5,06]***	0,0929 [4,46]***	0,0934 [4,41]***
SAD	-0,0044 [-1,77]*	-0,0040 [-1,59]	-0,0040 [-1,59]	-0,0038 [-1,51]	-0,0037 [-1,50]	-0,0044 [-1,70]*	-0,0045 [-1,70]*
Size		-0,0048 [-1,42]	-0,0044 [-1,16]	-0,0096 [1,88]*	-0,0094 [-1,71]*	-0,0078 [-1,36]	-0,0076 [-1,29]
MB			-0,0001 [-0,23]	0,0005 [0,11]	0,0005 [0,11]	0,0017 [0,38]	0,0017 [0,36]
Beta				0,0315 [1,51]	0,0312 [1,48]	0,0327 [1,55]	0,0322 [1,49]
Rec					-0,0007 [-0,13]	-0,0004 [-0,09]	-0,0006 [-0,11]
EP						-0,0006 [-0,95]	-0,0006 [-0,95]
MultiW							-0,0021 [-0,17]
R-Square	0,0304	0,0498	0,0520	0,0722	0,0723	0,0813	0,0813

Table 11. Regression tests of SAD effects on immediate reaction to positive profit warnings. ***, ** and * represent statistically significant at the 1%, 5%, and 10% levels, respectively.

CAR (-1, +1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0,0663 [8,65]***	0,0885 [4,72]***	0,0884 [4,69]***	0,0970 [4,97]***	0,0975 [4,94]***	0,0910 [4,35]***	0,0911 [4,28]***
SAD*Fall	-0,0064 [-2,12]**	-0,0057 [-1,88]*	-0,0057 [1,87]*	-0,0056 [-1,84]*	-0,0056 [-1,83]*	-0,0062 [-1,99]**	-0,0063 [-1,98]**
SAD*Winter	-0,0019 [-0,60]	-0,0019 [-0,58]	-0,0019 [-0,57]	-0,0016 [-0,49]	-0,0015 [-0,47]	-0,0022 [-0,67]	-0,0022 [-0,66]
Size		-0,0044 [-1,29]	-0,0040 [-1,04]	-0,0093 [-1,81]*	-0,0088 [-1,61]	-0,0073 [-1,27]	-0,0072 [-1,24]
MB			-0,0001 [-0,23]	0,0005 [0,12]	0,0005 [0,11]	0,0017 [0,37]	0,0017 [0,37]
Beta				0,0320 [1,53]	0,0315 [1,50]	0,0330 [1,56]	0,0329 [1,53]
Rec					-0,0011 [-0,22]	-0,0009 [-0,18]	-0,0009 [-0,18]
EP						-0,0006 [-0,93]	-0,0006 [0,36]
MultiW							-0,0003 [-0,03]
R-Square	0,0435	0,0596	0,0602	0,0827	0,0831	0,0915	0,0915

Tables 12 and 13 show the regression results of SAD effects on the PEAD of positive profit warnings. The SAD variable is not significant. Because the SAD variable is significant in the case of negative profit warnings in Table 8, this implies that the sign of the profit warning matters. Beta variable becomes significant at 5% level in the last model when MultiW variable is added. Interestingly, the MultiW is highly significant at 5% level, close being significant at 1% level. As the coefficient is negative, this suggests that investors' response to positive profit warnings is smaller if a company has already announced several positive profit warnings. This is the only regression where MultiW is statistically significant. Furthermore, the result is also economically highly significant as the model suggests that the response could be even 5,22% smaller, if the company has announced several positive profit warnings in the past. Moreover, the reaction might be strengthened by the risk of the company.

Results from Table 13 do not differ from Table 12. The MultiW variable has some interesting properties. As the variable is not significant in the case of the immediate reaction, this implies that around the profit warning day, the market does not take the past warnings into consideration. However, in the longer run, the market starts to adjust and reflect the past information. This suggests that the market may overreact to positive profit warnings of certain companies around the profit warning day. Interestingly, this is not the case with negative profit warnings.

As Tables 12 and 13 show, SAD does not affect the PEAD of positive profit warnings. This finding is contrary to findings of Lin (2015), who reports that the effect of SAD does not depend on the direction of earnings surprises. My results suggest that the direction matters. Specifically, the SAD effect impacts the PEAD of negative profit warnings but not positive profit warnings.

