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# January effect in Finnish stock market 2010-2019

School of Acoounting and Finance
Master's thesis in Finance
Master's Degree Programme in Finance

Vaasa 2022

**UNIVERSITY OF VAASA**
**School of Accounting and Finance**
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**Title of the Thesis:** January effect in Finnish stock market 2010-2019
**Degree:** Master of Science in Economics and Business Administration
**Programme:** Master's Degree Programme in Finance
**Supervisor:** Vanja Piljak
**Year of completing the thesis:** 2022 **No. of pages:** 74

**ABSTRACT:**

The thesis' goal is to investigate the occurrence of the January effect in the Finnish stock market from 2010 to 2019. The January effect was tested on a daily basis by looking at logarithmic stock returns. The research method was least squares linear regression.

At this thesis we tested daily returns from the period of 2010-2019 for four different indices to test January effect. Indices are OMX Small Cap GI, OMX Mid Cap GI, OMX Large Cap GI and OMX Helsinki GI. In all indices despite OMX Helsinki GI we had 2511 observation during period of 2010-2019. OMX Helsinki GI has 2153 observations.

The January effect is a stock market calendar anomaly in which stock returns peak in January. In previous research, the January effect has been linked to the effect in small-cap stocks. Because of the seasonal nature of the anomaly, the January effect has been found to contradict the efficient market hypothesis, as the high stock returns in January do not follow a random pattern but are predictable.

Tax and window dressing hypotheses are thought to be the main causes of the January effect. Investors will sell their loss-making shares in December, according to the tax hypothesis, in order to reduce their tax burden. According to the Window dressing hypothesis, institutional investors will sell loss-making shares in December in order to improve the performance of their investment portfolios for reporting purposes. Hypothetical trading will end in January, when stock prices will begin to rise, causing the stock market to experience a January effect.

The thesis' findings strongly suggest that the January effect occurs in the Finnish stock market. Especially when testing the OMXH Small Cap GI and OMXH Mid Cap GI indices. The January effect has been observed in the shares of small market value companies in particular. The January effect was also discovered to be stronger in early January.

**KEYWORDS:** Stock markets, calendar anomalies, January effect, behavioral finance.

**VAASAN YLIOPISTO**
**Laskentatoimen ja rahoituksen yksikkö**

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|---|---|
| **Tekijä:** | Drilon Maxhuni |
| **Tutkielman nimi:** | January effect in Finnish stock market 2010-2019 |
| **Tutkinto:** | Kauppatieteiden maisteri |
| **Oppiaine:** | Rahoitus |
| **Työn ohjaaja:** | Vanja Piljak |
| **Valmistusvuosi:** | 2022 **Sivumäärä:** 74 |

**TIIVISTELMÄ:**

Tämän pro gradu tutkielman tavoite on tutkia tammikuun ilmiön esiintymistä Suomen osakemarkkinoilla vuosina 2010–2019. Tammikuuilmiötä testattiin tarkastelemalla päivittäisiä logaritmisia osaketuottoja. Tutkimusmenetelmänä käytettiin pienimmän neliösumman lineaarinen regressio.

Tässä pro gradu tutkielmassa testasimme neljän eri indeksin päivittäisiä tuottoja ajanjaksolta 2010–2019. Indeksit, joita käytetään tammikuuilmiön testaamista varten ovat OMX Helsinki Small Cap GI, OMX Helsinki Mid Cap GI, OMX Helsinki Large Cap GI ja OMX Helsinki GI. Kaikista indekseistä on saatavilla 2511 havaintoa, paitsi OMX Helsinki GI. Tästä indeksistä on saatavilla 2153 havaintoa.

Tammikuuilmiö on osakemarkkinoiden kalenterianomalia, jossa osake tuottaa tammikuussa enemmän kuin muina kuukausina. Aikaisemmissa tutkimuksissa tammikuuilmiö on liitetty pienten yritysten tuottoihin niin, että pienet yritykset tuottavat tammikuussa enemmän kuin muina kuukausina. Tammikuuilmiö on ristiriidassa tehokkaiden markkinoiden hypoteesin kanssa, sillä tammikuun korkeat tuotot eivät noudata satunnaiskävelyä, vaan tammikuun tuotot ovat ennakoitavissa.

Verotus ja Window Dressing hypoteesin uskotaan olevan tammikuuilmiön vaikutuksen pääasialliset syyt. Sijoittajat myyvät verohypoteesin mukaan joulukuussa kaikki tappioliset osakkeensa vähentääkseen verotaakka, kun taas Window Dressing – hypoteesin mukaan institutionaaliset sijoittajat myyvät joulukuussa kaikki tappioliset osakkeet parantaakseen sijoitussalkkunsa tuottoa raportointia varten ja näin näyttää paremmalta. Näiden hypoteesien käyttö loppuu tammikuussa, jolloin osakekurssit alkavat nousta reilusti, jolloin osakemarkkinat kokevat tammikuuilmiön. Tämän takia tämä on ennakoitavissa ja syy siihen miksi tammikuuilmiö on ristiriidassa tehokkaiden markkinoiden hypoteesin kanssa.

Opinnäytetyön havainnot ja tulokset viittaavat vahvasti siihen, että tammikuuilmiö esiintyy myös Suomen osakemarkkinoilla. Erityisesti OMXH Small Cap GI ja OMXH Mid Cap GI indeksejä tarkastaltaessa. Tammikuuilmiön vaikutus on havaittu erityisesti esiintyvän pienten markkina-arvon omaavien yritysten osakkeissa. Tammikuuilmiön havaittiin myös olevan voimakkaampi tammikuun alussa.

**AVAINSANAT:** Osakemarkkinat, kalenteri anomaliat, tammikuuilmiö, behavioristinen rahoitus

## Table of contents

## Figures



## Tables

# 1 Introduction

Traditional financial theory describes the financial market as an efficient entity and the investors operating in the market as rational actors maximizing their benefits. In an efficient market, information is available to all investors, making it possible to make investment decisions based on information. In addition, the information is included in the prices of the securities, which is why the prices of the securities on the market are correctly priced. According to the efficient market hypothesis described above, an investor cannot make extra profits from the stock market, as an efficient market is always one step ahead of the investor. If the potential for excessive profits exists, an efficient market will be able to eliminate these opportunities quickly. (Fama 1970.)

In reality, however, the financial markets are not functioning as described above, and the market is experiencing inefficiencies and securities prices may be distorted due to over- or underreaction of investors. Investors have also been found to be driven by their emotions and other psychological factors rather than rationality. Indeed, behavioral financial theory has emerged alongside traditional financial theory to explain the irrational behavior observed in the market and the inefficiency of the market. Behavioral financial theory seeks to provide more humane interpretations of market and investor behavior that traditional financial theory cannot explain with its rigorous model. (Ritter 2003.)

Perhaps the best known of the anomalies is the January effect. The January effect refers to higher stock returns in January than in other months. The effect emerged significantly in the late 1970s, among other anomalies. The January effect was first observed in the U.S. market and later in several international markets. Connections have been observed between different anomalies, for example, the January effect has been found to occur in conjunction with the enterprise size anomaly and the turn of the month effect. This means that studies have found that the January effect is particularly prevalent in small-cap stocks, and that January's excess returns have been concentrated in early January. Several possible causes have been presented for the January effect, but none of the hypotheses has received unambiguous support. Of the hypotheses studied and most widely accepted is the tax-loss hypothesis. According to the tax-loss selling hypothesis, investors will sell their loss-making shares in December to minimize their taxation through the deductibility of capital losses. After the end of the tax year, the selling pressure will disappear and return the share prices to their equilibrium level, which in turn will cause high returns in January (Lynch, Puckett & Yan 2014). Although several studies suggest that the tax-loss selling hypothesis helps to explain the excess returns in January, it does not fully explain them. Portfolio rebalancing hypotheses have also been extensively studied, based on the temptation of institutional investors to modify their portfolios around the turn of the year. In some recent studies, the January effect has either disappeared from the market, or at least worsened. Similar observations have been made for other anomalies. On the other hand, some recent studies have also found that the January effect is still present. Anomaly studies are sensitive to the methods used, which partly explains the conflicting results.

According to the efficient market hypothesis, the development of security prices cannot be predicted in advance, but prices fluctuate randomly in the market. However, due to the January effect, an investor familiar with the financial markets and the January effect can earn extra income from the market by adjusting his investment activities to the January effect. Indeed, the January effect can be seen as a kind of manifesto against theories of traditional finance. If an efficient market were to overcome market irregularities, how is it possible that the January effect will continue to flow in the stock market, offering investors profitable January returns year after year? (Malkiel and Fama 1970.)

## 1.1 Purpose of the study

The purpose of this thesis is to study whether the January effect occurs in the Finnish stock market. The aim is to get the most up-to-date picture possible. The January effect has been studied extensively internationally but not so much in the Finnish stock market.

There are many reasons to this, that are presented later. The results of the thesis bring an interesting perspective with the geographical delimitation. The study also focuses on whether it is possible to limit the occurrence of the January effect to an effect occurring in the Finnish stock market in certain types of stocks.

## 1.2 Structure of the study

This master's thesis is structured as follow. Chapter 2 reviews traditional financial theory, followed in Chapter 3 by a review of the literature review on the January effect. Chapter four deals with asset pricing anomalies. Chapter 5 presents the methodology and data, after which the results of the study are comprehensively reviewed in Chapter 6. At the end of the study, in Chapter 7, conclusions are presented based on the results of the study.

## 1.3 Research hypotheses

The following research hypotheses were set for the study:

H0: The return for January is not significantly different from the return for other months
H1: The return for January is significantly different from the return for other months
H2: The January effect is significantly stronger in small companies
H3: The January effect occurs more strongly during the first two weeks of January than during the rest of the year

The occurrence of the January effect has been studied extensively in several different stock markets internationally. In the light of their results, most of the studies presented in this thesis have provided support for the occurrence of the January effect. In addition, e.g., Wahlroos and Berglund (1986) and Dahlquist and Sellin (1996) have found in their research that the January effect is present in the Nordic stock market. Therefore, based on previous research, it can be assumed that the results of this thesis also show the presence of the January effect in the Finnish stock market.

The January effect has been observed to be strongest in the first half of January and then to decline towards the end of the month. For example, Keim (1983) found that the January effect is more intense during the first five trading days of the year. Moller and Zilca (2008), on the other hand, found that the incidence of anomaly is strongest during the first two weeks. As the excesses according to the January effect have been observed in previous studies, especially during the first two weeks of January, it can be assumed that the daily income in the first two weeks of January observed in the thesis is higher than the monthly income in January.

Based on previous studies, it can be stated that the January effect is an anomaly affecting the shares of small companies in particular. For example, Moller and Zilca (2008) found that the smaller the share of a company, the stronger the January effect in the company's earnings per share. Corresponding results were also obtained e.g., Wahlroos and Berglund (1986) with Finnish data. As the January effect has been strongly linked to the effect observed in the shares of small companies in a previous study, it is assumed that the January effect is also observed most strongly in the shares of companies with a small market value in the shares listed on the Finnish stock exchanges.

# 2 Theory

## 2.1 Efficient market hypothesis

An efficient market is a market with objective estimates of the true values of investments. It is a certain degree of degree to which stock prices reflect all available and relevant information. The concept of market efficiency was introduced by Malkiel and Fama (1970), whose theory of an effective market hypothesis stated that an investor would not be able to perform better than the market because all pre-existing information is included in stock prices.

The central teaching of financial theories is to ensure that the market hypothesis is based on an assumption in order to invest in the market rationally. Barberis and Thaler (2003) say that the value of a security is equal to its base value if the agents are sensible and there is no Friction in the market. This is the sum of the expected future cash flow, where investors take all possible information about the information decisions and the discount rate is consistent. The hypothesis that actual prices reflect core values is an efficient market hypothesis. Investors often see a large number of failures, arbitrators who want the market to eliminate their influence.

