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Modelling the Return Distribution of Salmon Farming Companies

– A Quantile Regression Approach

Fredrik Jacobsen
Master of Science in Business Administration

Preface

This master thesis completes my Master of Science in Business Administration at Norwegian University of Life Science (NMBU).

The subject of this study is to model the return distribution of salmon farming companies in the seafood sector at the Oslo Stock Exchange by using quantile regression, and to show how the results from the quantile regression analysis can be implemented and applied in a Value-at-Risk analysis. This has given me a broader understanding of the salmon farming industry and insight into the risk and return characteristics of salmon farming company stocks.

I would like to thank my supervisors, Marie Steen and Sjur Westgaard, for valuable guidance and constructive feedback throughout the process of writing this master thesis.

Fredrikstad, 09.05.2017

Abstract

The salmon farming industry has gained increased attention from investors, portfolio managers, financial analysts and other stakeholders the recent years. Despite this development, very little is known about the risk and return of salmon farming company stocks, and especially how the relationship between risk and return varies under different market conditions, given the volatile nature of the salmon farming industry. We approach this problem by using quantile regression to examine the relationship between risk factors and stock price returns over the entire return distribution at both the industry and firm-level. As potential risk factors, we include the market return, changes in the salmon price, changes in exchange rates, changes in the long-term interest rate and the lagged stock return of the industry leader.

The results show that the market return, changes in the salmon price and the lagged stock return of the industry leader have a positive and significant impact on stock price returns. Furthermore, while the risk factor sensitivities are quite stable across quantiles at the industry-level, there are larger differences across quantiles at the firm-level. This implies that the relationship between risk factors and stock price returns varies under different market conditions, at least at the firm-level. In addition, the companies have different risk and return characteristics that might be of particular interest for investors when it comes to asset allocation and hedging decisions. Finally, we also show how the results can be implemented and applied in Value-at-Risk analysis, where these different characteristics are taken into consideration.

Sammendrag

De seneste årene har lakseoppdrettsnæringen fått økt oppmerksomhet fra blant annet investorer, porteføljeforvaltere, analytikere og andre interessenter. Til tross for denne utviklingen har det blitt viet lite oppmerksomhet til avkastning og risiko for børsnoterte lakseselskaper, og spesielt hvordan forholdet mellom avkastning og risiko varierer under forskjellige markedsforhold, med hensyn på lakseoppdrettsnæringens volatile karakter. Vi tar for oss dette problemet ved å bruke kvantilregresjon til å undersøke sammenhengen mellom risikofaktorer og avkastning over hele fordelingen til avkastningene på både bransje- og selskapsnivå. Som potensielle risikofaktorer inkluderer vi markedets avkastning, endringer i laksepris, endringer i valutakurser, endringer i den langsiktige renten og bransjelederens avkastning forrige periode.

Resultatene viser at markedets avkastning, endringer i laksepris og bransjelederens avkastning forrige periode har en positiv og signifikant påvirkning på avkastningene til lakseselskapene. Videre viser resultatene at avkastningenes følsomhet overfor endringer i risikofaktorer er nokså stabil på tvers av kvantiler på bransjenivå, men at det er større forskjeller på tvers av kvantiler på selskapsnivå. Dette innebærer at forholdet mellom risikofaktorer og avkastninger varierer under forskjellige markedsforhold, i det minste på selskapsnivå. I tillegg har selskapene ulike avkastnings- og risikoegenskaper som kan være av særlig interesse for investorer når det gjelder kapitalallokering og sikringsbeslutninger. Avslutningsvis viser vi også hvordan resultatene kan implementeres og brukes i en Value-at-Risk analyse, hvor disse forskjellige egenskapene er tatt i betraktning.

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1 Introduction

In the recent years, the seafood sector at the Oslo Stock Exchange has had a substantial growth with many of the companies in the salmon farming industry reaching an all-time high. Only the last ten years the market value of companies in the seafood sector at the Oslo Stock Exchange has grown from 14 to 148 billion NOK (Oslo Stock Exchange, 2016). A possible explanation for this trend can be related to the increasing number of listed salmon farming companies and the recent supply and demand situation for salmon, which pushed the salmon price to new levels in 2016. This development has given the industry increased attention among investors, portfolio managers, financial analysts and other stakeholders. Moreover, the salmon farming industry is also an important export industry for Norway, and especially after the big drop in oil prices in 2014, which has raised the question of what Norway will subsist on in the future. Today, salmon farming is the biggest source of income for Norway in the aquaculture industry, accounting for approximately 67 % of the Norwegian fish export, and in 2016, the salmon export volume was 980 000 tons, worth 61,4 billion NOK (Norwegian Seafood Council, 2017).

Although the salmon farming industry has become increasingly popular over the years due to its high profitability and growth, it is important to remember that salmon farming is a cyclical industry, and historically, salmon farming companies have experienced substantial variability in their profitability. This raises some important questions from an investor's perspective about the risk and return of salmon farming companies and how risk factors affect stock price returns.

Knowledge of risk factors that determine stock price returns has long been of interest among academics and practitioners, and a growing literature has demonstrated that stock price returns at the industry and firm-level are sensitive to both common market-wide and industry-specific risk factors[1]. However, there are some limitations with the models used in these studies. They all use linear factor models under the assumption that stock price returns are linearly dependent on the risk factors, even though there is evidence of nonlinearity between risk factors and stock price returns in the financial literature, and linear factor models are therefore unable to capture a nonlinear dependency structure. Moreover, in risk management, investors and risk managers are often interested in the relationship between risk factors and stock price returns under more extreme market conditions, in which linear factor models are mostly insufficient, as they only focus on the relationship at the conditional mean.

[1] For example, Faff and Chan (1998) in the gold industry, Boyer and Filion (2007) in the oil and gas industry, and Misund (2016a) in the salmon farming industry.

The aim of this study is to take such characteristics into consideration when modelling the return distribution of salmon farming companies. Therefore, we use quantile regression in this study, which allow for changing betas across different quantiles, to examine how potential risk factors affect stock price returns over the entire return distribution. Using quantile regression, as first introduced by Koenker and Basset (1978), will give a better understanding of the relationship between risk factors and stock price returns, and given the volatile nature of the salmon farming industry, this approach can uncover if the relationship varies under different market conditions. Furthermore, since quantile regression provides direct estimates of the tail distribution, i.e. the upper and lower quantiles, we also show how the results from the quantile regression analysis can be implemented in the estimation of Value-at-Risk (VaR). As such, we estimate VaR and perform a scenario analysis to stress test the VaR estimates to illustrate how tail risk responds to changes in risk factors. In addition, we perform a backtesting procedure as a robustness check to validate the VaR estimates, which also will give an indication of the accuracy of the estimated tail distributions. Overall, the results from this study will give investors in the salmon farming industry a better understanding of the relationship between risk factors and stock price returns under different market conditions, and additionally, show how the results can be implemented and applied in a VaR analysis.

Although quantile regression has become an attractive approach for modelling the dependency structure between financial variables and for estimating VaR models, there is to our knowledge no studies that apply quantile regression to examine the relationship between risk factors and stock price returns of companies in the salmon farming industry. As such, we contribute to the literature by showing how risk factors affect stock price returns of salmon farming companies, not only at the conditional mean, but over the entire return distribution using different quantiles. This will provide valuable information to investors and risk managers about the risk and return of salmon farming companies, and potentially uncover interesting risk and return characteristics that are not captured by linear factor models, which might be important for risk management, asset allocation and hedging decisions.

The remainder of this study is organized as follows. It begins in section 2 with an overview of the development in the salmon farming industry, followed by a literature review in section 3. Thereafter, the methodology is presented in section 4, and the data and descriptive statistics in section 5. This is followed by the empirical results and analysis in section 6. Finally, section 7 presents some concluding remarks.

2 The salmon farming industry

During the last three decades, the salmon farming industry in Norway has developed from being a local small-scale industry to become a global multinational industry and an important export industry for the Norwegian economy. The main drivers for this development has been strong productivity growth and technological improvements (Asche et al, 2007; Asche, 2008; Nilsen, 2010; Vassdal and Holst, 2011; Asche et al, 2013a; Roll, 2013), which has resulted in lower production costs and improved competitiveness for the industry. This has led to an increase in production volume of Atlantic salmon from only a few thousand tons in 1980 to over 2,0 million tons in 2015, with Norway as the main producer, accounting for over 50 % of total production. In figure 1, the global supply and supply growth of Atlantic salmon the ten last years are shown, and the figure distinguishes between supply from Norway and Chile, the two largest producers, and other salmon producing countries.

