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**SEASONAL AFFECTIVE DISORDER ON THE STOCK MARKET: NORDIC  
EVIDENCE**

Master's Thesis in Finance

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**ABSTRACT**

Seasonal Affective Disorder (SAD) causes seasonal depression in a part of the population in several countries. It presents itself, when daylight hours decrease and has been found to be more prevalent, when moving away from the equator. This thesis examines the implications and inefficiencies the disorder may cause on some of the northernmost stock markets, the stock markets of the Nordic countries. The topic is approached from the perspectives of efficient markets and behavioral finance. The efficient market part presents the principles of asset pricing on efficient markets. In the behavioral finance part, the irrational behavior of investors is explained through psychological biases. The chapter also introduces the concept of limits to arbitrage and four anomalies that are connected to the SAD phenomenon.

In the empirical part, a regression is run for large cap and small cap indices from Finland, Sweden, Denmark and Norway. Large cap and small cap indices are examined separately to find out, if SAD affects large and small companies differently. Iceland is studied as comparison to these countries, because the prevalence of SAD is especially low there regardless of its extremely northern location. Daily returns of these indices are regressed on a SAD variable, which measures the length of night at a certain latitude, and a fall dummy, which allows the effect of SAD to be asymmetrical. A tax-loss dummy and a Monday dummy are used as additional explanatory variables.

A statistically significant SAD effect is found in all other indices, but the Danish small cap index and the Icelandic All Share index. The effect is asymmetrical for all indices excluding the Finnish large cap index. This means that the effect shifts returns from fall to winter. The coefficients for SAD are quite consistent for the large cap indices, varying from 0,025 % in Norway to 0,022 % in Finland, Sweden and Denmark. The consistency of the coefficients is lower for small cap indices, ranging from 0,028 % in Sweden to 0,014 % in Finland. Based on these results, no claim can be made about small cap companies experiencing a larger SAD effect or vice versa.

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**KEY WORDS:** Seasonal Affective Disorder, Stock Returns, Efficient Markets, Behavioral Finance, Stock Market Anomalies





## 1. INTRODUCTION

Seasonal affective disorder (SAD) is a medical condition with psychological and physiological symptoms. It presents itself during the winter season, when daylight hours decrease. It causes depression and anxiety to a part of a population. (Avery, Eder, Bolte, Hellekson et al. 2001.) At the same time depression and anxiety have been linked to lower risk-taking in financial as well as other matters (Kamstra, Kramer & Levi 2003). This might mean that on stock markets affected by SAD, expected returns are higher, when the level of risk-aversion lowers.

SAD has been found to be more prevalent in higher latitudes (Magnusson 2000). This suggests that the prevalence of SAD would be higher than average in Nordic countries. Therefore, if SAD has an effect on stock markets, the effect should be observable in the markets of Nordic countries. There is also evidence of smaller companies being more locally owned (see for example Grinblatt & Keloharju 2001 and Ivkovic & Weisbenner 2005.) Therefore, it would be logical to assume that the SAD effect would be stronger in smaller companies.

A thorough search of relevant literature yielded no results concerning differences in the effect of SAD between large cap and small cap companies. This makes examining large cap indices and small cap indices separately especially interesting. Furthermore, the stock exchanges of the Nordic countries are all among the northernmost stock exchanges of the world, and therefore the changes in length of night are among the most extreme of cities with stock exchanges. On the darkest day of the year, the sun can be seen for less than seven hours in Copenhagen, less than six hours in Stockholm and approximately five and a half hours in Oslo and Helsinki. In the city with the northernmost stock exchange in the world, Reykjavik, the sun can be seen for less than three and a half hours.

The concept of SAD affecting stock returns through changes in risk aversion has been somewhat controversial (see for example Jacobsen & Marquering 2008, Jacobsen & Marquering 2009 and Keef & Khaleed 2011). Therefore additional research concerning the effect is called for. Studying the phenomenon in northern stock exchanges far from the equator, where the effect should be most pronounced, seems very interesting. The new dimension of comparing the effect between large cap and small cap indices should also provide some interesting results and fresh points of view.

### 1.1. Purpose of the study

According to the efficient market hypothesis created by Fama (1970) no seasonal irregularities should be observable on stock markets in the long run. However, several studies have been made concerning different seasonal patterns on stock markets. Some of these calendar anomalies, like the January effect, have been studied exhaustively for several decades and in several countries (see for example Kato & Schallheim 1985, Bhardwaj & Brooks 1992 and Gu 2003). Others, like the SAD phenomenon, are relatively new and therefore less research has been made on them. While more anomalies are discovered, many of them start to overlap. For this reason the anomalies that most clearly overlap with the SAD-phenomenon are discussed in this study.

This thesis attempts to find out, if a SAD effect exists on stock markets of Finland, Sweden, Denmark and Norway. The large cap indices of each country are compared to small cap indices to find out if the SAD-effect is more pronounced in smaller companies. The method used in this thesis is regression analysis.

Along with the aforementioned Nordic countries, the SAD-effect in the Icelandic stock market is studied as an interesting comparison. Although Reykjavik is the northernmost stock exchange in the world, especially strong SAD-effect cannot be expected, because the prevalence of SAD in Iceland is relatively low, 3,80 %. This is significantly lower than the prevalence measured by the same methods in east coast of the United States, which is closer to the equator. (Magnusson & Stefansson 1993.)

### 1.2. Structure of the study

This thesis consists of seven chapters. Chapter one introduces briefly the topic and the research problem. The second chapter introduces the traditional way of thinking about finance, along with some basic concepts. The principles of efficient markets are covered through the efficient market hypothesis. It also explains the relationship of risk and return and presents two basic asset pricing models. These principles are explained, because SAD affecting stock returns argues with them profoundly.

In the third chapter a behavioral way to study finance is presented. Reader is steered towards a psychological way of thinking about finance. The chapter explains the

foundations of behavioral finance, which are psychology and limits to arbitrage. In the end of the third chapter, anomalies, which are phenomena that should not exist in efficient markets, are discussed and some behavioral viewpoints and explanations are offered.

The fourth chapter reviews the literature concerning the seasonal affective disorder more profoundly. It presents physical and psychological proof of the phenomenon using medical research. Later in the chapter financial research is examined and the effect of the SAD phenomenon to the stock and other markets is discussed. Different results from several markets are compared and commented.

Chapter five begins the empirical part of the thesis. It describes the data, hypotheses and methods used. The sixth chapter presents and discusses the results of the regressions. The final chapter, chapter seven, draws conclusions. It goes over the most important findings of the thesis and links them to the research problem. Finally, some interesting extending research topics are presented.

## 2. EFFICIENT MARKETS

There are many descriptions of the role of financial markets. Fama (1970) states that the primary role of capital markets is to allocate ownership of the economy's capital stock. According to Knüpfer & Puttonen (2009: 50), the four main functions of financial markets are:

1. Efficient allocation of funds between surplus and shortfall sectors. On efficient markets there are no trading costs and taxes.
2. Providing information. Investors have the latest information of the characteristics, risks and returns of their investments. Prices contain information about the expectations of the market as a whole.
3. Improving liquidity of assets. On liquid markets investors can realize their financial assets. For example, if an investor buys a corporate bond, he/she does not have to hold the bond for its whole maturity. He/she has the opportunity to sell it to other investors on the financial market. This makes lending and borrowing easier, because both sides can have maturities of their choosing.
4. Diversification of risk. An investor has the opportunity to invest in different companies and asset classes. Through an investment fund an investor can achieve a broad diversification with relatively low costs.

This research studies the effects of the SAD-phenomenon in all four of these functions as well as its relation to efficient markets, which are discussed in the subchapter 2.1.

### 2.1. The efficient market hypothesis

The traditional financial theories are based on the assumption of efficient capital markets. Fama (1970) presents three forms of market efficiency:

1. Weak form: Market prices reflect the information embedded in past prices. If this form holds, it is not possible to earn constant excess profits based on analysis of past returns.

2. Semi-strong form: Market prices reflect all publicly available information. If this form holds, prices adjust immediately to public information and it is not possible to earn constant excess profits by analyzing, for example, earnings announcements or merger proposals.

3. Strong form: Market prices reflect all information, including insider information. It is not possible to earn constant excess profits on a strong form efficient market.

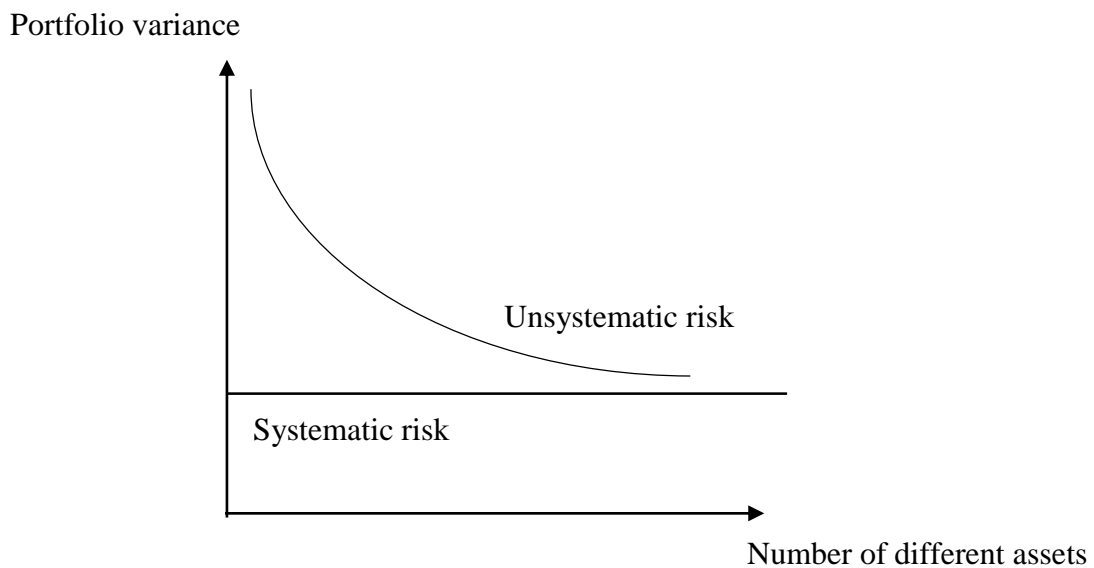
The hypothesis assumes that there are no transaction costs or informational imperfections on the market. It is easy to observe that this is not the case on real markets. This, however, doesn't mean that the market is necessarily inefficient. Only, if there are investors, who can constantly make better evaluations of the available information and earn excess profits from the markets, can one describe the markets inefficient (Fama 1970).

