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Market Efficiency in Announcements of Petroleum Discoveries

An empirical analysis for the Norwegian continental shelf

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ABSTRACT

This is an event study which investigates the stock price behavior of oil and gas companies in the days surrounding announcements of petroleum discoveries. The pre-announcement period is examined in order to test for indications of information leakage. The analysis in the post-announcement period is a test of market efficiency and competing theories of return behavior following firm-specific events. I find no indications of information leakage, and the market seems to adjust efficiently to the announcements. However, there are some weak indications of a positive post-announcement drift. Due to some power issues, I leave this an open question for further research.

FOREWORD

This thesis is the final stage in my Master in Financial Economics degree at the Norwegian School of Economics (NHH) in Bergen, Norway. The choice of topic was driven mainly by my interest in the oil and gas industry as well as a desire to learn more about econometrics, a subject area of which I had little preexisting knowledge. I also wanted to choose an original topic - one which had the potential to contribute to a meaningful field of research.

The process of writing the thesis has been both challenging and educational. There is a vast amount of studies devoted to similar research questions, but there are no directly comparable results. Broadly, this study is a crossover of the traditional event study and the previous work in short-term reversal studies. This necessitated an extensive literature review. Understanding the sometimes complex statistical concepts in the earlier work and how it applies to the specifics of this study was particularly strenuous, but also enlightening. Data selection did at first seem very straightforward, but considerations which came up along the way led to a somewhat reiterative and time consuming process. Altogether, the work has been very rewarding and has increased my understanding of empirical finance in many respects.

I would like to extend my gratitude to Hanqing Wang, my supervisor, for excellent guidance and advice, and for being remarkably accommodating through the whole process.

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Kenneth Vik

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1. INTRODUCTION

1.1 PURPOSE & MOTIVATION

The petroleum industry is one of the largest industries in the world. A critical success factor for producers in this industry is replenishing reserves through exploration drilling. These endeavors carry with them high levels of uncertainty and can potentially have a large impact on firm value. Broadly, this paper seeks to examine how the stock market reacts before and after announcements of petroleum discoveries.

Valuation of discoveries is not an easy affair. It requires skill in interpreting geological and seismic data which creates information asymmetry between geologists on the one side and analysts and investors on the other. Further, available information is often of low quality when a discovery is initially announced, and these announcements are required to be conservative. According to an anonymous analyst at a well-known Norwegian investment bank, the valuation techniques employed upon announcements are often crude. It is therefore interesting to analyze the aftermath of the discoveries in the stock market. This research question will mainly contribute to the debate on market efficiency, behavioral finance and related subject areas in empirical finance. Specifically, I investigate if there is evidence of overreaction or underreaction. The uncertainty surrounding announcements and the degree of news coverage that these events receive creates an atmosphere in which behavioral biases might thrive. To my knowledge, no previous studies have been published that examine the stock market's reaction to petroleum discoveries.

There are quite a few examples in the media of suspicions and cases of insider trading on information about drilling results. Despite regulatory actions, the information content of drilling results is particularly susceptible to leakage. The information is potentially very price-sensitive, especially for smaller companies, and there are many individuals privy to the information. The second goal of this thesis is therefore to look for empirical evidence of information leakage. Of course, a pre-announcement run-up of the stock price is not conclusive evidence of insider trading, but it certainly should be of concern to regulators. Because of this research question, I focus on the Norwegian Continental Shelf (NCS) only in order to keep the analysis under one governing authority.

1.2 APPROACH

This paper can be classified as an event study – an econometric technique of empirically assessing the impact of an event on stock prices. The procedure is common in tests of market efficiency and the information value of corporate events.

This paper examines the stock price movements both before and after the announcements. An adaptation of the classical event study approach popularized by Fama, Fisher, Jensen and Roll (1969) will allow for such an investigation. It involves calculating abnormal returns (AR), cumulative abnormal returns (CAR), and cumulative average abnormal returns (CAAR) around the event dates. This approach leads to general insights into the price formation process around the event which can be displayed graphically and interpreted easily. It therefore seems appropriate to apply given no preexisting research on reactions to discoveries, and it may yield additional insights which reveal interesting topics for further research.

The calculations of CAR mentioned above will form a foundation from which I can employ two alternative testing strategies. First, I will segregate observations into two subgroups based on whether the announcement day abnormal return is negative or positive. Then abnormal returns for the pre-event and post-event windows are used to determine whether there is evidence of underreaction, overreaction and information leakage in the two subsamples. Significance is gauged using t-tests. The approach is a combination of the traditional event study and tests of over- and underreaction after large relative price changes.

The second approach is a simple regression model designed to test whether pre- and post-event returns are correlated with event day returns. In the post-event window, negative correlation would be consistent with overreaction while positive correlation would be consistent with underreaction. For the pre-event window, positive correlation would be consistent with information leakage.

1.3 RESULTS

The results largely confirm the predictions of the efficient markets hypothesis. The market and its investors are able to interpret the news and incorporate their effects into the stock price in an efficient manner. There are some indications of a positive drift following announcements, an effect which can be explained by behavioral biases, the Uncertain

Information Hypothesis as well as the conservative nature of drilling announcements, but the significance of this result is low. Imposing an additional selection criterion demanding that the firm itself announces the news seems to amplify the effect, but a larger sample size is needed to investigate the drift using this criterion.

There is no significant correlation between pre-announcement and announcement-day returns, nor is the CAAR for this period significant. The sign of the output variables is in fact opposite of that which would be expected in the presence of information leakage - thus insider trading does not seem to be a prevalent issue for announcements of oil and gas discoveries. This indicates that the regulations enforced by the Norwegian governmental agencies in cooperation with the Oslo Stock Exchange for the management of insider information in exploration drilling are well functioning.

1.4 OUTLINE

The next section will be a quick introduction to exploration and production, which is necessary background information for the rest of the paper. The subsequent section will present theoretical concepts and previous studies which provide context and highlight possible explanations for the observed behavior of stock prices. The two methodologies are discussed in detail in chapter four, and the data collection process as well as the data characteristics is described in chapter five. The discussion is detailed enough to be replicable and to highlight potential issues in inference. The results are presented and discussed in chapter six.

2. BACKGROUND

2.1 THE EXPLORATION & PRODUCTION (E&P) PROCESS

The Petroleum Act §1-1 maintains that the State of Norway has the proprietary right to all subsea petroleum deposits, and also the exclusive right to resource management on the Norwegian continental shelf (NPD, 2012)[1]. Resource management is carried out jointly by the Ministry of Petroleum and Energy and the Norwegian Petroleum Directorate through a licensing system. It is through this system that proprietary rights to the deposits are ultimately transferred to the E&P companies.

The first step in this process is approving an area for exploration activity. This is a comprehensive process which entails an evaluation of the impact on industry, trade, environment, pollution and social effects (Petroleum Act §3-1), and is subject to political debate. The exploration and production (E&P) companies contribute to the debate by providing geological and seismic data which is used to assess the size and extractability of the deposits. The Ministry announces which blocks of the NCS that have been approved and create production licenses comprising one or several adjacent blocks.

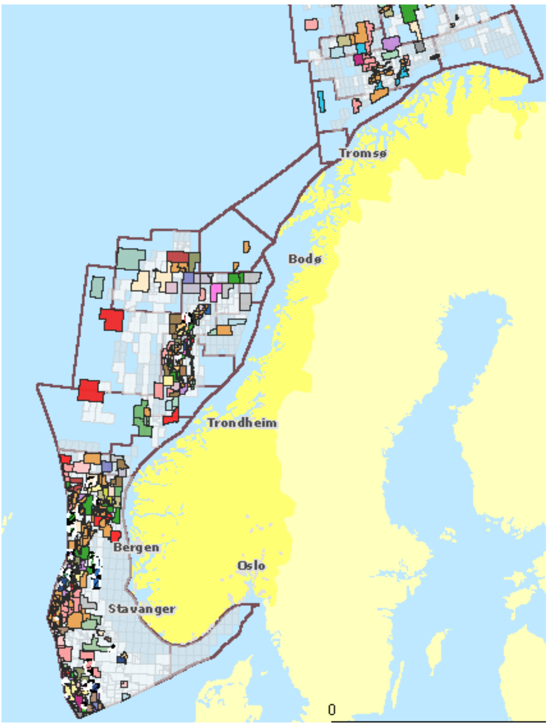


Figure 1 - Overview of production licenses (NPD FactMap, 2013)

A production license gives the exclusive right to exploration and production in the areas covered by the license (Petroleum Act §3-3). E&P companies are invited to submit applications, either individually or as groups. The ministry grants licenses on the basis of factual and objective criteria, and the licensees become the owners of the resources produced from the license (Petroleum Act §3-5).

[1] The Petroleum Act is not available in English, but a translation is offered on the website referred to as (NPD, 2012).

Most licenses on the NCS are awarded to joint ventures, which typically comprise three to four companies. One of the companies is appointed as the operator and assumes the responsibility of managing the day-to-day operations of the field, while the others participate through joint operating and accounting agreements (Statoil, 2011). These agreements ensure that cost and revenue from the licenses are shared among the partners in accordance with their respective stake in the license. Thus, for a single discovery of oil or gas there are multiple companies whose stock price can be affected.

2.2 THE TIMELINESS OF DISCLOSURE REQUIREMENTS

The type of information which must be disseminated to the market for listed companies is regulated by the respective stock exchange. For the Oslo Stock Exchange, the rule is that information must be disclosed if it is expected to have a significant effect on the value of the firm (Oslo Stock Exchange, 2009). The rules are similar for the New York Stock Exchange (NYSE, 2012). Although I have not reviewed regulations for all stock exchanges included in the sample, they are likely to be similar. Even if they were different, there are international agreements in place because the partners in a single joint venture may be listed on different exchanges, and it is usually in the best interest of the firm to guide the market's expectations. It thus seems reasonable to hold as a general rule that the companies will announce news that is expected to have a substantial effect on the value of the firm.

Although I will not use stock exchange notices for data selection, the background knowledge is useful for two main reasons. First, one potential problem in this study is that many of the announcements have low information value and thus have a high relative noise level. Because companies disclose information which is expected to be price-sensitive, either through stock exchange notices or other press releases, I can "screen" observations on whether or not the firms themselves announce the news. Second, it indicates at what point in the drilling process disclosure requirements are triggered. The information gathered will increase with drilling depth. For a small firm, simply finding hydrocarbons of unknown magnitude early in the drilling process might have a large impact on firm value and thus trigger a disclosure requirement. A hypothetical announcement at the end of the drilling process where the full set of information gathered is announced may thus come several weeks after the initial announcement. These implications will be considered in the methodology section when determining the length of the event windows.

For drilling on the NCS, there has been some debate on the involvement of the NPD in announcements. In 1973, it was decided by administrative orders that press releases regarding drilling results on the NCS should be prepared in coordination with the NPD, and that the NPD should be the first party to disclose the results (Oslo Stock Exchange, 2009). The NPD would serve as an objective and authoritative third party to ensure that announcements are objective and homogenous across firms. Because stock prices may be sensitive to this type of information, following a set of prescribed rules for reporting is important, but it causes a delay in the process of announcing the news which increases the risk of insider trading. Therefore, the Oslo Stock Exchange changed its view in a circular in 2009 and maintained that the companies should not defer disclosure and instead follow the general rule from the Securities Trading Act §5-3 of immediate disclosure of price-sensitive information (Oslo Stock Exchange, 2009). This will also be considered in determining the length of the event windows, especially the pre-event window where I test for information leakage.

3. THEORY

This section will present relevant theoretical concepts as well as previous research on related subjects. The aim is to provide context and point out issues in testing which will later be considered in the methodology section.

Essentially, all theory and literature presented in this chapter can be traced back to or relates to the debate on market efficiency. I will first present the efficient markets hypothesis and its implications for asset pricing before discussing possible reasons for why empirical tests may find it to be untrue. This will serve to underline statistical considerations and to formulate alternative explanations for the results. The overreaction and underreaction phenomena are given special attention in a separate section which includes a literature review, with a special focus on short-term studies. The last section will briefly discuss some previous evidence of information leakage and insider trading.

3.1 THE EFFICIENT MARKETS HYPOTHESIS

The efficient markets hypothesis (EMH) proposes that stock prices fully reflect all available information (Fama, 1970). It was developed independently by both Eugene Fama and Paul Samuelson in the 1960's (Lo, 2007). The major assertion of the EMH is that it is not possible to earn excess returns on a risk-adjusted basis because the stock market is highly competitive, and all information is therefore instantaneously impounded in the stock price. Empirical deviations from this assertion are called market anomalies.

