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Evaluating the Predictive Power of Leading Indicators Used by Analysts to Predict the Stock Return for Norwegian Listed Companies

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Evaluating the Predictive Power of Leading Indicators Used by Analysts to Predict the Stock Return for Norwegian Listed Companies

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Abstract

This paper studies the predictive power of leading indicators used by interviewed analysts to predict the monthly excess stock returns for some of the most influential Norwegian companies listed on the Oslo Stock Exchange. The thesis primarily seeks to evaluate whether a multiple factor forecast model or a forecast combination model incorporating additional explanatory variables have the ability to outperform a five common factor (FCF) benchmark forecast model containing common factors for the Norwegian stock market. The in-sample and out-of-sample forecasting results indicate that a multiple factor forecast model fails to outperform the FCF benchmark model. Interestingly, a forecast combination model with additional explanatory variables for the Norwegian market is expected to outperform the FCF benchmark forecast model.

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Table of Contents

1.0 Introduction

Financial markets have created a unique platform for trading and investing. Since more accurate stock prediction is directly related to yielding larger profit opportunities, stock market prediction has caught the attention of several investors, analysts and researchers. Therefore, for decades, a considerable number of studies have dealt with the predictability of return in the stock market, containing various predictors, techniques and models to examine whether there are statistically and economically predictive patterns in stock returns (e.g., Rapach, Wohar & Rangvid, 2005; Ang & Bekaert, 2007; Grandhmal & Kumar, 2019).

This paper seeks to assess the monthly predictive power of specific leading indicators used by analysts to predict the excess stock return for selected Norwegian companies listed on the Oslo Stock Exchange (OSE). For this purpose, similarly to Rapach, Strauss & Zhou (2009), an out-of-sample forecast exercise of the excess return of each company is conducted to investigate the leading indicators' ability to directly forecast the excess stock return. The analysis concentrates on the relevance of particular economic, industry specific and company specific variables related to each company. In order to identify the leading indicators used by analysts, semi-structured interviews were conducted with analysts before secondary data were collected. The thesis further evaluates whether a multiple factor forecast model or a forecast combination model incorporating additional lagged explanatory variables have the ability to outperform a five common factor (FCF) benchmark forecast model containing common factors for the Norwegian stock market. For the common factors, a multi-factor model based on Fama & French (1993) and Carhart (1997,) with liquidity as an additional factor, as described by Næs, Skjeltorp & Ødegaard (2009), is adopted. In comparing the performance of the forecasts relative to the benchmark model, the out-of-sample predictions are evaluated using R^2_{OS} statistics to measure the reduction in mean square prediction error (MSPE), based on work done by Campbell & Thompson (2008).

As emphasised by Bodie, Kane & Marcus (2014, p. 350), successful analysts and investors are finding themselves competing to discover relevant information before the rest of the market becomes aware of that information. Through leading indicators, they may get a sense of where the economy is heading in the future, identifying market conditions, thus developing trading strategies aiming to detect profit opportunities. This involves the assumption that fundamental publicly available information has some predictive relationship to future stock returns (Enke & Thawornwong, 2005, p. 927). However, analysis of stock returns might be one of the most difficult fields in the finance industry. This is due to the numerous amounts of influential and highly interrelated factors interacting in a complex manner (Zhong & Enke, 2017, p. 126). Factors affecting return predictability are both non-economic and economic and include economic variables, industry specific variables, company specific variables, psychological variables and political variables (Enke & Thawornwong, 2005; Wang, Wang, Zhang, & Guo, 2011). This paper only examines the relevance of particular economic, industry specific and company specific variables related to the specific companies. The rationale for this is grounded in the difficulties associated with identifying and obtaining data related to non-economic factors, although the analysts do admit that they also compete on their ability to interpret a huge number of soft factors. Furthermore, a potential issue with this study is the suspected possibility of the interviewed analysts leaving out important matters in their identification of leading indicators, in order to not compromise their own strategies. If this suspicion holds true, it constitutes a weakness of the study.

Due to the complexity, Spiegel (2008, p. 1453-1454) and Cooper & Priestley (2009, p. 2801) emphasise that research on stock return predictability is controversial for a number of reasons, and often contentious. A major point of discussion in the literature is whether stock prices are predictable or not. Moreover, several eminent and influential financial theories suggest that stock market returns and movements cannot be predicted, and if they were, a situation of stock market inefficiency would exist (Bodie et al., 2014, p. 350). Stock predictability is in contradiction with one of the most accepted and influential modern financial theories, the Efficient Market Hypothesis (EMH) (Fama, 1970). The hypothesis states that stocks are accurately priced at the fair market value on exchange and reflects all available information, i.e. the price would be unaffected by revealing the information set to all market participants (Malkiel, 1992), implying that no abnormal returns can be obtained by examining past prices and returns of stocks (Balling, Poel, Hespeels & Gryp, 2015, p. 7047). However, there is strong empirical evidence that rejects the aforementioned hypothesis (Grossman & Stiglitz, 1980; De Bondt & Thaler, 1985; Lo & MacKinlay, 1988; Lee, Lee & Lee, 2010), underscoring the point of developing and improving models for predicting the future behaviour and value of a specific stock or an overall market.

Sharp (1964) and Lintner (1965) developed a single-factor model, known as the Capital Asset Pricing Model (CAPM). This model is based on the idea that asset return is determined by an asset's systematic risk since unsystematic risks of individual assets can be eliminated by diversification in an efficient portfolio. According to Rossi (2016, p. 604), CAPM marks the beginning of asset pricing theory. Since then, researchers have made modifications and formulated various asset pricing models to explain the determinants of asset returns. For instance, the three-factor asset pricing model developed by Fama & French (1993) was designed to overcome some of the limitations in CAPM. It does so by including a size risk factor and a value risk factor along with the market risk factor. Furthermore, Carhart (1997) suggested to expand on the three-factor model by including an additional factor, which takes the momentum effect into account. The models have been subject to rigorous testing over the years and multi-factor models seem to have slightly more predictive power than the simple CAPM (Sanusi & Ahmad, 2016).

In this study of the predictive power of leading indicators used by analysts of Norwegian listed companies, a five-factor model based on Fama & French (1993) and Carhart (1997), with liquidity as an additional factor, as described by Næs, Skjeltorp & Ødegaard (2009), is adopted. The five common factor (FCF) benchmark forecast model contains common factors for the Norwegian stock market and is used as a benchmark for the purpose of evaluating whether a multiple factor forecast model or a forecast combination model incorporating additional explanatory variables can outperform the benchmark forecast. There is little available research on this field, and the ambition of this study is to contribute to the field of research by studying the predictive power of specific factors, as used by the interviewed analysts of the companies in question. The study also investigates whether or not the leading indicators suggested by analysts of these companies show the expected relevance when evaluating predictive power.

The Oslo Stock Exchange (OSE) is Norway's only regulated marketplace for trading of shares, equity certificates and other securities. OSE has been growing steadily over the period 1980-2006 both in terms of trading volume and values (Næs, Skjeltorp & Ødegaard, 2009, p. 8). The companies listed on the exchange operate in a range of diverse industries; however, a majority of these take part in large industries such as gas, oil and banking. A prominent characteristic of the OSE is that the exchange always has a few very large companies dominating the value of the exchange (Næs, Skjeltorp & Ødegaard, 2009, p. 8). During the interviews with the analysts, they emphasised that the industries on OSE in general are highly cyclical, meaning that the firms have great sensitivity to overall global markets, implying that Norwegian companies are highly affected by global growth.

Among the few extant studies focusing on the Norwegian stock market, Næs, Skjeltorp & Ødegaard (2009) find that returns on the OSE reasonably can be explained by a multi-factor model consisting of the market index, a size index and a liquidity index. Furthermore, their results show that OSE is positively correlated with changes in oil prices, as opposed to most stock markets in the rest of the world, which typically experience decline when the oil price increases. Hysing-Dahl (2009) investigates how various factors in the real-economy affects the Norwegian stock market, and found oil prices, industrial production, dollar exchange rate, interest rates (short-term and long-term) and foreign capital markets to be the most relevant macroeconomic factors. In this spirit, the evaluation of Fosby & Dahl (2016) digs deeper by also focusing on the factors affecting the underlying sectors on OSE.

Similar to the studies mentioned above, numerical factors affecting the Norwegian stock market are examined by applying statistical techniques. However, unlike previous studies, this study concentrates on the predictive power of specific leading indicators for ten Norwegian companies, as used by interviewed analysts to predict the excess stock return. In other words, this study is interested in investigating whether a multiple factor forecast model or a forecast combination model incorporating additional explanatory variables can outperform a five common factor (FCF) benchmark forecast model containing common factors for the Norwegian market.

Until now, there are no previous studies analysing the predictors affecting stock returns for specific Norwegian companies. This knowledge gap provides a great opportunity for research, and an interesting challenge for this thesis. Various commonly used financial factors, macro-economic factors and company specific factors are evaluated as explanatory variables for a company's excess return in an out-of-sample forecasting exercise. To find out if the factors of interest have predictive power for companies' excess stock return, a standard predictive regression analysis was initially performed to evaluate the coefficient.

Based on work done by Rapach, Strauss & Zhou (2009), an out-of-sample forecast exercise of the excess return was conducted using a recursive estimation window. The entire sample of N observations is divided into an in-sample period and an out-of-sample period. In addition, for each company, the in-sample period is used to generate the prediction forecast model, while the out-of-sample data is used to evaluate the prediction forecast model. To evaluate the predictive power of the factors used by the analysts, a five common factor (FCF) model containing common factors for the Norwegian stock market (Næs, Skjeltorp & Ødegaard, 2009) is used as a benchmark for expected excess stock return. Finally, based on work done by Campbell & Thompson (2008), R_{OS}^2 statistics is used to investigate whether a multiple factor forecast model or forecast combination model outperforms the five common factor (FCF) benchmark forecast model. With this work, this study contributes to the field of research considering the predictability of stock return, specifically related to the Norwegian stock market.

The primary objective of this paper has been to investigate the predictive power of leading indicators used by analysts to forecast the stock return for some of the most influential Norwegian listed companies on the Oslo Stock Exchange (OSE), specifically Equinor ASA and Aker BP ASA (energy sector), DNB ASA and Gjensidige Forsikring ASA (finance sector), Mowi ASA and Orkla ASA (consumer staples sector), Yara International ASA and Norsk Hydro ASA (material sector) and Tomra Systems ASA and Kongsberg Gruppen ASA (industrial sector). The sample period for this study covers the period 1990 through 2019, making use of monthly statistics from within this period.

In nine of the ten studied cases, it was found that the multiple forecast models created based on selected factors used by analysts, by themselves failed to provide a better significant statistical role in explaining the excess stock return relative to the five common factor (FCF) benchmark forecast model over the out-of-sample period, even though the variables themselves are confirmed to possess valuable and relevant predicting power. Interestingly, in seven of the ten cases, the results from comparing the performance of the combined predictive regression forecasts to the benchmark model, show evidence of improved predictability when incorporating specific additional explanatory variables to the FCF benchmark model. In other words, even though the suggested factors used by Norwegian analysts are not the major predicting factors, the factors offer prediction value when combined with the common factors. For four companies, namely Equinor, Mowi, Tomra Systems and Kongsberg Gruppen, the results deviated. In the case of Equinor, both models were found to outperform the FCF benchmark model. For Mowi as well as the two cases from the industrial sector, Tomra Systems and Kongsberg Gruppen, the complete opposite results were experienced in that none of the models were able to outperform the FCF benchmark model. For those three cases, at least the numeric factors made available through the research undertaken while writing this paper, did not help to explain excess stock return. This might confirm the high predictive power of the FCF benchmark model, but there is reason to believe that further study of other (soft) factors might be useful. In this analysis, macro specific and sector specific factors are generally found to be reliable indicators. The company specific financial factors, on the other hand, did not show the expected relevance when evaluating predictive power.

The rest of the paper is organised as follows: Section 2 explains the empirical methodology. Section 3 describes the data. Section 4 describes the selected companies. The results are presented company-wise in Section 5, and Section 6 concludes the findings of this study.

