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Turn of the Month Anomaly in Finland

Accounting and Finance

Bachelor's thesis

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The topic of this thesis is the turn of the month anomaly in the Finnish stock market. The turn of the month anomaly is a calendar anomaly where stock returns have been observed to be better on average during the turn of the month than on other trading days. Firm size has also been observed to influence the occurrence of the phenomenon. The phenomenon is more strongly observed among small firms than among large firms. The purpose of this paper is to investigate whether the phenomenon is present in the Finnish stock market during the period 2012-2023. The second purpose of the paper is to investigate whether the possible occurrence of the phenomenon differs across different size classes of firms.

The literature review presents a theoretical framework for financial markets, consisting of the efficient market hypothesis, the random walk model and different pricing models. The literature review also discusses behavioral finance, which allows the reader to better understand why anomalies can occur in the market compared to traditional financial theory. The report then examines the turn of the month anomaly in more detail, as well as previous research on it.

The empirical part of the study is conducted using a linear regression model. The study is conducted for four different indices: the OMXH Helsinki PI, the Finnish Stock Exchange's general index, and the OMX Helsinki Small Cap PI, OMX Helsinki Mid Cap PI and OMX Helsinki Large Cap PI, which are derived from the general index. A linear regression model is used to examine the daily returns of each index separately at the end of the month and on other days. As a result, it is found that at the general index level, the returns on the turn of the month do not differ from the returns on other trading days in Finland. However, the anomaly occurs for small and medium-sized enterprises in the period under study. For these size classes of companies, the returns on the turn of the month were statistically significantly higher than the returns on other days. However, the anomaly did not occur for large companies.

Key words: anomalies, turn of the month anomaly, stock returns, the efficient market hypothesis, behavioral finance

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Tämän tutkielman aiheena on kuunvaihdeanomalia Suomen osakemarkkinoilla. Kuunvaihdeanomalia on kalenterianomalia, jossa osakkeiden tuottojen on havaittu olevan keskimäärin parempia kuukauden vaihteessa kuin muina kaupankäyntipäivinä. Yrityksen koon on myös havaittu vaikuttavan ilmiön esiintymiseen. Ilmiö on havaittu voimakkaammin pienissä kuin suurissa yrityksissä. Tämän työn tarkoituksena on tutkia, onko ilmiötä esiintynyt Suomen osakemarkkinoilla vuosina 2012-2023. Työn toisena tarkoituksena on tutkia, onko ilmiön esiintymisessä eroja eri kokoluokan yrityksissä.

Kirjallisuuskatsauksessa esitellään rahoitusmarkkinoiden teoreettinen viitekehys, joka koostuu tehokkaiden markkinoiden hypoteesista, satunnaiskulkumallista ja erilaisista hinnoittelumalleista. Kirjallisuuskatsauksessa käsitellään myös käyttäytymistieteellistä rahoitusta, jonka avulla, verrattuna perinteiseen rahoitusteoriaan, lukija ymmärtää paremmin, miksi anomalioita voi esiintyä rahoitusmarkkinoilla. Tämän jälkeen raportissa esitellään tarkemmin kuunvaihdeanomalia sekä sitä koskeva aikaisempi tutkimus.

Tutkimuksen empiirinen osa toteutetaan lineaarisella regressiomallilla. Tutkimus tehdään neljälle eri indeksille: OMXH Helsinki PI:lle, joka on Suomen pörssin yleisindeksi, sekä OMX Helsinki Small Cap PI:lle, OMX Helsinki Mid Cap PI:lle ja OMX Helsinki Large Cap PI:lle, jotka ovat johdettu yleisindeksistä. Lineaarisen regressiomallin avulla tutkitaan kunkin indeksin päivittäisiä tuottoja kuunvaihteen aikana sekä muina kaupankäyntipäivinä. Tuloksena havaitaan, että yleisindeksin tasolla kuunvaihteen tuotot eivät eroa muiden kaupankäyntipäivien tuotoista Suomessa. Kuitenkin pienten ja keskisuurten yritysten kohdalla anomalia esiintyy tarkastelujaksolla. Näiden kokoluokkien yritysten osalta kuukaudenvaihteen tuotot olivat tilastollisesti merkitsevästi korkeampia kuin muiden päivien tuotot. Anomalia ei esiintynyt suurten yritysten joukossa.

Avainsanat: anomaliat, kuunvaihdeanomalia, osaketuotot, tehokkaiden markkinoiden hypoteesi, käyttäytymistieteellinen rahoitus

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1 Introduction

Investors have always tried to find ways to get better than average returns from financial markets. According to the efficient market hypothesis of financial theory (Fama, 1970), security prices should satisfy the strong conditions of an efficient market. Strong conditions require that security prices include all possible information, including inside information. However, a number of empirical studies (Agrawal & Tandon, 1994, Woo et al., 2020; Dimson, 1988; Latif et al., 2011) have shown that various anomalies occur in financial markets, which, by exploiting them, allow investors to obtain above-average returns. The turn of the month (TOM) effect is one such anomaly. One of the calendar anomalies suggests that, in comparison to other trading days, stock market returns are greater on the final trading days of the previous month and the first trading days of the subsequent month. Other calendar anomalies are for example the January phenomenon, the Halloween indicator, and the weekday anomaly. (Agrawal & Tandom, 1994.)

This phenomenon has been empirically studied in a number of different regions and time periods. Researchers that were among the first to examine the occurrence in the US stock market were Ariel (1987) and Lakonishok & Smidt (1988). Agrawal and Tandom (1994) extended their study to the global level. In 2014, Sharma and Narayan (2014) added firm size and industry to the study of the turn of the month effect. Their key finding was that the turn of the month effect is observed in every industry, and especially among small firms, the effect is significantly larger than among large firms. Because of the positive evidence from previous studies, the turn of the month effect was selected as the subject of this study. What makes it particularly interesting is that the anomaly has not disappeared from the market but has occurred in a several periods, geographical areas, and industries. The research examines the turn of the month anomaly on the Finnish stock exchange (OMXH). By understanding the potential existence of this effect, an investor can take advantage of it and create a strategy that can deliver above-average returns.

Turn of the month anomaly has been observed in several different decades around the world, but no unequivocal reason has been given for the phenomenon. Possible explanations have been offered such as the timing of major corporate announcements, the timing of cash flows from individuals and institutional investors, the timing of trading due to information asymmetries and taxation. (Lakonishok et al., 1988.) Behavioral finance and human psychology have also been used to explain the phenomenon, e.g. Jacobs and Levy (1988). However, the best-known explanation, the liquidity hypothesis, has been put forward by Ogden (1990). The liquidity hypothesis is based on the unequal distribution of investors' income flows. Investors' income streams, such as wages and dividends, are often concentrated at the beginning of the month, whereas payments are distributed throughout the entire month. As a result, investors' liquidity position is better at the turn of the month.

1.1 Purpose of the study

The purpose of the study is to find out whether the effect is occurring in Finland and the research question is: *Does the turn of the month effect occur in the Finnish market during the period 2012-2023?* The aim of the study is therefore to investigate the occurrence of the turn of the month anomaly in the Finnish stock market between 2012 and 2023. According to earlier research (Sharma & Narayan, 2014), distinct size classes of companies have observed differences in the effect's prevalence, which is why the study will also compare the occurrence of the effect in different size classes of companies. The second research question is: Are there differences in the prevalence of the turn of the month anomaly in different sizes of companies? The period chosen is the present one, as the study aims to assess the occurrence of the anomaly in the modern era. Before 2012, the world has experienced many major economic crises, whose impact is wanted to be excluded from the result. However, the period is wide enough to provide sufficient data for a reliable study. The aim of the study is also to analyse why the phenomenon occurs, based on previous literature. However, since the exact cause of the phenomenon has not been explained conclusively, it is not the purpose of this study to identify an unambiguous reason for the phenomenon if it occurs in the Finnish stock market.

This study examines the impact of TOM on the general index of Helsinki Stock Exchange. In addition, the impact of the effect of the phenomenon is examined for the different size classes of indices derived from the general index. The selected indices will be presented in more detail later in the study. As a result, the study provides information on whether an investor could have obtained above-average returns by exploiting this anomaly over the period in question. In addition, the results provide information on whether the investor could have benefited more from different size classes of companies.

1.2 Research problem

The primary research problem of this study is the existence of the turn of the month anomaly in the Finnish stock market. As mentioned earlier, despite the efficient market hypothesis that all available information is already incorporated into stock prices, empirical evidence suggests the existence of various anomalies in the market.

This study aims to investigate whether the TOM effect is observable in the Finnish stock market and, if so, whether it varies across firm sizes. The research problem can be divided into the research questions presented earlier. In this study, the problem is investigated through empirical research. The methodology and hypothesis will be presented later in the report.

The answers to these issues can provide valuable information for investors seeking to maximize their returns, as well as for researchers and investors interested in market efficiency and behavioral finance.

This research problem is important because if the TOM phenomenon occurs in the Finnish market, it could provide investors with a potentially profitable trading strategy. On the other hand, if the TOM effect is not observed, it could strengthen the validity of the efficient market hypothesis in the Finnish market.

1.3 Research structure

The research report consists of five chapters. Chapter 2 forms the theoretical part of the report. Chapter 2 discusses traditional theories of finance. It covers the efficient market hypothesis and different pricing models. The aim of the chapter is to give the reader an idea of how financial markets work and how returns on underlying assets are theoretically constructed. It also deals with behavioral finance. Behavioral finance is partly a critique of traditional finance theory, which aims to explain irrational behavior in markets. This gives the reader an idea of why anomalies can occur in markets and how such behavior has been explained. Chapter 2 reviews previous research on turn of the month anomalies. It also discusses the explanations provided in the previous literature for the existence of anomalies.

