Louvain School of Management

and Norwegian School of Economic

Implications of the Wealth Tax on the Norwegian Stock Market

Have the introduction of valuation discount on stocks affected the returns in December on the Oslo Stock Exchange?

Author's:
Adam Bratt
Peter Sekkesæter

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Supervisor's:
Tore Leite (NHH)
Philippe Grégoire (LSM)

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Abstract

The Norwegian wealth tax has since 2017 experienced yearly changes to its valuation rules for stocks. Since an individual's wealth is measured on the 1st of January each year, it can lead to tax mitigating strategies to be implemented. Owning stocks compared to cash leads to a lower measured wealth and a lower tax liability. The thesis investigates if the introduced valuation rules has led to different returns on the Oslo stock exchange. Theory suggests Norwegians prefer to own domestic and large cap stocks. Regressions are performed on data in two different periods. One period having the valuation discount (2023-2017) and the other without the discount (2016-2008). The periods are also divided between all companies and only large cap companies. The result from the regression tells there is no difference between the two periods for all companies. However, there is a difference when only large cap companies are included. The thesis therefore concludes there is a difference in returns for large cap companies when the valuation discounts is present. If the results can be explained by the valuation rules in the wealth tax will require more research.

Key Word: Norway, wealth tax, tax mitigation, calendar anomalies, January effect, adaptive market hypothesis, liquidity, volatility, linear regression

1. Introduction

In this chapter, an introduction on the background information needed to understand the research question is presented. Next, the background discussion presents the relevance of our topic. Then we introduce the problem discussion where it is explained how different asset allocations can create tax benefits. The research design is thereafter outlined showing the methodology used to analyse market data. Furthermore, the aims and contributions of the thesis is discussed, highlighting its significance to both the finance and political sectors, and conclude with a review of the limitations of the research. This chapter sets the stage for a comprehensive analysis of stock returns in December and tax-avoidance behaviours in Norway.

1.1 Background

Norway stands out as one of the few nations, among the Organization for Economic Cooperation and Development (OECD) countries, that maintains a wealth tax. History tells us this has not always been the case. Many OECD countries used to enforce a wealth tax but have over time removed it. Today only Switzerland and Spain enforce it apart from Norway, highlighting a distinctive approach toward wealth taxation within these economies. Switzerland distinguishes itself with a flexible framework that allows for personalized discussions and agreements with affluent individuals, showcasing a tailored approach to wealth management (Limberg & Seelkopf, 2021). On the other hand, Spain had planned to abolish its wealth tax in 2008. However, the onset of the financial crisis halted these plans, leading to an indefinite postponement. Despite this, wealth tax rates in Spain are determined regionally, resulting in a varied landscape where some regions have set their rates at zero percent (Astarita, 2015). This diversity in wealth tax application puts Norway in a unique economic position, marking it as an economic anomaly worth of further exploration. Such a backdrop provides a rich context for investigating the implications and outcomes of wealth taxation in Norway, offering valuable insights into its impact on economic structures and individual wealth management.

The wealth tax in Norway has existed for a long time and it has undergone many changes throughout the years, mostly related to which political party that has been in power. The changes made to the tax include at what percentage level the net wealth is taxed at, it has been lowered from 1% to 0,85%. The most recent change made is that if one person's wealth is above 20 MNOK, it is taxed at 1,1% (Skatteetaten, 2023). What makes the Norwegian wealth tax unique is the way different assets are treated and measured towards a person's wealth. The assets a person can own have different discounts; these discounts have been changed on a yearly basis. They are for the years 2023-2021 summarized in table 1 below:

Table 1 - Asset discounts in wealth tax valuation

Asset	**2021**	**2022**	**2023**
Primary housing	25%	25%, 50% of price > 10mn	25% 70% of price > 10mn
Secondary housing	90%	95%	100%
Commercial property	55%	75%	80%
Property abroad which is not rented out	55%	75%	80%
Agricultural and forest	55%	75%	70%
Power generation facilities	55%	75%	70%
Other income generating property	55%	75%	70%
Business as partnership	55%	75%	80%
Shares	55%	75%	80%
Funds	55%	75%	80%
Other income generating assets	55%	75%	70%
Cash	100%	100%	100%

(Skatteetaten, 2023)

The percentages are how much of the market value each asset is discounted to determine one person's individual wealth. Many of these assets are not in the scope of this study. The assets that are relevant for this study are stocks and funds. These two types of assets have also gone through yearly changes of the discount. For the year 2016, the discount for stocks and funds where at 0%, meaning 100% of the stock value was measured towards the wealth. From 2017 and to 2023 the discount changed yearly, summarized in table 2 below:

Table 2 - Evolution of stock & fund discount

Asset / Year	Stocks	Funds
2023	20%	20%
2022	25%	25%
2021	45%	45%
2020	35%	35%
2019	25%	25%
2018	20%	20%
2017	10%	10%
2016	0%	0%
2015	0%	0%

(Skatteetaten, 2023)

The wealth one person owns is measured each year on the 1st of January and is calculated by measuring the assets the person owns, applying the mentioned discounts, and then deduct any debt the person has. This number is then multiplied with the rate, either 0,85% or 1,1 %, if the measured wealth is over 20 MNOK. Additionally, there is also a threshold for when a person needs to pay the tax. If the measured wealth is below 1,7 MNOK, the tax does not apply. Any measured wealth over the threshold is then taxed (Skatteetaten, 2023).

The wealth tax has been covered and studied from different angles. One paper studied the effect on Norwegians subject to the wealth tax and their portfolio composition. The author found no change as one person wealth grew. The portfolio composition between risky assets such as stocks and keeping money in the bank account remained the same (Ring, 2020). It is important to note the data used for the analysis only stretched up until 2016. It did not include data when the discounts for stock ownership was enforced. Another paper focused on how people who own private firms spends their spare cash. The authors found it is very lucrative for them to reinvest their spare cash as on average, privately held firms have a valuation discount of 68%. For new firms, it could be as high as 91% (Bjørneby et al., 2023). A third paper focused on the implications when the discounts of stock ownership was introduced. The authors found that the top percentile of people own 92% of the stocks and paid 93% of all wealth tax revenues. Hence, it is beneficial for them to have these discounts in place. This makes stocks more beneficial to own than other types of assets, such as cash on a bank account, thus making planning of portfolio composition between all possible assets lucrative (Thoresen et al., 2022).

Measuring a person's wealth at a specific date can impose challenges of measuring the true value of one individual's wealth. Assets in the portfolio can fluctuate in value throughout the year and redistributions can be made up to the measurement day to lower the measured wealth and hence the payable tax. The reason it is measured as a snapshot and not as an average throughout the year is the higher associated costs of continuously monitor each individual's wealth (Morgan, 2023).

1.2 Problem Discussion

The way the Norwegian wealth tax is constructed and enforced leaves room for tax-planning. A person can make changes in the composition of the assets in his or her portfolio towards the end of the year to lower the measurable wealth, resulting in a lower tax burden.

This is possible for two reasons. First, each asset has different valuation rules. Keeping cash on a bank account is valued at 100% for the wealth measurement whereas other assets such as stocks have a valuation discount. The second reason is that the wealth is measured as a snapshot on the 1st of January. The portfolio of assets held that day is only considered for the measured wealth. Any assets held during other days of the year will not be considered for the taxable wealth. Therefore, people could employ strategies to reduce their measurable wealth towards the end of the year and pay less in tax.

A common strategy used by Norwegians to lower the wealth tax, both historically and currently, involves investing their wealth in real estate. However, only your primary house is valued at 25% for the wealth measurement. Secondary houses are valued at 100% as of 2023. Previously secondary houses also experienced a discount, but not anymore. Hence, secondary houses are a worse asset than stocks which still offer a discount (Skatteetaten, 2023). Nevertheless, people still invest a large portion of their portfolio in housing. This has lead Norwegians in general to be overexposed to housing in their portfolio (Gjøsund & Bruaas, 2019). However, investing in the housing market can be time consuming and has high costs associated with purchases and sales. One reason behind people still investing in housing was the assumption that prices would increase making the investment more favourable (Fagereng et al., 2020). To mitigate this behaviour, changes were made to the valuation rules, both to housing and stock valuation. These changes have strengthened the incentives to buy stocks instead of investing in the property market (Thoresen et al., 2022).

These changes also presented new strategies for lowering the measurable wealth. Before, there was no difference between owning stocks or funds compared to having cash in a bank account. Now, it is favourable for people to own stocks and funds compared to keeping the money in the bank account if the person is a subject for the wealth tax. A strategy which could be used by individuals is to buy shares towards the end of the year with spare cash, hold the shares so they appear for the wealth measurement, and then sell them afterwards. Employing this strategy means the measurable wealth is lower for the individual, hence lower measurable wealth results in a lower tax liability. This tactic means taking a brief, non-speculative position in the stock market purely for tax mitigation purposes.

Should this strategy be widely adopted, it could lead to an artificial inflation of stock prices. From 2008 until 2016 there was no wealth discount for capital invested in stocks. In 2017 a discount on stocks was introduced which could create an incentive to perform tax-avoidance by asset allocation in stocks. The new tax rules create a situation similar to that of tax-loss selling hypothesis where incentives to trade shortly before the end of the year is present (Sikes, 2014). However, unlike the tax-loss selling hypothesis, which are mainly present in small companies, the effect of wealth tax avoidance would likely only be present in large companies. This is because wealthy individuals would not want to take speculative positions in the market. But rather take advantage of large companies which does not have a volatile price (Astakhov et al., 2019). Hence, driving up the trading volume of large companies and consequently the price. The aim of this thesis is to investigate whether the introduced evaluation discount has affected returns in December, looking for differences between the period of 2023-2017 and 2016-2008.

Norway is a well-developed country with easy access to international markets. The valuation of assets is the same if you invest in the domestic market or abroad. Consequently, wealthy individuals could invest in foreign markets to avoid wealth tax. However, due to the quick and non-speculative nature of the trade makes it prevalent that home bias will affect the decision. Stocks that the investors are familiar with have a larger chance to be picked based on the home bias theory (Riff et al., 2021).

This proposed strategy would throughout the years have different levels of tax mitigation effects. When the valuation discount was introduced in 2017, stocks only had a 10% valuation discount, making the incentives low compared to 2021, when the valuation discount was at 45%. Hence, strong incentives for individuals to buy stocks with cash that otherwise would have been kept in their bank account has increased. From 2021until 2023 the stock discount has reversed where it has decreased each year.

Each year since the introduction of the valuation discount, the level has changed, meaning that the market in general don't know how to act, presenting opportunities where higher levels of returns in December can be observed. This behaviour is in line with the Adaptive Market Hypothesis, which was first presented by Lo in 2004. As market participants are human, they will all react in different ways when market conditions change, hence formulating strategies to make a profit on the new regulations very challenging. As time moves on, the market will stabilize, becoming efficient as the irregularities has been traded away (Lo, 2004). With new valuation rules each year, the market never had the time to stabilize. Hence, the market will react differently each year.

The December effect has been shown consistently across various markets on an annual basis (Chen & Singal, 2019). Should the Norwegian yearly pattern significantly diverge, it could imply that the wealth tax exerts a distinctive influence on the Norwegian stock market, potentially giving rise to a unique December effect in this market.

Based on the presented information, this thesis intentions are to investigate if Norway experiences different returns in the two periods and if big companies are different compared to the whole market. Thus, the following research questions are stated:

1) *Does the Norwegian stock market experience different returns during December between the period 2023-2017 and 2016-2008?*
2) *Is there a difference observed in the returns between large and all companies in these two periods in December?*

1.3 Research Design

The chosen approach for the research is quantitative with both inductive and deductive reasoning. First, theory about the subject is collected and summarized. Where a deductive approach would have formulated hypothesis and then either kept or rejected them, this approach applies the same methods used previously but formulates new assumptions based on the results. Secondly, data related to the subject is collected from the Oslo Stock Exchange. The used method will be a regression on the seasonal return in December. Results from a period with the wealth tax (2023-2017) will be compared with a period without wealth tax (2016-2008). Then based on the results, we will either be able to strengthen or dismiss the assumption on whether wealth tax influences the Norwegian stock market.

