Vaasan yliopisto
UNIVERSITY OF VAASA

Tommi Keski-Kastari

Calendar Anomalies

Nordic Evidence

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Author:	Tommi Keski-Kastari		
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ABSTRACT

This research is constructed in order to further analyze calendar anomalies in the Nordic stock markets. Calendar anomalies are price movements that appear during particular times of the year. Since Fama (1965) introduced the efficient market hypothesis, it has become a crucial part of the financial literature. Therefore, it is thoroughly discussed in this paper. Another important framework considering this research is behavioral finance, which has also gained importance within the anomaly literature. As the research is grounded in these topics, it is easier to understand the whole picture. The calendar anomalies themselves contradict the efficient market theory, as they are consistently producing abnormal returns. This study is mostly focused on the three widely acknowledged calendar anomalies, such as the January effect, the turn of the month effect, and the weekend effect. Also, other calendar-related anomalies are thinly introduced.

The data is gathered from Refinitiv and it covers the years between 2012 and 2022, with a focus on the main Nordic stock market indices. The Wilcoxon rank sum test, dummy variable regression, and two-sample t-test were chosen to conduct the empirical study. By employing these methodologies, the study aims to empirically assess the presence and significance of the chosen calendar anomalies in the Nordic stock markets. The findings indicate that the turn of the month effect is still persistent in the Nordic region, but due to the lack of evidence, the January effect and the weekend effect seem to be no longer present. The research expands comprehension of investor behavior and market efficiency. Market participants, financial professionals, and policymakers can navigate through the complicated nature of stock market behavior and make better decisions based on the observed findings.

KEYWORDS: Anomalies, Calendar Effects, Efficient Markets, Abnormal Returns, Stock returns, Behavioral Finance.

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TIIVISTELMÄ

Tämän tutkielman tarkoituksena on pureutua kalenteriperusteisten anomalioiden tutkimiseen Pohjoismaisilla osakemarkkinoilla. Näitä anomalioita voidaan kuvailla osakkeiden hintavaihtelulla, jotka usein toistuvat tiettyinä vuodenaikoina. Fama (1965) esitti ensimmäisenä tehokkaiden markkinoiden hypoteesin, josta on tullut kriittinen osa rahoituksen kirjallisuutta. Tämän vuoksi tätä teoriaa on käsitelty syvällisesti tässä tutkielmassa. Toinen tärkeä osa tätä tutkimusta on käyttäytymistaloustieteeseen perustuvat näkemykset, jotka esittävät psykologisia ja kognitiivisia selityksiä osakemarkkinoilla esiintyviin kalenterianomalioihin. Avaamalla näitä tärkeitä teorioita, on helpompi ymmärtää tämän tutkimuksen kokonaiskuva. Kalenterianomaliat ovat perinteisesti täydellisten markkinoiden oletusta vastaan, sillä ne tuottavat toistuvasti ylisuuria tuottoja. Tämä tutkimus keskittyy kolmeen tärkeimpään kalenterianomaliaan, Tammikuu-efektiin, kuunvaihde-efektiin sekä viikonloppu-efektiin. Myös muita kalenteriperusteisia anomalioita on käsitelty hieman lyhyemmin.

Tutkielman data on kerätty Refinitivistä ja se kattaa aikajakson 2012 – 2022. Kohteena on Pohjoimaiset osakemarkkinat ja niiden pääindeksit. Koska näiden anomalioiden tutkiminen on hiipunut lähes kokonaan, on tärkeää tarkastella ovatko ne palanneet osakemarkkinoiden keskuuteen. Tutkielmassa on käytetty kolmea erilaista menetelmää, Wilcoxonin järjestyssummatestiä, dummy-muuttujaregressiota sekä kahden otoksen t-testiä. Näitä metodologioita on hyödynnetty, jotta saataisiin kattavat tulokset mahdollisista anomalioista. Tulokset osoittavat, että kuunvaihde-efekti näyttäytyy edelleen merkittävänä, mutta tammikuu-efekti ja viikonloppu-efekti näyttävät poistuneen Pohjoismaisilta osakemarkkinoilta. Tämä tutkielma laajentaa ymmärrystä sijoittajien käyttäytymistä kohtaan ja sitä voidaan hyödyntää eri tahojen toimesta poikkeuksellisten markkinaliikkeiden ja yleisen sijoittamiskulttuurin tarkkailemisessa.

AVAINSANAT: Anomalies, Calendar Effects, Efficient Markets, Abnormal Returns, Stock returns, Behavioral Finance.

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1 Introduction

Since Fama (1965) proposed the efficient market hypothesis, the financial literature has undergone a significant transformation. Market efficiency became a relevant topic within financial research as a result of his analysis. Market efficiency has been highlighted as an important perspective in all stock market-related studies. Since then, academics and even ordinary investors have increasingly concentrated their attention on this perspective. Further research has discovered contradictory evidence for and against the efficient market theory, which has shifted the focus on recurring price patterns in the stock markets. As a consequence, these persistent price movements have been labeled as anomalies. At the moment, it can be stated that the level of information varies across different markets, but no market is completely information efficient. These findings have opened a broad space for further research on anomalies.

In fully efficient markets, asset prices reflect all available information. There should be no additional expenses, such as trading costs or taxes. The information referred to encompasses all decisions made by organizations, governments, and other business entities. The information also includes risk outlooks and macroeconomic situations. In general, information flows within efficient markets in such a way that each asset is priced appropriately. One of the key features is the ability to sell and buy assets at any time, which eliminates liquidity concerns. Fama (1970) classified market information levels into three categories: weak form, semi-strong form, and strong form. The actual level is determined by the availability of information. When all information is available, the market is more likely to be placed in a strong form.

According to Sullivan (2001) anomalies can be considered as evidence against the efficient market hypothesis since asset prices are not optimally priced. He proposed that markets are not fully efficient or that asset pricing models are out of date. A similar opposing view was presented by Burton (2003) who highlighted that investors tend to make mistakes, which affects market efficiency. Furthermore, Grossman and Stiglitz (1980) stated that scholars would have no incentive to reveal previously unknown information if asset prices immediately adjusted for it.

In order to analyze the relevancy of calendar anomalies, the empirical section is constructed based on previous research. Following Ariel (1987) and Bordeaux (1995), a paired two-sample t-test was executed. The two-sample t-test is a statistical test that compares the means of two groups and determines whether the difference is statistically significant. Anyway, it is important to note that this method has several limitations, as calendar anomalies may be related to other environmental factors as well. Therefore, other empirical tests are applied in order to get robust results. The other parametric test that is utilized is the single dummy variable regression, which is based on Chien et. al (2002). The regression slope in this method examines the differences between the two variables, which are determined for the January effect, the turn of the month effect and the weekend effect. For example, the average return in January and the average return for the remaining months of the year. Whereas the regression intercept evaluates the variable under examination, which in this case is the average return in January.

As the research requires another way to look at the issue, a non-parametric Wilcoxon rank sum test is also applied since it does not deal with parameters. This method is followed by Kunkel et. al (2003) and Lim et. al (2010). The Wilcoxon rank sum test can be extensively conducted to investigate populations in ranked order. This test is useful for identifying differences between data sets since it is unaffected by extreme outliers and does not depend on the normal distribution. The results can be seen from a wider perspective by taking measurements from both parametric and non-parametric tests.

1.1 Purpose of the study

The purpose of this study is to examine various anomalies in the Nordic stock markets and how they relate to the efficient market hypothesis and behavioral finance. This study will focus on several calendar anomalies, but more precisely on the January effect, the turn of the month effect, and the weekend effect. The study will also examine the implications of these anomalies in terms of behavioral finance. Furthermore, this study aims to investigate the possible explanations for these anomalies. The results of this paper will contribute to the existing literature on market anomalies and behavioral finance. Since anomaly research has significantly decreased in the last decade, particularly for the North Euroapean markets, this paper aims to fill the gap by analyzing current stock market data. Therefore, the data sample has been condensed into the most recent decade.

1.2 Research structure

An overview of the study's components is presented in this part, along with the research framework. A range of theory concepts, a literature review, data, methodology, and empirical findings are all included in the research to accomplish this. This section outlines each element of the research with a brief explanation. It also introduces how the whole paper is constructed. After an introduction, the research questions and hypotheses are presented. Following these, the first element of the research structure is the theoretical background.

The theoretical background provides a foundation for understanding the research questions and hypotheses. The theoretical background chapter involves the following theories: efficient market theory, which suggests that financial markets are efficient and incorporate all available information into asset prices. Random walk theory, which proposes that stock prices follow a random walk and that future prices cannot be predicted based on historical price information. Capital Asset Pricing Model, which is a model that predicts the expected return on an asset based on its beta. It measures the asset's sensitivity to market risk. Anomalies, which refer to reoccurring price patterns in the stock markets. Data mining, which touches on the process of discovering patterns and trends in large datasets. It is discussed how it can affect the findings of this research and other studies related to anomalies.

Behavioral finance forms the second component of the research structure. The study of behavioral finance delves into the psychological variables that affect financial judgment. These ideas are included in this chapter: fundamental risk, which refers to the risk associated with the underlying fundamentals of companies. Noise trader risk, which arises from the actions of irrational investors who do not incorporate all available information into their decisions. Implementation costs, which refer to the costs associated with executing trades in the stock markets. Behavioral biases, which refer to the systematic errors in decision-making that are related to cognitive and emotional factors.

The literature review is the third component of the study structure. This part offers a critical assessment of the collection of articles already published about market anomalies and their explanations. The following abnormalities will be reviewed: The January effect, which refers to the tendency for stocks to outperform in January. The research will evaluate tax-loss selling and window dressing explanations for this anomaly. The turn of the month effect, which refers to the tendency for stocks to outperform around the turn of the month. The paper will investigate the pay day explanation for this anomaly. The weekend effect, which refers to the tendency for stocks to underperform on Mondays. The blue Monday hypothesis is evaluated as an explanation for this anomaly.

Data and methodology compose the fourth element of the study structure. The data sample is broadly described, and the applied methodology is presented based on previous literature. The fifth element of the research structure is empirical results. The empirical results will demonstrate the findings of the research and its implications. The results will show whether the calendar anomalies identified in the literature review are still present in the Nordic stock markets.

1.3 Research Hypotheses

Since this paper is focusing on the appearance and relevancy of calendar anomalies in the Nordic stock markets, the following hypotheses were selected.

$H_1 =$ January returns are significantly higher than in other months of the year
$H_2 =$ Turn of the month outperforms the rest of the month
$H_3 =$ Monday returns are significantly lower than Friday returns

By referencing the key articles on the subject, Rozeff and Kinney (1976), Ariel (1987), and Cross (1973), these selected hypotheses are closely related to their research and to the core of calendar anomalies. This paper expands the research into North European countries since the previous studies mostly focused on other stock markets, especially the U.S. Research on calendar anomalies is also lacking in this century, so the intention is to investigate current data and find evidence to determine whether calendar effects have reappeared in the Nordics.

