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To what extent do sell recommendations impact stock prices? An event study on DNB's weekly portfolio and how their recommendations can be exploited with shorting strategies.

Amund Linnerud

Stian Lande Walbeck

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Supervisor: Colin Green

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Norwegian University of Science and Technology

Faculty of Economics and Management

Department of Economics

Preface

This thesis concludes the two-year Master of Science in Financial Economics at the Norwegian University of Science and Technology (NTNU). Our interest of recommendation effects was awakened by a series of e24.no and DN.no articles regarding large stock price increases for stocks recommended by banks in the weekly portfolio competition. When looking closer at the effect we speculated that the abnormal movements could be exploited for excessive returns. Formulating our own research question made the modelling and writing more motivating.

We would like to thank our supervisor, Colin Green, for his guidance and support during this process. Finally, we wish to thank each other for a good partnership throughout this semester.

Abstract

A sell recommendation on a stock is an analyst's opinion on already available public information. Theory regarding recommendations states that if no new firm relevant information is disclosed the stock price should not move abnormally. Contrary to theory, previous studies on the Norwegian and international markets find significant event day price movements and our findings are in line with these results. We evaluate the stock price response to a sell recommendation in Dagens Næringsliv's 'weekly portfolio'. The portfolio of interest is constructed by DNB and is published Mondays just before the Oslo Stock Exchange opens. Based on our findings we create several shorting strategies in an attempt to earn excess return above the reference index.

The results are found with the use of an event study. Each time a stock in the weekly portfolio is taken out we look at how the return behaved during the 5 days before and after. The stock's 'normal' return is predicted by the Market Model. The difference between the actual and normal return is referred to as the abnormal return and is aggregated across stocks and time to find the average response to being excluded from the portfolio. Robustness tests like removing extreme values, excluding time periods and by splitting the firms according to market capitalization are conducted to validate the model. To asses the size of the abnormal return we create shorting strategies and their returns are compared with the return of relevant Mondays on OSEBX.

An average abnormal stock price decline of 1.34% appears to be statistically significant but economically insignificant. The baseline strategy's return during the relevant period is lower than the comparable return of OSEBX. An optimized small cap strategy outperforms the index on a risk adjusted basis, but by taking transaction costs into account the excess return vanishes.

Sammendrag

En salgsanbefaling på en aksje er en analytikers oppfatning av allerede tilgjengelig offentlig informasjon. Teori om anbefalinger sier at hvis det er ingen ny og relevant informasjon om en aksje, bør ikke aksjekursen bevege seg unormalt. I motsetning til teorien finner tidligere studier på norske og internasjonale markeder betydelige prisbevegelser etter en anbefaling og våre funn er i tråd med disse resultatene. Vi ser på aksjekursresponsen på en salgsanbefaling i Dagens Næringslivs ukentlige portefølje. Porteføljen av interesse er fra DNB og publiseres mandager like før Oslo Børs åpnes. Basert på våre funn lager vi flere shortingstrategier i et forsøk på å oppnå meravkastning over referanseindeksen.

Resultatene er funnet ved bruk av en hendelsesstudie. Hver gang en aksje i ukesporteføljen er tatt ut ser vi på hvordan aksjekursen bevegde seg i løpet av 5 dager før og etter. Aksjens 'normale' avkastning er predikert med markedsmodellen. Forskjellen mellom den faktiske og den normale avkastningen refereres til som den unormale avkastningen og aggregeres over aksjer og tid for å finne den gjennomsnittlige bevegelsen av å bli ekskludert fra porteføljen. Robusthetstester som fjerning av ekstreme verdier, ekskludering av tidsperioder og oppdeling av selskapene i henhold til markedsverdien gjennomføres for å validere modellen. For å vurdere størrelsen på den unormale avkastningen konstruerer vi shortingstrategier, og avkastningen sammenlignes med avkastningen på relevante mandager på OSEBX.

En gjennomsnittlig unormal aksjekursnedgang på 1,34% ser ut til å være statistisk signifikant, men ikke nok til være økonomisk lønnsomt. Avkastningen til grunnstrategien i den relevante perioden er lavere enn referanseindexen OSEBX. En optimalisert strategi bestående av selskaper med lav markedsverdi har en høyere risikojustert avkastning enn OSEBX, men den blir lavere når man regner med transaksjonskostnader.

Contents

1 Introduction

Every Monday Dagens Næringsliv (DN) publishes DNB's weekly portfolio. This active portfolio consists of four to ten stocks and DNB competes with other large Norwegian banks on who the best stockpicker is. The recommended stocks often receive much media attention in DN and other newspapers. This surge in interest appears to put upward pressure on the stock, consequently leading to a price increase and vice versa for sell recommendations. Theory strongly suggests that analyst recommendations should not influence prices, at least not in a semi-strong form of market efficiency where all public information is already reflected in the stock price [1]. Hence, no abnormal profit should be made by following stock recommendations. In reality, the opposite proves true, and we look closer at the phenomenon. By modelling stock behaviour, we conclude with the use of event study methodology that, on average, stock prices drop 1.34% more than it should compared to its expected return. To profit on this discovery we designed several shorting strategies and backtested them on actual data. Due to several factors the baseline shorting strategy does not beat the market. However, when shorting an optimised portfolio just before the update is announced yields abnormal profits and the small cap strategy has proven to beat the market in four out of five years on a risk adjusted basis.

Shorting is a common strategy allowed in most countries. Shorters bet on a decline of the price, in practise, the investor borrows a stock and sells it in the market. At some point in the future the investor must 'cover' his position, which is done by buying it at current market price and returning it to the person lending it originally. Market participants never know which stock DNB is going to take out, but by shorting the whole portfolio we should profit when one of the stocks are taken out. The stocks not taken out should, according to the random walk hypothesis [2], move randomly over time with zero-mean and normally distributed returns. In our sample, the stocks taken out violates this hypothesis and this market imperfection can be exploited.

Small investors do not have the time nor resources to follow all the equities on the Oslo stock exchange. Therefore, many of them may rely on recommendations from brokers and banks. The main reason for banks to freely distribute their advice is the publicity that comes with it. A population trading more frequently means more fees and higher revenue for the brokerages. But, for the population to engage in such activities they must have trust in the advice given. If a brokerage changes type of recommendation often with the sole purpose of generating more trades and fees their reputation will diminish and media will stop their coverage. This dynamic aligns the incentives of the investors and brokerages. Another reason for publishing their recommendations is to gain the favour of people putting their money in actively traded funds. For example, if DNB have superior stock picking abilities, then a rational investor will surely choose a DNB managed fund over any other providers.

According to DNB, their weekly portfolio recommendations are based on internal recommendations by the respective sector analyst. The recommendations are then sorted on their technical signs such as momentum, trend and Relative Strength Index to optimise the timing. The stocks fulfilling the criteria and fitting with the current portfolio diversification will be given the respective buy, hold or sell recommendation. For a stock to receive a hold or sell recommendation it must already be in the portfolio.

1.1 Contribution

The weekly portfolio competition between the large banks is unique and little research has been conducted to check its influence on the market. DN is the third largest newspaper and the largest financial newspaper in Norway, and their financial advice articles are popular. According to Aksjenorge [3], around 363,000 Norwegians owned at least one stock at the end of 2018. Many of these people trade on their own and read financial newspapers to get information about which stocks to buy or sell. The traction caused by the coverage evidently affect stock prices and volume significantly. The lack of research on the weekly portfolio and the results we find demonstrate a gap in the literature. It is a gap we wish to address. By doing so we can shed light on aspects the investor should consider before acting on the recommendations. Additional understanding of market behaviour promotes higher efficiency and transparency. An investor blindly following recommendations could in practise create a 'losing' portfolio because he often buys and sells too late. A large body of literature focuses on the long- and short-term effects of buy, sell and hold recommendations. However, these typically examine the performance of a stock after it is recommended, and few consider shorting the stock before the sell advice is given.

1.2 Related Literature

The Efficient Market Hypothesis developed by Eugene Fama [1] states that stocks trade at fair value and that investors cannot beat the market consistently. This is because the price already reflects all relevant information about the stock. Fama further defines 3 forms of efficiency - weak, semi-strong and strong. The level of efficiency is heavily debated and the level may vary over time, between countries, sectors and according to the definition used. The weak form claims that historical prices cannot be used to predict future prices. Semi-strong efficiency suggests that all public information is already reflected in the price. The strong form states that all information, insider and public, is accounted for in the price. Since the recommendations do not disclose new information it should not move prices in a strong or semi-strong efficient market. The recommendations merely reflect the analyst's opinion on already available information. Our data suggests that it does affect the price, hence, we suggest that there is a weak form of efficiency. The fact that banks spend large amounts of resources to develop advanced models to predict stock prices also conforms with this belief. Investors following this advice either believe in a weak form of efficiency, that the DNB understands the firm's fundamentals better than others, or that DNB has insider information. In practice, the investor's reasoning is irrelevant to us as we only focus on how to exploit the abnormal movement of the stock after a recommendation is published.

Many research papers have been dedicated to the search for the effects of analyst recommendations. One of the most cited on the topic is by Womack [4], who provides evidence that buy and sell recommendations of stocks by security analysts at major U.S. brokerage firms show significant, systematic discrepancies between pre-recommendation prices and eventual values. The paper further emphasises the large initial movements of the stock when recommended. For a sell recommendation the stock declined abnormally between 1% and 2%, depending on the model used to calculate abnormal behaviour. The dataset used included around 500 observations between 1989 and 1991. Another significant finding in the paper is that buy recommendations occur seven times more often than a sell, suggesting that brokers are reluctant to issue sell recommendations. Since analysts are so hesitant to issue sell recommendations Womack advocated that they carry more information. Womack also argues that the data shows significantly larger stock movements for sell recommendations than for buy recommendations.

Lidén [5] discusses whether the observed abnormal return on the publication day has a temporary effect or a permanent effect. A temporary effect would suggest that the 'price-pressure' hypothesis dominates, which is when recommendations create temporary buying- or selling pressure from investors rebalancing their portfolio. The permanent effect could be explained by the 'information' hypothesis. This theory suggests that the recommendations disclose relevant information and the fundamental market value of the company should be adjusted accordingly. Lidén's study on the Swedish market shows a positive publication-day effect for buy recommendations that was almost fully reversed after 20 days. This may suggest an overreaction due to the positive media coverage. On the other hand, a sell recommendation does not have the same effect, the price continues to drift downwards after a large initial drop and does not revert to its mean. He concludes that buy recommendations behave according to the price-pressure hypothesis, while sell recommendations experience information hypothesis behaviour. Lidén argues that this behaviour results from structural differences between sell and buy recommendations, where a sell recommendation more often discloses fundamental news. His data covers 364 sell recommendations between 1995 and 2000 where the effect was a price decline of 1.5% with a t-value of -8.89 on the publication day. The Swedish market resembles the Norwegian market and an educated guess is that it will behave similarly.

The paper by Lidén also finds evidence of information leakage to clients before publication. A similar tendency was detected in the 1980s in the US where a Wall Street Journal columnist passed information to a broker saying which stocks were going to be favoured [6]. The excess return of 6.25% was then shared between them. The practice was revealed and both parties were sentenced for fraud. Our analysis assumes no leakage of information or any collaboration between the journalists at DN and a third party. This would also be highly illegal and a scandal if it became known to the public.

Chang [7] et al. provides solid proof that adjusted stock returns can also be explained by the magnitude of stock recommendation revisions, brokerage houses' publicity, firm size, firm age, and stock price momentum. These factors are incorporated and assigned much of the variety in our dataset. A small company with infrequent trading should therefore react much more than a large firm like Equinor on the same type of sell recommendation.