1.4 Aim and Knowledge Contribution

The intention of this thesis is to contribute to the research area of seasonality and the effect of wealth tax on the stock market. It exists numerous research articles about the wealth tax and its implications on the economy, especially regarding savings. Research includes how it effects people's active savings, portfolio composition between safer and riskier assets, and how it leads to both tax avoidance and evasion. This thesis will contribute to the stock market perspective look first if there is a December effect, then explore how the Norwegian wealth tax might be driving this pattern.

By conducting a thorough analysis of stock market performance during December, the research will provide investors with valuable insights regarding any significant anomalies or trends that occur at year-end. Such information is crucial for investors aiming to optimize their investment strategies based on seasonal market behaviours.

Furthermore, the implications of this research extend beyond the financial community. It will also inform policymakers. If a December effect driven by the Norwegian wealth tax is identified, the findings could serve as empirical evidence for politicians and regulatory bodies. This would allow them to make more informed decisions regarding tax policies, potentially leading to adjustments in the wealth tax structure to mitigate unintended market behaviours. Thus, this thesis has a possibility to not only enhances academic understanding of market seasonality but also contributes to more effective economic policymaking, ensuring that financial regulations foster a stable and efficient market environment.

1.5 Limitations

This research encounters several challenges, notably the difficulty in isolating the effects of wealth tax changes from other influencing macroeconomic factors, regulatory changes, and global market trends, complicating the establishment of clear causality. Additionally, the reliance on theoretical frameworks primarily developed within the American economic context may not accurately reflect the unique characteristics of Norway's smaller market. The focus on large, highly liquid firms further complicates the analysis, as the high trading volumes and liquidity in these firms are not affected by the subtle impacts of some wealth tax motivated trades. Moreover, the frequent annual modifications to Norway's wealth tax policy could prevent the development of consistent tax avoidance strategies and obscuring long-term trends in investment behaviour and stock market responses.

1.6 Outline

The rest of the paper is divided into the following parts:

Chapter 2.0 focuses on previous research, their methods, and conclusions.

Chapter 3.0 introduces the chosen research method and its design. The selection of data and the creation of the datasets will be described and motivated. Lastly, a critical review of the method will be presented.

Chapter 4.0 presents the descriptive statistics and findings from the empirical research, whereas chapter 5.0 analyses the findings and are discussed with regards to the earlier presented research.

Chapter 6.0 concludes the findings, answers the research questions, and suggestions for additional research.

Chapter 7.0 discusses the study limitations in terms of the chosen method, the chosen data and how the datasets were created.

2. Literature Review

2.1 Introduction

To investigate if the wealth tax in Norway has affected the returns on the Oslo Stock Exchange relevant research regarding the topic will be presented in the following chapter. First a brief overview of the efficient market hypothesis will be given as it provides the fundamentals of how stock markets are thought to behave. In contradiction to the efficient market hypothesis, a short overview of market anomalies will be presented. A focus will be given to calendar effects, especially the January effect. Then the tax-loss selling and window-dressing hypothesis will be introduced which are two possible explanations for the January effect. In relation to the January effect, the December effect will be presented. Continuing, the adaptive market hypothesis will be presented as a compliment to the efficient market hypothesis.

Next part of the literature review will explore specific stock and market characteristics. A focus will be given to large cap companies. The properties of large cap companies will be discussed in terms of volatility and liquidity. Then it will be covered how the individual investor behaves in the market which includes home and familiarity bias. Lastly, research about the wealth tax in Norway and its implication will be presented.

2.2 Efficient Market Hypothesis

The concept of efficient markets has been well known for a long time. The hypothesis was formulated in 1970 by Eugune Fama (Fama, 1970). His work was based on numerous previous pioneering research. See (Bachelier, 1900) (Working, 1934) (Cowles & Jones, 1937) (Samuelson, 1965) (Roberts, 1967). The hypothesis states that markets are efficient on three different levels. Weak, Semi-Strong, and Strong. The three different forms are dependent on the type of information which is considered. The weak form states historical prices can't be used to predict tomorrow's price. Semi-Strong uses historical prices complemented by publicly available information. The strong form states, no matter what information is available, even inside information, one can't systematically outperform the market (Fama, 1970).

As the hypothesis gained traction it was scrutinized by many researchers. A review paper concluded that most research done in the 80s and 90s disproved the theory (Sewell, 2011). During this time, all investors did not have access to the same relevant information and tools, which is a possible explanation for the results. Moving closer to present day, papers published in the 21st century has concluded the efficient market hypothesis is here to stay (Yen & Lee, 2008) (Sewell, 2012).

2.3 Market Anomalies

The general belief is that stock markets are efficient as explained above. But there are some studies that have found instances when stock markets are not efficient. These are called anomalies. A stock market anomaly is a phenomenon where stock market behaviour deviates from the expected, based on traditional financial theories. These anomalies are consistent abnormal returns that contradict the Efficient Market Hypothesis (Sewell, 2012). Anomalies may arise due to various factors such as market inefficiencies, investor psychology, or specific institutional practices (Beyer et al., 2013) (Haug & Hirschey, 2006) (Sikes, 2014).

An important aspect of finding and investigating market anomalies is the time aspect. Anomalies can be divided into three different categories: calendar, fundamental, and technical anomalies (Latif et al., 2011). Calendar effects are related to what type of day or date it is of the week, month, or year. An example is the January Effect. Fundamental effects are related to information regarding the company. Examples are ratios such as price to earnings and price to book value. Technical anomalies are how patterns can be found in data related to a specific company. Examples include price and volume trends (Latif et al., 2011). Continuing, only calendar effects will be presented more in depth as it is the only anomaly relevant for the topic.

2.3.1 Calendar Effects

Calendar effects are when abnormal returns are present in relation to any specific day or date. Some of the calendar anomalies that exist are the Weekend effect. The effect was discovered during the 1980s. The effect is that traded stocks has best returns on Fridays and the worst on Mondays. As market has become more efficient through the years the effect has diminished. (Kohers et al., 2004) (Miss et al., 2019). The next effect is the turn of the month effect. It states that the returns of the last day of the month and the first few days of the following month have higher returns than the other days of the month. Recent studies have found the effect still present in developed markets. The effect is clearly present in smaller companies than bigger companies and is also dependent on the sector, some sectors experience the effect more than others (Sharma & Narayan, 2014).

January Effect

The January effect, also called turn of the year effect and the small stock effect, represent a higher stock return in January. The effect was first documented in 1976 and has evolved over the years. At first, the effect stated the returns was higher in January than any other month of the year. 3,48% in January compared to only 0,42% in the other months on average over a broad market index (Rozeff & Kinney, 1976). Later studies found the effect to be even more prevalent in small companies compared to large companies and in the first trading week of January (Keim, 1983). Another study in the same period adds to the evidence of the small company effect. The effect was not found in large companies, only in small companies. As large companies have small bid-ask spreads and high trading volumes, strategies are easy to formulate and implement. With investors aware of the effect, the effect was exploited and thus it disappeared. For small companies it is not the same. They have lower volume and higher bid-ask spreads thus making strategy implementation more costly and investors have not been able to take advantage of the effect in the same way. Therefore, the effect still exists for small companies (Lakonishok & Smidt, 1988).

More recent studies have revisited the January effect. Using a sample of data for the period 1995-2004 it was found the effect has not declined overall but has become concentrated in the first two weeks of January (Moller & Zilca, 2008). As for company size, a more recent study used data from 1963 to 2010 and found portfolios of small companies have high levels of the January effect (Beyer et al., 2013). Studies done on complete market data has confirmed the historical existence of the January effect but as moving closer to present day, the effect has slowly disappeared. One study used a regression with dummy variables for each month on monthly data dating back over a century, they found the effect appearing and then disappearing on a broad market index (Zhang & Jacobsen, 2013). Reasons for the slowly disappearing calendar anomalies are that since these anomalies has become known for investors, they will exploit the opportunity. With the opportunities being exploited they will disappear, thus making the markets more efficient (Marquering et al., 2006) (Perez, 2018) (Rossi & Gunardi, 2018) (Plastun et al., 2020). Historically, the level of returns has changed. When it was discovered, the broad market index experienced 2% higher returns in January compared to the other months (Zhang & Jacobsen, 2013). The effect on the broad market index disappeared, but small companies still experienced higher returns, ranging between 8-16% higher compared to other months (Moller, & Zilca, 2018).

Tax-loss selling Hypothesis

The tax loss selling hypothesis was first stated by Wachtel in 1942 when he observed price movements during December and January was different from the rest of the year in the Dow-Jones Industrial Average (Wachtel, 1942). He noted tax selling was the reason for these movements. Corporations and individuals sold their loss-making stocks at the end of the year to get tax credit and then bought them back in January. This pushes the prices down below expected market levels in December and then the returns in January becomes relatively higher than other parts of the year (Wachtel, 1942).

Later studies which have used historical data spanning a century to determine the reasons for its existence has not come up with a clear answer for explaining the January effect. They came to the same conclusions as stated earlier. The effect is only present for small cap companies and is more concentrated around the turn of the year (Haug & Hirschey, 2006). As for explanations they explored the tax-loss selling hypothesis, they rejected the idea that institutional investors engage themselves in the behaviour on the basis that tax-rules has changed throughout the investigated period, but the effect has remained. For individual investors they have not ruled out the hypothesis as a partial explanation. Additional explanations for the effect are behavioural. One of those are the Window Dressing Hypothesis (Haug & Hirschey, 2006) (Sikes, 2014).

Window Dressing Hypothesis

The window dressing hypothesis is the theory that fund, and asset managers adjust their portfolios before each reporting period. They sell the assets in their portfolio's that has performed badly and buy assets that has performed well. The rationale behind the behaviour is that fund managers are evaluated not only on the return of the portfolio, but also on their individual stock picks. By engaging in the behaviour portfolio managers can "*window dress*" their portfolio by selling the bad performers, making the portfolio looking better and have no stocks who have performed badly when it is time to publish annual reports. By only having winners, the portfolio will look better in the eye of the investors (Lakonishok et al., 1991).

In comparison to the tax-loss selling behaviour which has an economic rationale behind it, this hypothesis is based on behavioural theories. The changes made in the composition of the portfolios will have no effect on performance or tax benefits. The only effect is how fund managers are perceived on their ability to pick stocks. Additional research has shown institutional investors engage themselves in window dressing. Institutions sell small cap stocks which have performed bad in December and buy back small cap stocks in January. Both small cap winners and losers, this behaviour contributes to the January effect, even considering the fact they primarily hold large cap stocks (Ng & Wang, 2004). Similar studies have been made and have come to the same conclusion. Small cap stocks with poor performance are sold at the end of December and then bought back in January (Lync et al., 2014).

December effect

The December effect is a seasonal occurrence of abnormal returns in the month of December. The main theory behind the effect is that investors sell losing stocks, leading to a depreciation of these stocks in December. Research on the American market show that the effect is driven by sales of losing stocks and significantly lower volume traded (Chen & Singal, 2019). This strengthen the assumption that there is no abnormal value creation in December but rather an incentive to sell losing stock as presented by the window dressing hypothesis.

In contrast to the January effect, the December effect usually involves liquid stocks with larger market capitalization. This makes the December effect easier to exploit (Chen & Singal, 2019). Geographically the January effect is present in both the US and Europe. However, the December effect is only present in Europe according to Plastun et al., (2020).

The impact of firm size on the December Effect has been a significant area of study, with research suggesting that the size of a firm can influence its stock performance during this period. According to the Efficient Market Hypothesis, stock prices at any given time reflect all known information, and thus no consistent seasonal patterns should exist. However, empirical evidence suggests otherwise, especially for smaller companies. For instance, smaller companies, which are typically less liquid and more sensitive to tax-loss selling, show more pronounced price declines in December, followed by recoveries in January (Ritter, 1988) (Sarr & Lybek, 2002).

