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January Effect on Nordic stock indices

Evidence from small and large cap stock indices

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ABSTRACT:

This study investigates the January effect on the Nordic stock market. The main object of this study is to evaluate if the January effect is present in the Nordic countries' small and large cap stock indices. Additionally, this thesis aims to evaluate whether the January effect is more pronounced in small cap indices, as the previous literature suggests. In total, ten different small and large cap stock indices are selected from five Nordic countries to investigate this anomaly.

The theoretical background of this study is based on the efficient market hypothesis (EMH), in which it is assumed that stock market perform efficiently, hence there should not be market anomalies, such as the January effect. In the January effect it is assumed that stocks offer higher returns during January compared to the other months, which contradicts the assumptions of EMH, hence opens a discussion for alternative theories. Because of this, behavioral finance related theories are discussed in this study, as they provide an alternative view of market efficiency, suggesting that markets may not be as efficient as the EMH indicates.

This study employs OLS regression with dummy variable to evaluate whether the January effect is present on Nordic stock indices between the years 2015 and 2024. This method is often used to investigate the presence of the January effect in previous studies. The results of this study show statistically significant evidence of the January effect's presence in only one index. This evidence is found from Finnish small cap index. For the other indices, the results show insignificant findings. These results indicate that the January effect is present among small cap stocks in Finland

KEYWORDS: January Effect, Efficient market Hypothesis, Behavioral Finance, Nordic stock market, Calendar anomalies

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TIIVISTELMÄ:

Tämä tutkielma tutkii tammikuuilmiötä Pohjoismaiden osakemarkkinoilla. Tämän tutkielman päätarkoitus on selvittää, että esiintyykö Pohjoismaisten pien- ja suuryhtiöistä koostuvista osakeindekseistä tammikuuilmiötä. Tämän lisäksi tutkielmassa pyritään arvioimaan, että korostuuko tammikuuilmiö erityisesti pienyhtiöissä, kuten aikaisempi kirjallisuus aiheesta osoittaa. Tämä tutkielma hyödyntää yhteensä kymmentä eri pienyhtiö- ja suuryhtiö osakeindeksiä viidestä eri Pohjoismaasta tammikuuilmiön tutkimisessa.

Tämän tutkimuksen teoreettinen tausta pohjautuu tehokkaiden markkinoiden hypoteesiin, jonka mukaan osakemarkkinat toimivat tehokkaasti, eikä osakemarkkinoilla tulisi esiintyä anomalioita, kuten tammikuuilmiötä. Tammikuuilmiössä osakkeiden tuottojen oletetaan olevan suuremmat verrattuna muihin kuukausiin, mikä on ristiriidassa tehokkaiden markkinoiden hypoteesiin olettamuksien kanssa ja täten avaa keskustelun vaihtoehtoisille teorioille. Tämän takia tässä tutkimuksessa esitellään behavioristisia näkökulmia, sillä ne tarjoavat vaihtoehtoisen näkemyksen osakemarkkinoiden tehokkuuteen. Nämä teoriat olettavat, että markkinat eivät välttämättä ole yhtä tehokkaat, kuten tehokkaiden markkinoiden hypoteesi -teoria antaa olettaa.

Tässä tutkielmassa käytetään dummy-muuttajaregressiota, jonka avulla tutkitaan, onko tammikuuilmiötä havaittavissa Pohjoismaiden osakemarkkinoilla aikavälillä 2015–2024. Tätä menetelmää käytetään usein aikaisemmissa tammikuuilmiöön liittyvissä tutkimuksissa. Tämän tutkielman tulokset osoittavat tilastollisesti merkittävää näyttöä tammikuuilmiöstä vain yhdessä tarkastelluista indekseistä. Tämä havainto tehdään vain Suomen pienyhtiöindeksissä. Muiden indeksien osalta tulokset eivät ole tilastollisesti merkittäviä. Nämä tulokset viittaavat siihen, että tammikuuilmiötä esiintyy vain suomalaisissa pienyhtiöiden osakkeissa.

AVAINSANAT: Tammikuuilmiö, Tehokkaiden markkinoiden hypoteesi, Behavioristinen rahoitusteoria, Pohjoismaiden osakemarkkinat, vuodenaika-anomaliat

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1 Introduction

Since Wachtel's (1934) findings that suggest stock markets to have seasonal patterns, academics and finance professionals have argued whether the January effect is true and the possible causes behind it. Specifically, during 1980's this effect was widely studied by many academics who provided evidence that investors can achieve better returns during January, especially from smaller stocks (See Gultekin & Gultekin, 1983; Roll, 1983, Wahlroos & Berglund, 1984). These studies provide evidence of the effect's presence, even though Fama (1970) concludes in his study that stock market functions efficiently, suggesting that stocks are always traded around their fair value. This theoretical view implicates that there should not be anomalies, such as the January effect (Kamoune & Ibenrissoul, 2022).

Furthermore, this traditional finance theory assumes that investors act rationally, and the stock markets are efficient, hence it should not be possible for investors to earn abnormal returns in any situation (Kamoune & Ibenrissoul, 2022). However, economists started to study rationality and people’s decision making during 1970’s and came up with alternative explanation that assumes that people may not be as rational, as EMH suggests when they are making finance related decisions (Kamoune & Ibenrissoul, 2022). This alternative explanation is known as behavioral finance, which is seen complementing the modern finance theories by suggesting that neither stock market nor investors function rationally (Kamoune & Ibenrissoul, 2022). The inconsistences between these two different viewpoints have opened the discussion for different behavioral bias and market anomalies, such as the January effect.

The January effect has attracted significant attention within academic research all over the world and many previous studies have offered different reasons for this effect presence. For example, this effect is often linked to different behavioral and institutional factors which are tax-related reasons, year-end portfolio adjustments, and increased investor optimism at the beginning of each year (see Roll, 1983; Ritter, 1988; Ciccone, 2011). Furthermore, the Corporate Finance Institute (2025) argues that there are also other reasons behind the January effect. For example, some people invest their year-end cash bonuses into the financial markets, which increases the demand for stocks and prices at the beginning of the year (Corporate Finance Institute, 2025). However, more recent studies suggest that this effect has diminished from the financial markets, showing that there is no January effect in stock markets (see Patel 2016; Perez, 2018). Because of the mixed previous international evidence, this thesis will focus on investigating whether the anomaly can be found from Nordic stock markets.

1.1 Purpose of the study

This study’s main goal is to evaluate if the January effect is present in the Nordic market area. This is done by using recent daily returns data from 2015 to 2024 of ten different small and large cap stock indices from the Nordic market area. The earlier literature show mixed evidence of this anomaly's presence in Nordic markets, which makes it reasonable to investigate the subject further. Furthermore, there can be seen a decreasing trend in the January effect's presence in the Nordic market area. This is because early studies show supporting evidence, and more recent opposing evidence. Supporting evidence is provided, for example, by Gultekin and Gultekin (1983) who finds that investors can achieve higher mean returns in Norway, Sweden, and Denmark. Additionally, Wahlroos and Berglund (1984) show similar evidence for the Finnish stock market.

Despite these early studies showing evidence of this anomaly, the more recent studies' evidence implies that there is no January effect spotted in Nordic markets. For example, Norvaisiene and Stankeviciene (2022) studies this effect in Nordic markets and the authors does not find any significant evidence of this anomaly's presence in this market area. Giovanis (2009) finds similar evidence that show January's returns to not differ significantly of the returns of the other months. Because of the mixed evidence, this thesis tries to contribute to previous literature by utilizing more recent and broad datasets to evaluate the presence of this effect.

1.2 Research hypotheses

Because the earlier studies show both supporting and opposing evidence of the January effect, the hypothesis for this study is formed based on the mixed findings of those earlier studies. The null hypothesis indicates that there is no January effect present in the observed index. To be more specific, it states that there is no significant difference between January's daily returns compared to other months' daily returns in the observed index. The more recent studies show evidence that suggest the January effect has diminished from the stock markets over time and there is no difference between the returns (see Norvaisiene & Stankeviciene, 2022; Giovanis, 2009; Patel, 2016; Li & Zhang & Zheng 2018) Therefore, the null hypotheses for this study can be formed as follows:

$H_0: \beta_1 = 0$, January's daily returns does not differ significantly from other months' daily returns during the observed period from 2015 to 2024

The alternative hypothesis for this study Indicates that daily returns vary between January and rest of the months. This hypothesis indicates that there is January effect present in the observed index, yet the coefficient has to be positive for January and the regression analysis' p-value has to be under 0,05 significance level. If these conditions are met, then it indicates that there is a January effect in the observed index. On the other hand, a negative coefficient would indicate that the returns are lower in January, meaning that there is no January effect, since investors cannot achieve better returns. As discussed in the subchapter above, the previous literature show evidence of the presence of the January effect in the Nordic markets, and often links it to being stronger among small cap stocks (see Gultekin & Gultekin, 1983; Wahlroos & Berglund, 1984; Hansen & Lunde, 2003) Because of these studies show difference between the returns, the alternative hypothesis can be formed as follows:

$H_1: \beta_1 \neq 0$, January's daily returns differ significantly from other months' daily returns during the observed period from 2015 to 2024

1.3 Structure of the study

This thesis consists of six different main chapters that discuss essential topics around the January effect. The first chapter of this study introduces the introduction-, purpose-, and research hypotheses of this study. The second chapter discusses the theoretical background of this study, which includes the Efficient Market Hypothesis (EMH) and behavioral finance related aspects. The third chapter focuses on the literature review of studies regarding the January effect. The fourth chapter discusses the data and methodology used in this thesis. The fifth chapter introduces the results of the empirical study, and the sixth and the last discusses the conclusions of the study.

2 Theoretical Background

In this chapter, different aspects of market efficiency and behavioral finance theories will be discussed to provide understanding of stock market dynamics and the January effect. This chapter will also discuss Random Walk Theory, which is closely related to EMH. Also, this chapter will discuss the Prospect theory and cognitive biases, to provide comprehensive overview of the market efficiency.

2.1 Efficient Market Hypothesis (EMH)

According to Fama (1970), the term market efficiency refers to stock markets' ability to process and reflect information efficiently. Leković (2018) states that the concept of EMH is introduced to the world by Fama (1970) in his study of market efficiency. Malkiel (2003) states in his study that the main principle of the EMH is that it suggests that financial markets are informationally efficient. Furthermore, Shleifer (2000) argues that if the EMH holds in the financial markets as Fama (1970) suggests, then active stock picking does not bring additional value to investors or any fund on a continuous basis. Fama (1970) proposes in his study that market efficiency tests should be categorized into three different forms to study more in depth how markets process information. According to Fama (1970), these three forms are named to be weak-, semi-strong-, and strong form tests. Furthermore, He argues in his study that dividing the efficiency test into three different forms is important, since by doing so, the level of information can be determined where the hypothesis fails to hold. These three different forms will be discussed in the next sub chapters.

2.1.1 Weak-form efficiency

Fama (1970) claims that in the weak form the information is limited only to include historical price data. Fama (1970) suggests that the weak form efficiency is strongly associated with random walk theory, hence the past information about asset prices cannot be used to determine price movements in the future. According to Kamoune and

Ibenrissoul (2022) if financial markets function as weak form efficiently, then the stock's price movements should be random and not predictable, as the the random walk suggests. They state in their study that because of this assumption, investors should not be able to gain abnormal returns. According to Timmerman and Granger (2004), if future stock prices could be forecasted based on historical data, then investors could gain enormous abnormal returns continuously, hence markets would not work efficiently.

Fama (1970) states that the prior evidence that supports the weak-form efficiency arises from random walk related studies. Before Fama (1970) published his study from EMH, Kendall (1953) finds similar evidence that weekly asset price changes appear to be random and do not follow any particular path. Even though the price movements appear to be random in weak form, Fama (1970) finds that there is a minor predictability in the returns in some cases. However, he further states in his study that these returns are too small to profit from after subtracting costs that are caused by trading. The main conclusion of Fama's (1970) tests for weak efficiency is that investors are not able to achieve excess returns by using historical information to predict future returns

2.1.2 Semi-strong form efficiency

According to (Fama, 1970) in the semi-strong form the information does not only take historical prices into account, but extends the information included further. Fama (1970) states that the semi-strong form also includes, for example, issues of new securities, stock-split announcements, and companies' annual reports. He states in his study that the semi-strong form focuses especially on how quickly securities' prices adjust to information about those above-mentioned events. Later on, Fama (1991) suggests adjustment to the title of Semi-strong tests to be event studies from now on. Shleifer (2000, p. 6) states that that in this form of efficiency investors are not able to gain abnormal returns based on publicly available information. Shleifer (2000, p. 6) further argues that semi-strong form information will not benefit investors who tries to predict future returns. Fama (1991) adds that in the event studies, the stock markets is assumed adapt to new company specific information quickly.