The critique towards efficient market hypothesis often questions the rationality of traders. According to the hypothesis, market participants are rational and they make trades to maximize their wealth the way financial models suggest. If an irrational trader would make a too optimistic buy, rational investors would sell and eliminate the effect. However, according to Shiller (2003), it is in no way clear that rational investors would have the power or the willingness to drive prices towards fundamentals. He defines smart money as investors, who have the ability to solve complex theoretical optimization models. Smart money has even been documented to amplify the effect of irrational traders (De Long, Shleifer, Summers & Waldmann 1990). The "rational" traders have acted "irrationally" and anticipated a price increase caused by irrational investors.

If it is possible to earn constant excess profits with a SAD based strategy, even the weak form of market efficiency fails to hold. The market participants, who are affected by SAD, would be acting irrationally. However, Fama (1991) states that it is not necessarily against market efficiency for expected returns to vary over time. If the variation of expected returns can be predicted by a financial model, the actions of investors might be defined rational. A model that allows risk aversion to vary over time is presented later in this chapter.

## 2.2. Risk and return

Risk and return have a fundamental connection on financial markets. The riskier an asset, the higher the return demanded by investors. Risk of an investment can be measured by volatility. Volatility of an asset means the standard deviation of its returns during a certain period of time. It can be calculated from daily, weekly, monthly or yearly data. (Knüpfer et al. 2009: 132–133).



**Figure 1.** The relationship of systematic and unsystematic risk. (Knüpfer et al. 2009: 144)

Volatility measures the total risk of an investment. It can be divided into systematic risk and nonsystematic risk. Systematic risk is the part of total risk that affects the whole market. Sources of systematic risk include inflation, exchange rates and interest rates. Unsystematic risk is the firm specific part of total risk. It consists of the uncertainty and surprises concerning the company in question. The amount of unsystematic risk can be controlled by diversifying the investments of a portfolio. Systematic risk can be considered more important, because one cannot get rid of it through diversification. (Knüpfer et al. 2009: 146–147.) The relationship of systematic and unsystematic risk is presented in figure 1.

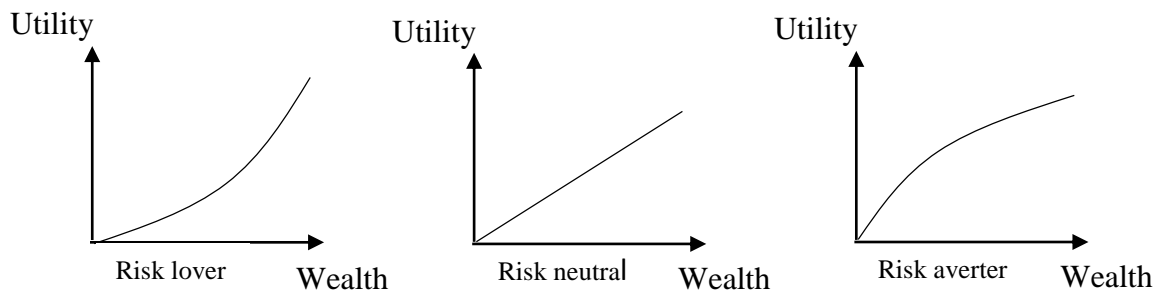
The systematic risk of a stock can be measured by beta. Beta presents the sensitivity of an individual stock to changes in the market portfolio (Knüpfer et al. 2009: 146).

According to Knüpfer et al. (2009: 146–147), it can be calculated mathematically as follows:

$$(1) \quad \beta_i = \text{COV}_{i,m} / \sigma_m^2$$

Where,  
 $\beta_i$  = the beta coefficient of security  $i$   
 $\text{COV}_{i,m}$  = the covariance between the returns of security  $i$  and the market portfolio  
 $\sigma_m^2$  = the variance of the return of the market portfolio

Investors can be rational, even though they do not maximize their risk adjusted returns. Instead, they maximize their utility, which is a result of the investments expected risk and return and their personal preferences. The personal preference of an investor is called his/her rate of risk aversion. Risk averse investors prefer certainty to higher returns to a certain degree. (Bodie et al. 2009: 162–163.) Figure 2 presents the utility functions of a risk lover, risk averter and a risk neutral investor.



**Figure 2.** The utility functions of a risk lover, a risk neutral and a risk averter (Copeland, Weston & Shastri 2005: 53).

Merton (1980) presents a measure for investors relative risk aversion. He introduces this measure as  $\lambda$ . This measure is discussed more thoroughly as a part of the conditional Capital Asset Pricing -model presented in subchapter 2.3.1. The idea behind the SAD phenomenon is that risk aversion  $\lambda$  could vary through time and especially through seasons.



### 2.3. Asset pricing models

Of the several financial models found in financial theory, this thesis concentrates on two market equilibrium models. These models are the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). According to Copeland et al. (2005: 147–148) these models determine the market price for risk and the measure of risk for a single asset.

These models are presented, because different versions of them are used to measure the SAD phenomenon in concerning research. The models and their different versions overlap, but at the same time they have differences in factors that explain returns (Copeland et al. 2005: 147).

#### 2.3.1. CAP-model

The CAPM is used to calculate the expected return of a security in a simplified world. It is based on modern portfolio theory and was developed in articles by Sharpe (1964), Lintner (1965) and Mossin (1966). The model makes several assumptions that do not hold in the real world. Despite its shortcomings, it is widely used and its accuracy is deemed acceptable. (Bodie et al. 2011: 281–282.)

According to Bodie et al. (2011: 295) The CAPM can be presented mathematically as follows:

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

Where:  $E(r_i)$  = Expected return of security  $i$   
 $r_f$  = Risk-free rate  
 $\beta_i$  = Beta coefficient of security  $i$   
 $E(r_m)$  = Expected return of the market portfolio

This version of the CAPM presents the relationship of the expected return of a security to the expected return of the market. Fama & French (1993) introduced an extension to the CAPM. This multifactor model consists of three factors, which are an overall market factor such as found in the traditional CAPM, a size factor (small minus big, SMB) and a book-to-market factor (high book-to-market minus small book-to-market, HML). Fama & French (1996) find that the multifactor model has more explanatory power than the traditional CAPM. However, they recognize that it does not work universally.

According to Campbell & Cochrane (2000), asset pricing models that take time-varying information into account, are likely to perform better than models that are constant in time. Bekaert & Harvey (1995) test a conditional CAPM presented originally by Merton (1980). This model treats the measure of risk aversion  $\lambda$  as a conditionally expected price of covariance risk. This model also allows time variation in the price of risk. The risk free rate is not a component of the model, because the return is determined at  $t-1$ .

Pricing of security  $A$  can be presented with the model mathematically as follows (Bekaert et al. 1995):

$$(3) \quad E_{t-1}(r_{i,t}^A) = \lambda_{i,t-1} \text{cov}_{t-1}(r_{i,t}^A, r_{i,t})$$

Where,  $E_{t-1}(r_{i,t}^A)$  = conditionally expected excess return on security  $A$  in country  $i$  on time  $t$ ,  
 $\lambda_{i,t-1}$  = conditionally expected price of covariance risk in country  $i$  on time  $t$ ,  
 $r_{i,t}$  = return on the market portfolio of country  $i$  on time  $t$ ,  
 $\text{cov}_{t-1}$  = conditional covariance operator.

On a national level the model simplifies to (Bekaert et al. 1995):

$$(4) \quad E_{t-1}(r_{i,t}) = \lambda_{i,t-1} \text{var}_{t-1}(r_{i,t})$$

This is basically the same model as model number three. The difference is that the covariance between security  $A$  and the market portfolio becomes variance, because the model describes the whole market of a country instead of a single security.

### 2.3.2. Arbitrage pricing theory

APT is a factor model developed by Ross (1976). APT relies on three assumptions. First, security returns can be described by a factor model. Second, there are enough securities to diversify unsystematic risk away. Third, markets will not allow arbitrage opportunities to persist. (Bodie et al. 2009: 323–324.)

According to Copeland et al. (2005: 176) APT can be presented mathematically as follows:

$$(5) \quad R_i = E(R_i) + b_{i1}F_1 + \dots + b_{ik}F_k + \epsilon_i$$

Where,  $R_i$  = the random rate of return of the  $i$ th asset,  
 $E(R_i)$  = the expected rate of return of the  $i$ th asset,  
 $b_{ik}$  = the sensitivity of the return of the  $i$ th asset to the  $k$ th factor,  
 $F_k$  = the mean zero  $k$ th factor common to the returns of all assets,  
 $\epsilon_i$  = a random zero mean noise term for the  $i$ th asset.

APT consists of several undetermined factors. These factors can be for example interest rates or the growth rate of the gross domestic product. Because firm specific risk is diversifiable, the factors are macroeconomic. (Nikkinen, Rothovius & Sahlström 2008: 76–78.) The CAPM and the multifactor model presented by Fama et al. (1993) are actually just APT with determined factors.

### 3. BEHAVIORAL FINANCE

Lead by Fama (1970), efficient markets dominated the academic studies of finance in the 1970s. It was later realized that following the efficient market theory rigorously could lead to major misinterpretations of financial situations such as stock market bubbles (Shiller 2003). According to Shiller (2003), theoretical efficient market models should not be trusted blindly on real markets. The debate between behavioral finance and efficient markets is still alive today (see for example Kim, Shamshuddin & Lim 2013 and McMillan & Wohar 2013).