Chapters 3-5 form the empirical part of the report. Chapter 3 presents the data used and the methodology. Chapter 3 also formulates the hypotheses for the empirical study. Chapter 4 presents the results of the study. The results are also compared with previous literature. The final chapter summarizes the study and presents the conclusions. The chapter also provides further research topics. The chapter also discusses how an investor might benefit from the phenomenon.

2 Literature review

This chapter presents a literature review. The literature review consists of three parts. First, it presents the main theoretical frameworks of financial markets, followed by a section dealing with behavioral finance. The last part of the literature review consists of a review of previous studies on the turn of the month effect. It also presents the phenomenon in more detail. At the beginning of each subsection, the topics covered in the subsection are explained in more detail.

2.1 Theoretical background of financial markets

This section presents the main theoretical frameworks of financial markets. Theories explain how markets work, how efficient they are and how returns are determined. The section discusses the efficient market hypothesis (Fama, 1970) and the random walk model (Malkiel, 1973).

2.1.1 The efficient market hypothesis

Fama (1970) has presented one of the most important hypotheses in finance: the efficient market hypothesis. According to this hypothesis, when securities consistently reflect all available information, markets are considered efficient. According to the theory, new information is immediately transmitted to security prices, preventing the investor from exploiting the information to achieve a better average return.

The efficiency of the market can be divided into three levels. When moving from one level to the next, the conditions of the previous level always apply. The conditions of the weak form are fulfilled when security prices include all possible historical information. At the semi-strong level, the conditions require that security prices also include all public information. When security prices reflect all private information in addition to these, the strong form conditions are met. Meeting these conditions means that it is not possible to achieve above average returns even with inside information. (Fama, 1970.)

In practical terms, this means that previous price information cannot be used to obtain abnormal returns if the market satisfies the weak form criterion. For instance, technical analysis cannot produce returns that are above average. Prices for security should not be contingent on time or any other transient factor. Therefore, all relevant information should be included in security prices, except for past price data. The price change then proceeds according to a random walk. (Slezak, 2003.)

Meeting the semi-strong conditions means that, in addition to technical analysis, an investor cannot achieve abnormal returns based on fundamental analysis either. Since security prices include all historical and public information, these analyses cannot be used to predict future prices. Financial reports as well as significant news and announcements, such dividend announcements, are considered public information. (Fama, 1970.)

According to the strongest form of Fama's (1970) efficient market hypothesis, security prices include all private information in addition to historical information. According to Ross et al. (2012), in efficient markets new information is immediately reflected in security prices. Prices have time to adjust to future information before investors have time to take advantage of it. If the market satisfies this, it means that no one is generating abnormal returns. Investors should therefore only expect a normal return. According to Rossi & Gunardi (2018), there is a growing number of studies against the efficient market hypothesis. They argue that studies on the existence of calendar anomalies reject the hypothesis of efficient markets. However, the results are inconsistent. Their study showed no evidence for calendar anomalies, whereas previous studies do. Therefore, calendar anomalies need to be examined on a case-by-case basis.

2.1.2 The random walk model

Kendall (1953) analyzed in his study that stock prices are impossible to predict because they move randomly. He found that price data behaved in a non-systematic way, making analysis, and forecasting very challenging. According to Bodie et al. (2008), the efficient market hypothesis states that the formation of security prices is determined by a random walk process. This process implies that the stock price changes randomly and unpredictably. Consequently, the theory states that it is impossible to forecast that if a stock price increases one day, it will increase the next (Chitenderu et al., 2014). If price changes were predictable, this would be evidence of market inefficiency. However, random walk does not imply market irrationality, but is the result of rational investors reacting to the information they receive before other market participants (Bodie et al., 2008).

There is a strong link between the efficient market hypothesis and the random walk model. Future prices are not influenced by past price information, and previous data cannot be utilized in predicting the best time to invest because prices change randomly. (Chitenderu et al., 2014.) However, studies against this have been presented. Disanaike (1997) in his study, observed irrational behavior in the market as overreaction to events. Market efficiency and random cost patterns may also vary across markets. In more developed countries, regulation and supervision is more stringent, which increases market efficiency.

2.2 Pricing models for securities

This chapter presents the main concepts of financial theory for the formation of normal returns on securities. Although the models are called pricing models, they are models of the return generation. Understanding the formation of normal returns is essential because anomalies are exploited to achieve abnormal returns. The best-known models are modern portfolio theory of Markowitz (1952), the Capital Asset Pricing model of Sharpe (1964), Lintner (1965) and Mossin (1966) and the arbitrage pricing model (Ross, 1976).

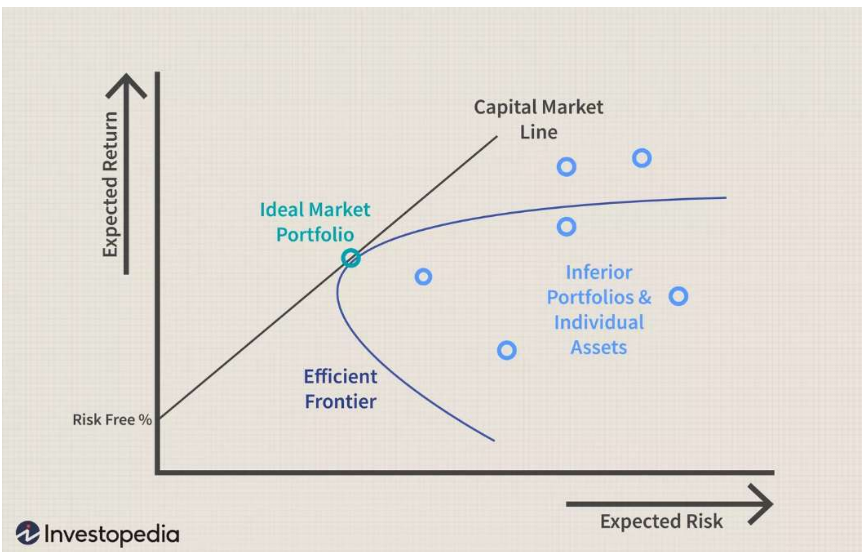
2.2.1 Modern portfolio theory

Modern portfolio theory is based on Markowitz's 1952 article "Portfolio Selection". It is based on the idea that investors are risk averse, and that risk can be reduced by diversifying the portfolio. He found that stock returns are systematically correlated and that selecting the least correlated stocks will give the best diversification benefit to the portfolio. This benefit is achieved by moving securities in different directions. Even if the correlation is positive, diversification can still provide benefits (Knüpfer & Puttonen, 2014). The main concepts in the theory are risk and return. According to portfolio theory, the overall risk and return levels of an investment portfolio are more important than those of individual investments.

Risk is defined as the uncertainty about the possibility of future losses on investments. It is therefore the deviation from the expected value of the return. Risk is divided into systematic and non-systematic or idiosyncratic components. The idiosyncratic part is the movement of the price of a single security, while systematic risk is the impact of market developments on a single asset (Knüpfer & Puttonen, 2014). According to portfolio theory, investors seek to minimize unsystematic risk by diversification. This allows for a lower overall risk to the portfolio than any single asset in the portfolio. In other words, it is possible to create less variance for the portfolio than for the individual assets within it. The return on a portfolio is the weighted average of the returns of the portfolio's assets. Diversification is therefore beneficial for the risk-return relationship (Markowitz, 1952). The systematic part of the risk is still borne by the investor. The systematic part, or market risk, affects all firms at the same time and is measured using the beta (Knüpfer & Puttonen, 2014). The beta coefficient is presented in more detail in the following section.

According to the theory, an investor seeks to maximize the return on his portfolio relative to the risk. The idea is that given two assets with the same expected return, a rational investor will invest in the asset with less risk. This creates an efficient frontier of assets, where no efficient portfolio offers a better return for the same level of risk. By increasing the risk level of the portfolio, the investor is able to achieve a better return. In other ways, if an investor wants a lower risk level, it also means a lower expected return (Markowitz, 1952).

Sharpe (1964) introduced his own addition to Markowitz's portfolio theory by adding the possibility of a risk-free interest rate. On this basis, he introduced the concept of the capital market line. The capital market line consists of a risk-free interest rate and a market portfolio. Any rational investor will position himself in the capital market line according to his risk preferences, and the only way to increase the expected return is to increase the risk. The capital market line is shown with the efficient front in the figure below.



Picture 1 Capital Market Line (Investopedia, 2023)

The figure shows the expected return on the y-axis and the risk on the x-axis. The capital market line lies between the risk-free rate and the tangent point of the efficient frontier. A rational investor chooses his portfolio along this line because a better expected return with less risk is not available from other options. A risk-averse investor will invest in a risk-free rate, otherwise the investor will choose a point on the straight line according to his risk preferences. Between the risk-free rate and the market portfolio, the investor allocates his assets to these investments. If the investor wants his expected return to be higher than the market portfolio, he can choose to take out a loan to invest in a point on the capital market line with a higher expected return and higher risk.