There are several previous studies that examine how quickly new information is adjusted into the price of stocks. For example, Scholes (1972) points out that there should not be prolonged abnormal returns after secondary stock offerings from which investors could benefit from. The author further writes that when companies offer additional stock offering, investors have enough time to study whether this is a good or bad sign for the company, hence the price will adjust to around its fair value when the stock offering occurs. This finding supports Fama's (1970) statement about semi strong efficiency. However, Ball and Brown (1968) finds contradicting evidence that suggests that the reported income is anticipated by the financial markets even before the report of annual income is released. Additionally, Ball and Brown (1968) suggests that earning reports accommodate useful information to investors, since not all information is incorporated into securities' prices after these reports become public. Also, Holthausen and Larcker (1992) notices in their study that investors can achieve abnormal returns for their investments by utilizing the information of publicly available financial statements after they are released.

2.1.3 Strong-form efficiency

In the strongest form of efficiency, it is assumed that the stocks' prices reflect all available information, which can impact their current market price (Fama, 1970). Later, Fama (1991) suggests change for the name strong-form tests to be more definitive one called tests for private information. This form takes private information alongside public information into account, which is vital for the formation of securities' price (Fama, 1991). According to Leković (2018), it is assumed in the strong form that stock prices adjust promptly to any kind of new information, which means that finding stocks that are either over- or undervalued is simply random. This assumption indicates that it should not be possible that investors beats the market constantly (Leković, 2018). However, if investors cannot beat the markets, it would make the active investing strategies useless. This is because these active strategies try actively to beat the markets to provide their clients higher returns than the markets.

However, Niederhoffer and Osborne (1966) demonstrates in their study that New York Stock Exchange employees may benefit from their exclusive access to information, which can lead them to achieve higher returns. They point out in their study these traders have access to specific information about trades, which can help them to trade better. Additionally, Scholes (1972) finds similar findings that highlights that insiders from corporations may possess information, which is not yet reflected in stock prices. In terms of market efficiency, this finding indicate that markets may not be fully efficient (Scholes, 1972). Nevertheless, Fama (1991) states that on average, stock prices respond rapidly to information regarding capital structure changes, investment decisions, changes in dividends, and corporate control transactions. Other previous study, which evaluates the strong form efficiency shows that insider trading or the use of private information can lead to above-average risk adjusted returns (see Seyhun, 1986; Betzer & Theissen, 2009)

2.1.4 Random Walk Theory

It can be observed from Fama (1970) study that the Random Walk theory is closely related to the formation of EMH and weak form tests. According to Thaler (1987) random walk theory suggests that price movements cannot be predicted by using historical data, which simply means that investors cannot benefit from the use of historical data in predicting future market movements. Fama (1970) claims that the random walk model can be seen formed from two different assumptions. He suggests in his study that the first assumption is that the stock prices fully reflect available information, and every price movement is independent from each other. He further argues in his study that this assumption means that the previous prices do not influence the current stock price. The second assumption, according to his study is that the continuous changes in stock's returns follow the same distribution, which means that these distributions are identical. Because of these two assumptions, it should not be possible for investors to predict future stock prices based on historical stock price data (Chitenderu & Maredza & Sibanda, 2014).

Furthermore, the Random Walk Theory assumes that when many market participants trades based on all available information, the stock's price will wander randomly near the stock's fundamental value (Chitenderu et al., 2014). Additionally, Siegel (1988, p.244) discusses the randomness of stock price movements. The author conducts a computer simulation, which randomly generates different numbers. The author states that if stock price movement is random, then it cannot be distinguished from the charts if the price movements are made by random number generator or if they are actual stock price changes. The author finds that it is not possible to distinguish differences between actual and made up data (Siegel, 1998, p. 244).

The Random Walk theory also receives criticism in the financial literature. Dias, Heliodoro, and Godinho (2020) finds contrary findings when they test the weak form of market efficiency in sixteen different markets around the world between 2002 and 2019. They state in their study that they find evidence against the random walk assumption because their observed indices show that there is predictability during different time periods. This more recent study shows contractionary findings to Fama (1970) and Siegel (1998) studies, which states stock movements are random and not predictable. On the other hand, Lo and MacKinlay (1988) studies the weekly stock market returns and the autocorrelation of returns between the period of 1962 and 1985. Their study finds evidence that shows that there is autocorrelation in the stocks' returns, which opposes the assumption of random walk. The autocorrelation means that if a stock performs negatively today, it can be predicted that it will also perform negatively tomorrow (Lo and MacKinley, 1988). Furthermore, Keim and Stambaugh (1986) study also focuses on stock price prediction. They decide to utilize forecasts that have different predetermined variables to examine whether the stock prices can be predicted. They claim in their study that they find evidence which indicates that stock returns can be predicted and there is seasonality in the stock returns (Keim & Stambaugh, 1986). This finding indicates that stock prices do not follow the random walk, as the theory suggests (Keim & Stambaugh, 1986).

2.1.5 Criticism to EMH

EMH has gained significant amount of academic interest since its introduction to the world. According to Malkiel (2003), a few decades ago several finance professionals were starting to believe that there is at least some predictability in stock prices returns. This is challenging the EMH, which assumes that tomorrow's price change will be unrelated to the price changes observed today (Malkiel, 2003). Many previous studies show evidence of stock markets not working rationally in terms of market efficiency. For example, Rashes (2001) claims in his study that the stock tickers that have almost similar symbols tend to move in sync with other tickers, even though the companies are totally unrelated to each other. This indicates that there is irrational pricing in the market, and the findings are not in line with the assumptions of EMH. Furthermore, Shleifer (2000, p. 79) finds in his study that closed-end funds frequently trade at prices below their net asset values (NAV), which potentially reveal irrational discounts. Shleifer (2000, p. 89) also finds evidence suggesting that individual investor sentiment has an impact on stock prices.

Thaler (1987) concludes that there are signs that markets are not always functioning efficiently, as there are found to be anomalies that contradicts the basic assumptions of EMH. Furthermore, Fama (1991) discusses about the joint-hypothesis, which shows evidence opposing market efficiency. To be more specific, the Joint hypothesis problem refers to testing EMH independently apart from asset pricing model (Fama, 1991). The author adds that it Is problematic to test independently asset-pricing models apart from market efficiency tests and suggests that there may be failures in asset-price models and not in the EMH theory itself. In the author’s earlier study, it is highlighted that market efficiency has to be evaluated together with a model for expected returns, which means that efficiency has to be evaluated jointly (Fama, 1970). If the efficiency is not tested jointly, it can make the evaluation of market efficiency more complex, as it is unclear whether the inefficiency in the markets arises from asset pricing models or the markets themselves (Fama, 1991).

Furthermore, Kamoune & Ibenrissoul (2022) concludes that there is evidence of investors irrationality, which contradicts the EMH assumptions. The authors argue in their study that investors must understand how the price of securities is formed and act accordingly to new information immediately after publication to be rational and maximize their expected returns from the market (Kamoune & Ibenrissoul, 2022). Because of this, it can be assumed that not all investors have the skills and knowledge to trade rationally. According to Tversky & Kahneman (1986), there are evidence of different types of irrational behavior in the markets. Tversky and Kahneman (1986) describes that people's behavior may differ from the widely accepted rationality assumptions. The authors further describes in their study that these market inefficiencies are too consistent to be written off as some random mistakes. They also state that these inefficiencies are as well too widespread to just be dismissed and too essential in the financial literature to be resolved by only adjusting normative frameworks.

2.2 Behavioral Finance

The base of Behavioral finance was developed during the 1980's by a group of scholars to complement the traditional finance theories because they occasionally failed to provide significant evidence that investors are rational and markets work efficiently (DeBondt & Forbes & Hamalainen & Muradoglu 2010, p. 30). According to Kamoune and Ibenrissoul (2022), behavioral finance can be seen as a field in finance that emphasizes combining traditional finance theories with theories of cognitive psychology and human behavior to explain why individuals do not always act rationally, hence, the markets are not fully efficient. The main object of rational investor is described to be maximizing the wealth by utilizing all available information at the current moment, yet behavioral finance assumes that not all the investors are rational (Chauhan & Dhami, 2018). The authors further points out that there is, for example, a possibility that people make financial decisions under fear, which cannot be considered rational. The key difference between traditional and behavioral finance is that traditional finance theories focus on trying to examine and provide evidence of the financial markets' rationality by using various mathematical formulas, and behavioral finance seeks to explain how people actually behave and make their investment decisions using different behavioral biases (Kamoune & Ibenrissoul, 2022). It is common to study behavioral aspects by using different qualitative surveys and field studies that shed light on how humans really make their decisions regarding to investments (Kamoune & Ibenrissoul, 2022). The authors claim in their study that in traditional finance, emotions do not play part in the investors' decision-making process. Because of this, behavioral finance provides different alternative theories of social sciences, cognitive psychology, and emotional responses of trading to explain human behavior instead of mathematical methods to investigate how the stock market functions (Kamoune & Ibenrissoul, 2022). Furthermore, behavioral finance seek to offer different views and explanations for investors decision making process, rather than only focus on wealth maximation (DeBondt et al. 2010, p. 30).

2.2.1 Prospect theory

The fundamental foundation for behavioral finance originates from prospect theory, which concentrates on how people react to gains and losses, hence, to changes in their wealth (Ritter, 2003). According to Kamoune and Ibenrissoul, (2022), the prospect theory was developed and introduced to the world by Kahneman and Tversky (1979). They further state in their study that Kahneman Tversky (1979) lays the foundations to prospect theory and it has an important role in describing investors decision making and irrationality within the decision they do. Kahneman and Tversky (1979) point out in their study that when there is two positive outcomes from which to choose, people usually select the one which has higher possibility to win, even though they would get less money. On the other hand, they show in their study that when there is two different negative outcomes, then people are more willing to take risk, even though there is higher possibility of losing that money. This indicates that people evaluate potential winnings differently than potential losses (Kahneman & Tversky, 1979). This asymmetry can be explained by the finding that people are risk averse (Kahneman & Tversky, 1979). According to the authors people also tend to people react excessively to losses, which represents the asymmetry and loss aversion. Wang (2023) describes loss aversion to be vital part of behavioral finance, since loss aversion shows humans tendency to be influenced by emotional factors. According to Dreher (2012), humans react almost two times more to the possibility of losing than winning, when they have to make choice between two risky scenarios. Barberis and Thaler (2003) concludes that Prospect theory can be the most relevant theory besides utility theory to explain human behavior in the stock market. It is assumed in the utility theory that people make choices to maximize their level of wealth and make decisions rationally (Ritter, 2003). However, the prospect theory contradicts this by stating that there are also irrational factors that influences humans' decision making (Kamoune & Ibenrissoul, 2022). Furthermore, individuals are not perfect and do not function rationally all the time, which means that people systematically make decisions that are not in line with rationality (Barberis & Thaler, 2003). Because the Prospect theory and behavioral finance suggests that people are irrational, it is important to also investigate individual investors' behavior with other theories that focus on different cognitive biases. These will be discussed in the next subchapter to give a broader understanding of different biases that may influence investors' behavior, anomalies, and market efficiency.

2.2.2 Cognitive biases

This subchapter discusses different cognitive biases and investors' irrational behavior, which are linked to behavioral finance. Cognitive psychology covers different aspects of how people think or reason their actions and often the research on the subject indicates that people do not make rational choices (Ritter, 2003). The authors claim that this is caused by the way we humans think. One of the widely recognized cognitive biases is overconfidence, which often shows people overemphasizing recent market events in their decision making (Ritter, 2003). For example, if Finnish stock market continuously underperforms, then investors could start to avoid investing into it even if market conditions changes, because they are confident that the stock markets in Finland will continue to underperform.

