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Dispersion in Analysts' Forecasts and Momentum Strategies in the Norwegian Stock Market

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Contents

Abstract

Research has shown that stock prices tend to drift in the same direction as revisions in consensus forecasts provided by financial analysts. In this paper we create momentum portfolios by an EPS-earnings revision ratio, and examine raw and abnormal returns for different holding periods for Oslo Stock Exchange (OSE) listed companies in the period 2005-2011. By using the two portfolios with the most and least favourable EPS-revision ratios, a long-short momentum portfolio is created, where we buy the stocks with the most favourable revisions and sell the stocks with the least favourable revisions. We find the ultimate holding period for the portfolios to be three months following the analysts' forecasts. Our long-short momentum portfolio gives a significant risk free abnormal return of 1% per month. We thereafter introduce the dimension of dispersion in analysts' forecasts into the analysis, by dividing each portfolio into two sub portfolios by their level of dispersion. The results show that by going long in the sub portfolio with the lowest dispersion and short the sub portfolio with the highest dispersion, we obtain a significant risk free monthly return of 1,33% over the sample period. These findings cannot be explained by classic asset pricing models and contradict the market efficiency hypothesis in its semi-strong form.

1.0 Introduction

The evidence of investors holding other portfolios than the market portfolio is considerable (De Long et. al 1990). Many investors typically pick stocks based on their own research or the advice of analysts, and hence we find it interesting to further study the value of analyst recommendations and forecasts. While the same information is available to all analysts, disagreement does exist in how the analysts interpret the data (Kurz and Motolese 2001). Analysts typically differ in their projections, and thus their beliefs are dispersed. Dispersion of beliefs seems to occur as a result of individual expectations and different weighting on the various elements of available public information, and refers to the difference in expectations that the various market participants have in regard to the future status of the market (Jongen et. al. 2008; Au, 2007).

Uninformed trades are mixed with informed ones (Fan and Lyon, 2001). How the financial markets aggregate dispersed information is linked to market efficiency. Ever since Cowles (1933), a claim has been that there should, in a semi-strong efficient market, not be possible to make arbitrage profits on publicly available information. Most studies aiming to provide investors with profitable trading strategies have failed to do so (Au, 2007). Yet, extensive resources are being used to predict future earnings as well as to come up with profitable trading strategies (Dische, 2002). The data of dispersion and distribution of professional forecasts may be obtained from databases such as Institutional Brokers' Estimate System (IBES). Low dispersion in analysts' forecasts is sometimes thought of as a signifier of herding (Ciccione, 2005). Cooper et. al (2001) demonstrated that analysts who give the leading consensus forecasts are the most informative, while those who follow the rest give forecasts of less value. This paper will be based on the notion that some earnings forecasts are of higher investment value than others, and that the dispersion in the forecasts provides investment value.

Chan et. al. (1996) show that the market only gradually responds to new information. A challenge to the overall concept of an efficient market is the superior returns generated by underreaction in the market to earnings news, as traditional asset-pricing models fail to provide explanations to this phenomenon (Dische, 2002). This paper will aim at replicating some of the research done by Dische (2002) in terms of method, while differencing itself by using analyst forecast data of Norwegian listed companies. This paper will search for investment strategies based on two elements from analysts' forecasts: an earnings-per-share (EPS) revision ratio and the dispersion in forecasts.

2.0 Previous Literature/Literature Review

In accordance to Griffin and Tversky (1992), investors focus on the strength and extremeness of news with insufficient regard to its statistical weight of credence. Barberis et al. (1998) proposed a model where investors of the conservative kind adjust their beliefs to new information too slowly. This gave rise to momentum strategies as the market only responds gradually to new information (Chan et. al. 1996). Liang (2003) looked at the link between dispersion in analyst forecasts and post-earnings announcement drift (PEAD), and found that when the dispersion is low there is more PEAD. Thus, investment strategies, based on stock recommendations with the highest analyst consensus, should yield the higher return. The research of Dische (2002) concludes that when the dispersion of analysts' forecasts decrease, short-term returns increase. This is consistent with the findings of Au (2007). These previous results may be regarded as troubling in the context of market efficiency, as the *negative* relationship between uncertainty/dispersion and return is not consistent with the notion that more reliable information should improve market efficiency (Lee, 2007).

The article of Dische (2002), from which the structure and method of this paper is based upon, showed that the dispersion of consensus forecasts made by financial analysts contains incremental information that may be used to predict future returns. Another finding was that stock prices tend to drift in the same direction as revisions in consensus forecasts provided by financial analysts. The study was executed with stocks from the German market and was consistent with previous research in terms of PEAD. The underreaction to news in the German market allowed a momentum trading strategy to be performed with success. The strategy presented consisted of buying portfolios containing stocks with the highest earnings revisions and selling those with the lowest. This was also performed earlier for the Swiss market by Dische and Zimmerman in 1999 with the same conclusion. Buying portfolios with low analyst forecast dispersion and selling those with high analyst dispersion improved the return of this trading strategy (Dische, 2002).

Ball and Brown (1968) were the first to observe the phenomenon of PEAD. Various PEAD strategies, with the purpose of generating abnormal returns, have been presented and analyzed to be profitable. Bernard and Thomas (1989) showed that the transaction costs concerned with implementing investment strategies based on PEAD were negligible in comparison to the significant abnormal returns these strategies may yield. A self financing investment strategy, presented by Jagadeesh and Titman (1993), yielded a monthly abnormal return of 1%. The possibility of these results being a product of data snooping bias was later evaluated and rejected in Jagadeesh and Titman (2001), which concluded that the profits created by momentum had continued in the 90's. Rouwenhorst (1998 and 1999) confirmed the profitability of momentum based trading.

Dispersion may start with an analyst diverging from the shared opinion of others about a stock (Kim and Zapatero, 2011). For stocks with large std. deviations from the mean, bold earnings revisions have high profitability of underperforming compared to the recommendations of other analysts. There will in other words be risk concerned with presenting earnings revision forecasts that deviates from the mean. Banerjee (1992) refers to the phenomenon that everyone is doing what everyone else is doing as herd behavior. Herding leads to earnings revisions clustering around a mean, hence low dispersion. Analysts that tend to herd by distorting their own information provide biased forecasts (Youssef and Rajhi, 2010). Anderson et. al (2005) argues that high dispersion is a measure of heterogeneity of beliefs, which is a factor it is common to ignore in classic asset pricing models. Portfolios with a high degree of dispersed earnings revision forecasts will have advancing more exposure to the market risk factors, consistent with the notion of dispersion being able to capture underlying risk components in the analyzed firms (Qu et. al, 2003).

Jiang, Lee and Zhang (2004) find results that contradict Dische (2002). As proxies for uncertainty they use firm age, return volatility, trading volume, and duration of firms' future cash flows. Thus, they find a positive association between information uncertainty and PEAD. Lee (2007) aims to reconcile these conflicting results by explaining the results in Dische (2002), concerning negative association between analyst dispersion and PEAD, with inaccuracy in the measurement of uncertainty extracted from analyst forecast data. Lee (2007) then shows that forecasts updated late after earnings announcements provide information of higher accuracy than the forecasts that are updated early after such announcements. Similar to Dische (2002), Lee (2007) finds a negative correlation of cumulative abnormal returns (CARs) and forecasts dispersion. Lee (2007) does however conclude with a *positive* association between analyst forecast dispersion and PEAD after controlling for market's response to earnings news and early analyst herding, which he feels Dische (2002) has failed to recognize the importance of. Although low dispersion in analysts' forecasts may be interpreted as a sign of analyst herding, an underlying assumption we make is that high uncertainty, measured by high dispersion, is a signal of large forecast errors. This interpretation has earlier been suggested by Liang (2003) and Dische (2002). We will regard number of forecasts together with low analyst dispersion as a sign of strength.

