Preliminary Master Thesis

News Impact by Announcement Frequency and Time Interval Between Announcements on Norwegian Equities

Hand-in-Date:
01.03.18

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Abstract

This paper looks at the impact of all announcements on the Oslo Stock Exchange over the last twenty years, with respect to the frequency of news in the respective security over a twelve-month window, and with respect to the interval between the current news-event and the one before it. We use event study methodology to measure abnormal returns, and by separating events into positive, negative, and neutral classifications before creating inter-classification deciles to study impacts of different frequencies and intervals. Interim analysis seems to indicate that securities with lower announcement frequencies and/or higher time intervals between announcements, demonstrate significantly higher abnormal returns relative to their counterparts. Results hold for both positive and negative events, with a higher inter-decile spread for positive events relative to negative ones.

Introduction

This paper aims to analyze the impact of news on Norwegian securities. More specifically, it looks at the impact of news with respect to the frequency of news, and the time between news across the Oslo Stock Exchange (OSE). It does so by drawing on the conventional event study-methodology, effectively conducting an event-study covering all news events on the OSE between 1987 - 2017. Our motivation for the study, stems primarily from an intuitive suspicion that long intervals between news events in stocks will cause higher impacts relative to lower-interval events, all else equal. This relies, in part, on the assumption that companies who informs investors more frequently will be priced closer to their true intrinsic value, and therefore should experience more appropriate (typically milder) reactions to new information. It follows that the normal rates of news releases will depend on differences in industry and the nature of each specific firm, but we suspect that higher-frequency securities may tend to be larger and more liquid firms, which experience a larger degree of coverage by institutional investors and media, exacerbating the difference in efficiency between low- and high-frequency-, or low- and high-interval firms. The topic of the study is, to our knowledge, not extensively covered elsewhere, but overlaps with many related areas of literature, e.g., market efficiency literature, particularly the subset of efficiency literature focused on post-earnings announcement drift and impact of new information. To appropriately address the research question, we separate events into decile-sized bins with respect to frequency of news and time intervals between news, i.e., from high- to low frequency events and high-, to low time-interval events, and aggregate results from the individual security level to obtain results representative of the entire stock exchange, before verifying the significance of our findings. Interim analysis seems to indicate that securities with lower announcement frequencies and/or higher time intervals between announcements, demonstrate significantly higher abnormal returns relative to their counterparts. Results hold for both positive and negative events, with a higher inter-decile spread for positive events relative to negative. The remainder of this preliminary paper is organized in five main sections, starting with the introduction, followed by the literature review; theory; data; and methodology.

Literature review

The subset of literature most important to this paper largely falls under *market efficiency*, and we find literature with a focus on market reactions to news events particularly relevant; specifically, literature on reaction to news events, and reactions to earnings announcements. For our analysis we will be conducting an event study, and so in this section we will review both the literature surrounding event studies and the literature relevant to market reactions to news information.

The literature on event studies was largely popularized by Fama, Fisher, Jensen, and Roll (1969) and has since grown to become a common method for measuring the impact of an event. Event studies are designed to measure the impact of an event by measuring the generated abnormal returns. At the same time, as highlighted by MacKinlay (1997) and Brooks (2014) among others, event studies are often considered to be tests for market efficiency: given rationality in the marketplace, there should be an immediate reaction to the event on the announcement date and no further reaction on subsequent trading days, given no new significant information. Though much of the literature early on looked at events such as dividend initiation, stock splits, acquisitions, or security offerings (Barber & Lyon 1997), event studies can be applied in most cases where there is an easily definable event; in our case, any filing from the OSE will be classified as an event. Traditional event study methodology will be covered more extensively in the methodology section, but to a large extent stays true to the methodology laid out by MacKinley (1997) and Brooks (2014). Notable differences in the methodology of this paper to classic event study methodology is first, that we believe modern markets require days rather than week in absorbing the impact of the average news event, and so establish a short event-window, and second, that we will attempt to analyse extensively, potentially controlling for size (as measured by total trading turnover), number of possible confounding news, industry, analyst coverage and time-period (decade), and more.