2 Theoretical Background

Since efficient market theory was initially proposed in the early 1960s, discoveries in the field of finance have advanced significantly. The efficient market theory, at least to some extent, has been overtaken by behavioral finance, which is extensively discussed in recent academic literature. Behavioral finance draws on a variety of perspectives from other social sciences, including sociology and psychology (Shiller, 2003).

2.1 The Efficient Market Hypothesis

The efficient market theory is based on the idea that capital markets operate efficiently with the resources and information available. The theory posits that when new information is presented, markets will quickly and accurately reflect it in the prices of securities. This theory also assumes that investors make rational and risk-averse decisions when investing (Hodnett & Hsieh, 2012).

Levy (1967) was a pioneering figure in the differentiation of information efficiency within the framework of efficient markets by proposing the distinction between weak and strong forms. Building upon this, Fama (1970) proposed a more nuanced perspective of efficient markets by categorizing them into three forms: weak form, semi-strong form, and strong form. This classification of information levels is crucial as it enables the identification of instances where the efficient market hypothesis is not holding.

Fama's (1970) theory has become a widely recognized and frequently employed framework in contemporary financial research. Despite its limitations, it serves as an important point of reference for understanding how market information is affecting prices. The theory of efficient market hypothesis is represented by three forms of informational efficiency, each of which reflects to the cost of obtaining securities and the accuracy and speed at which information is incorporated into asset prices.

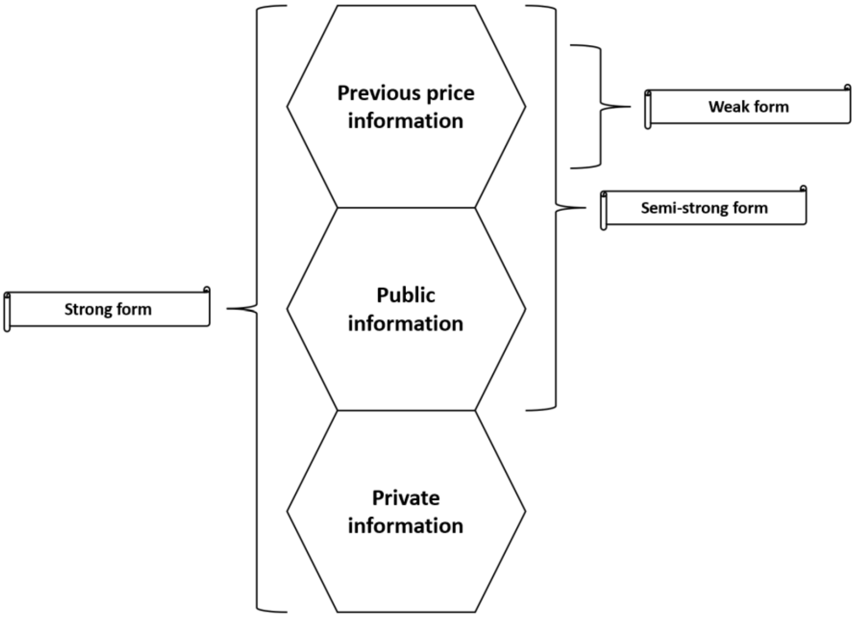

Figure 1. Stages of Market Efficiency.

According to Slezak (2003) the least efficient information level is called the weak form. At this level of information, current security prices reflect all the historical information available. This information includes historical data on price and volume. Nevertheless, it is impossible to estimate future prices by using only historical prices and volumes. This represents the fact that long-term abnormal returns cannot be attained by exploiting past price data, which also indicates that the use of technical analysis cannot be relied upon to consistently generate above-average results. Security prices should not depend on time or any other provisional reliance. This suggests that asset prices should absorb all pertinent information, excluding prior price data. As a result, prices are altering based on a random walk (Slezak, 2003).

The semi-strong form of the efficient market theory relies on the belief that asset values immediately respond to new information that is available to the public. The semi-strong form reinforces the idea that neither technical nor fundamental analysis can be utilized to generate excess returns over the long term. Researchers have examined the semi-strong form by applying methods that gauge how quickly stock prices react to the disclosure of fresh public information. The public information includes financial reports, dividend notifications, and other important news (Fama, 1970).

The strong form of efficient market theory takes into account all data, including both private and public information. Nobody is able to produce greater returns in the strong form. The strong form structures are studied by using tests of experts' suggestions, mutual funds, and pension funds that may outperform the market as a whole (Fama, 1970).

Fisher and Jordan (1991) conceptualized that, in the event of perfect market efficiency, stock market volatility would be such that incoming information would instantly and precisely adjust the price range, making it impossible for investors to achieve excess returns. This idea is supported by Nikkinen et al. (2008), who argue that stockholders can achieve similar long-term results through a passive trading strategy, such as investing in a market index, as they can through an active trading strategy.

2.2 Random Walk Theory

A random walk theory is an economic concept promoting the premise that stock prices fluctuate in an irregular manner, making it impossible to anticipate future stock prices. According to the random walk theory's assumption, it is impossible to predict that a stock price which rises one day will rise again the next. Price movements are better described as having an unexpected style of development because there is no association between past prices and future prices (Chitenderu et al. 2014).

The efficient market theory and the random walk concept are strongly connected. The past price data should not be utilized as a benchmark for investing decisions since future prices do not correlate with the historical prices. The optimal opportunity for timing investments cannot be determined from historical price information because future prices will continue to move inconsistently. According to the efficient market theory, market participants engage in the markets at different moments, which maintains stock values close to their equilibrium level (Chitenderu et al. 2014).

Kendall and Hill were British academics who investigated the movements of stock and commodity prices. They assumed to detect recurrent price patterns, but the price patterns indicated no consistency. According to their results, the suggestion was that stock and commodity prices are following a random walk because the study did not identify any clear price cycles. Thus, they stated that every price has the same probability distribution and that asset values are generally on the upswing in the long run (Kendall & Hill, 1953).

2.3 Capital Asset Pricing Model

The capital asset pricing model was initially presented by William Sharpe in 1964. In Sharpe's view, the equilibrium level of capital asset prices is formed by investors' rational behavior, which is centered on asset diversification. Investors can access any point along the capital market line through diversification. It is feasible to increase investment returns by taking on more risk. The correlations between risk and the anticipated rate of return are shown in the graph below. These elements interact together to structure the capital market line. For rational investors it is possible to acquire any point from the capital market line (Sharpe, 1964).

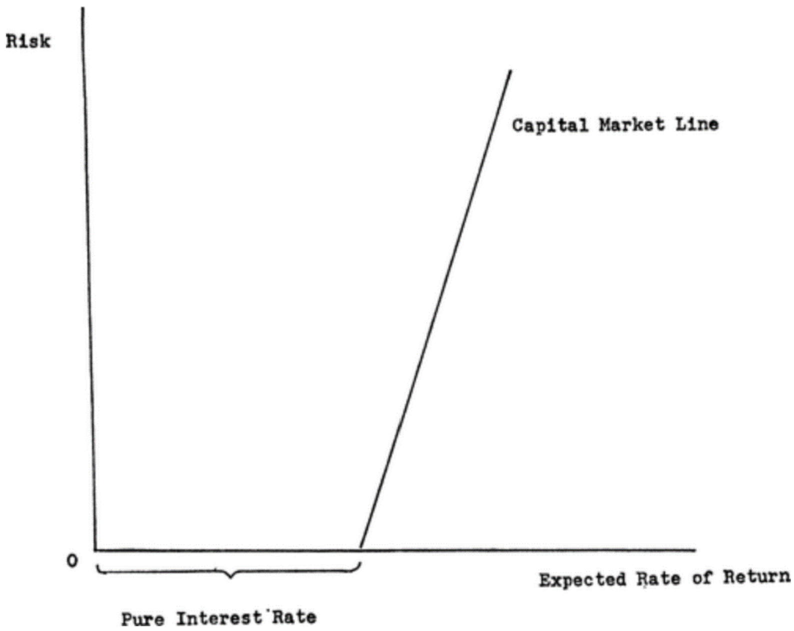

Figure 2. Expected Rate of Return (Sharpe, 1964).

The portfolio selection theory of Markowitz provides the foundation of the capital asset pricing model. Markowitz's model describes that market participants are aiming to maximize their expected rate of return while reducing portfolio variation. It sets conditions in algebra for asset weights. In the capital asset pricing model this is transformed into a testable prediction linking risk and return. The formula is shown below (Fama & French, 2004).

$$E(R_i) = R_f + \beta_i[E(R_m) - R_f] \tag{1}$$

Where $\mathrm{E(R_i)} = \text{Expected return for investment}$

$\mathrm{R_f} = \text{Risk} - \text{free rate}$

$\beta_\mathrm{i} = \text{Beta of the investment}$

$\mathrm{E(R_m)} = \text{Expected market return}$

In the realm of finance, risk and return are inextricably linked. The underlying principle is that the higher the level of risk associated with an asset, the greater the potential return. Investors require higher profits when faced with a higher level of risk. As the level of risk increases, so does the expectation of returns. Volatility, which is a measure of an asset's overall risk, is directly correlated with increased risk. Volatility can be calculated using various time frames, such as monthly or annual data, by assessing the fluctuations in prices and cash flows over a specific time frame. The formulas for computing volatility and stock returns can be seen in the following equations (Knüpfer & Puttonen, 2014:109-111).

Stock return inside an investment period:

$$HPR = \frac{P_s P_b + D}{P_b} \tag{2}$$

Where HPR = Investment period return

$\mathrm{P_s}$ = Stock price at the end of the investment pediod

$\mathrm{P_b}$ = Stock price at the beginning of the investment period

D = Amount of dividends paid during the investment period

Volatility:

$$\sigma = \sqrt{\frac{[\sum R_i - \bar{x}]}{(n-1)}} \tag{3}$$

Where σ = Standard deviation of the returns

$\mathrm{R_i}$ = Return for a given time period i

$\bar{\mathrm{x}}$ = Mean return

n = Number of observations

The Sharpe ratio is among the most well-known investment performance indicators. After the asset's risk has been taken into account, it compares the predicted return on each unit against a risk-free asset. It can be determined by the disparity between the investment return and the risk-free return divided by the investment's standard deviation. It illustrates the additional return that investors can achieve by adding one unit of risk. Below is an equation for the original Sharpe ratio (Sharpe, 1994).

$$S = \frac{R_p - R_f}{\sigma_p} \tag{4}$$

Where $\mathrm{S} = \text{Sharpe ratio}$

$\mathrm{R_p} = \text{Expected portfolio return}$

$\mathrm{R_f} = \text{Risk} - \text{free rate}$

$\sigma_\mathrm{p} = \text{Portfolio's standard deviation}$

2.4 Calendar Anomalies

Anomalies are generally found in financial markets through empirical analysis of historical market data. A vast amount of data, including stock prices, trading volumes, and other relevant factors, is investigated by analysts to search for patterns that differ from the expectations of efficient market theory or other traditional financial models. When researchers discover ongoing, statistically significant characteristics that seem to contradict the principles of efficient markets or other widely recognized theories, they have identified an anomaly. These recurring price patterns may result in abnormal returns, odd trade volumes, or other irregularities. The suggestion is that it may be possible to generate risk-free profits. This has clearly increased attention towards anomalies, and it can be seen as a growing trend of anomaly research in the fields of finance and economics.