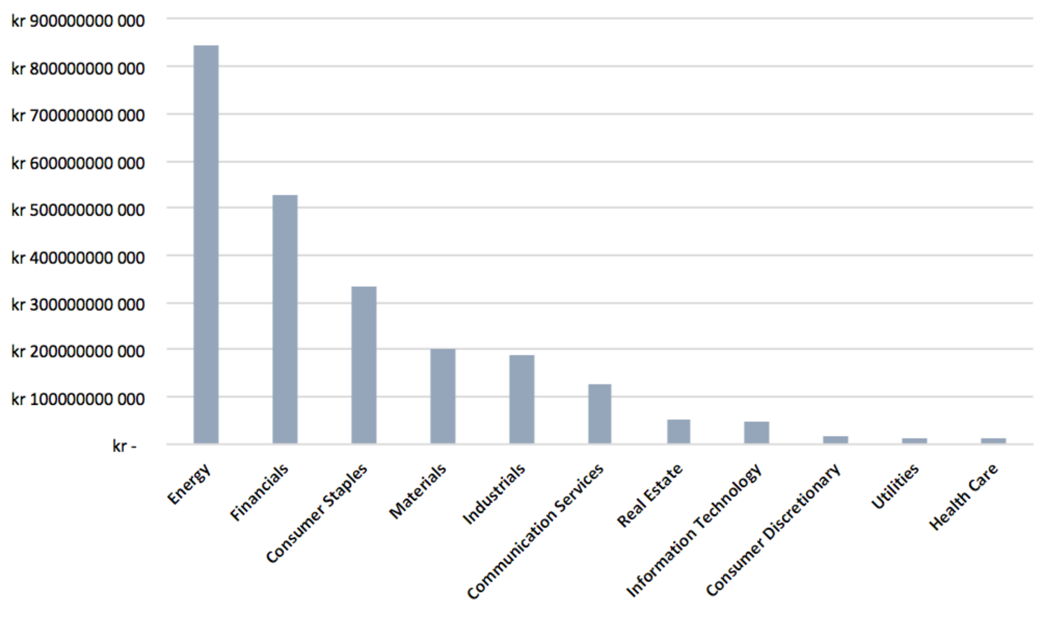
2.0 Methodology

2.1 Selection of Sectors and Companies

This paper evaluates the predictive power of leading indicators used by analysts to predict the stock return for specific Norwegian listed companies. A starting point for the selection of companies studied in this paper has been the access to the private list of investable Nordic shares of an emerging Oslo-based asset management company, which has an expressed interest in the results of this study. All Norwegian listed companies were extracted out, and sorted after the universal classification system, namely the Global Industry Classification Standard (GICS) (S&P Global, 2020). The selection has a methodological anchoring based on the sector and company's market capitalisation. The process filtered and kept five candidates within the five largest sectors on Oslo Stock Exchange, namely energy, finance, consumer staples, materials and industrials, see Appendix 1 for a further description of the sectors, respectively presented in Figure 1 and Figure 2.

Figure 1

Graphical presentation of sectors on the Oslo Stock Exchange (OSE) sorted after market capitalisation, using data as of June 30th, 2019.



From the in total 25 candidates, the two largest companies within each sector in terms of market value were chosen. Thus, the predictors of ten companies' stock return are investigated in this paper, specifically Equinor ASA and Aker BP ASA (energy sector), DNB ASA and Gjensidige Forsikring ASA (finance sector), Mowi ASA and Orkla ASA (consumer staples sector), Yara International ASA and Norsk Hydro ASA (material sector) and Tomra Systems ASA and Kongsberg Gruppen ASA (industrial sector).

Figure 2

Graphical presentation of the most influential Norwegian listed companies on the Oslo Stock Exchange (OSE), within the five largest sectors on Oslo Stock Exchange, namely energy, finance, consumer staples, materials and industrials. The figure shows five candidates within each sector sorted in terms of market capitalisation, using data as of June 30th, 2019.

All Stocks	AVG VOL	AVG PRICE	TURNOVER(NOK)	DARKPOOL ADJ	Company Market Cap	Currency	GICS Sector Name	GICS Industry Name	Company Name	Analysts
EQNR.OL	3 033 130.3	195.9	kr 594 266 059	kr 891 399 088	kr 562 397 482 341	NOK	Energy	Oil, Gas & Consumable Fuels	Equinor ASA	31
AKERBP.OL	787 200.5	275.1	kr 216 555 402	kr 324 833 102	kr 88 279 335 838	NOK		Oil, Gas & Consumable Fuels	Aker BP ASA	24
SUBC.OL	1 682 493.4	103.6	kr 174 243 057	kr 261 364 586	kr 31 415 531 020	NOK		Energy Equipment & Services	Subsea 7 SA	25
TGS.OL	405 492.8	257.7	kr 104 503 438	kr 156 755 157	kr 24 607 866 938	NOK		Energy Equipment & Services	TGS ASA	15
DNO.OL	5 628 821.5	16.4	kr 92 367 273	kr 138 550 909	kr 16 782 107 392	NOK		Oil, Gas & Consumable Fuels	Dno ASA	10
DNB.OL	1 753 630.6	158.5	kr 277 993 935	kr 416 990 903	kr 255 178 339 981	NOK	Financials	Banks	Dnb ASA	23
GJFS.OL	530 778.8	149.3	kr 79 235 402	kr 118 853 104	kr 85 900 000 000	NOK		Insurance	Gjensidige Forsikring ASA	18
AKER.OL	113 848.0	587.6	kr 66 895 841	kr 100 343 762	kr 36 477 169 870	NOK		Diversified Financial Services	Aker ASA	6
STB.OL	1 435 124.9	67.8	kr 97 279 657	kr 145 919 486	kr 29 387 685 036	NOK		Insurance	Storebrand ASA	13
SRBANK.OL	253 078.3	96.6	kr 24 455 006	kr 36 682 509	kr 26 631 536 170	NOK		Banks	Sparebank 1 SR Bank ASA	9
MOWI.OL	1 446 026.3	195.3	kr 282 397 945	kr 423 596 918	kr 103 152 643 394	NOK	Consumer Staples	Food Products	Mowi ASA	11
ORK.OL	1 589 270.2	70.6	kr 112 206 165	kr 168 309 248	kr 77 112 695 810	NOK		Food Products	Orkla ASA	10
SALM.OL	262 663.7	424.2	kr 111 423 306	kr 167 134 959	kr 42 116 272 825	NOK		Food Products	SalMar ASA	9
LSG.OL	1 037 102.3	65.8	kr 68 243 904	kr 102 365 857	kr 33 700 124 800	NOK		Food Products	Leroy Seafood Gr. ASA	9
BAKKA.OL	115 892.4	464.6	kr 53 844 221	kr 80 766 331	kr 23 256 438 940	NOK		Food Products	P/F Bakkafrost	8
YAR.OL	616 361.0	370.8	kr 228 531 127	kr 342 796 690	kr 113 308 558 620	NOK	Materials	Chemicals	Yara International ASA	20
NHY.OL	6 726 806.5	38.7	kr 260 155 744	kr 390 233 616	kr 63 244 557 617	NOK		Metals & Mining	Norsk Hydro ASA	22
ELK.OL	1 659 315.8	28.1	kr 46 556 472	kr 69 834 708	kr 13 994 076 543	NOK		Chemicals	Elkem ASA	8
BRGD.OL	109 750.1	83.4	kr 9 151 752	kr 13 727 627	kr 9 901 936 469	NOK		Chemicals	Borregaard ASA	3
NOMIN.OL	139 975.3	2.5	kr 351 275	kr 526 913	kr 322 093 569	NOK		Metals & Mining	Nordic Mining ASA	2
TOM.OL	271 899.8	227.4	kr 61 837 524	kr 92 756 287	kr 41 596 982 647	NOK	Industrials	Commercial Services & Supplies	Tomra Systems ASA	5
KOG.OL	176 575.0	124.8	kr 22 028 358	kr 33 042 538	kr 21 502 451 669	NOK		Aerospace & Defense	Kongsberg Gruppen ASA	8
AFGRA.OL	28 408.3	144.4	kr 4 103 346	kr 6 155 019	kr 16 757 343 120	NOK		Construction & Engineering	Af Gruppen ASA	3
VEI.OL	154 412.8	88.2	kr 13 621 900	kr 20 432 850	kr 11 095 349 520	NOK		Construction & Engineering	Veidekke ASA	5
WALWIL.OL	318 135.0	30.1	kr 9 568 481	kr 14 352 722	kr 10 719 841 265	NOK		Marine	Wallenius Wilhelmsen ASA	6

2.2 Research Design

In the context of the quantitative research method made use of in this study, examining the predictive power of leading indicators used by analysts to predict the stock return for selected Norwegian listed companies, statistical and graphical techniques are applied. As a source to identify and get a deeper understanding of leading indicators used by analysts, semi-structured interviews with analysts on a one-to-one basis were conducted as a part of the research design opted for in this paper. A semi-structured interview is an interview where the researcher is guided by a list of questions, which is specific to the choice of topic (Bryman & Bell, 2015, p. 481). The semi-structured interview technique enabled covering key questions related to obtaining their most prevailing drivers of stock return over a cycle. In other words, the mix of fundamentals that would cause an analyst to gain maximum conviction that this stock is long-term undervalued, or vice versa. However, to explore topics in depth, which provided interesting and important information of both the background of the companies and the indicators affecting them (see Section 4 for a full description), all interviews contained parts of open discussion where the interviewee had the opportunity to talk freely. The findings are the foundation of the quantitative secondary data collected (see Section 3 for explanation) and are the factors evaluated and tested to investigate whether or not the leading indicators suggested by analysts of selected listed companies show the expected relevance when evaluating the predictive power. According to Saunders, Lewis & Thornhill (2009, p. 258), a combination of secondary and primary data is often used to answer most research questions, and it is the suspicion of this paper that the secondary data sources will enrich the validity of the study.

For this thesis, evaluating indicators used by analysts for specific companies, a sample of selected members of the target population were interviewed. Listed companies on OSE provide information to their investors about the analysts following and covering their company on a daily basis on their website. The list of analysts for each of the companies studied, was set as the target, as these analysts possess valuable knowledge for one or more of the companies being studied. In this way, the paper was able to make use of specific analysts covering different companies that have relevant knowledge. Each of the ten companies were discussed in interviews with at least two analysts. However, the participants will be held anonymously, in order to not compromise their strategies. The emerging Oslo-based asset management company, from which the preliminary list of investable Nordic shares was obtained, contributed with the identification and initial contact to trusted potential interview candidates. From this phase, the contact with one analyst covering a specific sector or company led to other relevant analysts specialised in other companies studied. According to Saunders et al. (2015, p. 303), this approach is referred to as the snowball effect, from the contact with analysts within one company, other members of the same target population are reached.

2.3 Evaluation Method

To investigate the monthly predictive power of leading indicators used by analysts to predict the stock return for the Norwegian listed companies, the study follows Rapach, Strauss & Zhou (2009) out-of-sample forecasting methodology, and based on work done by Næs, Skjeltorp & Ødegaard (2009), makes use of a five common factor (FCF) model containing common factors for the Norwegian stock market as a benchmark. The FCF benchmark model is composed by combining the Fama & French (1993) three-factor model, momentum effect factor (which is known as the Carhart (1997) four-factor model) and a liquidity factor (constructed by Næs, Skjeltorp & Ødegaard (2009) for the Norwegian market). The following five common factor (FCF) forecast model is used as a benchmark forecast for the expected excess stock return:

$$R_t - R_{ft} = \alpha_t + \beta_{rp}\left(R_{Mt} - R_{ft}\right) + \beta_{smb}SMB_t + \beta_{hml}HML_t + \beta_{mom}PR1YR_t + \beta_{liq}LIQ_t + \epsilon_t \, , \tag{1}$$

where R_t is the total return of a stock at time t, R_{ft} is the risk-free rate of return at time t, R_{Mt} is the total market portfolio return at time t, $R_t - R_{ft}$ is the expected excess return, $R_{Mt} - R_{ft}$ is the excess return on the market, SMB_t is the size premium, HML_t is the value premium, $PR1YR_t$ is the difference between the average return of the top and the bottom portfolios, LIQ_t is a liquidity factor, $\beta_{rp,smb,hml,mom,liq}$ is the factor coefficients and ε_t is a error term.

In this paper the company's actual excess stock return, the dependent variable, is calculated as the percentage change in stock price minus the risk-free interest rate. In order to discover if the factor of interest at time t has predictive power on the dependent variable at time $t + 1$, a simple linear regression analysis is conducted using the full sample N. In this methodology, the excess returns are regressed on the factor suggested by the analysts. To predict the excess return at time $t + 1$, the independent variables is lagged if it is not reported as an expectation. Thus, assuming that the independent variable's value at $t + 1$ is the expected value at time t. The method is repeated for all factors individually. The statistically significant coefficients of the independent factors are further included and tested in the predictive regression models. The rest will be excluded from the analysis continuing onward.

The standard predictive regression model for excess return is expressed as:

$$r_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1} \, , \tag{2}$$

where r_{t+1} is the excess return, x_t is the predictor variable of interest and ε_{t+1} is a error term.