For the literature on reaction to news, there is to our knowledge no available literature on the effect of news with respect to time and frequency, and we instead review the literature on market reactions to news by looking primarily at the literature on the 'post-earnings announcement drift' (PEAD). In 1968, Ball and Brown discovered the phenomenon of PEAD, showing that cumulative abnormal returns tend to drift upwards following good news and downwards after bad news, on a firm basis. Bernard and Thomas (1968), and Jegadeesh and Titman (1993) later showed that abnormal returns were likely not caused by changes to systematic risk or to delayed stock price reactions to common factors, but rather that markets fail to fully recognize the implications of new information for future earnings. Investors seem to initially underreact to firm-specific news, which is further supported and refined by Chan, Jegadeesh, and Lakonishok (1996); Daniel, Hirshleifer, and Subrahmanyam (1998); and, Hirshleifer (2001). These contributions among others, have helped provide an understanding of what is known today as the momentum factor, where one buys recent winners and sells recent losers. Two articles of particular interest to us is Zhang (2006) and Hirshleifer, Lim, and Teoh (2009). Zhang refines the concept of PEAD by focusing on information uncertainty and the ambiguity of new information that investors face. His evidence support the phenomenon of PEAD, and finds that firms with higher information uncertainty has greater drift. He points to two potential sources of information uncertainty, the first being volatility in firms' fundamentals, and the second being poor information. Hirshleifer, Lim, and Teoh, proposes the *investor distraction hypothesis*, suggesting that limited investor attention may cause market under-reactions. They test this by looking at the level of overreaction and the intensity of news flow measured by the daily number of announcements. Results showed that not only are there definite signs of PEAD in their study, but that extraneous news seems to amplify the effect. Specifically, they find that the inter-decile spread of announcement-period abnormal returns between firms with high and low earnings surprises being 7.02% for low-news days and 5.81% for high-news days. Both results are relevant for us; specifically because we expect to see increased efficiency in higher news-event frequency stocks as proposed by Zhang (2006), since more information is distributed to the public and because firms with lower information uncertainty tends to be bigger and more mature and typically have more analyst coverage; and Hirshleifer, Lim, and Teoh (2009) is relevant because the article looks at the effect of news as a function of the daily frequency of total news, which draws many parallels to our focus on the effect of news frequency and time-interval between events.

Theory

Market Efficiency

Whether markets are efficient is an important and central question in financial theory. The Efficient Market Hypothesis (EMH) originated in the 1960s and has been studied extensively for several decades. An efficient market, defined by Fama (1970) is 'a market in which prices always fully reflect available information'. In other words, market prices incorporate all new information rationally and instantaneously. Building on this, Jensen (1978/2002) states that a market is efficient with respect to an information set if it is *impossible* to make risk adjusted returns, net of all costs, by trading on the basis of this information set. In essence, market efficiency relies on the assumption that market participants are fully rational, and that given this assumption, markets will fully and correctly react information. Fama (1970) proposes three forms of market efficiency: *weak form efficiency*, *semi-strong form* and *strong form efficiency*, where the definition of information set varies for the three respective forms. First, under *weak form efficiency*, market prices should reflect past prices. Second, under semi-strong efficiency, market prices should reflect both past price history and all publicly available information. Last, under strong form efficiency, market prices should reflect all information, public and private. Out of the three, semi-strong efficiency is the most widely accepted version of the hypothesis. In the current empirical landscape, semi-strong form tests for market efficiency have become synonymous with *event studies* (Fama, 1991), but a central issue to testing efficiency is the *joint hypothesis problem*. When testing for market efficiency, one is effectively testing two hypotheses: market efficiency, and the asset pricing model employed. As a consequence, researchers are faced with the issue of market efficiency not being entirely testable (Fama, 1991). To test abnormal returns and efficiency, the researcher needs a model of equilibrium, a correctly specified asset pricing model to compute expected returns.

Factor Investing

Factor investing typically refers to the practice of investing in securities which display certain characteristics that have performed favourably in the past. As highlighted by MSCI (2013), the oldest and most well-known model of stock returns is the Capital Asset Pricing Model (CAPM), driven by systematic and idiosyncratic risk. Later, Ross (1976) proposed the arbitrage pricing theory (APT), showing that the expected return of a financial asset can be modeled as a function of various macroeconomic factors or theoretical market indices. The factors under the APT were not defined, and was instead thought of as being empirical in nature. MSCI goes on to highlight that long term equity portfolio performance can largely be explained by factors, and that factor investing is the investment process that aims to harvest these risk premia through exposure to factors. Currently, they identify six equity risk premia factors: Value, Low Size, Low Volatility, High Yield, Quality and Momentum, which are grounded in academic research and has solid explanations as to why they have provided a premium, historically. This is of high relevance to this paper, as frequency or interval between news could both be traded on as factors, but likely can also be explained by the six factors listed above.

