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TITLE:

**Earnings Announcements and Stock Returns – An Event Study of the Norwegian Stock Market**


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## Abstract

This master’s thesis is an event study concerning earnings announcements in the Norwegian stock market between 2018 and 2020. The purpose of this study is to test the efficient market hypothesis proposed by Eugene Fama on the Norwegian stock market, and we want to test exactly how firms in the Norwegian market react to earnings announcements. Several studies have been done regarding how the market in various countries reacts to earnings announcements, but few studies have been done on the Norwegian market. Previous research has used both event studies and difference-in-difference methods to observe the actual impact of the markets reacting to earnings announcements. In our thesis, we conducted an event study to see if the market reacted efficiently to the earnings announcements, deviating from the expected values. We also performed a difference-in-difference analysis to observe how much impact an earnings announcement had on a company`s return compared to companies that hadn't released any announcement. Our thesis showed that the Norwegian market seemingly acts efficient to earnings announcements under ordinary market conditions, but that it`s harder to estimate the observed market reactions in periods with high market volatility, such as in 2020. We also showed that in periods with high volatility, the market seemingly values other factors more highly, which causes less observed effect from the release of earnings announcements.

## Preface

This thesis concludes our 2-year master`s degree in Applied Finance here at the University of Stavanger. Writing this thesis has been a meaningful experience but also demanding and exhausting. Especially given the current restrictions, which have caused us to write a lot more from home than initially planned. During our time here at UiS, we have gained insight and knowledge into several disciplines. Everything from macroeconomic factors to investments and resource planning. Still, the area that piqued our interest was market efficiency. An area which in many ways can be seen as quite contradictory in the way that analysts spend thousands of hours to beat a market which in theory should be impossible to beat. This made us want to gain more insight into how markets work in reality. Thus, we landed on our chosen topic.

We want to thank our advisor, Siri Valseth, for her advice and the time spent helping us during this process.

Stavanger, June 2021.

Fredrik Lange Berge and Audun Aspelund Pedersen.

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# 1. Introduction

In 1965, Eugene Fama stated that all available information should be reflected in the value of a security, while Ball and Brown (1968) showed that over half of the information regarding a firm is captured through their income statement. In other words, when firms release their earnings announcement, it’s not a meaningless document but rather crucial information containing numbers that can tell an investor a story about the firm´s value. The reason why investors pay so much attention to firms' earnings is because of how we assign value to a given security. The basic approach to estimate a firm's value is to accumulate all its discounted cashflows until liquidation. However, the issue with this approach is to consider how an investor can know how much a firm will earn many years into the future. That’s why the investors pay a lot of attention to firms' earnings announcements because they give us the tools to estimate how the firms' earnings are developing and how much the firm will earn in the future, thus making it possible to estimate the value of the firm. This is also why whenever a firm's earnings deviate from the markets expected values, the firm's valuation also changes. According to Fama (1970), market efficiency makes the market correct itself whenever there is a change in the value of a security. The three types of market efficiencies are strong, semi-strong, and weak form, where even weak form of market efficiency states that all information that is of public access should be reflected in a firm's valuation.

Apart from professional investors, we can assume that few people do valuations of firms themselves. According to Verdipapirfondenes forening (VFF, (2020), as many as 40% of the Norwegian population do some form of investing in stocks, and we can assume that not all of them have an economic background. For everyday people to make safer investments, it is important that the market is efficient or that they at least receive the appropriate return according to the chosen risk. We want to analyze if Norwegian companies experience efficient price reactions whenever they experience earnings that deviates from the market's expectation in the chosen time period from the first quarter in 2018 until the last quarter in 2020. We also want to analyze if other types of factors, such as if the COVID-19 pandemic had any influence on the market efficiency in the Norwegian stock market.

We conduct an event study to best capture the effects of the companies' earnings announcement. An event study is a method that is commonly used to measure the impact of an event, such as earnings announcements. It’s a method that has been used in several existing research papers, often in terms of testing the impact a variable can have on the market (Binder, 1998; Erlien, 2011; Fama, Fisher, Jensen, & Roll, 1969; Kothari, 2001; MacKinlay, 1997). An event study demands that one must define something as an event, in addition, to define the period when this "event" occurs as an event window. In our case, we will use whenever a company releases its earnings announcements as the "event" and the twenty trading days prior- and post the announcement date as the event window. To succeed in terms of using an event study, we will try to establish "normal" market condition to see how the company's stock prices deviate from this whenever they are releasing an earnings announcement. We will, similar to MacKinlay (1997), calculate the companies' abnormal returns and use this as a measure regarding how much they are impacted by the earnings announcement. To forecast the companies expected earnings, we will use a seasonal drift term model developed by Brown & Kennelly (1972). To forecast the companies standardized return, we will be using CAPM. Our aim is to test the market efficiency in the Norwegian stock market. Hence, our event study will consist of the companies listed on the OSEBX-index.

The most essential part when using an event study to analyze if the market is efficient is to correct for other factors which could influence the abnormal return of the stocks. In other words, even if we can prove the existence of abnormal returns in the event of surprise earnings announcements, it wouldn't be useful unless we can control other factors which can cause an abnormal return. Therefore, we will strengthen our event study by combining it with a difference-in-difference approach, inspired by Firth (1976), to better isolate the effect of the actual earnings announcements. By using this combination of event-study methodology combined with our difference-in-difference approach, we believe this study can contribute to the existing literature regarding market efficiency, as we have not seen this specific approach used on the Norwegian stock market in other previous studies.

In this paper, we want to answer two essential research questions regarding market efficiency and earnings announcements. The first being if the Norwegian stock market reacts efficiently to earnings announcements. The other is to what extent the Norwegian companies react to the earnings announcements.

# 2. Background and Literature Review

## 2.1 Information Content and Value Relevance of Earnings

There has been proven to be a clear connection between earnings and the valuation of firms (Beaver, 1968). For this reason, financial statements are one of the most crucial factors for investors when evaluating firms (Kothari, 2001). Kothari also notes that investors are, in fact, not investing based on the firm's current value but rather the firm's intrinsic value. The difference between these two values is an indication of the expected rewards from investing in the security. Farmer & Lo (1999) state that investors pay according to the firm's return, higher returns make the price of the stock increase, and if the returns are expected to increase, the investors are willing to bear a higher risk of holding the stock.

### 2.1.1 Earnings Predictability

There have been several empirical studies conducted to observe both the nature and predictability of earnings. Dichev & Tang (2009) emphasize that precise earnings prediction is a difficult task that depends on both economic and accounting factors. Ball & Brown (1968) explains in their article that companies' income, to a large degree, moves together and that half of the information regarding a firm is captured through the income statement. Kothari (2001) states that even though future earnings can, to some degree, be seen as a random walk, they can still be predicted using the current price of the security. Since the stock price is based on earnings, future earnings will be reflected in the current price. Under the assumption that the market is efficient, the size of the change in earnings would be irrelevant, as this is already reflected in the price. It should be noted that this is from the market's perspective.

According to Das, Levine, & Sivaramakrishnan (1998), there are several factors to consider when predicting future earnings. The first is that analysts are more precise in predicting a firm's future earnings using analysts' forecasts compared to predicting future earnings based on historical earnings. However, analysts were found to be biased as they, on average, were a bit optimistic when estimating future earnings. They also stated that there is a significant difference between earnings variability and earnings predictability. In many cases, large earnings variability could be due to the firms having a high degree of seasonal operations, which would lead to large variations in earnings. However, this would not affect the predictability of the earnings.

Bernard & Thomas (1989) researched how the earnings announcement for one specific period influences the following earnings announcements. They found a post-earnings announcement drift related to the subsequent period of an earnings announcement. The market tended to act positively or negatively, depending on the earnings in period *t*, in the days surrounding the earnings announcement of period *t+1*. Bernard & Thomas (1990) continue the research from Bernard & Thomas (1989) by showing that stock prices do not fully reflect the implications that current earnings have been proven to have on future earnings. The market seems to overestimate the impact the current earnings in period *t* have on future earnings in the periods *t+1* up to *t+4*. They found evidence to support that the stock prices partially reflect naïve earnings expectation, which means that future earnings will be equal to earnings for the comparable quarter of the prior year (Bernard & Thomas, 1990).

### 2.1.2 Previous Research on Earnings and Returns

In this section, we summarize important previous research on earnings announcements and their informational value.

Beaver (1968) and May (1971) revealed that earnings announcements are associated with larger price changes than during periods without any financial reporting. These results support the opinion that earnings announcements carry information that can affect firm value. Market capitalization is another factor that diversifies the responses to the earnings of different companies. Chambers & Penman (1984) found that the price reactions to small companies' earnings appear to be larger compared to those of larger companies. Their results also stated that if the earnings number is perceived as “bad news”, the price variability seen the days after a significant earnings surprise is larger than if the earnings number is perceived as “good news”.

It is crucial to be aware of how return variance can cause implications when studying price reactions to earnings news. Beaver (1968) documented that variance increased around earnings announcements, which cause an increased expected or required return (Ball & Kothari, 1991). Ball and Kothari (1991) applied the capital asset pricing model (CAPM) of expected returns for each day of the event period in their study. After controlling risk variation, they concluded that stocks experience abnormal returns on the event day.

There is no doubt that most of the previous research in the field of earnings announcements has been performed on the US market using data from American companies. Nevertheless, we were still able to find research performed on other markets. Al-Baidhani (2018) researched the stock price response to earnings announcements in Japan. The findings in his research show a significant positive cumulative abnormal return when earnings increase and a negative cumulative abnormal return if earnings decline. Isakov and Pérignon (2001) investigated the dynamics of the implied volatility or implied standard deviation (ISD) around earnings announcement dates in Switzerland. They found that the average ISD slightly increased before the information disclosure. This can indicate that the market expects some uncertainty on the event date. On the announcement date, the average ISD decreased for the next four days, indicating some level of persistence in instantaneous volatility and the presence of events containing bad news. It took several days until the ISD returned to its long-term level after an earnings announcement that confirms the presence of persistence in shocks to volatility. Sponholtz (2008) researched the information content of earnings announcements in Denmark. This research found abnormal volatility in the days surrounding an event, indicating that the information is of value to the stock market. Sponholtz also found evidence suggesting a slow adjustment to the information in Denmark. The paper drew attention to the fact that Denmark is a small market and that small markets can experience less investor sophistication which in turn can lead to less pre-announced information. Dimitropoulos & Asteriou (2009) studied the relationship between earnings and stock returns in the Greek capital market. The overall results of this research demonstrated significant value relevancy of accounting earnings prepared under the Greek GAAP accounting principles.

## 2.2 Earnings Announcements

### 2.2.1 Information Asymmetry

Kim & Verrecchia (1994) argued that there most likely exists more information asymmetry in the period of an announcement than in non-announcement periods, which makes certain traders superior in decision-making compared to other traders. The paper is concerned with public financial accounting data, particulary earnings announcements. They state that "[…] earnings announcements, provides a source of private information to certain traders through their information processing activities" (Kim & Verrecchia, 1994, p. 58). The presented model captures the number of information processors that are endogenous to the market, allowing earnings announcements to create asymmetry through the activities of traders processing public announcements into private information. More public information reduces the potential information asymmetries, reduces the bid-ask spreads, and increases market liquidity in an announcement period. On the contrary, Vega (2006) claims that whether the information is public or private is irrelevant. The important matter is whether this information is related to informed or uninformed traders.

### 2.2.2 Reaction to Earnings Announcements

The timing of reactions to earnings announcements has been frequently investigated in event studies. Chambers & Penman (1984) study the relationship between stock price behavior and earnings reports in pooled cross-sectional time-series data. An interesting finding from this study is that it appears to be larger price movements to earnings reports for small firms than large firms. This corresponds to Atiase (1980), as it appears to be a reversed interplay between the size of a company and the stock price effects from earnings reports. Less information may be the reason smaller firms generate larger price reactions than larger firms. However, these studies do not take account of other factors that influence stock returns. Bartov, Radhakrishnan & Krinsky (2000) researched the plausible effect earnings announcements have on stock returns related to shares which institutional investors obtain. The key finding in their article is that proxies for transaction costs, i.e., stock price, trading volume, and firm size have a relatively small influence on post-announcement abnormal returns when institutional variables are held explanatory.

### 2.2.3 Post-Earnings Announcements

There are numerous extensive studies in the field of earnings announcements. The provided literature reviews have explained pre-earnings announcements, and now, we will investigate the post-earnings announcements drift. Ball & Brown (1968) were the first to study the abnormal returns after an earnings announcement. They found that the return of the stock was influenced by good and bad information, driving it upwards when experiencing good news and downwards for bad news. Bernard & Thomas (1989) attempted to discriminate between two alternative explanations for post-earning announcements: (1) a failure to adjust abnormal returns for risk; and (2) a delay in the reaction to earnings reports. The evidence was consistent with a delay in reaction to earnings reports.

Moreover, Bhushan (1994) stated that the magnitude of post-earnings announcement drift is positively related to trading costs. The chosen proxy was trading volume and share price of a stock, and these factors were significant to determine transaction costs for stocks. This is the opposite outcome of what Radhakrishnan & Krinsky (2000) found, indicating that studying prior-earnings announcements and post-earnings announcements can give mixed results.

## 2.3 Efficient Markets

### 2.3.1 The Efficient Market Hypothesis

Eugene Fama defined an efficient market as "[…] a market where, given the available information, actual prices at every point in time represents very good estimates of intrinsic values" (Fama, 1965, p. 90). Fama later simplified the definition as "[…] a market in which prices always "fully reflect" all available information is called "efficient"" (1970, p. 383). Fama (1970) also defined some market conditions that are in line with the efficient market hypothesis.

To define a market that fully reflects all available information, the degree of efficiency can be divided into three parts: weak-, semi-strong- and strong form. The weak form of market efficiency states that the price reflects all information regarding historical prices. In the semi-strong form, information related to public announcements is also reflected in the price. The last and most strict form is the strong form of market efficiency, which assumes that all information, including insider information, is reflected in the price.

Fama (1970) found extensive evidence in support of the efficient market hypothesis. However, he still noted that there are real-world market frictions that can be potential sources of market inefficiency.

Most prior research has been focused on developed markets, where researchers found that the markets usually react quickly to news. In later studies, there has been more focus on researching market efficiency in emerging markets. Sehgal and Bijoy (2015) researched how stock prices react to quarterly earnings announcements in the Indian market. In their research on the period 2002-2011, they observed significant pre-event abnormal returns in 32 of 37 quarters. Regarding post-event abnormal returns, this was observed in 35 of 37 quarters. According to this paper and the observed results, the Indian market was inefficient on a semi-strong form of efficiency. This implies that investors, in theory, have the possibility of earning abnormal returns in the Indian market.

Results from previous studies found the strong form of market efficiency hard to validate. Investors with access to insider information might have the opportunity to earn abnormal returns. Still, most countries have laws prohibiting insider trading. Finnerty (1976) researched how well insiders do relative to the market in general. He found that in the short-run, insiders were able to identify profitable situations in their own companies.

### 2.3.2 Market Anomalies

Anomalies are irregularities or unexpected price behavior that are not consistent with the prediction of the efficient market hypothesis (Hayes, 2021). The existence of market anomalies has been explored by several studies (Latif, Arshad, Fatima, & Farooq, 2011). Latif et al. (2011) state that many stock exchanges in the world experience deviations from the rules of the efficient market hypothesis. These deviations are what we call anomalies. Such "[…] anomalies could occur once and disappear, or could occur repeatedly" (Latif et al., 2011, p. 10).

#### *Examples of Anomalies*

The first example of an anomaly is the size effect. Banz (1981) studied the relationship between stock return and the market value of common stocks on the New York Stock Exchange. Banz found that the relationship between the expected return and the market risk of a security is not linear. This is contradictory to the linear relationship suggested by the capital asset pricing model (CAPM) developed by Sharpe (1964) and Lintner (1965). The findings in Banz (1981) show that smaller firms have higher risk-adjusted returns. According to Schwert (2002), the size effect seems to have weakened or disappeared. Still, Fama and French (2012) examined North America, Europe, Japan, and Asia Pacific. They found that except for Japan, value premiums are larger for small stocks. This is an indication that this anomaly might still exist.

The turn-of-the-year effect is another anomaly. Keim (1983) researched the empirical relation between abnormal returns and market value of common stocks in the US market month-by-month. This paper found that the daily abnormal return distribution was higher in January than the eleven other months within a year. Ritter and Chopra (1989) used a value-weighted- rather than an equally weighted portfolio. They found that small-firm returns were positive even for the Januaries where the market returns were negative. "This is consistent with the portfolio rebalancing explanation of the turn-of-the-year effect" (Ritter & Chopra, 1989, p. 149).