Table 12. Regression tests of the SAD effect on post-earnings announcement drifts of positive profit warnings. ***, ** and * represent statistically significant at the 1%, 5% and 10% levels, respectively.

CAR (+2, +50)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0,0012 [-0,08]	0,0194 [0,57]	0,0196 [0,58]	0,0029 [0,08]	0,0008 [0,02]	0,0059 [0,16]	0,0194 [0,52]
SAD	-0,0011 [-0,24]	-0,0005 [-0,10]	-0,0004 [-0,09]	-0,0013 [-0,25]	-0,0014 [-0,27]	-0,0008 [-0,16]	-0,0009 [-0,19]
Size		-0,0042 [-0,68]	-0,0060 [-0,86]	0,0044 [0,47]	0,0027 [0,26]	0,0014 [0,13]	0,0063 [-0,60]
MB			0,0044 [0,57]	0,0015 [0,19]	0,0016 [0,21]	0,0007 [0,09]	-0,0011 [-0,14]
Beta				-0,0624 [-1,64]	-0,0603 [-1,57]	-0,0612 [-1,58]	-0,0760 [-1,99]**
Rec					0,0049 [0,53]	0,0047 [0,51]	0,0013 [0,15]
EP						0,0004 [0,39]	0,0003 [0,32]
MultiW							-0,0547 [-2,44]**
R-Square	0,0006	0,0051	0,0085	0,0351	0,0380	0,0395	0,0968

Table 13. Regression tests of SAD effects on post-earnings announcement drifts of positive profit warnings. ***, ** and * represent statistically significant at the 1%, 5% and 10% levels, respectively.

CAR (+2, +50)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0,0088 -[-0,63]	0,0137 [0,40]	0,0139 [0,41]	-0,0016 [-0,05]	-0,0030 [-0,08]	0,0050 [0,13]	0,0183 [0,49]
SAD*Fall	-0,0002 [-0,05]	0,0004 [0,08]	0,0005 [0,10]	-0,0003 [-0,07]	-0,0003 [-0,06]	0,0003 [0,06]	0,0005 [0,10]
SAD*Winter	0,0104 [1,13]	0,0108 [1,16]	0,0110 [1,17]	0,0096 [1,03]	0,0091 [0,96]	0,0103 [1,06]	0,0074 [0,77]
Size		-0,0045 [-0,73]	-0,0064 [-0,92]	0,0035 [0,37]	0,0022 [0,22]	0,0003 [0,03]	0,0050 [0,47]
MB			0,0046 [0,60]	0,0018 [0,23]	0,0019 [0,24]	0,0005 [0,06]	-0,0012 [-0,15]
Beta				-0,0588 [-1,54]	-0,0573 [-1,49]	-0,0587 [-1,51]	-0,0731 [-1,90]*
Rec					0,0035 [0,37]	0,0032 [0,34]	0,0004 [0,04]
EP						0,0007 [0,61]	0,0005 [0,51]
MultiW							-0,0522 [-2,30]**
R-Square	0,0138	0,0191	0,0227	0,0462	0,0476	0,0513	0,1025

I suggest that SAD does not have an effect on PEAD of positive profit warning because of the negativity bias. As bad information is processed more thoroughly than good information (see Baumeister et al. 2001), there is a possibility that responses to positive warnings are not revisited as carefully. As the negativity bias is connected with depression (see Dai et al. 2016), the SAD effect might generate negativity bias among investors. This means that investors remember negative profit warnings better and let the increasing amount of daylight raise their optimism levels, which leads to a higher PEAD. However, investors do not revisit their thoughts about positive profit warnings because of the tendency to not remember positive information so well. As the response to positive information was already positive, even though smaller during the SAD season, the increasing amount of daylight does not make the “already positive information” more positive. After starting to recover from the depression caused by SAD, because of the negativity bias, investors focus more on the past negative information.

The regression results support Hypothesis 4; SAD lowers the immediate market response to positive profit warnings but it does not have an effect on the immediate response to negative profit warnings. Therefore, Hypothesis 4 can be accepted. Hypothesis 5 has partial support, as the PEAD is higher during the SAD season in the case of negative profit warnings. However, the results suggest that SAD does not have an effect on the PEAD of positive profit warnings. I suggest that the negativity bias could be one explanation for this. This means that Hypothesis 5 can be accepted in the case of negative profit warnings but not in the case of positive ones. There is not enough evidence to accept Hypothesis 6. My results suggest that the SAD effect is mainly driven by the fall.

