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Market Efficiency and Technological Developments in the Norwegian Stock Market

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# Market Efficiency and Technological Developments in the Norwegian Stock Market

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## Abstract

In this paper, we investigate technological developments in the financial market and whether the Norwegian stock market has become more efficient. Explaining efficiency in the market, we apply a price-synchronicity measure, R-squared, proposed by Richard Roll (1988) and evaluate the alphas of the yearly regression models. Further, to explain how stocks adjust to new information, in the short term, we use event studies. Based on the price-synchronicity measure, we find no evidence that the market has become more or less efficient. However, based on the cumulative average abnormal return (CAAR), we find that the standard deviation is significantly lower in the period from 2008-2018 compared to 1997-2007. Our conclusion is, therefore, that the Norwegian stock market has become more efficient. We identify three key characteristics that technology could have influenced market efficiency; *increased availability of information, reduction of trading costs and lower barriers,* and *existence of broad base of investors.*

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## 1. Introduction and Motivation

According to the efficient market hypothesis, financial market prices should reflect the currently available information. Depending on the investor's beliefs, the value of the asset should quickly increase or decrease to its intrinsic value when new information is published. However, the incomprehensible growth of Information and Communication Technology (ICT) has made the price of information to decrease, and the availability has increased significantly. Grossman and Stiglitz (1980) propose a compelling argument which is highly relevant to our study; "*...as the cost of information goes to zero, the price system becomes more informative.*" Following this logic, when information is cheap, investors are more informed and make better investment decisions. On the other hand, informed investors, when information is expensive, would have more opportunities to exploit their informational superiorities and thus make abnormal returns.

Arguably, increased accessibility and competition through technological enhancements lead to lower cost of information and more efficient capital markets. This argument encourages our research question; *have financial markets become more efficient due to technological advancements?*

To answer this question, we apply the intuition behind Roll's measure of price-synchronicity, R-squared, to capture firm-specific return (Roll, 1988). However, there has been an ongoing debate of whether a high or low R-squared infer firm-specific information. We, therefore, provide a comprehensive analysis to conclude the representation of R-squared in this paper. Additionally, we calculate alpha using the market model, the CAPM, and the Fama French three-factor model. Bernt Arne Ødegaard has provided data for the Fama French model on the Norwegian stock market data. Describing how quickly stock prices fully incorporate new public information, we combine the price-synchronicity measure with event studies, where event studies represent the majority of our analysis. Answering these questions, we get a better understanding of whether the Norwegian stock market has become more efficient and how the role of active and passive management has changed.

Estimating the price-synchronicity measure, we use the Norwegian stock market data from 1983-2018. We provide yearly R-squared for every company listed on the Oslo Børs All-Share Index (OSEAX). To compare, we separate the measure into four periods. The first period from 1983-1991, the second-period from 1992-2000, the third period from 2001-2009, and the fourth period from 2010 – 2018.

Furthermore, we look specifically at events and news provided by Netfonds and conduct event studies based on the efficient market hypothesis. Conducting event studies from the period 1997-2018, gives us a better understanding of how investors react to events, in the short-term, and how it has changed over time. In the last part of our paper, we give explanations and propositions on how technology has influenced market efficiency.

## 2. Literature Review and theory

In the handbook of economic growth, part 1, Levine (2005) categorize the economic role of the financial sector into five categories: (1) Information production about possible investments and capital allocation, (2) Monitoring investments and performance, (3) mobilization and pooling of household savings, (4) Facilitating of trading, diversification, and risk management, (5) financing of trade and consumption. We will mainly focus on examining (1), both in terms of the growth of information technology and the efficient market hypothesis.

The role of information production in financial markets is a part of classic literature in economics going back to Schumpeter (1912) and Hayek (1945). In the use of knowledge in society (1945), Hayek brilliantly describes the importance of private property, the price system, and the dispersion of knowledge necessary for economic coordination. Hayek further argues that knowledge is the primary function of the price system. Hence, prices serve as a knowledge substitute to sufficiently overlap personal-knowledge and "fields of vision," such that our resources and plans get coordinated. Following the logic of Hayek, we argue that technological developments in recent decades have significantly increased individuals access to knowledge through the internet, lowered the barriers between personal-knowledge and "fields of vision," which leads to increased market efficiency.

The above discussion stimulates the argument by Grossman and Stiglitz (1980) "*…if the price of information goes to zero, more individuals are informed, the more informative is the price system.*" Furthermore, according to Levine (2005), there are considerable costs associated with evaluating firms, managers, and market conditions before making investment decisions. However, information and communication technology (ICT) has significantly reduced the price of information, evaluating firms, managers, and market conditions, which causes the market to become more efficient.

Furthermore, Boyd and Prescott (1986), argue that financial intermediaries may reduce the costs of acquiring and processing information. Thus, improve resource allocation. Information and communication technology has made it possible for individuals to undertake costly processes of researching investment opportunities. Therefore, an increase in the supply of research, analysis, and investment guiding has emerged. When markets become larger and more liquid, Levine (2005) argues that agents have better incentives to expend resources in researching firms. From this, we argue that technology has enabled the existence of a broad base of investors and, thus, increased liquidity.

Kyle (1984) and Holmstrom and Tirole (1993) further emphasize how markets become more liquid. Holmstrom and Tirole (1993), argue that stocks are volatile and influenced by many factors beyond the control of management, thus the stock market is no better informed about managerial performance than the board of directors. Nevertheless, the board can observe management closely, thus taking into account the circumstances of the level of performance obtained. However, they further argue that even though this kind of reasoning may be intriguing, they overlook the most significant virtue of stock prices – their integrity.

Bai, Philippon, and Savov (2016), argue that the most common measure of informativeness is price-synchronicity (Roll, 1988). This is based on the correlation between firm's return and a market or industry benchmark. High correlation between the firm's return and the market or industry benchmark is represented as low informativeness.

Greenwood and Jovanovic (1990), and King and Levine (1993b), provide growth models in which information production in financial markets enables efficient investments. To measure informativeness, Bai, Philippon, and Savov (2016), provide a welfare-based measure of price informativeness which is based on Greenwood and Jovanovic (1990), and King and Levine (1993b) growth models.

There are several papers that adopt the price-synchronicity measure, R-squared. These include Morck, Yeung, and Yu (2000), Durnev, Morck, Yeung, and Zarowin (2003), and Chen, Goldstein, and Jiang (2007). Durnev, Morck, Yeung, and Zarowin (2003) in particular emphasize how Roll (1988) observes low R-squared statistics for common asset pricing models due to vigorous firm-specific returns variations not associated with public information. Thus, showing that the measure of price-synchronicity is positively related to the correlation between returns and future earnings at an industry level. This helps us validate price-synchronicity as a measure of informativeness to investigate whether it has become increasingly difficult to extract abnormal returns in the Norwegian stock market due to the growth of information and communication technology.

In this paper, we try to combine the theory presented by Roll (1988), which is backed by several papers explained above, of price-synchronicity in order to measure the informativeness of Norwegian stocks and how it has changed. We will combine this with the efficient market theory presented by Fama and French. Using R-squared as the price-synchronicity measure and event studies to explain how the increase of information and communication technology has made financial markets more efficient. If our hypothesis is true, we should be able to explain a positive correlation between the increase of ICT and the difficulties for investors to generate abnormal returns. Our thought is that if we compare the price-synchronicity together with event studies, from 1983 up to date, we should be able to see whether the stock market has become more informative and hence more efficient due to the increase of ICT.

## 3. Theory and Methodology

This part of the study explains the methods and theory applied to answer the research question. First, we elaborate on the efficient market hypothesis (EMH), Price-synchronicity measure, R-squared, and event studies. Secondly, we explain the models we have applied to get an understanding of expected returns, abnormal returns (AR), cumulative abnormal returns (CAR), and cumulative average abnormal returns (CAAR).

### 3.1 Efficient Market Theory

For decades the question of whether active investors can make returns above the market returns and if the stock market can be forecasted has been investigated. Some of the early research that touches on the efficient markets include the French mathematician, Louis Bachelier (1900), recognized as the father of financial mathematics. Others include Alfred Cowles (1932) and Richard Wycoff (1933). However, Eugene Fama was the one who popularized the efficient market hypothesis (EMH), in his paper, Efficient Capital Markets: A Review of Theory and Empirical Work (1970). Eugene Fama characterized market efficiency into three categories; (1) weak-form efficiency; (2) semi-strong-form efficiency; and (3) strong-form efficiency. In this paper, we focus on semi-strong-form.

(1) *The weak-form efficiency* is defined as the inability for market participants to make abnormal returns above the market by utilizing historical price information.

(2) *The semi-strong-form efficiency* is defined as the inability for investors to make abnormal returns above the market by utilizing all publicly available information. Security prices should, therefore, quickly adjust to new information.

(3) *The strong-form efficiency* is defined as the inability for market participants to make abnormal returns above the market by utilizing both public and private information.

The efficient market hypothesis is dependent on some essential arguments. Firstly, there is difficulty in testing market efficiency because there is no particular test which explains market efficiency. Secondly, financial market efficiency can change. In some periods, the market may fully reflect all publicly available information and historical data. However, in other periods, e.g., in times of financial distress, there may be anomalies for investors to exploit. Thirdly, testing the market efficiency and the asset pricing model applied induces the joint hypothesis problem (Fama, 1991). Therefore, we need an appropriate model of equilibrium to compute the expected returns and evaluate abnormal returns.

### 3.2 Price Synchronicity Measure, R-squared

In 1988, Richard Roll introduced a measure, R-squared, to explain systematic, or non-diversifiable factors. Consequently, several papers have emerged, covering the concept of price-synchronicity and R-squared. Morck, Yeung, and Yu (2000) also propose that price-synchronicity, defined as the R-squared from asset pricing regressions, can be a measure of the amount of firm-specific information reflected in returns (Skaife, Gassen, and LaFond 2005). We define R-squared according to econometric theory as:

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} = 1 - \frac{\sum_{i=1}^{n}\hat{u}_i^{\,2}}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Here,

$\sum_{i=1}^{n}(y_i - \bar{y})^2$ = Total Sum of Squares (SST),

$\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2$ = Explained Sum of Squares (SSE),

$\sum_{i=1}^{n} \hat{u}_i{}^2$ = Sum of Squared Residuals (SSR).

### 3.3 Event Studies

To be able to evaluate how the stock price adjusts to new information has changed, we need a method for measuring event impact. For this purpose, we have used classic event study literature presented by Fama (1970-1991), Armitage (1995), McKinlay (1997), and Kothari and Warner (2004), among others.

***Defining the Event***

Classic event study literature defines an event as news released by the financial press or by the companies. In our study, we focus on both, which are provided by Newsweb. However, we neglect news published several times and contains the same information or information that should not yield any abnormal returns, such as invitations to presentations, general meetings, etc.

***The Estimation Window***

Since we include overlapping events, to some extent, we have chosen to include two time-periods, (+/-) seven days with 15 observations and (+/-) two days with five observations, capturing the short-term effects of events. Barber and Odean (2008) propose a fascinating argument in this regard, *"...investors are net buyers of attention-grabbing stocks, e.g., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns*." (Barber and Odean, 2008). Thus, excluding overlapping events would induce another bias were firms with higher news frequency would not be captured by what Daniel Kahneman calls the illusions of validity (Kahneman, 2011).