A third anomaly is the value effect. Norges Bank Investment Management (NBIM, 2012) has published a discussion note on the value effect where they define that “The value effect is the excess return that a portfolio of value stocks (stocks with a low market value relative to fundamentals) has, on average, earned over a portfolio of growth stocks (stocks with a high market value relative to fundamentals)” (NBIM, 2012, p. 1). Basu (1977) examined this effect by researching the relationship between the investment performance of equity securities and their P/E ratios. Basu found that the low P/E portfolios seem to have earned higher absolute and risk-adjusted returns than the high P/E securities on average. Ball (1978) states that the anomaly most likely exists because earnings variables proxy for omitted variables or that there are other misspecification effects in the two-parameter model.

#### *The Three-Factor Model*

There are two common methods of estimating assets’ returns, one being CAPM, as earlier mentioned, the other one is the three-factor model suggested by Fama and French (1992). Fama and French (1996) applied a three-factor model to test if anomalies, such as the value and size effect, disappear. They found that “[…] except for the continuation of short-term returns, the anomalies largely disappear in a three-factor model” (Fama & French, 1996, p. 55). Bondt and Thaler (1985) found that the three-factor model can explain the reversal of long-term returns. On the other hand, Jegadeesh and Titman (1993) found that the three-factor model fails to explain the short-term returns.

## 2.4 Time-Series Models for Estimating Expected Earnings

We have seen several examples of time-series being used to make future forecasts based on past data (Griffin, 1977; Lorek, McDonald, & Patz, 1976; Watts & Leftwich, 1977). According to Box and Jenkins (1976), future forecasts of earnings consist of both a seasonal component and a component for the adjacent quarter. By utilizing these two components, one can create a moving average which would work as a relatively precise forecast for earnings. Lorek et al. (1976) showed that using this time-series method to predict a firm's future earnings was superior to the management forecast. This was also confirmed by Griffin (1977).

### 2.4.1 Time-Series Models

Foster (1977) analyzes five different time-series models which are used to forecast earnings. The main difference between the forecasting models is the use of drift term, whereas they take account for seasonality or if they use a "naive" assumption, ignoring both seasonality and drift. We will to a certain degree, explain the different models to justify the decision we have made in terms of choosing a time-series model to forecast earnings. The models analyzed in Foster (1977) article are:

*Model 1:* $E(Q_t) = Q_{t-4}$

*Model 2:* $E(Q_t) = Q_{t-4} + \delta$

Model 1 and 2 forecast earnings based on a seasonal pattern, while the difference between 1 and 2 is that model 2 considers drift as well. Brown & Kennelly (1972) classify these two models as naïve models since the models go under the assumption that the earnings in a quarter will be the same as the earnings quarter for the previous year (model 1) or that the earnings will be similar as a quarter in the previous year, except for the drift adjustment. The drift adjustment consists of adjusting the forecast based on the average earnings history for that specific stock.

*Model 3:* $E(Q_t) = Q_{t-1}$

*Model 4:* $E(Q_t) = Q_{t-1} + \delta$

Model 3 and 4 forecast quarterly earnings based on the previous quarter, and in similarity with models 1 and 2, the difference between the models is drift term. The issue with these models is that they exclude seasonality from the forecasting. As Foster (1977) empirically shows, they give poorer results when used to measure the market's expectation in terms of forecasting the earnings for the next quarter.

*Model 5:* $E(Q_t) = Q_{t-4} + \phi_1(Q_{t-1} - Q_{t-5}) + \delta$

Model 5 is an extension of model 2, and it includes both the quarterly component and the adjacent quarter to quarter component. "Using the Box-Jenkins notation for multiplicative seasonal models, it is a $(1,0,0) \times (0,1,0)_{s=4}$ model" (Foster, 1977, p. 6)

### 2.4.2 Other Available Methods for Estimating Expected Earnings

As previously mentioned, one can use time-series models to estimate expected returns. Another approach one can use is to forecast the expected earnings by analyzing the stocks directly. This approach has been employed countless times in existing literature (Banker &

Chen, 2006; Beaver, Clarke, & Wright, 1979; S. A. Sharpe, 2002). One of the problems with this approach is the time consumption of estimating every stock separately. One might also wonder which approach is the best to use. Research by Livnat & Mendenhall (2006) compared the post-earnings announcement drift when using a time-series model and historical data to define the earnings surprise and using analyst forecasts and actual earnings from I/B/E/S. Their study showed that the post-earnings announcement drift was significantly lower when using historical data and the time-series model. The I/B/E/S database is known as the Institutional Brokers' Estimate System, where investors can access key estimates regarding the future earnings of publicly traded American companies (Kenton, 2020).

## 2.5 Event Studies

In an efficient market, there should be an immediate reaction to an event that influences information regarding one or more stocks. The following price reaction to the event should not be influenced in any way by the return regarding the previous period of the market, assuming the market is efficient sufficiently (Kothari, 2001).

According to MacKinlay (1997), event studies have been a frequently used method to estimate the economic impact of an event. An advantage of using an event study is that the event's impact should be reflected directly on the market, given the market consists of rational consumers. Ball & Brown (1968) argued that analytical models, which were mostly used in economic papers, had shortcomings. In their article, they explained the issue with analytical models as unable to capture all relevant factors when measuring the impact of an event. In addition, there would be too many unverifiable factors to consider when using an analytical model, even when considering that the model used was a precise one. Hence, the most accurate way of measuring the impact of an event would be to observe the actual observable outcome. A major flaw of this approach is that it ignores the extent to which the model forecast corresponds to observed behavior (Ball & Brown, 1968).

Fama, Fisher, Jensen, & Roll (1969) looked at how stock prices adjust to information implying a stock split. They analyzed data from a period stretching over 33 years. Hence, they needed to isolate the effect of the stock split during that period. Using a regression analysis running over several months, both prior- and after the stock split, they could obtain information regarding how the stock price had changed due to the split. When analyzing the results from the regression analysis, they also had to exclude months where the residuals had significantly higher/lower values compared to the other sample months to obtain a result as accurate as possible in terms of how the stock split had affected the stock price.

### 2.5.1 Long Horizon and Short Window Event Studies

According to Kothari (2001), there are two forms of event studies: short-window event studies and long-horizon post-event performance studies. The article states that a main difference between the two studies is the inferential issues, which are more complicated when doing long-horizon studies.

The article also states that the advantage of conducting short window event studies is the lack of other events that could influence the test results. Short-window events studies usually confirm market efficiency. Long horizon-event studies look at how the market reacts to an event one- to five years post-event. The assumption underlying long-horizon event studies is that the market under- or overreacts to events, and it takes a certain amount of time for the market to stabilize. This is believed to be due to irrational behavior from the investors along with underlying biases. The issue regarding long-horizon events studies is that there are difficulties with estimating risk and obtaining clean data since these types of studies are stretching over a long period of time.

### 2.5.2 Introduction to Event Study Methodology

Controlling how an event influences a stock return, one needs to observe the relation between the stocks' return during that specific time period and a broad stock market index (Fama et al., 1969). To test the market efficiency in the form of an event, it is important to have some “normal returns” to compare it to (Fama, 1991). Fama (1991) furthermore states that the reason behind this form of joint hypothesis testing is because it is insufficient to properly test market efficiency, as there is no way of stating what defines as a “normal” market. Since defining a normal market isn`t obtainable, one needs to assign some standardized values for what could be considered a “normal” market and test the market efficiency against that. So, when measuring the event's outcome against a standardized market, the standard approach of event studies is to measure the abnormal return as residuals (Binder, 1998). If the abnormal return changes in relation to the event date, the event's outcome exceeded the market's expectations for that event (MacKinlay, 1997).

We will go further into detail on how to perform an event study in the empirical part of the thesis, including our reasoning for choosing this specific method.

## 2.6 Difference-in-Difference Analysis

Snow (1855) was the first person to use the difference-in-difference model in scientific research. He analyzed the cholera outbreak in England to determine if cholera was transmitted through the air or water. The measuring technique he used was by comparing districts in London that were located close to each other but had a different water supply. This made him able to study the ceteris paribus effect of the water supply going to different regions. One of the first instances of difference-in-difference analysis in economics was conducted in the article, "*Shortcomings of Marginal Analysis for Wage-Employment Problems"* (Lester, 1946). The paper analyzed how wages affected the employment level of firms. The method used was by comparing companies from the northern- and southern states in the US regarding how employment was affected by a rise in the minimum wage. He also compared companies that had a generally considered high minimum wage to companies with a generally low minimum wage. The study concluded that a rise in minimum wage generally had a trivial effect on the level of employment. The main idea behind conducting a difference-in-difference analysis is to generate a binary model that consists of a group that has been exposed to the explanatory variable and a group that has not been exposed to that variable (Lechner, 2011).

Meyer (1995) stated in his article that a difference-in-difference analysis should contribute by isolating the explanatory variables so that they are easily identifiable. This could be done by finding comparable data, where the only difference would be the exogenous variables of interest. The article states that several research papers experience struggles in identifying comparable data so that the only difference in variables is the exogenous variables one wants to examine. However, Meyer emphasizes that the advantages of a difference in difference method are the simplistic aspect of it. Given that the data is comparable so that one can isolate a few explanatory variables, one can narrow down the range of possible explanatory variables for a certain outcome.

### 2.6.1 Difference-in-Difference in Estimating Stock Prices

The difference-in-difference method has also been used for assessing the price volatility of stocks. Wang, Li, & Cheng (2009) use this method to assess if the introduction of the Hong

Kong Hang Seng Chinese Enterprise Stock Index (H-share index) futures would affect the volatility of the underlying index spot price. They do this by using the H-share index as a sample group while using Red chip stocks, which is similar to the underlying stocks of the H-share index in terms of size, risk, and location, as a control group. By conducting a regression analysis, while controlling for both the same factors in the sample group as in the control group, they were able to show that the H-share index had experienced significantly higher volatility after the introduction of the H-share futures. Xie & Mo (2014) uses a difference-in-difference method to assess how the CSI 300 stock index reacts to the introduction of futures. They emphases the importance of having both a sample- and a control group that moves in parallel in the absence of futures introduction. To control as many factors as possible, they use a regression model which accounts for both individual factors of the sample- and control stocks and macro-economic factors which could influence the stock price.

### 2.6.2 Difference-in-Difference Methodology

According to Harris (1989), there are two approaches one could use when comparing stocks, using the difference-in-difference method. The article used these two approaches when comparing the volatility of the S&P 500 stocks against none-S&P 500 stocks. The first approach consists of carefully choosing the securities that one wants to use as control stocks compared to the sample stocks. The other approach consists of conducting a cross-sectional analysis of covariance regression models to account for the other factors which could influence the stock price. Harris used a method where he included different explanatory variables in the regression model to see if other factors explain the stock market's reaction. He used two separate regression models, one for the group with earnings announcements and one for the group without.

The regression model used in the article was:

$$STD_i = b_0 + b_1 InS\&P_i + b_2(AbsBeta_i \times MkSTD) + b_3 InvPrice_i + b_4 LogMkVal_i \\ + b_5 NoTradeFreq_i + e_i$$

The regression model estimates the log price relative standard deviation of the stock return (STD) by using the *InS&P* variable as a dummy variable for whether the stock is included in the S&P 500 or not. The other variables are independent, and they measure the coefficient of the stock`s absolute beta times the constant market standard deviation, inverse price level, log market value, and the no-trade frequency.

The advantage of using this model is that one can assess other factors which could influence the share price, compared to only looking at the effect from the earnings announcement. The disadvantage of using this model is that it would require a lot of information about each stock which would be a subject of potential errors.

Firth (1976) uses a difference-in-difference approach to measure how the earnings announcements of one firm affect the share prices of competitive firms in the same industry. Using a group of sample firms within the same industry, he looked at how their share price deviated from forecasted values in the interval window of when the benchmark firms' earnings were announced. The study showed that there was a clear correlation between the stock price of the firms within the same industry and the state of the earnings announcement. If one firm in the group had an earnings announcement that exhibited positive earnings compared to what was forecasted, the share price of the other firms increased, and vice versa when the earnings were negative compared to the value forecasted.

## 2.7 The Post-Earnings Announcement Drift

“Post-earnings announcement drift is the tendency for a stock’s cumulative abnormal returns to drift in the direction of an earnings surprise for several weeks following an earnings announcement” (Livnat & Mendenhall, 2006, p. 177).

Ball and Brown (1968) were among the first to detect a drift in stock prices related to earnings announcements. Their study showed an upward drift in the estimated cumulative abnormal return after announcements containing good news. After announcements containing bad news, they found a downward drift. In accordance with this, Jones and Litzenberger (1970) also found evidence that the market gradually reacts to quarterly earnings announcements. Foster, Olsen, and Shevlin (1984) concluded that systematic drift in the return of a security was only present in a subset of earnings models used to estimate the unexpected earnings component. Bernard and Thomas (1989) also examined drift effects. They used an investment strategy based on holding a long position in companies where the unexpected earnings fall in the upper quintile (good news) and a short position in companies where the unexpected earnings fall in the lower quintile (bad news). Using this strategy, they found evidence of drift effects in the US market.

Earlier studies on post-earnings announcement drift (PEAD) have mainly been performed on the US market. Still, research has also been done on the European market. Eilifsen, Knivsflå and Sættem (2001) studied the Norwegian stock market. Their research found a "[…] significant reduction in stock price volatility in the post-announcement period relative to the pre-announcement period for companies traded on the Oslo Stock Exchange in the period 1990-1995" (Eilifsen et al., 2001, p. 187). Their objective was to examine the effects of earnings announcements on stock return volatility. The methodology used in this study was a model of price behavior, where the observed return variance is divided "[…] into three components: (i) an intrinsic variance portion that can be attributed to the volatility of the underlying business, (ii) a price adjustment component that captures the effect of an imperfect price adjustment process, and (iii) a noise term [...]" (Eilifsen et al., 2001, p. 188). Consequently, this methodology provides a tool for empirically testing the effects of information dissemination in the capital market. Kallunki (1996) performed research on earnings announcements and stock returns in the Finnish market. His findings showed a delay in market reactions to negative earnings announcements, but not for positive earnings announcements.

### 2.7.1 Explanations of Post-Earnings Announcement Drift

There has been suggested a variety of possible explanations of PEAD in the existing literature. Different studies have used different research designs and methodology. Some examples are models based on time series predictions of earnings, analyst forecasts, or models based on the stock price. Furthermore, to estimate normal returns and scale the earnings surprise, different approaches have also been used. Foster et al. (1984) suggest four explanations to the post-announcement security return behavior: "the misspecified asset pricing model explanation, the use of hindsight information explanation, the time-period explanation, and the information market explanation" (p. 575).

The first explanation regarding the misspecified asset pricing model explanation refers to different asset pricing models used to estimate normal returns. The second explanation regarding the use of hindsight information is that the information is available to the market at the time of the event. The explanation for the time-period phenomena refers to differences in drift in different periods. For the fourth explanation, namely, the information market explanation, Foster et al. (1984) express that "This explanation posits that the market for information could explain the pattern of post-announcement drifts" (p. 581).

Bernard and Thomas (1989) presented competing explanations of PEAD that fall into two categories. The first suggests that at least a portion of the price response to new information is delayed. The delay might occur because traders fail to assimilate available information or because certain costs exceed gains from immediate exploitation of information for a sufficiently large number of traders. An example of such costs can be the costs of implementing and monitoring a trading strategy. The second explanation suggests that misestimation in the CAPM used to measure abnormal return can lead to the researcher failing to adjust returns fully for risk. “As a result, the so-called abnormal returns are nothing more than fair compensation for bearing risk that is priced but not captured by the CAPM estimated by researchers” (Bernard & Thomas, 1989, p. 2). One of their tests suggests an alternative explanation for a delay: “[…] that prices are affected by investors who fail to recognize fully the implications of current earnings for future earnings” (Bernard & Thomas, 1989, p. 2).

As previously mentioned in part 2.4.2, Livnat & Mendenhall (2006) examined PEAD. They researched if differences in earnings measurements and deviation in the source of the earnings can cause different results from analyzes of drift. They found that neither restating earnings nor including “special items” in reported earnings contributed significantly to the disparity in drift magnitudes. Their findings showed that drift is significantly larger when the earnings surprise is defined using the analyst forecast than through time series.

Bartov et al. (2000) used institutional ownership as a proxy for investor sophistication. They found that the institutional holdings variable is negatively correlated with the observed post-announcement abnormal returns. Furthermore, they found “[…] that post-earnings-announcement drift is related to the percentage of ownership of institutional investors and that this relation exists even when transaction costs and firm size are controlled” (Bartov et al., 2000, p. 61). Jegadeesh & Livnat (2006) estimated earnings and revenue surprises. They found that the PEAD was stronger when the revenue surprise was in the same direction as the earnings surprise.

## 2.8 Significance Testing in Empirical Studies

To ensure the reliability and validity of the results, one needs to test the significance. The following subchapters will present examples of parametric and non-parametric tests that have previously been used in event studies. In chapter 3, we will explain and show the test we are using for this event study.