Data

4.1 Datasets

The data used for the study is collected from multiple sources. First, we use price data for all securities listed on the OSE during the twenty-year time span of our analysis; second, we collected a complete dataset of all news events filed by the OSE over the same period; and third, we rely on Fama-French factors for the OSE as collected by Ødegaard (2018).

4.1.1 Price Data

The main dataset was collected using *Datastream,* the database for financial and economic research data from Thomson Reuters. Prices are reported on a daily basis, and the set includes data on volume-, market capitalization-, opening price-, intra-day low-, intra-day high-, and the closing price for all securities. It does not, however, include delisted stocks by default, so to remove potential survivorship bias in our sample data, we will also collect corresponding data on 'dead stocks' which we will merge with the remaining price data. *Datastream* outputs a .csv-file for the full twenty years exported, regardless of listing time, so that all columns are of equal length, corresponding to a datetime index in the first column. This is problematic for some elements of our analysis, e.g., when using a 12-month rolling window to estimate the frequency of events in a single security; when running regressions specified on a normalization window going back in time; and more, as these operations will return misleading numbers when run on an empty series. To address this issue, we transform the dataset into single files for each security and dynamically trim the dataset to the day after our first news event, given that we have both price-data and Fama-French-data for the period; this way every security time-series can be trimmed dynamically and analysed individually, before results are aggregated.

4.1.2 News Data

To acquire relevant news data, we first approached the exchange directly, and were offered a detailed set of data at a price, but instead opted to collect the data ourselves from *Newsweb*, the official outlet of the OSE. This meant settling for less detailed data, but we do not expect this to impact results. The data is aggregated from two sources by Newsweb[1], and the dataset includes all of the most important characteristics for our analysis: the time of filings; the date of filings; the source of the announcement; and, the title of the filing. Tiles of news-filings largely summarize the contents of the news when possible, e.g., a filing on insider trading would typically be titled 'Mandatory Notification of Trade'; this can be useful for sanity checks during analyses, but we find that knowing the contents of a filing is not necessary considering the way we classify news, which will be covered more in the methodology section. In other words, while the full contents of the messages are excluded, they are not needed.

4.1.3 Fama-French Factors

While Kenneth French maintains publically available datasets on the Fama-French 3 and 5 factor model, we cannot take advantage of this, because all factors are sampled from different markets. Instead we were lucky enough to find the Fama-French 3 factor portfolio as calculated by Fama and French (1998) using norwegian data, supplied by Bernt Arne Ødegaard (2018). The data spans from 1980-2017, and is available on a daily frequency matching our data.

[1] While news are aggregated on 'Newsweb.no', our dataset stems from two news-sub-providers: OSI and GlobeNewswire. OBI is an acronym for 'Oslo Børs Informasjon' (Oslo Stock Exchange Information) and is the part of the OSE responsible for maintenance and sales of market data (Oslo Børs 2018), and GlobeNewswire is the American equivalent of OBI, a Nasdaq company and one of the world's largest newswire distribution networks (Nasdaq GlobeNewswire 2018).

4.2 Descriptive Statistics

In this section we will primarily look at exploratory figures from the combined dataset, consisting of all three sources of data. For a better look at the original datasets (price, news, and factors) please see Appendix 1. First of all we look at the spread of announcements over time as described in figure 1, below:

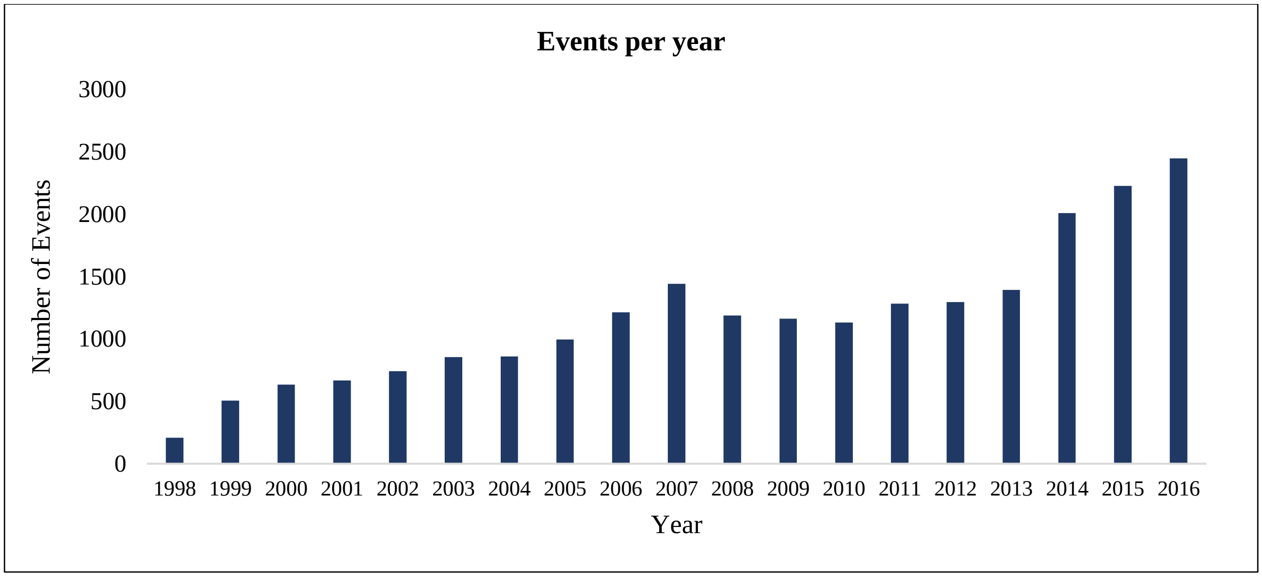

Figure 1: Event Per Year

As shown above, the majority of our data is collected in more recent times, an asymmetry that will become larger once we fully incorporate dead stocks into our dataset. Next, the distribution of announcements across time periods of the day, and weekday is demonstrated below in table 1:

Percentage of Announcements by Day and Time Period

	Monday		Tuesday		Wednesday		Thursday		Friday		Average	
Time Period	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg
Pre-Market	37,0%	43,3%	42,9%	43,0%	43,9%	47,4%	44,0%	47,9%	41,4%	45,2%	41,8%	45,3%
Trading Hours	59,4%	53,1%	53,2%	53,9%	53,1%	49,3%	54,1%	47,9%	55,6%	50,0%	55,1%	50,8%
Post-Market	3,7%	3,6%	3,9%	3,1%	3,0%	3,3%	1,9%	4,2%	3,1%	4,8%	3,1%	3,8%
Observations	655	467	697	575	798	665	943	743	853	620	789	614

Table 1: Percentage of Announcements by Day and Time Period

As table 1 makes clear, there is a slight preference for post-market announcements for negative news relative to positive news, and a preference for pre-market announcements for negative news relative to positive news. Lastly, we classify news and create deciles to examine the spread between deciles as shown below in table 2:

Decile Averages sorted by 12-Month Announcement-Frequency

	Interval		Frequency		Observations		CAR [0,2]		BHAR [0,2]	
Deciles	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
D1 (low)	88,96	62,74	6,07	6,12	461	336	7,53 %	-6,16 %	7,65 %	-6,18 %
D2	17,11	18,57	11,57	11,61	426	353	7,24 %	-5,39 %	7,32 %	-5,41 %
D3	14,74	15,60	14,94	15,02	392	339	7,33 %	-6,07 %	7,34 %	-6,12 %
D4	13,68	13,43	18,02	18,01	410	325	6,38 %	-5,44 %	6,39 %	-5,46 %
D5	11,90	11,85	20,97	21,02	395	327	5,53 %	-5,64 %	5,48 %	-5,59 %
D6	11,24	11,09	23,99	24,03	372	278	6,19 %	-4,75 %	6,26 %	-4,73 %
D7	9,43	10,99	27,47	27,46	451	347	5,19 %	-5,08 %	5,21 %	-5,01 %
D8	9,88	9,67	31,88	31,68	422	327	6,33 %	-4,68 %	6,33 %	-4,66 %
D9	9,07	8,83	38,07	37,49	332	278	4,99 %	-5,13 %	4,93 %	-5,06 %
D10 (high)	7,97	8,00	56,22	54,59	400	319	3,61 %	-4,33 %	3,62 %	-4,26 %
D10-D1	80,99	54,74	-50,14	-48,48			3,93 %	-1,83 %	4,03 %	-1,92 %

Table 2: Decile Averages sorted by 12-Month Announcement-Frequency

The deciles of table 2 are created with respect to frequency, which highlight our interim findings of higher average abnormal returns for lower frequencies of announcements. Specifically, we can point to the 3.93% CAR[0,2] spread between the lowest frequency- (D1) and the highest frequency decile (D10) in positive announcements, and the CAR[0,2] spread of 1.83% in negative announcements. This result is highly interesting, and to us seems to confirm that there is a relationship between frequency and abnormal returns of events worth examining further.