There are three versions of the EMH; strong form, semi-strong form and weak form, which differ in their interpretation of required information level as follows (Bodie, et al., 2005).

i. *Weak form* – Prices reflect all historical price information
ii. *Semi-strong form* – Prices reflect all publicly available information
iii. *Strong form* – Prices reflect all information, including insider information

The underlying information level of the three forms as listed above is additive. That is, semi-strong form assumes prices reflect historical price information as well as publicly available information, and strong form efficiency assumes prices reflect all of the above in addition to private information.

Market efficiency relies on a number or assumptions. First, investors must be rational in information processing and decision making. Rational information processing means that investors must update expectations according to Bayes' law and rationality in decision making means that decisions must be consistent with Subjective Expected Utility (Barberis & Thaler, 2003). This need not be literally true, as irrationality of individual investors is allowed as long as the market as a whole is rational. If irrationality does cause mispricing in the market, the EMH relies on the process of arbitrage to correct the mispricing. Thus market efficiency implicitly inherits the assumptions of arbitrage, which are discussed below.

Under these circumstances, stocks will always be correctly priced given the available information. It is not possible to "beat the market" by information motivated trading in an informationally efficient market - any excess return should require excess risk. Of course, the assumptions as presented so far are very strict, and they are not congruent with the pragmatic definition of efficiency. However, the assumptions in different studies which test for market efficiency will vary, especially regarding the dynamics of arbitrage, so the strict definition is necessary to present.

Jensen (1978, p. 97) gives a more encompassing definition of market efficiency, which is closer to the current practical interpretation:

"A market is efficient with respect to information set θ_t, if it is impossible to make economic profits by trading on the basis of information set θ_t."

Jensen defines economic profits as risk adjusted returns net of all costs related to trading, mainly transaction costs and information acquisition costs (Jensen, 1978). The refined definition is necessary because markets are not frictionless, which is the implicit assumption in the assertion that stock prices fully reflect all information. Instead, security prices should adjust until the marginal cost of trading and acquiring information exceeds the benefit of exploiting the mispricing (Elton, et al., 2009). Also, it is not in practice assumed that arbitrage is risk free and requires no capital. It is sufficient that risk is low compared to the reward, creating a possibility for excess risk-adjusted return in trading strategies designed to exploit the anomaly. It is assumed, however, that there are a sufficient amount of arbitrageurs, or rather a sufficient amount of arbitrage capital (Lo, 2007). This may seem obvious, but the distinction between the strict and practical version is not trivial because previous studies have drawn conclusions on market efficiency without properly adjusting for cost and risk (Lo, 2007).

3.1.1 Tests of Market Efficiency

The definitions of the three forms of efficiency as listed above were initially developed by Fama (1970) to facilitate tests of efficiency at different levels. Whether or not stock prices do reflect the presumed information set is not empirically testable per se, it is the implications for the return generating process that form testable hypotheses. Fama therefore more recently updated his interpretations of the three levels in terms of these implications (Elton, et al., 2009). Weak form tests are taken to mean tests of return predictability, semi-strong form tests are tests of the speed of which stock prices update to new information, and strong form tests examine whether or not prices reflect nonpublic information (Elton, et al., 2009).

Return predictability

The strict definition of weak form efficiency above is that prices reflect all historical price information. Another way to frame the assertion is that stock prices are martingales, which implies that the past is not useful in predicting the future. Fama (1965) explains that historically, there were two conflicting views on this subject. One the one hand, proponents of “chartist theory” believed that one could predict prices by means of technical analysis. In contrast, proponents of the random walk hypothesis (RWH) maintained that asset prices fluctuate randomly. According to the EMH, the information used by the chartists to predict price movements should already be reflected in the stock price. The rationale is that if future price levels are predictable, agents in the market who know this will bid up the price until it reaches that level, thus arriving at that price level presently[2] (Bodie, et al., 2005). The EMH can be viewed as the theoretical justification for the RWH, and they both imply that it is not possible to predict future asset prices or returns.

Informational efficiency

This last line of reasoning above can be used more generally for the other two forms as well. If new and unanticipated information which affects the fundamental value of a firm becomes known, the stock will suddenly be mispriced and the price will then be corrected through the

[2] The argument suffers from what is known as the market efficiency paradox. If all information is already impounded in the stock price, there is no incentive for stock picking. Yet if no one is interested in stock picking, the information would not be impounded. The EMH can therefore only hold if there are a sufficient amount of investors who do not accept it to be true.

supply and demand mechanics of the stock market. This can happen either through a large population of arbitrage-seeking investors or a handful with deep pockets, e.g. institutional investors (Schwert, 2003). If information is disseminated rapidly the adjustment should also be rapid. If not, the argument that prices should instantaneously adjust only holds if the investors who are privy to the information are sufficiently deep pocketed. If a delay occurs, or if systematic errors in interpreting a specific type of information exist in previous price movements, traders will realize this and eliminate the anomaly by designing exploitative trading strategies (Fama, 1965). For the information set in semi-strong form efficiency, the implication is that fundamental analysis will not be fruitful. For strong-form efficiency, the implication is that insider trading is not profitable.

Tests of return predictability are still prevalent and comprise the main bulk of research on efficiency. Semi-strong form tests are also frequently used. Most event studies interested in the effect of corporate events on firm value and how quickly these effects are impounded in price examine semi-strong form efficiency. Strong form tests are not very relevant in practice. Jensen (1978, p. 99) argues that the strong form is "*an extreme form which few people have ever treated as anything other than a logical completion of the set of possible hypotheses*". However, tests of whether specific groups of investors, such as mutual fund managers or insiders in a company, can earn excess profits are often classified as strong-form tests (Elton, et al., 2009).

3.1.2 Classification of the Tests in This Study

The objective for the post event window is to investigate market efficiency by means of testing whether there are significant excess returns or correlation. It is important to note that there might be updated pieces of information regarding the drilling results in the subsequent days which the stock market may react to. Therefore, if a post-announcement drift is found it could be caused by either a delayed response to the initial information or reactions to the subsequent information releases (or extraneous factors). Only the first case would be inconsistent with the criteria from the semi-strong EMH that prices instantly react. The second case would in fact be a violation of the *weak form* EMH as stock prices would fail to reflect what the announcements imply, on average, for subsequent updates.

For the pre-event window, the null hypothesis assumes that the market is *not* efficient in the strong form. An accepted null of no excess returns and no correlation would be *consistent* with strong-form efficiency. However, if the null is rejected, the alternative hypothesis is not that the market *is* efficient in the strong form. In other words, we cannot prove anything in hypothesis testing; only disprove what efficiency implies for returns. The issue does not matter very much, and is not worth belaboring. The goal is to find evidence of information leakage, not strong-form efficiency, but it can be classified as a strong-form test.

3.2 MARKET ANOMALIES - POSSIBLE EXPLANATIONS FOR THEIR EXISTENCE AND PERSISTANCE

Market anomalies are deviations from the EMH found through empirical research. The EMH has been tested extensively since its inception, and several anomalies have been unearthed. In theory, once an anomaly is discovered and knowledge of its existence is disseminated the mispricing should be corrected immediately by arbitrageurs who capitalize on the low-risk opportunity. Schwert (2003) explains that many anomalies are in fact reduced after evidence is published, but others remain persistent through time. This section will discuss some possible reasons why they might exist, as well as the inevitable ambiguity in testing the EMH due to factors such as the joint test problem. The discussion is concerned with both reasons why they might counterfactually be found, as well as reasonable explanations for why they might exist. The latter brings us into the field of behavioral finance.

3.2.1 The Joint Test Problem

The joint test problem is the idea that any test of market efficiency is simultaneously a test of whether or not the normal return model used is adequate (Fama, 1970). That is, whether it is correctly specified, whether there are statistical issues in its estimation, and whether its assumptions about investor preferences are correct (Kothari & Warner, 2007) (Lo, 1997). Essentially, the problem is that in trying to determine the effect of one factor (discovery) on another (stock price), ceteris paribus estimation is needed. That is, all other factors must be held constant in order to isolate the effect. Complete isolation is of course not feasible in practice as no asset pricing model exists which exactly determines what the return should be at any given point in time, considering all factors besides the factor of interest in the study. The effect is that evidence against the EMH will never be accurate enough to constitute conclusive proof.

Because of the limitations of asset pricing models, studies of market efficiency are prone to statistical errors. These statistical errors might cause false conclusions of anomalies, i.e. type 1 errors. For example, one common problem in event studies is increased risk (volatility) in the event window (MacKinlay, 1997). Parameters of the normal return model are normally calculated from an estimation window prior to the event, and therefore the beta(s) might be too low in some cases. If excess returns are found, they could be a fair compensation for risk instead of evidence of market inefficiency. The statistical biases of normal returns model will certainly be a major reason why market anomalies may exist, or rather appear to exist. I will elaborate on these in the Chapter 4, so that they can be discussed in relation to the methodology of this paper. It is important to stress, however, that the main consequence of the joint test problem is that we may never conclusively infer market efficiency or inefficiency.

3.2.2 Data-mining

As Schwert (2003), Fama (1998) and several other authors point out, with so many studies conducted in the aim of finding anomalies it is inevitable that they will be found in certain samples. After all, it would be quite surprising if no anomalous evidence was found after literally thousands of studies. There is always a chance that a pure statistical coincidence conforms to some researcher's hypothesis. This issue is exacerbated by the fact that researchers engage in data-snooping (Lo, 2007). Not only may data by chance conform, the hypothesis may be formed *after* finding anomalous evidence.

Tests must therefore be run for different samples, and perhaps also using different methodologies. If an anomaly is not found in a subsequent test, it could be due to one of two reasons; either the investors in the market have realized the mistake and corrected it or it was not there in the first place (Schwert, 2003).

3.2.3 Market Microstructure

Market microstructure is concerned with how trading mechanisms affect the price formation process (O'Hara, 1995, p. 1). The main issues are liquidity, non-synchronous trading, bid-ask spreads and the bid-ask bounce, which are all related issues. When discussing the validity of a study which finds an anomaly, the aforementioned issues, along with other statistical problems caused by the normal return model, are often cited as possible reasons why the effect may exist without deviating from rationality or the EMH.

If a security is illiquid, quoted prices may become stale – the information set they represent is outdated because a significant amount of time has passed since they were last traded. For example, if there are news close to the end of a trading day 0, and the market does not trade for the rest of day 0 but instead on day 1, it will seem as if the stock responded to a piece of information on day 1. Liquidity is a problem that I will have to deal with when using observations form small companies. There is also some risk associated with illiquidity (Amini, et al., 2013).

Illiquidity also raises the issue of non-synchronous trading. When using closing prices of securities we assume that the observations represent the market clearing price at the end of each day, while in truth the prices might be stale. Non-synchronous trading may lead to false abnormal returns and cross-autocorrelation[3], and is a common issue in event studies.

The bid-ask spread is the difference between the lowest price quoted by a seller (ask) and the highest price quoted by a buyer (bid). In effect, the bid-ask spread is a transaction cost charged by the stock exchange. Poorer liquidity will likely increase the bid-ask spread, so the issue is likely to be larger for smaller stocks (Elton, et al., 2009). Other transaction costs include brokerage fees and potential endogenous changes in the bid and ask prices due to large trades (Elton, et al., 2009). These transaction costs will defer trading, possibly causing anomalies to exist because it is not profitable to try to exploit them.

If there is high selling (buying) pressure on the event day, there might be an overrepresentation of the bid (ask) price in closing prices in the cross-section of observations compared to the day before or after. According to Cox and Peterson (1994) this could lead to spurious abnormal returns on the next trading day and consequently lead to false conclusions of reversals or overreactions. This phenomenon is known as the bid-ask bounce, and has been found to explain much of the turn-of-the-year (January) effect (Cox & Peterson, 1994).

[3] Cross-autocorrelation is when one security's return is correlated with another across time. For example, a high return for security A today may on average result in a high return for security B tomorrow (Lo & MacKinlay, 1990). A possible explanation for this is that low-volume stocks react slower to market-wide news than do high-volume stocks (Chordia & Swaminathan, 2000).