Following Rapach, Strauss & Zhou (2009), an out-of-sample forecast exercise of the excess return is conducted using a recursive estimation window. The evaluation method is useful for avoiding overfitting the data (Clark, 2004). More specifically, the historical data in the entire sample of N observations for r_t and x_t are divided into two periods, an in-sample period and an out-of-sample period. The in-sample period is composed by approximately ⅔ of the first m observations and the out-of-sample period is composed by approximately ⅓ of the last q observations. Which, respectively, means the oldest and newest observations in the sample. In the following regression models, the in-sample observations (m) are used to generate a forecasting model for future excess return.

To further test the relevance of each of the significant factors suggested by model (2), a multiple regression including all the significant factors to the excess return is conducted. The multiple factor forecast model for excess return is given by:

$$\hat{r}_{t+1} = \hat{\alpha} + \hat{\beta}_1\, x_{1,t} + \hat{\beta}_2\, x_{2,t} + \ldots + \hat{\beta}_i\, x_{i,t}\ , \tag{3}$$

where $\hat{\alpha}$ and $\hat{\beta}_i$ are the ordinary least squares (OLS) estimates. In which i represents the number of the factors. The predictive forecast model will generate the expected excess return $\hat{r}_{t+1}$ for the out out-of sample period at time $t+1$.The independent variables $x_{i,t}$ is filled with the factors' value corresponding with the out-of-sample q. Thus, model (3) will only consist of the statistically significant factors, to generate the out-of-sample expected excess return observations.

Work done by Goyal & Welch (2003) find that numerous individual economic variables with in-sample predictive ability are unable to deliver consistent out-of-sample forecasts relative to the historical averages. The lack of consistent out-of-sample evidence led Rapach, Zhou & Strauss (2009) to study a combination approach for the equity premium. In specifics, combining two individual predictive regression model forecasts. Based on their findings, the study tests if a forecast combination has the ability to improve the excess return forecast. The combination forecast model of $\hat{r}^{\star}_{t+1}$ takes the combined effect of the significant factors in the multiple factor forecast model and the FCF benchmark forecast model for the Norwegian market:

$$\hat{r}^{\star}_{t+1} = \hat{\alpha} + \hat{\beta}_1 x_{1,t} + \hat{\beta}_2 x_{2,t} + \cdots + \hat{\beta}_i x_{i,t} + \beta_{rp}(R_{Mt} - R_{ft}) + \beta_{smb} SMB_t + \beta_{hml} HML_t + \beta_{mom} PR1YR_t + \beta_{liq} LIQ_t \quad (4)$$

At this point, three predictive forecast models generating the expected return for the out-of-sample period exist. Thus, three different out-of-samples are forecasted. Firstly, the out-of-sample expected excess returns are generated by including the five common factors, represented by model (1). Secondly, the out-of-sample expected excess returns are generated by including the statistically significant factors, shown by model (3). Finally, model (4) is used to generate the third out-of-sample forecast for the combined forecast model.

These predictions are further compared to the actual out-of-sample excess return observations q. The error term represents the deviation of each forecasted out-of-sample observation from its corresponding actual observation in q. The prediction errors from the five common factor (FCF) benchmark forecast model is given by:

$$\epsilon_{t,fcf} = r_t - \bar{r}_t , \quad (5)$$

where $\epsilon_{t,fcf}$ is the error term of the expected observation by the five common factor (FCF) benchmark forecast model, r_t represents the actual returns in the out-of-sample q at time t, $\bar{r}_t$ is the expected return generated by model (1). Thus, the formula is used to calculate the error term for each expected observation in q. Further, the prediction errors from the multiple factor forecast model are given by:

$$\epsilon_{t,factors} = r_t - \hat{r}_t , \quad (6)$$

where $\hat{r}_t$ is the expected excess returns generated by model (3). Finally, the predictions errors from the combination forecast model is given by:

$$\epsilon_{t,combination} = r_t - \hat{r}^{\star}_t , \quad (7)$$

where $\hat{r}_t^{\star}$ is the expected excess returns generated by the combination forecast model (4).

2.4 Forecast Evaluation Criteria

For the purpose of achieving what it sets out to do, this paper evaluates whether a multiple factor forecast model or a forecast combination model incorporating additional explanatory variables can outperform the FCF benchmark forecast model containing common factors for the Norwegian market. Based on work done by Campbell & Thompson (2008), R_{OS}^2 statistics is used to compare the error term of the different models. R_{OS}^2 is computed as:

$$R_{OS}^2 = 1 - \frac{\sum_t^T (r_t - \hat{r}_t)^2}{\sum_t^T (r_t - \bar{r}_t)^2}, \tag{8}$$

where $\hat{r}_t$ is the fitted value from the predictive regression model estimated by the factors used by analysts, and $\bar{r}_t$ is the estimated excess return by using the five common factors. The R_{OS}^2 statistics measure the reduction in mean square prediction error (MSPE) for the predictive regression model or forecast combination model relative to the five common factors (FCF) benchmark forecast model. When R_{OS}^2 is positive, $R_{OS}^2 > 0$, the multiple factor forecast or the forecast combination outperforms the FCF benchmark forecast according to the MSPE metric (Rapach, Strauss & Zhou, 2009, p. 8). Meaning that the forecast has a smaller root mean squared error term than five common factors. Thus, implying a stronger predictive stock return power than the five common factors.

According to Rapach, Strauss & Zhou (2009, p. 9), evidence that R_{OS}^2 is significantly greater than zero, raises the issue of economic significance as its values are typically small for predictive regression models. In the opinion of Goyal & Welch (2003, p. 644), the in-sample correlation conceals a systematic failure of the out-of-sample factors. However, Campbell & Thompson (2008, p. 1524-1526) argue that even very small positive R_{OS}^2 values are meaningful for investors because they can signal an economically return predictability over historical averages which can generate large improvement in portfolio performance.

3.0 Data

In this study several data sources are used. The sample of stock returns is obtained from Norges Bank (the central bank of Norway). The sample period covers the period 1990 through 2019, making use of monthly statistics from within this period. This set of data is divided into an in-sample and an out-of-sample period, which differs for each company according to availability of data. The in-sample period is used to generate the prediction model, while the out-of-sample data is used to evaluate the prediction model. In this paper, the excess stock return is calculated as following:

$$r_t = \ln(p_{t+1}) - \ln(p_t) - Rf_{t+1}$$

The percentage change in stock prices is calculated approximately as the difference of the natural logarithm of the stock price at time $t + 1$ and the natural logarithm of the stock price at time t. This approximation allows capturing the continuances compounding growth rate of stock prices. Several explanatory variables to forecast the monthly excess stock return are considered. The financial explanatory variables, which are considered in the predictive forecast models, for all companies, are price-to-book ratio (P/B), price-to-earnings ratio (P/E), earnings per share (EPS), return on equity (ROE), return on investment (ROI), EBITDA margin and dividends. Furthermore, the combined ratio, book-to-bill ratio, capital expenditure (CAPEX), revenue, the level of research and development (R&D) expenses and defence expenditure are considered as explanatory variables for specific companies. For the financial variables, the computer software system Bloomberg Terminal is used to extract data. The data extracted covers the period 1990 through 2019 quarterly. Additionally, oil price, gas price, gross domestic product (GDP) and exchange rates (NOK/USD, NOK/EUR and SEK/EUR) are retrieved monthly from Bloomberg Terminal, while the interest rates (short-term and long-term), Norwegian InterBank Offered Rate (NIBOR) and dividends are obtained from Norges Bank. The commodity prices considered, include urea, nitrogen, natural gas, aluminium and salmon, are from IndexMundi. The data for the Fama & French three-factors, momentum and liquidity are obtained from Bernt Arne Ødegaard's website. The data is initially processed in Microsoft Excel. Statistical tests and regression analysis are done in STATA.

4.0 Company Description

4.1 Equinor ASA

Equinor ASA, formerly Statoil ASA, is a Norwegian energy company engaged in oil and gas exploration and production activities. Equinor is the largest operator on the Norwegian continental shelf, and since its establishment in 1972 has played a crucial role in the effort to build up the Norwegian national oil industry and to ensure that the largest possible share of the revenues from the oil business accrues to Norwegian society. Equinor is one of the largest groups in the Nordic region and has a leading international position with their worldwide exploration. They have operations in around 40 countries. Furthermore, they are a key player in several of the world's most important oil and gas provinces. In 2017, international operations accounted for 36 % of the company's production. In recent years, the company has built up operations in renewable energy sources, such as solar energy and offshore wind (Tollaksen, Ryggvik & Smith-Solbakken, 2020).

Within the sector there exists better and worse companies in term of environmental aspects. The interviewed analysts suspect that the companies' ability to reduce their carbon footprint will be an important factor that could affect the valuation of the company in the future. For instance, over the past years, and especially in 2019, a lot of investors have excluded oil and gas companies from their investment mandates, as they are not in compliance with the Paris Agreement. Equinor is one of the companies with ambitions to become greener (Equinor, 2020). According to the analysts, there have been a multiple contraction due to the fact that people are more uncertain about the future of oil and gas as a part of the global energy mix. Also, there exists a risk that the state over time will become less supportive towards the industry, especially in regards of the pressure related to greener energy.

According to the analysts, Equinor is, over time, a very receptive company in terms of changes in oil and gas prices, meaning that Equinor can be hit hard by low gas prices, as in 2019 (Hovland, 2020). Further, the analysts explain that since the downturn in oil, which started in 2014, the CAPEX announcements have become a jolly root for investors in the market. Thus, if the company starts spending more in CAPEX, people are generally expecting lower dividend pay-outs.

4.2 Aker BP ASA

Aker BP ASA, formerly Det norske Oljeselskap ASA, is a Norwegian energy company engaged in oil and gas exploration and production activities. Aker BP has a long history of merger and acquisitions. When Det norske Oljeselskap ASA in 2006 agreed to join forces with BP Norge AS, the aim was to create a leading independent exploration and production company in Norway. Measured in production, Aker BP is one of the largest independent listed oil companies in Europe. Aker BP has become a full-fledged oil company with a number of explorations, development and operation activities on the Norwegian continental shelf. The company operates primarily in the mature areas of the North Sea. The remaining resources are invested primarily in the Barents Sea and in the more immature areas in the North Sea. In 2019 they had a total production of around 155 900 barrels per day (Aker BP, 2020).

While Equinor is a company with ambitions to become greener (Equinor, 2020), Aker BP on the other hand does not want to invest in renewables (Ripegutu, 2020). Still, Aker BP and Equinor are equally exposed to overall trends regarding uncertainty about the future of oil and gas in the global energy mix, and the pressures related to greener energy. Compared to Equinor, Aker BP is less dependent on gas prices as it is only a small part of their revenue mix. In 2019 Equinor was hit hard by low gas prices among other factors (Hovland, 2020), while Aker BP made a decent year. Aker BP is also a more deal-driven company. When the analysts elaborate that Aker BP is more of a growth case, he implies that they are more driven by company specific factors.

4.3 DNB ASA

DNB ASA is Norway's largest financial institution and was in 2017 the country's sixth largest company measured by turnover (Lilleholt, Gram & Ekberg, 2019). DNB offers a range of financial services, including loans, savings, advisory services, insurance and pension products for retail and corporate customers. The company's operations are divided into four business segments: the personal customers segment, the small and medium-sized enterprises segment, the large corporates and international customers segment and the trading segment. Within the personal customer segment is home mortgage, car loans, consumer loans, refinancing and property, savings and investments, Internet banking, mobile services, cards, insurances, pension and foreign exchange. The small and medium-sized enterprises segment cover sales of products and services to small and medium corporate customers in Norway. The large corporates and international customers segment cover the company's Norwegian and international corporate customers. Lastly, the trading segment comprises market making and trading activities. The Company operates in Europe, the Americas and Asia (Reuters, 2020).

In the Nordic region the banking industries is quite consolidated, meaning that larger banks have a very large share of the total market. Compared to European banks, banks in Norway and other Scandinavian countries have been more cost-efficient, taken down cost especially in the front office side and invested more in digitalization. The interviewed analysts covering the financial sector on OSE argued that banks are derivatives of how the economy in the countries that the bank operates in develops. Thus, for instance looking at DNB where around 80 % of the loans are in Norway, the development of the Norwegian country is very important for the perception of how DNB is developing. On a quarterly basis, the Norwegian central bank surveys executives from over 300 enterprises and organisations about recent economic developments and the outlook ahead (Norges Bank, 2020). The analysts suggest that the “Regional Network reports” is an appropriate forward-looking indicator of how the Norwegian economy is developing.