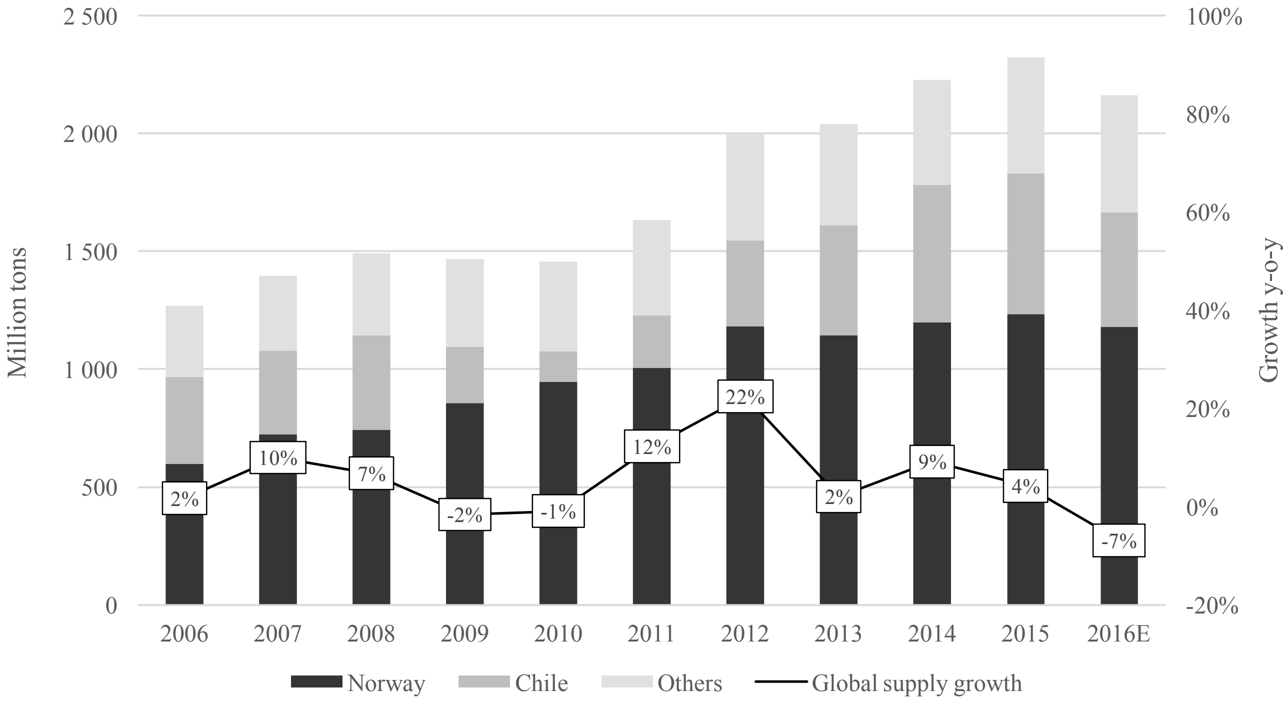

Figure 1. Global supply and supply growth of Atlantic salmon 2006-16. **Source:** AGB Sundal Collier.

As the figure shows, there has been a substantial growth in total supply since 2006, but there is large variability in the growth rate. The negative supply growth in 2009 and 2010 was mainly caused by a major disease attack in Chile, which greatly reduced the global supply of Atlantic salmon, and in terms of revenue loss, this was the worst disease attack in the history of salmon aquaculture (Asche et al, 2009). However, biological challenges are nothing new in the salmon farming industry and it is also the reason why there is a negative supply growth in 2016. Today, the industry is experiencing large challenges with sea lice. According to Marine Harvest, the industry leader, the industry has reached a production level where the biological boundaries are being pushed, and that further growth can no longer be driven by the industry alone (Marine Harvest, 2016). In addition, the Norwegian government has stopped all calls for new production licenses in Norway until the industry can control its challenges with sea lice.

Along with the increase in production volume of Atlantic salmon, the salmon farming industry has become more mature and the productivity growth has slowed down (Asche and Bjørndal, 2011; Vassdal and Holst, 2011; Asche et al, 2013a). In the maturing process, the industry has changed from being an industry consisting of many small companies to be a more integrated industry with fewer and larger companies (Kvaløy and Tveterås, 2008; Asche et al, 2013b). In addition, the production has become more feed intensive and the unit production cost and sales price have gone from being productivity driven to input-factor price driven (Asche and Oglend, 2016), indicating that input-factor prices might become more important in determining the price of salmon as well as in the valuation of salmon farming companies in the future.

Over the last 10-15 years, there has been a securitization of the salmon farming industry, with Oslo Stock Exchange as the main marketplace for salmon farming company stocks. This has led to an increased interest for the industry in the financial community, and in early 2017, there are eight salmon farming companies listed at the Oslo Stock Exchange as well as several related companies such as suppliers. Another explanation for the increased interest can be attributed to the establishment of Fish Pool in 2006, which has emerged as an important marketplace for trading financial derivatives such as forwards, futures and options on the spot price of salmon. This has given producers and buyers a tool to hedge against changes in the price of salmon to reduce their risk, and speculators and arbitrageurs a trading opportunity, which is an important part of a functioning derivatives market. However, while the trading volume of future contracts grew fast in the first five years, there has been a decline in growth after 2011.

Even though the salmon farming industry has been a success story in terms of profitability and stock price growth in the recent years, it is known for its cycles in profitability. The main source for these cycles is price risk (Asche and Sikveland, 2015), and recent studies have demonstrated that the salmon price volatility has increased since the early 2000s, indicating even higher price risk for producers and buyers (Oglend and Sikveland, 2008; Oglend, 2013; Dahl and Oglend, 2014; Bloznelis, 2016). In figure 2, the cycles in profitability for Norwegian salmon producers are shown, and in 2002-2003, average operating margin was even negative.

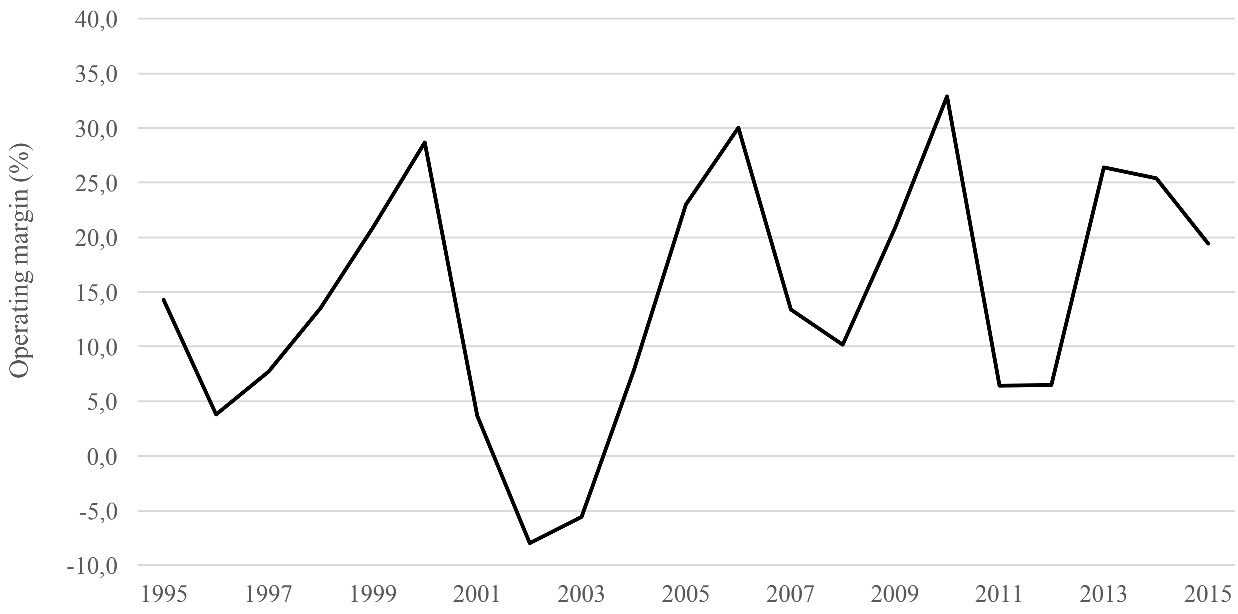

Figure 2. Average operating margin for Norwegian salmon producers 1995-2015. Operating margin is earnings before interest and taxes (EBIT) in percentage of operating income. **Source:** The Norwegian Directorate of Fisheries.

During this period, several salmon producers went bankrupt due to low salmon prices, which in periods also was below the production cost, and a recent study has shown that salmon farming companies increase the risk of bankruptcy in periods with low profitability (Misund, 2016b). However, the situation is quite different nowadays, where a limited supply along with a strong demand that can be attributed to the development in downstream operations such as product development, systematic marketing and improved logistics (Kinnucan et al, 2003; Asche et al, 2011; Asche and Bjørndal, 2011; Brækkan, 2014; Brækkan and Thyholdt, 2014), pushed the salmon price to new levels in 2016. In addition, a depreciation of the Norwegian krone the last few years, in relation to the big drop in oil prices in 2014, has pushed the salmon price higher measured in NOK/kg. This combination has given the Norwegian salmon farming companies super margins and is the main reason for the substantial stock price growth in the seafood sector. However, as a consequence of the biological challenges in the industry, the production cost has also started to increase along with the salmon price. In figure 3, we have illustrated the salmon price development in the period 1995-2016, and the figure clearly shows the abnormal salmon prices that has been in the recent years if we take a historical perspective.

Figure 3. The spot price of salmon over the period 1995-2006. The salmon price is the Nasdaq Salmon Index (weekly observations). **Source:** Nasdaq.

Historically, the salmon price has mainly been determined by changes in global supply due to a relatively strong demand for salmon (Marine Harvest, 2016). A part of this is due to the fact that the production cycle for salmon is three years long, and since it is difficult and expensive to adjust the production level in the short term, the short-term supply is very inelastic. This has, along with exogenous shocks in supply, a large effect on the salmon price volatility. However, with the situation the industry is experiencing today, where biological challenges and capacity restrictions limits further supply growth, it is likely that demand growth will be more important in determining the price of salmon going forward if this situation does not change.

3 Literature review

This section describes the relevant literature and aims to show how this study contributes to the existing financial literature. First, we review previous studies examining determinants of stock price returns in the salmon farming industry in order to identify relevant risk factors to include in the model. Identification of relevant risk factors is an essential part in developing a proper factor model, and omitted variables may lead to misspecification of the model. Thereafter, we show how quantile factor models have been applied in other segments of the stock market and in what way these models have contributed to our understanding of the relationship between risk factors and stock price returns.