Shleifer and Vishny (1997) state that when investors are rational, this suggests that obtaining surplus returns is impossible, as did Malkiel and Fama (1970). Thus, the efficient market hypothesis is the result of a balance in a market that is competitive among rational investors. However, the efficient market hypothesis is not entirely dependent on the rationality of investors. There are various cases where investors are not fully rational, but the market is projected to remain rational.

The economic efficiency of financial markets is today the theoretical basis of monetary and financial theory. This is because much attention is paid to the efficient market hypothesis, usually by examining the predictability of return on equity. According to

Lehmann (1990), there are two explanations for such predictable fluctuations: 1) market inefficiency and overreaction of stock prices are due to speculation, 2) predictability in the change in expected returns along with projected changes in the market. The significance of the predictable return on asset returns for market efficiency is unclear. Namely, this effect is declared by two competitive explanations. On the other hand, financial markets can be efficient and asset pricing theory considers foreseeable changes in expected returns. On the other hand, predictable volatility may reflect an excessive reaction of stock prices to speculation, or, in an inefficient market, it may reflect cognitive misconceptions among investors. When new information about a security enters the market, the response to the news should be quick and correct.

### 2.1.1 Forms of Market Efficiency

Fama (1970) divided market efficiency according to three conditions. The first is the effectiveness of weak terms, the second is the effectiveness of semi-strong terms, and the third is the effectiveness of strong terms. According to Fama (1970), weak conditions are met if stock prices include all the information about the past price development of the shares. Semi-strong conditions are met if the share prices contain all public information. Strong conditions, on the other hand, are met when share prices include both public and insider information. The efficiency conditions are reflected in the prices in such a way that the price-forming information mentioned in each efficiency condition cannot be used to help generate additional revenue in the future. For example, in the effectiveness of weak terms, old information cannot be used to generate additional returns because they are already reflected in the share price.

Fama (1970) also proposed three conditions under which information is fully reflected in stock prices and the market is thus efficient: 1) no transaction costs in securities trading, 2) all information is available to all market participants free of charge, and 3) the factors that affect market prices and are taken into account must be agreed by investors.

These conditions are sufficient for market efficiency, but not necessary. Often these do not materialize in practice.

### 2.1.2 Criticism of efficient market hypothesis

In his research, Jensen (1978) found that markets are efficient in relation to new information if this new information cannot be used to make a profit by trading in the subject of the new information. As there are transaction costs in the real-world market, Jensen's definition may leave some of the new information not reflected in prices, as the effect of the new information on the price is not sufficient to cover the transaction costs. (Jensen 1978.)

The aim of Grossman and Stiglitz (1980) in their research was to redefine an efficient market as a concept because they showed in their study that because information is chargeable in the market, prices may not fully reflect all available information. This is because there would be no incentive for market participants to obtain paid information, as if prices already reflect this information, they would not be able to make a profit with paid information. On the other hand, if all parties collectively failed to obtain paid information, market prices would not reflect this paid information and operators would have an incentive to pay for it in order to make a profit. (Grossman & Stiglitz 1980.)

After several articles presented the hypothesis of an efficient market in a critical light, Fama (1991) decided to revisit the topic in response to critics. Fama (1991) stated that the information and trading costs criticized in the studies of Jensen (1978) and Grossman et al. Instead, Fama (1991 presented a larger problem, the joint hypothesis problem, which addresses the potential flaw in the pricing model, such as the Capital Asset Pricing Model (CAPM).

Thus, any anomalies found in the investigations may be due to market inefficiencies, or the weakness of the pricing model and the division between them is unclear. Due to the common hypothesis problem, it is practically impossible to draw precise and precise conclusions about market efficiency, but the efficient market hypothesis is still valid as part of the study of market efficiency, as it provides an important theoretical benchmark for empirical research. (Fama 1991.)

Malkiel (2003, 80) summed up the discussion of the efficient market hypothesis by stating that the market cannot be fully efficient, and that human error is a necessary part of market functioning, but despite these, the market is significantly efficient in utilizing and reflecting information.

## 2.2 Random walk hypothesis

Random walk in economic theories means that all future changes in prices are random. Although staring at stock prices could convince you that there are some predictable factors in the time series, they are only statistical biases. Burton G. Malkiel, Professor of Economics at Princeton University, came to this conclusion and wrote A Random Walk Down Wall Street, among others. (Malkiel 2019, 142.)

Malkiel (2019) illustrated this statistical bias to his students by creating an imaginary $ 50 share, the price of which was determined by the coin tossed each day. From the clave, the share price rose by 0.5% and from the krona decreased by 0.5%. The students made the observation that the time series formed by the throws formed a graph resembling a normal stock price chart and even appeared to have certain cycles.

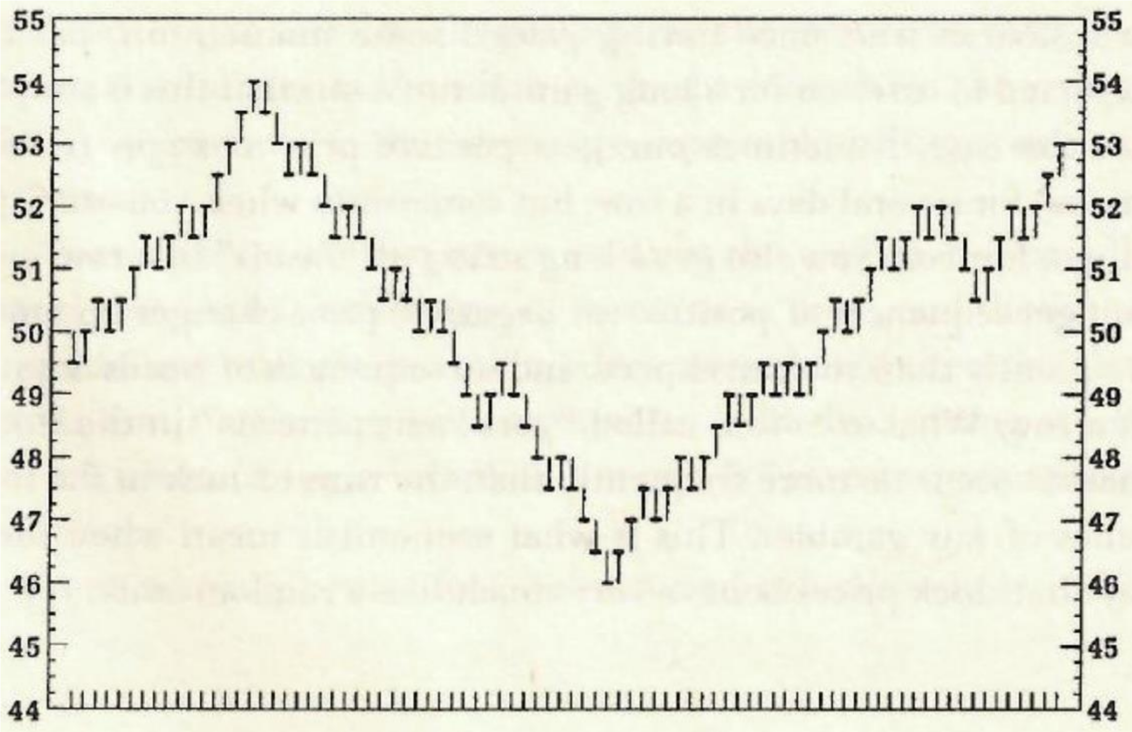


**Figure 2**. Hypothetical stock chart by coin flipping (Malkiel 2019).

Malkiel writes (2019) that what is crucial in these cycles is the lack of regularity. The fact that the episode would show an uptrend is no coincidence. He said that he had shown another similar chart made by a similar analyst to his friend, who thought that the company was giving a very strong buying signal. Disappointment was reportedly bitter when the information on how to make the chart was given. (Malkiel 2019.)

When throwing a coin, throwing a crown and a clave both have a 50% probability. Also, previous rolls do not affect the next roll in any way, so the next roll can always have the same probability on either side of the coin. This series is called a random expense in mathematics if it is obtained by a random method. In a mathematical sense, the stock price curve behaves just like this, with a few exceptions. Some stocks are experiencing a long uptrend, linked to long-term earnings and dividend growth. When this is taken into account in the calculations, it can again be observed that a rise and fall of a stock on a daily basis, as well as a coin toss, are equally likely. (Malkiel 2019.)

The importance of random walk in making investment choices is considerable. By random walk, Malkiel (2019) meant that because the choice is so difficult, it is better to own everything and get their average return. In other words, passive investment is active and technical, i.e., based on exchange rate movements, more profitable than investing in the long run.

## 2.3 Behavioral finance

Behavioral finance is a field of research that has emerged to complement the theory of finance, because traditional theories of finance have not been able to explain the inconsistencies, i.e., anomalies, in the market. Behavioral financing is based on the idea that not all investors in the market are rational maximizers of the expected benefits, as is assumed in traditional financing. (Ritter 2003.)

Traditional financing also assumes that if irrational players enter the market, rational investors will take advantage of the bad trading decisions made by these players, and thus no anomalies will arise. In behavioral financing, the idea is that there are not enough rational investors in the market looking for the mistakes of other investors to be able to cancel all trades made by irrational investors, and thus anomalies arise and market efficiency suffers. (Shleifer 2000).

In the field of behavioral finance, there are two important components on which research is based. The first element is the limits to arbitrage, the underlying idea of which is that it may be difficult, if not impossible, for rational investors to reverse the arbitrage caused by irrational operators by exploiting the resulting arbitrage. The second component is cognitive bias, which includes all the things that make an investor irrational. This division was first presented by Shleifer and Summers (1990, 19–20).

In theory, arbitrage means a certain surplus. In practice, however, all arbitrage cases involve risk, in which case arbitrage refers to an investment whose expected return is higher than the risk involved in the investment. (Ritter 2003.)

Although some market investors are rational and recognize arbitrage caused by irrational investors, the use of arbitrage is not risk-free for a rational investor (Shleifer & Summers 1990). In reality, virtually all arbitrage is risky, due to the fact that, unlike the textbook model, capital is required to exploit arbitrage if the arbitrator has to hold its position open for too long (Shleifer & Vishny 1997).

There are two types of risk to arbitrage. The first is fundamental risk, which means that, for example, when a share is sold short, a rational investor has the impression that the price of a mispriced share is falling. At the same time, when selling, a person should invest in the complete substitute of the share he or she has sold short in order to protect himself or herself from unpleasant (i.e., in this case, price-raising) news about the share's industry. In this short way, the seller would earn the value of the substitute as much as he loses in his short position. The problem, however, is that there are no complete substitutes available on the stock market, which means that the seller will not be able to fully hedge against the underlying risk. (Barberis & Thaler 2003.)

The second is the risk posed by irrational investors, noise trader risk, which means that in the short term a security's pricing error may worsen before it is corrected to its correct level. If a rational investor is willing to accept the possibility that the price of a security is not correct, he must also accept the possibility that the deviation from the correct price will increase further (Barberis & Thaler 2003,). An example is a short sale, where the transaction costs increase the longer the investor keeps his short position open. If a rational investor who has taken a short position has to wait a long time for the price of a security to return to the right level, he may be forced to close his position at a loss when the capital required for transaction costs runs out. (Shleifer & Summers 1990).

In addition to the mentioned risks, the problem may be that even rational investors may make mistakes in perceiving the correct price of the security, which makes the utilization of the arbitrage even more risky. Rational investors are aware of this and are therefore reluctant to take such large positions that the prices of mispriced securities would return to their correct levels. (Shleifer & Summers 1990.)

Extensive research shows that due to the risks of arbitrage, rational investors will not be able to return prices to the right level after the deviations caused by irrational investors, contrary to the efficient market hypothesis. This is also reflected, for example, in the emergence of the January effect, because if rational investors made effective use of arbitrage, the January effect would not be found. (Shleifer & Summers 1990.)

