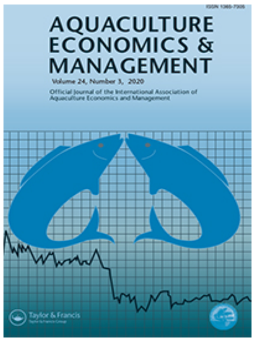

Taylor & Francis
Taylor & Francis Group

Aquaculture Economics & Management

ISSN: 1365-7305 (Print) 1551-8663 (Online) Journal homepage: https://www.tandfonline.com/loi/uaqm20

Modeling the return distribution of salmon farming companies: A quantile regression approach

Marie Steen & Fredrik Jacobsen

To cite this article: Marie Steen & Fredrik Jacobsen (2020) Modeling the return distribution of salmon farming companies: A quantile regression approach, Aquaculture Economics & Management, 24:3, 310-337, DOI: 10.1080/13657305.2020.1765896

To link to this article: https://doi.org/10.1080/13657305.2020.1765896

Published online: 22 May 2020.

AQUACULTURE ECONOMICS & MANAGEMENT
2020, VOL. 24, NO. 3, 310–337
https://doi.org/10.1080/13657305.2020.1765896

Taylor & Francis
Taylor & Francis Group

Modeling the return distribution of salmon farming companies: A quantile regression approach

Marie Steen and Fredrik Jacobsen

School of Economics and Business, Norwegian University of Life Sciences, Ås, Norway

ABSTRACT
As the companies have grown larger, the salmon farming industry has received increased attention from investors, financial analysts and other representatives of the financial community. Still, little is known about the risk and return characteristics of salmon farming companies' shares. This paper approaches this topic by applying quantile regression to investigate the relationship between risk factors and monthly stock price returns over the entire return distribution at both industry and firm level. The results show that the overall market return, changes in the salmon price and the lagged returns for the major company in the industry have a positive impact on company stock price returns. The risk factor sensitivities are quite stable across quantiles at industry-level, there are substantial differences at the firm level, but formal testing cannot reject the hypothesis that the quantiles are equal. This implies that the relationship between risk factors and stock returns may vary under different return levels reflected in the salmon price cycles. We show how the results can be implemented and applied in a Value-at-Risk analysis.

KEYWORDS
Quantile regression; risk factors; salmon prices; salmon stock price; Value-at-Risk; volatility

Introduction

In recent years, there has been a significant growth in the market-cap of the seafood sector at the Oslo Stock Exchange and in particular salmon farming companies that have had large returns. Since around 2009, the market value of companies in the seafood sector at the Oslo Stock Exchange has grown from NOK 14 to NOK 148 billions in at the end of 2019. The growth in overall market value is partly due to more salmon farming companies having been listed, the value of all listed companies have grown significantly. Farmed salmon has become a major export commodity for Norway. While wild fish for a very long time made up the major share of Norway's seafood exports, salmon farming today is the biggest source of income in the aquaculture industry, accounting for

CONTACT Marie Steen marie.steen@nmbu.no Norwegian University of Life Sciences, Box 5003, Ås 1432, Norway.

approximately 68% of the Norwegian fish exports (Cojocaru et al., 2019; Straume et al., 2020). In 2018, the salmon export volume was 1.1 mill tons, worth NOK 67,8 billion, or roughly USD 7.3 billion according to the Norwegian Seafood Council 2017.

Salmon farming is a cyclic industry that historically has experienced substantial variability in prices and profitability (Asche et al., 2016, 2017; Misund & Nygård, 2018). 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 what and how risk factors influence stock price returns has long been of interest among academics and practitioners. A growing literature has demonstrated that, in general, 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 typically 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 dependence 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 provide limited guidance, as they usually focus on the relationship at the conditional mean.

The aim of this study is to model salmon farming companies' risk-return characteristics over the entire return distribution. Using quantile regression allows for changing parameters across different quantiles, to examine how potential risk factors affect stock price returns over the entire return distribution. Quantile regression, first introduced by Koenker and Bassett (1978), may give a better understanding of the relationship between risk factors and stock price returns. Given the volatile nature of the salmon farming industry, the quantile approach can uncover whether the risk-return relationship varies in the relation to the return level. Furthermore, since quantile regression provides direct estimates of the tail distribution, the results can be implemented in the estimation of Value-at-Risk (VaR). We estimate VaR for eight salmon farming companies listed at Oslo Stock Exchange during the period 2007–2016. We then 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 back-testing 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 could give investors in the salmon farming industry a better understanding of the relationship between risk factors and stock price returns under different levels of returns and, additionally, show how the results can be implemented and applied in a VaR analysis.

The remainder of this article is organized as follows. First, a brief overview of the development in the salmon farming industry is presented, followed by a literature review. Thereafter, the data and methodology are discussed. Finally, the analysis and empirical results, discussion and conclusions are given.

The Norwegian salmon farming industry and risk factors

Since the early 1990s, the salmon farming industry in Norway has developed from being a local small-scale industry to become a multinational industry and an important export industry for the Norwegian economy. The main drivers behind this development have been strong productivity growth and technological improvement (Asche, 2008; Asche, Guttormsen, et al., 2013; Asche et al., 2007; Nilsen, 2010; Rocha-Aponte & Tveterås, 2019; Roll, 2013, 2019; Vassdal & Holst, 2011), 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 almost 2.5 million tons in 2018, with Norway as the main producer, accounting for over 50% of global production. Figure 1 shows the global supply and supply growth of Atlantic salmon during the period 2006–2018, and the figure distinguishes between supply from Norway and Chile, the two largest producers, and other salmon producing countries.