Behavioral finance can be approached in different ways. Shleifer & Summers (1990) treated it as an alternative to the efficient markets approach. Many modern textbooks consider it as an add-on to classic finance (see for example Brealey, Myers & Allen 2011). According to Shiller (2003), behavioral finance studies finance from a social science perspective including psychological and sociological dimensions. These different ways to approach behavioral finance do not conflict with each other. However, they all have fundamental contradictions with the efficient market theory.

In this chapter the behavioral way of thinking about finance is explained. After discussing the foundations and basic studies of the school of thought, four anomalies are presented. These particular anomalies are explained, because they overlap with the SAD phenomenon.

#### 3.1. Limits to arbitrage and psychology

Shleifer et al. (1990) identify the “two pillars” of behavioral finance, limits to arbitrage (also limits of arbitrage) and investor psychology. They contradict the efficient market approach by claiming that on real markets riskless arbitrage is extremely rare, or totally non-existent. They also argue that investor psychology plays a big part in the price formation of securities.

Arbitrage is theoretically an investment strategy that guarantees profits with no risk. Perfect arbitrage requires no capital, so arbitrageurs would want to take infinite positions until the arbitrage possibility disappears. In practice, however, arbitrage is defined as a strategy that exploits market inefficiency. The idea is to buy underpriced and sell

overpriced securities to make profits, when prices return to fundamental values. Nothing guarantees that prices actually would return to fundamentals on real markets, so this kind of trading is almost never risk-free. This creates the limits to arbitrage. (Brealey et. al. 2011: 356.)

A basic example of a situation with limits to arbitrage is for example the following: Consider Nokia-stock, which is traded in the Helsinki stock exchange and the New York stock exchange. If the price of the stock is not the same on both markets, one should short the higher priced one and buy the lower priced one to arbitrage the situation. However, even this basic example of arbitrage is not completely risk-free. Shleifer & Vishny (1997) present two main sources of risk for this kind of situation:

1. There is no guarantee that the prices will converge in the short term. This creates a problem, because the investor has to pay interest to the lender on his short position.
2. The two exchanges have different trading hours. The investor might have to cover his/her short position outside the trading hours of the market he/she is long in. He/she would have to find capital to cover the short position and bear the risk of the possible depreciation of his/her long position.

Limits to arbitrage can also be linked to psychology. While capital constraints create a “hard” limit to arbitrage possibilities, the fear of the actions of irrational investors create a “soft” limit. Arbitrageurs may have sufficient capital and knowledge to arbitrage a certain situation. However, it is possible that the misperceptions of irrational traders deepen, thus prices will be driven even farther from fundamentals. If the mispricing deepens too much, arbitrageurs will be forced to liquidate their positions, when expected returns are highest. (Shleifer et al. 1997.) This creates a situation, where possible arbitrageurs are capable of arbitrage, but may be unwilling to take action, because of the risk created by irrational traders.

Psychology plays a big role in the price formation of securities. Barberis & Thaler (2003) summarize seven psychological biases people have been documented to suffer from, when forming expectations. They think these are most interesting from a financial point of view. These biases are presented in appendix 1.

All of these biases are a part of human irrationality. From a point of view concerning SAD, point two, optimism and wishful thinking, and point seven, availability biases, are

the most interesting (appendix 1). SAD-sufferers can be thought to regain their optimism, when days begin to lengthen and their rate of risk aversion lowers. When days shorten, their rate of risk aversion rises and they move to less risky assets because of their personal experiences and feelings rather than the events and realities of the market.

### 3.2. Anomalies

A financial anomaly can be described as a persistent deviation from market efficiency (Nikkinen et al. 2008: 86). An anomalous pricing of a security can be thought to be driven by investors' psychological biases instead of real information on the market. According to Copeland et al. (2005: 404) anomalies may not be exploitable by investors because of transaction costs, but acknowledging them could improve the returns of investors, who would trade anyway.

Anomalies are often analyzed in order to understand or even predict them. Novy-Marx (2014) studies the abilities of several periodic factors to predict a set of well-known market anomalies. These factors include the political party of the US president, global warming, a temperature anomaly known as El Niño and different planetary cycles. Some of these factors seem quite far-fetched, and Novy-Marx (2014) makes a good point about the difficulties of data driven search for factors behind anomalies. He concludes that even if an anomaly is statistically significantly explained by some factor, the link between the factor and the anomaly should be convincing.

A SAD based explanation for the seasonal variation in stock returns differs from the phenomena studied by Novy-Marx (2014) through its extensively studied links to depression (see for example Rosenthal 1998 and Magnusson 2000). When depression is linked to financial risk aversion (see for example Eisenberg, Baron & Seligman 1998 and Kramer & Weber 2012), SAD appears to be a much more plausible predictor of seasonal movements in the stock market compared to the factors studied by Novy-Marx (2014).

There are several different groups of anomalies. The SAD effect is a calendar anomaly due to its seasonal characteristics. It presents itself on a yearly basis. From the four anomalies presented in the next subchapters, January effect and Halloween indicator can also be categorized as calendar anomalies. All four anomalies presented below can be thought to overlap with the SAD effect. The links between them and the SAD effect are examined in chapter 4.

### 3.2.1. Size anomaly

Size anomaly (also small firm effect) is originally found by Banz (1981). He finds that small firms have on average greater risk adjusted returns than large firms. Banz (1981) also finds that while the effect presents itself in stocks of firms with small market capitalization, there are no significant differences in returns between middle-sized or large companies.

Fama & French (1992) also find the same effect. They claim that if the effect persists, it should be a previously unknown risk factor, which would not contradict the efficient market theory. Fama et al. (1993) embed a size factor according to the size anomaly as a part of their multifactor model presented in subchapter 2.3.1. They find that the size anomaly used as a factor in a multifactor model improves the explanatory power of the model.

There are several possible reasons to the size effect. It might be that financial models used to test the anomaly are misspecified and small firms entail risk that the models are not able to measure. Small firms are also traded less frequently and might thus understate the actual risk they entail, at least on short interval data. (Roll 1981.) Nikkinen et al. (2008: 87) note that the anomaly has grown weaker after its original discovery.

### 3.2.2. January effect

Rozeff & Kinney (1976) were the first to bring January effect to the attention of modern finance. However, it was actually first introduced much earlier by Wachtel (1942). Both studies find the stock market to yield abnormal returns on January. January effect is the best known financial anomaly and majority of the investment community knows of its existence (Haugen & Jorion 1996).

Keim (1983) examines the US stock market from 1963 to 1979 and finds a negative correlation between abnormal returns and company size. He also finds this correlation to be more significant in January than any other month. According to Keim (1983), almost half of the abnormal returns of the size effect are explained by the January effect.

Several explanations for the effect are presented in concerning literature. The two most significant of these are the tax-loss selling hypothesis by Wachtel (1942) and the window

redemption hypothesis by Haugen & Lakonishok (1988). The first suggests that investors sell their losing stocks at the end of the year for tax benefits and buy them back at the beginning of the year. The second claims that fund managers sell their risky assets at the end of the year to make their funds seem more attractive. They will then also buy back risky stocks at the beginning of the year to beat the index. (Moller & Zilca 2008.)

### 3.2.3. The Halloween indicator

The Halloween indicator (also the Halloween effect or Sell-in-May-effect) is based on the old market saying “Sell in May and go away”. The first statistically significant results about the existence of the effect are produced by Bouman & Jacobsen (2002). They find significantly higher returns on a period from November to April than the remainder of the year in 36 of the 37 countries under examination. The abnormal returns are also higher, when risk is taken into account. The differences in standard deviations are marginal and not significant in any of the examined countries. Bouman et al. (2002) examine several different possible explanations for the effect, but the only one they find to have an impact is the effect of vacations to trading activity. They suggest that the effect caused by vacations might be caused by changes in risk aversion or liquidity constraints. However, according to the efficient market theory, arbitrageurs should take advantage of such easily predictable behavior.

Jacobsen & Zhang (2012) make a study with all available stock market data. Their data is from 108 countries and as long periods as data is available for each country. They find statistically significantly higher returns in November-April in 35 countries versus only two in May-October. The effect can be found in several developed and emerging markets around the world, but the effect is strongest after 1960 in developed Western European countries. Overall, their results suggest that the effect has strengthened in recent years.

Because the November-April period includes January, one might think that the January effect is at least a part of the explanation behind the Halloween effect. However, Bouman et al. (2002) find that after controlling for the January effect abnormal profits can still be earned in 14 of the 20 countries, in which both Halloween and January effects are found. They also find the Halloween effect on many emerging markets, where there is no significant January effect.

The Halloween effect can also be thought to overlap with the SAD effect. While the trading strategy formed from the Halloween effect suggests to be long on stocks from



November to April, the original SAD-based strategy tested by Kamstra et al. (2003) suggests on the northern hemisphere to be long from fall equinox to spring equinox (September 22<sup>nd</sup> to March 20<sup>th</sup>). These two periods are relatively close to each other with a difference of just a little over a month separating them. They might actually be different approaches towards the same seasonal pattern found in stock returns. The conflict between the two anomalies is the timing on the southern hemisphere, where, according to a SAD-based strategy, one should be long conversely compared to the northern hemisphere.

#### 3.2.4. Home Bias

Investors have been proven to weigh their domestic equity markets too heavily in their portfolios. This has happened despite the fact that the benefits of international diversification have been recognized for decades. (See for example Levy & Haim 1970) The amount of research concerning the phenomenon increased in the 1990s. According to French & Poterba (1991), investors tend to expect higher returns from their domestic markets implied by their portfolio patterns. They also note that this does not seem to stem from institutional constraints, but the choices of investors.

Tesar & Werner (1995) extend the topic by documenting a preference not only to domestic stock, but to the stock markets of countries with close geographical proximity. For example, US investors (in addition to investing too heavily in their domestic market) overweight Canadian stocks in their international portfolios. An additional note is that investors seem to have a higher transaction rate in the international part of their portfolio compared to the domestic part. An explanation might be that investors have, or think they have, more information about their local companies compared with foreign companies, and therefore change the foreign companies in the portfolio more often.