3.0 Contribution and Research Question

As far as our knowledge goes, there are no other empirical IBES-based papers examining the combination of analysts' earnings forecasts and the dispersion of estimates in the Norwegian Stock market. The Norwegian media has recently questioned the value of analyst recommendations, making the topic highly relevant. Womack (1996) has earlier revived the value incorporated in analyst recommendations with the result that stock prices are influenced by the recommendations of analysts immediately as well as in subsequent months. The performance of funds and portfolio managers compared to the market index may easily be examined in any financial newspapers. We do however intend on creating a more advanced investment vehicle on the basis of analyst recommendations and diversity of forecasts i.e. dispersion. The outcome of this research process will add material to the discussion regarding the value of potential profitable information that one may obtain from financial analysts.

The profitability of trading on momentum strategies differs from market to market. We intend on enlighten the possibilities of making such arbitrage profits as researched by Dische (2002) in the Norwegian stock market. Our findings will then form as basis for a discussion on market efficiency. Our contribution in this research field does also form our motivation for choosing this topic. Analyzing the possibilities for arbitrage profits in the Norwegian stock market by a method that earlier has been proven to be successful by Dische (1999, 2002) will enlighten the ability of this trading strategy to function in different markets.

We will examine to what extent the dispersion in analysts’ forecasts in the Norwegian stock market can be useful to predict future stock prices. Our research questions are (1) whether it is possible to create momentum portfolios of Norwegian stocks, based on an earnings revision ratio and the dispersion in analysts’ forecasts that can make significant risk free abnormal returns (arbitrage)? And (2) to what extent we can find any significant violation of market efficiency in our results?

4.0 Data and Methodology

Our data of analysts’ forecasts on the Oslo Stock Exchange (OSE) will be obtained from the Institutional Brokers' Estimate System (IBES). IBES monitors different estimates for earnings, where their database for international forecasts started in 1987 (Thompsen Reuters 2012). The data software we will use in the paper is EViews. We will base our paper on the so-called consensus forecast estimate for earnings-per-share (EPS), which is the average of all estimates for a fixed period of time. In IBES this is calculated by summarizing the EPS estimates for the current period, from all of the contributing firms, for the specified fiscal time period and dividing the sum by the number of EPS estimates in the calculation.

Our structure for data and methodology is based on similar studies as e.g. Dische (2002). IBES started to cover companies listed on OSE in 1987. In the period 1987-2004 IBES covered OSE companies are few (between 20-40). In this paper we will create sub-portfolios of our sample, and start the sample period in 2005 due to scarce IBES data material available for OSE listed companies in the prior years. The potential sample size is the 215 firms listed on OSE (Oslo Børs 2011) in the time period from January 2005 until December 2011. We have used monthly observations and thus the potential number of observations per company is 84 (7 years * 12 months). To avoid bias related to the dispersion in forecasts we will only include the stocks that are covered by a minimum of three analysts for at least one year in our sample. In the data we see two tendencies: (1) when analysts start to cover a stock for the first time (in the IBES data) the number of estimates (analysts covering the stock) increases over time; and (2) the number of Norwegian stocks in the data increases during the sample period. Thus, in our data we have excluded start-up periods for new listed companies, as well as other periods, which have less than three EPS estimates. Chordia and Shivakumar (2000) investigated to what extent the macro economy affects momentum strategies. The findings indicated that momentum strategies perform well in recessions, while they do not in the case of periods of favorable macroeconomic periods. We will not exclude any period on the basis of an extraordinary event (e.g. the financial crisis), but we will consider whether such periods have significant impact on the results.

In accordance to Dische (2002) a favorable side of using the mean EPS estimated forecasts on a fixed one-year horizon in this paper is that the estimates are for a forecasting horizon that is one year ahead, thus we do not have to consider effects associated with the end of fiscal year, which is December for the companies we will include in the data. As a measure for the level a stock has of new information during a period we will evaluate the impact of changes in EPS by using an EPS revision ratio. The ratio represents the average change in the analysts' forecasts on a monthly basis. It will be computed as the average monthly change in EPS divided by mean absolute value of the consensus forecast last period.

Table 1 gives descriptive statistics of analysts' forecasts. The most important elements in this table are the five "EPS-Revision by Portfolios" columns. After acquiring the EPS revision ratios we have sorted the stocks into five equally weighted portfolios, in descending order by their revision ratios. Thus, the first portfolio includes the most upward revision ratios and the last portfolio will include the most downward revisions, on a monthly basis. The "Dispersion" column represents the average dispersion in analysts' forecasts, which is the IBES coefficient of variation, computed as the standard deviation of all analysts' estimates, on a firm level, as a percentage of the absolute mean value of all estimates for a given firm. "Number of Firms" is the number of OSE listed firms that are covered by three or more analysts for a given year in our data. "Analysts per Firm" is the average number of analysts covering the firms. "PE" is the average price-earnings ratio.

By examining the whole sample, the number of covered firms and, to some extent the number of analysts, increases during the sample period. This indicates that there has been an increasing interest among financial institutions in estimating earnings forecasts for OSE companies. The dispersion among the estimates and the price-earnings ratio do not show a clear pattern of development during the sample period, except for a small growth for the latter.

By examining the portfolios individually, the average EPS-revision ratio for portfolio 1 (P1) is 97%. This is highly affected by its average value from 2007 of 319%. The major reason for this inflated number is the consensus estimate for the company Norwegian Air Shuttle from March 2007, a month before it

Table 1: Descriptive Statistics of Analysts' Forecasts

The Descriptive Statistics are for companies listed on Oslo Stock Exchange (OSE), covered by a minimum of three IBES analysts for at least 12 months in the period 2005-2011. Monthly forecasted EPS estimates are obtained, for the next fiscal year, from Institutional Brokers' Estimate System (IBES). "Number of Firms" is the number of firms included in the sample for each year, "Analysts", "PE" and "Dispersion" are average numbers for all portfolios. EPS-Revision is calculated as the difference in estimates between two monthly periods as a percentage of the absolute value of the last estimate. EPS-Dispersion is the IBES Coefficient of Variation, calculated as the standard deviation of estimates as a percentage of the absolute value of the consensus estimate. The stocks are divided into five equally weighted portfolios (P1-P5), sorted by their EPS-Revision ratios. Both EPS-Revision ratios and EPS Dispersion numbers for the portfolios are the average on a yearly basis.