DN's weekly portfolio has run from the early 2000's and has motivated a couple of other master's dissertations. One of them is Bjerknes [8] who in 2010 looked at the recommendation effect for the period between 2005 and 2010. He applied the same event study method as described by MacKinlay [9] on around 900 sell and buy recommendations from seven different brokerages. However, during that time period the recommendations were published in the physical newspaper the day after it was distributed to the brokerage's paying clients. This distorts the effect and could bias the result. For the time period we look at, DNB's recommendations are published online at DN.no on the Monday before Oslo Børs opens and are *only* distributed to DN. Bjerknes' thesis also discusses some trading strategies, but, the viable ones try to exploit the buy recommendations. The shorting strategy he presents relies on investors knowing which stocks are going to be taken out, and we believe this to be an invalid assumption. Bjerknes does conclude with similar main results as us, the sell recommendation causes an abnormal negative return of 0.6% on average for all the stocks.

To delve into the mechanics of our research question we will apply an event study methodology first developed by Fama et al. in the 1960s and formalized by MacKinlay in 1997[9] . In short, we observe the stock taken out five days prior and after the event and layer all the cases on top of each other. The result is a graph showing the abnormal return, on average, when taken out. Informative statistics can be created, and inference is valid with a large enough sample size. Some critique of the method has been provided, but it refers mostly to longer time intervals and our 11-day window should not be biased according to Dimson [10]

2 Data Collection and Descriptive Statistics

The weekly portfolio competition has been running since the early 2000s and a number of different banks and brokerages have participated. We have chosen to solely focus on DNB's portfolio since it is the largest bank and therefore should have the largest impact on the market. It is also the bank that has been in the competition the longest.

2.1 Data Collection

DNB's weekly portfolio updates are published online at DN.no before 9 am every Monday or the first working day of the week. DNB's homepage keeps one year of recommendations on a rolling basis. Hence, to find older updates we looked at the record in Dagens Næringsliv, where we found the relevant articles back to the beginning of 2014. Attempts to retrieve older articles and updates proved futile since both DNB and DN did not have them publicly available and they declined our request when asked for older data. This limits our dataset and analysis to five years. To organise the data effectively we created an Excel sheet where the stock names were in the first row and the dates in the first column. There is no online database, therefore we manually entered them into Excel. The specific recommendation was assigned a number: 1 bought, 2 keep and 3 sell. We recognise that this approach is prone to errors since we manually collected it. However, by registering all the individual stocks each time, not only the sell recommendations, we were able to spot when we had overlooked a stock previously since there would be a gap in the dataset. Another issue was that DN's articles were sometimes incomplete or wrong. A stroke of luck however is that DN every now and then publish a table with the dates of inclusion and exclusion of their recent stocks. This made it easy to doublecheck the data we had.

Daily prices and traded value from the respective stocks and the OSEBX index for the period were collected using a Python program, which took a ticker list from all the stocks in DNB's portfolio as input, downloaded their closing prices from Netfonds's database and returned it as a CSV file in the same format as the table containing the recommendations. This made it easy to systematize the data across spreadsheets and to extract only the price and traded value for a given stock on the day it was taken out of DNB's portfolio.

2.2 Descriptive statistics

Our data spans from 02.01.2014 to 21.12.2018 and relevant descriptive statistics are shown in table 1. During this period 228 weekly portfolio updates have been published by DN, and DNB has made a total of 137 sell recommendations. 164 stocks were included in DNB's portfolio, however, many of them were included twice or more. A total of 58 unique stocks were included during the period, with Telenor being the most frequent counting 11 times. See table A1 in the appendix for the full frequency list of individual stocks. The total number of stocks in DNB's portfolio is higher than the total number of sell recommendations. This is because when the portfolio is closed at the end of the year, the stocks still in the portfolio are not considered as a sell recommendation. Also, in 2016 the competition and coverage were paused between the 7th of June and the 13th of September because Nordea withdrew and too few competitors participated. When the competition began again, DNB had made some changes to their portfolio, but the stocks which were included before and not after are not considered as a sell recommendation.

The weekly update is not limited to a number of sell and buy recommendations and the amount of stocks in the portfolio varies from four to ten with an average of 7,5. DNB does not recommend their own stock even though it is one of largest companies listed. DNB covers just below 100 of the 184 stocks on Oslo Børs as of April 2019. These numbers vary a bit over time, but the important point is that not all stocks are covered. Hence, the range of possible stocks is somewhat limited and to use the OSEBX index as a benchmark is not a perfect match.

Table 1: Descriptive Statistics of DNB's weekly portfolio.

	2014	2015	2016	2017	2018	**Total**
Weekly portfolio updates published by DN	49	49	36	47	47	**228**
Total number of stocks in DNB's portfolio	29	36	40	28	31	**164**
Unique stocks in DNB's portfolio	21	24	29	23	29	**58**
Sell recommendations	23	29	30	28	27	**137**

3 Statistical concepts and method

Inference from the data must be based on credible methods and this section provides an overview of the aspects needed to do so.

3.1 Statistical concepts

To draw conclusions from our data we rely on the normal distribution of returns. The central limit theory states that averages of observation samples of random variables independently drawn from independent distributions become normally distributed when the number of observations is sufficiently large. We assume that 137 observations are enough for the sample mean to correctly predict the population mean. That is, if the inference on our data says that, on average, the sell recommendation decreases the stock price abnormally by 1.34% this would be true for the population as well.

Another useful application of the normal distribution arises when we choose our observation interval. The weekly portfolio recommendations are published between 8.45 a.m. and 8.55 a.m. This is before the stock exchange opens, but pre-trade auctions are in effect. This means that investors can place orders on the the recommended stocks on prices below/above the official opening price for the day. Hence, using the official opening price would not reflect the full effect of getting recommended. However, it is the only data available to us and we have therefore chosen to use the closing price for the day ahead. This means that the analysis reflects price movements between close Friday and close Monday. A critique could be that news during the weekend could distort the price and bias our result. However, we believe that the news are just as likely to be negative as positive. We assume normal distribution of the returns during the weekend. To argue for this view we have calculated all the returns between close Friday and open Monday to show that there is no tendency to increase or decrease. If anything, there is a small skew towards positive weekend returns. The graph is calculated from 4917 observations where we only look at the stocks included in the respective year.

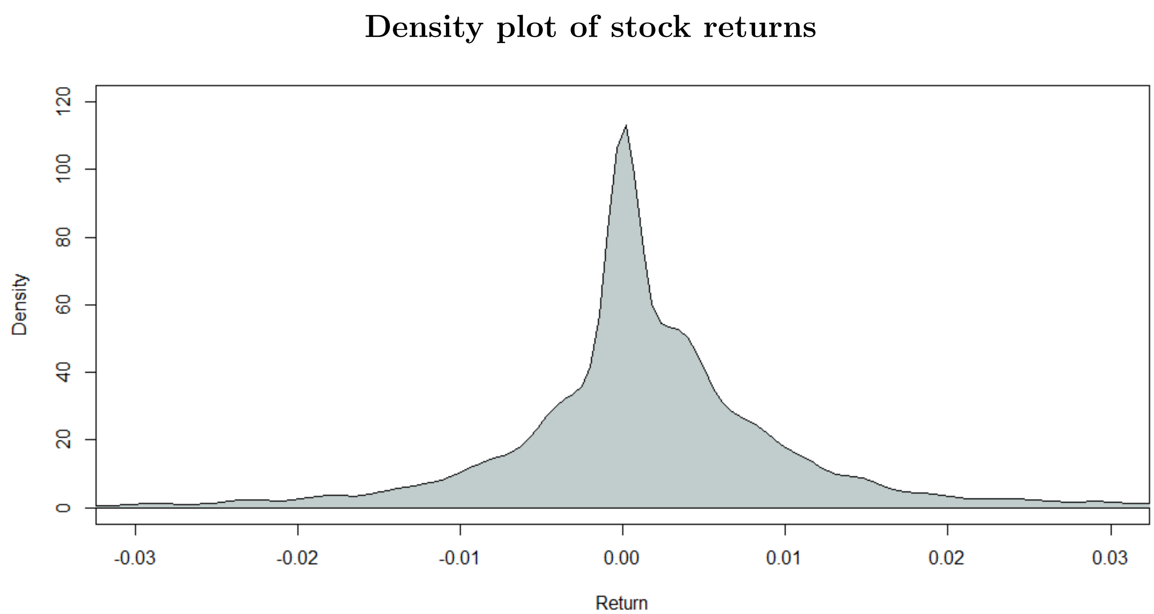

Figure 1: Distribution of the returns from close Friday to open Monday for all stocks included in DNB's weekly portfolio between beginning of 2014 and end of 2018.

Table 2: Summary statistics of the returns from close Friday to open Monday for all stocks included in DNB's weekly portfolio between beginning of 2014 and end of 2018.

Observations	**Average**	**Median**	**Max**	**Min**	**Std dev**
4917	0.0017	0.0000	-0.1274	0.1434	0.0116

From figure 1 and table 2 we see the density and statistics of the returns from close Friday to open Monday. We observe that the returns are close to normally distributed with a mean around zero. While is is possible to test whether the dataset is normally distributed or not, we feel a visual test is sufficient. We believe the assumptions of the weekend returns being normally distributed to be fair based on a visual test.

3.2 Event Study Methodology

To examine how the respective stock reacts to a sell recommendation we apply the event study methodology described by MacKinlay [9]. The method is appropriate when analysing many distinctive and similar shocks that happen in the same market. By aggregating the specific events we can find the average response of the shock. We look at the price movement in an 11 day time window. The objective is to test whether the price movement on the day the stock receives a sell recommendation is significantly different from zero. The random walk hypothesis is assumed to be valid in the short term, meaning that, on average, the price movement from day to day is zero. Any statistically significant deviation from this suggests that the sell recommendation has an effect on the stock price.

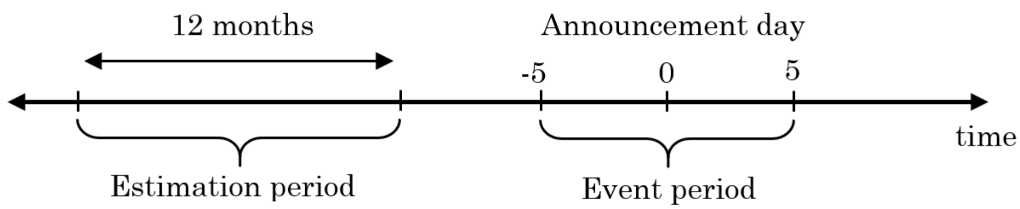

Figure 2: Timeline of the event study showing that the Market Model's predictors are based on the 12 months estimation period ahead of the event. The announcement day is day '0'.

Figure 2 illustrates the timeline of our event study. The estimation period is used to calculate the parameters in our model. The estimation period does not include the event period in order to prevent it from influencing the normal performance of the model parameter estimates. E.g. the parameters used to calculate the abnormal return of the stocks in DNB's portfolio for 2014 is calculated using data from 2013.

To conduct inference on the dataset we require a measure of abnormal and expected return. The abnormal return is defined as the actual ex post return of the stock over the event window minus the expected return over the same time period. For stock i and event date t the abnormal return is defined as

$$AR_{i,t} = R_{i,t} - E[R_{i,t}] \tag{1}$$

where $R_{i,t}$ is the actual observed return and $E[R_{i,t}]$ is the expected return.