3.1 Determinants of stock price returns in the salmon farming industry

In the financial literature, there are only a few studies examining risk factors for salmon farming companies and how they affect stock price returns, but most of them are master theses and have conflicting and partly strange results (Syltesæter and Utgård, 2012; Kleven and Løken, 2012; Reinhardt, 2013; Grafsli et al, 2016). A possible explanation for this is the fact that stock prices of salmon farming companies are very volatile, and when using data with low frequencies, the results may be unstable and lack precision. However, a more recent study has demonstrated that stock price returns of salmon farming companies are sensitive to both common market-wide and industry-specific risk factors (Misund, 2016a), and we will use this study as a starting point to determine which risk factors to include in the model. In the following, we divide the review into two parts. First, we review findings related to common market-wide risk factors, and then, we review findings related to industry-specific risk factors, where each part will be summarized by our choice of risk factors.

In order to establish an understanding of the relationship between a set of potential common market-wide risk factors and stock price returns of salmon farming companies, Misund (2016a) uses a multifactor model with monthly data from 2006 to 2016 to examine if stock price returns are sensitive to market excess return (OSEAX), the Fama-French-Carhart factors (SMB, HML and UMD), changes in the oil price and changes in exchange rates (NOK/EUR and NOK/USD). It is, however, worth noting that the proxy he uses as the market is the Oslo Stock Exchange All-Share Index, and that the Fama-French-Carhart factors represent the size (small minus big firms), value (high minus low book-to-market ratio) and momentum (upward trending minus downward trending stocks) premium. The results show that an equally-weighted portfolio of all the salmon farming companies is sensitive to both the market excess return and the Fama-

French-Carhart factors SMB and HML, which indicate that the industry is tilted towards large caps and value stocks. Furthermore, the results show that the overall industry is less risky than the market in general, indicating that the recent growth in stock prices is not explained by high systematic risk. The same results are found for most of the companies when they are examined individually. Regarding changes in exchange rates and changes in the oil price, Misund (2016a) concludes that these are not direct determinants of stock price returns neither at the industry nor firm-level.

Although the above findings give an indication of which common market-wide risk factors that serve as determinants of stock price returns for salmon farming companies, a difficult task is to identify the most important risk factors in order to model the return distribution. For instance, we find that the Main Index at the Oslo Stock Exchange (OSEBX) is better suited as the market than the All-Share Index[2], and therefore, we include the Main Index at the Oslo Stock Exchange as the market in our model. Moreover, since our approach can shed new light on the relationship between risk factors and stock price returns, we include changes in exchange rates in our model, although Misund (2016a) concludes that changes in exchange rates are not direct determinants of stock price returns. In addition, several studies have shown the importance of exchange rates in the salmon farming industry (Tveterås and Asche, 2008; Larsen and Kinnucan, 2009; Larsen and Asche, 2011; Straume, 2014; Yarmoradi and Rygh, 2016), and it is therefore possible that changes in exchange rates have an impact on stock price returns in periods with more extreme market conditions. Finally, we will include changes in the long-term interest rate in our model, which also have been done in studies examining risk factors of stock price returns for companies in other volatile industries (e.g. Faff and Chan, 1998; Tufano, 1998; Sadorsky, 2001; Boyer and Filion, 2007; Drobetz et al, 2010; Tjaalanda et al, 2016). Changes in the long-term interest rate might affect both the future cash flow of the salmon farming companies and the required rate of return for investors, and hence, the stock price.

Looking at the industry-specific risk factors, Misund (2016a) examines if shocks in production, biomass and sea temperature as well as changes in the salmon price have an impact on stock price returns, and he finds that changes in the salmon price is the most important risk factor at both the industry and firm-level. Zhang et al (2016) also find a strong relationship between the salmon price and the stock price of Norwegian salmon farming companies by using a Johansen

[2] The Main Index had the highest explanatory power for salmon farming company stock returns when we compared several stock indices as the market, using a single factor market model.

cointegration test with weekly data from 2007 to 2013. However, they find the relationship to be stronger between smaller companies than larger companies, and hence, show that there exists heterogeneity between companies' response to changes in the salmon price. They also present two possible explanations for this. First, they argue that larger companies own a stronger ability to manage fluctuations in the salmon price than smaller companies, and second, they argue that larger companies have a higher level of internationalization, and hence, are more diversified in terms of plant locations. Regarding the other industry-specific risk factors related to shocks in inventory, they were only found to be a minor contributor in determining stock price returns.

Another interesting finding by Zhang et al (2016), is the detection of a long-run relationship between the stock price of the industry leader and two of the other companies, where a rise in the stock price of the industry leader is followed by a rise in the stock price of the other two. This might indicate that there exists a lead-lag relationship in the industry. If this is the case, this contradicts the efficient market hypothesis that new information is expected to be reflected in stock prices simultaneously, and one can use the stock price of the industry leader to predict future movements in stock prices of the other companies within the industry. In the financial literature, there are several explanations for this phenomenon such as thin trading, stock market overreaction and slow diffusion of information (Lo and MacKinlay, 1990; Brennan et al, 1993; Badrinath et al, 1995; Chordia and Swaminathan, 2000; Hou, 2007). However, the aim of this study is not to uncover why a lead-lag relationship might exist in the salmon farming industry, but based on the above findings, it is likely that the lagged stock return of the industry leader is an important factor in explaining stock price returns in the salmon farming industry. As such, based on the discussion above, we will include changes in the salmon price and the lagged stock return of the industry leader in our model.

3.2 Quantile factor models in the stock market

Over the years, several studies have used quantile factor models to examine the relationship between risk factors and stock price returns. For instance, Allen et al (2011) analyze the return distribution of 30 stocks of the Dow Jones Industrial Average obtained from the Fama-French three-factor model. They find that there are large and sometimes significant differences in the relationship between risk factors and stock price returns across the quantiles, indicating that the relationship is far more complex than the assumptions inherent in OLS[3]. Moreover, they find OLS to be less effective when it comes to analyzing the extremes within the return distribution.

[3] OLS is the estimation technique used to estimate standard regression models (linear factor models).

Looking at the emerging stock markets of the BRICS (Brazil, Russia, India, China and South Africa) countries, Mensi et al (2014) use quantile regression to examine how global economic factors influence the performance of BRICS stock markets to identify their co-movement under different market conditions. The results show that the dependency structure between the BRICS stock markets and the global economic factors (S&P500, oil, gold, VIX) is often asymmetric, except for the volatility index, which showed no impact on the BRICS stock markets. Overall, by using quantile regression, they uncover that the BRICS stock markets are useful for global investors in bearish markets, in terms of downside risk management, since the co-movements with the global stock market (S&P500) were lower in the lower quantiles.

Others have also used quantile regression to examine the impact of one particular risk factor on stock market returns. Lee and Zeng (2011) examine the impact of changes in the real oil price on the real stock market return of the G7 countries. The results show that the responses of stock markets to oil price shocks are diverse among the G7 countries, and that the quantile regression estimates are quite different from OLS models. Furthermore, the results imply that asymmetric oil price shocks impact the real stock returns of the G7 countries mostly under extreme market conditions, in other words, investors are more pessimistic (optimistic) to bad (good) news when the stock market performs poorly (well). Tsai (2012) estimate the relationship between the stock market of six Asian countries (Singapore, Thailand, Malaysia, the Philippines, South Korea and Taiwan) and their corresponding exchange rates. It is, however, worth noting that he uses the exchange rates as the dependent variable and stock market returns as the independent variable. The results show a positive relationship between exchange rates and stock market returns for all of the six Asian countries, indicating that an increase in the stock market return will lead to an appreciation of the domestic currency. Moreover, the positive relationship is more obvious when exchange rates are extremely high or low. Looking at the U.S. stock market, Jareño et al (2016) examine the sensitivity of the U.S. stock market to changes in the interest rate. After decomposing the nominal interest rate into the real interest rate and the inflation rate, they find that several sectors are exposed to both changes in the real interest rate and the inflation rate, even though important differences are detected between sectors and over time. Moreover, the results show that the effect tends to be more pronounced during extreme market conditions.

Recently, there has also been conducted some master theses that use quantile factor models in specific industries, such as the shipping industry (Ekrem and Kristensen, 2016) and the oil and gas industry (Skjøld, 2016). Ekrem and Kristensen (2016) model the relationship between stock price returns and a set of macroeconomic factors across the conditional return distribution. The macroeconomic factors included in their model are the market excess return, changes in the oil price, the volatility index, changes in exchanges rates and changes in the long-term interest rate, and the findings show that the risk factor sensitivities differ across quantiles, indicating that the risk factor sensitivities vary under different market conditions. Furthermore, in their estimation of VaR, the findings show signs of asymmetric tail risk, with higher exposure in the lower tail. Skjøld (2016) examines the conditional return distribution of oil and gas companies obtained from a five-factor model with the market return, the price of oil and natural gas, the US dollar index and the volatility index as fundamental risk factors. The overall results show that the risk factor sensitivities change noticeably in the tails of the conditional return distribution compared to the median, and that there are different levels of tail risk for a short/long investor.

From the literature review of studies applying quantile factor models in various segments of the stock market there are some common findings that tend to recur. For instance, several studies find a nonlinear relationship between risk factors and stock price returns, and that the risk factor sensitivities tend to be more pronounced during extreme market conditions. This indicates that quantile factor models might be more suitable for examining the relationship between risk factors and stock price returns than linear factor models. Whether this also applies to the salmon farming industry is what this study aims to uncover, since this will have implications for risk management, asset allocation and hedging decisions.

4 Methodology

This section briefly describes the theoretical framework used in this study. First, we outline and explain the quantile regression model and the estimation technique used to obtain the regression coefficients. Then, we define VaR and show how the regression coefficients from the quantile regression model easily can be implemented to estimate VaR, before we explain the backtesting procedure for VaR.

4.1 Quantile regression models

Quantile regression aims to describe the conditional distribution of the dependent variable using its quantiles, and it is done by estimating a regression line through a scatter plot as in standard regression. However, while the standard regression line passes through the average of the points in the scatter plot, the quantile regression line passes through a quantile of the points. As such, by estimating the regression coefficients for a set of quantiles, given a value for the independent variable, we can describe the entire conditional distribution of the dependent variable using the regression coefficients for each quantile.