Table 1: Descriptive Statistics of Analysts' Forecasts														
					EPS-Revision by Portfolios					**EPS Dispersion by Portfolios**				
Year	**Nmb of Firms**	**Analysts**	**Dispersion**	**PE**	1	2	3	4	5	1	2	3	4	5
2005	47	7	37,7	31	0,75	0,06	0,01	-0,02	-0,42	55,48	13,33	19,06	16,09	84,71
2006	65	8	28,2	36	0,70	0,04	0,00	-0,02	-0,32	38,54	15,25	21,73	15,86	49,61
2007	88	8	47,2	41	3,19	0,03	0,00	-0,03	-0,35	40,83	14,89	38,36	14,49	127,28
2008	97	8	41,6	35	0,56	0,06	0,00	-0,04	-0,53	46,66	27,82	19,71	18,48	95,56
2009	93	8	49,9	39	0,38	0,03	-0,01	-0,06	-0,92	49,52	26,94	57,04	25,35	90,61
2010	103	9	41,7	37	0,72	0,04	0,00	-0,03	-0,57	36,80	26,54	36,25	21,86	87,17
2011	107	10	44,4	58	0,50	0,04	0,00	-0,05	-0,81	46,26	30,86	31,28	22,24	91,60
Average	86	8	42,0	40	0,97	0,04	0,00	-0,03	-0,56	44,87	22,23	31,92	19,19	89,51

announced it would buy the Swedish low-cost airline FlyNordic and becoming the largest Scandinavian airline company in the segment low-cost. This event changed the consensus EPS estimate from -1% in February 2007 to 427% in March, resulting in an EPS-revision ratio of 428%. The average EPS-Revision number for P3 is 0, as this portfolio consists of the companies that have had the smallest change in the mean forecasts in the sample period. By examining the EPS Dispersion columns, the highest and lowest dispersion estimates are to be found in P1 and P5; the portfolios with the most positive and negative consensus forecasts, whereas the average number is approximately twice as high for P5 than P1, indicating that the analysts disagree most on companies which are given negative forecasts.

4.1 Revision Strategies

At this point we have five equally weighted portfolios (P1-P5) sorted and listed in descending order in table 2. We further have two sections of columns consisting of raw returns and corresponding p-values, where the latter tell us the significance level of each return. The returns that are significantly different from zero on a five percent level are colored in dark grey. The first section is Average Monthly Raw Returns (AMRR), with five different holding periods, ranging from the interval [0,1] to [9,12] months after the analysts have given their forecasts. The second section is Cumulative Raw Returns (CRR) for five different periods. For the five portfolios we, at the AMRR level, se a pattern of no significant returns different from zero, while from the CRR section we see more significant returns as the cumulative periods increase. In the last two rows we have a long-short strategy where we go long in P1 and short P5, hence we buy the portfolio with the most positive EPS-Revision Ratios and sell the portfolio with the most negative EPS-Revision Ratios. We here find more significant results. From AMRR the two first intervals of [0,1] and [1,3] are highly significant and giving monthly returns of 1,3% and 0,9%, respectively.

Table 2: Raw Returns of Portfolios

The raw returns are for companies listed on Oslo Stock Exchange (OSE), covered by a minimum of three IBES analysts for at least 12 months in the period 2005-2011. Monthly forecasted EPS estimates are obtained, for the next fiscal year, from Institutional Brokers' Estimate System (IBES).

Companies are sorted into five equally weighted portfolios by their EPS-Revision. EPS-Revision is calculated as the difference in estimates between two monthly periods as a percentage of the absolute value of the last estimate. Average Monthly Raw Returns (AMRR) are the average returns in the holding periods [0,1], [1,3], [6,9] and [9,12]. Cumulative Raw Returns (CRR) are the cumulative returns for the holding periods [0,1], [0,3], [0,6], [0,9] and [0,12]. A row of p-values is to be found below each row of portfolio return.

Table 2: Raw Returns of Portfolios

	Average Monthly Raw Returns (AMRR)					Cumulative Raw Returns (CRR)				
EPS-Revision Portfolios in descending order (most to least favourable)	[0,1]	[1,3]	[3,6]	[6,9]	[9,12]	[0,1]	[0,3]	[0,6]	[0,9]	[0,12]
P1	0,0090	0,0107	0,0101	0,0052	0,0076	0,0090	0,0359	0,0771	0,1055	0,1511
	0,30	0,13	0,14	0,41	0,25	0,30	0,05	0,02	0,01	0,00
P2	0,0082	0,0061	0,0050	0,0025	0,0025	0,0082	0,0242	0,0410	0,0648	0,0872
	0,33	0,39	0,41	0,68	0,69	0,33	0,22	0,16	0,10	0,06
P3	0,0066	0,0075	0,0047	0,0087	0,0000	0,0066	0,0241	0,0409	0,0786	0,1068
	0,41	0,23	0,41	0,21	1,00	0,41	0,13	0,11	0,03	0,02
P4	-0,0017	0,0033	0,0060	0,0044	0,0042	-0,0017	0,0069	0,0313	0,0533	0,0822
	0,84	0,63	0,32	0,51	0,51	0,84	0,69	0,27	0,15	0,07
P5	-0,0038	0,0016	0,0063	0,0061	0,0015	-0,0038	0,0062	0,0306	0,0599	0,0886
	0,71	0,82	0,35	0,42	0,84	0,71	0,76	0,33	0,17	0,09
P1-P5	0,0128	0,0091	0,0037	-0,0009	0,0060	0,0128	0,0297	0,0464	0,0456	0,0625
	0,03	0,02	0,33	0,82	0,08	0,03	0,01	0,02	0,07	0,03

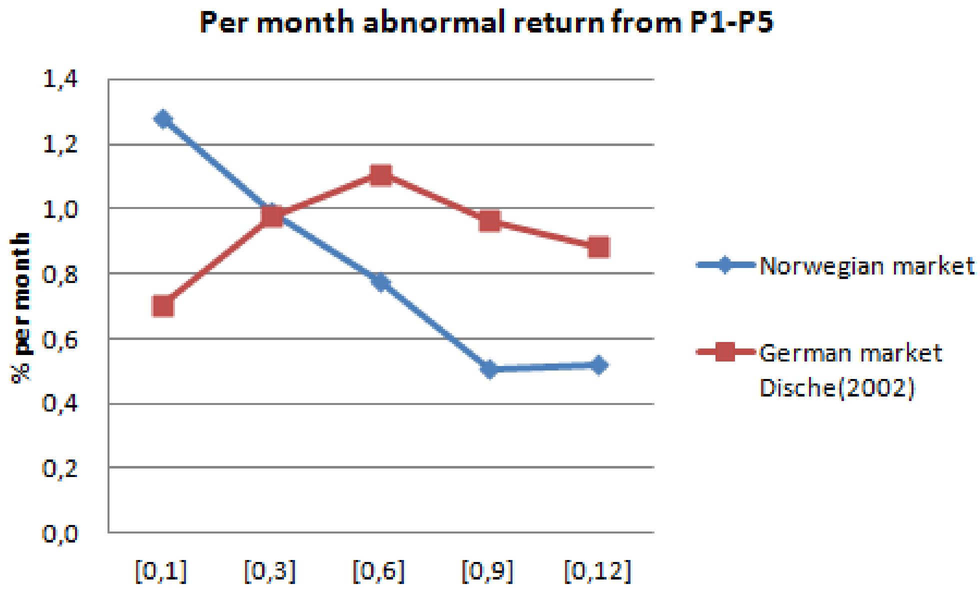
Table 3: Abnormal Returns of Portfolios

The table shows market-adjusted abnormal returns for companies listed on Oslo Stock Exchange (OSE), covered by a minimum of three IBES analysts for at least 12 months in the period 2005-2011. Monthly forecasted EPS estimates are obtained, for the next fiscal year, from Institutional Brokers' Estimate System (IBES). Companies are sorted into five equally weighted portfolios by their EPS-Revision. EPS-Revision is calculated as the difference in estimates between two monthly periods as a percentage of the absolute value of the last estimate. Average Abnormal Monthly Returns (AAMR) are the average returns in the holding periods [0,1], [1,3], [6,9] and [9,12]. Cumulative Abnormal Returns (CAR) are the cumulative returns for the periods [0,1], [0,3], [0,6], [0,9] and [0,12]. A row of p-values is to be found below each row of portfolio return.