Calendar anomalies are a subcategory of anomalies, and the name itself reflects the timing of their occurrence. Calendar anomalies are price movements that appear during particular times of the year. The most widely recognized calendar anomalies, such as the January effect and the turn of the month effect, were initially discovered in the 1900s. However, it took decades for researchers to pay serious attention to these repeating price cycles after the calendar anomalies were first observed (Jacobs & Levy, 1998).

Multiple calendar anomalies have lately been recognized. After Rozeff and Kinney (1976) discovered evidence of the January effect from the New York Stock Exchange, the history of calendar anomaly findings began. Following Rozeff and Kinney (1976), Ariel (1987) presented evidence of the turn of the month effect after analyzing information from the U.S. stock markets. Another prominent calendar irregularity discovered by Ariel (1990) is the holiday effect. The holiday effect has unique characteristics when contrasted with other calendar anomalies. The average return on trading days before the market closes for the holiday season is significantly higher than the average return on trading days during the rest of the year.

The Halloween Effect, commonly known as "Sell in May and Go Away," was discovered by Bouman and Jacobsen (2002). This phenomenon indicates that stock market returns are higher between November and April than they are between May and October. Cross (1973) discovered results suggesting that trading days within the course of a week might have widely divergent profits. Since then, the day-of-the-week effect has been acknowledged in several industry sectors. According to Cross (1973), In the New York Stock Exchange, Fridays are the most favorable days to gain positive returns and in contrast, Mondays are the worst days for positive returns. Nevertheless, individual nations may have their own particular price movements.

According to Thaler (1987) equity markets serve as a relevant location to search for anomalies. There are plenty of valid reasons why anomalies are generally found in these types of markets. First of all, equity markets are regarded as the most efficient markets since information is easily accessible to the public. This eliminates underlying assumptions like transaction expenses and market breakdowns as a source of anomaly appearances, even though these markets tend to be event-driven. Also, historical data is widely available, dating back to the 1920s, which provides a century of data to study (Thaler, 1987).

Due to the accessibility of historical information, calendar anomalies can be thoroughly investigated from a number of viewpoints, including different time frames and geographical market locations. As the price patterns appear to repeat themselves, it can be stated that calendar anomalies are comparatively simple to benefit from. This contradicts with the efficient market theory and also raises the question of how long these price trends can continue (Jacobs & Levy, 1988).

2.5 Data Mining

A limited data collection can be utilized to generate what is known as "data mining bias" when testing specific hypotheses. Generalizations should not be made with modest data sets as the foundation of a particular theory has a great chance of being misleading. Calendar anomalies, at least to some extent, share instances of biased-driven findings. Observations from limited samples are typically insufficient. Sullivan et al. (1998) note that the possibility of attaining desired outcomes by accident cannot be ruled out. Thus, the small subset of data makes it impossible to properly confirm the results (Sullivan et al. 1998).

Data-mining bias was examined by Sullivan et al. (1998) to discover proof that calendar anomalies are an inaccurate phenomenon. The research suggest that when analyzing a greater range of data, the influence of calendar irregularities appears to reduce its significance. The authors were in favor of taking a broader approach to the issue rather than drawing all the implications from a single academic study.

According to Marquering et al. (2006), identifying anomalies has just reached a preliminary stage. They state that traders may believe markets to be even more ineffective than anticipated when recent studies on anomalies have been revealed. By analyzing yearly t-statistics, the authors investigated anomalies such as the Holiday effect, the January effect, and the turn of the month effect. They examined the time span of the t-statistics and determined whether the coefficient was zero based on each anomaly. It allows to understand the magnitude of the anomaly for each year throughout the whole time frame. They discovered that the annual trend of the Holiday effect between the 1970s and 1980s was present. After the publication of (Lakonishok & Smidt, 1988) the Holiday effect was found to be even stronger the following year, but soon after the publication the effect had a significant decline until it disappeared.

The weekend effect, as described by Lakonishok and Smidt (1988), suggests that, in comparison to other trading days of the week, Fridays have much greater returns and Mondays have significantly lower returns. According to Marquering et al. (2006), this phenomenon has not held its relevance since the original paper by Lakonishok and Smidt (1988) was published. Marquering et al. (2006) found consistent results by utilizing dynamic analysis, which revealed that the weekend effect had already vanished in the present.

According to Rozeff and Kinney (1976), January returns on the New York Stock Exchange were excessively greater than other business months from 1904 to 1974. Between 1960 and 2003, Marquering et al. (2006) provided contradictory evidence. They discovered that January returns were substantially higher than average returns only between 1960 and 1976. Following this time frame, the average January returns from 1987 to 2003 were not statistically significant in comparison to other business months.

By providing a way for researchers to find patterns and trends in sizable datasets, data mining can play a vital role in the study of calendar anomalies. Researchers can examine broad datasets using data mining techniques to spot calendar irregularities that conventional statistical analysis might not recognize. Data mining can also negatively affect research if researchers test multiple hypotheses on the same dataset until they find a statistically significant result. This can lead to invalid findings where calendar anomalies are identified but they are not statistically significant in reality. Data mining depends on the quality of the data, and if the data is inaccurate or incomplete, the discoveries might be false.

3 Behavioral Finance

According to Razek (2011) surroundings are currently an important factor in all financial and investment decision-making. A significant percentage of the financial decision-making process has been widely examined by academics. Thus, the enigma of irrational behavior is only partially resolved due to the dynamics of the environment. Changing circumstances and the impact between market participants result in constantly evolving behavioral science and human behavior. With the education of behavioral finance, it is possible to reduce the biased thinking and guide investors towards rational decision-making (Razek 2011).

Behavioral finance has extensively incorporated sociological and psychological perceptions. It can be argued that the seeds of behavioral finance were already sprouting after MacKay published his research on crowd behavior in financial markets in the 1840s. Burrel (1951) later presented a paper that looked at the psychological factors that influence investors' decisions. In the late 1900s, research on this topic began to rapidly expand. The literature on behavioral finance has advanced significantly as academics have recently begun to expressly study financial behavior (Razek, 2011). Behavioral finance implies that when making investment decisions, investors act rationally only to a limited extent. Despite the fact that behavioral finance research is still in its early stages, numerous studies have been conducted to determine how investor behavior affects asset returns and the financial industry as a whole.

Market behavior was explained by Sheifler and Summers (1990) using two different investor categories. They separated rational and irrational investors. Investors that create completely logical expectations based on asset information are known as arbitrageurs, which refers to someone that utilizes a risk-free investment method that ensures positive returns. The second group, irrational investors are setting their expectations primarily based on their opinions and underlying sentiments. So, the use of fundamental knowledge differentiates arbitrageurs from irrational investors. It is also notable that there are some concerns that restrict arbitrage, such as fundamental risk and the uncertainty of future price movements (Sheifer & Summers, 1990).

Most market participants are influenced by psychological factors, at least subconsciously. This is not often happening immediately or visibly, but incrementally as investors minds get affected by their surroundings and by other people around them. In some cases, the environment massively guides traders to get involved with specific trends, industries or companies, which can also lead to market bubbles. These psychological factors are affecting the decision-making process, which might be one of the explanatory particles of whether anomalies occur based on crowd behavior (Fenzl & Pelzmann 2012).

3.1 Fundamental Risk

When purchasing assets at any value, investors are taking a risk. Asset values may be negatively impacted by unexpected news and abruptly approaching crises. Investors should tolerate their deficit, if the asset needs to be realized at a lower value than it was originally bought. This kind of risk is defined as fundamental risk. Arbitrageurs who short the asset they own with a substitute, can protect themselves from the fundamental risk. Nevertheless, it may be extremely difficult to find an exact replacement for the asset. On top of that, investors cannot completely avoid taking risk when investing. Also, if unanticipated and unfortunate news appears, the basic risk still remains (Brooks & Byrne, 2008).

Arbitrageurs take into account all available information and avoid taking any sort of risk. Therefore, they can be considered as constrained. If we assume that arbitrageurs are shorting stocks with prices higher than anticipated and the stocks will pay future dividends, they are holding a risk. This is because of the possibility that dividends might be higher than anticipated. This scenario has a significant impact on profits, since arbitrageurs are losing their positions. Another situation occurs if market prices are exceedingly high and arbitrageurs are shorting the stocks. In this case, they run the danger of future stock prices increasing even more. Short sellers would suffer losses once more. Due to these restrictions, arbitrageurs cannot drive prices down to fundamental levels (Shleifer & Summers, 1990).

3.2 Noise Trader Risk

An opposing approach regarding anomaly research was presented by Shleifer and Vishny (1997). According to them, noise traders are to blame for the existence of anomalies. Noise trading is an investment approach that relies on sentiment and impulsive feelings. Investors that closely follow the prevailing market trends and have a tendency to respond overwhelmingly to imminent situations like news updates, crises, or even rumors are characterized as noise traders. As a result, high volatile equities may produce excess returns that deviate from the equilibrium level. Since noise traders do not adjust new information rationally, anomalies emerge. After numerous publications of anomalies, investors have slowly started to comprehend the logic behind this phenomenon (Shleifer & Vishny, 1997).

3.3 Implementation Costs

Arbitrage is the process of generating abnormal profits without taking any risks. Exploiting anomalies would be classified as an arbitrage strategy if they were consistent over time. Additional returns could be obtained on a regular basis if anomalies were not subjected to the risk of becoming less productive. However, due to liquidity concerns and the possibility of businesses failing or declaring bankruptcy, the risk can never be zero percent. Furthermore, it is impossible to entirely bypass the expenses related to the implementation process.

Due to the implementation expenses, arbitrageurs have fewer opportunities to profit from the mispricing. Implementation expenses include transaction fees such as premium costs, monetary fees, commissions, bid-ask spreads, and legal concerns. In addition to the direct costs, there are time and effort costs. These expenses are associated with discovering and understanding the abnormal price deviations. Often, arbitrageurs are required to spend time and money to educate themselves. Arbitrageurs also need to take into account the cost of resources required to take advantage of the mispricing, meaning they need enough capital for the execution of trading (Herschberg, 2012). All of these implementation expenses are limiting the exploitation of anomalies.