In addition to Ritter (2003) description of overconfidence, Shefrin (2007) defines overconfidence as humans' inability to reflect on how they understand their own abilities, skills, and intelligence. Furthermore, Barber and Odean (2001) states that theoretical models of this show that people who are overconfident with their skills tend to trade excessively. The authors state in their study that they investigate the trading behavior between men and women, and they state that in the financial field it is more common for men to be overconfident with their skills. Furthermore, their study finds that the number of trades is related to the decreasing profits. Also, they claim in their study that men tend to trade excessively, and the number of trades men do accounts for 45% more than women's. They further state that the average profits for men were significantly lower than women's profits during the observed period. Ritter (2003) also concludes that the overconfidence is more common amongst men than women, which can impact their trading performance. The author further argues in his study that overconfident people often invest too heavily in local firms which they are more familiar with, even though it is not good for the diversification (Ritter, 2003). The author gives an example which argues that this is commonly shown when people invest their money into the firms they work for (Ritter, 2003). This finding further confirms that people do not always act rationally. Furthermore, Ciccone (2011) argues that stock market can be seen as an environment where confident people can act on their beliefs. Furthermore, Siccone (2011) finds a link between optimistic investors' behavior and the January effect, which may be explained to some degree with irrational psychological tendencies.

Another widely discussed cognitive bias is Herding bias, in which it is assumed that individuals tend to reason their actions on how majority of people act (Chauhan & Dhami 2018). Bikhchandani and Sharma (2001) study suggests that herding behavior on the stock market can occur when traders and investors mimic the investment choices of their colleagues and not follow their own investment plans. According to Bikhchandani and Sharma (2001), financial markets also include rational herding, which is different from irrational herding. According to their study If herding occurs after some fundamental changes happen in the financial markets, then herding cannot be observed as a behavioral bias, since there is new information available that impacts the stock price. This can be seen as financial markets correcting themselves after new information is included in the stock prices. However, there is behavioral herding that is not rational. For example, Welch (2000) decides to study the herding behavior among analysts. The author finds that if an analyst makes either a buy or sell recommendation, the next two analysts' recommendations are related to the original recommendation, which causes a relationship between the recommendations. According to the study's results, these are clear signs of herding among analysts that cannot be considered rational.

There is also a cognitive bias that focuses on anchoring. Cen, Hilary, and Wei (2013) state that this cognitive bias makes people do decisions that can be considered sub-optimal, and they find it to impact market efficiency negatively. The authors state they try to evaluate whether anchoring can be found from analysts' earnings forecasts. The authors argue that they find evidence which indicates that analysts anchor their estimates of the forecasted earnings per share (FEPS) ratios of a company to be similar to the estimates announced by their colleagues. Also, the authors find evidence in their study which indicates that analysts may not be willing to announce FEPS ratios that differ from what the industry norm is, even though the FEPS ratio could be different from the industry norm. This may lead to irrational and biased forecasts and impact companies' stock prices either negatively or positively (Cen et al., 2013). Furthermore, they find that companies that have high FEPS tend to produce abnormal returns in the future, especially during the time of earnings announcements.

Another bias that is found to influence investors' decision making is a disposition effect, in which investors are not willing to sell their stocks at loss, even though it might be the correct choice for them (Barberis & Thaler, 2003) According to the authors, if the selling price of a security is below the original buying price, investors are not often willing to sell them away. Odean (1998) observes brokerage data from the United States and finds that investors more often sell their stocks that are gaining positive returns, than stocks that decreases in value, which indicates that investors hold on hope that the stock's value increases in the future. Barberis and Thaler (2003) argue that this kind of market behavior cannot be rationalized with taxation, since from a taxation point of view it is not rational to sell the stocks that increase in value and not sell stocks that are losing in value. Moreover, the authors conclude that it is unrealistic to claim that shareholders would sell their best performing stocks due to information that the returns of these investments will be weak in the future. According to the authors, this kind of behavior cannot be considered rational. However, studies show that investors on average are still prone to sell the better performing stocks too soon and hold on to the stocks that do not perform well for too long (Odean, 1998).

Another behavioral finance explanation is according to DeBondt et al. (2010, p. 30), that humans do not have strong intuition. The authors claim that people who invest may not have the knowledge of basic principles of investing and securities. The authors also state that this can be the reason behind behavioral biases and patterns in human’s behavior. Furthermore, Zahera and Bansal (2018) investigates different behavioral biases in investment decision making and states that behavioral finance has a significant part in understanding how financial markets function. Additionally, the authors suggest that behavioral aspects should be considered more when making investments decisions, because these aspects may influence the investment’s returns.

Ritter (2003) also gives some criticism to behavioral finance and cognitive biases, since it can be hard to pick what different bias to highlight in different situations. Furthermore, Fama (1998) discusses about the market efficiency and behavioral finance and the author show a disapproving opinion to behavioral finance related theories. Furthermore, the author states that when anomalies are evaluated individually, they are not reliable. This is because these anomalies tend to fail to appear after some reasonable alternative method is used to evaluate them (Fama, 1998).

3 Literature review of January effect

This chapter focuses on introducing a literature review of the January effect. Early studies and more recent studies are included to provide a solid overview of the current state of the effect. Several studies will be introduced that covers international evidence of the January effect, since there are not many papers published that focus specifically on the January effect in the Nordic market area. According to Perez (2018), this anomaly was first studied and introduced to the world by Wachtel (1942), who finds that there are abnormal returns to achieve during January from the U.S stock markets. Since the Wachtel's (1942) study was published, many other academics and finance professionals have concentrated on investigating this subject further and the possible reasons behind the effect.

3.1 Reasons behind the January effect

According to Ciccone (2011) the reasons behind the effect is often stated to be either caused by window dressing or tax-loss selling. These two different theories will be discussed in this subchapter. Additionally, this subchapter briefly discuss other reasons that are found to impact the January effect. Ritter (1988) argues that the first formal evidence of this effect is published by Rozeff and Kinney (1976). According to Rozeff and Kinney (1976) investors can achieve higher returns during January in the U.S stock market. The authors state that they decide to utilize monthly returns to study the January effect during the period between the years 1904 and 1974 in the U.S stock market. The authors suggests based on their results that there is strong evidence that shows the presence of the effect during the observed period, yet the only period that shows insignificant evidence of the January effect is found from years between 1929 and 1940.

According Henker and Paul (2012), tax-loss selling relates to investors selling stocks away that have decreased in value at end of a tax year. The author states this is done to offset the taxes that are due from selling profitable stocks. Furthermore, the author argues that this is the most recognized cause for the January effect. The author further claims that smaller stocks tend to decrease more as a result of excessive selling at the end of the year. When the excessive selling ends, the small cap stocks tend to increase in value more and provide investors higher returns during January (Henker & Paul, 2012). Ritter (1988) suggests in his study that investors' behavior during the time when year changes indicate that there is taxation related matters behind stock selling. This can cause the stock returns to be higher in January, since the investors buy these earlier sold stocks back at the beginning of the January (Ritter, 1988). The author examines in his study how the individuals' buying and selling behavior affects the stock returns at the beginning of the year. The author decides to utilize data that covers the years between 1970 and 1985 from NYSE. The gathered data includes daily volumes of buying and selling, which are needed to evaluate investors' buying and selling behavior (Ritter, 1988). The author's study finds that during December the buy and sell ratio is low, which can indicate that investors sell the stocks away before the year changes because of taxation related matters.

Ritter (1988) argues that as soon as new year begins there is noticeable increase in the buy and sell ratio, which indicates that investors does not invest the money back to the market before the year changes. Furthermore, it can be seen that when investors put their money back into the market, they are more pronounced to buy small cap stocks (Ritter, 1988) Because of this, the returns are found to be higher among small cap stocks during January compared to large cap stocks' returns (Ritter, 1988). Furthermore, it is important to note that the author decides to study January's returns with OLS regression, and he employs dummy variables to capture excess daily returns of small and large cap company portfolios. The OLS regression is also employed in other January effect studies that include time series data (see Patel, 2016; Wagner et al., 2022).

Gultekin and Gultekin (1983) find similar results that supports the findings of Ritter's (1988) study. The authors find similar results from international stock markets that show that the mean returns are higher at the beginning of a new tax year. However, they state in their study that they cannot make direct statements about the relationship between January effect and Tax-loss selling, yet their results show that there is unique patterns found when tax periods changes. The authors expand the field of study by including 17 different industrialized countries to examine the stock market's seasonality. The study shows that there is quite a remarkable difference between the monthly returns of different market areas. For example, Norway, Sweden, and Denmark was included in Gultekin and Gultekin (1983) study, which are also studied in this thesis. Gultekin and Gultekin (1983) study's results show that in these countries investors may gain higher returns on January. These results suggests that this thesis could also find similar results from these Nordic countries. Overall, Gultekin and Gultekin (1983) study's results suggest that investors can achieve abnormal returns in the developed countries. These results show opposite views of market efficiency and supports the alternative hypothesis of this thesis. Contradicting findings are found by Eduah, Debrah, Sidoo, and Mettle (2024), who argue in their study that the January effect is more pronounced within emerging markets than developed ones.

Furthermore, Roll (1983) presents in his study that the investors often do portfolio adjustments before year changes, which may impact the returns stocks in January positively. The author tries to evaluate if the January effect can be explained with tax related matters and finds evidence that supports this. The author further states that these small cap stocks are found to be impacted more of tax-loss selling than large cap companies. Furthermore, the author concludes that higher returns during January is more clearly found among small cap stocks because they are more volatile. The author also suggests in the study that these reasons can be seen as a cause for the presence of the January effect. These findings supports the evidence which is shown in the above studies (see Ritter, 1988; Gultekin & Gultekin, 1983). Furthermore, the evidence of higher January returns also supports the alternative hypothesis of this thesis.

There are also studies that show contradicting evidence against tax-loss selling hypothesis. Van Den Bergh and Wessel (1985) examines whether taxation related matters influence the stock returns on January, However, they focus on stocks that are listed to Amsterdam's stock exchange. The authors state that they gather monthly return data from the period between 1966 and 1982 from over sixty different stocks. According to Van Den Bergh and Wessel (1985), they find that the January effect is present in the observed stocks during the time period. However, they suggest in their study that tax-loss selling could not explain much of the January effect, since in countries like Netherlands where people does not pay taxes from capital gains, the effect is still found. Because of this, it cannot be stated that the main reason behind the effect is tax-loss selling, since even in countries where is no capital taxation, there still is January effect observed (Van Den Bergh & Wessel, 1985). Furthermore, Dahlquist and Sellin (1994) finds similar evidence, when studying whether the January effect in Swedish market can be reasoned with tax related matters. The authors does not find evidence that could confirm that high January returns are caused by tax-loss selling.

Lakonishok et al., (1991) investigates the window dressing hypothesis by utilizing data from 769 different pension funds and their investment strategies. Their study finds that usually fund managers tend to oversell the stocks that are not performing well. The authors state that specifically during the last quarter of the year it is normal for the fund managers to oversell stocks that are losing value. Furthermore, the authors suggest that fund managers tend to oversell these underperforming stocks because they want their fund performance statistics to look better for their sponsors (Lakonishok et al., 1991). This can be seen as window dressing, since the fund managers intends to sell the underperforming stocks to avoid showing them in their portfolio reports at the end of each year (Lakonishok et al.,1991).

The window dressing also relates to the finding that fund managers are often evaluated based on individual stock picks, which means that fund managers are also being judged by other factors than fund performance alone (Lakonishok et al.,1991). There are studies that show window dressing to have some impact on the January effect. For example, Musto (1997) states that the higher returns that are calculated for January cannot be explained by tax-loss selling. However, the author suggests that window dressing may explain the higher returns in January better. This is because the institutions seem to make short temporarily changes to their portfolios before the reporting days to showcase their portfolios to look less risky than they actually are (Musto, 1997). This statement supports the Van Den Bergh's and Wessel's (1985) study, which states that the tax-loss selling does not affect the January effect.

