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SEASONALITY IN STOCK RETURNS:

Seasonal Affective Disorder on Nordic Indices

Master's Thesis in Finance

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ABSTRACT

The general theory of market efficiency assumes that the markets are efficient and deviations, in other words anomalies, do not exist. The theory of behavioural finance takes different approach because inefficiencies and deviations are appearing in the real world. This thesis concentrates on a seasonal anomaly called the Seasonal Affective Disorder (SAD). When the daylight is decreasing, SAD effect causes seasonal depression for people in different locations and the impact seems to be more powerful when moving away from equator to up north. The main aims are to solve significance of controversial weather variables and examine the inefficiencies and the implication in some Nordic stock markets, which can be caused by the SAD during the years 2000-2016.

In this thesis, the efficient market section goes through the principles of asset pricing, dynamics of the efficient market theory and limits of arbitrage. The behavioural finance section explains by means of psychological biases, why investors could act irrationally. The topic introduces fundamental and calendar anomalies, including the SAD phenomenon. The empirical part run regression for Finnish indices with and without weather variables. The aim is to solve necessity of weather variables due to contradictory conclusions of recent research work about the SAD with weather variables. The regressions are run without weather variables also for all Nordic indices because the second aim is to find out the seasonal impact of the SAD to stock returns. Daily log returns are used in the regression analysis with seasonal dummies and SAD variables, which tells the length of the night in specific latitude.

A Significant seasonal pattern of average stock returns and a weak SAD phenomenon are appearing among all indices during 2000-2016. However, the weather variables seem to be unnecessary for empirical analysis. The SAD is asymmetrical for several indices but in opposite direction than a known theory assumes.

KEY WORDS: Seasonal Affective Disorder, Efficient Markets, Behavioural Finance, Anomalies

1. INTRODUCTION

Fama's (1965) Efficient Market Hypothesis has been one of the most cited theories in the field of market efficiency in finance for a remarkable period of time. The theory assumes that all new information including future stock performance is already reflected in today's stock prices and investors are acting rationally. In 1970's, the theory of Efficient Market Hypothesis was being questioned because abnormal stock returns were discovered in certain periods of time. In other words the researchers started to discover anomalies, which are known as patterns in stock returns. (Olsen 1998.)

Arbitrage, also known as a chance to get profit from the difference of purchase and sale price of the asset, exists as a result of market inefficiencies. The efficient market approach states that most of the investors will take the available arbitrage opportunities but that excess returns are eliminated by the same behaviour of a large amount of such investors so the existence of arbitrage returns are override by the efficient market hypothesis. However, recent research in the finance of field has identified several number of anomalies which means that specific investment strategies have historically earned higher returns than those identified by they systematic risk. (Sheilfer & Vishny 2007.)

Since Fama's theory was published, it has been controversial and has gotten a critic from authors. Several new theories exist that have been introduced to argue with Fama's Efficient Market Hypothesis, for example the theory of behavioural finance. Behavioural finance theory hypothesize that investors react randomly and their behaviour is not connected to any specific finance theory even if they are given the exact same information and a time period. Moreover, investors seem to be frequently subjected to biases, errors and perceptual illusions (Shefrin 2002:3). They have also known to act contradictory to rational behaviour which means that investors are willing to pay more for an asset if they have the right to sell it afterwards and they are not to obliged to hold it forever. In Efficient Market Hypothesis theory, where the market is functionally efficient and all investors are equally rational, there would be no speculative behaviour among investors. The criticism against Fama's (1965) the Efficient Market Hypothesis developed behavioural finance.

Seasonal affective disorder (SAD) is a one of behavioural finance's phenomena. SAD a phenomenon is medical state of mind that has links to anxiety and depression. It causes lower risk-taking in life general, as well as when making financial decisions. SAD effect has been observed more commonly in higher latitudes, which means that the further away one goes from the equator the more powerfull the SAD effect gets. That is why the Nordic countries are used in this thesis and also it is interesting to see how SAD affects to local markets. Previous studies have not done as extensive research on these MSCI Nordic indices that are used in this thesis. (Kamstra, Karamer & Levi 2003; Avery, Eder, Bolte & Hellekson 2001.)

Also previous literature has argued about the necessity of weather variables. Garret, Kamstra & Kramer (2005) experimentally drop them out from their study and successfully use conditional asset pricing model which allows the risk premium to vary over time. De, Silva, Pownall & Wolk (2012) also present in their study that weather variables do not have any powerful impacts when the effect of good weather on price's fluctuation is analysed. Nevertheless, Kliger, Raviv, Rosett, Bayer & Page (2015) get consistent results with Kamstra et al. (2003) and that is what this thesis tries to find out, does the weather variables have significant impact when they are affiliated with regression. Depression associated with shorter days lead into greater level of risk aversion, so this thesis wants to solve how great the impact is to Nordic indices and is a "fall" variable enough to express the impact on stock returns.

1.1 The purpose of the thesis

The purpose of this thesis is to find out how Seasonal Affective Disorder can explain the seasonal patterns in stock returns. In the first hypothesis, there have been used also weather factors along the other factors because then the effect of weather conditions on stock returns can be clarify more precisely. However, some researchers like Garret et al. (2005) deny the significance of those variables. So the first hypothesis considers the necessity of weather variables and focuses only on the Finnish indices.

The first hypothesis and its alternative hypothesis are defined as:

(1) H_0: Weather variables are necessary to define the effect of Seasonal affective disorder to indices.
H_1: Weather variables are not necessary to define the effect of Seasonal affective disorder to indices.

The second hypothesis is used to examine the potential effects that SAD has on indices in three different Nordic countries; Finland, Sweden and Norway. The hypothesis tests if the SAD effect is symmetrical in fall and winter. The second hypothesis and its alternative hypothesis are defined as:

(2) H_0: Seasonal affective disorder does not explain the returns of Nordic Indices.
H_1: Seasonal affective disorder explains the returns of Nordic Indices.

As it is mentioned above the hypotheses are tested for indices. In the chapter five, the variables that are used in the regression model, are defined. Finally, the results are discussed in the chapter six.

1.2 The structure of the thesis

This thesis is outcome of seven chapters. The first chapter introduces shortly the topic and the research problem. The second chapter presents the efficient market hypothesis as well as other related principles of finance. The principles are explained because the SAD phenomenon is arguing against the traditional principles. Therefore understanding other deviations, in other words anomalies, are explained in that chapter. The third chapter takes a look at some psychological perspectives to financial thinking. The chapter contains the most important foundations of behavioural finance, which are concept of limits to arbitrage and psychology.

The fourth chapter is literature review about the seasonal affective disorder more precisely. It shows some proofs of this phenomenon in physical and psychological way. The fifth chapter is the beginning of the empirical part of the thesis. It introduces the data, hypotheses and methodology that are used. The sixth chapter presents the results and the last one, chapter seven, concludes all the chapters discussing some of the results and goes over the most important findings.

2. THE EFFICIENT MARKET HYPOTHESIS

In the 1950s economics started to analyse economic time series. Maurice Kendall (1953) argues that stock prices are able to show the future prospects of the company, and also repetitious fluctuations in economic performance appear in those prices. However, to his great surprise, he found that he failed to identify any predictable patterns in stock prices. The prices seemed to act randomly and unpredictably; there was a fifthy-fifthy possibility that the prices would go up or that they would go down. It quickly started to seem obvious that random price movements indicated a well-functioning or an efficient market, and not a market that is acting inefficiently. (Bodie, Kane & Marcus 2011.)

Fama's (1970) *efficient market hypothesis* has acted as a basis for the academic studies over decades. He states that the primary role of capital markets is an ownership allocation. It is all about the choice between active and passive investment-management strategy. Several researchers base their studies on Fama's (1970) findings, although they do not share exactly the same opinion. For example, Harrison & Kreps (1978) presented a contrary theory. They suggested that in order to earn excess profits on assets, all investors must actively manage their portfolios instead of using a passive buy and hold investment strategy. They found out that even if every market participant can receive the same available information, they would still end up making different individual investment decisions. That is the so-called speculative behaviour. If the markets are efficient, there would be no need for any speculation. Speculative behaviour is also one of the keystones of behavioural finance. The random walk theory is important for understanding of the functions of efficient markets. Next this section goes through the random walk and definition of efficient market, and later on, deviations from efficiency, the so-called anomalies are looked more closely.

2.1 Random walk

The core idea of efficient market hypothesis is that information is not blocked and it can rapidly spread over stock prices, therefore tomorrow's price changes would reflect tomorrow's news and the changes would also be independent from today's price changes. The price changes may not be estimated if the news are not published, therefore price changes are occasional. Also more local as well as foreign investors are able to access to the markets so therefore more information is reflected in the current prices. The fair determining of the prices and market efficiency will be contributed by increased number of foreign investors in the market. (Gumus & Zeren 2014.)

Many studies reveal that stock prices follow a *random walk*. In the imaginary situation where it is possible to forecast stock prices, investors would likely continue purchasing undervalued stocks whose price is going to increase and sell the overvalued stocks whose price is going to fall. That kind of strategy would provide investor certain profits daily. However, there should not be so called "free lunches" or sure profits in the markets because all new information, regarding future stock performance, should be already reflected in today's stock prices. Nevertheless, Kendall (1953) was the first who examine price series and found that the series are wandering around. His conclusion was that explains that since the new information should be unpredictable, the stock prices must also wander unpredictably. This wandering conducted the main argument that stock prices should follow a so-called *random walk*. Nowadays the idea that all information should be fully included to current stock prices is generally known as the same as efficient market hypothesis. (Bodie et al. 2011: 372-373; Fama 1970.)

2.2 Three stages of the efficient market hypothesis

The financial market has a many descriptions. Initially, Fama (1970) states that the main role of the financial markets is to allocate ownership of the economy's capital stock. He presents three categories of market efficiency. The efficient market hypothesis (EMH) is simplified as an expression that security prices fully reflect all available information.

Fama's (1970) categories are called the weak, semi-strong and strong.

1. A weak-form tests how well past returns, price movements and trading volumes predict future returns. If the weak-form holds, it is not possible to have constant excess returns that are based on analysis of past returns.
2. The semi-strong form is not only focused in the historical data only. It tests how quickly security prices reflect public information announcements. Also other general information should be included or reflected to the asset price. In this form, information consists of a company's future earnings forecasts and production line information as well as information of management competency.
3. The strong form tests does any investors have some private information which is not reflected to the market prices.

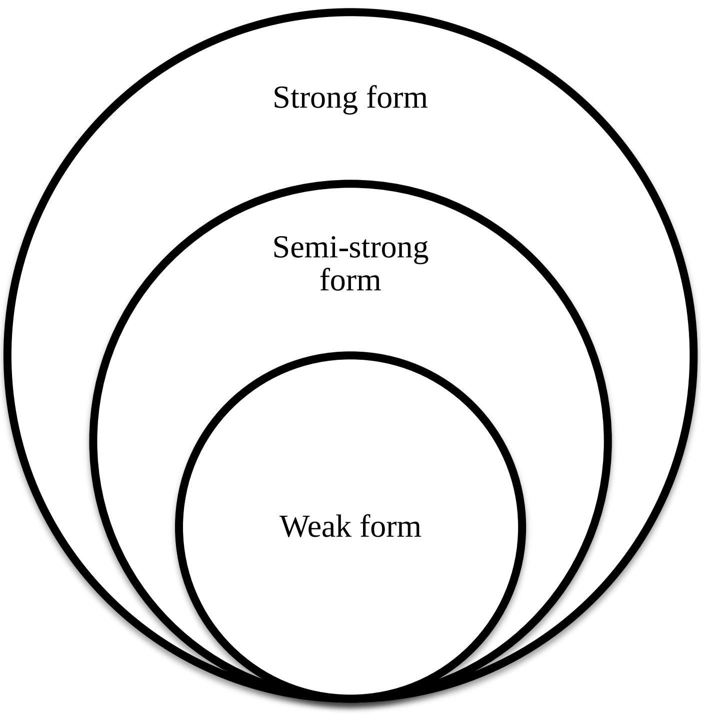

Figure 1. Different stages of market efficiency. (Fama 1970.)

If the different forms of efficient market hypothesis held it, would be impossible to exploit abnormal returns or arbitrage. However, there are plenty of strategies based on different type of market weaknesses, for example, anomalies that investors insist to exploit when they are making trading decisions.

Also Knüpfer & Puttonen (2009:50) define the four most important functions of financial markets. The functions go hand in hand with the EMH. Deviations or so called anomalies can hurt these assumptions as it can be seen when the section goes further. The functions are as follows:

1. To make efficient fund's allocation between surplus and shortfall sectors. There are no trading costs and taxes on the efficient markets.
2. Providing information. Investors are able to have all the latest information of risks and returns of their investments and also they have all information of other characteristics. Prices include information about the all market expectations.
3. Improvement of assets' liquidity. The liquid markets ensure that investors can realize their financial assets. For example, if an investor buys a corporate bond, he/she has the opportunity to sell it to other investors on the financial markets, therefore he/she does not have to hold the bond for its whole maturity. This makes lending and borrowing easier, because lenders and borrowers can have maturities on the asset that they want to hold.
4. Diversification of risk, which means that an investor has the possibility to invest in different companies and asset classes. An investor can have extensive diversification with relatively low costs through an investment fund.