2.2.2 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) was developed by Sharpe (1964), Lintner (1965) and Mossin (1966) independently. The model is based on Markowitz's portfolio theory. According to the CAPM, the required rate of return on an investment is obtained by adding a risk premium to the risk-free rate, which is reflected by the beta coefficient. Sharpe (1964) presented the formula as follows:

$$E(r_i) = r_f + \beta_i \left(E\left(r_m - r_f\right)\right).$$

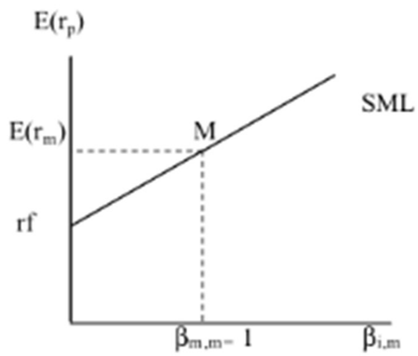
In the model, the return on the asset $E(r_i)$ consists of the risk-free rate r_f, together with a company-specific risk premium. The risk premium is the product of the variable β_i and the difference between the expected return on the market portfolio and the risk-free rate, $E\left(r_m - r_f\right)$. The beta coefficient indicates the systematic risk of instrument i. (Fama & French, 2004) Beta can be expressed as follows:

$$\beta_i = \frac{cov(r_i, r_m)}{var(r_m)}.$$

Where $cov(r_i, r_m)$ is the covariance between the returns r_i on security i and the returns r_m on the market as a whole. $Var(r_m)$ is the variance of market returns r_m (Jensen, 1972). The interpretation of the beta coefficient thus describes the ratio of the covariance between security and market returns to the total variance of market returns. Beta can be interpreted as a measure of the sensitivity of a security to the returns of all investment assets. It therefore reflects the tendency of a security to react to the market. If beta is equal to 1, the security's returns are perfectly correlated with the market. If beta is set to 0, there is no correlation at all. The interpretation of beta can also be described as follows. If the beta is less than 1, the security moves less than the market average. If $\beta > 1$, the volatility of the security is higher than the markets. The higher the beta, the greater the compensation the investor demands for the risk he is taking. (Fama & French, 2004.)

CAPM provides a return on capital requirement for the security being calculated. The return requirement, or discount rate, can in turn be used in various valuation models if the objective is to calculate a price for a security (Niskanen & Niskanen, 2013). The CAPM model summarizes

Markowitz's efficient frontier as the securities market line (SML). The stock market line graphically looks like the following:



Picture 2 Security market line (Szylar, 2013)

In the figure, the x-axis still shows the risk, but here as a beta coefficient. The y-axis is the expected return (Szylar, 2013). The market portfolio is found at point M, which includes all stocks. The beta of the market portfolio is 1. According to Jensen (1968), all correctly priced stocks lie on the stock market line. Thus, securities above the line are underpriced and those below are overpriced. According to the efficient market hypothesis, a portfolio cannot generate excess returns on a regular basis. This allows us to examine whether the level of return exceeds the normal return under the CAPM (Jensen, 1968). This study does not directly examine excess returns, but understanding how normal returns are generated in the market makes it easier to understand the results. Since this study examines the difference in index returns at the turn of the month compared to other days, the index return can be viewed as a market return. If the market return differs on different days, it means that the anomaly is producing excess returns at the market level, in line with this principle.

2.2.3 Arbitrage pricing theory

Alternative pricing models have been developed to replace the capital asset pricing model because empirical results have not supported its effectiveness (Lehmann & Modest, 1988). Arbitrage pricing theory (APT) was first introduced by Ross (1976). The central idea of the model is that a security's return is affected by risk factors common to all securities as well as by security-specific risk factors. The common risk factors are systematic risk factors and the security-specific risk factors are non-systematic risk factors. By diversifying investments widely, the impact of unsystematic risk factors on portfolio returns can be avoided (Lehmann & Modest, 1988). Arbitrage pricing theory also assumes that investors are willing to increase their returns if the level of risk does not change. If the level of return can be improved without increasing risk, it is arbitrage (Nikkinen et al. 2002).

Lehmann and Modest (1988) present an arbitrage pricing model as follow:

$$R_{i,t} = E(R_i) + \sum_{k=1}^{K} \beta_{i,k}\delta_{k,t} + \varepsilon_{i,t}.$$

$R_{i,t}$ is the one-period return of security i at time t, $E(R_i)$ is the expected return of the security, $\beta_{i,k}$ is the sensitivity of the security's return to the value of factor k, and $\delta_{k,t}$ is the value of factor k common to all securities at time t. Finally, $\varepsilon_{i,t}$ denotes the security-specific, or non-systematic risk. To achieve arbitrage-free markets, the following condition can be added to the expected return $E(R_i)$ of a security:

$$E(R_i) = \lambda_0 + \beta_{i,1}\lambda_1 + \cdots + \beta_{i,k}\lambda_k.$$

In the condition λ_0 is the cross-sectional point, λ_k is the risk premium for factor k. The condition must hold for a large number of securities but is not necessary for all. If the equation does not hold for a small fraction, these securities can be used to generate risk-free excess returns. However, if the number of such securities is small enough, the unsystematic risk they contain cannot be diversified away. This leads to a situation where the required premium for bearing the risk of the portfolio formed by them is higher than the potential arbitrage profit (Lehmann & Modest, 1988).

APT is considered to have numerous advantages over CAPM. APT does not rely in any way on an efficient market portfolio, its theoretical assumptions are lighter, which makes the model empirically more useful. APT contains lighter assumptions about the rational investor, which makes it a slightly better reflection of reality. In addition, APT can consider more than one period and can include multiple factors to model returns (Ross & Roll, 1980).

2.3 Behavioral Finance

Behavioral finance is based on the idea that traditional financial models do not pay enough attention to people's actual behavior. This is based on observations of irrational movements of prices against expectations. In addition to irrational investors, another criticism of behavior finance is the limited scope for arbitrageurs when trading costs and the exploitation of false models are considered (Bodie et al., 2008). Drawing on cognitive psychology, this literature review presents the most common biases and heuristics that have been found to occur in investor behavior and decision-making (Barberis et al., 2003). Heuristics refers to the way humans simplify their decision-making process according to a set of rules of thumb. The most essential biases and heuristics in behavioral finance include representativeness bias, conservatism, overconfidence, and prospect theory (Kahneman et al., 1979).

2.3.1 Cognitive psychology

Cognitive psychology refers to the way people think (Ritter, 2003). People make systematic errors both in thinking and in decision-making. Different beliefs and preferences lead to these errors (Barber & Thaler, 2003). People make a large number of different decisions every day, and to facilitate this, people create these different heuristics. A heuristic refers to a decision-making technique that aims to simplify the decision-making process, such as a rule-of-thumb. These processes can lead to irrational decisions that modern financial theory cannot account for. (Ritter, 2003.)

Tversky and Kahneman (1974) have presented three heuristics used in decision making: representativeness, availability, and anchoring. The representativeness bias is based on different stereotypes. Thus, people make assumptions and decisions according to their own stereotypes. According to Tversky and Kahneman (1974), the representativeness bias is particularly relevant when one wants to assess the likelihood that a given thing belongs to a certain category. Representativeness bias also occurs when estimating the probability that a given thing will influence the occurrence of another thing. In financial markets, the representativeness bias is reflected in the underestimation of the long-run average and the overestimation of the importance of recent history in decision making. (Ritter, 2003.)

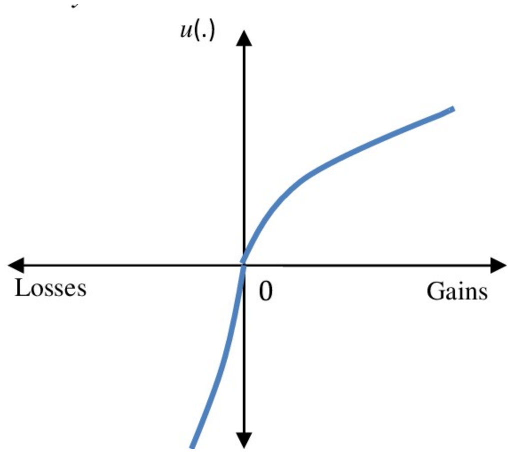
Availability bias is also used to estimate the probability of a given event. Decision making is based on easily available or familiar information, which does not tell the whole truth. For example, a decision may be based on one's own previous experience of the issue. Anchoring, on the other hand, is a type of decision making in which a decision is anchored to a certain initial value that is adjusted to be appropriate for the final decision. (Tversky & Kahneman, 1974.)

Conservatism in behavioral finance means that investors do not react quickly enough to new evidence but stick to their old beliefs. This causes markets to underreact to new information

(Bodie et al., 2008). People do not react quickly enough to change, however, as the situation persists, people adapt and may overreact. In other words, first people behave according to conservatism, and then, as they adapt, they behave according to the representativeness heuristic. (Ritter, 2003.)

Overconfidence, as the name suggests, refers to the tendency of people to have too much confidence in their own abilities and skills. In the stock market, for example, this can mean believing in one's own ability to pick the best performing companies with too little diversification. (Ritter, 2003.) The volume of trading by investors has been found to have a negative impact on investment performance. Barber and Odean (2001) have found that the more an investor trades, the worse he or she performs. Overconfidence has been put forward as an explanation for this.

Kahneman and Tversky (1979) have presented a behavioral model of decision making under uncertainty. This is called prospect theory. The theory emphasizes that investors make decisions based on potential gains and losses, not just on the outcome. The theory considers people's tendency to exploit various biases and heuristics. According to prospect theory, investors take less risk when they are in profit, and more risk when they are in loss. The change in the corresponding utility caused by a loss is therefore much greater than the change in the utility caused by a gain. Investors therefore tend to avoid losses by investing large amounts of resources to do so. In the utility function of prospect theory, risk aversion is therefore not constant. (Kahneman & Tversky, 1979) This is illustrated in the graph of the utility function below.



Picture 3 Prospect theory utility function (Palma et al., 2013)

2.3.2 Limits to arbitrage

As mentioned earlier, arbitrage plays an important role in the pricing of securities. In behavioral finance, however, limits to arbitrage play a major role, as they set the conditions under which rational investors can exploit and eliminate pricing errors in the market (Barberis & Thaler, 2003).

In practice, arbitrage requires capital and risk-taking, although theoretically it is risk-free (Merton, 1987). However, risk minimization is typical of arbitrageurs, who therefore avoid high-volatility markets (Shleifer & Vishny, 1997). If the market is efficient, the market price is then equal to the fundamental value, i.e. there is no possibility of arbitrage. According to behavioral theory, there is no reason to doubt that pricing errors will be exploited if they occur in the market. However, it does question the stage at which this occurs. A strategy that exploits pricing errors may prove to be risky and costly, and therefore the attractiveness of exploiting it may not be in line with traditional financial theory. Reasons for riskiness include fundamental risk, noise trading, and the implementation costs (Barberis & Thaler, 2003).