### 2.8.1 Parametric Tests

Parametric tests are only used where a normal distribution is assumed. The most widely used tests are the t-test, ANOVA, linear regression, and Pearson rank correlation (Savani & Barrett, 2009). Parametric tests are, in general, more powerful than non-parametric tests because they require a smaller sample size (Chin & Lee, 2008). Furthermore, Chin & Lee states that non-parametric tests are approximately 95% as powerful as parametric tests.

#### *Student t-test*

William Sealy Gosset developed the Student t-test in 1908. Gosset was an Englishman publishing under the pseudonym Student. He developed the t-test and t-distribution (Britannica, 2020). According to Britannica (2020), the Student t-test is "a method of testing hypotheses about the mean of a small sample drawn from a normally distributed population when the population standard deviation is unknown". A commonly used null hypothesis to be tested in event studies is that quarterly earnings announcement does not influence the stock return (MacKinlay, 1997). To test whether the earnings announcements influence the abnormal return, one can use the Student t-test to test if the cumulative average abnormal return (CAAR) is significantly different from zero. For the test to be characterized by a Student t-distribution, the return must be normally distributed. Violations of the normality assumption can lead to type 1 or type 2 errors (Dennis, Emmanuel, & Paul, 2020).

#### *Standardized Residual Test*

Patell (1976) introduced an event study parametric test that was later called the standardized-residuals method in Boehmer, Masumeci, and Poulsen (1991). The test can be used to test if the CAAR is equal to zero, assuming that abnormal return is uncorrelated and the variance is constant over time (Patell, 1976). Boehmer, Masumeci, and Poulsen (1991) found that the test is well specified when there is no increased event-induced variance.

### 2.8.2 Non-parametric Tests

Non-parametric tests are free of specific assumptions concerning the distribution of returns. MacKinlay (1997) mentions that the most common non-parametric tests for event studies are the sign- and rank tests, which will be further discussed in the following subchapters.

### *Rank Test*

The Corrado rank test may be an appropriate alternative when the security returns have fat tails, meaning the security return is not normally distributed. According to Corrado (1989), the test is well specified no matter how skewed the cross-sectional distribution of excess return is. Corrado and Zivney (1992) later proposed an adjusted version of the test that allows for missing returns. Kolari & Pynnonen (2010) states that the rank test from Corrado (1989) and the modified rank test from Corrado & Zivney (1992) have problems in their application to cumulative abnormal returns (CARs). Kolari & Pynnonen (2010), therefore, proposed a generalized rank (GRANK) testing procedure that can be used for testing CARs and single-day abnormal returns. Their testing found that the proposed GRANK testing procedure was able to outperform previous rank tests of CARs.

### *Sign Test*

The sign test is often used when conducting event studies. The sign test is based on the sign of the abnormal return. The test requires that the cumulative abnormal returns are independent across securities and that the expected proportion of positive abnormal returns under the null hypothesis is 0,5. Under the null hypothesis, it is equally probable that the cumulative abnormal return will be positive or negative (MacKinlay, 1997). Brown & Warner (1980, 1985) observed that it requires an equal amount of positive and negative abnormal returns to correctly specify the sign test.

Cowan, Nayar & Singh (1990) and Sanger & Peterson (1990) used a variation of the sign test known as the generalized sign test. The generalized sign test is based on a comparison of the ratio of positive cumulative abnormal returns over the event window against the ratio from a period that is unaffected by the event window (Cowan, 1992). Cowan found that in cases where there is an event-induced increase in the variance or stocks are illiquid, the generalized sign test is better than the rank test.

## 2.9 How the Coronavirus can Influence Stock Markets

There is already some early research on how the Coronavirus has impacted stock markets. He, Liu, Wang, and Yu (2020) empirically analyzed daily return data from stock markets in China, Italy, South Korea, France, Spain, Germany, Japan, and the USA. Their objective was to explore the direct effects and spillovers of the Coronavirus on stock markets. This paper used data on the period of 1 June 2019 to 16 March 2020. They found “that (i) COVID-19 has a negative but short-term impact on stock markets of affected countries and that (ii) the impact of COVID-19 on stock markets has bidirectional spill-over effects between Asian countries and European and American countries” (He et al., 2020, p. 275).

Topcu and Gulal (2020) studied how the Coronavirus impacted emerging stock markets over the period of 10 March 2020 to 30 April 2020. They found that the Coronavirus's negative impact on emerging stock markets was gradually falling and had begun to taper off by mid-April. They also found that the impact COVID-19 had on emerging markets was highest in Asia and lowest in Europe. In addition, they found that the response time and size of stimulus packages provided by governments play a role in offsetting the effects of the Coronavirus.

Chowdhury, Khan & Dhar (2021) researched the impact COVID-19 had on the global stock markets and economic activities. This research is on the four continents Asia, Europe, America, and Africa. The event study methodology was used to measure the impact on stock markets, while they applied a panel vector autoregressive model to measure the impact on economic activities. In the analysis, they looked at COVID-19 variables such as “number of lockdown days”, “restrictions in internal movement”, “restrictions in international travel,”. “fiscal measure”, and “confirmed cases”. Their research found that all the pandemic variables used had a negative impact on stock markets. Moreover, the variables “restrictions on movement” and “lockdown days” negatively impacted economic activities. Interestingly, European stock markets suffered more than the other markets in this research.

# 3. Empirical Methods

This part of the paper will present and address the empirical methods we are using for this event study.

## 3.1 Time-Series Models for Estimating Expected Earnings

As mentioned in part 2.4.2, there are two frequently used ways of forecasting a company's earnings; the time-series model and the analyst forecast. For this paper, we have chosen to use the time-series approach. The underlying reason why we are not using analyst forecasts is based on the size of our dataset. Making a complete analysis of each company in our dataset would be time-consuming. Another reason is based on the research by Livnat & Mendenhall (2006), as mentioned in part 2.4.2, where they found that the post-earnings announcement drift was significantly lower when the earnings were forecasted using a time-series model, which makes it a better approach for this purpose.

To choose a forecasting model, we have decided to use a seasonal moving-average model, which is the same as model 2, as referred to in section 2.4.1. The choice is based on Foster`s (1977) results, where he estimates the preciseness of various forecasting models. This model yields, according to Foster, a more precise estimate of forecasted earnings compared to the other models, which had a similar simplistic approach. Using an autoregressive (AR) model was also considered. Still, based on the number of stocks and the number of forecasts needed, it seemed less practical considering the time it would take. The chosen forecasting model is shown again here as Equation 1:

$$E(Q_t) = Q_{t-4} + \delta \tag{1}$$

Where $E(Q_t)$ is the company's forecasted earnings for the given quarter. $Q_{t-4}$ is the company's corresponding earnings from one year ago, which is used to account for cyclical patterns. While $\delta$ is the moving average of the company's earnings last year, which is used to account for increasing or decreasing conjunctures.

## 3.2 Event Study Methodology

This section will review the methodology for conducting an event study. The purpose of using event studies is to detect any abnormal returns associated with earnings announcements (abnormal returns will be described more thoroughly in section 3.2.2). The general procedure for conducting an event study has not changed drastically from the method Ball and Brown (1968) introduced in the late 1960s. Apart from a few improvements, there is "[…] a general flow of analysis" (MacKinlay, 1997, p. 14). The intention is to measure any abnormal stock returns associated with an event, which in this case are earnings announcements for our selected firms. In this methodological review, we will start by discussing models for measuring a stock's normal return. In other words, returns predicted in the absence of the event. Then we will describe the methodology for measuring abnormal returns. Lastly, we present the procedure for calculating cumulative abnormal returns, which is the aggregated abnormal return for the specific event. This analysis follows the methodological approach for event studies as described by MacKinlay (1997).

### 3.2.1 Estimating the Market Model

In this paper, we have chosen to employ the market model to estimate abnormal returns. The model was originally developed by Treynor (1961) and Sharpe (1964) and has been seen as a benchmark standard for many years in terms of calculating expected returns for a stock. The choice of this model is based upon the fact that it is widely used in previous research, and it is used to derive the expected return for a company based on its $\beta$, where the beta is the company's correlation with the market (Stapleton & Subrahmanyam, 1983). Other models like the 3-factor model developed by Fama & French (1992) were also considered, but for simplistic motives, we choose the more widely used CAPM approach. The CAPM approach is also considered more practical, with potentially fewer variables that could cause errors (Bartholdy & Peare, 2005). In this paper, we have chosen to use the following market model shown as Equation 2. This market model has been used in previous research such as (Binder, 1998; Lee & Varela, 1997; MacKinlay, 1997; Saens & Sandoval, 2005).

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{2}$$

$$E(\varepsilon_{it} = 0) \qquad\qquad var(\varepsilon_{it}) = \sigma^2_{\epsilon_i}$$

where $R_{it}$ is the return of security $i$ in the time $t$, $\alpha_i$ is a constant parameter, $\beta_i$ is a parameter for the market return $R_{mt}$ and it includes an error term $\varepsilon_{it}$.

### 3.2.2 Abnormal Return

MacKinlay (1997) defined abnormal return as "the actual ex post return of the security over the event window minus the normal return of the firm over the event window" (p. 15). When we are using the market model to measure the normal return, the abnormal return for the sample is given by Equation 3:

$$AR_{i\tau} = R_{i\tau} - \widehat{\alpha_i} - \widehat{\beta_i} R_{m\tau} \tag{3}$$

where $AR_{i\tau}$ is the abnormal return for security $i$ in time $\tau$, $R_{i\tau}$ is the actual return, $\alpha_i$ is a constant parameter and $\beta_i$ is a parameter for the market return $R_{m\tau}$.

### 3.2.3 Cumulative Abnormal Return

The abnormal return observations must be aggregated to draw overall inferences for the event of interest. Aggregated abnormal return is often called cumulative abnormal return (CAR). The aggregation is along two dimensions, through time and across securities (MacKinlay, 1997). The formula we use to estimate cumulative abnormal return is Equation 4:

$$CAR_i(\tau_1, \tau_2) \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \tag{4}$$

The abnormal returns for the individual securities can be aggregated using $AR_{i\tau}$ from (3) for each of the event periods. Given that there are $N$ events, the aggregated abnormal returns and variance for period $\tau$ is calculated using Equations 5 and 6:

$$\overline{AR_\tau} = \frac{1}{N} \sum_{i=1}^{N} AR_{i\tau} \tag{5}$$

$$var(\overline{AR_\tau}) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma_{\varepsilon_i}^2 \tag{6}$$

where $\sigma_{e_i}^2$ is the disturbance variance from the market model (Equation 2), and N is the number of events.

Then we can aggregate the average abnormal returns over the event window using the same approach as we used to calculate the CAR for each security $i$. This can be done for any interval in the event window. We calculate the Cumulative average abnormal return ( $\overline{CAR}$) and the variance of the $\overline{CAR}$ using Equations 7 and 8:

$$\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_\tau \tag{7}$$

$$var(\overline{CAR}(\tau_1, \tau_2)) = \sum_{\tau=\tau_1}^{\tau_2} var(\overline{AR}_\tau) \tag{8}$$

## 3.3 Difference-in-Difference Methodology

In this section, we will review the methodology for conducting a difference-in-difference analysis. We use difference-in-difference as a supplement to our event study. The reason for using this method is to understand how the stock market reacts to earnings announcements and whether the stock market has reacted to the earnings announcement or if the reaction can be seen as a result of other factors. The advantage of conducting a difference-in-difference analysis is to test variables that can explain the market's reaction and then use these results to reinforce or disprove the results from the event study.

### 3.3.1 Use of Difference-in-Difference

As previously mentioned, the intended use of this method is to compare a treatment- and a control group. In our dataset, there will be a group of companies that have not released earnings announcements during the event window, and we will compare these companies to a benchmark company that has released an event window earnings announcement. The reason behind the choice of this method is to see how- and if earnings announcements influence a company's stock price at all. There are several approaches one could use to apply the difference-in-difference method. We have chosen to use Firth`s (1976) method, where the effect of the earnings announcement is isolated, as the only variable to be analyzed. As described in section 2.6.2, the method consists of comparing firms within the same industry during an event window where only one of the firms has had their earnings announcement made public. This is done to see how an earnings announcement affects the market in general and not simply the firm releasing it. We will also conduct a difference-in-difference analysis to see if companies' stock prices move together despite only one of the companies having released their earnings announcement. This is so that we can estimate if there are other variables that could be the reason why some stocks experience abnormal returns during the event window. Like Firth (1976), we will use firms within the same industry with a twenty-one-day event window. This will be described in more detail in section 4.1.2. In terms of forecasting the expected return of the sample stocks, we will use the market model as described in 3.2.1.

## 3.4 Significance Testing

To ensure the reliability and validity of our results, we need to test the significance of the results. Regarding return distribution, there are strong assumptions in the parametric tests. An alternative to the parametric tests is non-parametric tests, as mentioned in part 2.8.2, these tests are free of specific assumptions regarding the return distribution. Still, as mentioned in part 2.8.1, Chin & Lee (2008) states that non-parametric tests are approximately 95% as powerful as parametric tests.

Based on previous research presented in part 2.8, we have chosen to use parametric significance testing. For this event study, we perform a Student t-test to test if the earnings announcements have any effects on the returns. This is related to the first research question: if the Norwegian stock market reacts efficiently to earnings announcements. We test whether the cumulative average abnormal return ($\overline{CAR}$) is significantly different from zero. The assumptions we use are that the $\overline{CAR}$ follows a normal distribution, the mean is zero, and the variance is $var\left( \overline{CAR}(\tau_1, \tau_2)\right)$.

$$t = \frac{\overline{CAR}(\tau_1,\tau_2)}{var( \overline{CAR}(\tau_1,\tau_2))} \tag{9}$$

# 4. Data Description

## 4.1 Event Study Definition

### 4.1.1 The Event and Event Date

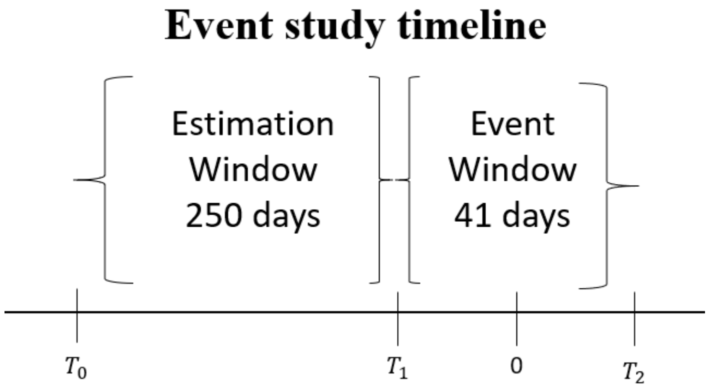
For this research paper, the events we are interested in are earnings announcements from companies listed on the Norwegian stock exchange. This study covers earnings announcements for 12 quarters in the selected time period between Q1 2018 and Q4 2020. Ahead of every earnings announcement, the different firms announce the date the report will be published, so the event date is easy to define. Regarding the event dates, there are some definitions to be made. For companies that release the report before or during trading hours, the event date will be the publishing date. For companies that publish the report after trading hours, the event will be defined as the first trading day after the report was published. The event dates- and the earnings are retrieved from Thomson Reuters Datastream using the software Refinitiv Eikon.

### 4.1.2 Event- and Estimation Window

When conducting an event study, we need to specify the length of an event window and an estimation window. The purpose of the estimation window is to estimate what the "normal" stock returns of the chosen companies should be during the event window and at the event date. This is done so that we can subtract the estimated normal returns from the actual returns to obtain the abnormal returns. As suggested by MacKinlay (1997), we define the estimation window as the 250 trading days before the event window. A 250-day estimation window has also been used in other event studies (Al-Baidhani, 2018; Eilifsen et al., 2001; Erlien, 2011; Law et al., 2020).

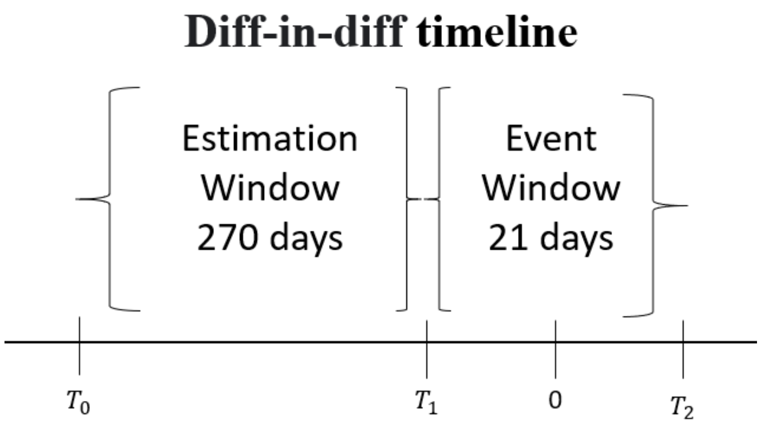
The purpose of the event window is to set a time parameter. In this event window, we want to capture the effects of public information collecting before the event date. In the period after the event date, we are looking for signs of post–earnings-announcement drift. For this event study, we apply a 41-day event window suggested by MacKinlay (1997). The 41-day event window consists of the twenty trading days before the event date, the event date, and the twenty trading days after the event date. Figure 4.1 below is a visualization of the timeline for the event study.