2.3 Risk and Share Evaluation

Kahneman and Tversky (1979) questioned the effectiveness of expected utility theory as a model of decision making under a certain risks in their study. People are not concerned enough on the final outcome. They are rather making their investment decisions based on potential losses and profits of the assets. The greater profit an asset is gaining, the greater an impact is to investor’s decision making. Therefore, the figure of value function below is asymmetrical. Same kind of figure can be found in the prospect theory section (3.2.2) where the topic's details have explained.

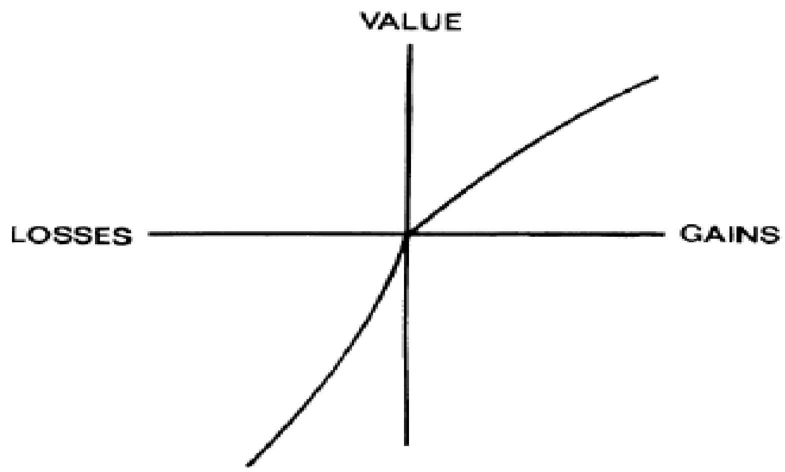

Figure 2. Value function. (Kahneman & Tversky 1979.)

According to Shefrin & Statman (1985) people tend to sell their shares too early. If investors can wait a bit longer before selling their shares it is quite possible that the price of the shares will increase, so they can sell the them for a higher price. On the other hand, waiting too long can cause losses because price of the share decreases too much. Shefrin & Statman (1985) name that phenomenon as *disposition effect* where investors sell winners too early and ride losers too long.

In addition, the psychology studies have shown that there is a relationship between heightened risk aversion and depression, like “*winter blues*” or *seasonal affective disorder* also known as SAD. The change of risk aversion in financial markets can influence the equilibrium price (Bierwag & Grove 1965.)

Campbell, Grossman & Wang (1993) examine the relationship between an aggregate stock market trading volume and the serial correlation of daily stock returns because they want to find out the possible consequence of heightened risk aversion on trading volume.

They were using a model that consists of risk-averse “market makers” that adapt to buying or selling pressure from “liquidity” or “non-informational” traders. The main finding is that increased risk aversion increases trading volume but decreases returns. Wang (1994) investigates existing links between trading volume and stock returns. He presents that trading volume and stock price changes are positively correlated. The positive relation is gets stronger when the information asymmetry increases.

As it can be noticed that risk and return have an essential relationship on financial markets. Investors demand higher returns when the risk of the asset increases. The risk of an investment can be measured by *volatility* and volatility means the standard deviation (STD) of an asset’s return during a certain period of time. Volatility can be calculated from different data periods; daily, weekly, monthly or yearly. (Knüpfer et al. 2009: 132-133.)

The total risk of an investment or volatility has two parts; *systematic risk and unsystematic risk.* Unsystematic risk is known as a firm specific risk whereas systematic risk is a part of total risk that affects the market as a whole. Systematic risks consists of inflation, interest rates and exchange rates whereas unsystematic risk is firm specific and it consists of the uncertainty and surprises for the specific firm. The firm can decrease unsystematic risk by diversification of portfolio but systematic risk cannot be eliminated by diversification. (Knüpfer et al. 2009: 146-147.)

2.4 Capital Asset Pricing Model (CAPM)

One of the keystone of the modern finance or assumptions of economy is Capital Asset Pricing Model (CAPM). It has been developed by William Sharpe (1964), John Lintner (1965) and Mossin (1966). It is based on well-known Markowitz’s portfolio theory. In Markowitz’s theory, the main aim is to find a spot where the investors are able to have the highest possible returns with minimum standard deviation of risk. CAPM describes the relationship between the risk of an asset and asset’s expected return. It is also one of the tools that measure risk. (Bodie et al. 2011:281-282.)

Mathematically CAPM can be defined as follows:

(1) $$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right]$$

Where: $E(r_i)$ = Expected return of security *i*

r_f = Risk-free rate

β_i = Beta coefficient of security

$E(r_m)$ = Expected return of the market portfolio

CAPM assumes that investors are price-takers which means that they are acting in away that asset's price is not affect by their own trades. They are also planning within a single-period horizon and the time period for holding the assets is identical. The trades are made to simple financial assets such as stocks and bonds. CAMP also assumes that there does not exist any taxes or transaction costs and information is free and highly obtainable for all investors. The investors also share the same economic view and knowledge. All investors should have same expectations and they are all mean-variance optimizers which means that they use will use the same returns and the same expected covariance matrix of asset returns in order to generate the optimal risky portfolio (Markowitz portfolio selection model). (Bodie et al. 2011.)

As it has been said before, CAPM show the relationship of the expected return of an asset to the expected return of the market. However, Fama & French (1993) present an expansion to CAPM, the model named as a multifactor model. The multifactor model consists of the three factors, that are book-to-market factor (high book-to-market minus low book-to-market), a size factor SMB (small minus big) and overall market factor, which can be found in the traditional CAPM. Fama & French (1996) argue that the multifactor model has more explanatory power than the traditional one has.

In reality, CAPM's assumptions can not be realistic. Investors do not have same market expectations. All investors do not hold the same kind of asset portfolio as the market portfolio is. Risk premium on the markets does not always depend on the average degree of risk aversion and risk premium of individual assets is not proportional to the market portfolio's risk premium. However, CAPM is easy to use and it gives at benchmark prediction of the relationship between the risk and return. (Kihn 2011.)

2.5 Arbitrage pricing theory (APT)

Ross (1976) develop a factor model called Arbitrage pricing theory (APT). In a same way as CAPM, APT presents the relationship of expected return to risk but the method is a quite different. APT has three assumptions. First is that security returns can be described by a factor model. Second states that there are enough securities to diversify unsystematic risk away and the third states that markets will not allow arbitrage opportunities to exist (Bodie et al. 2009: 323-324).

According Copeland et al. (2005: 176) APT's mathematical definition is:

(1) $$r_j = r_i + b_{i1}F_1 + b_{i2}F_2 + \cdots + b_{in}F_n + \epsilon_i$$

Where, r_j= the random rate of return of the *i*th asset,

r_i= the expected rate of return of the *i*th asset

b_{in}= the sensitivity of the return of the *i*th to the *k*th factor,

F_1= the mean zero *k*th factor common to the returns of all assets,

ϵ_i= a random zero mean noise term for the *i*th asset.

APT consists of several undetermined factors, for example interest rates or the growth rate of the gross domestic product. The factors are macroeconomic because firm specific risk is diversifiable. The CAPM and the multifactor model presented by Fama et al. (2003) is actually just APT with determined factors. (Nikkinen, Rothovius & Sahlström 2008.)

APT emphasize the distinction between the diversifiable risk an non-diversifiable risk. It strongly assumes that an equilibrium in the capital markets will prevent all arbitrage opportunities. Extremely strong pressure to normalize pricing relationships will appear even if a limited number of investors become aware of disequilibrium. The APT also uses a well-diversified portfolio that is constructed from a large number of securities, unlike CAPM, which is constructed from unobservable “market” portfolio. (Bodie et al. 2011.)

2.6 Anomalies; so called violations of EMH

Kuhn (1970) defines an anomaly as a violation of the expectations, which are caused by archetypes. Anomalies are identified through empirical analyses and they can be described as empirical difficulties that reflect differences between the observed and theoretically expected data. In financial context, an anomaly is any deviation from the market efficiency. By studying different anomalies, many researchers have found a connections between stock prices and abnormal returns. Several anomalies have been observed to disappear soon after they are discovered. However, some of the ones continue to appear and even new anomalies are continuously discovered. In the next chapter anomalies are divided to fundamental and calendar anomalies according their features. (Kuhn 1970; Schwert, 2002; Bodie et al. 2011:388.)

Researchers analyse anomalies because they have wanted to understand patterns of anomalies and even predict them. For example, Novy-Marx (2014) studies the possibility to predict several well-known market anomalies with several periodic factors. The political party of the US president, different planetary cycles and El Nino, a known as a temperature anomaly, are some these factors. He finds out some difficulties in data driven search with factors behind anomalies; if an anomaly is statistically explained by some factor there should be a believable link between the anomaly and the factor.

2.6.1 Fundamental anomalies

Historical statistics of the market participants like firm’s market capitalization, stock’s price to earnings ratio or dividend prospects can be used to predict abnormal returns. An analysis that based on the firm’s financial reports is called fundamental analysis and often generated by market participants. The main purpose of the fundamental analysis is to help investors to invest right and help to create more accurate forecasts of stock returns and future earnings. (Bodie et al. 2011:377-378.)

The value effect is well-known fundamental anomaly. It assumes that so-called “value stocks” tend to earn higher average returns than those so-called “growth” stocks. The value stocks can be identified by calculating price-to-book or price-to-earnings ratio. Basu (1981) find that the stock of high E/P firms outperform the stock low E/P firms. Also portfolios that invest on stocks with proportionately low price-to-book (P/B) values have the tendency to outperform the market.

DeBondt and Thaler (1985) trail the returns to “loser” and “winner” portfolios for 36 months after portfolio formation and notice a slow drift upward in the cumulative abnormal returns (CARs) of loser stocks that had performed poorly in the recent past. They assume that the result is an evidence of excessive pessimism following poor performance which makes the stocks of loser firms profitable investments. Ball, Kothari and Shanken (1995) argue that poor stock return performance will generally lead to higher leverage, thus the value of the stock decreases more than the value of the firm’s debt. The rise in leverage should lead to higher expected returns and higher risk than would be reflected in risk estimates from a period before the drop in stock price. They have also pointed out that many of the stocks earning the highest returns have very low prices, so that microstructure effects, such as a large proportional bid-ask spread, can reduce subsequent performance by large amounts.

Small firm effect, also known as size anomaly is presented first time by Banz (1981). He notice that small firms tend to have greater risk adjusted returns than large firms but there is no significant difference between middle-sized companies' and large-sized companies' returns. Fama & French (1992) also find the same anomaly. They though that if the effect lasts for a long time, it should be an unrecognized risk factor, which would not violate the efficient market theory. Based on that, Fama et al. (1993) add a size factor to the multifactor model. They notice that the size factor improves the explanatory power of the model.

Reasons behind the size effect are not totally clear. Financial models that test the size effect are not fully able to measure the risk or they are unspecified. Also small firms are generally less traded and therefore a total risk might be underestimated, at least on short duration data. It has been also noticed that the appearance growth of this anomaly has slowed down after its discovery. (Roll 1981; Nikkinen et al. 2008.)

2.6.2 Calendar anomalies

January effect, also known as *turn-of-the-year effect*, is the most famous calendar anomaly. It was named "turn-of-the-year effect" when some researchers, for example Keim and Reinganum (1983), find out that most of the abnormal returns (measured relative to the CAPM) appear during the first two weeks of January and mainly among small firms. Watchtel (1942) introduced the phenomenon and suggests that stock prices tend to rise in January because of investors' decision to buy after the year-end tax-induced sell-off. In the period of modern finance, Rozeff & Kinney (1976) investigate monthly returns of the New York Stock Exchange (NYSE) for the time period 1904-1974. They found that higher returns tend to appear in January than during other months. The average return for January was 3,5 % which was much higher compared to the around 0,5% returns for the other months.

Seyhun (1988) examines two potential explanation for the January effect. The first of the explanations states that, for small companies positive returns are compensation for rising risk of trading against conscious or informed traders. The second explanation states that the positive returns are form because of price pressure from predictable seasonal changes in demand for different securities.

However, most of the studies come to the conclusion that the January effect mainly appear among small firms. For example, Bhardwaj &Brooks (1992) note that the January effect is a phenomenon tied to affirm size. They were not the only authors who consider January effect as a size anomaly. Lakonishok & Smidt (1988) do not find any statistical differences between January returns and other monthly returns of the Dow Jones Industrial Average index (DJIA), which includes only large firms. Also Thaler (1987) find out that equally-weighted stock indices used in the research papers, gives a higher weight to small firms' shares. Hence, January anomaly can be associated mainly with small firms.

Roll (1981) argue that the higher volatility of small-capitalization stocks might arise from substantial short-term capital losses that investors want to realize for income tax purposes before the year ends. This selling pressure can lead lower prices of small-cap stocks in December and causing a recovery in early January as investors repurchase these stocks to re-establish their investment positions. Overall, in this thesis the possibility of January effect has to be taken into for account because it lays on SAD-period and the most of the companies of Nordic indices are not so large.