Table 3: Abnormal Returns of Portfolios										
	Average Abnormal Monthly Returns (AAMR)					**Cumulative Abnormal Returns (CAR)**				
EPS-Revision Portfolios in descending order (most to least favourable)	[0,1]	[1,3]	[3,6]	[6,9]	[9,12]	[0,1]	[0,3]	[0,6]	[0,9]	[0,12]
P1	0,0053	0,0049	0,0036	-0,0002	0,0044	0,0053	0,0165	0,0329	0,0331	0,0479
	0,13	0,03	0,12	0,94	0,04	0,13	0,02	0,01	0,03	0,01
P2	0,0045	0,0002	-0,0014	-0,0029	-0,0006	0,0045	0,0047	-0,0032	-0,0076	-0,0159
	0,15	0,91	0,40	0,14	0,71	0,15	0,44	0,68	0,50	0,21
P3	0,0029	0,0016	-0,0017	0,0033	-0,0032	0,0029	0,0046	-0,0032	0,0062	0,0036
	0,33	0,42	0,43	0,41	0,10	0,33	0,43	0,73	0,64	0,83
P4	-0,0053	-0,0026	-0,0004	-0,0010	0,0011	-0,0053	-0,0125	-0,0129	-0,0191	-0,0210
	0,07	0,22	0,80	0,62	0,56	0,07	0,02	0,11	0,06	0,15
P5	-0,0075	-0,0042	-0,0001	0,0007	-0,0016	-0,0075	-0,0133	-0,0136	-0,0125	-0,0146
	0,04	0,10	0,96	0,77	0,51	0,04	0,05	0,21	0,38	0,41
P1-P5	0,0128	0,0091	0,0037	-0,0009	0,0060	0,0128	0,0297	0,0464	0,0456	0,0625
	0,03	0,02	0,33	0,82	0,08	0,03	0,01	0,02	0,07	0,03

As this paper is exploring the momentum effect of the analysts' forecasts we are highly interested in the CRR. At the 5% level we find four out of five periods to be significant at the 5% level, and all of them at a 10% level. As the long-short portfolio requires no initial outlay, significant returns from this strategy will represent an arbitrage opportunity. In table 3 we have adjusted the returns for the market, thus the table provides abnormal returns. In the market we include all companies in our sample, hence all OSE companies that are covered by a minimum of three IBES analysts for at least 12 months in the period 2005-2011. The sections are denoted Average Abnormal Monthly Returns (AAMR) and Cumulative Abnormal Returns (CAR). Compared to the previous table we first see that there are more significant returns on a five percent level in Table 3 (two significant holding periods for P1 and one for P5 at the 5 % level), than Table 2. The returns have improved to be significant, which indicates that the market has given negative returns for several periods. The poor performance of the market is related to the financial crisis, starting in August 2007 (ref), which represents a large part of our sample. Taking a look at the significant returns from the five portfolios in the AAMR section, they are all from P1 and P5, so in these two portfolios we find the most positive and negative returns. We observe significant abnormal performance in the four last periods in the CAR section for P1.

The most significant effects are still, after adjusting the five portfolios for the market, to be found in the long-short portfolio. A holding period of one month, following this strategy, has given a return of 1,3%, while a holding period of three months gives a monthly return of 1% (2,97% divided by three months). Both returns are highly significant, with p-values of 3% and 1%, respectively. A portfolio with a holding period of one month needs to be rebalanced every month, while the three months holding period every third month. Thus, the transaction costs associated with closing out and rebalancing the portfolios will be three times higher for the one-month holding period, and we let this serve as an argument for considering a three month holding period for this investment strategy throughout the rest of this paper. Hence, future tests in this paper will be conducted on the three months holding period. We have also observed that the "momentum-period" in the Norwegian market is shorter than in the German market, as we found it optimal to hold the portfolio in three months; while the research of Dische (2002) shows that a holding period of 6 months is optimal for this strategy before rebalancing in the German market.



The above figure shows a monthly abnormal return comparison for the self-financing portfolio long P1 and short in P5 for the Norwegian and German market, whereas the vertical axis represents number of holding periods. The plot clearly shows declining profitability as the number of holding months increases for the Norwegian market, while the plot of abnormal profits for the German market is more bell-shaped with a peak at the optimal holding period of 6 months. It is interesting to observe that the per-month return for a 3-month holding period before rebalancing is almost identical for the Norwegian as for the German market.

4.2 Introducing the Effect of Dispersion in Analysts' Forecasts

We hereby have found statistical support for momentum strategies to be profitable in the Norwegian Market. In this section we introduce the dimension of dispersion in analysts' forecasts into our analysis. The dispersion represents the level of agreement in the consensus forecasts between the analysts. A high dispersion will indicate that analysts disagree on the forecasted earnings estimates, while a low dispersion will indicate the opposite. From the last section the largest abnormal returns are found using P1 and P5, hence these two portfolios form a good basis for a long-short strategy.

We now sort our EPS-Revision portfolios by their dispersion into two equally weighted sub-portfolios: High and Low (indicating the level of dispersion). The dispersion is the IBES coefficient of variation, computed as the standard deviation of all analysts' estimates, on a firm level, as a percentage of the absolute mean value of all estimates for a given firm. Thus, we now have four portfolios: P1 High, P1 Low, P5 High and P5 Low, where low and high represent the level of the dispersion. The aim of doing this is to examine to what extent the dispersion in forecasts contains information of patterns of returns in the sample.

Table 4: Sub-Portfolios by Dispersion in Consensus Forecasts

The table reports abnormal returns for companies listed on Oslo Stock Exchange (OSE), covered by a minimum of three IBES analysts for at least 12 months in the period 2005-2011. Monthly forecasted EPS estimates are obtained, for the next fiscal year, from IBES. Companies are sorted into five equally weighted portfolios by their EPS-Revision. The EPS-Revision is calculated as the difference in estimates between two monthly periods as a percentage of the absolute value of the last estimate. The EPS-Revision portfolios are then sorted by their dispersion in to two equally weighted sub-portfolios: High and Low (indicating the level of dispersion).

Table 4: Sub-portfolios by dispersion in consensus forecasts

	Earnings-revision portfolios	Short: P1 Low	Short: P1 High	Short: P5 Low	Short: P5 High
Long	P1 Low		-0,0129 0,26	0,0324 0,02	0,0398 0,01
Long	P1 High	0,0129 0,26		0,0195 0,22	0,0269 0,09
Long	P5 Low	-0,0324 0,02	-0,0195 0,22		0,0074 0,64
Long	P5 High	-0,0398 0,01	-0,0269 0,09	-0,0074 0,64	

The dispersion is the IBES coefficient of variation, computed as the standard deviation of all analysts' estimates, on a firm level, as a percentage of the absolute mean value of all estimates for a given firm. The table reports cumulative returns for a long-short strategy, of combinations of the sub-portfolios of P1 and P5. The holding period is three months.