*Figure 4.1 Timeline for the event study*




In our difference-in-difference analysis, we will be using a 21-day event window instead of using a 41-day event window. This is the same as Firth (1976) used in his research study. The underlying reason why we chose a shorter event window is that we need to compare earnings announcement releases in non-overlapping periods. We believe that a 41-day event window will capture more data surrounding the announcement date. However, this would make it extremely difficult to gather data from enough firms with earnings announcements that don’t overlap each other. Since the event window we use for the difference-in-difference approach will be shorter, we can use a 270-day estimation window compared to a 250-day estimation window used in our event study. Figure 4.2, shown below, is a visualization of the timeline for the difference-in-difference analysis.

*Figure 4.2 Timeline for the difference-in-difference analysis*




### 4.1.3 Classifications of Earnings Surprises

When measuring the impact of the earnings announcement, we need to classify each earnings announcement as either positive, negative, or neutral. MacKinlay (1997) used a five-percent range between the stock's abnormal return and “normal” return, where if the abnormal return were five percent higher/lower than the “normal” return, the observation would be classified as positive/negative. If the abnormal return were in-between the five-percent range, the observation would be classified as neutral. We have, however, chosen a ten-percent range to classify our observations. This was done to secure enough observations that could be classified as neutrals so that we could analyze the data in a better way.

## 4.2 Data Collection and Selection

When selecting firms to be included in the data sample, some criteria must be defined. The first one being that the firm must have published earnings reports for at least ten consecutive quarters before the first quarter in the sample. The next criterion is that the firm must have been listed on the Oslo Stock Exchange for at least 250 trading days (estimation window) before the earnings announcement date in Q1 2018 (Start of sample period). In this paper, earnings per share (EPS) are used to measure the earnings in the analysis. Our third criterion affects financial companies. Because financial companies often have different accounting standards and requirements, we chose to exclude them. The differences might affect the reported EPS, which would make it hard to compare them to the other companies. To identify the financial companies, we have used the Industry Classification Benchmark (ICB). Our last criterion is that the companies included in this event study publish quarterly earnings announcements. Companies with other interim frequencies are therefore excluded.

We have used the Oslo Børs Benchmark Index (OSEBX) as a proxy for the market return to capture the return for the market in the selected time period. This index includes the largest and most traded firms listed on the Norwegian stock exchange. As of 31 March 2021, the index consists of 69 firms (“Oslo Børs Benchmark Index Factsheet,” 2021). There are other indexes that we could have used. Still, as the OSEBX contains most of the companies that are considered to have a “large” market cap in the Norwegian stock market, we consider that this index is relatively representative of the Norwegian stock market.

## 4.3 The Coronavirus and its Impact on the Data

For this thesis, it is crucial to consider how the coronavirus impacted the Norwegian stock market in 2020. The reason for this being that our event study ranges from Q1 2018 to Q4

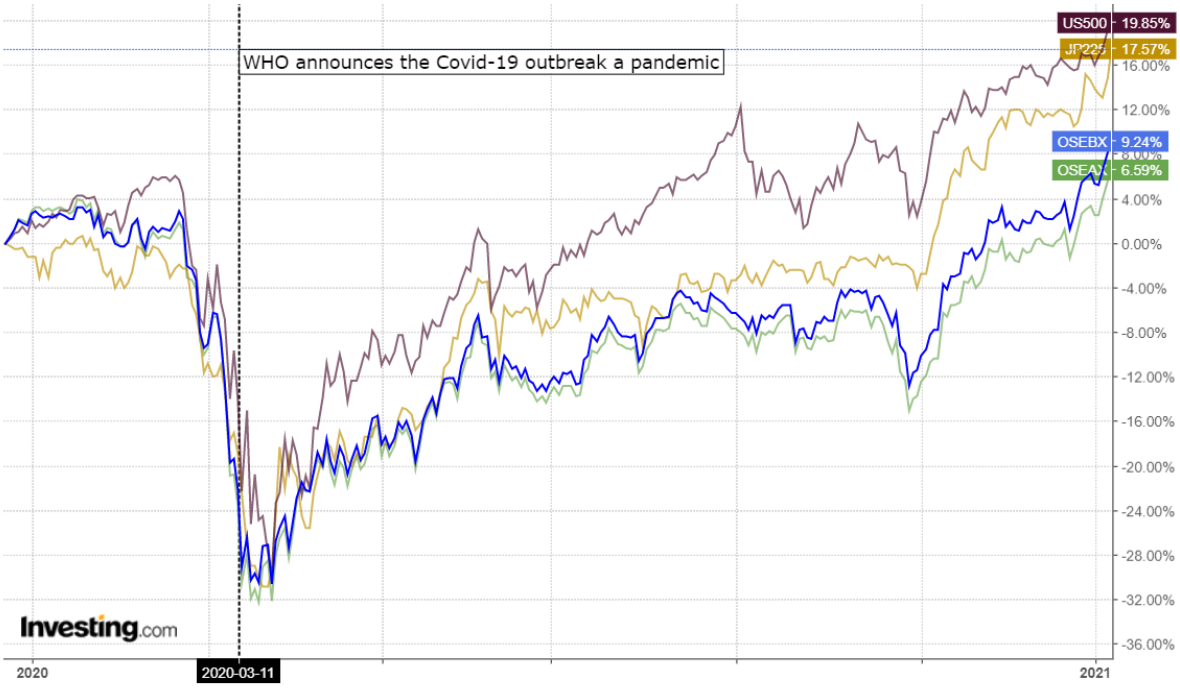
2020, where the stock prices in the Norwegian market has been largely affected by the COVID-19 pandemic during the period ranging from Q1 2020 to Q4 2020, and thus possibly will have a significant effect on our results.

The WHO declared the COVID-19 outbreak a pandemic on 11 March 2020 (Ducharme, 2020). One day later, the Norwegian government held a press conference. The purpose of the press conference was to inform of the situation and to provide rules and regulations that would be enforced to reduce the spread of the virus. People were encouraged to stay at home and avoid unnecessary travel. Gyms, schools, cinemas, pubs, and more had to close (Melgård, Oterholm, & Gjerstad, 2020). Closed businesses, of course, meant a significant decline in revenue for several sectors. Moreover, social distancing regulations went into place, and people lost their jobs, thus decreased consumer spending habits. More or less, every sector experienced a downturn early in 2020, but many stocks have recovered since the initial impact.

For the stock markets, we have used TradingView through Investing.com ("OSE Benchmark (OSEBX)," 2021) to compare OSEBX, OSEAX, S&P 500, and Nikkei 225. OSEBX is the Oslo Børs Benchmark Index, which consists of the largest and most traded companies listed on Oslo Børs. OSEAX is the Oslo Børs All-Share Index, which includes all shares traded on Oslo Børs. The S&P 500 is an American index, "the index includes 500 leading companies and covers approximately 80% of available market capitalization" ("S&P 500®," 2021). Nikkei 225 is the premier index of Japanese stocks, consisting "of 225 stocks in the 1st section of the Tokyo Stock Exchange" ("Nikkei Stock Average (Nikkei 225)," n.d.)

We can see from Figure 4.3 that the S&P 500, Nikkei 225, OSEBX, and OSEAX all experienced a large decline as the number of COVID-19 cases grew in the first months of the crisis. The most significant effect COVID-19 had on the stock market was an initial plunge between late January and early March. For example, the S&P 500 fell 10.6% between late January and March and another 14.9% in early March. The numbers from OSEAX and OSEBX show the same trends as for S&P 500 and Nikkei 225.

*Figure 4.3: Impact of coronavirus on stock markets since the start of the outbreak ("OSE Benchmark (OSEBX)," 2021).*




As mentioned in section 2.9, there has already been some early research published on how the COVID-19 pandemic has impacted the stock markets. The key finding from Figure 4.3 shows that the global stock markets fell significantly at the beginning of March 2020. Moreover, the figure shows that both the S&P 500 and Nikkei 225 reacted faster and grew more than both the Norwegian indexes. This is in line with previous research, as mentioned in section 2.9, where Chowdhury et al. (2021) found that European stock markets suffered more than the other markets.

# 5. Results

## 5.1 Graph Description

Our results are divided into thirteen different graphs, which are displayed down below in our result section. In Figures 5.1 to 5.9, we have shown the average abnormal return for each company in our dataset, containing 47 different firms listed on the OSEBX. A complete list of every firm we used in our dataset can be found in part A of the Appendix. For each firm, we calculated their expected return using the market model, which is Equation 2 in section 3.2.1, before calculating their abnormal return by subtracting their expected return from the actual return. In addition to this, we used Equation 1 in part 3.1 to forecast the companies' earnings to compare it against their actual earnings. If the firm had actual earnings that were ten percent higher than forecasted in the event window of their earnings announcement, they were classified as positive-surprise, classified negative-surprise if actual earnings were ten percent lower than forecasted, and neutral-surprise if their earnings were in between this range. These calculations were done on each firm for each quarterly earnings announcement they had during the period between Q1 2018 and Q4 2020. This means that each firm would have twelve events over the course of these three years and potentially experience several negative-, neutral- or positive earnings surprises over the course of this timeframe. We are emphasizing this so that it's clear that a firm, in itself, isn't classified as positive-surprise or negative-surprise, but only their earnings announcement. To find the cumulated abnormal return, we added each firm's abnormal return for each trading day of the course of the event window.

As the OSEBX mainly contains large-cap firms, we weighted each firm`s abnormal- and cumulative abnormal return equally, even though there is a size difference in terms of market cap on some of the firms on the OSEBX. We have created several graphs for different periods because we want to better isolate the effect of the actual event, which is the earnings announcement. By dividing our range of years up into several graphs, it helps us to better account for other factors which influenced the stock price in a specific year, such as the COVID-19 pandemic. An important aspect to note is that even though our graphs look at AR and CAR during the event window of the earnings announcement, there is a wide specter of firm-specific and macroeconomic factors that influence the stock prices, not solely the earnings announcements. We will briefly describe what each graph shows before all our results are thoroughly discussed in section 6.0 of the thesis.

Figures 5.1 to 5.3 give us the AR- and CAR for all the companies on the OSEBX from Q1 2018 until Q4 2020. These results are important in order to observe if the Norwegian stock market reacts efficiently to earnings announcements. Figure 5.1 gives us the AR- and CAR for companies that have experienced a positive earnings surprise. Figures 5.2 and 5.3 give us the AR- and CAR for consecutively companies with a neutral/negative earnings surprise. These three graphs will be the foundation for our main analysis of market efficiency. The reason for this being that these three graphs give an indication of how earnings announcements affect the stock price of a company and how the market efficiency works in order to correct the stock price in the event of an earnings surprise. Figures 5.4 to 5.13 are supplementary graphs that we will use to explain the results from Figures 5.1 to 5.3 more efficiently.

Figures 5.4 to 5.6 give us the AR- and CAR for the time period ranging from Q1 2020 to Q4 2020. These graphs are made to isolate the possible effect the COVID-19 pandemic will have on our overall results (in Figures 5.1 to 5.3). What we mean by this is that we believe that highly volatile stock prices could, as an example, be one of many factors that would make it more difficult to observe an earnings-surprise effect on the stock market.

Figures 5.7 to 5.9 give us the AR- and CAR from Q1 2018 to Q4 2019. In other words, they show the effect of earnings announcement without considering the data from 2020. Moreover, these graphs show us how the firm reacts to earnings announcements not considering extraordinary events, such as the COVID-19 pandemic.

In the section of our results showing the difference-in-difference approach in our event study (Figures 5.10 to 5.13), it's important to note that we have used a different dataset compared to the one used for Figures 5.1 to 5.9. In our difference-in-difference approach, we have, similarly to the other analyses used companies from the OSEBX, used the market model for estimating return, and a seasonal moving average equation to forecast earnings. The main difference is that we have only used the companies belonging to the energy sector on the OSEBX in our dataset, in addition to an event window consisting of 21 trading days. These graphs are important for showing that stock prices react to a lot of other factors apart from earnings announcements and that even though a firm has released an earnings announcement which in itself should imply some price change, there are still many other factors in the market that can influence the stock price.

Figures 5.10 and 5.11 are part of a difference-in-difference analysis we conducted to observe how the company's stock prices are affected by another company's release of an earnings announcement. The graphs show the AR- and CAR of companies in the energy sector on the OSEBX, where classifications of announcements have been based on whether our benchmark firm, Equinor, has had a positive, neutral, or negative earnings surprise. In other words, if Equinor`s earnings are higher than ten percent of what was forecasted, we would classify all the other companies' AR in that event window as positive-surprise AR. As stated, this is done to see if the stock price is affected by another company's earnings announcement. An important note is that none of the companies used in the dataset for Figures 5.10 and 5.11 have released any earnings announcement themselves during the event window.

Figures 5.12 and 5.13 show, similarly to Figures 5.10 and 5.11, the AR and CAR of companies in the energy sector in the event window of Equinor's earnings announcements. The companies we use as comparisons for Equinor are other companies in the energy sector on the OSEBX, where Equinor is the only company that has released earnings announcements during the event window. The purpose of this analysis is to see how similar firms move together in terms of stock prices, whether they have released any earnings announcements or not.

When estimating forecasted earnings for each company, we used Equation 1 from section 3.1. As we have explained in section 3.1, this forecasting model considers seasonal differences in earnings combined with a drift term. The drift term is the moving average of earnings from the previous years. Even though these estimations of forecasted earnings have been proven to be accurate in previous research, it doesn't imply that our forecasted values are in line with the market's expectations. There could be several reasons why the market expects a higher or lower return than forecasted based on historical data.

In many cases, historical data has simply displayed nothing more than the company's previous return. Examples of events that could influence a company's earnings could be the announcement of new projects in the future. This would not likely immediately influence the earnings, but it could influence the stock price since one could assume that there would be an expectation of an increased cash flow in the future. There could also be negative press releases, which would also affect the stock prices, but not necessarily earnings. These are just a few examples of explanatory factors behind why the market's expectation of earnings could differ from our forecasted values.

We used the Capital Asset Pricing Model (CAPM) to estimate the expected return for each of the stocks in our dataset, which has been widely used to assess stock return in a relatively extensive amount of literature. Like our forecasting model, using CAPM to estimate expected return doesn’t necessarily mean that our estimations will be in line with the markets' expected return. An example of this is the COVID-19 pandemic mentioned in section 4.3, which is just an example of a situation where there would be difficult to calculate a precise estimate of the market's expected stock return.

## 5.2 Descriptive Statistics

Our results in Figures 5.1 to 5.3 consist of 524 event windows distributed over 47 different companies, ranging from Q1 2018 until Q4 2020. We used companies from the OSEBX-index, which consisted of 63 companies. Some of the companies missing from our dataset are removed due to not meeting the classification we set for the companies to be included in our dataset, which we have elaborated in section 4.2. There were in total 185 “positive surprise” earnings announcements, 50 “neutral surprise”, and 289 “negative surprise”. We can already from the distribution observe that there is skewness in the number of earnings announcements classified in each category. As an example, we can see that the number of earnings announcements classified as negative is almost six times as high as earnings announcements classified as neutral. We used a ten-percent range between the forecasted values and the actual values to classify earnings as neutral, as explained in section 4.1.3. The reason we didn`t choose to use a percentage range greater than ten because even though this would have given us more “neutral” earnings announcement, these values would have been further away from being considered neutral.

An important note is that we haven't obtained the same number of event windows in each graph. This is mainly because some of the graphs range over shorter periods. Especially in Figures 5.10 to 5.13, we have significantly fewer observations than in the previous graphs. This is because these graphs only use the companies listed as energy companies on the OSEBX. Another explanation behind this is that we could only use energy companies with earnings announcements that didn’t interfere with Equinor’s event window of the announcement. Complete descriptive statistics are shown separately with each graph, and a full list of all the companies we used in our dataset is shown in Appendix A.