2.4 Adaptive Market Hypothesis

Research have found that the Efficient Market Hypothesis does not always hold. Studies have tried to come up with new theories that can complement or even replace it. One theory which has gained traction is the Adaptive Market Hypothesis. It is founded on the principle of behavioural economics. Market participants are human and will therefore not always be rational in their actions. The first paper mentioning the Adaptive Market Hypothesis argued that participants are changing their actions based on current market conditions. What happens is that as market conditions changes, participants will change their strategies. The participants will also use their experience implementing their new strategies. Meaning some will be able to profit from the changes whereas others will lose when market conditions change. With the changing market conditions, markets will experience different levels of efficiency at different times (Lo, 2004).

Market conditions can change for instance during market bubbles and crashes. It has been found that markets become less efficient during these times. Therefore, abnormal returns and arbitrage opportunities are created. Participants are changing their strategies and as all have different experiences, they will not all choose the same strategy. But as time moves on, the market will become more efficient as the participants converge towards the same strategy (Guedes et al., 2022).

The Adaptive Market Hypothesis is not only applicable during bubbles and crashes. It can also be applied to changing market regulations. As new regulations are introduced, the market participants are uncertain what strategy will be the best and since all have different experiences, several strategies will be applied. As time move on, the market will stabilize and any strategy that is profitable will be exploited and traded away (Lo, 2005).

During times of crisis, such as the COVID-19 pandemic, this hypothesis is particularly relevant as it offers insights into how markets adapt to significant shocks and changes in information flows. For smaller economies the effectiveness of the market is worse. Research show that each market acts independently to new information making patterns very hard to predict. Nevertheless, each market shows consistency with the adaptive market hypothesis even in times of crisis (McGroarty & Urguhart, 2016). Research on larger stable countries, such as the US, experience very little change in market efficiency (Lin & Okorie, 2021). Consequently, showing strong tendencies of adapting to new information even during times of uncertainty.

2.5 Stock & Market Characteristics

2.5.1 Volatility

The Beta of a stock measures the systematic risk. That is, risk that cannot be diversified away (Damodaran, 2005). Betas represent the individual stock volatility relative to the market's volatility. If a share has a beta of one, the price moves in perfect correlation to the market. A beta above one will experience higher volatility than the market, moving in the same direction. A beta below one also experiences higher volatility than the market but in the opposite direction to the market movement (Lakonishok & Shapiro, 1984). A low beta on a stock means that the stocks movement will be less reliant on the shifts of the market. However, a low beta stock could still experience strong price fluctuation caused by other influences.

Beta is measured by dividing the covariance between the return of the individual stock and the market with the market return (Lakonishok & Shapiro, 1984). Research have found that betas are linked to certain company characteristics. The characteristics can either be the sector the company is in or the broader market. This type is mostly relevant in time of crisis. As the market in general is volatile, certain companies depending on the sector are less volatile. One factor that is relevant through time is company size. Smaller companies tend to have higher betas than bigger companies (Campbell & Vuolteenaho, 2004) (Alexeev et al., 2017). In Norway large cap companies are those valued at over one billion euro (Nordnet, 2024). However, this does not imply that large companies are immune to volatility; nevertheless, they tend to exhibit less volatility compared to their smaller counterparts. An additional factor which has been researched is company age. The paper found a robust pattern of declining beta over the age of the firm meaning that older companies on the market has a lower beta than young companies. The authors suggests that the stock familiarity to the investors plays an important role when picking individual stocks (Chincarini et al., 2020). Large companies typically experience less volatility due to their high liquidity and low bid-ask spread (Steeley & Chelley-Steeley, 1996). Consequently, large firm stocks can be viewed as a cheap way of participating in the stock market with low risk of price depreciation/appreciation.

2.5.2 Liquidity

Described in short, liquidity is how easy it is to convert an asset into cash and vice versa to a low cost. Perfect liquidity means one investor can sell large parts of an asset instantly without it affecting the price of the asset and at no cost. Low liquidity is the opposite (Lie, 2006). Stock markets are highly liquid compared to other financial assets, nevertheless there are still differences in liquidity between stocks.

How to measure liquidity has long been a topic of research and it does not exist a consensus about one measurement which should be used (Aitken & Comerton-Forde, 2003). There are many factors that will affect the liquidity of one security and many measurements that can be used. They have been divided into two categories, trade-based measures, and order-based measures. Trade-based measures look at historical data whereas order-based measures use current data (Aitken & Comerton-Forde, 2003). For the scope of this paper only trade-based measures will be investigated. The measurements include, but are not limited to, trading value, trading volume, frequency, and turnover ratio (Aitken & Comerton-Forde, 2003). Since there is not one measurement that is correct for all situations the measurement needs to be chosen accordingly to the situation (Sarr & Lybek, 2002).

One measurement of liquidity which has been well documented in literature is company size. Papers measuring liquidity on historical daily data have used company size as one of their measurements for liquidity, acknowledging that size is usually correlated with high trading volume, and consequently a fair market value. The findings suggest firm size has a direct implication on liquidity (Gallant et al., 1992) (Goyenko et al., 2009) (Darolles & Foll, 2014).

A factor that will affect liquidity is the type of owners a specific stock has. The owners can either be institutional or individual. With more diversity between owners, especially an increase of institutional owners will drive competition between them. Additionally, more information will be incorporated into the price, reducing uncertainty about the stock leading to a decrease in information asymmetry and adverse selection. With this decrease, the liquidity of the specific stock will increase as well (Wang, 1993) (Easley & O'Hara, 2004). In the initial stages, more institutional owners will increase the liquidity. However, as the share of institutional owners increases even more, the liquidity will start to decrease. Research has found there is a non-linear u-shaped relationship between institutional ownership and liquidity. With institutional ownership levels beyond 35-40%, the liquidity will start to decrease (Agarwal, 2007). Nevertheless, large firms tend to have a high percentage of institutional ownership which has a correlation with higher shareholder value and profitability (Thomsen & Pedersen, 2000).

Housing has long been a desired asset for investors. However, the real estate market is a time-consuming process with high intermediary fees. An international analysis found a strong correlation between real estate and the stock market (Titman & Quan, 1997). Additional research on the housing market shows significant returns over the medium to long term period (Miller & Kluger, 1990). Nevertheless, the housing market is not beneficial for short term investments as it is a time-consuming process with high fees. Which in essence makes housing an illiquid asset.

2.5.3 The individual investors

Both individuals and institutions are participants on the stock market. They possess different characteristics when it comes to trading and choosing stocks. At the baseline, institutional investors have more elaborate tools and methods when they choose stocks to invest in compared to the individual investors. This difference will influence how the two types of investors choose stocks. Research in this area have shown that institutional investors own a broader range of stocks, whereas individual holds fewer different types of stocks (Li et al., 2017). This follows the principle "*investing in what you know*" which many individuals use. This is called a familiarity bias. It means when individuals choose to invest in stocks, they tend to choose stocks from companies they are familiar with as it feels safer. This bias has been confirmed by many different academic articles (Massa & Simonov, 2006) (De Vries et al., 2017) (Lei & Mathers, 2023). Similar to the familiarity bias is the home bias. It shows a tendency among individual investors to mostly only own local stocks and have little to no diversification in an international context (Lei & Mather, 2023).

Home and Familiarity Bias

Home bias refers to the tendency of investors to prefer domestic over foreign equities, often allocating a disproportionately large part of their portfolios in companies from their own country. This phenomenon persists despite the well-established financial principle of diversification, which suggests that investors can reduce risk by spreading investments across a broader array of assets and geographies. Nevertheless, individual investors continue to show a strong tendency to value well-known equities in their country disproportionately high. This phenomenon is repeatedly presented in different studies (Riff et al., 2021) (Lei et al., 2024). Furthermore, endowment bias and familiarity bias strengthen the effect. Firstly, endowment bias shows the tendency for people to hold on to stocks for too long due to emotional attachment or loss aversion. Secondly, familiarity bias tells us that familiar brand names have a higher attraction power than those unfamiliar (Baker & Nofsinger, 2010).

2.6 The wealth tax

Wealth has shown a tendency to gather among the richest making the wealth division larger (Moller & Keiser, 2000). The theoretical background for the wealth tax is to reduce economic disparity within the country (Shakow & Shuldiner, 2000). It is structured as a progressive tax on an individual's net wealth, which includes all assets such as property, investments, and savings, minus any liabilities, such as debt. The effectiveness of wealth taxes in achieving redistributive goals have proven to be significantly dependent on their design and integration within the broader tax system. Exemptions and deductions can significantly impact the progressive nature of the tax (Miller & Adam, 2021).

Research investigating the wealth taxation compared to capital income taxation found that wealth taxation is more effective in redistributing the tax burden toward less productive entrepreneurs, thereby increasing the overall productivity and output in the economy (Ocampo et al., 2019). This research further suggest that an optimal level of wealth tax will have a higher contribution to the state than an optimal income tax.

Miller & Adam (2021) argue in their research that wealth tax can be justified theoretically but has practical limitations that makes its effect less productive compared to other reforms. The research found that wealth tax penalizes savings and discourages the incentive to work. Further research find that wealth tax encourages investing into the economy forcing a larger part of an individual net wealth into stocks (Miller & Adam, 2021). Nevertheless, a substantial weakness of wealth tax research is that very few countries have implemented the tax, hence few subjects to study.

2.6.1 Valuation

Additional challenges with measuring the true value of a person’s wealth are that not all assets included in the portfolio are easy to value. Assets such as stocks and funds, which are traded on a public market are easy to value as they have a market value which is changed daily. A house is present on a housing market which will reflect an approximate true value. On the other hand, shares in privately held firms are harder to value as they are rarely traded and have no marketplace which is accepted by many (Gamage et al., 2021). As these assets are hard to value and are mostly undervalued, they are attractive to own as it will lower the measured wealth (Morgan, 2023). Often only valued at book value. Nevertheless, with the attractive valuation comes drawbacks, these assets are very illiquid. They are not traded on any public market. Investing in privately held firms could mean a lookup period for several years (Berzins et al., 2019).

The valuation of an individual's wealth in Norway happens once a year on the 1st of January. This is rooted in the costly administrative challenge of having a monthly or continuous valuation process (Morgan, 2023). Therefore, the window for tax-related asset allocation is short. Housing and privately owned stocks are time consuming processes. Consequently, not an optimal asset to take a short-term non-speculative position in. Large publicly traded firms offer high liquidity and low transaction fees, making it a preferable asset for short-term trades (Gamage et al., 2021).

2.7 Criticism of Sources

Research regarding market anomalies dates back decades. The models and type of data that has been used has varied. Some researchers have used a simple model where the dependent variable was the stock returns and the independent variable was one dummy variable, especially when testing for the January effect (Rozeff & Kinney,1976). Later studies testing for the January effect have used more elaborate models where they assigned one dummy variable for each month (Moller & Zilca, 2008) (Beyer et al., 2013) (Zhang & Jacobsen, 2013). Later studies have also applied more advanced statistical tools than performing a regression. It includes, but are not limited to, long run event studies and time series models such as ARIMA and GARCH (Moller & Zilca, 2008) (Rossi & Gunardi, 2018). Common for these studies is that all have found evidence for the January effect. Later studies however have not found it on broad market indexes, these studies have focused on company size. Depending on the investigated market, the market has been divided into portfolios, ranging from ten portfolios to three portfolios based on company size (Haug & Hirshey, 2006) (Beyer et al., 2013). An additional aspect for research on the January effect is the type of data used. Most studies done have used monthly returns, other have used daily returns. The one thing in common for studies using daily returns is that they have tested the effect in a shorter period than a month (Moller & Zilca, 2008) (Lync et al., 2014). To conclude, running a regression with dummy variables for each month and on monthly returns is generally accepted. Testing for company size and creating portfolios, a judgement call needs to be made depending on the number of companies included in the sample.