The analysts point out that the banking industry is typically exposed to a lot downside risk. Meaning that banking analysts have to learn more about sectors that are struggling. For instance, if one goes back ten years then one had to learn about the shipping industry, because after the financial crisis the shipping companies had taken up too much debt and banks were losing money to the industry. So back then the shipping industry was relevant for the banks. Further, the oil downturn, which started in 2015, led banks to lose a lot of money on oil related companies. At this point, oil was important, now there is some uncertainty regarding clothing retailers. These industry specific trends exist; but it is difficult to predict which sectors will be of high impact for the banking industry. However, the analysts suggested several accounting measures and the Norwegian InterBank Offered Rate (NIBOR) to be important indicators for DNB. NIBOR is a reference rate in the currency exchange market, known as the currency swap rate. NIBOR is therefore derived from interest rates in the foreign money markets. This interest rate is often used at interbank level as a reference for money market rates between banks.

4.4 Gjensidige Forsikring ASA

Gjensidige Forsikring ASA is a Norwegian general insurance provider and is one of the leading players in non-life insurance in the Nordic region. Furthermore, it is the parent company within the Gjensidige group. Its product portfolio comprises such types of insurance, as car, home, vacation home, personal property, boat, valuables, life and health, pet, travel, student abroad and youth insurance. The group offers its insurance products to private and commercial customers in Norway, Sweden, Denmark, Latvia, Estonia and Lithuania. In addition, it offers online banking, loans and savings in Norway (Reuters, 2020).

Insurance companies typically earn money in two ways, where the profit drivers are (1) collecting higher premiums than the size of their underlying cost base and claims, and (2) the investment result. The working capital, meaning the difference between current assets and current liabilities, of insurance companies is typically negative, implying that the insurance companies are very liquid as they get paid from the customer before they need to pay anything out. In other words, insurance companies are mostly a prepaid business. For instance, it can take approximately three years before a claim is actually happening, meaning a negative working capital equal to approximately three times the annual premiums. This money is then used for investment purposes, and the return they get from these investments is thus a second source of revenue.

For several years four players have dominated the non-life insurance market. Over the past few years other players have grown, and in the last couple of years there has been some consolidation. Although there are several competitors within this industry, it is an industry with low price competition in the Norwegian market. However, the competition in non-life insurance is very favourable for the companies, especially if one look at the profitability and market shares of the largest players in Norway; Gjensidige, IF, Tryg and Fremtind (Finans Norge, 2020).

In terms of global growth, the analysts argue that Gjensidige is a more defensive company and less sensitive to the state of the economy in comparison to banking and other commodities such as energy, oil and gas. This is based on the fact that it is a less cyclical industry. According to the analysts, this is a common perception among analysts and investors. The analysts point out the combined ratio, long-term rate level and dividends as important company specific factors for Gjensidige. The combined ratio is a cost and claim ratio, which is calculated by taking the sum of incurred losses and expenses and then dividing them by the earned premium. Insurance companies use this profitability indicator to measure how well it is performing in its daily operations. For instance, a ratio below 100 % indicates that a company is making an underwriting profit, while a ratio above 100 % is indicating paying out more money in claims than they receive from premiums. According to the analysts, if the combined ratio is increasing, meaning that the margin is declining, this will typically have a negative impact on insurance companies. The long-term interest rates refer to government bonds maturing in ten years. Bonds are subject to interest rate risk, since rising rates will result in falling prices and vice versa. In the opinion of the analysts, Gjensidige is one of the stocks on OSE that is most similar to a bond. The reason for perceiving Gjensidige as a stock that is close to a bond is that the company's cash flow is perceived as very stable. According to the analysts, even if the macro environment in Norway deteriorates it will not impact the insurance results that much. When the long-term rate falls, that typically leads to a revaluation of the Gjensidige stock, which is also the case for other peers in Denmark and Finland; Tryg, Top and IF. In the opinion of the analysts, increasing dividends by a small fraction for insurance companies would be a good indicator for a good and stable market in the future. This can partly be explained by investors perceiving the stability in the dividends from an insurance company as greater, meaning that they perceive the increase as a level that is more likely to continue.

4.5 Mowi ASA

Mowi ASA, formerly Marine Harvest ASA, is one of the world's leading seafood companies, with focus on Atlantic salmon. The company operates within three segments: feed, farming, and sales and marketing. During the last decades, and particularly after 2012, the interest in fish farming companies, Mowi included, has been formidable on the stock exchange. According to Tveterås, Reve, Haus-Reve, Misund & Blomgren (2019, p. 65), the market value of these listed companies has multiplied, and a main reason behind the increase are largely related to increased salmon prices.

The Norwegian aquaculture industry is quite unique and knowledgeable, enabling world leading research and innovation. In Norway, salmonids are mainly farmed, such as atlantic salmon, rainbow trout and arctic charr. These three species accounts for 97.5 % of all fish farming in Norway and are one of Norway's largest export goods (Misund, 2019). Salmon have biological and environmental criteria that must be met to enable farming in the sea. Few areas of the world meet these criteria. Optimal water temperatures and strong currents are important requirements in order to create appropriate conditions. When it is warmer, the fish tends to eat more, thus growing faster. As the fish will be ready to harvest earlier, the supply increases, which often leads to a drop in prices. On the other hand, too heated water creates environments of parasites and algae, which are some of the biggest challenges for fish farming today (iLaks, 2019). Because of the limitations and strict restrictions in the sea, many companies are looking at farming fish at land and further offshore facilities in order to grow.

Salmon products are exported to all over the world as many countries, especially in Europe and North America, depend on imports to meet their demand. Norwegian and Chilean production are the main drivers for export. For instance, much of Norwegian exports go to the EU, but also to North America and Asia (Tveterås et al., 2019, p. 19-22). In Norway, politicians have an expressed desire for a multiplication of the seafood industry by 2030 and 2050 (iLaks, 2019). However, the interviewed analysts explain that outside Norway and the Nordic countries, salmon is a niche product. Implying that the global consumption is low. Over time, they expect the income growth in the US and countries like China and Brazil to be an important factor for demand. In addition to food and health trends, as salmon is a more environmentally friendly protein to produce compared to beef and chicken (Norwegian Seafood Council, 2019).

According to the analysts, the price of farmed salmon fish will be the most important factor determining Mowi's share price, elaborating that historically, if the salmon price were to decline the share price would fall, and vice versa. Explaining that this was the rule until 2016-2017, before regulations were imposed. The price formation for salmon is global, where the supply and demand relationship for Atlantic salmon affects the price achieved by the producers. The supply and the price are affected by a lot of factors, such as biological and environmental conditions. Tveterås et al. (2019, p.19) explain that prices have shown a growing trend over time, driven by positive shifts in global demand, however with considerably volatility. From being sort of a niche market with low profits, the industry has experienced a super profit kind of environment, not being able to increase supply in line with demand growth. Over the past few years, the import price to the EU has been almost twice as high as in 2001-2002 (Tveterås et al., 2019, p.19). However, according to the analysts, the expected supply and prices are more stable now, expecting that demand is likely to pick up eventually. The demand is a function of the price, where the price again is largely set by the supply.

4.6 Orkla ASA

Orkla ASA is a Norwegian leading supplier of branded consumer goods and concept solutions to the grocery, out-of-home, specialised retail, pharmacy and bakery sectors. The Nordic and Baltic regions and selected countries in Central Europe are Orkla's principal markets. The company's branded consumer goods business consists of four business areas, including Orkla Foods, Orkla Confectionery & Snacks, Orkla Care and Orkla Food Ingredients. In addition, the Orkla Consumer & Financial Investments business area consists of Consumer Investments and Industrial & Financial Investments. Through the Orkla Investments business area, the company manages financial investments and is also the largest shareholder in Jotun, one of the world's leading manufacturers of paint and powder coating. Orkla is also a significant power producer (Orkla, 2019).

Even though Orkla is a major producer and leading supplier of goods to the grocery market, and has a significant market share, they do not have much negotiation power. For instance, as the market in Norway is strongly consolidated, there are only three major buyers (REMA 1000, Coop and NorgesGruppen) of their products. The same can be argued for the Swedish market. As Orkla is mainly selling goods, the gross domestic product (GDP) of the relevant countries they are selling to is by the analysts suggested to be a good indicator for future growth. The annual rapport states that Orkla aims to achieve long-term organic growth at least in line with market growth (Orkla, 2019). According to the analysts, Orkla is working on small margin improvement. Thus, a main driver for Orkla is their ability to follow trends in the market, in addition to having their products in the right channels. For instance, trends related to more out of home eating mean less buying in grocery stores. This has led Orkla to invest more in companies in this sort of channels. Soft factors related to environmental and health trends are also important determinants of their product portfolio mix. More of their products, especially from the Orkla Care segment, which includes personal care and hygiene, are going more to discount stores where they until recently have been underrepresented. On the growth side, it is also important to remember that Orkla is a very large company, if they sell more of one product category, it will probably be at the expense of another category. However, Orkla has the advantage of economies of scales and synergies across the group.

4.7 Yara International ASA

Yara International ASA is a Norwegian company that produces, distributes and sells nitrogen-based mineral fertilizers and related industrial products to the agricultural industry and industrial users. Yara consists of three segments: sales and marketing of fertilizer products and solutions for agriculture, industrial and environmental solutions, and the production in the manufacturing plants. In short, Yara is a global firm specializing in agricultural products and environmental solutions and has become the world’s leading fertilizer company (Yara, 2020).

The fertilizer market is not only significant in terms of size, but also an essential industry severing global food production. For large countries, especially such as China and India, fertilizers are a requirement in order to being able to feed the people and secure the food production (Yara Fertilizer Industry Handbook, 2018). As fertilizers are a seasonal business, weather factors are crucial for Yara, for instance how early the spring season starts in the different regions. In addition, to how much of the nitrogen fertilizers are washed out due to bad weather conditions. The analysts explain that farmers will need fertilizers the question is when. They further argue that it is quite impossible to forecast the weather, but one can try to estimate farmer's behaviour. The three main nutrients are Nitrogen, Phosphorus and Potassium. Nitrogen is the largest and most important primary nutrient, accounting for 57 % of total consumption, and Yara is the leading producer of this nutrient. Like any other commodity, the analysts point out that fertilizer prices are cyclical and highly affected by the input- and currency factors. The analysts explain that approximately 70 % of the cost in production is related to natural gas.

Urea is the main nitrogen fertilizer product. According to the analysts, urea is the main benchmarking price for Yara, and since most of the fertilizer prices tend to follow urea, earnings will follow urea. The urea market is large, and the fastest growing nitrogen product. In 2016 the urea production was 174.3 million tonnes (Yara Fertilizer Industry Handbook, 2018). The main urea exporters are gas-rich countries or regions with small domestic markets. However, there are some exceptions. China has a huge domestic capacity and is one of the largest producers of the needed commodities to produce fertilizers, such as ammonia and urea. However, they are also one of the largest consumers. The urea price is determined by the supply and demand situation of the raw material. In cyclical industries, with periods of overcapacity and undercapacity, the price is usually determined by the marginal cost of the swing producers. For urea the relative pricing between the main urea export hubs (Russia, China, North Africa and Arab Gulf), depends on where the marginal volumes take place. Explained differently, if the allocation of capacity to export changes, for instance if China reduces its export, the demand will pull to others and often a price movement will be seen (Yara Fertilizer Industry Handbook, 2018). Thus, to which degree the Chinese exports, and covers some of the shortages around the world, will affect the fertilizer markets short term swings.

4.8 Norsk Hydro ASA

Norsk Hydro ASA is a Norwegian fully integrated aluminium company with operations in various activities along the aluminium industry's value chain. Hydro is a global supplier of aluminium, and the company is involved in activities in more than 50 countries on all continents. In addition to the production of primary aluminium, rolled and extruded products and recycling, Hydro is engaged in bauxite extraction, refining of alumina and energy production, making them the only company to cover all areas of the global aluminium industry (Hydro, 2020).

Bauxite is the most common raw material used to produce alumina, which is the raw material required for aluminium metal production. Aluminium is used for very different applications for many different products. Vehicles, buildings & constructions and packaging are some of the most important end-users for aluminium. According to the analysts, Hydro is part of a very cyclical industry, implying that they are very exposed to macro events. For instance, they explain that slow economic growth will affect aluminium prices negatively, and thereby impact Hydro’s share price. Thus, proposing aluminium price as the most important factor determining their earnings and stock price. The price of aluminium is basically a reflection of what the world looks like, and how the world will develop and grow (GDP growth). Thus, the market in general is suggested to be an important driver for aluminium prices, where China plays an important role as swing producer on the supply side.