*Figure 5.1: AR and CAR for the companies experiencing a positive earnings surprise.*

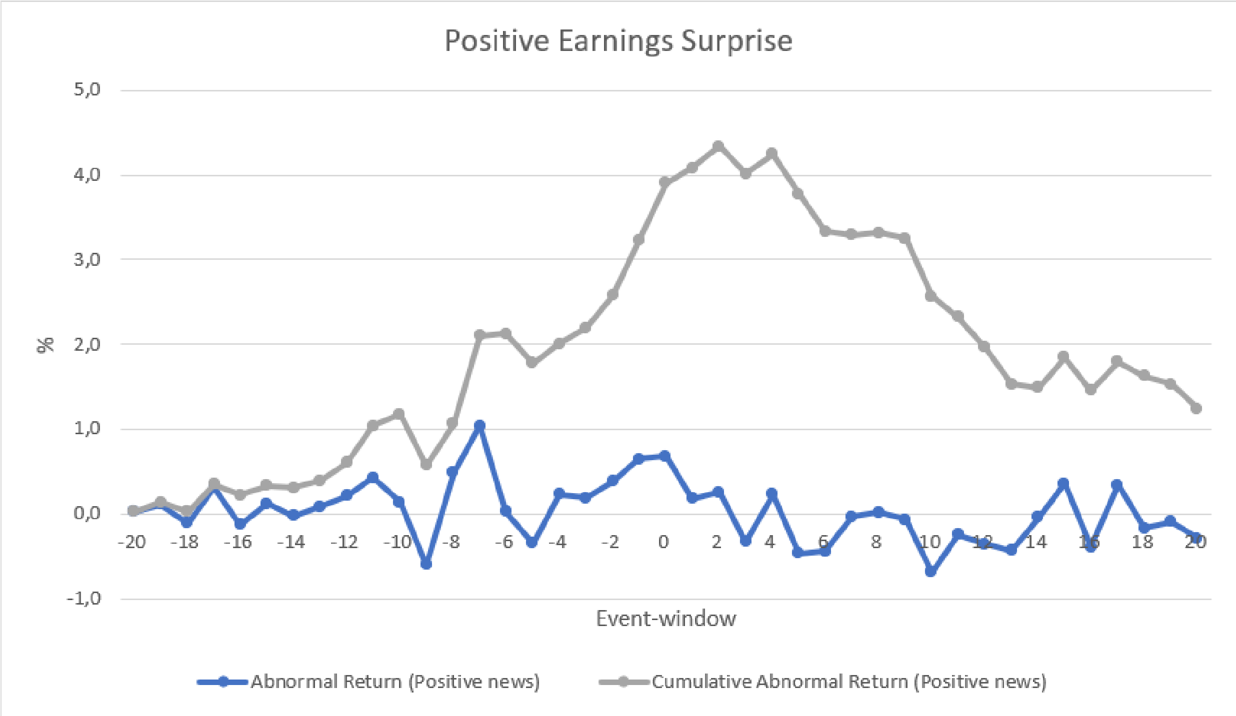



*Figure 5.2: AR and CAR for the companies experiencing a neutral earnings surprise.*

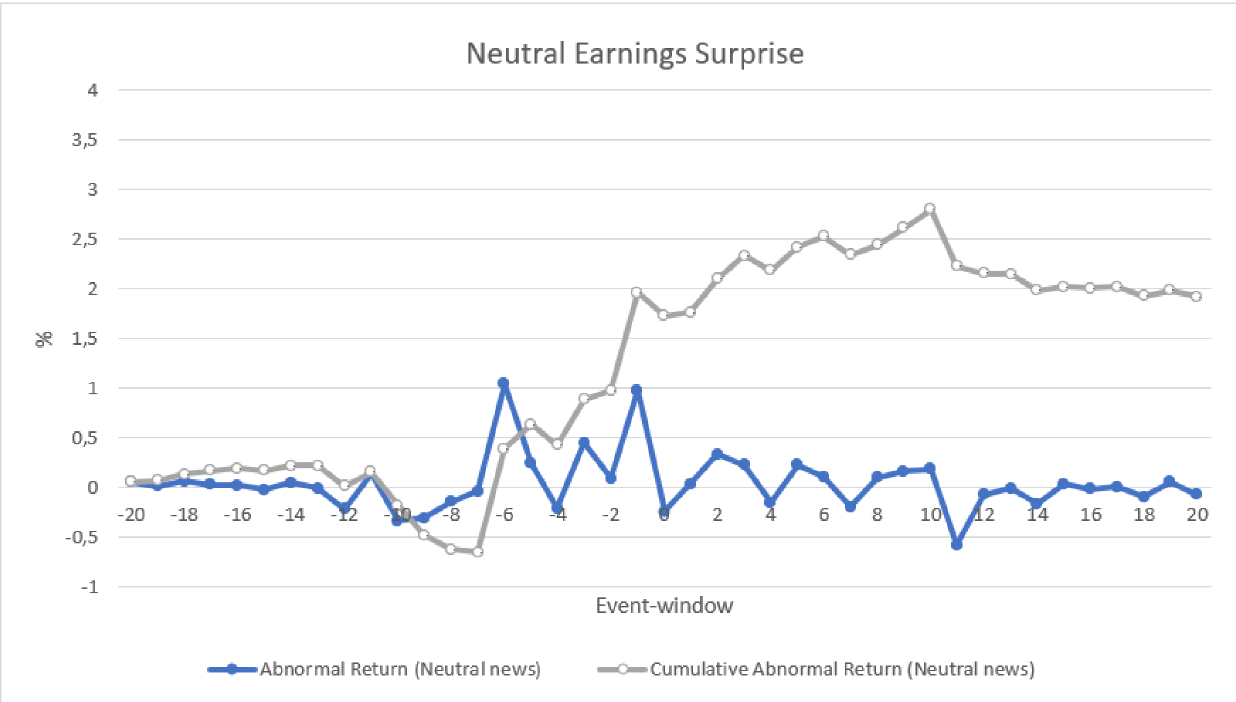
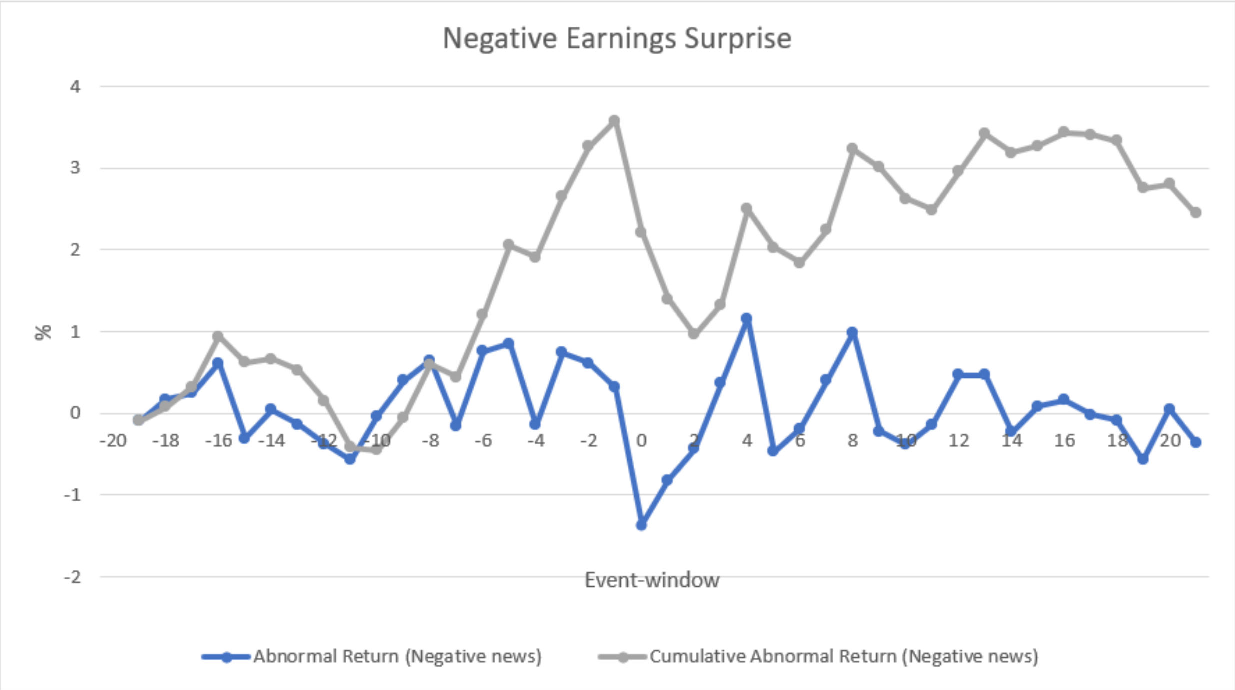


*Figure 5.3: AR and CAR for the companies experiencing a negative earnings surprise.*




## *Figures 5.1 to 5.3*

An important note is that we chose to present the complete results for our full timeframe first (Q12018-Q42020). This is despite the fact that these results seem to go against the general knowledge regarding how companies would react to earnings higher/lower than expected. These results will be thoroughly discussed, but at first glance, it seemingly proves how many other factors are affecting the stock price besides earnings announcements.

Looking at the results of the AR estimations in Figures 5.1 and 5.3, we see that both event windows with positive- and negative earnings surprises seem to follow market efficiency on the specific day of the earnings announcement. The surprising aspect is that the neutral surprise companies (Figure 5.2) also seem to be affected by the earnings announcement by having a higher AR compared to the AR of the companies which experienced a positive earnings surprise. Furthermore, we observe from the CAR that companies with positive earnings surprises, in fact, have the lowest CAR in total. Based on the logical assumption, the companies with earnings higher than expected should have a higher AR relative to companies which experienced a negative earnings surprise. We must also admit that the high CAR of companies which experienced a negative earnings surprise was not as expected. The reasonable assumption would be to assume that companies with earnings lower than forecasted would experience a price drop. These somewhat unexpected results could be due to several reasons, but at first glance, there are seemingly other variables affecting the stock price. We will discuss this further in section 6 of the paper.

## *Figures 5.4 to 5.6*

As mentioned in section 4.3, we know that the COVID-19 pandemic affected the return of several stocks in 2020. Since several stocks displayed a large degree of volatility, especially in the time period when many countries all over the world went into lockdown, we thought it would be necessary to isolate the earnings announcements between Q1 2020 and Q4 2020 in a section of its own. As we want to test market efficiency, it is important that other factors do not overshadow the effect of earnings announcements for us to obtain as precise a result as possible. For this reason, we wanted to do a time series on the effect of earnings announcements reported in 2020. This was done to estimate if the COVID-19 pandemic influenced the average result for all the three years we were analyzing.

*Figure 5.4: AR and CAR for the companies experiencing a positive earnings surprise in 2020.*

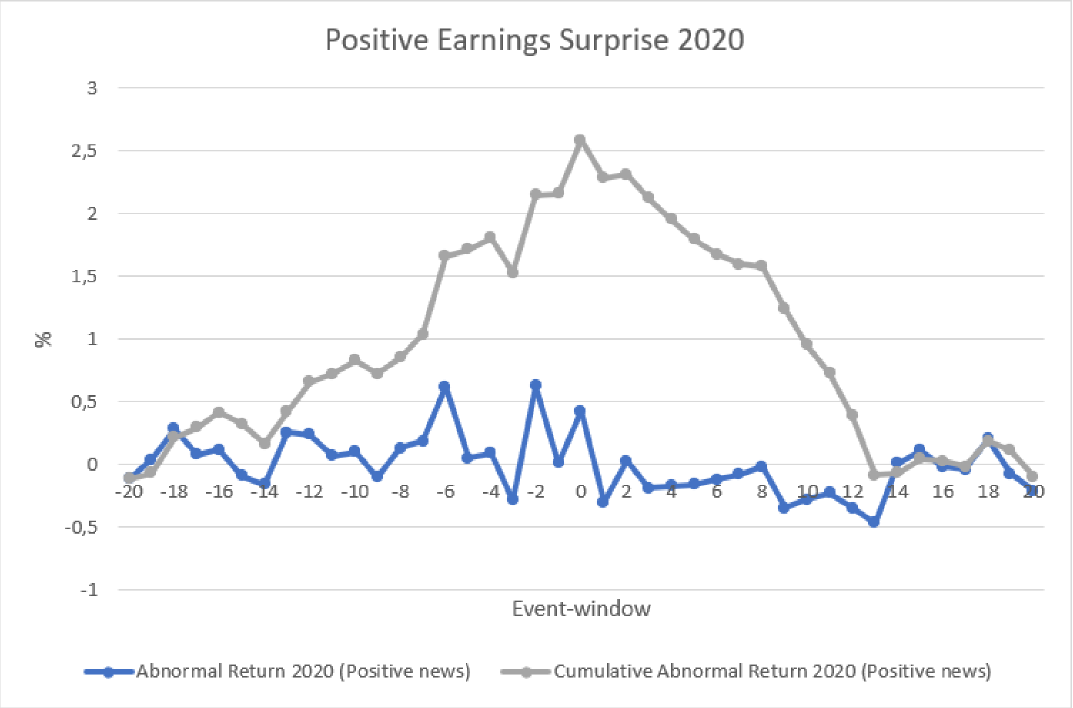


*Figure 5.5: AR and CAR for the companies experiencing a neutral earnings surprise in 2020.*

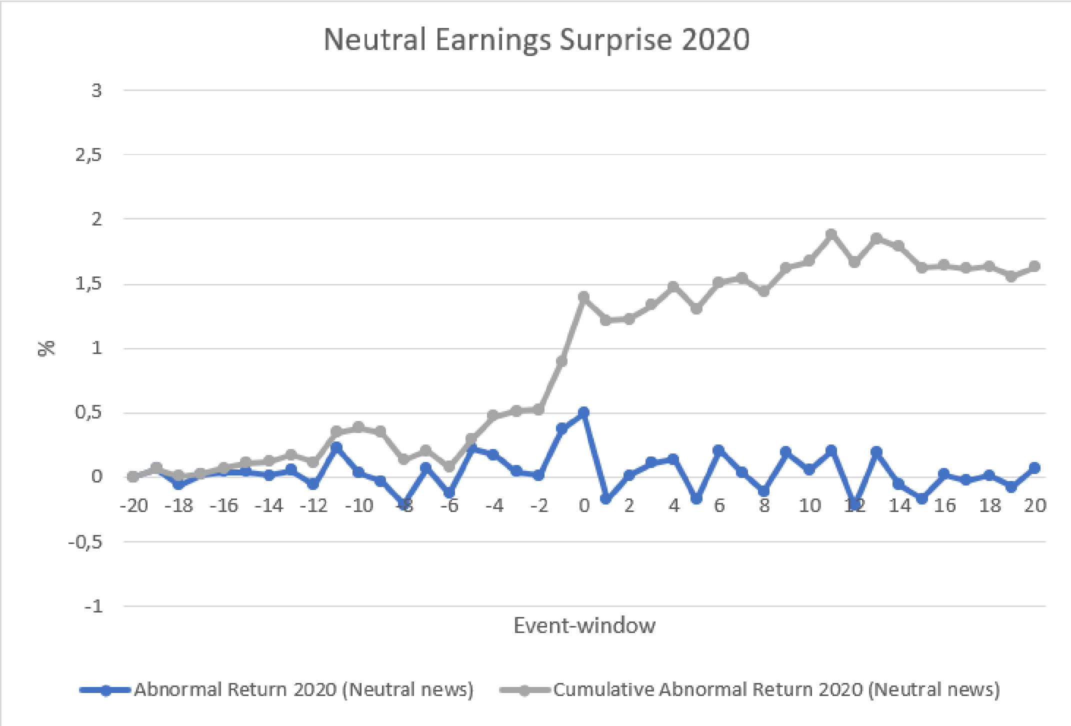
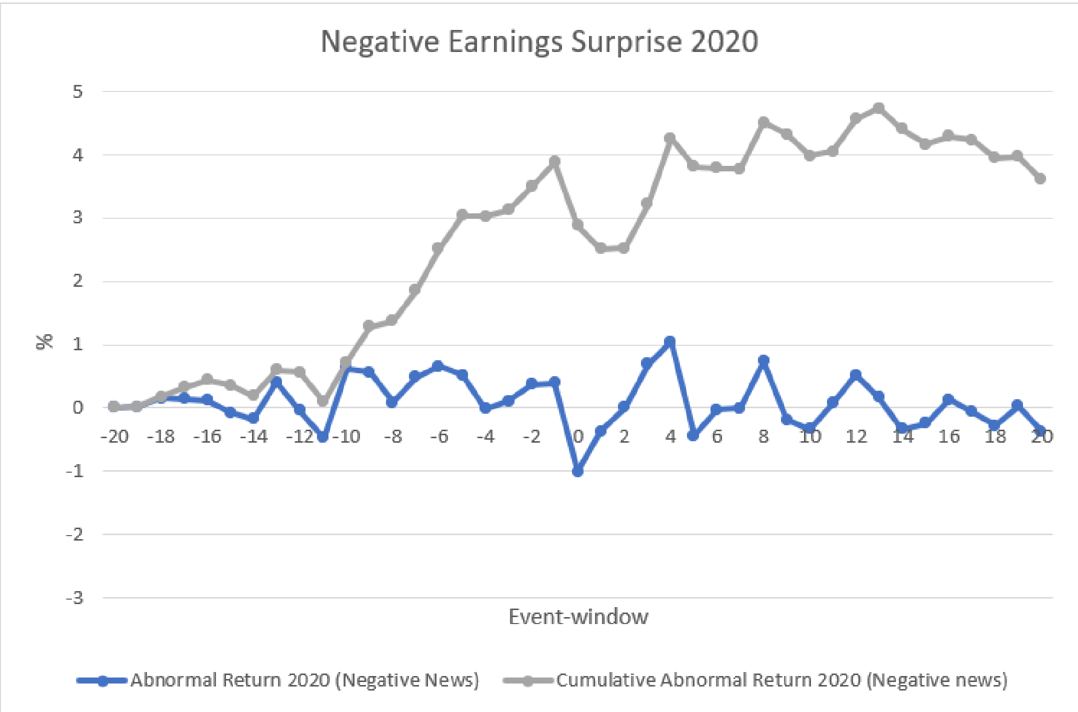



*Figure 5.6: AR and CAR for the companies experiencing a negative earnings surprise in 2020.*




There were in total 176 earnings announcements over the period from Q1 2020 to Q4 2020. 65 of the earnings announcements were classified as positive, 17 as neutral, and 94 as negative.