While there has been a substantial growth in total supply since 2006, there is a large variability in the growth rate. The negative supply growth

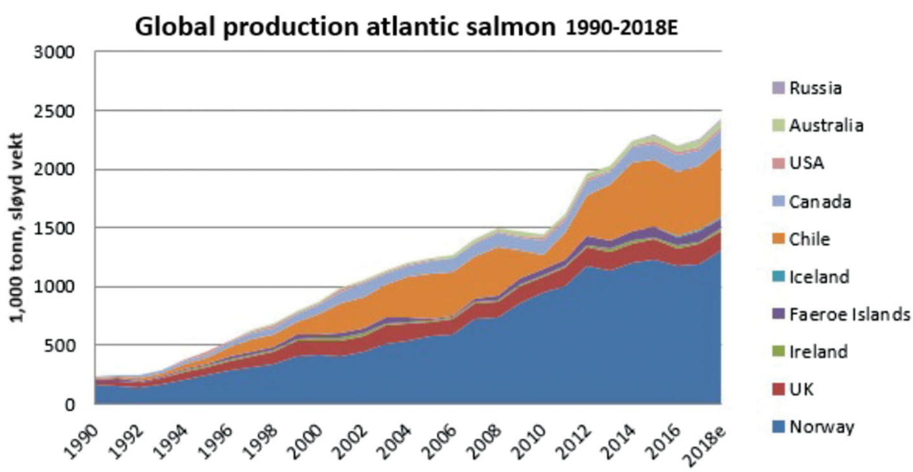

Figure 1. Global supply and supply growth of Atlantic salmon 2006–16. Source: AGB Sundal Collier.

in 2009 and 2010 was mainly caused by the severe disease 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 (e.g., salmon lice, escapes, fish welfare, sustainability and production optimization) are nothing new in the salmon farming industry and it is the reason why there is a negative supply growth in 2016. Today, the industry is experiencing large challenges with sea lice. According to the industry leader, Marine Harvest, the industry has reached a production level where the biological boundaries are being pushed, and further growth can no longer be driven by the industry alone (Marine Harvest, 2016). In addition, the Norwegian government has stopped almost all calls for new production licenses in Norway until the industry can control its challenges with sea lice.[2]

Along with the increase in the production volume of Atlantic salmon, the salmon farming industry has become more mature and productivity growth has slowed down (Asche & Bjorndal, 2011; Asche, Guttormsen, et al., 2013; Vassdal & Holst, 2011). During this development, the industry has changed from being an industry consisting of many small companies to a more integrated industry with fewer and larger companies (Asche, Roll, et al., 2013; Asche et al., 2018; Kvaløy & Tveterås, 2008). 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 & Øglend, 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 15 years, a securitization of the salmon farming industry has taken place, with Oslo Stock Exchange as the main marketplace for salmon farming company equity stocks. By early 2017, there were eight salmon farming companies listed at the Oslo Stock Exchange as well as several related companies such as suppliers. Fish Pool ASA,[3] established in 2005, is an international marketplace, licensed by the Norwegian Ministry of finance and under the surveillance of The Financial Supervisory Authority of Norway, for buying and selling commodity derivatives with fish and seafood as underlying products. Fish pool does not offer physical trading, only financial contracts (Ankamah-Yeboah et al., 2017; Asche, Øglend, et al., 2015; Sollibakke, 2012).[4] Fish Pool has given producers and buyers a tool to hedge against price risk, and opportunities for investors. However, while the trading volume of futures contracts grew fast between 2006 and 2010, Fish Pool has seen a strong decline in growth and considerable fluctuations in the years following 2011.

Although the salmon farming industry during recent years has been a success story in terms of profitability and stock price growth, the industry

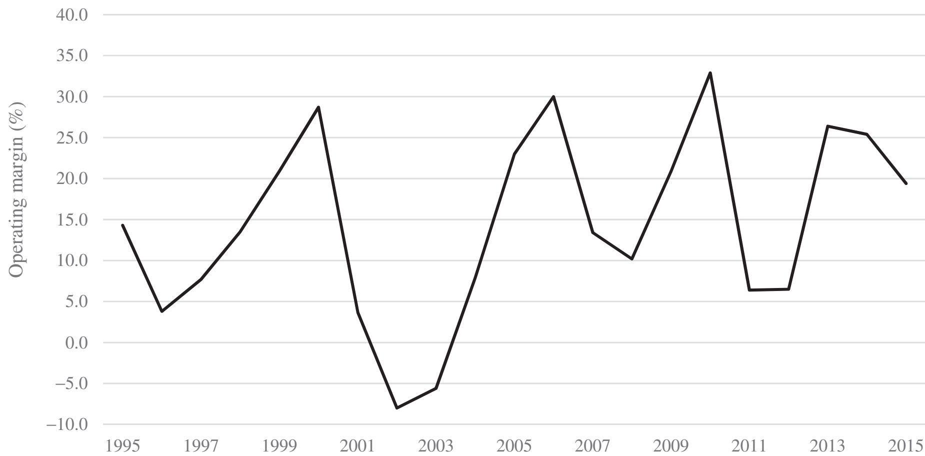

Figure 2. Average operating margin for Norwegian salmon producers 1995–2015. *Note*: Operating margin is earnings before interest and taxes (EBIT) in percentage of operating income. Source: The Norwegian Directorate of Fisheries.

has experienced major cycles in profitability. The main source for these cycles is price risk (Asche & 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 (Anderson et al., 2019; Asche, Dahl, et al., 2015; Asche et al., 2018, 2019; Bloznelis, 2016; Dahl, 2017; Dahl & Jonsson, 2018; Dahl & Øglend, 2014; Dahl & Yahya, 2019; Øglend, 2013; Øglend & Sikveland, 2008). Figure 2 visualizes the cycles in profitability for Norwegian salmon producers, and in 2002–2003, average operating margin was even negative.

During this period, several salmon producers went bankrupt due to low salmon prices (Misund, 2018a). However, the situation is currently quite different, 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 (Asche & Bjorndal, 2011; Asche et al., 2011; Braekkan, 2014; Braekkan et al., 2018; Kinnucan et al., 2003) pushed the salmon price to new levels in 2016. In addition, a depreciation of the Norwegian krone in the last few years, largely due to the big drop in oil prices in 2014, has pushed the salmon price higher measured in NOK/kg. Thus, the Norwegian salmon farming companies have had high profit margins which is probably an important reason for the substantial stock price growth in the seafood sector (Asche & Sikveland, 2015). However, due to a considerable amount of imported ingredients in salmon feed combined with a weak Norwegian currency, the production cost has also started to increase along with the salmon price (Asche & Øglend, 2016; Misund et al., 2017). In Figure 3, we have illustrated the salmon price development in the period 1995–2016, and the

Figure 3. Weekly price of salmon over the period 1995–2016 (Nasdaq Salmon Index, Source: Nasdaq).

figure clearly shows the abnormal salmon prices that have been in the recent years if we take a historical perspective.