3.4 Behavioral Biases

Since behavioral finance began to dominate financial research, behavioral biases have been widely recognized. Investors frequently struggle to observe the information and render inaccurate assessments of the eventual price course in the markets. They may forecast that future scenarios will affect pricing differently or expect that the rate of return should be higher. This section covers important studies of previously discovered behavioral biases that are rather crucial to the study of anomalies.

The prospect theory, first introduced by Kahneman and Tversky (1979), describes why investors behave depending on the value of wins and losses rather than on the overall result. The authors presented the idea that investors took less risk when they were on the profit side and increased their risk-taking when they were losing. Later, Shefrin and Statman (1985) presented the disposition effect, which suggested that investors have a behavioral tendency to cling onto losing assets for too long while selling winning assets relatively early. The implication suggests that investors are acting irrationally. The disposition effect is acknowledged across numerous nations and a variety of asset categories. It is known to emerge in all kinds of investor groups, with beginners and even with more experienced investors.

Kim and Ha (2016) investigated the disposition effect from two angles by sorting investors into different groups. The first group had investors with a focus on promotion, while the second group had investors with a focus on prevention. The first group, investors who are promotion-oriented, are committed to exploiting chances, earning profits, and minimizing losses. The second group of investors is concerned with avoiding mistakes, achieving zero losses, and minimizing overall losses. Substantial variations were found between the two reference groups. The disposition effect was minimal or nonexistent for those who were focused on promotions. However, the disposition effect appeared significantly stronger for those who were prevention-focused (Kim & Ha, 2016).

According to Bikhchandani et al. (1992) herding behavior refers to the tendency of investors to follow the actions of others, rather than making independent investment decisions. The authors argue that herding behavior is driven by a lack of information and a desire to conform to the actions of others. They propose that investors tend to imitate the investment decisions of others, leading to a lack of independent thinking and overvaluation of certain securities. They also found that herding behavior is more likely to occur among individual investors than institutional investors. Their findings indicated that herding behavior can lead to market inefficiencies and can exacerbate market bubbles. Therefore, investors should be aware of herding behavior and try to avoid being influenced by the actions of others (Bikhchandani et al. 1992). Based on this research, it is possible that investors herding behavior strenghtens the effect of calendar anomalies.

Coval and Moskowitz (1999) studied the anchoring bias, which is a common behavioral bias that refers to the tendency of individuals to rely on past market performance or historical events when making investment decisions. The authors propose that investors tend to anchor their investment decisions to past market performance and events, leading to overvaluation of securities that have performed well in the past, and undervaluation of securities that have performed poorly in the history. Following Coval and Moskowitz (1999), Gervais and Odean (2001) found that investors tend to hold on to losing investments for longer periods of time, due to their beliefs that the investments will eventually return to their original value. In a more recent study by Doran et al. (2018), anchoring bias can lead to poor performance of mutual funds. Their study suggests that mutual fund managers tend to anchor their investment decisions to past market performance, leading to poor performance of the funds.

Behavioral models are facing a number of difficulties if they are evaluated empirically. Assessing the models by employing compiled input is challenging. It is caused by the utility-maximizing investors who are switching between entering and leaving the stock market instead of just retaining the portfolio for prolonged durations. As a consequence, behavioral model tests are problematic since they lack comprehensive information on investor behavior. A thorough understanding of the investment strategy and knowledge of the anticipated holding period are necessary for accurate testing (Coval & Shumway, 2005).

Coval and Shumway (2005) investigated whether psychological biases have an impact on equity values on the Chicago Board of Trade. The authors contrasted rational investor behavior with typical behavior. They split the trading period into two sections to determine whether investors who have profitable morning hours increase or decrease their afternoon risk profile. Their findings indicated that investors were far more risk-averse after winning since the results suggested that investors would increase the risk-taking, if the morning ended with a loss. Most of their tests had the same outcome, including panel regressions, pooled OLS regressions, Fama-MacBeth averages of trader-by-trader, and day-by-day regression coefficients.

4 Literature review

The objective of this chapter is to probe more thoroughly into the analysis of calendar anomalies and the explanations behind their occurrance in the stock markets. The aim is to improve the knowledge of anomalies and their typical functions, and also to investigate whether it is possible to capitalize on them. Watchel's (1942) research is considered one of the earliest studies that examine seasonal price patterns in stock markets. His findings suggested that the stock market tends to perform well in the months of December to April and underperform from May to November. According to current research, the majority of anomalies are disappearing or their timing is shifting. Theoretically, anomalies are losing their effect after investors notice the potential of these price patterns. In this century, irregularities may prove to be changing course. The debate is heating up, and some anomalies can be proven to be vanished. At the same time, new anomalies have been discovered.

4.1 January Effect

The January effect is a calendar anomaly that has been widely studied in financial literature. It refers to the tendency for small-cap stocks to experience higher returns in the month of January compared to other months of the year. This phenomenon has been observed in various stock markets around the world. It has also been the subject of numerous studies in the field of finance. This chapter will provide an overview of the January effect, including its historical origins, potential explanations, and implications for investors.

Rozeff and Kinney (1976) are considered the first to study the January effect, and their research is widely recognized. Their implications were that the January returns for small-cap stocks were systematically higher compared to other months of the year. Following these results, Grossman & Stiglitz (1976) found consistent evidence from the Canadian stock market. Thaler (1987) also argued that the January effect is robust across many different stock markets. Hirschey and Haug (2006) came to the same conclusion in the

U.S. stock markets when they argued that the January returns for small-cap stocks are considerably higher.

Khan and Rabbani (2018) examined the presence of the January effect in the Japanese stock market by utilizing data from the TOPIX and Nikkei 225 indices spanning from 1970 to 2017. The authors employed a least-squares regression model to analyze the data. The results of their analysis revealed that prior to the Japanese recession of 1990, the January effect appeared to be present in both bull and bear markets. However, post-1990, the January effect was observed to be less prominent in years where market performance was poor and more pronounced in years where market performance was strong.

The tendency for small-cap stocks to outperform large-cap stocks in January is known as the "small-firm January effect." Easterday et al. (2009) investigated whether this effect is consistent with efficient markets or if it is instead caused by institutional factors and behavioral biases. They estimated the average returns of small and large stocks using a data sample from the U.S. stock market from 1963 to 2006 and tested whether the effect was compatible with investors' learning and arbitrage efforts by applying cross-sectional and time-series regression models. The authors found that the small firm January effect is still present, but it has diminished in magnitude over time, which suggests that this effect is inconsistent with efficient markets. Additionally, they discovered that the effect is stronger in companies with less analyst attention, which may point to informational inefficiencies.

According to Ritter & Chopra (1989), who tested NYSE returns from the period of 1935-1986, smaller companies and stocks with higher volatility exhibit a stronger January effect. They suggest that the January effect is influenced by portfolio rebalancing because these equities are more likely to be affected by adjustments to portfolio weights and trading activity around the year-end rebalancing. The authors discovered that overweighted equities typically outperform portfolios in December and underperform in January, which they interpret as proof that portfolio managers are rebalancing their holdings at the end of the year.

Thaler (1987) examined several potential explanations for the January effect, including tax-loss selling, window-dressing, and turn of the year optimism. He argued that these explanations are not fully consistent with the evidence and that the January effect may be related to market inefficiencies, such as limits to arbitrage and transaction costs. For investors, it appears to be an exceptional opportunity to purchase stocks in late December when the prices are still comparatively low and later sell them in January after the prices have increased in value to make profits.

In a more recent study by Patel (2016), which focused on the U.S. stock index, developed stock index, three major regional stock indices, and emerging stock market index between 1997 and 2014, regardless of whether the volatility was high or moderate, none of the six stock indices exhibited the January effect. Additionally, the findings suggest that neither bullish nor bearish market conditions are necessary for the January impact to be present. Consequently, the results indicate that the January effect is no longer a stock market return phenomenon.

4.1.1 Tax-loss Selling Hypothesis

Tax-loss selling is thought to be one of the main reasons that is causing the January effect since investors have obligations to pay taxes on their net capital gains. Taxation is causing investors to reduce their tax liabilities to the bare minimum, resulting in selling pressure on the stock market, particularly for underperforming stocks. Several nations have set the end of the tax year to the end of December. Therefore, investors have a greater tendency to sell investments that have produced negative results in December. Following the December sales, investors are likely to repurchase their assets at the opening of the year in order to reduce their tax burden. After losses are deducted in taxes at the end of the year, the same stocks frequently face buying pressure in the first trading days of January (Chen & Singal, 2003).

The Tax Reform Act was passed in the U.S. in 1986. That relocated the mutual fund tax year ending to the end of October. Even though the relocation had no effect on individual taxpayers, it seemed to have an impact that shifted the December-January price movement to October-November for large-cap corporations in the U.S. meaning that large-cap stocks faced selling pressure in October and buying pressure in November (Chen & Singal, 2003).

Sias and Starks (1997) compared how both individuals and organizations were acting on the stock market. They researched a sample across the years 1978 and 1992 from the New York Stock Exchange. The findings from this particular time period provided validation for the tax-loss selling theory. Sias and Starks (1997) discovered that during the final four trading days of December, losing stocks held by individuals had much lower earnings than losing stocks held by organizations. Transaction data further supported the tax-loss selling hypothesis as it indicated that individually owned losing stocks were primarily sold in late December. At the turn of the year, the trading activities of individual investors were more influential than those of institutional investors, which were determining price changes throughout the bid-ask spread.

Lynch et al. (2014) found that the January effect is stronger for small-sized stocks. The sample evaluated included the years 1999 through 2005 and concentrated on the institutional trading of American stocks. They discovered that stock returns at the beginning of the year were lower for stocks with institutional trading than for those without. In light of their discovery concerning equities with little or no institutional trading, it was noticed that they experienced higher returns compared to the whole sample, which indicates that individual investors are most likely to be responsible for the turn of the year return patterns. The study advanced knowledge of institutional trading patterns at the beginning of the year, but the authors recognized that the results might not apply to all institutional investors in general.

Grinblatt and Keloharju (2004) have convincingly shown that Finnish investors engage in tax-loss selling activity by tracking repurchases and charting the daily pattern of sales around the turn of the year and their relationship to the capital gains or losses of investors. Stock repurchases toward the end of the year tend to occur almost immediately after the stocks are sold, and the repurchases are also closely related to the extent of the capital losses on those stocks.