The Halloween effect come from the old financial saying ”sell in May and go away”. Bouman & Jacobsen (2002) are the first ones who find statistically significant proves about the existence of Halloween effect. They find substantially higher returns from November to April comparing to the rest of the year in 36 of the 37 countries that they had under investigation. In addition, abnormal returns are higher and standard deviation is not significant in any examined countries. They try to find different explanations for the effect by forming two portfolios, a Halloween-strategy-based (buy in October, sell in May) and another that was kept for a whole year. The Halloween-strategy-based portfolio seems to be more profitable. Also Jacobsen & Zhang (2012) discover statistical significant higher returns From November to April in 35 countries and only two cases where returns were statistically higher from May to October. According Bouman et al. (2002) the only relevant explanation can be the effect of vacations in trading activity. Those vacations themselves can be caused by changes in risk aversion or liquidity constraints that cause part of the SAD anomaly. The Halloween effect based strategy suggests to be long on stocks from November to April on the northern hemisphere when Sad-based strategy suggests to be long from fall equinox to spring equinox on the northern hemisphere. These two periods might be just a different approach to seasonal pattern of stock returns According efficient market theory, arbitrageurs might easily take advantage from this kind of predictable phenomena.

Day-of-the-week anomaly or *Monday effect* is the famous pattern in the rate of return. It means that other days in the week have lower returns on average for unknown reason. Starting from the French (1980) and Gibbons & Hess (1981), there exist many evidences that support the theory of higher returns on Friday and lower returns on Monday. This effect can be contributed by speculative short selling, trading on Saturday and firm's size. In other theory, Mondays might follow prevailing the trend of Friday. It means that if markets had been up on Friday, it should continue upward trend on Monday. The average Monday returns have appeared to be positive after positive Friday returns and highly negative after negative Friday returns. Settlement effects, measurement errors and timing of earnings announcements can be behind the effect in this theory. (Sias & Stark 1995.)

Stock are negative or positive in specific days compared to average daily returns. For example, Keim & Stambaugh (1984) state that between Fridays and Mondays returns tend to be negative but they also tend to be positive on the other days of the week. They also argue that firm size and returns are correlated. French (1980) notice that stock prices are increasing more on Mondays comparing to the other days due to weekend that is between the "real" market days. As it can be seen from the results of this thesis, there exists very weak but significant Monday effect among indices.

3. BEHAVIOURAL FINANCE

"Behavioural finance argues that some financial phenomena can plausibly be understood using models in which some agents are not fully rational. The field has two building blocks:

1. ***Limits to arbitrage**, which argues that it can be difficult for rational traders to undo the dislocations caused by less rational traders; and*
2. ***Psychology**, which catalogues the kinds of deviations from full rationality we might expect to see."*

–Barberis & Thaler 2002: 1.

According common approaches of finance, there are three kinds of theories of decision making under uncertainty. Bell & Tversky (1988) are distributing those theories to *normative*, *descriptive* and *prescriptive*. Normative theories present how rational agents should behave, descriptive theories state how those agents actually behave and lastly the prescriptive theories give advises to agents how to behave when they are facing their own cognitive limitations. In the past, finance or economics has been a normative area of study. Modern finance or economics is facing psychology nowadays, that has been a descriptive area of study. In psychology, the scientists usually observe what humans do or how they act, and then start to create theories and related models. In finance the authors are hypothesising agents and the whole market behave in rational way, thus a model and/or a theory is proposed. Behavioural finance is arguing with the traditional finance; researchers are debating should the field of finance be more descriptive or not. (Kihn 2011.)

The theory of behavioural finance assumes that the traditional financial theory ignores how the living people make decisions and that is a stumbling block for the traditional theory. Behavioural finance interprets the anomalies as consistent with several "irrationalities" that seems to exist because of individuals making irrational and complicated decisions.

These irrationalities can share into two categories:

1. Investors do not process information correctly and that is why they end up to doing incorrect probability distributions about future rates of return

   and

2. Even if they know a probability distribution of returns, they often make inconsistent decisions. (Bodie et al. 2011.)

The existence of irrational investors is not a valid enough reason to cause inefficiency to capital markets. Therefore, the next aspect of the behavioural finance assumes that the actions of such arbitrageurs are limited, and thus unable to force prices to force intrinsic value. So in this chapter the idea is to clarify the background of the behavioural finance through two main blocks: psychology and limits to arbitrage.

3.1 Theory of arbitrage, 1st block

Trading activity is based on the investors' needs. Moreover, it can also be driven by behavioural factors which means that investors suffer from psychological biases such as limited attention, heterogeneous beliefs and overconfidence (explained in chapter 3.2.1). Fluctuation of trading activity enables different anomalies. Anomalies are due to market mispricing which leads to higher arbitrage opportunities for highly active or specialized investors. (Chou, Yang & Huang 2013.)

"*The simultaneous purchase and sale of the same, or essentially similar security in two different markets for advantageously different prices*" (Sharpe & Alexander 1990). The before mentioned phrase is a great definition of arbitrage. The arbitrage is financial abuse of security mispricing in some a specific away where risk-free profits are possible to earn.

It comprises of the simultaneous purchase and sale of equivalent securities because the aim is to get profit from discrepancies in their prices. The equilibrium in market prices is a required principle of capital markets because it excludes arbitrage opportunities. If arbitrage opportunities exist in the markets, the result will be a strong pressure to restore equilibrium. (Bodie et al. 2011.)

In theory, arbitrage does not need capital and it does not contain any risk. How an arbitrageur behave in real life? Behaviour of an arbitrageur can be described, for example as follows; the arbitrageur buys a cheaper stock or other asset and sells it for more expensive price in another market so the arbitrageur is getting an advantage of a price difference between two or more markets and that is a benefit of arbitrage. Arbitrage has a critical role in the analysis of securities markets, thus its main aim is to bring prices to face their fundamental values and keep to market efficient. The market will keep itself efficient when adequate amount of individual and active arbitrageurs are foreclose each others. (Shleifer & Vishny 1997.)

However, Shleifer & Vishny (1997) argue that the definition of arbitrage is not fully realistic. Even if arbitrage opportunities do not exist it does not mean that the markets are efficient, and the arbitrageurs must accept additional risk. Two sources of risks have been identified that limit the arbitrageurs from trading; *the fundamental risk and the noise trader risk* ("the noise trader" is the trader who act irrationally). They argue that, in reality, arbitrage resources are concentrated for the few investors that are highly specialized in trading a few assets, and so they are far from investors who use diversified trading strategy. As a conclusion, these investors are concentrating about total risk not just on about systematic risk. Next, this thesis will go through the major limits of arbitrage; *fundamental risk, noise trading and implementation costs*.

3.1.1 Fundamental risk

When an investor buys a stock at specific price, it is always possible that the price of the stock might fall because of some event or new information. If an asset is necessary to liquidate before the price increase again, the investor should accept a loss. So fundamental risk is a loss potential. Investors, for example arbitrageurs, can protect themselves against the fundamental risk by shorting a close substitute asset. This strategy is called ‘’law of one price’’ (LOOP). The LOOP assumes that identical assets must have the same price in all competitive markets otherwise arbitrage opportunities exist. Nevertheless, even if the assets would be perfect subtitutes, arbitrageurs remain vulnerable for specific and surprising information about the firm. Famous economist John Maynard Keynes has said that markets can remain irrational longer than investor can remain solvent, which means that the fundamental risk acquired in exploiting evident profit opportunities, will limit the activity of traders. (Lamonth &Thaler 2003; Bodie et al. 2011.)

3.1.2 Noise trader risk

Sheifer and Vishny (1997) present a different approach to understanding anomalies. According them the noise trading causes anomalies. The first step of this approach is to understand the source of noise trading which might cause the mispricing. Noise trading is the behaviour of an investor who might base his/her decisions to sell or buy without rational fundamental data. Those investors easily follow trends and overreact when the new and sudden information becomes available. The second stage is to estimate the costs of arbitrage for the market. In the noise trading, the volatile securities will expose greater average returns and harm equilibrium. Nonetheless, Sheifer and Vishy (1997) argue that anomalies become understood very slowly and investors will not take information seriously until a phenomenon has been taken to public inspection.

De Long et al. (1990) claim that arbitrage does not eliminate the effects of noise trading because noise trading itself is creating the risk. An arbitrageur want to short an asset when bullish noise traders have pushed its price up when, as a consequence, the noise traders can become even more bullish. So an arbitrageur has to take a position that is counted for greater price when he or she has to buy an asset back. Conversely, if noise traders are pessimistic and have dragged the asset’s price down, an arbitrageur has to be aware that in the future noise traders might become even more pessimistic and they might drag the price down even further. The fear of loss should limit the original arbitrage position.

Noise trading is based on transactions made by traders who have incorrect individual beliefs or incorrect information of an asset’s fundamental value. As it has been shown that rational investors are risk averse, which means that their ability to do investments is limited and risky. Arbitrageurs can not eliminate the error by noise traders. De Long et al. (1990) show that risk created by unpredictable behaviour of irrational investors has a capacity significantly decrease the attractiveness of an arbitrage. If arbitrageurs have short horizons and their only worry is about liquidating their investment in a mispriced asset, their irrationality will be limited even in the absence of fundamental risk. That can cause a higher divergence between market and fundamental values of the assets.

De Long et al. (1990) also argue that several number of financial market anomalies can be explained by the idea of noise trader risk. The opinions of noise traders are unpredictable and the arbitrage requires less the risk than average. This misunderstanding provides a situation that is even more extreme than today. The behaviour of arbitrageurs can be seen as a response to noise trading.

Froot & Dabora (1999) present some evidences that stock prices are influenced the location of trade. They introduce “Siamese twin” stocks that have almost identical economic and financial states so they should move together. They are two companies that have agreed to operate their business together but they keep their identities. According these assumptions there should not be limits to arbitrage and the relative pricing pattern is generally known. Also according the efficient market theory there should not appear any deviations from efficiency. However, the difference of twin stock’s prices appear to be correlated with the markets where they have traded most intensively than they should.

The paper introduces explanations why “Siamese twin” stocks do not move together despite of them having same financial states. The first explanation is tax-induced investor heterogeneity and the second is that the institutional inefficiencies might explain movements. High liquidity or inclusion in domestic-market which means that the other twin may be classified as a ”domestic” stock. The third explanation is that the noise trading. Behaviour of irrational traders have stronger impact to locally traded stocks than foreign traded. (Froot & Dabora 1999; Bodie et al. 2011.)

Figure 3. shows how the prices of two twin stocks had deviated from their “parity” ratio. The ratio for Royal Dutch and Shell is 60:40=1,5 because Royal Dutch receive 60% of the total cash flow and Shell receives 40%. They are traded separately but companies share the profits of from the joint company with 60/40 ratio. Again, if the market is efficient the relative differential or value between Royal Dutch and Shell should be zero.

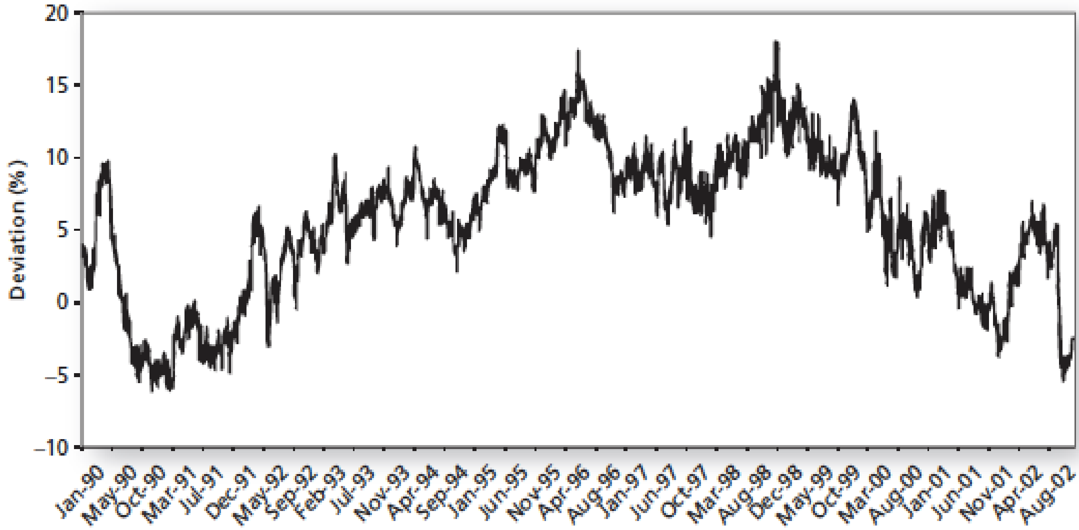

Figure 3. Pricing of Royal Dutch relative to Shell (deviation from parity). (Bodie et al. 2011.)

3.1.3 Implementation costs

As the fundamental risk and noise trader risk, also the notable implementation costs can limit arbitrageurs to take advantages from mispricing. Those so called implementation costs are short-sales constraints, taxes, commissions, price impact, information costs and legal constraints. Short-selling a security always includes costs: short-sellers may have to return the borrowed security on short notice, interpretation of the horizon of the short sale is uncertain; investors like a mutual or pension fund managers face tight limits on their purpose to short securities. Therefore implementation costs make it difficult to exploit a planned trading strategies. It also can be highly expensive to exploit information concerning the mispricing. Implementation costs limit the ability of arbitrage to bring prices to face their fair value. (Kihn 2011: 65-66; Bodie et al 2009: 388.)

3.2 Investor Psychology, 2nd block

DeBondt & Thaler (1995) state that conventional financial theory totally ignores how people actually behave. To deserve economists' attention, the behavioural finance theory should be able to explain a range of anomalous patterns of returns in different contexts, and generate new empirical conclusions. Behaviourists state that some anomalies can easily be explained by the investor's irrational behaviour. In this section the main focus is the find why investors make such systematic errors despite all the given rational information.