In Table 4 we have created different combinations of our long-short arbitrage strategy for the dispersion portfolios from P1 and P5. The table provides return data from a holding period of three months and the corresponding p-values. In the table the left column states which of the portfolios we buy, and similarly the "Short" row states which we sell.

The similar colors refer to the same results with different signs in front, since these are consisting of the same portfolios, whereas they differ in regards to which is long and short. The first remarkable finding is that the portfolios consisting of P1 Low and any P5 portfolio provide remarkable better and more significant returns than the similar portfolios consisting of P1 High. Thus, the return from P1 Low is stronger than P1 High. This implies a negative relationship between momentum profits and dispersion. Not surprisingly, the combinations of long in one of the P1 portfolios and short in any of the P5 portfolios yields a significant positive return, bearing in mind that the Low and High portfolios are crafted from the P1 and P5 portfolios. What is to be regarded as a striking finding is that the returns are improved in a remarkable positive direction by introducing dispersion.

According to Dische (2002) portfolios managers understand the roles of investors, analysts and executives in the so called earnings game. The earnings estimates given in IBES are based on institutional analysts' calculations. The analysts obtain the major part of their relevant information from company executives. These have incentives to create a positive future prospect for their company in which they are in charge. Assuming that analysts play a role as investment bankers they have clients they want to please, and they hence have incentives to communicate optimistic earnings forecasts. As portfolio managers understand these different roles they will tend to react more dramatically to negative revisions than to positive revisions, according to the incentives of analysts and executives. So portfolio managers will tend to sell when there are only a few downward revisions, whereas they will only buy when there is a broad agreement of the positive prospects among the analyst. Thus, stock prices will tend to underreact less to bad news and more to good news, according to this earnings game.

The most positive and significant result is to be found where we go long in P1 Low and short P5 High, which is the key finding of this study. This provides a highly significant return of 4% from a three month holding period or a incremental monthly return of 1,33%, without initial outlay. In comparison, a portfolio of long P1 High and short P5 High provides a less significant (p value of 9%) return of 2,7% for a three months holding period, or an incremental monthly return of 0,9%. Thus, in addition to a highly significant risk free return on the basis of analysts' earnings forecasts and dispersion, we also find a relative difference in returns between the different dispersion portfolios.

Table 5: Returns Before and After the Financial Crisis

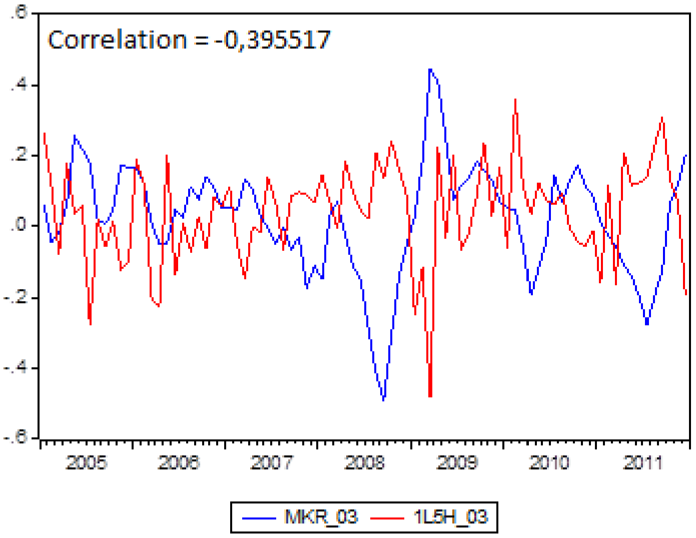
The table reports abnormal returns for companies listed on Oslo Stock Exchange (OSE), covered by a minimum of three IBES analysts for at least 12 months in the period 2005-2011. Monthly forecasted EPS estimates are obtained, for the next fiscal year, from IBES. Companies are sorted into five equally weighted portfolios by their EPS-Revision. The EPS-Revision is calculated as the difference in estimates between two monthly periods as a percentage of the absolute value of the last estimate. The EPS-Revision portfolios are then sorted by their dispersion into two equally weighted sub-portfolios: High and Low (indicating the level of dispersion). The dispersion is the IBES coefficient of variation, computed as the standard deviation of all analysts' estimates, on a firm level, as a percentage of the absolute mean value of all estimates for a given firm. The table reports cumulative returns for a long-short strategy, which goes long in P1 Low and short in P5 High. The holding period is three months. The sample has been divided into two sub-periods: before and after the financial crisis.

Table 5: Returns before and after the Financial Crisis		
Sub-periods	**Portfolio**	**Low-High**
1/2005-7/2007	P1 - P5	0,0036
		0,88
8/2007-12/2011	P1 - P5	0,0610
		0,00

In Table 5, the returns from the strategy of going long in P1 Low and short in P5 High have been divided into two sub periods: 1/2005-7/2007 and 8/2007-

12/2011. The reason for this interval is the financial crisis, which started in August 2007. The results show that the strategy performs poorly in the first interval with a non-significant monthly return of 0,12%. Nevertheless, the last period provides a significant return of 2% per month. Thus, the profitability of our investment strategy is highly affected by financial turbulence.

5.0 Market Correlation



By examining the returns from our investment strategy (red) in a plot and comparing with the market return (blue) from the same period, we see that the strategy performs well in bearish markets by generating positive returns, while underperform in bullish markets. This is further confirmed by the negative correlation coefficient of -0,39 with the market. This is aligned with the results from Table 5, as the market had a poor performance in the financial crisis, where our portfolio P1 Low – P5 High produced a return of 2% per month.

By combining two assets that is negatively correlated will the volatility of returns be reduced (Tran, 2006). This strategy may hence be used as a hedging tool following this logic.

$$\beta_i = \frac{cov(R_i, R_m)}{Var(R_m)} = \frac{\rho_{i,m}\,\sigma_i \sigma_m}{Var(R_m)}$$

The standard beta formula shows that a negative correlation with the market also implies a negative beta, and our investment strategy may thus be used to hedge shocks in the financial market to aggregate wealth (Campbell et. al 2010).

6.0 Market efficiency

Market efficiency in its semi-strong form, should as previously discussed be improved by more reliable information. Hence we would not expect the portfolios constructed of low-dispersion analyst forecast stocks to produce significant abnormal returns. Our results do conclude upon that the analysts' earnings revisions as well as the dispersion in analysts' consensus forecasts do provide investment value. Ali et. al (2009) find that stocks with higher degree of consensus among analysts experience better operating performance. The percentile of firms with better long-run earnings prospects are found to provide earnings guidance to analysts that are more accurate and unbiased. If we assume that investors do not use dispersion in analysts' consensus forecasts in order to infer the future earnings of the analyzed firms, then forecast dispersion contains valuation information not incorporated in the current stock prices.

Similar to Dische (2002) and Lee (2007) we find a negative relation between cumulative abnormal returns and analyst dispersion; a result that cannot be explained by a standard asset pricing model and goes against market efficiency in its semi-strong form. Dische (2002) find empirical support of investors adapting insufficiently to new information thus underweight relevant statistical evidence, which supports the school of behavioral finance.