3.2.4 Behavioral Finance's Explanations – Cognitive Biases and Limits to Arbitrage

The final major issue is concerned with investor rationality, which brings us into the field of behavioral finance. The previous sections on why market anomalies might be found in research were mainly explanations of why they might counterfactually exist. Behavioral finance, by contrast, proposes that markets in some cases will exhibit signs of departure from efficiency due to the presence of irrational investors coupled with limits to arbitrage (Barberis & Thaler, 2003).

Behavioral finance is a relatively new field of research. Barberis and Thaler (2003) claim that it was partly the inability of traditional theories to explain anomalous phenomena that led to the emergence of behavioral finance. This is particularly due to the underlying assumption in traditional theories that investors are rational, which according to behavioral economists is false (Lo, 2007). The work of Daniel Kahneman and Amos Tversky (1973, 1974, 1979, and 1982) in decision theory and behavioral biases forms the backdrop. Their findings are largely from an experimental setting where they examined how people make decisions. Kahneman and Tversky showed that individuals use heuristics[4] to assign probabilities to values. Investors are therefore prone to cognitive biases in information processing and decision making. The results led to the development of prospect theory as well as experimental evidence of a plethora of behavioral biases. These results have been applied to the field of finance as a descriptive, rather than normative approach to explaining investor and market behavior.

There are a few specific biases that should be defined before the next section on overreaction and underreaction. The following definitions are mostly quoted from Hens & Bachmann (2008) because of their focus on investment, but a citation is due Kahneman and Tversky, e.g. (1974).

Representativeness and Availability

Hens & Bachmann (2008, p. 71) describe the representativeness heuristic as *"the tendency for individuals (1) to estimate probabilities depending on their pre-existing beliefs even if the conclusions are statistically invalid and (2) to believe that small samples (e.g. a sequence of returns) represent entire populations (e.g. all returns from which the realization is drawn)."*

[4] Heuristics are methods of problem-solving based on «rules-of-thumb» reasoning.

Statement (2) is of particular interest. It may lead investors to think that firms performing well will continue to do so in the future (Hens & Bachmann, 2008). If this is widespread, it may cause overreaction in that prices depart from intrinsic value and later revert. It may therefore explain investor behavior in speculation bubbles and also shorter term overreaction. The availability bias describes the tendency of investors to overweight information which is easy to recall (Kahneman & Tversky, 1974). It may amplify the representativeness heuristic (Hens & Bachmann, 2008).

Anchoring and Conservatism

Hens & Bachmann (2008) explain anchoring as being influenced in judgment by some arbitrary figure - the anchor - even when the figures are not informative. Conservatism means that investors overweight prior beliefs and underweight recent data. Hens & Bachmann (2008) explain that conservatism may be described as a consequence of anchoring, in which case the anchor is previous levels of the stock price or previous values of the firm. This is an obvious contradiction to the representativeness bias, and also predicts the opposite effect - underreaction due to slow updating of expectations.

Ambiguity aversion

Ambiguity aversion, or uncertainty aversion, was first documented in Ellsberg (1961). It describes the tendency of individuals to prefer options where the probability distributions are known. It is closely related to risk, but whereas perceived risk can be represented by probabilities, ambiguity refers to situations where the outcomes are too uncertain to be assigned a probability measure due to a lack of precise information (Epstein, 1999). The effect is that trading may be deferred where there is a lack of precise information (Easley & O'Hara, 2010).

The key question is whether these biases will be relevant to asset pricing and whether they are plausible explanations for market anomalies. Proponents of the EMH would argue that the process of arbitrage would push stock prices towards their fundamental value, i.e. the equilibrium price with rational expectations (Lo, 2007). Behavioral economists, on the other hand, would argue that this will not necessarily happen due to a collection of issues known as limits to arbitrage.

Limits to arbitrage

The textbook definition of arbitrage requires no risk and no capital, and yields an immediate payoff. However, arbitrage opportunities require taking offsetting positions in other assets, and these positions will rarely be perfect (Barberis & Thaler, 2003). The arbitrage portfolio will therefore be subject to fundamental risk. The security which was initially mispriced might continue to move in the direction of the mispricing. For example; if a security was underpriced, and an investor therefore went long in that security, an unexpected negative firm-specific event might occur which pushed the price down further (Barberis & Thaler, 2003). The fact that arbitrage is risky is a major deference to arbitrage trading, and by itself falsifies the strictest interpretation of the EMH.

The irrationality that caused the mispricing in the first place might also continue and exacerbate the mispricing. This is a problem if portfolios are not held until the arbitrage payoffs are realized. Shleifer & Vishny (1997) explain that contrary to the assumptions implicit in the EMH and models such as the CAPM and APT, arbitrage trading is mostly carried out by institutional investors rather than a large number of small traders. This poses a significant problem in the event that mispricing exacerbates. Investors in a fund might observe temporary losses in the arbitrage positions and withdraw capital from the fund. The arbitrageur might then be forced to liquidate holdings prematurely, taking losses instead of cashing in on the arbitrage opportunity (Shleifer & Vishny, 1997). Further, the fear of this happening might limit investors' aggressiveness in exploiting mispricing (Barberis & Thaler, 2003). This could lead to a slow convergence towards intrinsic value, rather than an immediate correction. These arguments are even more compelling if the providers of capital are creditors who require immediate repayment if the value of the portfolio or fund reaches some predetermined low (Barberis & Thaler, 2003).

Exploiting mispricing will also require the incurrence of implementation costs such as transaction and information acquisition costs. This will of course limit the profitability of arbitrage trading. Moreover, there will be a tradeoff between offsetting risk and transaction costs. More assets in the portfolio might offset more risk, but transaction costs will increase. These costs should only be considered limits to arbitrage when the theoretical version of efficiency is used as opposed to the pragmatic version.

Arbitrage opportunities are often referred to as "free lunches". In practice, arbitrage trading entails risks, costs and capital and is by no means free. As a result, mispricing may exist and persist because even if investors come to know of them they may be unprofitable to exploit. Barberis and Thaler (2003) write that correct prices imply that there is no free lunch, however; the fact that there is no free lunch does not necessarily imply that prices are correct. Market forces may simply not be powerful enough to correct them.

Now, it was explained in section 3.1 that the EMH does not necessarily assume that arbitrage is riskless and requires no transaction costs. Jensen (1978) recognized transaction and implementation costs in his definition. But I included transaction costs above, as an argument of behavioral finance that markets are not efficient. EMH proponents may still make the argument that markets are efficiently adjusting until the costs equal the benefits, and take this as evidence in favor of the EMH (Lo, 2007). But then the argument of arbitrage does not rule out that there is mispricing in the market, only that it is unprofitable to exploit. In other words, there is a gray area where anomalies are not taken as evidence of inefficiency as small anomalies are allowed to persist in an efficient market as defined by Jensen.

3.3 OVERREACTION AND UNDERREACTION

One of the most intriguing pieces of evidence against market efficiency is overreaction and underreaction. When the market underreacts, stock prices continue to move in the same direction as an initial shift. This is also referred to as continuation, and is related to momentum. If there is an overreaction, the market adjusts beyond fundamental value, and the price is eventually reversed. Accordingly, overreaction is often referred to as reversal. There is empirical evidence for the existence of both phenomena in stock markets, but the implications for efficiency are still debated and are yet unclear. Behavioral economists argue that the phenomena exist due to cognitive biases and limits to arbitrage. The main counter-argument is that it is too early to reject efficiency due to possible alternative justifications such as increased risk or ambiguity or the microstructure issues discussed above. This section will present a mix of previous literature and theory, with special focus on short-term over- and underreaction. I will start with a short introduction to the history of how behavioral finance became a viable alternative hypothesis to the EMH.

3.3.1 Overreaction

The article by Werner De Bondt and Richard Thaler (1985) "*Does the Stock Market Overreact?*" was somewhat of a breakthrough for behavioral finance. They found that firms that performed well during the past three to five years tended to perform poorly in the following months. Influenced by the work of Kahneman and Tversky, they attributed the results to overreaction caused by the representativeness heuristic. In a stock market setting, the representativeness heuristic means that investors overweight recent performance relative to past. Biased investors will therefore buy stocks that have recently gained and sell stocks that have recently dropped. Hens & Bachmann (2008) explain that the availability bias could cause overreaction in stock markets. It is certainly related. Availability in this context means that investors remember recent stock returns more easily and therefore overweight them compared to prior returns, so this could be an underlying causal factor to the representativeness heuristic. The major consequence of overreaction is that contrarian investment strategies – buying losers and selling winners – can potentially earn excess profits, which should of course not happen in efficient markets.

3.3.2 Underreaction

In contrast to De Bondt and Thaler's results, Bernard and Thomas (1990) examined performance after earnings announcements and found that markets underreacted. That is, prices seemed to drift upwards for good news firms and drift downwards for bad news firms in the 60 days following an earnings announcement. This phenomenon was first documented by Ball and Brown (1968), and is known as the *post-earnings announcement drift* (PEAD). While overreaction can be explained by the representativeness and availability heuristics, underreaction is often attributed to conservatism and anchoring (Hens & Bachmann, 2008). In short, investors are biased towards the previous price level or value, and it takes time for them to update their beliefs about the value of the firm. Therefore, new information will slowly be impounded in the stock price rather than instantly. Hens and Bachmann (2008) explain that conservatism might arise because processing new information and updating beliefs is costly, and that information which is difficult to interpret is weighted less. This will definitely be a relevant point for drilling announcements, as they are often difficult to decipher effectively. A related phenomenon is the momentum effect found by Jegadeesh and Titman (1993). They conduct a relative performance study and find that stocks that performed well over a year tend to perform well also in the following three to six months.

3.3.3 Ambiguity aversion and the Uncertain Information Hypothesis

Eugene Fama, in his classic 1965 paper on the behavior of stock prices, stated that mispricing caused by uncertainty would not persist (1965, p. 39):

> *«If uncertainty concerning the importance of new information consistently causes the market to underestimate the effects of new information on intrinsic values, astute traders should eventually learn that it is profitable to take this into account when new information appears in the future. »*

In contradiction to Fama's statement, Brown, Harlow and Tinic (BHT) (1988) formulate what they dub the *Uncertain Information Hypothesis* (UIH). Its premise is that when unanticipated significant news arrives the market must set a price before the full ramifications of the news are known. BHT claim that rational and risk-averse investors will price these securities in such a way that leads to higher returns in the post-event window due to increased risk, regardless of whether the news are good or bad. More precisely, after good news the stock price should increase, but not as much as it would conditional on the news release and with commensurate risk. The stock price should adjust slowly as the ramifications are gradually understood and uncertainty is reduced. This is a modification of the EMH which loosens the requirement that stock prices must instantly react, which is the current interpretation of semi-strong form efficiency (see 3.1.1). BHT find empirical evidence that supports the hypothesis. Consequently, they argue that the effect might lead researchers to incorrectly conclude with underreaction to good news and overreaction to bad news in the short term.
The UIH explains the increased premium in terms of increased risk, and BHT's assumptions do not depart from rationality. However, if investors were ambiguity averse, the same effect would be expected as they would prefer to invest in stocks with less uncertainty.

Corrado and Jordan (1997) later criticize the methodology of BHT and replicate the approach with slight modifications[5]. They conclude that the modified results are consistent with price reversals for both negative and positive events, typically lasting for around two days (Corrado & Jordan, 1997). Bernard and Thomas (1990) also refute the UIH as an alternative explanation due to the fact that their bad news firms experience a negative drift, which is opposite to the prediction of the UIH, but their argument does not necessarily hold in the very

[5] BHT used the relatively low threshold of ±2.5 percent excess returns as the proxy for significant informational surprises. Corrado and Jordan explain that the 60-day post-event window used by BHT should on average include 6 observations of either negative or positive subsequent events. They therefore argue that BHT do not "effectively discriminate between positive and negative events" (Corrado & Jordan, 1997, p. 53). Their response is to simply increase the threshold and they report difficulties in obtaining empirical justification for the theory.

short term. Despite criticism, the UIH received interest from researchers and remains a viable alternative explanation to underreaction and overreaction. Amini et al (2013) provide a literature review of reversal studies which reveals a large body of evidence in favor of the UIH. However, whether results indicating an overreaction to negative events and an underreaction to positive events are caused by cognitive biases or uncertainty is an open and empirical question. The issue is especially noteworthy after announcements of drilling results because of the high level of uncertainty and potentially large ramifications.