8. CONCLUSIONS

A listed company must publish a profit warning if its profit or financial position differs substantially from the expected profit or financial position of the company. This ensures that investors are aware of all relevant information about the company and can make rational investment decisions. (Karjalainen et al. 2008: 153–154.)

Seasonal affective disorder (SAD) is a medical condition that is characterized by a depressed mood during times when the amount of daylight is low (Molin et al. (1996). SAD causes heightened risk aversion among investors which means that investors bend more towards choices that involve less risk.

Using daily data from the Finnish stock market in 2011–2017, I study the market reaction to positive and negative profit warnings. Additionally, as the main interest of this study, I examine how SAD affects investors' response to profit warnings.

Both negative and positive profit warnings generate significant abnormal returns on the announcement day. Abnormal returns are observed even two days after the negative profit warning. However, the same is not observed in the case of positive profit warnings. This implies that the market has difficulties to adjust accordingly to negative information. Examination of CAAR(+1, +5) of negative profit warnings reveals that this period is statistically highly significant.

There have been controversial results about the effect of size and MB ratio of a company to profit warnings (see Jackson et al. 2003; Bulkey et al. 2005; Jackson et al. 2007; Hirshleifer et al. 2009; Church et al. 2010). My results suggest that size nor MB ratio affect investors' response to profit warnings. Size and MB ratio are statistically significant at 10% in some regression models, but when more variables are added, they lose their significance. Moreover, the regression results show that in the case of negative profit warnings, the riskier the firm is, the bigger the immediate reaction to the profit warnings is. The same is not observed in the case of positive profit warnings, which suggest that the risk of the company does not matter how investors react to positive profit warnings. Furthermore, analyst recommendations show no statistically significant results.

PEAD of profit warnings show no statistical significance for the control variables, expect the MultiW variable that has a negative coefficient and is statistically highly significant in the case of positive profit warnings. This implies that if a company has already announced several positive profit warnings, the market response to the next profit warning is smaller. Furthermore, the magnitude of this effects seems to be connected to the risk of the company. However, as MultiW is not significant in the case of negative profit warnings, this suggests that the market does not care if the company has already announced several negative profit warnings. The response is not more negative as one could expect. As several prior studies focus only on negative profit warnings, my results suggest that investors might respond differently to negative and positive profit warnings.

As the main interest of this study, I find that SAD affects the immediate response to positive profit warnings but not negative profit warnings. The immediate response to positive warnings is lower during the SAD season. This is explained by the heightened risk aversion caused by SAD. However, because of the ostrich effect, suggested by Lin (2015), SAD does not affect the immediate response to negative profit warnings. Investors tend to pretend that the negative information does not exist. I also find that SAD affects the PEAD of negative profit warnings but not the PEAD of positive profit warnings. Because of the amount of daylight starts to increase after the winter solstice, investors start to recover from SAD symptoms. This means that the PEAD is higher during the SAD season than during the non-SAD season. However, the results suggest that this is true only in the case of negative profit warnings, as the SAD variable in the regressions is statistically insignificant in the case of PEAD of positive profit warnings.

I suggest that because of the negativity bias, investors revisit their thoughts about negative profit warnings and tend to ignore positive profit warnings in the past. When the amount of daylight is low, SAD sufferers feel depressed, and they tend to ignore negative news. However, when the amount of daylight starts to increase, investors start to recover from SAD symptoms. As investors start to gain their confidence and optimism levels back, they are more willing to revisit their thoughts about negative profit warnings. However, they do not revisit their thoughts about positive profit warnings because of the negativity bias; they tend to remember the negative information better. This could be a reason why the PEAD of negative profit warnings is explained by the SAD variable and why the PEAD of positive profit warnings is not. Naturally, this is just an assumption and one possible suggestion to this asymmetry. A further empirical analysis should be conducted to have substantial support for such assumption.