Alongside with country level biases, home bias is also documented within countries. Grinblatt et al. (2001) find that investors, are more likely to invest in companies that have their headquarters in close proximity of their home municipalities. They also discover that investors, whose native tongue is Finnish, are more likely to invest in companies that publish their interim reports in Finnish. They also note that after the language is controlled for, investors show a preference towards companies, whose CEOs are of same cultural origin. The effect of these preferences is stronger with households and less financially savvy institutions compared to financially savvy institutions. This suggests that the bias

is driven by retail investors, whose actions cannot always be thought of as rational in an efficient market sense.

Ivkovic et al. (2005) find similar results by examining US stocks through the data of individual accounts from a large broker. However, they also note that locally biased investors earn on average 3,2% higher returns on their local holdings compared to their non-local holdings. This would suggest that the anomaly is at least partially driven by information asymmetries in favor of investors investing in local companies.

#### **4. LITERATURE REVIEW OF SEASONAL AFFECTIVE DISORDER**

In this chapter the SAD phenomenon is discussed more thoroughly. First, an overview of the most important research concerning the phenomenon is presented. Second, a more detailed look into physiological and psychological research concerning the disorder is taken. Finally, the effects found in previous research are gone over more precisely from the point of view of the financial markets.

Risk taking behavior of investors plays a big role in pricing of securities. Seasonal affective disorder has been linked to depression, which has been documented to lead to a higher level of risk-aversion (Eisenberg et al. 1998). If a part of investors suffer from seasonal changes in the level of risk aversion, this can lead to seasonal variation in equity returns (Kamstra et al. 2003).

Kamstra et al. (2003) were first to study the possibility of earning excess returns by timing the market according to the SAD phenomenon in several different stock markets. They claim that SAD sufferers create a seasonal pattern in the stock market by moving into less risky assets, when days shorten. The same people would then move back into riskier assets, when days begin to lengthen. The basic idea is to be out of the stock market, while days shorten and long in the stock market, when the days begin to lengthen. This would yield excess returns, if their hypothesis about an increase in the level of risk aversion held.

The results of the research of Kamstra et al. (2003) support their hypothesis. Even after controlling for seasonal patterns, like tax-loss-trading and environmental effects, like sunshine and temperature, the strategy seemed to yield statistically significantly better results than a buy-and-hold-strategy on several markets. The effect was stronger in general in the northern hemisphere and seemed to be greater the higher the latitude. This kind of a strategy required only two trades per year, so trading costs would not consume all profits. The results of Kamstra et al. (2003) are examined in more detail later in this chapter.

Garrett, Kamstra & Kramer (2005) try to capture the SAD effect with a conditional version of the CAP-model that allows the price of risk to vary over time. This model is the model number four from chapter 2.3.1, presented originally by Bekaert et al. (1995). Their results suggest that the SAD effect is fully captured by this type of a model. This

discovery supports the previous hypothesis by Kamstra et al. (2003) by treating the SAD effect as a consequence of changes in risk aversion over time.

SAD affecting stock returns has also spawned critique. Jacobsen et al. (2008) confirm the existence of a statistically significant seasonal effect, but they question the fact that it would be caused by SAD. They suggest that in future research a simple seasonal dummy is used instead of individual causes such as the SAD phenomenon or weather. They claim that stronger empirical and physiological evidence is needed to prove, what causes the changes in risk aversion.

The research of Jacobsen et al. (2008) started a debate between them and Kamstra, Kramer and Levi. Kamstra, Kramer & Levi (2009) comment the research of Jacobsen et al. (2008) by criticizing their methodology and presenting several problems with their research. Kamstra et al. (2009) do admit that the SAD effect does not explain all of the variation in risk aversion, although they find it to be an important part of this variation.

Jacobsen et al. (2009) publish a response to the comment of Kamstra et al. (2009). They explain the mistakes made in the original research by Jacobsen et al. (2008) and claim that the main point of the research, whether it is SAD that causes the seasonal pattern, still stands. Jacobsen et al. (2009) show that the seasonal variation on stock markets can be statistically significantly “explained” in several countries by other seasonal events, like the rise in ice cream consumption during the summer. Although, it is quite unlikely that ice cream consumption would actually explain stock returns in the real world, Jacobsen et al. (2009) make a good point about the necessity of further research concerning the link between stock returns and the SAD phenomenon.

Keef et al. (2011) join the critics of the original research made by Kamstra et al. (2003). Keef et al. (2011) claim that the seasonal effect is significant, but cannot be explained by the depressed mood caused by SAD. Keef et al. (2011) also criticize some of the results used against Kamstra et al. (2003). They arrive to a similar conclusion with Jacobsen et al. (2009), which is that more research about the explanation behind the seasonal variation of stock returns is required.

Kelly & Mesche (2009) critique the econometric and psychological evidence of the original study by Kamstra et al. (2003). Kelly et al. (2009) expand the original study and find results against SAD affecting the stock market. However, in one of their more recent papers, Kamstra, Kramer & Levi (2011) claim that Kelly et al. (2009) have misinterpreted

most of the psychological evidence they used to criticize Kamstra et al. (2003). Kamstra et al. (2011) also examine the econometric results of Kelly et al. (2009) and find them to strongly support the existence of the SAD phenomenon. Even though the research concerning SAD on the stock market has increased substantially after Kamstra et al. (2003), these mixed results and different conclusions call for further research and results concerning the phenomenon.

#### 4.1. Psychological and physiological background

Partonen & Lönnqvist (1998) state that symptoms caused by the onset of SAD typically include social withdrawal, decreased activity, sadness, anxiety, lowered sex-drive, poor quality of sleep and increased appetite and weight. When SAD sufferers recover after winter solstice, their cognitive functions usually improve. Light therapy has also been documented to be an effective treatment for SAD. This supports the theory of decreasing daylight hours being the driver behind SAD.

According to Rosenthal (1998: 3–4) 6 % of the US population suffer from SAD. Additionally, 14 % of the population suffer from a milder version of the disorder, which is often called the winter blues. Rosen, Targum, Terman & Bryant et al. (1990) find that rate of SAD sufferers is significantly higher in northern latitudes in the US. The clinical features of SAD are consistent across different industrialized cultures (Partonen et al. 1998). This might mean that people living in different countries even further north would be affected at least at the same rate, or even more.

Magnusson (2000) makes an overview of the epidemiological studies concerning SAD. He finds that results of the concerning studies are somewhat scattered, for example the prevalence estimates of SAD ranged from 0 % to 9,7 %. The prevalence was greater at higher northern latitudes and varied across ethnic groups. However, Magnusson (2000) concludes that SAD is a relatively common disorder and for the general population its onset begins in September and depressive symptoms peak in winter.

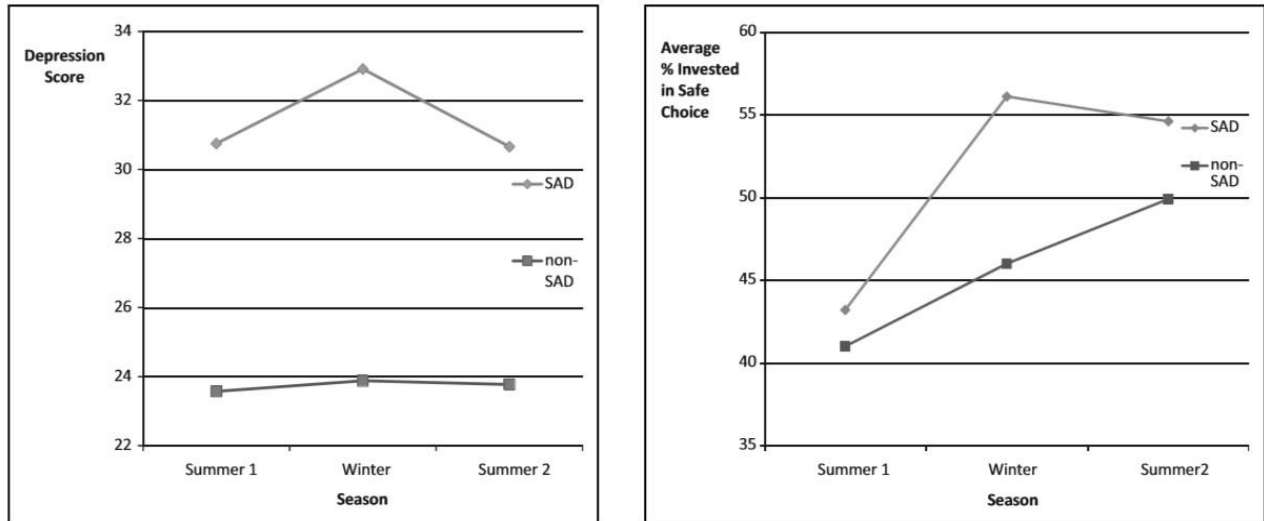
Even though Magnusson (2000) finds evidence of higher northern latitudes having higher prevalence of SAD, there is at least one exception. Magnusson et al. (1993) examine the phenomenon in Iceland. Despite being far up in the North, the prevalence of SAD was found to be only 3,80 %, which is significantly lower than for example in the USA. Cott & Hibbeln (2001) explain the low prevalence of SAD in Iceland by much larger

consumption of fish compared to other Nordic countries and the US. They claim that Omega 3, and other fatty acids that fish contain, lower not only the SAD induced depression, but also depression in general. For this reason Icelandic stock markets are studied in this thesis as a comparison to the other Nordic markets.

The carrying theme of this thesis is the effect that SAD has on risk aversion. Eisenberg et al. (1998) experiment with people suffering from different degrees of depression. Risk aversion was distinguished from passivity by changing risky and safe choices to be the action requiring one. They find significant correlation between depressive symptoms and risk aversion.