Next psychological biases are driven by heuristics. Heuristics are the rules of how people learn something more by accident. People learn things by the trial and error. This chapter introduces the main psychological biases and their expected effects on financial markets. Additionally, one of the main theory of in behavioural finance, the prospect theory is introduced. (Kihn 2011: 93-94.)

3.2.1 Behavioral biases

Errors in information processing can lead investors misinterpret the realistic probabilities of possible events or rates of return. One of the important biases is called *forecasting errors*. Kahneman and Tversky (1973) argue that investors are given too much attention to recent experiences compared to relevant previous beliefs when they are making predictions of market movements. They also tend to make predictions that are too extreme. For the example, DeBondt and Thaler (1990) present that the P/E anomaly can be explained by earnings expectations that are too high or extreme. (Bodie et al. 2011.)

Investors tend to overestimate the accuracy of their predictions and abilities. For example, commonly 90% of drivers think that he or she has better driving skills than average people have. Therefore the second important bias is called *overconfidence.* Barber and Odean (2001) present an interesting example about overconfidence. They set against trading activity and average returns of brokerage accounts that are women or men owned. They find out that men trade more actively than women. The greater overconfidence among men is well documented in the psychology literature. The other findings present that the men’s more intensive trading activity usually predicts a poor investment performance. Overconfidence is the one of the strongest behavioural phenomena. Barber and Odean (2001) state that the rational investor would make regular deposits, withdrawals and try to rebalance their portfolio as well as they try to minimize the amount of taxes paid in the end of the year. In contrast overconfidence drives investors to act irrationally.

Conservatism is the third bias. It means that investors tend to be too slow, or in other words too conservative refresh their beliefs to be consistent with the new information. Therefore they might underreact/overreact to the firm related news in the beginning, and that is why the prices will fully reflect new information gradually. Sort of bias can increase momentum anomaly in the stock market returns. (Barber & Odean 2001.)

Representativeness is the fourth of the psychological biases. It have a great impact on individual investor’s decision making because people usually make theirs predictions and assumptions based on their previous knowledge and therefore eliminate other relevant aspects (Shefrin 2002: 16). The winner-loser effect, also known as the contarian investment strategy or the momentum strategy, is an good example about the representativeness. De Bondt & Thaler (1985) argue that most people seems to overreact to dramatic news events and less care about news that they consider to be ‘’not so dramatic’’. The investors are optimistic towards recent winners whereas they tend to be over pessimistic towards recent losers thus the winner stocks become overvalued and the looser stocks undervalued. Jagadeesh & Titman (1993) argue against the findings of De Bondt & Thaler (1985). They introduce a so-called momentum strategy that also based on representativeness. However, Jagadeesh & Titman (1993) advise to buy stocks, that have recently performed well and sell stocks that have recently performed poorly. In addition, the holding period should be no longer than 12 months.

Representativeness also describes that people usually do not take into account the sample size. Commonly investors are acting like the small sample is just as representational as the large sample. Therefore they can form decisions too quickly and based on a small sample. Investors also tend to generalize apparent trends too far into the future. It can be easily seen that such a pattern is consistent with correction of anomalies and overreaction.

However, high stock returns or short-lived run of good earnings reports could lead investors to re-estimate their assessments of future performance that generates buying pressure which extend the increase of the prices.

The availability bias is the last psychological bias. According to Kahneman & Tversky (1974), people tend to often trust their decisions on the information that they have at that moment, instead of using their opinions or predictions from more sensible information. They think the past events when they want to get some significant information to help predict different scenarios of the upcoming event. Recently happened events, and in particular the events that have happened to relative people or friends tend to affect more to decisions. Kahneman & Tversky (1974) also state that so-called availability bias often causes forecasting errors in financial markets.

3.2.2 The Prospect Theory

The paper by Kahneman and Tversky (1979) question the effectiveness of expected utility theory which describes investor's decision making under the risk. They introduced the prospect theory that shows how investor's choices systemically violate the utility theory. The prospect theory is behavioural theory that shows how people choose between the probable alternatives that include risk and where the outcomes are known. People tend to make decisions based on potential losses and profits of the assets rather than taking into account the final outcome. The greater profit probability, the greater impact on investor's decision making can be observed. Therefore, this value function, defined by Kahneman & Tversky (1979), is demonstrated in panel B at figure 3. The figure is asymmetrical that means people tend to choose a sure gain. If people have to choose between a sure loss and the possibility of losing double amount but there still exists 50% of chance to not lose anything, they rather choose the latter option. The figure's convexity in panel B shows how losses describes that tendency.

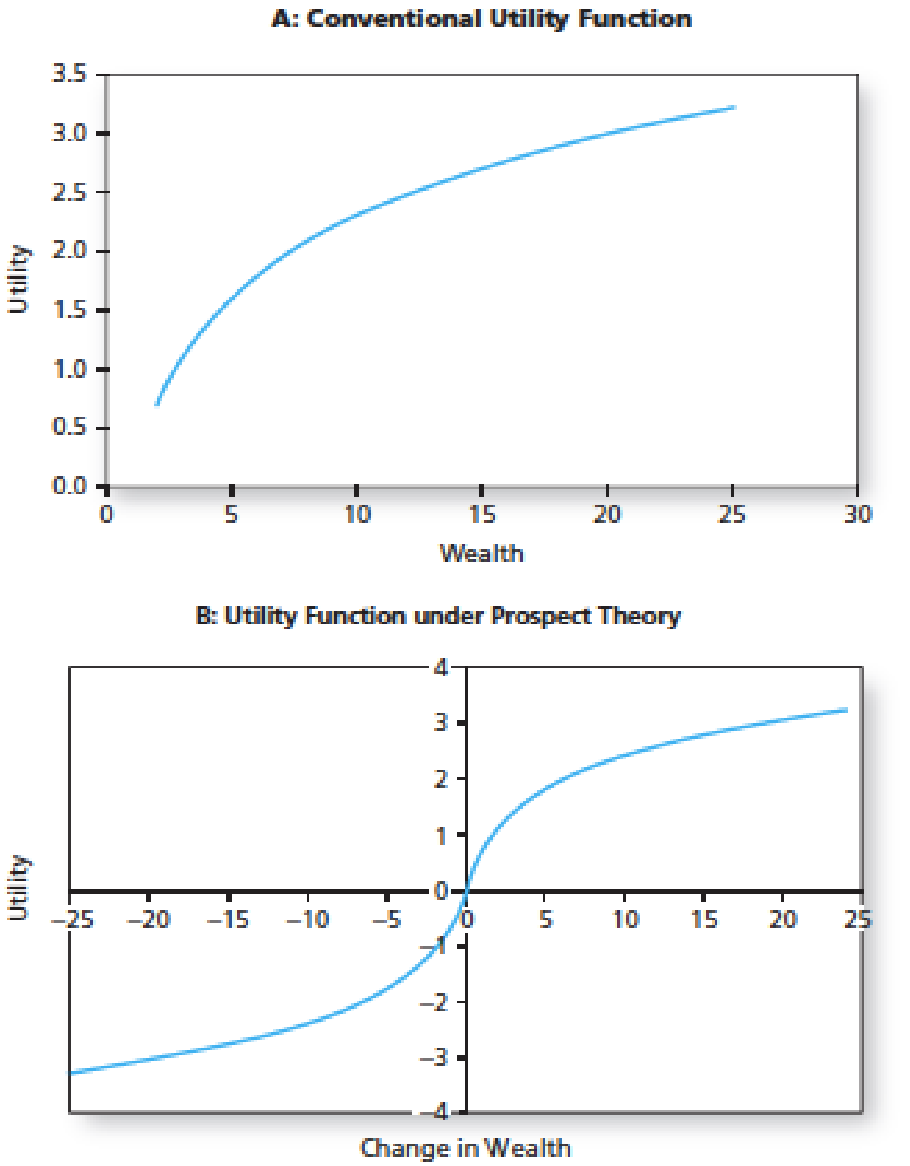

Figure 4. Prospect theory. **Panel A** conventional utilitity function has described in terms of wealth and therefore it is concave shaped, which is caused by risk aversion. In **Panel B**, utility function is described in terms of losses relative to current wealth under a loss aversion. Therefore there is a convex shape to the left from the origin which is increasing with risk-seeking behaviour in terms of losses. (Bodie et al. 2009.)

4. SEASONAL AFFECTIVE DISORDER (SAD)

This chapter covers the background of the Seasonal Affective Disorder (SAD) phenomenon. This part of the study is also an overview what previous studies have presented. The mostly commonly, previous studies have stated that the SAD is observed mainly on people who are living far away from the equator. SAD phenomenon or effect is affecting investor's risk taking behaviour which is playing a significant role of pricing securities. People who life far away from equator have been linked to higher level of risk aversion which can lead to higher variation of equity returns in different seasons. (Rosenthal et al. 1984; Kamstra et al. 2003.)

Seasonal Affective Disorder is medically defined form of depression, where "*affective*" means emotional. SAD have been also known as a ''*winter depression*" because the symptoms are appearing during the winter months more likely than other months. Usually SAD goes along with chronic fatigue and prolonged sadness, therefore the most ordinary symptoms that people tend to have are difficulties in concentrating, loss of energy, social withdrawal, loss of interest in sex, anxiety and sleep disturbance. People who are affected by SAD, have a high or increased tendency to emotional sensitivity, consideration of idiosyncratic ideas and imagination. All of those symptoms are linked to the risk taking behaviour that affect to investing behaviour which naturally affect to assets prices. (Bagby et al. 1996; Kamstra et al. 2003.)

Rosenthal (1998) find out that reduced daylight will take a different form among about 10 million Americans, and this particular phenomenon is significantly documented all over the world. Furthermore, 14 per cent of the Americans suffer from a milder version of the seasonal affective disorder. Same kind of results has been observed across several industrialized cultures. SAD is a condition of mind that affects many people during the seasons, especially people who are living in the north. Research in psychology field has documented significant link between depression and decreased risk taking behaviour that strongly affects to asset prices. Also Avery (2003) scientifically define the SAD as a form of depressive disorder. According him, the psychologically explanation is related to level of serotonin dysregulation in the brain. Furthermore, changes have observed in specific area of brains due to diminish of daylight.

Kamstra et al. (2003) study first the possibility to earn excess returns by timing the market actions along with the SAD effect in differently located stock markets. According them, there exists a great seasonal pattern in the stock markets because of the investors who are affected by the SAD. Investors are moving into less risky assets when days are shorten and getting back into riskier assets when days are lengthen. Therefore the main idea is to be out of the stock market when days are shorten and to be long in the stock market, when the days start to lengthen. According Kamstra et al. (2003), this would give a chance to gain abnormal returns.

The study of the Kamstra et al. (2003) shows that the effect is generally more powerful in the northern hemisphere but it is the most powerful in the most northern latitudes. Even if the seasonal patterns and environmental effects (e.g. temperature and sunshine) have been controlled, their strategy seemed to gain significantly greater profit than a buy-and-hold-strategy on various markets. The strategy based on the results of Kamstra et al. (2003) requires only two trades in the year thus the profits would not be much decreased by trading costs. The results of Garrett, Kamstra & Kramer (2005) also support the previous hypothesis, which is considering the SAD as a consequence of changes in risk aversion over time period. They examine the SAD phenomenon with a conditional version of the CAP-model that allows the changes in the price of risk. The results are showing that the SAD can be fully explained by this type of a model.

SAD explaining the variation in the stock returns has also strike a chord of critique. For example, the study of Jacobsen et al. (2008) claim that stronger physiological and empirical evidence has to be presented, what causes the changes in the investors risk aversion. However, they admit the existence of a statistical seasonal effect, but they challenge the fact that the effect was caused by SAD. They think that future research will need a simple seasonal dummy rather than individual variables, like the SAD phenomenon or weather.

Kamstra, Kramer and Levi (2009) respond to critique with a counter critique. They present that Jacobsen et al. (2008) have several problems in their research. However, they admit that the SAD effect does not explain all of the variation in risk aversion but at least it is an important part of it. Also Keef et al. (2011) point out that the seasonal effect is surely significant, but it can not be explained by the depression caused by SAD. They also emphasize that more relevant research work about the seasonal variation in stock returns is needed. Of course, more critique against original study of Kamstra et al. (2003) exists among financial research papers. Because of that critique the research concerning about the SAD effect has increased notably. Mixed conclusions increase the demand for the further research.

4.1 SAD on the financial markets

In their original research, Kamstra et al. (2003) have indices' data from countries at several latitudes, from both side of the equator. The indices are from Sweden, Great Britain, Germany, Canada, New Zealand, Japan, Australia and South Africa. Their results strongly support that the SAD effect causes in the variation of stock returns during the year. Figures 5, 6 and 7 show monthly means of daily percentage returns for each of the individual indices. The horizontal axis of the figure starts from the month when autumn equinox exists in that specific country. The month is March for the Southern Hemisphere and September for the Northern Hemisphere. All the individual graphs are put into the figures 5, 6 and 7. Although the average annual patterns differ, they typically show weak mean returns in early autumn, followed by strong returns soon after the longest night of the year. However, again the north latitudes are presenting more significant impacts of the SAD effect.