Psychologists have observed several patterns of behavior in people's behavior based on people's beliefs and preferences (Barberis & Thaler 2003). The following sections cover some of the most common mistakes people make in their investment decisions.

People tend to rely too much on their own abilities (Ritter 2003). This manifests itself in a number of different ways in the behavior of investors. Barber and Odean (2001) found that the more people trade, the less successful they are. In addition, they found that men traded more than women and were also less successful.

In connection with excessive credit for one's own abilities, people regret failed decisions if they have been exceptional in relation to a person's “ordinary” decisions. This means that if an experienced investor decides to invest in a different asset from his usual investment and the investment is not profitable, the investor will regret this decision more than if he had invested his assets as before, even if the losses were the same. If the investment had been made in a similar object in which the investor had previously invested, it would have been easier for the investor to blame bad luck on the losses. (Bodie, Kane & Marcus 2009.)

Representativeness means that people give too much weight to recent events in relation to the overall picture. This is reflected, for example, in the stock market, so that when stock returns are high for a long time, investors begin to see these high returns as normal. This is also due to the fact that when a company gives a good earnings announcement, the company's share price may still fall because investors' expectations have been overly optimistic. (Ritter 2003.)

Conservatism, the basic idea of which is the reluctance of people to change their own thought patterns and imaginations, is partly at odds with representativeness. This means, for example, that investors do not want to change their mind about a particular security, even though its returns have changed. Conservatism may appear as an anomaly when a company makes an earnings announcement, and the company's share price may react to this in another three months. (Barberis & Thaler 2003.)

Heuristics is a form of problem solving known in cognitive psychology. Different rules of thumb are a good example of heuristics designed to make people's decisions easier (Ritter 2003, 431). In behavioral finance, one of the best-known theories related to heuristic decision-making is the Prospect Theory of Kahneman and Tversky (1979). The idea of the theory is that people determine the perceived benefit in relation to gains and losses and not in relation to the absolute value of the outcome. In addition, the study found that the perceived disadvantage of a loss outweighs the perceived benefit of a similar profit (Kahneman & Tversky 1979). The following is a well-known graph of the relationship between losses and profit to the perceived benefit to the investor presented in the study by Kahneman and Tversky (1979).

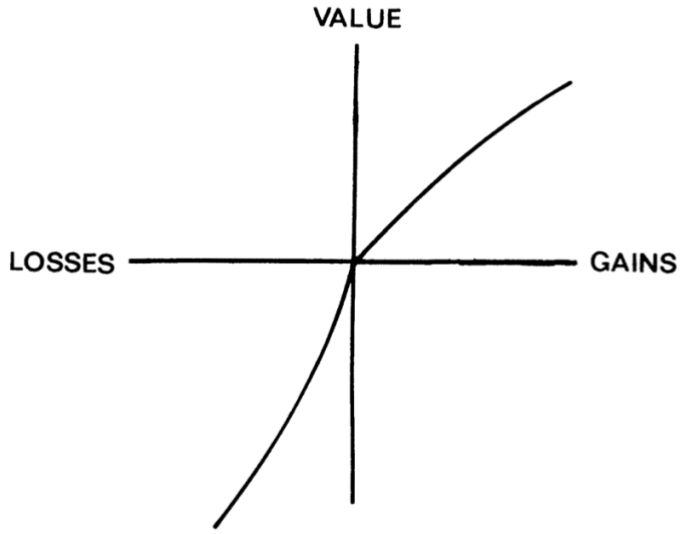


**Figure 2.** A hypothetical value function (Kahneman and Tversky 1979).

As can be seen from the figure 2, people, in this case investors, try to avoid losses to the last, while they are not willing to sacrifice as much for the same amount of profit. Thus, it can be said that investors are risk lovers if they are at a loss compared to the initial amount invested, while for profitable investments, investors are risk averseness. (Kahneman & Tversky 1979.)

As above, behavioral financing in this respect is much closer to the real world, as is Faman's (1970) hypothetical market hypothesis, which has investors as rational decision-makers.

## 2.4 Asset pricing models

In an efficient market, stock-related information is reacted quickly and correctly, so that the prices of various investments are close to the correct values. In the long run, the market is expected to remain in balance, although in the short run there may be under- and over-pricing. There are various models for valuing shares. The CAPM model and the ATP model have received the most research attention.

### 2.4.1 Capital asset pricing model

The CAPM, or Capital Asset Pricing Model, is a developed model for calculating the expected return on a portfolio and securities. The CAP model was developed by Wil-Liam Sharpe (1994) in the 1960s. In the 1950s, Harry Markowitz (1952) developed modern portfolio theory, according to which there is both unsystematic risk and systematic risk in the market. Unsystematic risk is due to company-specific risks, such as bankruptcy. Systematic risk is built, for example, on inflation. Only Market risk matters when non-systematic risk is diversified. The risk-free interest rate, market return and beta factor constitute the expected return in the CAPM model. The template can be written open as follows. (Fama and French 2004: 25-26.)

(1) $$E(R_i) = R_f + \beta_i\big(E(R_m) - R_f\big)$$

where, $E(R_i)$ = Expected return

$R_f$ = risk-free rate

$E(R_m)$ = Expected return of the market

$\beta_i$ = Beta

The risk-free interest rate often reflects government-issued bonds that are considered safe returns. The market risk premium, multiplied by the beta factor, is obtained by deducting the risk-free return from the market return. The beta multiplier tells you how much systematic risk there is in a stock. The beta factor can be calculated from the following formula. (Fama and French 2004: 28-29.)

(2) $$\beta_i = \frac{COV_{(R_i R_m)}}{VAR(_{R_m)}})$$

where, $COV_{(R_i R_m)}$= Measure of stock's return relative to that of the market

$VAR_{(R_m)}$ = Measure of how the market moves relative to its mean

There are many simple assumptions in the CAPM model. Meaning that the model does not always provide complete indicators for solving financial problems. Nikkinen, Rothovius and Sahlström (2002) present basic assumptions related to the CAPM model.

- There are no transaction costs in the market
- Investors can buy and sell any number of investment commodities
- There are no taxes
- In the market, the targets to be invested have been selected using Harry Markowitz's portfolio theory.
- No one dominates the market
- Short selling allowed
- The market can both invest and borrow at a risk-free interest rate
- The expectations of people operating in the market about the returns and risks of investment assets are uniform
- Every investment commodity can be bought and sold in the market

The CAPM model can be used to calculate the expected return on an investment instrument from market equilibrium when the basic assumptions mentioned above are valid. (Nikkinen et al. 2002). The mathematical formula of the CAPM model is shown in formula number 1.

### 2.4.2 Fama and French three-factor model

As with all asset pricing models, the risk model of Fama and French (2020) is often used to assess whether a portfolio or security produces an average return that is not due to the sensitivity of risk factors. The first factor is the market factor, the second is the size factor and the third is the value factor. To test whether a portfolio has generated additional returns that are not due to market, size, or value factors.

The Fama and French three-factor model can be written open as follow:

$$r_{p,t} = \alpha_p + \beta_{MKT,p} MKT_t + \beta_{SMB,p} SMB_t + \beta_{HML,p} HML_t + \epsilon_{p,t} \qquad (3)$$

where, $r_{p,t}$ = Expected return

$\beta_{MKT,p}, \beta_{SMB,p}\ ja\ \beta_{HML,p}$ = Sensitivity for market-, size- ja value factor

$MKT_t, SMB_t\ ja\ HML_t$ = market factor-, size factor- and value factor returns

$\alpha_p$ = Risk-free rate

There are many types of factors. Market factor, which is the market return minus the risk-free return. If the factor gets a positive value, it indicates that the market has outperformed a risk-free return, such as government bonds. The whole factor that is the return of small companies minus the return of large companies. If the factor gets a positive value, it indicates that small companies have produced more than large companies. The value factor, which is the return on growth companies minus the return on value companies. If the factor gets a positive value, it means that growth companies have outperformed value companies. (Fama and French 2020.)

### 2.4.3 Carhart four factor-model

Mark Carhart (1997) added a fourth factor to the Fama and French three-factor model, namely the momentum factor (UMD). Carhart employs Jegadeesh and Titman's findings in his fourth factor (1993). The monthly momentum losers are subtracted from the monthly momentum winners to arrive at the factor. The momentum phenomenon is based solely on technical analysis and refers to the tendency of up trending assets to continue to rise and, conversely, the tendency of sinking securities to continue to fall. Momentum has been found in both small and large equities, and it also influences other asset types in addition to securities. The duration of the momentum phenomenon is usually restricted to 3-12 months. If the stock has risen in the last 3-12 months, it is predicted to climb more in the future. Similarly, if a stock has decreased in the last 3-12 months, it is projected to fall further in the future. Winners will keep winning, while losers will keep losing. Because the momentum investor does not believe the market is totally efficient, the four-factor model does not support the efficient market hypothesis. However, due to the theory's coherence, this model is described in this thesis. (Carhart 1997.)

The Carhart four factor model can be written open as follow:

$$R_i - R_f = a_i + \beta_i(R_m - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 UMD + e_i \ , \tag{4}$$

where, $R_i$ = expected return
$R_f$ = the risk-free rate
$a_i$ = estimated alpha
$R_m - R_f$ = excess return of the market portfolio
SMB = the size factor (small minus big)
HML = the value factor (high minus low)
UMD = the momentum factor (winner minus loser)
$\beta_{1,2,3,4}$ = beta coefficients
$e_i$ = the random error variable

### 2.4.4 Fama and French five factor model

Fama and French (2015) intorduced five-factor model, which is an extended model of a three-factor model, the new factors of which are firm profitability (RMW, robust minus weak) and investment (CMA, conservative minus aggressive). In other words, shares of highly profitable firms perform well and shares of aggressively investing firms perform below average. (Fama and French 2015.)

The five-factor formula can be described as follows:

$$(5) \quad R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + \beta_2 SMB + B_3 HML + \beta_4 RMW + \beta_5 CMA + e_{i\,,}$$

where, $R_i$ = expected return

$R_f$ = the risk-free rate

$\alpha_i$ = estimated alpha

$R_m - R_f$ = excess return of the market portfolio

SMB = the size factor

HML = the value factor

RMW = firm profitability factor

CMA = investment factor

$\beta_{12345}$ = beta coefficients

$e_i$ = the random error variable

Fama and French (2015) state that the five-factor model is still better than the three-factor model they previously developed. The five-factor model explains 71-94% of the variation in expected stock returns in the U.S. stock market, according to researchers. However, the researchers note that the model cannot explain the returns on small stocks, which invest heavily and have low profitability. Another criticism is the value factor, HML, which turns out to be a rather insignificant factor in the model because other factors in the model together can explain the role of the value factor as an explanator of returns almost completely (Fama & French 2015.)

### 2.4.5 Arbitrage pricing theory

In 1976, Ross developed arbitrage pricing theory (ATP) as an alternative to the CAP model because ATP has more flexible assumption requirements. ATP uses fewer assumptions and is more difficult to use than the CAP model. The return and price of a share depend on the so-called factors that indicate the sensitivity of stock returns to risk factors. (Ross 2013.)

The arbitrage pricing formula can be described as follows:

(6) $$E_{(r_j)} = r_f + b_{j1}RP_1 + b_{j2}RP_2 + b_{j3}RP_3 + b_{j4}RP_4 + \cdots + b_{jn}RP_n$$

where, $E(r_j)$ = expected return

$r_f$ = risk-free rate of return

$b_j$ = sensitivity of the asset price to factor

RP = factor

Arbitrage describes a situation in which a risk-free return can be obtained by trading in various instruments such as shares and derivatives. In practice, action involves risk, although theory says otherwise. Arbitrage has a significant impact on market efficiency, as when pricing errors are exploited to reap the benefits of arbitrage, prices are corrected, and the market remains efficient. (Shleifer and Visny 1997: 35-36.)