### 3.4 Models Applied[1]

In this section, we present, discuss and clarify the models applied in this paper. Mackinlay (1997) emphasizes the benefits of using a factor model over a constant mean model. However, the appropriate model in which one should choose is less clear when studying seven-day and two-day study. As a solution, we employ all three and compare them.

***The Market Model:***

$$R_{it} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{it} \quad (2)$$

$$\alpha_i = R_{it} - \beta_i R_{m,t} - \varepsilon_{it} \quad (2.1)$$

$R_{it}$ = Firm, *i,* return for time *t.*

$R_{m,t}$ = Market return for time *t.*

***Capital Asset Pricing Model (CAPM):***

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{m,t} - R_{ft}) + \varepsilon_{it} \quad (3)$$

$$\alpha_i = R_{it} - R_{ft} - \beta_i (R_{m,t} - R_{ft}) - \varepsilon_{it} \quad (3.1)$$

$R_{it}$ = Firm, *i,* return for time *t.*

$R_{m,t}$ = Market return for time *t.*

$R_{ft}$ = Risk-free rate at time, *t.*

$(R_{m,t} - R_{f,t})$ = Risk Premium.

***Fama-French 3-Factor Model[2]:***

$$R_{it} - R_{ft} = \alpha_i + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i} SMB_t + \beta_{3i} HML_t + \varepsilon_{it} \quad (4)$$

$$\alpha_i = R_{it} - R_{ft} - \beta_{1i}(R_{mt} - R_{ft}) - \beta_{2i} SMB_t - \beta_{3i} HML_t - \varepsilon_{it} \quad (4.1)$$

$R_{it}$ = Firm, *i,* return for time *t.*

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[1] If the model holds, we expect alpha, $\alpha_i$, to be zero. Under general econometric assumptions of homoscedasticity, we assume epsilon, $\varepsilon_{it}$, to be zero with a constant variance of $\sigma^2_\varepsilon$ (Wooldridge 2016, p. 45).

[2] The data for the Fama-French 3-Factor Model was provided and approved by Bernt Arne Ødegaard through his website: http://finance.bi.no/~bernt/

$R_{m,t}$ = Market return for time *t.*

$R_{ft}$ = Risk-free rate at time, *t.*

$(R_{m,t} - R_{f,t})$ = Risk Premium.

$SMB_t$ = Small minus Big at time, t. This factor refers to the small firm effect and the size effect, the size of the company is based on market capitalization.
$HML_t$ = High minus Low at time, t. This factor refers to the companies with a high book value to market value ratio. The low refers to companies with a low book value to market value ratio.

The market model introduced by William Sharpe (1964) and John Lintner (1965), is still an attractive model, even though it only captures the significance of the market return. Fama and French (2003), argue that the attraction of CAPM is its intuitive prediction about how to measure risk and thus, the relationship between risk and expected return. Therefore, we include the capital asset pricing model (CAPM) and the Fama-French 3-factor model. Additionally, the CAPM is considered an equilibrium model in contradiction to the market model. However, we should make the reader aware of the market model's simplicity, as the market return is the only factor that affects returns. When only including one covariate, market return, the R-squared of the regression will equal the correlation squared between the firm and the market. We are then able to get an impression on how the individual firm's correlation with the underlying market varies, which in our study is the OSEAX.

### 3.5 Abnormal Returns

Abnormal return is the return on a stock beyond what would be predicted by the asset pricing models employed (Bodie, Kane, Marcus, and Jain, 2014). We, therefore, calculate abnormal returns for individual firms, i, for a pre-specified time period, t:

$$\mathrm{AR}_{i,t} = \mathrm{R}_{i,t} - \mathrm{E}(\mathrm{R}_{i,t}) \tag{5}$$

Here, $AR_{it}$, $R_{it}$, and $E(R_{it})$ are the abnormal return for the individual firm on a specific day, the actual return of the firm, and the expected returns provided by the asset pricing model.

### 3.6 Cumulative Abnormal Return (CAR)

Abnormal return on the announcement day is a poor indicator of the total impact of news. A better indicator is therefore to calculate the cumulative abnormal return (CAR). CAR is the sum of the abnormal returns within a specified period of time. We define CAR for company i, as:

$$CAR_i(t_0, t_1) = \sum_{t=0}^{T=1} AR_{i,t} \qquad (6)$$

Here $t_0$ represents the time before the event, and $t_1$ represents the end of the day event window. We will apply both an event period of (+/-) seven days (15 observations) and (+/-) two days (5 observations).

***Significance of Cumulative Abnormal Returns in event studies***

Before calculating the cumulative average abnormal returns, we apply a t-test to include firm-specific CAR, significantly different from zero. Following the logic behind MacKinlay (1997), we construct the following test statistic:

$$\theta_i = \frac{CAR_i(t_0,t_1) - 0}{var(\ \sum_{i=1}^{N} CAR_i(t_0,t_1)\ )^{1/2}} \qquad (7)$$

Here, theta, θ, is the test statistic, for company *i*, $CAR_i\,(t_0,t_1)$ is the Cumulative Abnormal Return for specific security within a specific event period. 0 is the expected CAR under the null-hypothesis, $var(\ \sum_{i=1}^{N} CAR_i(t_0, t_1)\ )^{1/2}$ is the standard deviation of all the Cumulative Abnormal Returns for one specific security, i. In other words, we test the CAR’s, security by security.

### 3.7 Cumulative Average Abnormal Return (CAAR)

Lastly, we measure the average of CAR, cumulative average abnormal return. We aggregate all the security CAR's in one specific event period and divide by N, the total number of firms that have CAR significantly different from zero, within that period of time. This is important because it gives us an indication of some variability around this single value, and how, on average, the CAR's have changed. We define CAAR mathematically as:

$$CAAR(t_0, t_1) = \frac{1}{N} \sum_{i=1}^{N} CAR_i(t_0, t_1) \qquad (8)$$

Here, CAAR is the sum of the cumulative abnormal return for all firms, i, in a specified period of time divided by the total amount of firms that has CAR significantly different from zero, within that period of time.

## 4. Data

This section explains the type of data we have included in our analysis, as well as our collection, sorting, and cleaning methods. First, we discuss data collection, then sorting, and lastly some other effects that could have influenced our data and analysis.

### 4.1 Data Collection

Our paper includes data from several sources. News data were collected based on the official outlet of the OSE, Newsweb. However, to investigate the impact of all available news from various issuers, Netfonds database has been used. News collected through Netfonds is mainly based on the OSE database, but also a gathering of news from other financial institutions and websites. Furthermore, we collected our data earlier in 2019, before the merger between Nordnet and Netfonds, which changed the original outlay. Due to our lack of knowledge with different programming languages, we were not able to collect news-data through an API. Thus, all news has been retrieved manually. The sample spans all events of all companies that were active at the end of 2018.

The firm-specific price data were collected from Eikon, a Thomson Reuters database available for students at the BI Norwegian Business School. Closing prices have been our most important variable, which includes daily prices for all companies that were active during the period from 1983-2018. The Price-synchronicity measure, R-squared of the regression model, includes price data from all active companies within each year. I.e., including securities that are dead today, but has been actively listed before. In the event study analysis, we use price data from all the active companies listed at the end of 2018. Because news-data only goes as far back as of 1997, when Newsweb was established, we are restricted to go beyond 1997.

Nonetheless, analyzing returns from two perspectives, R-squared, including alpha, and event studies, provide opportunities to identify what impact public information and events have on the stock price in the short-term as well as in the long term.

The factor data collected from Bernt Arne Ødegaard is used to calculate the expected returns for the two models explained in chapter three; the CAPM and the Fama French three-factor model. Factors include; Risk premium (RP), Small minus Big (SMB), High minus Low (HML), and the daily risk-free rate.

The all-shares index (OSEAX) consists of all listed shares on OSE and is used as the market index, which is adjusted for corporate actions daily and dividend payments.

### 4.2 Sorting data

A large amount of data strengthens the possibility of a good analysis. Daily prices from 1983 until the end of 2018 give us around 1,800,000 prices. News data include roughly 188,000 announcements that are spread over the same 233 companies actively listed on OSE at the end of 2018.

Some publicly published news seems to be unimportant and is considered noise, which should not impact stock prices. Examples of such announcements are invitations to meetings, financial calendars, invitations to presentations, etc. Before sorting out the noise, our data contained over 215,000 news, thus we eliminate approximately 27,000 news announcements.

Overlapping events remain in our sample, which introduces the concept of overweighting bias. However, our thesis investigates the impact of technological developments and information on market efficiency. Thus, reducing the impact of overweighting bias would reduce the impact of high-frequency issuance of news, which could be a consequence of information technology. Capturing more frequent issuance of news is therefore in our best interest. However, to reduce the impact of overweighting bias, we investigate two time-periods when analyzing events. A (+/-) seven-day period and a (+/-) two-day period.

| Date | Time | Year | Ticker | Event |
|---|---|---|---|---|
| 26/04/2018 | 16:23:55 | 2018 | NHY | Norsk Hydro: Primary insiders purchase shares under Long-Term Incentive program and shares to employees (OBI) |
| 03/04/2018 | 08:00:29 | 2018 | NHY | Norsk Hydro: Sale of shares to employees (OBI) |
| 20/02/2018 | 08:12:25 | 2018 | NHY | The Capital Group Companies - Disclosure of acquisition/disposition of large shareholdings -Norsk Hydro ASA (OBI) |
| 07/02/2018 | 13:43:23 | 2018 | NHY | Renteregulering (OBI) |
| ... | ... | ... | ... | ... |
| 08/12/2017 | 13:46:59 | 2017 | NHY | Oslo Børs - NHY06 - Nytt lån til notering / New bond issue to be listed 11.12.2017 (OBI) |
| 04/05/2017 | 07:00:47 | 2017 | NHY | Norsk Hydro: Ex dividend NOK 1.25 today (OBI) |
| 02/05/2017 | 15:05:09 | 2017 | NHY | Norsk Hydro : Salg av aksjer til ansatte (OBI) |
| 03/04/2017 | 12:32:42 | 2017 | NHY | Norsk Hydro: Primary insiders purchase shares under Long Term Incentive program and shares to employees (OBI) |
| ... | ... | ... | ... | ... |
| 03/05/2016 | 07:01:37 | 2016 | NHY | Norsk Hydro : Ex utbytte kr. 1,00 i dag (OBI) |
| 28/04/2016 | 06:58:54 | 2016 | NHY | Norsk Hydro: Sale of shares to employees (OBI) |

**Table 1** – Example of news data.

The table above is an example of how we have structured our news data in excel. It was further imported into Matlab, where we did our calculations and quantitative analysis.

The graph below is an overview of the amount of news published yearly and its growth. This is the news published through Newsweb, which gives us a perspective of the increase in events in the last two decades.