3.3.4 Previous evidence of short-term price reversals and delayed price responses

The main bulk of studies on short term over- and underreaction define the event is a large relative price change. Other studies have used announcements and trading volume (Pritamani & Singal, 2001). Although I will not use a relative price change to weed out observations, these studies contain the most general conclusions and it is better to review these than a specific type of announcement.

Atkins and Dyl (1990) examine post-event behavior of stock prices after being listed in the Wall Street Journal as the top losers or winners. They conclude that the market seems to initially overreact and reverse for both negative and positive events, but the effect was much less significant for positive news. They do not, however, conclude with market inefficiency after transaction costs because the bid-ask spread is high. The two-day abnormal return following decreases was 2.26 percent, but the bid-ask spread was 3.57 percent. For increases, the bid-ask spread was 3.29 percent, while the two day abnormal return was -0.77 percent.

Bremer and Sweeney (1991) perform a similar study exclusively on extreme price decreases and find that reversal lasts approximately two days. They also note that the results do not necessarily imply that a trading strategy exploiting it will be profitable, but they emphasize that the results are inconsistent with the notion that stock prices should instantly react. The results are therefore consistent with both the UIH and overreaction, but they do note that the abnormal returns can partly be explained by a high bid-ask spread. Later, Bremer, Hiraki and Sweeney (1997) examine predictable patterns after large stock price changes on the Tokyo Stock Exchange. They find significant positive abnormal returns after price decreases over 10 percent, but they do not find any patterns of returns after large increases.

Cox and Peterson (1994) study three-day post-event performance after one-day declines of 10 percent of more. They find that prices reverse significantly, but conclude that there is no evidence of overreaction due to two additional findings. First, the large selling pressure on the day of the large drop causes an overrepresentation of bid prices relative to ask prices, i.e. a bid-ask bounce. Cox and Peterson show that this accounts for a major part of the positive abnormal returns in the following three days. Second, they find that the remaining abnormal returns are decreasing in time and argue that this is due to increased liquidity in more recent years, which leads to a reduction in the bid-ask spread.

While the above studies only use relative price measures, Pritamani and Singal (2001) apply a more refined approach. They use relative price changes, volume changes, and public announcements as proxies of information releases simultaneously instead of focusing on just one. The first selection criterion is large price changes, and then they a screen observations based on whether or not there was a public announcement on that day for the firm. For relative price changes only, post-event returns reverse for both positive and negative news, which is consistent with overreaction. The results are economically insignificant but sometimes statistically significant, which is generally the conclusion of the aforementioned studies. When screening on public announcements in addition the effect increases and actually changes sign. They find that investors earn an average of 1.20 percent cumulative average return (CAR) in the 20-day interval following positive announcements, and -1.62% following negative reactions. When the observations are screened on volume changes also, this effect is amplified and the 20-day cumulative abnormal return increases to 2 percent and -1.68 percent for positive and negative news, respectively. These results are consistent with underreaction for both positive and negative news, which contradicts the aforementioned studies, their own results not conditioned on announcements, as well as the UIH. Finally, they examine different types of announcements and find that underreaction in response to earnings announcements and changes in analyst forecasts are even larger. They employ an out-of-sample trading strategy for the most refined example, i.e. observations for which there are large price changes, volume increases, and announcements regarding earnings or changes in analyst forecasts. The result is a 20-day abnormal return of 1-1.5% after adjusting for transaction costs, excluding commissioning costs, and they consequently claim proof of market inefficiency.

The takeaway here is that large price decreases are typically reversed in the few following days, but the effect could vary within subsamples such as those events accompanied by company announcements. My sample size cannot afford screening on relative price changes, so these findings are not directly comparable as there will be small price changes also. Amini et al (2013), through a literature review, find that there is some evidence to suggest that large price changes are associated with reversals and small changes are associated with continuations. If there is a reversal for negative news it may be difficult to separate an overreaction effect and increased uncertainty. For positive news, a reversal would imply negative returns in the following days, while the UIH and underreaction hypothesis would predict positive returns. There is some opposing evidence on the sign of post positive event excess returns, and the effects seem to be smaller than for decreases. This could also be due to the effect varying in sign across different subsamples. While these studies are not based on specific events, they do reveal some important considerations and possible alternative explanations. Some alternative explanations were also considered introductorily in this paper. I will interpret information asymmetry as essentially the same as ambiguity or uncertainty. A more interesting alternative explanation to keep in mind is that investors are affected by the conservative nature of announcements, and therefore fail to recognize the true implications for firm value.

3.4 CONCLUDING REMARKS ON MARKET EFFICIENCY

The purpose of this chapter so far was to present previous evidence and theory in order to provide context and also highlight possible explanations for results. There are many problems in testing for market efficiency, some of which are yet to be discussed in the methodology section. However, the tests still provide useful information and if evidence is strong, statistical inference will be valid. As Eugene Fama (1991, p. 1576) states; *"academics largely agree on the facts that emerge from the tests, even when they disagree about their implications for efficiency."* Several anomalies have been found and present powerful evidence against the EMH. For practical purposes however, most markets are approximately efficient, and the EMH continues to be a cornerstone of financial theory. Jensen wrote early on in this debate that "*I believe there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis*" (Jensen, 1978, p. 96). The debate on efficiency continues today because there is still no widely accepted normative theory to describe deviations from the EMH.

Because of the conflicting evidence and theory on the nature of the reaction, it is difficult to hypothesize whether the market might exhibit tendencies of continuation or reversal. The statistical tests are therefore investigative and two-sided in order to accommodate both directions.

3.5 INFORMATION LEAKAGE AND INSIDER TRADING

While it is difficult to hypothesize what will happen in the post-event window, for the pre-event window the intuition is simple. Investors with inside information would trade to profit from the assumed direction of the event-day return. If a market is strong-form efficient, investors with private information about a firm could not earn excess returns by trading on this information. In practice, it is not strong-form efficiency which limits the investor's profits but rather the laws and regulations which prohibit this behavior (Elton, et al., 2009). In this short section which concludes the theory chapter I will discuss how this study relates to previous research on insider trading and also discuss a couple of particularly interesting previous studies.

Context

First of all, it is not necessarily illegal for an insider in a company to transact in the company stock. It becomes illegal if the trading is carried out on the basis of private and material information which is presumed to affect the stock price[6]. Much of the literature on insider trading seems to focus on whether reported insider trades which are announced through stock exchange notices make excess profits. These trades are not necessarily illegal, so the results of these studies are not directly relevant for this study. Further, these studies examine the profitability of the actual trades of insiders. In order to do that for a specific event, such as discovery announcements, one would need to examine trades of constituents of insider lists in connection with the discoveries. That would require a radical change in methodology and cannot accommodate a dual research question such as the one in this study, but it is an interesting option for further research.

[6] This definition is taken from the U.S. Securities and Exchange Commission (SEC, 2013). Although laws and regulations are decided by different governing bodies for each stock exchange, it is assumed that the laws are similar (see 2.2).

There is also a line of research which uses the traditional event study methodology to determine the abnormal returns around firm announcements, e.g. the study by Agapova and Madura (2011) discussed below. This coincides with one of the approaches in this paper, the CAAR method, but this paper is somewhat differentiated from these studies also. Naturally, they typically focus on one specific stock exchange or country in order to keep the analysis under one governing authority. In this study, what the firms in the sample have in common is that they are subject to the rules and regulations pertaining to insider information for drilling results on the NCS, some of which were discussed in section 2.2, but not a specific country or stock exchange. However, most observations are from companies listed in the USA and Norway (see appendix 8.1.3 for a list of observations per company). The most relevant question to answer through the following literature review is whether or not there is evidence of insider trading on these exchanges.

Evidence

There is a fairly large amount of research for the US, especially after Regulation Fair Disclosure (RFD)[7]. Agapova and Madura (2011) offer recent evidence in a thorough event study using the abnormal returns around company issued market guidance in the US. They find strong evidence for information leakage, both before and after RFD. They also find that the degree of leakage is larger when (1) the information content is larger, (2) the level of information asymmetry is higher and (3) when firms are small and trading volume is high. The last finding is especially interesting. Agapova and Madura predict that the degree of information leakage for both small firms and low-volume stocks should be comparatively higher due to larger information asymmetry, but they found the opposite effect for volume. Subrahmanyam (2005) offers a hypothesis which justifies the evidence: Illegal insider trading is easier to disguise when trading in stocks with higher liquidity. Agapova and Madura cite several earlier studies which confirm the evidence of information leakage for the US market in connection with research on RFD. I will not duplicate their literature review here.

The evidence is more limited for the Oslo Stock Exchange. Eckbo & Smith (1998) conduct a study for the OSE where they form portfolios of actual insider trades and evaluate the performance of these portfolios. These trades are based on stock exchange notices and are not necessarily illegal, but they do find some interesting evidence. Insider portfolios did not

[7] Through RFD, implemented in 2000, companies must disseminate news about the company market wide rather than informing a small group of investors, hence the term fair disclosure.

perform abnormally well, a result which was robust to a variety of factors including the size of the trade and whether the investor sold or bought. Moreover, the insider portfolios do not outperform the average mutual fund in their sample. They compare their results with a traditional event study approach, which finds some weak evidence of leakage. Both the methodology and results in this latter test are consistent with the earlier studies for other markets. They argue quite convincingly in favor of the portfolio approach, and therefore conclude that there is no evidence of information leakage for the OSE.

4. METHODOLOGY

For the most part, I will follow the approach and notation of Craig A. MacKinlay's often cited paper "Event Studies in Economics and Finance" (1997). In brief, the procedure involves calculating the mean cumulative abnormal returns (CAR) around the event date and using t-tests to determine the significance level of the CARs for various intervals. This will allow for a graphical representation of the average effect of the discovery announcements, and the CARs are used as a foundation from which I can carry out the two strategies of testing the null hypotheses in the post- and pre-announcement event windows.

For the announcements to have an effect on stock price, they must convey information which differs from what is priced in by the market. In other words, the reactions can be positive, negative or null, depending on the market's expectations. The full-sample mean is therefore not efficient in testing for efficiency and over- and underreaction as negative and positive reactions are offsetting. The two testing strategies differ in how they deal with this problem.

The first method, which I have named the CAAR (cumulative average abnormal return) approach, involves classifying announcements as either good or bad news before testing hypotheses of whether there is excess return in these subsamples around the event dates. The specific null hypotheses are:

(1) There is no excess return around the date of announcements
(2) There is no excess return after announcements
(3) There is no excess return before announcements

Hypotheses 1 is mainly included for logical completion but is to some extent a premise for hypotheses 2 and 3.

There is no third-party proxy available for gauging expectations of drilling results, so the grouping of positive and negative events is done on the basis of the event-day abnormal return. Thus, this approach is similar in methodology to previous research on short term over- and underreaction where a fixed price change threshold is applied. While a threshold is tested, the discussion will revolve around tests where the only criterion for discrimination is the sign due to a large reduction in sample size.

The second approach is based on OLS regression and tests the same hypotheses, but without the explicit grouping. Pre- and post-announcement window CARs are regressed on announcement day abnormal returns and the coefficients in the regression are used for hypothesis testing. The formal hypotheses for this method are:

(4) There is no correlation of returns after and immediately after announcements
(5) There is no correlation of returns before and immediately after announcements

Hypotheses 2 & 4 both test for an under- or overreaction, while 3 & 5 both test for information leakage.

The two methods will be described in more detail in their respective subsections. Below is a step-by-step outline of the methodology section. Steps 1 through 4 will be common to both methods.

1. Define the event windows
2. Estimate normal returns
3. Compute abnormal returns
4. Aggregate abnormal returns across time
5. CAAR testing method
6. OLS testing method

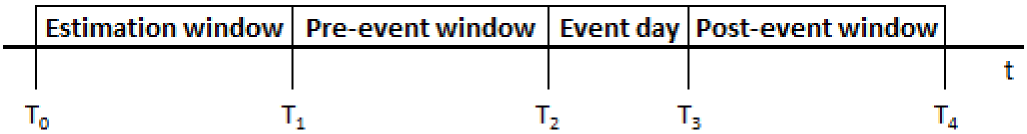
Statistical considerations will be included throughout where they apply.

4.1 CHOOSING EVENT AND ESTIMATION WINDOWS

The event window is the period in which we investigate the behavior of stock prices. The estimation period is the period in which we estimate parameters for the normal return model. The window selection is dependent on the research question, statistical considerations, as well as the nature of the event.