The linear quantile regression model or the *q*th quantile linear regression model, as introduced by Koenker and Basset (1978), is given by,

$$Y_t = \alpha^q + \beta^q X_t + \varepsilon_t^q \tag{4.1}$$

where Y_t is the dependent variable, X_t is the independent variable, α^q and β^q are the regression coefficients, and ε_t^q is the error term, which has an unspecified distribution function. By letting $q \in (0,1)$, representing the different quantiles, the regression coefficients will depend on q.

The conditional *q*th quantile is derived according to the following minimization problem,

$$\min_{\alpha,\beta} \sum_{t=1}^{T} (q - 1_{Y_t \leq \alpha + \beta X_t})(Y_t - (\alpha + \beta X_t)) \tag{4.2}$$

where

$$1_{Y_t \leq \alpha + \beta X_t} = \begin{cases} 1 & if\ Y_t \leq \alpha + \beta X_t, \\ 0 & \text{otherwise.} \end{cases} \tag{4.3}$$

Quantile regression models have several advantages over standard regression models, as they are less sensitive to outliers and avoid assumptions about the distribution of the error process.

4.2 Value-at-Risk models

VaR is a measure for the loss level that is expected to be exceeded with a selected probability if a stock or portfolio is held over some time, and it has two basic parameters, i.e. a significance level α (or confidence level 1-α) and a risk horizon (Alexander, 2009). The significance level is the selected probability and the risk horizon is the period over which we measure the potential loss.

Although there are many ways to model VaR, an interesting feature of the quantile regression model is that it allows for estimating VaR directly, because VaR can be seen as a particular conditional quantile of the return distribution (Chernozhukov and Umantsev, 2001). The VaR model can therefore be expressed as,

$$VaR_t^q \mid X_t = \alpha^q + \beta^q X_t \quad (4.4)$$

where VaR_t^q is the estimated VaR for a given significance level (the conditional qth quantile), α^q and β^q are the regression coefficients, and X_t is the independent variable at a given value. As such, once the regression coefficients for the different quantiles are estimated, we only need a value for the independent variable to estimate VaR for any given significance level. It is still important to mention that, since we use risk factors as the independent variable to model VaR, and not the volatility, the VaR obtained from this procedure is the systematic VaR or total risk factor VaR (Alexander, 2009). However, we also include the alpha in this study, which usually enter the unsystematic part of the risk, and thus, we aim to capture the total risk of the stock or portfolio.

4.3 Backtesting procedure for Value-at-Risk

Backtesting refers to testing the accuracy of VaR over a historical period when the true outcome is known. The general approach to backtesting VaR is to record the number of occasions over a historical period on which the actual loss exceeds the VaR estimate and compare this number with the pre-specified significance level. The total number of exceedances divided by the total number of observations in the data sample should be as close to the pre-specified significance level as possible. Moreover, the exceedances should be randomly distributed over the sample (no clustering of exceedances), since we do not want VaR to overestimate or underestimate the tail risk in certain periods.

There are usually two tests that are used to validate the accuracy of VaR models, i.e. the Kupiec test and the Christoffersen test. The Kupiec (1995) test is a likelihood test designed to uncover whether the VaR model provides correct unconditional coverage. More precisely, let H_t be an indicator sequence, where H_t takes the value 1 if the observed return, Y_t, is below the estimated VaR quantile, VaR_t^q, at time t:

$$H_t = \begin{cases} 1 & if\ Y_t \leq VaR_t^q, \\ 0 & \text{otherwise.} \end{cases} \quad (4.5)$$

However, equation (4.5) is only true for q less than 50 %. For q greater than 50 %, we have

$$H_t = \begin{cases} 1 & if\ Y_t \geq VaR_t^q, \\ 0 & \text{otherwise.} \end{cases} \quad (4.6)$$

Under the null hypothesis of correct unconditional coverage, the test statistics is

$$\begin{aligned} -2\ln(LR_{UC}) = -2[&n_0 \ln(1 - \pi_{exp}) + n_1 \ln(\pi_{exp}) \\ &- n_0 \ln(1 - \pi_{obs}) - n_1 \ln(\pi_{obs})] \sim \chi_1^2, \end{aligned} \quad (4.7)$$

where n_1 and n_0 are the number of violations and non-violations, respectively, π_{exp} is the expected proportions of exceedances and $\pi_{obs} = n_1/(n_0 + n_1)$ is the observed proportions of exceedances. However, this test only tests if the empirical frequency of exceedances is close to the pre-specified significance level. It does not test whether several quantile exceedances occur in rapid succession or whether they tend to be isolated. Therefore, in order to test whether the exceedances are randomly distributed over the sample, we also perform the Christoffersen test. Christoffersen (1998) provides a joint test for correct coverage and detecting whether a quantile violation today influences the probability of a violation tomorrow. The test statistics is defined as follows,

$$\begin{aligned} -2\ln(LR_{CC}) = -2[&n_0 \ln(1 - \pi_{exp}) + n_1 \ln(\pi_{exp}) - n_{00} \ln(1 - \pi_{01}) \\ &- n_{01} \ln(\pi_{01}) - n_{10} \ln(1 - \pi_{11}) - n_{11} \ln(\pi_{11})] \sim \chi_2^2, \end{aligned} \quad (4.8)$$

where n_{ij} is the number of times an observation with value *i* is followed by an observation with value *j*. $\pi_{01} = n_{01}/(n_{00} + n_{01})$ and $\pi_{11} = n_{11}/(n_{11} + n_{10})$. It is, however, worth mentioning that the Christoffersen (1998) test is only sensitive to one violations immediately followed by another, ignoring all other patterns of clustering. For both tests, the model is correctly specified under the null hypothesis, and hence, we want to keep the null hypothesis.

5 Data and descriptive statistics

The data in this study consist of eight salmon farming companies listed at Oslo Stock Exchange, and representing all the salmon farming companies in the seafood sector. Unfortunately, this is to some extent a very small sample, but most of the companies in the salmon farming industry are either subsidiaries or privately owned, which limits the companies to include in the sample. Moreover, some of the companies were listed during the sample period and are therefore only included in an equally-weighted portfolio we use as a proxy for the overall industry from the date they were listed[4].

As in the study by Misund (2016a), we perform our analysis at both the industry and firm-level. This allows us to examine the industry as a whole, but also to examine if some of the individual companies have different characteristics that can be of particular interest for investors. Because of the limited sample of companies, we have eight companies included in the equally-weighted portfolio for the industry-level analysis, and only five companies for the firm-level analysis. In table 1, all the companies are presented, and both their ticker code and market value as well as their market value in percentage of the total seafood sector are shown. In addition, to examine if there are differences between large and small companies in the firm-level analysis, companies that make up less than 10 % of the total seafood sector are considered as small companies.

Table 1
Presentation of the salmon farming companies

Company	Ticker code	Market value	Market value (%)	Firm Size
Marine Harvest	MHG	65 757	39,9 %	Large
SalMar	SALM	24 394	14,8 %	Large
Lerøy Seafood	LSG	26 693	16,2 %	Large
Grieg Seafood	GSF	8 596	5,2 %	Small
Austevoll Seafood	AUSS	15 238	9,2 %	Small
Bakkafrost*	BAKKA	15 136	9,2 %	Small
Norway Royal Salmon*	NRS	7 543	4,6 %	Small
The Scottish Salmon Company*	SSC	1 645	1,0 %	Small

Note: Market values are in MNOK. Market value (%) is their market value in percentage of the total seafood sector. A company is considered as small if their market value (%) < 10 %. Companies marked with * are not included in the firm-level analysis. **Source**: Oslo Stock Exchange (01.03.2017).

[4] The equally-weighted portfolio is constructed by taking the arithmetic average of stock price returns for all the salmon farming companies.

In this study, we use daily data aggregated to weekly frequency by taking the average of daily data within a particular week[5]. Then, all the data have been logarithmically transformed in order to calculate the weekly return (in percentage). While the stock prices for all the salmon farming companies are collected from Netfonds, denominated in NOK and adjusted for reversed splits and splits, the risk factors are collected from several sources. Thus, we have given an overview of the risk factors and their sources in table 2. In addition, we have included the abbreviation we will use for the risk factors in the following and how we expect the risk factors will influence stock price returns of the salmon farming companies.

Table 2

An overview of the risk factors

Risk factor	Abbreviation	Expected effect	Source
Main Index at the Oslo Stock Exchange	OSE	+	Netfonds
Spot price of salmon	SP	+	Nasdaq
Exchange rate NOK/EUR	EUR	-	Norwegian Central Bank
Exchange rate NOK/USD	USD	-	Norwegian Central Bank
Long-term interest rate	INT	+/-	Norwegian Central Bank
Lagged stock return of the industry leader	IL	+	Netfonds

Note: The spot price of salmon is the Nasdaq Salmon Index stated in NOK/kg and the long-term interest rate is the yield to maturity on a 10-year Norwegian government bond. The expected effect is how we expect that the risk factors will influence stock price returns of the salmon farming companies.

We use the Nasdaq Salmon Index as the spot price of salmon, because several previous studies examining the salmon price use this price[6]. However, it is important to mention that the salmon price was calculated by NOS clearing before 2013, but has since been replaced by the Nasdaq Salmon Index. Moreover, we include both the exchange rates NOK/EUR and NOK/USD since they are the two most important sources to exchange rate risk for salmon farming companies listed at the Oslo Stock Exchange. While EU is the primary market, USA is an important market since many of the salmon farming companies have subsidiaries in Chile, in which USA is one of the primary markets. As a proxy for the long-term interest rate, we use yield to maturity on a 10-year Norwegian government, since most of the salmon farming companies are Norwegian.