According to Shleifer and Vishny (1997), arbitrage means the purchase of the same or substantially similar security from two different marketplaces at different prices. In this way, it is possible to take advantage of price changes in two or more similar securities in different markets. As a result of market inefficiencies, arbitrage exists and ensures that prices do not differ significantly from fair value in the long run. Many investors take advantage of market inefficiencies, as a result of which price differentials quickly disappear, and new equilibria are formed.

Theoretically, according to Shleifer and Vishny (1997), arbitrage does not require capital and there is no risk. When an arbitrator takes advantage of a cheaper security and sells a more expensive one, its future net cash flow is zero because it receives its profit in advance. Arbitrage has a critical role to play in the analysis of securities markets, as its effect is to bring prices close to fundamentals and to keep the market efficient.

# 3 Literature review

## 3.1 January effect

The January effect is a calendar anomaly in the stock market that emerges itself in the form of excessive stock returns in January. The average return on shares will be higher in January than in any other month of the year due to the anomaly. Numerous researchers have studied the January effect, which is one of the most well-known anomalies in financial markets. (Patel 2016.)

The January effect manifests itself in the stock market as a result of investors' stock trading. Investors will be eager to sell off the loss-making shares in their portfolios at the end of December, resulting in a drop in the prices of the shares that have been sold. Investors, on the other hand, will buy back the loss-making shares previously traded into their investment portfolios at the turn of the year. The January stock market will emerge as a result of January's buying behavior and the cessation of its sales. This will raise share prices and cause the January stock market to emerge. Lynch, Puckett, and Yan (2014). Private investors have an incentive to trade as described above because they can influence their own taxation at the end of the year. In Chapter 4.1.1, the causes of the January effect are discussed in greater depth.

The January effect dates back to the 1940s, when Sidney B. Wachtel (1942) discovered it while researching the price development of the Dow Jones Industrial Average Index between 1927 and 1942. Wachtel (1942) discovered that an increase in the index occurred at the turn of December to January in almost every year of the interval (11 out of 15 years). Wachtel (1942) was the first to investigate the January anomaly, though he did not use the term January effect in his research.

Rozeff and Kinney, who studied financial market seasonality in 1976, can be considered forerunners in the study of the January effect. An autocorrelation test was used to look at seasonal returns in the study, but the test found no evidence of higher January stock returns than in other months. However, when monthly stock returns were examined using parametric and non-parametric tests, January stock returns were statistically significantly higher than other months. The only exception was the period from 1929 to 1940. (Rozeff and Kinney 1976.)

The groundbreaking study of the January effect by Rozeff and Kinney (1976) has since been criticized. Small company shares have been criticized for receiving too much weight in the study because it was conducted using a balanced index rather than looking at the company's value. The January effect would not have been observed if the study had taken into account company market values, because it did not affect the shares of the largest companies in the term. This would have influenced the study's findings on the occurrence of the anomaly. (Haug & Hirschey 2006; Ritter 1988.)

Indeed, previous research has linked the January effect to a stock market anomaly involving small businesses. In his research, Keim (1983) discovered a link between the January effect and small company stock prices. From 1963 to 1979, he studied the monthly changes in stock prices on the New York Stock Exchange and the American Stock Exchange. The shares were divided into ten different portfolios based on the company's size, and the smaller the company's share, the better the January returns.

Other studies have since corroborated Keim's (1983) observations of the January effect as an anomaly for small businesses. When studying the January effect, Haugh and Hirschey (2006) used Fama-French factors. The size of the company was discovered to be a factor influencing the January effect, as shares of small companies had the highest January returns. When studying the US stock market, Moller and Zilca (2008) discovered a similar relationship between firm size and the January effect. Equities, which are shares of small companies with a market capitalization, had the best January returns.

The January effect has been observed in previous surveys of shares whose share prices had been declining before the turn of the year, in addition to small cap shares. Branch and Chang (1990), for example, discovered that stocks with lower prices in December generate high returns in January. In addition, low-priced shares showed returns consistent with the January effect. A strong January effect was overstated, particularly in low-cost stocks, which had fallen in December. For their part, Ortiz, Ramirez, and Vicente (2010) looked at the seasonality of returns on the Spanish stock market and discovered that the January effect is strongest in small-cap stocks with unprofitable share prices the previous year.

Within a month, the duration of the January effect has been observed to vary. The strongest stock returns in January were discovered to be in the first half of the month, after which the intensity of the effect faded. The occurrence of the January effect peaked during the first five trading days of January, according to Keim (1983). According to Moller and Zilca (2008), stock prices reach their highest returns in the first half of January, and as the month progresses, returns begin to decline.

The January effect contradicts Fama's efficient market hypothesis, which states that if the market is efficient, an investor cannot earn additional profits in the stock market (Fama 1970). If an anomaly exists in an efficient market that provides investors with excessive returns, the anomaly should be quickly eliminated through investor arbitrage. Arbitrage trading is the process of earning a risk-free return on the market without having to pay a risk-free interest rate. In efficient markets, rational investors seek to profit from anomaly revenues through arbitrage trading after detecting the anomaly's presence in the market for long enough that the trading causes the anomaly to leave the market. The January effect, on the other hand, has outlasted the efficient market hypothesis in the stock market, and investor arbitrage has failed to eliminate stock market anomalies. (Easterday, Sen & Stephan 2009.)

With an event study in which the zero day was set to the last day of the year, Klock (2014) investigated the relationship between the January effect and the fulfillment of weak conditions in the efficient market hypothesis. According to the efficient market hypothesis, investors cannot profit from the market by using historical data because future price movements cannot be predicted based on previous price movements. As a result, it should be impossible to forecast future January returns using returns caused by the January effect in previous years. The study looked at the rise and fall of loss-making stock prices from 2010 to 2012. Before the zero moment, the share prices were found to be unprofitable, but after the zero moment, the share prices became profitable due to the January effect. As a result of the January effect, the study discovered that weak conditions predicted by the efficient market hypothesis are not realized in the stock market.

Beladi, Chao, and Hu (2016) investigate whether the January effect and the redistribution of shares, i.e. the split, are related. The investigation covered the years 1926 to 2012, and the shares under investigation were those of publicly traded companies in the United States. The study discovered that there is a clear positive correlation between January and the positive earnings per share of the split announcement, and that the market reaction to these announcements is more positive in January than in other months. Split notifications, particularly for small businesses, showed the January effect. (Beladi et al. 2016.)

A study of calendar anomalies in emerging markets by Seif, Docherty, and Shamsuddin (2017) found no statistically significant January effect in only two of the markets studied, namely the Turkish and Hungarian markets. In contrast, returns in other markets were highest in December compared to other months. The tax hypothesis or the window dressing hypothesis, according to the researchers, cannot explain the unusually high returns in December.

Perez (2018) examined 106 different indices in 86 countries and domains, such as Europe and Hong Kong, in one of the most recent studies on the January effect. The study's data covered approximately 92.3 percent of the global market capitalization. The study's time period differed depending on the index under consideration, as all historical data for all indices was analyzed where possible, and data for the last 15 years for each index up to June 2017 was analyzed to improve comparability. The majority of the January effect is disappearing from the market, according to Perez (2018), though the study highlighted a few markets where the January effect is still present, such as the Nigerian market. The research even discovered a "reverse January effect," meaning that returns in January were significantly lower than in other months. In Estonia, for example, the Tallinn Stock Exchange's general index posted lower returns in January than in previous months (Perez 2018).

### 3.1.1 The best-know hypotheses to explain January effect

#### 3.1.1.1 Portfolio rebalancing hypothesis

Portfolio rebalancing hypotheses are theories based on institutional investors' desire to rebalance their portfolios at the end of the year. Lee, Porter, and Weaver (1998), Haugen and Lokonishok (1998) presented two hypotheses about portfolio redesign, the Window Dressing hypothesis and the Performance Hedging hypothesis. Sales can be considered the premise of the Window Dressing hypothesis. Portfolio managers will rebalance their portfolios at the turn of the year, according to the hypothesis, due to the reporting obligation. Portfolio managers will be required to provide detailed reports on the fund's shares at the beginning of the year, resulting in the sale of small, risky, and underperforming shares in December and the replacement of them with well-known and highly successful shares. This will give fund investors the impression that they are investing in a risk-free and safer mutual fund. Portfolio managers will replace shares bought in December with shares they believe will perform well in the future in January. Frequently, the shares are those that were sold in December. The Performance Hedging hypothesis is based on the portfolio manager's personal incentives. Portfolio managers are graded on a set of criteria, which influences their investment decisions. Portfolio managers will sell risky shares before the new year, rebalance their portfolios more in line with metrics, and then repurchase small risky shares they previously sold in January, which they believe will outperform the given metrics next year. Although Window Dressing and Performance Hedging start from slightly different places, they both lead to portfolio reorganization and are frequently grouped together in the context of the January effect. Furthermore, the term Window Dressing is frequently applied to Performance Hedging-style behavior.

Ritter and Chopra (1989) looked at the risk-return behavior of small firms in January using data from 1935 to 1986 to test the portfolio rebalancing hypothesis and other explanations. Based on the beta coefficient, which is a measure of the company's market capitalization and risk, they divided the shares into twenty portfolios. The shares were divided into five groups based on their size, and each of these five groups was further divided into four groups based on the beta coefficient. Ritter and Chopra (1989) look at how these portfolios perform at the end of the year. Small businesses outperformed the overall market in January, and high-beta small businesses outperformed low-beta small businesses. They also discovered that when using market value-weighted portfolios in January, there is no seasonality in the risk-return ratio. This response was consistent with previous weight-restricted portfolio research, implying that the risk-return seasonality observed in January is merely a reflection of small-cap stock behavior in January.

Based on the findings, Ritter and Chopra (1989) evaluated the various hypotheses for the January effect. They look at whether there is a link between the tax hypothesis status and the beta factor for the tax hypothesis. Whether the previous year's earnings per share were positive or negative determined the tax hypothesis status. Because the researchers found no link, they concluded that the tax hypothesis could not account for the January effect. The researchers acknowledged that the simple method they used might not be able to completely separate the effect of the tax hypothesis. They then look into the possibility of incorrect risk measurement. The hypothesis is based on the fact that small firms are more sensitive to market risk in January than in December or February because their beta coefficients are higher in January. The hypothesis was refuted by Ritter and Chopra, who discovered that small business returns are positive in January even when the market portfolio returns are strongly negative.

Finally, they put portfolio rebalancing hypotheses to the test. According to these hypotheses, in January, demand for equities should shift from low-risk to high-risk securities, and this shift in demand should result in high returns on risky securities. They discovered a link between the beta factor and the January returns. Furthermore, as previously mentioned, small company returns were positive in January, despite the market portfolio's strong negative return. According to the researchers, these findings backed up portfolio rebalancing hypotheses. (Ritter and Chopra 1989).

The tax hypothesis and the portfolio rebalancing hypothesis were compared as explanators of the January effect by Sias and Starks (1997). They looked at NYSE stocks from 1978 to 1992. Sias and Starks (1997) began to investigate the behavior of stocks according to their ownership base because the tax hypothesis relies on the behavior of private investors and the portfolio rebalancing hypotheses on the behavior of institutional investors. They compared the behavior of predominantly privately held shares to that of predominantly institutionally held shares using that data. They also look at the buying and selling behavior of private and institutional investors around the year 1991's turn.

The January effect is clearly stronger in equities held primarily by private investors, according to Sias and Starks (1997). Returns on privately held shares were remarkably low in December, even when the company size remained constant. Furthermore, in January, the average return on privately held shares was significantly higher than the average return on institutionally held shares. As a result, the findings backed up the tax hypothesis.