To predict how the stock would behave if no sell recommendation was given the Market Model is used. It is the most common model and is often preferred over the alternative 'Constant Mean Return Model' due to its superior explanatory power. A third option is to extend the Market Model to a Factor Model but according to MacKinlay [9] the additional gain from the multifactor models is limited and is therefore not applied in this case. The Market Model and its properties are defined as

$$\begin{aligned} &R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t} \\ &E[\epsilon_{i,t}] = 0 \\ &VAR[\epsilon_{i,t}] = \sigma^2_{\epsilon_i} \end{aligned} \tag{2}$$

The model says that the return on stock i at time t depends on the return on a market portfolio, $R_{m,t}$, the stock's responsiveness as measured by β_i and the intercept α_i. We have chosen to use the Oslo Stock Exchange Benchmark Index (OSEBX) as our market portfolio as it is an investible index which comprises the most traded shares listed on Oslo Børs. It also makes it a good comparison when looking at the alternative-cost of our trading strategy. OSEBX is semi-annually revised and free float and dividend payment adjusted. $\epsilon_{i,t}$ is the disturbance term for stock i at time t, and has expected value of zero and a constant variance. Its purpose is to capture any unexpected shock that affects the stock return.

The coefficient β_i is estimated using the Ordinary Least Squares (OLS) approach. It is a measure of systematic risk for the individual stock i and is calculated using the daily returns for the year prior to when it was taken out.

$$\hat{\beta}_i = \frac{\sum_{t=1}^{T}(R_{i,t} - \bar{R_i})(R_{m,t} - \bar{R_m})}{\sum_{t=1}^{T}(R_{m,t} - \bar{R_m})^2} \tag{3}$$

The averages $\bar{R_i}$ and $\bar{R_m}$ are defined as

$$\bar{R_i} = \sum_{t=1}^{T} \frac{1}{N} R_{i,t} \qquad \bar{R_m} = \sum_{t=1}^{T} \frac{1}{N} R_{m,t} \tag{4}$$

$$\hat{\alpha}_i = \bar{R_i} - \hat{\beta}_i \bar{R_m} \tag{5}$$

The alpha parameter is the intercept from the regression and shows the difference between the average stock return and the return predicted by CAPM. The efficient market hypothesis suggests that this is equal to zero. The expected return of stock i at time t is defined as

$$E[R_{i,t}] = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} \tag{6}$$

Substituting (2) and (6) into (1) we get

$$\begin{aligned} AR_{i,t} &= \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t}) \\ &= \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t} - \alpha_i - \beta_i R_{m,t} \\ &= \epsilon_{i,t} \end{aligned} \tag{7}$$

If the general Ordinary Least Squares conditions hold, the estimator is consistent and unbiased so that $\hat{\alpha}_i = \alpha_i$ and $\hat{\beta}_i = \beta_i$. The parameters cancel each other out, and the abnormal return is explained solely by the residual. This is intuitive since if there is no unexpected movements in the stock it should behave according to the model. And if it behaves as predicted there is no abnormal return. The predicted abnormal return is defined as $\widehat{\mathrm{AR}}_{i,t}$.

From equation (7) we formulate our null hypothesis, stating that the predicted abnormal return, represented by the residual, for the day of recommendation equals zero.

$$
\begin{aligned}
H_0 &: \widehat{\mathrm{AR}}_{i,t} = 0 \\
H_A &: \widehat{\mathrm{AR}}_{i,t} \neq 0
\end{aligned}
\tag{8}
$$

By failing to reject the null hypothesis the conclusion would be that DnB's stock recommendation does not affect the stock price. A rejection of H_0 would support our theory of abnormal return.

The null hypothesis is tested using a two sided t-test. This test is effective when checking whether the mean of two samples is significantly different from each other. Since our null hypothesis states that the abnormal return is zero we will test if the mean of the return on the event day is statistically different from zero. The t-test is valid under the assumptions of random sampling, normal distribution, large enough sample size and same variance in the two samples.

$$
t_t = \frac{\overline{\widehat{\mathrm{AR}}}_t - E[\overline{AR_t}]}{\sigma_t/\sqrt{N}} \tag{9}
$$

$\overline{\widehat{\mathrm{AR}}}_t$ is the predicted average abnormal return for all the stocks at time t and $E[\overline{AR_t}]$ is the expected average abnormal return, which under the null is equal to zero. σ_t is the standard deviation of the predicted average abnormal return and N is the number of observations. If the t-test statistic is above a critical value, the null can be rejected and we accept the alternative hypothesis. The critical value is found in the t-distribution table with $N-1$ degrees of freedom. For a large sample like our data, the critical value for a 5% significance level is ± 1.96 and ± 2.576 for a 1% significance level.

To draw overall inferences for the event of interest, that is, the day DNB takes a stock out of their portfolio, we aggregate the predicted abnormal return over a time-window and across the stocks. Our time-window for the cumulative abnormal return (CAR) is five days before and after the event, and is defined in equation (10). The CAR can also be illustrated graphically and if our H_0 is rejected the graph would show a significant drop at the event day. If we fail to reject H_0 the graph would be a relatively straight line with no statistically significant deviations.

$$\widehat{\mathrm{CAR}}_i = \sum_{t=-5}^{5} \widehat{\mathrm{AR}}_t \tag{10}$$

4 Results and robustness testing

4.1 Results from the event study

By following the procedure explained in the last section we get the following graph that represents the cumulative abnormal return. The 11 day event window covers a total of 1494 predicted abnormal returns.

Cumulative Abnormal Return during the event window

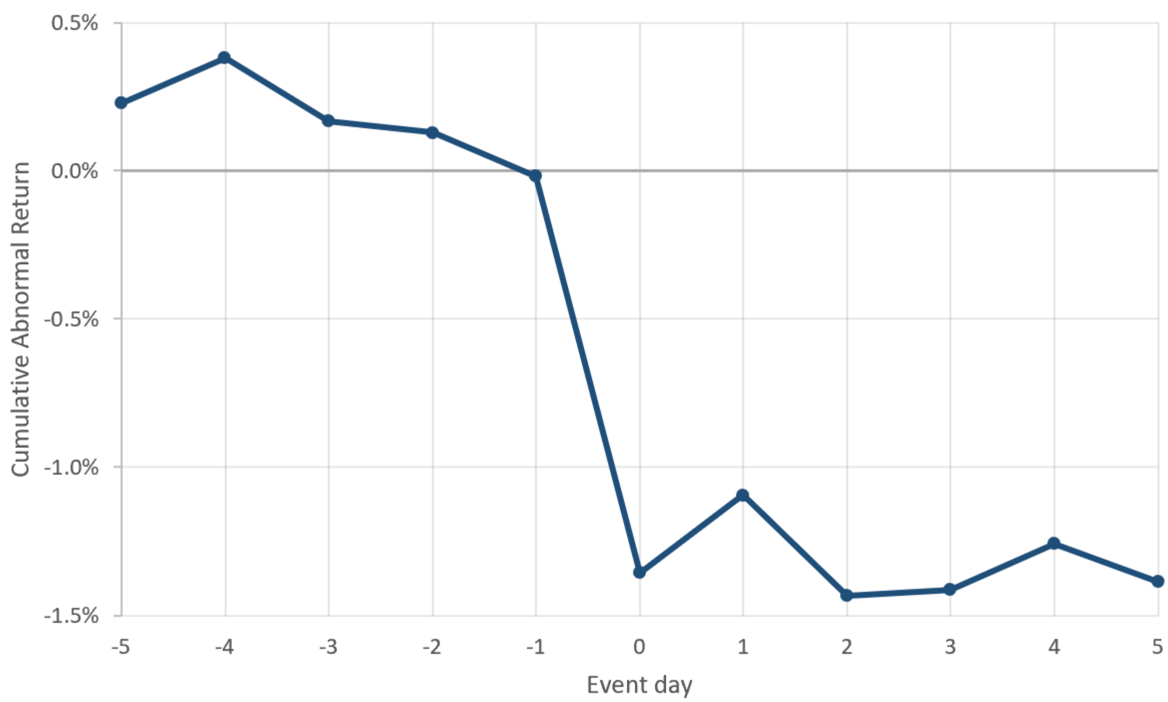

Figure 3: Cumulative Abnormal Return during the event window for the stocks given a sell recommendation by DNB in their weekly portfolio. The X-axis is days where '0' is the event day, '-1' represents the day ahead and '1' is the day after the event and so on. The Y-axis is the percentage point deviation between the predicted return from the Market Model and the actual return.

The horizontal axis represents the days, where t = 0 is the day the sell recommendation is given, usually the Monday and is referred to as the event day. t = 1 is the day after the event, usually a Tuesday. t = -1 is the day before, usually a Friday etc. The large drop happens from the closing time on t = -1, until closing time on the event day. The points represents the cumulative abnormal return and is the the graphical version of table 3. Hence, a flat line would be the theoretical model with no abnormal return. During the days before the event, from t = -5 to t = -1 the line is almost flat and with a significance level of 5% the distance away from zero is statistically insignificant. This means that the actual market behaviour is close to what the Market Model predicted. Also, it supports the comment from DNB that they do not disclose any recommendation to insiders before it is published. The drop between t = -1 and t = 0 is a movement the model did not predict, and is on average 1.34% with a t-value of -6.73. Based on this we can conclude that there is a significant negative abnormal return on the stocks DNB takes out of their portfolio between close Friday and close Monday with a 5% and 1% significance level. The movement after the event day resembles the market model as well, except the return on day t = 2. Its t-value of -2.13 is significant at 5% but we have no explanation for this.

Table 3: Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	St dev	t-value	DF	p-value
-5	0.23%	0.23%	0.0208	1.277	136	0.2036
-4	0.15%	0.38%	0.0203	0.879	136	0.3809
-3	-0.21%	0.17%	0.0224	-1.113	136	0.2678
-2	-0.04%	0.13%	0.0214	-0.214	136	0.8313
-1	-0.15%	-0.02%	0.0200	-0.862	136	0.3904
0	**-1.34%**	**-1.36%**	**0.0231**	**-6.730**	**136**	**0.0000**
1	0.26%	-1.09%	0.0184	1.646	134	0.1021
2	-0.34%	-1.43%	0.0185	-2.130	134	0.0350
3	0.02%	-1.41%	0.0174	0.136	133	0.8918
4	0.16%	-1.26%	0.0180	0.999	133	0.3197
5	-0.13%	-1.39%	0.0201	-0.728	133	0.4679

Figure 4 shows the abnormal return for each day with a 95% confidence interval. Meaning that were this procedure to be repeated on numerous samples, the fraction of calculated confidence intervals (which would differ for each sample) that encompass the true population parameter would tend toward 95% [26].