The findings of this study suggest that the sign of the profit warnings matters how investors will react to the information. Specifically, SAD affects the immediate reaction to positive profit warnings but not the immediate reaction to negative profit warnings. Moreover, SAD affects the PEAD of negative profit warnings but not the PEAD of positive profit warnings. However, the results suggest that most, if not all, of the SAD effect is prevalent in the fall. After dividing the SAD effect to the fall and winter, the results suggest that the SAD effect is mainly driven by the fall. Furthermore, I do not find statistically significant asymmetric effect in SAD, i.e. that PEAD is higher in the winter. However, in the case of positive profit warnings, the difference of returns in the sample is almost 5% but is still not statistically significant. Nonetheless, the economic significant is high and the statistical insignificancy may be due to the small sample size.

To best of my knowledge, this is the first research to link SAD to profit warnings. The results of this study suggest that SAD affects the financial market in Finland. The results of this study can be used by professional investors who try to benefit from temporary market mispricing. However, this study calls for a further investigation of this topic. Specifically, increasing the sample size from outside of Finland could provide more robust results. Additionally, further research about the ostrich effect and negativity bias related to the SAD is needed to fully understand the possible implications between these phenomena.

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APPENDIX

Appendix 1. List of the profit warnings used in the thesis.

12/01/2011	Stockmann PLC
14/01/2011	Lassila & Tikanoja PLC
14/01/2011	Componenta PLC
21/01/2011	Suominen Group PLC
01/02/2011	Vaisala PLC
01/02/2011	Marimekko PLC
02/03/2011	Digia PLC
14/03/2011	Vacon PLC
24/03/2011	Finnair PLC
24/03/2011	Turkistuottajat PLC
31/03/2011	Orion PLC
04/04/2011	Nokian Tyres PLC
06/04/2011	Finnlines PLC
12/04/2011	Okmetic PLC
20/04/2011	Stockmann PLC
20/04/2011	Metso PLC
17/05/2011	Efore PLC
31/05/2011	Elcoteq PLC
31/05/2011	Nokia PLC
13/06/2011	Atria PLC
13/06/2011	Oral Hammaslääkärit PLC
15/07/2011	Wulff-Group PLC
18/07/2011	Ahlstrom PLC
19/07/2011	Oriola PLC
26/07/2011	HKScan PLC
04/08/2011	Ahlstrom PLC
05/08/2011	Tiimari PLC
13/09/2011	Sievi Capital PLC
14/09/2011	Aspocomp PLC
19/09/2011	Panostaja PLC
20/09/2011	Incap PLC
21/09/2011	Neste Oil PLC
27/09/2011	Uponor PLC
07/10/2011	Rautaruukki PLC
07/10/2011	Finnair PLC
10/10/2011	Konecranes PLC
12/10/2011	YIT PLC
18/10/2011	Ahlstrom PLC
19/10/2011	Sampo PLC
20/10/2011	Viking Line PLC
18/11/2011	Kemira PLC
25/11/2011	Turkistuottajat PLC
08/12/2011	Metsäliitto Group
08/12/2011	Aspo PLC
15/12/2011	Pohjola Pankki PLC
20/12/2011	Raisio PLC
21/12/2011	Sievi Capital PLC
22/12/2011	Tulikivi PLC
11/01/2012	Teleste PLC
18/01/2012	Viking Line PLC
23/01/2012	Finnlines PLC
26/01/2012	Ålandsbanken
27/01/2012	Martela PLC
07/02/2012	Uponor PLC
24/02/2012	Aspo PLC
20/03/2012	Lännen Tehtaat PLC
23/03/2012	Tectia PLC
11/04/2012	Nokia PLC
12/04/2012	Nurminen Logistics PLC
12/06/2012	Cargotec PLC
13/06/2012	Saga Furs PLC
19/06/2012	Incap PLC
29/06/2012	Pöyry PLC
10/07/2012	Outokumpu PLC
17/07/2012	Wulff-Group PLC
07/08/2012	Honkarakenne PLC
10/08/2012	Aspo PLC
07/09/2012	Componenta PLC
11/09/2012	Tikkurila PLC
25/09/2012	Nurminen Logistics PLC
27/09/2012	Rautaruukki PLC
15/10/2012	Aktia PLC