Fundamental risk is the risk that an investor's view of the correct market price of a stock change during the investment horizon. New relevant information may enter the market, causing the market price to change, for example, to end up falling. An investor may sell a substitute short, such as a company in the same industry, as a hedge, but this is not considered to eliminate all risk. In practice, it is difficult to find a perfect substitute, which makes it impossible to completely eliminate the risk. (Barberis & Thaler, 2003)

Noise trading is based on sentiment and impulsive emotions. Noise traders are investors who closely follow market trends and react strongly to immediate events such as news, crises, or rumors. Because noise traders do not react rationally to new information, they might create market anomalies. This has been suggested to be one of the reasons for the existence of anomalies (Shleifer & Vishny, 1997). This makes the pricing error exploited by the arbitrageur risky, as noise trading adds unpredictability to stock price movements. The risk arises if the arbitrageur has to close his position before the unfavorable direction has left the market (De Long et al., 1990).

Implementation costs reduce the profit generated by arbitrage. The first implementation costs already arise from the acquisition of resources related to the discovery of the pricing error. Trading also incurs transaction costs, such as brokerage fees, bid-ask spreads, and the price effect of the completed trade. (Herschberg, 2012.) Often arbitrage also requires short selling to bring the exploitable price difference to an attractive level (Cochrane, 2011). When all costs are considered, including taxes, arbitrage eliminates pricing errors to the point where the returns exceed the associated costs.

2.4 Turn of the month anomaly

As stated at the beginning of this report, the turn of the month anomaly (TOM) is one of the calendar anomalies, according to which stock market returns are higher than average on the last trading days of the previous month and the first trading days of the following month compared to other trading days. Other calendar anomalies are for example the January phenomenon, the Halloween indicator, and the weekday anomaly. This chapter describes the prevalence of the TOM based on previous studies, and presents the liquidity hypothesis, which has been proposed to explain the anomaly.

2.4.1 The prevalence of the anomaly

The first observation of the turn of the month anomaly was made by Ariel (1987). He found that stock market returns were on average higher at the beginning of the month between 1963 and 1981. In Ariel's study, above average returns were generated during the first nine trading days of the month in the US stock market. The cumulative daily return for these days was 1.411%, and for the last nine days has been -0.21%. Lakonishok and Smidt (1988) presented results consistent with Ariel's using -1, +1, +2 and +3 as the trading days of the turn of the month, where -1 stands for the last day of the previous month, +1 for the first day of the following month, and so on. Lakonishok and Smidt's results show that the returns on these days were statistically higher compared to other days in the Dow Jones Industrial Average index between 1897 and 1986. In their results, the average return on the turn of the month was 0.473%, and the average return on any of the other four days over the same period was 0.0612%.

Kunkel et al. (2003) extended the geographical range of the study to cover different parts of the world. Their study covered 19 stock market indices from different countries. These countries included for example: Australia, Brazil, Canada, Hong Kong, Japan, Malaysia, Mexico, New Zealand, and the United States. The countries were therefore located on several geographic continents, including Europe, Asia, America, and Africa. They found that the TOM was persistent in 16 of the 19 indices selected. As a result, they found that the four-day turn-of-the-month return covers on average 87% of the return for the whole month. They also determined TOM to be a global phenomenon rather than solely a US market.

Since anomalies are assumed to disappear from the market as a result of their recognition, McConnel and Xu (2008) continued to investigate anomalies from where Ariel ended his own study. They thus focused specifically on the period between 1987 and 2005. They found that the anomaly continued to occur during this period and was not limited to small firms, low-priced stocks or just the US market. They used the same four-day definition for turn of the month as Lakonishok and Smidt (1988). They found that all positive market returns were generated around the four days of the lunar transition, with no average compensation for risk taking on the other days. 31 of the 35 countries had statistically significant TOM abnormal positive returns. They also argued that the phenomenon is persistent, as its occurrence has been observed for more than 100 years.

The impact of firm size and industry on the TOM was introduced by Sharma and Narayan (2014). They included these variables in their analysis because the stocks traded are not homogeneous. The subject data were divided into 14 industries, and the main result was that the anomaly occurs in each industry. Firm size was found to have a clear effect on the strength of the phenomenon. According to a study by Sharma and Naraya (2014), the anomaly is significantly stronger among small firms than among large firms.

The turn of the month anomaly has been studied extensively in different countries and regions. In Turkey, between 1988 and 2014, the anomaly was found to produce an average return of 0.46% over a three-day period. The average return for other days was 0.09%. (Kayacet & Lekpek, 2016.) In Asian markets, the anomaly has been studied by Aziz and Ansari (2018). A statistically significant anomaly occurred in the largest Asian markets between 2000 and 2015. They also found that during the financial crisis of 2007-2009 the phenomenon was not observed in these markets. In Eastern and Central European markets, TOM has been studied by Arendas and Kotlebova (2019). They found that the phenomenon was statistically significant in seven out of eleven countries. In the Thai stock market, TOM returns were found to be eight times higher than on other days (Tangjitprom, 2011). The US stock market has also been studied by Nikkinen et al. (2016). They found that the S&P100 index returns at the end of the month are statistically different from the first to the third day of the month. In Finland, this phenomenon has been studied by Booth et al. (2001). Their results show that statistically significant positive abnormal returns occur in Finland on days -1 and +3. The return on the last day of the month is

0.225% and on the third day 0.115%. They also argue in their study that higher returns on equities are related to liquidity, which is connected to big traders' cash accumulation at the end of the month. The liquidity theory will be discussed later in this report (Booth et al., 2001).

The turn of the month anomaly has therefore been observed in several different time periods in different geographical areas. Sometimes the anomaly has been observed, but on the other hand it has not been observed in all markets. The reasons for the anomaly have also been given in varying ways. It is likely that the anomaly is not caused by a single factor, but by a number of factors (Lakonishok & Smidt, 1988).

2.4.2 Explanations for the anomaly

Lakonishok & Smidt (1988) provide explanations for this phenomenon, such as the timing of major corporate announcements, the timing of cash flows from individuals and institutional investors, the timing of trading due to information asymmetries and taxation.

Psychological and behavioral approaches have also been suggested as a reason for the anomaly. Jakobs and Levy (1988) argue that the anomaly is related to time turning points, when people assign high priorities to this time period. In this case, the turning point is the turn of the month, which would result in higher returns than in other periods.

The best-known explanation, however, is the liquidity hypothesis proposed by Odgen (1990). According to his theory, the turn of the month effect is due to the fact that investors receive their salaries and other income at that time. Investors' expenses, on the other hand, are spread over the whole month. This improved liquidity leads to greater trading interest, which causes stock prices to rise at the turn of the month. Booth et al. (2001), who studied the Finnish stock market, found support for this theory. The results of their investigation revealed a positive relationship between TOM returns and a number of liquidity metrics, including FIM volume, stock volume, and transaction volume. According to their empirical data, liquidity tends to rise at the turn of the month.

3 Data and methodology

This chapter presents the data and methods used in the study. Before that, research hypotheses are formulated for empirical testing. The study is based on four Finnish stock indices: the OMXH Helsinki PI (OMXHPI), the OMX Helsinki Small Cap PI (OMXHSCPI), the OMX Helsinki Mid Cap PI (OMXHMCPI) and the OMX Helsinki Large Cap PI (OMXHLCPI), which are separated by company size. In line with their names, the small cap index includes companies with a small market capitalization, mid cap medium-sized companies and large cap large companies of the Helsinki Stock Exchange. The small cap segment includes companies with a market capitalization of less than EUR 150 million. Mid cap includes companies with a market capitalization between 150 million euro and 1 billion euro, while large cap includes companies with a market capitalization of more than 1 billion euro. (Nasdaq, 2024.) The abbreviation PI stands for Price Index, meaning that the index only takes into account changes in the price of companies' shares. The price index was selected for the study because the total return from dividends does not affect the occurrence of the anomaly, but the anomaly occurs as a variation in price. The possible impact of dividends on price, however, is reflected in the price index. The data is retrieved from the financial platform Investing.com and the study is done using the Eviews-software.

3.1 Research hypotheses

Based on previous knowledge and research questions, hypotheses are formulated for empirical testing. The first and main hypothesis is:

H_0: The returns are higher at the turn of the month in Finland than on other trading days.

H_1: There is no difference in returns at the turn of the month compared to other days in Finland.

Where H_0 is null hypothesis and H_1 is alternative hypothesis. Since the study also aims to find out whether the occurrence of the anomaly differs across different size classes of firms, the second hypothesis of the study is:

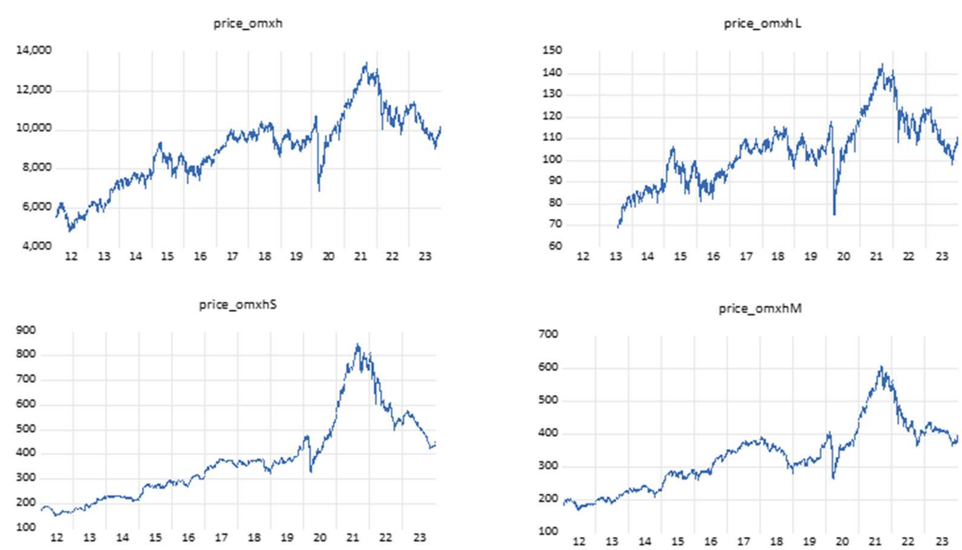
H_0: The turn of the month anomaly is more strongly present for small firms than for large firms in Finland.