[5] We use data with high frequency (daily aggregated to weekly) in this study because data with lower frequencies (e.g. monthly) are shown to give more unstable estimate when we have very volatile prices.

[6] See for example, Oglend and Sikveland (2008), Oglend (2013), Zhang et al (2016) and Misund (2016a).

The sample period in this study covers the period from week 27, 2007 to week 52, 2016. We start the sample period in week 27, 2007 since both SalMar and Grieg Seafood became publicly traded a few weeks earlier that year. During the sample period, there are several events of major impact including the financial crisis in 2007-08, the large drop in the salmon price in 2011[7], the Russian boycott of Norwegian salmon in 2014, the volcano eruption in Chile in 2015 and the algal boom the following year, which both caused a large loss of salmon. In figure 4, the price development for the salmon farming industry (represented by the equally-weighted portfolio) and the Main Index at the Oslo Stock Exchange over the sample period are shown. Most of the events mentioned above appear in the figure, but even more noticeable is the price development of the salmon farming industry compared to the Main Index at the Oslo Stock Exchange in the latest years.

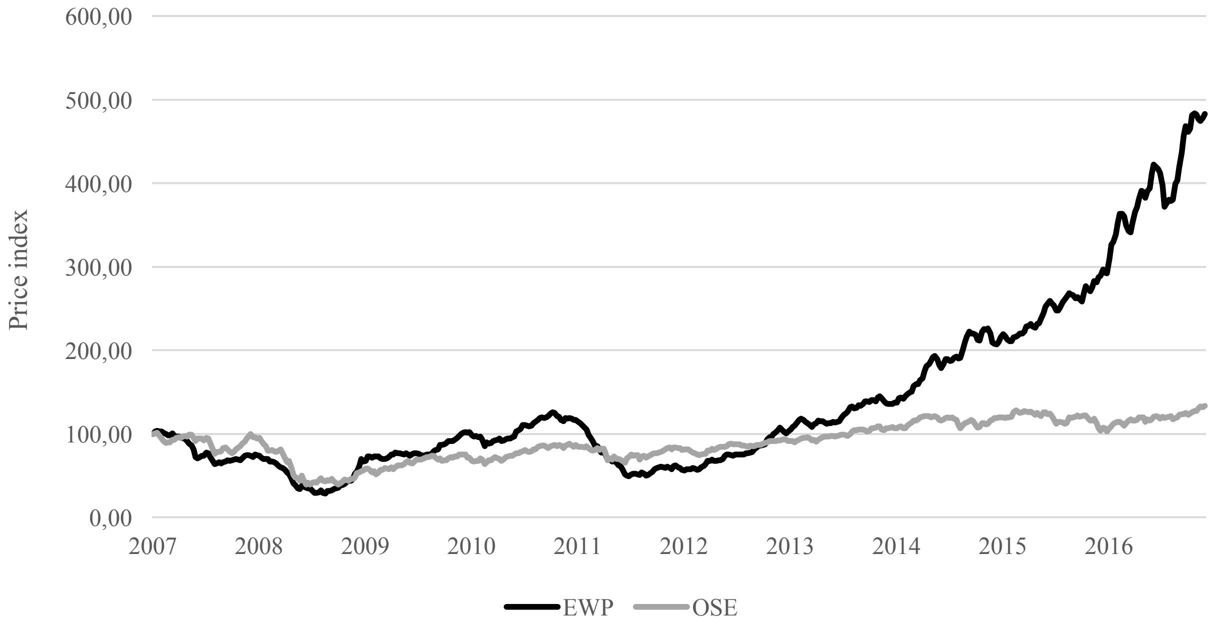

Figure 4. Price development for the salmon farming industry and Oslo Stock Exchange. Both the equally-weighted portfolio (EWP) and the Main Index at the Oslo Stock Exchange (OSE) have been indexed (week 27, 2007=100).

Table 3 presents the descriptive statistics including the historical 5 % and 95 % VaR for the data sample. Given the latest stock price growth in the salmon farming industry, it comes as no surprise that the mean weekly return on the equally-weighted portfolio of 0,27 % are quite high compared to the mean weekly return at the Oslo Stock Exchange (0,06 %). This is also the case for the individual companies, although the mean weekly return range from 0,08 % to 0,38 %.

[7] The large drop in the salmon price was mainly a consequence of the increased supply from Chile after the major disease attack the previous years.

However, a potential explanation for the stock price growth of the salmon farming companies is the substantial increase in the salmon price, which has a mean weekly return of 0,25 %. The table also shows the decline that has been in the long-term interest rate over the sample period, which is as expected considering the current low interest rate. In addition, the table shows that NOK has depreciated slightly against EUR and USD over the sample period, although the mean weekly return for both the exchange rates are quite low. Looking at the standard deviation and the minimum and maximum weekly return, the table shows that the salmon farming companies have been more volatile than Oslo Stock Exchange over the sample period. This is, however, as expected, and especially for the individual companies, due to a high degree of unsystematic risk. Moreover, the salmon price has been very volatile over the sample period, with the highest volatility of all the risk factors, demonstrating the importance of risk management to reduce price risk. Finally, the table presents some properties of the historical return distributions, and all the salmon farming companies have a skewed distribution with fatter tails and higher peaks than a normal distribution. Such distributional properties also highlight the importance of a factor model that allows for non-normality, because this leads to asymmetric tail distributions, also shown by most of the historical VaR estimates.

Table 3

Descriptive statistics for the data sample

	Mean	St. Dev	Min	Max	Kurtosis	Skewness	5 % VaR	95 % VaR
EWP	0,27	3,40	-15,45	13,40	3,70	-0,49	-5,22	5,16
MHG	0,16	5,27	-36,46	17,04	9,49	-1,52	-7,48	7,22
SALM	0,38	4,08	-16,17	19,23	3,25	-0,19	-6,70	5,92
LSG	0,26	4,20	-21,60	29,93	6,46	0,22	-6,47	6,45
GSF	0,26	5,82	-28,46	32,08	6,03	0,12	-8,56	8,69
AUSS	0,08	4,56	-26,13	26,24	5,87	-0,30	-6,47	6,53
OSE	0,06	2,94	-16,17	13,92	5,07	-0,99	-5,01	3,69
SP	0,25	6,92	-20,37	18,58	-0,05	0,01	-10,23	12,62
EUR	0,03	0,95	-4,21	4,75	3,20	0,33	-1,28	1,61
USD	0,08	1,47	-5,53	7,81	1,79	0,48	-2,12	2,61
INT	-0,22	3,79	-20,51	14,50	3,06	-0,22	-5,87	6,06

Note: N = 494 observations. All the data are logarithmically transformed and based on weekly returns from week 27, 2007 to week 52, 2016. All values expect for kurtosis and skewness are given in percent. None of the salmon farming companies have normally distributed returns according to the Jarque-Bera test.

Table 4 presents the correlations matrix for the equally-weighted portfolio and the risk factors. The equally-weighted portfolio is mainly included to see how the risk factors have correlated with the overall industry over the sample period, as a first indication of the relationship between the salmon farming industry and the risk factors. The highest correlation is as expected between the overall industry and Oslo Stock Exchange, with a positive correlation of 0,55. In addition, changes in the salmon price, changes in the long-term interest rate and the lagged stock return of the industry leader have a positive correlation. The exchange rates, however, have a negative correlation with the overall industry. Looking at the correlations between the risk factors, all of them are lower than 0,50 except for the correlation between the two exchange rates, which has a correlation of 0,56. However, this is not high enough to cause problems with multicollinearity.

Table 4

Correlation matrix for the equally-weighted portfolio and the risk factors

	EWP	OSE	SP	EUR	USD	INT	IL
EWP	1,00						
OSE	0,55	1,00					
SP	0,21	-0,06	1,00				
EUR	-0,19	-0,33	0,10	1,00			
USD	-0,22	-0,45	0,13	0,56	1,00		
INT	0,10	0,26	-0,10	-0,09	-0,23	1,00	
IL	0,33	0,04	0,19	-0,09	-0,06	-0,04	1,00

Note: N = 494 observations. All the data are logarithmically transformed and based on weekly returns from week 27, 2007 to week 52, 2016.

We also tested all the variables for stationarity using the augmented Dickey-Fuller test and the test was conducted with a constant, no trend term and with up to two lags. The null hypothesis of a unit root was rejected for all the variables, indicating that each variable is stationary in first difference at the 1 % level of significance[8]. Stationary variables are necessary in the regression analysis, because non-stationary variables might lead to spurious results.

[8] The test results are presented in table A.1 in the appendix.

6 Empirical results and analysis

In this section, we first model the conditional return distribution of salmon farming companies at the industry and firm-level using the selected risk factors described in section 3 and 5. Then, we estimate VaR using the estimated regression coefficients from the 5 % and 95 % quantile, where we also perform a scenario analysis to stress test the VaR estimates. Finally, we perform the backtesting procedure to test the performance of the VaR models, i.e. the robustness of the estimated tails of the return distributions.

6.1 Modelling the return distribution using quantile regression

In order to model the conditional return distribution, we use the entire sample period to examine the relationship between the risk factors and stock price returns at the 5 %, 10 %, 25 %, 75 %, 90 %, 95 % and the median quantile. Using these quantiles will provide a good estimate of the return distribution, and we use more quantiles in the tails, since investors and risk managers are usually more interested in the tails of the return distribution. This is also in line with previous studies using the quantile regression approach.