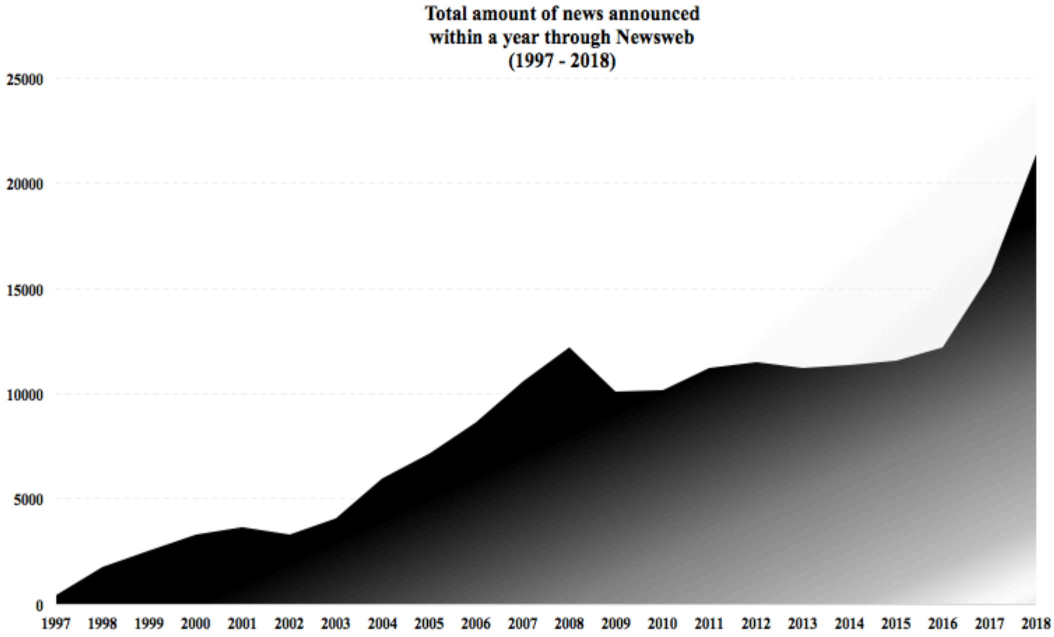


**Figure 1** – Overview of the amount of news-announcements within a year published through Newsweb. A significant increase in the amount of news published.

### 4.3 Other effects

Considering some other effects that could have influenced our impact on returns, are the weekend effect and new listings on OSE. The weekend effect, which was first reported by Frank Cross (1973), emphasizes that stock returns on Mondays are often significantly lower than those of the immediately preceding Friday. The weekend-effect is not adjusted for in our analysis. However, we do consider listing effects to be an important issue. The reason for this is that public opinion could be significantly lower or higher than the IPO value, causing tremendous fluctuations in the stock price during the first few days of trading, which means that we include those firms with full price data for the whole year. I.e., if a company was listed in September 1987, we include it next year.

## 5. Analysis

In this section of the paper, we provide an overview of our main research question, analysis, and results. We start by looking at the R-squared's representation and further proceed with a discussion of how the R-squared measure and alpha has evolved from 1983-2018. The next part of the analysis will cover short-term market efficiency by looking at event studies. Lastly, there will be an overall evaluation of the results.

### 5.1 Price synchronicity Measure R-squared

***Do a low R-squared represent firm-specific information and, thus, higher market efficiency?***

Discussed earlier, there has been an ongoing debate of whether a low R-squared, of the regression models, represents a higher level of firm-specific information and higher firm-specific returns. Intuitively, greater incorporation of firm-specific information would yield in low R-squared. Analyzing R-squared at the country level, Morck et., al (2000), find evidence that stock prices move together more in under-developed economies than in developed economies. Thus, Morck et., al (2000), interpret higher R-squared values as returns that reflect market-level information and lower R-squared values representing firm-specific information.

Durnev et., al (2003), concludes that a lower market model R-squared exhibit higher association between higher returns and future earnings in current stock returns. These findings support Roll's (1988) first intuition that higher firm-specific returns variation of total variations signals more information-laden stock prices and, therefore, more efficient markets. Both of the studies discussed above conclude that lower market model R-squared exhibits a higher level of firm-specific information and thus, increased market efficiency.

Pagano and Schwartz (2003), by contrast, infer market quality from the synchronicity of individual stock returns, with respect to market returns, and interpret an increase in R-squared as evidence of increased market efficiency. Kelly (2007), considers information costs, trading costs, and liquidity to characterize the impediments to informed trading. His findings suggest that greater information costs, greater trading costs, and lower liquidity are consistently associated with low market model R-squared. This evidence suggests that firms with low R-squared may be those firms with a greater possibility of mispricing. Chang and Luo (2010), Teoh et al. (2009), and Wang and Yang (2009) suggested that lower R-squared reflects a greater amount of firm-specific uncertainty or investors overreacting to new firm-specific information.

In our analysis, we calculate the yearly R-squared based on The Market Model, The Capital Asset Pricing Model (CAPM), and the Fama French Three-Factor Model. Figure 2 presents a plot of the average yearly R-squared. Our results show that there is an increase in average R-squared in times of financial distress, which is something one would expect because there exhibits an increase in correlation with the market returns. Additionally, significant alphas are primarily negative in these times as well. Following the logic of Morck et., al. (2000) and Durnev et., al. (2003), we argue that in times of financial distress companies face a higher level of uncertainty in predicting their future earnings, which causes security returns to increase their correlation with the market. However, in the same period, there are also a high number of alphas significantly different from zero. From this, we conclude that a low R-squared indicates that investors incorporate more firm-specific information about the company's future earnings, and thus, the market is more efficient. The average R-squared increases primarily in distressed times, which we argue is due to the uncertainty of a company's future earnings, and increased correlation with the market.

Further, we proceed by concluding that an increase in R-squared of the models indicates more market-wide information. Conversely, a lower R-squared represent more firm-specific information, and thus, higher market efficiency. The next question we will answer is how the R-squared, price-synchronicity measure, has evolved from 1983 – 2018.

***How has the R-squared measure evolved from 1983 - 2018?***

In our paper, we try to investigate whether the Norwegian stock market has become more efficient. One of the measurements we apply is price-synchronicity, presented by Richard Roll (1988). As we have concluded from the discussion above, we interpret a lower R-squared as higher price efficiency because when R-squared is low market participants incorporate more firm-specific information.

Whether the R-squared alone indicates increased or decreased market efficiency is difficult to assess, see figure 2 and table 2. Likewise, by calculating the average R-squared between different time-periods, table 2 and 3, we find no evidence of increased or decreased market efficiency.

According to the R-squared, we can only conclude that market efficiency has been relatively stable, with some changes in distressed times. Nonetheless, we can extract some valuable information from our results. In times of financial distress, we can observe a higher average R-squared across all firms. This is reasonable, as discussed above, because the R-squared of the models; market model; CAPM; and Fama French Three Factor, provide us with an estimate of how well the independent variables explain the dependent variables. By looking at the market model, we can interpret an increase in R-squared as the increase in the correlation-squared between the company returns and the market returns. However, we also find evidence that the alphas for the firms increase in distressed times. It, therefore, comes naturally for us to calculate the yearly Abnormal returns (AR), cumulative abnormal returns (CAR), and the cumulative average abnormal return (CAAR) to see how the alphas have changed over time and compare these with the R-squared.

### 5.2 Abnormal Returns (AR), Cumulative Abnormal Returns (CAR), and Cumulative Average Abnormal Returns (CAAR)

The above discussion proposes a further inquiry; *how have the yearly abnormal returns changed over time, without looking at specific events?*

Figures 3 - 8, visualize significant cumulative abnormal returns (CAR) and average CAR, based on a two-sided significance level of 10%, 5%, and 1%. Some periods generate larger CAR than other periods, such as 1987, 2000, and 2008. Nonetheless, the market seems to be efficient. Following the logic behind Morck et, al (2000) and Durnev et, al (2003) we should expect a higher CAR in periods with high R-squared, justifying that a high R-squared represents a decrease in market efficiency. In times of financial distress, stocks incorporate more market-wide information, causing the correlation between firm returns and market returns to increase.

The average cumulative abnormal return (CAAR) is close to zero at all times, despite some CAR significantly different from zero in times of distress. At the one percent significance level, the CAR is negligible.

It is difficult to conclude whether the market has become more or less efficient, based on our calculations of R-squared and abnormal returns. As discussed above, the yearly R-squared fluctuates considerably, but one could argue that there is an increase in CAR from 1983-2018. Nonetheless, the average is minimal. Unfortunately, based on R-squared and abnormal returns, we cannot conclude that the market has become more or less efficient.

Despite these unfortunate results, there is some valuable information to extract. We have confirmed that firm-specific returns have an increased correlation with the market in distressed times, which causes R-squared and alpha to increase. An increased R-squared, thus, signifies that firms are priced according to market-wide information, which designates less efficient markets.

The discussion above proposes an interesting question; *how does security returns adjust to new information?* To answer this question, we will apply a short-term event study analysis. This is a highly relevant question to ask in our paper because technology has made information more available at a smaller price. As Grossman and Stiglitz (1980) argue: "*when the cost of information goes to zero, the price system becomes more informative."* Thus, looking at specific events, we can see how investors react to new information in the short-term, and how it has changed over time.

### 5.3 Event Studies

We have discussed the price-synchronicity measure, R-squared, and abnormal returns based on the market model, the CAPM, and the Fama French Three-factor model in general terms. In this part of the analysis, we want to look at specific news and events to be able to explain whether the Norwegian stock market has become more efficient based on how it is reacting to news on a daily short-term basis.

To answer the question of whether the market has become more efficient, we started by gathering news and events from Netfonds. However, Netfonds did not start providing firm-specific news before 1997, we are therefore constrained to the period from 1997 to 2018, and are not able to provide event study analysis beyond 1997. Nevertheless, our results, nurture some interesting discussions which we find highly relevant to answer our research question.

Since we examine how the investor's response to new information has changed, we include most of the news published by Netfonds for each firm listed on OSE. By listed firms on OSE, we cover all currently listed firms on OSE as of 2018. After this consideration, we are left with 233 mature and newly listed firms to analyze. Since we are interested in how the efficiency of the Norwegian stock market has evolved, we include most of the events provided by Netfonds but exclude events that are considered unimportant. Examples of such announcements are invitations to general meetings, filings regarding the financial calendar, and invitations to presentations. Despite this, we try to capture the irrationality of the market and therefore include all other events, which includes overlapping events. It is therefore important for the reader to notice our neglection of overweighting bias. However, to reduce the impact of overweighting bias, we calculate CAR and CAAR for the event periods of (+/-) seven days and (+/-) two days, totaling 15 and five observations.

It is important to remember that neglecting one bias, overweighting bias in our case, is not necessarily bad. By neglecting overweighting bias, we refuse to impose another bias, frequency bias. We define frequency bias as the rate of news-frequency a firm supplies the market. This is important because we try to make sense of whether the Norwegian stock market has become more efficient due to technological developments. Technological developments include the exceptional growth of the internet and especially information provided on the internet. A higher news-frequency would likely be correlated with an increase in price efficiency, as proposed by Grossman and Stiglitz (1980). Including overlapping events would, thus, provide information about investors' reaction to events and multiple events as well, which is important to capture the rationality of the market participants. This leads us to our second part, defining the event period.

Secondly, we calculate AR, CAR, and CAAR for both a period of (+/-) seven days and (+/-) two days, to reduce the impact of overweighting bias. We find (+/-) one week reasonable to capture how investors react in the short/medium-term, however, we include a (+/-) two-day period as well, to capture investors short-term reaction. An overview of the amount of news published by Netfonds is provided in figure 1.