H_1: There is no difference in the prevalence of the turn of the month anomaly between small and large firms.

3.2 Data

The data consists of the four indices mentioned above. Since the purpose of the study is to determine whether the Helsinki Stock Exchange is experiencing the turn of the month anomaly, the OMXHPI has been chosen as the main index for this purpose. Since the purpose of the study is also to investigate whether the occurrence of the anomaly differs for different size classes of companies, the indices OMXHSCPI, OMXHMCPI and OMXHLCPI have been chosen for this purpose. The study uses daily data, as the anomaly occurs at the daily level at the turn of the month. Data is retrieved from the beginning of 2012 to the end of 2023. However, no data for the large cap index could be found for the entire period, which is why its data is based on August 2013. However, this does not affect the estimation as the period is long enough to investigate whether an anomaly occurs. This period was selected because the objective is the occurrence of anomaly in the modern era. Before 2012, the world experienced many major economic crises, whose impact is wanted to be excluded from the result. However, the period is wide enough to provide sufficient data for a reliable study.

The graphs below show the development of each index.



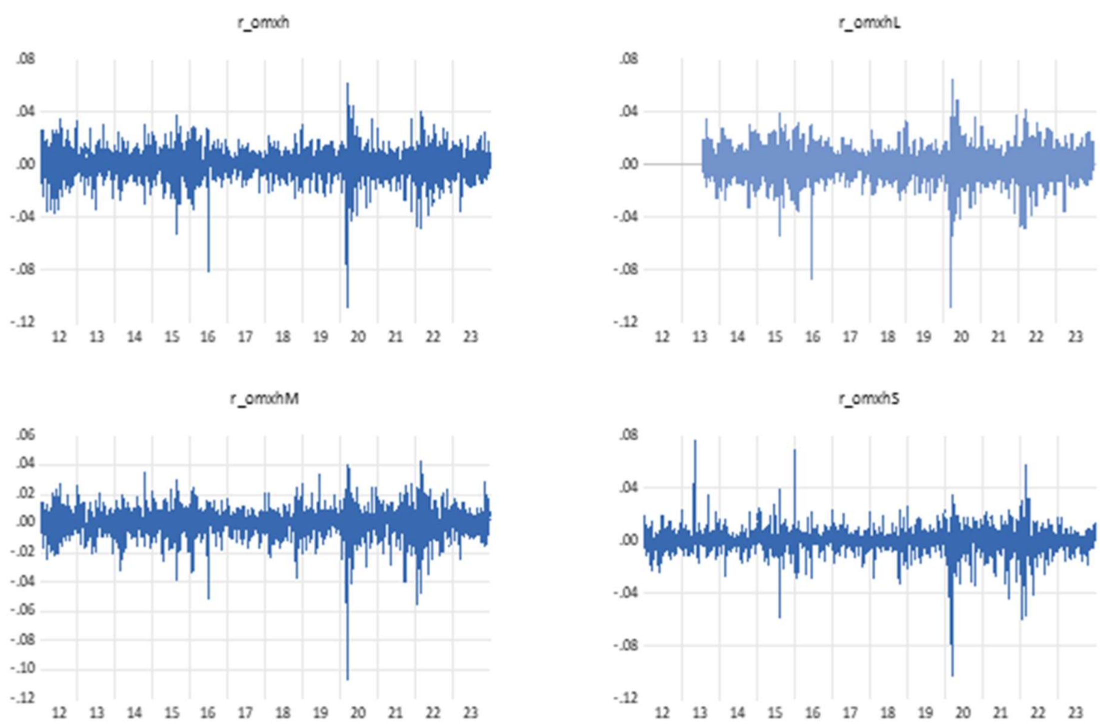
Picture 4 Performance of indices

As the graphs show, each index has been in an uptrend over the period. However, the trend varies considerably. For the purpose of the study, the index trends were converted into daily continuous (logarithmic) returns using the following formula:

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

where R_t is the return at time t, P_t is the price at time t, and P_{t-1} is the price at time t-1. In this context, price refers to the index point value of the index in question. In this study, I use nominal returns to estimate the differences between returns on TOM and other days.

The underlying assumption of the regression analysis is the normal distribution of the data, which is better respected by continuous returns than by price data. The graphs of the returns are shown below.



Picture 5 Index returns

The assumption of a normal distribution of returns can be tested using the Jarque-Bera test. The null hypothesis of the test is that the data are normally distributed, and the test is based on the skewness and kurtosis of the data (Lim, 2011). At each index, the null hypothesis of the test can be rejected, with a p-value < 0.0001. The skewness and kurtosis values also do not support normal distribution. For each index, the returns are peaked and slightly skewed to the left. Test results and ratios are presented in Appendix 1.

Since the turn of the month effect examines the average returns over a certain time period, it is worthwhile to take a closer look at the ratios in the data. Table 1 shows the full-time period key figures for each index.

Table 1. Descriptive statistics

Indices key figures for the whole period

	OMXH	OMXHLCPI	OMXHMCPI	OMXHSCPI
Mean	0.0002	0.0002	0.0003	0.0003
Median	0.0005	0.0004	0.0008	0.0006
Maximum	0.062	0.064	0.042	0.076
Minimum	-0.108	-0.108	-0.107	-0.102
Std. Dev.	0.011	0.011	0.009	0.009
Skewness	-0.7	-0.7	-1.07	-0.96
Kurtosis	9.3	9.9	12.1	18.6
Observations	3012	2618	3012	3012

The daily returns of the general index and the large cap index have been slightly lower compared to the mid cap and small cap. The standard deviation is also higher. However, it is more relevant to analyse the indicators for the turn of the month and for other days when examining the TOM effect. Descriptive statistics for other days' returns are presented in Table 2 and for TOM returns in Table 3.

Table 2. Descriptive statistics for other days

	OMXH	OMXHLCPI	OMXHMCPI	OMXHSCPI
Mean	0.00019	0.0002	7.98E-05	0.0001
Median	0.0005	0.0006	0.0007	0.0005
Maximum	0.062	0.064	0.042	0.07
Minimum	-0.108	-0.108	-0.107	-0.102
Std. Dev.	0.011	0.011	0.009	0.009
Skewness	-0.86	-0.89	-1.22	-1.39
Kurtosis	10.4	11.0	13.2	19.8
Observations	2438	2227	2438	2438

Table 3. Descriptive statistics for the turn of the month days

	OMXH	OMXHLCPI	OMXHMCPI	OMXHSCPI
Mean	0.00026	4.25E-05	0.001	0.0012
Median	0.0004	0.00017	0.0014	0.0012
Maximum	0.0045	0.046	0.033	0.076
Minimum	-0.048	-0.048	-0.048	-0.03
Std. Dev.	0.011	0.011	0.0089	0.009
Skewness	-0.05	-0.05	-0.29	0.91
Kurtosis	4.34	4.33	5.28	12.7
Observations	574	501	574	574

As an interesting observation, the median returns for the general index in Helsinki and the large cap index at the turn of the month are lower than on other days. However, for the general index, the mean of the returns is higher at the turn of the month, while for the large cap index, the mean of the returns at the turn of the month is lower. For medium-sized and small companies, on the other hand, the TOM returns are clearly higher, both in terms of mean and median. However, this comparison does not allow us to say whether there is a statistical difference between the returns and whether the anomaly actually occurs. The table also shows that the maximum and minimum values of all indices except the small cap index have been reached on other days. The TOM returns are much closer to the normal distribution than on other days, and unlike the other indices, the returns of the small cap index are slightly skewed to the right. However, the Jarque-Bera test also rejects the null hypothesis of a normal distribution of lunar returns, with p-value<0.0001. The test results are presented in Appendix 2.

3.3 Methodology

The study is conducted using a linear regression analysis estimated using the least squares method. The least square method has been shown to produce BLUE estimators (best linear unbiased estimator) that estimate regression coefficients by minimizing the square of the error terms. (Dougherty, 2007) A similar regression model is constructed for all four indices. The model is formulated as follows:

$$R_t = \alpha + \beta_1 D_t + \varepsilon_t.$$

In the model, R_t is still the index return at time t, α is the constant term, β_1 is the regression coefficient and D_t is the dummy variable. The dummy variable takes the value of 1 if the date is a turn of the month day, otherwise the value of the dummy variable is zero. ε_t is the error term of the model, which describes the difference between the observed value and the estimated value.

To define the dummy variable, I use the definition from previous literature (cf. Lakonishok & Smidt, 1988, McConnel & Xu, 2008, Booth et al., 2001), where the trading days for the turn of the month are -1, +1, +2 and +3. The dummy variable is therefore set to value of one, if trading day is the last day of the previous month (-1) or the first three trading days of the following month (+1,…,+3).

The model is estimated for each index. In particular, we are interested in the coefficient of the dummy variable that describes the average difference in returns at the turn of the month compared to other trading days. The null hypothesis of the coefficient's statistical significance and the alternative hypothesis are as follows:

$$H_0: \beta_1 = 0$$
$$H_1: \beta_1 \neq 0.$$

If we can reject the null hypothesis and value of the coefficient of the dummy variable is statistically significantly different from zero, it can be concluded that the returns at the TOM are significantly different from the returns on other trading days.

