An Empirical Study of the Salmon Market

Is there a relationship between the spot price of fresh farmed salmon and a portfolio of salmon farming companies listed on Oslo Stock Exchange?

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Preface

With this thesis we will complete our master's degree in financial economics at University of Agder in Kristiansand. The process with our master thesis has been challenging, but on the other hand very exciting and has contributed to an increased knowledge about the salmon market and analyzing skills. We have throughout our process used Microsoft Excel to gather our data and STATA to analyze.

We want to thank our supervisor, Professor Valeriy Ivanovich Zakamulin, for feedbacks and helpful advice during this process. We also want to thank Kontali Analyse for providing us with an unpublished report of the salmon market they have assembled.

Written by,
Tord Magnus Hopsdal and Shandy Carl A. Nilsen

Abstract

Salmon has become one of the most important export incomes for Norway, and it is an industry that is still growing. Norway holds a big part of the salmon market, if big fluctuations occur in the salmon market, it may also have a big impact on the Norwegian business sector. It is therefore a huge motivation for us to investigate this market and the purpose of this master thesis is to examine whether if there exists a relationship between a portfolio consisting of salmon farming companies listed at Oslo Stock Exchange and the spot price of fresh farmed salmon. We therefore want to analyze this relationship and see if we can find any evidence suggesting a correlation between our two variables using different models. The analysis is based on a unique dataset with weekly observations of our portfolio and the salmon price between 2000 and 2018. We will first estimate our dataset in a vector autoregressive model and then test for causality. Later, we expand our model to an error correction model and a vector error correction model to investigate the long-term relationship. Our findings indicate a strong significant relationship between the variables, both in short-term and long-term, where the error correction term slowly corrects for previous periods disequilibrium towards the steady state. In the short-term our findings indicate a unidirectional relationship where the spot price could be predicted by previous values of portfolio index. But in the long-term there is a two-way relationship where they both influence each other.

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1 Introduction

Our world consists of 70% water, however, only 6% of the global food production originates from the ocean. 6% does not sound like a significant number, so how can the seafood industry in Norway be one of the most important export incomes for us? If we now look at this number at another perspective, we can see from the 6% we mentioned above, Norway holds 2% and therefore a total of 33% of the total seafood production (Norges Sjømatråd, 2019a). This makes Norway one of the market leaders in this industry, and it is an industry that is still in growth. If we look at Figure 1, we see that the value of salmon is almost 70% of the total seafood export in 2018. In other words, the salmon industry is a huge export market for Norway, as well as an important market if we consider how much export income it generates, job opportunities and knowledge when it comes to technology about the seafood industry. This is one of our main motivations of why we want to investigate this market and see if we can find any evidence on how the salmon price and salmon companies behave against each other. This leads us the following research question:

"Is there a relationship between the spot price of fresh farmed salmon and a portfolio of salmon farming companies listed on Oslo Stock Exchange?"

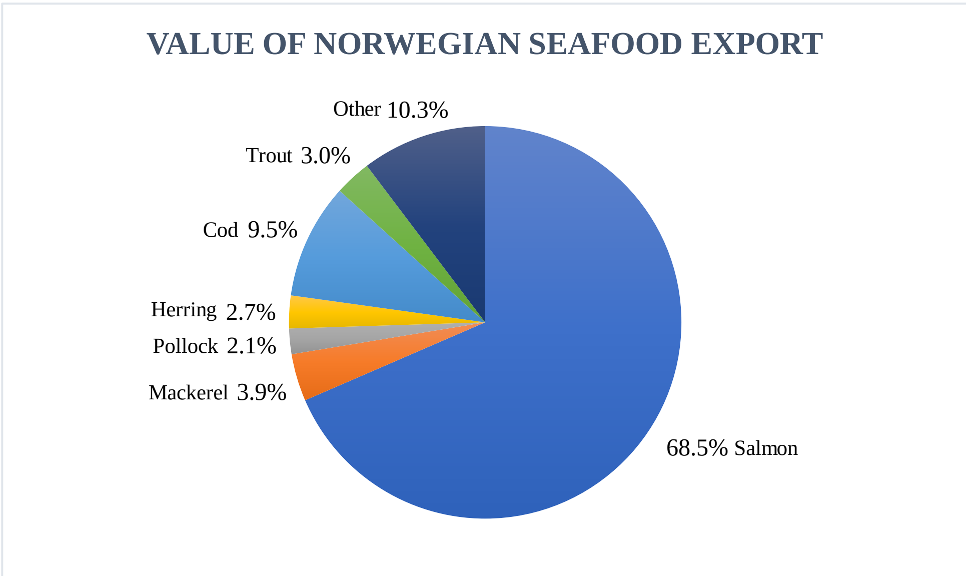

Figure 1 Value of Norwegian seafood export in 2018 (Norges Sjømatråd, 2019b).

We have now established that the salmon industry is a big part of Norway´s export production, hence, if big fluctuations occur, it may have big effects on salmon companies and investors. We have not found any research papers on our specific research question. However, there are some articles that indicate that the salmon price has an effect on salmon companies, but these statements are not supported by any previous empirical research papers (Hovland, 2019). When it comes to existing research papers it was hard to find any documented results. However, in Brooks book "*Introductory Econometrics for Finance"*, it was mentioned some examples within finance where cointegration might be expected to hold. For example, between spot price and future price for a given commodity, and between the ratio of relative prices and an exchange rate. (Brooks, 2014, p. 374). They did not mention a relationship between spot price for a given commodity and a corresponding stock price. Nevertheless, this statement from Brooks gave us motivation to find evidence for the relationship we want to investigate.

On the other hand, there are some research papers on the relationship between spot price and future price for salmon. Chen and Scholtens found out in their paper that there are some evidence suggesting cointegration between spot price and forward price. (Chen & Scholtens, 2018). Finally, we want to include Andersen, Roll and Tveterås´ paper *"The Price Responsiveness of Salmon Supply in the Short and Long Run".* They look at supply elasticity, and their results indicates that salmon producers have limited power to respond to price changes in the short-term. However, in the long-term, salmon producers have a more flexible production, meaning they can change production based on changes in the price (Andersen, Roll & Tveterås, 2008). This paper gave us some indications that there also might be a long-term relationship between changes in salmon price and stock price for salmon farming companies. It increased our motivation to look for empirical evidence for a long-term relationship using advanced methodology and models. There might be a significant risk for salmon companies and investors if the salmon price suddenly decreases, especially if there is a long-term relationship. It is therefore a huge motivation for us to analyze these variables and our goal is to find a causal relationship, and if any, describe it.

The models we use in our study are the vector autoregressive model, error correction model and vector error correction model. They all have different approaches when estimating a relationship, and we want to compare the results we achieve and see which model that suggests the most interesting evidence.

Based on our findings, there is a strong significant long-term relationship between these two variables mentioned. In the short-term, we have a unidirectional relationship where the spot price of salmon could be predicted by previous values of our portfolio index, but the portfolio index could not be predicted by previous values of the spot price of salmon. However, in the long-term there is a cointegrated relationship where they influence each other.

The rest of the thesis is organized as follows. Section 2 covers general information about the salmon market in Norway, the international salmon market, demand and supply, and our portfolio index where we briefly mention the companies in our portfolio. In Section 3, we present and explain the dataset we use, where we have gathered the dataset, and how we restricted our time frame. Section 4 covers the methodology we have used in our analysis, and Section 5 includes all our empirical results from our different models. We discuss our findings in Section 6, where we also point out how we could have improved our analysis and what we could have done for further research on this specific research question. Lastly, we present our final conclusions in Section 7.

2 Domestic and international salmon market

2.1 Salmon market in Norway

We have been fishing in Norway for generations, but it was in the 1970s we first started using cages for salmon to increase the production level. However, it all started before this when the pioneers of salmon fishing started experimenting on how they could implement different methods of fishing. This resulted in both positive and negative experiences, but this information was quickly spread around in the industry, and step by step the knowledge started to increase. They started in the 1970s by moving land-based fishing facilities out in the ocean. This resulted in increased production, reduced cost, reduced risk, and was a revolutionary step for the market. The technology of fishing facilities has increased drastically from the 1970s, and they are still trying new technology to optimize their productions (Norges Fiskeri- og Kysthistorie). From Figure 2, we can see how the quantity of salmon exported from Norway has increased together with the salmon price. The quantity exported had a growth at almost 200% from 2000 to 2012 when the salmon price just had some slightly adjustments up and down, but after 2012 the quantity exported has been more or less stable. However, in the period with the stable growth, the salmon price can show a drastic increase (Statistics Norway, 2019a). This is an indication that the demand of salmon was still high after the supply was starting to get stable and may be one of the reasons why we have seen such a remarkable increase in salmon price the last seven years. If the quantity of salmon exported had continued to grow after 2012 like it did before, we might not have seen such an increase in price.