The study also examined the potential link between tax-loss selling and the return pattern observed in December and January. The authors found that the temporal pattern of returns and net buying pressure, which results from repurchases connected to earlier sales that would be repurchased later, are identical. Specifically, returns were small or slightly negative at year-end and significantly positive during the first few trading days of the following year. Around the turn of the year, small firms also exhibit the most significant change in the temporal pattern of repurchases. Moreover, a positive correlation exists for small firms between the daily buying pressure caused by tax-loss selling and daily returns. Therefore, the January effect seems to closely resemble the net buying pressure observed in the study's sample period (Grinblatt & Keloharju, 2004).

4.1.2 Window Dressing Hypothesis

According to Haugen & Lakonishok (1988) the window dressing hypothesis is regarded as an alternative theory to explain the January effect. In order to appear better in the annual reports, it is speculated that institutions will sell their losing investments and replace them with prior winners in the stock market. Lakonishok et al. (1991) investigated this phenomenon from the perspective of pension fund managers. They looked at a sample of 769 American pension funds and discovered that weakly performing stocks were more likely to be sold near the end of each quarter. Also, the end of the year faced the greatest selling pressure for losing stocks. As a result, the evidence was in favor of the window dressing hypothesis.

Bildersee & Kahn (1987) conducted a block trade study of the New York Stock Excange between 1978 and 1983 in order to find evidence for the window dressing hypothesis. They discovered that, towards the end of each quarter, stock trading activity increased. The window dressing theory is strongly supported by the results, which revealed that institutional trading was the main factor in this discovery. The results of the nonparametric tests and the regression analysis further suggested that institutional window dressing is more likely in the stocks of companies that have recently underperformed. Although mutual fund managers' actions cannot be directly generalized to other business operations, they do imply that documentation requirements have an impact on executives' actions.

The window dressing hypothesis above was not supported by Chen and Singal (2001). According to them, the same effect should also appear after semi-annual reports are released. At the turn of June and July, there is no tax-related selling of stocks, but semi-annual reports are released. They did not find significant similarity between the five trading-day period at the turn of December and January compared to the five trading-day period at the turn of June and July. Hirschey and Haug (2006) were also against this assumption. According to them, if window dressing was a reasonable hypothesis, it should be occurring among large institutional investors as a large-cap phenomenon. The window dressing hypothesis is hence restricted, as the January effect occurs mostly for small-cap stocks.

4.2 Turn Of The Month Effect

Ariel (1987) discovered that during the period of 1963 and 1981, stock market returns were typically higher in the first halves of the months, which was the first notation of the turn of the month effect, also known as the TOM effect. Following Ariel's (1987) findings, Lakonishok and Smidt (1988) obtained consistent results by using trading days -1, +1, +2, and +3 as the turn of the month. The last trading day of the month is considered as -1, the first trading day of the following month is +1, the second trading day of the following month is +2, and the third trading day of the following month is +3. Their findings indicated that across 1897 and 1986, the four-day trading period in the Dow Jones Industrial Average was statistically greater compared to the stock market returns of other trading days throughout the month.

Consistent results regarding the turn of the month effect with Lakonishok & Smidt (1987) were obtained by Kunkel et. al (2003). In their study, 19 stock market indices from various countries were examined by applying both parametric and nonparametric tests, including OLS dummy variable regression, a three-way ANOVA model, and the WSR test. Kunkel et. al (2003) provided results indicating that all three of these models supported the turn of the month effect's appearance. The anomaly was persistent in 16 out of the 19 countries between the sample period of 1988 and 2000. These countries were located in Europe, Asia, North America, and Africa.

McConnel and Xu (2008) reviewed data of 35 nations from 1926 until 2005 using the same four-day-based separating criterion. For the trading days -1, +1, +2, and +3, they noticed that earnings were greater and statistically significant in 31 out of 35 countries. In contrast to the average return of the other trading days of the month, earnings of -1, +1, +2, and +3 on bills and bonds were negative, although significantly less. According to McConnel and Xu (2008), increased risk-free rates, higher interest rates, or higher volatility were not determined to be the causes of the turn of the month effect. Because the turn of the month effect has lasted for more than a century in the majority of nations, they argue that this phenomenon is a standard.

4.2.1 The Payday Hypothesis

According to Ogden (1990), the turn of the month effect is caused by American investors who receive their salaries, interest payments, and royalties near the end of each month. Booth et. al (2001) found support for Ogden's (1990) theory, which considers that higher stock returns at the beginning of the month are related to stronger liquidity brought on by large traders accumulating cash at the month's end. Booth et. al (2001) studied the Helsinki Stock Exchange between 1991 and 1997. According to their analysis, there is a favorable association between turn of the month returns and liquidity indicators such as FIM volume, share volume, and transaction volume. This liquidity hypothesis is further supported by the finding that there were more internalized trades and bid quotes during the turn of the month.

The payday theory was challenged twice by McConnel and Xu (2008), who were unable to perceive enough evidence to support the claim. The theory was tested with the NYSE's daily volume of trade and the daily cash flow into mutual funds between the years 1926 and 2005. The trading volume was marginally lower around the turn of the month compared to other trading days, which was considered a blatant example of the payday hypothesis being refuted. According to McConnel & Xu (2008) several investors control securities indirectly via institutional funds, and they may have a portion of their salary deposited directly into an institutionally managed pension fund. The flow rates of mutual funds should then follow the same kind of movement at the beginning of the month, if the payday hypothesis is a plausible theory. In their analysis, which included data between 1998 and 2005, different trends were discovered that were not in line with the payday hypothesis (McConnel & Xu, 2008).

4.2.2 Macroeconomic News Announcement Hypothesis

Nikkinen et. al (2007) studied the turn of the month effect in the S&P 100 index. They found supportive evidence of its existence with Ariel (1987) and Lakonishok & Smidt (1988). Their study perceived this anomaly by providing a new perspective on its underlying reasons. They suggested that higher TOM returns are generated due to macroeconomic news announcements since the returns at these periods were not statistically significant after accounting for the news announcements. These results were obtained by utilizing information from implied volatilities of options to account for changes in the expected risk premium. It is possible that the positive returns on announcement days during the first half of the month are due to a rise in estimated risk premiums because the measure indicated higher risk premiums on significant announcement days, such as the release day of the Employment Situation Report. However, the metric was shown to be insufficient in capturing the effects of news releases, which may be related to errors observed in the options market, greater liquidity, or investors overreacting, which results in larger realized returns. Though the fundamental process is not entirely clear, there is significant evidence to support the authors' claim that TOM is caused by macroeconomic news reports (Nikkinen et. al 2007).

4.3 The Weekend Effect

Following the publication of Cross (1973) the weekend effect was recognized. It postulates that there exists a systematic pattern in stock returns across different days of the week. Scholars have observed that stock returns tend to exhibit a higher tendency on certain days of the week, with Fridays displaying a higher average return and Mondays displaying a lower average return. This trend has been widely acknowledged in the literature and is commonly referred to as the weekend effect. However, it is important to note that the magnitude of this effect varies across different countries, and further research is needed to fully understand the underlying mechanisms of this phenomenon.

Cross (1973) introduced the weekend effect to public awareness. The implications of his findings were that the median return was significantly higher on Fridays compared to Mondays. His sample consisted of 844 sets of Fridays and following Mondays between 1953 and 1970, during which the New York Stock Exchange was open for trading. His research suggested that the weekend effect was persistent for 17 years out of the 18-year period. After Cross (1973), Jaffe and Westerfield (1985) studied the weekend effect in four different markets: the U.K., Canada, Japan, and Australia. Their research results were consistent with Cross (1973) in these four markets.

In later studies, the weekend effect has proven to be vanished. According to Steeley (2001) the weekend effect has disappeared in the U.K. since the 1990s. In his examination of stock returns from the FTSE100 index between the years 1991 and 1998, he discovered that on days when announcements were made, returns on Mondays and Fridays were significantly lower compared to other trading days of the week. However, when examining days without announcements, only a slight indication of the weekend effect was observed. The low returns on Mondays seemed to be attributed to the release of news announcements. Furthermore, he determined that days without announcements did not exhibit a significant difference in returns compared to other weekdays.

Pettengill et al. (2003) reached similar conclusions regarding the disappearance of the weekend effect in the United States, albeit from a different perspective. The authors utilized data from the S&P 500 index and the NYSE's smallest decile. They discovered no relationship between trading days and the Monday seasonal effect. Their evidence supported the idea that institutional investors are reducing transaction costs through arbitrage trading activity, which is considered a major factor contributing to the diminishing weekend effect.

In a more recent study, Alt et. Al (2011) studied the U.S., the U.K. and the German stock markets in order to find evidence of lower Monday returns. Their concerns were the empirical tests that are generally conducted on the day of the week studies. According to the authors, these tests fail to sufficiently account for the multiplicity effect. They decided to conduct a multiple-level alpha procedure. The timeframe investigated covered the years between 1970 and 2008, and the results indicated that Mondays performed poorly in the 1970s and 1980s, but later in the 1990s and 2000s, the performance normalized.

4.3.1 The Blue-Monday Hypothesis

The Blue-Monday Hypothesis posits that the mood of investors plays a significant role in the asset pricing framework. Essentially, it suggests that investors exhibit a natural tendency towards negativity on Mondays, which results in a greater willingness to sell securities on Mondays and a lower tendency to buy securities on Mondays (Gondhalekar & Mehdian, 2003). Pettengill (1993) examined the Blue-Monday hypothesis by conducting an experiment consisting of two paired investment simulations. Participants were instructed to divide their wealth among seven securities over several investment rounds, and their portfolio choices during a Monday trial were compared to Friday trials. Pettengill (1993) found support for the Blue-Monday hypothesis since participants on Mondays invested a significantly lower proportion of their wealth in high-risk securities such as stocks and a significantly higher proportion of their wealth in Treasury bills. These results indicate a more risk-averse investment behaviour on Mondays, which generally occurs as lower buying pressure.

4.4 Other Calendar Anomalies

This chapter covers a few other notable calendar anomalies that have been discussed in the financial literature. Bouman and Jacobsen (2002) published a paper about the Halloween effect, which is commonly presented as "Sell in May and Go Away". This phenomenon indicates that stock market returns are higher between November and April than they are between May and October. The authors found robust evidence of this anomaly in 36 countries around the world. The effect appeared to be strongest in Europe, but other developed and emerging markets indicated similar returns. Their methods included general regression techniques, where they utilized a seasonal dummy variable. Haggard and Witte (2010) found evidence related to Bouman and Jacobsen (2002). Their research focused on the U.S. stock market from 1954 to 2008, and the results also indicated strong significance in favor of the Halloween effect.

According to Bouman and Jacobsen (2002) there are several possible underlying reasons why the Halloween effect occurs. They proposed, for example, data mining, risk-based approach, differences in interest rates and trading volume, the timing of vacations and the influence of news announcements. The risk-based explanation states whether the risk between November and April is higher compared to the period between May and October. This explanation was refuted as the authors investigated the standard deviation, which indicated similarity throughout the year.