In Norway, there are seven aluminium plants producing primary aluminium, of which Norsk Hydro owns four of these, in addition to one co-owned together with Rio Tinto Alcan. The Norwegian companies are based on exports and account for about 4 % of the world’s aluminium production and ¼ of the European production. The industry is one of the most research-intensives in Norway (Norsk Industri, 2020). The analysts explain that greener products, leaving a lower carbon footprint than other aluminium products, receive a higher premium and the greatest environmental benefits. In this aspect, Hydro is globally considered as one of the companies with the lowest footprint within the industry.

4.9 Tomra Systems ASA

Tomra Systems ASA is a Norwegian industrial company with worldwide expertise in reverse vending machines for automated collection of used beverage containers in plastic, glass and aluminium. The company creates sensor-based solutions for resource productivity within the business streams of reverse vending, material recovery, food, recycling and mining. Within the reverse vending machine business, Tomra is the world's largest manufacturer and supplier. The reverse vending business stream comprises the development, production, sales and service of reverse vending. The material recovery business stream includes the pick-up, transportation, processing and recycling empty beverage containers on behalf of beverage producers/fillers in North America. Through their primary segments, collection solutions and sorting solutions, Tomra enables circular economy that optimises resource recovery and minimises waste (Tomra, 2020)

Tomra is a company with a clear green profile, building machines for a green shift in the whole world. The fight against plastic and focus on reducing waste has in recent years grown rapidly. For instance, large conglomerates experience high social pressure to operate in line with environment friendly solutions. According to the analysts, there are a lot of soft factors, which are difficult to predict, playing an important role for Tomra.

Companies that contribute with sustainable solutions, positive social development and good corporate governance for all stakeholders are often labelled as ESG companies. ESG refers to the central factors measuring environmental, social and cooperate governance in a company (AksjeNorge, 2020). Companies with a green profile are now getting multiple expansions and higher valuations relative to comparable competing companies (McKinsey & Company, 2020). According to the analysts, this can partly be explained by investors expecting consumers in the future, whether it is two, five, ten or twenty years ahead, to want products that green companies are providing. Furthermore, many investors are betting on tightening regulations to be implemented, with regard to climate and environment. Explaining that companies that do not follow regulations, or that are slow to translate, will either go out of business or get a higher cost of capital over time since they will get fines or not the same access to capital as other companies.

4.10 Kongsberg Gruppen ASA

Kongsberg Gruppen ASA is a Norway-based company engaged in the supply of technology systems and solutions to customers in the oil and gas industry, the merchant marine and the defence and aerospace industries. The company's operations are structured into three operating segments: the Kongsberg Maritime segment delivers products and systems for dynamic positioning, navigation and automation for commercial vessels and offshore installations, as well as products and systems for seabed surveys, surveillance, hydroacoustics, for fishing vessels and fisheries research; the Kongsberg Defence & Aerospace segment is a significant supplier of products and systems for command and control, weapon control systems and surveillance, remote weapon stations and missiles, and other activities, which include Kongsberg Digital, offering maritime training simulators and digitization solutions for the energy sector, among others (Reuters, 2020).

Kongsberg Gruppen is a huge company with a lot of mowing parts. In essence, the company is divided into two main parts, a defence side and maritime side, operating in two different strategic markets. The common denominator is the development of high-tech systems. Historically the maritime segment contributed the most on the earnings side, as the rig-cycle and shipping boom benefited Kongsberg. Over the last years they have been doing a lot of investments in defence-and missile systems. Resulting in the fifth-generation missile, creating significant long-term potential for the company, as Kongsberg is the world's only supplier. Markets outside Norway constitute an ever larger and more important part of the business and represented almost 80 % of operating revenues in 2015. The company is today a global high-tech group with presence in over 25 countries worldwide (Kongsberg, 2016). The analysts find it difficult to point to a main driver. However, they argue that there are many company specifics of importance for Kongsberg and suggest investigating the level of research and development (R&D) impact on the excess return, in addition to defence spending and the book-to-bill ratio. The book-to-bill ratio calculates whether demand for a good or service is rising or falling, by comparing current orders taken to previous invoices sent for a specified period. A ratio above one implies more orders were received than filled, indicating strong demand, while a ratio below one implies weaker demand.

5.0 Results

The results will be presented company-wise by using the methodology described in Section 3 to evaluate the predictive power of the independent factors, used by analysts, on the companies' excess stock return. The table in Appendix 3 individually reports the regression estimates of the specific leading indicators used to predict excess return for selected Norwegian listed companies, using the standard predictive regression model from Eq. (2). The results from this table examines whether the leading indicator used by analysts has predictive power at a 5 %, 10 % or 15 % statistical significance level respectively. The statistically significant coefficients of the independent factors are further included and tested in the regression model forecasts. The rest will be excluded from the analysis continuing onward. Further, the results from the multiple factor forecast model from Eq. (3) and forecast combination model from Eq. (4) incorporating additional explanatory variables for each company will be reported. Finally, the paper illustrates whether a multiple factor forecast model or forecast combination model have the ability to outperform the five common factor (FCF) benchmark forecast model.

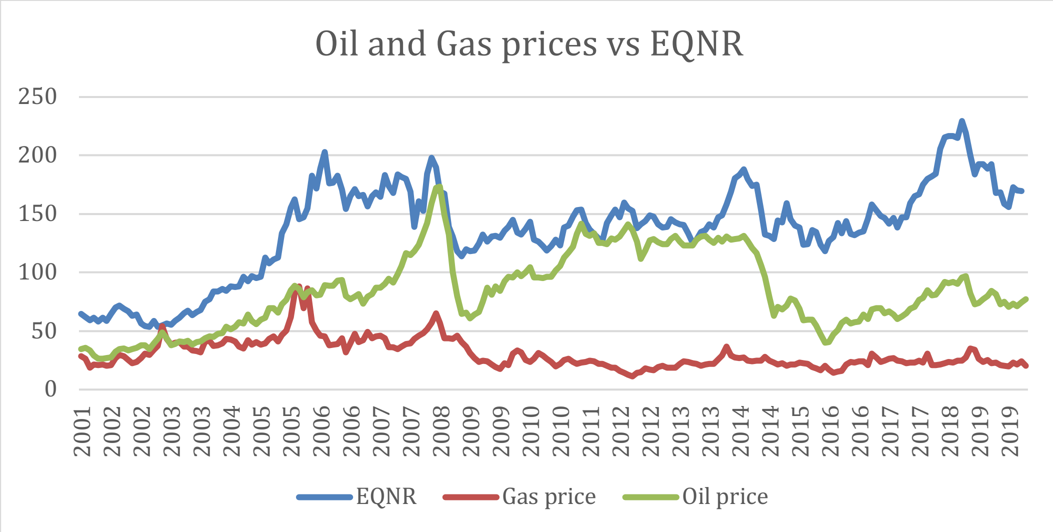
5.1 Equinor ASA

During the interviews, the analysts revealed several factors in which they depend on in their analysis for the two companies analysed in the energy sector. For instance, ROE, CAPEX, P/B and dividends were mentioned as reliable indicators of future performance for both Equinor and Aker BP. However, in the case of Equinor, the analysts believed oil and gas price expectations to be obvious factor candidates for these companies. From the results of Appendix 2, one can observe that three of the in total eleven suggested factors have a significant relationship to Equinors's excess return, namely oil and gas prices and P/B ratio.

Figure 5.1 reports the correlation between oil and gas prices and Equinor's stock price. Although both factors are significant from Appendix 2, oil have a stronger correlation to Equinor's stock price. This observation is consistent with the fact that Equinor portfolio includes more oil production than natural gas.

Figure 5.1

Graphical presentation of the historical correlation between oil and gas prices and Equinor's last price, using monthly data covering the period 2001 through 2019.



To further test the importance of oil and gas prices and P/B ratio, the factors are used to build model (3). Thus, creating a multiple factor forecasting model dependent on these factors. Table 5.1.1 presents oil price as the main significant indicator, at a 5 % level. Gas price is presented as highly significant factor at a 10 % level. P/B ratio, however, does not seem to have a significant relation with excess returns when including oil and gas prices in the regression. At this stage of the analysis, the results from model (3) identify oil and gas prices as the major relevant indicators to predict the excess stock return for Equinor. In an attempt to further test the influence of these indicators, both indicators are added to the FCF model. Thus, for Equinor the combination model (4) consists of the common factors and oil and gas prices. The results in Table 5.1.1 confirms that both indicators are still highly significant and have a high predictive power.

Table 5.1.1

The predictive power of leading indicators used by analysts to predict the excess stock return for Equinor. This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 2001 through

2014 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	0.004 (0.77)	-0.003 (-0.75)
P/B	-0.012 (-0.62)	
Gas price	0.041 (1.46*)	0.040 (2.13***)
Oil price	0.298 (4.06***)	0.166 (3.04***)
Risk premium		0.625 (5.33***)
SMB		-0.580 (-5.08***)
HML		0.186 (2.11***)
PR1YR		0.314 (3.83***)
LIQ		-0.019 (-0.13)
m	162	162
Adjusted R^2	0.0613	0.5231
F-statistic	7.54***	26.23***

The results of Table 5.1.2 further evaluate the predictive power of the factors used by analysts and the combined model, compared to the FCF benchmark model. The positive R^2_{OS} value, although very small, implies that the analysts' factors succeeded in outperforming the FCF model. In addition, the combined model also outperforms the FCF model at an even higher rate. As a result, the analysis has strong evidence supporting the claim that oil and gas prices are reliable indicators to predict Equinor excess stock return.

Table 5.1.2

This table reports the results of comparing Equinor's predictive regression forecasts to the five common factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R^2_{OS} is positive, $R^2_{OS} > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

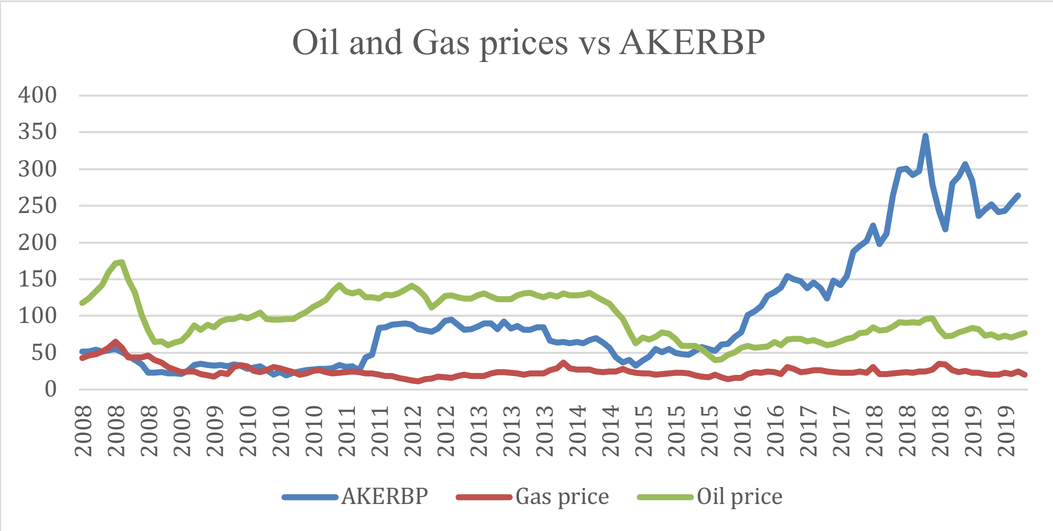
	Model (3)	Model (4)
R^2_{OS}	0.003	0.013

5.2 Aker BP ASA

Although Aker BP operates similarly to Equinor, the analysts in the interviews pointed out major differences between the two companies. For instance, while Equinor is heavily dependent on both oil and gas prices, Aker PB is less dependent on gas prices. They described Aker BP as a growth case, implying that the firm is driven by company specific factors. Once comparing Figure 5.2 with Figure 5.1, the analyst's opinion appears valid. Aker BP's stock price show a weaker correlation with oil and gas prices compared to Equinor.

Figure 5.2

Graphical presentation of the historical correlation between oil and gas prices and Aker BP's last price, using monthly data covering the period 2008 through 2019.



The analysts suggested numerous factors and endorsed them to be relevant in forecasting Aker BP's excess return. However, after examining the available quantitative data for the proposed factors, oil price was the only significant factor, as presented in Appendix 3. Consequently, oil price is the only explanatory variable used in building the factors forecast model in Table 5.2.1. From the same table, one can observe that oil price still is significant in the combined model.