4.1.1 Event Windows

The total event window is decomposed into a pre-event window, the announcement or event day, and the post-event window as follows:



The event day is at t = 0. The general notation is necessary because I will vary the length of the event windows. However, T2, the end of the pre-event window, will always be at t = -1, the end of the day before the event day, and T3, the start of the post-event window, will always be at t = +1, the day after. The lengths (L) of the windows are:

Estimation window: L_1: T1 – T0
Pre-event window: L_2: T2 – (T1 + 1)
Event day: L_3: T3 – (T2 + 1) = 1
Post-event window: L_4: T4 – T3

The pre-event window

For the issue of information leakage, it is relevant to know the amount of time that passes from striking oil or gas until the information is passed on to the public. There is no universal answer to this. First of all, in exploration drilling the information content gradually increases with drilling depth. Also, there is not a fixed stage in the process of drilling that triggers an announcement. That is, some announcements are at an early stage of drilling, perhaps just notifying the public that hydrocarbons have been discovered[8]. This happens in situations where there is danger or suspicion of information leakage, or if the market is highly anticipant. Because the information value is increasing up until the announcement date, and also the number of people privy to the information increases[9], we would expect the risk of insider trading to be highest the day or two before the announcement.

The post-event window

In the post-event window, aside from statistical considerations, we are most interested in how long we might reasonably expect the event to have an effect on the stock price. As part of the objective of this study is to examine whether the stock market underreacts or overreacts, we should leave the window large enough so that subsequent announcements, i.e. updates of

[8] As will be discussed in chapter 5, if there are several subsequent announcements, the first one is included. This is done because if not there would be a justifiable reaction in the pre-event period, which is obviously unwanted.

[9] The operator will inform the partners in the license as well as the NPD of the results. Based on discussions with the NPD, this is usually the day before the announcement.

estimates, are included in the window. These updates may come in the few days preceding or several months or even years later.

Statistical considerations

The main statistical consideration is that an increasing event window will reduce the power of the tests (Brown & Warner, 1985). Also, an increasing event window will increase the risk of including extraneous events, potentially damaging the validity of the results.

In summary, I want to keep the window as short as possible while still capturing as much of the effect as possible. Because of this tradeoff of statistical efficiency versus information value I experiment with multiple lengths of event windows. For reasons outlined above, the pre-announcement window will be tested for 2 and 5 calendar days. The post-announcement window will be tested at 2, 5, 10, 20 and 30 days. The shorter windows are more reliable and valid, while the 30 day window will potentially provide additional information.

Estimation window

In determining the estimation window, there is a tradeoff between statistical efficiency and the possibility that the company's risk has changed over time. Here I will follow the convention of using about a year's worth of trading days, which is also recommended by MacKinlay (1997).

It is worthwhile to note here that the estimation window will include other discoveries. Also, there was no attempt at correcting for extraneous events in the estimation window which means that in some cases the variance is likely to be overestimated (Thompson, 1988). Unfortunately, this would cause a downward bias and reduction in power. On the other hand, this downward bias is positive in the event that discoveries are associated with increased volatility. That is, the downward bias will decrease the likelihood of a type 1 error caused by using a low estimate of risk, and thus strengthen validity.

4.2 THE MODEL FOR NORMAL RETURN

There are several methods available for modeling normal (predicted, expected) returns. An important consideration in selecting a model is to achieve a high level of precision in the expected return estimates. This will reduce the variance of the calculated abnormal returns and consequently increase power. I also seek to limit the amount and magnitude of statistical biases introduced, and in that respect it is important that the model is correctly specified.

The market model, which is a less restrictive form of the CAPM[10], will be applied here. It appears to be the most frequently applied method and is generally recommended (MacKinlay, 1997). The market model assumes that asset returns are normally distributed and given by the expression (MacKinlay, 1997):

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

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

Where;

R_{it}	= return on the stock i at time t
R_{mt}	= return on the market index at time t
ε_{it}	= zero mean disturbance term with variance $\sigma^2_{\varepsilon_i}$
$\alpha_i, \beta_i, \sigma^2_{\varepsilon_i}$[11]	= model parameters to be estimated

A local market index is used for the market return. This is the norm in international event studies (Campbell, et al., 2010). Specifically, DataStream's *LI* (Local Index) function is used, which returns a local index linked to the securities. All securities are listed on fairly large exchanges.

Because I have daily data, I use log returns because they conform better to the assumption of normally distributed errors and are inexpensive to implement (Henderson Jr., 1990). The price is adjusted for dividends, so the following formula applies (Henderson Jr., 1990):

$$R_{it} = \ln(1 + Return) = \ln\left[1 + \left(\frac{P_{t+1}}{P_t} - 1\right)\right] = \ln\left(\frac{P_{t+1}}{P_t}\right)$$

[10] MacKinlay (1997) explains that while the CAPM is built on economic arguments the market model is purely statistical and does not make restrictions based on rational investor behavior.

[11] NOTE: The *i* indexer should be interpreted as the observation, rather than the firm, because firms will be included multiple times. B_i is therefore the beta of for the firm in the observation denoted by i.

The model parameters alpha, beta and the variance of the disturbance term must be measured for each observation through ordinary least squares (OLS) regression. Below are the expressions of the estimates that are calculated for each observation (MacKinlay, 1997).

$$\hat{\beta}_i = \frac{\sum_{t=T_0+1}^{T_1}(R_{it} - \hat{\mu}_i)(R_{mt} - \hat{\mu}_m)}{\sum_{t=T_0+1}^{T_1}(R_{mt} - \hat{\mu}_m)^2}$$

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i\hat{\mu}_m$$

$$\hat{\sigma}_{\varepsilon_i}^2 = \frac{1}{L_1 - 2}\sum_{t=T_0+1}^{T_1}\left(R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt}\right)^2$$

$$\hat{\mu}_i = \frac{1}{L_1}\sum_{t=T_0+1}^{T_1} R_{it} \qquad \hat{\mu}_m = \frac{1}{L_1}\sum_{t=T_0+1}^{T_1} R_{mt}$$

Since the sample will almost exclusively consist of firms in the petroleum industry, including an industry index and possibly the oil price could increase performance. If more variance is explained by the independent variables, the variance of the abnormal returns (prediction errors) would be reduced and consequently increase the power of the test. Dyckman et al *(1984)* showed, explicitly for the oil and gas industry, that failure to account for "industry clustering" reduces the power of the model to detect abnormal returns. However, since the event window is relatively short, the inclusion of an industry factor should not affect results significantly. Also, if local industry indexes were used some firms would constitute a large part of the index, there could be multiple event-firms in the index, and there are potential spillover effects[12]. The simpler market model is therefore preferred.

Assumptions and statistical considerations

The assumptions underlying the model follow from its linear specification and OLS estimation procedure. An extensive body of research[13] has accumulated over the years testing the performance of the model as applied to the event study methodology. Performance is tested empirically, usually using a simulation procedure similar to that of Brown & Warner

[12] The results of one well might impact the expectations of deposits in nearby areas, thereby affecting firms with stakes in neaby licenses.

[13] See e.g. (Henderson Jr., 1990) (MacKinlay, 1997) (Brown & Warner, 1980) (Brown & Warner, 1985) (Thompson, 1988) (Ahern, 2009) (Kothari & Warner, 2007) (Dyckman, et al., 1984) for examples and summaries.

(1980 & 1985). These studies generally find that the market model performs well in a variety of conditions. MacKinlay (1997) explains that the market model is well specified given three assumptions; asset returns are multivariate normal and independently and identically distributed through time. The assumptions, although strong, do not generally lead to problems because they are empirically reasonable and even if they do not hold, inferences are generally robust to deviations (MacKinlay, 1997).

There are, however, some statistical issues which must be discussed both with regard to the model itself as well as the estimation procedure. These include increased risk, liquidity, non-synchronous trading and serial correlation.

Increased risk

The market model may inadequately adjust for risk, and therefore yield excess return, when in truth the increased returns are a fair compensation for increased risk. This is important to consider in event studies as a stock often becomes more risky (volatile) following an important announcement (MacKinlay, 1997). However, it will not make a major difference when the event windows are short. Also, other discoveries are included in the estimation window, as mentioned, which reduces the chance of a type 1 error due to event-induced uncertainty or risk. The issue is therefore ignored.

Liquidity and non-synchronous trading

Poor liquidity could cause biases in the market model regression in several ways. First, securities that do not trade on a given day are assigned a zero return. If there are many non-trading days, the beta will be understated and the variance of abnormal returns will increase.

A related bias occurs from the problem known as non-synchronous trading. All prices are assumed to be set at the end of the trading day while in reality they may be set hours or even days before. When the stock return and the market return are measured over different time intervals the beta in the market model estimation is biased and inconsistent (Brown & Warner, 1985). The issue is increasing in decreasing liquidity because illiquid stocks will trade less frequently.

One simple way of dealing with the problem is to use weekly returns instead of daily returns, but that would decrease the amount of observations. Since most of the firms in the sample have liquid stocks, I prefer to use daily data. As is elaborated in the data section, some observations were excluded due to infrequent trading.

Serial Correlation

Another issue is the evidence of serial correlation (autocorrelation) in daily returns. If there is serial correlation returns will not be independent through time. According to Brown and Warner (1985) non-synchronous trading could explain some of the effect. The effect is that parameter accuracy will be overstated, which would increase the chance of a type 1 error. Also, if there is serial correlation in the abnormal return estimates in the event windows, the effect is indistinguishable from overreaction and underreaction. It could bias the results either downward or upward, depending on which case of misreaction there is and whether the autocorrelation is negative or positive.

I test for serial correlation using the Durbin-Watson statistic and find no observations with significant results.

4.3 CALCULATING AND AGGREGATING ABNORMAL RETURNS

The abnormal (excess) return is the actual return less the corresponding predicted return. It is thus synonymous to the prediction error (ε_{it}) in the market model equation. Let $\widehat{AR}_{it}$ denote the abnormal return for the stock (observation) at each t over the event window. The abnormal return can then be expressed as:

$$\widehat{AR}_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt}$$

Where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the parameter estimates from the market model regression. This estimate of abnormal return will be used directly in the OLS regression equation as the announcement day excess return, and it will also be used to segment the observations into good and bad news for the CAAR method.

MacKinlay (1997) argues that for a sufficiently large estimation window[14], the variance can be expressed as:

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[14] The full variance expression is:

$$\sigma^2(\widehat{AR}_{it}) = \sigma^2_{\varepsilon_i} + \frac{1}{L_1}\left[1 + \frac{(R_{mt} - \hat{\mu}_m)^2}{\hat{\sigma}^2_m}\right]$$

where the second component is variance due to the sampling error of α and β, and L1 is the length og the estimation window (MacKinlay, 1997). It is assumed here that the lenght of the window (240 days) is large enough to assume that the sampling error variance is low enough to be ignored.

$$\sigma^2\left(\widehat{AR}_{it}\right) = \sigma_{\varepsilon_i}^2$$

That is, the variance of the prediction error from the market model regression is the appropriate measure of variance of abnormal returns for each t in the event window (MacKinlay, 1997). The main assumption is that the event does not significantly increase risk. We could use these estimates to test a hypothesis of whether or not returns for a given observation at a given point in time in the full event window are statistically different from zero. However, the hypotheses I want to test require event windows which are larger than one day, so the returns must be aggregated across time. The estimate of cumulative abnormal return for any observation, from time t_1 to t_2 is calculated from:

$$\widehat{CAR}_i(t_1, t_2) = \sum_{t=t_1}^{t_2} \widehat{AR}_{it}$$

The inputs t_1 and t_2 are varied to match different event windows. Since the estimation window is large, the variance of $\widehat{\mathrm{CAR}}_i$ is assumed to be approximated by its asymptotic property (MacKinlay, 1997):

$$\sigma_i^2(t_1, t_2) = (t_2 - t_1 + 1)\sigma_{\varepsilon_i}^2$$

As evidenced by this equation, the variance is increasing in the length of the event window. This marks the end of the commonality between the two testing strategies.