The relevant underlying assumptions of the regression model concern the properties of the error term. The error terms in the estimated model should be statistically independent of each other, normally distributed and constant in variance (homoscedastic). Statistical independence of the disturbance terms means that they should not be autocorrelated. Autocorrelation therefore means that the values of previous observations affect the values of the following observations. If, on the other hand, the disturbance terms are not constant in variance, then heteroskedasticity is implied. (Dougherty, 2007.) To test the validity of these assumptions, I used the autocorrelation and Breusch-Pagan-Godfrey heteroskedasticity tests. If these assumptions do not hold, the model is estimated using Huber-White's heteroskedasticity consistent standard error, which accounts for the lack of assumptions. The normal distribution assumption is not needed in this case, because of the central limit theorem. It states that the distribution of the sample means of a sufficiently large sample asymptotically approximates the normal distribution. (Lim, 2011.) A practical limit is a sample size of n>30, which is met by the data used here.

The results also report the model's explanatory power R^2, which is however expected to be very small. As the purpose is not to explain returns, this does not affect the analysis of the results. Based on previous studies, descriptive statistics and the hypotheses presented earlier, the expected result of the study is that the returns on the turn of the month are statistically different from the returns on other trading days in the small cap index and mid cap index. Based on descriptive statistics, the same result cannot be expected in the large cap index. For the overall index, one can expect that there is a difference, but the anomaly does not appear as strong as for the small and mid cap index.

4 Results

This chapter presents the results of the study. Relevant values from the results are tabulated and presented in more detail. The occurrence of the turn of the month anomaly is studied using the regression model presented earlier. The value of the coefficient of the dummy variable, and its statistical significance, is essential for the analysis of the results. If the coefficient is statistically significant, the null hypothesis of the coefficient can be rejected, and it is found to be statistically different from zero. The conclusion of this result is that the return at the turn of the month is on average different from the returns on other trading days. If the null hypothesis of the coefficient is accepted, i.e. the coefficient is not statistically significantly different from zero, no difference in the average returns between the days in question can be found.

4.1 Turn of the month anomaly in Finland

The regression model for each index was first estimated using the normal OLS method. The result of the estimation was tested with the Breusch-Pagan-Godfrey heteroskedasticity test. None of the models proved to be heteroskedastic, with p-values > 0.4. Next, I estimated the autocorrelation of the disturbance terms. The disturbance terms were found to be autocorrelated for the general index, mid cap and small cap index. Therefore, it was decided to use White's robust standard errors to estimate the final results. The heteroskedasticity test results and autocorrelation graphs can be found in appendices four and five. The assumption of normal distribution of the error terms does not hold in the model either. The skewness of the distributions of the error terms is very close to normal, with a skewness between -0.71 and -1.07. However, the kurtosis of the distributions is much higher than the normal distribution, with kurtosis between 9.3 and 18.5. The Jarque-Bera test also rejects the null hypothesis of a normal distribution, with a p-value < 0.0001. However, in line with the central limit theorem mentioned earlier, this is not a problem.

Table 4. Estimation results

Table four below shows the results of the regression model. The output of the estimation can also be seen in appendix 6.

		OMXH	OMXHLCPI	OMXHMCPI	OMXHSCPI
Constant	coefficient	0.00019	0.0002	7.98E-05	0.00011*
	t-value	0.84	0.84	0.42	0.63
	p-value	0.4	0.4	0.68	0.53
TOM	coefficient	7.2E-05	-0.00017	0.00094**	0.0011***
	t-value	0.14	-0.3	2.27	2.76

		OMXH	OMXHLCPI	OMXHMCPI	OMXHSCPI
	p-value	0.89	0.76	0.02	0.0058
F-test	F-value	0.02	0.087	4.76**	7.53***
	p-value	0.89	0.77	0.03	0.006
R-squared		0.000007	0.00003	0.0016	0.0025
Number of observations		3012	2618	3012	3012

*** Significant at the 1 % level

** Significant at the 5 % level

* Significant at the 10 % level

The results show that there was a statistically significant difference between the returns at the turn of the month and the returns on other trading days for mid cap and small cap indices during the period. The continuously compounded TOM returns for mid-cap firms are 0.00094 higher than on other days at the 5% significance level. Converted into percentage returns, the daily return on the TOM is on average 0.09% higher than on other days. Small firms' continuously compounded returns are on average 0.0011 higher at the 1% significance level than on other days. In percentage terms, the return per day is therefore 0.11% higher at the turn of the month. Since there is only one explanatory variable in the models, the results of the F-test are consistent with the statistical significance of the dummy variable. Thus, the estimates for the mid cap and small cap indices are also fit by the F-test.

For large firms, the coefficient of the dummy variable takes a negative value. This suggests that for these firms, the returns at the turn of the month would be lower than on other days. However, the coefficient is not statistically significant, so it cannot be concluded that the coefficient is actually different from zero. There is therefore no difference in returns for large firms.

In the general index, the coefficient of the dummy variable is very small. It is also not statistically different from zero. This does not indicate that the returns at the turn of the month are different from the returns on other days at the general index level.

The explanatory power of each model is very close to zero. This does not cause any problems in the interpretation of the coefficient, as it is not intended to explain returns. Although the number of observations for large companies is lower than for other indices, the result can still be generalized as the number of observations is sufficiently large. However, for large companies, this does not allow us to determine whether the phenomenon occurred from the beginning of 2012 to August 2013.

Based on previous literature, the study proposed two hypotheses. The first hypothesis was:

H_0: The returns are higher at the turn of the month in Finland than on other trading days.

H_1: There is no difference in returns at the turn of the month compared to other days in Finland.

Based on the results, the null hypothesis can be rejected. At the general index level, the turn of the month returns are not statistically significantly different from the other trading days. This result differs in part from previous studies. For example, Booth et al. (2001) have investigated the occurrence of the anomaly in Finland in the past. They used the same definition for the TOM. In their results, the anomaly is strongly present. However, a study has been done much earlier, which suggests that the occurrence of the anomaly has disappeared in this period. More recent studies such as Arendas & Kotlebova (2019) in Eastern and Central Europe, Tangjitprom (2011) in Thailand, Nikkinen et al. (2016) in US Market and Kayacet & Lekpek (2016) in Turkey showed that the anomaly has however appeared in this time period worldwide. However, these studies also included countries where the anomaly was not reflected in returns. Based on this, the study in this paper does not differ so much from previous results, as the anomaly has only been partially observed in the world.

The second hypothesis of the study was:

H_0: The turn of the month anomaly is more strongly present for small firms than for large firms in Finland.

H_1: There is no difference in the prevalence of the turn of the month anomaly between small and large firms.

The null hypothesis can be accepted on the basis of the results. The anomaly is statistically significant among small and medium-sized enterprises. This finding is supported by previous literature. Sharma and Naraya (2014) found that firm size significantly affects the occurrence of the phenomenon. However, the difference is that the phenomenon does not occur at all among large firms in the Finnish stock market.

The phenomenon has been explained with timing of major corporate announcements, information asymmetries, taxation (Lakonsihok & Smidt, 1988), behavioral approaches (Jakobs & Levy, 1988) and with liquidity theory (Odgen, 1990). Booth et al. (2001) showed in their study that the anomaly exists in Finland and that the result is positively correlated with various liquidity metrics. This study did not investigate the relationship with other variables. The

Finnish stock market is small by international standards, which means that increasing volume may affect the price in the form of larger changes, especially for small and medium-sized firms. This link should therefore be investigated further if we want to find out why this effect occurs among small and medium-sized enterprises.

In summary, compared to the result of Booth et al. (2001), the phenomenon has disappeared from the Finnish stock market in general. However, it does occur in certain size classes of firms, small and medium sized. In answer to the research question, it can be stated that the phenomenon does not occur on a general level in the Finnish stock market between 2012 and 2013. It does, however, occur among small and medium-sized companies during this period.

In line with the efficient market hypothesis, such phenomena should disappear from the market as investors' awareness of the phenomenon increases. This can be said to have happened partially. According to the efficient market hypothesis, an investor should not be able to regularly generate a return above the normal return produced by the pricing models presented earlier. The results of this study suggest that this is the case in Finland at the general index level and among large companies. As the TOM returns regularly diverge among small and medium sized companies, the present study does not allow to conclude that these theories are fully valid. However, underlying factors such as liquidity, taxation, timing, and normal return formation require further investigation to conclude the causes of this phenomenon more accurately.

5 Conclusions

The purpose of this study was to investigate whether the turn of the month anomaly occurs in the Finnish stock market and whether its prevalence differs across different size classes of firms. The need for the study was justified by the possibility for investors to use the information to generate excess returns, and by the impact on decision-making, for example in the timing of market entry. For the study, daily data was collected from four different indices. The indices selected were the Helsinki Stock Exchange's general index and three different size indices derived from it. The indices were price indices that exclude dividends. The study was conducted using regression analysis, the results of which showed whether there was a statistical difference between the indexes' TOM returns compared to other trading days. The regression model was chosen as the methodology based on previous literature.

The report presented the theories relevant to financial markets and the anomaly. The theory provides the reader with an understanding of how returns should be generated in the market and what kind of returns an investor should expect in an efficient market. A critique of these was also presented based on behavioral finance theory, which was intended to give the reader a picture of why anomalies can occur in markets contrary to the expectations of traditional theory. The paper also presented the results of previous studies against which the results of this study were compared.

The hypothesis of this study was that an anomaly exists in the Finnish stock market. This hypothesis was rejected on the basis of the results. The results did not show that there was a statistically significant difference in the returns of the general index at the turn of the month compared to other days. The presence of an anomaly in the Finnish market has been observed previously (Bootl et al. 2001). On this basis, it was concluded that, in line with the efficient market hypothesis, the anomaly has disappeared in Finland.