Table 5.2.1

The predictive power of leading indicators used by analysts to predict the excess stock return for Aker BP. This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 2007 through 2015 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	-0.002 (-0.17)	0.002 (0.19)
Oil price	0.452 (2.70***)	0.259 (1.51*)
Risk premium		0.670 (1.74**)
SMB		-0.113 (-0.26)
HML		0.641 (1.90**)
PR1YR		-0.485 (-1.57*)
LIQ		0.186 (0.39)
m	108	108
Adjusted R^2	0.06	0.12
F-statistic	7.30***	3.37***

The negative R_{OS}^2 for model (3) indicates that the factor model fails to predict better than the FCF benchmark model. On the other hand, the positive R_{OS}^2 for model (4), indicates that oil price has an improved predictive ability when combined with the FCF benchmark model. As a result, although analysts believe the company specific factors to drive Aker BP stock prices, the results suggest only oil price to be a reliable indicator. The results occurred may be explained by the fact that the analysts shared few company specific factors they rely on in their analysis.

Table 5.2.2

This table reports the results of comparing Aker BP's predictive regression forecasts to the five common factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R_{OS}^2 statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R_{OS}^2 is positive, $R_{OS}^2 > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

	Model (3)	Model (4)
R_{OS}^2	-0.236	0.030

5.3 DNB ASA

The results of Appendix 3 show that both dividends and NIBOR are significant at a 5 % level. Since DNB borrow at NIBOR, the negative correlation with NIBOR, shown in Appendix 3, can be interpreted as DNB's margin decreasing when NIBOR increases. At least for the short-term, this can be explained by NIBOR changing daily, while DNB only changes interest rates few times a year. However, according to Raknerud, Vatne & Rakkestad (2011, p. 23), bank groups with a large share of market financing, such as DNB, are more vulnerable when NIBOR increases.

The results in Table 5.3.1 indicate that NIBOR keeps showing relevance. The results further suggest, as expected by the analysts, that dividends do not appear to be a good indicator of DNB' excess return. This can be explained by the fluctuation in dividends, as banking is very exposed as part of a cyclical industry. For banks the market can be good at one point in time, but then some macro downturn will have them to adjust in the future. Furthermore, Table 5.3.1 reports the results of combining NIBOR and the FCF model, which are used to predict the excess return. The error terms are thus generated by comparing each of the predicted out-of-sample to the actual out-of-sample excess returns, which will be evaluated next.

Table 5.3.1

The predictive power of leading indicators used by analysts to predict the excess stock return for DNB. This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 1994 through 2012 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	0.004 (0.50)	-0.008 (-1.32)
Dividends	-0.011 (-0.590)	
NIBOR	-0.294 (-2.54***)	-0.067 (-0.75)

Risk premium		1.354 (10.41***)
SMB		-0.621 (-3.55***)
HML		0.395 (3.31***)
PR1YR		-0.150 (-1.20)
LIQ		0.343 (1.940**)
m	230	230
Adjusted R^2	0.0267	0.4312
F-statistic	3.56***	29.93***

Table 5.3.2 presents the results of comparing the squared errors from the previous two predictions with the out-of-sample prediction error when using the FCF. As a result, the combination model, including NIBOR, seems to add additional prediction power to DNB's excess stock return. However, the multiple factor model representing factors used by analysts fails to outperform the FCF model.

Table 5.3.2

This table reports the results of comparing DNB's predictive regression forecasts to the five common factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R_{OS}^2 statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R_{OS}^2 is positive, $R_{OS}^2 > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

	Model (3)	Model (4)
R_{OS}^2	-0.621	0.056

5.4 Gjensidige Forsikring ASA

After testing the factors suggested by the analysts, Appendix 3 show three of these factors to have a significant relation with GJF's excess stock return at a 15 % level, namely the combined ratio, long-term interest rate (LTI) and dividends. At this point, the results are consistent with the analysts' beliefs, which are that the combined ratio, LTI and dividends are some of the most influential indicators.

The OLS estimates of the multifactor regression including the mentioned significant factors are presented in Table 5.4.1. Although the analysts believed dividends to be a good indicator of GJF's excess return, the results show something different. The relationship between the excess return and dividends seem to lose its significance when interrupted by the influence of the other two factors. However, the combined ratio and LTI keeps showing relevance. Further, Table 5.4.1 provides the estimate results of the combined model. For Gjensidige, the combined model was created by including the combined ratio and LTI to the FCF model. What may be observed, is that not many of the common factors seem to be highly relevant to GJF stock returns. This corresponds well with the analyst's perception, that insurance companies are considered being less sensitive to the state of the economy. This makes GJF's stock perceived as one of the most defensive stocks on OSE. Thus, so far, the result is in line with what the analysts pointed out.

Table 5.4.1

The predictive power of leading indicators used by analysts to predict the excess stock return for Gjensidige Forsikring. This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 2011 through 2016 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	0.019 (2.14***)	0.015 (2.14***)
Dividends	0.015 (0.62)	
Combined ratio	-0.342 (-2.13***)	-0.177 (-1.83**)
Long-term interest	0.131 (1.45*)	0.151 (2.20***)
Risk premium		0.115 (0.46)
SMB		-0.191 (-0.81)
HML		0.353 (2.12***)
PR1YR		0.191 (1.18)
LIQ		-0.350 (-1.49*)
m	69	69

Adjusted R^2	0.0609	0.1997
F-statistic	0.95	3.42***

The results of Table 5.4.2 show that the combined model performs better than the FCF model. In the case of Gjensidige, it appears that adding analysts' factors, namely the combined ratio and LTI, provides a stronger predictive power than the common factors alone. However, the table also reports that a multiple factor model including the factors used by analysts by themselves fail to form a better prediction model.

Table 5.4.2

This table reports the results of comparing Gjensidige Forsikring's predictive regression forecasts to the five common factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R_{OS}^2 statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R_{OS}^2 is positive, $R_{OS}^2 > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

	Model (3)	Model (4)
R_{OS}^2	-0.149	0.098

5.5 Mowi ASA

All factors individually tested for Mowi are represented in Appendix 3. This table illustrates that salmon price is the most significant factor, along with dividends at a 5 % level. Furthermore, the exchange rates, NOK/EUR and NOK/USD, are significant at a 10 % level. This can be explained by Mowi's major exporting activities to Europe and North America. At this stage of the process, the results seem to be fully in line with the analysts' expectations.

The results in Table 5.5.1 provide evidence that the main influencing factors on the excess returns are salmon price and dividends. However, it must be mentioned that the results are built on a relatively small in-of-sample observations due to lack of data for dividends. Further, the results of the combined model reported in Table 5.5.1 show limited relation between the excess stock return and salmon prices, the same can be argued for the common factors. Mowi has shown unique growth and development during the past twenty years, this can partly explain the weak relationship between excess returns and the common factors. Another reason may be related to limited observations in-of-sample. However, as mentioned earlier, fish farming companies experience other highly relevant risk factors related to biological environmental challenges, such as salmon lice and water temperatures. Data on this matter was not possible to collect, and as a result, the paper was unable to study these factors further.

Table 5.5.1

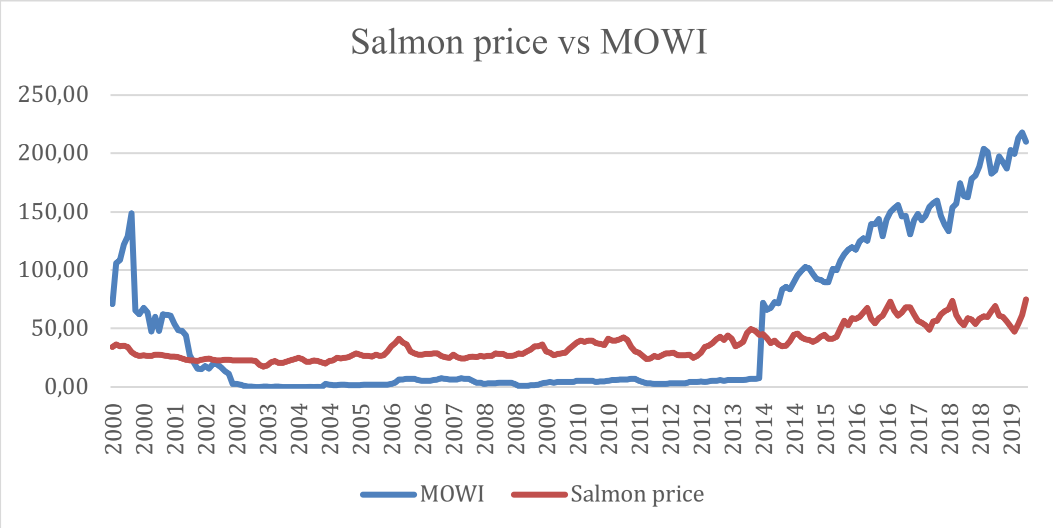
The predictive power of leading indicators used by analysts to predict the excess stock return for Mowi. This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 2012 through 2017 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	0.085	-0.021
	(0.50)	(-0.31)
NOK/EUR	0.095	
	(0.48)	
NOK/USD	1.943	
	(1.24)	
Salmon price	1.076	0.091
	(1.85**)	(1.37)
Dividends	0.114	0.801
	(3.06***)	(2.26***)
Risk premium		0.475
		(0.20)
SMB		1.604
		(0.91)
HML		1.843
		(1.39)
PR1YR		0.476
		(0.36)
LIQ		0.276
		(0.18)
m	51	51
Adjusted R^2	0.1328	0.1040
F-statistic	2.91***	1.83*

While the analysts believed that the salmon price has a major impact on the company's stock prices, the results of this study shows otherwise. This can be explained by looking at Figure 5.5, represented below. The figure shows a clear drift in the correlation between Mowi's stock price and salmon price over the last six years.

Figure 5.5

Graphical presentation of the historical correlation between salmon price and Mowi's last price, using monthly data covering the period 2000 through 2019.



By observing the results reported in Table 5.5.2, the R_{OS}^2 value of both suggested models are negative. In other words, both analysts' factors and the combination model have failed to provide a better prediction model than the FCF model.

Table 5.5.2

This table reports the results of comparing Mowi's predictive regression forecasts to the five common factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R_{OS}^2 statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R_{OS}^2 is positive, $R_{OS}^2 > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

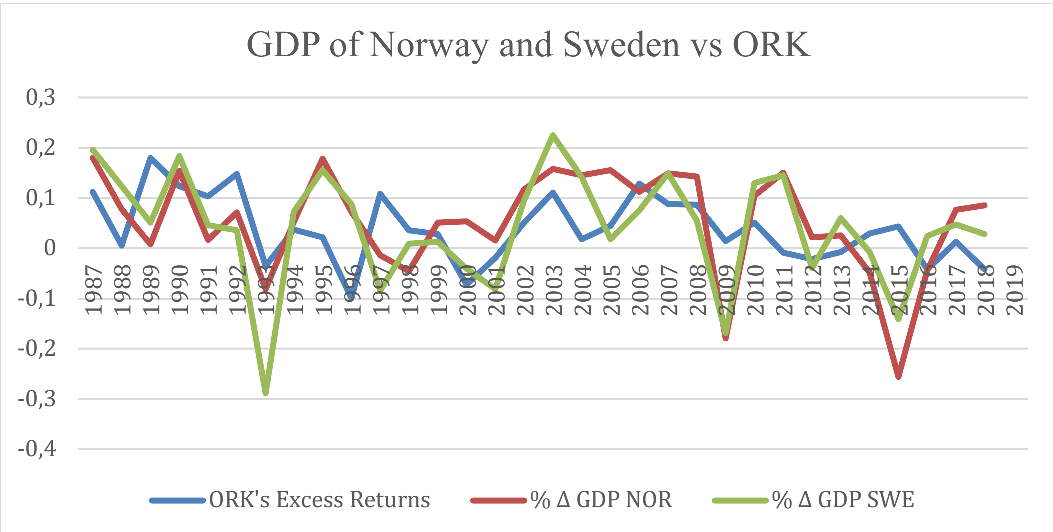
	Model (3)	Model (4)
R_{OS}^2	-0.392	-0.727

5.6 Orkla ASA

For Orkla, the Norwegian common factors are highly significant in predicting the companies excess return, as reported in Appendix 2. As mentioned, the analysts particularly revealed high confidence in the EBITDA margin, GDP and exchange rates. The results from the standard predictive regression model, reported in Appendix 3, turn out to be consistent with their beliefs. The EBITDA margin is significant at a 15 % level. As mentioned before, Orkla has high sales turnover and are working on improving small profit margins. Therefore, the analysts believe that a strategic increase in the operating profit margin, will have a considerable impact on the firm's performance and thus the stock price. Furthermore, the analysts had a considerable focus on GDP, in both Norway and Sweden, as important indicators. These were both significant at a 10 % level. Figure 5.6 supports this by showing a clear positive correlation between the excess return and both GDPs for the collected data until 2014 (in-sample). However, it seems like the out-of-sample period, 2014-2019, does not have a positive correlation. Already at this early stage, it is observable that the predicted out-of-sample will most likely have a high deviation from the actual values. This makes the reliability of GDP as an indicator highly questionable.