Nardinelli (2002) showed that analysts do not to a full extent incorporate all information that is to be considered relevant when they update their earnings revisions and find support of a semi-strong market. Given the assumption that analysts only have access to publicly available information, we could expect the strategy to perform well in periods by chance, but the plot of returns shows remarkable consistency over time when it comes to the hedging capabilities of our strategy. Abarbanell and Lahavy (2003) affirm that to regard analyst forecasts as biased and inefficient is incorrect, which further support the notion that analyst forecasts may be used for profitable investment purposes.

A key factor linked to the investment value of a momentum portfolio is whether the patterns of serial correlation show consistency over time (Malkiel, 2003).

Our long-short strategy works well as a hedging vehicle over the sample period. Critics may claim that various combinations of samples and variables eventually will produce a significant abnormal return that challenges the hypothesis of efficient markets and that the transaction costs concerned with executing such strategies will be greater than the profits. We have found an investment vehicle for the Norwegian market that produce returns that makes the transaction costs concerned with the implementation negligible such as Bernard and Thomas (1989). Grossman and Stiglitz (1980) stress that if the market was to be regarded as fully efficient, no incentive for investors to uncover advantageous information would exist. Once known, methods for making arbitrage are usually exploited to the extent that they are no longer profitable. The “dispersion-effect” as Dische earlier has presented thus seem to show remarkable consistency.

Critics to the various behavioral models are many, however standard asset pricing models fail to explain returns generated by investment strategies such as the one presented in this paper. Fama (1998) criticizes behavioral financial models based on psychological processes within the market participants. This is mainly because one needs many different behavioral models in order to explain the reason for the existence of the various anomalies, which fails on an inconsistency bias between the models. Fama further argues that the market may be efficient even if a few market participants are able to generate arbitrage profits. Fama also points out that some models, e.g. the model by Barberis, Schleifer and Vishny (1998), does well on the anomalies it is designed to explain while fail to explain long-term returns observed in the literature.

One of the ultimate questions presented by Dische (2002) was whether what he refers to as the “dispersion-effect” would continue to exist after the publication of his paper. Our research suggests that for the Norwegian stock market, it does. One explanation for the persistence of this effect lies in the nature of investment strategies such as the one presented in this paper, as well as in Dische and Zimmermann (1999) and Dische (2002). They may be hard to identify as well as execute. We did however experience that these difficulties diminished as we were able to use visual basic macros that in a time-efficient manner sorted out the stocks for the different portfolios.

The behavioral theory of conservatism first introduced by Edwards (1968) states that investors who are to be regarded as less than rational adjust their beliefs only gradually to new information. The theory of conservatism is further supported by the model introduced by Barberis, Schleifer and Vishny (1998), where individuals are too slow in updating their beliefs. The dispersion effect may be regarded as an outcome of investor conservatism, where insufficient statistical weight is put on new evidence when the earnings revisions are updated. We were able to find statistical evidence for this effect in the Norwegian stock market.

The concept of PEAD (Ball and Brown 1968) has endured various checks for robustness as well as with extensions to recent data (Bernhard and Thomas 1989; Chan et. al 1996). We found a positive correlation between PEAD and low analyst dispersion similar to Liang (2003), and thus documented this effect to exist in the Norwegian market. In accordance with Qu et. Al. (2003) this thesis is written in light of the notion that dispersion captures an essential informational risk component. Our results suggest that the dispersion in the forecasts provides investment value, hence supporting this notion.

7.0 Conclusion

We have found that analysts' earnings revisions as well as the dispersion in analyst forecasts may be used to construct portfolios that may be used as a profitable investment vehicle. Dische (2002) both suggests and confirms that stronger momentum should exist in low dispersion stocks, a result similar to what we have obtained for the Norwegian market. We further conclude upon that the abnormal returns yielded from similar strategies in other markets are not results of data tampering as we were able to obtain abnormal returns for the Norwegian market with the investment strategy presented in this paper. The potential profits generated from this strategy, especially if used for hedging purposes, will be greater than the transaction costs involved. Our findings contradict the market efficiency hypothesis in its semi-strong form, and cannot be explained by classic asset pricing models. Various behavioral models try to explain why momentum based strategies such as the one presented here might work, some of which limited with regard to the generalizing aspect of the theories. As more research is being made regarding analyst behavior to explain our findings, one might come closer to answering the question regarding why this strategy works and why the dispersion-effect persists across markets.

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Dispersion in Analysts' Forecasts and Momentum Strategies in the Norwegian Stock Market

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Table Of Contents

1.0 Introduction

The evidence of investors holding other portfolios than the market portfolio is considerable (De Long et. al 1990). Many investors typically pick stocks based on their own research or the advice of analysts, and hence we find it interesting to further study the value of analyst recommendations and forecasts. While the same information is available to all analysts, disagreement does exists in how the analysts interpret the data (Kurz 1994). Analysts typically differ in their projections, and thus their beliefs are dispersed. Dispersion of beliefs seems to occur as a result of individual expectations and different weighting on the various elements of available public information, and refers to the difference in expectations that the various market participants have in regard to the future status of the market (Jongen et. al. 2007; Au, 2007).

Uninformed trades are mixed with informed ones (Fan an Lyon, 2001). How the financial markets aggregate dispersed information is linked to market efficiency. Ever since Cowles (1933) a claim has been that there should, ina semi-strong efficient market, not be possible to make arbitrage profits on publicly available information. Most studies aiming to provide investors with profitable trading strategies have failed to do so (Au, 2007). Yet, extensive resources are being used to predict future earnings as well as to come up with profitable trading strategies (Dische 2002). The data of dispersion and distribution of professional forecasts may be obtained from databases such as Institutional Brokers' Estimate System (IBES). Low dispersion in analysts' forecasts is sometimes thought of as a signifier of herding (Ciccione, 2005). Cooper et. al (2001) demonstrated that analysts who give the leading consensus forecasts are the most informative, while those who follow the rest give forecasts of less value. This paper will be based on the notion that some earnings forecasts are of higher investment value than others, and that the dispersion in the forecasts provides investment value.

Chan et. al (2006) show that the market only gradually responds to new information. A challenge to the overall concept of an efficient market is the superior returns generated by underreaction in the market to earnings news, as traditional asset-pricing models fail to provide explanations to this phenomenon (Dische, 2002). This paper will aim at replicating some of the research done by Dische (2002) in terms of method, while differencing itself by using analyst forecast data of Norwegian listed companies. This paper will search for investment strategies based on to elements from analysts' forecasts: an earnings-per-share (EPS) revision ratio and the dispersion in forecasts. The paper will as far as our knowledge go be the first empirical study to examine earnings forecasts in the Norwegian stock market.

2.0 Previous litterature/litterature review

In accordance to Griffin and Tversky (1992) inevstors focus on the strength and extremeness of news with insufficient regard to its statistical weight of credence. Barberis et al. (1998) proposed a model where investors of the conservative kind adjust their beliefs to new information too slowly. This gave rise to momentum strategies as the market only responds gradually to new information (Chan, 1996). Liang (2003) looked at the link between dispersion in analyst forecasts and post-earnings announcement drift (PEAD), and found that when the dispersion is low is there more PEAD. Thus, investment strategies, based on stock recommendations with the highest analyst consensus, should yield the higher return. The research of Dische (2002) concludes that when the dispersion of analysts' forecasts decrease, short-term returns increase. This is consistent with the findings of Au (2007). These previous results may be regarded as troubling in the context of market efficiency, as the *negative* relationship between uncertainty or dispersion is not consistent with the notion that more reliable information should improve market efficiency (Lee, 2007).