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 (Asche et al., 2017; Øglend, 2013), and therefore on risk and return for salmon equity.

There are only a few studies examining risk factors for salmon farming companies and how they affect stock price returns. Misund (2018a) and Misund (2018b) use a multifactor model with monthly data 2006–2016 in order to find whether stock price returns are sensitive to market excess return (OSEAX); the Fama-French-Carhart factors (SMB, HML and UMD[5]), and changes in the oil price as well as changes in exchange rates (NOK/EUR and NOK/USD). Their 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 toward large caps and value stocks. Furthermore, their analysis shows that the industry is less risky than the stock 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 individually. Regarding changes in exchange rates and changes in the oil price, Misund 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 for salmon farming stock returns, it is difficult to identify the most important risk factors in order to model the return distribution for salmon stocks. We use the Main Index at the Oslo Stock Exchange (OSEBX) to adjust for the general market risk. Furthermore, we include changes in exchange rates in our model, as several studies have shown the importance of exchange rates in the salmon farming industry (Larsen & Asche, 2011; Larsen & Kinnucan, 2009; Tveteras & Asche, 2008). Finally, we include changes in the long-term interest rate as an explanatory variable, which also have been done in studies examining risk factors of stock price returns for companies in other volatile industries (Faff & Chan, 1998; Sadorsky, 2001; Sadorsky & Henriques, 2001; Tjaaland et al., 2015; Tufano, 1998). 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.

With regards to the industry-specific risk factors, Misund (2018a) examines whether 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. Likewise, Zhang et al. (2016) find a strong relationship between the salmon price and salmon farming stock returns. However, they find the relationship to be stronger for smaller compared to larger companies suggesting that larger companies have a stronger ability to dampen the effects from fluctuations in the salmon price. We include changes in the salmon price as an explanatory variable in our model.

Zhang et al. (2016) furthermore find a long-run relationship between the stock price of the industry leader (Marine Harvest) and two of the other companies (Lerøy Seafood and Grieg Seafood), where a rise in the stock price of the industry leader is subsequently followed by a rise in the stock price of the other two, in the way that the larger company is leading the smaller. This might indicate that there exists a lead-lag relationship in the industry. Consequently, we include changes in the salmon price and the lagged stock return of the industry leader, Marine Harvest, in our model.

In general finance literature, several studies have applied factor models estimated for multiple quantiles to examine the relationship between risk factors and stock price returns. For instance, Allen and Powell (2011) analyze the return distribution of 30 Dow Jones Industrial stocks. They find that there are large and statistically significant differences in the relationship between risk factors and stock price returns across the quantiles. Moreover, they find OLS to be less effective when it comes to analyzing the extremes within the return distribution. Looking at BRICS (Brazil, Russia, India, China and South Africa) markets, Mensi et al. (2014) use quantile regression to examine how global economic factors influence the risk and return at different return levels. The results show that the dependence 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 markets. Overall, they conclude that the BRICS stock markets are less correlated at lower quantiles.

Others have also used quantile regression to examine the impact of one particular risk factor. 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 stock market response to oil price shocks are diverse among the G7 countries, and that the quantile regression estimates are quite different results from OLS estimates. 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 appear to be more pessimistic (optimistic) to bad (good) news when the stock market performs poorly (well).

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. Several studies (e.g. Ciner 2001) find a nonlinear relationship between risk factors and stock price returns, and that the risk factor sensitivities tend to be more pronounced during extreme conditions. This indicates that factor models estimated for multiple quantiles might be more suitable for examining the relationship between risk factors and stock price returns than standard OLS factor models. Whether this also applies to the salmon farming industry is what this study aims to uncover, since there are implications for risk management, asset allocation and hedging decisions.

Quantile regression and Value-at-Risk

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. 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. 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 qth quantile linear regression model, as introduced by Koenker and Bassett (1978), is given by:

$$Y_t = \alpha^q + \beta^q X_t + \varepsilon_t^q \tag{1}$$

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 qth quantile for Y is derived according to the following minimization problem,

$$\min_{\alpha,\ \beta} \sum_{t=1}^{T} (q - 1_{Y_t \leq \alpha + \beta X_t})(Y_t - (\alpha + \beta X_t)) \tag{2}$$

where

$$1_{Y_t \leq \alpha + \beta X_t} = \begin{cases} 1 & if\ \ Y_t \leq \alpha + \beta X_t, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Quantile regression models have several advantages over standard regression models, as the estimated parameters are less sensitive to outliers.

Value-at-Risk (VaR) models measure 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, for instance historical simulation as in Dahl (2017), an interesting feature of the quantile regression model is that it allows for estimating VaR directly, since VaR can be seen as a particular conditional quantile of the return distribution (Chernozhukov & Umantsev, 2001). In our case, Y_t^q, as below in Equation (4), is the conditional VaR, or CVaR, at a quantile q.

$$Y_t^q = \alpha^q + \beta^q X_t + e_t^q \tag{4}$$

where Y_t^q is the estimated CVaR 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. In such a model, VaR is conditional upon the factor X (there can be more than one factor). Once the regression coefficients for the different quantiles are estimated, we only need a value for the independent variable to estimate CVaR for any given significance level. It is still important to mention that, since we use risk factors as the independent variable to model CVaR, and not the volatility, the CVaR obtained from this procedure is the systematic CVaR or total risk factor CVaR (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.

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, 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:

$$H_t = \begin{cases} 1 & if \;\; Y_t \leq VaR_t^q, \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

However, Equation (5) is only true for q less than 50%. For q greater than 50%, we have

$$H_t = \begin{cases} 1 & if \;\; Y_t \geq VaR_t^q, \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

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

$$\begin{aligned} -2\ln(LR_{UC}) = -2\big[n_0 \; \ln(1-\pi_{\exp}) + n_1 \; \ln(\pi_{\exp}) \\ - \; n_0\ln(1-\pi_{obs}) - n_1 \; \ln(\pi_{obs})\big] \sim \chi_1^2, \end{aligned} \tag{7}$$

where n_1 and n_0 are the number of violations and non-violations, respectively, $\pi_{\exp}$ is the excepted 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,

$$-2\ln(LR_{CC}) = -2\left[n_0 \ln(1-\pi_{\exp}) + n_1 \ln(\pi_{\exp}) - n_{00} \ln(1-\pi_{01}) - n_{01} \ln(\pi_{01}) - n_{10} \ln(1-\pi_{11}) - n_{11} \ln(\pi_{11})\right] \sim \chi^2_2, \quad (8)$$

which has a chi-square distribution with 2 degrees of freedom under the null hypothesis of correct coverage and independence, and 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 test is only sensitive to one violation immediately followed by another, ignoring all other patterns of clustering. For both tests, the null hypothesis is that the model is correctly specified. Thus, we want to keep the null hypthosis and will use a higher level of significance. I.e., the lower observed value, the better, and the higher level of significance, the stricter test. This is the opposite of hypothesis testing for significance in ordinary regression models. See, e.g., Steen et al. (2015) for a more detailed presentation.