Furthermore, Tinic and West (1984) offers differing explanation for the January effect, which does not relate straight to the taxation matters or window dressing. According to the authors they evaluate if the relationship between risk and return differ during different months, and they find evidence about this relationship to be positive only during January. They further argue that during the other months there are no evidence of this, which means that this is unique only for January's returns. To be more specific, the authors utilize two parameter asset pricing models to investigate whether risk premiums exhibit seasonal patterns in the stock market. The authors find that the higher returns are associated with higher beta stocks that are commonly small cap stocks, and these results can be found only in January.

Anderson, Gerlach, and DiTraglia (2005) suggests that there are also psychological factors that may explain why stocks provide higher returns during January. The authors state in their study that they investigates this January anomaly using experimental research method, which excludes factors that are not psychological. Their study states that this method allows them to use differences in people's values and learning effects as variables, which can show if there is psychological factors that impact the January effect. Their study's results state that psychological factors could indeed be the reason for higher January returns (Anderson et al., 2005).

3.2 Other empirical evidence of the January effect

This subchapter will discuss studies that show evidence that is in line with the alternative hypothesis of this study. These studies include both Nordic countries and international evidence. Moller and Zilca (2008) decides to investigate this effect in the U.S stock markets by grouping the stocks based on their market cap to investigate if the stock's size affects the January returns. The authors find in their study that the effect seems to be higher among small cap stocks than in large cap stocks, when they use monthly returns to measure the effect. To get more comprehensive results on whether the presence of the effect changes during specific periods, the authors decides to study this effect on a daily return level. According to the authors they divide the dataset into two different subperiods. Furthermore, they argue that the first period includes daily data from 1995 to 2004, and the second group contains daily data from 1965 to 1994. Their study's results show that this effect is present during the beginning of the month in the more recent dataset, yet the abnormal returns seem to decline towards the end of the month in the U.S stock market. Furthermore, they state that the abnormal returns are the highest on the sixteenth of January in the more recent dataset. These findings are in line with the alternative hypothesis of this study, as the study suggest the presence of January effect.

Ciccone (2011) finds similar results as Moller and Zilca (2008), when studying the January effect in the U.S. markets by gathering data between years 1983 to 2007. The authors compare the mean monthly returns of different size companies between January and other months and find that among small cap stocks there is a notable January effect found. Furthermore, they find that small stocks perform better when their performance is compared to large cap stocks. Additionally, the authors find that this effect has increased among small cap stocks during the observed period, which means that this effect is more profound during this century in comparison to the 1980's. This is interesting finding, since it shows contradictory findings to Patel's (2016) study and Perez's (2018), which finds the effect to be decreased during past decades.

Wagner et al. (2022) study show also supporting evidence of the January effect, as they examine the seasonalities among stock returns. Wagner et al., (2022) study examines stock market seasonality and specifically the January effect. The authors state that they examine the January effect in stock returns using data from the main stock market indices from the U.S. Specifically, they state in their study that they use CRSP value weighted, and equal weighted market index returns, which are gathered from NYSE, AMEX, NASDAQ. Furthermore, they add that they also include the aggregated returns of S&P 500 index. Furthermore, the authors collect data from monthly net asset values and returns of US-based mutual funds, which focuses on investing in US based equities. (Wagner et Al., 2022).

The authors utilize standard regression analysis to examine the January effect of the previously mentioned indices' returns. Additionally, the authors use dummy variables to divide the stock returns between January and other months. Their study's results suggests that the returns in January are significantly higher in the equal-weighted indices in comparison to other months. Furthermore, they observe that the January effect is more distinct within small-cap stocks. This finding supports the second alternative hypothesis of this thesis. Additionally, Wagner et al., (2022) argue that stock returns during January is likely driven mostly by seasonal fund inflows. They also state that the fund flow patterns are more pronounced for retail funds compared to institutional funds.

Agnani and Aray (2008) also decides to investigate the January effect on the U.S stock market between different volatility regimes. They state that they utilize Markow switching model in their study to evaluate the January returns and volatility between low and high volatility regimes. According to the authors this model allows them to divide these regimes and study them independently. Their data includes U.S stocks and it is retrieved from the years between 1940 and 2006 from the U.S indices. The authors find that the effect is found in all different size portfolios that they created, hence the effect seems to decline in more recent data in their study. More Interesting finding is that the study claims that the small cap portfolios' returns are increasing during the observed period and not declining. This finding is not in line with other studies that suggest that the January effect is diminishing, and the January effect is no longer present in the stock markets (see Gu, 2003; Perez, 2018; Patel, 2016).

There are only a few published studies that specifically focus on the Nordic countries and most of them dates back to the 1980's and 1990's. Previous literature from the January effect in Nordic stock market is provided by Wahlroos and Berglund (1984), which studies the pricing anomalies of stocks in Helsinki Stock Exchange. The authors find that investors can achieve higher returns from small cap stocks during January. Furthermore, the authors state that they cannot rule out the possibility of tax-loss selling to impact the higher returns associated with January. Moreover, they argue that during January both large and small cap stocks offer higher returns, but the phenomenon is more visible within smaller stocks. To be more specific they argue that portfolios that includes small stock generate 2-6,5% during January, yet similar portfolio which contains large cap stocks only 1,5-2,5% risk-adjusted returns. These findings supports the alternative hypothesis of this study.

Moreover, similar evidence of the presence of this effect is found from Swedish stock market. Dahlquist and Sellin (1994) studies stock market seasonality in Swedish stock market by utilizing data from 1919 to 1989. The authors find that investors are able to achieve higher returns in January and June. More recent study from Swedish stock market is published by Gao and Li (2019) who utilizes daily, monthly, and yearly stock price data from years between 1912 and 1978, finds similar evidence as Dahlquist and Sellin (1994). Their study finds significant evidence that January effect is present in Swedish stock market (Gao & Li, 2019). It is vital to note that the data utilized in the study is not recent, as the data ends to the year 1978. However their study shows significant evidence for one of the Nordic countries, and the results supports the alternative hypothesis of this thesis.

3.3 Mixed evidence of the January effect

Norvaisiene and Stankeviciene (2022) studies the stock market seasonality in Baltic and Nordic stock markets by utilizing data from these markets from 2004 to 2019. The authors state that the study uses OMX Nordics 40 index to study the anomaly's presence in Nordic area. The authors argue that they utilize daily logarithmic returns to get more robust results, and they employ OLS regression with dummy variables to separate the January's return from other months (Norvaisiene & Stankeviciene, 2022). The methodology is very similar than the methodology used in this thesis, which helps the comparability of the results. Norvaisiene and Stankeviciene (2022) claims that significant evidence of the effect can only be found from Baltic markets and the effect does not exist in Nordic markets. It is important to note that this study uses aggregated index to study the anomaly in Nordic markets, hence it might impact the returns, since previous literature shows the effect to be more related to small cap stocks (see Roll, 1983; Ritter, 1988). Furthermore, Giovanis (2009) finds similar results as Norvaisiene and Stankeviciene (2022) from Nordic stock indices. The author studies the seasonalities in international stock markets by including data from 51 countries in the study. Giovanis (2009) study also includes indices from Finland, Sweden, Norway, and Denmark and studies whether there is January effect found with using GARCH model. The study finds insignificant returns for January, which means that the January effect does not exist in these countries' indices.

Furthermore, Patel (2016) tries to evaluate in his study the presence of the January Effect. The author's study aims to capture January whether the January effect exists by using international data from 1997 to 2014. Patel (2016) incorporates various stock indices in his study from both developed and emerging markets to test the anomaly. The objective of his study is to investigate whether the January Effect still exists in stock returns, as there is recent evidence that there are no excess returns anymore to achieve during January (Patel, 2016).

Patel (2016) claims that in the evaluation of the January effect it is vital to divide the measured time period into three different sub-periods to explore the presence of the January Effect under different market conditions. Patel (2016) decides to create sub-periods, to capture how the January effect evolves over time. The author claims that first period includes data from time before the financial crisis 1997-2007, the second includes data from financial crisis period 2008-2009, and the third includes data from the post financial crisis period 2010-2014. By dividing the whole measured period into three different time periods, the study aims to assess, for example, if bear- and bull markets influence the presence of the January effect during the measured time period (Patel, 2016). The author gathers data from the selected indices' index values from the last trading day of each month. Furthermore, the author states that study employs a standard return formula to measure return for every month. The study employs the January effect by using linear regression, in which dummy variable is used to separate January with other months.

The result of the Patel (2016) study shows that in the whole observed period, the January effect does not seem to exist in the developed markets anymore. Furthermore, he notices that their findings indicate that the mean returns for January are negative, hence there is no January effect. The study indicates similar results for Asian markets. This study provides a broad perspective on the anomaly as a whole, as it investigates broadly different market areas around the world (Patel, 2016). The study's data also includes countries from the same market area as this thesis, thus in aggregated level because Nordic countries are located in Europe. However, it is important to mention that this study does not separate small-cap stock indices and large-cap indices. This may impact on the results, since the January effect is often found in small-cap stock indices in previous studies (Wagner et. al, 2022; Betzer&Theissen, 2009). It is important to point out that the results between different studies may vary based on the selected method for calculations of monthly returns. It is important to mention that Patel (2016) study utilizes mean returns in measuring the January effect. However, his study employs OLS-regression, which can give different results, since the author utilizes standard returns, which may not be the most suitable for linear regression.

Li et al. (2018) examines the seasonality in stock returns between the developed and emerging markets. They gather stock return data from 42 different markets from around the world. The data sample of observed markets is divided into include 21 markets from developed markets and 21 markets from emerging ones (Li et al., 2018). Their study also includes observations from Finland's, Denmark's, Iceland's, and Norway's stock market, which are studied in this thesis. According to Li et al., (2018) the study is conducted by grouping the stocks into ten different categories based on the historical month specific returns. They further state that the stocks are being split between winner- and loser stocks, which are equally weighted. The authors uses regression analysis, and Newey-West t-statistics test to test the significance of their findings. Their study's results states that there is significant evidence of this anomaly in developed markets, yet the results indicate the opposite for the emerging markets. Their study's results specifically states that there is significant evidence found of the presence of the January effect in Norway and Finland. These results indicate that it could be possible to find similar returns from these countries' indices in this thesis. Similar evidence is also provided by Hansen and Lunde (2003), who studies different seasonalities across the world. Their study also involves data from Denmark, Norway, and Sweden, and they don't find significant evidence of that would show that the January effect is present among these Nordic countries.

Perez (2018) studies whether the is January effect found from 106 different stock indices around the world in both developed and emerging markets. The author's study also includes all the Nordic countries, yet they does not separate the indices by size. This thesis will study these countries' indices and separates the small and large cap indices to get broader overview of the January effect. Perez (2018) utilizes monthly closing prices of the indices to calculate monthly returns for each index. The authors tests the normality of the indices' returns by employing a Lille test and Anderson-Darling test. They find that most of the indices does not follow normal distribution, hence they utilize Kruskal-Wallis and Wilcoxon Rank Sum test to evaluate further this effect in these indices. However, one of the indices that follows normal distribution is Norwegian all share index (Perez, 2018). Furthermore, the authors states that they use the Wilcoxon test to evaluate the difference between the January returns and other months' returns. The results show that in the OMX Helsinki index there is no evidence of higher returns in

January. Also, the study shows that the January effect can be found in OMX Stockholm All index. However, the result is only significant with only one other month, that is compared to January's returns. Additionally, the study states that there is no January effect either in Norwegian, Danish, or Icelandic indices that are observed (Perez, 2018).

Mehdian and Perry (2002) studies the January effect on the U.S stock market indices and utilizes data from the years 1964 to 1998. The authors utilizes daily stock index values to calculate daily returns for the indices and employes regression analysis with dummy variables to examine the January's returns. The authors divides the analysis between the period before and after the 1987 market crash. The authors find that for the whole period from 1964 to 1998 there is evidence of this effect's presence. However, when the analysis is conducted separately for the pre and post-crash periods, the authors find that after the market crash there is no significant evidence of January effect within 0,05 significance level (Mehdian & Perry, 2002). These findings suggest that the January effect has diminished from the U.S stock markets over time and there is no significant evidence of this effect after the year 1987 (Mehdian & Perry, 2002).