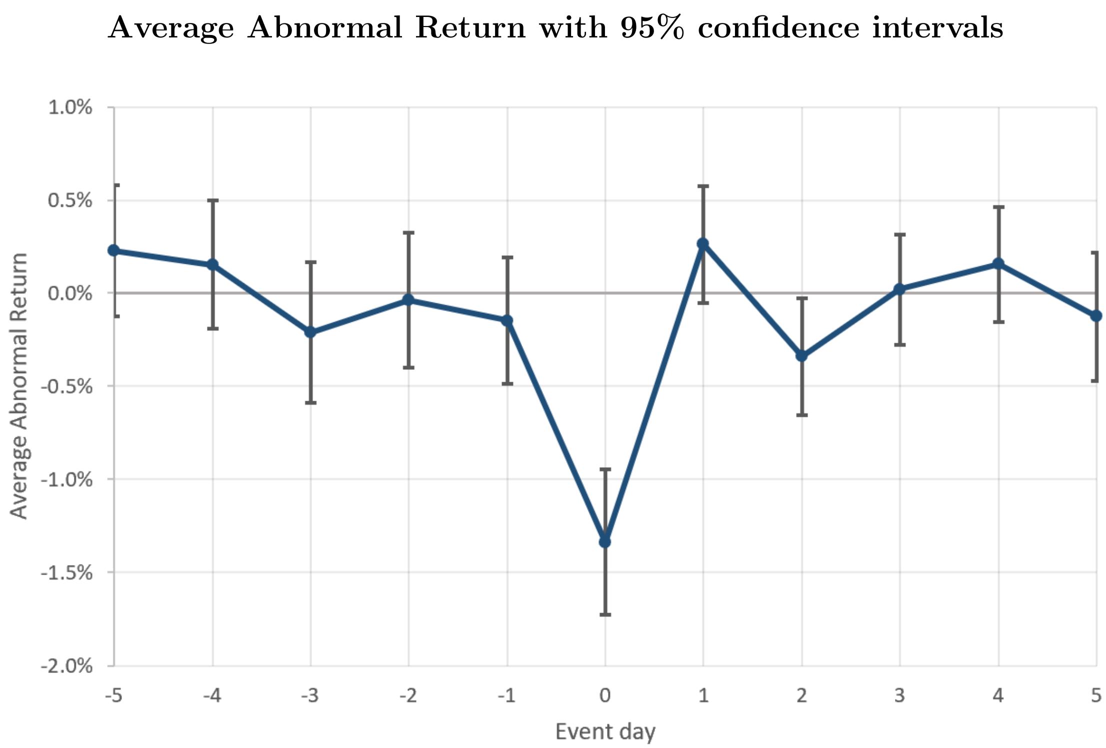

Figure 4: The abnormal return with 95% confidence intervals over the event window for the stocks given a sell recommendation by DNB in their weekly portfolio. The X-axis is days where '0' is the event day, '-1' represents the day ahead and '1' is the day after the event and so on. The Y-axis is the the average percentage point deviation between the predicted return from the Market Model and the actual return.

The confidence interval graph supports the CAR graph, and it is clear that the event day drop is significantly different from zero.

Similar to the findings of Womack [4], we find that the drop is between 1% and 2% for pre-recommendation prices and eventual values. His dataset is three times as large, but quite old. The information flow in 1989 and in present day markets is not even comparable, but the effects of the recommendations still affect the market with the same magnitude. The dataset used by Lidén [5] showed a decline of 1.5% and the master's thesis by Bjerknes [8] concludes with a significant drop of 0.6%. All the previous literature supports our result of a significant drop.

4.2 Robustness

> *"Statistical models are always simplifications, and even the most complicated model will be a pale imitation of reality"* - Keele [11]

It is nearly impossible to specify a model correctly. We have chosen a model which resembles the market, but we must recognise its shortcomings. Instead of optimising the specification of the Market Model we modify the dataset with plausible alternatives. If our robustness tests find similar or the same results as the original model we can regard our model as more certain and it increases the validity of our inferences.

By excluding extreme movements in the event-window we still end up with the same result. Dividing the stocks according to market capitalisation also yields similar results, where smaller firm are more prone to recommendations than the large firms. Removing certain years from the dataset and re-running the procedure also shows a comparable drop. It is important to realise that the statistical properties deteriorate when the dataset becomes smaller, but we believe the results still give important insights.

4.2.1 Extreme values

By excluding the outliers we decrease the chance of including stock movements that are not the result of receiving a sell recommendation. Stock specific news like quarterly reports, accusations of infringements, change in management, takeover news etc. that just happen to coincide with DNB recommendations can affect the price a lot. To avoid the inclusion of events like these, we have run tests where predicted abnormal returns above 5% to 8% are omitted from the dataset. Setting lower limits removes too many observations and higher removes too few.

Table 4 shows the t-test results from the different limits and the number of observations that are omitted from each day. See appendix table A2 to A5 for the full tables including all event days.

Table 4: Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The 'Limit' column represents the level at which extreme values above are excluded. The 'Omitted obs' column shows how many observations that are excluded. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Limit	Day	Omitted obs	Average AR	Std Dev	t-value	DF	p-value
	-1	4	-0.32%	0.0142	-2.576	132	0.01
5.00%	**0**	**9**	**-1.01%**	**0.0163**	**-7.007**	**127**	**0.00**
	1	5	0.14%	0.0155	1.014	129	0.31
	-1	3	-0.35%	0.0147	-2.771	133	0.01
6.00%	**0**	**4**	**-1.10%**	**0.0187**	**-6.744**	**132**	**0.00**
	1	1	0.21%	0.0176	1.390	133	0.17
	-1	3	-0.35%	0.0147	-2.771	133	0.01
7.00%	**0**	**4**	**-1.10%**	**0.0187**	**-6.744**	**132**	**0.00**
	1	0	0.26%	0.0184	1.640	134	0.10
	-1	3	-0.35%	0.0147	-2.771	133	0.01
8.00%	**0**	**4**	**-1.10%**	**0.0187**	**-6.744**	**132**	**0.00**
	1	**0**	0.26%	0.0184	1.640	134	0.10

Comparing with table 3 we observe that the average predicted abnormal return on day t = 0 has decreased for all limits. Day t = 0 is also the day with the most excluded observations, however, the t-statistics are still significant at a 1% significance level. The average predicted abnormal return for day t = -1 has also decreased for all limits and is now significant. When increasing the limit from 6% to 8% the number of omitted variables for day t = -1 does not change and the respective results are therefore identical. With a limit of 5% and 8%, day t = 2 becomes significant at a 5% significance level with an average predicted abnormal return of -0.29% and -0.34% respectively. With a limit of 6%, day t = -3 also becomes significant with an average predicted abnormal return of -0.34%. Day t = 1 and the other days in the event window have about the same result as in table A8 and remain insignificant. This is because these omitted observations had no or little effect on the average or that there were no omitted observations these days.

4.2.2 Market capitalisation

Another potential factor causing bias could be the size of the firm. Chang et al.[7] argues that a smaller firm with less frequent trading on the stock market is more sensitive to recommendations than a larger firm. This is intuitive since when the trading volume is low there are fewer stocks available and with a spike in either buy or sell orders the effect becomes larger. By splitting the dataset where we compare the abnormal return of the smallest firms to the largest firms we can check the validity of the statement. The dataset is divided into three segments based on their market capitalisation (mcap) value from the end of the year they were in DNB's portfolio. A stock that was in DNB's portfolio more than one year can therefore be in two different categories if its mcap changed a lot. 'Small' is firms up to 9 billions NOK in mcap, 'medium' is in the range of 9 billions to 25 billions and 'large' contains firms above 25 billions. The mcap values are set to their respective intervals to create equal size portfolios and not on any definition of what a small, medium or large firm actually is.

Figure 5 shows the abnormal return for the different mcap categories and it is in line with the findings by Chang et al.[7]; small firms react more than larger firms. In fact, each time we decrease the mcap, the event day decline in abnormal returns becomes larger.

Cumulative Abnormal Return for portfolios with different market cap

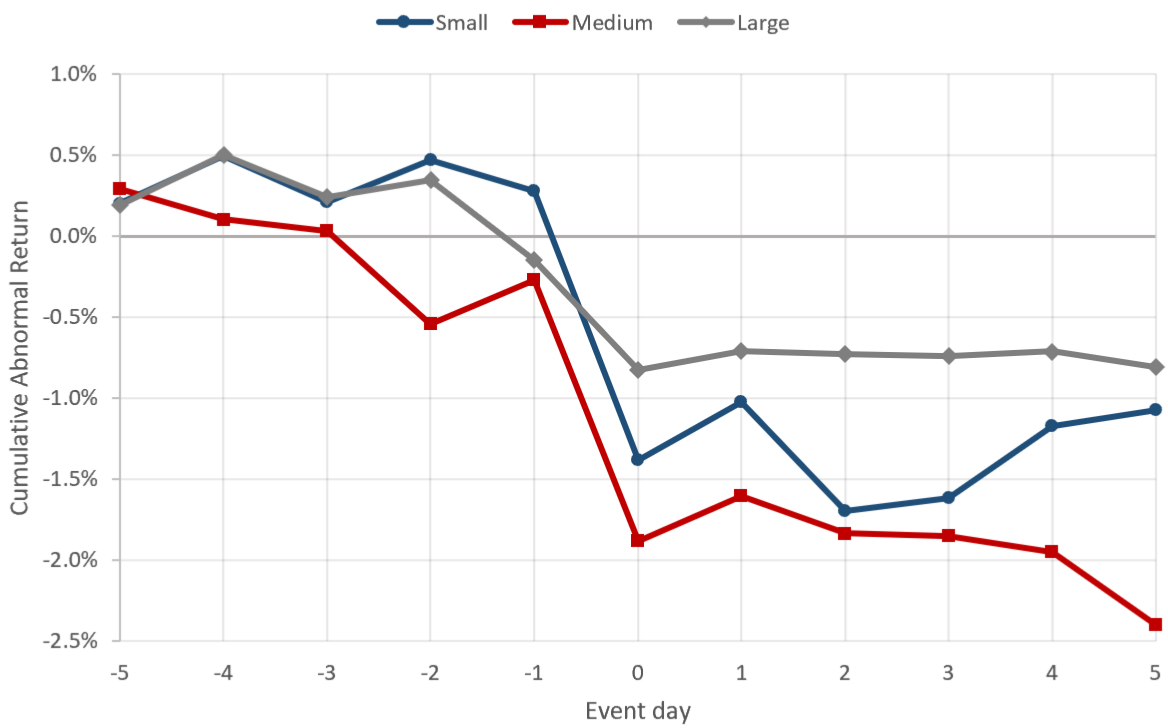

Figure 5: Cumulative Abnormal Return for portfolios with different market cap. 'Small' is firms with mcap lower than 9 billion NOK, 'medium' is between 9 billion and 25 billion NOK, and 'large' contains firms above 25 billion NOK. The X-axis is days, where '0' is the event day, '-1' represents the day ahead and '1' is the day after the event and so on. The Y-axis is the cumulative percentage point deviation between the predicted return from the Market Model and the actual return.

The respective drops are -0.68% (-3.442), -1.61% (-3.570), and -1.66% (-5.062) for large, medium and small firms. The t-value is given in parenthesis and for number of observations above 30 the critical value is ±2.042 at a 5% significance level. The t-statistic for each drop is above 2, suggesting that they are significantly different from zero. Another test conducted divided the dataset into two, where 14 billion mcap is the middle.

The results were more statistically robust, with -1.79% (-5.994) for the bottom half and -0.88% (-3.554) for the top half. See table A9 and A10 in the appendix for the complete results.

Since many of the firms are included several times, either in the same year, or in another year, the result must be viewed with caution. For example, in the ‘large’ firm portfolio, there are only 11 different firms, and Telenor is taken out from the weekly portfolio 11 times. This problem is less prominent for the small cap firms. Another issue is that some of the large firms, especially Equinor, affect the return of the index and hence the market model estimation. The prediction of abnormal return is based on the difference between the expected and actual return. When the stock affects the index we are likely to have a bias. For instance, in the start of 2019, Equinor represents 18.6% of the index [12], hence, when Equinor is taken out of the portfolio and subsequently drops (increases) in price the index will also drop (increase). The abnormal return will be skewed because Equinor and OSEBX co-move and the difference between the actual and predicted return will be too small. A solution could be to use another market as index, but this is beyond the scope of this thesis and will not be pursued any further.

4.2.3 Excluding specific years

Certain years could have a large enough impact to make the average of the whole five year dataset skewed. For example, an economic recession like the one experienced around 2008 could have changed the conclusion. When shorting during a large recession the profits are big and our strategy might appear better than how we expect it to perform in a ‘normal’ market. To examine this potential bias one year at the time is excluded. The event study methodology is then run on the remaining observations, usually around 110. The data output can be found in the appendix table A11 to A15, while the graphical result is shown in figure 6.