2.8 Conclusion

Summarizing the literature review it can be concluded that stock markets are efficient according to the Efficient Market Hypothesis. But there are instances where anomalies can be found such as calendar effects, one of them being the January effect. The effect has gone through changes over the years. Today the effect only exists for small companies. For large companies, strategies to profit from the discrepancies are easier to formulate and cheaper to implement. They possess smaller bid-ask spreads, higher liquidity and more easily accessible information is available. Hence, the effect still exists for small companies and not large companies. The effect can partly be explained by the tax-loss selling hypothesis and the window dressing hypothesis. What they have in common is that bad performing stocks are sold at the end of year, thus making returns lower in December compared to the other months. The effect is primarily found in small cap stock as they are more sensitive to the previously mentioned hypothesis. However, it is not limited to small cap stocks, it has also been observed in large cap stocks but not to the same extent.

During bubbles and crashes markets have been found not to be effective according to the Efficient Market Hypothesis. Thus, a complementary hypothesis has been formulated. As market conditions change, people will change their strategies based on experience. Some will be successful others will not. Very quickly however, the strategies will converge making the markets efficient again. This means markets are in the long run effective but can experience short periods of inefficiencies.

Wealth taxes are designed to mitigate economic disparities by taxing net wealth progressively, although their effectiveness varies based on their design and integration into the broader tax system. While they can redistribute the tax burden effectively and enhance economic productivity, practical limitations include discouraging savings and work incentives.

Of possible assets to invest in, participating in the stock market offers high liquidity. Comparing the possible stocks to invest in, buying shares in larger companies offers the best liquidity in the stock market. They also offer the least volatile prices. Comparing how individual stock prices changes compared to the market, larger companies have more stable prices. This can be linked to the age of the company as it has been found that older companies have more stable prices. Another aspect of stable prices is the home and familiarity bias. Individual investors prefer stocks which they know. It is not only limited to the domestic market but also companies that are well known on the domestic market.

3. Research Design

3.1 Problem, Purpose, and Contribution

The purpose of this thesis is to investigate whether the valuation discount stocks have, have had an influence on stock returns on the Oslo Stock Exchange. Further, it will be investigated if large companies experience different returns compared to the whole market. The results are not only useful for policy makers deciding the discount levels but also for investors who participate in the market. For the policy makers it is important so they can adjust discount levels to either mitigate or incentivize certain behaviour from individuals affected by the wealth tax. For investors it is important so they can implement trading strategies to profit from the discrepancies in stock prices depending on the month of the year. This thesis will contribute by comparing returns in one period not affected by the valuation discount to one period which has experienced the valuation discount. The period 2023-2017 has had the valuation discount compared to 2016-2008 who did not have the valuation discount.

3.2 Scientific perspective

The scientific perspective of the thesis is quantitative, with a mixed inductive and deductive approach. It also takes a positivistic approach. The quantitative approach starts with examining theories on the subject from which specific hypotheses are formed. Then numerical data is used to verify the stated hypotheses. They are either kept or rejected (Holton & Burnett, 2005). The thesis uses historical stock data, specifically price data. This data is then examined with well-established methods from the literature, which makes the approach quantitative and deductive. The thesis then takes an inductive approach by trying to confirm a new theory not tested before. The advantage of keeping the initial approach deductive ensures validity (Holton & Burnett, 2005). Lastly, positivism assumes that the world is objective and that researchers seek out facts in terms of relationships among variables (Holton & Burnett, 2005).

3.3 Data selection

The aim of this study is to investigate whether the Norwegian wealth tax has influenced price levels in December on the Oslo Stock Exchange. To investigate it, price data from the market is needed. The data used in this study is retrieved with the LSEG Datastream tool. To divide the companies and construct portfolios based on size, size data is collected using the same tool. Monthly data is used to avoid unnecessary noise which daily data have. Furthermore, monthly data is preferred when investigating underlying trends over several years (Morse, 1984) (Wilson et al., 2001). The monthly price data is collected with the closing price of the trading day of each month. Data on company size is collected on the final day of each November so the portfolio can be constructed of the biggest companies going into December.

3.4 Selection and Delimitation

To avoid skewness and unbiased results, the collected data will go through a delimitation process. When examining effects over several years it is important to keep the data constant. Therefore, only companies that have been listed on the Oslo Stock Exchange for the whole period will be included in the sample. This has resulted in 102 companies that all have been listed during the investigated period. See appendix 9 for the complete list. Further, a portfolio of the biggest companies will be created. The complete company list is sorted on company size, where size is determined on the last day of November each year. This assures that the list is accurate and contains the biggest companies going into December. See appendix 10 for the biggest companies each year.

3.5 Linear Regression

Many previous studies have tested seasonal effects in stock markets. Previous studies testing for monthly effects such as the January effect has used a linear regression with the dependent variable being the monthly returns and the independent variable being a dummy variable taking the value of 1 if the observation is in January and 0 otherwise (Rozeff & Kinney, 1976) (Lakonishok & Smidt, 1988). More recent studies have changed the methodology to include more than one dummy variable. Instead of one dummy variable, one dummy variable for each month has been used. Arguments for this method are that if the return volatility is higher in January compared to the other months of the year, the null is rejected incorrectly (Chien et al., 2002) (Zhang & Jacobsen, 2013), With this background, the chosen model which will be tested will be the following:

$$r_t = \alpha_1 + \alpha_2 D_2 + \alpha_3 D_3 + \cdots + \alpha_{12} D_{12} + \varepsilon_t$$

where r_t is the monthly return and t = month, $\alpha_1$denotes the average return for December and α_2 to α_{12} are the differences in returns between December and the rest of the months. D_2 to D_{12} are the dummy variables for November to January. Taking the value of one if the observation is in the month of the year, otherwise zero. ε_t is the error term which is assumed to be normally distributed. To test whether the returns in December are significant from the rest of the month, the following hypothesises are stated:

$$H_0: \quad \alpha_2 = \alpha_3 = \cdots = D_{12} = 0$$

$$H_1: \alpha_i \neq 0 \; for \; at \; least \; one \; i \, \epsilon \, [2{,}12]$$

The stated model tests if the returns in any of the other months compared to December are differentiated from 0. If at least one of the coefficients are significant from 0, the null is rejected and the returns in December are different from the rest of the year. If all the coefficients are jointly insignificant, the returns are not different in December compared to any other month of the year. To test the significance of the variables an OLS regression will be applied to the collected data. After obtaining the results, a t-test will be performed on the coefficients. Four different regressions will be performed. The first one is for all the chosen companies in the period of 2023-2017, the second one is for the same companies but for the period 2016-2008. The third and fourth regression is the same periods but for only the biggest companies.

3.5.1 Construction of Variables

The dependent variable r_t is constructed in the following way. The collected data is the stock price of the chosen companies. From the data logarithmic returns are calculated. To obtain the correct monthly returns, the price data used is the closing price of the last trading day of each month compared to the previous month. Logarithmic returns are used to mitigate any effect of non-normal distribution of the returns. Since returns are used, the maximum negative value can be -1, whereas the maximum theoretical positive value can be infinite. By transforming them to logarithmic value, they will become more equally distributed around the mean. Additional benefits with the logarithmic scale are the effect of extreme values will be reduced (Cont, 2001). For the independent variables, the dummy variables take the value of 1 when the observation is in the month and 0 otherwise.

3.5.2 Construction of Portfolios

Previous studies regarding the January effect have investigated how company size affects the presence of the effect. The conclusions are that the effect has disappeared for larger companies and is still present for small companies (Marquering et al., 2006) (Perez, 2018). With the background of what this thesis aim is, a portfolio of only the largest companies on the Oslo Stock Exchange will be created. For each year, the portfolio will be created with the 34 largest companies. The company value is determined on the last day of each November. Thus, the largest companies going into December will be investigated. Previous studies have divided the selected companies into five equal portfolios (Beyer et al., 2013) However, since the sample of 102 companies would result in small samples if divided into quintiles, it was decided that the portfolio should contain 1/3 of the biggest companies. Thus, resulting in a portfolio size of 34 companies. See appendix 10 for the portfolio composition each year.

3.6 Method evaluation

Performing a linear regression analysis can impose several problems. First, the observations need to be normally distributed. As previous studies have concluded, stock returns have the behaviour of being fat tailed. The same article concluded, even with the fat tails, t-tests can be used on stock return data (Jansen & de Vries, 1991). To investigate the normality of the collected observations, skewness and kurtosis values will be calculated together with graphical illustration with both a histogram and a Q-Q plot. An additional problem that could arise is the presence of heteroscedasticity. A scatter plot together with a Q-Q plot will be created on the residuals from the OLS regression and if any patterns arise, a Breusch-Pagan test will be conducted. If heteroskedasticity is present, appropriate measures will be taken such as running a robust regression instead.

3.7 Reliability and Validity

This study utilizes historical price data, all collected from the same stock market, where all companies are traded in the same currency. This will ensure stable results over time. Anyone replicating this study with the same data will get the same results. Hence, this study is considered reliable. For validity, the study intends to test if there is a difference in returns between two time periods. One period having the valuation discount for stocks and the other period not having it. The chosen method has previously been employed in studies where the presence of the January effect has been tested. However, the chosen method can only tell if the returns in December are different than the other months of the year. Hence, no conclusion can be drawn if the valuation discount plays an affect or not as there are many other possibilities that can explain the results.

4. Empirical Results

The following chapter present the descriptive statistics from the data sample and the results from the performed regression. The stated hypothesis is also tested.

4.1 Descriptive Statistics

Before performing the linear regression, a scatter plot was created to visualize the data. From the scatter plots, several extreme values were observed which was removed from the sample. For the scatter plots, see appendix 1. Starting from the top, with All Companies 2023-2017, and going down there was 17, 15, 27, and 37 removed observations.

Table 3. Descriptive Statistics

Data Set	# Obs	Mean	St. Dev	Min	Max	Skewness	Kurtosis
All Companies 2023-2017	8551	0,0011	0,1274	-0,9923	0,9993	-0,2099	9,8745
All Companies 2016-2008	10989	-0,0087	0,1423	-0,9941	0,9930	-0,5482	6,6486
Big Companies 2023-2017	2841	0,0076	0,0945	-0,3907	0,3913	-0,0599	1,6039
Big Companies 2016-2008	3636	0,0065	0,1026	-0,3972	0,3980	-0,2633	1,5349

Source: Own calculation of data from LSEG Datastream
Note: All values are transformed with the natural logarithm

Table 3 present the descriptive statistics for the four different datasets later used in the regression analysis. The first dataset includes all monthly returns for the chosen companies in the period 2023-2017. The second dataset are the same companies but for the period 2016-2008. The third and fourth datasets are the same periods but only with the biggest companies for each individual year included.

The mean is positive except for one dataset, when only big companies are included, the mean is higher. That indicates in the chosen periods, big companies have performed better compared to the whole market. Between the two periods, companies between 2023 and 2017 have performed better. The standard deviation for big companies is lower compared to all companies. That is an indication that big companies have more stable returns than medium and small companies. For the period 2023-2017, the values are lower which is a sign the markets have in general become more stable.

The maximum and minimum values tell the same story as the standard deviation. With only big companies, the returns are more stable and thus, fewer extreme values are observed. This trend can also be seen in the calculated values for kurtosis. With fewer extreme values as big companies have, the calculated kurtosis becomes lower. Between the two periods, the values for biggest companies are very close to each other meaning the returns have remained the same around the mean. There is however a difference for all companies. The value is higher implying the tails are heavier, meaning more observations are far from the mean and the market has become more stable over time. With the difference, big companies have remained somewhat stable over time, but medium and small sized companies have become more stable closer to present day, which can be seen from table 3. The kurtosis values for all companies are quite high, indicating many observations are in the tails which could be problematic for the regression analysis. Considerations will be taken, and any necessary changes made.

For skewness, the values are small and negative. Meaning the observations are to the most part distributed equally on both sides of the mean. The negative values tell the distributions have a slightly longer left tail. As the minimum and maximum values are very alike for all datasets, it is a sign that more of the observation are above the mean than having larger extreme values. Comparing the datasets, it can be seen big firms have smaller negative values compared to all companies. Between the periods the values also have smaller negative values. It is a sign once again that big companies have more stable returns and that the market have become more stable over time. Interpreting all these numbers together, the market has become more stable over time. Big companies have performed better and have more stable returns. For a more detailed descriptive statistics showcasing the values for each month in each dataset, see appendix 5 to 8. The same patterns seen in table 3 can be observed for each month as well.