Figure 5.6

Graphical presentation of the historical correlation between the percentage change in GDP for both Norway and Sweden and Orkla's stockholders yearly excess returns, using yearly data covering the period 1987 through 2018.



The exchange rates, NOK/EUR and SEK/EUR are respectively significant at a 5 % and a 15 % level and have a direct effect on Orkla's costs. The company has cash inflow in Norwegian krone and Swedish krona, while most of its cash out flows are in euro. Thus, the significance can be logically explained.

The statistically significant factors are used to create model (3) in the analysis of Orkla. From Table 5.6.1, one may notice that the exchange rates are the only factors holding its significance. Further, the combination model (4), studies the effect of incorporating the exchange rates to the FCF benchmark model. Table 5.6.1 are still reporting the exchange rates as significant factors when combining with the FCF model.

Table 5.6.1

The predictive power of leading indicators used by analysts to predict the excess stock return for Orkla. This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 2000 through 2013 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	0.000 (-0.01)	-0.002 (-0.37)
GDP NOR	0.101 (0.88)	
GDP SWE	-0.024 (-0.25)	
EBITDA margin	0.010 (0.98)	
SEK/EUR	0.524 (1.47*)	0.498 (1.74**)
NOK/EUR	0.720 (2.00***)	0.379 (1.45*)
Risk premium		0.722 (4.94***)
SMB		-0.312 (-2.06***)
HML		0.144 (1.26)
PR1YR		0.232 (2.13***)
LIQ		-0.428 (-3.13***)
m	166	166

Adjusted R^2	0.0479	0.4775
F-statistic	1.76*	19.97***

By means of the estimates from Table 5.6.2, the predicted out-of-sample resulted in higher sum square of errors than the FCF model. In other words, the factors presented in model (3) did not seem to create a better prediction model than the FCF model. However, the five common factors are tailored to represent the Norwegian market. Therefore, adding an external factor, such as SEK/EUR improves the predicting power for Orkla. The positive R_{OS}^2 are consistent with the claim. As a result, Orkla is a cost-sensitive company, which makes the factors impacting its costs highly important to anticipate its performance. Thus, the exchange rate seems to be of relevance in predicting Orkla's stock price.

Table 5.6.2

This table reports the results of comparing Orkla's predictive regression forecasts to the five common factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R_{OS}^2 statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R_{OS}^2 is positive, $R_{OS}^2 > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

	Model (3)	Model (4)
R_{OS}^2	-0.084	0.030

5.7 Yara International ASA

The analysts consider Yara's stock price to be especially sensitive to the market price of natural gas, nitrogen and urea. In addition, they revealed high confidence in company specific financial ratios such as EPS and EBITDA margin. All the factors individually tested for Yara are represented in Appendix 3. In fact, the results of Appendix 3 show several significant factors, namely the top line growth expectations (revenue), EBITDA margin and CAPEX, significant at a 10 %, 5 % and 5 % level respectively. Moreover, urea price is a highly significant factor as anticipated by analysts. However, the results did not find natural gas price nor nitrogen to be significant with the company's excess returns.

The multiple factor model (3) provides the first prediction model in this paper. The results of this model presented in Table 5.7.1, indicates that the urea price and top line growth (revenue) expectations still are showing significance. Both factors are significant at 10 % level for the in-sample period. Further, the regression estimates of model (4), incorporating the additional explanatory variables showing significance from model (3) to the FCF model, are presented on the right side in Table 5.7.1. The results find the price of urea and top line growth to be significant in the combined model, which indicate a possible improved forecasting power.

Table 5.7.1

The predictive power of leading indicators used by analysts to predict the excess stock return for Yara International. This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 2004 through 2016 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	0.002 (0.19)	-0.004 (-0.50)
CAPEX	0.022 (1.00)	
EBITDA margin	0.010 (1.03)	
Urea price	0.185 (1.81**)	0.144 (2.76***)
Revenue	0.152 (1.92**)	0.169 (3.02***)
Risk premium		0.696 (2.43***)
SMB		-0.781 (-3.46***)
HML		-0.045 (-0.28)
PR1YR		0.008 (0.05)
LIQ		-0.648 (-2.04***)
m	144	144
Adjusted R^2	0.1126	0.4867
F-statistic	2.50***	18.75***

The results in Table 5.7.2 show that the factors suggested by the analysts do not provide better out-of-sample predictions than the FCF model. On the other hand, the combined model provides improved out-of-sample predictions compared to the FCF model, suggesting that the price of urea and top line growth should be incorporated as explanatory variables when predicting Yara's stock returns.

Table 5.7.2

This table reports the results of comparing Yara International's predictive regression forecasts to the five common factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R_{OS}^2 statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R_{OS}^2 is positive, $R_{OS}^2 > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

	Model (3)	Model (4)
R_{OS}^2	-0.082	0.021

5.8 Norsk Hydro ASA

From the results of Appendix 3, it is illustrated that statistically significant factors correlating with the excess return for NHY are aluminum price, exchange rate (NOK/USD and NOK/EUR), dividends and P/B ratio. Table 5.8.1 shows the OLS results of the regression model including all the significant factors. The table reports aluminum price as the only factor still being significant at a 10 % level. Based on these results, the change in aluminum price appears to be a relevant factor for predictive NHY's excess return. The results in the second column of Table 5.8.1 studies the effect of adding aluminum price to the FCF model. The table reports all coefficients to be statistically significant, suggesting that the model has a higher explanation power, compared to the FCF model alone.

Table 5.8.1

The predictive power of leading indicators used by analysts to predict the excess stock return for Norsk Hydro This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 2000 through 2013 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	0.006 (0.88)	-0.004 (-0.86)
NOK/EUR	-0.138 (-0.34)	
NOK/USD	0.130 (0.55)	
Dividends	0.012 (0.81)	
P/E	-0.004 (-0.13)	
Aluminium price	0.295 (1.93**)	0.179 (1.84**)
Risk premium		0.968 (7.10***)
SMB		-0.654 (-4.96***)
HML		0.334 (3.24***)
PR1YR		0.180 (1.84**)
LIQ		-0.330 (-2.05***)
m	164	164
Adjusted R^2	-0.0009	0.6328
F-statistic	0.97	47.82***

The results of Table 5.8.2 show that the combined model performs better than the FCF model. This provides evidence to include aluminum price as an explanatory variable to the FCF model, when predicting NHY's excess return. However, as expected from the previous analysis, the results in the table confirm that a multiple factor model including the factors used by analysts by themselves fail to improve the predictive ability for the company's excess return.

Table 5.8.2

This table reports the results of comparing Norsk Hydro's predictive regression forecasts to the five common factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R^2_{OS} is positive, $R^2_{OS} > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

	Model (3)	Model (4)
R_{OS}^2	-0.317	0.050

5.9 Tomra Systems ASA

As mentioned previously, Tomra has a clear green profile and belongs to a favorable industry when it comes to the green shift in the world. Even though the potential growth for Tomra is promising, the factors related to the sustainability of this growth is ambiguous. Analysts revealed many soft factors to be relevant for Tomra's future performance. For instance, they believe innovations, the development of trends and future regulations to be the major influencers for such companies. In this paper non-numeric factors are not part of the analysis. However, analysts suggest few factors with maintainable historical effect. After testing the suggested factors, it appears that P/B ratio and dividends are indeed significant factors for Tomra's excess returns, following the reported results in Appendix 3.

The multiple factor forecast model created for Tomra consists of P/B ratio and dividends. The results of these factors, presented in Table 5.9.1, show statistical significance for the in-sample period at a 15 % level. To further evaluate the relevance of these factors, they are combined with the FCF in the combination model, also reported in Table. 5.9.1.

Table 5.9.1

The predictive power of leading indicators used by analysts to predict the excess stock return for Tomra Systems. This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 1994 through 2014 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	0.004 (0.48)	-0.005 (-0.59)
Revenue	0.029 (0.75)	
P/E	0.055 (1.52*)	0.040 (1.08)
Dividends	0.048 (1.54*)	0.021 (0.71)
Risk premium		0.510 (2.61***)
SMB		-0.135 (-0.61)
HML		-0.312 (-1.94***)
PR1YR		0.314 (1.97***)
LIQ		-0.644 (-2.56***)
m	252	252
Adjusted R^2	0.01	0.22
F-statistic	1.95*	9.47***

The negative R^2_{OS} for both models show evidence that the suggested factors fail to outperform the FCF benchmark model, neither by themselves nor in combination with the common factors. The results might confirm the high predictive power of the FCF benchmark model, but the paper also suspects that further study of soft factors might be useful for Tomra's excess returns.

Table 5.9.2

This table reports the results of comparing Tomra Systems' predictive regression forecasts to the five common factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R^2_{OS} statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R^2_{OS} is positive, $R^2_{OS} > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

	Model (3)	Model (4)
R^2_{OS}	-0.121	-0.073

5.10 Kongsberg Gruppen ASA

When individually testing the independent factors suggested by the analysts for Kongsberg Gruppen, several factors appeared to be significant. Most of these factors were company specific factors such as R&D, ROI, book-to-bill ratio and dividends, further explored in Appendix 3. In addition, analysts also referred to governmental defence expenditure as a major influential factor in predicting the companies excess return. The results of model (2), presented in Appendix 3, confirms the relevance of these factors. R&D, book-to-bill ratio and dividends are significant at a 5 % level, while ROI and defence expenditure are significant a 10 % level.

Further, in the analysis of evaluating the predictive power of leading indicators used by analysts, the significant factors are used to create the multiple factor model (3) for Kongsberg Gruppen. The results of Table 5.10.1 show that dividends, ROI and defence expenditure are able to maintain the same significance level as when tested individually, however, book-to-bill ratio and R&D lose their significance. Additionally, the study examines whether the mentioned significant factors have the ability to provide a better significant statistical role in explain the excess return when combined with the FCF benchmark model. Table 5.10.1 report the estimates for the combination model (4).

Table 5.10.1

The predictive power of leading indicators used by analysts to predict the excess stock return for Kongsberg Gruppen. This table reports the in-sample regression estimates for the multiple factor forecast model from Eq. (3), incorporating the significant factors, further explored in Appendix 3. Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable is simply the excess return. The table also reports the in-sample regression estimates for the combined forecast model from Eq. (4). The combination forecast model takes the combined effect of incorporating additional explanatory variables, the significant factors reported from the model in Eq. (3), to the five common factors (FCF) constructed for the Norwegian stock market (presented in Appendix 2). For the common factors, used as a benchmark for expected excess return, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The in-sample period, m, covers the period 2003 through 2014 monthly. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	Model (3)	Model (4)
Intercept	0.008 (1.20)	0.015 (0.68)
R&D	0.007 (0.34)	
Book-to-bill	-0.043 (-1.55*)	0.022 (0.82)
Defence exp.	0.113 (1.71**)	-0.076 (-1.13)
ROI	-0.088 (-1.66**)	0.003 (0.17)
Dividends	-0.040	-0.016

	(-2.08***)	(-1.05)
Risk premium		0.431 (2.16***)
SMB		0.210 (1.01)
HML		-0.120 (-0.74)
PR1YR		-0.149 (-1.00)
LIQ		-0.429 (-1.68**)
m	144	144
Adjusted R^2	0.0523	0.2104
F-statistic	2.32***	4.56***

Table 5.10.2 reports the results of the level of inaccuracy for each of the suggested models in comparison with the benchmark model. The results illustrate that neither of the models is able to predict better than the FCF model. To conclude, there is no evidence that the factors used by analysts add value to predict Kongsberg's stock returns.

Table 5.10.2

This table reports the results of comparing Kongsberg Gruppen's predictive regression forecasts to the five com factor (FCF) benchmark forecast. For the common factors used as a benchmark for expected excess stock return in the Norwegian stock market, further explored in Appendix 2, a multi-factor model based on Fama & French (1993) and Carhart (1997) with liquidity as an additional factor (Næs, Skjeltorp & Ødegaard, 2009), is adopted. The R_{OS}^2 statistics measure the reduction in mean square prediction error (MSPE) for the predictive multiple factor forecast model Eq. (3) and the forecast combination model Eq. (4) relative to the FCF benchmark forecast Eq. (1). When R_{OS}^2 is positive, $R_{OS}^2 > 0$, the forecast has a smaller root mean squared error term than the FCF benchmark forecast according to the MSPE metric. Thus, implying a stronger predictive stock return power than the benchmark.