All the lines have the same trend as the total cumulative abnormal return graph of our baseline model. The event day drop is significant for each scenario at a significance level of 1%. The largest drop occurs when the data from 2014 (dark blue) is excluded and the smallest happens when the data from 2018 (orange) is left out. This means that the data from 2014 does not show a large event day drop. 2018 on the other hand has the largest event day drop. By dropping the observations from 2016 the line in grey shows how the model behaves differently. This is because several extreme values appear in the days before the event. Overall, the model still holds and this robustness test strengthens our baseline model further.

Cumulative Abnormal Return for portfolios with different years excluded

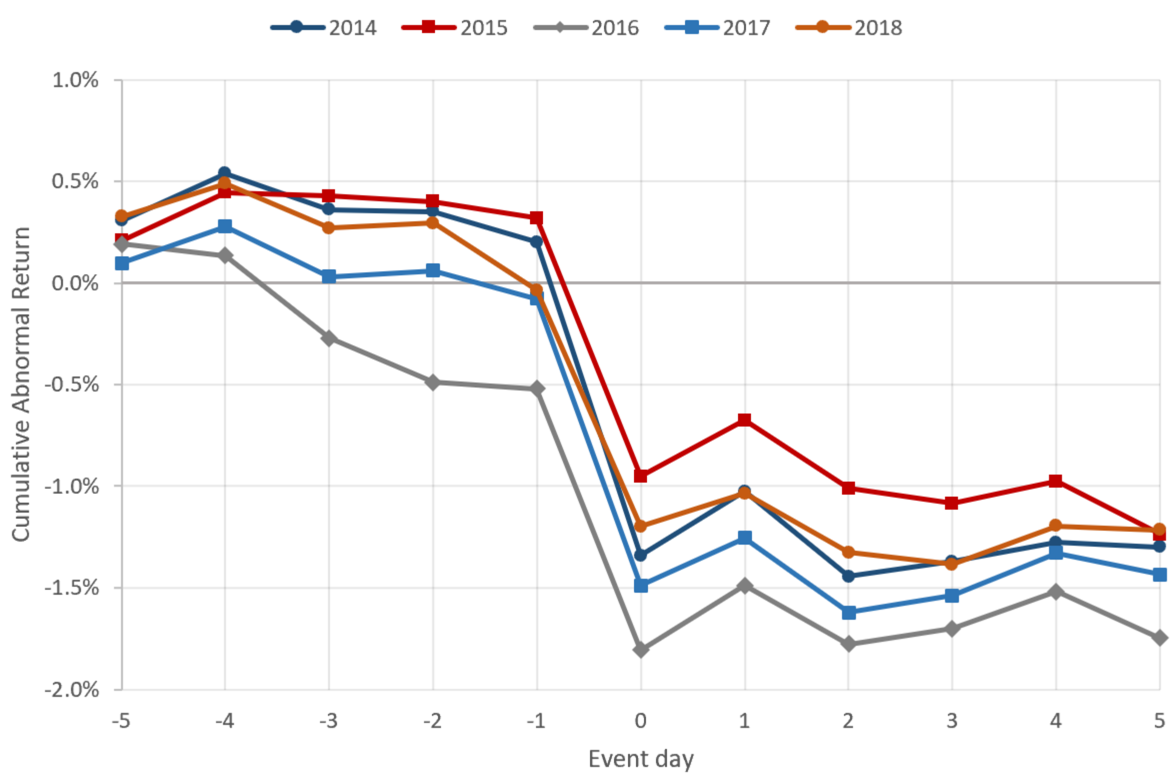

Figure 6: Cumulative Abnormal Return (CAR) for portfolios with different years excluded. For example, '2014' shows the CAR for the stocks in the years between 2015 and 2018. The X-axis is days, where '0' is the event day, '-1' represents the day ahead and '1' is the day after the event and so on. The Y-axis is the cumulative percentage point deviation between the predicted return from the Market Model and the actual return.

4.2.4 Monday effect

After French [13] documented unusual stock returns over weekends, several studies have confirmed the Monday effect in different time periods and countries [14]. These significant negative returns on Mondays are puzzling and we look at whether it is present in our dataset and to what extent it may explain the movement we observe on our event day.

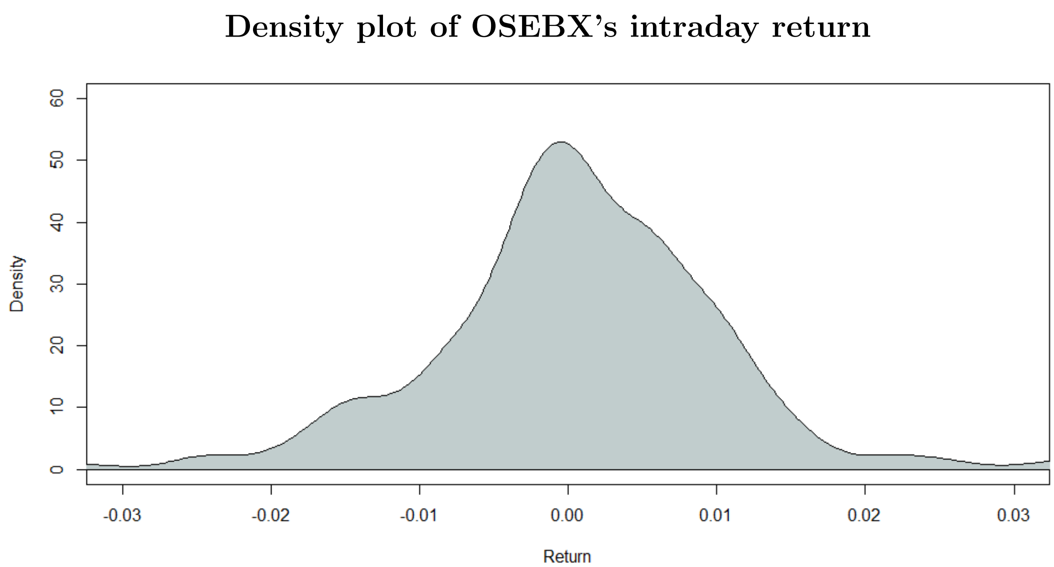

Figure 7: Distribution of returns intraday Monday over the whole period for OSEBX.

From figure 7 and table 5 we see that the average intraday return on the Monday of the OSEBX for the period 2014 to end of 2018 is not significantly different from zero. This does not support the Monday effect theory and we assume that it is not a factor in our model. This can also be deduced from figure 4 where we see that the Monday ahead and after the event does not differ significantly from zero.

Table 5: Summary statistics of returns intraday Monday over the whole period for OSEBX

Observations	Average	Median	Max	Min	Std dev
251	0.0002	0.0003	0.0341	-0.0519	0.0102

5 Shorting Strategy

Using the results from the event study we now look at whether the abnormal drop in a stock's price after a sell recommendation can be exploited. We only discuss realistic strategies which do not require inside information from DNB regarding which stocks they will hold or sell. The strategies are tested on historical data and will only show how they performed in the past, not how they will perform in the future.

5.1 Shorting

The concept of shorting has roots back to the 17th century, where some traders bet on a price decline in the Dutch East India Company [15]. The underlying mechanism still applies today, where an investor sells a stock which is borrowed from someone else. The shorter pays an interest to the lender for the duration of borrowing and at a point in the future the shorter buys back the stock in the market and returns it to the lender. The method profits if the price drops between the time the shorter sells the stock and buys it back.

5.2 The baseline strategy

From the event study we know that the stocks DNB takes out of their portfolio, on average, drop from Friday to Monday. A strategy where we short the stocks already in the portfolio from Friday close to Monday close should therefore yield a positive return. However, we do not know which stock is going to be taken out, or if any stock is going to be taken out at all. To overcome this obstacle we could short the entire portfolio. The idea is that the stocks not taken out will behave according to the random walk hypothesis with an expected return of zero. A hold recommendation should not move the stock price in a specific direction [17][16]. By shorting the entire weekly portfolio we get an expected return of zero if no stocks are given a sell recommendation, but if one of the stocks are taken out we should profit. This is before we look at transaction costs. Since we look at the price movement from Friday afternoon to close Monday the portfolio must be shorted just before close on Friday. To asses the performance of the strategy we will backtest it and use the Sharpe ratio. This is done by looking at how the strategy would have done ex-post by running it on historic data. Figure 8 shows the return of our baseline strategy versus the return of OSEBX for every relevant Monday. A relevant Monday is defined as the first trading day of the week where we know DNB will publish its portfolio, regardless of it including revisions. This excludes any Monday during Christmas, public holidays or other pauses in publication.

Figure 8: The baseline strategy and OSEBX on every relevant Monday. A relevant Monday is defined as a Monday when DN published the weekly portfolio. The X-axis shows the years, and the Y-axis shows the percentage change in value from the first weekly portfolio update in our dataset.

Table 6 shows the statistics of the strategy compared to OSEBX every relevant Monday. In total, the baseline strategy underperformed the reference index with a return of 1.08% versus 5.35%. The strategy, however, did better in two out of five years (2015 and 2016). The plotted cumulative returns in figure 8 look like they mirror each other and the correlation between the daily return of the strategy and OSEBX on relevant Mondays is -0.76. The standard deviation of the return each relevant Monday is also quite similar for the two strategies.

Table 6: The baseline strategy and OSEBX statistics. The total standard deviations are the standard deviation for the whole period. 'Relevant Mondays' is the number of times the strategy is traded. The OSEBX strategy only has one transaction per Relevant Monday as it only trades the index but the baseline strategy has multiple transactions. The 'transactions' is the number of short transactions for the baseline strategy and is divided into Sell and Hold recommendations.

	2014	2015	2016	2017	2018	**Total**
Return						
Baseline strategy	-4.93%	9.71%	4.75%	-8.63%	1.26%	**1.08%**
OSEBX	2.79%	-5.76%	-2.73%	10.20%	1.46%	**5.35%**
Std Dev						
Baseline strategy	0.0098	0.0151	0.0128	0.0096	0.0117	**0.0119**
OSEBX	0.0064	0.0125	0.0143	0.0070	0.0091	**0.0101**
Relevant Mondays	49	49	36	47	47	**228**
Transactions						
Sell	23	29	30	28	27	**137**
Hold	295	267	240	325	326	**1453**
Total	318	296	270	353	353	**1590**

The performance of the baseline strategy was not what we expected given the results from the event study. This can be explained by several reasons. First, during the respective time period the reference index had an overall return of 47% and running a shorting strategy in a bull market proves to be difficult. Second, and most important, is the weighting of the portfolio. Even though one stock is taken out and decreases accordingly, it is only a small part of the shorted portfolio. On average the portfolio consists of seven stocks, meaning that if one stock got a sell recommendation the expected abnormal return of the shorting portfolio is 1.34%/7 which is 0.19%. Another factor is that DNB does not give a sell recommendation every week, hence the expected return is even lower. Out of the 1590 shorting positions during 228 relevant Mondays, only 137 were a sell recommendation. That means that the stocks we are interested in only accounted for 8.6%.

An interesting exercise is to look at the performance of a strategy where we know which stock DNB is going to take out. If we were to only short DNB's sell recommended stocks over the period we would yield a total of 338%. This is unrealistic as it requires that we know beforehand which stocks DNB takes out of their portfolio. If we look at the performance of a shorting strategy consisting of only the hold recommendations, the corresponding return would be -25%. This shows that the return of the baseline strategy is driven by the shorting of sell recommended stocks, but that the shorting of all the hold recommendations eradicate the overall return. Table 7 shows the annual returns of the sell- and hold only strategies.