Looking at the AR for both the companies with a positive-surprise earnings announcement and the companies with a negative-surprise earnings announcement (Figures 5.4 and 5.6), we see that the AR seems to be largely impacted on the day of the announcement. The observation that companies with earnings above/below the expected outcome experience an impact on the stock price on the announcement day is in line with general theory regarding market efficiency, so at first glance, these results seem plausible. However, when observing the cumulative abnormal return, we see that the companies that experienced neutral or bad news have a significantly higher cumulative return than the companies that experienced a positive earnings surprise. We will discuss these results further in section 6.

*Figure 5.7: AR and CAR for the companies experiencing a positive earnings surprise in 2018/2019.*

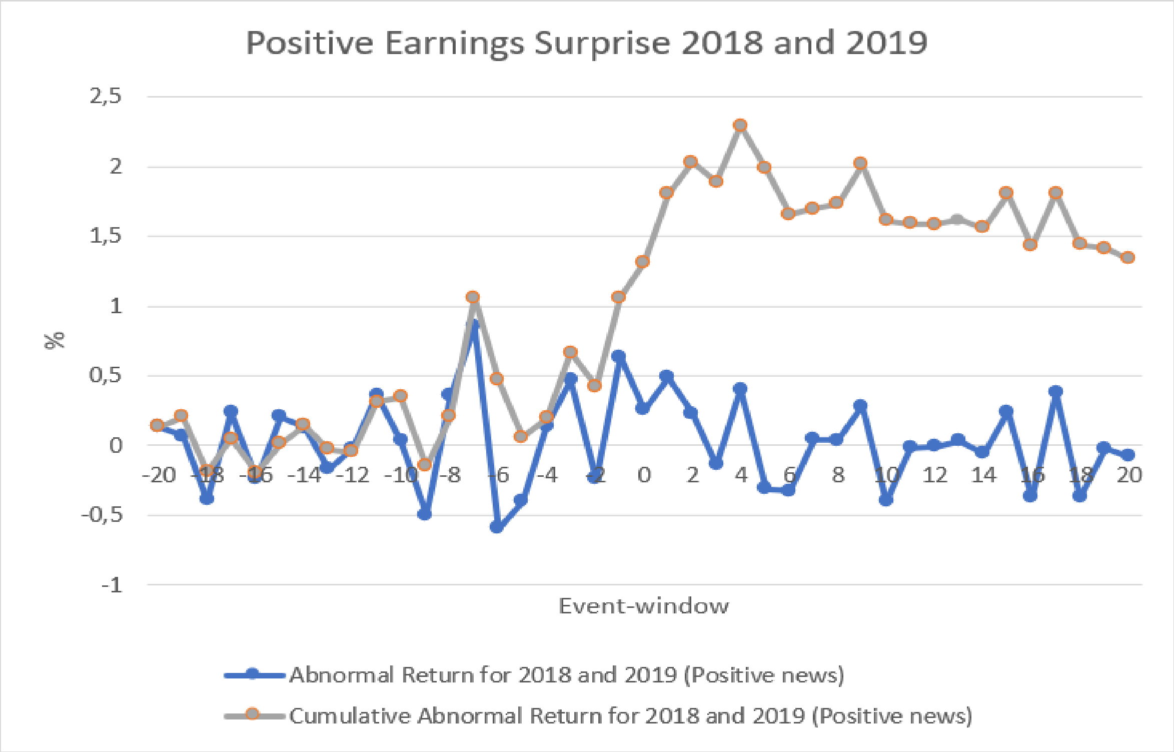


*Figure 5.8: AR and CAR for the companies experiencing a neutral earnings surprise in 2018/2019.*

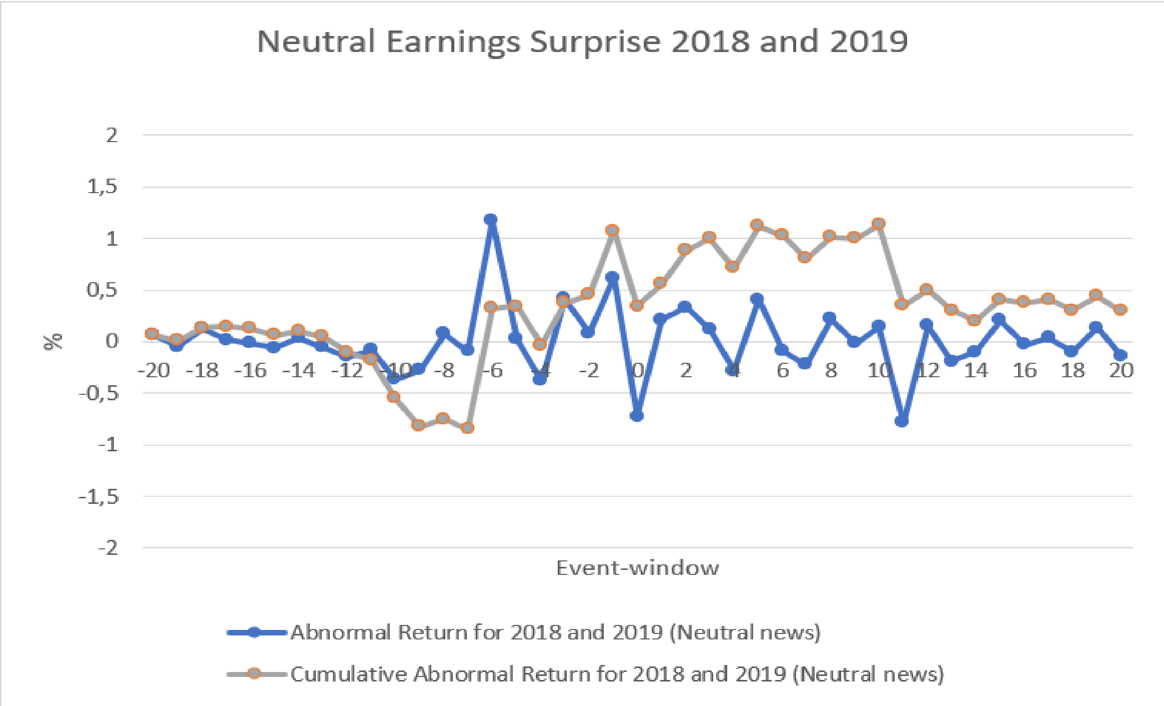
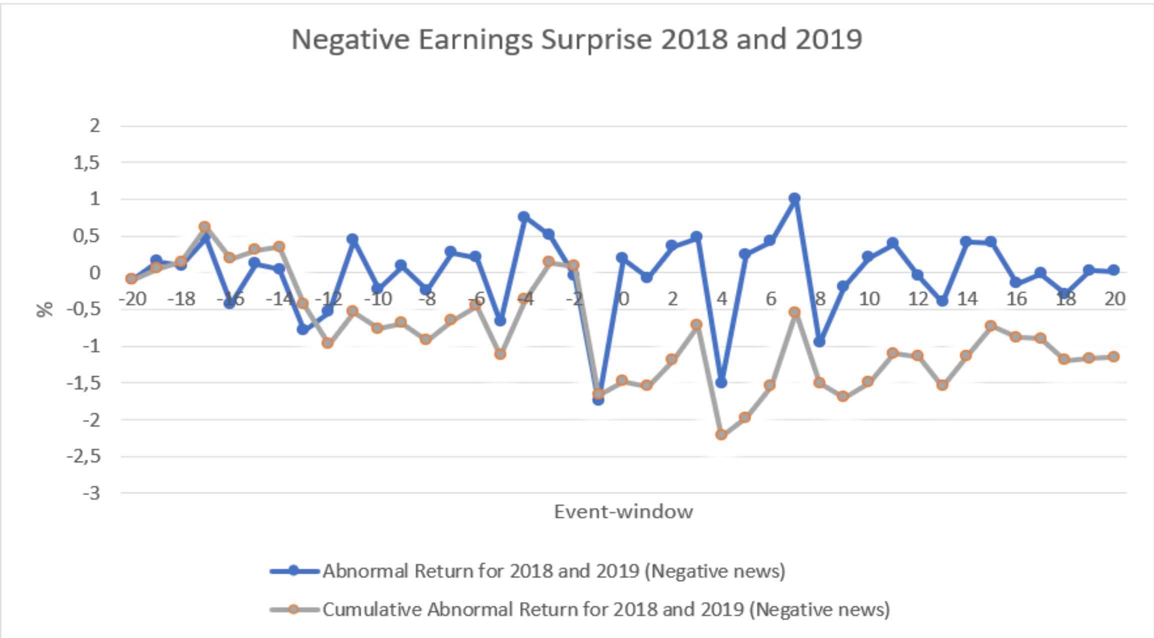



*Figure 5.9: AR and CAR for the companies experiencing a negative earnings surprise in 2018/2019.*



### *Figures 5.7 to 5.9*

In Figures 5.7 to 5.9, we observe the impact of the earnings announcement in the period from Q1 2018 to Q4 2019, in other words, excluding the earnings announcements from 2020. There were in total 348 event windows, where 120 had a positive earnings surprise, 33 had a neutral, and 195 had a negative earnings surprise.

At first glance, these results seem to be more in line with traditional market efficiency. We see that the CAR of the event windows containing a positive earnings surprise is significantly higher than for the neutral and negative earnings surprise. We also see that the event windows containing a neutral earnings surprise are significantly higher than the negative surprises.

### *Figures 5.10 and 5.11*

To observe how the earnings announcement not only affects the firms releasing the announcement but also other firms in the same industry, we conducted a difference-in-difference analysis similar to Firth (1976). For our dataset, we used all companies operating within the energy sector on the OSEBX as our sample. We used Equinor and their earnings announcements as a benchmark measure for all the other firms in the sample. We classified the other companies thereafter based on whether Equinor's earnings announcement contained a positive, neutral or negative earnings surprise. This was done in the event windows consisting of twenty-one days surrounding Equinor's earnings announcements.

We choose the energy sector because this is by far the largest selection of companies on the OSEBX. To obtain as many observations as possible in the difference-in-difference analysis, we needed as large a sample of firms as possible. This is because to include a company's abnormal return in the sample. We needed the company to have released its earnings announcement outside the event window of Equinor`s earnings announcement. Since the event window we used consisted of 21 trading days, many companies in the energy sector needed to be excluded from the sample as they had earnings announcements released at the same time as Equinor. After excluding all other companies' abnormal returns, which interfered with our event windows, we were left with 33 observations in total, 12 had a positive earnings surprise, and 21 had a negative earnings surprise. There were no neutral observations as Equinor didn't have any neutral earnings surprises from Q1 2018 to Q4 2020.

*Figure 5.10: AR and CAR for the companies in the energy sector without any earnings announcement during the event window, when Equinor experienced a positive earnings surprise.*

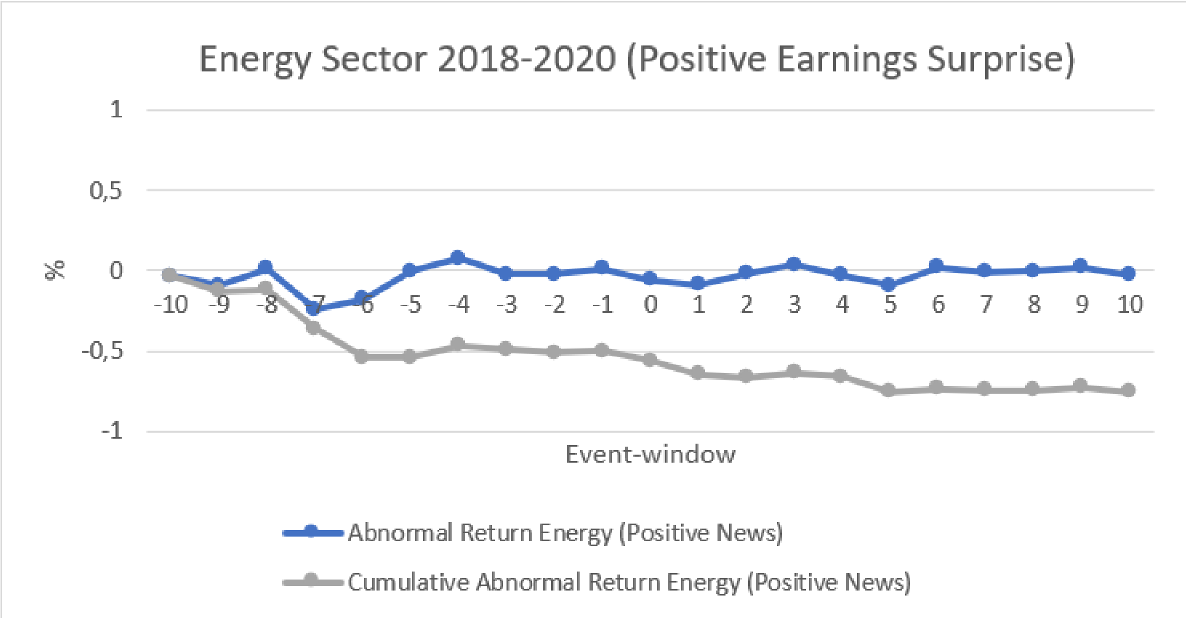
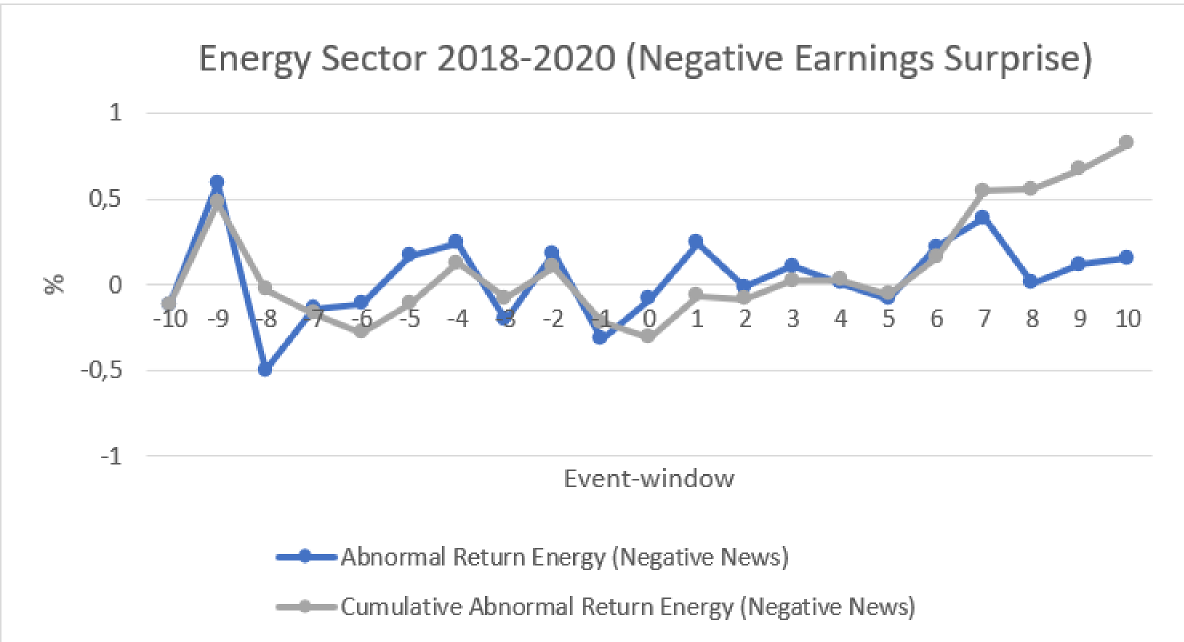



*Figure 5.11: AR and CAR for the companies in the energy sector without any earnings announcement during the event-window, when Equinor experienced a negative earnings surprise.*




The results from our difference-in-difference model reveal that it seems like there is little to no correlation between whether Equinor`s earnings announcement contains a positive- or negative earnings surprise and the return of the other companies in the energy sector. Surprisingly, we see that the cumulative abnormal return is significantly higher when Equinor has had a negative earnings surprise compared to when they have had a positive. This is something we will examine more closely in the discussion section.