The quantile factor model we use to estimate the regression coefficients are as follows,

$$R_{i,t} = \alpha_i^q + \beta_{i,OSE}^q R_{OSE,t} + \beta_{i,SP}^q R_{SP,t} + \beta_{i,EUR}^q R_{EUR,t} + \beta_{i,USD}^q R_{USD,t} + \beta_{i,INT}^q R_{INT,t} + \beta_{i,IL}^q R_{IL,t} + \varepsilon_{i,t}^q \tag{6.1}$$

where $R_{i,t}$ is the stock return of company or portfolio i at time t, $R_{OSE,t}$ is the market return at time t, $R_{SP,t}$ is the change in the salmon price at time t, $R_{EUR,t}$ is the change in the NOK/EUR at time t, $R_{USD,t}$ is the change in the NOK/USD at time t, $R_{INT,t}$ is the change in the long-term interest rate at time t, $R_{IL,t}$ is the lagged stock return of the industry leader at time t, α_i^q is the constant, and $\varepsilon_{i,t}^q$ is the error term. Moreover, the beta coefficients are the risk factor sensitivities we want to estimate in order to model the conditional return distribution.

In table 5, the results from the industry-level analysis using equation (6.1) are presented and all calculations are performed in Stata (bsreg commando), where the standard errors are obtained using the pairs-bootstrapping method by Buchinsky (1995). In addition to the results from the quantile factor model, we have also presented the results from a linear factor model to compare the estimated beta coefficients from the two models.

Table 5
The regression results for the equally-weighted portfolio

Quantile	α	β_{OSE}	β_{SP}	β_{EUR}	β_{USD}	β_{INT}	β_{IL}	Pseudo R^2/R^2
5 %	-0,04***	0,61***	0,14***	-0,42	0,16	0,11	0,17*	0,30
10 %	-0,03***	0,69***	0,08**	-0,12	0,21	0,05	0,14**	0,27
25 %	-0,01***	0,56***	0,09***	0,12	0,07	0,00	0,14***	0,22
50 %	0,00**	0,66***	0,09***	0,08	0,07	-0,06	0,14***	0,22
75 %	0,02***	0,70***	0,09***	0,10	0,00	-0,01	0,14***	0,24
90 %	0,03***	0,67***	0,08***	-0,01	-0,09	-0,05	0,17***	0,28
95 %	0,04***	0,70***	0,10***	-0,13	0,31	-0,06	0,18***	0,30
OLS	0,00	0,66***	0,09***	-0,02	0,06	-0,01	0,18***	0,43

Note: Pseudo R-squared is the explanatory power of the quantile factor model (Koenker et al. 1999) and the ordinary R-squared is the explanatory power of the linear factor model. *, ** and *** indicate that the regression coefficients are significantly different from zero at 10 %, 5 % and 1 % level, respectively.

The market beta is significant across all quantiles and range from 0,56 to 0,70, indicating that salmon farming company stocks are less risky than the market in terms of systematic risk over the entire return distribution. This also implies that the recent stock price growth in the salmon farming industry is not explained by high systematic risk, which is consistent with the findings by Misund (2016a). However, the market beta is slightly higher in the upper quantiles of the return distribution compared to the lower quantiles, expect for the 10 % quantile, showing that the market beta varies under different market conditions although the variations is quite small.

The beta coefficient from the salmon price is significant across all quantiles, demonstrating that changes in the salmon price is an important risk factor for stock price returns of salmon farming companies over the entire return distribution. This also support previous studies showing that the salmon price is an important determinant of company performance in the salmon farming industry (Oglend and Sikveland, 2008; Asche and Sikveland, 2015; Misund, 2016a). However, while the beta coefficient from the salmon price is quite stable across quantiles, it is somewhat higher in the 5 % quantile, indicating that changes in the salmon price can explain more of stock price returns in periods with large stock price reductions.

Looking at the beta coefficients from the exchange rates, all of them are insignificant across all quantiles, although they are quite high in some of the quantiles. Therefore, we also come to the same conclusion as Misund (2016a), that changes in exchange rates are not direct determinants of stock price returns for salmon farming companies. There might be several reasons for this. Firstly, the effect of changes in exchange rates might be passed through to salmon prices, also called pricing-to-market, and a recent master thesis has shown that Norwegian salmon exporters do this to several markets (Yarmoradi and Rygh, 2016). Secondly, the existing literature on the relationship between changes in exchange rates and stock price returns at the industry and firm-level suggest that the relationship is both economically and statistically small (e.g. Griffin and Stulz, 2001; Doidge et al, 2003) and that firms dynamically adjust their behavior in response to exchange rate risk (Dominguez and Tesar, 2006).

The beta coefficient from the interest rate is also insignificant across all quantiles, indicating that changes in the long-term interest rate do not explain stock price returns on a weekly basis. However, a possible explanation for this is that the long-term interest rate serves as a proxy for both the state of the economy, the borrowing cost and the required rate of return for investors, in which the first imply a positive relationship and the others imply a negative relationship. In addition, the long-term interest rate can be seen as a substitute to stocks and that an increase in the long-term interest rate therefore might depress stock prices through the substitution effect, which also imply a negative relationship. Thus, it is possible that the effect from changes in the long-term interest rate is neutralized due to contradictory effects.

The beta coefficient from the lagged stock return of the industry leader is significant across all quantiles, demonstrating that the industry (represented by the equally-weighted portfolio) tends to follow the industry leader. Hence, if the stock price of the industry leader goes up one week, the stock price of a portfolio of the companies will go up the next week. This indicate that the efficient market hypothesis does not hold. In the financial literature, this phenomenon is usually attributed to the speed of adjustment for individual stocks, where smaller companies within an industry react slower to new information, and hence, create a lead-lag effect within the industry (Chordia and Swaminathan, 2000, Hou, 2007). But for this hypothesis to hold, we expect to see a greater effect for small companies than large companies in the firm-level analysis. Moreover, the beta coefficient is quite stable across all quantiles, showing that the lead-lag effect does not vary much under different market conditions, although the beta coefficient is somewhat higher in the upper and lower quantile of the return distribution.

Before we go onto the firm-level analysis, it is worthwhile to briefly mention the estimated beta coefficients from the linear factor model. As shown in table 6.1, the linear factor model provides almost the same results as the quantile factor model, since there are only small variations across quantiles for most of the risk factors. However, the market beta is slightly different in the tails of the return distribution, as mentioned above, and since the market beta from the linear factor model equals the median quantile, it does not capture the right tail exposure. In the following, we will examine whether the same results apply at the firm-level.

In table B.1 to B.5 in the appendix the results from the firm-level analysis are presented and we will in the following highlight the most important findings. The general impression is that the market beta and the beta coefficients from the salmon price and the lagged stock return of the industry leader are most important also at the firm-level. However, there are larger differences across quantiles for the individual companies compared to the industry portfolio, showing that the exposure to the risk factors vary much more under different market conditions at the firm-level[9]. Of the individual companies, SalMar and Lerøy Seafood have the lowest market beta in general, also shown by the market beta from the linear factor model, but the market beta is quite different across quantiles for the two companies. While the market beta for SalMar is highest in the upper and lower quantiles of the return distribution, the market beta for Lerøy Seafood is highest in the median quantile. For the other companies, with a generally higher market beta, Marine Harvest and Austevoll Seafood have the highest market beta in the 5 % quantile, while Grieg Seafood has the highest market beta in the 95 % quantile. These findings suggest that the individual companies react differently to the market return under different market conditions.

Looking at the beta coefficient from the salmon price, there are also some differences between the individual companies. For instance, Marine Harvest has the lowest exposure to changes in the salmon price with a quite low beta coefficient across all quantiles, and, it is only significant in the middle quantiles. This suggests that changes in the salmon price is a less important risk factor for stock price returns of Marine Harvest, in line with the findings by Zhang et al (2016), who argued that large companies are less sensitive to changes in the salmon price. For the other companies, the beta coefficient is generally higher and significant across most of the quantiles, but the findings suggest that the individual companies react differently to changes in the salmon price under different market conditions, as for the market return.

Before we summarize the results from the quantile regression analysis, we will eventually look at the beta coefficient from the lagged stock return of the industry leader. The results indicate that all the individual companies, except for Lerøy Seafood, tend to follow the industry leader.

[9] A part of this might, however, be explained by more regression noise due to a higher degree of unsystematic risk at the firm-level, as shown by the lower Pseudo R-squared.

As such, we have indication of both cross-autocorrelation and autocorrelation within the salmon farming industry. There might be several explanations for such patterns, but the hypothesis that small companies create the lead-lag effect due to slow diffusion of information, does not hold[10]. However, other explanations can be attributed to investors' tendency to overreact to new market information (De Bondt and Thaler, 1985, 1987; Lo and MacKinlay, 1990) and herding behavior (Bikhchandani et al, 1992; Nofsinger and Sias, 1999), leading to predictable patterns in stock prices. For instance, an interesting finding is that Marine Harvest, the industry leader itself, has a higher beta coefficient in the upper and lower quantile of the return distribution, indicating that positive (negative) stock price returns one week tend to be followed by positive (negative) stock price returns the next week in a larger degree when Marine Harvest performs well (bad). Such patterns are not as evident for the other companies, even though the beta coefficients vary across quantiles, showing that the individual companies react differently to the lagged stock return of the industry leader under different market conditions, as for the other risk factors.

The overall findings suggest that the market return, changes in the salmon price and the lagged stock return of the industry leader are the most important risk factors for stock price returns of salmon farming companies at both the industry and firm-level. However, while the findings at the industry-level are more stable across quantiles, there are larger differences across quantiles at the firm-level. Moreover, there are also large differences between the individual companies, showing that the companies exhibit different risk and return characteristics. Such findings have implications for both risk management, asset allocation and hedging decisions. In the following we will demonstrate how the results from the quantile regression analysis can be implemented and applied in a VaR analysis.