Table 7: The annual return from the sell and hold recommendation strategies. 'Sell only' consists of all the stocks in DNB's weekly portfolio which we short when they are given a sell recommendation. 'Hold only' consists of all stocks which are shorted when they have a hold recommendation in DNB's weekly portfolio.

	2014	2015	2016	2017	2018	**Total**
Return						
Sell only	8.68%	46.86%	42.47%	22.08%	57.80%	338.08%
Hold only	-7.26%	1.63%	-2.10%	-12.28%	-7.33%	-25.00%

5.2.1 Shorting Small Cap firms

As in section 5.1.2 we divide the stocks into three categories based on their market capitalisation. Figure 9 illustrates the cumulative return from shorting strategies based on this division and how the OSEBX performed on relevant Mondays.

Cumulative return of different mcap shorting strategies and OSEBX

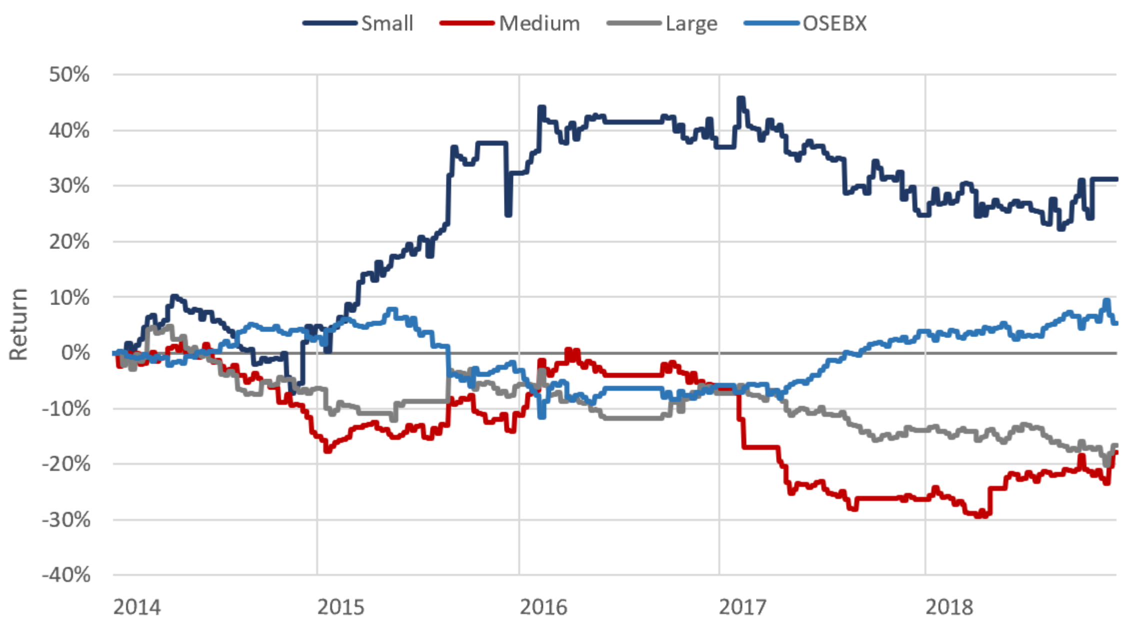

Figure 9: Performance of small, medium and large cap shorting strategy vs OSEBX return on relevant Mondays. A relevant Monday is defined as a Monday when DN published the weekly portfolio. The X-axis shows the years, and the Y-axis shows the percentage change in value from the first weekly portfolio update in our dataset. 'Small' are firms with mcap lower than 9 billion NOK, 'medium' is between 9 billion and 25 billion NOK, and 'large' are firms above 25 billion NOK.

We see that the small cap firms outperform the other strategies and OSEBX. However, the small cap firm return is driven primarily by the return in 2015 and it appears more volatile than the others. The medium and large cap strategy decreased in value most of the years, and the overall return is far below the reference index. The relevant Mondays are defined as a Monday where DN published the portfolio, regardless of DNB having any updates.

Table 8 shows the annual returns of the different strategies, and provides the numbers behind figure 9. The category including the smallest firms has the highest total return with 31.26% and the medium and large size firms both end up with a negative return of -17.98% and -16.68% respectively. This result is in line with the result from section 5.1.2 where smaller firms had a higher abnormal return than larger firms, however, we did not expect the large difference between small and medium size firms.

Table 8: Intrayear return for portfolios with different market cap. 'Small' are firms with mcap lower than 9 billion NOK, 'medium' is between 9 billion and 25 billion NOK, and 'large' are firms above 25 billion NOK. OSEBX is the return for all Mondays where DN published DNB's weekly portfolio. The bold values highlights which return was highest that year.

	2014	2015	2016	2017	2018	**Total**
Return						
Small	**4.75%**	**26.37%**	3.45%	-8.90%	5.22%	**31.26%**
Medium	-15.11%	4.64%	**5.09%**	-21.08%	**11.34%**	**-17.98%**
Large	-6.30%	0.70%	-1.80%	-7.21%	-3.08%	**-16.68%**
OSEBX	2.79%	-5.76%	-2.73%	**10.20%**	1.46%	**5.35%**

Looking closer at each year we see that 2015 was by far the best year for the small firm strategy with a return of 26.37%. Excluding this year would give the strategy a total return of 3.87%, which still is better than the other strategies, but one can argue that the high return in 2015 was an exception that is unlikely to happen again. In comparison, OSEBX had a return of 11.79% if 2015 is excluded. The standard deviation of the returns also follow the same pattern where the smallest firms move more than the larger firms, see appendix table A16 where also the amount of relevant Mondays and yearly transactions are shown. This can also be seen in figure 9 where the lines for the medium and larger firms are less volatile than for the smaller firms. The categories are divided such that they are almost equally present in DNB's weekly portfolio. Each strategy had on average two stocks in its portfolio every relevant Monday. The proportion of sell recommendations in relation to the total transactions is also similar for each category with 9.2%, 7.9% and 8.6% for Small, Medium and Large respectively.

Figure 10 shows the historical performance of the 9 billion small cap shorting strategy versus OSEBX for the 2014-2018 period. The return of this strategy is 31.26% against 6.74% for the reference index during the relevant Mondays. A relevant Monday is now defined as the first trading day of the week where we know DNB will publish its portfolio, but it must include a small cap stock. For instance, if the portfolio has only medium and large cap firms we abstain from shorting. If the portfolio has small cap firms but DNB does not give any sell recommendation we still include the short.

Figure 10: Performance of small cap strategy vs OSEBX return on relevant Mondays. A relevant Monday is defined as a Monday when DN published the weekly portfolio and it included at least one small cap firm. 'Small' are firms with mcap lower than 9 billion NOK. The X-axis shows the years, and the Y-axis shows the percentage change in value from the first weekly portfolio update in our dataset.

This strategy performs substantially better than the baseline strategy. The main reason is the weights in the portfolio. In the baseline strategy the portfolio consisted on average of seven stocks, the new strategy has on average three stocks. Therefore, when a stock is taken out it represents a much larger share of the total portfolio and hence a larger effect. We observe that most of the gain is still achieved during 2015. We also see that the strategy performs well when OSEBX moved downward or flat. In bull periods the strategy loses.

According to the Three Factor Model by Fama and French [20] small firms increase more in price and outperform larger firms, this is known as the Small Firm Effect (SFE). NBIM's research from 2012 documents that small cap stocks outperformed large cap stocks by three percent per annum over the period 1927-2011 [21]. They further state that the outperformance of small cap stocks cannot be attributed solely to market risk and their research suggest that the SFE may be a proxy for a non-diversifiable risk factor such as cash flow risk, business cycle risk or liquidity risk. These arguments and facts together with the bull market in our time period suggest that shorting small cap firms would be a losing strategy. But, the opposite is true. Explanations of this behaviour are speculative, but Womack [4] argued that sell recommendations carry more weight than buy recommendations since they are issued less often. However, the DNB weekly portfolio has equal amounts of sell and buy recommendations. Our argument for the larger effect is that it is caused by the abnormal surge in demand and this creates a downward pressure. Since the small cap stock is less liquid the drop becomes more substantial. Another aspect is the arguments DNB has for giving a sell recommendation, which could include disclosure of fundamental negative news about the firms and the price drop is a reaction to this.

5.3 Assessing the Shorting portfolios

To compare the return of a portfolio to an index it is important to incorporate the volatility of the returns. A rational investor demands compensation for risk, in our case measured by volatility (standard deviation), as the investor is risk averse. The compensation is the expected return.

5.3.1 Sharpe ratio

A common analytic tool to asses and compare portfolio performance is the Sharpe ratio developed by William Sharpe (1966). The ratio is also known as reward-to-variability since it examines the return of the portfolio by adjusting for its risk. For example, assume two portfolios with expected return of 10% next year based on its historical returns. One of the portfolios has had a steady increase through the years, while the other often has several big swings up and down. The first portfolio is said to have low risk, or low volatility while the other is risky, or with high volatility. We have assumed a risk averse investor with rational behaviour, and the investor will therefore always choose the investment with the lowest volatility compared to its return. The Sharpe ratio does exactly this, it divides expected excess return by the portfolio's standard deviation.

$$SharpeRatio = \frac{E(R) - RF}{\sigma} \tag{11}$$

A high positive value means that the investment has a high return compared to its riskiness and is preferred over an investment with lower Sharpe ratio. The expected excess return is the expected return of the portfolio minus a risk free rate. There is no such thing as a risk free rate, we have therefore chosen to follow the result from PwC's yearly report of the Norwegian market. They conduct a survey where the respondents are from the Norwegian finance industry and the answers are based on the actual risk free rate they use. The report shows that the majority use the 10 year government bonds [18]. According to Norges Bank [19], the respective yearly average rates are shown in table 9.

The Sharpe ratio we will use is the ex-post Sharpe, which is the same as equation 11 but with realised returns rather than expected. The ratio is dimensionless, but in general, the higher the Sharpe ratio, the better the fund's historical risk-adjusted performance. However, it can be misleading when the return is negative, since the ratio will also be negative. A negative ratio means that it would have been better to put the money in the risk free asset. However, when comparing two strategies the one with the highest Sharpe, or if negative the one with the Sharpe closest to zero, will be the best strategy.

The return in table 9 is found by accumulating the returns of the shorting strategy and OSEBX for each relevant Monday during the year. From the Sharpe ratio calculations we observe that the shorting portfolio has the highest reward to variability in four out of five years. It also has the highest average Sharpe ratio. The table must be viewed with caution as extreme years affect the results to a large degree. According to Frazzini et al. the Sharpe ratio for SP500 was 0.39 over the 30 year period up to 2013 [22]. There is no official statistics for Oslo børs for such a long time. During the time period we have chosen to look at, 2014 to 2018, Oslo børs increased by around 50%. In a historical perspective this is very large.

Table 9: Sharpe Ratio calculations. The 10-year risk free rate is an annual average of daily quotes from Oslo Stock Exchange at 4 pm (calculations by Norges Bank). The Sharpe Ratio is calculated with formula 11 and the bold numbers highlight the highest Sharpe ratio for that year.