In the same fashion, Stanton, Reeck, Huettel & LaBar (2014) find that happy mood increases the gambling propensity of individuals. They induced happy, sad or neutral mood in the test subjects and had them make economic decisions with certain and risky payoffs. Inducing happy mood in subjects increased their likelihood to choose the risky choice, while no change in gambling frequency was found for subjects induced with sad or neutral mood. The increased preference of the risky choice can be interpreted as lowered risk aversion, which is in line with the findings of Eisenberg et al. (1998).

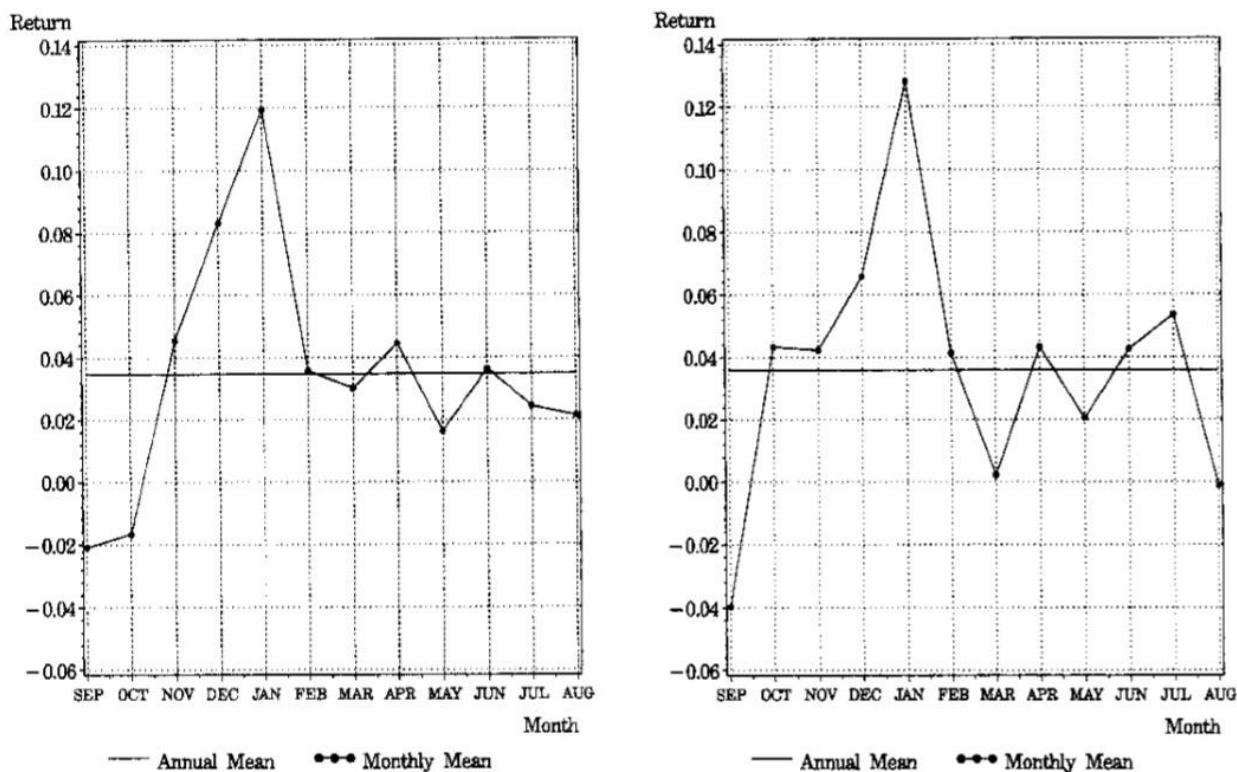
One of the more recent psychological studies about SAD affecting financial risk aversion is made by Kramer et al. (2012). They conduct a survey for 5000 SAD sufferers and non-SAD sufferers. The survey is carried out with real financial payoffs. As presented in figure 3, Kramer et al. (2012) find that SAD-sufferers move to less risky choices in the same rate as their depression scores rise. Noteworthy of this study is that it was made under extreme financial circumstances from summer 2008 to summer 2009. Even though the second summer of the study displays a relatively small drop on risk aversion for SAD sufferers, one can see that SAD sufferers change their risk preferences much more aggressively than non-SAD sufferers, when moving from summer to winter. The upward curve of non-SAD sufferers risk aversion is likely to be explained by the 2008-2009 financial crisis.



**Figure 3.** Seasonal fluctuations in depression score and financial risk aversion over time (Kramer et al. 2012).

#### 4.2. Effects on the financial markets

In their original study Kamstra et al. (2003) examine four indices from the US and eight indices from around the world. The foreign indices are from Sweden, Britain, Germany, Canada, New Zealand, Japan, Australia and South Africa. Figure 4 presents the monthly mean daily returns of the indices grouping them into the average of the US indices and the average of the foreign indices. Before calculating the average, the results from southern hemisphere are shifted by six months to align the seasons. It can be observed from figure 4 that September, which is the beginning of the onset of SAD for the general population, has the lowest returns in both groups. The highest returns are in turn found in January, the month after winter solstice.



**Figure 4.** Annual and monthly means of daily returns in the US (left) and foreign countries (right) (Kamstra et al. 2003).

Kamstra et al. (2003) test a trading strategy, where an investor invests his/her whole portfolio in Swedish and Australian stock markets for 20 years starting from the early 1980s. The idea is to be long on the Swedish stock market for the northern hemispheres fall and winter and move to the Australian market for the southern hemispheres fall and winter. This SAD-based strategy outperformed a neutral strategy, in which the investor holds both markets with equal proportions for the whole period, by an annual average of 7,9 percent points. An opposite strategy, where the investor would have been long on the markets in an opposite fashion, would have underperformed the neutral strategy annually by 8,0 percent points. Kamstra et al. (2003) also find that the SAD-based strategy does not cause extra risk, at least in the form of volatility of returns.

Kaplanski & Levy (2009) examine the seasonal variation of the VIX-index. The VIX-index measures implied volatility derived from the prices of options. It is often called the fear index, because it is the estimate of the future volatility of risky assets (Whaley 2000).



Kaplanski et al. (2009) find a seasonal pattern on the VIX-index, which behaves according to the SAD phenomenon. Investors perceived risk peaks, when daylight hours decrease. This supports the theory of people moving out of risky assets during the onset of SAD. However, Kaplanski et al. (2009) find that the effect can only be found significant in perceived risk, not the actual market risk measured by volatility. This suggests that risk adjusted excess returns could be available, if actual risk and the risk that investors experience differ.

Kaplanski, Levy, Veld & Veld-Merkoulova (2015) find further evidence of SAD affecting investor expectations. They study investor sentiment by examining a broad group of Dutch investors. They find the return expectations of SAD sufferers for the Dutch and the US markets to be significantly lower in the fall compared to other seasons. A SAD variable ranging from 1 to 4 depending on the severity of SAD is also found to be correlated to the mood of the whole sample.

If investors move to less risky securities, when days shorten, the effect should also be visible in the less risky asset classes. Kamstra, Kramer & Levi (2014) examine the seasonal changes in the returns of US treasury bills, which are commonly thought of as a risk free asset. They find an opposite pattern than the one found on equities. US treasury bills seem to yield higher returns during the fall, up to 80 basis points in October compared to April. Kamstra et al. (2014) control for several possible explanations behind this difference and find that a proxy for seasonal variation in risk aversion explains over 60 % of the difference.

The effect of SAD can also improve correct pricing on the markets. Dolvin, Pyles & Wu (2009) find that SAD affects stock analysts' earnings estimates. Analysts tend to be more pessimistic on estimates made during SAD months. However, analysts have been found to be generally too optimistic (for example, see Lim 2001). The increased pessimism therefore offsets an existing positive bias in analysts' estimates and makes them more accurate as a whole. Dolvin et al. (2009) also find that the effect of SAD is significant with analysts from the northern states of the US, but not with those from southern ones.

Pyles (2009) examines the effects of SAD on the returns of publicly traded real estate investment trusts (REITs). He finds results similar to the ones found from overall markets by, for example, Kamstra et al. (2003). The same seasonal effect as in normal equities is, however, only found in the smallest 40 % of REITs. According to Pyles (2009) this is to be expected, because the returns of REITs are easier to predict compared to normal stocks

and thus entail less risk. Smaller REITs are closer to normal equities considering risk and it is logical that the seasonal effect similar to normal equities is found in them.

Another interesting finding by Pyles (2009) is that even though institutional investors were allowed on the REIT market after 1993, the influence of SAD does not disappear. Pyles (2009) gives three potential explanations for the influence to remain in an environment, where returns are largely driven by institutional investors, who are (or should be) financial professionals. First, there can be an undefined component on fall and winter returns driven by institutional investors. Second, a large percentage of non-institutional investors are affected by seasonal depression. Third, institutional managers are not immune to psychological biases such as seasonal depression. The second of these explanations seems unlikely, when several medical professionals have documented that only a small part of the general population suffers from diagnosed seasonal depression like SAD (see for example Magnusson 2000). The third explanation, however, would seem plausible, because of the SAD effect Dolvin et al. (2009) find on financial analysts, who are also financial professionals.

Kliger, Gurevich & Haim (2012) find that the calendar date of an IPO and its respective seasonal mood influence the returns of IPOs substantially in both the short and the long run. The difference between excess returns of IPOs issued in “depressing” and “cheerful” days is 5–10 % of the offering. The effect seems to be even stronger with companies that are less publicly exposed. Kliger et al. (2012) attribute these seasonal mood related effects to the lack of trading history, which they find to serve as an anchor in the valuation process (see also point 7 in appendix 1). Dolvin & Fernhaber (2014) also find results that support SAD influencing IPO underpricing. They find that younger firms suffer from even heavier underpricing during SAD periods, which is consistent with the findings of Kliger et al. (2012), if younger firms are thought of as the less publicly exposed ones. According to Dolvin et al. (2014), this effect can be mitigated by using a higher quality underwriter or changing the share retention decision.