Methodology

The main question to be tested is whether news in firms with a high frequency of news will have a lower impact than corresponding news in firms with a low frequency of news, in the last twelve months. Simultaneously we wish to examine whether the same relationship exists when analysing firms with respect to the time interval between a news event, and the last news event before it. Our hypotheses are that firms with higher announcements frequency will demonstrate lower absolute abnormal returns, relative to lower frequency firms; and similarly, firms with lower time intervals between announcements will demonstrate lower absolute abnormal returns than high interval firms. The two statements may be somewhat interchangeable, as we expect firms with higher frequency of announcements to have lower mean intervals between announcements. To test the hypotheses, we draw heavily on conventional event study methodology[2]. First, we compute abnormal returns over relevant time windows, for individual events, before aggregating across firms and time, to get average cumulative abnormal returns (ACAR) and sorting results by news classification (positive, negative, neutral). Then, we want to compare ACARs across frequency- and interval-sorted deciles, and estimate the average inter-decile spread in ACARs; this will be covered more extensively in section 5.2. The remainder of this section will discuss and highlight the most important aspects of event study methodology as implemented in this paper.

5.1 The Event

For this study, the definition of events and the event times (t=0) are very clear: we consider all news or company filings released through Newsweb to be relevant, and our data contains the title of the filings, as well as the date, time, company, and ticker.

For the analysis, we follow conventional event study methodology and define three windows of time surrounding an event: a post-event window, a pre-event window, and a normalization (estimation) window. First, for the post-event window typical event study methodology suggests allowing enough time after the event to see the full effect of the event. This could mean including extra minutes, or extra months, depending on what is studied. In our case, we would argue that there is no clear appropriate post-event window, as the time required to assimilate new information by the market will depend on the ambiguity of the filing. In other words, we imagine that the market would price a $10 million grant receival more quickly than news about a company entering a new market, simply because of the level of uncertainty embedded in either message. Additionally, we expect the market to price-in both messages more quickly today than twenty years ago, i.e., the rate of assimilation will likely have increased over time, as trading infrastructure and the flow of information has improved. In sum, estimating an event-window is challenging, but with the majority of our data coming from the last decade we expect the average announcement to be priced-in in minutes to hours, rather than days, and therefore consider a two-

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[2] See Mackinlay (1997), Peterson (1989), Brooks (2014), and Kothari & Warner (2004).

day post-event window to be appropriate. A pre-event window is also included in the study, not primarily to measure the impact of the event, but to analyze and control for unusual behavior in the run-up to the events. For this purpose, we estimate that a one day window will be sufficient. Lastly, for the normalization window, Brooks (2014) highlights that longer estimation windows will generally increase the precision of parameter estimation, but raise the likelihood of the window containing a structural break; Armitage (1995) suggests using 100-300 days. Our estimation window is set at 126 days, or approximately six months. The windows as discussed are illustrated below:

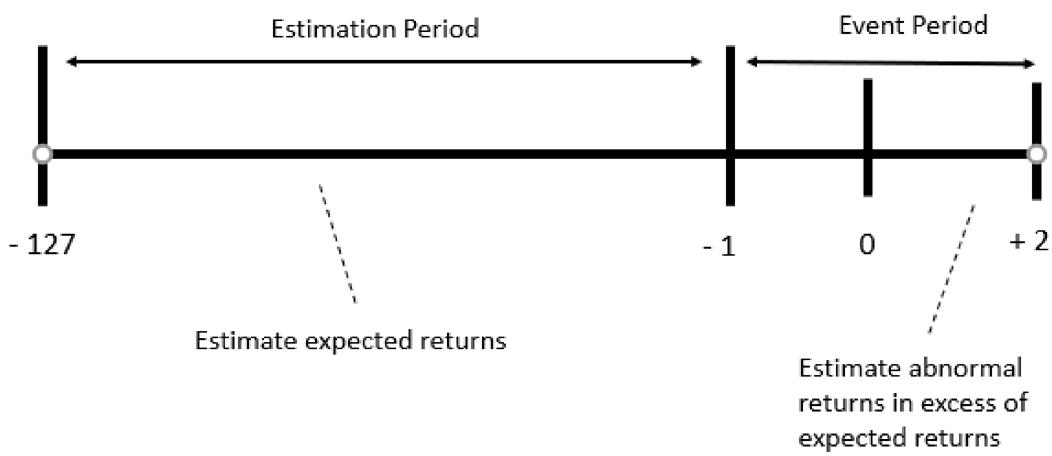

Figure 2: Time Windows

5.1.1 Abnormal Returns

For the study, we want to measure the impact inferred by an event, and we want to exclude confounding factors to the best of our ability. To estimate the effect of a news announcement, captured by the abnormal return, we therefore adjust individual firm excess returns (R_i - R_f) in the news-event window by a model representing the normal/expected return for the individual security, i.e., we calculate the returns above a measure of the expected return, estimated for the individual firm *i*, for each day *t*, in the event window:

$$AR_{it} = R_{it} - E(R_{it}) \quad (1)$$

where AR_{it}, R_{it}, and $E(R_{it})$ are the abnormal returns, actual returns and normal returns respectively. The normal, or expected returns can be calculated in different ways, and for this paper we will look at three models: The Market Model, the Constant Mean Model, and the

Fama-French 3-factor model. The benefit of using a factor model over a constant mean model is that the variation in the abnormal return can be reduced, since some of the variation in returns explained by the variation in market factor returns is removed (Mackinlay, 1997). Consequently, we can more easily identify the effect of news announcements. The benefit of factor models is dependent on the model's goodness of fit (R-squared), and Mackinlay states that the variance reduction benefit becomes smaller when adding more factors. With this in mind, we employ the market model for the main part of our study, but for robustness, we will report findings and any discrepancies using the constant mean model and the Fama-French 3-factor model. For firm *i* in the sample, the models are:

$$Constant\ Mean: \qquad R_{it} = \mu_i + \varepsilon_{it} \tag{2}$$

$$Market: \qquad R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \tag{3}$$

$$Fama-French: \qquad R_{it} - R_{ft} = a_i + b_i\left(R_{mt} - R_{ft}\right) + s_i SMB_t + h_i HML + e_{it} \tag{4}$$

Where for the market model[3] R_{it}, R_{mt} are returns on firm *i* and the market portfolio *m* respectively for the time *t*, and ε_{it} is a zero-mean error term. The market portfolio is the excess return of the market, represented by the Oslo Børs All-Share Index (OSEAX) minus the risk-free rate. The market model and the Fama French-model are estimated by ordinary least squares (OLS) regression.

5.1.2 Classifying Events

Events are separated into three main categories: positive, negative, and neutral. This is done to examine the effect of positive and negative news relative to each other, rather than to analyse market averages. We classify by labelling any news event with abnormal returns in the first observation (AR_1), higher than one standard deviation of the returns in the normalization window, as a positive event and vice versa for negative events; observations within a standard deviation is classified as a neutral announcement. It is important to note that we are using information that would only be observable ex-post when classifying the events, and we therefore do not expect the demonstrated returns of this study to be fully reproducible in practice.

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[3] For further explanations on model specifications and parameters related to the Constant Mean Model and the Fama-French Model, see MacKinlay (1997) and Kothari & Warner (2004), respectively.

5.1.3 Abnormal Return Aggregation

The cumulative abnormal return for firm *i* for an event τ is the sum of abnormal returns in the event window, and is defined as

$$CAR_{i,\tau}[T_0, T_T] = \sum_{t=T_0}^{T_T} \mathrm{AR}_{i,\mathrm{t}} \tag{5}$$

Where T_0 is the time of the event, and T_T signifies the end date of the post-event window, and *t* signifies each day in the event window, in the case that we are examining the post-event CAR; we could also examine the complete event window in which T_0 would signify the start of the pre-event window. To account for the compounding effect investors experience, we will also compute buy-and-hold returns (BHARs) for the event window the following way

$$BHAR_{i,\tau}[T_0, T_T] = \prod_{t=T_0}^{T_T}(1 + R_{it}) - \prod_{t=T_0}^{T_T}(1 + R_{m,t}) \tag{6}$$