4.4 CAAR TESTING METHOD

In order to draw inferences about the event effects the observations must be aggregated across observations. This is simply done by calculating the mean:

$$\overline{CAR}(t_1, t_2) = \frac{1}{N}\sum_{i=1}^{N} \widehat{CAR}_i(t_1, t_2)$$

This is done for the whole sample and the two subsamples of positive and negative events. Finally, an estimate of variance is needed. Assuming that there is no cross-sectional dependence in abnormal returns, the covariance term is set to zero and the expression for variance is (MacKinlay, 1997):

$$var\left(\overline{CAR}(t_1,t_2)\right)=\frac{1}{N^2}\sum_{i=1}^{N}\sigma_i^2(t_1,t_2)$$

The nulls, for both subsamples and for all event windows, are tested with the test statistic:

$$\theta_1=\frac{\overline{CAR}(t_1,t_2)}{var(\overline{CAR}(t_1,t_2))^{1/2}}\sim N(0,1)$$

4.4.1 Statistical considerations for CAAR method

Clustering

In the variance estimate above for the cross-section it is assumed that the covariance between abnormal returns is zero. There are two reasons for which this assumption may not necessarily hold; there will be some cases of overlapping event windows (time clustering) and firms are concentrated in one industry (industry clustering). When aggregating abnormal returns across firms in event time, the prediction errors from the market model may therefore be correlated. This would bias the standard deviation of abnormal returns downward and the test statistic upward, leading to increased probability of a type 1 error (Kothari & Warner, 2007). The issue has been studied extensively in the literature, and important papers include Brown & Warner (1980), Collins & Dent (1984), Bernard (1987) and Petersen (2006).

Including an industry index in the normal return model would be one method of reducing some of the effect (Brown & Warner, 1985). However, as discussed in section 4.2, market models and market-industry models generally perform similarly, especially for short-term studies. This indicates that intra-industry cross-dependence does not seem to be a significant issue (Thompson, 1988).

Clustering caused by overlapping event windows will affect the results to some degree. Two samples are used in this study, as will be elaborated in the chapter on data and sample description. For the smaller sample, 74% of the event dates are unique, and the average number of discoveries per event date is 1.44. The bias in the variance estimate is therefore likely to be very small. For the larger sample, 40% of the dates are unique, and the average number is 2.52. The concern is larger for this sample, but I will not attempt to resolve the issue. The methods available are rather complicated and therefore out of scope. The result is that for the larger sample, there will be some degree of increased risk of a type 1 error.

Cross-autocorrelation

Aggregating also imposes a possible problem of cross-autocorrelation, i.e. if firm A's returns today are correlated with firm B's returns tomorrow (Lo & MacKinlay, 1990). This could be a problem if some of the firms which discover petroleum are illiquid, so that the information from the discovery is not impounded until the next day. Cross-autocorrelation is only a minor issue as the observations are generally well spread out over time, but again somewhat larger for the full sample.

4.5 OLS TESTING METHOD

If the null hypotheses of no abnormal returns during either the post or pre-announcement windows are correct, then there should be no correlation between the announcement day return and the event window returns. The following regression equation is used:

$$CAR_i(t_1, t_2) = \delta_1 + \delta_2\left(AR_{i,t=0}\right) + \varepsilon$$

If the announcement day return is the same sign as the post-announcement return, then there is evidence of underreaction. If the signs are opposite there has been a reversal, which is consistent with overreaction. Similarly, if the pre-announcement return is the same sign as the announcement day return, there is evidence of information leakage.

The coefficient δ_2 is used to determine the sign and significance of misreaction. Significance is tested using the t-statistic and the p-value in the regression output. If the coefficient is positive (negative) for the post-announcement regression, there is underreaction (overreaction). A positive beta in the pre-announcement period would be a sign of information leakage. However, the sign will only be positive if there is partial information leakage. If the information has fully been reflected in the stock price, the beta should (in absence of any other affects) be zero.

This approach offers another way to deal with the issue of positive and negative reactions because a positive announcement followed by a positive drift is for my purposes the same as a negative announcement and a negative drift – both are evidence of underreaction. However, the model will be poor in the case that the nature of the misreaction differs between the subsamples. That is, if there is a positive or negative drift associated with both negative and positive news the coefficient is not an appropriate way to test for under- and overreaction. To illustrate, examine figure Figure 2 – illustration for OLS results interpretationFigure 2. If there is e.g. underreaction to positive news and overreaction to negative news the coefficient in the linear approximation might not detect any effects even if there is a significant amount of misreaction. The alpha value could indicate that the effect might be present, but the economic meaning of the alpha is in this case uncertain.

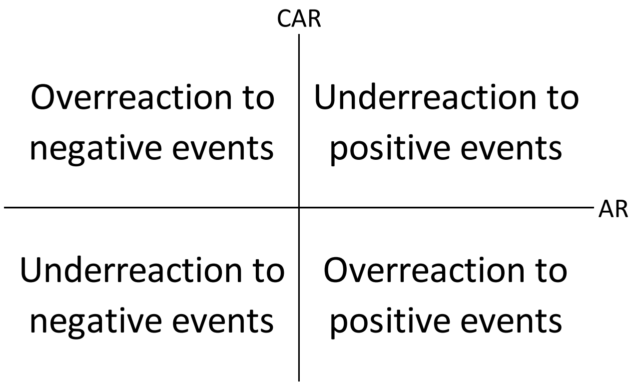

Figure 2 – illustration for OLS results interpretation

There is one more caveat with regard to this method. The hypothesis seeks to test whether or not the two variables CAR and AR are correlated. Consider the scenario where there is underreaction, but the amount of underreaction is independent of the event-day abnormal return. In this case, the slope in the regression should be zero and any underreaction in the market would be difficult to detect.

The regressions are carried out in STATA with White standard errors.

5. DATA AND SAMPLE DESCRIPTION

In this section I will first discuss the process of collecting data as well as considerations in selecting the announcements. I will also describe how price data was gathered, and finally present descriptive statistics of two different samples used.

5.1 Announcement and Wellbore Data

The NPD has compiled a uniquely rich and detailed database on drilling results which is publicly available on their website (NPD, 2013). As of February 2013, the total number of wells drilled on the NCS was just over 1550, of which 411 were classified as discoveries by the NPD (2013). For each discovery, there are typically multiple companies with stakes in the license. The NPD has compiled a list named "Petroleum register" which lists the historical ownership percentages of firms in the licenses (NPD, 2013). Using these two lists, I created a unique observation, or event ID, for each firm in each discovery. The dates of the NPD's press releases for the discoveries were gathered for each observation. In section 2.2, I explained that for part of the time interval this study examines, the NPD were to release the news before the companies. After the NPD press release dates were gathered from their press release database, I used Factiva searches to confirm announcement dates, note any previous announcements, and to check whether or not the firm itself announced the news. Some discoveries which were not included in the NPD database were found through these searches, and these events were included in the dataset.

Selecting the appropriate announcement date

First of all, market efficiency is judged on the profitability of a trading strategy designed to exploit systematic mispricing. There must thus be a clear trigger which initiates trading. Announcements are largely heterogeneous and can occur at varying times in the drilling process. The information content will vary from minimum disclosure announcements to full production testing. I must with respect to the research questions in all cases use the first announcement that indicates that oil was found. If not, I could get positive movements in the pre-event windows and falsely conclude with information leakage, and the effect of over- or underreaction would also be lost. This issue makes it necessary to search for previous news of the discovery. This is carried out through Factiva and Google, using search criteria such as the wellbore name, field name, company name and dates.

Wildcat and appraisal wells

Another important question is whether to include appraisal wells or just wildcat wells. Wildcat wells are exploratory wells in new areas, and appraisal wells are drilled nearby a discovery to assess the size by improving geological data. The distinction between the two is not clear-cut. The previously known geological data will vary and in some cases can be greater for a wildcat well than for an appraisal well. Moreover, the wells may have multiple purposes. For example, a wildcat well may be drilled in search for a separate deposit that is close to a previous discovery, and thus additionally serve as an appraisal well for that nearby discovery. Finally, appraisal wells may be drilled up to several years after the initial wildcat, and they may be announced as and considered a discovery in the same way that wildcats are. The distinction is thus not necessary for my intents and purposes, on the condition that a sufficient amount of time has passed since the respective wildcat was announced. A sufficient amount of time must at the minimum be the length of the event windows, but in the final data set the shortest length is about a year.

Classifying drilling announcements as discoveries

Another issue is that the NPD's classification of discoveries cannot be used exclusively because two similar announcements may be classified differently ex post. The NPD's definition of a discovery is as follows:

"A discovery is a petroleum deposit or several petroleum deposits collectively, which have been discovered in the same well, in which through testing, sampling or logging there has been established a probability of the existence of mobile petroleum (includes both commercial and technical discovery)." (NPD, 2013)

Consider two initial announcements which said simply that hydrocarbons had been discovered. If closer examination reveals that one of the deposits was very limited and one was large, the foremost may not be classified as a discovery. Both of these announcements must be included to avoid a selection bias. Because market efficiency will be judged by the profitability of a trading strategy, there needs to be a clear trigger for trading. This trigger is set at the minimum level – any type of discovery, whether the firm deems it commercially viable or not. The potential selection bias would cause positive developments in expectations over time to be included and negative developments to be excluded, and a positive drift would therefore be justified. This was accounted for by not filtering on the discovery field in the NPD database, but instead on the results field[15].

Screening on firm announcement

One of the main challenges of this study is that announcements may sometimes convey little information value. Announcements will only affect the stock price if they (1) have a significant impact on firm value and (2) differ from the expectations in the market. There are three parameters which determine the economic relevance for the company; the size of the discovery, the size of the company, and the share of the license through the joint venture agreement. Mathematically adjusting the information-noise ratio would be complex and the announcements are largely heterogeneous. Relative price and volume changes are not used because they would reduce the sample too much. I instead follow (loosely) Pritamani and Singal (2001) and use their additional screen on whether or not the company itself announced the news as a proxy for information value. This allows me to conveniently circumvent the problems in adjusting for the aforementioned determining factors.

The announcement criterion does not necessarily exclude those observations where the market is correct in its expectations. Although firms will according to the discussion in section 2.2 announce discoveries which are expected to have a significant impact on firm value, there is no reason to believe that they would not announce the news if the market was correct in its expectations. If I wanted to exclude these observations, I would have to use a threshold for price change, volume change or a third party estimate such as analyst forecasts, which is prominent in studies of e.g. the post earnings announcement drift (PEAD). Third party estimates are not available and relative changes would decrease the sample too much. Including these low-impact events is not necessarily a bad thing, however, because the market may still systematically under or overestimate the value of the discoveries which would cause a drift or later shift in the stock price.

This announcement requirement does reduce the sample drastically, and I will therefore report results with and without this criterion.

Confounding events

In a perfect world, the normal returns model would predict all other factors besides the event we are studying. Several authors note that confounding events can cause serious questions

[15] The parameters are Oil, Gas, Condensate, Dry, Shows of all of the above, and combinations of all of the above.

about validity. The importance is increasing in a decreasing sample size, as it weakens the aggregation effect. I cannot solely rely on the “law of large numbers” to neutralize these other events, i.e. assume that they on are random and on average have a stock price effect close to zero.

Ideally we would want to exclude all observations that have experienced a price change during the event and estimation windows due to some other event. Significant events in the estimation window could lead to an artificially high beta and reduce power (Thompson, 1988), and more seriously, the abnormal returns found in the event windows could be due some other extraneous event. In practice, events must be excluded on the basis of some criteria. The problem with defining a fixed list of events and excluding on that basis is that expectations regarding the event are unknown. That is, the event may already be impounded in the stock price. Further, events will have different impact on different companies. For example, a large company such as ExxonMobil may be awarded new licenses every day and it wouldn’t have much effect on the stock price. If a smaller company was granted a license, it might have a large effect on the stock price. Defining the granting of a license as a fixed event would therefore not be very effective. The events included on this “blacklist” would have to be events which are expected to have a relative effect, such as a stock split. Also, I could not be too rigorous in the search because I have a limited amount of events. To sum up, the problem is basically that there are too few observations to fully rely on the effects being neutralized, which necessitates a search for confounding events, but to keep a reasonable number of observations I cannot do an extensive cleaning. Finally, searching through the event and estimation window for confounding events would prove too time-consuming. Correcting for other discoveries would not be too difficult, but then again this would cause a downward bias because there are no announcements of dry wells in my dataset, nor is ready-to-edit data for international wells available.

Nonetheless, I did clean the data for the most obvious cases of confounding events in the 10-day period surrounding the announcements, but only for the smaller sample. It is more critical to do this for the smaller sample as the aggregation effect is smaller. The search was carried out simultaneously while searching for previous company announcements of discoveries in Factiva, Google and company websites. This resulted in the exclusion of 24 observations. Reasons included takeover talks, large price reactions to earnings announcements, a strike, and a large divestment to name some.