Gu (2003) finds similar evidence, which supports the significant decline of January effect in different Russel indices. The author states that early literature of January effect does not observe different dynamics of the January effect. The author suggests that previous studies often utilize short time periods and use constant dummy variables for January and mean returns, which can impact the results. For example, if the returns are abnormally high only in one specific year, then it would outweigh other observations in the calculations (Gu, 2003). Because of this, Gu (2003) decides to investigate the January effect with a power ratio method. The author argues that this method allows the data to be segmented, which allows the study to investigate the years individually. The authors argue that by doing this, the markets trends can be identified and studied. The data is collected from years between 1988 and 2000 from U.S. stock markets, and the study involves value weighted indices, since they provide more visible results of the large cap stock's impact (Gu, 2003). The main findings of Gu's (2003) study implies that the January effect has decreased from the observed indices over time and this can be seen happening among both small and large cap stocks (Gu, 2003). These results supports strongly the findings of Perez (2018), who also finds this effect to be decreased.

Similar evidence is also provided by Li and Gong (2015) from the Japanese stock market. The authors argue in their study that the effect was stronger before it became public knowledge to investors. The authors show this by utilizing data from 1975 to 2008. According to the authors, the effect is present in the markets during the period between 1975 and 1984 in both small and large cap stocks. However, they argue in their study that between 1985 and 2008, there is no evidence among small cap stocks, yet the effect is present among large cap stocks. Additionally, they argue in their study that the January effect's size increases with larger stocks. This is an interesting finding, as it shows contradicting evidence about the assumption that the January effect is more pronounced within smaller stocks (see Ritter, 1988; Roll, 1983. Furthermore, Li and Gong's (2015) study show opposing results to Patel's (2016) study in which the author argues that the decrease in the effect is more clearly seen within larger stocks.

Enow (2024) further examines the January effect across international stock markets and utilizes international stock index data from main market areas around the world to evaluate whether the effect is present globally. His study gathers data from the U.S, Germany, Japan, South Africa, and France from the years between 2019 and 2024. Enow (2024) further states the OLS-regression is employed to study the effect in these markets and uses daily average returns in the regression. The results of Enow (2024) study show that there are no signs of the January effect in the observed indices. These results are also in line with Perez (2018) findings

3.4 Literature gap

There are not many studies published about the January effect that focuses specifically on the Nordic stock market. Many studies that focuses on this effect in the Nordic market area focuses on aggregated indices, such as OMX Nordic 40. For example, Norvaisiene and Stankeviciene (2022) studies the stock market seasonality in Baltic and Nordic stock markets. The authors uses OMX Nordic 40 index to evaluate the stock market seasonality in Nordic area (Norvaisiene & Stankeviciene, 2022). This does not offer very broad in depth analysis of the effect, since it aggregates the whole market area by using one single index that contains stocks from every Nordic country. Because of this, this thesis broadens the evaluation to include indices from every Nordic country. This is important because this study wants to investigate this subject more in depth.

Also, the studies regarding the January effect usually focuses on a one specific country or utilizes the main indexes from different countries. These studies includes several Nordic countries, yet not all of them (see Gultekin & Gultekin, 1983; Dahlquist & Sellin, 1994; Wahlroos & Berglund, 1984; Perez, 2018). This makes the comparison and evaluation of the January effect more complex, since these studies utilize different methods and data in their calculations. This is the reason why this thesis utilizes similar indices for all of the Nordic countries to evaluate whether this effect is present. Furthermore, this thesis does not use aggregated main indexes of these countries that includes all kind of different size stocks, as this thesis aims to also evaluate if the January effect can be found from either small or large cap indices.

Moreover, by doing this this study can evaluate if the effect is more of a small cap anomaly. Several studies that investigates the January effect that includes some of the Nordic countries often utilizes one index that aggregates the countries' stock market, hence not separate small and large cap indices (Giovanis, 2009; Perez, 2018; Li et al., 2018; Norvaisiene & Stankeviciene, 2022). Because there is only limited number of studies of January effect in Nordic countries, there is a gap in the literature that can be evaluated with using more recent data.

4 Data and methodology

This chapter introduces the data and methodology utilized in this study. First, the data that is utilized in this thesis will be discussed. After the data section, this chapter will discuss the methodology which is used to investigate the January effect.

4.1 Data

This thesis examines the January effect across the Nordic region's small- and large cap stock indices. The data is extracted from the Nasdaq database and includes Small- and large cap stock index data from Finland, Sweden, Norway, Denmark, and Iceland. These indexes are shown in the Table 1. Below on the next page. For each Nordic country this thesis employs country specific small and large cap indices, and the data is gathered from 30.12.2014 to 31.12.2024. The reason for including the last trading day closing price data from 2014, is that the equation for logarithmic calculation includes P_{t-1}. Because of this, the first trading day's return can be calculated for 2015.

The data utilized in this study is extracted from Nasdaq's Database, which offers comprehensive selection of stock indices from Nordic stock markets. The stock indices selected for this study provide data for Nordic countries' small -and large cap stocks. This study focuses on stock indices instead of individual stocks, since the indices offer a broad view of each market area's stock performance in both small and large cap stocks. Selecting indices instead of individual stocks also enables a more robust examination of the January effect in these market areas. It is important to note that small and large cap indices are selected for every country, yet there is no large cap index for Iceland that would provide broad data for period between 2015-2024. For this reason, the all stock index is selected to represent the counter Index for small cap index. The stock indices selected are found from the table 1. Below, which shows the information about these indices in more depth.

Country	Index ticker	Index Name	Index Type
Finland	OMXHLCGI	OMX Helsinki Large Cap GI	Market capitalization-weighted
Finland	OMXHSCGI	OMX Helsinki Small Cap GI	Market capitalization-weighted
Iceland	OMXISCGI	OMX Iceland Small Cap GI	Market capitalization-weighted
Iceland	OMXIGI	OMX Iceland All-share GI	Market capitalization-weighted
Norway	NQNOSC	NASDAQ Norway Small Cap Index	Market capitalization index, float adjusted
Norway	NQNOLC	NASDAQ Norway Large Cap Index	Market capitalization index, float adjusted
Denmark	NQDKSC	NASDAQ Denmark Small Cap Index	Market capitalization index, float adjusted
Denmark	NQDKLC	NASDAQ Denmark Large Cap Index	Market capitalization index, float adjusted
Sweden	NQSESC	NASDAQ Sweden Small Cap Index	Market capitalization index, float adjusted
Sweden	NQSELC	NASDAQ Sweden Small Cap Index	Market capitalization index, float adjusted

Table 1. Information on Nordic indices

The index type information on the table 1. Above is retrieved, from Nasdaq (2020) and Nasdaq (2024). The daily stock index data collected from Finland and Iceland indices is based on market capitalization of performance indices (Nasdaq, 2020). The indices' weighting is measured by dividing each stock's market value by the market value of all stocks included in the indices (Nasdaq, 2020). The index values are calculated each week from Monday to Friday. The only exceptions are public holidays when stock markets are closed (Nasdaq, 2020). Because of this, there may be different number of trading days observed in each included country, yet the observed time period is the same for each country’s stock indices. Nasdaq (2020) defines the small cap stocks that are included in the indices are required to have a market value under 150 million euros. The large cap stocks that are included in the large cap indices are required to have market value that exceed one billion euros. The overview of these indices’ performance can be seen from the tables below.