6.2 Estimation and stress testing of Value-at-Risk

In risk management, only estimating the risk factor sensitivities are not sufficient, because beta only measure the sensitivity to a risk factor, ignoring the risk of the factor itself. Therefore, we need other risk measures to assess the risk associated with the risk factors, and a widely adopted risk measure for this is VaR. As such, we will in the following estimate the 5 % and 95 % VaR using the estimated alpha and beta coefficients from the quantile regression analysis, which will give investors and risk managers further insight into their risk exposure and potential tail loss,

[10] It is important to mention that this can still be one of the reasons for the lead-lag effect, but it cannot explain the effect alone. In addition, we still have too little evidence since three of the companies we have categorized as small are excluded from the firm-level analysis.

for both a long and short position. In addition, we perform a scenario analysis to stress test the VaR estimates in order to illustrate how tail risk responds to changes in risk factors. However, we limit the scenario analysis to only examine how the VaR estimates for the equally-weighted portfolio vary under different assumptions about the market return and changes in the salmon price. Nevertheless, this will show how the VaR estimates are conditioned on the risk factors, and we use the market beta and beta coefficient from the salmon price since they differ the most in the upper and lower quantile.

Table 6 presents the 5 % and 95 % VaR for the equally-weighted portfolio and the individual companies using the mean weekly return for the risk factors over the sample period as an input. Since we use weekly data in this study, 5 % VaR is the loss level that is expected to be exceeded in 5 out of 100 weeks if the stock or portfolio is hold over a long period of time.

Table 6
5 % and 95 % VaR estimates

	EWP	**MHG**	**SALM**	**LSG**	**GSF**	**AUSS**
5 % VaR	-3,93 %	-6,76 %	-5,40 %	-5,71 %	-7,25 %	-5,95 %
95 % VaR	3,84 %	7,64 %	6,11 %	6,09 %	7,06 %	5,55 %

Note: The VaR estimates are obtained using the estimated alpha and beta coefficients from the quantile regression analysis and the mean weekly return for the risk factors are used as an input.

As the table shows, there are clear signs of asymmetry, especially for the individual companies, demonstrating that there is different tail risk for an investor with a long position compared to an investor with a short position, given the input we have used for the risk factors. Furthermore, Grieg Seafood and Austevoll Seafood, the two companies we have categorized as small in this study, have higher tail risk in the lower tail compared to the upper tail of the return distribution unlike Marine Harvest, SalMar and Lerøy Seafood. However, the 5 % and 95 % VaR estimates can change remarkable if we change the input for the risk factors, especially when the value for the risk factors are high (either positive or negative), which is illustrated in the scenario analysis presented in table 7 and 8. As a baseline VaR, we use the estimated alpha coefficient from the 5 % and 95 % quantile, i.e. the value of all the risk factors is set to zero.

Table 7

Scenario analysis of the 5 % VaR estimate for the equally-weighted portfolio

	-10,0 %	**-7,5 %**	**-5,0 %**	**-2,5 %**	**0,0 %**	**2,5 %**	**5,0 %**	**7,5 %**	**10,0 %**
-10,0 %	-11,5 %	-9,9 %	-8,4 %	-6,9 %	-5,4 %	-3,8 %	-2,3 %	-0,8 %	0,7 %
-7,5 %	-11,12 %	-9,60 %	-8,07 %	-6,55 %	-5,02 %	-3,49 %	-1,97 %	-0,44 %	1,08 %
-5,0 %	-10,78 %	-9,26 %	-7,73 %	-6,21 %	-4,68 %	-3,15 %	-1,63 %	-0,10 %	1,42 %
-2,5 %	-10,44 %	-8,92 %	-7,39 %	-5,87 %	-4,34 %	-2,81 %	-1,29 %	0,24 %	1,76 %
0,0 %	-10,10 %	-8,58 %	-7,05 %	-5,53 %	**-4,00 %**	-2,47 %	-0,95 %	0,58 %	2,10 %
2,5 %	-9,76 %	-8,24 %	-6,71 %	-5,19 %	-3,66 %	-2,13 %	-0,61 %	0,92 %	2,44 %
5,0 %	-9,42 %	-7,90 %	-6,37 %	-4,85 %	-3,32 %	-1,79 %	-0,27 %	1,26 %	2,78 %
7,5 %	-9,08 %	-7,56 %	-6,03 %	-4,51 %	-2,98 %	-1,45 %	0,07 %	1,60 %	3,12 %
10,0 %	-8,74 %	-7,22 %	-5,69 %	-4,17 %	-2,64 %	-1,11 %	0,41 %	1,94 %	3,46 %

Note: The table is estimated using values for market returns on the horizontal axis and values for changes in the salmon price on the vertical axis. The baseline VaR (in bold) is the estimated alpha coefficient.

Table 8

Scenario analysis of the 95 % VaR estimate for the equally-weighted portfolio

	-10,0 %	**-7,5 %**	**-5,0 %**	**-2,5 %**	**0,0 %**	**2,5 %**	**5,0 %**	**7,5 %**	**10,0 %**
-10,0 %	-4,3 %	-2,5 %	-0,8 %	1,0 %	2,7 %	4,5 %	6,2 %	8,0 %	9,7 %
-7,5 %	-4,05 %	-2,30 %	-0,54 %	1,21 %	2,96 %	4,72 %	6,47 %	8,23 %	9,98 %
-5,0 %	-3,80 %	-2,05 %	-0,30 %	1,46 %	3,21 %	4,97 %	6,72 %	8,47 %	10,23 %
-2,5 %	-3,56 %	-1,80 %	-0,05 %	1,71 %	3,46 %	5,21 %	6,97 %	8,72 %	10,48 %
0,0 %	-3,31 %	-1,56 %	0,20 %	1,95 %	**3,71 %**	5,46 %	7,22 %	8,97 %	10,72 %
2,5 %	-3,06 %	-1,31 %	0,45 %	2,20 %	3,95 %	5,71 %	7,46 %	9,22 %	10,97 %
5,0 %	-2,81 %	-1,06 %	0,69 %	2,45 %	4,20 %	5,96 %	7,71 %	9,46 %	11,22 %
7,5 %	-2,57 %	-0,81 %	0,94 %	2,70 %	4,45 %	6,20 %	7,96 %	9,71 %	11,47 %
10,0 %	-2,32 %	-0,56 %	1,19 %	2,94 %	4,70 %	6,45 %	8,21 %	9,96 %	11,71 %

Note: The table is estimated using values for market returns on the horizontal axis and values for changes in the salmon price on the vertical axis. The baseline VaR (in bold) is the estimated alpha coefficient.

According to the baseline VaR estimates, there is almost the same downside risk for an investor with a long position compared to an investor with a short position, but as we move away from the baseline VaR, this change quickly. Moreover, since the market beta and the beta coefficient for the salmon price are different in the 5 % and 95 % quantile, the VaR estimates do not change linearly. For instance, a higher market return, *ceteris paribus,* increase the 95 % VaR estimate more than the 5 % VaR estimate and vice versa. This demonstrate one of the benefits of using the regression coefficients from the quantile regression analysis to estimate VaR, as asymmetric and nonlinear characteristics are taken into consideration. That said, another important issue is how accurate the VaR models are, which we will examine in the following.

6.3 Backtesting of the Value-at-Risk models

In order to test the accuracy of the VaR models (the estimated regression coefficients from the 5 % and 95 % quantile), we perform a backtesting procedure over the entire sample period for both the equally-weighted portfolio and the individual companies. This will give an indication of the performance of the VaR models, and hence, the robustness of the estimated tails of the return distributions. In table 9, the test statistics from the Kupiec and Christoffersen test are presented and the VaR models are correctly specified regarding unconditional and conditional coverage under the null hypothesis.

Table 9
The Kupiec and Christoffersen test statistics

	Kupiec test statistics		**Christoffersen test statistics**	
	5 % VaR	**95 % VaR**	**5 % VaR**	**95 % VaR**
EWP	0,45	0,75	6,15	5,89
MHG	0,02	0,02	0,67	12,35
SALM	0,45	0,45	6,15	0,67
LSG	0,45	1,50	3,58	1,67
GSF	0,00	1,57	4,51	8,31
AUSS	0,22	0,00	1,72	0,51

Note: The critical values are 6,63 (1 % level), 3,84 (5 % level) and 2,71 (10 % level) for the Kupiec test, and 9,21 (1 % level), 5,99 (5 % level) and 4,61 (10 % level) for the Christoffersen test. The backtesting procedure are performed over the entire sample period (N = 494 observations).

For the equally-weighted portfolio and the individual companies, both the 5 % and 95 % VaR provide good unconditional coverage, i.e. they capture the right number of exceedances as the pre-specified significance level. This indicates that the estimated coefficients from the 5 % and 95 % quantile are sufficient estimates of the tails of the return distributions. However, we also want the 5 % and 95 % VaR to provide good conditional coverage, i.e. they capture the right number of exceedances and the exceedances are randomly distributed over the sample period, because we do not want tail risk to be overestimated or underestimated in certain periods. As the table shows, there are larger differences between the test statistics in the Christoffersen test, indicating that not all the VaR models provide equally good conditional coverage. Nevertheless, except for the 95 % VaR model for Marine Harvest, we keep the null hypothesis, that the VaR models are correctly specified. However, it is important to mention that a weakness with the backtesting procedure is that the tests are performed in-sample over the same sample period as we have used to model the return distributions. Therefore, the results tell nothing about the out-of-sample performance or the forecasting ability of the VaR models.

7 Concluding remarks

The salmon farming industry has over the years grown to become an important export industry for the Norwegian economy, and recently, the industry has also experienced high profitability and substantial stock price growth. This development has attracted several investors and other stakeholders, which has given the industry increased attention the latest years. However, in a historical perspective, the salmon farming industry is known for its cycles in profitability, which raises some important questions regarding risk and return for salmon farming company stocks. In particular, what risk factors that determine stock price returns, the magnitude of their impact, and if this varies under different market conditions, given the volatile nature of the industry. A better understanding of these questions is essential for understanding the financial performance of the salmon farming companies.