Summary of criteria

For any discovery in the NPD dataset, defined simply as hydrocarbons being discovered in either a wildcat or an appraisal well, the first announcement date is recorded given that there are no confounding events. From this I arrive at the sample referred to as the full sample. For the smaller or screened sample, the criterion that the firm must itself announce the news is added.

5.2 Price data

Very few companies are engaged in exploration drilling directly through the listed company. I therefore used the stock price for the parent company – the Global Ultimate Owner (GUO) in the Orbis[16] database. Where there was missing information I used company websites and news databases to determine the ownership structure. There are also many private companies involved and these were excluded from the sample. Data for stock prices (transaction *P*), bid (*PB*) and ask (*PA*) prices, local market indexes (*LI*) as well as volumes (*VO*) were gathered from Thomson Reuters DataStream.

There was also an exclusion criterion here. A few of the stocks were quite thinly traded. This is a microstructure issue which could lead to a misinterpretation of abnormal returns because e.g. information may be impounded in the stock price at a different date than when the information actually caused investors' expectations to change.

[16] Includes Amadeus and Zephyr

5.3 Description of the final dataset

Before screening there are 461 events, of which 240 are positive and 221 are negative as defined by the sign of the event-day abnormal return. After screening there are 77 positive and 64 negative events for a total of 141.

Sample	Total	Positive	Negative	Significantly Positive	Significantly Negative
Full sample	461	240	221	26	11
Screened sample	141	77	64	16	5

Table 1 – Overview of observations. Significance is tested using t-tests with the variance estimate equal to the variance of the prediction error of the market model.

The number of significant movements on the event day is rather low, indicating that there are few large deviations from market expectations.

Table 2 shows summary statistics for the variables which are used for hypothesis testing for both the CAAR and OLS testing methods.

	FULL SAMPLE					SCREENED SAMPLE				
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
pre_5	461	0.06%	3.65%	-17.64%	17.39%	141	0.27%	4.10%	-14.49%	17.39%
pre_2	461	-0.03%	2.21%	-12.71%	11.88%	141	-0.09%	2.59%	-12.71%	8.85%
event_day	461	0.30%	2.78%	-10.99%	30.69%	141	0.82%	4.32%	-7.48%	30.69%
post_2	461	0.07%	2.70%	-26.94%	12.93%	141	0.20%	2.93%	-10.24%	12.93%
post_5	461	0.36%	3.97%	-17.09%	28.44%	141	0.60%	3.96%	-9.99%	14.15%
post_10	461	0.48%	5.21%	-16.89%	36.27%	141	0.79%	4.81%	-10.83%	17.71%
post_20	461	0.55%	7.46%	-24.08%	44.48%	141	0.63%	6.75%	-13.64%	24.03%
post_30	461	0.70%	10.53%	-67.03%	48.64%	141	1.38%	11.74%	-63.10%	48.24%

Table 2 – Summary statistics of the variables used for hypothesis testing.

The data is gathered from the 17-year period 1996 to 2012, but the sample conditioned on announcements does not contain any observations prior to 2001 due to difficulties in finding news releases. The number of observations per year, displayed below, varies in the willingness to invest on the NCS. The full sample includes a substantial amount of observations from earlier years (pre 2001), but the distribution of observations through time is otherwise quite similar.

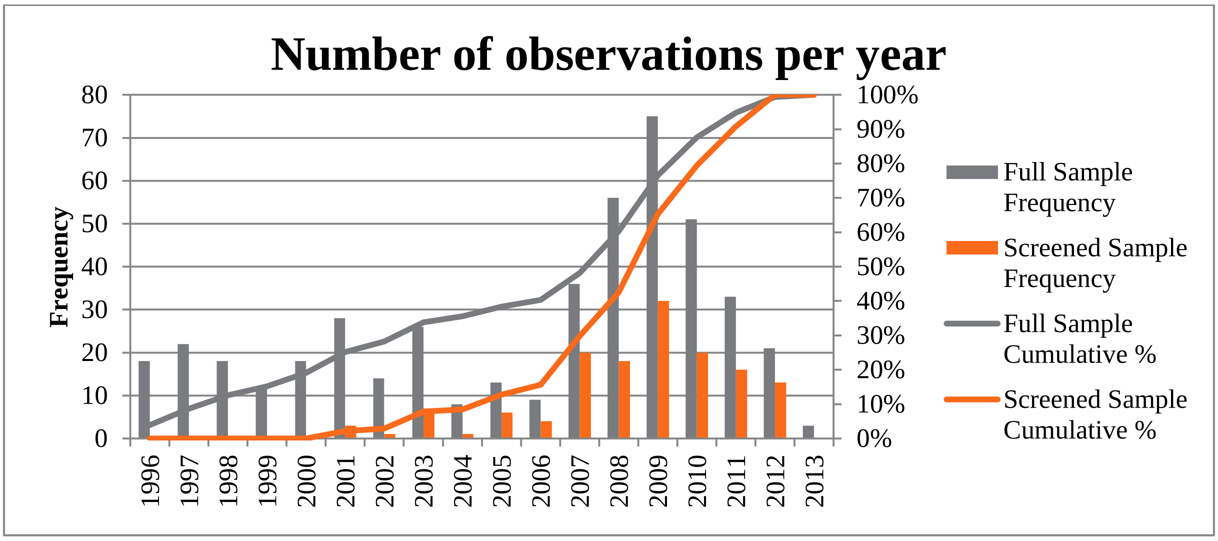

Figure 4 – Number of observations per year for both subsamples.

The full sample comprises observations from 44 unique companies, while the screened sample consists of 21. See appendix 8.1.2 for a graphical overview of the number of observations per company.

It is also useful to compare some firm characteristics between the two samples. These are presented in Table 3 below. The main difference is the average firm size, which is approximately cut in half after screening. This is expected. The purpose of the screen is to proxy for information value, and discoveries for larger companies will be less price-sensitive for a given discovery size and ownership percentage. The three ratios presented do not differ considerably between the two samples.

	FULL SAMPLE					SCREENED SAMPLE				
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Market Value (MUSD)	451	65 000	93 100	5	495 000	137	32 300	38 000	5	153 000
Capex / Total Assets	451	0,10	0,05	-0,03	0,39	137	0,12	0,07	0,01	0,39
Debt / Equity	451	1,66	0,92	0,19	6,79	137	1,63	0,81	0,19	6,09
EBITDA / Total Assets	451	0,20	0,15	-0,43	0,58	137	0,19	0,21	-0,43	0,58

Table 3 – Summary statistics of firm characteristics for the two subsamples. 10 observations were excluded from this analysis due to missing data. See appendix 9.1.1 for a description of the data and calculations.

6. RESULTS

This section will report results from two samples (full and screened), two methodologies (CAAR and OLS) and two subsamples (positive and negative) as well as the average effect. I will both present and discuss the results in the same section due to the fairly large amount of output. The results from the two samples are similar. Because the full sample includes more observations, I will present and discuss the results of this sample first. The screened sample will be presented subsequently and the discussion will mostly focus on the discrepancies between the results of the two samples.

6.1 FULL SAMPLE

6.1.1 OLS Results

Table 4 below summarizes the regression output for the alternative event windows for the full sample. The significance of the coefficients and parameters are generally low and constitute little evidence against the null hypothesis. There is only one significant value at the 95% level: the positive intercept for the 10-day post-event period. The finding is only weakly significant, but the 5-day post-event period is also significant at the 90% level.

The interpretation of the intercept is not very clear, but one possibility is that the market underreacts to positive news and overreacts to negative news, in which case the model would perform poorly (see section 4.5). Another possibility is that there is misreaction, but no magnitude effect. That is, the market does exhibit tendencies of misinterpreting the announcements, but the magnitude of the subsequent correction does not depend on the size of the event-day abnormal return.

The largest coefficient for the post-event period is 0.09 for the two days following the announcement, which is quite small. There is also no evidence of correlation between pre-announcement performance of and event-day performance, which is good news for regulatory authorities. In fact, the coefficient is negative, which is of course opposite of what is expected if there is information leakage.

Coefficient	pre_5	pre_2	post_2	post_5	post_10	post_20	post_30
Event-day AR (δ_2)	-0.133	-0.0883	0.0916	0.0149	-0.0589	0.00371	-0.0792
	(-1.41)	(-1.49)	(1.15)	(0.15)	(-0.48)	(0.02)	(-0.26)
Intercept (δ_1)	0.00104	-0.0000653	0.000396	0.00355*	0.00496**	0.00545	0.00721
	(0.61)	(-0.06)	(0.32)	(1.90)	(2.01)	(1.57)	(1.48)
N	461	461	461	461	461	461	461
R-sq	0.010	0.012	0.009	0.000	0.001	0.000	0.000
Interval (t_1,t_2)	(-5,-1)	(-2,-1)	(1,2)	(1,5)	(1,10)	(1,20)	(1,30)
Regression Equation	$CAR_i(t_1,t_2) = \delta_1 + \delta_2(AR_{i,t=0}) + \varepsilon$						

Table 4 – Full sample OLS results. T-statistics in parentheses. [* p < 0.10, ** p < 0.05, *** p < 0.01]

A scatterplot of event-day return versus post-announcement return is shown in figure 4 for the 10-day window, which has the significant intercept. The observations are mostly scattered around the origin. This is expected because there are many events with low information value, and these will be approximately normally distributed with a mean of zero. The correlation is therefore also low.

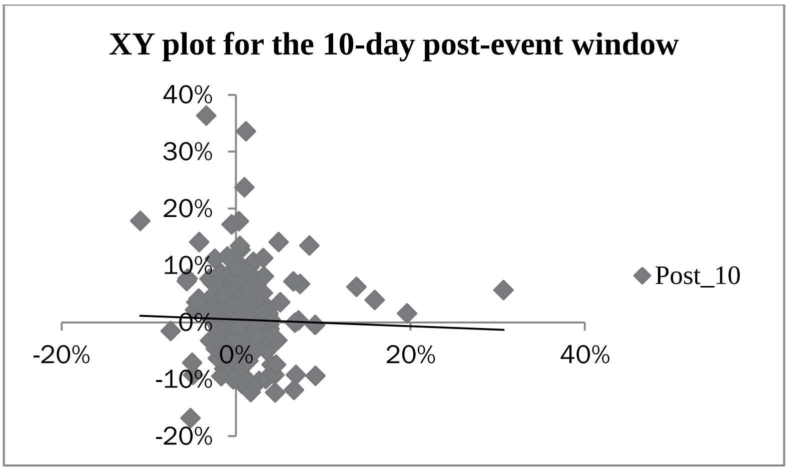

Figure 5 – Scatterplot of CAR versus AR for the post_10 regression

6.1.2 CAAR Results

The results from the CAAR method are similar to those of the OLS method, and the significance levels are low for this method also. For the pre-event window, positive (negative) events have negative (positive) average CARs, curiously, but the effect is not significant.

Subsample	N	Pre_5	Pre_2	Event_day	Post_2	Post_5	Post_10	Post_20	Post_30
Positive	240	-0,19 %	-0,20 %	1,69 %	0,10 %	0,30 %	0,35 %	0,32 %	0,38 %
		(-0,67)	(-1,16)	(13,59)***	(0,58)	(1,07)	(0,89)	(0,58)	(0,57)
Negative	221	0,34 %	0,15 %	-1,21 %	0,03 %	0,43 %	0,62 %	0,79 %	1,04 %
		(1,28)	(0,92)	(-10,34)***	(0,18)	(1,64)	(1,68)*	(1,51)	(1,62)
Total	461	0,06 %	-0,03 %	0,30 %	0,07 %	0,36 %	0,48 %	0,55 %	0,70 %
		(0,33)	(-0,27)	(3,49)***	(0,55)	(1,88)*	(1,77)*	(1,43)	(1,49)

Table 5 – Full sample CAAR results. T-statistics in parentheses, asterisk indicates significant value. [90%, ** 95%, ***99%, judged by student's t-test]*

The event day abnormal return is significant for both subsamples and the total, proving that announcements affect the stock price of involved firms and that the initial reaction is on average positive. A graphical representation of the results is included in figure 5 below.

In the post-event window, there are indications of an upward drift for both positive and negative events. For negative events, the drift seems to continue for the whole event window, while the apparent drift for positive events ceases after the 5-day period. There are three variables which are significantly positive at the 90% level in the post-event window. These are the 10-day post-event period for negative events and the 10- and 5-day post-event periods for the total sample. No variables are significant at the 95% level.