The effect of SAD has also been linked to the post earnings announcement drift. Lin (2015) finds smaller immediate response of investors to earnings news during the time of lowest daylight hours. SAD does not seem to have an effect on the negative earnings surprises, but it causes stronger immediate effects to positive earnings surprises during the winter and weaker in the fall. Similar behavior can be found in abnormal trading volumes for positive earnings surprises. The three-day abnormal volume is lower during the fall and higher during the winter, but negative surprises do not seem to be effected.

Lin (2015) proposes that the fact that negative earnings surprises are not affected results from an “Ostrich effect”, where people try to avoid hearing bad news, when they are likely. This behavior can be thought to be somewhat linked to the point five of appendix 1, Belief perseverance.

Kaustia & Rantapuska (2015) study the effects of mood on trading behavior of investors. Their data consists of about 1.2 million individual Finnish investors and about 45 000 Finnish institutions. They find SAD to have a relatively little effect on the tendency to buy and sell, but trading volume seems to be affected positively. The clearest patterns they find during the summer holiday season. Trading volume is lower and investors seem to sell more. This supports the vacation explanation behind the Halloween effect presented by Bouman et al. (2002). Even though Kaustia et al. (2015) have a large amount of data, one has to bear in mind that the results are from a small country with a relatively small stock market.

Kamstra, Kramer, Levi & Wermers (2013) publish a working paper, where they find seasonal flows of capital in mutual funds in the US, Canada and Australia. These seasonal flows seem to behave as the SAD caused change in risk aversion would suggest. The flows are economically significant containing tens of billions of dollars. The paper does not examine returns of mutual funds, but according to its results, studying the seasonal returns of funds with different risk levels would seem beneficial.

## 5. DATA AND METHODOLOGY

This thesis studies the effect of the SAD phenomenon on nine indices in five countries. For each country, excluding Iceland, an index consisting of the most traded companies and an index consisting of the smallest companies is examined. These indices are OMX Helsinki 25 Price Index and OMX Helsinki Small Cap Price Index for Finland, OMX Stockholm 30 Price Index and OMX Stockholm Small Cap Price Index for Sweden, OMX Copenhagen 20 Price Index and OMX Copenhagen Small Cap Price Index for Denmark, Oslo SE OBX Price Index and Oslo Exchange Small Cap Total Return Index for Norway and OMX Iceland All-Share Price Index for Iceland.

The choice to use price indices is based on the substantially longer history and resulting larger amount of observations. An exception to this had to be made for Norwegian small cap companies because of data availability. Additionally, because of their longer histories, the indices of most traded companies are used instead of the actual large cap indices. Only one Icelandic index is studied in this thesis. The OMX Iceland All-Share Price Index was chosen to represent the stock market of the whole country, because it has the longest history of available data. Not being able to compare Icelandic large and small cap indices is not a problem, because Iceland is studied as a comparison to the other Nordic countries, because of its unique properties concerning SAD prevalence.

All of the indices are value weighted and, with the exception of Oslo Exchange Small Cap Total Return Index, dividends are not included. Although, it would be more logical to examine total return indices that include dividends, the histories of the respective total return indices were so much shorter that the logical choice was to examine price indices. The data for all of the indices is obtained from Datastream, except for OMX Iceland All-Share, which is obtained from the Nasdaq OMX Nordic website and Google Finance.

### 5.1. Data description

In this thesis daily returns, calculated as the difference of the natural logarithms of returns on time  $t$  and  $t-1$ , are used. The data is from as long as it is available in each case. The longest series is for OMX Stockholm 30 and the shortest for the small cap indices of Finland, Sweden and Denmark, as can be seen from table 1.

**Table 1.** Descriptive statistics of the raw data. All figures except skew and kurtosis are percentages.

Country	Index	Mean	Stand. dev.	Minimum	Maximum	Skew	Kurtosis
Finland	OMXH25	0,027	1,46	-9,40	9,29	-0,15	6,72
	3.5.1988-19.3.2015						
	OMXH Small Cap	0,032	0,78	-4,99	7,60	0,15	11,12
	1.1.2003-19.3.2015						
Sweden	OMXS30	0,039	1,43	-8,53	11,02	0,02	7,59
	2.1.1986-19.3.2015						
	OMXS Small Cap	0,049	0,85	-7,12	7,01	-1,07	12,66
	1.1.2003-19.3.2015						
Denmark	OMXC20	0,032	1,15	-11,72	9,50	-0,29	9,20
	4.12.1989-19.3.2015						
	OMXC Small Cap	0,017	0,63	-6,30	4,25	-0,98	12,98
	1.1.2003-19.3.2015						
Norway	Oslo SE OBX	0,028	1,50	-24,00	11,12	-1,00	18,99
	2.1.1987-19.3.2015						
	Oslo SE Small Cap	0,036	1,02	-7,52	5,72	-0,91	9,32
	1.1.1996-19.3.2015						
Iceland	OMXI All Share	0,026	1,15	-36,63	5,06	-10,25	302,60
	5.1.2001-19.3.2015						

The average daily returns range from 0,049 % for OMXS Small Cap to 0,017 % for OMXC Small Cap. The standard deviations of daily returns are higher for large cap indices compared to their respective small cap indices, Oslo SE OBX being the most volatile at 1,50 %. The largest falls are experienced in Norway and Iceland. Oslo SE OBX fell 24,00 % during the Norwegian banking crisis in 1987. The OMXI All Share experienced a 36,63 % daily fall, when the trading restrictions of two large banks, Exista Hf and Straumur-Burðarás fjárfestingarbanki Hf, were removed in late 2008. The plummeting of two companies caused a fall of this magnitude, because the Icelandic stock market is rather small, and, especially before the financial crisis, concentrated on the banking sector.

The minimum returns are lower for each large cap index compared to their respective small cap indices. In the same fashion, the maximum values are higher for the large cap indices. Even though one could initially think that small cap indices are more likely to

have higher extreme values, those being higher for the large cap indices is not abnormal, because they have a larger set of observations.

Most indices are negatively skewed, which is typical for stock markets, but, interestingly, OMXH Small Cap and OMXS 30 are positively skewed. All of the return series are also kurtotic, OMXH 25 having the lowest kurtosis at 6,72. OMX Iceland All-Share has distinctly the highest kurtosis at 302,60, followed by Oslo SE OBX at 18,99. The extreme level of the kurtosis in Iceland is likely to be caused by the low amount of extreme values. Even though the minimum value of the Icelandic returns is lowest of all of the Nordic countries, the amount of these extreme values does not seem to be extensive, and the majority of the observations are likely to be concentrated.

## 5.2. Hypotheses

There are two hypotheses that are tested in this thesis. The first one addresses the main question of the thesis, if SAD is a factor behind the seasonal pattern in stock returns. The first hypothesis and its alternative hypothesis are defined as:

- (1)             $H_0$ : Seasonal affective disorder does not affect stock returns.  
                   $H_1$ : Seasonal affective disorder affects stock returns.

The second hypothesis is used to examine the potential effect that SAD has on stock returns further. It tests, if the effects of SAD are symmetrical in fall and winter. This aspect is examined to find out that alongside with the length of night, does the direction it is moving affect stock returns. The second hypothesis and its alternative hypothesis are defined as:

- (2)             $H_0$ : The effects of SAD are symmetrical between fall and winter.  
                   $H_1$ : The effects of SAD are asymmetrical between fall and winter.

These hypotheses are tested for each index, using the variables defined in subchapter 5.3. The acceptances and rejections of the hypotheses are talked over alongside with the results of the regressions in chapter 6.

### 5.3. Methodology

This thesis examines the effect of SAD on Nordic stock markets using single regressions for each index. The main explanatory variable analyzed is the length of the night in the fall and winter relative to the mean annual length of night, which is 12 hours. Following Kamstra et al. (2003), this variable  $SAD_t$  is defined as:

$$(6) \quad SAD_t = \begin{cases} H_t - 12, & \text{for trading days in the fall and the winter} \\ 0, & \text{otherwise} \end{cases}$$

Where  $H_t$  is the time from sunset to sunrise in a particular location at time  $t$ .  $H_t$  is defined using standard approximations from spherical trigonometry. In order to calculate the number of hours of night at latitude  $\delta$ , the sun's declination angle  $\lambda_t$  is required.

$$(7) \quad \lambda_t = 0,4102 * \sin[(2\pi/365)(julian_t - 80,25)]$$

Where  $julian_t$  represents the number of the day in the year ranging from 1 to 365. It equals 1 for the first of January, 2 for the second of January and so forth. After obtaining the declination angle, the number of hours of night in the Northern Hemisphere can be calculated as:

$$(8) \quad H_t = 24 - 7,72 * \arccos[-\tan(2\pi\delta/360)\tan(\lambda_t)]$$

Where  $\arccos$  is the arc cosine.

Results of Palinkas, Houseal & Rosenthal (1996) and Palinkas & Houseal (2000) suggest that the depressive effect of SAD may be asymmetric around winter solstice. This asymmetry is the idea behind SAD affecting stock markets. The risk aversion of SAD sufferers increases, when daylight hours decrease. These same people would then increase their risk taking, when daylight hours start to increase. Therefore, the SAD effect should be allowed to be asymmetric in the fall and the winter. This can be achieved by introducing a fall dummy  $D_t^{\text{fall}}$ , for days of the year in the fall.

$$(9) \quad D_t^{\text{fall}} = \begin{cases} 1, & \text{for trading days in the fall} \\ 0, & \text{otherwise} \end{cases}$$

Trading days in the fall are from fall equinox (22.9.) to winter solstice (19.12.) each year. This dummy variable allows the SAD effect to differ between fall and winter. However, the differing is not required. If the coefficient of this variable proves to be insignificant, the effects are symmetric between the two periods.

Finally, following Kamstra et al. (2003), the regression is defined as follows:

$$(10) \quad r_t = \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_1 \text{SAD}_t + \beta_2 D_t^{\text{fall}} + \beta_3 D_t^{\text{monday}} + \beta_4 D_t^{\text{tax}} + \varepsilon_t$$

Where,

$r_t$  = The logarithmic period  $t$  return of an index.