To answer these questions, we use quantile regression to examine the relationship between risk factors and stock price returns of salmon farming companies, not only at the conditional mean, but over the entire return distribution using different quantiles. In accordance with our a priori expectations, we find that the market return, changes in the salmon price and the lagged stock return of the industry leader have a positive and significant impact on stock price returns. But for changes in exchanges rates and changes in the long-term interest rate, the results are mostly insignificant, and we conclude that these are not direct determinants of stock price returns.

At both the industry and firm-level, the findings suggest that the market return has the largest impact on stock price returns. However, while the market beta is quite stable across quantiles at the industry-level, the market beta differs more across quantiles at the firm-level. This is also the case for the two other risk factors with a significant beta coefficient, indicating that the risk factor sensitivities tend to vary more under different market conditions at the firm-level. Thus, showing that the quantile factor model is more suitable for examining the relationship between risk factors and stock price returns of salmon farming companies, at least at the firm-level. In that way, investors and risk managers can take into consideration risk and return characteristics that are not captured by linear factor models in their daily operations.

In addition to the quantile regression analysis, we also show how the results can be implemented and applied in a VaR analysis, since VaR can be seen as a particular conditional quantile of the return distribution. More precisely, we estimate the 5 % and 95 % VaR and show how the VaR estimates are conditioned on the risk factors by performing a scenario analysis where we stress test the VaR estimates. The findings from the VaR analysis suggest that the equally-weighted portfolio of all the companies and the individual companies both exhibit asymmetric tail risk, and that this is largely dependent on the value of the risk factors. Furthermore, a change in one of the risk factors, *ceteris paribus*, influence the 5 % and 95 % VaR differently in most cases due to a nonlinear relationship between risk factors and stock price returns. Overall, this show the practical use of the quantile regression approach, where characteristics such as asymmetry and nonlinearity can be taken into consideration.

There are, however, some limitations with this study. Firstly, we have a very small data sample, since most of the companies in the salmon farming industry are either subsidiaries or privately owned. This leads to a smaller number of observations which can have an adverse effect on the regression coefficients, in terms of biased estimators and imprecise standard errors. However, according to the in-sample backtesting procedure, the regression coefficients from the 5 % and 95 % quantiles, in which there are even fewer observations, are sufficient estimates of the tails of the return distributions. Secondly, we use daily data aggregated to weekly frequency in this study, which exclude possible risk factors that only provide data with a lower frequency. Thus, by using lower frequency data, it is possible to include more risk factors that also might help to increase the explanatory power of the factor models.

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Appendix

A The test results from the augmented Dickey-Fuller test

In table A.1, the test statistics from the ADF test are presented and all calculations are performed in OxMetrics 7 (PcGive), using the following equation at the first difference,

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \varepsilon_i$$

where ΔY_t is the change in the dependent variable, Y_{t-1} is the lagged dependent variable, ΔY_{t-i} is the lagged change in the dependent variable with up to p lags (two lags in this case), α is the constant and ε_i is the error term.

Table A.1
The test statistics from the ADF test

		ADF	
Number of lags	**0**	**1**	**2**
EWP	-14,46***	-11,78***	-7,82***
MHG	-16,10***	-13,10***	-9,63***
SALM	-20,16***	-16,91***	-12,54***
LSG	-18,65***	-14,78***	-10,36***
GSF	-14,63***	-11,67***	-9,01***
AUSS	-17,27***	-14,87***	-10,10***
OSE	-19,79***	-14,77***	-11,00***
SP	-21,84***	-20,68***	-15,54***
EUR	-18,59***	-14,92***	-13,08***
USD	-18,94***	-14,96***	-12,32***
INT	-19,01***	-16,30***	-11,82***
IL	-16,09***	-13,10***	-9,67***

Note: *, ** and *** indicate that the variable is stationary in first differences at the 10 %, 5 % and 1 % level of significance, respectively.

B The regression results from the firm-level analysis

In table B.1 to B.5, the results from the firm-level analysis using equation (6.1) are presented and all calculations are performed in Stata (the bsreg commando), where the standard errors are obtained using the pairs-bootstrapping method by Buchinsky (1995). In addition to the results from the quantile factor model, we have also presented the results from a linear factor model.

Table B.1

The regression results for Marine Harvest

Quantile	α	β_{OSE}	β_{SP}	β_{EUR}	β_{USD}	β_{INT}	β_{IL}	Pseudo R^2/R^2
5 %	-0,07***	0,94***	0,07	0,60	-1,02	-0,10	0,26**	0,25
10 %	-0,04***	0,69***	0,05	0,44	-0,27	-0,05	0,27**	0,19
25 %	-0,02***	0,85***	0,06*	0,28	0,15	-0,02	0,23***	0,17
50 %	0,00	0,79***	0,07**	0,41	0,04	-0,01	0,19***	0,16
75 %	0,02***	0,76***	0,08**	0,23	0,09	-0,07	0,17**	0,12
90 %	0,05***	0,69***	0,08	-0,03	0,04	-0,10	0,22**	0,10
95 %	0,08***	0,74***	0,07	0,53	-0,28	0,07	0,31**	0,11
OLS	0,00	0,84***	0,06**	0,17	-0,02	-0,05	0,28***	0,29

Note: Pseudo R-squared is the explanatory power of the quantile factor model (Koenker et al. 1999) and the ordinary R-squared is the explanatory power of the linear factor model. *, ** and *** indicate that the regression coefficients are significantly different from zero at 10 %, 5 % and 1 % level, respectively.

Table B.2

The regression results for SalMar

Quantile	α	β_{OSE}	β_{SP}	β_{EUR}	β_{USD}	β_{INT}	β_{IL}	Pseudo R^2/R^2
5 %	-0,05***	0,62***	0,21***	-0,65	0,29	0,18	0,11	0,18
10 %	-0,04***	0,61***	0,16***	-0,28	0,32	0,07	0,15**	0,14
25 %	-0,02***	0,55***	0,10***	-0,11	0,20	-0,01	0,14***	0,10
50 %	0,00**	0,32***	0,08**	-0,05	-0,04	-0,05	0,10***	0,08
75 %	0,02***	0,38***	0,10**	-0,11	0,00	-0,01	0,07	0,08
90 %	0,04***	0,39***	0,09**	-0,40	-0,05	0,00	0,00	0,07
95 %	0,06***	0,52***	0,10	0,09	0,16	-0,15	0,02	0,11
OLS	0,00	0,50***	0,11***	-0,31	0,15	0,02	0,10***	0,18

Note: See table B.1.

Table B.3
The regression results for Lerøy Seafood

Quantile	α	β_{OSE}	β_{SP}	β_{EUR}	β_{USD}	β_{INT}	β_{IL}	Pseudo R^2/R^2
5 %	-0,06***	0,51***	0,14***	-1,08*	0,41	0,17	0,03	0,20
10 %	-0,04***	0,50***	0,13***	-0,54	0,00	0,10	0,14	0,16
25 %	-0,02***	0,61***	0,10***	0,23	0,08	0,12**	0,20***	0,13
50 %	0,00*	0,64***	0,11***	0,37	0,20	0,04	0,08	0,11
75 %	0,02***	0,58***	0,13***	0,06	-0,01	0,02	0,02	0,12
90 %	0,04***	0,57***	0,14***	-0,14	0,21	0,03	0,10	0,12
95 %	0,06***	0,41**	0,16***	0,15	-0,04	-0,04	0,10	0,11
OLS	0,00	0,57***	0,13***	0,09	0,17	0,12**	0,04	0,20

Note: See table B.1.

Table B.4
The regression results for Grieg Seafood

Quantile	α	β_{OSE}	β_{SP}	β_{EUR}	β_{USD}	β_{INT}	β_{IL}	Pseudo R^2/R^2
5 %	-0,07***	0,70***	0,13	-0,87	0,44	0,09	0,26**	0,19
10 %	-0,05***	0,65***	0,08	-0,64	0,19	0,14	0,26**	0,18
25 %	-0,02***	0,69***	0,12***	-0,05	-0,03	-0,01	0,30***	0,15
50 %	0,00	0,78***	0,10***	0,05	0,02	-0,12*	0,28***	0,14
75 %	0,02***	0,82***	0,12***	0,08	-0,20	-0,12	0,30***	0,16
90 %	0,05***	0,91***	0,17**	-0,24	-0,13	-0,12	0,23**	0,16
95 %	0,07***	0,96***	0,22**	-0,20	0,08	-0,10	0,15	0,17
OLS	0,00	0,80***	0,12***	-0,15	-0,02	-0,08	0,32***	0,28

Note: See table B.1.

Table B.5
The regression results for Austevoll Seafood

Quantile	α	β_{OSE}	β_{SP}	β_{EUR}	β_{USD}	β_{INT}	β_{IL}	Pseudo R^2/R^2
5 %	-0,06***	0,86***	0,09	-0,64	-0,15	0,01	0,08	0,24
10 %	-0,04***	0,72***	0,06	0,05	-0,20	0,03	0,10	0,20
25 %	-0,02***	0,77***	0,10**	-0,21	0,12	-0,01	0,17***	0,18
50 %	0,00	0,78***	0,06**	0,08	0,11	-0,07	0,17***	0,16
75 %	0,02***	0,83***	0,09***	0,27	0,03	-0,05	0,15***	0,16
90 %	0,04***	0,77***	0,15***	-0,11	-0,09	-0,14*	0,16***	0,20
95 %	0,05***	0,74***	0,15**	0,22	-0,41	-0,08	0,20**	0,22
OLS	0,00	0,86***	0,08***	0,13	-0,05	-0,04	0,16***	0,35

Note: See table B.1.

Norges miljø- og biovitenskapelig universitet
Noregs miljø- og biovitskapelege universitet
Norwegian University of Life Sciences

Postboks 5003
NO-1432 Ås
Norway