Both winning and losing shares, which had a positive return the previous year, showed the same pattern. The results of the losing shares add to the tax hypothesis's credibility. The winning share results are more ambiguous, as the January effect was also particularly strong in privately owned shares, contradicting the tax hypothesis. Private individuals sold both winners and losers during December, according to trade data from the turn of the year 1991. (Sias and Starks 1997).

The winning shares held by institutional investors outperformed those held by private investors in late December, and winning shares held by institutional investors outperformed winning shares held by private investors in early January, proving portfolio rebalancing hypotheses. The portfolio rebalancing hypothesis was also supported by the trading data, with institutional investors being net buyers of winning shares in December 1990. However, the overall findings suggested that in January, private investor behavior was a more significant explanatory factor than institutional investor behavior. (Sias and Starks 1997).

Lee, et al. (1998) were the first to attempt to distinguish the Window Dressing and Performance Hedging hypotheses in an empirical study using data from 1976–1993. The detailed reports on the shares held by the funds underlying the Window Dressing hypothesis are prepared for mutual funds based on the tax year, and more than 60% of U.S. mutual funds have a tax year that does not coincide with a calendar year. They divided the data into subperiods on the basis of a study published by Keim (1983), as the study raised the January effect to a much more significant and well-known phenomenon than previous studies. Window Dressing limits the opportunities to take advantage of the January effect, as it will require a reduction in small stocks in the portfolio during December, while taking advantage of the effect would require the acquisition of small stocks in December. One solution is to choose a tax year for the fund that differs from the calendar year, allowing both Window Dressing behavior and the January effect to be exploited. When comparing periods before and after the 1983 calendar year, the number of funds opting for a different tax year had increased significantly, and the number of funds opting for a different calendar year had a significantly higher percentage, especially for funds focused on small businesses. Comparing the changes in funds to the occurrence of the January effect, the researchers conclude that Window Dressing cannot be behind the January effect.

In addition, Lee, et al. (1998) compared January returns between two portfolios, which were divided according to whether or not the tax year of the portfolio funds was a calendar year. Because Performance Hedging behavior is independent of the tax year, as portfolio managers bonuses are paid on a calendar year basis, portfolio returns should not differ. On the other hand, because Window Dressing behavior is tax year-dependent, portfolio returns should be different.

The researchers did not find statistically significant differences in portfolio returns and also concluded from this that Performance Hedging is a more likely cause of the January effect than Window Dressing. In addition, researchers seek to distinguish hypotheses by examining the returns of funds after the tax year. According to Window Dressing behavior, funds would buy risky small stocks again after the tax year, raising the funds' returns in the month after the tax year. However, the tax year was not relevant to the next month’s earnings, which further suggested that the Window Dressing hypothesis was not true.

In their study, Chen and Singal (2004) questioned the hypothesis. Because the tax and portfolio rebalancing hypotheses predict similar returns behavior, separating the effects by looking at January returns is difficult. Chen and Singal (2004) got around this problem by looking at both January and June-July returns. The idea is that the funds will be required to publish a statutory half-yearly report. If funds restructure their portfolios, stock prices should reflect this in June-July, and because the tax hypothesis is unaffected during the summer months, the effect would be solely due to portfolio rebalancing. On the other hand, Chen and Singal (2004) found no large positive returns in July on the 1993–1999 data, implying that the January effect is not due to portfolio rebalancing. Furthermore, large company returns in July were higher than small company returns, contradicting the portfolio rebalancing hypothesis. A third discrepancy is that Chen and Singal (2004) mention a low volume of trading during the summer months, whereas the portfolio rebalancing hypothesis would require a large volume of small-company shares.

#### 3.1.1.2 Tax-loss selling hypothesis

In studies on the January effect, the tax-loss selling hypothesis is often linked to private investors. According to the tax-loss selling hypothesis, private investors seek to influence the amount of taxation imposed on them by trading in shares. At the end of the year, private investors sell their loss-making shares so that they can realize their losses in the tax year through a loss-making sale and thus reduce the amount of tax on them. (Lynch et al. 2014.)

Already Wachtel (1942) speculated that behind the rise in the value of shares in January was the efforts of investors to influence the amount of taxation imposed on them. According to him, the January effect is the result of changes in the price of shares that have been subject to a tax-based sale. At the end of the year, investors will sell their loss-making shares, which will cause the prices of those shares to fall. However, the sale of shares that were sold at the end of the year will stop at the turn of December into January, as the tax benefits have already been earned through the December share sale. In January, stock prices will begin to return to their correct level after the sale of them ends. Thus, Wachtel (1942) argued that the excess returns in January were due to the return of the market to its normal state.

At the end of the year, the tax-based sale of shares is targeted at loss-making shares whose prices are already low. The tax-based sale of shares by investors will already cause the loss-making share prices to fall further. At the turn of the year, there will be a turning point in investors' operations, as at the turn of the year a new tax year will also be introduced, when investors will no longer have to realize their losses due to tax-based reasons. In this case, the prices of shares that faded before the turn of the year will return to their normal level after the slump. With the rise in share prices, there is a January effect in the stock market. (Fountas & Segredagis 2002.)

The realization of losses in December will give investors a clear tax benefit. If they waited for the sale of the loss-making shares until January, the tax benefits from the sale would not be realized until the end of the following tax year. By selling their loss-making shares as early as December, investors can take advantage of their tax deductions during the current year without having to carry forward tax benefits to the following year. (Poterba & Weisbenner 2001.)

The tax hypothesis explaining the January effect has received widespread attention in previous research on the January effect. Grinblatt and Keloharju (2004), among others, studied the tax-based sale of shares in Finnish shares between 1996 and 2000. The study examined the tendency of investors to realize their profits or losses around the turn of the year. Investors were found to be operating in accordance with the tax hypothesis, as they were found to sell loss-making shares off their portfolios, especially at the end of the year.

Support was also found for the tax-based trading of shares towards the end of the year, e.g. in a study by D’mellon, Ferris and Hwang (2003), they also found that investors were selling a large number of shares at the end of the year, the sale of which made it possible to realize tax losses. In addition, the investigation revealed that there was a change in investors' trading at the turn of the year, as at the turn of the year investors were found to be selling profitable shares instead of losses. When the sale of the winning shares was left to the next half of the year, investors were also able to reduce the previous year's tax burden.

Although the tax-loss selling hypothesis is often linked to private investors in connection with the January effect, institutional investors can also accelerate the emergence of the January effect through a tax-driven share transaction. Sikes (2014) examined whether the tax-based trading of shares by institutional investors affects the occurrence of the January effect. The study divided institutional investors according to whether their activities encourage tax-based stock trading. Institutional investors engage in tax-based stock trading driven by their clients' preferences and requests. According to the study, institutional investors will also sell tax-based shares at the end of the year, thus contributing to the January effect. Institutional investors were found to realize their losses in the last quarter of the fiscal year with significantly higher share sales than in previous quarters.

#### 3.1.1.3 Window Dressing hypothesis

The Window dressing hypothesis involves trading shares similar to the tax hypothesis of private investors. Like private investors, institutional investors will be selling off their loss-making stocks as the year draws to a close. However, institutional investors are not motivated by tax-related reasons, but by their efforts to make their own investment portfolios more successful for year-end reporting. The performance of institutional investors over the past year appears to be more productive when they sell loss-making stocks out of their portfolios before year-end reporting. The increased sale of loss-making shares will cause the value of the shares to decrease until the sale of the shares ends at the turn of December, when the share prices will start to rise again. The January effect has arisen in the stock market with trading. (He, Ng & Wang 2004.)

Institutional investors manipulate their portfolios to make their operations in the market appear successful in the light of earnings reporting. The sale of loss-making shares and the purchase of profitable shares are both ways to manipulate the portfolio more efficiently in the light of public reports. The operation according to the Window dressing hypothesis can be seen as a way for professional investors to improve their own investment portfolio. (He et al. 2004.) The investment behavior of institutions according to the Window dressing hypothesis is an agency problem related to the activities of institutional investors that arises between institutional investors and their clients. The agency problem is the result of the efforts of institutional investors to create a distorted picture of reality with the most productive portfolios. (Sikes 2014.)

He et al. (2004) seeks to detect differences in the behavior of institutional investors at the end of different calendar quarters. Institutional investors were classified on the basis of whether they invest mainly in their clients or in their own funds. For example, banks and life insurance companies were classified in the first category, while, for example, pension funds, foundations and universities were considered to invest primarily in their own funds. The study found that institutional investors who invested mainly in their clients' funds were more likely to rely on the window dressing hypothesis than institutional investors who invested their own funds primarily. Institutions investing in external funds succumbed to improving their investment portfolios because they believed that a more profitable investment portfolio would increase their customer base. In addition, the window dressing hypothesis of institutional investors was found to be stronger at the end of the last quarter of the year than at the end of the previous quarters. The window dressing hypothesis at the end of the year puts pressure on the January phenomenon. (He et al. 2004)

The tax-loss selling hypothesis and the window dressing hypothesis have gained the oldest foothold in previous studies as the main factors explaining the January effect. In addition, in the previous literature, hypotheses have often been described as mutually exclusive. However, in the light of the January effect, the operation according to both hypotheses causes a similar movement in share prices. In both hypotheses, the sale of shares at the end of the year is targeted at loss-making share prices, which will become increasingly unprofitable at the end of the year as a result of the sale. In January, prices will start to rise after sales have ceased, generating high January returns for the market. As operations according to the two most popular hypotheses cause the market to behave similarly, those who have studied the January effect have had difficulty determining which of the January effect is observed in the stock market. (He et al. 2004.)

In their study, He et al. (2004) found that tax-loss selling, and window dressing hypotheses are not mutually exclusive underlying the January effect. They found that the January effect in the price of shares held by private investors was due to the tax - loss selling hypothesis. At the same time, however, the January effect of the stock market was partly explained by the window dressing hypothesis of institutional investors. Thus, the two hypotheses that strongly influenced the January effect may be valid in the stock market simultaneously without being mutually exclusive.

Lynch et al. (2014) study the effect of institutions' investment behavior on January share prices. The study observed the trading of shares by institutional investors in 1999-2005. Trading was monitored around the turn of the year, as trading in shares was reviewed during the last and first ten days of the year. The January effect was found to be strongest in equities that were not traded by institutional investors at the turn of the year. Thus, the activity of private investors was found to be the main source of the January effect instead of institutional investors. The activity of institutional investors according to the window dressing hypothesis was found to have a small effect on the emergence of the January effect, but in a large picture the effect of institutional investors on the emergence of the January effect was quite small compared to the role of private investors.

#### 3.1.1.4 Information hypothesis

Barry and Brown (1994) investigated the relationship between firm size anomaly and available information by examining the producer of NYSE shareholders between 1931 and 1980. As a measure of the information available, they used the length of the company's listing period. They found that this rough measure of available information is strongly related to the enterprise size anomaly and is able to explain at least part of this anomaly. However, the effect of the listing period was independent from January.

Bhardwaj and Brooks (1992) examined the returns of shareholders in neglected firms. Failure to do so suggests that these companies are less viewed by analysts, journalists, and institutional investors, leading to asymmetric information between investors and corporate management and insiders. Asymmetric information, in turn, leads to higher equity risk and higher returns through a risk premium. In their study, Bhardwaj and Brooks used NYSE and AMEX shares as data, and from 1977 to 1988. Researchers used the number of analysts investigating the share as a measure of negligence. The researchers found that the premium for non-compliance occurred mainly in January. However, when the share price was taken into account, the impact diminished significantly, and scholars considered the share price to be the most significant explanatory factor for January's high returns.

Chen and Singal (2004) also questioned the information hypothesis in their study. According to them, the hypothesis would require high returns for small companies also in April, July and October, as companies are required to provide quarterly reports. But researchers have already noticed that there are no high returns in July when examining the portfolio rebalancing hypothesis. The information hypothesis would also require a smaller trading volume in small-cap stocks in December as investors await new information in January. That is, the trading volume of small stocks should be higher in January than in December and higher in July than in June. However, in the study by Chen and Singal (2004), the volume in December was even higher than in January.