	2014	2015	2016	2017	2018	Average
Return						
Short	4.75%	26.37%	3.45%	-8.90%	5.22%	6.18%
OSEBX	3.03%	-4.87%	-3.77%	10.20%	2.70%	1.46%
Std Dev						
Short	0.018	0.027	0.015	0.015	0.018	0.019
OSEBX	0.006	0.013	0.015	0.007	0.008	0.010
Risk Free	2.52%	1.57%	1.33%	1.64%	1.88%	1.79%
Sharpe Ratio						
Short	**1.2**	**9.1**	**1.4**	-7.0	**1.9**	**1.3**
OSEBX	0.8	-4.9	-3.5	**12.2**	1.1	1.1

5.4 Transaction Costs

The shorting strategy shorts all the stocks in the weekly portfolio. The baseline strategy consists of seven stocks on average, while the small cap portfolio has three. There is no simple way to short the complete portfolio, each stock must be shorted individually. The prices vary between the brokerages, but Nordnet has the largest product base and we present the prices they charge. Intraday shorting costs the same as going long in a stock, and for an active trader this is 0.029% in commission or 39 NOK in minimum brokerage fee [23]. This must be paid twice, first when the stock is sold and when it is bought back. Since the stocks must be held overnight there is an initial fixed cost of 250 NOK and an interest of at least 4.5% in addition to the transaction cost. With small shorting positions the transaction costs become substantial, but scaling up the positions diminish the costs in relative terms.

Table 10 shows the strategy of shorting three stocks once per week for 40 Mondays. The commission is calculated using the initial starting cash, and assuming that stays constant over the whole year. The first example has each position at 10,000 NOK and we see that if the strategy is employed 40 times the transaction costs are above the initial starting cash. Scaling the three positions up to one million each reduces the yearly share to 5%.

Table 10: Transaction costs for a shorting strategy if we assume a portfolio of three stocks for different levels of starting cash. The prices are taken from Nordnet [23] May 2019. To apply the strategy the investor must pay a fixed cost, interest if the stocks are held overnight and a commission to the broker. The per year calculation is done with the assumption that the strategy is traded 40 times during the year. The 'share' is the per year cost divided by the starting cash.

Starting cash	Fixed cost	Interest	Commission	Total	Per year	Share
30,000	750	11	117	878	35,123	117%
300,000	750	110	174	947	37,918	14%
3,000,000	750	1110	1740	2729	109,183	5%

5.5 Limitations of the shorting strategy

From our main result we theorised that the abnormal drop in a stock's price after a sell recommendation could be exploited. Our attempt to short the complete DNB weekly portfolio proved futile, losing money compared to OSEBX and the risk free rate. The biggest weakness of the baseline strategy is that when only one out of seven stocks on average is taken out in half of the portfolio updates, the effect of the 1.34% drop becomes insignificant. A self evident direction was therefore to shrink the portfolio size, and from the robustness tests we knew that small cap firms outperformed large cap firms. The tweaking of composition towards small cap firms yielded positive returns, but extreme values affected the returns too much. Based on the results we do not recommend the strategy presented, going long in the index for the whole period would have given a higher return, lower transaction costs and is less time consuming.

The small cap shorting portfolio clearly has a high volatility and its return is skewed because of 2015 and 2017. Without the extreme gain during 2015 the strategy would have a negative Sharpe ratio for the period between 2014 and 2018. This is because the average return would be lower than the risk free return available in the market. The large loss of the strategy in 2017 is also an extraordinary event. OSEBX gained 20% during the year, which is much larger than its average return, this certainly makes a shorting strategy more difficult. Our data availability is limited to five years and extreme values therefore have the ability to influence our results.

The time interval for our short position is from close Friday to close Monday. This strategy had to be employed since the recommendation is published around 8:45 am and investors could trade on the information during the opening auction. The probability of noise and unpredictable changes increases since firm relevant news are sometimes published during the weekend. A way around this would be to use hourly or minute by minute stock prices from 8:45 am and throughout the day. This would isolate the event and contain less noise. While technically available, they are extremely costly and out of reach for a Master's thesis. Our solution was to prove the normal distribution of returns during the weekend and assume that on average the expected return is zero. Another issue with the time interval is the extra costs. With three positions at one million each traded 40 times per year results in transaction costs of 5%. This amount must be deducted from the potential profit of the strategy. We observe that only 2015 yields positive returns if the shorting portfolio is financed by borrowing at the risk free interest rate.

Another issue when attempting to execute the trading strategy in the Norwegian stock market is the limited amount of stocks available for shorting. As of April 2019 there were 45 different stocks available to rent for shorting [24]. The list is continuously revised, but at no point does it cover all the stocks on the exchange. In general, the stocks on the list are the most traded stocks and therefore often the larger stocks.

This creates a problem with our small cap shorting portfolio. Nordnet informs that by calling them they could arrange special trades, but it will incur additional costs.

Backtesting also has limitations we must acknowledge. Our choice of a 9 billion market cap for the shorting portfolio is found by optimising the return in retrospect. This is a clear bias from our side and invalidates some of our results. For backtesting to provide reliable results, the strategy should have been developed without looking at historic returns and then tested. By optimising the portfolio we skew the results and the deductions are less likely to be applicable for future returns. For example, shrinking the market cap to 7 billion and running the strategy yields a 29.8% return for the whole period, but 2015 alone has a 35.9% increase. This strategy gets beaten almost every year and the Sharpe ratio is negative if 2015 is excluded. An extension we could have pursued is looking at the way DNB chooses which stock to take out of their portfolio. DNB informed us that the weekly portfolio is taken from the in-house sector specialists and the timing is based on the technical signs each stock has. By isolating the technical signs DNB looks at based on historical choices, we could have predicted which stock is most likely to be taken out and then short them. This proved laborious as DNB does not publish their strategy. We decided to not pursue this any further, but we recognise the potential gain from that strategy.

6 Conclusion

The sell recommendations published by DNB is the analyst's opinion on already available public information. Theory regarding recommendations is clear, if no new firm relevant information is disclosed then the stock should not move abnormally. Previous studies on the Norwegian and international markets disprove this with significant event day price movements. Our findings are in line with these studies.

DNB's effect on the market was an average abnormal price movement of 1.34% on the event day and is different from zero at a 1% significance level. The result is found by subtracting the predicted stock return from the actual return and then aggregating across all stocks and 137 events. This movement is caused by the investors believing the analyst's opinion on the price more than the current market price. This behaviour suggests that the market efficiency is of weak form, meaning that not all public information is reflected in the stock price. This conclusion is supported by the fact that DNB spends many millions on firm and market research. If prices reflected all relevant information then further research by DNB would only confirm the prevailing price and 'hold' recommendations would be published, rather than 'buy' and 'sell'.

The conclusion is drawn from a relatively small dataset and several robustness tests are therefore employed to assess its validity. Tests where datapoints were excluded based on criteria such as firm size, year and the size of the return all supported our original conclusion.

One way to take advantage of the predicted price decline is to short the respective stock. The baseline model shorts all the stocks in the portfolio every relevant Monday. This strategy loses to the reference index, which in our case is the OSEBX on the same Mondays. By optimising the strategy based on the results from the size robustness test, we constructed a portfolio with small cap firms. This approach beats the index on a risk adjusted basis in four out of five years, but transaction costs and few stocks available for shorting makes it unprofitable and impossible.

An interesting direction to pursue further is the mechanisms through which a recommendation influences the share price. If no fundamental news regarding the firm is disclosed, then how can the price movement be explained? Is it institutional investors exploiting the inefficiency, or algorithm traders benefitting from superior trading and information speed or is it the average reader of DN trusting the stockpicker's skill and following the recommendations? Closer investigation on who trades on the recommendations and why they do are interesting topics within behavioural finance which are yet to be explored extensively.

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8 Appendix

Table A1: Frequency of individual stocks in DNB's portfolio where the top line shows how many times the respective stock has been given a sell recommendation.

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**11**
AKERBP	AKER	AVANCE	BAKKA	BWLPG	DNO	BRG	SALM	TEL
ATEA	AUSS	GOGL	BWO	SNI	MOWI	LSG		
DETNOR	AXA	GSF	EQNR			STB		
ENTRA	B2H	NHY	GJF					
EVRY	EPR	SBANK	ORK					
NOD	FRO	SBO	NAS					
NOFI	HLNG	SRBANK						
PLCS	KOG	NRC						
PRS	KVAER	SUBC						
RCL	NPRO							
TGS	OPERA							
TIL	OCY							
VARDIA	ODL							
WWASA	QFR							
WWI	TOM							
WWL	VEI							
XXL	YAR							

Table A2: Omitted at 5% - Summarizing output showing the average abnormal return (AR) for each event day the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The 'Omitted obs' column shows how many observations that are excluded. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is 1.96.

Day	Omitted obs	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	6	0.04%	0.04%	0.0143	0.3308	130	0.7413
-4	3	0.01%	0.05%	0.0178	0.0491	133	0.9609
-3	6	-0.26%	-0.22%	0.0169	-1.7802	130	0.0774
-2	2	-0.05%	-0.26%	0.0169	-0.3293	134	0.7424
-1	4	-0.32%	-0.58%	0.0142	-2.5757	132	0.0111
0	**9**	**-1.01%**	**-1.59%**	**0.0163**	**-7.0073**	**127**	**0.0000**
1	5	0.14%	-1.45%	0.0155	1.0141	129	0.3124
2	3	-0.29%	-1.74%	0.0164	-2.0102	131	0.0465
3	2	-0.06%	-1.81%	0.0161	-0.4541	131	0.6505
4	3	0.11%	-1.70%	0.0159	0.7758	130	0.4393
5	4	-0.09%	-1.79%	0.0147	-0.7102	129	0.4789

Table A3: Omitted at 6% - Summarizing output showing the average abnormal return (AR) for each event day the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The 'Omitted obs' column shows how many observations that are excluded. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is 1.96.

Day	Omitted obs	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	4	0.12%	0.12%	0.0156	0.8990	132	0.3703
-4	1	0.09%	0.21%	0.0188	0.5265	135	0.5994
-3	4	-0.34%	-0.14%	0.0180	-2.1909	132	0.0302
-2	2	-0.05%	-0.18%	0.0169	-0.3293	134	0.7424
-1	3	-0.35%	-0.54%	0.0147	-2.7707	133	0.0064
0	**4**	**-1.10%**	**-1.63%**	**0.0187**	**-6.7444**	**132**	**0.0000**
1	1	0.21%	-1.42%	0.0176	1.3905	133	0.1667
2	1	-0.29%	-1.71%	0.0175	-1.8915	133	0.0607
3	0	0.02%	-1.69%	0.0174	0.1358	133	0.8922
4	1	0.11%	-1.58%	0.0172	0.7144	132	0.4762
5	4	-0.09%	-1.67%	0.0147	-0.7102	129	0.4789

Table A4: Omitted at 7% - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The 'Omitted obs' column shows how many observations that are excluded. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ± 1.96.

Day	Omitted obs	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	3	0.17%	0.17%	0.0164	1.1772	133	0.2412
-4	1	0.09%	0.25%	0.0188	0.5265	135	0.5994
-3	1	-0.29%	-0.04%	0.0203	-1.6888	135	0.0936
-2	2	-0.05%	-0.09%	0.0169	-0.3293	134	0.7424
-1	3	-0.35%	-0.44%	0.0147	-2.7707	133	0.0064
0	**4**	**-1.10%**	**-1.54%**	**0.0187**	**-6.7444**	**132**	**0.0000**
1	0	0.26%	-1.28%	0.0184	1.6398	134	0.1034
2	1	-0.29%	-1.57%	0.0175	-1.8915	133	0.0607
3	0	0.02%	-1.55%	0.0174	0.1358	133	0.8922
4	0	0.16%	-1.39%	0.0180	0.9950	133	0.3215
5	3	-0.05%	-1.44%	0.0156	-0.3326	130	0.7400

Table A5: Omitted at 8% - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The 'Omitted obs' column shows how many observations that are excluded. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ± 1.96.