The article of Dische (2002), from which the structure and method of this paper is based upon, showed that the dispersion of consensus forecasts made by financial analysts contains incremental information that may be used to predict future returns. The study was executed with stocks from the German market and was consistent with previous research in terms of post earnings announcement drift. The underreaction to news in the German market allowed a momentum trading strategy to be performed with success. The strategy presented consisted of buying portfolios containing stocks with the highest earnings revisions and selling those with the lowest. This was also performed earlier for the Swiss market by Dische and Zimmerman in 1999 with the same conclusion. Buying portfolios with low analyst forecast dispersion and selling those with high analyst dispersion improved the return of this trading strategy (Dische, 2002).

Ball and Brown (1968) were the first to observe the phenomenon of PEAD. Various PEAD strategies, with the purpose of generating abnormal returns, have been presented and analysed to be profitable. Bernard and Thomas (1989) showed that the transaction costs concerned with implementing investment strategies based on PEAD were negligible in comparison to the significant abnormal returns these strategies may yield. A self financing investment strategy, presented by Jagadeesh and Titman (1993), yielded a monthly abnormal return of 1%. The possibility of these results being a product of data snooping bias was later evaluated and rejected in Jagadeesh and Titman (2001), which concluded that the profits created by momentum had continued in the 90's. Rouwenhorst (1998 and 199) confirmed the profitability of momentum based trading.

Jiang, Lee and Zhang (2005) find results that contradict Dische (2002). As proxies for uncertainty they use firm age, return volatility, trading volume, and duration of firms' future cash flows. Thus, they find a positive association between information uncertainty and PEAD. Lee (2007) aims to reconcile these conflicting results, by explaining the results in Dische (2002) (negative association between analyst dispersion and PEAD) with inaccuracy in the measurement of uncertainty extracted from analyst forecast data. Lee (2007) then show that forecasts updated late after earnings announcements provide information of higher accuracy than the forecasts that are updated early after such announcements. Similar to Dische (2002) Lee (2007) finds a negative correlation of cumulative abnormal returns (CARs) and forecasts dispersion. Lee (2007) does however conclude with a *positive* association between analyst forecast dispersion and

PEAD after controlling for market's response to earnings news and early analyst herding, which he feels Dische (2002) has failed to recognize the importance of. Although low dispersion in analysts' forecasts may be interpreted as a sign of analyst herding, an underlying assumption we make is that high uncertainty, measured by high dispersion, is a signal of large forecast errors. This interpretation has earlier been suggested by Liang (2003); Dische (2002). We will initially regard number of forecasts together with low analyst dispersion as a sign of strength. This will anyways not interfere with the analysis of the trading strategy, but will rather be relevant when discussing the semi-strong market efficiency of the Norwegian stock market and PEAD on the basis of our findings.

3.0 Our contribution and motivation

As far as our knwledge goes there are no other empirical IBES-based papers examining analysts' earnings forecasts in the Norwegian Stock market.

The profitability of trading on momentum strategies differs from market to market. We intend on enlighten the possibilities of making such arbitrage profits as researched by Dische (2002) in the Norwegian stock market. Our findings will then form as basis for a discussion on market efficiency.

Our contribution in this research field does also form our motivation for choosing this topic. Analysing the possibilities for arbitrage profits in the Norwegian stock market by a method that earlier has been proven to be successful by Dische (1999, 2002) will enlighten the ability of this trading strategy to function in different markets. The conclusions we may draw on the basis of our research in this intriguing field of finance is of high interest to us.

4.0 Research Questions

In our paper we will examine to what extent the dispersion in analysts' forecasts in the Norwegian stock market can be useful to predict future stock prices. Our questions are (1) whether it is possible to create momentum portfolios of Norwegian stocks, based on an earnings revision ratio and the dispersion in analysts' forecasts that can make significant risk free abnormal returns (arbitrage)? And (2) to what extent we can find any significant violation of market efficiency in our results?

5.0 Data and Methodology

Our data of analysts' forecasts on the Oslo Stock Exchange (OSE) will be obtained from the Institutional Brokers' Estimate System (IBES). IBES monitors different estimates for earnings, where their database for international forecasts started in 1987 (Thompsen Reuters 2012). The data software we will use for the regressions in the paper is EViews.

We will base our paper on the so-called consensus forecast estimate for earnings-per-share (ESP), which is the average of all estimates for a fixed period of time. In IBES this is calculated by summarizing the EPS estimates for the current period, from all of the contributing firms, for the specified fiscal time period and dividing the sum by the number of EPS estimates in the calculation.

Our structure for data and methodology is based on similar studies as e.g. Dische (2002). The potential sample size is the 215 firms listed on Oslo Stock Exchange (OSE) (Oslo Børs 2011) in the time period from January 1987 until January 2012. We will use monthly observations and thus the potential number of observations per stock is 300 (25 years * 12 months). To avoid bias related to the dispersion in forecasts we will only include the stocks that are covered by a minimum of three analysts for at least one year in our sample size. In the data we see two tendencies: (1) when analysts start to cover a stock for the first time (in the IBES data) the number of estimates (analysts covering the stock) increases over time; and (2) the number of Norwegian stocks in the data increases during the sample period. Thus, in our data we expect to exclude start-up periods for most stocks, as well as other periods, which have less than three EPS estimates. Chordia and Shivakumar (2000) investigated to what extent the macro economy affects momentum strategies. The findings indicated that momentum strategies perform well in periods of favorable macroeconomic states, while they do not in the case of recessions. Nevertheless, initially we will not exclude any period on the basis of an extraordinary event (e.g. the financial crisis), but we will rather consider whether such periods have significant impact on the results. Hence, if we find such evidence we will consider whether or not to include the observations in the data. In addition we also expect the number of stocks in our data set to increase over time.

In accordance to Dische (2002) a favorable side of using the mean EPS estimated forecasts on a fixed one-year horizon in this paper is that the estimates are for a forecasting horizon that is one year ahead, thus we do not have consider effects associated with the end of fiscal year, which is December for the companies we will include in the data. As a measure for the level a stock has of new information during a period we will evaluate the impact of changes in EPS by using an EPS revision ratio. The ratio represents the average change in the analysts' forecasts on a monthly basis. It will be computed as the average monthly change in EPS divided by mean absolute value of the consensus forecast last period.

5.1 Regressions

The general regression for this paper will be:
(1) $(r - r_f) = \alpha + \beta(r_m - r_f)$, where (2) $\alpha = (r - r_f) - (\beta \times (r_m - r_f))$. This regression is similar to a Jensen's Alpha (eq. 2) regression, except for minor differences. The market return is in this paper based on all stocks on OSE that are covered by a minimum of three IBES analysts. Since we in this paper also sort the data, based on EPS-revision ratios and dispersion, we have a different concept, but the generalized purpose of the alpha remains unchanged. The Jensen's Alpha (eq. 2), is a measurement of abnormal performance over time. A significant positive Jensen's alpha indicates that the portfolio has outperformed the market. In the case of an insignificant Jensen's alpha one cannot conclude whether the portfolio has outperformed or underperformed the market. In the case of a significant negative Jensen's alpha, one could deduce that the portfolio has underperformed the market. The economic understanding of the beta (eq. 1 and

2) is that it indicates the riskiness of the fund relative to the market. The market has a $\beta=1$, so if for a given portfolio the $\beta<1$, the portfolio is less risky than the market, a $\beta>1$ will indicate that the portfolio is more risky than the market. To estimate the alpha, we will first control the data for heterosceasticity and autocorrelation. The risk free rate will be based on Norwegian governmental bonds, downloaded from the Norwegian Central Bank's webpage. This data is in yearly return, so we need to transform it into monthly compounded interest. Based on this and the market return, we compute the market risk premium. Note: Future regressions in this paper will take the same form as eq. 1, while the return-variable will be different. The hypotheses in this paper will all have a significance level of 5%. Thus, the null-hypotheses will be rejected only if the alphas have significant values, represented by p-values < 5% (or corresponding t-values).