The second hypothesis of the study was that the anomaly is stronger among small firms than among large firms. This hypothesis was accepted. Although the phenomenon was not observed at the level of the overall index, it was strong at the 1% significance level for small firms. The effect was also present at the 5% level of significance for medium-sized enterprises. For large enterprises, the anomaly was not observed.

The reasons behind the results were discussed. Several explanations for the anomaly have been proposed in previous literature, but no single consistent cause has been found. Explanations can be sought in terms of behavioral finance, the timing of major events and the distribution of liquidity over the different phases of the month. Each of these may contribute to why the anomaly occurs among small firms. This opens the possibility for further research into the underlying causes of the phenomenon. At the same time, it could provide insights into what makes the difference between the phenomenon occurring only in smaller firms and why it is not observed in general.

Further research could also be carried out into how Finland's geographical location and market size affect the occurrence of the phenomenon compared to other countries. It would also be interesting to know when the anomaly disappeared in Finland in general. The sample of the Booth et al. (2001) study ends in 1997, which is why one topic for further research could be to investigate the phenomenon between 2000 and 2012. However, the scope for exploiting the phenomenon in Finland is limited to small firms in the period covered by this study. Based on this, it would have been possible for an investor to create a strategy to generate excess returns. However, this still requires further research. To develop a strategy, the expected normal return should be considered, and the abnormal return generated by the strategy should be estimated. The abnormal return should be compared to the risk it poses. In formulating a strategy of this kind, it should be noted, however, that the anomaly among small and medium-sized enterprises may disappear in the future. However, it would be interesting to know what kind of impact an anomaly-based strategy would have had on the return and risk for small and medium-sized enterprises over the period in question.

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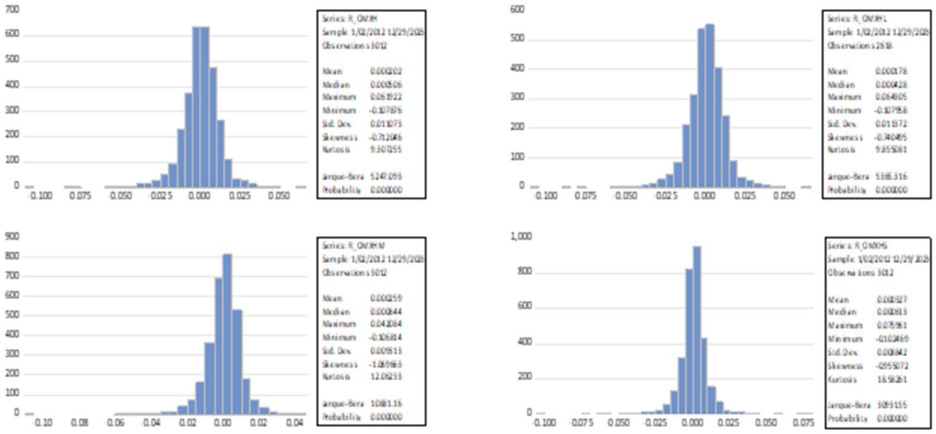
Appendices

Appendix 1 Descriptive statistics for whole sample



Appendix 2 Descriptive statistics for other days returns

	R_OMXH	R_OMXHL	R_OMXHM	R_OMXHS
Mean	0.000188	0.000210	7.98E-05	0.000112
Median	0.000533	0.000564	0.000747	0.000465
Maximum	0.061922	0.064305	0.042084	0.070141
Minimum	-0.107876	-0.107958	-0.106814	-0.102469
Std. Dev.	0.011090	0.011419	0.009412	0.008848
Skewness	-0.864199	-0.892635	-1.217073	-1.385346
Kurtosis	10.43657	11.05767	13.23562	19.78089
Jarque-Bera	5921.280	6008.154	11244.55	29385.51
Probability	0.000000	0.000000	0.000000	0.000000
Sum	0.459140	0.443719	0.194645	0.273725
Sum Sq. Dev.	0.299724	0.275927	0.215878	0.190792
Observations	2438	2117	2438	2438

Appendix 3 Descriptive statistics for TOM returns

	R_OMXH	R_OMXHL	R_OMXHM	R_OMXHS
Mean	0.000260	4.25E-05	0.001022	0.001237
Median	0.000357	0.000169	0.001370	0.001194
Maximum	0.045080	0.046245	0.033108	0.075961
Minimum	-0.048204	-0.048452	-0.047539	-0.030401
Std. Dev.	0.011012	0.011178	0.008850	0.008765
Skewness	-0.050421	-0.054832	-0.291274	0.914918
Kurtosis	4.341487	4.332336	5.281126	12.72688
Jarque-Bera	43.28335	37.30667	132.5676	2342.889
Probability	0.000000	0.000000	0.000000	0.000000
Sum	0.149403	0.021288	0.586628	0.710009
Sum Sq. Dev.	0.069488	0.062469	0.044875	0.044020
Observations	574	501	574	574

Appendix 4 Heteroskedasticity Test for each index

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.013148	Prob. F(1,3010)	0.9087
Obs*R-squared	0.013157	Prob. Chi-Square(1)	0.9087
Scaled explained SS	0.054555	Prob. Chi-Square(1)	0.8153

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/27/24 Time: 11:33
Sample: 1/03/2012 12/29/2023
Included observations: 3012

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000123	7.16E-06	17.17892	0.0000
D01	-1.88E-06	1.64E-05	-0.114665	0.9087

R-squared	0.000004	Mean dependent var	0.000123
Adjusted R-squared	-0.000328	S.D. dependent var	0.000353
S.E. of regression	0.000353	Akaike info criterion	-13.05754
Sum squared resid	0.000376	Schwarz criterion	-13.05355
Log likelihood	19666.66	Hannan-Quinn criter.	-13.05611
F-statistic	0.013148	Durbin-Watson stat	1.749753
Prob(F-statistic)	0.908718		

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.087256	Prob. F(1,2616)	0.7677
Obs*R-squared	0.087320	Prob. Chi-Square(1)	0.7676
Scaled explained SS	0.386379	Prob. Chi-Square(1)	0.5342

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/27/24 Time: 11:33
Sample: 7/31/2013 12/29/2023
Included observations: 2618

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000130	8.37E-06	15.57835	0.0000
D01	-5.65E-06	1.91E-05	-0.295391	0.7677

R-squared	0.000033	Mean dependent var	0.000129
Adjusted R-squared	-0.000349	S.D. dependent var	0.000385
S.E. of regression	0.000385	Akaike info criterion	-12.88612
Sum squared resid	0.000388	Schwarz criterion	-12.88163
Log likelihood	16869.93	Hannan-Quinn criter.	-12.88449
F-statistic	0.087256	Durbin-Watson stat	1.733430
Prob(F-statistic)	0.767719		

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.604031	Prob. F(1,3010)	0.4371
Obs*R-squared	0.604311	Prob. Chi-Square(1)	0.4369
Scaled explained SS	3.327954	Prob. Chi-Square(1)	0.0681

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/27/24 Time: 11:34
Sample: 1/03/2012 12/29/2023
Included observations: 3012

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.85E-05	5.82E-06	15.20392	0.0000
D01	-1.04E-05	1.33E-05	-0.777195	0.4371

R-squared	0.000201	Mean dependent var	8.66E-05
Adjusted R-squared	-0.000132	S.D. dependent var	0.000288
S.E. of regression	0.000288	Akaike info criterion	-13.46958
Sum squared resid	0.000249	Schwarz criterion	-13.46559
Log likelihood	20287.19	Hannan-Quinn criter.	-13.46815
F-statistic	0.604031	Durbin-Watson stat	1.762486
Prob(F-statistic)	0.437105		

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.010737	Prob. F(1,3010)	0.9175
Obs*R-squared	0.010744	Prob. Chi-Square(1)	0.9174
Scaled explained SS	0.093783	Prob. Chi-Square(1)	0.7594

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/27/24 Time: 11:35
Sample: 1/03/2012 12/29/2023
Included observations: 3012

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.83E-05	6.60E-06	11.85082	0.0000
D01	-1.57E-06	1.51E-05	-0.103618	0.9175

R-squared	0.000004	Mean dependent var	7.80E-05
Adjusted R-squared	-0.000329	S.D. dependent var	0.000326
S.E. of regression	0.000326	Akaike info criterion	-13.21833
Sum squared resid	0.000320	Schwarz criterion	-13.21434
Log likelihood	19908.81	Hannan-Quinn criter.	-13.21690
F-statistic	0.010737	Durbin-Watson stat	1.704536
Prob(F-statistic)	0.917479		

Appendix 5 ACF Graphs & Ljung-Box Q-statistics

Date: 03/25/24 Time: 19:45
Sample (adjusted): 1/03/2012 12/29/2023
Included observations: 3012 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.044	0.044	5.8790	0.015
		2	-0.016	-0.018	6.6444	0.036
		3	0.031	0.033	9.6335	0.022
		4	-0.010	-0.013	9.9377	0.041
		5	-0.013	-0.011	10.482	0.063
		6	-0.032	-0.032	13.508	0.036
		7	0.032	0.035	16.535	0.021
		8	0.005	0.001	16.608	0.034
		9	-0.002	0.001	16.618	0.055
		10	-0.015	-0.018	17.333	0.067
		11	-0.007	-0.006	17.495	0.094
		12	-0.033	-0.033	20.804	0.053
		13	-0.037	-0.031	24.981	0.023
		14	-0.002	-0.001	24.989	0.035
		15	0.028	0.028	27.329	0.026
		16	0.007	0.005	27.495	0.036
		17	-0.008	-0.008	27.674	0.049
		18	-0.017	-0.020	28.535	0.054
		19	0.017	0.018	29.366	0.060
		20	0.028	0.030	31.788	0.046
		21	-0.028	-0.027	34.198	0.035
		22	-0.017	-0.018	35.102	0.038
		23	-0.019	-0.023	36.191	0.039
		24	-0.044	-0.043	42.159	0.012
		25	0.017	0.023	43.037	0.014
		26	0.061	0.060	54.468	0.001
		27	0.008	0.003	54.644	0.001
		28	-0.028	-0.028	57.111	0.001
		29	0.005	0.003	57.183	0.001
		30	-0.038	-0.042	61.667	0.001
		31	-0.034	-0.024	65.241	0.000
		32	-0.016	-0.010	66.000	0.000
		33	0.000	0.000	66.001	0.001
		34	0.010	0.003	66.289	0.001
		35	0.012	0.008	66.717	0.001
		36	-0.000	-0.006	66.717	0.001