4.2 Empirical Results

To test if there are any differences in returns between the two time periods, four different regressions are performed with the above presented datasets. After the performed regression, Q-Q plots were created on the residuals and fitted values, see appendix 1. Based on the graphs, heteroscedasticity could be present, thus a Breusch-Pagan tests was performed on all regression residuals. The tests concluded that heteroskedasticity is present in all of them. To get a robust result, robust regressions was performed, and the results are presented in table 4.

Table 4. Robust regressions

Month	All firms 2023-2017	All firms 2016-2008	Biggest firms 2023-2017	Biggest firms 2016-2008
December	0,0186***	0,0178***	0,0088	0,0346***
p-value	*(<0,0001)*	*(<0,0001)*	*(0,1053)*	*(<0,0001)*
November	-0,0182***	-0,0286***	-0,0039	-0,0295***
p-value	*(<0,0001)*	*(<0,0001)*	*(0,6166)*	*(<0,0001)*
October	-0,0158***	-0,0080*	0,0052	-0,0061
p-value	*(0,0007)*	*(0,0846)*	*(0,5078)*	*(0,4083)*
September	-0,0256***	-0,0227***	-0,0038	-0,0303***
p-value	*(<0,0001)*	*(<0,0001)*	*(0,6258)*	*(<0,0001)*
August	-0,0256***	-0,0378***	-0,0056	-0,0457***
p-value	*(<0,0001)*	*(<0,0001)*	*(0,4680)*	*(<0,0001)*
July	-0,0040	-0,0103***	0,0140*	-0,0191***
p-value	*(0,3871)*	*(<0,0001)*	*(0,0723)*	*(0,0096)*
June	-0,0278***	-0,0445***	-0,0187**	-0,0572***
p-value	*(<0,0001)*	*(<0,0001)*	*(0,0166)*	*(<0,0001)*
May	-0,0218***	-0,0329***	-0,0072	-0,0373***
p-value	*(<0,0001)*	*(<0,0001)*	*(0,3563)*	*(<0,0001)*
April	0,0062	-0,0123***	0,0179*	-0,0162**
p-value	*(0.1822)*	*(0,0080)*	*(0,0218)*	*(0,0286)*
March	-0,0346***	-0,0201***	-0,0162**	-0,0140*
p-value	*(<0,0001)*	*(<0,0001)*	*(0,0396)*	*(0.0591)*
February	-0,0152***	-0,0184***	0,0023	-0,0155**
p-value	*(0,0011)*	*(<0,0001)*	*(0,7680)*	*(0,0366)*
January	-0,0056	-0,0126***	0,0049	-0,0347***
p-value	*(0,2290)*	*(0,0068)*	*(0,5251)*	*(<0,0001)*
Observations:	8541	10979	2846	3625

Source: Own calculation of data from LSEG Datastream.
Note: All values are transformed with the natural logarithm.
***p<0,01, **p<0,05, *p<0,1.

Table 4 displays the result from the robust regression made on each dataset with the model presented in part 3.5 Linear Regression. The first thing that can be seen is the difference in results for big companies between 2023-2017 and the other three datasets. The three other datasets only have small differences between them. Looking at each individual month, the returns for December are all significant except the previously mentioned dataset. This means the returns can be differentiated from zero in December. Moving down month by month, the mentioned dataset do not have many months that are significant compared to the other three. There are only two months that are significant at the 5% level and none at the 1% level. The other three have 9, 11, and 8 months at the 1% level. Including the 5% level, the numbers are 9, 11, and 10 months respectively. This gives indications that the returns for all companies have remained equal between the two periods and that big companies in the period 2016-2008 are very similar to all companies in both periods. However, for big companies between 2023-2017, something has changed.

Using the model and the results one can calculate the expected return for a given month. By adding the coefficient for December with another month, the expected return is obtained. Taking the coefficient 0,0186 which is the expected return in December from the first dataset, one simply adds the coefficient from another month from the same dataset. Taking the coefficient from November, -0,0182, results in an expected return of 0,0004. Taking another month, for example September, -0,0256, the result is a negative expected return from the model. An observation with all the significant coefficients except December is that they are all negative, implying the returns are highest in December and all other months have lower returns. Testing the stated hypothesis, the null is rejected for all datasets at the 5% level, implying the returns in December can be differentiated from at least one other month of the year. At the 1% level, the null is rejected for three of the datasets and kept for one.

Applying the model for each individual month, it can be seen the expected return for each month only changes from positive to negative in two months for the datasets with all firms, them being November and February. Meaning the expected returns for all companies between those two periods have remained almost equal. Adding the fourth dataset, it can be observed that the expected return remain almost equal to the first two datasets. With the third dataset, with the biggest companies between 2023-2017, the result is completely different. With the two months that are significant at the 5% level, the expected return becomes negative while all other non-significant months becomes positive. However, those results are hard to interpret as the intercept, December returns, are not significant and many of the other months are not significant either. This once again, gives indications that for big companies between 2023-2017, something has changed.

5. Discussion and Critical Reflection

This chapter will analyse, interpret, and compare the results with the previous research mentioned in chapter 2 - Literature Review. First it will be done with Descriptive Statistics and then with the Regression Results.

5.1 Descriptive Statistics

Analysing the descriptive statistics in table 3 there are some patterns which are in line with previous research and some contradictions. For the mean, it is visible that the datasets with only the biggest companies are larger compared to all the companies. There are some possible explanations for that. The returns showcased are transformed to logarithmic values, thus putting less weight on the positive values. Another contributing factor to the results is the chosen companies. Only companies that were listed during the whole period were included. This will eliminate any newly listed companies that could experience high growth. The transformation and exclusion of some companies could thereby explain the somewhat unexpected means.

It is visible that standard deviation is bigger when all firms are included compared to when only the biggest firms are included. This is expected and can be linked to previous research. First, bigger firms have lower volatility, meaning a more stable share price, thus a lower standard deviation (Alexeev, 2017). The stable share price comes from their high liquidity. Larger individual trades will not affect the price to the same extent as it does for smaller companies (Lie, 2006). Larger companies also have higher trading volume which increases their liquidity (Goyenko et al., 2009) (Darolles & Foll, 2014). Looking at the difference between the two periods, it can be seen the standard deviation have become slightly lower from the first to the second period. Even with the inclusion of data between the years 2023-2020 which has experienced volatile markets from the pandemic, invasion of Ukraine, and sharp increases of interest rates. Even with those events, the market has become more stable.

Following the same reasoning as for standard deviation, the difference in minimum and maximum values can be explained. The bigger companies do not have the same extreme values as the whole market have. With the high trading volume, high liquidity, and low volatility, the monthly returns are not extreme for big companies. Continuing with skewness it can be observed that the two periods have different levels. In 2023-2017 the value is less negative than the period 2016-2008. It tells us that more observations are above the mean thus implying more positive returns. It can also be seen that the skewness is different in the same periods depending on the portfolio. The portfolios with only the biggest companies have a smaller negative value compared to all companies. Implying the observations are more centred around the mean and there are fewer larger observations. This is once again expected as larger companies have more stable share prices. Lastly, the kurtosis tells the same story as the minimum and maximum values. When all companies are included, the data have a somewhat high kurtosis, but when only the big companies are included, it drops down to acceptable levels. This is once again expected as stock returns tend to have heavy tails as small companies can experience comparable extreme returns. When only the biggest companies are included the kurtosis values return to normal. It is once again expected as big companies have more stable share prices and do not experience extreme returns as small companies do. Drawing conclusions from Table 3 it can be seen, most of the values are expected and can be linked to previous research. The values show large companies experience stable share prices compared to the whole market.

Examining the descriptive statistics for each month, the results are in line with previous research. The tables found in appendix 5-8 show that the month of January do not have the highest returns. The datasets with all companies do not have the highest mean in January. The result is the same for the datasets with only the biggest companies. This is the same results as previous and recent research (Haug & Hirschey, 2006) (Beyer et al., 2013) (Zhang & Jacobsen, 2013). Focusing on the month of December and its effect, research says there are incentives to sell stocks in the month. The effect is primarily found in smaller companies because of their lower liquidity, but it is not limited to those (Chen & Singal, 2019) (Plastun et al., 2020). Comparing the datasets it can be found the means have changed for this month. Comparing the datasets with all companies the mean has increased whereas the datasets with only the biggest companies has decreased. In the period 2016-2008 it had the highest mean and in 2023-2017 it was close to 0.

5.2 Empirical Results

From the empirical results in table 4, it was concluded all four datasets did have different and significant returns in other months compared to December at the 5% level but not at the 1% level. There are however differences in the results. Examining the two datasets with all companies included the results are very similar. The coefficients are similar, the months which are significant are similar. This means on the broad market index; no visible change has been observed between the two periods. On the other hand, examining the two datasets with only the big companies, differences are observed. For the period 2016-2008 the results are very similar to the results with all companies, many of the same months are significant for all three datasets. However, for the period 2023-2017, there are big differences. Only two of the months are significant at the 5% level whereas the other had many months significant at the 1% level, the coefficient for December is not significant, and the coefficients, significant or not generally have different values. Indicating there have been a change in market behaviour in the month of December for big companies. If it were to be a change in market behaviour for all companies, the results would been different for that dataset as well.

With all the significant coefficients being negative, the returns on the Oslo stock exchange experiences their highest levels in December. Applying the model would result in lower expected returns in any other month than December. This contradicts previous research which has found no such pattern. Previous research for the tax loss selling and window dressing together with the December effect has found evidence that the behaviour exists to some extent for all companies and large companies, especially on European markets (Ng & Wang, 2004) (Chen & Singal 2019) (Plastun et al., 2020). If the theories would be applied on the Oslo stock exchange, it would mean the returns would be lower and not higher in December as the result indicates. Meaning the results contradict the observed patterns in other markets.

6. Conclusions

This thesis aims to investigate if returns on the Oslo stock exchange has changed between two periods which are differentiated by different valuation rules in the Norwegian wealth tax system. The first period covering 2016-2008 had no discount for stocks. New valuation rules for stocks were introduced in 2017 giving them a valuation discount. The period then ends in 2023 which is the latest full year with available data. The valuation discount for stocks gives individuals incentives to alter their portfolio composition towards the end of the year, buying stocks with cash, holding the stocks through first of January and then sell them. This means individuals who engage themselves in this behaviour takes a short-term non-speculative position in the stock market. Making these changes results in a lower measurable tax and thus a lower tax liability as cash is valued at 100%.

As the wealth tax is measured as a snapshot on the first of January and not throughout the year, altercations to the portfolio are possible before the wealth is measured. It is not only stocks that have the mentioned valuation discount. Primary housing also has a valuation discount. Privately held firms are valued at book value and not at market value giving them an indirect valuation discount. These assets are however problematic as they are not well suited for taking the desired short-term, non-speculative position stocks can offer.

Norwegians are not limited to buying stocks in their home country, but theories such as home and familiarity bias tells that individuals prefer to buy stocks in their home country and in companies they know. For the desired non-speculative position, big companies are preferred as they have the right characteristics. They offer high liquidity, meaning large individual trades will not affect the price and they also offer low volatility. Big companies also have the benefit of having more institutional owners which contributes to the increased liquidity and lower volatility as they all contribute to giving the stock the right price by integrating information in the price. These characteristics are confirmed, when comparing the descriptive statistics for the created datasets.

Investigating effects at the end of the year, it is important to consider the implications of the well-established and well researched January effect. Recent studies have shown the effect still exist but only for small companies. Looking at broad market indexes and large companies the effect does not exist anymore. Additional aspects for the January effect are the possible explanations it has, the tax loss selling hypothesis and the window dressing hypothesis which has been merged into the less known December effect. These two hypotheses exist primarily for small companies. However, they do still exist for larger companies but only to a small extent.