$\rho_1 r_{t-1}$  &  $\rho_2 r_{t-2}$  = Lagged dependent variables. Used where necessary to control for residual autocorrelation.

$\text{SAD}_t$  = The SAD variable. Defined as explained in equation 6.

$D_t^{\text{fall}}$  = Fall dummy. Defined as explained in equation 9.

$D_t^{\text{monday}}$  = A dummy variable, which equals 1, when period  $t$  is the first trading day of the week and 0 otherwise.

$D_t^{\text{tax}}$  = A dummy variable, which equals 1, when period  $t$  is the last trading day or one of the five first trading days of the year and 0 otherwise.

$\varepsilon_t$  = The error term

Monday and tax-loss dummies are included, because they are known calendar anomalies overlapping the SAD phenomenon. It is especially important to control for tax-loss trading, because for most of the countries returns seem to peak in January.



Kamstra et al. (2003) also use cloud cover, precipitation and temperature as explanatory variables. Garret et al. (2005) omit these variables, when testing their version of the regression, because they are relatively insignificant. For the same reason, cloud cover, precipitation and temperature are not used in this thesis.

## 6. RESULTS

This chapter examines the results of the regressions for each country. The results are presented one country at a time in their respective subchapters. This approach was chosen to make comparing the SAD effect between large and small companies easier. The countries and large cap and small cap indices are compared to each other in subchapter 6.6.

Statistical significance of the coefficients is measured with the heteroscedasticity robust t-values of White (1980). Autocorrelation is controlled for by including one or two lagged dependent variables where necessary.

### 6.1. Finland

As can be seen from table 2, SAD is significant on the 1 % level for OMXH25 and on the 5 % level for OMXH Small Cap. Interestingly, the effect seems to be symmetrical for OMXH25, since the fall dummy is not significant. OMXH Small Cap on the other hand seems to experience an asymmetrical effect, since its fall dummy is significant on a 1 % level.

**Table 2.** Regression results for stock indices in Helsinki. The results are presented as percentage points, excluding the  $R^2$  coefficient. Statistical significance is measured with Whites heteroscedasticity robust t-values. The latitude of the city can be seen after the city's name.

<b>HELSINKI (60°10')</b>				
Variable	<b>OMXH25</b>	t	<b>OMXHSCAP</b>	t
$\rho_1$	0,058	3,31	0,121	3,92
$\rho_2$	-	-	0,075	2,77
$D_{\text{monday}}$	-0,045	-1,00	-0,020	-0,51
$D_{\text{tax}}$	0,114	0,81	0,368	2,65
$D_{\text{fall}}$	-0,056	-1,11	-0,105	-2,94
SAD	0,022	2,67	0,014	2,18
$R^2$	0,0052		0,0392	

The results contain some interesting properties. For example, the prices of large Finnish companies do not seem to rise slower in the fall compared to winter. Then again, the appreciation of small cap companies seems to be stronger after winter solstice compared to the fall period. This is suggested by the statistically significant negative fall dummy in OMXH Small Cap. Alongside with having the highest t-value of the Finnish data, the absolute value of the coefficient is farthest from zero of the Finnish results.

Other dummy variables are insignificant, with the exception of the tax dummy for the OMXH Small Cap. This suggest that prices of large Finnish companies are not affected by tax loss trading, but small companies are. This seems logical, because of the lower volume of trades. There is also no observable Monday effect in either of the Finnish indices.

The regressions are able to explain 0,52 % of the returns of OMXH25 and 3,92 % of the returns of OMXH Small Cap. Based on the results above, for hypothesis 1, the null hypothesis is rejected for both OMXH25 and OMXH Small cap and the alternative hypothesis is accepted. For hypothesis 2, the null hypothesis is accepted for OMXH25 and rejected for OMXH Small cap. The effect of SAD on returns of Finnish stocks can therefore be considered symmetrical for large companies and asymmetrical for small companies.

## 6.2. Sweden

The results from Sweden are similar to results from Finland with some exceptions. As can be seen from table 3, SAD is significant on the 1 % level for both OMXS30 and OMXS Small cap. The fall dummies are also significant, on the 5 % level for OMXS30 and on the 1 % level for OMXS Small Cap. This suggests that the SAD effect is asymmetrical in Sweden both in large and small companies.

**Table 3.** Regression results for stock indices in Stockholm. The results are presented as percentage points, excluding the  $R^2$  coefficient. Statistical significance is measured with Whites heteroscedasticity robust t-values. The latitude of the city can be seen after the city's name.

STOCKHOLM (59°17')				
Variable	OMXS30	t	OMXSSCAP	t
$\rho_1$	0,023	1,30	0,104	2,51
$\rho_2$	-	-	0,078	2,10
$D_{\text{monday}}$	-0,023	-0,51	-0,071	-1,59
$D_{\text{tax}}$	-0,012	-0,10	0,102	0,96
$D_{\text{fall}}$	-0,104	-2,08	-0,123	-2,87
SAD	0,022	2,68	0,028	4,09
$R^2$	0,0018		0,0289	

The coefficients are in general higher than those of Finland in table 2. The coefficient of SAD in OMXS Small Cap is higher than the SAD coefficient of OMXS30. In the same fashion as in Finnish results, the coefficients of the fall dummies are higher than the coefficients of SAD. Other dummy variables prove to be insignificant for both Swedish indices. Therefore no tax loss effect or Monday effect is detected in Sweden.

The regressions explain 0,18 % of the returns of OMXS30 and 2,89 % of the returns of OMXS Small Cap. For hypothesis 1, the null hypothesis is rejected and the alternative hypothesis is accepted for both indices. The null hypothesis of hypothesis 2 is also

rejected for OMXS30 and OMXS Small Cap. The effect of SAD can therefore be found significant and asymmetrical for both indices.

### 6.3. Denmark

Table 4 presents the results of the regressions from Denmark. OMXC Small Cap is the first index of the study, where SAD is found to be insignificant. However, the fall dummy is significant for OMXC Small Cap. For OMXC20, SAD and the fall dummy are both significant. The level of SAD coefficient of OMXC20 is close to the levels of SAD coefficients of the large cap indices of Finland and Sweden.

**Table 4.** Regression results for stock indices in Copenhagen. The results are presented as percentage points, excluding the  $R^2$  coefficient. Statistical significance is measured with Whites heteroscedasticity robust t-values. The latitude of the city can be seen after the city's name.

COPENHAGEN (55°40')				
Variable	OMXC20	t	OMXCSCAP	t
$\rho_1$	0,058	2,83	0,156	4,17
$\rho_2$	-	-	0,114	3,41
$D_{\text{monday}}$	-0,023	-0,59	0,003	0,10
$D_{\text{tax}}$	0,143	1,40	0,290	3,55
$D_{\text{fall}}$	-0,088	-2,07	-0,087	-2,73
SAD	0,022	2,63	0,006	0,92
$R^2$	0,0059		0,0591	

The tax-loss dummy is significant on the 1 % level for OMXC Small Cap. The significance and the coefficient are also highest of the Danish results. Other additional dummy variables turn out to be insignificant. Tax loss effect is therefore detected in OMXC Small Cap, while no such effect can be found in OMXC20. Monday effect is not detected in either of the indices.

The regressions are able to explain 0,59 % of the returns of OMXC20 and 5,91 % of the returns of OMXC Small Cap. For hypothesis 1, the null hypothesis is rejected on the 1 % level and the alternative hypothesis is accepted for OMXC20. For OMXC Small Cap, the null hypothesis is accepted and therefore SAD is not a factor behind its returns. For hypothesis 2, the null hypothesis is rejected on the 5 % level for OMXC20 and the alternative hypothesis is accepted. Therefore, SAD effect is asymmetrical for OMXC20. For OMXC Small Cap, SAD effect is not found. It seems to, however, experience lower than average returns in the autumn.

#### 6.4. Norway

It can be seen from table 5 that SAD is significant and positive for both Oslo OBX and Oslo Small Cap. The fall dummies are also significant, and negative, which suggests an asymmetrical SAD effect for both indices. The coefficients of SAD and the fall dummies in Norway are highest of the Nordic indices.

Monday dummy is significant and negative on the 1 % level for Oslo Small Cap. For Oslo OBX the Monday dummy is not significant. Tax dummies are also not statistically significant for either Norwegian indices. The regression is able to explain 0,48 % of the returns of Oslo OBX and 2,99 % of the returns of Oslo Small Cap.

**Table 5.** Regression results for stock indices in Oslo. The results are presented as percentage points, excluding the  $R^2$  coefficient. Statistical significance is measured with Whites heteroscedasticity robust t-values. The latitude of the city can be seen after the city's name.

OSLO (59°57')				
Variable	OSLO OBX	t	OSLO SCAP	t
$\rho_1$	0,029	1,01	0,121	4,77
$\rho_2$	-0,031	-1,42	0,071	3,18
$D_{\text{monday}}$	-0,089	-1,86	-0,100	-2,63
$D_{\text{tax}}$	0,105	0,85	0,141	1,23
$D_{\text{fall}}$	-0,167	-3,05	-0,123	-2,90
SAD	0,025	2,98	0,026	3,79
$R^2$	0,0048		0,0299	

Based on the above results, the null hypotheses of hypothesis 1 are rejected on the 1 % level and the alternative hypotheses are accepted for both indices. SAD is therefore found to be a factor behind the returns of both indices. The fall dummies are also significant on the 1 % level. Hence, the null hypotheses for hypothesis 2 are rejected and the alternative hypotheses are accepted for both indices. The SAD effect is therefore found to be asymmetrical for both indices. The effect of SAD and the asymmetry of the effect in Norway are highest of the studied countries.

### 6.5. Iceland

Table 6 shows that results from Iceland behave in a manner that the low prevalence of SAD would suggest. The coefficient of SAD and the fall dummy prove to be statistically insignificant. This supports the theory that SAD induced mood swings are a factor behind the seasonal anomaly in stock returns. The tax loss dummy is also statistically insignificant, but the Monday dummy is significant on the 1 % level.