5.2 Revision Strategies

Table 1 gives descriptive statistics of analysts' forecasts. The most important elements in this table are the five "EPS-Revision by Portfolios" columns. After acquiring the EPS revision ratios we will sort the stocks in five equally weighted portfolios, in descending order by their revision ratios. Thus, the first portfolio will include the most upward revision ratios and the last portfolio will include the most downward revisions, on a monthly basis. The portfolios will be compared to their related average dispersion in analysts' forecasts, while the other columns give average yearly descriptive information for all stocks. "Number of Firms" is the number of OSE listed firms that are covered by three or more analysts for a given year in our data. "Analysts per Firm" is the average number of analysts covering the firms. From the "Price/Earnings median and mean" we can examine whether the mean is skewed. "EPS" is the mean earnings-per-share, while "Dispersion" is the dispersion in the consensus forecasts, which is the IBES coefficient of variation of all earnings estimates (computed as the standard deviation of all analysts' estimates, on a firm level, as a percentage of the absolute mean value of all estimates for a given firm).

From Table 2 we can examine both the average monthly abnormal returns and the cumulative abnormal returns (CARs) from the five portfolios created in Table 1. Thus, all the returns are adjusted for market returns, where the market is represented by an index of all stocks on OSE that are covered by three or more analysts in the IBES data. The brackets give the holding period in months. For the different periods of average monthly returns (AMR) and CARs we run regressions. Our hypotheses will be:

H_0: The market adjusted AMR_i or the CAR_u of $portfolio_p$ is not significantly different from zero, for i=[0,1],…,[9,12] and u=[0,1],…,[0,12] and p=1,…,5
H_A: The market adjusted AMR i or the CAR u of portfolio p is significantly different from zero, for i=[0,1],…,[9,12] and u=[0,1],…,[0,12] and p=1,…,5

The next step is to find a portfolio X that constantly achieves higher returns than portfolio Y and construct a portfolio, X-Y, which buys X and shorts Y (the last two rows in Table 2). We test the hypotheses:

H_0: The market adjusted AMR_i or the CAR_u of portfolio X-Y is not significantly different from zero, for i=[0,1],…,[9,12] and u=[0,1],…,[0,12]
H_A: The market adjusted AMR_i or the CAR_u of portfolio X-Y is significantly different from zero, for i=[0,1],…,[9,12] and u=[0,1],…,[0,12]

If the results give statistical support for rejecting H_0 for all periods of AMR, we find support for the existence of a momentum arbitrage portfolio, X-Y. If we find such evidence in our data, we will examine which of the periods u of CAR that has the highest abnormal returns per month, to create an optimal holding period Z.

5.3 Introducing the Effect of Dispersion in Analysts' Forecasts

After examining the existence of momentum arbitrage strategies, the effect of dispersion in analysts' forecasts will now be introduced in Table 3. Now, within every $portfolio_p$ (p=1,…,5) three equally weighted sub-portfolios (SP) will be created, based on the dispersion in analysts' forecasts. The SPs will be ranged by high dispersion (SP_1), medium dispersion (SP_2) and low dispersion (SP_3). The numbers of portfolios is now 15, in addition to a low-minus-high (SP_3-SP_1) portfolio. The latter will examine the relationship between momentum and dispersion in consensus forecasts. The abnormal returns and t-values, for the period of Z months, will be reported in Table 3. The hypotheses will be:

H_0: The market adjusted return for SP_i or SP_3-SP_1 is not significantly different from zero, for for i=1,…,3
H_A: H_0: The market adjusted return for SP_i or SP_3-SP_1 is significantly different from zero, for i=1,…,3

In Table 4 we will divide the market-adjusted returns from the stocks X and Y, in addition to a long-short strategy X-Y into different sub-periods. The analysis in this table is similar to the one in Table 3, but at an incremental level.

If the null-hypotheses for a self-financing portfolio in 5.2-5.3 is consistently rejected for all holding periods, we have found an arbitrage portfolio that gives abnormal returns. Assuming that no costs related to the implementation of this strategy will exceed the abnormal return, the finding might contradict market efficiency in its semi strong form.

Table 1: Descriptive Statistics of Analysts' Forecasts

			Price/Earnings				EPS-Revision by Portfolios (most to least favourable)						EPS Dispersion by Portfolios				
Year	Nmb. Of firms	Analysts per firm	Median	Mean	EPS	Dispersion	Port. 1	Port. 2	Port. 3	Port. 4	Port. 5		Port. 1	Port. 2	Port. 3	Port. 4	Port. 5
1987																	
1988																	
1989																	
…																	
2012																	
Average																	

Table 2: Returns of Portfolios										
	Average Monthly Returns (AMR)					**Cumulative Abnormal Returns (CARs)**				
EPS-Revision Portfolios in descending order (most to least favourable)	[0,1]	[1,3]	[3,6]	[6,9]	[9,12]	[0,1]	[0,3]	[0,6]	[0,9]	[0,12]
Portf. 1										
	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. 2										
	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. 3										
	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. 4										
	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. 5										
	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. X - Portf. Y										
	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)	(t-stat)

Table 3: Market adjusted abnormal returns over Z months (portfolios based on EPS-revisions and dispersion analysts' forecasts)				
	Sub Portfolios (SP) by Dispersion in Analysts' Forecasts			
EPS-revision portfolios (from table 1)	High SP1	Medium SP2	Low SP3	Low-High SP3-SP1
Portf. 1				
	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. 2				
	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. 3				
	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. 4				
	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. 5				
	(t-stat)	(t-stat)	(t-stat)	(t-stat)
Portf. X - Portf. Y				
	(t-stat)	(t-stat)	(t-stat)	(t-stat)

Table 4: Market-adjusted returns over Z months in subperiods (based on EPS-revisions and dispersion in analysts' forecasts)					
Sub-period	Portfolio	High	Medium	Low	Low-High
1/1987-12/1990	Portf. X	SP1	SP2	SP3	SP3-SP1
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. X-Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
1/1991-12/1994	Portf. X				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. X-Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
1/1995-12/1998	Portf. X				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. X-Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
1/1999-12/2002	Portf. X				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. X-Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
1/2003-12/2006	Portf. X				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. X-Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
1/2007-12/2011	Portf. X				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)
	Portf. X-Portf. Y				
		(t-stat)	(t-stat)	(t-stat)	(t-stat)

6.0 Thesis Progression

This is a plan of the progression of our thesis.

Thesis Progression Plan	
Time period	**Objective**
Jan 15th	Preliminary Thesis
Jan - Feb	Data Collection
Feb - March	Data Screening
March - April	Analysis and Hypothesis Testing
April - May	Writing
May - September	Finishing

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