The adaptive market hypothesis states that market participants react differently when the market conditions change but very quickly converge and adapts the same strategy making any inefficiencies quickly disappear. The introduction of the valuation discount meant new market conditions and as all participants reacts differently inefficiencies will appear. If the valuation discount where to be kept at a constant level for every year, the participants would adapt, and an effect would be hard to find. But as the valuation discount has changed every year, market participants face new conditions each year and do not know how to react. Meaning inefficiencies could exist each year.

To summarize, Norwegians who are subjectable to the wealth tax will choose stocks from large well-known companies listed on the Oslo stock exchange. Any effects from the January effect, which include small companies, can be disregarded as only companies on the whole market and big companies will be used. The adaptive market hypothesis suggests the effect will be there for all included years.

The strategy, proposed in the first chapter, where Norwegians who are a subject to the wealth tax could invest their spare cash in stocks short-term, receive a lowered measured wealth and thus a lower tax burden would mean returns goes up in December. The result from the regression shows this is not the case on the whole market index. The returns have remained almost the same when the results from the two periods are compared. However, theory suggest, people would prefer large companies, with the reasons mentioned above. The results when comparing the whole market only tells that the market in general has not changed when it comes to returns for each specific month of the year.

The theory suggests that individuals, who would engage themselves in the described behaviour would choose large companies for the reasons mentioned above. Then the expected result would be that for large companies, the returns would be higher in the second investigated period compared to the first one. The results tell something else. The returns in the first period for big companies are very much the same as for the whole market with only small differences. For the second period something has changed for big companies. December has gone from being the month with the highest return to a month where it cannot be differentiated from zero.

The result shows there is a difference in returns between the periods, however not what could be expected from the proposed strategy. If it can be linked to the wealth tax or not will require more research. The obtained results can however answer the stated research questions. There is not an observed difference in returns between the two periods for all companies in December. There is however an observed difference in returns for large companies in December between the two periods.

6.1 Future research

Further research should address the limitations of this study. The thesis identified patterns in stock market behaviour that could potentially be attributed to the wealth tax. However, definitive conclusions regarding causality cannot be done. Future research should prioritize methodologies aimed at isolating the specific effects of wealth tax on stocks. This could involve controlled studies that adjust for new economic variables or implement more refined econometric models to better capture the direct impacts of these tax policies.

A comparative analysis across different countries would also be valuable. Such research would help determine whether the patterns observed are unique to the Norwegian market or if they are consistent in various economic environments where similar taxes are implemented. This cross-national approach could compare stock returns to investigate whether the Norwegian market returns are different.

It would be particularly interesting to further focus on trading volumes in Norway during December, with an emphasis on understanding how the valuation discounts may influence trading volume. Analysing whether there are changes in trading activity for December could strengthen the claim that the Oslo stock exchange experience an anomaly. Consequently, further strengthening the assumption that wealth tax regulations influences the stock market. If increased trading volumes are observed, it could suggest that investors are actively adjusting their portfolios to maximize tax benefits before the end of the year.

Ideally, a future study would include access to individual trading data from wealthy investors. This would allow researchers to directly compare the investment behaviours of individuals affected by wealth taxes with those not impacted. Observing the trading behaviour of the target group would make it easier to draw conclusion on the effects of the tax on investor decision-making and consequently market outcomes. This level of detailed research would provide better understanding of the relationship between wealth tax policy and stock market activity, making it possible to draw clear conclusions.

7. Limitations

The research performed in this thesis is limited to firms on the Oslo stock exchange spanning from 2008 until 2023.

One of the primary challenges encountered in this research is the difficulty in isolating the effects attributable solely to the wealth tax. Given the complexity of economic systems and market dynamics, it is challenging to assert definitively that observed changes in stock market behaviour are exclusively due to modifications in wealth tax policy. Other macroeconomic factors, regulatory changes, or global market trends could also influence the observed phenomena. This limitation underscores the difficulty in establishing causality where multiple influencing factors are at play.

The majority of the theoretical frameworks and literature reviewed are based on studies and theories developed in the context of the American economy. Norway, as a smaller market, may exhibit unique characteristics that deviate from larger economies. Therefore, the applicability and relevance of American-based theories may not capture the entirety of the economic behaviours observed in Norway.

The thesis primarily investigates investment behaviours in large, highly liquid firms. In such firms, the high trading volume and the liquidity of the stocks make it difficult to significantly move stock prices. This high level of liquidity can hinder the observable effects wealth tax could have on stock prices. The effect could be subtle changes that the thesis does not manage to uncover.

The wealth tax in Norway has undergone annual modifications, which adds a layer of complexity to the analysis. These frequent changes can prevent individuals and investors from adapting or developing consistent tax avoidance strategies, which might otherwise be reflected in predictable investment patterns. This variability could hinder the ability to draw clear conclusions about the long-term effects of wealth tax policies on investment behaviour and stock market fluctuations.

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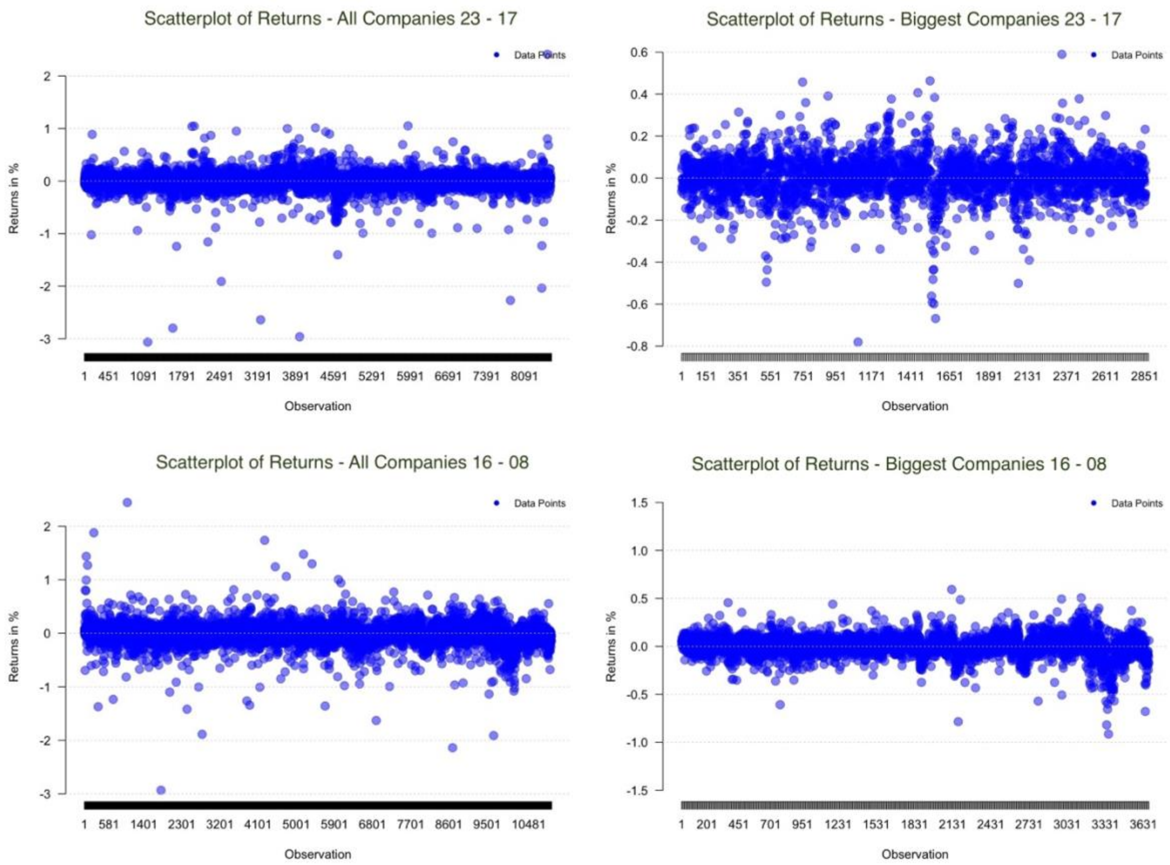
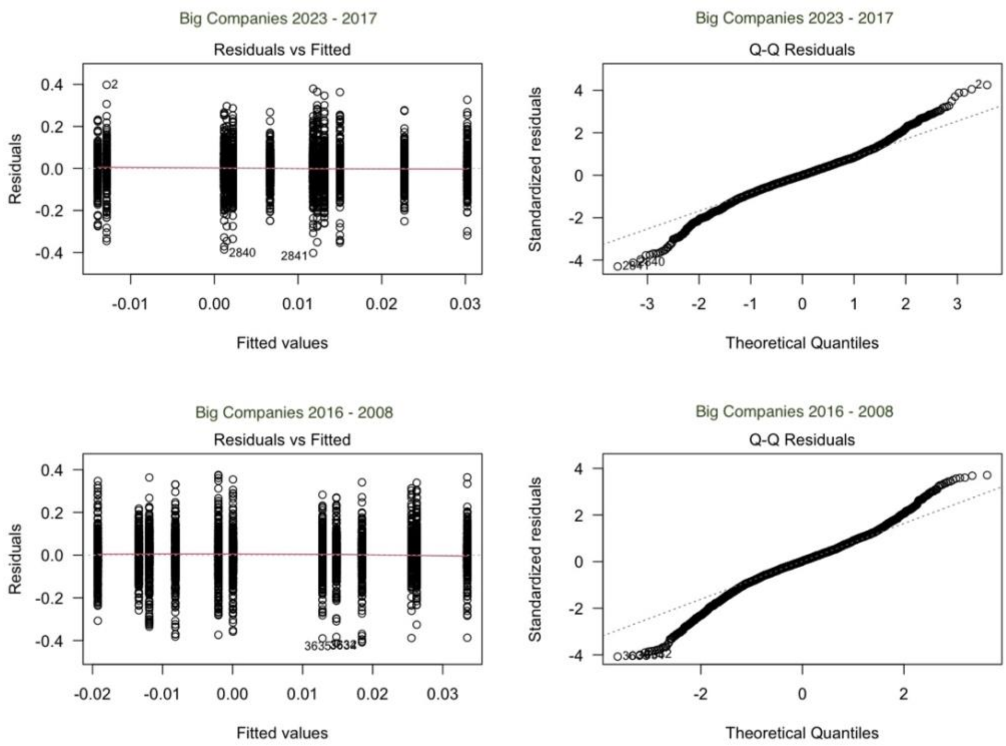
9. Appendix