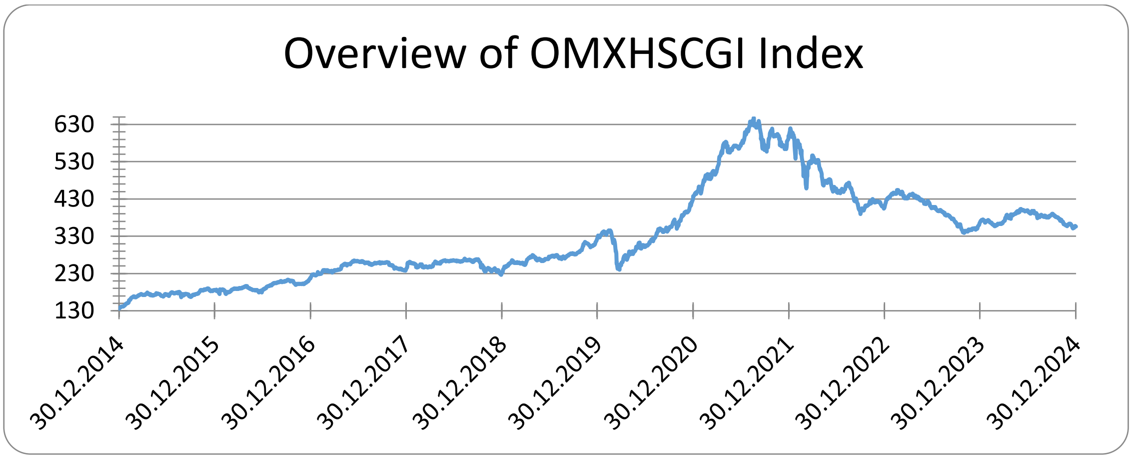

Figure 1. Overview of the OMX Helsinki Small Cap GI Index

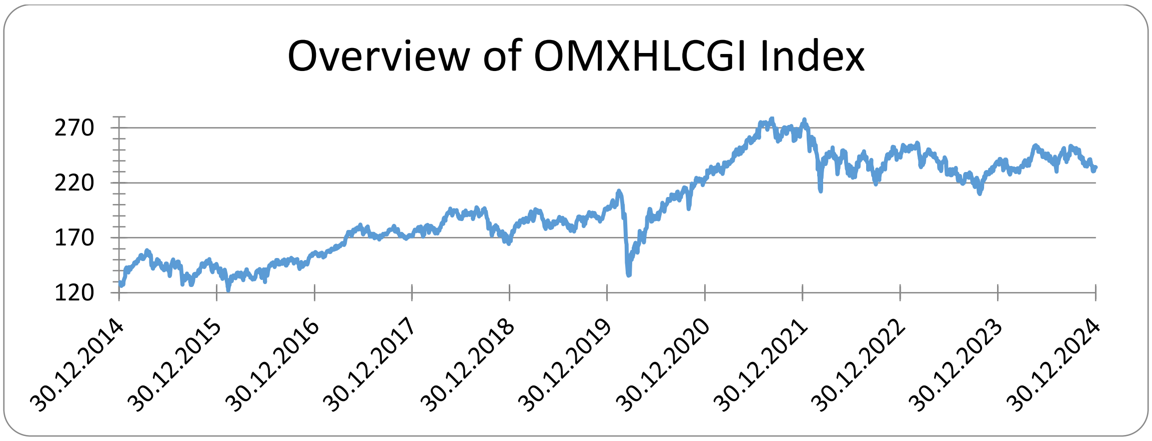

Figure 2. Overview of the OMX Helsinki Large Cap GI Index

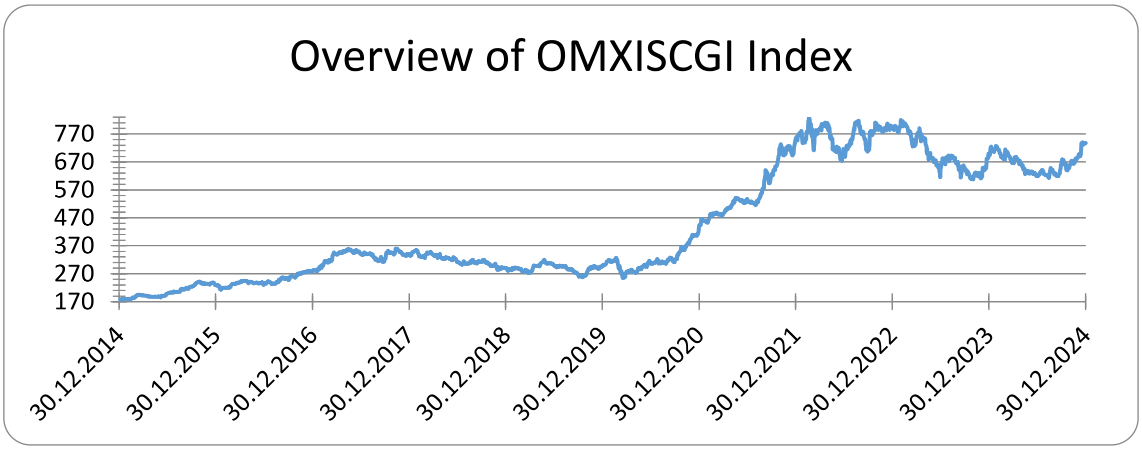

Figure 3. Overview OMX Iceland Small Cap GI Index

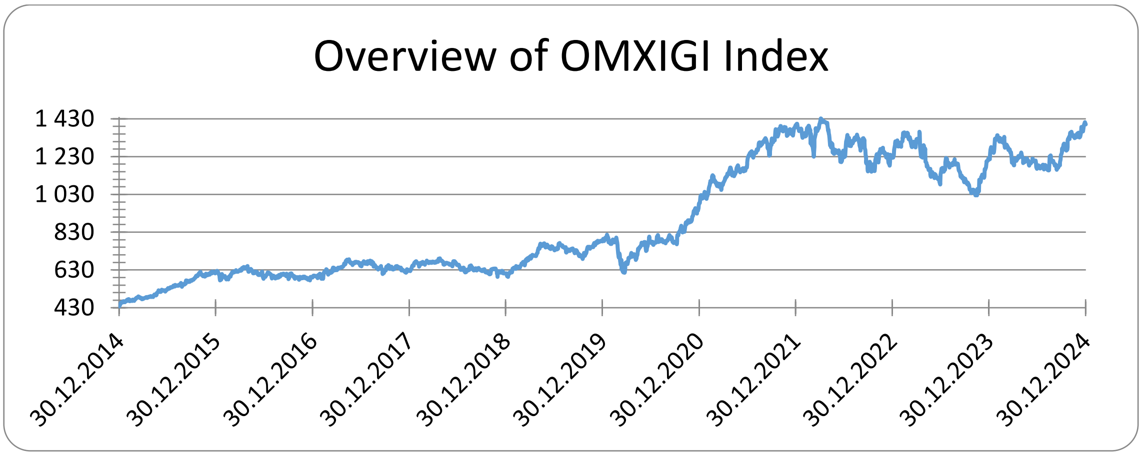

Figure 4. Overview of OMX Iceland All-Share GI Index

For the indices from Sweden, Norway, and Denmark, the observed indices utilize free float adjusted market capitalization, which means that company's market value is calculated by including only shares that are available for trading (Nasdaq, 2024). The reason for selecting these indices is that there were no data available for GI indices from the last ten years from every index, so corresponding indices were selected to keep comparability between country specific small and large cap indices simpler. Additionally, all of these Nasdaq indices are categorized into small- and large cap segments based on top-down approach, which makes the comparison of these indices more reliable (Nasdaq, 2024). The small cap indices include stocks that represent the bottom 10% of the lowest market value and large cap indices include the top 75% of stocks of the total market value in the country’s total stock market value (Nasdaq, 2024). The daily closing price for these indices is formed based on the last trading prices of the stocks that are included in the indices (Nasdaq, 2024). The overview of these indices’ performance can be seen from the tables below.

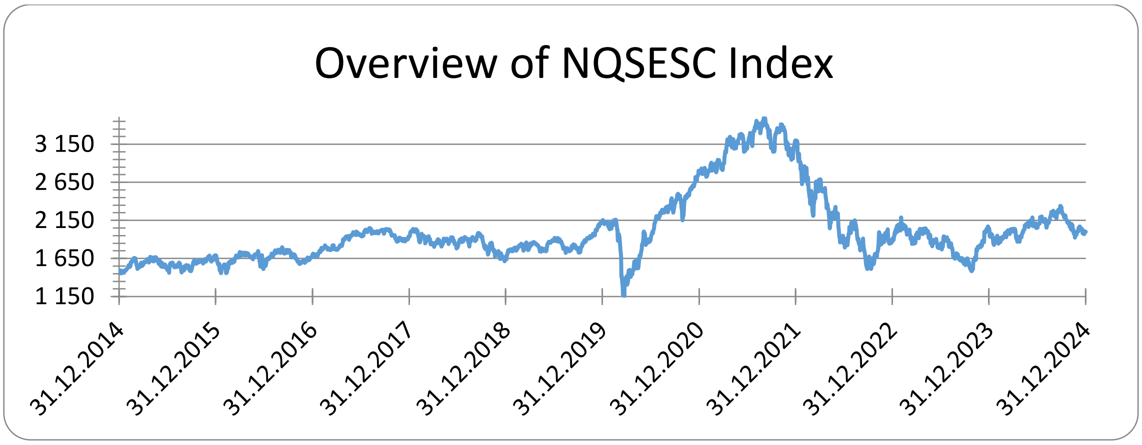

Figure 5. Overview of NASDAQ Sweden Small Cap Index

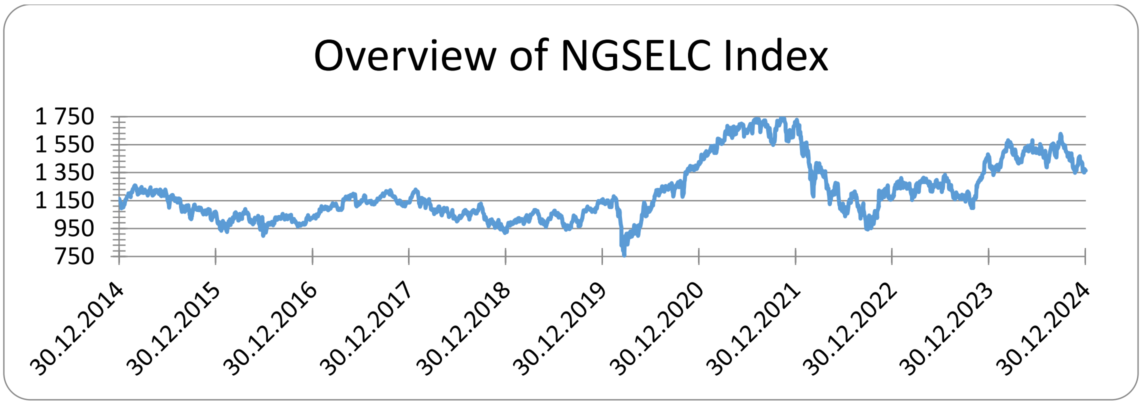

Figure 6. Overview of NASDAQ Sweden Large Cap Index

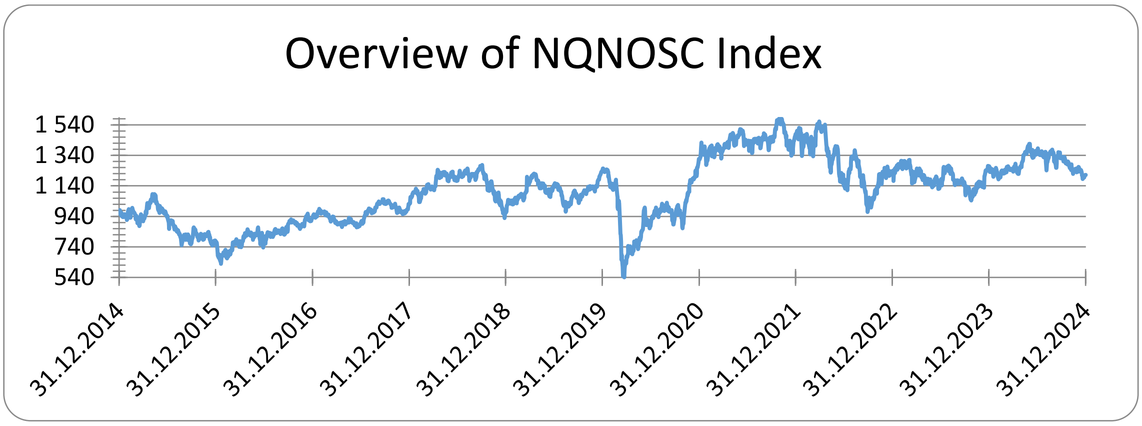

Figure 7. Overview of NASDAQ Norway Small Cap Index

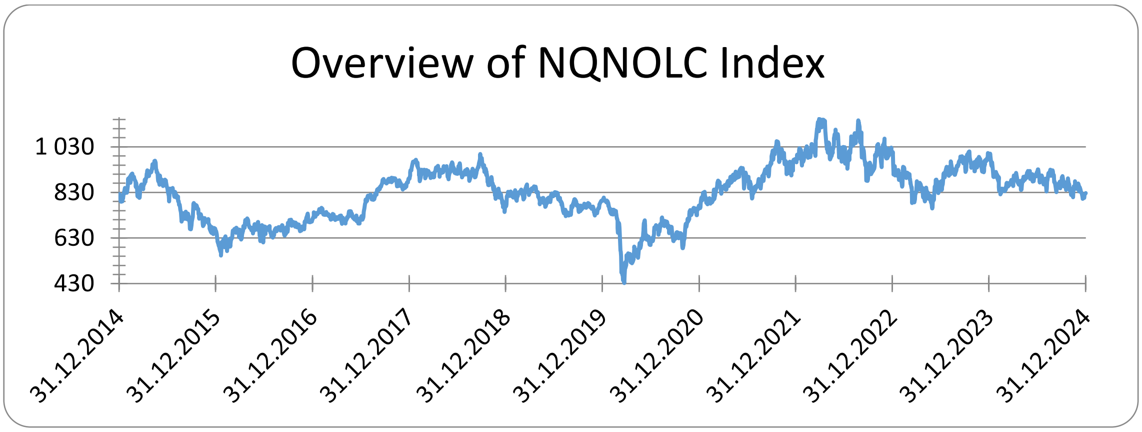

Figure 8. Overview of NASDAQ Norway Large Cap Index

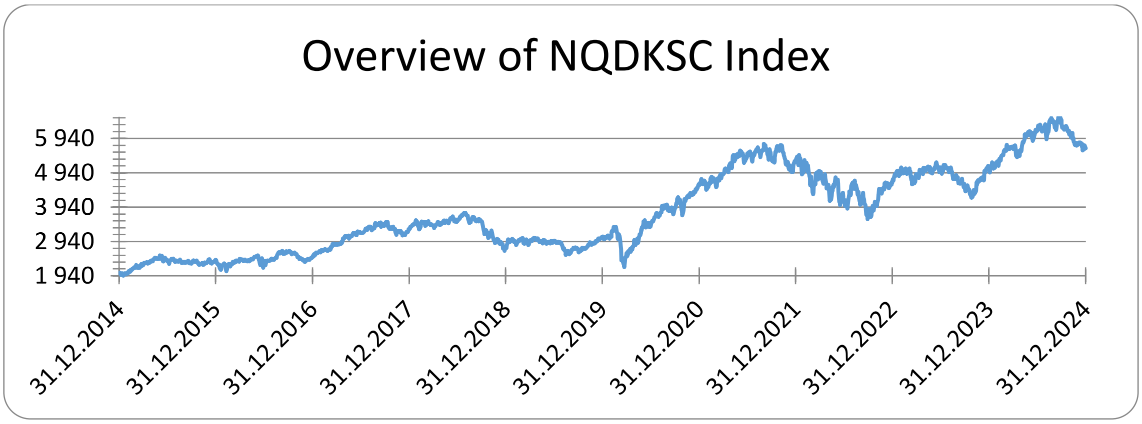

Figure 9. Overview of NASDAQ Denmark Small Cap index

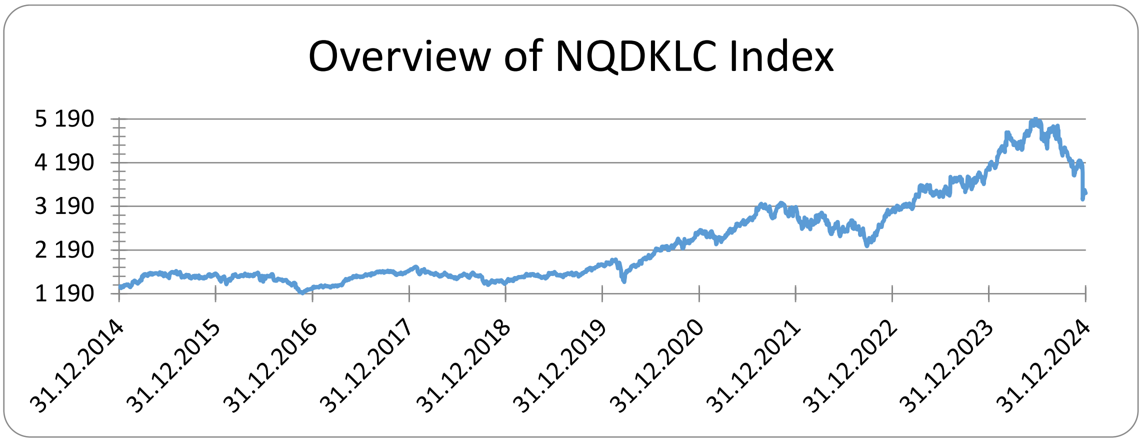

Figure 10. Overview of NASDAQ Denmark Large Cap Index

4.2 Methodology

This study utilizes OLS regression with dummy variables to evaluate if January effect can be found from Nordic stock markets. The methodology is inspired by other previous studies that utilizes Linear regression models to research the subject (see Eyuboglu & Eyuboglu, 2016; Patel, 2016; Pandey & Samanta, 2022, p. 118; Norvaisiene and Stankeviciene, 2022). Additionally, this study uses the daily logarithmic returns, which are calculated from the daily index value changes for each index.