### *Figures 5.12 and 5.13*

To test market efficiency in the most accurate way possible, we needed to conduct another difference-in-difference analysis to estimate the effects of other factors that could influence the stock price. To test the actual impact of the earnings announcement, we continued to use all companies in the Norwegian energy sector as a control sample against our benchmark firm, Equinor. Similar to our difference-in-difference analysis in the section above, we compared the average abnormal return and the cumulative abnormal return between our sample firms and Equinor during an event window where none of the other companies, except Equinor, had released any earnings announcement. We chose to do this to show that there most likely are other factors involved than just the earnings announcement to determine the stock price. Even though our paper is concerning earnings announcements, we need to address other factors in the market. This is done to better capture the effect of the earnings announcements.

*Figure 5.12: Average abnormal return for Equinor and companies without earnings announcement.*

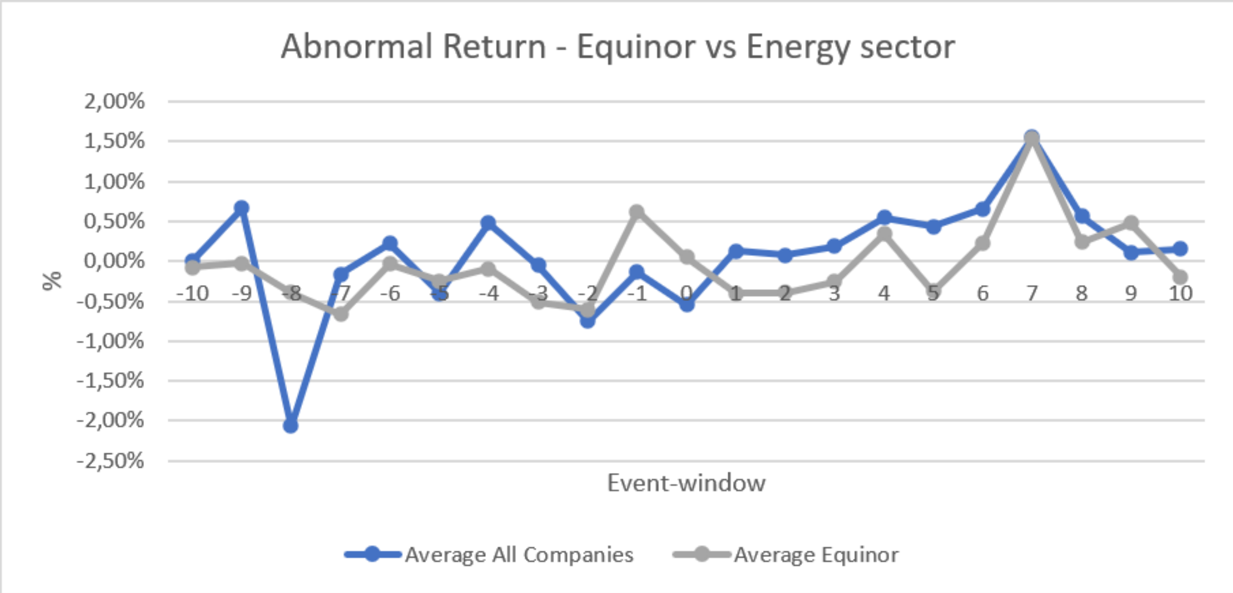
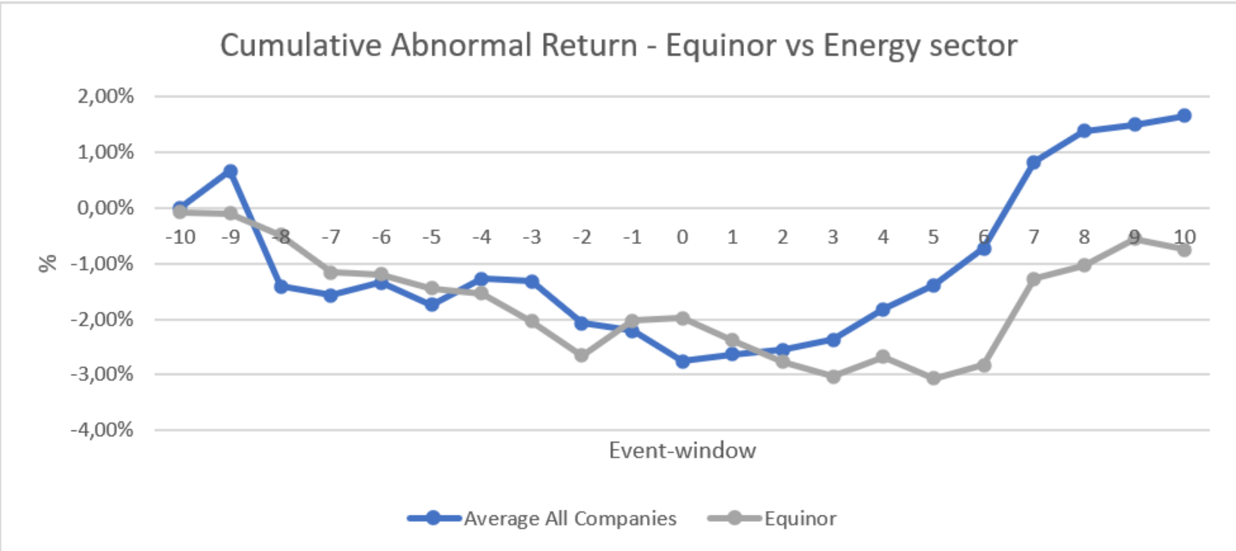



*Figure 5.13: Cumulative abnormal return for Equinor and companies without earnings announcement.*




From Figures 5.12 and 5.13, we can observe that the stock prices of the sample firms move relatively similar to the stock prices of Equinor, even though none of the sample firms have released any earnings announcement. Except from the third day of the event window, we see from Figure 5.12 that most of the observations regarding AR seem to move relatively close together.

# 6. Discussion

## 6.1 Hypothesis test

As stated in the introduction of this thesis, the concept that we are testing is market efficiency. Using companies' AR after an earnings announcement is simply a tool we can use to see if companies are correctly priced after an announcement.

Before we can begin discussing our results, we must first and foremost confirm that there exists an AR in correlation to the release of earnings. To do so, we will carry out a formal hypothesis test to see whether there exists such a concept as market efficiency. According to Brown and Ball (1968), a large part of the information regarding a firm is captured through the income statement, which implies that the earnings announcement should affect the stock price. Several other studies support this theory, including Fama (1965), Kothari (2001), and Bernard & Thomas (1989), of which they all proved that there is a correlation between available information regarding a security and its price in the market. Since an earnings announcement that differs from the anticipated earnings is information that shouldn't already be reflected in the market, we will consider it a factor that should affect the price of the security. There are, of course, considered to be different forms of market efficiency, ranging from weak form to strong form. If we consider only a weak form of market efficiency to exist, we should observe an abnormal return in the time period following the announcement. If we believe a strong form of market efficiency exists, we should observe an abnormal return also prior to the announcement. Either way, if there exists any form of market efficiency, we should experience an abnormal return during our event window.

We will followingly conduct a t-test, which is described in section 3.4. We use Equation 9 from section 3.4 to perform the tests. Our null- and alternative hypothesis is based on the results in Figures 5.1 to 5.3. Our null hypothesis states that the cumulative abnormal return is equal to zero, while the alternative hypothesis states that the cumulative abnormal return is different from zero.

H0: $\mu = 0$

H1 $\mu \neq 0$

If our null hypothesis is confirmed, it would be an argument against market efficiency. The values used to conduct the t-test can be found in Appendix B.

Tcar(positive) = CARpositive/Standarddeviation(CAR) = 0.95 ≠ 0

Tcar(neutral) = CARneutral/Standarddeviation(CAR) = 1.78 ≠ 0

Tcar(negative) = CARnegative/Standarddeviation(CAR) = 1.93 ≠ 0

From our t-test, we see that the null hypothesis is rejected, meaning that our results prove that there indeed exists an AR with significant values related to earnings announcements. To conclude, whether the market is efficient, we still must examine our results further.

Even though our hypothesis tests are in line with theory regarding market efficiency, it still seems like not all our results support existing literature on the topic. Take Figure 5.1 as an example, where we observed the AR and CAR of companies that experienced earnings higher than forecasted. Looking at the results in Figure 5.1 isolated, they seem to be in line with previous research. The CAR at the end of the event windows were positive, and results showed high amounts of AR both on the announcement day in addition to the days prior to the announcement. These results are supported by Al-Baidhani (2018), which showed that stock prices rise when earnings increase. It is also supported by Ball and Kothari (1991), which stated that stock prices experience an AR on the announcement day should the earnings be higher or lower than forecasted. However, the results regarding the companies which experienced a neutral- or negative earnings surprise (Figures 5.2 and 5.3) differ significantly from existing literature. The CAR for both results were positive and even higher than the companies which had a positive earnings surprise. It's a bit puzzling that companies that apparently have had earnings lower or the same as expected should outperform companies with earnings higher than expected, and therefore should be underpriced in the market. Assuming the markets are efficient, the most obvious answer is to assume that there are other significant macroeconomic- or firm-specific factors that influence the stock price.

To explain our results from Figures 5.1 to 5.3 more closely, we must look at the event study consisting only of the 2020-numbers found in Figures 5.4 to 5.6. As we have explained in section 4.3, we have already raised concerns regarding how stock prices from 2020 would affect the result of the study, especially considering the COVID-19 pandemic. We can observe from section 4.3 that the S&P 500 index fell in the period from January to late March by

25.5%, and from late March to early December, the index rose by 67%. In other words, the stock market can be seen as highly volatile in this period. As we see from Figures 5.4 to 5.6, the companies with a positive earnings surprise had a slightly negative CAR. In contrast, the companies with neutral- or negative earnings announcements had a largely positive CAR.

If we only account for earnings announcement as a factor for the stock price, these would be highly irregular according to market efficiency. We will, for that reason, investigate alternative explanations to understand our results better.

### *The market isn`t efficient during a global crisis:*

As we have mentioned earlier in this section, we have observed that the stock market has been highly volatile during 2020. This should evidently not be an underlying reason why the negative/neutral surprise-companies outperformed the positive surprise-companies in terms of CAR during the event period. Even though the market is performing relatively poorly compared to a "normal" year, the companies which have earned more than the forecasted values should have a slightly higher return compared to companies that have earned less than forecasted, assuming that all companies are on average affected by the same market conditions. There are, of course, significant differences in how different companies react to market conditions, and an important note to our dataset is that it contains a large percentage of energy companies. This would indicate that factors that are affecting the energy companies in specific would affect our results more compared to if we had used a different sample of companies. According to Fama (1970), a weak form of market efficiency indicates that all publicly available information is reflected in the stock price. Since earnings announcement is relatively easily accessible information, this should be reflected in the stock prices. However, when we look at the results for the time period ranging from Q1 2018 to Q4 2019, we see from Figures 5.7 to 5.9 that the market does indeed seem to be efficient. From Figure 5.7, we see that the companies experiencing a positive earnings surprise had a CAR of 1.34. At the same time, Figures 5.8 and 5.9 show that the companies experiencing a neutral- and negative earnings surprise had a CAR of 0.29 and –1.15.

We can also see from Figure 5.7 that AR values of the positive-surprise companies are consistently high at- and surrounding the announcement day. These results are very much consistent with the market efficiency theory because it's reasonable to assume that a security should be priced higher when the earnings are higher than expected, as fundamental valuation theory states that a firm's value equals the net present value of all its cashflows. It's important to note that even though the results between 2018 and 2019 seemingly are in line with existing literature regarding earnings announcements, we don’t have any evidence to prove that the abnormal earnings are caused solely by the release of the earnings announcement. As our event windows consist of 41 trading days, there will, of course, be several other factors that are affecting the stock price. We could better isolate the earnings announcement as the only factor affecting the stock price by using a shorter event window. Still, we believe this would compromise the complete picture of both pre-announcement- and post-announcement effects. We also must add that even though the market's reactions to earnings announcements in 2018 and 2019 are different from the reactions in 2020, it doesn’t mean that the market wasn’t efficient in 2020, but simply that there were other more dominant factors that caused the reactions to the stock prices. Based on our results that seemingly show that the market is efficient in 2018 and 2019, we must examine the results more closely from Q1 2020 to Q4 2020 (Figures 5.4 to 5.6) to find out why the market doesn’t seem to be efficient in that year.

An explanation behind why the earnings announcement doesn’t seem to be reflected in the stock prices in 2020 could be that the market isn’t as efficient during a global crisis such as the COVID-19 pandemic. This would be the simplest explanation, but it may be more reasonable that the market values different types of factors and that these factors overshadow the effects of earnings announcements. A weakness in our model is that it doesn’t account for factors other than earning announcements, and for that reason, we have no possibility of proving which other factors affect the stock price.

Another explanation behind why the neutral/negative surprise companies had a higher CAR in 2020 could be due to inaccurate forecasting relative to the market's expectations. We used a forecasting model, previously used by Brown & Kennelly (1972), which is a forecasting model that considers seasonal patterns and a drift term. The model we used is Equation 1, which is explained in part 3.1. This indicates that the forecasted return for the companies in our analysis is mainly based on the earnings in the corresponding period, in addition to a moving average drift term which accounts for an increasing/decreasing pattern in the company's earnings. The advantage of using this model is that it considers seasonal differences instead of simply forecasting the earnings based on the previous quarter. We believe this to be a more accurate estimate, especially under normal circumstances, considering that many companies' operational income is cyclical according to the seasonable variability which exists in some industries. The model also considers a drift term based on the moving average of the company's stock price, which is added to give a more accurate estimate to companies experiencing growth, for example.

We believe that our model would be more accurate if we had implemented a variable for factoring in the COVID-19 pandemic. As is evident from the research done by Chowdhury et al. (2021), the pandemic put large restraints on economic activity in large parts of the world. This would make it more probable that companies on the OSEBX experienced lower earnings in 2020 compared to what they did in the years prior. This would make our forecasted values for 2020 unprecise. We believe that this explains a lot of the results we obtained in Figure 5.6, where the companies that experienced a negative earnings surprise had the highest CAR. Since our forecasting model is mainly based on cyclical earnings, most of the companies would experience lower earnings in the Q3 and Q4 of 2020, as the pandemic had gone on for almost a year at that point. While most of the companies on the OSEBX would experience a lower return based on global restrictions, thus putting their earnings announcement in the negative surprise category. At the same time, the stock market did increase heavily, as a recovery from the decrease earlier in the same year. This assumption would indicate that a large percentage of the companies in our dataset would be listed as negative-surprise companies. At the same time as their stock prices, in fact, were expected to increase. Should our assumption be correct, it just comes to show that there are other factors that affect the stock prices and that a surprising reaction to an earnings announcement isn't necessarily an argument against market efficiency. We want to add that it is important to clarify that our results for 2020 are not evidence against market efficiency. We still used this model despite it giving an unprecise estimate in terms of earnings because we wanted to use the same forecasting models for all three years in the event study.

Another element in our analysis that could also be a subject of error is the capital asset pricing model (CAPM). The issue with CAPM is that when estimating the expected return of the companies in our dataset, it doesn't consider other firm-specific incidents which could affect the stock price. We should, of course, be aware of a large part of unsystematic risk as we have a relatively large dataset containing different types of firms. However, it could still be that our results are affected by one incident in one specific firm in our dataset. Based on our results, it also seems like the CAPM gives a more accurate result under “normal” circumstances in comparison to the pandemic of 2020. However, the advantage with CAPM is that it does account for Beta, which is the company's correlation to the market return, and it should, in that aspect, to a certain degree reflect the large market volatility. Another element we must address in our results is the size of the companies in our dataset. Our dataset consists solely of companies listed on the OSEBX-index, which only contains companies of a certain size. According to Chambers and Penman (1984), one can often observe larger price reactions to earnings announcements in smaller companies. Since all the firms in our dataset are considered large- or medium-capped companies, this could be a factor that would affect the event study results. In Figures 5.1 to 5.9, we haven't weighed the companies according to size, which could also influence the results. An AR from a large company would obviously affect the market more than AR from a small company, but since the OSEBX-index doesn't contain any small-cap companies, we didn't feel this was important to account for.

## 6.2 Validity

To test the market efficiency based on the release of earnings announcements, we needed to account for other factors that could influence the stock price. We conducted two difference-in-differences analyses to see if companies' stock returns reacted to other companies' earnings announcements (Figures 5.10 and 5.11) and if companies that hadn't released an earnings announcement in the event window acted similarly to the companies that did (Figures 5.12 and 5.13).