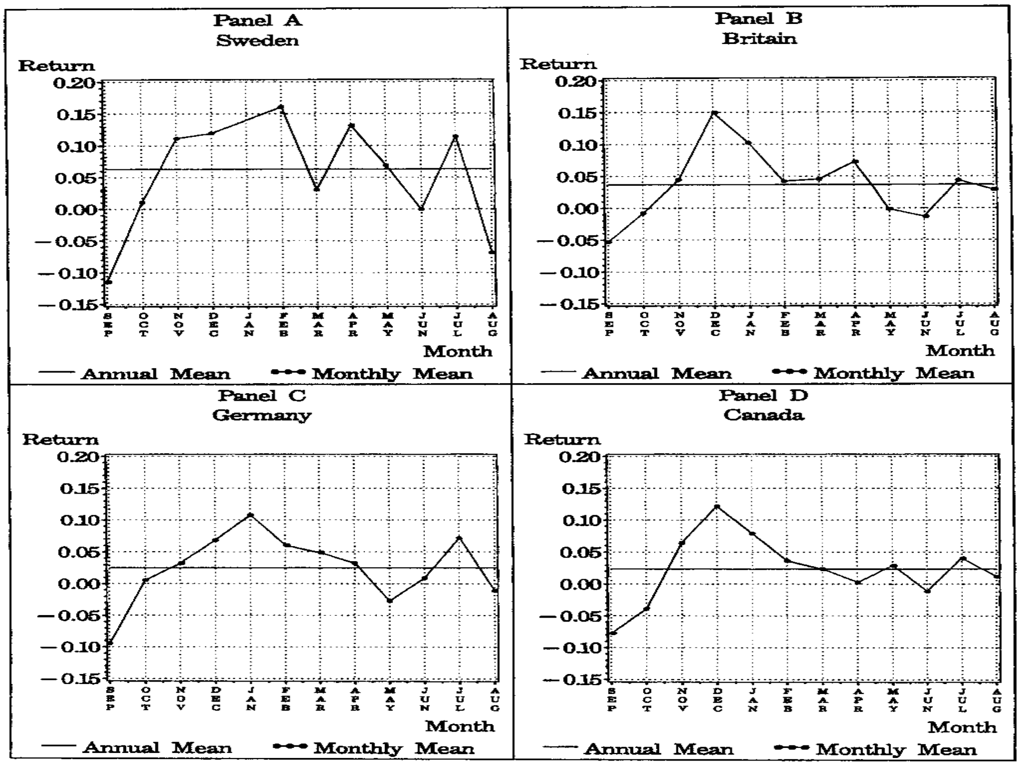

Figure 5. Individual graphs of data for Sweden, Great Britain, Germany and Canada. (Kamstra et al. 2003.)

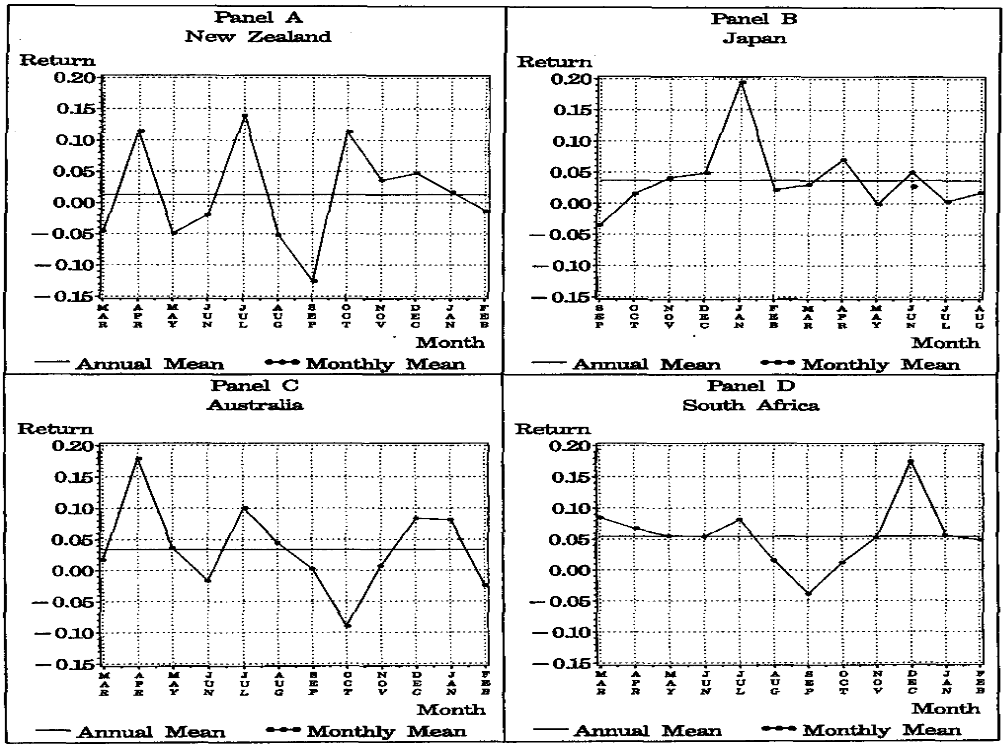

Figure 6. Individual graphs of data for New Zealand, Japan, Australia and South Africa. (Kamstra et al. 2003.)

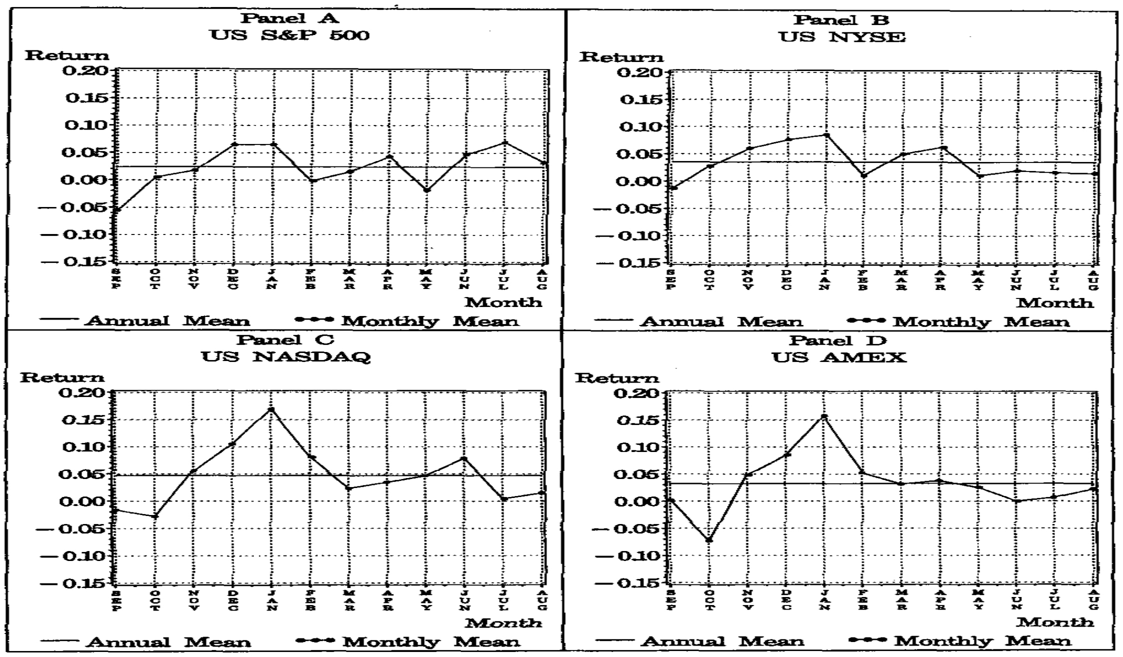

Figure 7. Individual graphs of data for US indices. (Kamstra et al. 2003.)

On the next page, Figure 8. summarize the monthly means of the daily percentage average returns from all four indices in the United States (right) and the foreign indices (left). Both graphs are showing the same results, the lowest returns in US indices and foreign indices are in the September, which is the onset of SAD, whereas the highest returns are observed in January, one month after the winter solstice.

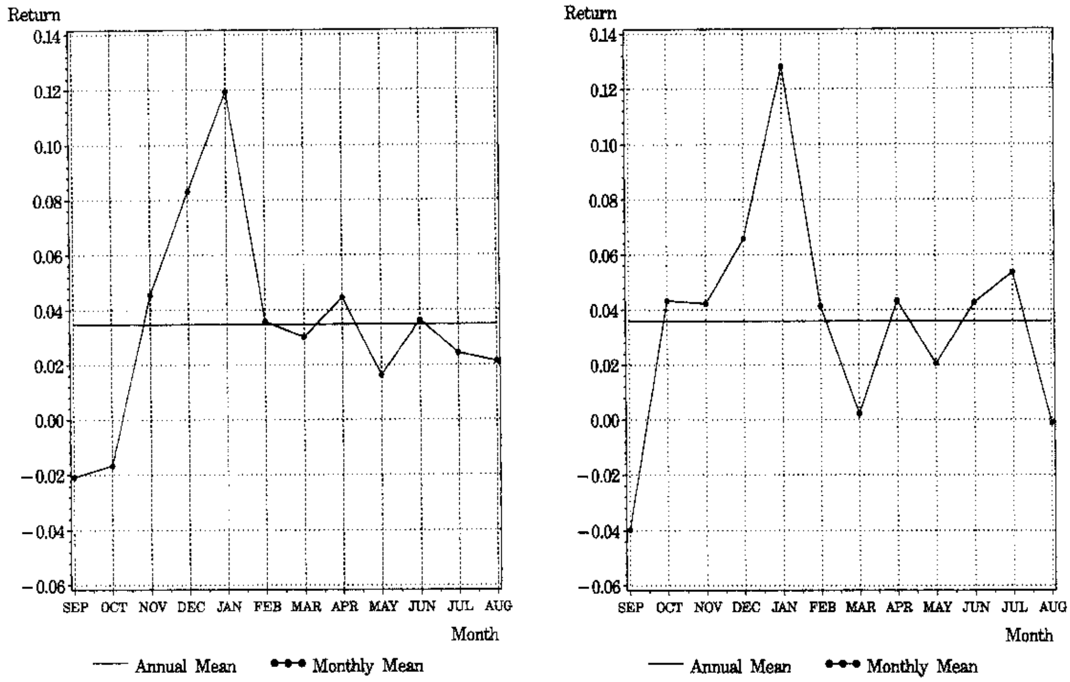

Figure 8. Annual and monthly means of daily returns in the US (left) and foreign countries (right) (Kamstra et al. 2003.)

In conclusion Kamstra et al. (2003) find out that average market returns are lower in the fall and winter. They also find that the SAD effect is not symmetric. Returns tend to be in the lowest point when the amount of the daylight is decreasing (fall months). However, winter returns tend to be higher than in the fall returns on average but they are generally lower than returns in spring or summer. That is caused by slowly increase in the amount of daylight. Kamstra et al. (2003) argue that these results are robust to markets across the globe, including different hemispheres.

In the addition, Kamstra et al. (2003) made a test, where an investor follow the trading strategy that requires to invest his whole portfolio in Swedish and Australian stock markets. The time period was 20 years starting from the beginning of 1980s. The investors hold a long position on the Swedish stock market for the northern hemisphere's fall and winter and then move the long position to Australian markets for the southern hemisphere's fall and winter. That kind of SAD based strategy beats a neutral strategy. The over all annual average was 7,9 per cent and the opposite strategy outperform the neutral strategy with 8,0 per cent. They also notice that extra risk do not appear in the SAD-based strategy, for example in the fluctuation of volatility of the returns.

4.2 Other studies about SAD

Kamstra, Kramer & Levi (2014) research seasonal changes in US treasury bills returns. US treasury bill is commonly known as a synonym to risk free asset. Their main finding was an opposite pattern, where US treasury bills gain higher returns during the fall than during the spring. The difference was 80 basis points in October compared to April. This was a reverse pattern compared to one that they found on equities. They also try to explain what causes this difference and find out that a proxy for seasonal variation in risk aversion explains about 60 per cent of the difference. In addition, Kamstra, Kramer, Levi & Wermers (2013) fid that seasonal flows of capital act as the SAD in mutual funds. It cause a change in investor’s risk aversion level

Dolvin, Pyles & Wu (2009) find out that SAD effect can be affected by market analysts` earning estimates. The earning estimates tend to be more pessimistic during the SAD period. The positive bias is leveling off because of the increasing pessimism and therefore analysts tend to be more careful with their estimates. They also notice that the depressive mood of the SAD phenomenon is more significant with analysts in northern states of the US and less significant with those who are living in the southern states of the US. Therefore their main conclusion was that, the SAD effect helps prices to face the real values on the markets.

VIX-index is a fear factor of risky assets because it measures a future volatility of risky assets. Kaplanski & Levy (2009) find a seasonal pattern on the VIX-index. The seasonal pattern follows same line with the SAD effect, which means that investors shy away from risk when daylight hours are decreasing. This observation supports the theory of investors are abandoning risky assets during the outbreak of the SAD period. However, only the perceived risk can make the effect significant, not the real market risk estimated by volatility. Therefore risk adjusted excess returns can be gained if actual risk and the risk that investors will observe differs. Kaplanski, Levy, Veld & Veld-Merkoulova (2015) discover more evidences that the SAD affects to investor's expectations. They did some investigation among group of Dutch investors when they find out that the investor's return expectations seems to be lower among the investors who are affected by the SAD effect. The expectations are significantly lower in the fall compared to other seasons.