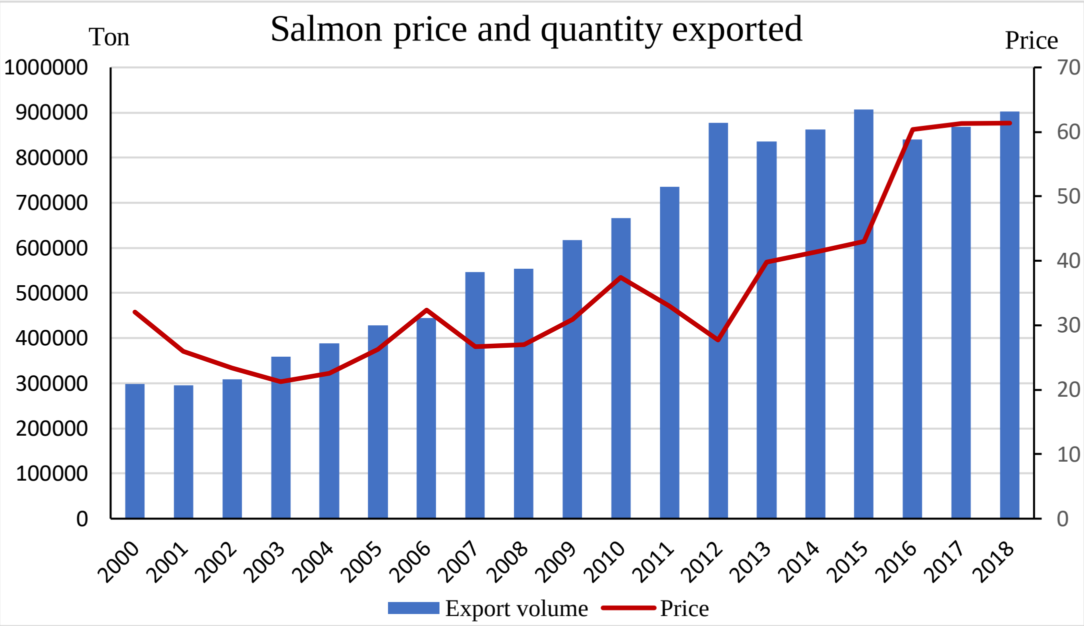

Figure 2 Salmon price and quantity exported from Norway since 2000-2018 (Statistics Norway, 2019a).

Another possible factor of why we have seen such a high increase in salmon price and demand from 2012, is how the sushi market has entered and rapidly spread all around Europe. This factor has increased the demand for salmon, and especially Norwegian salmon which is known to be one of the best in the market (Stabell, 2014). A high demand in Europe with a stable supply exported from Norway is a possible explanation of the price increase. We are continuing to see an increase in the beginning of 2019. In February 2019, the value of salmon exported increased by 11% if we compare it by the same month last year. This increase has also reflected over to salmon companies, where for example Mowi can show a 12% growth and Greig Seafood a 13% growth from January to March this year. This gives us a strong indication that salmon price is a big driving force for salmon companies (Hovland, 2019).

The volatility of salmon price has increased together with the increasing salmon price, and continues to affect salmon farming companies, which we mentioned above (FAO, 2018). The volatility in the salmon market was examined by Øglend in 2013, where he looked at several factors that most likely contributed to a more volatile market. He looked at restriction in total allowable biomass, which was introduced in 2005, the establishment of Fish Pool in 2006, developments in demand for salmon and the Chilean salmon crisis that started late 2008. His conclusion was that the volatility of Atlantic salmon from Norway has had an increasing trend since the start of year 2000 (Øglend, 2013, p. 285 & 297).

2.2 Salmon companies listed on Oslo Stock Exchange

There are nine companies listed on Oslo Stock Exchange that participate in the salmon market. Some companies control all aspects of the production, some companies have only fishing facilities and some companies also participate in other markets, for example white fish. However, we decided to include them all because salmon is a huge part of every company.

2.2.1 Austevoll Seafood (AUSS)

Austevoll Seafood was established in 1981 and have since then acquired a number of companies within their business area. They operate as a global company where they have several subsidiaries that operate with different activities within their complementary nature. This include fishing vessels, canning plant, salmon farming, freezing plants and marketing and sales. They started in the eighties and nineties with pelagic wild catch before they started to increase their business in the early 2000s by acquisition of several companies, including the salmon industry. In 2006 they were listed on Oslo Stock Exchange where they have had a 268% growth rate overall, with a highest closing price at 101.1 NOK, and a lowest closing price at 6.26 NOK. However, since Austevoll Seafood operates in more industries than just salmon, for example pelagic fish, the stock price is most likely affected by other factors than just salmon (Austevoll Seafood ASA, 2019).

2.2.2 Bakkafrost (BAKKA)

Bakkafrost was established in 1968 and has since then become one of the leading producers of salmon. This company is one of the most vertically integrated producers of salmon in our portfolio and controls all aspects of production. In 2009 they had an all-time high when it comes to production volumes, operating profit and revenue, and decided to list their company on Oslo Stock Exchange the year after. They have an overall growth rate at 1652%, with a highest closing price at 466.4 NOK, and a lowest closing price at 25 NOK (Bakkafrost, 2019).

2.2.3 Grieg Seafood (GSF)

Grieg Seafood was established in 1992 and have over the years become one of the leading producers of salmon. They have farming facilities located in Rogaland, Finnmark, Canada and Shetland, where they all produce salmon. What started as a small company in Norway in 1992, has now become a global company with facilities all around the world. Their operations are built on experience, innovation and technological solutions, and in 2007 they implemented a strategy where they can recycle fresh water to save energy which has provided great results. They have an overall growth rate on 359%, with a highest closing price at 100 NOK, and a lowest closing price at 2.4 NOK (Greig Seafood, 2019).

2.2.4 Lerøy Seafood Group (LSG)

Lerøy is a world leading seafood company with roots back to 1899. What started as a small company with main focus on white fish, has now expanded to a global production of salmon and trout, and sale and distribution of seafood. They are exporting seafood to 80 different countries and had in 2017 a turnover on 18.6 billion NOK. Lerøy has from the start been a pioneer within Norwegian and international seafood industry and are often first in line to try different solutions and different markets. They have an overall growth rate 2932%, with a highest closing price at 60.65 NOK, and a lowest closing price at 0,96 NOK (Lerøy, 2019).

2.2.5 Norway Royal Salmon (NRS)

Norway Royal Salmon was established in 1992 by 34 different salmon farmers who wanted to run and operate a sale and marketing division for their products. They started early with acquisitions by different salmon facilities all over Norway, and their strategy is to grow from a medium-sized company to one of the leading salmon companies in Norway. They were listed on Oslo Stock Exchange in 2011 and since then they have a total growth rate at 959%, with a highest closing price at 194.8 NOK, and a lowest closing price at 5.12 NOK (Norway Royal Salmon, 2019).

2.2.6 Mowi (MOWI)

Mowi was established in 1964 and started working with salmon the year after. They have become the biggest fish farming company in Norway and one of the market leaders in the industry. They cover the whole supply chain in Norway, all the way from producing salmon in facilities to sale and marketing. They have over the years become a global company with businesses in 24 different countries and they are the only company in our portfolio that is listed on New York Stock Exchange as well as Oslo Stock Exchange (Mowi, 2019).

2.2.7 SalMar (SALM)

SalMar was established in 1991 and have over the past 25 years went from a one concession fish farm facility, to the third largest farming company for salmon in Norway. Their production has become vertically integrated as well as they have started to get significant ownership interest in UK. They were listed on Oslo Stock Exchange in 2007 and has a total growth rate at 1275%, with a highest closing price at 381.39 NOK, and a lowest closing price at 14.39 NOK (SalMar, 2019).

2.2.8 The Scottish Salmon Company (SSC)

The Scottish Salmon Company was established in 2009 and is a 100% Scottish based producer. They control every part of the value chain and are now exporting out to 26 countries around the world. Salmon is their only focus, although they are a fairly new company, their salmon is known to be one of the best. They were listed on Oslo Stock Exchange in 2010 and have had a total growth rate at 255%, with a highest closing price at 11.9 NOK, and a lowest closing price at 1.94 NOK (The Scottish Salmon Company, 2019).

2.2.9 Salmones Camanchca (SALMON)

Salmones Camanchca was established in 1965 and started by catching and processing shrimps and lobsters. In 1980 they saw possibilities to expend their business further, which resulted in a strategy that was more focusing on agriculture, and by that salmon. They have had a tremendous growth from this day and have established an international market position exporting to more than 50 countries. They were listed on Oslo Stock Exchange in the beginning of 2018 and have had a total growth rate at 32.7%, with a highest closing price at 61.5 NOK, and a lowest closing price at 44.1 NOK (Camanchca, 2019).

2.3 International market

When it comes to Atlantic salmon, Norway is a big market leader and held more than 50% of the global production in 2017. One of the reasons why Norway is such a dominant market leader is because of the perfect conditions along our coastline (EY, 2017). However, there are other countries we want to mention before starting on our analysis. The second largest salmon producer is Chile. Salmon production has over the last 20 years become one of the most important export drivers in Chile. There is not a natural habitat for Atlantic salmon in Chile as it is in Norway, however, conditions like stable sea temperatures make it well-suited for breeding in fishing facilities (International Salmon Farming Association, 2018). During the first half of 2018, Chile´s overall production increased by 19% where Atlantic salmon accounted for 81.6%. Together with a high salmon price, Chile can show a noteworthy increase in the salmon market. As a result of what they have done the last 20 years, the salmon industry has provided education opportunities as well as significant improvements in quality for its inhabitants. Norway and Chile have by far the largest salmon production in the world, additionally, Norway and Argentina agreed in 2018 to a cooperation to study the possibility of developing salmon farming in Argentina. There are in other words big developments in South America when it comes to salmon farming, where Chile is the market leader in that region (FAO, 2019). Table 1 represents the production volume for each country when it comes to salmon. As we have mentioned above, Norway and Chile take a big part of the market, followed by United Kingdom, Canada, Faroe Islands and Australia.