### 5.4 Results

Based on the event period (+/-) seven days, our calculated cumulative abnormal return (CAR) increases over time, as shown in figure 11. One of the reasons behind an increasing CAR could be explained by the fact that more firms are actively traded on OSE today, than in 1997. Therefore, a more appropriate question to ask is, *how has the cumulative average abnormal returns changed over the period 1997 - 2018?*

Answering the question above provides an indication of how big the CAR's are relative to how many firms with abnormal returns significantly different from zero. By calculating CAAR, we get some interesting results. Our CAAR for the event period (+/-) seven days, shows a decrease in CAAR over time. This represents a decrease in the average CAR over the time period 1997-2018, see figure 11 and 12.

Furthermore, we find that the standard deviation of CAAR is roughly 32% higher for the period in between 1997-2007 compared to the period from 2008-2018 when we base our calculations for the seven-day event period. As discussed above, we wanted to include the calculation of a smaller event day interval, thus we have also calculated the standard deviation for CAAR over the period 1997-2007 and 2008-2018, based on the two-day event period. Similarly, we find that the standard deviation of CAAR is significantly higher, 29%, for the period 1997-2007 compared to the period from 2008 to 2018.

As previously discussed, to reduce the impact of overweight bias, we calculated CAR and CAAR for a two-day event period. By the number of observations, we observe a decrease of approximately 11%. However, there is still a large number of observations totaling around 38,000 observations for the two-day period and 42,000 observations for the seven-day event period, see table 4.

Our findings suggest, according to the event study analysis, that there is a decrease in the variation of the overall cumulative average abnormal returns (CAAR). Based on these results, we argue that the Norwegian stock market has become more efficient. This guides us to another question; *why has the Norwegian stock market become more efficient?* As is indicative from the heading of our paper, we will in the next chapter discuss some technological developments within the financial markets and how they may have affected market efficiency.

## 6.0 Technological Developments and Its Impact on Market Efficiency

Technology has been fundamentally changing the global financial marketplace. In this section, we will look at technological sources that could explain the improvement in market efficiency. We will primarily focus on four key requirements for a well-functioning securities market, proposed by Avolio, Gildor, and Shleifer (2001): *the availability of accurate information*, *the existence of a broad base of investors with access to this information*, *legal protection of these investor's rights*, and *a liquid secondary market unencumbered by excessive transaction costs and constraints*.

### 6.1 Benefits of Technology on Market Efficiency

An obvious contributor that benefits securities markets and affect market efficiency, is cheap, real-time delivery of the vast amount of data. Any investor – institutional or retail – with an internet connection has now 24-hour access to news, current and historical asset prices, economic data, financial reporting data, analyst forecasts, investment advice, and the opinion of other investors. Additionally, web technology provides investors with continuous updates and performance of their investment portfolios. The quantity of information available today is staggeringly large compared to some decades ago.

Other clear contributions of technology which can affect market efficiency are the reduction in trading costs and the corresponding improvement in the liquidity of secondary markets. Advancing information and communication technology and increased competition amongst providers of financial services lower the barriers to entry for investors. When trading costs and other barriers decrease, the marginal investor may become less sophisticated, less experienced, and less able to derive fundamental security values from raw information. According to Jones (2001), the average one-way trading cost (half-spread plus NYSE commission) fell from 1% to 0.20% over the last 20-years.

Because of information and communication technology, there has also been an increase in the existence of a broad base of investors, which is mainly due to the increased availability for securities through several internet platforms. But also the lowered trading costs that are associated with trading abroad.

Lastly, the efficient market hypothesis states that only material nonpublic information (MNPI) would benefit investors seeking to earn above-average returns on investments. However, one argument would be that increasingly sophisticated technology would enhance strong regulations regarding insider trading. Here increased publication of news by companies through sources like Netfonds could improve market efficiency, as we have shown to be true on average.

Market efficiency is a continuum, as Fama (1991) states. The lower the transaction costs in a market, including costs obtaining information and trading, the more efficient the market will become. Technological change and the age of information, has reduced barriers to communication, making institutions and brokers unnecessary to make educated buys and sells. Furthermore, as a third-party agency that acts as a go-between for buyers and sellers in financial markets, clearing houses make financial markets more stable and efficient. The clearinghouse is responsible for settling the exchange member´s trade accounts, maintaining margin accounts and collecting money. With millions of daily trades, the interaction between participants would be costly and take time.

If the financial market is perfectly efficient, active management should not be considered by the average investor. The average investor should, therefore, hold the market portfolio. However, there are some outliers that have consistently achieved risk-adjusted returns above the market. Examples of such outliers are Renaissance Technologies (founder; Jim Harris Simons) and Bridgewater associates (founder; Ray Dalio), among some others. Even though there are some outliers, forecasting and predictability have always been comprehensive. In his book, superforecasting, Tetlock points out that some people are better forecasters than others. However, about 2% are superforecasters, which may explain the outliers (Tetlock, 2015).

Considering our results, it seems irrational that the average investor should invest in actively managed investments, if the purpose is to make excess returns above the benchmark, as it has become increasingly difficult. Thus, we believe that there will be an increased demand for index funds in the future, especially for private investors. The reason for this is mainly due to the reasons mentioned above. Increasingly sophisticated markets with comprehensive technological developments, such as algorithmic trading and machine learning, make the average investor, and experts as well, less prone to make excess returns above the market. Therefore, as the market becomes more efficient and more sophisticated, the average investor should shift towards investing their portfolio in index funds. And, as we can see from the research done by the Norwegian Fund and Asset Management Association (VFF), more private investors are choosing to have a larger part of their portfolio in index funds, even though it is too early to conclude whether this trend will persist (Dagens næringsliv, 2017).

From the above discussion, we believe that there are three primary characteristics of technological advancements that have affected market efficiency. These include; *(1) increased availability of information, (2) increased competition, reduced trading costs, and increased liquidity in secondary markets, and (3) the existence of a broad base of investors.*

## 7.0 Limitations

Before the conclusion, we would like to discuss some caveats for the reader to be aware of, regarding data and other effects that may have influenced our results in this paper.

Firstly, we include news from several sources through Netfonds, this could influence our results. As discussed throughout the paper, we wanted to include as many news and events as possible to figure out whether an increase in published information has made it increasingly difficult to generate abnormal returns. Additionally, we have included both mature and newly issued firms in the event study analysis. Therefore, the regressions on newly issued firms may have little data, which will provide poor results. However, on average, we believe covering 233 firms is suitable to gain justifiable results.

Secondly, news data were collected manually, simply because we were not able to collect it through a programming language. Nonetheless, we were able to collect a large amount of news-data and included news from several sources that have been published through Netfonds. Including several events highly relevant to answer our research paper. However, this increases the likelihood of overweighting bias and could influence our results.

Thirdly, we have used two analytical frameworks to answer our research question. We wanted to include the Probability of Informed Trading (PIN) as a supplement to answer our research question. However, there were some difficulties in retrieving high-frequency data which removed our ability to calculate PIN. Despite this, there may be other ways of answering our research question as well. Some examples could be to compare different funds and portfolios that have integrated new technology, such as machine learning and algorithmic trading, to achieve risk-adjusted abnormal returns. Nonetheless, since there are few funds that manage to generate consistent risk-adjusted abnormal returns, above the market, we believe event study is an appropriate analytical tool that answers our research question

## 8.0 Conclusion

We have investigated whether the Norwegian stock market has become more efficient and discussed how technological advancements may have contributed to an increase in market efficiency. We find no evidence, based on the price-synchronicity measure, R-squared, that the market has become more efficient. However, in our event study, we find evidence that there is an increasing cumulative abnormal return across firms. Nonetheless, on average, the standard deviation of CAAR is significantly higher in the period from 1997-2007, compared to 2008-2018. These results are also consistent when we evaluate a smaller event period of (+/-) two days. Implicitly, this means that active investors seeking to outperform the market benchmark would, on average, have a harder time generating excessive risk-adjusted returns. In other words, investors who are less sophisticated would benefit extensively by holding an index portfolio. There are three key characteristics we identify could infer greater market efficiency: *(1) increased availability of information, (2) reduction of trading costs and lower barriers of entry, and (3) existence of a broad base of investors.* These findings indicate that investors today are more informed and they are able to value Norwegian stocks accordingly. One of the explanations could be algorithms and algorithmic trading combined with machine learning that evaluate new information and quickly buy and sell. Further analysis on how algorithmic trading has affected the market efficiency would be an interesting study.

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# Appendix

## Figures

**Figure 1** — Overview of the amount of news-announcements within a year published through Newsweb. A significant increase in the amount of news published.