Day	Omitted obs	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	2	0.22%	0.22%	0.0175	1.4592	134	0.1469
-4	1	0.09%	0.31%	0.0188	0.5265	135	0.5994
-3	1	-0.29%	0.01%	0.0203	-1.6888	135	0.0936
-2	2	-0.05%	-0.04%	0.0169	-0.3293	134	0.7424
-1	3	-0.35%	-0.39%	0.0147	-2.7707	133	0.0064
0	**4**	**-1.10%**	**-1.49%**	**0.0187**	**-6.7444**	**132**	**0.0000**
1	0	0.26%	-1.23%	0.0184	1.6398	134	0.1034
2	0	-0.34%	-1.57%	0.0185	-2.1296	134	0.0350
3	0	0.02%	-1.55%	0.0174	0.1358	133	0.8922
4	0	0.16%	-1.39%	0.0180	0.9950	133	0.3215
5	1	-0.05%	-1.44%	0.0180	-0.3079	132	0.7586

Table A6: Small cap - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.20%	0.20%	0.0262	0.5633	52	0.5742
-4	0.30%	0.50%	0.0253	0.8505	52	0.3965
-3	-0.28%	0.21%	0.0279	-0.7444	52	0.4579
-2	0.26%	0.47%	0.0240	0.7743	52	0.4401
-1	-0.19%	0.28%	0.0196	-0.7058	52	0.4815
0	**-1.66%**	**-1.38%**	**0.0238**	**-5.0617**	**52**	**0.0000**
1	0.36%	-1.02%	0.0198	1.3137	52	0.1912
2	-0.67%	-1.69%	0.0220	-2.2253	52	0.0277
3	0.08%	-1.62%	0.0182	0.3092	52	0.7576
4	0.44%	-1.17%	0.0197	1.6460	52	0.1021
5	0.10%	-1.07%	0.0195	0.0523	52	0.9584

Table A7: Medium cap - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.29%	0.29%	0.0186	1.0143	40	0.3122
-4	-0.19%	0.10%	0.0186	-0.6559	40	0.5130
-3	-0.07%	0.03%	0.0219	-0.2058	40	0.8372
-2	-0.57%	-0.54%	0.0245	-1.5007	40	0.1358
-1	0.27%	-0.27%	0.0269	0.6448	40	0.5201
0	**-1.61%**	**-1.88%**	**0.0289**	**-3.5698**	**40**	**0.0005**
1	0.28%	-1.60%	0.0218	0.8262	40	0.4101
2	-0.23%	-1.84%	0.0185	-0.8069	40	0.4211
3	-0.02%	-1.85%	0.0163	-0.0687	40	0.9454
4	-0.10%	-1.95%	0.0184	-0.3310	40	0.7411
5	-0.45%	-2.40%	0.0271	-0.1668	40	0.8678

Table A8: Large cap - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.19%	0.19%	0.0151	0.8439	42	0.4002
-4	0.30%	0.50%	0.0142	1.4085	42	0.1613
-3	-0.26%	0.24%	0.0141	-1.2026	42	0.2312
-2	0.11%	0.35%	0.0124	0.5727	42	0.5678
-1	-0.49%	-0.15%	0.0102	-3.1713	42	0.0019
0	**-0.68%**	**-0.82%**	**0.0126**	**-3.4421**	**42**	**0.0008**
1	0.12%	-0.71%	0.0124	0.6098	40	0.5430
2	-0.02%	-0.73%	0.0123	-0.0976	40	0.9224
3	-0.02%	-0.74%	0.0177	-0.0567	39	0.9549
4	0.03%	-0.71%	0.0150	0.1230	39	0.9023
5	-0.10%	-0.81%	0.0100	-0.0956	39	0.9240

Table A9: Bottom half - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.07%	0.07%	0.0242	0.2552	68	0.7990
-4	0.22%	0.30%	0.0244	0.7635	68	0.4465
-3	-0.08%	0.22%	0.0272	-0.2357	68	0.8141
-2	0.19%	0.41%	0.0236	0.6536	68	0.5145
-1	-0.15%	0.26%	0.0225	-0.5351	68	0.5935
0	**-1.79%**	**-1.53%**	**0.0248**	**-5.9935**	**68**	**0.0000**
1	0.20%	-1.33%	0.0208	0.8009	68	0.4246
2	-0.36%	-1.69%	0.0213	-1.3908	68	0.1666
3	0.05%	-1.63%	0.0176	0.2597	68	0.7955
4	0.31%	-1.32%	0.0195	1.3202	68	0.1890
5	-0.02%	-1.34%	0.0191	-0.0085	68	0.9932

Table A10: Top half - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.38%	0.38%	0.0168	1.8825	67	0.0619
-4	0.08%	0.46%	0.0154	0.4322	67	0.6663
-3	-0.35%	0.11%	0.0161	-1.7875	67	0.0761
-2	-0.27%	-0.15%	0.0188	-1.1668	67	0.2453
-1	-0.15%	-0.30%	0.0173	-0.7135	67	0.4768
0	**-0.88%**	**-1.18%**	**0.0203**	**-3.5014**	**67**	**0.0006**
1	0.32%	-0.85%	0.0158	1.6746	65	0.0963
2	-0.32%	-1.18%	0.0152	-1.7160	65	0.0884
3	-0.02%	-1.19%	0.0173	-0.0756	64	0.9399
4	-0.01%	-1.20%	0.0163	-0.0440	64	0.9650
5	-0.24%	-1.45%	0.0212	-0.1149	64	0.9087

Table A11: Exclude 2014 - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.31%	0.31%	0.0222	1.480	113	0.1411
-4	0.23%	0.54%	0.0211	1.177	113	0.2413
-3	-0.18%	0.36%	0.0238	-0.794	113	0.4286
-2	-0.01%	0.35%	0.0229	-0.047	113	0.9624
-1	-0.15%	0.20%	0.0214	-0.759	113	0.4494
0	**-1.54%**	**-1.34%**	**0.0238**	**-6.853**	**113**	**0.0000**
1	0.31%	-1.03%	0.0195	1.707	111	0.0900
2	-0.42%	-1.44%	0.0193	-2.272	111	0.0247
3	0.07%	-1.37%	0.0177	0.445	110	0.6568
4	0.09%	-1.28%	0.0191	0.511	110	0.6104
5	-0.02%	-1.30%	0.0176	-0.013	110	0.9895

Table A12: Exclude 2015 - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.21%	0.21%	0.0172	1.261	107	0.2094
-4	0.24%	0.44%	0.0208	1.180	107	0.2401
-3	-0.02%	0.43%	0.0220	-0.073	107	0.9419
-2	-0.03%	0.40%	0.0204	-0.140	107	0.8888
-1	-0.08%	0.32%	0.0207	-0.407	107	0.6843
0	**-1.27%**	**-0.95%**	**0.0223**	**-5.926**	**107**	**0.0000**
1	0.28%	-0.67%	0.0188	1.526	107	0.1293
2	-0.34%	-1.01%	0.0193	-1.802	107	0.0737
3	-0.07%	-1.08%	0.0176	-0.428	106	0.6696
4	0.11%	-0.98%	0.0182	0.606	106	0.5458
5	-0.26%	-1.24%	0.0191	-0.136	106	0.8923

Table A13: Exclude 2016 - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.19%	0.19%	0.0213	0.931	106	0.3536
-4	-0.06%	0.13%	0.0186	-0.315	106	0.7530
-3	-0.41%	-0.27%	0.0182	-2.317	106	0.0220
-2	-0.21%	-0.49%	0.0195	-1.136	106	0.2578
-1	-0.03%	-0.52%	0.0195	-0.175	106	0.8617
0	**-1.28%**	**-1.80%**	**0.0219**	**-6.006**	**106**	**0.0000**
1	0.32%	-1.49%	0.0164	1.981	104	0.0496
2	-0.29%	-1.78%	0.0152	-1.959	104	0.0522
3	0.08%	-1.70%	0.0174	0.448	104	0.6550
4	0.18%	-1.52%	0.0166	1.131	104	0.2602
5	-0.23%	-1.75%	0.0213	-0.107	104	0.9149

Table A14: Exclude 2017 - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.10%	0.10%	0.0208	0.486	108	0.6280
-4	0.18%	0.28%	0.0216	0.883	108	0.3785
-3	-0.25%	0.03%	0.0237	-1.091	108	0.2773
-2	0.03%	0.06%	0.0224	0.134	108	0.8933
-1	-0.14%	-0.08%	0.0219	-0.660	108	0.5103
0	**-1.41%**	**-1.49%**	**0.0241**	**-6.061**	**108**	**0.0000**
1	0.23%	-1.26%	0.0193	1.255	106	0.2116
2	-0.37%	-1.62%	0.0196	-1.916	106	0.0575
3	0.08%	-1.54%	0.0169	0.503	105	0.6158
4	0.21%	-1.33%	0.0190	1.136	105	0.2578
5	-0.11%	-1.44%	0.0219	-0.049	105	0.9611

Table A15: Exclude 2018 - Summarizing output showing the average abnormal return (AR) for each event day and the cumulative abnormal return (CAR) which is the accumulation of the average ARs. The standard deviations and the t-values are on the average AR. A t-test is used to determine if the average AR is significantly different from zero and since the degrees of freedom (DF) > 120 the critical value is ±1.96.

Day	Average AR	CAR	Std Dev	t-value	DF	p-value
-5	0.33%	0.33%	0.0223	1.543	109	0.1251
-4	0.16%	0.49%	0.0193	0.881	109	0.3798
-3	-0.22%	0.27%	0.0234	-0.979	109	0.3294
-2	0.02%	0.30%	0.0214	0.114	109	0.9096
-1	-0.33%	-0.03%	0.0162	-2.133	109	0.0348
0	**-1.16%**	**-1.20%**	**0.0230**	**-5.251**	**109**	**0.0000**
1	0.16%	-1.04%	0.0179	0.942	107	0.3477
2	-0.29%	-1.33%	0.0187	-1.604	107	0.1109
3	-0.06%	-1.38%	0.0172	-0.354	106	0.7235
4	0.19%	-1.20%	0.0170	1.147	106	0.2533
5	-0.02%	-1.22%	0.0203	-0.010	106	0.9922

Table A16: MCAP-splitting strategies statistics. The total standard deviation is the standard deviation for the whole period. 'Relevant Mondays' is the number of times the strategies are traded. The 'total transactions' is the number of shorting transactions for each strategy and is the sum of Sell / Hold recommendations.

	2014	2015	2016	2017	2018	**Total**
Returns						
Small	**4.75%**	**26.37%**	3.45%	-8.90%	5.22%	**31.26%**
Medium	-15.11%	4.64%	**5.09%**	-21.08%	**11.34%**	**-17.98%**
Large	-6.30%	0.70%	-1.80%	**-7.21%**	-3.08%	**-16.68%**
Std Dev						
Small	0.0184	0.0273	0.0149	0.0151	0.0179	**0.0191**
Medium	0.0131	0.0151	0.0167	0.0190	0.0178	**0.0164**
Large	0.0136	0.0172	0.0132	0.0080	0.0104	**0.0124**
Relevant Mondays						
Small	48	39	35	47	42	**211**
Medium	47	49	36	29	43	**204**
Large	49	33	33	47	47	**209**
Total transactions						
Small	108	65	101	187	114	**575**
Medium	92	178	107	39	89	**505**
Large	118	53	62	127	150	**510**
Sell / Hold						
Small	8/100	10/55	10/91	13/174	12/102	**53/522**
Medium	6/86	9/169	14/93	4/35	7/82	**40/465**
Large	9/109	10/43	6/56	11/116	8/142	**44/466**