Country	2017	2018	change 17-18
Norway	1 207 900	1 253 400	4%
Chile	564 000	677 000	20%
United Kingdom	177 000	153 000	-14%
Canada	139 000	146 200	5%
Faroe Islands	80 300	71 700	-11%
Australia	61 200	61 300	0%
USA	21 700	19 000	-12%
Ireland	17 000	14 300	-16%
Iceland	11 500	13 600	18%
Others	10 700	9 100	-15%
Total	2 290 300	2 419 000	5%

Table 1 Production volume in ton of Atlantic salmon for each country (Kontali Analyse, 2019).

2.4 Demand and supply

Demand and supply will always have an effect on how the price of any product will evolve in the future, and the salmon price is no exception. When it comes to demand, there are a lot of different factors that may have an impact. First of all, an increasing world population also increases the demand for food. A global population growth together with a growing middle class will increase the demand for food, and salmon may be one of the products that will be affected by this demand. There are several reasons for that, and one of them is the health issues. Health benefits of salmon have increasingly been promoted the last decade from global health authorities. The fact that salmon for example contains high quality proteins, Omega-3, vitamin D and B12 vitamins, makes it desirable for the world population. Another possible factor is that salmon is a climate friendly product if we compare it to other protein sources. Environmental issues are getting more and more attention and may have an effect when the population is deciding what kind of protein source they want to consume. Lastly, the protein from salmon is produced at a very efficient way if we compare it to for example chicken, pork or cattle. By efficient we mean how much animal protein that is produced per unit compared to how much protein they are fed. These three examples may be one of the reasons why salmon has a high demand in the world. As a healthy, climate friendly and resource efficient product, it fits well with the global trends (Marine Harvest, 2018, p. 18-21).

The global supply of Atlantic salmon has tremendously increased if we go ten years back and has an annual growth at 8% from 1995. However, in the recent years, the annual growth has diminished to 5%. There are however some logical explanations to this. One of the reasons is that the production has come so far that biological boundaries are being pushed to the limit. It is not only the industry or regulations that controls the supply, we now have to include biological factors as a measurement. We have to make some technological progress if we want to continue at this pace we have seen the recent years. Another reason of why the supply has diminished is because it is not enough feasible coastline for salmon production. For instance, optimal sea temperature range between 8° to 14° Celsius, at the same time that there must be a certain current that provides enough water through the farm. This restricts the supply power of salmon farming companies and may be one of the reasons why the supply has been stagnating (Marine Harvest, 2018, p. 25-26).

If we now compare the high demand where health, climate friendly and resource efficiency may increase the demand, together with the supply where we have seen a diminishing trend where biology and not enough feasible coastlines may be a factor, it is possible that this is one of the reasons why the salmon price has increased the last seven years.

3 Data

In our master thesis we have used different sources to assemble our data for our analyze. First, we got access to a financial database called Titlon through our university (Titlon, 2019). We could then find the data we needed for our portfolio index. The stock prices in our portfolio index are adjusted, which means that the closing price we use in our analyze is adjusted for dividends.

The second dataset we wanted to assemble was the salmon price. We find that the Fish Pool Index could be an accurate index for our analyze (Fish Pool, 2019b). However, since Fish Pool could not provide salmon price from before 2006, we decided to use the salmon price from Statistics Norway because they could provide data from 2000 (Statistics Norway, 2019a). We then had a time frame from 2000 in week 1 where our salmon price started, to 2018 in week 28 where our stock price ended, on a weekly frequency.

Since data from Statistics Norway is registered at the end of the week, we also selected the closing price at the end of each week for our stock price because this price would be the closest estimate where both stock price and salmon price were registered. At the end we had 964 observations for each variable.

3.1 Portfolio Index

Our portfolio consists of nine companies listed on Oslo Stock Exchange. They are all participants in the salmon market, but some of them are also operating in other markets like white fish. However, we decided to include them all because the salmon industry is a big part of every company. We could have analyzed each of the companies separately, but this procedure would perhaps have been more exposed by risks that are very specific to the corresponding company. To avoid this, we made an equally weighted portfolio where the firm specific risk for each company would be reduced by diversification.

3.1.1 Stock price and portfolio index

As mentioned above, we use the financial database Titlon to gather the data we need for our portfolio. We could find data from the day each company was listed on Oslo Stock Exchange to week 26 in 2018. Titlon could not provide data further than week 26 in 2018, which is the reason why our time frame ends there. We then limited our time frame from week 1 in 2000, because Statistics Norway does not provide data further back. When we had gathered all the data for each company and calculated the returns, we started making a portfolio. The start for our equally weighted portfolio index is in 2000 week 1. At this point it was only one company listed on Oslo stock Exchange. Since we have calculated the returns for each company, which means $r_t = \frac{P_t}{P_{t-1}} - 1$, we start our portfolio index in week 1 at a selected value at 100 NOK, and thereafter calculate the returns from each company equally weighted from the day they were listed. This means that from 2000w1 to 2002w22, MOWI contributes 100% in our portfolio index. Next, from 2002w23 to 2006w42, MOWI and LSG contributed by 50% each. This continues all the way to SALMON, where they all contribute with $\frac{1}{9}$ part each. From Table 2, we have calculated the descriptive statistics of every company in our portfolio. This statistic represents when each company started in our portfolio, as well as the number of observations, mean, standard deviation, minimum and maximum.

Company	Start	Observation	Mean	Std. dev	Min	Max
MOWI	2000w1	964	0.19%	9.66%	-54.17%	60.87%
LSG	2002w23	838	0.55%	5.11%	-17.80%	57.06%
AUSS	2006w43	610	0.35%	5.18%	-23.57%	30.83%
SALM	2007w19	581	0.57%	4.96%	-19.35%	20.45%
GSF	2007w26	575	0.49%	6.96%	-28.15%	48.63%
SSC	2009w29	414	0.48%	6.02%	-24.61%	34.91%
BAKKA	2010w13	431	0.76%	4.23%	-15.79%	15.58%
NRS	2011w15	376	0.77%	5.22%	-21.12%	17.65%
SALMON	2018w5	21	1.43%	3.90%	-5.51%	13.35%

Table 2 Descriptive statistic of every company´s return, sorted after the day they were included in our portfolio index.

Afterwards, we convert our portfolio index from a linear scale to a logarithmic scale because we then get the change between two values as a ratio instead of the change in differences between two values. This gives us a more distinct graph of how the portfolio has developed. From Figure 3, we can see how our portfolio index has developed the last 18 years, and we will first look at the period between 2000 and 2011. We cannot see any clear trend in this period, it has rather more instability where there is no clear pattern to notice. There might be some indication of an increasing trend between 2003 and 2012, but there are still some large fluctuations upwards and downwards. However, if we now look at the period between 2012 and 2018, there is a clear trend upwards. This may indicate that the salmon market has become more stable, with a constant demand for the product our companies in our portfolio can offer.

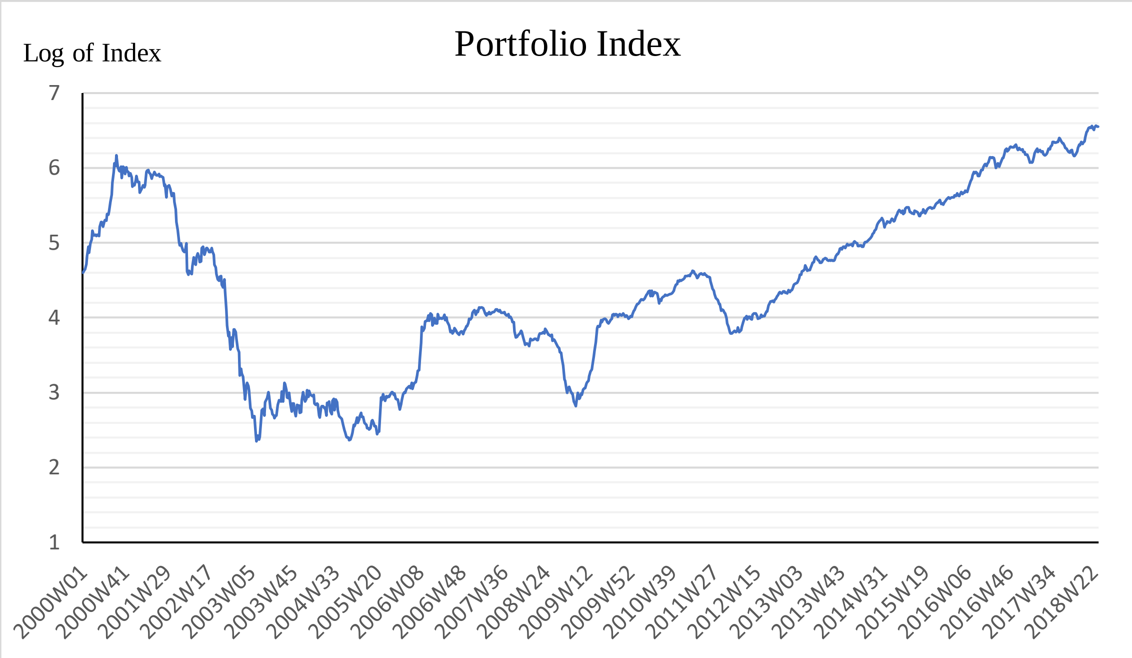

Figure 3 Portfolio Index in logarithmic scale.