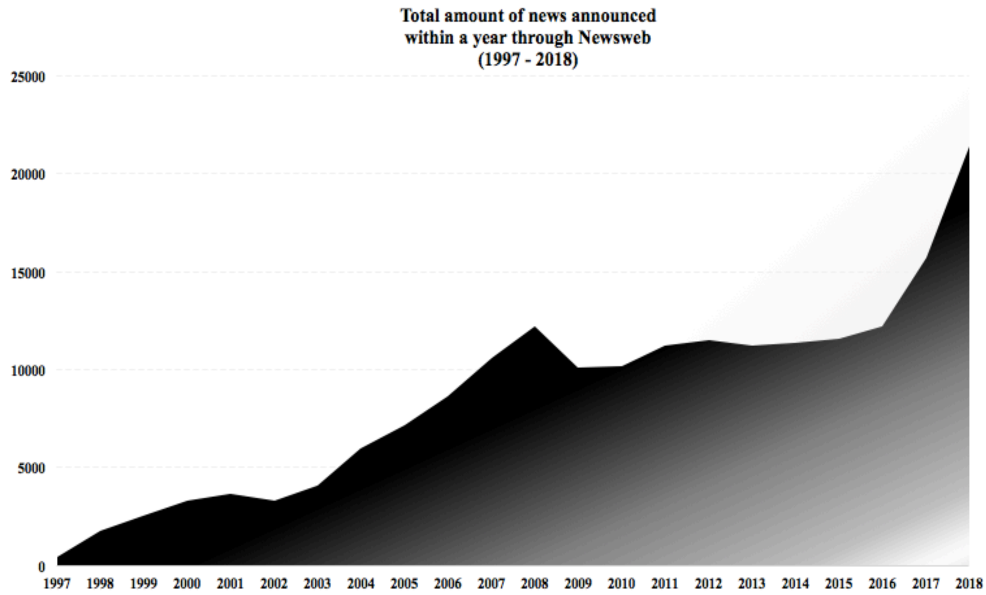



**Figure 2** – Overview of average yearly R-squared.

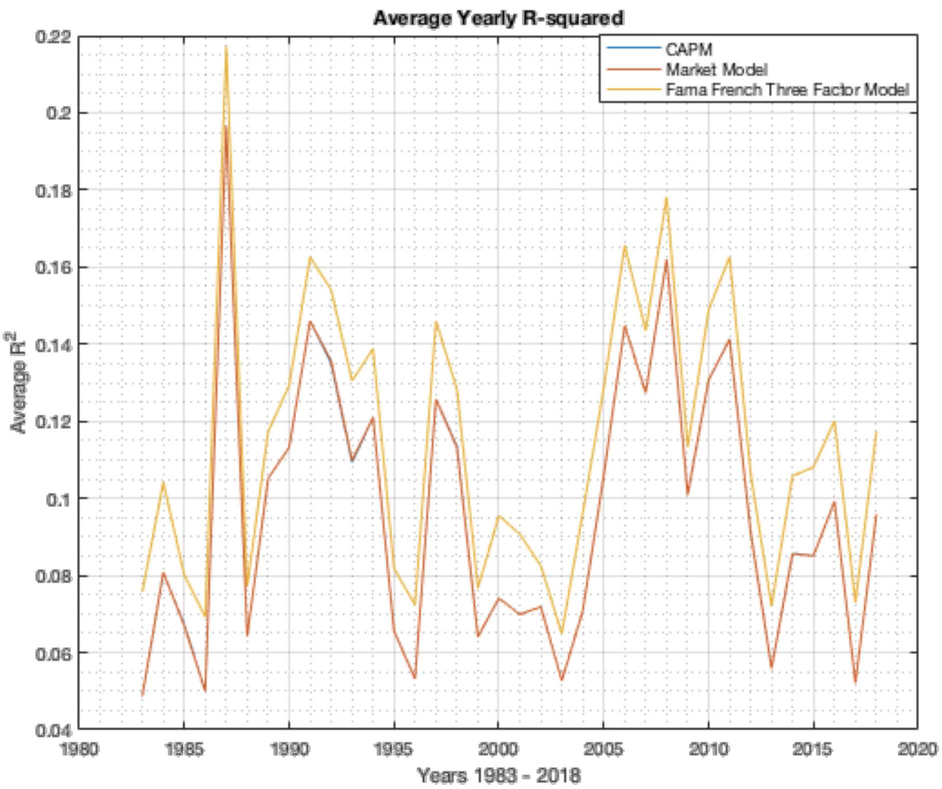


**Figure 3** – Yearly Cumulative Abnormal Returns for all total firms. Based on The Market Model.

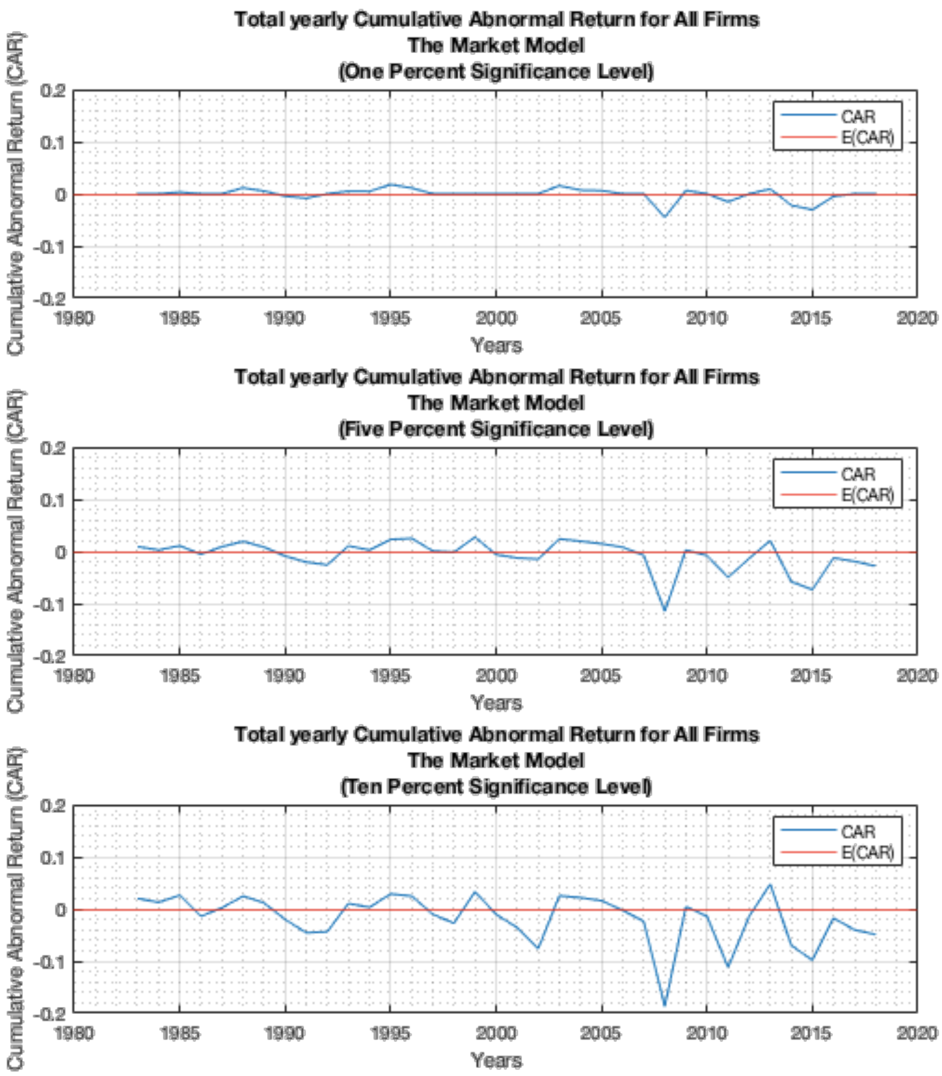


**Figure 4** – Yearly Cumulative Average Abnormal Returns for all firms. We divide by the amount of firms that have alpha significantly different from zero. Based on the Market Model.

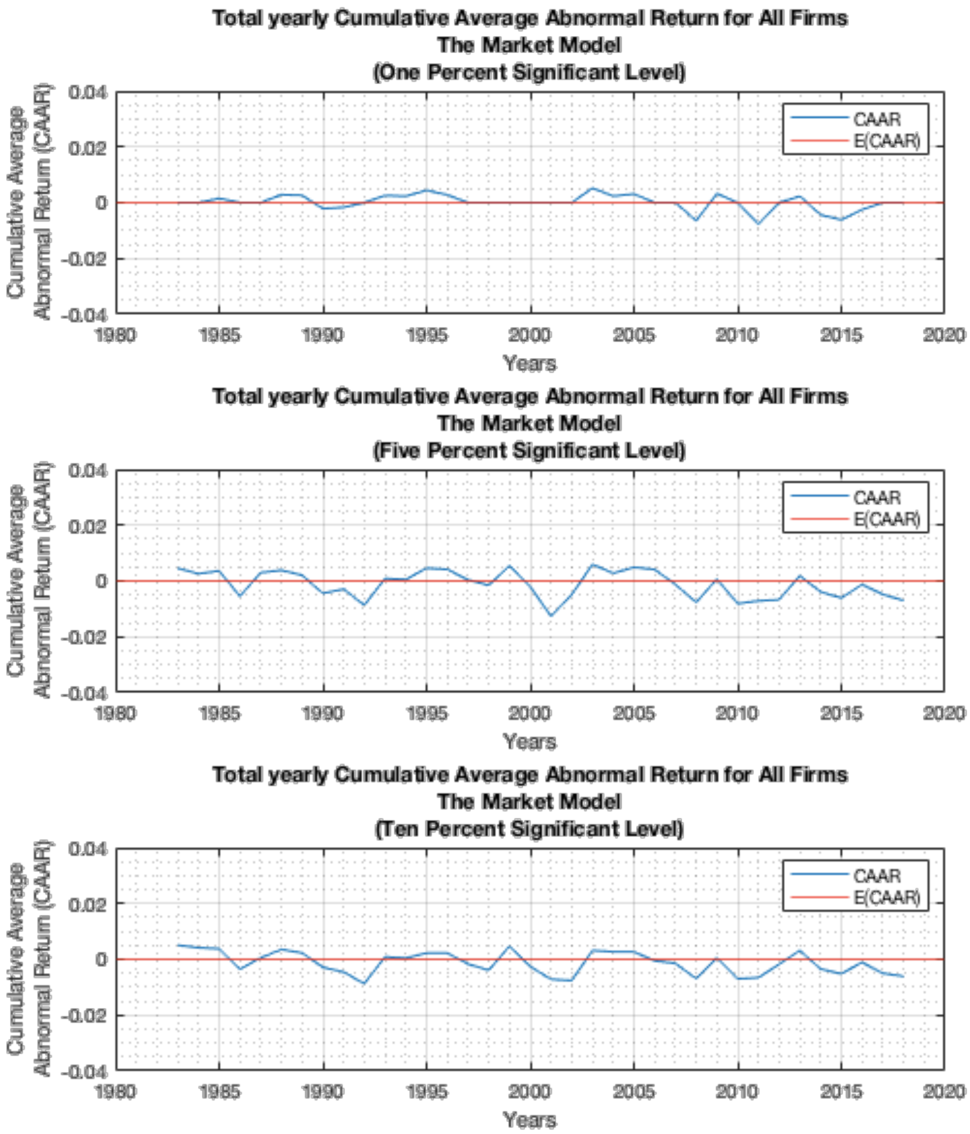


**Figure 5 -** Yearly Cumulative Abnormal Returns for all total firms. Based on the CAPM.

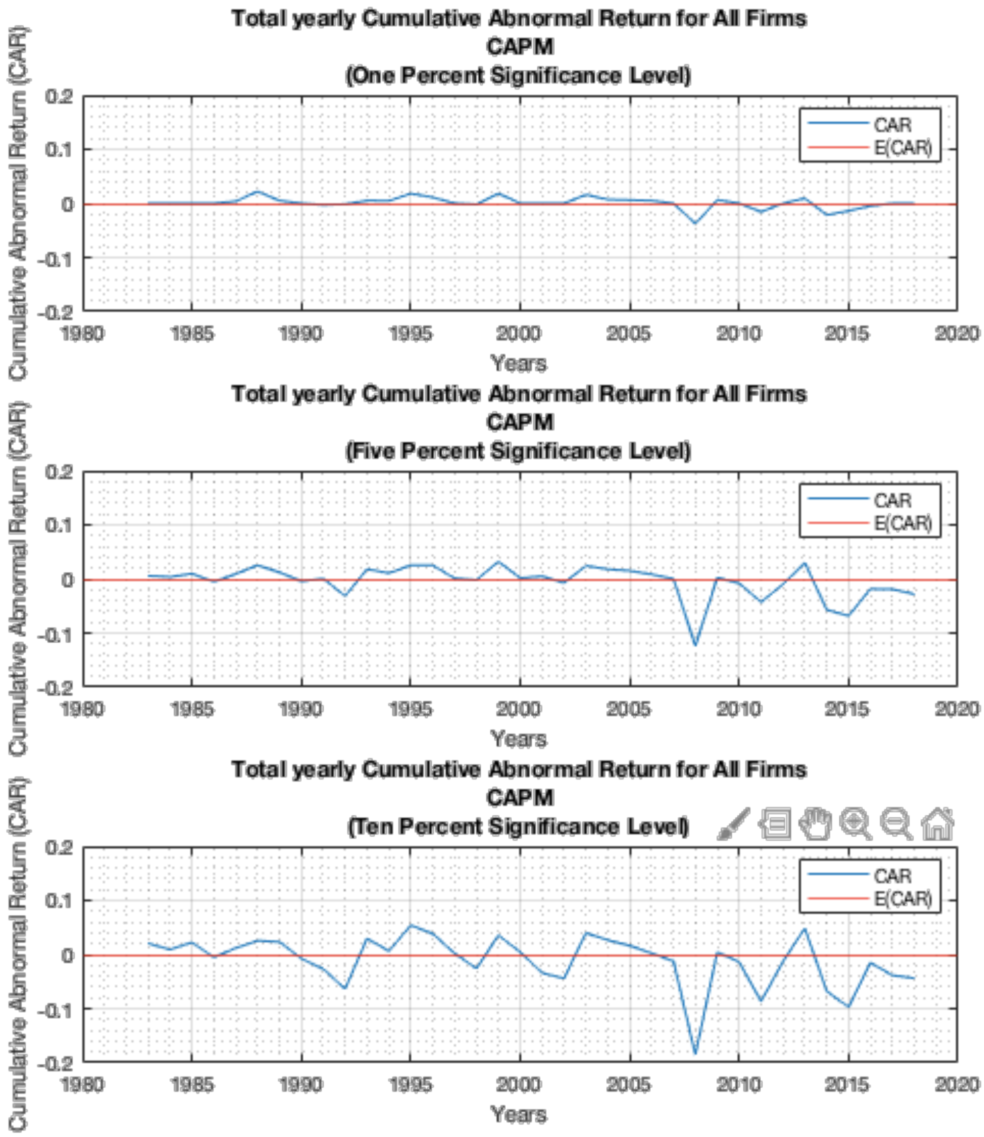


**Figure 6** – Yearly Cumulative Average Abnormal Returns for all firms. We divide by the amount of firms that have alpha significantly different from zero. Based on the CAPM.