It has also been suggested that the January effect would be related to insider trading. Underlying the hypothesis is the idea that behind the excess returns in January would be compensation for the increased risk of trading with informed investors, insiders. Insiders in small companies are expected to have more non-public information at the turn of the year, and thus at the turn of the year, outside investors have the potential for large losses in the stock market. Seyhun (1988) studied the impact of insider trading on the January effect using the Security and Exchange Commission database on insider trading between January 1975 and October 1981. The data consisted of 790 companies listed on the NYSE and AMEX, of which 21 did not report insider trading during the review period, so 769 companies were ultimately analyzed. The research showed that some insiders in small businesses accelerated their share purchases by December, while those intending to sell delayed their sales to January to take advantage of the January effect. This suggested that some insiders in small businesses saw the January effect as a revenue opportunity. However, looking at insider trading in January as a whole, it could be concluded that the price pressures in January are not due to insider actions and insider trading activity will not increase significantly in January. Consequently, the actions of insiders and the resulting risk compensation could not be attributed to the January effect.

Hillier and Marshall (2002) investigated the tax hypothesis and the impact of insider trading on the January phenomenon on the London Stock Exchange with data from 1986-1997. Researchers also found a significant January phenomenon in the UK. However, the phenomenon did not occur regularly every year, and in 1991 there was even a reverse January effect with remarkably low returns. The effect occurred in the UK regardless of the size of the company. In the UK, the tax year ends on the fifth day of April, so the tax hypothesis cannot explain the excess returns in January. However, the researchers found significant excess returns in the 20-day period after the tax year, although the January effect was observed regardless of the size of the company. However, the effect of the January effect was more significant than the effect under the tax hypothesis in April. The combined effect of the 20-day period following the end of January and the tax year covered an average of 90% of the annual return on shares. For insider trading, data were only available from 1991 onwards, but the findings were largely the same as in the Seychun (1998) study. Insiders bought more of their own shares than usual in December and correspondingly sold less than usual. However, this was not found to be related to the excess returns in January.

Kim (2006) examined the relationship between information and the January phenomenon from a slightly different starting point. He provided a risk-based rational explanation for the phenomenon by proposing a two-factor model for calculating returns that included a market risk factor and a risk factor related to information uncertainty. The risk factor proposed by Kim (2006) was related to the uncertainty of return information caused by the volatility of returns. When return information is volatile, investors have greater uncertainty about a company's future returns, and through this, investors also face greater risk. When the actual earnings information is finally released, the likelihood of unexpected return surprises, positive or negative, is higher. Thus, investors will demand higher returns in the next period from those companies with greater variability in return forecast errors.

#### 3.1.1.5 Other reasons

Keamer (1994) began to look for an explanation for the January effect of macroeconomic factors. He developed a five-factor equilibrium model for modeling returns. The yield differential between the company's bonds and government bonds was used as the bankruptcy factor, and the yield spread between government bonds and short-term, zero-interest Treasury Bills was used as the maturity risk factor. Among the macroeconomic factors, the inflation factor and the consumption growth factor were included. The fifth factor in the model was the stock market factor. For estimation and testing, Kramer (1994) used 20 years of data from January 1970 to December 1989. In his data, Kramer observed a clear January phenomenon and, testing different equilibrium models, explained. In fact, the seasonal multifactor model eliminates the significance of January returns, and Kramer said this provided strong support for the impact of macroeconomic seasonality on the January effect of low-priced equities.

Bhardwaj and Brooks (1992) examined the relationship between the difference between the share price, transaction costs, and bid and ask offers to the January effect. The study covered the shares of NYSE and AMEX from 1967 to 1986. They found that the January effect was mainly related to the share price and not the company size. When the different transaction costs of low-priced and high-priced stocks were taken into account, in the period 1982–1986 after the transaction costs, high-priced shares dominated the low-priced shares at all investment horizons between one day and two years. Significant negative returns were generally observed for low-priced stocks, and the opposite was true for high-priced stocks. However, the results were time dependent. Using the 1982–1986 estimates of transaction costs, low-priced stocks performed better than high-priced stocks, taking transaction costs into account for the period 1967–1976. In the next ten years, after the January effect was observed, the situation was the opposite. The unconnectedness of informed investors to eliminate the excess returns on low-priced stocks in January, according to the researchers, is explained by the potentially high transaction costs and the bias in these returns due to the difference between bid and ask offers.

Clark, McConnell, and Singh (1992) came to a different conclusion in their study. They examine the extent to which there is seasonal variation in the difference between bids to buy and sell shares. Clark, et al. also investigated whether this fluctuation can explain January's excess returns. The data of the study consisted of the monthly returns on NYSE shares in 1982-1987 and the relative and absolute difference between the bids and offers at the end of the month. A random purchase of 520 shares was used in the study. Yes, the researchers found seasonality in both the relative and absolute difference between bids and offers, especially in low-priced stocks, and the phenomenon of January, especially in low-priced stocks. However, they did not find a correlation between the changes in the difference between January yields and bid and ask offers.

Rogalski and Tinic (1986) suggest that the excess returns observed in January were due to errors in risk measurement. According to them, the problem with previous studies was that these assumed that risk would remain constant throughout the year, even though financial market equilibrium models do not require such an assumption. They studied the relationship between returns and risk with data from 1963–1982 and found that the beta ratios for small stocks increased in January. Thus, they did not see the abnormally high returns in January at all as abnormally high returns, but as compensation for the higher risk. However, Ritter and Chopra (1991) rejected the hypothesis, as they found positive returns for small firms in January even when the return on the market portfolio is strongly negative.

One explanation has been provided for the missing risk factors in the models. Seyhun (1993) studied the January effect using stochastic dominance with data from 1926-1991. The results showed that the January returns of small companies dominated other size-based portfolios as well as weight-restricted and market-weighted indices. Similarly, January returns in all portfolios dominated other months returns with first-degree, second-degree, and third-degree stochastic dominance. According to Seyhun (1993), the results also suggested that the phenomenon was based on either hypothesis inconsistent with market efficiency, such as the tax hypothesis and portfolio restructuring hypothesis, or explanations based on differences in transaction costs and bid-ask spreads.

Several studies, including Lakonishok, Shleifer & Vishny (1994) have eroded the basis and credibility of efficient markets by making observations of abnormal returns, or anomalies, that cannot be explained by theories. In this study, anomalies refer to stock market indicators that result in higher-than-average returns on equity portfolios. The B/M anomaly reflects the historically better average return on equities of high B/M shares.

# 4 Asset pricing anomalies

## 4.1 Halloween effect

The Halloween effect, also known as the Sell in May anomaly, is a recurring pattern in stock returns in various stock markets around the world. The effect refers to the asymmetry of stock market returns during a calendar year; the stock market performs better in the six-month period constrained by early November and late April than in the six-month period between early May and late October. In a perfect market, such an asymmetry should not occur, nor in a capital market that meets poor efficiency criteria. (Bouman & Jacobsen 2002.)

The interest in the Halloween effect is due to two factors in particular. Firstly, whether the market is efficient and, secondly, whether a potential shortfall in market efficiency can be exploited by systematically earning excessive returns through an investment strategy based on the Halloween effect. The effect was first studied, and its existence confirmed by Bouman & Jacobsen (2002). Since then, the topic has naturally been of interest to researchers and new results have been presented for and against it. In addition, the studies have provided a number of assessments of what explains the existence of the effect in the absence of an exhaustive explanation.

Also in their recent study, Zhang & Jacobsen (2013) examined the seasonal nature of the stock market extensively. With more than 300 years of data, researchers show that the Halloween effect has been present in the stock market for almost the entire existence of the stock market itself. Over the ten-year investment horizon, the investment strategy based on the Halloween effect has won the market in nine out of ten cases throughout the period under review. The study also shows that July and October are the worst months for investors. In addition, it is observed that the January effect did not appear until around the middle of the 19th century.

In a recent study, Baur (2013) finds an autumn effect in the gold market that may have something to do with the occurrence of the Halloween effect. According to the results, the change in the price of gold is statistically significant and positive only in the autumn (September-November). The explanation for this is the presence of autumn in the historically turbulent period in the stock market. Investors are shifting their positions to gold as a safe haven, which will increase demand and raise prices while causing stock prices to fall. The same will happen in the winter, but vice versa, strengthening the stock market. As a result, the Halloween effect is also intensifying. The study raises the question of whether, for example, an annual rotation could be made between shares, risk-free interest rate and gold, earning significant excess returns.

Lucey & Zhao (2008) use their own data to find that the January effect has a significant effect on the existence of the Halloween effect. If the January anomaly is controlled, the existence of the Halloween effect is no longer statistically significant. However, researchers find that the Halloween strategy has a fairly good market timing ability in predicting the winter market (bull market) and the summer market in about 70% of cases correctly. According to them, the January effect is explained in particular by the January and corporate size anomalies.

## 4.2 Turn of the month effect

The turn of the month effect means that the average return on shares is higher around the month-end than on other days. The effect has been observed internationally in several stock and derivatives markets. The effect was discovered by Ariel (1987) when studying the cumulative earnings of shares with data from 1963-1981. He divided the month into two parts, the first of which began on the last day of the previous month. The results were surprising, as the returns for the second half of the month were in fact negative for both the weight-restricted and market value-weighted index and the results were statistically very significant. In the weight-restricted index, the cumulative return on the first 9 trading days was 1.411% on average, while the cumulative return on the last 9 trading days was -0.21%. Also, during the four subperiods, the return in the first half of the month was higher than in the second half of the month.

Lakonishok and Smidt (1988) studied the turn of the month effect with the DJIA (Dow Jones Industrial Average) data from 1897–1986. They found the effect to be particularly strong between days -1 and 3 (-1 means the last trading day of the month and 3 the third trading day of the month). The cumulative return for these four days was 0.437%, while the return for the average four-day period was only 0.0612%. The results observed were statistically significant. The return at the turn of the month also exceeded the average monthly return, which was 0.349%. In other words, turn of the month, DJIA's return was in fact negative. Between days 5 and 9, the average daily return was -0.001% and between days -5 and -9, -0.032%. The results were also consistent across subperiods.

Boudreaux (1995) studied the turn of the month effect in seven stock markets. The stock exchanges in Denmark, France, Germany, Norway, Singapore / Malaysia, Spain and Switzerland were included in the study. In the study, a period of five days (-1 to 4) was defined as the turn of the month The study was conducted with data from 1978-1992. A statistically significant the turn of the month effect was observed in the Danish, German, and Norwegian stock markets. An inverse effect was observed in Singapore / Malaysia, with yields statistically significantly lower at the turn of the month. For countries other than those mentioned, yields were higher at the turn of the month, but the results were not statistically significant. The results were similar when January returns were excluded to eliminate the January effect.

Ziemba (1991) found that the turn of the month effect occurred in Japan a week earlier than in the rest of the world. What is interesting about this observation is that in Japan, most wages are paid for this at the same time. Thus, Ziemba's results would support the idea that the turn of the month effect is due to an increase in liquidity.

Ogden (1990) proposed a liquidity hypothesis as the cause of the phenomenon. The month change is a typical payment date in the United States for salaries, dividends, and interest on loans, among other things. Thus, the majority of investor income is timed to the end of the month, while expenses are evenly distributed throughout the month. Through this, the investor needs cash and liquid funds and to minimize transaction costs, invest in illiquid shares only when the cash flow is large enough. As investors' cash is usually highest at the turn of the month, demand for shares is also at its highest at the turn of the month. That is, in the months when the liquid assets in the economy are at their highest, the turn of the month effect should occur at its strongest, and in the months when the liquid assets in the economy are at their lowest, the effect should not occur. As monetary policy affects liquid assets, monetary policy should also affect the turn of the month effect. (Ogden 1990.)