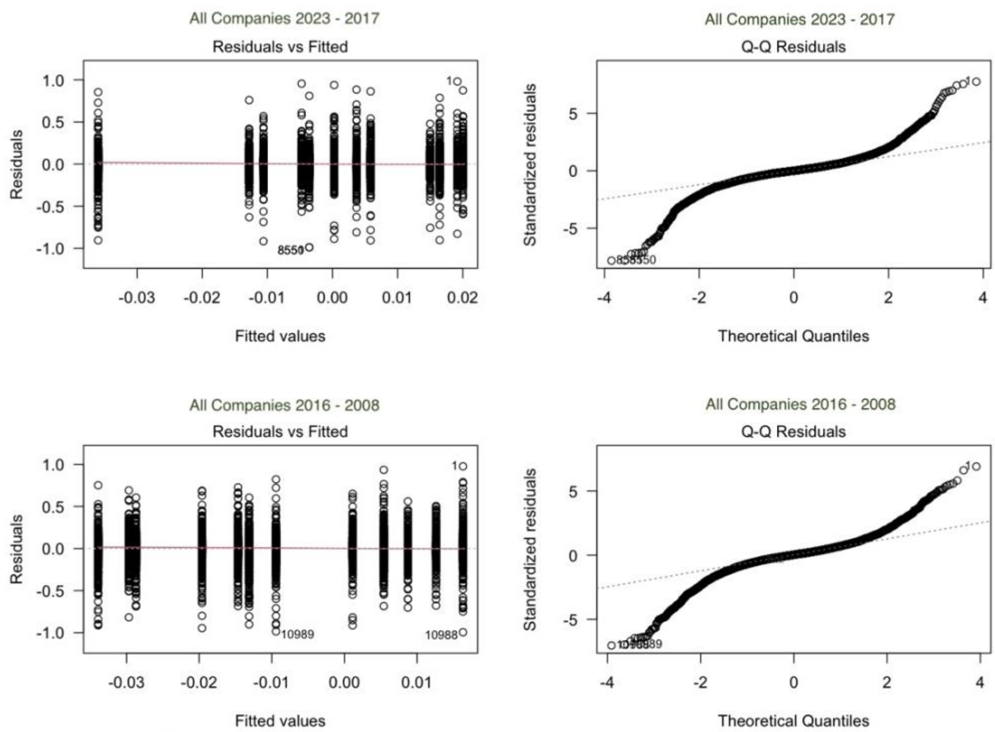
Appendix 1: Scatterplots of returns



Appendix 2: Residuals vs fitted and QQ plot for Big Firms



Appendix 3: Residuals vs fitted and QQ plot for All Firms



Appendix 4: OLS Regression table

Month	All Companies 2023-2017	All Companies 2016-2008	Biggest Companies 2023-2017	Biggest Companies 2016-2008
December	0,0192***	0,0163***	0,0067	0,0335***
p-value	*(5,27e-05)*	*(0,0005)*	*(0,2601)*	(8,00e-09)
November	-0,0155**	-0,0359***	0,0056	-0,0334***
p-value	*(0,0208)*	*(5,56e-08)*	*(0,5071)*	*(4,70e-0,5)*
October	-0,0227***	-0,0294***	0,0052	-0,0150*
p-value	*(0,0007)*	*(8,55e-06)*	*(0,5439)*	*(0,0683)*
September	-0,0239***	-0,0502***	-0,0055	-0,0454***
p-value	*(0,0004)*	*(3,29e-14)*	*(0,5184)*	*(4,90e-08)*
August	-0,0298***	-0,0450***	-0,0052	-0,0469***
p-value	*(9,03e-06)*	*(1,02e-11)*	*(0,5416)*	*(1,16e-08)*
July	-0,0042	-0,0075	0,0161*	-0,0207**
p-value	*(0,5328)*	*(0,2512)*	*(0,0585)*	*(0,0117)*
June	-0,0320***	-0,0460***	-0,0206**	-0,0527***
p-value	*(1,85e-06)*	*(3,56e-12)*	*(0,0154)*	*(1,37e-10)*
May	-0,0189***	-0,0310***	-0,0045	-0,0355***
p-value	*(0,0048)*	*(2,83e-06)*	*(0,6001)*	*(1,51e-05)*
April	0,0009	-0,0037	0,0236***	-0,0072
p-value	*(0.8980)*	*0,5750*	*(0,0056)*	*(0,3793)*
March	-0,0552***	-0,0151**	-0,0195**	-0,0078
p-value	*(2e-16)*	*(0,0215)*	*(0,0225)*	*(0,3312)*
February	-0,0133**	-0,0257***	0,0065	-0,0187**
p-value	*(0,0470)*	*(9,91e-05)*	*(0,4441)*	*(0,0232)*
January	-0,0027	-0,0109*	0,0083	-0,0417***
p-value	*(0,6855)*	*(0,0989)*	*(0,3250)*	*(09e-07)*
Observations	8540	10978	2845	3624

Source: Own calculation of data from LSEG Datastream.
Note: All values are transformed with the natural logarithm.
***p<0,01, **p<0,05, *p<0,1.

Appendix 5: Descriptive statistics for data “All Companies 2023-2017”

Month	No. of Observations	Means	St. Dev	Minimum	Maximum
December	714	0,0249	0,0049	-0,8519	1,7164
November	714	0,0129	0,0058	-0,6400	1,4302
October	714	0,0027	0,0048	-0,9482	1,2391
September	714	0,0008	0,0049	-0,9390	1,5846
August	714	-0,0058	0,0047	-0,8966	0,7475
July	714	0,0219	0,0043	-0,5234	1,7500
June	714	-0,0071	0,0041	-0,4746	1,1092
May	714	0,0132	0,0066	-09286	1,8454
April	714	0,0284	0,0052	-0,4370	1,4468
March	714	-0,0244	0,0058	-0,7537	1,2661
February	714	0,0155	0,0064	-0,8696	1,8557
January	714	0,0241	0,0054	-0,9532	1,2324

Source: Own calculation of data from LSEG Datastream.
Note: All values are transformed with the natural logarithm.

Appendix 6: Descriptive statistics for data “All Companies 2016-2008”

Month	No. of Observations	Means	St. Dev	Minimum	Maximum
December	918	0,0182	0,0054	-0,6241	2,4645
November	918	0,0135	0,0071	-0,6346	3,2086
October	918	0,0083	0,0048	-0,5113	2,5661
September	918	0,0076	0,0043	-0,8821	0,8053
August	918	0,0080	0,0052	-0,7171	0,9500
July	918	0,0133	0,0131	-0,9467	10,5010
June	918	0,0024	0,0075	-0,7389	5,5357
May	918	-0,0104	0,0065	-0,8519	3,3750
April	918	-0,0039	0,0049	-0,4844	1,8947
March	918	-0,0067	0,0051	-0,8485	1,5610
February	918	-0,0027	0,0061	-0,8037	1,1636
January	918	-0,0044	0,0046	-0,7579	1,0507

Source: Own calculation of data from LSEG Datastream.
Note: All values are transformed with the natural logarithm.

Appendix 7: Descriptive statistics for data “Biggest Companies 2023-2017”

Month	No. of Observations	Means	St. Dev	Minimum	Maximum
December	238	0,0089	0,0052	-0,3941	0,3160
November	238	0,0183	0,0073	-0,2874	0,4583
October	238	0,0170	0,0066	-0,3234	0,4789
September	238	0,0026	0,0066	-0,3908	0,3069
August	238	0,0046	0,0052	-0,2912	0,3474
July	238	0,0261	0,0052	-0,2042	0,3497
June	238	-0,0083	0,0057	-0,2510	05021
May	238	0,0045	0,0067	-0,5419	0,3353
April	238	0,0410	0,0076	-0,2510	0,8036
March	238	-0,0173	0,0082	-0,4876	05798
February	238	0,0185	0,0068	-0,2202	0,4331
January	238	0,0204	0,0068	-0,2869	0,4596

Source: Own calculation of data from LSEG Datastream.
Note: All values are transformed with the natural logarithm.

Appendix 8: Descriptive statistics for data “Big Companies 2016-2008”

Month	No. of Observations	Means	St. Dev	Minimum	Maximum
December	306	0,0382	0,0053	-0,2975	0,4889
November	306	0,0032	0,0062	-0,3513	0,4254
October	306	0,0165	0,0074	-0,5993	0,8088
September	306	-0,0219	0,0080	-0,5438	0,6384
August	306	-0,0077	0,0052	-0,2379	06272
July	306	0,0174	0,0054	-0,3140	0,3438
June	306	-0,0136	0,0061	-0,2787	0,3881
May	306	0,0036	0,0069	-0,3511	0,4526
April	306	0,0353	0,0065	-0,2586	0,6580
March	306	0,0299	0,0053	-0,3041	0,4033
February	306	0,0189	0,0065	-0,4555	0,5778
January	306	-0,0056	0,0067	-0,4928	0,3810

Source: Own calculation of data from LSEG Datastream.
Note: All values are transformed with the natural logarithm.

Appendix 9: The sample of all included companies

EQUINOR	GOODTECH	REC SILICON
DNB BANK	GRIEG SEAFOOD	ROMREAL
AKER BP	GYLDENDAL	SALMAR
NORSK HYDRO	HAVILA SHIPPING	SANDNES SPAREBANK
TELENOR	HEXAGON COMPOSITES	SCANA
AKER	HOLAND OG SETSKOG SPAREBANK	SCHIBSTED A
YARA INTERNATIONAL	HUNTER GROUP	SEABIRD EXPLORATION
KONGSBERG GRUPPEN	INTEROIL EXP.&. PRDN.	SIEM OFFSHORE
ORKLA	ITERA	SKUE SPAREBANK
TOMRA SYSTEMS	JAEREN SPAREBANK	SOGN SPAREBANK
ABG SUNDAL COLLIER HOLDING	JINHUI SHIPPING AND TRANSPORTATION	SOLSTAD OFFSHORE
AF GRUPPEN 'A'	KITRON	SPAREBANK 1 HELGELAND
AKASTOR	KONGSBERG AUTV.HOLDING	SPAREBANK 1 SMN ORDS
AKVA GROUP	LEROY SEAFOOD GROUP	SPAREBANK 1 SOROST- NORGE
AMSC	MAGNORA	SPAREBANK 1 SR-BANK
ARCTICZYMES TECHNOLOGIES	MEDI-STIM	SPAREBANKEN MORE
ARENDALS FOSSEKOMPANI	MELHUS SPAREBANK	SPAREBANKEN OST
ARRIBATEC GROUP	MOWI	SPAREBANKEN SOR
ATEA	NAVAMEDIC	SPAREBANKEN VEST
AURSKOG SPAREBANK	NEKKAR	SPB.1 OSTFOLD AKRS.
AUSTEVOLL SEAFOOD	NEL	SPB.1 RINGERIKE HADELAND
BELSHIPS	NORDIC MINING	STOLT-NIELSEN
BLUENORD	NORWEGIAN AIR SHUTTLE	STOREBRAND
BONHEUR	NRC GROUP	STRONGPOINT
BORGESTAD 'A'	OCEANTEAM	SUBSEA 7
BOUVET	ODFJELL A	TECHSTEP
BW OFFSHORE	OLAV THON EIEP.	TGS
BYGGMA	OTELLO CORPORATION	TOTENS SPAREBANK
CARASENT	PETROLIA E&P HOLDINGS	VEIDEKKE
CONTEXTVISION	PGS	VOSS VEKSEL- OG LANDMANDSBANK
DNO	PHILLY SHIPYARD	WILHS.WILHELMSEN HDG.'A'
EIDESVIK OFFSHORE	PHOTOCURE	FRONTLINE (OSL)
ELECTROMAG.GEOSVS.	PROSAFE	ODFJELL B
GAMING INNOVATION GROUP	REACH SUBSEA	WILH WILHELMSEN HOLDING B

Appendix 10: Biggest companies for each year

2023	2022	2021
EQUINOR	EQUINOR	EQUINOR
DNB BANK	DNB BANK	DNB BANK
AKER BP	AKER BP	TELENOR
TELENOR	NORSK HYDRO	NORSK HYDRO
NORSK HYDRO	TELENOR	YARA INTERNATIONAL
MOWI	YARA INTERNATIONAL	MOWI
YARA INTERNATIONAL	MOWI	AKER BP
SALMAR	KONGSBERG GRUPPEN	TOMRA SYSTEMS
KONGSBERG GRUPPEN	ORKLA	ORKLA
ORKLA	AKER	SALMAR
AKER	TOMRA SYSTEMS	AKER
FRONTLINE (OSL)	SALMAR	KONGSBERG GRUPPEN
SUBSEA 7	STOREBRAND	SCHIBSTED A
STOREBRAND	SUBSEA 7	STOREBRAND
TOMRA SYSTEMS	SPAREBANK 1 SR-BANK	LEROY SEAFOOD GROUP
SPAREBANK 1 SR-BANK	FRONTLINE (OSL)	SPAREBANK 1 SR-BANK
SCHIBSTED A	LEROY SEAFOOD GROUP	NEL
LEROY SEAFOOD GROUP	NEL	ARENDALS FOSSEKOMPANI
SPAREBANK 1 SMN ORDS	SCHIBSTED A	AF GRUPPEN 'A'
STOLT-NIELSEN	OLAV THON EIEP.	AUSTEVOLL SEAFOOD
TGS	TGS	OLAV THON EIEP.
OLAV THON EIEP.	AUSTEVOLL SEAFOOD	SUBSEA 7
AUSTEVOLL SEAFOOD	AF GRUPPEN 'A'	ATEA
VEIDEKKE	SPAREBANK 1 SMN ORDS	SPAREBANK 1 SMN ORDS
ATEA	STOLT-NIELSEN	VEIDEKKE
NEL	ATEA	BONHEUR
BLUENORD	DNO	FRONTLINE (OSL)
AF GRUPPEN 'A'	VEIDEKKE	SPAREBANKEN VEST
WILHS.WILHELMSEN HDG.'A'	ARENDALS FOSSEKOMPANI	DNO
SPAREBANKEN VEST	BONHEUR	TGS
DNO	BLUENORD	GRIEG SEAFOOD
NORWEGIAN AIR SHUTTLE	SPAREBANKEN VEST	NORWEGIAN AIR SHUTTLE
PGS	WILHS.WILHELMSEN HDG.'A'	REC SILICON
SPAREBANK 1 SOROST- NORGE	NORWEGIAN AIR SHUTTLE	BOUVET