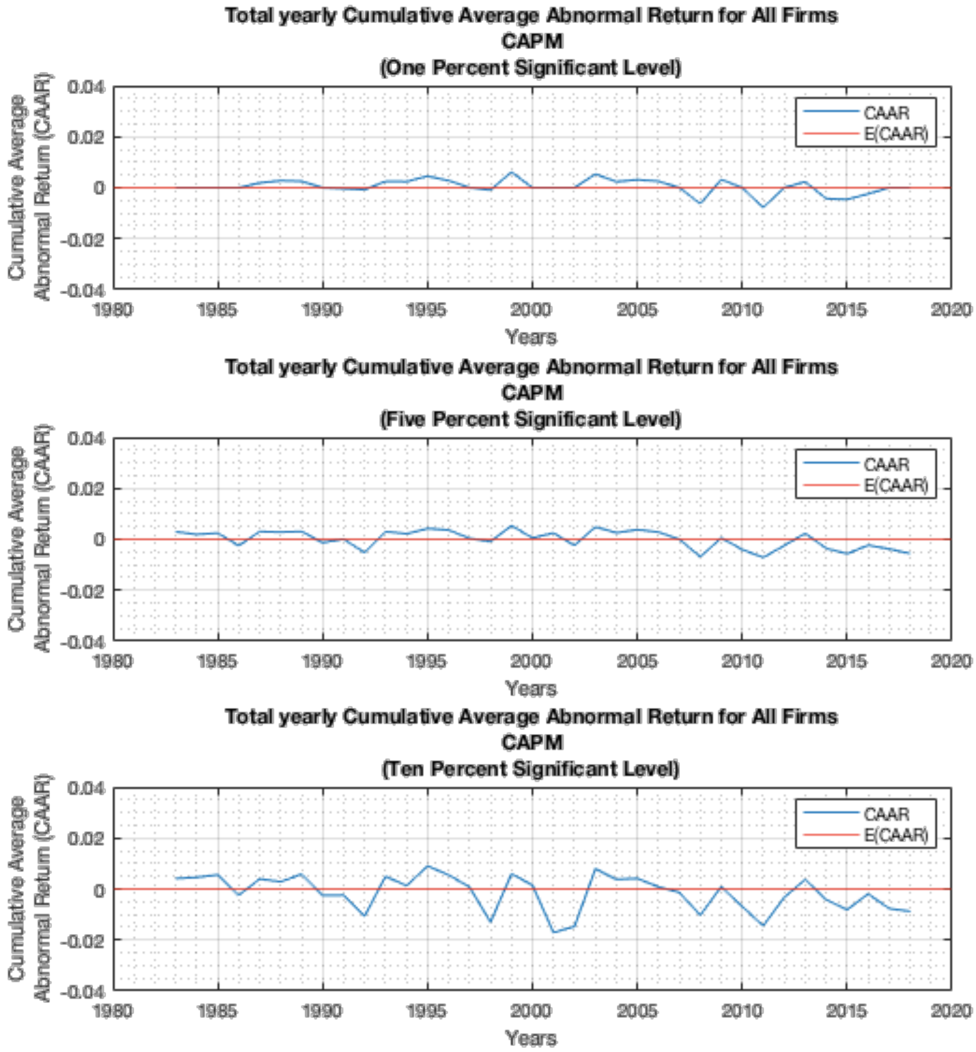


**Figure 7 -** Yearly Cumulative Abnormal Returns for all total firms. Based on the Fama French Three-factor model.

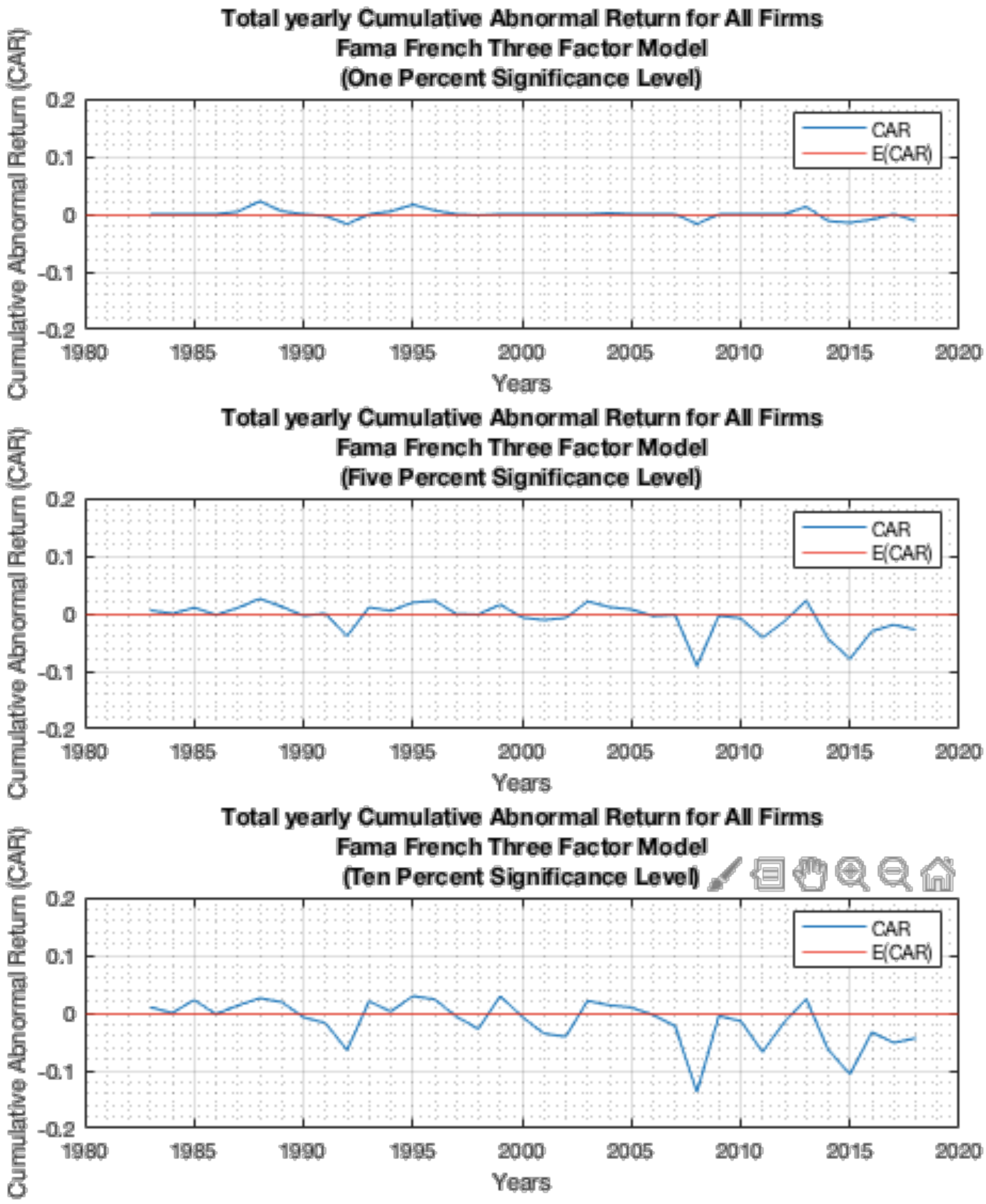


**Figure 8** – Yearly Cumulative Average Abnormal Returns for all firms. We divide by the amount of firms that have alpha significantly different from zero. Based on the Fama French Three-factor model.

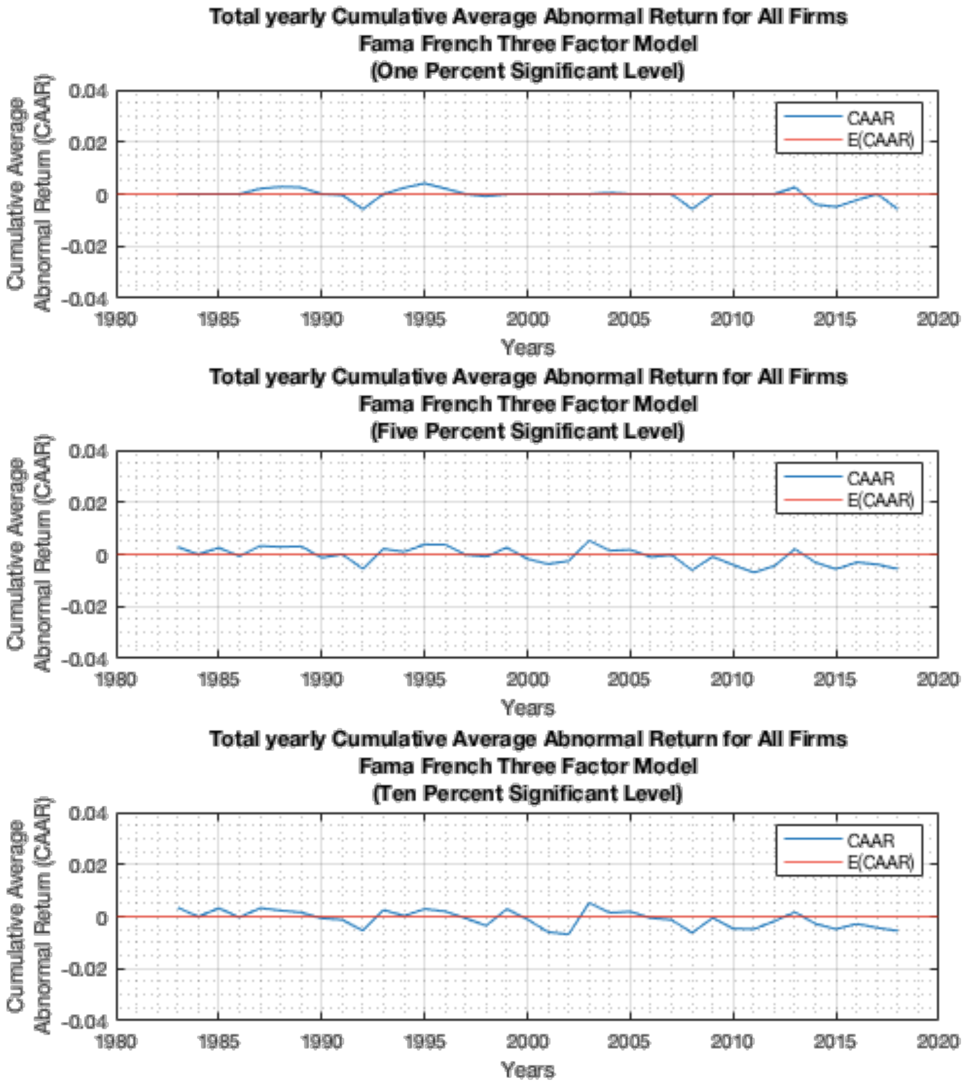


**Figure 9 –** Example. Overview of plots for Cumulative abnormal returns for all firms for one specific event period. Example is based on two-sided significance level of 5% with an event period of +- 2 days.