Ogden (1990) examined the values of the market value-weighted index and the weight-limited index between 1969 and 1986 to determine the effect of monetary policy on the turn of the month effect. The results obtained by Ogden supported the hypothesis, income transfers during the turn of the month at least partially explained the turn of the month effect. The high returns at the turn of the month were only noticeable in the months of loose monetary policy; during the tight monetary policy, the returns at the turn of the month were even worse than the average returns in other trading days of the month.

## 4.3 The day of the week effect

The weekday effect refers to the observation that stock returns at the beginning of the week, especially on Monday, are worse than on other days of the week. This seasonal variation has also been observed in the stock markets of many countries, including Finland. The explanation for the weekday effect is, among other things, the timing of the publication of bad news about companies on Friday after the market closed, which is reflected in the fall in the exchange rate on Monday.

Keim & Stambaugh (1984) studied the weekday effect with more extensive data. Their research covered the years 1928-1982, and their data also included a wider range of stocks than in previous studies. The noteworthy value of the study was that between 1928 and 1952 the NYSE was also traded on Saturdays. Monday's returns were significantly negative throughout the review period. During the short weekend period (1928-1952), Monday’s returns were even slightly more negative than in the final period. In the initial period, Saturday's returns were remarkably high, up to twice as high as the next largest, Wednesday. Friday's returns were lower in the initial period, when the stock exchange was also open on Saturdays, than in the final period of the long weekend. In fact, Friday’s returns were the second lowest in the initial period right after Monday. In the closing period, Friday's returns were clearly higher, so the high returns occurred on the last trading day, regardless of whether the day was a Friday or a Saturday.

Keim & Stambaugh (1984) also studied the effect of firm size on the weekday effect with data from 1963-1979. They formed 10 portfolios of all NYSE and AMEX shares by size and found Monday returns to be regularly negative across all portfolios. Although the Monday returns of the different portfolios could not be considered identical, no systematic link was found between the size of the company and the Monday returns. In addition, the average return on all portfolios increased as the week progressed, and Friday’s returns were the highest on average. However, as the week progressed, rising returns were evident in small-cap stocks, and as a result, Friday's high returns were strongly dependent on the size of the company.

In a more recent study, Pettengill (2003) observed a change in the weekday effect for large firms. First, it was found that Monday's returns for large companies were no longer significantly lower than other days' returns. Next, it was found that Monday’s returns for large companies were no longer negative. Eventually researchers found that the returns of large companies on Monday were even higher than the returns of other days.

For small businesses, the same was not observed, and revenues remained high on Fridays and negative on Mondays. One explanation for the effect is the reduction in transaction costs, which allows for arbitrage against the weekday phenomenon.

The possible causes of the weekday effect can be divided into four categories. The first relates to statistical errors. It has been argued that the observed weekday effect is the result of appropriate data mining. However, studies with several different data, different markets and different methods suggest that this explanation is incomplete. It has also been suggested that the results may be due to the use of erroneous methods. Tests that assume returns are normally distributed are often used, although it has been found that earnings per share do not follow a normal distribution. However, the weekday effect has also been observed with methods that do not require an assumption of a normal distribution of income. (Pettengill 2003.)

The second category relates to market microstructures. The market is not frictionless, and market organizations can lead to even rational reactions to seasonal regularities in prices. Fama (1991) noted that on Monday, average returns differ from other days by less than the typical bid-ask spread of a single share, and thus the effect can be explained by market microstructures. An explanation has been sought, for example, for the delay between trade and payment and for transaction costs, but the results have been very mixed. (Pettengill 2003.)

The third category relates to information flows. In an efficient market, prices should react quickly to new information. If the market-relevant information flow follows a clear weekly formula, it can also be assumed that the return on shares will follow a regular formula. The impact of information flows has been studied at both the micro and macro levels. At the micro level, researchers have sought to find regular formulas, for example, corporate dividends. At the macro level, issues such as the timing of monetary policy releases have been studied. For example, it has been suggested that companies tend to delay the publication of bad news over the weekend to avoid confusion in the market.

The effect has been observed but attempts to link it to the weekday effect have only been successful partly. In addition, it has been found that, for example, dividend and income releases explain only a small part of the weekday effect. The fact that the weekday effect consists of a large proportion of securities earning small negative returns, rather than the fact that few securities earn large negative returns, also speaks against the micro-level information effects. In the case of company-specific negative news, the effect should be reversed. Indeed, studies have found that macro-level news has a greater impact than company-specific news. (Pettengill 2003.)

The fourth category deals with the behavior of both private and institutional investors. It is directed that informed small stakeholders have time to process information on weekends and these investors make their decisions on Mondays. Since small investors have been found to be net sellers, this behavior should affect the weekday effect. Stockbrokers ’recommendations, which are mostly positive buying recommendations, also tend to be timed later in the week. Explanations of psychological factors have also been sought for individual investors. According to these explanations, investors are less optimistic on Mondays, leading to stock sales and falling prices. On Fridays, optimistic investors will buy shares and prices will rise. According to a rational behavioral explanation, prudent small investors will not buy shares on Mondays for fear of potential losses in trading with informed investors who sell their shares over the weekend based on unfavorable information they received. Institutional investors, on the other hand, are often less active on Mondays, as Monday is often used for strategic planning. (Pettengill 2003.)

# 5 Methodology and data

The January effect is intended to determine whether average returns in January are exceptionally high (or low) compared to the average returns in other months, and whether there are statistically significant differences in stock returns or whether the market is efficient in the absence of an anomaly. The null hypothesis of the study is that the average share return in January does not differ statistically significantly from the average share return in other months. The hypothesis is tested using least squares linear regression.

As a research method, linear regression of least squares is common among calendar anomalies, such as the January effect. Uniform research methods can confirm the comparability of the results between this study and other related studies. Although the least squares linear regression is incomplete as a method in this case, partly because stock market data are rarely normally distributed, the method is well suited for studying seasonal anomalies (Brooks 2008).

The study uses the daily logarithmic returns of the indices, as the normal distribution of logarithmic returns is more appropriate for use with the regression model than the distribution of percentage returns (Gray & French 1990).

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

In the formula, $P_t$ expresses the return of the stock index at time t and the return of $P_{t-1}$ at time t-1, respectively. $R_t$ describes the logarithmic return of the index at time t. The daily closing rates of the index are used in the calculation, and $R_t$ is thus calculated by taking the natural logarithm of the ratio of the closing price of that day to the closing price of the previous day. When dealing with the January moon phenomenon, the linear regression can be presented as follows (Maaniitty 2007):

$R_t = \propto + \beta_i D_t + \varepsilon_t$

In the formula, $R_t$ represents the return on the index at time t, alpha is a constant term, beta is the regression coefficient, and $D_t$ is the dummy variable that gets a value of one for the variable month, in this case January, otherwise it is set to zero. Epsilon is a normal distribution error term with an expectation value of zero. The equation gives the average January return for each index. If the return for January does not differ significantly from the average return for the other months, the beta factor will be zero. Thus, the null hypothesis can be written as follows:

$H_0$: β1 = 0

If the returns for January differ from the average returns for the other months, the statistical significance of the deviations is determined using the F-test variable. The p-value of the F-test value must be 0.05 or less in order to say that the January effect exists at a significance level of 5%, which is the general significance level when studying the January effect. In addition, for this study, the statistical significance of the January dummy variable is examined using the p-value of the t-test variable. As with the F-test variable, the t-test variable must have a value of 0,05 or less in order for the explanatory variable to be statistically significant at the 5% significance level.

The study examines four different indices for time period of 2010-1029 of the Nasdaq OMX Helsinki Stock Exchange, which are OMX Helsinki Small Cap GI and OMX Helsinki Mid Cap GI, OMX Helsinki Large Cap GI and OMX Helsinki GI. The use of these indices is based on the results of the research presented above, which suggest that the January effect may occur especially in the shares of small companies. Therefore, it is justified to use the own index of small companies, i.e. the OMX Helsinki Small Cap GI index, in addition to the general index of OMX Helsinki GI, where the weight of each company in the index is its market value as a share of the total market value of listed companies. By using the OMX Helsinki Small Gap GI Index, the possible January effect in the shares of small companies will not be diluted, as may be the case when large companies dominate the weightings of the OMX Helsinki GI General Index. The use of the OMX Helsinki Mid Cap GI and OMX Helsinki Large Cap GI indices ensures that all companies listed on the Helsinki Stock Exchange are taken into account and that a possible January effect in medium - sized or large companies is also observed in this study.

The OMX Helsinki Small Cap GI, OMX Helsinki Mid Cap GI, OMX Helsinki Large Cap GI and OMX Helsinki GI indices are all indices that have taken into account the dividend deduction (Gross Index, GI). The market value of OMX Helsinki Small Cap GI companies is less than EUR 150 million, the market value of OMX Helsinki Mid Cap GI companies is between EUR 150 million and EUR 1 billion and the market value of OMX Helsinki Large Cap GI companies is billion or more.

The price information for each index is available on the Nasdaq OMX Nordic website. Historical exchange rate data can be found for all indices except OMX Helsinki GI, for which data are missing for the period from 4.1.2010 to 31.5.2011. As a source of information, the Nasdaq OMX Nordic website is very reliable.

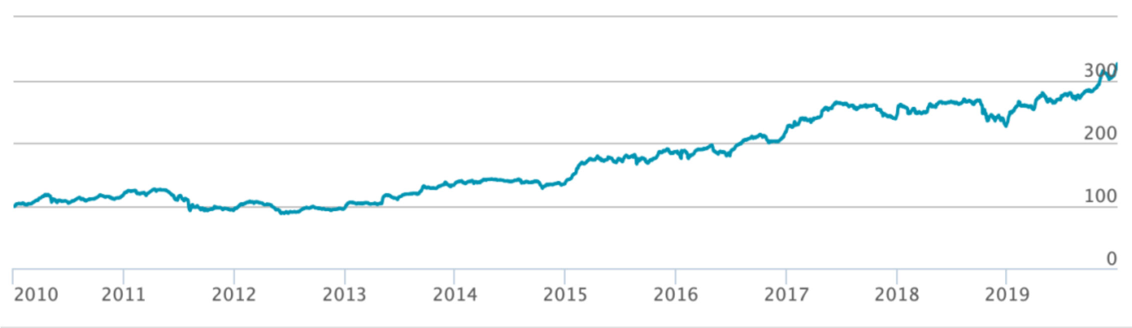


**Figure 3** OMX Helsinki Small Cap GI – Index 2010-2019 (OMX Helsinki Small Cap GI 2022).


**Figure 4** OMX Helsinki Mid Cap GI – Index 2010-2019 (OMX Helsinki Mid Cap GI 2022).


**Figure 5** OMX Helsinki Large Cap GI – Index 2010-2019 (OMX Helsinki Large Cap GI 2022).


**Figure 6** OMX Helsinki GI – Index 2010-2019 (OMX Helsinki GI 2022).

# 6 Empirical results

| *January OMX Helsinki Small Cap GI* | |
|---|---|
| Mean | 0,0032 |
| Standard Err | 0,0007 |
| Median | 0,0026 |
| Standard De | 0,0098 |
| Sample Vari | 0,0001 |
| Kurtosis | 12,1095 |
| Skewness | 1,8384 |
| Range | 0,0966 |
| Minimum | -0,0239 |
| Maximum | 0,0727 |
| Sum | 0,6648 |
| Count | 206 |

| *Other months OMX Helsinki Small Cap GI* | |
|---|---|
| Mean | 0,0003 |
| Standard Error | 0,0002 |
| Median | 0,0006 |
| Standard Deviation | 0,0075 |
| Sample Variance | 0,0001 |
| Kurtosis | 10,6540 |
| Skewness | -0,0113 |
| Range | 0,1363 |
| Minimum | -0,0574 |
| Maximum | 0,0789 |
| Sum | 0,6102 |
| Count | 2303 |