Changing interest rates and lower trading volume might have their own impact on the Halloween effect. If central banks are gravitating towards increasing interest rates during the interval of May to October or lowering the interest rates between November and April, it is plausible that these actions might affect the anomaly. In addition, substantially lower trading activity can have its own effect. Bouman and Jacobsen (2002) tested these explanations, and their evidence did not support central banks to have a tendency to change interest rates over a specified timeframe in any of the studied countries. Also, the trading volume did not indicate any significance by being lower during the summer, though it seemed to be slightly higher during the winter. However, the length and timing of vacations appeared to match the timing of lower returns. The impact of news announcements was also refuted, as their research found no seasonal factor in the news (Bouman & Jacobsen 2002).

Another well-known anomaly is the holiday effect, which appears just before major holidays. According to Ariel (1990), the average rate of return on trading days before a holiday season is significantly higher than the average return on trading days during the rest of the calendar year. He separated trading days into pre- and post-holiday intervals. The final trading day before the twelfth annual holiday in the U.S. when stock markets close, is referred to as the pre-holiday interval. Any other trading day throughout the year is considered a post-holiday interval. Following Ariel's (1990) classification, Robins and Smith (2019) conducted their own research on the holiday effect. The authors analyzed information from the NASDAQ, Amex, and New York Stock Exchange stock markets across 1926 and 2017. According to their study, all low-cap stocks experienced a strong holiday effect. However, after 1978, the effect started to vanish for large-cap and value-weighted stocks.

In a study published by Marquering et al. (2006), eight different holidays were analyzed: Christmas, Presidents' Day, Good Friday, Thanksgiving, Labor Day, and Independence Day. The data was compiled using a sample of the Dow Jones Industrial Average from 1960 to 2003. They discovered that the pre-holiday effect was weakened for large-cap corporations but maintained for small-cap companies. Nonetheless, the authors stated that the holiday effect appears to be losing relevance as time passes.

Marret and Worthington (2009) investigated the Australian stock market's reaction to holidays. From 1996 to 2006, they contrasted the returns on small-cap stocks. Information was extracted from the Global Financial Data database. The analysis included the following holidays, New Year's Day, Australia Day, Easter Friday, Easter Monday, The Queen's Birthday, Christmas Day, and Boxing Day. The last trading day before a holiday is referred to as the pre-holiday period, while the first trading day after a holiday is referred to as the post-holiday period. Their findings demonstrated that the mean average returns for pre-holiday trading were roughly five times greater in comparison to other trading days (Marret & Worthington, 2009).

Marret and Worthington (2009) proposed the holiday spirit hypothesis as a reason for the holiday effect's existence. The primary idea behind the holiday spirit hypothesis is based on the psychology that affects traders' actions. According to this perspective, investors' emotions and confidence are boosted by holiday excitement and exaggerated optimism, which causes them to be tempted to buy stocks just before the holiday seasons.

5 Data and Methodology

Various anomalies and price patterns in the financial markets have been observed over time. The January effect, the turn of the month effect, and the weekend effect are three of the most well-known anomalies on which this study is focused on. The purpose of this study is to determine whether these three anomalies are present in the Nordic stock markets. Observed stock market indices are from Sweden, Finland, Denmark, Iceland, and Norway. The Nordic stock market is researched through the five stock indices, which also serve to measure the overall performance of the region. Each stock index's price change and dividends over a specific time period are captured by the total return index. The total return indices offer more precise results since dividends can have a significant impact on stock returns.

Country	**Stock Exchange**	**Stock Market Index**
Sweden	Stockholm Stock Exchange	OMX Stockholm (RI)
Finland	Helsinki Stock Exchange	OMX Helsinki (RI)
Denmark	Copenhagen Stock Exchange	OMX Copenhagen (RI)
Iceland	Nasdaq Iceland	OMX Iceland All Share (RI)
Norway	Oslo Stock Exchange	Oslo Exchange All Share (RI)

Table 1. Countries, Stock Exchanges and Stock Market Indices.

The data sample is gathered from Refitnitiv, which is a globally recognized database for historical stock price information. The data is a collection of historical daily stock price data for each of the five indices from January 2012 to December 2022. The adjusted closing price is chosen to determine the daily price data. The time period could be extended for a longer period, but the intention is to determine the most recent price movements in the Nordic region. However, as Sullivan et. al (1998) stated, research with a smaller range of data might reduce the significance of the results.

The price trends of all of the studied indices demonstrate a noticeable similarity. Starting in 2011, the value of each index experienced steady growth. However, in the early stages of 2015, a slight dip in the prices was observed in each index, which was later recovered and culminated in a peak in the early spring of 2020. Due to the COVID-19 pandemic, all of the indices witnessed a remarkable decline in prices following the peak. Subsequently, a rapid recovery took place, and each index made all-time highs in late 2021 and early 2022. However, following these all-time highs, each index experienced a heightened volatility and declining prices. Below is an illustration of each studied index and their returns.

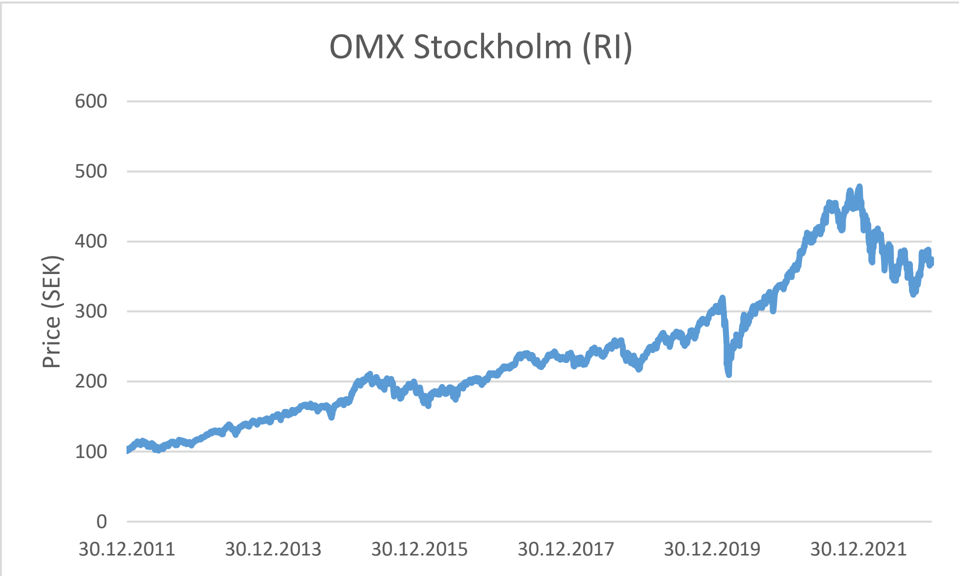

Figure 3. OMX Stockholm (RI) Returns.

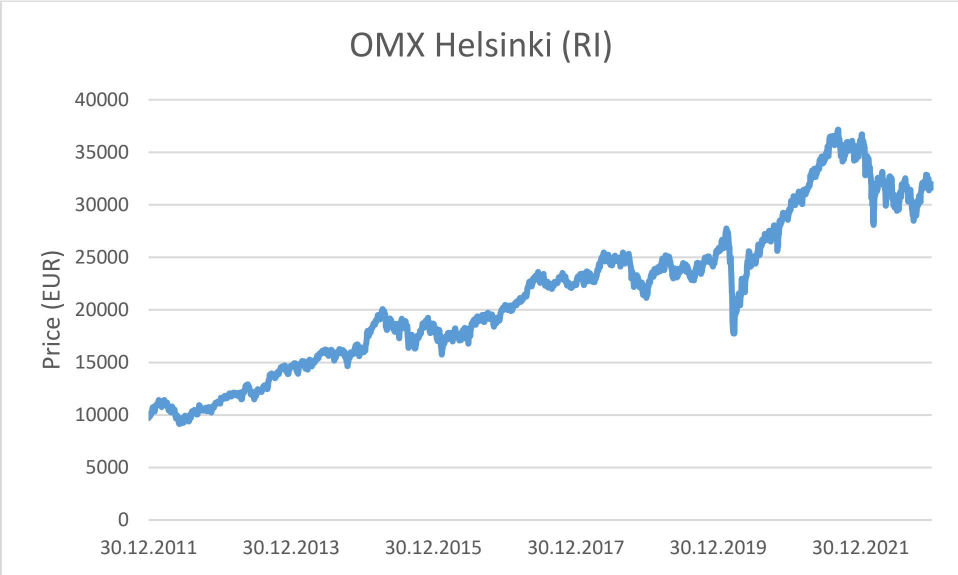

Figure 4. OMX Helsinki (RI) Returns.

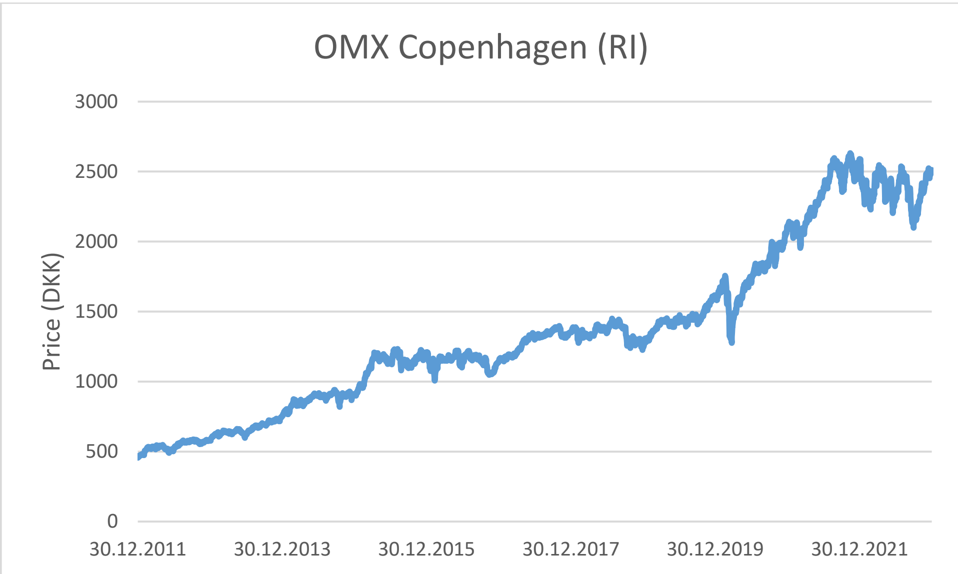

Figure 5. OMX Copenhagen (RI) Returns.