16/10/2012 Ahlstrom PLC
31/10/2012 Yleiselektroniikka PLC
07/11/2012 Ruukki Group PLC
27/11/2012 Ahlstrom PLC
28/11/2012 Saga Furs PLC
31/10/2012 Yleiselektroniikka PLC
07/11/2012 Ruukki Group PLC
27/11/2012 Ahlstrom PLC
28/11/2012 Saga Furs PLC
05/12/2012 Suominen PLC
12/12/2012 Marimekko PLC
14/12/2012 Wulff-Group PLC
18/12/2012 Incap PLC
04/01/2013 Honkarakenne PLC
09/01/2013 Stockmann PLC
10/01/2013 Elektrobit PLC
10/01/2013 Nokia PLC
11/01/2013 Vaisala PLC
21/01/2013 Ålandsbanken
23/01/2013 Martela PLC
31/01/2013 Suominen PLC
06/02/2013 Exel Composites PLC
11/02/2013 Componenta PLC
13/03/2013 Citycon PLC
15/03/2013 Technopolis PLC
22/03/2013 Sanoma PLC
15/04/2013 Biohit PLC
16/04/2013 Stockmann PLC
18/04/2013 Ilkka-Yhtymä PLC
19/04/2013 Lemminkäinen PLC
29/05/2013 PKC Group PLC
04/06/2013 YIT PLC
13/06/2013 Saga Furs PLC
17/06/2013 Wulff-Group PLC
25/06/2013 YIT PLC
23/07/2013 Sanoma PLC
05/08/2013 Tulikivi PLC
19/08/2013 Keskisuomalainen
10/09/2013 Neste Oil PLC
11/09/2013 YIT PLC
11/09/2013 Kone PLC
12/09/2013 Scanfil PLC
20/09/2013 Nurminen Logistics
24/09/2013 Wulff-Group PLC
25/09/2013 HKScan PLC
01/10/2013 Etteplan PLC
04/10/2013 Nokian Tyres PLC
09/10/2013 Stora Enso PLC
10/10/2013 Vaisala PLC
14/10/2013 Konecranes PLC
17/10/2013 Outotec PLC
17/10/2013 Metso PLC
21/10/2013 Atria PLC
24/10/2013 Finnari PLC
28/10/2013 Saga Furs PLC
13/11/2013 Finnari PLC
28/11/2013 Lemminkäinen PLC
19/12/2013 Martela PLC
19/12/2013 Metso PLC
22/12/2013 Saga Furs PLC
09/01/2014 Caverion PLC
09/01/2014 Stockmann PLC
17/01/2014 Ramirent PLC
21/01/2014 Uponor PLC
21/01/2014 Kemira PLC
23/01/2014 Vacon PLC
28/01/2014 Ilkka-Yhtymä PLC
10/02/2014 Suominen PLC
10/02/2014 Componenta PLC
11/02/2014 Incap PLC
05/03/2014 Restamax PLC
14/04/2014 Atria PLC

14/04/2014	Oral Hammaslääkärit PLC
15/04/2014	Alma Media PLC
06/05/2014	Ilkka-Yhtymä PLC
02/06/2014	Finnair PLC
03/06/2014	Fiskars PLC
12/06/2014	Stockmann PLC
16/06/2014	HKScan PLC
08/07/2014	Citycon PLC
10/07/2014	Ålandsbanken
15/07/2014	Oriola PLC
28/07/2014	Outotec PLC
30/07/2014	Martela PLC
01/08/2014	Lassila & Tikanoja PLC
04/08/2014	Aspo PLC
29/08/2014	Neste Oil PLC
12/09/2014	Vacon PLC
15/09/2014	Scanfil PLC
02/10/2014	Apetit PLC
07/10/2014	Honkarakenne PLC
09/10/2014	Yleiselektroniikka PLC
10/10/2014	Oriola PLC
14/10/2014	Stockmann PLC
17/10/2014	Aspo PLC
21/10/2014	Marimekko PLC
24/10/2014	Restamax PLC
13/11/2014	Atria PLC
20/11/2014	Aspo PLC
03/12/2014	Leipurin PLC
08/12/2014	Oriola PLC
16/12/2014	Ramirent PLC
17/12/2014	Martela PLC
20/12/2014	Neste Oil PLC
08/01/2015	Olvi PLC
19/01/2015	Stora Enso PLC
26/01/2015	YIT PLC
10/02/2015	Affecto PLC
18/03/2015	Apetit PLC
14/04/2015	Stora Enso PLC
14/04/2015	Okmetic PLC
21/04/2015	Neste Oil PLC
23/04/2015	Outokumpu PLC
24/04/2015	Orion PLC
08/06/2015	QPR Software PLC
12/06/2015	Technopolis PLC
17/06/2015	Alma Media PLC
01/07/2015	PKC Group PLC
16/07/2015	Sanoma PLC
27/07/2015	Fiskars PLC
03/08/2015	Yleiselektroniikka
17/08/2015	Investors House PLC
18/08/2015	Konecranes PLC
31/08/2015	Etteplan PLC
22/09/2015	Outokumpu PLC
12/10/2015	Stora Enso PLC
19/10/2015	Componenta PLC
21/10/2015	Vaisala PLC
23/11/2015	Destia Group PLC
05/01/2016	Aspocomp Group
18/01/2016	Alma Media PLC
19/01/2016	Stora Enso PLC
26/01/2016	Uponor PLC
08/02/2016	Elecster PLC
29/02/2016	Sponda PLC
15/03/2016	Etteplan PLC
18/03/2016	Investors House PLC
01/04/2016	Okmetic PLC
12/04/2016	Asiakastieto Group
22/04/2016	Caverion PLC
25/04/2016	Digia PLC
27/04/2016	Caverion PLC
02/05/2016	Honkarakenne PLC
09/06/2016	Martela PLC