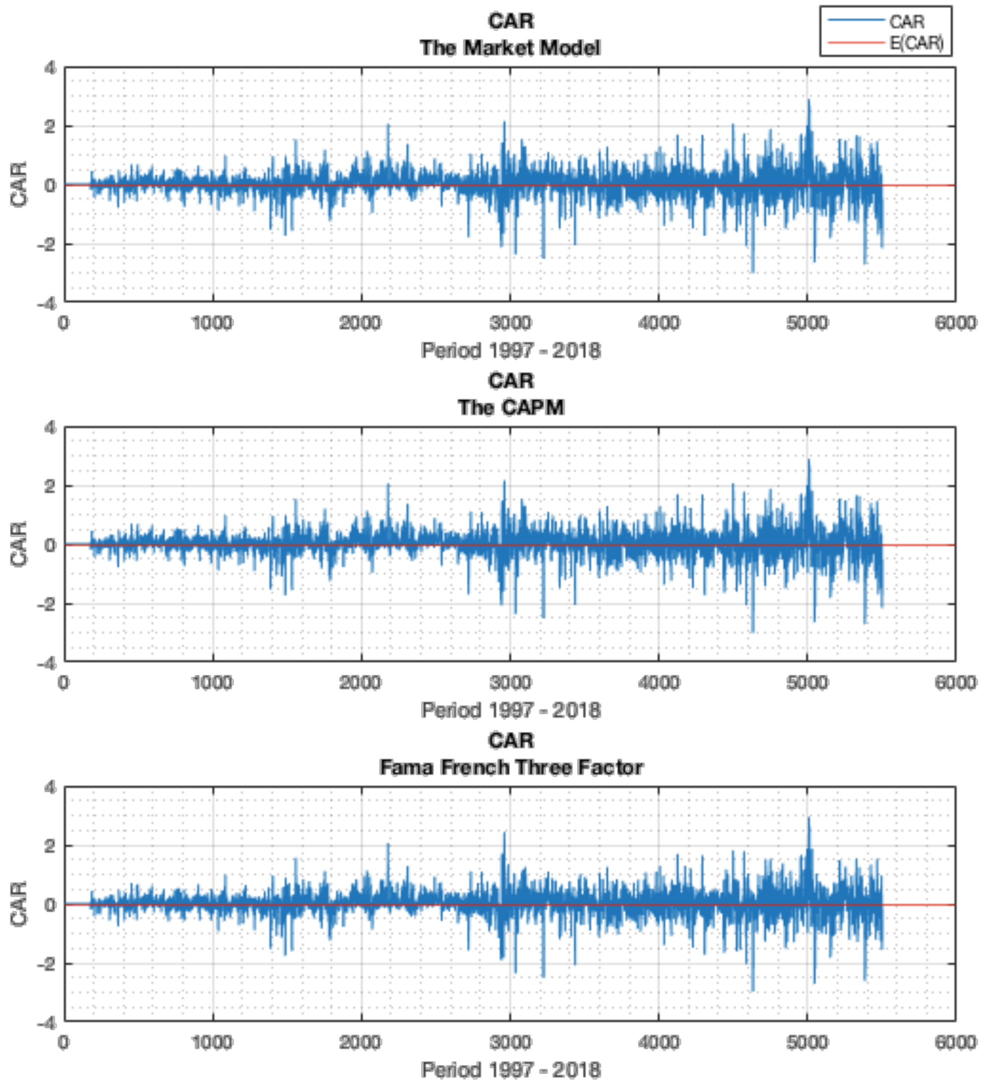


**Figure 10** – Cumulative Average Abnormal Returns. We divide Cumulative Abnormal Returns with the total amount of firms that have significant CAR in the specified event period. This example below is based on our analysis with a 5% significance level for an event period of +- 2 days.

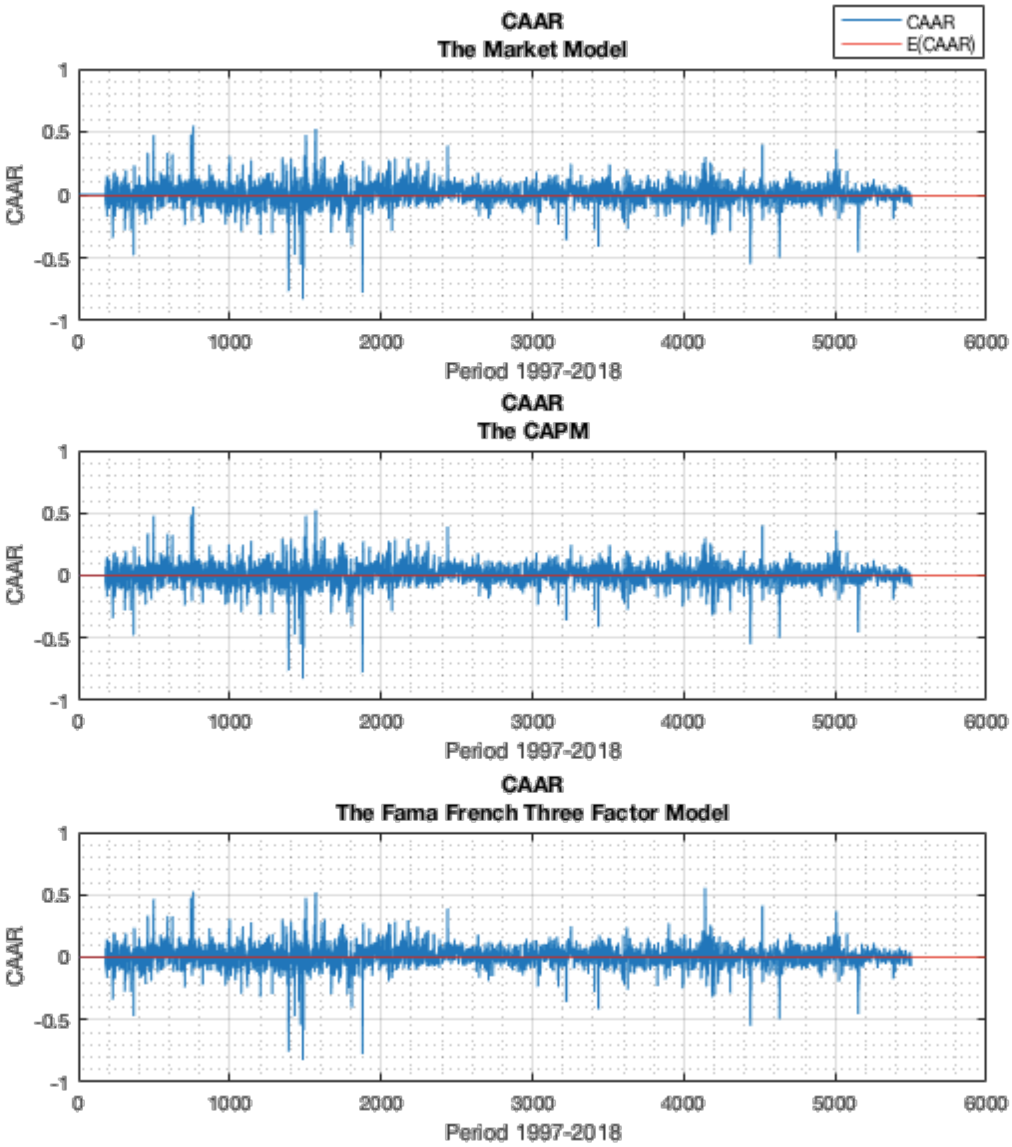


**Figure 11** – Example. Overview of plots for Cumulative abnormal returns for all firms for one specific event period. Example is based on two-sided significance level of 5% with an event period of +- 7 days.