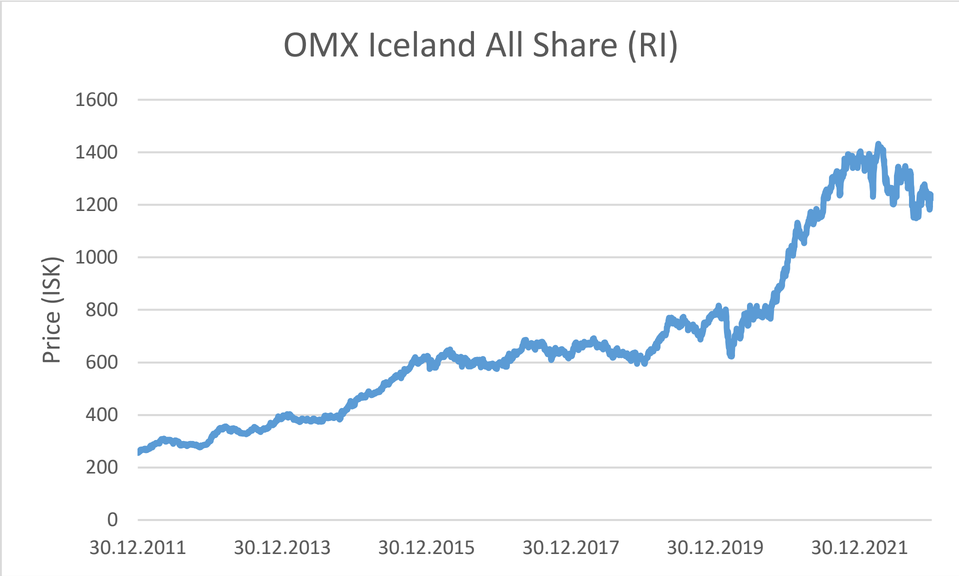

Figure 6. OMX Iceland All Share (RI) Returns.

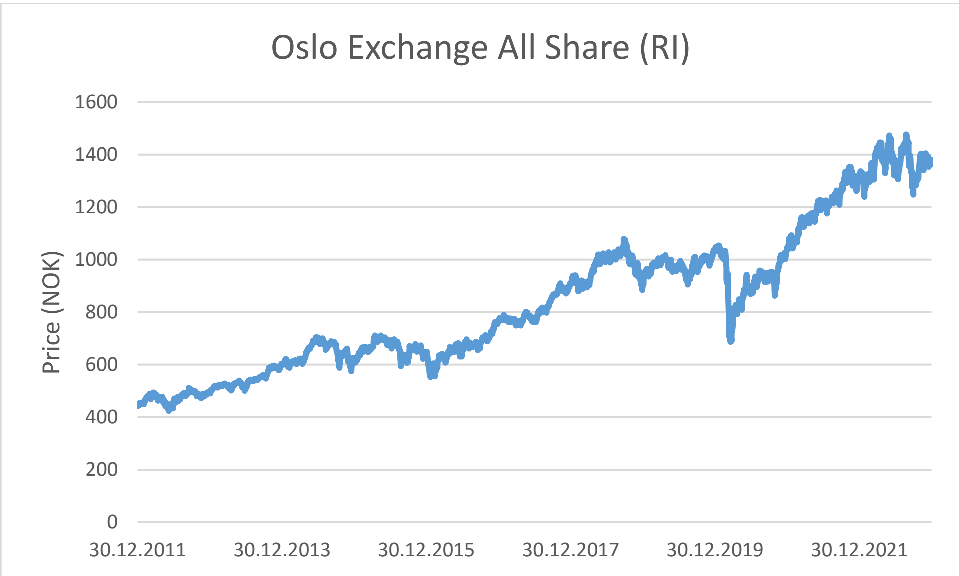

Figure 7. Oslo Exchange All Share (RI) Returns.

5.1 Methodology

In order to examine the existence of the January effect, the turn of the month effect and the weekend effect, three sets of parametric and non-parametric tests were chosen for this research. Since previous academic papers have gathered robust evidence of the calendar anomalies by using dummy variable regression, a paired two-sample t-test and the Wilcoxon rank sum test, these methods were considered to be effective in this particular research.

Similar to Bordeaux's (1995) methods, a paired two-sample t-test was applied in order to investigate all of the following anomalies, the January effect, the turn of the month effect and the weekend effect. The t-test is a statistical test that compares the means of two groups and assesses whether the difference between them is statistically significant. It calculates a t-value, which represents the difference between the means relative to the variability within the groups. The first research question of this paper was to examine if January returns are higher than in other months of the year. The January returns are regarded as the first pair of the t-test and the average returns of other eleven months as the second pair of the t-test.

The second research question in this study is focused on turn of the month returns with the objective to determine whether they are higher than returns on other trading days of the month. Following Ariel (1987), Jaffe and Westerfield (1985) the first pair of the t-test represents the total return of the turn month trading days. Each month's final trading day was taken into account as well as the first three trading days of the following month. The returns of these days were used to capture early-month returns since prior research has demonstrated that the monthly effect can be attributed to large returns occurring early in the month. So, the considered trading days are presented as -1, +1, +2, and +3. If the market was closed due to a holiday or a weekend, the next available trading day was selected. The second pair of the t-test, which is determined as the rest of the month, includes all the trading days of the month excluding the trading days -1,+1,+2,+3.

The average daily return of the rest of the month was computed and multiplied by four to reach similar four-day period.

The third research question was to investigate whether Monday returns are significantly lower than Friday returns. The first pair of values represent Friday returns, and the second pair of values are considered Monday returns. In case the market was closed on a Friday, the last trading day of the week was selected, and if the stock market was closed on a Monday, the value used was the first trading day of the week.

For all these three referred pairs, a two-sample t-test for means was conducted. The t-value is then compared to a critical value from the t-distribution table with n-1 degrees of freedom to determine whether the difference between the means is statistically significant. The equation for the paired two-sample t-test is shown below.

$$t = \frac{\bar{x}d}{[sd \,/\, \sqrt{n}]} \tag{5}$$

Where $\bar{x}\mathrm{d} =$ Mean difference between the paired observations

$\mathrm{sd} =$ Standard deviation of the differences

$\mathrm{n} =$ Number of paired observations

$\mathrm{t} = \mathrm{t} - \mathrm{value}$

It is important to pay attention to the limits of the two-sample t-test since it does not fully explain all the results. There are several disadvantages involved. Calendar anomalies may be related to other factors that affect stock prices, such as macroeconomic events, news announcements, industry-specific trends or investors irrational behavior. The values can also be influenced by extreme values, which can have a significant impact on the research results. The paired two-sample t-test also assumes that the observations are independent. However, this assumption may not fully hold, as the returns for different months or days may be correlated over time.

The simple linear regression has been applied to similar studies by several authors such as Keim & Stambaugh (1984), French & Roll (1986), and Lakonishok & Smidt (1988). Chien et. al (2002) conducted a single dummy variable regression based on some of the studies mentioned above. Since these methods are considered robust to examine the seasonal behavior in the stock markets, a single dummy variable regression was chosen as another test for this paper. The regression is presented below.

$$Y_t = B_0 + B_1 X_t + \varepsilon_t \tag{6}$$

Where $\mathrm{Y} =$ Market returns

$B_0 =$ The regression intercept

$B_1 =$ The regression slope

$X_t =$ The dummy variable

$\varepsilon_t =$ The error term

The regression slope evaluates the differences between the two chosen variables. For example, the average return in January and the average return for the remaining months of the year, whereas the regression intercept evaluates the variable under examination, which in this case is the average return in January. The dummy variable is 1 if the month is January and otherwise the dummy variable is 0. The estimate should not deviate significantly from zero if the average return in January is consistent with the average return for the rest of the year. Accordingly, the equation is conducted for the turn of the month returns and rest of the month returns and between Friday returns and Monday returns.

Another method applied in this study is the Wilcoxon rank sum test, which follows the previous research of Kunkel et. al (2003) and Lim et. al (2010). The Wilcoxon rank sum test is broadly exploited in order to examine populations in ranked order. Some of the benefits of this test are that it is not affected by extreme outliers and it does not rely on presumptions of data being drawn from a specific probability distribution, such as the normal distribution. The Wilcoxon rank sum test is a non-parametric test that is considered as effective as regular parametric tests when observing differences between data sets. But non-parametric tests are considered even more robust if the assumptions of parametric tests are not holding hold (Kunkel et. al 2003). In addition, the null hypothesis of normal distribution is rejected in this paper, which implies that the returns gathered are not normally distributed. Therefore, the use of the Wilcoxon rank sum test is considered robust.

The non-parametric methods in this study compare two independent random data sets, which are pooled together, and then the observations are ranked. Ties are assigned as the average of the next available ranks. The smaller rank sum from the two samples is chosen as the value of the summed ranks. The test statistic approaches the normal distribution as the number of sample observations increases. First, the expectation value is calculated as shown below.

$$E(T) = \frac{n_1(n_1 + n_2 + 1)}{2} \tag{7}$$

Where

$\mathrm{E(T)} =$ Excpectation value of summed ranks

$\mathrm{T} =$ Sum of ranks of the smaller rank sum sample

$n_1 =$ Number of observations in sample 1

$n_2 =$ Number of observations in sample 2

Next, the standard error for the summed ranks is counted as follows:

$$SE(T) = \sqrt{\frac{n_1 n_2(n_1 + n_2 + 1)}{12}} \tag{8}$$

After the standard error, the calculations of the test statistic described as W are shown beneath. Then the distribution of the test statistic is approximated by the normal distribution.

$$W = \frac{T - E(T)}{SE(T)} \tag{9}$$

6 Empirical Results

In this chapter, the results are presented and their implications are discussed. Below in Table 2, the two-sample t-test results for the January effect indicate that there are no significant excess returns in any of the studied indices. As the table shows, the t-values do not get over the critical value at any of the studied confidence levels. Although the January returns are slightly higher than the average monthly returns of the remaining years in each country, the difference is not statistically significant, which suggests that the January effect does not appear in the Nordic region.

Country	January avg.	Rest of the year (monthly avg.)	Paired t-Statistic	p-value
Sweden	0,013	0,012	0,076	0,941
Finland	0,020	0,010	0,717	0,490
Denmark	0,017	0,014	0,184	0,858
Iceland	0,029	0,012	1,339	0,210
Norway	-0,001	-0,009	0,701	0,499

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

Table 2. The January Effect (t-test).

Table 3 is focused on the turn of the month effect. The two-sample t-test results indicate significant excess returns in all the studied indices. In Denmark, Iceland, and Norway, t-values are significant even at a 1% confidence level. In Sweden, the t-value is confirmed with a 5% significance level and in Finland with a 10% significance level. The p-values provide similar support for the effects’ significance. This suggests that the turn of the month effect continues to be present in all of the Nordic main indices. The highest impact seems to appear in Denmark, Iceland, and Norway, while in Sweden and Finland, the effect is less significant.