According to Shai (2025), it is common for financial studies to utilize logarithmic returns over simple returns. Furthermore, Mota (2012) writes that logarithmic stock returns are often assumed to be normally distributed in finance math. Additionally, the normality linked to logarithmic returns allows this study to use OLS regression model, which is based on the normality assumption. Furthermore, Miskolczi (2017) states that there is benefits for using logarithmic returns over simple returns, if the changes of values in the data revolves around zero. Daily returns are often small in the indices, which further confirms their use in this study. The logarithmic returns are also widely used in previous studies to examine the January effect around the other seasonalities across the world (see Eyuboglu & Eyuboglu, 2016; Li & Liu, 2010; Pandey & Samanta, 2016; Alvarado & Demmler, 2019). The equation for calculating daily logarithmic returns for each individual index is derived from the Miskolczi (2017, p. 130) study as follows:

(1) Logarithmic daily return

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where R_t is the logarithmic return of the index at time t, P_t is the return of the index at time t, and P_{t-1} is the return of the index at the time of t-1.

This study utilizes an OLS regression model which incorporates a dummy variable to investigate whether the mean daily returns in January significantly differ from those in other months. The regression includes only one independent variable, which is a January dummy. The January dummy is marked with 1 for January's returns and 0 for other months' returns. By doing this, this study can compare the mean daily returns between January and other months. However, it is important to note that there are many other factors that may impact January effect's presence. The equation for this linear regression model used on this study is formed from Patel (2016, p. 319-320) study as follows:

(2) OLS-regression

$$R_{it} = \beta_0 + \beta_1 January + \varepsilon_t$$

Where R_{it} denotes the daily returns for each index, the β_0 denotes the mean daily return for each index's other months, $\beta_1 January$ denotes the mean daily returns' difference between January and other months, ε_t denotes the error term.

The following description is derived from Patel (2016) study. In the regression model (2) above, the intercept β_0 demonstrates the mean daily logarithmic returns for all the other months except January. The coefficient $\beta_1 January$ corresponds to a dummy variable with a value of 1 for January's daily logarithmic returns and 0 for the other months' daily returns. This coefficient estimates the difference between the mean daily logarithmic returns in January and the mean daily return in other months. Because of this, if $\beta_1 January$ is positive it indicates the presence of the January effect in the observed index.

Furthermore, the positive value's p-value have to be within 0,05 significance level to be considered significant. This kind of result would mean that the null hypothesis can be rejected, and the January effect is present in the observed index. However, if the value is negative and the p-value is within 0,05 significance level, then the result would indicate negative January effect. The hypothesis of this regression and study are presented in the subchapter 1.2.

There are both advantages and limitations in using linear regression. According to Anandhi and Nathiya (2023), linear regression is simple and easy to employ and interpret when evaluating the connection between X and Y. The author states that the problem with linear regression is the linearity assumption. Furthermore, they state that there is also assumption of no autocorrelation and constant error variance. Additionally, the outliers may impact negatively to the regression's results (Anandhi &Nathiya, 2023). There are other assumptions associated with linear regression, such as omitted variable bias, which is considered during the selection for proper method to study this effect in this study. According to Wilms et al. (2021) excluding out important variables may impact the beta coefficient's estimates. However, this study intentionally uses only one independent variable because the primary goal of this study is to evaluate the anomaly's presence, rather than focus on the factors that may influence its possible presence.

The data used in this thesis is checked for autocorrelation in this study. Also, the regression analysis will provide insights into the linearity of data, as it includes normal probability plots. The plot shows an upward trend for all observed indices, however there are outliers noticed, which may impact the model's accuracy, hence the results of it. The Durbin-Watson test is also conducted to test autocorrelation of the datasets, since data should not be autocorrelated in linear regression (Anandhi & Nathiya, 2023). The

Durbin-Watson test can be conducted from the regression analysis results, since it provides the residuals of the data, from which the lagged residuals can be calculated, the sums for both residuals, and the squared residuals. The Durbin-Watson test employed in this thesis is derived from White's (1992) study, who argues that Durbin-Watson model can be formed as follows:

(3) Durbin-Watson test

$$d = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t-1}^{n} e_t^2}$$

Where d denotes the Durbin-Watson value, e_t denotes the residual at time t, n denotes the total number of observations in the residual data, e_{t-1}denotes the lagged residuals at time of t-1, and e_t^2 denotes the square of the residual at time of t.

5 Empirical Results

This chapter includes the results of the Durbin-Watson tests, descriptive statistics for each index, and results of OLS regression analysis with dummy variable. First the autocorrelation is tested for each index to evaluate whether there is autocorrelation in the data. If there is autocorrelation, it would indicate that the OLS regression is not the most suitable method to evaluate the dataset. According to Turner (2020) if the results of Durbin-Watson test positions between 1,5 and 2,5, then they can be accepted to have no autocorrelation. Furthermore, the author states that ideal values would be around 2 (Turner, 2020). The overall results of the Durbin-Watson test indicates that there is no autocorrelation in the data, and most of the values are close to 2, hence the independence assumption of OLS regression model is met.

Durbin-Watson test	*d*
OMX Helsinki Small Cap GI	1,92
OMX Helsinki Large Cap GI	1,93
OMX Iceland Small Cap GI	1,88
OMX Iceland All-Share GI	1,93
NASDAX Sweden Small Cap	1,89
NASDAX Sweden Large Cap	2,05
NASDAQ Norway Small Cap	1,94
NASDAQ Norway Large Cap	2,03
NASDAQ Denmark Small Cap	1,87
NASDAQ Denmark Large Cap	2,04

Table 2. Durbin-Watson test results

5.1 Results for Finnish Indices

The descriptive statistics for the Finnish indices can be found from table 3. Below. It can be observed from the table that mean daily returns seem to be higher in the Finnish small cap index during January, when compared to the other months. The total number of observations for observations in January for both indices is 207, while the number of observations for other months is 2307. The total amount of observations in both indices is 2514 in the period of 2015 to 2024. It can also be seen from the table 3. that the mean returns are higher for large cap index's January in comparison to other months' mean returns.

	OMX Helsinki Small Cap		**OMX Helsinki Large Cap**	
	January	*Other Months*	*January*	*Other Months*
Mean	0,002265	0,000214	0,000752	0,000193
Standard Error	0,000792	0,000183	0,000764	0,000236
Median	0,002329	0,000588	0,000987	0,000447
Standard Deviation	0,011390	0,008770	0,010998	0,011339
Sample Variance	0,000130	0,000077	0,000121	0,000129
Kurtosis	10,495167	15,736486	1,827735	7,776074
Skewness	-0,002203	-1,583462	0,511701	-0,803411
Range	0,130530	0,160113	0,078972	0,172104
Minimum	-0,060389	-0,102474	0,046210	-0,107905
Maximum	0,070140	0,057639	0,032762	0,064199
Sum	0,468838	0,494502	0,155715	0,444249
Count	207	2307	207	2307

Table 3. Descriptive statistics for Finnish indices

The table 4. Below provides results for the regression analysis of Finnish indices. The results show that the small cap index's coefficient for January is positive. Furthermore, the results show that its p-value is significant on 0,05 significance level. This shows that when the dummy variable is set to 1, then the mean return increases by 0,002051 units compared to other months' returns. This result is in line with the alternative hypothesis H_1, which means that the H_0 hypothesis can be rejected for this index. This indicates that the January effect is present among the Finnish small cap stocks. This finding is also in line with the results of Wahlroos and Berglund's (1984) study, who examines the January effect in Finnish stock market. This finding is in line with also several studies that uses international data to study this anomaly, which further supports the presence of the January returns among smaller stocks (See Roll, 1983; Ritter, 1988).

While the returns are statistically significant for the small cap index, the adjusted r-square value is only 0,00352. This means that the model only explains about 0,352% of the daily return variation. As discussed earlier in the methodology part, there are many other possible factors in the financial markets that influence the returns, and by adding more independent variables into regression could possibly improve the explanatory power of it. Furthermore, even though the coefficient appears to be higher for the Finnish large cap index, the finding is not statistically significant, as the p-value is not within the 0,05 significance level. This result is in line with the null hypothesis and means that this study fails to reject the H_0, which states that there is no significant difference between returns in January and other months. It can also be observed that there is quite a large difference between small and large cap indices' F statistic values. The F statistic value is 9,830788 for the small cap regression, which indicates that the dummy variable explains a part of the variation in returns between January and other months. The Significance F for the small cap index, on the other hand, shows that the model as a whole is statistically significant.

Regression Statistics	***Finland Small Cap***	***Finland Large Cap***
Multiple R	0,062436	0,013605
R Square	0,003898	0,000185
Adjusted R Square	0,003502	-0,00021
Standard Error	0,009014	0,011311
Observations	2514	2514

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*F stat*	*Significance F*
January Small Cap	0,002051	0,000654	3,135409	**0,001736**	9,830788	0,001736
january Large Cap	0,000560	0,000821	0,681951	0,495333	0,465057	0,495333

Table 4. Regression results for Finnish indices

5.2 Results for Swedish indices

The table 5. Below shows descriptive statistics for the Swedish indices. It can be observed from the table 5. that the number of observations for January is 214 for both indices. Additionally, there are 2370 observations for both indices' other months. The total number of observations for each index is 2583. The mean return in January is -0,000538 and 0,000171 in other months in Swedish small cap index, which indicates that the daily returns are negative in January. This suggests that there is no January effect among Swedish small cap stocks. Furthermore, this indicates that January constantly offers lower mean returns for investors. Additionally, it can be observed from the table that the mean return for January in the Swedish large cap index is higher than the daily returns of other months'. This indicates that there is a possibility to gain higher returns during January from large cap stocks in Swedish stock market.

	NASDAQ Sweden Small Cap		**NASDAQ Sweden Large Cap**	
	January	*Other Months*	*January*	*Other months*
Mean	-0,000538	0,000171	0,000134	0,000059
Standard Error	0,000974	0,000318	0,000975	0,000311
Median	0,002327	0,000456	0,001384	0,000300
Standard Deviation	0,014244	0,015470	0,014263	0,015142
Sample Variance	0,000203	0,000239	0,000203	0,000229
Kurtosis	1,965967	9,851629	1,822562	6,395147
Skewness	0,813880	-0,678388	-0,487487	-0,490130
Range	0,101286	0,272648	0,099734	0,230101
Minimum	0,061881	-0,173083	-0,056611	-0,144434
Maximum	0,039405	0,099566	0,043123	0,085667
Sum	0,115075	0,404982	0,028620	0,140988
Count	214	2370	214	2370

Table 5. Descriptive statistics for Swedish indices

The table 6. Below shows the results of the regression analysis for Swedish indices. It can be observed from the table that the adjusted R squares for both indices are very low. This indicates a lack of the explanatory power of the regression model. Furthermore, the coefficient for January returns in small cap index is -0,000709, which indicates that the daily returns in January are lower for small cap stocks in Sweden. This is interesting finding, since the results are not in line with the Finnish small cap index, yet the market area is quite similar between these two indices. It can also be observed from the results that the p-value for small cap index's January is 0,518462, hence the finding is not statistically significant. This finding is in line with the null hypothesis, which means the failure to reject the H_0 hypothesis. Furthermore, the coefficient for the large cap index's January returns is 0,000074, which indicates the presence of January effect. However, the p-value for the coefficient is not within the 0,05 significance level. This finding is in line with the H_0 hypothesis, which states that there is no difference between returns. These results supports the findings of Giovanis (2009) and Li et al. (2018), as there is no significant evidence of the effect's presence. However, Dahlquist and Sellin (1994) and Gao and Li's (2019) studies show differing results that are not in line with these findings estimated in this study. Additionally, The F statistic values are low for both indices, which means that the model does not explain much of the variation between daily returns.