In the conventional event study methodology, it is normal to aggregate abnormal returns across time and individual firms and test the hypothesis that the average abnormal return is zero. In on our case we want to compare average cumulative abnormal returns across frequency- and interval sorted deciles and estimate the average inter-decile spread in ACAR for events classified as positive, neutral and negative news as shown below:

$$\overline{CAR}(T_0, T_T)_{D_{10}-D_1}^{X} = \frac{1}{N_{D_{10}}} \sum_{\tau=1}^{N_{D_{10}}} CAR_{\tau,\mathrm{D}_{10}} - \frac{1}{N_{D1}} \sum_{\tau=1}^{N_{D_1}} CAR_{\tau,\mathrm{D}_1} \tag{7}$$

where

$$CAR_{\tau,\mathrm{D_n}} = \sum_{i=f}^{F} \sum_{t=T_0}^{T_T} AR_{t,i} \tag{8}$$

For the two equations, *f*, and *F* signifies the first and last firm number, *i* signifies the current firm, *D* signifies the decile in question, *t* signifies time, *N* is the number of inter-decile observations, and *X* is a placeholder for the sorting variable of the decile; either interval or frequency.

5.1.4 Cross-Sectional Regression

Following the computation and aggregation of abnormal returns, we want to test whether the frequency of news or interval between news can truly explain the variation observed, or whether they are serving as proxies for other factors, e.g., a higher frequency of announcements might be a proxy for company size. In addition, we want to control for microstructure effects on returns (thin trading, low liquidity, high bid-ask spreads). There is also an issue regarding the endogeneity of firms' announcement-policy which we will cover more in-depth at a later stage. With these issues in mind, we use the following cross-sectional models to test our hypotheses:

$$AR_\tau = \alpha + \beta Frequency_\tau + \varphi X_\tau + \varepsilon_\tau \tag{9}$$

$$AR_\tau = \alpha + \beta Interval_\tau + \varphi X_\tau + \varepsilon_\tau \tag{10}$$

where AR_j is the abnormal return for event $\tau = 1,\ldots,N$, *Frequency* is the 12-month news-frequency for firm *i* at the time of the event, *Interval* the time since last news event for firm *i*, *X* is an nx1 vector of firm characteristics (firm size, an industry factor for example for endogeneity) and φ is an 1xn vector of coefficients, α is the intercept and ε is the error component; we leave out subscript for company *i.* for notational ease. Our key hypothesis is that frequency or interval has an impact on abnormal return, i.e., $\beta \neq 0$. We have not settled on appropriate firm characteristics for the *X* vector at this stage, and this will need to be explored further; however, firm characteristics could include factors such as firm size, industry, proxy for attention (e.g., analyst coverage), trading volume, bid-ask spread, and more.

5.2 Considerations

5.2.1 Overlapping Events

The event windows as explained section 5.1 (see figure 2) shows a six-month estimation window, a one-day pre-event window, and a two-day post-event window. What this figure does not make immediately clear is the issue of managing repeat-events in the same security. With complete news-data for the last twenty years, we find a mean annual frequency of events, at 11 events per year, and frequency spans from zero to150 events annually. This is positive in the sense that we have a high number of events to analyze, but unfortunate in the sense that overlapping events introduces and overweighting-bias to the sample. Simply explained, if we have three events in the same day, and analyze them individually, we effectively triple-weigh these observations. To control for this issue, we implement a two-stage solution. First, we eliminate events that we consider to be unimportant (noise); these primarily include announcements relating to invitations to quarterly presentations, invitations to annual general meetings, and filings regarding the ordinary financial calendar. Thereafter we eliminate all remaining overlapping events by removing them from our sample altogether. The minimum event gap is shown below:

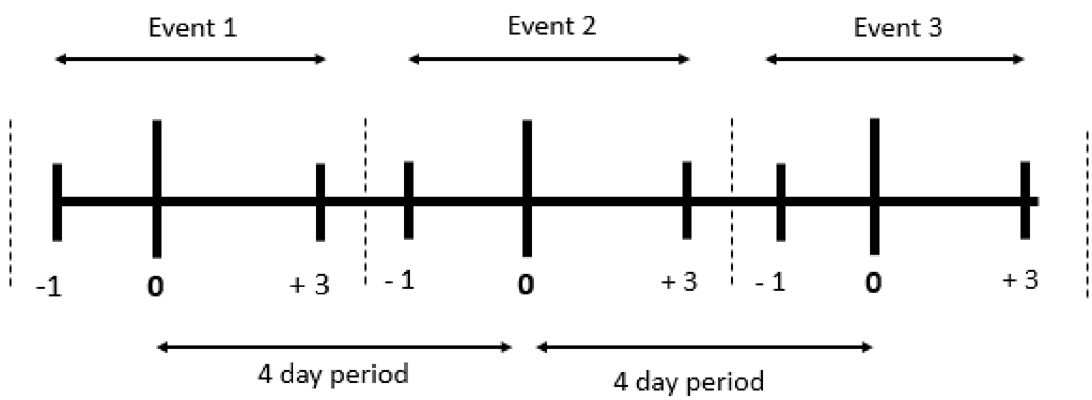

Figure 3: Minimal Event Distance

To effectively remove all overlapping events, from $event_1$ T_0 - $event_2$ T_0, the length between announcements must equal the sum of the lengths of our post-event window and our pre-event window. By removing the overweighting bias, we consequently introduce another bias, i.e., by eliminating (in this case) all events with lower intervals than 3 days; a sizable percentage of our dataset. Said differently, we skew the mean interval upwards, and the mean frequency downwards overall, and the longer we make our event window to be, the stronger this bias becomes. In sum, there is a clear trade-off between allowing for the time required to fully capture the impact of an event and retaining the number of observations and a mostly unbiased dataset. Moreover, as discussed previously, we imagine that the true appropriate event-window length will increase as we move back in time, exacerbating the issue.

5.2.2 Controlling for Listing Effects

To control for abnormal returns from listings, as documented by Kadlec & McConnell (1994) among others, we choose to eliminate the first month of trading for newly listed securities. We find it prudent to exclude post-listing periods to remove potentially large abnormal returns from

IPO premiums as well as the first few weeks following, to ensure that the specification of relevant adjustment models remain robust.

5.2.3 Time of Events

Datasets used for the study are specified on a daily basis, with price data being collected from the active midday trading hours, but announcements are made on a 24-hour basis. Consequently, we need to consider how to conduct the event study with respect to the time of the announcement. While with higher frequency data, we might be able to treat an announcement made pre-market differently to an announcement made mid-day, this is not possible with the current dataset specification. Instead we treat any announcement made before the close of the exchange as if it was made pre-market, i.e., attribute the full days returns to that event. Announcements made after trading stops however, are instead pushed to the next day.

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Appendix

Appendix 1A: Price Data

Date	AFG	AFK	…	WWI-OS	WWIB-OS
26/01/1998	5.73	506.97	…	70	70
27/01/1998	5.73	506.97	…	69	70
28/01/1998	5.73	506.97	…	68.75	70
29/01/1998	5.73	506.97	…	69	70
…	…	…	…	…	…
23/01/2018	129.5	3380	…	262.5	260
24/01/2018	132	3380	…	263.5	259
25/01/2018	131	3380	…	259.5	253
26/01/2018	118.5	3340	…	259	254

Appendix 1B: News Data

Statoil	Statoil	Statoil	Statoil
10/06-2002	10/06-2002	03/06-2002	03/06-2002
08:30:32	08:30:03	09:12:09	09:03:45
STL	STL	STL	STL
STL - UK GAS CONTRACT FOR STATOIL (OBI)	STL - STATOIL MED STORT GASSALG TIL UK (OBI)	STL - STATOIL GETS GO-AHEAD FOR SNØHVIT (OBI)	STL - STATOIL FÅR GRØNT LYS FOR SNØHVIT (OBI)

News data contains the company name, the date of the announcement, the time of the announcement, the company ticker, and the title of the announcement. The complete dataset contains all news related to a single company and includes a separate .csv file for each relevant company.

Appendix 1C: Pricing Factors Daily (Including Fama-French Factors)

Date	SMB	HML	PR1YR	UMD	Rf(1d)	EW	VW	Allshare
19861201	-0.004	0.000	-0.001	0.000	0.001	-0.003	-0.004	-0.003
19861202	-0.006	-0.002	0.013	0.006	0.001	-0.015	-0.014	-0.012
19861203	-0.003	-0.004	0.011	-0.002	0.001	-0.024	-0.019	-0.019
19861204	-0.007	0.000	0.015	0.013	0.001	-0.009	-0.006	-0.002
19861205	0.000	-0.005	-0.011	-0.004	0.001	0.006	0.002	0.000
19861208	0.005	-0.001	-0.004	0.003	0.001	-0.009	-0.010	-0.009
19861209	0.010	0.008	0.001	0.003	0.001	-0.009	-0.013	-0.017
19861210	0.000	0.005	-0.002	0.009	0.001	0.006	0.007	0.008
19861211	-0.017	-0.015	-0.010	-0.017	0.001	0.004	0.010	0.012