Data

We analyze data for eight salmon company stocks listed at Oslo Stock Exchange 2006–2016. Obviously, this is a small sample. However, the eight companies represent a large portion of Norwegian salmon farming production. We, therefore, use these eight companies to form an equally weighted "portfolio" to represent the salmon farming industry. The portfolio is constructed by taking the arithmetic average of stock price returns for the eight salmon farming companies.

We perform the analysis at both the industry and firm level. This allows us to examine the industry as a whole, as well as individual companies. In Table 1,[6] all companies are presented with their ticker code and market

Table 1. The salmon farming companies and market values in March 2017.

Company	Ticker code	Market value	Market value (%)	Average β_{SP}	Firm size
Marine Harvest	MHG	65 757	39.9%	0.07	Large
Lerøy Seafood	LSG	26 693	16.2%	0.13	Large
SalMar	SALM	24 394	14.8%	0.12	Large
Austevoll Seafood	AUSS	15 238	9.2%	0.10	Small
Grieg Seafood	GSF	8 596	5.2%	0.13	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.

value as well as their market value in percentage of the total seafood sector in March 2017. 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. Daily observations were aggregated to weekly frequency by taking the average of daily log returns within each week.

We use the Nasdaq Salmon Index as the spot price of salmon, like, e.g., Øglend and Sikveland (2008), Øglend (2013), Zhang et al. (2016) and Misund (2018a). Prior to 2013, salmon prices were reported by NOS, the Fish Pool clearing central. These price reports have since been replaced by the Nasdaq Salmon Index. 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 on the Oslo Stock Exchange.[7] While the EU is the primary market for the companies, many companies have subsidiaries in Chile, for which the USA is a primary market. 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. The sample period covers the period from week 27, 2007 through 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 with a major impact on the salmon market, including the financial crisis in 2007–2008, the large drop in the salmon price in 2011,[8] the Russian boycott of Norwegian salmon in 2014, the volcano eruption in Chile in 2015 and the algal boom the following year, the last two causing a large loss of salmon. Figure 4 shows the price development for the salmon farming

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

industry (represented by the equally weighted portfolio) and the Main Index (OSEBX) at the Oslo Stock Exchange over the sample period. 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.

Table 2 presents descriptive statistics including the 5% and 95% VaR for the data sample. Given increases in the share prices in the salmon farming industry, it comes as no surprise that the average weekly return on the equally weighted portfolio of 0.27% is quite high compared to the average weekly return at the Oslo Stock Exchange (0.06%). This is also the case for the individual companies, although the average weekly return ranges from 0.08% to 0.38%. A potential explanation for the stock price growth in salmon farming is the substantial increase in the salmon price, averaging .25% per week during the period 2007–2016. The table also shows the decline in the long-term interest rate over the sample period. Table 3 shows that NOK has depreciated slightly against EUR and USD over the sample period, although the mean weekly changes for both the exchange rates are quite small. Looking at the standard deviation and the minimum and maximum weekly return, the table shows that the salmon farming stocks have been more volatile than OSEBX. This is as expected, and especially for the individual companies, due to a high degree of unsystematic risk. Moreover,

Table 2. 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. Weekly log returns from week 27, 2007 to week 52, 2016. All values except 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 3. 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. * = statistically significant at 5% level. ** = statistically significant at 1% level.

the salmon price has been very volatile over the sample period, with the highest volatility of all the assumed risk factors. All companies have a skewed return distribution with fatter tails and higher peaks compared to 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 presents the correlations matrix for the equally weighted portfolio and the estimated risk factors. The equally weighted portfolio demonstrates how the risk factors have correlated with the overall industry over the sample period. The highest correlation is, as expected, between the overall industry and OSEBX, 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 are positively correlated to the overall industry. The exchange rates, however, are negatively correlated with the overall industry. Correlations between the risk factor are all lower than 0.50 except for the correlation between the two exchange rates (NOK/USD and NOK/EUR), which has a correlation of 0.56. However, this is not high enough to cause multi-collinearity problems.

Results and discussion

In order to model the conditional return distribution, we use the entire sample period (2006–2016) to examine the relationship between the risk factors and stock price returns at the 5%, 10%, 25%, 75%, 90%, 95% and the median. These quantiles provide a good estimate of the return distribution, and we use more quantiles in the tails, since investors and risk managers are usually more concerned about the tails of the return distribution.

The quantile factor model is given by

$$R_{i,t} = \alpha_i^q + \beta_{i,OSE}^q \; R_{OSE,t} + \beta_{i,SP}^q \; R_{SP,t} + \beta_{i,EUR}^q \; R_{EUR,t} + \beta_{i,USD}^q \; R_{USD,t} \\ + \; \beta_{i,INT}^q \mathrm{R}_{INT,t} + \beta_{i,IL}^q R_{IL,t} + \varepsilon_{i,t}^q \tag{9}$$

where $R_{i,t}$ is the stock return of company or portfolio i at time t, $R_{OSE,t}$ is the OSE market return, $R_{SP,t}$ is the change in the salmon price, $R_{EUR,t}$ is the change in the NOK/EUR, $R_{USD,t}$ is the change in the NOK/USD, $R_{INT,t}$ is the change in the long-term interest rate, $R_{IL,t}$ is the lagged stock return of the industry leader, α_i^q is the constant, and $\varepsilon_{i,t}^q$ is the error term.

Table 4 reports the industry-level analysis. The standard errors are obtained using the pairs-bootstrapping method by Buchinsky (1995). The results from the quantile factor models are supplemented by the results from standard factor models to compare the estimated beta coefficients.