Both methods show signs of a weak but positive post-announcement average abnormal return for both subsamples, which could perhaps explain why the 10-day post-event period had a significant intercept in the OLS method. It also reveals that the OLS method might not be appropriate in this case. It is not adept in detecting dependence in the variables if there is continuation after positive events and reversals after negative events because the underreaction and overreaction will be offsetting (See discussion in section 4.5).

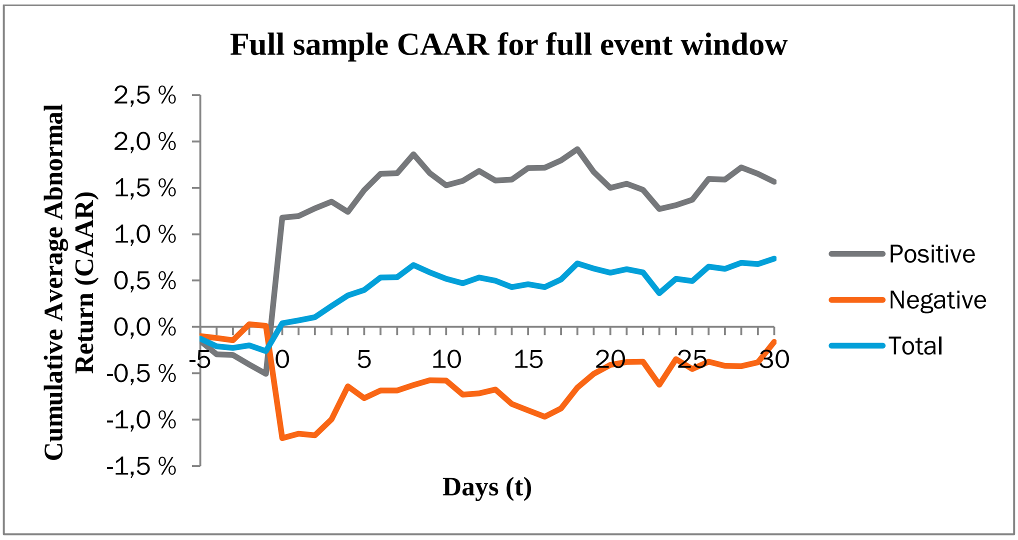

Figure 6 – Graphical representation of the CAAR for the interval (-5,30) for the full sample.

Although the general interpretation is that the market reacts efficiently to the news, there are some similarities between the results here and the previous studies on over- and underreaction. The positive events are associated with lower t-statistics than the negative events, which is similar to the results of the studies presented in section 3.3.4 on over- and underreaction. Also, the indication that post-announcement performance might be positive between both subsamples is consistent with the UIH, and alternatively ambiguity aversion. It is also consistent with the hypothesis that post-announcement performance may be positive due to the conservative nature of drilling announcements. Because there are some power issues I cannot confidently refute this claim, but the market seems be largely efficient.

6.2 SCREENED SAMPLE

The problem with the results presented above is that there are many events with low information value. Although the average effect is interesting, these observations will introduce a relatively large amount of noise compared to the information gained with regard to leakage, continuation and reversals. We would not expect the market to over- or underreact to news that has little or no effect on the value of the firm, nor would we expect insiders to trade on this piece of news. This sample thus only includes observations where the firm itself announces the news of the discovery, a requirement which proxies for information value. The reduction in the sample size is fairly large, from 461 to 141, which increases the variance estimate and consequently decreases the power of the test. The average firm size is about half as large as for the full sample.

6.2.1 OLS Results

Table 6 presents the regression output for the OLS method for this sample. All of the coefficient and intercepts are of equal sign as in the full sample regression, but the significance is generally lower.

Coefficient	pre_5	pre_2	post_2	post_5	post_10	post_20	post_30
Event-day AR ($\boldsymbol{\delta_2}$)	-0.0487	-0.0188	0.137	0.0764	-0.0183	0.0694	-0.0232
	(-0.55)	(-0.43)	(1.57)	(0.95)	(-0.18)	(0.53)	(-0.07)
Intercept ($\boldsymbol{\delta_1}$)	0.00310	-0.000780	0.000860	0.00538	0.00800	0.00578	0.0140
	(0.88)	(-0.34)	(0.37)	(1.63)	(1.94)*	(1.01)	(1.48)
N	141	141	141	141	141	141	141
R-sq	0.003	0.001	0.041	0.007	0.000	0.002	0.000
Interval ($\mathbf{t_1,t_2}$)	(-5,-1)	(-2,-1)	(1,2)	(1,5)	(1,10)	(1,20)	(1,30)
Regression Equation			$CAR_i(t_1,t_2) = \delta_1 + \delta_2(AR_{i,t=0}) + \varepsilon$				

Table 6 – Screened sample regression output. T-statistics in parentheses.

One notable discrepancy is that the 2-day post-event period has a higher coefficient; 0.137 for this sample versus 0.092 for the full sample. This could be due to the low-information events, which are still prevalent in this sample, drowning out a short-term underreaction. However, there is very little evidence overall to suggest that the market overreacts. In fact, two of the post-event variables have negative coefficients while three are positive.

6.2.2 CAAR Results

Table 7 and Figure 7 depict the results from the CAAR method. The trend is largely the same; there is a positive drift for both types of events, but in this sample there are no significant variables.

Subsample	N	Pre_5	Pre_2	Event_day	Post_2	Post_5	Post_10	Post_20	Post_30
Positive	77	-0.01%	-0.19 %	2.83 %	0.19 %	0.59 %	0.19 %	0.24 %	0.64 %
		(-0.01)	(-0.47)	(9.85)	(0.48)	(0.93)	(0.21)	(0.19)	(0.41)
Negative	64	0.60 %	0.02 %	-1.60 %	0.20 %	0.61 %	1.50 %	1.11 %	2.27 %
		(0.97)	(0.05)	(-5.80)	(0.52)	(0.98)	(1.72)	(0.90)	(1.50)
Total	141	0.27 %	-0.09 %	0.82 %	0.20 %	0.60 %	0.79 %	0.63 %	1.38 %
		(0.60)	(-0.33)	(4.07)	(0.70)	(1.34)	(1.24)	(0.71)	(1.25)

Table 7 – Screened sample CAARs and t-statistics

The cumulative average abnormal return estimates are higher, and especially for the negative events. By comparison, the full sample had a total 30-day post-event drift of 1.04% for that subsample, and for this sample it is 2.27% for the negative events. Like Pritamani and Singal (2001) conclude, screening on announcements seems to increase the magnitude. This illustrates the increase in information value which is dictated jointly by the discovery size, the stake in the license as well as the size of the firm. The difference between positive and negative events also seems clearer.

The interpretation, given the low significance levels, is clearly that the market efficiently reacts to the information. Unfortunately, the sample sizes for the subsamples are quite small, so the results should not be weighted too heavily and there is low power in detecting the hypothesized effects, especially for this sample.

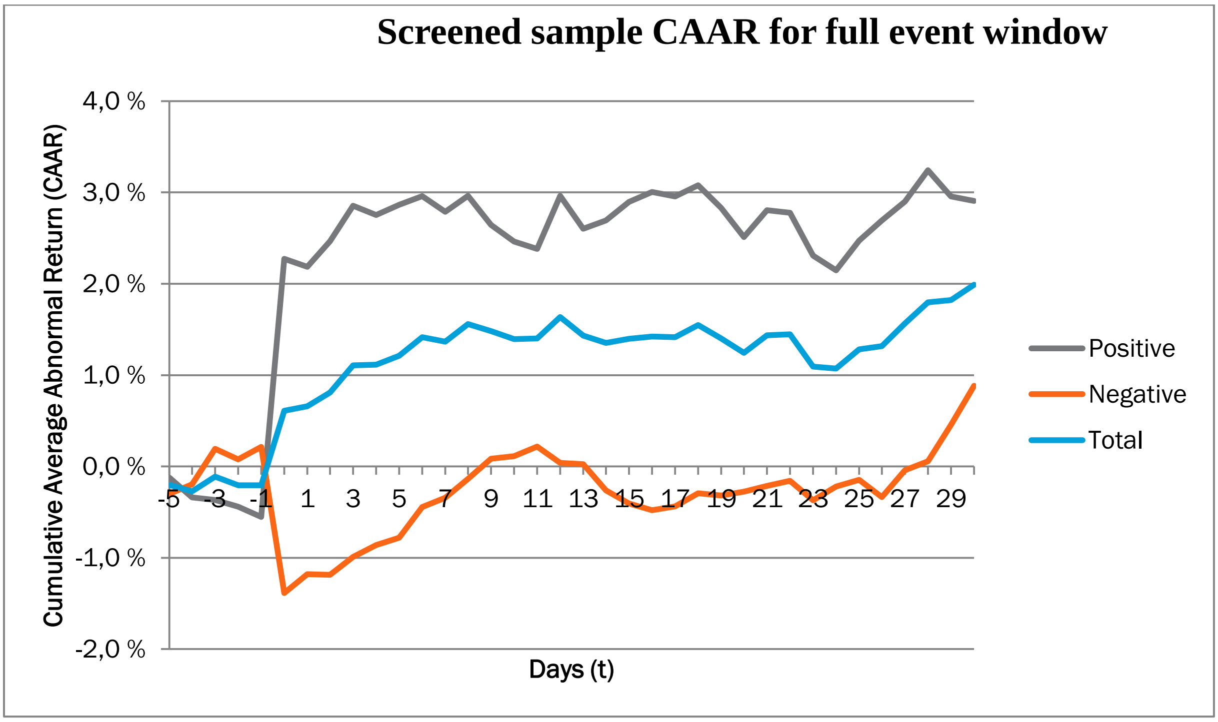

Figure 7 – Screened sample CAAR for the interval (-5,30)

7. CONCLUSION

This paper examines stock price behavior around announcements of oil and gas discoveries on the Norwegian continental shelf and finds little evidence of information leakage and market inefficiency.

The impetus for the over- or underreaction question was threefold. First, the amount of news coverage and potentially large surges and drops create an atmosphere which presumably would invite irrational behavior and irrational investors to partake in investing. Second was the evidence of under- and overreaction to other events, which has not been investigated previously for petroleum exploration drilling. Third was the fact that all announcements are required to be conservative, which possibly could induce a positive drift when the market gradually learns the true implications for the value of the company.

The results are generally consistent between the two methodologies and the two samples used. They are also mainly insignificant, suggesting that the market efficiently interprets the announcements and quickly incorporates their implications for value into the stock price. The argument for efficiency is even stronger when considering that any transaction and implementation costs would make trading strategies less profitable. However, there are some indications that post-announcement performance is associated with positive abnormal returns, for both negative and positive events. For the full sample CAAR method, the drift is significantly positive in the aggregate at the 90% level for the five and ten-day period. The average CARs were larger for the screened sample, albeit not significant, and a larger sample size may support the claim. The larger sample would also permit imposing a return threshold to exclude the low-information events which bias the pre- and post-announcement effects downward. This would be an interesting topic for further research, and data should be plentiful as there is no reason to constrain the analysis to the NCS when only the post-announcement period is examined.

The impetus for the research question regarding information leakage was partly newspaper articles of cases of insider trading as well as the high potential for information leakage due to many involved parties and potentially price-sensitive information.

No significant evidence is found, indicating that information leakage does not seem to be prevalent for this type of announcement. In fact, the output variables from the analysis are of opposite sign than what would be expected in the presence of information leakage, which would predict positive correlation. This should be interpreted as good news for regulatory authorities.

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8. Appendix

8.1.1 Description of firm characteristics

Data is collected from DataStream using the AFO excel add-in and a static request for date of the announcement. The calculations of the four variables and the DataStream mnemonics used are described in table 8 below.

Variable	**Data types and calculation**	**Description**
Market Value	X(P)~U$ * NOSH	The P mnemonic is the closing price adjusted for subsequent capital actions. NOSH is the number of shares. Price is converted to US dollars.
Capex / Assets	DWCX / DWTA	The last reported values in annual or quarterly financial statements of capital expenditure (DWCX) and total assets (DWTA).
Debt-to-equity ratio	WC03351 / WC03995	WC03351 is the book value of total liabilities. WC03995 is the book value of total shareholder equity.
Return on Assets (ROA)	DWED / DWTA	The last reported values in annual or quarterly financial statements of EBITDA (DWED) and total assets (DWTA).

Table 8 – Description and calculation of firm characteristics variables

8.1.2 Number of observations per company (GUO)