	Model (3)	Model (4)
R_{OS}^2	-0.554	-0.078

6.0 Conclusion

The paper investigated the monthly predictive power of specific leading indicators used by analysts to predict the excess stock return for ten of the most influential Norwegian companies on the Oslo Stock Exchange (OSE); Equinor and Aker BP (energy sector), DNB and Gjensidige (finance sector), Mowi and Orkla (consumer staples sector), Yara and Norsk Hydro (material sector) and Tomra Systems and Kongsberg Gruppen (industrial sector).

There is little research on the specific Norwegian stock market, and no previous studies analysing the predictors affecting stock returns for specific Norwegian companies. With this in mind, the predictive power of specific factors, as used by the interviewed analysts of listed Norwegian companies, was studied. The paper set to assess whether or not the leading indicators suggested by the analysts show the expected relevance when evaluating predictive power. With this work, the thesis contributes to the field of research concerning the predictability of stock return, specifically related to the Norwegian stock market.

Similarly to Rapach, Strauss & Zhou (2009), an out-of-sample forecast exercise of the excess return of each company was conducted to investigate the leading indicators' ability to directly forecast the excess stock return. The study has concentrated primarily on the relevance of particular economic, industry specific and company specific variables related to each company. To identify the leading indicators used by analysts, semi-structured interviews with analysts were conducted before secondary data were collected. Furthermore, whether a multiple factor forecast model or a forecast combination model incorporating additional lagged explanatory variables have the ability to outperform a five common factor (FCF) benchmark forecast model containing common factors for the Norwegian stock market, was evaluated. For the common factors, a multi-factor model based on Fama & French (1993) and Carhart (1997,) with liquidity as an additional factor, as described by Næs, Skjeltorp & Ødegaard (2009), was adopted. In comparing the performance of the forecasts relative to the benchmark model, R_{OS}^2 statistics is used, based on work done by Campbell & Thompson (2008).

In nine of the ten cases studied, the multiple forecast models based on selected factors used by analysts failed to provide a better significant statistical role in explaining the excess stock return relative to the FCF benchmark forecast model over the out-of-sample period, even though the variables themselves are confirmed to possess valuable and relevant predicting power. Interestingly, in seven of the ten cases, the results from comparing the performance of the combined predictive regression forecasts to the benchmark model, show evidence of improved predictability when incorporating specific additional explanatory variables to the FCF benchmark model. In other words, even though the suggested factors used by Norwegian analysts are not the major predicting factors, the factors offer prediction value when combined with the common factors. For four companies, namely Equinor, Mowi, Tomra Systems and Kongsberg Gruppen, the results deviated. In the case of Equinor, both models outperform the FCF benchmark model, confirming that oil and gas prices are highly relevant indicators for Equinor's excess returns. For Mowi as well as the two cases from the industrial sector, Tomra Systems and Kongsberg Gruppen, the complete opposite results were experienced in that none of the models were able to outperform the FCF benchmark model. For those three cases, at least the numeric factors made available through the research conducted, did not help to explain excess stock return. This might confirm the high predictive power of the FCF benchmark model, but additional studies of other (soft) factors might be useful in order to actually confirm this hypothesis. In this analysis, macro specific and sector specific factors were generally found to be reliable indicators. The company specific financial factors, on the other hand, did not show the expected relevance when evaluating predictive power.

In general, the study's empirical findings from the in-sample and out-of-sample forecasting evaluation indicate that a multiple factor forecast model, containing leading indicators used by analysts, fails to outperform the FCF benchmark model when predicting the expected excess return for the Norwegian market. However, when these indicators are incorporated as additional explanatory variables to the FCF benchmark model, the results show evidence of improved predictability. The evidence from this study suggest that a forecast combination model might outperform the FCF benchmark forecast model, depending on the availability of relevant data for the variables and correct interpretation of them. The practical implication of these results is that valuable knowledge and insights analysts possess, have the ability to add relevant prediction value for investors when combined with common factors for the Norwegian stock market.

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Appendices

Appendix 1 – Description of Sectors

All information about the sectors is gathered from the information page of the Oslo Stock Exchange.

Energy sector

The energy sector consists of companies whose businesses are dominated by either of the following activities: the construction or provision of oil rigs, drilling equipment and other energy related service and equipment, including seismic data collection. Thus, companies engaged in the exploration, production, marketing, refining, and/or transportation of oil and gas products, coal and other consumable fuels are included in this sector.

Finance sector

The finance sector includes companies involved in activities such as banking, mortgage finance, consumer finance, specialised finance, investment banking and brokerage, asset management and custody, corporate lending, insurance and financial investment.

Consumer staple sector

The consumer staple sector consists of companies that are less sensitive to economic cycles. The sector includes manufacturers and distributors of food, beverages and tobacco and producers of non-durable household goods and personal products. It also includes food & drug retailing companies as well as hypermarkets and consumer super-centers.

Material sector

The material sector encompasses a wide range of commodity-related manufacturing industries. Included in this sector are companies that manufacture chemicals, construction materials, glass, paper, forest products and related packaging products and metals, minerals and mining companies, including producers of steel.

Industrial sector

The industrial sector includes companies that have their core business in one of the following activities: the manufacture and distribution of capital goods, including aerospace and defence, construction, engineering & building products, electrical equipment and industrial machinery. Providers of commercial services and supplies, including printing, employment, environmental protection and office services are also included in the sector. Further, are the providers of transportation services, including airlines, couriers, marine, road & rail and transportation infrastructure.

Appendix 2 – Five Common Factor (FCF) Benchmark Forecast Model

Fama & French (1993) three-factor model, momentum effect factor (Carhart (1997) four-factor model) and a liquidity factor (constructed by Næs, Skjeltorp & Ødegaard (2009) is used as a five common factor benchmark forecast model for expected excess stock return. This table reports the regression estimates of Eq. (1) using Norwegian stock market data (obtained from Ødegaard). Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable for each company is simply the excess return. The independent variables are defined as follows; RP is the market risk premium ($R_{Mt} - R_{ft}$), SMB is the size premium, HML is the value premium, PR1YR is the difference between the average return of the top and the bottom portfolios and LIQ is the liquidity premium. The sample period covers the period is 1990 through 2019 monthly. The in-sample period, m, for each company differs according to the availability of data. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	EQNR	AKERBP	DNB	GJF	MOWI	ORK	YAR	NHY	TOM	KOG
Intercept	-0.002 (-0.57)	0.003 (0.20)	-0.004 (-0.89)	0.014 (1.87**)	0.012 (0.16)	-0.001 (-0.31)	0.002 (0.24)	-0.004 (-0.88)	0.003 (0.42)	0.001 (0.18)
RP	0.777 (6.80***)	0.811 (2.15***)	1.173 (9.64***)	0.187 (0.72)	0.674 (0.32)	0.647 (4.27***)	0.773 (3.13***)	1.046 (7.93***)	0.733 (5.22***)	0.496 (2.26***)
SMB	-0.642 (-5.44***)	-0.108 (-0.25)	-0. 651 (-4.55***)	-0.123 (-0.51)	2.134 (1.37)	-0.330 (-2.38***)	-0.875 (-3.34***)	-0.619 (-4.63***)	0.002 (0.01)	0.268 (1.21)
HML	0.228 (2.50***)	0.707 (2.10***)	0.314 (3.01***)	0.396 (2.25***)	2.301 (2.04***)	0.184 (1.67**)	-0.086 (-0.42)	0.360 (3.47***)	-0.314 (-2.44***)	-0.067 (-0.35)
PR1YR	0.369 (4.40***)	-0.537 (-1.73**)	-0.062 (-0.62)	0.176 (1.03)	1.019 (0.87)	0.216 (1.96***)	0.025 (0.12)	0.160 (1.62*)	0.333 (2.41***)	-0.138 (-0.38)
LIQ	0.111 (0.78)	0.235 (0.49)	0.107 (0.66)	-0.387 (-1.59*)	-0.021 (-0.01)	-0.457 (-3.00***)	-0.552 (-1.73**)	-0.285 (-1.75**)	-0.519 (-2.66***)	-0.516 (-1.98***)
m	162	108	230	72	51	168	144	164	252	144
F-statistic	30.62***	3.54***	41.22***	3.24***	1.33	25.28***	20.31***	54.06***	16.89***	5.20***
Adjusted R^2	0.48	0.11	0.47	0.14	0.03	0.45	0.43	0.62	0.22	0.16

Appendix 3 – Factors' Coefficients and t-statistics

This table individually reports the regression estimates of specific leading indicators used by analysts to predict the excess stock return for selected Norwegian listed companies, using the standard predictive regression model from Eq. (1). Coefficient estimates are time-series of cross-sectional OLS regressions. The dependent variable for each company is simply the excess return. To predict the excess return at time $t+1$, all independent variables are lagged one period if it is not reported as an expectation, assuming that the independent variable's value at $t+1$ is the expected value at time t. For each company, all observations in the sample are included. The sample period generally covers the period 1990 through 2019 monthly. However, the sample period differs according to the availability of data. The t-statistics are reported in parentheses under each coefficient. ***, **, and * represent 5 %, 10 % and 15 % significance level respectively.

	EQNR	AKERBP	DNB	GJF	MOWI	ORK	YAR	NHY	TOM	KOG
P/B	0.134 (3.71***)	0.057 (0.38)	0.011 (0.11)	-0.070 (-0.36)	-0.002 (-0.05)	0.123 (0.76)	0.012 (0.16)	-0.221 (-1.57*)	0.198 (1.74**)	0.049 (0.51)
P/E	0.0054 (0.29)	0.065 (0.99)	-0.085 (0.91)	-0.022 (-0.23)	0.001 (0.28)	0.000 (0.02)	0.021 (0.90)	-0.002 (-0.440)	0.013 (0.48)	0.033 (1.14)
EPS	0.0002 (0.44)	0.013 (1.39)	0.022 (0.73)	0.002 (0.07)	-0.008 (-0.71)	0.000 (0.83)	0.000 (0.03)	-0.009 (-0.970)	0.004 (0.16)	0.003 (0.32)
ROI	0.000 (0.000)	0.007 (0.80)	0.049 (0.32)	-0.113 (-1.38)	-0.0136 (-0.09)	0.0319 (0.50)	-0.007 (-0.24)	-0.012 (-0.260)	0.021 (0.65)	0.085 (1.67**)
ROE	0.001 (0.10)	0.002 (0.11)	0.024 (0.21)	-0.064 (-0.55)	-0.004 (-0.86)	0.003 (0.43)	0.005 (0.25)	0.002 (0.940)	0.003 (0.21)	-0.015 (-0.48)
EBITDA margin	0.000 (0.02)	0.020 (0.98)			-0.003 (-0.49)	0.023 (1.52*)	0.027 (4.77***)	0.000 (-0.050)	-0.046 (-1.44)	-0.000 (-0.02)
Dividends	-0.004 (-0.24)	0.042 (0.55)	-0.285 (-2.14***)	0.017 (1.56*)	0.297 (4.39***)	-0.001 (-0.08)	0.0235 (0.93)	0.724 (3.81***)	0.067 (2.25***)	-2.84 (-0.037***)
Revenue	-0.005 (-0.11)	-0.035 (-0.66)		-0.140 (-1.07)	0.292 (0.98)	0.046 (0.84)	0.336 (1.74**)	0.147 (0.750)	0.195 (1.62*)	0.146 (1.32)
Combined ratio				-0.125 (-1.99***)						
Book-to-bill										0.189 (2.13***)
CAPEX	0.011 (0.49)	-0.009 (-0.17)	0.000 (0.22)	0.003 (1.93**)	0.087 (0.72)	-0.003 (-0.18)	-0.034 (-4.34***)	0.007 (0.130)		-0.058 (-1.23)
R&D										0.136 (2.49***)
Oil price	0.343 (6.33***)	0.317 (2.33***)								
Gas price	0.060 (2.58**)	(-0.078) (-0.98)					-0.023 (-0.39)			
Long-term interest				0.081 (1.57*)						
NIBOR			-0.264 (-2.92***)							
NOK/EUR					1.600 (1.83**)	0.576 (2.23***)		0.553 (1.96**)		

NOK/US	0.99 (1.92**)			0.666 (4.01***)		
SEK/EUR		0.513 (1.49*)				
GDP NOR		0.164 (1.78**)				
GDP SWE		0.099 (1.76**)				
Salmon price	0.739 (2.07***)					
Nitrogen price			-0.213 (-0.64)			
Urea price			0.212 (2.39***)			
Aluminium price				0.297 (2.31***)		
Defence expenditure						0.444 (1.77**)