Table 4. 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 & Machado, 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. ‴ indicates that the regression coefficients are significantly different from one at 1% level, respectively.

The market beta ranges 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 suggests 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 (2018a). However, the market beta is slightly higher in the upper quantiles of the return distribution compared to the lower quantiles, except for the 10% quantile, showing that the market beta varies under different company returns although the variation is quite small.

The beta coefficient for the salmon price is statistically 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 (Asche & Sikveland, 2015; Misund, 2018a; Øglend & Sikveland, 2008). However, while the beta coefficient on the salmon price is quite stable across quantiles, it is somewhat higher in the 5% quantile, indicating that changes in the salmon price have a larger impact on stock price returns in periods with large stock price reductions.

With regards to the exchange rate betas, none of them are statistically significant.

The interest rate beta is statistically insignificant across all quantiles, indicating that changes in the long-term interest rate do not explain stock price returns on a weekly basis. 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 implies a positive relationship and the others imply a negative relationship.

The beta for the lagged stock return of the industry leader is statistically significant across all quantiles, demonstrating that the industry (represented by the equally weighted portfolio) is partly driven by the industry leader. The stock price of the industry leader goes up one week, the stock price of a portfolio of the companies will go up the subsequent week. This might indicate a violation of the Efficient Market Hypothesis. 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 & Swaminathan, 2000; Hou, 2007). This process, however, does not necessarily imply market inefficiency. The beta is quite stable across all quantiles, showing that the lead-lag effect does not vary much under different return levels, although the beta coefficient is somewhat higher in the upper and lower quantile of the return distribution.

In Tables A.1–A.5 in the appendix, the results from the firm-level analysis are presented. We will highlight the most important findings. The general impression is that the market beta and the beta coefficients for 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 return levels at the firm level.[9] SalMar and Lerøy Seafood have the lowest market betas, 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 levels.

The salmon price betas differ across companies. Marine Harvest has the lowest exposure to changes in the salmon price with a relatively low beta coefficients across all quantiles (0.7 on average), although statistically significant only 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 argue that large companies are less sensitive to changes in the salmon price. For the other companies (as shown in Table 1, the average beta range is 0.10–0.13), the beta is generally higher and statistically significant across most of the quantiles, however, the findings suggest that the individual companies react differently to changes in the salmon price under different return levels, even if it if not possible to find a clear relationship between beta and company size.

The beta coefficient for the lagged stock return of the industry leader indicates that all the individual companies, except for Lerøy Seafood, tend to follow the industry leader. As such, we have indication of both cross-autocorrelation and autocorrelation within the salmon farming industry. Again, we see a lead-lag effect, which may be attributed to investors' tendency to overreact to new market information (De Bondt & Thaler, 1985, 1987; Lo & MacKinlay, 1990) and herding behavior (Bikhchandani et al., 1992; Nofsinger & Sias, 1999), leading to predictable patterns in stock prices. Marine Harvest, the industry leader, 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 risk factors for stock price returns of salmon farming companies at both the industry and firm-level. While the findings at the industry-level are more stable across quantiles, there are larger differences across quantiles at the firm level, but not statistically different. 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.

In risk management, only estimating the risk factor sensitivities is not sufficient, Since beta only measures 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 VaR is a widely adopted risk measure for such analyses. 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, for both a long and a 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. We limit the scenario analysis to examine how the VaR estimates for the equally-weighted portfolio vary under different assumptions about the market return and changes in the salmon price. This will demonstrate how the VaR estimates are conditioned on the risk factors. We use the market beta and salmon price beta since they differ the most in the upper and lower quantiles.

Table 5 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, standard errors in parentheses. 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 holds over a long period of time. 95% confidence intervals calculated show that none of the confidence intervals for 5% and 95% VaR are overlapping, showing that they are significantly different from each other at 5% level, both for the industry and company level.

As can be seen from Table 5, 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. 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 markedly 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 Tables 6 and 7. As a baseline VaR, we use the estimated alpha coefficient on the 5% and 95% quantile, i.e., the value of all the risk factors is set to zero.

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

Table 5. 5% and 95% Value-at-Risk (VaR) estimates.

	EWP	MHG	SALM	LSG	GSF	AUSS
5% VaR	−3.93% (.0040)	−6.76% (.0073)	−5.40% (.0061)	−5.71% (.0044)	−7.25% (.0095)	−5.95% (.0060)
95% VaR	3.84% (.0024)	7.64% (.0078)	6.11% (.0039)	6.09% (.0046)	7.06% (.0057)	5.55% (.0057)

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. Standard errors in parentheses.

Table 6. 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 7. 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.

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 demonstrates 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.

In order to test the accuracy of the VaR estimates (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 estimates, and hence, the robustness of the estimated tails of the return distributions. We are using a standard backtesting procedure (Steen et al., 2015) which assesses the in-sample performance of the VaR-model. In-sample assessments of predictive power in general overstates the out-of-sample predictive power a statistical model and thus caution is required.

In Table 8, the test statistics from the Kupiec and Christoffersen tests are presented and the null hypotheses are not rejected, except from conditional coverage for 95% VaR for Marine Harvest Group, thus there is no strong empirical evidence against the specified model.

Table 8. 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 procedures are performed over the entire sample period ($N = 494$ observations). *, ** and *** denotes significance at 1%, 5% and 10% level, respectively.

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. 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.

Concluding remarks

From 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, which are the risk factors that determine stock price returns, their magnitude and impact and do these factors vary under different return levels? A better understanding of these questions is essential for understanding the financial performance of the salmon farming companies.

To answer some of 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 statistically significant impact on stock price returns. However, for changes in exchange rates and changes in the long-term interest rate, the results are mostly statistically insignificant, and we conclude that these have little impact on stock returns.

At both the industry and firm level, the findings suggest that the market return has the largest impact on stock returns. However, while the market beta is quite stable across quantiles at the industry-level, it differs across quantiles at the firm level. This is also the case for the two other statistically significant risk factors, indicating that the risk factor sensitivities tend to vary more under different market conditions at the firm level. Thus, showing that the factor model estimated for multiple quantiles is more suitable for examining the relationship between risk factors and stock price returns of salmon farming companies than standard OLS factor models, 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. But, the null hypothesis of equality of all betas across the different quantiles for each of the independent variables could not be rejected, neither at industry nor company level.