From the descriptive statistics in Table 3 which consists of the portfolio return, we have taken out some key numbers from the portfolio. We have 964 observations with a mean stock return at 0.38% and a standard deviation at 6.04% over a period from 2000 to 2018. The highest return is at 33.69%, and the lowest return is at -31.11%.

Observation	Mean	Standard deviation	Min	Max
964	0.0038	0.0604	-0.3111	0.3369

Table 3 Descriptive statistic of the portfolio return.

3.2 Salmon price

As mentioned above, the salmon price has had a positive growth the last seven years, but there are different approaches we can use when calculating the price. We have looked at two different sources, Fish Pool and Statistics Norway.

3.2.1 Fish Pool

Fish Pool was established in 2005 in Bergen and was the first international and authorized marketplace for buying and selling salmon contracts. They do not trade physical fish, but instead offer financial forward contracts which is reflected on the actual spot price for Fresh Atlantic Salmon. Therefore, Fish Pool has established a market place called Fish Pool Index for the spot price which is the basis of their financial salmon contracts at Fish Pool. Fish Pool Index consists of three different index which are Nasdaq Salmon Index, Fish Pool European Buyers Index and Statistics Norway. Fish Pool Index and forwards contracts are published on a weekly basis (Fish Pool, 2019a).

3.2.2 Statistics Norway

Statistics Norway (SSB) are publishing an average weekly export price of fresh and frozen salmon. The price is a statistical value when crossing the Norwegian border including the transport cost, also called FOB-value (Free On Board). Customs, added values or other expenditures are not included in the price. The statistics are based on administrate tasks obtained from the Custom Information System with the business sector (Statistics Norway, 2019b).

Fish Pool and Statistics Norway are both good sources when determining the salmon price, however we decided to use the weekly salmon price from Statistics Norway. It is also worth mentioning that both prices from SSB and FPI follows each other very closely (see Figure 4), but we decided to use Statistics Norway because they could give us a larger time frame in our analysis. As mentioned above, Statistic Norway provides data at the end of each week from year 2000. We could then gather our data in a time frame between 2000 and 2018. When we had our time frame, we converted it from a linear scare to a logarithmic scale because we want to look at the change in ratios between the variables.

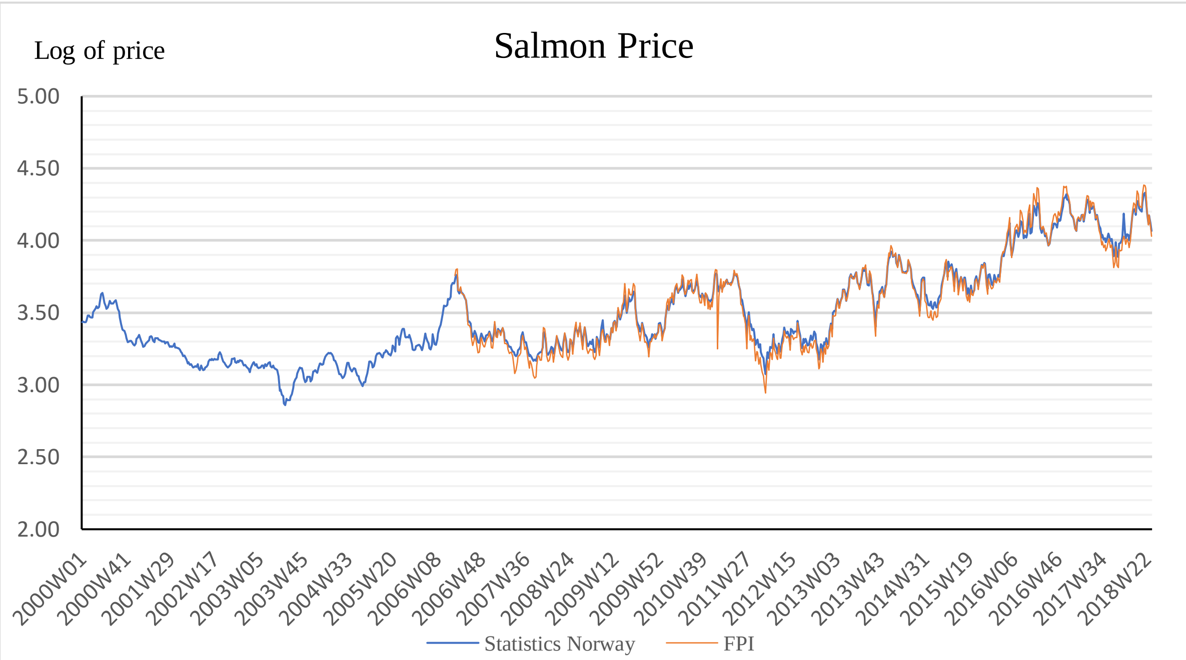

Figure 4 Salmon price in logarithmic scale.

From Figure 4, we can see how the salmon price has evolved over the past 18 years. We also here look at two different time frames and see how it has progressed, and we start with the beginning in 2000 to the end of 2011. It is hard to see any clear pattern, but it is quite stable with some increase and decrease occasionally, until we see a downwards line from week 20 to week 43 in 2011. If we now look at the time frame between 2012 and 2018, we can see that there is an upwards trend. It is not as strong or distinct as the portfolio index, and there are also more fluctuations upwards and downwards, but overall there is an upward trend.

From the descriptive statistic in Table 4, we have pointed out some key numbers from the changes in the spot price of salmon. From the 964 observations, we have a maximum return 16,88%, and a minimum return at -12.84%, with an overall mean at 0.15% and a standard deviation at 4.01%.

Observation	Mean	Standard deviation	Min	Max
964	0.0015	0.0401	-0.1284	0.1688

Table 4 Descriptive statistic of the salmon price return.

4 Methodology

There are different econometric techniques when forecasting the relationship between the salmon price and companies listed on Oslo Stock Exchange. In our thesis, we have three main econometric models: Error correction model (ECM), vector autoregressive model (VAR) and vector error correction model (VECM).

One of the main purposes with ECM is to determine if there exist a cointegrating relationship between our variables. This was first introduced by Yule back in 1926 where he tried to find out why we sometimes got, what he called nonsense-correlations, between time series (Yule, 1926). This is later been introduced as spurious regressions. It was not before the beginning of 1980, where Granger was one of the first to expose the danger of using non-stationary time series between variables, we were introduced to the topic of cointegration and error correction models (Granger, 1981). Later, the idea of linear relationship between non-stationary time series was introduced (Granger & Weiss, 1983). Based on these papers, Engle and Granger worked together with an extended paper where they looked at the long-term relationship between time series. They introduced it as the Engle & Granger two-step model (Engle & Granger, 1987). It is the two-step model we use in the second section in our analysis, and an important part of this model is the Augmented Dickey-Fuller (ADF) test. This test indicates if the time series follows a random walk by testing for unit roots (Dickey & Fuller, 1979).

However, Engle & Granger have some weaknesses where it can only have one variable designated as the dependent variable. We have therefore introduced Johansen´s work on this issue, where we treat all variables as endogenous, and included a vector error correction model (Johansen, 1995). We also included a vector autoregressive model where we have implied Sims work, who is one of the main researchers that have advocated for VAR models (Sims, 1990).

Additionally, we used "*Introductory Econometrics for Finance"* from Brooks (Brooks, 2014) and "*Principles of Econometrics"* from Hill, Griffith and Lim (Hill, Griffith & Lim, 2012) to get a better understanding of the methodology we will use.

4.1 Regression

Ordinary least squares (OLS) estimation are one of the cornerstone models that are used in general terms to describe and evaluate the relationship between a certain variable and one or several other variables. Based on these estimations we could attempt to draw conclusions that says something about movements in a given variable that are yet to be observed. (Brooks, 2014, p. 75). We specify the statistical model to a linear relationship as:

$$y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_t X_t + u_{t,} \tag{1}$$

where y_t is the dependent variable, also called regressand, and X_i´s are the independent variables, also called regressors. Both of these variables are observable. u_t is referred as an error term, and this error term is not observable. The coefficients, β_i, are unknown parameters, that measures how the expected value of the dependent variable, y_i, given the values of the independent variables, X_i, has changed. In other words, the β_i coefficients explain the causal relationship between the y_t and the X_i´s.

There are five underlying assumptions when we talk about linear regression, and when these assumptions are met, it is said that our regression model for best linear unbiased estimator, or BLUE as it is called. These underlying assumptions are (Verbeek, 2012, p. 7-18):

1. $E[u_t] = 0$: The expected value of the errors is zero.
2. $V[u_t] = \sigma^2 < \infty$: The variance of the errors is constant and finite for all values of X_t. This is called homoscedastic.
3. $cov(u_t, u_{t+1}) = 0$: The errors are uncorrelated to each other.
4. $cov(u_t, X_t) = 0$: No correlation between the errors and the related X-variate.
5. $u_t \sim N(0, \sigma^2)$: The errors are normally distributed.