According Dolvin & Fernhaber (2014) the SAD phenomenon is influencing to IPO underpricing. According them, younger films suffer more from underpricing during the SAD months. Kliger, Gurevich & Haim (2012) notice that the returns of the IPO are influenced by its respective seasonal mood and the calendar date, in the long and the short run. The excess returns of IPOs that are issued in ''cheerful'' or ''depressing'' date can differ 5-10 per cent of the total. This effect seems to be stronger among the companies that are less publicity exposed which is consistent with findings of Dolvin & Fernhaber (2014). They state that these seasonal mood related effects are caused by the lack of trading history, which they find to act as an anchor in the valuation process.

Kaustia & Rantapuska (2015) try to figure out how effects of good or bad mood affect to the trading behaviour of investors. One of the important finding was that the SAD phenomenon has a relatively small effect to the tendency sell or buy but the trading volume seems to be reacted positively. Their sample size was relatively large. The sample size consists of 1,2 million individual Finnish investors and 45 000 Finnish institutions. Their findings support the vacation explanation behind the Halloween effect. In addition, the most apparent patterns occur also during the summer holiday season. Investors tend to sell more and the trading volume decrease during vacations. However, the results are from small country that has relatively small stock market even though Kaustia & Rantapuska (2015) have large database thus the findings can not be generalized across the global.

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5. DATA & METHODOLOGY

This thesis' first purpose is to find out how the SAD phenomenon appears on the Finnish OMXH Helsinki CAP index and on the Nordic MSCI indices from Finland Sweden and Norway. Two Finnish indices have been selected for observation of variation between two different indices in the same country. The thesis' second purpose is to define the necessity of the weather variables in regression analysis when SAD phenomenon is under an investigation. For that second purpose, only the Finnish indices are used because of data availability and the weather variables are used only for the first single regression model. The weather data is from Finnish Meteorological Institute and it covers the same period than data of indices which is from 1 of January 2000 to end of July 2016. Data is consisting from hours of sunlight per day (h), airpressure (hPa), precipitation or rain (mm) and temperature (^{0}C).

As it has said above, to define the effect of SAD for MSCI Finland, Sweden and Norway the weather variables are dropped off from the second regression model. Kamstra et al. (2003) used precipitation, temperature, airpressure and cloud cover as explanatory variables but Garret et al. (2005) eliminate these variables because they seem to be relatively insignificant. It is extremely hard to manage large amount of the weather data from every country, but for the comparison between the regression models and necessity measurement precipitation, cloud cover, and temperature are used in the first regression model. The countries have been selected because they are located geographically in same level and have same features in their economic policies.

MSCI indices are designed to measure the performance of the large and mid-cap segments of the particular market. In this thesis indices are MSCI Finland, MSCI Sweden and MSCI Norway. The OMX Helsinki Cap is value-weighted index where a maximum weight of the stock is 10 % from the market value. The choice of using these indices is made because of the data availability, considering amount of observations and history. The purpose is to figure out with the data is there any deviations between the indices caused by the SAD phenomenon. In this thesis, all indices are total return indices. A return index (RI) is available for individual equities and unit trusts. It is showing a theoretical growth in value of a share for specific time period. It also assumes that dividends are re-invested to buy additional units of unit trust or equity at the closing price.

5.1 Data description

The difference of the natural logarithms of returns on time *t* and *t-1* are used to calculate daily returns. Time period of the data is from the beginning 2000 to end of the July 2016. Table 1 shows descriptive statistics of the untouched data. Average returns, standard deviation (volatility), minimum and maximum returns, skewness and kurtosis are showed for every index in the table 1.

Table 1. Descriptive statistics of the raw data. The first column shows indices and time period for the sample.

Index	Mean	Max.	Min.	Stand. Dev.	Skew	Kurtosis	Obser-vations
MSCI Finland 31.12.1999-29.7.2016	0,0034	19,46	-20,20	2,33	-0,14	10,10	4339
MSCI Norway 31.12.1999-29.7.2016	0,0433	11,07	-10,56	1,58	-0,14	8,07	4339
MSCI Sweden 31.12.1999-29.7.2016	0,0273	11,32	-9,07	1,74	0,15	6,77	4339
OMXHCAP Finland 31.12.1999-29.7.2016	0,0289	8,30	-7,73	1,32	-0,01	6,47	4339

The table one shows that average daily returns range from 0,0433% for MSCI Norway to 0,0034% for MSCI Finland. Interestingly the highest maximum return is for MSCI Finland (19,46%) index whereas the lowest maximum return is for OMX Helsinki Cap (8,30%). In the same fashion, the greatest minimum return is for MSCI Finland (-20,20 %) whereas the smallest minimum return is for OMX Helsinki Cap (-7,73%). Also the standard deviation is the highest for MSCI Finland (2,33%) which means that MSCI

Finland is the most volatile of these indices. High standard deviation is predictable because it goes along with the most extreme values of minimum or maximum return. The most indices are negatively skewed, expect MSCI Sweden, which is interesting because negative skewness is typical for stock markets. Positive skewness means that the sample has more values that are over the average and the figure is skewed to the right. Naturally, negative skewness is the opposite for positive skewness. All indices are positively kurtotic, the highest level is for MSCI Finland and the lowest level is for OMXH Cap. It means that all tops of distributions are higher than normal distributions.

The next figure shows average annual returns for every index in qualify period, which is in this thesis from beginning 2000 to end of July 2016. Average returns for every year are calculated from daily (includes every trading day) percentual returns. It can be easily seen that how economic fluctuation is reflecting to index returns. For example, it-bubble in the beginning of 21st century and last financial crisis in the end of 2000s caused significant drop for average annual returns. Those remarkable downturns might have an affect to final results because they are included to the time period.

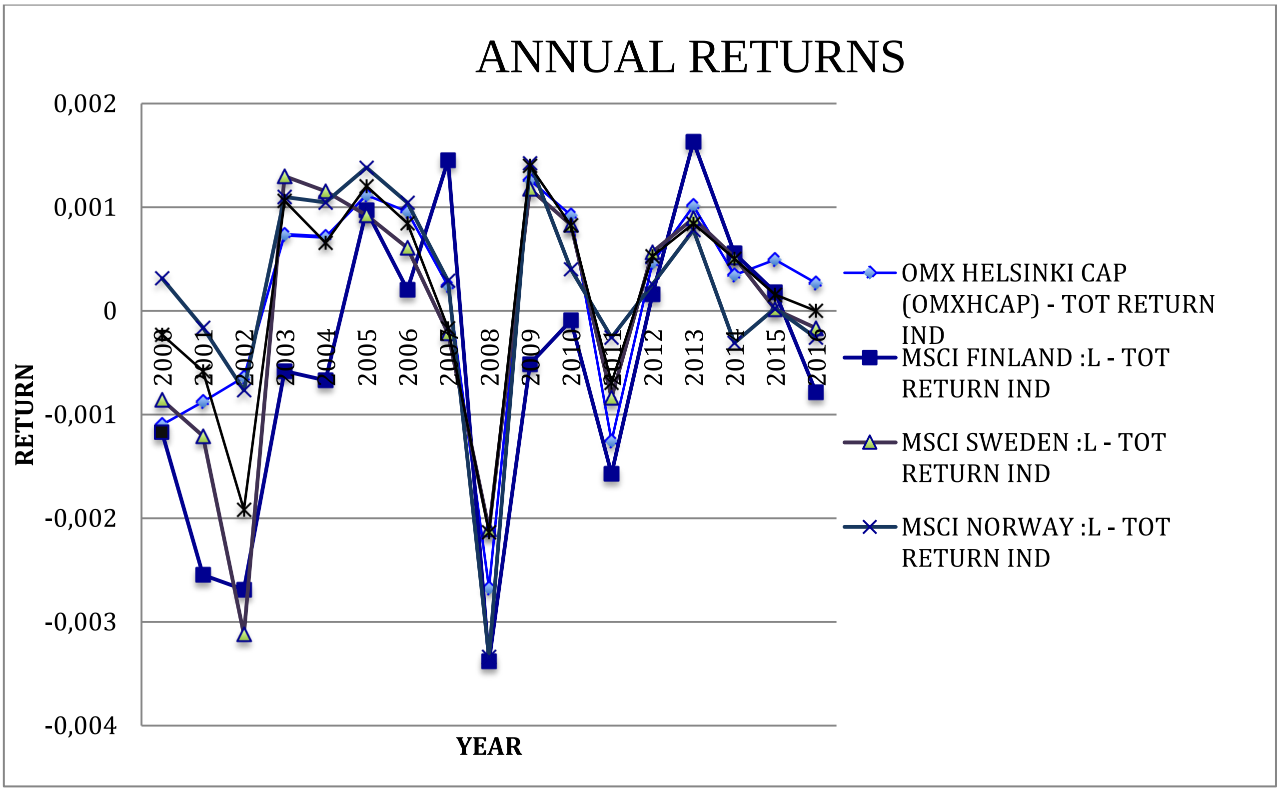

Figure 9. Annual returns of selected indices, from year 2000 to 2016.

Next figures are showing average monthly returns over 15 years. Interestingly, every figure is showing significant drop on September, except MSCI Finland where the drop is significantly smaller. After that returns generally start to increase but droped again after October. Only exception is Norway where returns peak on December. It can be seen from all figures that significant increase in returns started after January. That is consistent with the theory of SAD. The patterns also seems to follow the vacation pattern of stock returns, which means that returns are lower during summer holidays. The figures are showing results that are consistent with final results of this thesis which means that SAD phenomenon is assymmetrical but opposite direction than it was in the Kamstra's et al. (2003) research paper. The returns seems to slightly increase at the time in fall but total return is stays a slighty negative in SAD period which was from autumn equnoix to spring equinoix.

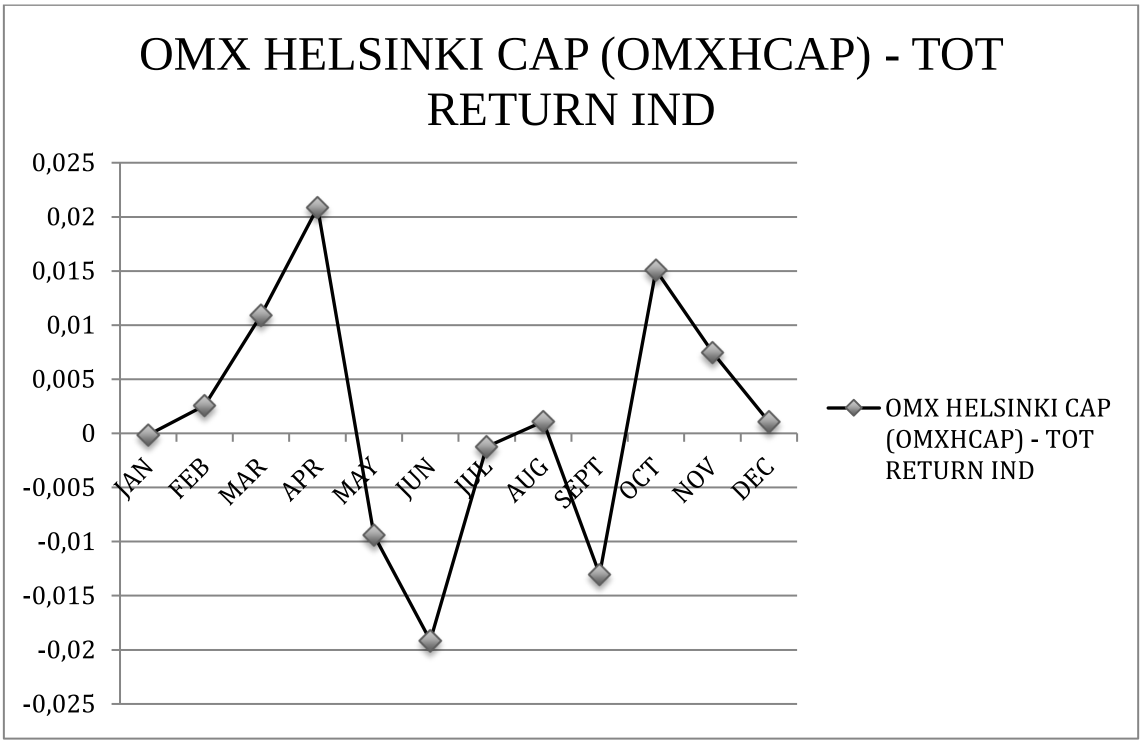

Figure 10. Average monthly returns (2000-2016) of OMXHCAP.