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 shows the practical use of the quantile regression approach, where characteristics such as asymmetry and nonlinearity can be taken into consideration.

Notes

1. Misund (2018a) and Misund and Nygård (2018) provide examples from the salmon farming industry.
2. New production capacity is allowed under the traffic light system, but the allocation of new capacity is linked to the amounts of sea lice on wild salmon (Osmundsen et al., 2017, 2020; Hersoug et al., 2019).
3. See: fishpool.eu/about for more information.
4. This also facilitates hedging relatively to products with prices that are highly but not necessariy perfectly correlated with the FishPool price (Misund & Asche, 2016; Bloznelis, 2018).
5. HML equals the outperformance of small versus big companies, SMB the outperformance of high versus small book/market companies and UMD is a zero-cost portfolio that is long previous 12-month return winners and short previous 12-month loser stocks
6. There is a certain degree of cross-ownership for these companies. Notably Austevoll holds 53% in Lerøy Seafood (2018). However, the companies are all traded as independent entities at Oslo Stock Exchange.
7. Although the majority of the salmon companies on the Oslo Stock Exchange are Norwegian, they typically hold assets in several other countries.

8. The large drop in the salmon price was to a large extent a consequence of the increased supply from Chile after the major disease attack the previous years. In addition, according to the press (e.g. newsinenglish.no, June 30, 2011) and industry analysts' comments in the summer/autumn of 2011, unforeseen overproduction in Norway had led to forced slaughtering in order to comply with the maximum allowable biomass regulation. This led to a sudden increase in supply, causing the price drop.
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.

Acknowledgments

The authors wish to thank the AEM Editor Frank Asche, Ole Gjolberg, Olvar Bergland and two anonymous reviewers for valuable comments and suggestions on a previous version of the paper. Any remaining mistakes are entirely the responsibility of the authors.

References

Alexander, C. (2009). *Market risk analysis, value at risk models* (Vol. 4). John Wiley & Sons.

Allen, D. E., & Powell, S. R. (2011). Asset pricing, the Fama—French factor model and the implications of quantile-regression analysis. In G. N. Gregoriou & R. Pascalau (Eds.), *Financial econometrics modeling: Market microstructure, factor models and financial risk measures* (pp. 176–193). Springer.

Anderson, J. L., Asche, F., & Garlock, T. (2019). Economics of aquaculture policy and regulation. *Annual Review of Resource Economics*, *11*(1), 101–123. https://doi.org/10.1146/annurev-resource-100518-093750

Ankamah-Yeboah, I., Nielsen, M., & Nielsen, R. (2017). Price formation of the salmon aquaculture futures market. *Aquaculture Economics & Management*, *21*(3), 376–399. https://doi.org/10.1080/13657305.2016.1189014

Asche, F., & Bjorndal, T. (2011). *The economics of salmon aquaculture* (Vol. 10). John Wiley & Sons.

Asche, F. (2008). Farming the sea. *Marine Resource Economics*, *23*(4), 527–547. https://doi.org/10.1086/mre.23.4.42629678

Asche, F., Cojocaru, A. L., & Sikveland, M. (2018). Market chocks in salmon aquaculture: The impact of the Chilean disease crisis. *Journal of Agricultural and Applied Economics*, *50*(2), 255–269. https://doi.org/10.1017/aae.2017.33

Asche, F., Dahl, R. E., & Steen, M. (2015). Price volatility in seafood markets: Farmed vs. wild fish. *Aquaculture Economics & Management*, *19*(3), 316–335. https://doi.org/10.1080/13657305.2015.1057879

Asche, F., Dahl, R. E., Gordon, D. V., Trollvik, T., & Aandahl, P. (2011). Demand growth for Atlantic salmon: The EU and French markets. *Marine Resource Economics*, *26*(4), 255–265. https://doi.org/10.5950/0738-1360-26.4.255

Asche, F., Guttormsen, A. G., & Nielsen, R. (2013). Future challenges for the maturing Norwegian salmon aquaculture industry: An analysis of total factor productivity change from 1996 to 2008. *Aquaculture*, *396–399*, 43–50. https://doi.org/10.1016/j.aquaculture.2013.02.015

Asche, F., Hansen, H., Tveteras, R., & Tveterås, S. (2009). The salmon disease crisis in Chile. *Marine Resource Economics*, *24*(4), 405–411. https://doi.org/10.1086/mre.24.4.42629664

Asche, F., Misund, B., & Øglend, A. (2016). The spot-forward relationship in the Atlantic salmon market. *Aquaculture Economics & Management*, *20*(2), 222–234. https://doi.org/10.1080/13657305.2016.1156192

Asche, F., Misund, B., & Øglend, A. (2019). The case and cause of salmon price volatility. *Marine Resource Economics*, *34*(1), 23–38. https://doi.org/10.1086/701195

Asche, F., & Øglend, A. (2016). The relationship between input-factor and output prices in commodity industries: The case of Norwegian salmon aquaculture. *Journal of Commodity Markets*, *1*(1), 35–47. https://doi.org/10.1016/j.jcomm.2015.11.001

Asche, F., Øglend, A., & Selland Kleppe, T. (2017). Price dynamics in biological production processes exposed to environmental shocks. *American Journal of Agricultural Economics*, *99*(5), 1246–1264. https://doi.org/10.1093/ajae/aax048

Asche, F., Øglend, A., & Zhang, D. (2015). Hoarding the herd: The convenience of productive stocks. *The Journal of Futures Markets*, *35*(7), 679–694. https://doi.org/10.1002/fut.21679

Asche, F., Roll, K. H., & Tveterås, R. (2007). Productivity growth in the supply chain—Another source of competitiveness for aquaculture. *Marine Resource Economics*, *22*(3), 329–334. https://doi.org/10.1086/mre.22.3.42629562

Asche, F., Roll, K. H., Sandvold, H. N., Sørvig, A., & Zhang, D. (2013). Salmon aquaculture: Larger companies and increased production. *Aquaculture Economics & Management*, *17*(3), 322–339. https://doi.org/10.1080/13657305.2013.812156

Asche, F., & Sikveland, M. (2015). The behavior of operating earnings in the Norwegian salmon farming industry. *Aquaculture Economics & Management*, *19*(3), 301–315. https://doi.org/10.1080/13657305.2015.1057880