As we can see from Figures 5.12 and 5.13, the average AR and the average CAR from the energy companies move relatively closely together with Equinor's AR and CAR. Since Equinor is the only company that has released earnings announcements in the event windows, it could indicate that other factors in the market affect the AR of the companies in our dataset and not the earnings announcement. This was expected, as one can only assume that other market factors would affect the Norwegian energy companies significantly. The issue regarding this analysis is that the sample only consists of 33 observations, making it difficult to conclude how much other factors affect stock prices compared to the earnings announcements. Ideally, we would have liked to conduct a difference-in-difference analysis on all the firms included on the OSEBX, but this wouldn't be obtainable, as an essential part of the data selection consists of picking firms that haven`t released earnings announcement in the same event window.

The analysis shown in Figures 5.10 and 5.11 was conducted to observe if a company's AR was affected by another company's earnings announcement. Based on our results, it does not seem to be a large degree of correlation. In fact, the only observation we can observe from the results seems to be negative. However, with only 33 observations, the dataset can be considered too small to give any conclusive results.

# 7. Conclusion

In this paper, we wanted to answer two essential research questions regarding market efficiency and earnings announcements. The first being if the Norwegian stock market reacts efficiently to earnings announcements. The other is to what extent the Norwegian companies react to the earnings announcements.

We wanted to investigate the market efficiency in the Norwegian stock market using earnings announcements. Based on our results, it's evident that Norwegian companies do follow the market efficiency. Figures 5.1 to 5.3 clearly show that companies experience a high abnormal return based on the state of the earnings surprise on the exact day of the announcement. In addition, we see that from the year 2018 to 2019, the stock prices in the Norwegian market act accordingly to the theory regarding market efficiency. What we mean by this is that the companies that are experiencing a positive-surprise earnings announcement have a correspondingly positive abnormal return, while the companies experiencing a neutral- or negative surprise have a correspondingly neutral- or negative abnormal return.

What's more interesting regarding our results is the observed abnormal return in the 2020 period. As is evident from our difference-in-difference analysis displayed in Figures 5.12 and 5.13, we can clearly observe how stock prices for different companies in the same sector move similarly to a certain degree, irrelevant to earnings announcement releases. In other words, we can see that there are clearly other factors that are affecting the stock price apart from earnings announcement. However, it's interesting to see how the company's stock prices seemingly go against the market efficiency theory during the COVID-19 pandemic. As we have explained in the discussion section, there could be several logical reasons behind these somewhat surprising results. These results could be due to our forecasting models, which would indicate that either CAPM or naïve forecasting models aren't efficient to use whenever there is high volatility in the market. The second explanation could be that the Norwegian stock market isn't efficient during high volatility periods, implying that companies experiencing positive surprise earnings are underpriced, and vice versa with negative surprise companies. This is just an alternative explanation, but based on general research regarding market reactions, there are most likely just other factors involved that are affecting stock prices. However, our results clearly indicate that the market seemingly reacts more efficiently to earnings announcements during more “normal” market conditions.

In our opinion, there are several things we could have improved to make the thesis better. A clear improvement would have been to select our data more carefully. When our analysis runs over three years, it heavily affects the results when one out of those three years has relatively atypical market conditions. There is, of course, an interesting aspect in terms of combining years with different market conditions in order of comparisons. Still, we feel it could have given our data more depth if we had chosen a larger time period to analyze. In addition to choosing a more extensive range of years, we wish we had included some years with market conditions like 2020 to understand those results better.

Moreover, we would also choose a different kind of difference-in-difference analysis which could have given us more information regarding other factors affecting the stock price, as an example, a difference-in-difference regression model which accounts for more factors. This could set a more specific value on how much earnings announcements affect firms. A more appropriate approach could be to do a fundamental analysis of two similar firms so that we with more certainty could establish that the only difference between the firms was the earnings announcement release. We believe that this would have helped us estimate the impact of positive surprise earnings announcements in a greater manner. The last improvement to our paper that we want to emphasize is the choice of forecasting models. We believe the thesis would be improved if we were more careful in choosing a forecasting model for earnings that had been a better fit for periods with large volatility. This could have helped us to be more confident regarding our abnormal returns for 2020.

### *Implications*

Our thesis implies that market efficiency during periods with large stock market volatility should be investigated further. This is something that could be done to see if companies with earnings surprises are wrongly priced in the market in terms of intrinsic value during periods of volatility. Another implication is that more research should be done on how to forecast company earnings during “uncommon” market conditions most accurately.

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# Appendix

## Appendix A: Complete list of all companies included in the event study

| *Full list of the included companies from OSEBX* |
|---|
| 1. *Aker BP ASA* |
| 2. *Aker Solutions* |
| 3. *American Shipping Company ASA* |
| 4. *Af Gruppen ASA* |
| 5. *Atea ASA* |
| 6. *Bonheur ASA* |
| 7. *Bergenbio ASA* |
| 8. *Bouvet ASA* |
| 9. *DNO ASA* |
| 10. *ABG Sundal Collier Holding ASA* |
| 11. *Entra ASA* |
| 12. *Equinor ASA* |
| 13. *Europris ASA* |
| 14. *Fjord1 ASA* |
| 15. *Frontline LTD* |
| 16. *Gaming Innovation Group Inc* |
| 17. *Golden Ocean Group Limited* |
| 18. *Grieg Seafood ASA* |
| 19. *Hexagon Composites ASA* |
| 20. *Idex Biometrics ASA* |
| 21. *Kitron ASA* |
| 22. *Kongsbergs Automotive ASA* |
| 23. *Kongsberg Gruppen ASA* |
| 24. *Leroy Seafood Group ASA* |
| 25. *Medistim ASA* |
| 26. *Mowi ASA* |
| 27. *Nel ASA* |
| 28. *Norsk Hydro ASA* |
| 29. *Olav Thon Eiendomsselskap ASA* |
| 30. *Orkla ASA* |
| 31. *PGS ASA* |
| 32. *Photocure ASA* |
| 33. *SalMar ASA* |

| |
|---|
| *34. Scatec ASA* |
| *35. Schibsted ASA* |
| *36. Telenor ASA* |
| *37. Tomra Systems ASA* |
| *38. Nordic Semiconductor ASA* |
| *39. Yara International ASA* |
| *40. Subsea 7 ASA* |
| *41. TGS NOPEC Geophysical Company ASA* |
| *42. BW LPG Limited* |
| *43. BW Offshore Limited* |
| *44. Asetek ASA* |
| *45. Wallenius Wilhelmsen ASA* |
| *46. Stolt-Nielsen Limited* |

# Appendix B: Full sample results for Figures 5.10 to 5.13

**Abnormal and cumulative return for each individual trading day during the event-window.**

| Date | AR% (Positive news) | CAR% (Positive News) | AR% (Neutral News) | CAR% (Neutral News) | AR% (Negative News) | CAR% (Negative News) |
|---|---|---|---|---|---|---|
| -20 | 0.0249 | 0.0249 | 0.0577 | 0.0577 | -0.0937 | -0.0937 |
| -19 | 0.1099 | 0.1348 | 0.0150 | 0.0727 | 0.1679 | 0.0742 |
| -18 | -0.1062 | 0.0286 | 0.0658 | 0.1386 | 0.2469 | 0.3211 |
| -17 | 0.3166 | 0.3452 | 0.0318 | 0.1704 | 0.6131 | 0.9342 |
| -16 | -0.1255 | 0.2197 | 0.0256 | 0.1960 | -0.3092 | 0.6251 |
| -15 | 0.1153 | 0.3350 | -0.0214 | 0.1746 | 0.0399 | 0.6650 |
| -14 | -0.0282 | 0.3068 | 0.0510 | 0.2256 | -0.1335 | 0.5314 |
| -13 | 0.0886 | 0.3953 | -0.0016 | 0.2240 | -0.3757 | 0.1558 |
| -12 | 0.2123 | 0.6077 | -0.2103 | 0.0136 | -0.5722 | -0.4164 |
| -11 | 0.4286 | 1.0363 | 0.1483 | 0.1619 | -0.0312 | -0.4477 |

| | | | | | | |
|---|---|---|---|---|---|---|
| -10 | 0.1363 | 1.1725 | -0.3369 | -0.1749 | 0.3989 | -0.0488 |
| -9 | -0.6010 | 0.5716 | -0.3032 | -0.4782 | 0.6474 | 0.5986 |
| -8 | 0.4885 | 1.0601 | -0.1406 | -0.6188 | -0.1573 | 0.4413 |
| -7 | 1.0404 | 2.1005 | -0.0298 | -0.6486 | 0.7584 | 1.1997 |
| -6 | 0.0266 | 2.1272 | 1.0420 | 0.3934 | 0.8561 | 2.0558 |
| -5 | -0.3505 | 1.7767 | 0.2466 | 0.6400 | -0.1465 | 1.9093 |
| -4 | 0.2298 | 2.0064 | -0.2062 | 0.4338 | 0.7425 | 2.6518 |
| -3 | 0.1838 | 2.1902 | 0.4531 | 0.8869 | 0.6102 | 3.2620 |
| -2 | 0.3826 | 2.5728 | 0.0942 | 0.9811 | 0.3177 | 3.5797 |
| -1 | 0.6460 | 3.2188 | 0.9826 | 1.9637 | -1.3644 | 2.2153 |
| 0 | 0.6814 | 3.9002 | -0.2347 | 1.7290 | -0.8144 | 1.4009 |
| 1 | 0.1828 | 4.0829 | 0.0356 | 1.7646 | -0.4362 | 0.9647 |
| 2 | 0.2572 | 4.3401 | 0.3408 | 2.1055 | 0.3687 | 1.3334 |
| 3 | -0.3297 | 4.0104 | 0.2300 | 2.3355 | 1.1621 | 2.4954 |
| 4 | 0.2330 | 4.2435 | -0.1452 | 2.1903 | -0.4693 | 2.0261 |
| 5 | -0.4702 | 3.7732 | 0.2320 | 2.4223 | -0.1881 | 1.8380 |
| 6 | -0.4430 | 3.3302 | 0.1112 | 2.5335 | 0.4025 | 2.2406 |
| 7 | -0.0364 | 3.2938 | -0.1889 | 2.3446 | 0.9923 | 3.2329 |
| 8 | 0.0203 | 3.3141 | 0.1035 | 2.4481 | -0.2250 | 3.0079 |
| 9 | -0.0659 | 3.2482 | 0.1683 | 2.6164 | -0.3849 | 2.6229 |
| 10 | -0.6844 | 2.5638 | 0.1886 | 2.8050 | -0.1347 | 2.4882 |
| 11 | -0.2437 | 2.3201 | -0.5768 | 2.2282 | 0.4666 | 2.9548 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 12 | -0.3539 | 1.9662 | -0.0712 | 2.1571 | 0.4650 | 3.4198 |
| 13 | -0.4339 | 1.5323 | -0.0047 | 2.1524 | -0.2335 | 3.1863 |
| 14 | -0.0433 | 1.4890 | -0.1645 | 1.9879 | 0.0829 | 3.2692 |
| 15 | 0.3561 | 1.8451 | 0.0392 | 2.0271 | 0.1616 | 3.4308 |
| 16 | -0.3884 | 1.4568 | -0.0139 | 2.0132 | -0.0203 | 3.4105 |
| 17 | 0.3366 | 1.7934 | 0.0092 | 2.0224 | -0.0816 | 3.3289 |
| 18 | -0.1687 | 1.6247 | -0.0879 | 1.9345 | -0.5749 | 2.7540 |
| 19 | -0.0960 | 1.5286 | 0.0577 | 1.9922 | 0.0498 | 2.8037 |
| 20 | -0.2884 | 1.2403 | -0.0713 | 1.9209 | -0.3546 | 2.4492 |
| σ | 0.3651 | 1.3054 | 0.2911 | 1.0782 | 0.5167 | 1.2669 |

**Full sample results day-to-day for Figure 5.10**

| Trading days | Abnormal Return Energy (Positive News) | Cumulative Return Energy (Positive News) |
|---|---|---|
| -10 | -0.034229936 | -0.034229936 |
| -9 | -0.094384294 | -0.12861423 |
| -8 | 0.008664306 | -0.119949924 |
| -7 | -0.242966856 | -0.36291678 |
| -6 | -0.176854504 | -0.539771283 |
| -5 | -0.003097252 | -0.542868535 |
| -4 | 0.075915419 | -0.466953116 |
| -3 | -0.023728452 | -0.490681568 |

| | | |
|---|---|---|
| -2 | -0.022503996 | -0.513185564 |
| -1 | 0.012477186 | -0.500708378 |
| 0 | -0.06120728 | -0.561915658 |
| 1 | -0.086446208 | -0.648361867 |
| 2 | -0.020031795 | -0.668393662 |
| 3 | 0.035363412 | -0.63303025 |
| 4 | -0.027658212 | -0.660688462 |
| 5 | -0.092881912 | -0.753570374 |
| 6 | 0.020805931 | -0.732764443 |
| 7 | -0.011173943 | -0.743938386 |
| 8 | -0.002365075 | -0.746303461 |
| 9 | 0.020398066 | -0.725905395 |
| 10 | -0.027774723 | -0.753680118 |

**Full sample results day-to-day for Figure 5.11**

| Trading days | Abnormal Return Energy (Negative News) | Cumulative Return Energy (Negative News) |
|---|---|---|
| -10 | -0.117104279 | -0.117104279 |
| -9 | 0.589112351 | 0.472008072 |
| -8 | -0.50093795 | -0.028929878 |
| -7 | -0.140401802 | -0.169331679 |
| -6 | -0.112999393 | -0.282331073 |

| | | |
|---|---|---|
| -5 | 0.166388808 | -0.115942265 |
| -4 | 0.241079622 | 0.125137357 |
| -3 | -0.206653915 | -0.081516558 |
| -2 | 0.180710564 | 0.099194006 |
| -1 | -0.322161643 | -0.222967637 |
| 0 | -0.086307767 | -0.309275404 |
| 1 | 0.239324641 | -0.069950764 |
| 2 | -0.0170642 | -0.087014964 |
| 3 | 0.106773946 | 0.019758982 |
| 4 | 0.00682524 | 0.026584222 |
| 5 | -0.084841113 | -0.058256891 |
| 6 | 0.215998019 | 0.157741128 |
| 7 | 0.385409273 | 0.543150402 |
| 8 | 0.009128201 | 0.552278603 |
| 9 | 0.115664317 | 0.66794292 |
| 10 | 0.15143836 | 0.81938128 |

**Full sample results day-to-day for Figure 5.12**

| Trading days | Average All Companies | Average Equinor |
|---|---|---|
| -10 | -4.06739E-05 | -0.000802538 |
| -9 | 0.006637517 | -0.000235496 |

| | | |
|---|---|---|
| -8 | -0.020692503 | -0.003901696 |
| -7 | -0.001649182 | -0.006643308 |
| -6 | 0.00225216 | -0.000367062 |
| -5 | -0.003988731 | -0.002490281 |
| -4 | 0.004774186 | -0.000906988 |
| -3 | -0.000530065 | -0.005092138 |
| -2 | -0.007494643 | -0.006070934 |
| -1 | -0.001387888 | 0.006214513 |
| 0 | -0.005488458 | 0.000505566 |
| 1 | 0.001309417 | -0.003981604 |
| 2 | 0.000781937 | -0.003914119 |
| 3 | 0.001851576 | -0.002560394 |
| 4 | 0.00542634 | 0.003433925 |
| 5 | 0.004389383 | -0.003776651 |
| 6 | 0.006542052 | 0.002343517 |
| 7 | 0.015536401 | 0.015433048 |
| 8 | 0.00559771 | 0.002425032 |
| 9 | 0.001085571 | 0.004821209 |
| 10 | 0.00154824 | -0.001943207 |

**Full sample results day-to-day for Figure 5.13**

| Trading days | Average All Companies | Equinor |
|---|---|---|

| | | |
|---|---|---|
| -10 | -4.06739E-05 | -0.000802538 |
| -9 | 0.006596843 | -0.001038033 |
| -8 | -0.01409566 | -0.00493973 |
| -7 | -0.015744842 | -0.011583037 |
| -6 | -0.013492682 | -0.011950099 |
| -5 | -0.017481413 | -0.01444038 |
| -4 | -0.012707227 | -0.015347368 |
| -3 | -0.013237292 | -0.020439507 |
| -2 | -0.020731935 | -0.026510441 |
| -1 | -0.022119823 | -0.020295927 |
| 0 | -0.027608281 | -0.019790361 |
| 1 | -0.026298864 | -0.023771965 |
| 2 | -0.025516926 | -0.027686084 |
| 3 | -0.02366535 | -0.030246477 |
| 4 | -0.01823901 | -0.026812553 |
| 5 | -0.013849627 | -0.030589204 |
| 6 | -0.007307576 | -0.028245687 |
| 7 | 0.008228825 | -0.012812639 |
| 8 | 0.013826535 | -0.010387606 |
| 9 | 0.014912106 | -0.005566398 |
| 10 | 0.016460346 | -0.007509605 |