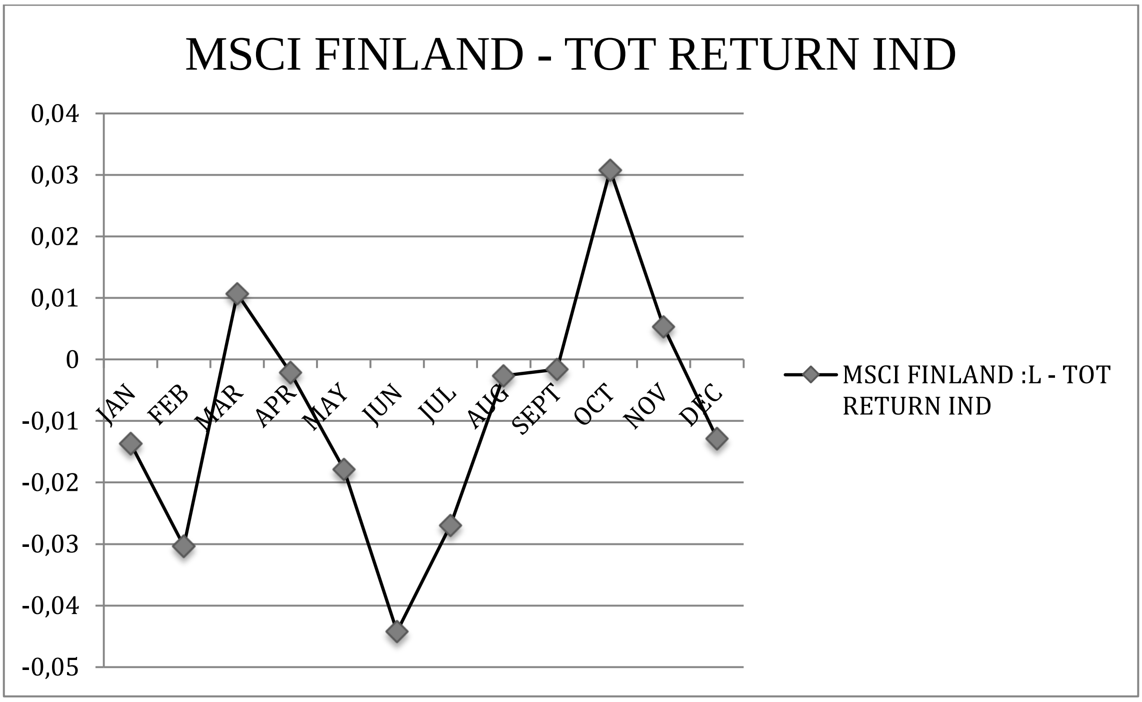

Figure 11. Average monthly returns (2000-2016) of MSCI FINLAND.

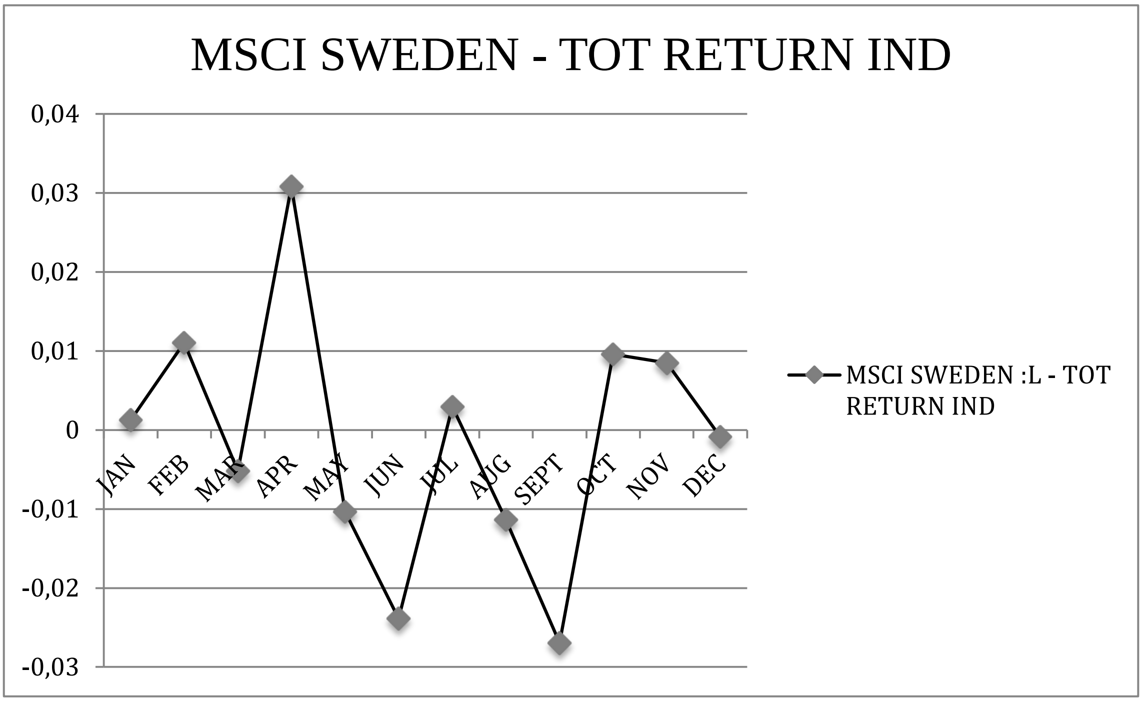

Figure 12. Average monthly returns (2000-2016) of MSCI SWEDEN.

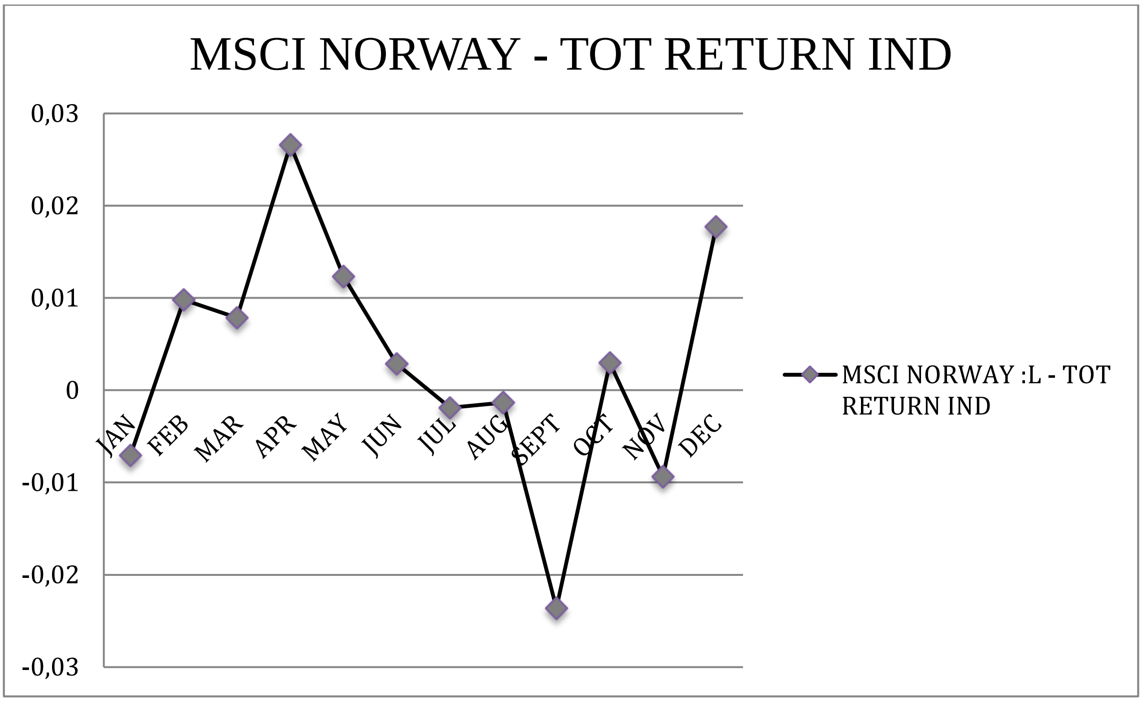

Figure 13. Average monthly returns (2000-2016) of MSCI NORWAY.

5.2 Methodology

SAD effect on Finnish and Nordic stock markets is measured by using single regression for the each index. The aim is determine impact of SAD variable to stock returns with the regression analysis. In the chapter six, statistical significance of the coefficients is measured with the heteroscedasticity robust t-values of White (1980). In this thesis, autocorrelation is controlled with one or two lagged dependent variables, depending on the necessity. Since the current returns can be predicted by lagged or previous return, there exists short-term predictability in the equity market.

This thesis use two regressions; in the first one has included the weather variables and its main aim is to determine how the weather affects to returns on Finnish indices. The second one has drop out the weather variables so the main explanatory variable that have been analyzed is the length of the night in the fall and winter relative to average annual length of the night, which is 12 hours.

Following Kamstra et al. (2003), the first regression is defined as follows:

(1) $$R_t = \beta_0 + \rho_1 r_{t-1} + \rho_1 r_{t-2} + \beta_1 SAD_t + \beta_2 D_t^{fall} + \beta_3 D_t^{monday} + \beta_4 D_t^{tax} + \beta_5 Cloudcover_t + \beta_6 Temperature_t + \beta_7 Rain_t + \beta_8 Air\ pressure_t + \varepsilon_t$$

And the second one is defined as follows

(2) $$r_t = \beta_0 + \rho_1 r_{t-1} + \rho_1 r_{t-2} + \beta_1 SAD_t + \beta_2 D_t^{fall} + \beta_3 D_t^{monday} + \beta_4 D_t^{tax} + \varepsilon_t$$

Where:

r_t = The logarithmic period *t* return of an specific index.

$\rho_1 r_{t-1} + \rho_1 r_{t-2}$= These Lagged dependent variables are used, if it is necessary to control for residual autocorrelation.

SAD_t= The SAD variable that is defined later in equation 3.

D_t^{fall}= Fall dummy that is defined later in equation 6.

D_t^{monday}= A monday dummy variable, which equals 1, when *t* is the first trading day of the week. Otherwise the day gets value 0.

D_t^{tax} = A tax dummy variable, which equals 1, when t is the last trading day or one of the five first trading days of the year. Otherwise the day gets value 0.

$Cloudcover_t$ = Cloudcover variable describes the cloud cover situation in period *t*.

Temperature_t= Temperature variable describes how warm or cold in degrees (^{0}C) are in period *t.*

Rain_t = Rain variable describes amount of rain (mm) in period *t.*

Air pressure_t = Air pressure variable describes air pressure conditions in period *t.*

ε_t= The error term

Weather observations cloud cover, temperature, amount of the rain and air pressure are measured from every trading day of the time period. Especially, air pressure and rain may have positive effect to stock markets because it has been observed that lack of cloud cover is positively correlated with daily stock returns. Other known calendar anomalies are overlapping SAD phenomenon so that is why tax-loss and Monday dummies are included. (Joshi & Bhattarai 2007.)

Following Kamstra et al. (2003), the main explanatory variable SAD_t is defined as:

$$\text{(3)} \qquad \text{SAD}_t = \begin{cases} H_t - 12, \text{for trading days in the fall and the winter} \\ 0, \text{otherwise} \end{cases}$$

H_t is a measure for a time that is between sunset and sunrise. The SAD measure is able to take only negative or positive values during the summer and winter whereas it equals zero at fall equinox, September 21, and spring equinox, March 20. The values are zero because the day and night have equal length at those dates. According Kamstra et al. (2003), the SAD variable get its peak (+6) on the winter solstice (21 of December) and is 0 during the spring and summer. Number of night hours, H_t, has been calculated with formula that examines the sun's declination angle λ_t.

Following Kamstra et al. (2003), the formula is:

$$(4) \qquad \lambda_t = 0.4102 \cdot \sin\left(\left(\frac{2\pi}{365}\right)(\text{julian}_t - 80.25)\right),$$

where julian_t is a variable that tells the number of days in the year and ranges from 1 to 365 which means that the first of January equals 1, the second of January equals 2 etcetera. After that the number of hours in Northern Hemisphere can be calculated as:

$$(5) \qquad H_t = 24 - 7{,}72 \cdot \arccos(-\tan\left(\frac{2\pi\delta}{360}\right)\tan(\lambda_t))$$

Where:

arcos = arc cosine and $\delta =$ latitude.

SAD is asymmetric around winter solstice. The asymmetricity is the main idea of depressive mood that affects to stock markets. People who are affected by SAD tend to be more risk averse when daylight hours start to decrease but then when daylight starts to increase their risk taking increase. For that asymmetricity, a fall dummy D_t^{fall} is defined as follows:

$$(6) \qquad D_t^{fall} = \begin{cases} 1 \text{ for trading days in the fall} \\ 0, \text{otherwise} \end{cases}$$

In this thesis, trading days of the fall dummy are defined from 22.9 (fall equinox) to 19.12 (winter solstice) each year. The effects are symmetric between two different periods when the coefficient of this variable turn out to be insignificant.

6. EMPIRICAL RESULTS

The chapter six examines the results of regression analysis for Finnish indices with the weather variables and for each Nordic MSCI index without the weather variables. The results are separated into different respective subchapters for each country. The first subchapter is considering the results of the impact of the weather variables on the Finnish indices. After that, the results of simplified regression without weather variables are showed in own table for every Nordic country. The last subchapter compares the results. One or two lagged variables are included (depending on the necessity) to control autocorrelation. Since the current returns can be predicted by lagged or previous returns, there exists short-term predictability in the equity markets. Based on ones-sided hypothesis tests, levels of significance are 10-, 5- and 1 per cent. All values are shown with four decimals therefore the smallest values are presented as zero point zero. “Known theory” or “theory of SAD effect means theory developed by Kamstra et al. (2003). The latitude of the stock exchange is after specific city’s name.

6.1 Finnish indices with weather variables

Following the methodology developed by Kamstra et al. (2003), Table 2. shows acquired results for MSCI Finland index with weather variables, such as rain, air pressure, temperature and cloud situation or sunlight.