Regression Statistics	***Sweden Small Cap***	***Sweden Large Cap***
Multiple R	0,012708	0,001358
R Square	0,000162	0,000002
Adjusted R Square	-0,000226	-0,000385
Standard Error	0,015372	0,015072
Observations	2584	2584

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*F stat*	*Significance F*
January Small Cap	-0,000709	0,001097	-0,645807	0,518462	0,417066384	0,518462
January Large Cap	0,000074	0,001076	0,069021	0,944978	0,00532367	0,941841

Table 6. Regression results for Swedish indices

5.3 Results for Norwegian indices

The table 7. Below shows descriptive statistics for Norwegian indices. Both indices have 214 observations for January and 2370 observations for other months. It is interesting to notice that this suggests that the mean daily returns are negative for both indices' January returns. The mean return for Norwegian small cap index is -0,000492 and for the large cap -0,000353.

	NASDAQ Norway Small Cap		**NASDAQ**	**Norway Large Cap**
Descriptive statistics	*January*	*Other Months*	*January*	*Other Months*
Mean	-0,000492	0,000137	-0,000353	0,000034
Standard Error	0,001136	0,000347	0,001108	0,000351
Median	0,000516	0,000843	0,000713	0,000331
Standard Deviation	0,016625	0,016892	0,016203	0,017081
Sample Variance	0,000276	0,000285	0,000263	0,000292
Kurtosis	2,071102	7,766290	2,307220	4,248717
Skewness	-0,431288	-0,857213	-0,125273	-0,463237
Range	0,119682	0,264157	0,129062	0,224220
Minimum	-0,062142	-0,166989	-0,062458	-0,138851
Maximum	0,057540	0,097168	0,066605	0,085369
Sum	-0,105320	0,324511	-0,075589	0,081536
Count	214	2370	214	2370

Table 7. Descriptive statistics of Norwegian Indices

The results of the regression analysis for Norwegian indices can be found from table 8. Below. The results show that the January variable's coefficient in the small cap index is -0,00063, which indicates that there is no January effect found in Norwegian small cap index. Additionally, the p-value for small cap index is 0,60141, which means that the finding is not statistically significant within 0,05 significance level. This means that there is no statistically significant difference between the returns in January compared to months, which is in line with the H_0 hypothesis. The results show similar findings also for the large cap index, hence the H_0 cannot be rejected. Additionally, the adjusted r-square is also very low for both of these indices, which indicates low explanatory power of the model. This is also the case for F statistic values for both indices, which suggest that the regression model does not explain much of the variation between daily returns. In conclusion, the results of this regression show that the there is no statistically significant difference between the mean returns in either index. Furthermore, the F statistic values are low for both indices, which indicates that the regression model does not explain much of the variation in returns between January and other months.

Regression Statistics	***Norwegian Small Cap***	***Norwegian Large Cap***
Multiple R	0,01028	0,00628
R Square	0,00011	0,00004
Adjusted R Square	-0,00028	-0,00035
Standard Error	0,01687	0,01701
Observations	2584	2584

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*F stat*	*Significance F*
January Small Cap	-0,00063	0,00120	0,52243	0,60141	0,27293	0,60141
January Large Cap	-0,00039	0,00121	0,31925	0,74956	0,10192	0,749563

Table 8. Regression results for Norwegian Indices

5.4 Results for Danish Indices

The table 9. Below shows Descriptive statistics for Danish indices. Both indices have the same number of observations. There are 214 observations for both indices’ January and 2370 for other months, which means that both indices have a total of 2584 observations. The daily mean returns seem to be higher in January in the small cap index compared to the returns of other months. However, the daily mean returns seem to be lower for January in the large cap index when compared to other months’ returns.

	Denmark Small Cap Index		Denmark Large Cap Index	
Descriptive statistics	*January*	*Other Months*	*January*	*Other Months*
Mean	0,00068	0,00037	0,00001	0,00040
Standard Error	0,00086	0,00027	0,00086	0,00029
Median	0,00241	0,00055	0,00034	0,00049
Standard Deviation	0,01259	0,01311	0,01257	0,01391
Sample Variance	0,00016	0,00017	0,00016	0,00019
Kurtosis	0,80544	6,16424	1,05908	12,31758
Skewness	0,41996	-0,67865	0,25371	-0,80096
Range	0,08098	0,18470	0,07533	0,26915
Minimum	0,04560	-0,13097	0,03771	-0,16865
Maximum	0,03538	0,05373	0,03762	0,10050
Sum	0,14653	0,88592	0,00272	0,94878
Count	214	2370	214	2370

Table 9. Descriptive statistics for Danish indices

The results of the regression analysis for Danish indices can be found from table 10. Below. The results show that in the small cap index the coefficient for January returns is 0,000311 in January, which indicates that the returns are higher in January compared to other months. However, it can be seen that the p-values for both small and large cap indices' January coefficient are not statistically significant at 0,05 significance level. The p-value for Danish small cap index's January coefficient is 0,738956. Furthermore, the p-value for the large cap index's January coefficient is 0,694112. Because of this, the H_0 hypothesis cannot be rejected, as the results do not show a statistically significant difference between the mean returns in either of the indices. In other words, the H_0 hypothesis is accepted. Additionally, as in all the previous indices, the adjusted R square is also low for both Danish indices, which indicates lack of explanatory power. Additionally, the F statistic values are low for both indices, which indicates that the regression model does not explain much of the variation in returns between January and other months. These results are in line with Li et al. (2018) and Giovanis (2009) studies, since there is no significant evidence of the effect's presence.

Regression Statistics	***Denmark Small Cap***	***Denmark Large Cap***
Multiple R	0,00656	0,00774
R Square	0,00004	0,00006
Adjusted R Square	-0,00034	-0,00033
Standard Error	0,01307	0,01381
Observations	2584	2584

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*F stat*	*Significance F*
January Small Cap	0,000311	0,000933	0,333272	0,738956	0,11107	0,738956
January Large Cap	-0,00039	0,000986	-0,39332	0,694112	0,154704	0,694112

Table 10. Regression results for Danish indices

5.5 Results for Icelandic indices

The table 11. Below shows descriptive statistics for Icelandic indices. According to this table, there are 2469 observations in total for the small cap index. Additionally, the table shows that the total number of observations for large cap index is 2492. There are 213 observations for January and 2256 observations for other months in the small cap index. In the large cap index, there are 214 observations for January and 2278 for the rest of the months. It can be seen from the table 11. That mean daily return of Iceland's small cap index is higher than the mean return for other months, which suggests that January effect may be present among Icelandic small cap stocks. Also, January's mean daily return in the large cap index seem to be higher than mean return in other months.

	OMX Iceland Small Cap GI		**OMX Iceland All Share GI Index**	
Descriptive statistics	*January*	*Other Months*	*January*	*Other Months*
Mean	0,000785	0,000562	0,001308	0,000389
Standard Error	0,000576	0,000208	0,000690	0,000207
Median	0,000031	0,000139	0,000709	0,000419
Standard Deviation	0,008410	0,009873	0,010087	0,009868
Sample Variance	0,000071	0,000097	0,000102	0,000097

Kurtosis	4,197948	3,997628	2,356407	5,250108
Skewness	0,020340	0,013514	0,474385	-0,418638
Range	0,073156	0,130506	0,072869	0,129604
Minimum	0,041203	-0,064859	-0,032647	-0,077062
Maximum	0,031952	0,065647	0,040222	0,052542
Sum	0,167240	1,267005	0,279902	0,885108
Count	213	2256	214	2278

Table 11. Descriptive statistics for Icelandic indices

The table 12. Below shows results for the Icelandic indices' regression analysis. The regression analysis shows that the coefficient for small cap index's January is 0,000224, which indicates the presence of the January effect. However, the p-value of the small cap index's January coefficient is 0,749245, which means that the results are not statistically significant. It can also be seen from the table 12. that the coefficient for the large cap index's January returns is positive, yet the coefficient is not statistically significant because the p-value is 0,193507, hence not in 0,05 significance level. Additionally, the F statistic values are quite low for both indices, which indicates that the regression model does not explain much of the variation in returns between January and other months. Furthermore, these results are in line with Li et al. (2018) study who does not find evidence of this effect from Iceland's stock markets.

Regression Statistics	***OMX Iceland Small Cap GI***	***OMX Iceland All Share GI***
Multiple R	0,006436	0,026056
R Square	0,000041	0,000679
Adjusted R Square	-0,000364	0,000278
Standard Error	0,009756	0,009887
Observations	2469	2492

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*F stat*	*Significance F*
January Small Cap	0,000224	0,000699	0,319671	0,749245	0,102189	0,749245
January Large Cap	0,000919	0,000707	1,300625	0,193507	1,691626	0,193507

Table 16. Regression analysis results for Icelandic indices

6 Conclusions

This study presented the key theoretical aspects behind stock market efficiency and behavioral finance, which are important frameworks to introduce to provide an understanding of how financial markets are assumed to function and whether it is possible to earn abnormal returns from the markets. The EMH provides a more traditional view of the financial market, suggesting that markets should be efficient, hence anomalies like the January effect should not exist. However, the behavioral finance related aspects challenges this traditional theory by arguing that investors or markets are not as efficient as EMH supposes. Furthermore, these aspects suppose that there may be predictability in the stock market and different anomalies.

This study employed a widely used OLS regression to investigate if investors can achieve higher returns during January compared to the rest of the months within Nordic region. The data is gathered from the years between 2015 and 2024 to provide evidence whether the anomaly exists in the observed market area. The findings of this study shows mixed evidence of the January effect for different countries. The results suggest that the January effect can only be found in Finnish small cap index, hence the January effect is only present in Finland, and is more linked to smaller stocks. This means that the alternative hypothesis is accepted only for Finnish small cap index. This finding is in line with earlier studies' findings and does not support the more recent studies' view that the effect is no longer present. Furthermore, this may imply that markets in Finland does not function perfectly efficient.

Overall, the regression analyses results suggest that for the rest of the indices, the null hypothesis can be accepted, since there is no statistically significant evidence of the presence of this effect. Furthermore, the findings indicate negative returns for Swedish and Norwegian small cap indices, yet the results are not statistically significant. This is also the case for Norwegian and Danish large cap indices. However, these findings opens a possibility for future research to determine whether there is a negative January effect nowadays present in the markets. Additionally, mean returns seems to be positive during January in Iceland, yet those cannot be considered as significant in 0,05 level. Because these results are not statistically significant, the markets seem to function efficiently in these four countries.

These empirical findings may provide investors assistance with the decision-making process regarding Nordic market area investments. Hower, it is important to note that previous performance is not indicator of future returns. Furthermore, the explanatory power of the regression analysis in this study is weak for the selected indices, which suggests that further research is recommended to confirm these findings. However, this seasonal anomaly is not widely studied in the Nordic market area recently, hence these results provide a solid contribution to the existing literature of the subject and provides a more recent view of this anomaly’s presence in the observed market region. Even though this anomaly was found in only one small cap index out of five, the result supports the early evidence, which argues this anomaly to be more related to smaller stocks. However, this cannot be generalized on a broader scale in the Nordic market area, since there is a lack of statistical evidence from other countries’ small cap indices.

Furthermore, future examination of this anomaly could focus on this effect at industry level in these Nordic countries. It would be fascinating to examine whether there are specific industries in which this effect is present or not. This kind of further analysis could provide in depth view of this anomaly’s presence between different industries, rather than focusing only on differences between small and large cap stock indices.

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