20/06/2016	Caverion PLC
20/06/2016	Ilkka-Yhtymä PLC
15/07/2016	Comptel PLC
20/07/2016	Okmetic PLC
02/08/2016	Valoe PLC
14/09/2016	Alma Media PLC
20/09/2016	Suominen PLC
30/09/2016	Keskisuomalainen PLC
19/10/2016	Caverion PLC
19/10/2016	Apetit PLC
19/10/2016	Basware PLC
20/10/2016	Lemminkäinen PLC
21/10/2016	HKScan PLC
26/10/2016	Consti Group PLC
09/11/2016	Lemminkäinen PLC
11/11/2016	Lehto Group PLC
24/11/2016	Aspo PLC
14/12/2016	Tikkurila PLC
21/12/2016	Incap PLC
13/01/2017	HKScan PLC
16/01/2017	Caverion PLC
18/01/2017	Scanfil PLC
19/01/2017	Stora Enso PLC
20/01/2017	Rapala VMC PLC
03/02/2017	Orava Asuntorahasto PLC
03/02/2017	Lehto Group PLC
10/02/2017	Honkarakenne PLC
24/03/2017	Valoe PLC
12/04/2017	Valmet PLC
08/05/2017	Affecto PLC
18/05/2017	Keskisuomalainen PLC
24/05/2017	Lehto Group PLC
29/05/2017	Investors House PLC
13/06/2017	Lassila & Tikanoja PLC
15/06/2017	Pöyry PLC
20/06/2017	Ilkka-Yhtymä PLC
20/06/2017	Taaleri PLC
21/06/2017	Asiakastieto Group
12/07/2017	HKScan PLC
13/07/2017	Oriola PLC
13/07/2017	Outokumpu PLC
13/07/2017	Alma Media PLC
14/07/2017	Teleste PLC
18/07/2017	Konecranes PLC
20/07/2017	SRV Group PLC
20/07/2017	Suominen PLC
21/07/2017	Raisio PLC
25/07/2017	Outotec PLC
27/07/2017	Raute PLC
07/08/2017	Investors House PLC
29/08/2017	Aktia Pankki PLC
06/09/2017	Exel Composites PLC
07/09/2017	Sanoma PLC
12/09/2017	Lemminkäinen PLC
15/09/2017	Consti Group PLC
20/09/2017	Wulff-Group PLC
26/09/2017	Kone PLC
26/09/2017	Stockmann PLC
11/10/2017	Taaleri PLC
13/10/2017	QPR Software PLC
13/10/2017	DNA PLC
13/10/2017	Honkarakenne PLC
25/10/2017	Asiakastieto Group
31/10/2017	HKScan PLC
01/11/2017	Elecster PLC
16/11/2017	Lassila & Tikanoja
30/11/2017	Silmäasema PLC
12/12/2017	Caverion PLC
12/12/2017	Scanfil PLC
13/12/2017	Metsä Group PLC
15/12/2017	Consti Yhtiöt PLC
18/12/2017	Oriola PLC
18/12/2017	Robit PLC
22/12/2017	Lehto Group PLC