4.2 Stationarity

A time series is a variable that we may observe over time, where an example may be the gross domestic product. The variable is called a stochastic or random process since the variable cannot be perfectly predicted. Let y_t be a time series, then y_t is defined as stationary if it has a constant mean and variance over time. Additionally, the covariance between two of the values from the series does not depend on the actual time at which the variables are observed, but on the length of time separating those two values (Hill, Griffith & Lim, 2012, p. 475-477).

1.	$E(y_t) = \mu$	Constant mean.
2.	$Var(y_t) = \sigma^2$	Constant variance.
3.	$Cov(y_t, y_{t+s}) = Cov(y_t, y_{t-s}) = \gamma_s$	Cov. depends on s, not t.

Let γ_t be a non-stationary time series. If γ_t must be differenced d times before it becomes stationary, then it is said that γ_t is integrated of order d and may be denoted as: $\gamma_t \sim I(d)$. Stationary time series may be denoted as $I(0)$, while an $I(1)$ time series contains one unit root. It is said that γ_t has as many unit roots as the number of times it needs to be differenced before it becomes stationary. When we look at how an $I(0)$ time series behaves against time, we see that it crosses the mean value frequently, while an $I(d)$ serie with $d > 0$ drifts far away from their mean and rarely crosses their mean value (Brooks, 2014, p. 259).

4.2.1 Spurious regression

One of the main reasons why it is important for us to know if a time series is stationary or non-stationary before we start on a regression analysis, is that there is a risk of obtaining results that may confirm significant relationship when there is none. This may occur when non-stationary time series are used in our regression analysis, and these regressions are called spurious regressions (Hill, Griffith & Lim, 2012, p. 472).

4.3 Autoregressive model

Autoregressive (AR) models has one variable, y_t, where the current value of y_t depends on the values that the variable had in earlier periods plus an error term. An AR model may be presented as follows:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + u_t, \tag{2}$$

where u_t is the error term which is a white noise disturbance. An AR model of order p can be denoted as $AR(p)$, where p is the number of lags considered in the model (Brooks, 2014, p. 360).

4.4 Unit Root Tests for Stationarity

Testing for unit roots is a critical aspect of modern time series analysis. When testing for unit roots, one could determine whether certain time series has a constant mean as well as constant variance over time. In other words, if the time series is stationary. OLS regression analysis assumes that the variables are stationary, and when non-stationary variables are used, we might obtain results that are spurious. One of the most used unit root tests is the Augmented Dickey-Fuller (ADF) test (Silva, Swankoski, Watt, Bullard & Iqbal, 2014, p. 157-158).

4.4.1 Dickey-Fuller test

As mentioned above, ADF test is used to test if whether a time series is stationary or non-stationary. Autoregressive, random walk models and stochastic processes may include or exclude a constant term and a time trend, and there are three ADF tests that are designed to take count of the constant terms and time trends.

Before we start defining the three different ADF tests, we will include the AR(1) model because the ADF tests are based on this model. The AR(1) process $y_t = \rho y_{t-1} + u_t$ is defined stationary when |ρ| > 1, and on the other hand, defined a non-stationary random walk process when ρ = 1. Hence, the value of ρ must be examined to determine stationarity or not.

- We have the AR(1) model: $y_t = \rho y_{t-1} + u_{t.}$
- Then we subtract y_{t-1} on both sides: $y_t - y_{t-1} = \rho y_{t-1} - y_{t-1} + u_{t.}$
- Where $y_t - y_{t-1} = \Delta y_t$: $\Delta y_t = (\rho - 1)y_{t-1} + u_{t.}$
- Where $(\rho - 1) = \gamma$: $\Delta y_t = \gamma y_{t-1} + u_{t.}$

Then, we can write the hypothesis in terms of either γ or ρ. Common for these three tests is the formulation of the hypothesis. This means that if we reject the null hypothesis, we have evidence of stationarity.

H_0: $(\rho - 1) = 0$ (Non-stationary) H_1: $(\rho - 1) < 0$ (Stationary)

Dickey-Fuller test 1– No constant and No trend:

$y_t = \rho y_{t-1} + u_t$ where $t = 1, 2, 3, \ldots$ and $y_0 = 0$.

The first Dickey-Fuller test does not include a constant or trend. If the ρ-value equals 0, we can reject the null hypothesis and confirm stationarity.

Dickey-Fuller test 2 – With constant and No trend:

$y_t = \alpha + \rho y_{t-1} + u_t$ where $t = 1, 2, 3, \ldots$ and $y_0 = 0$.

The second Dickey-Fuller test we include a constant in our model, but we still have no trend. However, the null hypothesis will still be rejected if the ρ equals 0, and we can confirm stationarity.

Dickey-Fuller test 3 – With constant and with trend:

$y_t = \alpha + \lambda t + \rho y_{t-1} + u_t$ where $t = 1, 2, 3, \ldots$ and $y_0 = 0$.

The final Dickey-Fuller test, we include both constant and trend. Although, it is still the same hypothesis as the two tests above; we reject the null hypothesis if ρ equals 0, and we can confirm stationarity (Hill, Griffith & Lim, 2012, p. 484-485).

4.5 Lag-order selection criterions

There are two different methods when selecting the lag order in VAR models. The first one is by using a likelihood ratio test based on X^2- distribution, while the other is likelihood based on information criterions (Nilsen, 2001, p. 1). The information criterions are a useful instrument to determine the optimal lag length in different VAR and VECM models.

In this section, the four different information criterions, as well as a sequence of likelihood ratio and their formulas will be explained. Before this, we have to define the log likelihood (LL) for a VAR model that was introduced by Hamilton (Hamilton, 1994, p. 295-296). The LL can be written as:

$$LL = -\left(\frac{T}{2}\right)\left\{\ln\left(\left|\hat{\Sigma}\right|\right) + Kln(2\pi) + K\right\}, \tag{3}$$

where T is the number of observations, K is the number of equations, and $\hat{\Sigma}$ is the maximum likelihood estimate of $[u_t u_t']$, where u_t is a $K \times 1$ vector of disturbances. With the LL we may estimate the likelihood ratio (LR), by letting LL(j) be the value of the LL with j number of lags which produces the LR statistic for lag order j (Hamilton 1994, 295-296):

$$LR(j) = 2\{LL(j) - LL(j-1)\}. \tag{4}$$

The other model-order statistics considered are the final prediction error (FPE), Akaike´s information criterion (AIC), Schwarz´s Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC). The first model-order statistics at interest is the FPE, that may be presetented as (Lütkepohl 2005, 147):

$$FPE = |\Sigma_u|\left(\frac{T+Kp+1}{T-Kp-1}\right)^K. \tag{5}$$

The other three information criterions, AIC, SBIC and HQIC, are quite similar, but they are computed by including a constant term from the LL. They may be written as:

$$AIC = -2\left(\frac{LL}{T}\right) + \frac{2t_p}{T}, \tag{6}$$

$$SBIC = -2\left(\frac{LL}{T}\right) + \frac{\ln(T)}{T} t_p, \tag{7}$$

$$HBIC = -2\left(\frac{LL}{T}\right) + \frac{2ln\{\ln(T)\}}{T} t_p, \tag{8}$$

where p is the number of lags and t_p is the total number of parameters considered in the model. These information criterions are computed and the lag-length with the lowest value are suggested by the corresponding information criterion. The lag-length that has the highest number of suggestions are chosen as the optimal lag-length.

4.6 Vector autoregressive model

The vector autoregressive (VAR) model has become one of the most successful, effective and easy to use models when we have a multivariate time series to analyze. It has proven to be especially valuable when it comes to describing dynamic behavior of economics (Zivot & Wang, 2006, p. 385). VAR models are often used for causal modelling and contains a system of regressions with more than one endogenous variable. In principle, VAR models are simple multivariate models where each variable may be explained by its own previous values and the previous values of the other variables in the model. A VAR model that contains only two different variables explains the causal relationship between these two variables, and is given as follows:

$$y_t = \beta_{1,0} + \sum_{i=1}^{N-1} (\beta_{1,i}\, y_{t-i} + \alpha_{1,i}\, X_{t-i}) + u_{1,t,} \tag{9}$$

$$X_t = \beta_{2,0} + \sum_{i=1}^{N-1} (\beta_{2,i}\, y_{t-i} + \alpha_{2,i}\, X_{t-i}) + u_{2,t,} \tag{10}$$

where X_t and y_t are two different variables that explains the causal short-term relationship between them and their own previous N values for both variables, where N is the number of lagged values that is considered in the model. The random errors, $u_{i,t}$, are white noise disturbance terms. These errors terms are correlated with $E(u_{i,t}) = 0$ and $E(u_{1,t}, u_{2,t}) = 0$ (Holden, 1995, p. 159).