**Table 1** Descriptive statistics, 2010-2019 OMX Helsinki Small Cap GI

As can be seen from Table 1, the average returns of the index under review in January are higher than the average returns of the other months. In terms of standard deviation, the standard deviations in January are larger than the standard deviations in the other months. Looking at the skew, it is noted that the average return in January is positively skewed, while the returns in the other months are negatively skewed. A positively skewed distribution means that a large proportion of the observations are below average, and a small proportion of the observations are above average, with the “tail” of the distribution graph to the right of the graph. In a negatively skewed distribution, the observations are naturally the opposite.

| | | | |
|---|---|---|---|
| Mean | 0,0017 | Mean | 0,0003 |
| Standard Error | 0,0007 | Standard Error | 0,0002 |
| Median | 0,0017 | Median | 0,0008 |
| Standard Deviation | 0,0094 | Standard Deviation | 0,0091 |
| Sample Variance | 0,0001 | Sample Variance | 0,0001 |
| Kurtosis | 1,5185 | Kurtosis | 5,6793 |
| Skewness | -0,1640 | Skewness | -0,3740 |
| Range | 0,0642 | Range | 0,1417 |
| Minimum | -0,0336 | Minimum | -0,0686 |
| Maximum | 0,0307 | Maximum | 0,0731 |
| Sum | 0,3442 | Sum | 0,6641 |
| Count | 206 | Count | 2303 |

**Table 2** Descriptive statistic, 2010-2019 OMX Helsinki Mid Cap GI

As can be seen from Table 2, the average returns of the index under review in January are higher than the average returns of the other months. In terms of standard deviation, the standard deviations in January are larger than the standard deviations in the other months. Looking at the skew, it is noted that the average return in January is negatively skewed, as the returns in the other months are negatively skewed. In a negatively skewed distribution, the observations are, of course, such that a large proportion of the observations are above average, and a small proportion of the observations are below average, leaving the “tail” of the distribution graph to the left of the graph.

| *January OMX Helsinki Large Cap GI* | |
|---|---|
| Mean | 0,0012 |
| Standard Error | 0,0008 |
| Median | 0,0013 |
| Standard Deviation | 0,0115 |
| Sample Variance | 0,0001 |
| Kurtosis | 0,5947 |
| Skewness | 0,0315 |
| Range | 0,0659 |
| Minimum | -0,0293 |
| Maximum | 0,0366 |
| Sum | 0,2419 |
| Count | 206 |

| *Other months OMX Helsinki Large Cap GI* | |
|---|---|
| Mean | 0,0003 |
| Standard Error | 0,0003 |
| Median | 0,0005 |
| Standard Deviation | 0,0120 |
| Sample Variance | 0,0001 |
| Kurtosis | 3,6211 |
| Skewness | -0,1786 |
| Range | 0,1572 |
| Minimum | -0,0824 |
| Maximum | 0,0749 |
| Sum | 0,7571 |
| Count | 2303 |

**Table 3** Descriptive statistics, 2010-2019 OMX Helsinki Lage Cap GI

As can be seen from Table 3, the average returns of the index under review in January are higher than the average returns of the other months. In terms of standard deviation, the standard deviations in January are smaller than the standard deviations in the other months. Looking at the skew, it is noted that the average return in January is positively skewed, while the returns in the other months are negatively skewed.

| *January OMX Helsinki GI* | | *Other months OMX Helsinki GI* | |
|---|---|---|---|
| Mean | 0,0014 | Mean | 0,0003 |
| Standard Error | 0,0009 | Standard Error | 0,0003 |
| Median | 0,0015 | Median | 0,0005 |
| Standard Deviation | 0,0112 | Standard Deviation | 0,0113 |
| Sample Variance | 0,0001 | Sample Variance | 0,0001 |
| Kurtosis | 0,8059 | Kurtosis | 3,6015 |
| Skewness | -0,0632 | Skewness | -0,2862 |
| Range | 0,0654 | Range | 0,1329 |
| Minimum | -0,0301 | Minimum | -0,0769 |
| Maximum | 0,0354 | Maximum | 0,0560 |
| Sum | 0,2429 | Sum | 0,6670 |
| Count | 168 | Count | 1985 |

**Table 4** Descriptive statistics, 2010-2019 OMX Helsinki GI

As can be seen from Table 1, the average returns of the index under review in January are higher than the average returns of the other months. In terms of standard deviation, the standard deviations in January are smaller than the standard deviations in the other months. Looking at the skew, it is noted that the average return in January is negatively skewed as the returns in the other months are negatively skewed.

The first regression analysis will be performed for full-term data from January 2010 to December 2019.

| | Coefficient | t Stat | P-value | F-value | Significance F | Adjusted R Square |
|---|---|---|---|---|---|---|
| OMX Small Cap GI January - dummy | 0,0030 | 5,2720 | 0,0000001 | 27,7938 | 0,0000 | 0,0106 |
| OMX Mid Cap GI January - dummy | 0,0014 | 2,0850 | 0,0372 | 4,3472 | 0,0372 | 0,0013 |
| OMX Large Cap GI January Dummy | 0,0008 | 0,9703 | 0,3320 | 0,9414 | 0,3320 | 0,0000 |
| OMX Helsinki GI January Dummy | 0,0011 | 1,2250 | 0,2207 | 1,5007 | 0,2207 | 0,0002 |

**Table 5** Results of the regression model for the whole reference period 2010-2019

It can be seen from Table 5 that the coefficient of the January dummy variable in the OMXH Small Gap GI Index is positive at 0.00296, and the p-value of the variable is significant at the significance level of five and even one percent. The p-value corresponding to the F-test value of the entire model is also significant at the significance level of 5% and 1%, i.e., when looking at the entire period 2010–2019, a statistically significant January effect can be observed in the OMXH Small Gap GI index. However, the review must take into account that the explanatory factor of the model is small, only 0.01057, i.e., the January dummy explains only 1.057% of the index observations. If suitable variables are added to the model, the explanatory factor of the model will increase higher, but this thesis wants to focus specifically on the effect of January effect. The observed January effect in the small shares index provides support for previous studies in which the January effect has been found to occur especially in the shares of small companies. We can reject null hypothesis based on this information and state that the alternative hypothesis is valid. There is statistically significant January effect in the OMXH Small Gap GI Index.

The p-value of 0.03717 for the F-test value of the OMXH Mid Cap GI Index indicates that the model is statistically significant at the 5% significance level. The January dummy of this index is also significant at a p-value of 5%. Thus, it is observed that the OMXH Mid Cap GI Index shows fading from the January effect throughout the period under review, and a potential statistically significant January effect can be observed when looking at shorter reference periods. Also, for the OMXH Mid Cap GI index, the explanatory factor of the regression model is small 0.00133, i.e., the January dummy explains only 0.133% of the index observations. Null hypothesis is rejected, and alternative hypothesis is accepted with significance level 5%.

There is no statistical significance in the OMXH Large Cap GI index, and in addition, the January-dummy coefficient is small. In the OMXH GI index, the January-dummy coefficient is positive, but as with the OMXH Large Cap GI index, the OMXH GI index has no statistical significance. Therefore, we focus on small and medium-sized companies. With this result we cannot reject null hypothesis.

We reject H0 for the OMXH Large Cap GI Index and OMXH GI index. We cannot reject null hypothesis for the OMXH Small Cap GI Index nor the OMXH Mid Cap GI Index. We accept HI for the OMXH Small Cap GI Index and OMXH Mid Cap GI Index. Also, we accept H2 for OMXH Small Cap GI Index.

| | OMXH Small Cap GI | OMXH Medium Cap GI | OMXH Large Cap GI | OMXH GI |
|---|---|---|---|---|
| Daily returns mean, 1-14, January | 0,0061 | 0,0032 | 0,0016 | 0,0019 |
| Daily returns mean, Rest of the year | 0,0003 | 0,0003 | 0,0004 | 0,0004 |
| t Stat | 6,7989 | 2,8379 | 0,0013 | 0,9535 |
| P-value | 1,31E-11 | 0,0046 | 0,9535 | 0,3404 |
| Coefficient | 0,0058 | 0,0029 | 0,3404 | 0,0013 |

**Table 6** Daily returns, first two weeks versus rest of the year.

Looking at daily returns, it is observed that the January effect appears to be higher in all indices than in the rest of the year during the first two weeks of the year. The P-value is significant at both the 5% and 1% significance levels in the OMXH Small Gap GI and OMXH Mid Gap GI indices. Based on this we can accept H3, the January effect occurs more strongly during the first two weeks of January than during the rest of the year in OMXH Small Cap GI and OMXH Mid Cap GI. We can reject H3 clearly for the OMXH Large Cap Gi and OMXH GI.

# 7 Conclusion

The aim of this master's thesis was to examine, using four different stock indices, whether there is a January phenomenon on the Helsinki Stock Exchange during the period 2010–2019. The fact that the Helsinki Stock Exchange has not been researching the January phenomenon for a long time added value to the study.

The theoretical review of the study sought to provide the reader with a clear picture of how efficient market theory, behavioral finance, calendar anomalies, and the January effect are related. The study then presented a previous study of the January effect, first for major international studies. It was noted that the January effect had previously appeared on the Helsinki Stock Exchange in a study by Berglund and Wahlroos (1986) and later in a study by Maaniity (2007).

In the empirical part, the least squares linear regression, which is a general research method for studying the January effect, was chosen as the research method. The OMXH Small Cap GI, OMXH Mid Cap GI, OMXH Large Cap GI and OMXH GI indices were chosen as the indices to be examined, as the January effect has been strongly linked to company size in previous studies on January effect. It was therefore decided to examine indices in which companies are pre-broken down by size. In addition, the OMXH GI Index, which describes all companies on the Helsinki Stock Exchange, was included. The returns of the indices were converted to logarithms to make them more suitable for use with the regression model. The regression model was used to test data for the entire period 2010–2019 to find the January effect.

Regarding the results, it can be stated that there is a statistically significant January effect on the Helsinki Stock Exchange in the OMXH Small Cap GI index of shares with a market capitalization. Throughout the study period 2010–2019, the OMXH Small Cap GI Index shows a statistically significant January effect at significance levels of 5% and 1%. For the OMXH Mid Cap GI Index, for the entire period 2010–2019, the null hypothesis could be refuted based on the value of the F-test variable at the five significance levels, but the p-value of the t-test variable for the January dummy variable was not statistically significant. The null hypothesis could not be rebutted for the OMXH Large CAP GI Index or the OMXH GI Index.

The results also indicate that the January effect is stronger in the first two weeks of January than in the rest of the year. This is especially true of the OMXH Small Cap GI and OMXH Mid Cap GI indices.

It can be deduced from the results that investors are earning additional returns in favor of the January effect, especially with the small-cap stocks. An efficient market needs to eliminate this anomaly, but it still exists for many reasons. Especially the first two weeks of January are the best performers in small companies and thus investors can easily earn additional returns. This is still not as easy and clear because investors and others are aware of the January effect, so they in on form predict this. It would also be good to see on a daily basis which day yields the most. Is it as soon as the year changes or could it be in the December side as well?

One of the most important findings of the thesis is the occurrence of the January effect in the Finnish stock market, and in addition, the results of the thesis provide strong evidence that the January effect is also present in the shares of small companies in Finland. However, the results of the thesis do not provide answers to why the January effect can be observed in the Finnish stock market, but it would require a broader study of the investment behavior of private and institutional investors around the turn of the year. An interesting topic for further research would be to investigate the strongest reasons behind the January effect in the Finnish stock market. Do Finnish investors act in accordance with the tax or window dressing hypothesis, or is there another reason behind this phenomenon?

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