**Table 6.** Regression results for OMX All Share Iceland. The results are presented as percentage points, excluding the  $R^2$  coefficient. Statistical significance is measured with Whites heteroscedasticity robust t-values. The latitude of the city can be seen after the city's name.

<b>REYKJAVIK (64°10')</b>		
Variable	<b>OMXIPI</b>	t
$\rho_1$	0,083	4,80
$\rho_2$	0,068	3,94
$D_{\text{monday}}$	-0,186	-3,63
$D_{\text{tax}}$	0,129	0,59
$D_{\text{fall}}$	-0,094	-1,77
SAD	0,005	0,68
$R^2$	0,0175	

The null hypotheses of both hypotheses are accepted and the alternative hypotheses rejected. Therefore no SAD effect, asymmetrical or symmetrical, can be found in the Icelandic stock market. The regression is able to explain 1,75 % of the returns in the OMX Iceland All-Share.

#### 6.6. Comparing results

The results of the large cap indices of the countries are remarkably similar. As can be seen from table 7, Oslo has the highest coefficient at 0,025 %, while the other large cap coefficients are all 0,022 %. Additionally, there are no notable differences in the statistical significances of these coefficients, all being significant on the 1 % level.

The coefficients of the small cap indices are less in line compared to the coefficients of the large cap indices. As table 7 shows, the significant coefficients range from 0,014 % in Helsinki to 0,028 % in Stockholm. The only statistically insignificant SAD coefficient of the studied indices (apart from Iceland) is found in the Danish small cap index.



**Table 7.** SAD coefficients for each index compiled from the regression results. The coefficients are significant on the 1 % level, with the exceptions of the coefficient of Helsinki Small cap index, which is significant on the 5 % level, and the coefficient of the Copenhagen Small cap index, which is not statistically significant. The coefficients are presented as percentage points.

<b>City and latitude</b>	<b>Large Cap</b>	<b>Small Cap</b>
<b>Helsinki</b> (60°10')	0,022	0,014
<b>Stockholm</b> (59°17')	0,022	0,028
<b>Copenhagen</b> (55°40')	0,022	(0,006)
<b>Oslo</b> (59°57')	0,025	0,026

The results do not suggest that the effect of SAD is in general higher among smaller companies compared to larger ones. In Stockholm and Oslo the coefficients of the small cap indices are higher than those of the large cap indices, but the differences are small, 0,006 and 0,001 percentage points respectively. In turn, the coefficient of the Helsinki large cap index is 0,008 percentage points higher than the coefficient of the local small cap index.

When the insignificance of the coefficient of the Copenhagen small cap index is taken into account along with the differences presented above, no clear argument can be made about the SAD effect being stronger with small cap companies. If anything, the consistency of the large cap results might be considered as proof of a stronger SAD effect among large companies. However, there is not enough evidence to make claims towards either direction.

## 7. CONCLUSIONS

This thesis studies the effect of SAD on stock returns of Nordic countries. Even though the whole concept of SAD affecting stock returns would seem like a psychological bias, it can also be thought to be within the boundaries of the efficient market theory. The conditions of market efficiency are not necessarily broken, if the risk aversion of investors is included in financial models, and it is allowed to change through time. From this perspective, the SAD effect appears to be in an interesting crossroads between the efficient market theory and behavioral finance.

Previous research is somewhat controversial about the role of SAD affecting the returns on stock markets. It has been possible to earn risk adjusted excess returns with a SAD based strategy in several different markets. Furthermore, unlike most calendar anomalies, the profits of a SAD based strategy would not be consumed by transaction costs. However, there is a body of research that questions the assumption that SAD is the driver behind this seasonal pattern of stock returns. It is likely that the discussion concerning the seasonal pattern in stock returns and the effect of SAD will remain heated until a cause for the pattern is proven more thoroughly. Proving powerfully that it is SAD above other reasons that causes the pattern would require a large amount of data of the individual trades of individual investors. It is of course also possible, and even likely, that the pattern consists of many factors, including the ones presented in this thesis, and cannot be attributed to a single factor.

The results obtained from Nordic countries support the theory of SAD being a factor behind the seasonal variation of stock returns. SAD is found to be significant for all studied indices from Finland, Sweden, Denmark and Norway with the exception of the Danish small cap index. The magnitude of the effect is remarkably similar among the large cap indices of different Nordic countries, ranging from 0,025 % for Norway to 0,022 % for Finland, Sweden and Denmark. For small cap indices, the effect is not as consistent. The strongest SAD effect found in this thesis is in Swedish small cap companies, 0,028 %. On the other hand, the effect is found to be insignificant in Danish small cap companies and lowest of the significant coefficients is found in Finnish small cap companies, 0,014 %. Therefore no argument can be made for a stronger SAD effect among smaller companies.

The SAD effect found in these indices is also asymmetrical, with the exception of OMXH25, the Finnish large cap index. This means that the amount of hours of darkness are a factor behind the returns of large Finnish companies, but the effect is symmetrical between fall and winter. Therefore, for large Finnish companies, there is no difference in the SAD effect between days with same amount of hours of darkness in the fall and winter. Then again, for the other studied indices, the effect is asymmetrical. This means that it is not the amount of hours of darkness alone that affects the returns, but also the direction of the change in the length of night.

Reykjavik stock exchange is the northernmost stock exchange in the world, but the prevalence of SAD is documented to be significantly lower in Iceland compared to, for example, the US and the other Nordic countries. When this low prevalence of SAD in Iceland is considered, the results obtained from OMX Iceland All-Share should not come as a surprise. The fact that the SAD variable does not explain returns in Iceland corroborates the theory of SAD explaining the seasonal pattern of stock returns.

All things considered the findings of this thesis contribute to existing research by finding a SAD effect from the stock markets of Nordic countries, Finland, Sweden, Denmark and Norway, where SAD is found to be more prevalent. Additionally, the size of a company does not seem to have an effect on the magnitude of the SAD effect in the Nordic countries. Even though the highest value for a SAD coefficient was found in OMXS Small Cap, the results from large cap indices were more consistent. One potential reason behind higher consistency of the large cap results might be foreign institutional investors, who invest in large cap companies in all Nordic countries. If these investors were suffering from SAD, or some other factor the SAD variable captures, the consistency of the results among large cap indices could be expected.

Taking advantage of the SAD effect on stock markets is not as simple as some of the previous research might suggest. Following a SAD based strategy would not increase conventional risk measures like volatility. However, if an investor would want to take advantage of the pattern, he/she would have to bear the risk of the anomaly disappearing or reverting itself. In fact, an interesting question is, why have arbitrageurs not taken advantage of this pattern of returns and made it disappear. At least a part of the reason might be that actions of financial professionals are not necessarily immune to seasonal depression. Another reason might be the fact that there are other factors, which have been suggested to cause the pattern. Potential arbitrageurs might not want to act without exact evidence of the cause of the pattern.

This lack of hard evidence is hard to overcome, even with the rather large amount of results favoring SAD as the cause of the seasonal pattern in stock returns obtained in previous research as well as this thesis. It is naturally possible that the commonly used SAD variable, due to its seasonal characteristics, captures a seasonal anomaly, which is actually caused by some other factor. However, with the psychological evidence presented earlier, SAD affecting stock returns seems relatively logical. Furthermore, the competing theories that explain the seasonal variation of stock returns, like the Halloween effect, also suffer from the same proving difficulties as the SAD effect.

Although several different financial securities and different markets have already been studied, many interesting topics remain. An interesting topic for research would be the returns of mutual funds of different risk levels. The funds with no institutional stakeholders could be chosen to test for a seasonal effect among retail (non-professional) investors. On the other hand, institutional investors could also be examined, because there are results, which suggest that they are not necessarily immune to seasonal changes in risk aversion.

Other fascinating subject of research would be currencies. If investors suffer from seasonal changes in risk aversion also in the currency market, it should be visible in the rates of safe haven currencies like the US Dollar and the Swiss Franc. It might also be interesting to study the prices of different derivatives through the seasons. Their price changes would provide beforehand information about investors' expectations concerning the pattern. Prices of equity index futures and options with maturities in fall and winter would reveal, if the effect is expected, at least to some degree.

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## APPENDICES

### **Appendix 1.** Psychological biases by Barberis et al. (2003):

1. **Overconfidence:** Overconfidence presents itself in two ways. People assign far too narrow confidence intervals. They are also generally bad at estimating probabilities. For example, events they estimate to be certain only occur 80 % of the time and events they estimate to be impossible occur 20 % of the time.

2. **Optimism and wishful thinking:** People tend to have unrealistic views of their own abilities. For example, 90 % of people think they are above average drivers.

3. **Representativeness:** People suffer from base rate neglect and sample size neglect. Base rate neglect causes people to be led by the way a question is presented. They have been documented to jump into conclusions based on their own experiences without any support from the concerning data. Sample size neglect means that people trust small sample sizes too much. People can, for example, put equal weight to a coin toss of three heads and three tails and a coin toss of 500 heads and 500 tails. Sample size neglect is sometimes called “the law of small numbers”.

4. **Conservatism:** People move too conservatively from base rates. This appears to conflict with representativeness, but that is not the case. If the data has an underlying model, people seem to overweight the data. However, if there is no model, people lean on their priors and react too little.

5. **Belief perseverance:** People tend to hold on to their opinions too tight and for too long. They are reluctant to search evidence that is in conflict with their view and if they happen to find such information, they are likely to treat it with extensive skepticism. A stronger version of belief perseverance is confirmation bias, where people misinterpret evidence that contradicts their hypothesis.

6. **Anchoring:** People adjust away from initial values too slowly. For example, people were asked in an experiment if the percentage of African countries in the UN was higher or lower than a randomly generated number between 0 and 100. The given initial value was found to affect their estimates significantly.

7. Availability biases: People put too much weight on their own experiences, when estimating probabilities. They also weigh recent events more heavily.