Table 2. Regression analysis results for MSCI Finland with the weather variables.

HELSINKI 60⁰ 10’	**MSCI FINLAND**		
Variable	Coefficient	*t*	*p*
$\rho 1$	-0,0005	-4,0794	0,0000
$\rho 2$	-0,0003	4,7041	0,0000
SAD	-0,0001	-3,2937	0,0010
DFALL	0,0001	1,3291	0,1839
DMONDAY	-0,0001	-1,9893	0,0467
DTAX	0,0003	1,4942	0,1352
SUNLIGHT	-0,0000	-0,1288	0,8975
TEMPERATURE	-0,0000	-0,2166	0,8285
AIRPRESSURE	-0,0000	-0,8291	0,4071
RAIN	0,0000	0,2425	0,8084
R^2	0,0364		

As it can be seen from the table 2, there are two variables that are significant. The SAD variable is significant on the level 1 % for MSCI Finland. According the results there is slightly statistical drop in stock returns in a period when the SAD affects. However, the fall dummy is not significant so therefore the effect appears to be symmetrical. Against known theory by Kamstra et al. (2003), the SAD variable is negative which means that there is a slight decrease in the whole SAD period therefore it can be assumed that investors become more risk averse and returns drop during the fall and winter, not just in the fall. There can be observed also a weak Monday effect on the MSCI Finland index, which means that according the results, the returns of the first-day-of-the-week are weaker than the average returns. The other variables are insignificant, they do not have any impact to MSCI Finland. Particularly the weather variables are all insignificant, which means that they do not have any impact to stock returns. In the lowest row, R-squared means that this model is able to explain 3,6 % of returns of MSCI Finland. Next table 3 shows obtained results for OMXH Cap index with weather variables.

Table 3. Regression analysis results for OMXH CAP with the weather variables.

HELSINKI 60^0 10'	OMXH CAP		
Variable	Coefficient	*t*	*p*
$\rho 1$	-0,0002	-7,7692	0,0000
$\rho 2$	0,0002	7,6281	0,0000
SAD	-0,0002	-4,0992	0,0001
DFALL	0,0000	4,0369	0,0001
DMONDAY	0,0000	2,5128	0,0120
DTAX	0,0001	3,2015	0,0014
SUNLIGHT	-0,0000	-0,0872	0,9305
TEMPERATURE	-0,0000	-1,1872	0,2352
AIRPRESSURE	-0,0000	-1,9925	0,0464
RAIN	0,0000	1,0792	0,2805
R^2	0,0275		

Table 3 provides some interesting results. One weather variable, air pressure, seems to have some small effect with 5% significant level to stock returns, while other weather variables do not have any impact. As it has been said before, high air pressure might have positive effect to stock returns because the investors tend to be in positive mood when weather is better. As it can be seen from the table that SAD variable is again significant and negative while fall dummy is also significant but positive. The returns will decrease slightly during whole SAD period, not just from autumn equinox to winter solstice but as it can be observed from the figure 10, returns actually rise during the some fall months which is consistent with significant and positive fall dummy. Therefore there seems to be asymmetry around winter solstice but to other direction than in known theory. However, the SAD effect is very weak according the results of the table 3.

Monday dummy is also statistically significant whereas the coefficients of Monday dummy and fall dummy are extremely small so therefore their impact to stock returns are not notable. Also tax dummy is significant which tells OMXH Cap stocks are slightly affected by tax-loss trading which means that stock returns are a bit higher than average. This regression is also able to explain 2,75% of returns.

Based on the results from two tables above the SAD phenomenon has a weak impact on both indices even when the weather variables are included. However, all weather variables are relatively insignificant. Therefore the null hypothesis is rejected which means that the alternative hypothesis “H_1: Weather variables are not necesary to define effect of the Seasonal affective disorder to indices” is accepted.

6.2 Finnish indices without weather variables

Next tables present the obtained results from Finnish indices when weather variables are not used. After that, findings from other Nordic indices are presented in individual subchapters. The methodology is the same than before in this thesis. The regression follows the method that is developed by Kamstra et al. (2003) but only the weather variables are drop out. Table 4 shows the results for MSCI Finland.

Table 4. Regression analysis results for MSCI Finland without the weather variables.

HELSINKI 60^0 10’	**MSCI FINLAND**		
Variable	Coefficient	*t*	*p*
$\rho 1$	0,0001	11,1911	0,0000
$\rho 2$	-	-	-
SAD	-0,0001	-3,2716	0,0011
DFALL	0,0000	1,5020	0,1332
DMONDAY	-0,0001	-1,8413	0,0656
DTAX	0,0002	1,4422	0,1493
R^2	0,030		

In table 4, only the SAD estimate is statistically significant in level of 1%. The results is parallel than the results for MSCI Finland with weather variables which means that these results are also showing a small decrease in stock returns during the whole SAD period. Again a weak SAD effect can be observed. Fall dummy is insignificant which means that the effect is symmetric. Other variables for MSCI Finland are insignificant. This regression is able to explain 3% of the returns.

Table 5 shows the results for OMXH Cap without weather variables. Interestingly all the variables seems to be significant on the 1% level but the coefficients are insignificantly small.

Table 5. Regression analysis results for OMXH CAP without the weather variables.

HELSINKI 60^0 10’	**OMXH CAP**		
Variable	Coefficient	*t*	*p*
$\rho 1$	-0,0002	-7,6563	0,0000
$\rho 2$	0,0001	7,5387	0,0000
SAD	-0,0000	-3,6067	0,0003
DFALL	0,0000	4,0432	0,0001
DMONDAY	0,0000	2,9733	0,0030
DTAX	0,0001	3,0910	0,0020
R^2	0,0232		

The obtained results show again that the returns slightly decrease during the time when SAD phenomenon affects. However, a coefficient of fall dummy does not show negative change which is inconsistent with the known theory of SAD effect. The effect is asymmetrical but to opposite way than known theory assumes. That asymmetry is consistent with seen pattern in figure 10. Monday dummy and tax dummy seems to be also statistically significant at 1% level but their impact to market is hard to confirm because coefficients are so small. The regression explains 2,32% of the returns.

The results for the Finnish indices are consistent with and without the weather variables. It can be observed that the weather variables are insignificant for measuring impact of SAD effect on indices. The most important finding is that the SAD effect, asymmetrical or symmetrical, has a weak impact on the Finnish indices. Probably this finding in not the most relevant when investors are thinking about their investment strategies but it is useful knowledge since the depressive effect is a part of investor’s market behaviour. It is also valuable to know that sort of seasonal pattern appears on the Finnish stock market. Therefore null hypothesis is rejected and the alternative hypothesis, “H_1: Seasonal affective disorder explain returns of Nordic indices” is accepted in this point. Next subchapters provide the results for Swedish and Norwegian indices.

6.3 Sweden

The results from Sweden are giving the same signs as the results from Finland. As it can be seen from table 6, the SAD variable is again significant on the 1% level but coefficient is again extremely small. Monday dummy is also significant on the 5% level when the other variables turn out to be in significant therefore the Monday effect can be observed in Swedish market which means that the Monday returns depend on Friday's stock exchange rate.

Table 6. Regression analysis results for MSCI Sweden without the weather variables.

STOCKHOLM 59^0 17'	**MSCI SWEDEN**		
Variable	Coefficient	*t*	*p*
$\rho 1$	-0,0002	-4,6399	0,0000
$\rho 2$	0,0001	4,0721	0,0000
SAD	-0,0001	-3,9726	0,0001
DFALL	0,0001	3,7954	0,0001
DMONDAY	0,0000	2,3142	0,0207
DTAX	0,0001	1,6114	0,1072
R^2	0,0544		

The regression is able to explain 5,44% of the returns. The returns also seem to be slightly lower during the SAD period but once again fall dummy is consistent with the figure 12 that shows increase in average returns after September's huge drop. Because of that small appearance of SAD effect the null hypothesis is rejected again and alternative H_1 is accepted.

6.4 Norway

Table 7 presents similar results for MSCI Norway. The SAD variable is significant on the 5% level and also fall and Monday dummies are significant on the level 10%. Same asymmetrical form appears with MSCI Norway than with other Nordic indices. Pattern of results are consistent with the development of average returns in figure 13. Other alternative variables are insignificant. Therefore MSCI Norway index is not affected by tax-loss trading.

Table 7. Regression analysis results for MSCI Norway without the weather variables.

OSLO 59^0 57'	**MSCI NORWAY**		
Variable	Coefficient	*t*	*p*
$\rho 1$	-0,0002	-5,0868	0,0000
$\rho 2$	0,0002	4,9752	0,0000
SAD	-0,0000	-2,0478	0,0406
DFALL	0,0001	6,6973	0,0580
DMONDAY	0,0000	1,7623	0,0781
DTAX	0,0000	0,6391	0,5227
R^2	0,0200		

The regression can explain 2% of the returns. The results show that there might be small observable SAD effect influence to MSCI Norway index, therefore null hypothesis *"H_0:* Seasonal affective disorder does not explain returns of Nordic indices" is rejected and H_1 is accepted. However, it has to be remembered that null hypothesis is rejected because there exists a potential seasonal pattern. Nevertheless it is not certain that behind the all fluctuation is the SAD effect, therefore further research concerning SAD and other seasonal related anomalies is needed.

7. CONCLUSIONS

This thesis research how the SAD phenomenon has affected to the Nordic indices during the years 2000-2016 and whether the weather variables are necessary to use in regression analysis that examines SAD effect. All the indices are far from the equator thus an effect of SAD should be greater and investors should be more risk averse from autumn equinox to spring equinox at those latitudes. SAD phenomenon seems to be a psychological bias which hurt boundaries of the efficient market theory. The results indicate that there exists some seasonal pattern of stock returns and the depressive mood of the SAD phenomenon has a weak impact to markets so the market returns are lower during the SAD period than they are on average. The results also suggest that the efficient market theory is not necessarily rejected, but investors' seasonal risk aversion can be included to traditional models. In addition, traditional models should be expanded with the more behavioural variables.

All results are surprisingly similar. The coefficients of the variables are really small but particularly the SAD variable tend to be significant therefore it can be assumed that there is a weak SAD effect during the fall and, most importantly, during the winter when an altogether return of index is slightly negative. That can be due to heightened risk aversion and depressive effect of the SAD. The results are showing opposite asymmetry than which has been presented earlier because fall dummy is not negative for any index. As the figures from average annual returns prove, generally after drop on September the average returns increase during the next two fall months. It is inaccurate that the returns are decreasing only during the fall and recovering or increasing during the winter after winter solstice. The returns are actually fluctuating and, as it said before, altogether return is negative over the whole SAD period.

Concerning the weather variables, the results do not show any prove that they would have any impact to the stock returns. In every case they were insignificant. According the results, they are useless in empirical analysis that investigates the SAD effect's impact to stock returns. Concerning other variables, interestingly Monday and tax-loss dummies appear to be statistically significant for OMXH Cap, MSCI Finland and MSCI Sweden.

MSCI Finland and MSCI Sweden indices' returns seems to be lower on the first day of the week whereas other indices seems to have more positive returns on Monday. OMXH Cap index returns seem to be higher during the tax time, which means in the end of the year.

In previous research it is shown that it would be possible to earn excess returns with SAD based strategy in several different markets. In this thesis appear some signs from that kind of possibilities. However, the SAD driven seasonal pattern of the stock returns can be questioned. The research concerning SAD should remain heated until the phenomenon can be proven more convincingly. It may require more data from individual investors and different factors than presented in this thesis and the pattern cannot be attributed to one factor. The short-term predictability in equity market cannot lie on SAD effect during the fall and winter, due to more significant factors that affects to stock returns.

However, the results obtained from the Nordic countries support the evidence that SAD have a weak effect behind the seasonal fluctuation of stock returns. The SAD phenomenon is significant for all indices from Finland, Sweden and Norway but the coefficients are very weak. Taking advantage of the SAD effect is not easy or simple as some previous research might present. If investor follows an investing strategy based on the SAD, the conventional risk might not increase but investor have to bear the risk of the anomaly reverting or disappearing itself. That arises the question why the arbitrageurs have not taken the advantage and make the anomaly disappear or have they already taken it and is that why the SAD effect appears to be so weak on the market?

One reason might be that the investors are not affected by the SAD or seasonal depression mood. Another reason is that there are other factors behind the pattern of stock returns. The lack of strong and reliable evidence is hard to ignore, even if notable amount of the results that have obtained the seasonal pattern in stock returns are supporting the existence of SAD effect. Despite the lack of reliable evidences, the psychological side supports the fact that logically the SAD phenomenon affects to stock returns. It is also possible that SAD variable created by Kamstra et al. (2003), captures a seasonal anomaly, which is actually caused by some other unknown factor. Furthermore, the competing theories that are trying to explain the seasonal variation of stock returns, for example the Halloween effect, also suffer from the same proving difficulties as the theory of SAD effect. The research could be extended by investigating the possibility of Halloween effect with combination of January effect and SAD effect.

As the final outcome, this thesis supports the existence of an interesting seasonal pattern on stock returns around the world, especially in Nordic indices. According this thesis' results, a weak SAD effect occurs in Finnish, Swedish and Norwegian stock markets. Also the speculation around the weather variables has come to the finish line because they seem to be insignificant or the more developed methods need to be invented.

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