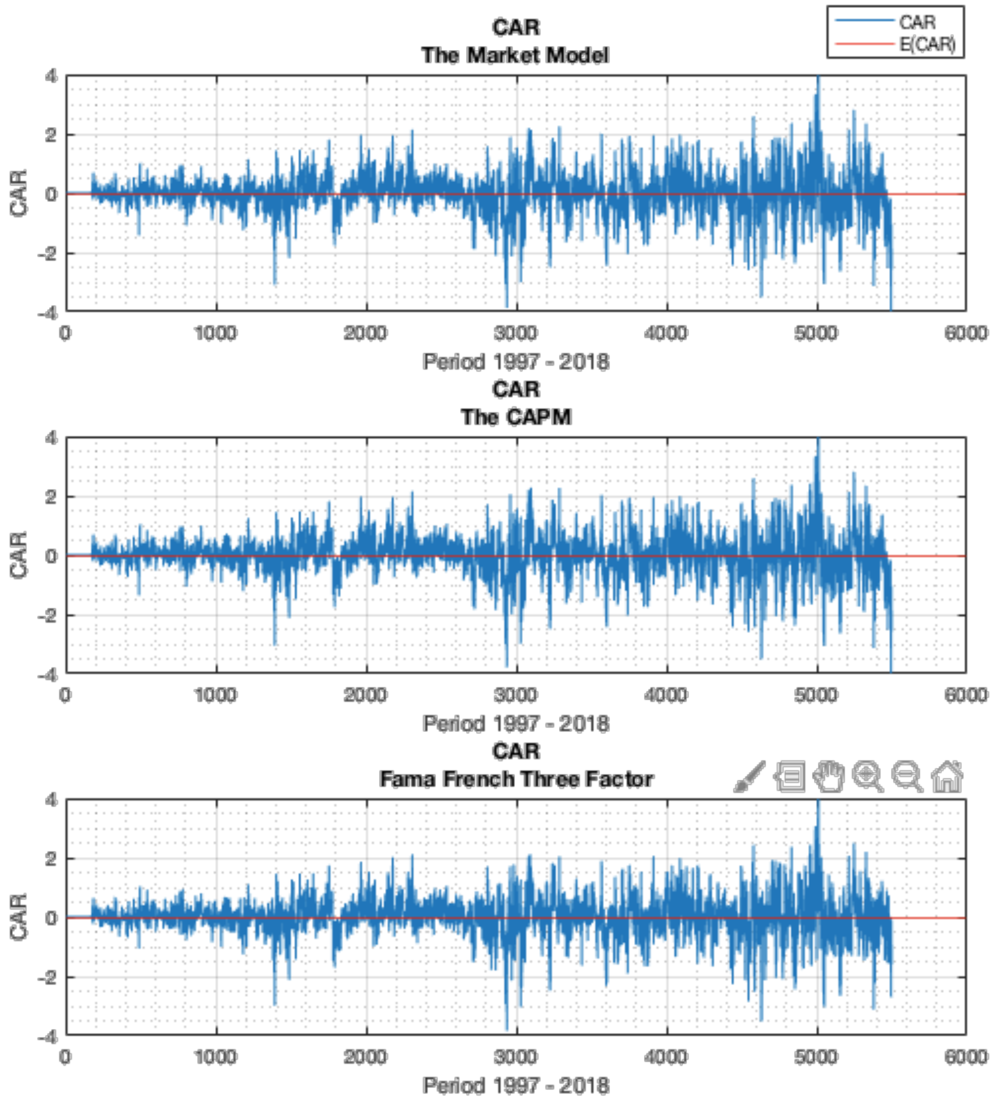
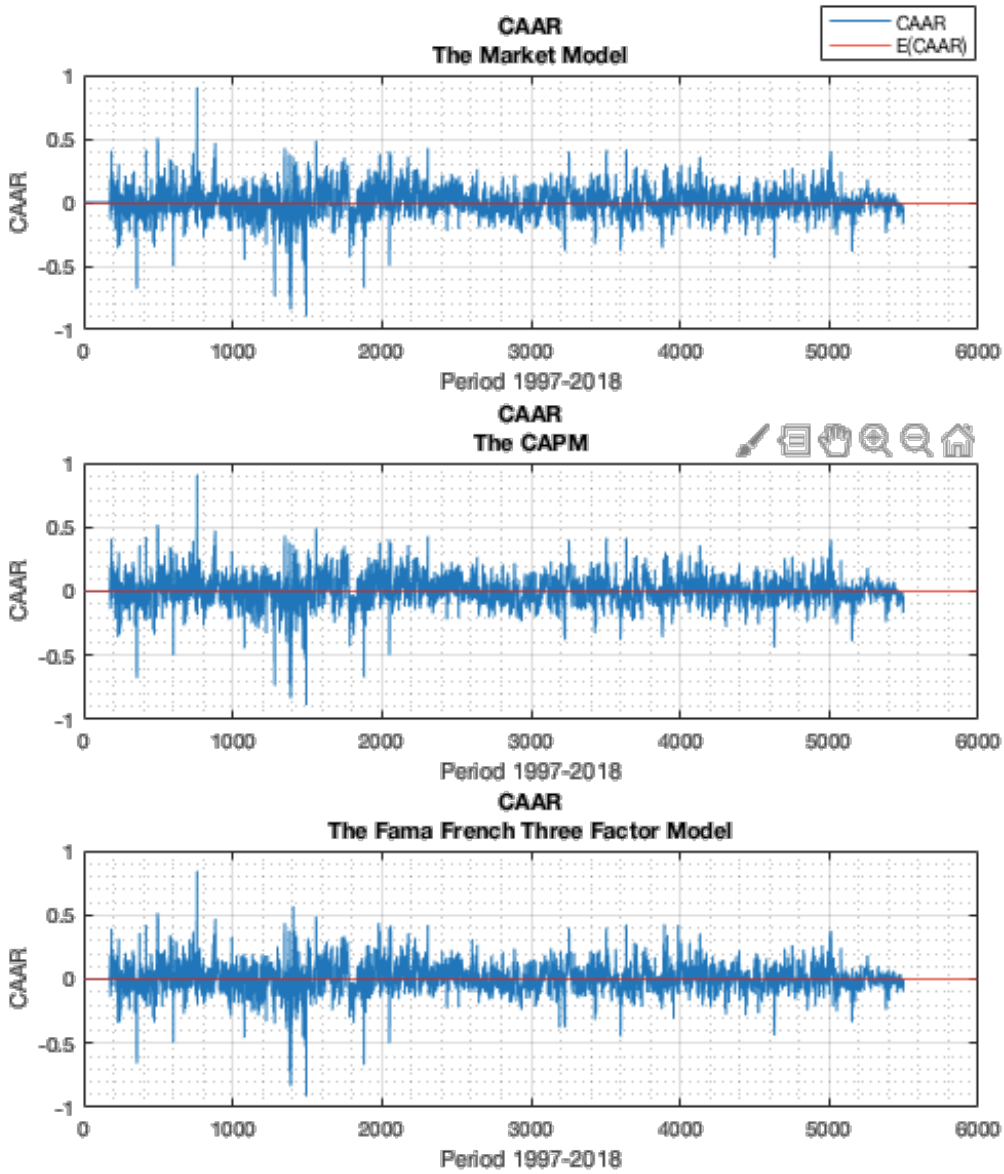


**Figure 12** – Cumulative Average Abnormal Returns (CAAR). We also here divide the Cumulative Abnormal Returns with the number of firms that show CAR significantly different from zero in the specified event period. The below plot is an example based on a 5% significance level for an event period of +-7 days.



# Appendix

## Tables

**Table 1** – Example of how we sorted news-data in excel.

| Date | Time | Year | Ticker | Event |
|---|---|---|---|---|
| 26/04/2018 | 16:23:55 | 2018 | NHY | Norsk Hydro: Primary insiders purchase shares under Long-Term Incentive program and shares to employees (OBI) |
| 03/04/2018 | 08:00:29 | 2018 | NHY | Norsk Hydro: Sale of shares to employees (OBI) |
| 20/02/2018 | 08:12:25 | 2018 | NHY | The Capital Group Companies - Disclosure of acquisition/disposition of large shareholdings -Norsk Hydro ASA (OBI) |
| 07/02/2018 | 13:43:23 | 2018 | NHY | Renteregulering (OBI) |
| ... | ... | ... | ... | ... |
| 08/12/2017 | 13:46:59 | 2017 | NHY | Oslo Børs - NHY06 - Nytt lån til notering / New bond issue to be listed 11.12.2017 (OBI) |
| 04/05/2017 | 07:00:47 | 2017 | NHY | Norsk Hydro: Ex dividend NOK 1.25 today (OBI) |
| 02/05/2017 | 15:05:09 | 2017 | NHY | Norsk Hydro : Salg av aksjer til ansatte (OBI) |
| 03/04/2017 | 12:32:42 | 2017 | NHY | Norsk Hydro: Primary insiders purchase shares under Long Term Incentive program and shares to employees (OBI) |
| ... | ... | ... | ... | ... |
| 03/05/2016 | 07:01:37 | 2016 | NHY | Norsk Hydro : Ex utbytte kr. 1,00 i dag (OBI) |
| 28/04/2016 | 06:58:54 | 2016 | NHY | Norsk Hydro: Sale of shares to employees (OBI) |

**Table 2 –** Average R-squared for all firms, with the three different models from 1983-2018.

| Average R-squared for all firms with different models | | | |
|---|---|---|---|
| **Years** | **Average R-squared (CAPM)** | **Average R-squared (Market Model)** | **Average R-squared (Fama French Three Factor Model)** |
| **1983** | 0,0487 | 0,0487 | 0,0757 |
| **1984** | 0,0807 | 0,0808 | 0,1042 |
| **1985** | 0,0672 | 0,067 | 0,0801 |
| **1986** | 0,0502 | 0,05 | 0,0692 |
| **1987** | 0,1967 | 0,1967 | 0,2173 |
| **1988** | 0,0642 | 0,0642 | 0,0771 |
| **1989** | 0,1052 | 0,1052 | 0,1173 |
| **1990** | 0,1132 | 0,1132 | 0,1293 |
| **1991** | 0,1460 | 0,146 | 0,1626 |
| **1992** | 0,1351 | 0,1351 | 0,1541 |
| **1993** | 0,1094 | 0,1098 | 0,1305 |
| **1994** | 0,1210 | 0,121 | 0,1388 |
| **1995** | 0,0656 | 0,0656 | 0,0818 |
| **1996** | 0,0532 | 0,0532 | 0,0724 |
| **1997** | 0,1257 | 0,1257 | 0,1460 |
| **1998** | 0,1134 | 0,1132 | 0,1283 |
| **1999** | 0,0641 | 0,0641 | 0,0767 |
| **2000** | 0,0741 | 0,0741 | 0,0955 |
| **2001** | 0,0699 | 0,0699 | 0,0907 |
| **2002** | 0,0719 | 0,0719 | 0,0825 |
| **2003** | 0,0527 | 0,0527 | 0,0649 |
| **2004** | 0,0708 | 0,0708 | 0,0962 |
| **2005** | 0,1059 | 0,1059 | 0,1286 |
| **2006** | 0,1448 | 0,1448 | 0,1656 |
| **2007** | 0,1274 | 0,1274 | 0,1435 |
| **2008** | 0,1621 | 0,1621 | 0,1782 |
| **2009** | 0,1009 | 0,1009 | 0,1133 |
| **2010** | 0,1307 | 0,1307 | 0,1489 |
| **2011** | 0,1413 | 0,1412 | 0,1626 |
| **2012** | 0,0913 | 0,0914 | 0,1065 |
| **2013** | 0,0559 | 0,0559 | 0,0720 |
| **2014** | 0,0857 | 0,0856 | 0,1058 |
| **2015** | 0,0851 | 0,0851 | 0,1081 |
| **2016** | 0,0992 | 0,0992 | 0,1201 |
| **2017** | 0,0521 | 0,0521 | 0,0730 |
| **2018** | 0,0959 | 0,0959 | 0,1173 |

**Table 3** – Overview of average R-squared based on different time periods.

| Overview of R-squared based on the different models | | | |
|---|---|---|---|
| | R-squared (CAPM) | R-squared (Market Model) | R-squared (Fama French Three Factor Model) |
| **Mean (1983 - 1991)** | 0,0969 | 0,0969 | 0,1148 |
| **Mean (1992 - 2000)** | 0,0957 | 0,0958 | 0,1138 |
| **Mean (2001 - 2009)** | 0,1007 | 0,1007 | 0,1182 |
| **Mean (2010 - 2018)** | 0,0930 | 0,0930 | 0,1127 |
| **Mean (1983 - 2018)** | 0,0966 | 0,0966 | 0,1149 |
| **Mean (1983 - 2000)** | 0,0963 | 0,0963 | 0,1143 |
| **Mean (2001 - 2018)** | 0,0969 | 0,0969 | 0,1154 |

**Table 4** – Overview over the standard deviations of Cumulative Average Abnormal Returns (CAAR's) with significance levels 10%, 5%, and 1%.

| | | *Descriptive Statistics* | | | | | |
|---|---|---|---|---|---|---|---|
| | | *+ - 7 days event period* | | | *+ - 2 days event period* | | |
| | Significane Level | No. Observations | Std of CAAR 1997 - 2007 | Std of CAAR 2008 - 2018 | No. Observations | Std of CAAR 1997 - 2007 | Std of CAAR 2008 - 2018 |
| **The Market Model** | 10 % | *42192* | 0.1061 | 0.0794 | *38159* | 0.0799 | 0.0586 |
| | 5 % | *36031* | 0.1223 | 0.0902 | *32491* | 0.0886 | 0.0675 |
| | 1 % | 26803 | 0.1486 | 0.1172 | *24070* | 0.1066 | 0.0901 |
| **The CAPM** | 10 % | *42163* | 0.1062 | 0.0788 | *38137* | 0.0803 | 0.0583 |
| | 5 % | *36041* | 0.1221 | 0.0899 | *32499* | 0.0884 | 0.0675 |
| | 1 % | 26823 | 0.1480 | 0.1166 | *24062* | 0.1069 | 0.0908 |
| **The Fama French Three Factor** | 10 % | *42194* | 0.1046 | 0.0771 | *38195* | 0.0793 | 0.0567 |
| | 5 % | *36050* | 0.1190 | 0.0887 | *32547* | 0.0874 | 0.0669 |
| | 1 % | 26780 | 0.1444 | 0.1140 | *24107* | 0.1050 | 0.0893 |