There are several advantages in the VAR model. One of these advantages is how flexible and expandable VAR models are, and its ease of generalization. A VAR model of n number of variables with l number of lags would have $(n^2 l) + n$ parameters, included constants in each equation. A generalized VAR model in matrix form may be given as:

$$z_t = A_0 + A_1\, z_{t-1} + \mathrm{A}_2\, \mathrm{z}_{t-2} + \cdots + \mathrm{A}_\mathrm{k}\, z_{t-k} + u_t, \tag{11}$$

where A_i is a matrix of parameters, z is a vector of variables, and u_t is a vector random error terms (Holden, 1995, p.159).

One of the most important advantages is that there is no need to specify which of the variables that are endogenous or exogenous, we assume that all variables are endogenous, which means that the variables are affected by elements in the system. (Brooks). The last advantage we want to include is that the VAR model has been argued, for example in Sims 1980, that the forecast we generate by a VAR is often better than "traditional structural" models (Brooks, 2014, p. 329). McNees also mention this advantage in his article where he looked at gross national product and unemployment rate. The result were more accurately when using a VAR model instead of using a "traditional" model (McNees, 1986, p. 13-14).

4.7 Granger causality

A Granger causality test may be used to determine if the observations in a time series can be used to predict observations in the future for another time series. If a variable X can be used to predict the future value of another variable y, it is said that y is Granger-caused by X (Granger, 1980, p. 330). This requires that y may be predicted by the lagged values of both y and X with a better prediction, rather than using only the lagged values of y. In other words, Granger causality means that if X Granger-causes y, then X is a useful predictor of y. The Granger causality statistic is based on the F-statistic and tests the coefficients on all values of one variable are zero. However, in large sample size the F-test can lose power and the chi-square test is preferred. To investigate whether y is Granger-caused by X, Equation 9 may be used to consider if the $\alpha_{1,i}$ is significantly different from zero such that the null hypothesis and the alternative hypothesis may be written as:

$$H_0\colon \alpha_{1,1} = \alpha_{1,2} = \cdots = \alpha_{1,N} = 0. \qquad\qquad H_1\colon \alpha_{1,i} \neq 0 \text{ for at least one } i = 1, 2, \ldots, N.$$

If the null hypothesis is rejected, it is said that y is Granger-caused by X (Stock & Watson, 2012, p. 580).

4.8 Cointegration

Michael P. Murry described cointegration in his article as follows: *"If there exist a stationary linear combination of non-stationary random variables, the variables combined are said to be cointegrated"* (Michael Murry, 1994, p. 37).

An important reason why we need to know if a time series is stationary or non-stationary is because when non-stationary time series are used in regression models, we might obtain spurious regressions. A spurious regression may imply a significant relationship when none is present. The exception is when we have two non-stationary time series, y_t and X_t, that are I(1) and the linear combination of these two is I(0), then y_t and X_t are said to be cointegrated. Cointegration means that these variables share a common stochastic trend, and there exists a long-term relationship.

To test if y_t and X_t are cointegrated we need to test a linear combination of these variables for stationarity. For example, the error term in the regression model $y_t = \beta_0 + \beta_1 X_t + u_t$. Since the error term, u_t, are not observable, we test if the OLS residuals are stationary. If u_t is stationary, y_t and X_t will never diverge too far from each other, and there exists a long-term relationship among the variables (Hill, Griffith & Lim, 2012, p. 488-489).

4.9 Error correction model

An error correction model (ECM) is used to predict the relationship between two time series, and estimate how a time series affects another, both in short-term and long-term. For example, consider two time series y_t and X_t, the ECM may be predicted as follows:

$$\Delta y_t = \gamma_0 + \gamma_1 \Delta x_{t-1} + \gamma_2 u_{t-1} + v_t, \text{ where } u_{t-1} = (y_{t-1} - \beta_0 - \beta_1 X_{t-1}). \qquad (12)$$

The ECM shows a two folded effect in the prediction of y, where the first is a consequence of changes in the regressor (X_t), and the second is a correction of a potential disequilibrium from the previous period. In the interpretation of this model, there are three coefficients of interest. The first coefficient is γ_0, which is the intercept, and stays at the same level for all t. The second coefficient is γ_1, which represents the short-term relationship between ΔX_t and Δy_t. The next coefficient is the γ_2, which refers to the proportion of the last period error that is corrected for. In other words, the speed of adjustment back towards the equilibrium. The final coefficient is β_1, which is defined as the long-term relationship between X and y (Brooks, 2014, p. 375-376).

4.10 Engle & Granger

Engle and Granger two-step procedure is a method used to estimate the parameters in cointegrated systems with an error correction model, and the two steps are conducted as follows. The first step is to make sure that all the individual variables are I(1), and then estimate the cointegrating regression using ordinary least squares. We then test the residuals from the cointegrated regression to ensure that they are I(0). If they are I(1), we need to estimate a model that contains only first differences. If the residuals are I(0) we may proceed to the next step. Thereafter, we use the residuals from the OLS regression from the previous step in an ECM. Any linear combination of the stationary cointegrating vector, $\hat{u}_{t-1}$, will also be a stationary cointegrating vector. Since all variables in this regression are stationary, it is now valid to perform interpretations in the second-stage regression (Brooks, 2014, p. 378).

4.11 Vector error correction model

A VAR model may be extended further where the model includes first difference terms and cointegrating variable. This further extended model is called a vector error correction model (VECM), and may be written as:

$$\Delta y_t = \beta_{1,0} + \sum_{i=1}^{N-1} (\beta_{1,i} \Delta y_{t-i} + \alpha_{1,i} \Delta X_{t-i}) + \gamma_1 \hat{u}_{t-1} + u_{1,t,} \tag{13}$$

$$\Delta X_t = \beta_{2,0} + \sum_{i=1}^{N-1} (\beta_{2,i} \Delta y_{t-i} + \alpha_{2,i} \Delta X_{t-i}) + \gamma_2 \hat{u}_{t-1} + u_{2,t,} \tag{14}$$

where the sum is the VAR component in first differences and explains the short-term relationship. The $\gamma_i \, \hat{u}_{t-1}$ represents the error-correction component and explains the long-term relationship. By testing the rank of γ, which is a vector that consist of an adjustment parameter and a cointegrating equation, we could figure out if $\hat{u}_{t-1}$ is stationary at level or if it needs to be differenced before it becomes stationary.

The Johansen trace test is a well-known method for testing for cointegration and gives the number of cointegrated vectors and linear stationary combinations in the model (Brooks, 2014, p. 386-387).

4.12 Johansen test

The Johansen test makes is possible to estimate all cointegrated vectors in a model with two or more time series. We can either look at the maximum eigenvalue test or the trace test, but both test statistics have a null hypothesis of no cointegration and an alternative hypothesis of cointegration. The eigenvalues (λ_i) are sorted in a decreasing order ($\lambda_1 \geq \lambda_2 \geq \ \lambda_n$). If we first look at the maximum eigenvalue test, the test statistic can be written as:

$$LR(r_0, r_0 + 1) = - T\ln (1 - \lambda_{r0 + 1}), \tag{15}$$

where the likelihood ratio statistics can be given by LR(0, 1), for testing whether if the null hypothesis with rank (Π) = 0, can be rejected over the alternative hypothesis which is that rank (Π) = 1, where Π is a vector or matrix of adjustment parameters and the cointegrating vector. In this test we are using the largest eigenvalues, such that if the rank of the matrix is zero, the largest eigenvalue will also be zero. Therefore, there are no cointegrating vectors. In the trace test, we test if the rank of the matrix Π is r_0. The test statistic can be written as:

$$LR(r_0, N) = -\mathrm{T} \sum_{i=r_0+1}^{N} \ln(1 - \lambda_i), \tag{16}$$

where the likelihood ratio statistics can be given as LR(0, n) for testing whether if the null hypothesis with rank (Π) = r_0 can be rejected over the alternative hypothesis where r_0 < rank (Π) ≤ N. The maximum number of possible cointegration vectors are symbolized with N (Dwyer, 2015, p. 4-6) (Johansen, 1995, p. 93-97).

5 Empirical results

In this section of our master thesis we will present our results and interpret our findings. Initially, we look at the variables separately and see if the variables are stationary after differencing once. Thereafter, we start with the VAR model and test for causality with the Granger causality test. Then, we test for cointegration by using the Engle & Granger two-step procedure, where we will end up with an ECM. This will give us an indication if there is a long-term relationship between our variables. Further, we will estimate a VECM that investigates the causal relationship of our variables in both short-term and long-term.