Country	Turn of the month (-1,+1,+2,+3 avg.)	Rest of the month (4-day avg.)	Paired t-Statistic	p-value
Sweden	0,002	-0,001	2,040**	0,043**
Finland	0,002	-0,001	1,826*	0,070*
Denmark	0,005	-0,001	3,728***	0,000***
Iceland	0,005	-0,001	4,108***	0,000***
Norway	0,005	-0,001	2,849***	0,005***

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

Table 3. The Turn Of The Month Effect (t-test).

Table 4 shows the results for the weekend effect. Looking at the table below, it can be stated that Monday returns are significantly lower than Friday returns only in Iceland, with a 1% significance level. As the table demonstrates, the t-values do not get over the critical values at any other indices. This suggests that the weekend effect is only remaining in Iceland and does not appear anymore in other Nordic markets.

Country	Friday avg.	Monday avg.	Paired t-Statistic	p-value
Sweden	0,001	0,000	1,171	0,242
Finland	0,001	-0,000	1,325	0,186
Denmark	0,001	0,001	-0,313	0,755
Iceland	0,001	-0,001	3,330***	0,001***
Norway	0,001	0,000	0,953	0,341

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

Table 4. The Weekend Effect (t-test).

In the second part of this chapter, the dummy variable regression results are presented. In this scenario, the null hypothesis would be that there is no significant distinction between returns in January and returns in other months of the year. This demonstrates that there is no systematic variation in returns between January and other months, indicating that the coefficient for the January dummy variable is equal to zero. Based on the regression results below in Table 5, the evidence for the January Effect is weak across all the studied indices. The coefficients for the January dummy variables are slightly positive in every case, but they are not statistically significant. The p-values are over 10% in each country, which demonstrates that the observed returns are failing to provide robust evidence of significantly higher January returns. Therefore, we cannot reject the null hypothesis.

Country	*Sweden*	*Finland*	*Denmark*	*Iceland*	*Norway*
Regression Statistics					
Multiple R	0,015	0,150	0,037	0,258	0,159
R Square	0,000	0,022	0,001	0,066	0,025
Adjusted R Square	-0,050	-0,027	-0,049	0,020	-0,023
Standard Error	0,041	0,036	0,038	0,034	0,026
Observations	22	22	22	22	22
ANOVA Regression					
F	0,005	0,458	0,027	1,422	0,520
Significance F	0,946	0,507	0,871	0,247	0,479
	Coefficients	*Coefficients*	*Coefficients*	*Coefficients*	*Coefficients*
Intercept	0,012	0,011	0,014	0,012	-0,009
January Dummy	0,001	0,015	0,003	0,017	0,008

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

Table 5. The January Effect (dummy variable regression).

The null hypothesis for the turn of the month effect would be that there is no significant difference in returns between the turn of the month (trading days -1, +1, +2, +3) and the rest of the month. Table 6 beneath shows the results for this regression, which implies that the null hypothesis will be rejected in all countries. The coefficients for the TOM dummy variables are positive in each index, and the p-values for the coefficients are 0,049, 0,074, 0,001, 0,000 and 0,006. Therefore, the turn of the month effect is considered statistically significant at the 1% level in Denmark, Iceland, and Norway. In Sweden, the turn of the month effect is significant at the 5% level, and in Finland, it is significant at the 10% level.

Country	*Sweden*	*Finland*	*Denmark*	*Iceland*	*Norway*
Regression Statistics					
Multiple R	0,122	0,110	0,212	0,240	0,168
R Square	0,015	0,012	0,045	0,058	0,028
Adjusted R Square	0,011	0,008	0,041	0,054	0,025
Standard Error	0,017	0,018	0,016	0,014	0,016
Observations	264	264	264	264	264
ANOVA Regression					
F	3,928	3,210	12,326	16,002	7,602
Significance F	0,049**	0,074*	0,001***	0,000***	0,006***
	Coefficients	*Coefficients*	*Coefficients*	*Coefficients*	*Coefficients*
Intercept	-0,002	-0,001	-0,002	-0,002	-0,001
TOM Dummy	0,004	0,004	0,007	0,007	0,005

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

Table 6. The Turn Of The Month Effect (dummy variable regression).

For the weekend effect, the null hypothesis is that there is no significant difference between returns on Mondays and Fridays. The dummy variable regression results are presented in Table 7. Based on the results, the p-values suggest that the weekend effect is statistically significant only in Iceland at the 1% level, indicating that Monday returns are significantly lower than Friday. However, in Sweden, Finland, Denmark, and Norway, the null hypothesis cannot be rejected since the p-values are not statistically significant at any of the significance levels.

Country	*Sweden*	*Finland*	*Denmark*	*Iceland*	*Norway*
Regression Statistics					
Multiple R	0,033	0,036	0,008	0,094	0,028
R Square	0,001	0,001	0,000	0,009	0,001
Adjusted R Square	0,000	0,000	-0,001	0,008	-0,000
Standard Error	0,011	0,012	0,011	0,009	0,011
Observations	1144	1144	1144	1144	1144
ANOVA Regression					
F	1,216	1,490	0,079	10,208	0,868
Significance F	0,270	0,223	0,779	0,001***	0,352
	Coefficients	*Coefficients*	*Coefficients*	*Coefficients*	*Coefficients*
Intercept	0,001	0,001	0,001	0,001	0,001
Monday Dummy	-0,001	-0,001	0,000	-0,002	-0,001

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

Table 7. The Weekend Effect (dummy variable regression).

The third part of this chapter focuses on the results of the Wilcoxon rank sum test. First, the January effect results are shown in Table 8, which demonstrates that the p-value is statistically significant only in Iceland at the 10% significance level. Sweden, Finland, Denmark, and Norway are not statistically significant as the p-value is substantially higher than the considered significance levels. The conclusion drawn from this table implies that the January effect is no longer persistent in the Nordics, excluding Iceland.

Country	*Sweden*	*Finland*	*Denmark*	*Iceland*	*Norway*
Wilcoxon rank sum test					
n1	11	11	11	11	11
n2	11	11	11	11	11
Sum	118	112	112	106	119
Expectation	126,5	126,5	126,5	126,5	126,5
Std. Error	15,23	15,23	15,23	15,23	15,23
Stat	-0,558	-0,952	-0,952	-1,346	-0,492
P-value	0,288	0,171	0,171	0,089*	0,311

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

Table 8. The January Effect (Wilcoxon rank sum test).

In table 9 below, the Wilcoxon rank sum test is conducted to determine whether the turn of the month produces higher returns compared to the returns of rest of the month. The results indicate that the turn of the month effect still exists in every Nordic country since the p-value is close to zero in each index. This evidence is robust at the 1% significance level in all studied countries.

Country	*Sweden*	*Finland*	*Denmark*	*Iceland*	*Norway*
Wilcoxon rank sum test					
n1	132	132	132	132	132
n2	132	132	132	132	132
Sum	14494	15809	15224	15167	15392
Expectation	17490	17490	17490	17490	17490
Std. Error	620,3	620,3	620,3	620,3	620,3
Stat	-4,830	-2,710	-3,653	-3,745	-3,382
P-value	0,000***	0,000***	0,000***	0,000***	0,000***

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

Table 9. The Turn Of The Month Effect (Wilcoxon rank sum test).

The following table number 10 shows the results for the weekend effect. In this table, the p-values do not indicate any significance in Sweden, Finland, Denmark, or Norway. Meaning that the Monday returns are not significantly lower than the Friday returns.

However, in Iceland, the p-value is closer to zero, which implies that the weekend effect is still pertinent there.

Country	*Sweden*	*Finland*	*Denmark*	*Iceland*	*Norway*
Wilcoxon rank sum test					
n1	573	573	573	573	573
n2	573	573	573	573	573
Sum	324690	324994	324000	309122	328227
Expectation	328616	328616	328616	328616	328616
Std. Error	5602	5602	5602	5602	5602
Stat	-0,701	-0,647	-0,824	-3,480	-0,069
P-value	0,242	0,259	0,205	0,000***	0,472

*** Significant at the 1% level

** Significant at the 5% level

* Significant at the 10% level

Table 10. The Weekend Effect (Wilcoxon rank sum test).

7 Conclusions

This study investigates the existence of calendar anomalies in the following Northern European countries: Sweden, Finland, Denmark, Norway, and Iceland. The all-share total return stock indices, which include dividends, were chosen for the investigation. The calendar anomalies that were under examination were the January effect, the turn of the month effect, and the weekend effect. The empirical tests were made based on previous research on stock returns, and the methods utilized included the two-sample t-test, the dummy variable regression, and the Wilcoxon rank sum test.

The empirical findings of the research indicate that the January effect is no longer present in the Nordic region, with only one exception. The non-parametric Wilcoxon rank sum test showed statistical significance for Iceland at the 10% significance level. The two-sample t-test and the dummy variable regression found no support for the January effect being present. These results suggest that investors in the Nordic region are not subject to this calendar anomaly, except in the Icelandic market, which had a little support for the January effect. Therefore, based on the results, it can be stated that the first hypothesis of this paper, ''January returns are significantly higher than in other months of the year" can be rejected due to the lack of statistical evidence.

However, the second hypothesis of this research, ''Turn of the month outperforms the rest of the month'' will be accepted. Both the parametric and non-parametric tests found support for the turn of the month effect, which seems to be persistent in all the studied indices but with varying degrees of significance. Based on the two-sample t-test and the dummy variable regression, Denmark, Iceland, and Norway exhibit a statistically significant turn of the month effect with a 1% significance level, while Sweden and Finland show significance with 5% and 10% levels, respectively. In addition, the Wilcoxon rank sum test is significant in all countries at the 1% significance level. These results indicate that the turn of the month effect has a clear influence in the Nordic market area.

Regarding the third research hypothesis, ‘’Monday returns are significantly lower than Friday returns’’ the evidence resulted in acceptance of the hypothesis in Iceland but rejection in Sweden, Finland, Denmark, and Norway. Based on the three conducted statistical tests, the weekend effect exhibits high statistical significance at the 1% significance level in Iceland, suggesting that investors in Iceland experience a price pattern where returns are lower on Mondays and higher on Fridays. In all the other Nordic countries, the weekend effect no longer exists.

Overall, these results provide some evidence of the existence and robustness of calendar anomalies in the Nordic region, which could potentially assist investors in their financial decision-making. However, it is essential to recognize that prior stock market performance cannot be relied on to predict future returns and that other factors may influence how the stock market behaves. Therefore, additional investigation is recommendable in order to confirm these results and generate a deeper understanding of the anomalies in the Nordic stock markets. Another way to continue with this research is to extend the time frame or seek validation from other surrounding countries.

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