Date: 03/25/24 Time: 19:46
Sample (adjusted): 7/31/2013 12/29/2023
Included observations: 2618 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.042	0.042	4.5189	0.034
		2	-0.020	-0.022	5.5449	0.063
		3	0.041	0.042	9.8779	0.020
		4	0.003	-0.001	9.9015	0.042
		5	0.002	0.003	9.9074	0.078
		6	-0.047	-0.049	15.769	0.015
		7	0.028	0.033	17.854	0.013
		8	-0.004	-0.009	17.895	0.022
		9	-0.024	-0.018	19.390	0.022
		10	-0.015	-0.016	19.987	0.029
		11	-0.013	-0.012	20.446	0.040
		12	-0.043	-0.043	25.224	0.014
		13	-0.027	-0.020	27.202	0.012
		14	0.006	0.006	27.299	0.018
		15	0.026	0.026	29.036	0.016
		16	0.004	0.004	29.077	0.023
		17	-0.033	-0.033	31.891	0.016
		18	-0.013	-0.016	32.330	0.020
		19	0.030	0.029	34.666	0.015
		20	0.019	0.019	35.602	0.017
		21	-0.029	-0.029	37.804	0.014
		22	-0.006	-0.009	37.911	0.019
		23	-0.016	-0.023	38.591	0.022
		24	-0.039	-0.036	42.551	0.011
		25	0.002	0.008	42.567	0.016
		26	0.047	0.048	48.528	0.005
		27	-0.006	-0.009	48.614	0.007
		28	-0.035	-0.031	51.815	0.004
		29	0.009	0.004	52.008	0.005
		30	-0.030	-0.038	54.399	0.004
		31	-0.026	-0.017	56.221	0.004
		32	-0.019	-0.012	57.175	0.004
		33	0.004	0.001	57.212	0.006
		34	0.018	0.010	58.043	0.006
		35	-0.012	-0.012	58.430	0.008
		36	-0.002	-0.005	58.441	0.010

Date: 03/25/24 Time: 19:46
Sample (adjusted): 1/03/2012 12/29/2023
Included observations: 3012 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.082	0.082	20.148	0.000
		2	0.042	0.035	25.355	0.000
		3	0.080	0.074	44.672	0.000
		4	0.015	0.002	45.374	0.000
		5	0.004	-0.003	45.422	0.000
		6	-0.024	-0.031	47.104	0.000
		7	0.042	0.045	52.366	0.000
		8	0.007	0.002	52.524	0.000
		9	-0.001	-0.000	52.526	0.000
		10	0.013	0.007	53.067	0.000
		11	0.009	0.006	53.288	0.000
		12	-0.005	-0.008	53.369	0.000
		13	-0.010	-0.009	53.679	0.000
		14	-0.009	-0.010	53.911	0.000
		15	0.038	0.041	58.294	0.000
		16	-0.008	-0.011	58.485	0.000
		17	0.027	0.028	60.717	0.000
		18	-0.005	-0.016	60.782	0.000
		19	-0.004	-0.003	60.831	0.000
		20	0.022	0.019	62.295	0.000
		21	-0.039	-0.038	66.814	0.000
		22	0.013	0.015	67.318	0.000
		23	-0.011	-0.012	67.682	0.000
		24	-0.056	-0.053	77.182	0.000
		25	0.018	0.026	78.183	0.000
		26	0.035	0.038	81.838	0.000
		27	0.005	0.002	81.914	0.000
		28	-0.033	-0.035	85.132	0.000
		29	0.010	0.009	85.457	0.000
		30	-0.023	-0.028	87.042	0.000
		31	-0.027	-0.011	89.259	0.000
		32	0.009	0.012	89.533	0.000
		33	-0.010	-0.009	89.830	0.000
		34	0.006	0.009	89.954	0.000
		35	0.016	0.016	90.710	0.000
		36	-0.005	-0.007	90.785	0.000

Date: 03/25/24 Time: 19:47
Sample (adjusted): 1/03/2012 12/29/2023
Included observations: 3012 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.051	0.051	7.7294	0.005
		2	0.093	0.091	33.729	0.000
		3	0.108	0.100	68.745	0.000
		4	0.032	0.016	71.891	0.000
		5	0.072	0.053	87.523	0.000
		6	0.002	-0.018	87.536	0.000
		7	0.028	0.014	89.966	0.000
		8	0.020	0.007	91.191	0.000
		9	0.003	-0.002	91.219	0.000
		10	0.049	0.040	98.467	0.000
		11	0.016	0.011	99.248	0.000
		12	0.004	-0.007	99.302	0.000
		13	0.002	-0.010	99.313	0.000
		14	-0.019	-0.023	100.36	0.000
		15	0.012	0.009	100.81	0.000
		16	0.006	0.009	100.91	0.000
		17	-0.009	-0.008	101.17	0.000
		18	-0.008	-0.010	101.35	0.000
		19	0.005	0.008	101.44	0.000
		20	0.024	0.024	103.25	0.000
		21	-0.033	-0.035	106.53	0.000
		22	0.018	0.017	107.51	0.000
		23	0.009	0.009	107.75	0.000
		24	-0.036	-0.033	111.60	0.000
		25	-0.013	-0.017	112.13	0.000
		26	0.026	0.035	114.25	0.000
		27	0.005	0.008	114.33	0.000
		28	0.004	0.004	114.38	0.000
		29	0.018	0.016	115.38	0.000
		30	-0.008	-0.015	115.57	0.000
		31	-0.015	-0.020	116.29	0.000
		32	-0.020	-0.021	117.56	0.000
		33	-0.007	-0.003	117.72	0.000
		34	0.008	0.016	117.90	0.000
		35	0.001	0.008	117.90	0.000
		36	0.010	0.011	118.22	0.000

Appendix 6 Estimation outputs

Dependent Variable: R_OMXH
Method: Least Squares
Date: 03/25/24 Time: 19:17
Sample (adjusted): 1/03/2012 12/29/2023
Included observations: 3012 after adjustments
Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D01	7.20E-05	0.000511	0.140714	0.8881
C	0.000188	0.000225	0.838379	0.4019

R-squared	0.000007	Mean dependent var	0.000202
Adjusted R-squared	-0.000326	S.D. dependent var	0.011073
S.E. of regression	0.011075	Akaike info criterion	-6.167539
Sum squared resid	0.369212	Schwarz criterion	-6.163548
Log likelihood	9290.314	Hannan-Quinn criter.	-6.166104
F-statistic	0.019613	Durbin-Watson stat	1.911270
Prob(F-statistic)	0.888634	Wald F-statistic	0.019800
Prob(Wald F-statistic)	0.888105		

Dependent Variable: R_OMXHL
Method: Least Squares
Date: 03/25/24 Time: 19:22
Sample (adjusted): 7/31/2013 12/29/2023
Included observations: 2618 after adjustments
Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D01	-0.000167	0.000557	-0.299803	0.7644
C	0.000210	0.000248	0.844394	0.3985

R-squared	0.000033	Mean dependent var	0.000178
Adjusted R-squared	-0.000349	S.D. dependent var	0.011372
S.E. of regression	0.011373	Akaike info criterion	-6.114299
Sum squared resid	0.338396	Schwarz criterion	-6.109814
Log likelihood	8005.617	Hannan-Quinn criter.	-6.112674
F-statistic	0.087457	Durbin-Watson stat	1.916516
Prob(F-statistic)	0.767459	Wald F-statistic	0.089882
Prob(Wald F-statistic)	0.764352		

Dependent Variable: R_OMXHM
Method: Least Squares
Date: 03/25/24 Time: 19:25
Sample (adjusted): 1/03/2012 12/29/2023
Included observations: 3012 after adjustments
Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D01	0.000942	0.000415	2.267578	0.0234
C	7.98E-05	0.000191	0.418788	0.6754

R-squared	0.001579	Mean dependent var	0.000259
Adjusted R-squared	0.001247	S.D. dependent var	0.009313
S.E. of regression	0.009307	Akaike info criterion	-6.515337
Sum squared resid	0.260753	Schwarz criterion	-6.511346
Log likelihood	9814.098	Hannan-Quinn criter.	-6.513902
F-statistic	4.760789	Durbin-Watson stat	1.839212
Prob(F-statistic)	0.029192	Wald F-statistic	5.141910
Prob(Wald F-statistic)	0.023426		

Dependent Variable: R_OMXHS
Method: Least Squares
Date: 03/25/24 Time: 19:27
Sample (adjusted): 1/03/2012 12/29/2023
Included observations: 3012 after adjustments
Huber-White-Hinkley (HC1) heteroskedasticity consistent standard errors and covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D01	0.001125	0.000407	2.761942	0.0058
C	0.000112	0.000179	0.626457	0.5311

R-squared	0.002497	Mean dependent var	0.000327
Adjusted R-squared	0.002165	S.D. dependent var	0.008842
S.E. of regression	0.008832	Akaike info criterion	-6.620126
Sum squared resid	0.234812	Schwarz criterion	-6.616135
Log likelihood	9971.909	Hannan-Quinn criter.	-6.618690
F-statistic	7.533410	Durbin-Watson stat	1.899813
Prob(F-statistic)	0.006092	Wald F-statistic	7.628326
Prob(Wald F-statistic)	0.005781		