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, *100*(5), 992–1026. https://doi.org/10.1086/261849

Bloznelis, D. (2016). Salmon price volatility: A weight-class-specific multivariate approach. *Aquaculture Economics & Management*, *20*(1), 24–53. https://doi.org/10.1080/13657305.2016.1124936

Bloznelis, D. (2018). Hedging salmon price risk. *Aquaculture Economics & Management*, *22*(2), 168–191. https://doi.org/10.1080/13657305.2017.1409292

Braekkan, E. H. (2014). Disentangling supply and demand shifts: The impacts on world salmon price. *Applied Economics*, *46*(32), 3942–3953. https://doi.org/10.1080/00036846.2014.948674

Braekkan, E. H., Thyholdt, S. B., Asche, F., & Myrland, Ø. (2018). The demands they are a-changin. *European Review of Agricultural Economics*, *45*(4), 531–552. European Review of Agricultural Economics. https://doi.org/10.1093/erae/jby003%J

Buchinsky, M. (1995). Estimating the asymptotic covariance matrix for quantile regression models a Monte Carlo study. *Journal of Econometrics*, *68*(2), 303–338. https://doi.org/10.1016/0304-4076(94)01652-G

Chernozhukov, V., & Umantsev, L. (2001). Conditional value-at-risk: Aspects of modeling and estimation. *Empirical Economics*, *26*(1), 271–292. https://doi.org/10.1007/s001810000062

Chordia, T., & Swaminathan, B. (2000). Trading volume and cross-autocorrelations in stock returns. *The Journal of Finance*, *55*(2), 913–935. https://doi.org/10.1111/0022-1082.00231

Christoffersen, P. F. (1998). Evaluating interval forecasts. *International Economic Review*, *39*(4), 841–862. https://doi.org/10.2307/2527341

Ciner, C. (2001). Energy shocks and financial markets: Nonlinear linkages. *Studies in Nonlinear Dynamics & Econometrics*, *5*(3), 3. https://doi.org/10.2202/1558-3708.1079

Cojocaru, A. L., Asche, F., Pincinato, R. B. M., & Straume, H.-M. (2019). Where are the fish landed? An analysis of landing plants in Norway. *Land Economics*, *95*(2), 246–257. https://doi.org/10.3368/le.95.2.246

Dahl, R. E., & Jonsson, E. (2018). Volatility spillover in seafood markets. *Journal of Commodity Markets*, *12*, 44–59. https://doi.org/10.1016/j.jcomm.2017.12.005

Dahl, R. E., & Øglend, A. (2014). Fish price volatility. *Marine Resource Economics*, *29*(4), 305–322. https://doi.org/10.1086/678925

Dahl, R. E., & Yahya, M. (2019). Price volatility dynamics in aquaculture fish markets. *Aquaculture Economics & Management*, *23*(3), 321–340. https://doi.org/10.1080/13657305.2019.1632390

Dahl, R. E. (2017). A study on price volatility in the aquaculture market using value-at-Risk (VaR). *Aquaculture Economics & Management*, *21*(1), 125–143. https://doi.org/10.1080/13657305.2017.1262475

De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, *40*(3), 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

De Bondt, W. F. M., & Thaler, R. (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance*, *42*(3), 557–581. https://doi.org/10.1111/j.1540-6261.1987.tb04569.x

Faff, R., & Chan, H. (1998). A multifactor model of gold industry stock returns: Evidence from the Australian equity market. *Applied Financial Economics*, *8*(1), 21–28. https://doi.org/10.1080/096031098333212

Hersoug, B., Mikkelsen, E., & Karlsen, K. M. (2019). "Great expectations" – Allocating licenses with special requirements in Norwegian salmon farming. *Marine Policy*, *100*, 152–162. https://doi.org/10.1016/j.marpol.2018.11.019

Hou, K. (2007). Industry information diffusion and the lead-lag effect in stock returns. *Review of Financial Studies*, *20*(4), 1113–1138. https://doi.org/10.1093/revfin/hhm003

Jareño, F., Ferrer, R., & Miroslavova, S. (2016). US stock market sensitivity to interest and inflation rates: A quantile regression approach. *Applied Economics*, *48*(26), 2469–2481. https://doi.org/10.1080/00036846.2015.1122735

Kinnucan, H. W., Asche, F., Myrland, Ø., & Roheim, C. A. (2003). Advances in economics of marketing and implications for aquaculture development. *Aquaculture Economics & Management*, *7*(1–2), 35–53. https://doi.org/10.1080/13657300309380330

Koenker, R., & Bassett,G. Jr, (1978). Regression quantiles. *Econometrica*, *46*(1), 33–50. https://doi.org/10.2307/1913643

Koenker, R., & Machado, J. A. F. (1999). Goodness of fit and related inference processes for quantile regression. *Journal of the American Statistical Association*, *94*(448), 1296–1310. https://doi.org/10.1080/01621459.1999.10473882

Kupiec, P. (1995). Techniques for verifying the accuracy of risk measurement models. *The Journal of Derivatives*, *3* (2), 73–84. (Winter 1995). https://doi.org/10.3905/jod.1995.407942

Kvaløy, O., & Tveterås, R. (2008). Cost structure and vertical integration between farming and processing. *Journal of Agricultural Economics*, *59*(2), 296–311. https://doi.org/10.1111/j.1477-9552.2007.00149.x