2020	2019	2018
EQUINOR	EQUINOR	EQUINOR
DNB BANK	DNB BANK	TELENOR
TELENOR	TELENOR	DNB BANK
YARA INTERNATIONAL	MOWI	MOWI
MOWI	AKER BP	YARA INTERNATIONAL
ORKLA	YARA INTERNATIONAL	AKER BP
NORSK HYDRO	ORKLA	NORSK HYDRO
AKER BP	NORSK HYDRO	ORKLA
TOMRA SYSTEMS	SALMAR	SALMAR
SALMAR	TOMRA SYSTEMS	LEROY SEAFOOD GROUP
SCHIBSTED A	AKER	AKER
AKER	LEROY SEAFOOD GROUP	TOMRA SYSTEMS
NEL	TGS	SCHIBSTED A
LEROY SEAFOOD GROUP	STOREBRAND	STOREBRAND
KONGSBERG GRUPPEN	SUBSEA 7	SUBSEA 7
STOREBRAND	SCHIBSTED A	TGS
SUBSEA 7	SPAREBANK 1 SR-BANK	AUSTEVOLL SEAFOOD
SPAREBANK 1 SR-BANK	KONGSBERG GRUPPEN	SPAREBANK 1 SR-BANK
AF GRUPPEN 'A'	FRONTLINE (OSL)	KONGSBERG GRUPPEN
VEIDEKKE	AF GRUPPEN 'A'	DNO
AUSTEVOLL SEAFOOD	AUSTEVOLL SEAFOOD	OLAV THON EIEP.
OLAV THON EIEP.	OLAV THON EIEP.	AF GRUPPEN 'A'
TGS	VEIDEKKE	ATEA
ATEA	GRIEG SEAFOOD	VEIDEKKE
SPAREBANK 1 SMN ORDS	ATEA	GRIEG SEAFOOD
HEXAGON COMPOSITES	SPAREBANK 1 SMN ORDS	SPAREBANK 1 SMN ORDS
FRONTLINE (OSL)	DNO	FRONTLINE (OSL)
ARENDALS FOSSEKOMPANI	BW OFFSHORE	NORWEGIAN AIR SHUTTLE
BONHEUR	NEL	BW OFFSHORE
GRIEG SEAFOOD	BONHEUR	ARENDALS FOSSEKOMPANI
SPAREBANKEN VEST	STOLT-NIELSEN	STOLT-NIELSEN
BOUVET	SPAREBANKEN VEST	PGS
BW OFFSHORE	HEXAGON COMPOSITES	WILHS.WILHELMSEN HDG.'A'
STOLT-NIELSEN	BLUENORD	NEL

2017	2016	2015
EQUINOR	EQUINOR	EQUINOR
TELENOR	DNB BANK	TELENOR
DNB BANK	TELENOR	DNB BANK
NORSK HYDRO	YARA INTERNATIONAL	YARA INTERNATIONAL
YARA INTERNATIONAL	NORSK HYDRO	ORKLA
ORKLA	ORKLA	NORSK HYDRO
MOWI	MOWI	MOWI
AKER BP	AKER BP	SCHIBSTED A
SUBSEA 7	SUBSEA 7	SUBSEA 7
STOREBRAND	SALMAR	LEROY SEAFOOD GROUP
SALMAR	LEROY SEAFOOD GROUP	TGS
AKER	AKER	SALMAR
LEROY SEAFOOD GROUP	STOREBRAND	KONGSBERG GRUPPEN
SCHIBSTED A	SCHIBSTED A	OLAV THON EIEP.
SPAREBANK 1 SR-BANK	TGS	STOREBRAND
TGS	OLAV THON EIEP.	VEIDEKKE
TOMRA SYSTEMS	AUSTEVOLL SEAFOOD	TOMRA SYSTEMS
KONGSBERG GRUPPEN	VEIDEKKE	AKER
OLAV THON EIEP.	KONGSBERG GRUPPEN	AF GRUPPEN 'A'
AUSTEVOLL SEAFOOD	AF GRUPPEN 'A'	AKER BP
AF GRUPPEN 'A'	SPAREBANK 1 SR-BANK	AUSTEVOLL SEAFOOD
ATEA	TOMRA SYSTEMS	NORWEGIAN AIR SHUTTLE
VEIDEKKE	FRONTLINE (OSL)	SPAREBANK 1 SR-BANK
SPAREBANK 1 SMN ORDS	NORWEGIAN AIR SHUTTLE	PGS
DNO	GRIEG SEAFOOD	DNO
GRIEG SEAFOOD	OTELLO CORPORATION	ATEA
WILHS.WILHELMSEN HDG.'A'	ATEA	OTELLO CORPORATION
ARENDALS FOSSEKOMPANI	DNO	STOLT-NIELSEN
FRONTLINE (OSL)	SPAREBANK 1 SMN ORDS	SPAREBANK 1 SMN ORDS
STOLT-NIELSEN	ARENDALS FOSSEKOMPANI	PROSAFE
NORWEGIAN AIR SHUTTLE	STOLT-NIELSEN	REC SILICON
BW OFFSHORE	WILHS.WILHELMSEN HDG.'A'	ARENDALS FOSSEKOMPANI
AKASTOR	PGS	WILHS.WILHELMSEN HDG.'A'
HEXAGON COMPOSITES	HEXAGON COMPOSITES	GRIEG SEAFOOD

2014	2013	2012
EQUINOR	EQUINOR	EQUINOR
TELENOR	TELENOR	TELENOR
DNB BANK	DNB BANK	DNB BANK
NORSK HYDRO	YARA INTERNATIONAL	YARA INTERNATIONAL
YARA INTERNATIONAL	NORSK HYDRO	NORSK HYDRO
ORKLA	ORKLA	ORKLA
SCHIBSTED A	SCHIBSTED A	SUBSEA 7
MOWI	SUBSEA 7	AKASTOR
SUBSEA 7	AKASTOR	SCHIBSTED A
DNO	MOWI	PGS
TGS	DNO	TGS
KONGSBERG GRUPPEN	STOREBRAND	MOWI
STOREBRAND	TGS	AKER
SPAREBANK 1 SR-BANK	KONGSBERG GRUPPEN	KONGSBERG GRUPPEN
SALMAR	PGS	STOREBRAND
OLAV THON EIEP.	AKER	PROSAFE
LEROY SEAFOOD GROUP	SPAREBANK 1 SR-BANK	AKER BP
OTELLO CORPORATION	AKER BP	DNO
AKER	OLAV THON EIEP.	OLAV THON EIEP.
NORWEGIAN AIR SHUTTLE	PROSAFE	SPAREBANK 1 SR-BANK
VEIDEKKE	STOLT-NIELSEN	TOMRA SYSTEMS
AUSTEVOLL SEAFOOD	LEROY SEAFOOD GROUP	LEROY SEAFOOD GROUP
ATEA	OTELLO CORPORATION	STOLT-NIELSEN
SPAREBANK 1 SMN ORDS	SALMAR	ATEA
AKER BP	NORWEGIAN AIR SHUTTLE	VEIDEKKE
PGS	TOMRA SYSTEMS	AUSTEVOLL SEAFOOD
TOMRA SYSTEMS	AUSTEVOLL SEAFOOD	BONHEUR
STOLT-NIELSEN	SPAREBANK 1 SMN ORDS	NORWEGIAN AIR SHUTTLE
AF GRUPPEN 'A'	VEIDEKKE	SALMAR
AKASTOR	WILHS.WILHELMSEN HDG.'A'	SPAREBANK 1 SMN ORDS
WILHS.WILHELMSEN HDG.'A'	ATEA	AF GRUPPEN 'A'
REC SILICON	REC SILICON	WILHS.WILHELMSEN HDG.'A'
PROSAFE	BONHEUR	OTELLO CORPORATION
BW OFFSHORE	AF GRUPPEN 'A'	SOLSTAD OFFSHORE

2011	2010	2009
EQUINOR	EQUINOR	EQUINOR
TELENOR	TELENOR	TELENOR
DNB BANK	DNB BANK	DNB BANK
YARA INTERNATIONAL	YARA INTERNATIONAL	YARA INTERNATIONAL
NORSK HYDRO	NORSK HYDRO	ORKLA
ORKLA	ORKLA	NORSK HYDRO
SUBSEA 7	AKASTOR	REC SILICON
AKASTOR	SUBSEA 7	AKASTOR
SCHIBSTED A	MOWI	STOREBRAND
STOREBRAND	PGS	SUBSEA 7
KONGSBERG GRUPPEN	SCHIBSTED A	MOWI
TGS	STOREBRAND	SCHIBSTED A
PGS	KONGSBERG GRUPPEN	FRONTLINE (OSL)
AKER	REC SILICON	PGS
AKER BP	FRONTLINE (OSL)	AKER
PROSAFE	TGS	TGS
MOWI	BW OFFSHORE	OLAV THON EIEP.
OLAV THON EIEP.	PROSAFE	KONGSBERG GRUPPEN
DNO	AKER	VEIDEKKE
STOLT-NIELSEN	LEROY SEAFOOD GROUP	PROSAFE
BW OFFSHORE	AUSTEVOLL SEAFOOD	AUSTEVOLL SEAFOOD
TOMRA SYSTEMS	OLAV THON EIEP.	BONHEUR
ATEA	DNO	LEROY SEAFOOD GROUP
SPAREBANK 1 SR-BANK	STOLT-NIELSEN	SPAREBANK 1 SR-BANK
BONHEUR	SPAREBANK 1 SR-BANK	STOLT-NIELSEN
VEIDEKKE	VEIDEKKE	WILHS.WILHELMSEN HDG.'A'
WILHS.WILHELMSEN HDG.'A'	BONHEUR	SALMAR
LEROY SEAFOOD GROUP	SALMAR	NORWEGIAN AIR SHUTTLE
AUSTEVOLL SEAFOOD	SPAREBANK 1 SMN ORDS	MAGNORA
SPAREBANK 1 SMN ORDS	ATEA	DNO
OTELLO CORPORATION	TOMRA SYSTEMS	TOMRA SYSTEMS
REC SILICON	WILHS.WILHELMSEN HDG.'A'	SOLSTAD OFFSHORE
AF GRUPPEN 'A'	NORWEGIAN AIR SHUTTLE	ATEA
ARENDALS FOSSEKOMPANI	SOLSTAD OFFSHORE	BW OFFSHORE

2008
EQUINOR
TELENOR
ORKLA
DNB BANK
YARA INTERNATIONAL
REC SILICON
NORSK HYDRO
FRONTLINE (OSL)
AKASTOR
AKER
KONGSBERG GRUPPEN
SUBSEA 7
PROSAFE
DNO
PGS
STOREBRAND
SCHIBSTED A
OLAV THON EIEP.
BONHEUR
TGS
STOLT-NIELSEN
TOMRA SYSTEMS
MOWI
WILHS.WILHELMSEN HDG.'A'
ODFJELL A
ARENDALS FOSSEKOMPANI
SALMAR
LEROY SEAFOOD GROUP
VEIDEKKE
BW OFFSHORE
SOLSTAD OFFSHORE
SPAREBANK 1 SR-BANK
SIEM OFFSHORE
OTELLO CORPORATION

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management
Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve, Belgique | **www.uclouvain.be/lsm**