5.1 Stationarity

We start our analysis by illustrating how the variables variate against time to look after common features and see if there are any indications of a long-term relationship. Figure 5 illustrates how the variables behave on an 18-year time span. The blue line represents our portfolio index and the orange line represents the spot price of fresh farmed salmon. Both variables are transformed to a logarithmic scale. From this figure, we could suggest that the variables are non-stationary, but there are indications on common patterns. In the first nine years, from 2000 to the beginning of 2009, there are none common patterns that are clearly observable. However, there are some historical events that may explain some of the fluctuations. For example, we believe the first

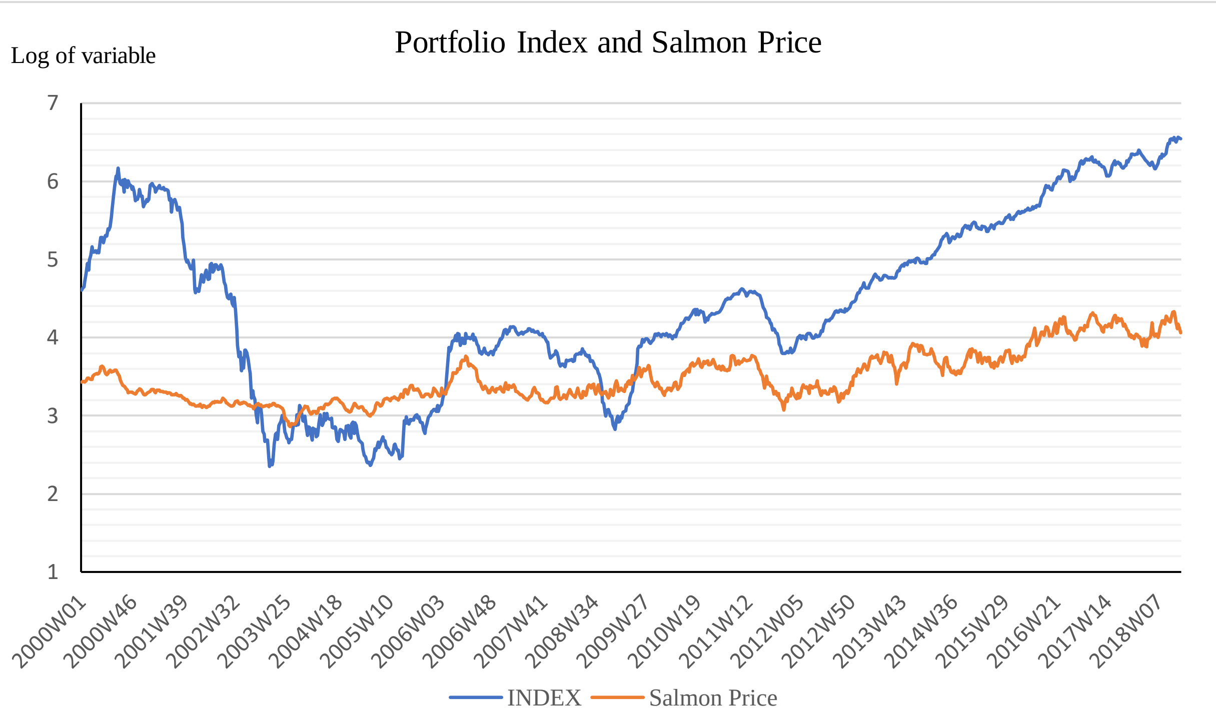

Figure 5 Index and salmon price in logarithmic scale.

decrease between 2001 and 2003 was the dot-com bubble that burst after years with vertiginous growth of stock market prices (Gama, Segura & Filho, 2017, p. 4). The second decrease that started in 2007-2008, was the financial crisis that started in America where the housing market and bank sector suffered the most (Kaufman, Barth & Jahera, 2015, p. 3). The portfolio index starts its first three years with extremely high values, where the salmon price behaves pretty stable. We see, especially from the beginning of 2009, that both variables have the same peaks and bottoms. From the beginning of 2012, both have an upward trend but in different levels. Based on this illustration, the variables have a common stochastic trend without drifting too far from each other, and we may suspect a cointegrated relationship between the variables.

One requirement for cointegrated variables is that the variables have to be I(1), and the first differences of the variables are I(0). As mentioned in the methodology section, the ADF-test helps us to detect whether a variable is stationary or not.

	Level		First difference	
Variable	Test statistic	p-value	Test statistic	p-value
lnINDEX	0.205	0.9725	-28.261***	0.000
lnFRESH	-1.485	0.5407	-27.488***	0.000

Table 5 ADF-test results for lnINDEX and lnFRESH at level and first differences.
*1%*** significance level with a critical value at -3.430,*
*5%** significance lever with a critical value at -2.860,*
10% significance level with a critical value at -2.570.*

Table 5 gives us a transcription of the results from the ADF-test of the variables, both at level and in first differences. As we see, the p-values on the left-hand side for both variables at level are notably high. Based on this output we cannot reject non-stationarity. Therefore, we will try to achieve stationarity by differencing both of the variables once. Figure 6 bellow illustrates how the first order differences of the variables behaves against time. The graphically inspection seems to indicate that the first differences are indeed stationary in the period from the beginning of 2006 to the end of our time frame. However, in the beginning of our time frame, the variance does not seem to be constant for both variables, therefore we believe that this may complicate our further analysis.

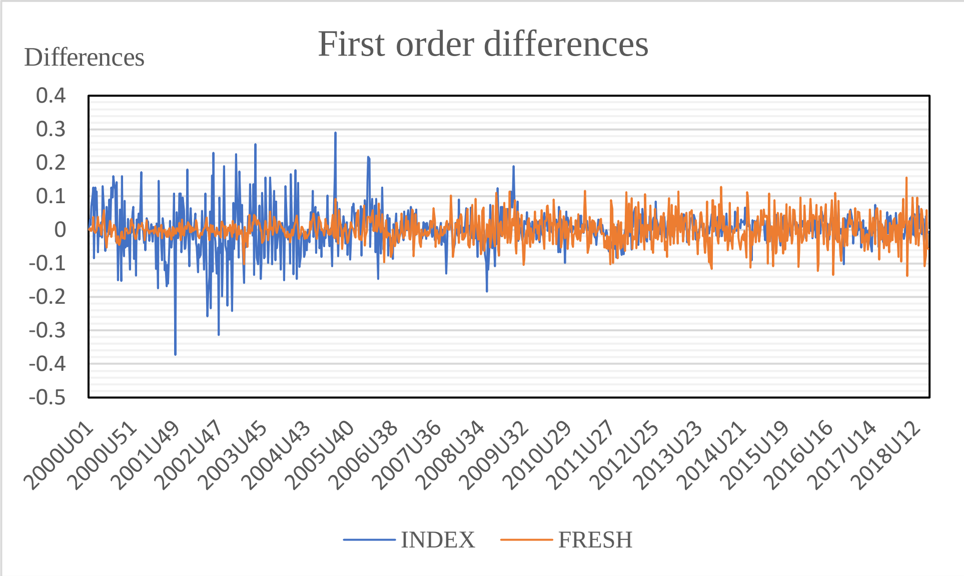

Figure 6 First order differences.

Again, we use the ADF-test. The right-hand side of Table 5 represents the output we got from the ADF-test after differencing the variables once. Since the p-value of the variables are both less than a significance level at 1%, we may reject the hypothesis of non-stationarity and we may suggest that there is evidence for stationarity. Hence, we may conclude that the variables are both I(1) processes.

5.2 Optimal lag-order selection

The information criterions from Table 6, show us the values calculated from the different information criterions, and tell us which lag length these criterions suggest to our models. We see that the option of 3 lags is suggested by LR, HQIC and SBIC. This is the lag option with the highest number of suggestions, and therefore we end up with three lags in our models. Our VAR model is based on Equation 9 and Equation 10 and contains the first differences of the variables. This model may be further extended to a VECM. The VAR model is presented as follows:

$$\Delta lnINDEX_t = \beta_{1,0} + \sum_{i=1}^{3} (\beta_{1,i}\, \Delta lnINDEX_{t-i} + \alpha_{1,i}\, \Delta lnFRESH_{t-i}) + u_{1,t.} \qquad (17)$$

$$\Delta lnFRESH_t = \beta_{2,0} + \sum_{i=1}^{3} (\beta_{2,i}\, \Delta lnINDEX_{t-i} + \alpha_{2,i}\, \Delta lnFRESH_{t-i}) + u_{2,t.} \qquad (18)$$

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	-1365.02	-	0.0589	2.8450	2.8489	2.8551
1	3078.59	8887.2	5.7e-06	-6.3946	-6.3830	-6.3642
2	3097.81	38.445	5.5e-06	-6.4262	-6.4069	-6.3756
3	3125.94	56.258*	5.3e-06	-6.4765	-6.4495*	-6.4055*
4	3130.23	8.5876	5.3e-06*	-6.4771*	-6.4424	-6.3859

Table 6 Information criterions of optimal lag length.
** represent suggestions from the corresponding information criterion.*

5.3 Results with VAR

In this section, we have made a VAR model containing the first differences of the variables, and three lags that we got suggested from the earlier information criterions. Table 7 below, represents the estimated coefficients in our VAR model.

	ΔlnINDEX		ΔlnFRESH	
Variable	Coefficient	p-value	Coefficient	p-value
$\Delta lnINDEX_{t-1}$	0.0744**	0.021	0.0889***	0.000
$\Delta lnINDEX_{t-2}$	0.0744**	0.022	0.0057	0.786
$\Delta lnINDEX_{t-3}$	0.0756**	0.020	0.0164	0.432
$\Delta lnFRESH_{t-1}$	0.0496	0.326	0.1400***	0.000
$\Delta lnFRESH_{t-2}$	0.0275	0.580	-0.2412***	0.000
$\Delta lnFRESH_{t-3}$	-0.0298	0.553	0.0434	0.178
Intercept	0.0014	0.462	0.0005	0.691

*Table 7 VAR model with lagged first differences of lnINDEX and lnFRESH at a significant level at 1%***, 5%** and 10%*.*

From Table 7, we see that not all short-term coefficients are significantly different from zero. When we look at portfolio index as the endogenous variable, we see that the only coefficients that are significant is its own lagged values. The coefficients for previous values of the spot price of salmon are not significant. At the opposite hand, where the spot price of salmon is the endogenous variable, we see that the coefficient of the first lagged value of the portfolio index as well as its own first two lagged values.