Larsen, T. A., & Asche, F. (2011). Contracts in the salmon aquaculture industry: An analysis of Norwegian salmon exports. *Marine Resource Economics*, *26*(2), 141–150. https://doi.org/10.5950/0738-1360-26.2.141
Larsen, T. A., & Kinnucan, H. W. (2009). The effect of exchange rates on international marketing margins. *Aquaculture Economics & Management*, *13*(2), 124–137. https://doi.org/10.1080/13657300902885220
Lee, C.-C., & Zeng, J.-H. (2011). The impact of oil price shocks on stock market activities: Asymmetric effect with quantile regression. *Mathematics and Computers in Simulation*, *81*(9), 1910–1920. https://doi.org/10.1016/j.matcom.2011.03.004
Lo, A. W., & MacKinlay, A. C. (1990). When are contrarian profits due to stock market overreaction? *The Review of Financial Studies*, *3*(2), 175–205. https://doi.org/10.1093/rfs/3.2.175
Marine Harvest (2016). *Salmon farming industry handbook 2015*. Marine Harvest ASA.
Mensi, W., Hammoudeh, S., Reboredo, J. C., & Nguyen, D. K. (2014). Do global factors impact BRICS stock markets? A quantile regression approach. *Emerging Markets Review*, *19*, 1–17. https://doi.org/10.1016/j.ememar.2014.04.002
Misund, B. (2018a). Common and fundamental risk factors in shareholder returns of Norwegian salmon producing companies. *Journal of Commodity Markets*, *12*, 19–30. https://doi.org/10.1016/j.jcomm.2017.12.007
Misund, B. (2018b). Valuation of salmon farming companies. *Aquaculture Economics & Management*, *22*(1), 94–111. https://doi.org/10.1080/13657305.2016.1228712
Misund, B., & Asche, F. (2016). Hedging efficiency of Atlantic salmon futures. *Aquaculture Economics & Management*, *20*(4), 368–381. https://doi.org/10.1080/13657305.2016.1212123
Misund, B., & Nygård, R. (2018). Big fish: Valuation of the world's largest salmon farming companies. *Marine Resource Economics*, *33*(3), 245–261. https://doi.org/10.1086/698447
Misund, B., Øglend, A., & Pincinato, R. B. M. (2017). The rise of fish oil: From feed to human nutritional supplement. *Aquaculture Economics & Management*, *21*(2), 185–210. https://doi.org/10.1080/13657305.2017.1284942
Nilsen, O. B. (2010). Learning-by-doing or technological leapfrogging: Production frontiers and efficiency measurement in norwegian salmon aquaculture. *Aquaculture Economics & Management*, *14*(2), 97–119. https://doi.org/10.1080/13657301003776649
Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of Finance*, *54*(6), 2263–2295. https://doi.org/10.1111/0022-1082.00188
Øglend, A. (2013). Recent trends in salmon price volatility. *Aquaculture Economics & Management*, *17*(3), 281–299. https://doi.org/10.1080/13657305.2013.812155
Øglend, A., & Sikveland, M. (2008). The behaviour of salmon price volatility. *Marine Resource Economics*, *23*(4), 507–526. https://doi.org/10.1086/mre.23.4.42629677
Osmundsen, T. C., Almklov, P., & Tveterås, R. (2017). Fish farmers and regulators coping with the wickedness of aquaculture. *Aquaculture Economics & Management*, *21*(1), 163–183. https://doi.org/10.1080/13657305.2017.1262476
Osmundsen, T. C., Olsen, M. S., & Thorvaldsen, T. (2020). The making of a louse – Constructing governmental technology for sustainable aquaculture. *Environmental Science & Policy*, *104*, 121–128. https://doi.org/10.1016/j.envsci.2019.12.002
Rocha-Aponte, F., & Tveterås, S. (2019). On the drivers of cost changes in the Norwegian salmon aquaculture sector: A decomposition of a flexible cost function from 2001 to 2014. *Aquaculture Economics & Management*, *23*(3), 276–291. https://doi.org/10.1080/13657305.2018.1551438

Roll, K. H. (2013). Measuring performance, development and growth when restricting flexibility. *Journal of Productivity Analysis*, *39*(1), 15–25. https://doi.org/10.1007/s11123-012-0265-3

Roll, K. H. (2019). Moral hazard: The effect of insurance on risk and efficiency. *Agricultural Economics*, *50*(3), 367–375. https://doi.org/10.1111/agec.12490

Sadorsky, P. (2001). Risk factors in stock returns of Canadian oil and gas companies. *Energy Economics*, *23*(1), 17–28. https://doi.org/10.1016/S0140-9883(00)00072-4.

Sadorsky, P., & Henriques, I. (2001). Multifactor risk and the stock returns of Canadian paper and forest products companies. *Forest Policy and Economics*, *3*(3–4), 199–208. https://doi.org/10.1016/S1389-9341(01)00064-8

Sollibakke, P. B. (2012). Scientific stochastic volatility models for the salmon forward market: Forecasting (un-)conditional moments. *Aquaculture Economics & Management*, *16*(3), 222–249. https://doi.org/10.1080/13657305.2012.704618

Steen, M., Westgaard, S., & Gjølberg, O. (2015). Commodity value-at-risk modeling: Comparing RiskMetrics, historic simulation and quantile regression. *The Journal of Risk Model Validation*, *9*(2), 49–78. https://doi.org/10.21314/JRMV.2015.146

Straume, H.-M., Anderson, J. L., Asche, F., & Gaasland, I. (2020). Delivering the goods: The determinants of Norwegian seafood exports. *Marine Resource Economics*, *35*(1), 83–000. https://doi.org/10.1086/707067

Tjaaland, S. H., Westgaard, S., Osmundsen, P., & Frydenberg, S. (2015). Oil and gas risk factor sensitivities for US energy companies. *The Journal of Energy and Development*, *41*(1/2), 135–173.

Tufano, P. (1998). The determinants of stock price exposure: Financial engineering and the gold mining industry. *The Journal of Finance*, *53*(3), 1015–1052. https://doi.org/10.1111/0022-1082.00042

Tveteras, S., & Asche, F. (2008). International fish trade and exchange rates: An application to the trade with salmon and fishmeal. *Applied Economics*, *40*(13), 1745–1755. https://doi.org/10.1080/00036840600905134

Vassdal, T., & Holst, H. M. S. (2011). Technical progress and regress in Norwegian salmon farming: A Malmquist Index approach. *Marine Resource Economics*, *26*(4), 329–341. https://doi.org/10.5950/0738-1360-26.4.329

Zhang, D., Myrland, Ø., & Xie, J. (2016). Firm size, commodity price, and interdependence between firm-level stock prices: The case of Norwegian salmon industry. *Applied Economics and Finance*, *3*(4), 179–189. https://doi.org/10.11114/aef.v3i4.1864

Appendix

Regression results from the firm-level analyses

In Table A.1–A.5, the results from the firm-level analyses using Equation (9) are presented. 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 A.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 & Machado, 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. ″ and ‴ indicate that the regression coefficients are significantly different from one at 5% and 1% level, respectively.

Table A.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 A.1.

Table A.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 A.1.

Table A.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 A.1.

Table A.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 A.1.