By the VAR model, we may imply that there is a unidirectional relationship. This indicates that our portfolio index may not be predicted by the previous values of the spot price of salmon, but the spot price of salmon may be predicted by the previous values of our portfolio index. We test this statement by the Granger causality test to strengthen our findings.

5.3.1 Causality test

It is interesting to investigate the Granger-causality between the spot price of salmon and our index portfolio. By looking at the Granger causality between these variables, we might see if one of our variables may be predicted by previous values of the other variable.

The first case we want to investigate is if our portfolio index may be predicted by previous values of the spot price of fresh farmed salmon. In the second case, we investigate is if the spot price of salmon may be predicted by previous values of our portfolio index. To investigate which variable that affects the other or if the variables affects each other both ways, we need to test the $\alpha_{1,i}$ coefficients from Equation 17 and the $\beta_{2,i}$ coefficients from Equation 18. The hypothesis from these two different cases is presented below and we use the Granger causality test to consider if we may reject the null hypotheses $H_{1,0}$ and $H_{2,0}$.

$$H_{1,0} : \alpha_{1,1} = \alpha_{1,2} = \alpha_{1,3} = 0 \qquad H_{1,1}: \alpha_{1,i} \neq 0 \; for\; atleast\; one\; i = 1, 2, 3.$$

$$H_{2,0}: \beta_{2,1} = \beta_{2,2} = \beta_{2,3} = 0 \qquad H_{2,1}: \beta_i \neq 0 \; for\; atleast\; one\; i = 1, 2, 3.$$

Dependent	Independent	Chi-squared	p-value
$\Delta lnINDEX_t$	$\Delta lnFRESH_t$	2.0432	0.563
$\Delta lnFRESH_t$	$\Delta lnINDEX_t$	20.116***	0.000

*Table 8 Results from Granger causality test. 1%*** significance level, 5%** significance level, 10%* significance level.*

Since the p-value from the first case is notably high (Table 8), we fail to reject $H_{1,0}$. This means that we do not have any evidence for our portfolio index to be Granger-caused by the spot price of salmon. On the other hand, we may reject $H_{2,0}$ on a significance level at 1%, which implies that the spot price of salmon is Granger-caused by our portfolio index.

Based on these results, we have evidence for a unidirectional short-term relationship. This indicates that our portfolio index could not be predicted by previous values of the price of salmon, but the price of salmon may be predicted by previous values of our portfolio index. These results suggest the opposite of our previous assumption where we thought it should be the opposite way; that our index could be predicted by previous values of spot price. However, both causality test and VAR look at the short-run relationship, which may be one of the reasons why we did not get the result we initially thought. Therefore, we include an error correction model and a vector error correction model to investigate at the long-term relationship.

5.4 Error correction model

In this section, we want to find if there exists a long-term equilibrium between the variables of interest. The most interesting term we find is the error correction term, which is in principle the same for both directions. Therefore, we only include the portfolio index as the dependent variable. Initially, since the information criterions suggested three lags, we used the Engle & Grangers two-step procedure with three lags in the error correction model. This did not give us any satisfying results with no significant coefficients. As a remedy, we did the same procedure by reducing the lag length by one lag. We repeated the same procedure until we got significant results, and we ended up with only one lag.

Now that we have established I(1) processes, we estimate the cointegrated regression by using an OLS regression, and then test the residuals for stationarity.

$$lnINDEX_t = \beta_0 + \beta_1 lnFRESH_t + u_t. \tag{19}$$

Figure 7 is a visual illustration of the residuals from the OLS regression which seems to certainly be trending from the beginning of year 2005. Based on a graphically inspection, we are not confident about stationary residuals and we believe that this may complicate our model later.

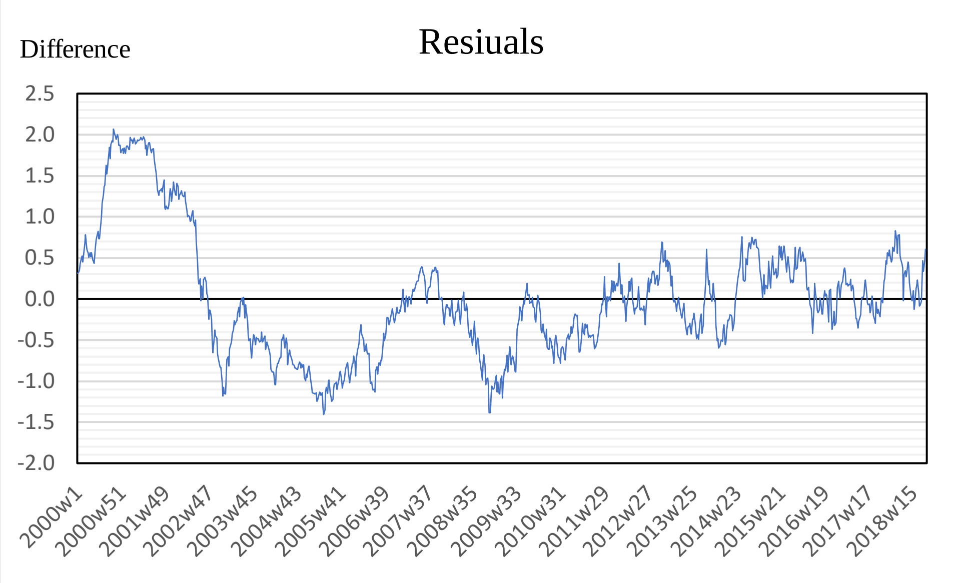

Figure 7 Residuals from OLS regression: $lnINDEX_t = \beta_0 + \beta_1 lnFRESH_t + u_t$.

Table 9 below displays the results when we used the ADF-test on the residuals produced from the OLS regression. Based on the results from the test, we see that the p-value is indeed higher than a significance level at 10%. This indicates that we could not reject the null hypothesis of non-stationarity and we do not have evidence for stationarity residuals.

Variable	Test statistic	p-value
Residual	-2.389	0.1450

*Table 9 ADF-test results for residuals from OLS regression. 1%*** significance level with a critical value at -3.430, 5%** significance lever with a critical value at -2.860, 10%* significance level with a critical value at -2.570.*

As a remedy to this complication, we try to include a trend term in the regression:

$$lnINDEX_t = \beta_0 + \beta_1 lnFRESH_t + \beta_2 WEEK + u_t. \tag{20}$$

Variable	Coefficient	p-value
$lnFRESH_t$	3.3325***	0.000
WEEK	-0.0011***	0.000
Constant	-4.4126***	0.000

*Table 10 OLS regression with trend. 1%*** significance level, 5%** significance level, 10%* significance level.*

This regression model gave us the coefficients presented in Table 10. Based on the results, we see that the regression with a trend term gave us more trustable results where all coefficients have a p-value less than a significance level of 1%. Now we may predict the residuals from the last regression and test these residuals for stationarity with a new ADF-test.

Variable	Test statistic	p-value
Residual $_{Trend}$	-3.008**	0.0341

Table 11 ADF-test results for residuals from OLS regression with trend term
*1%*** significance level with a critical value at -3.430,*
*5%** significance level with a critical value at -2.860,*
10% significance level with a critical value at -2.570.*

From the results of the last ADF-test in Table 11, we may reject the null hypothesis of non-stationarity, and therefore we have evidence for cointegrated variables. Since we now have achieved stationary residuals, it indicates that our variables are cointegrated. In other words, there are evidence for a long-term relationship between our portfolio index and the spot price of salmon. With these results we may proceed to the second step in the Engle & Granger two-step procedure, which gave us the following results from the error correction model:

Variable	Coefficient	p-value
$\Delta lnFRESH_{t-1}$	0.1651***	0.001
$\hat{u}_{t-1}$	-0.0083***	0.002
Intercept	0.0019	0.324

*Table 12 Error correction model. 1%*** significance level,*
*5%** significance level, 10%* significance level.*

Table 12 presents the coefficients and its p-values of the ECM. Both β_1 and β_2 are significantly different from zero with a p-value less than a significance level of 1%. The intercept, β_0, has a certainly high p-value and therefore not significantly different from zero. The estimation of the short-term relationship is represented with the β_1-coefficient that equals 0.1651. This could be interpreted as a 1% change in the growth rate of lnFRESH, we may expect a 0.1651% change in the growth rate of our portfolio. The estimated β_2-coefficient equals -0.0083. This coefficient is expected to be negative because this coefficient is supposed to correct for previous equilibrium errors and represents the long-run equilibrium. The β_2-coefficient at -0.0083, and is a result of $\Delta lnINDEX_{t-1} < (\beta_0 + \beta_1 \Delta lnFRESH_{t-1})$. This means that the ECM corrects its previous disequilibrium at a speed of 0.83% weekly to get back to the steady state. From the earlier OLS regression with trend term (Table 10), the long-term elasticity coefficient equals 3.3325. This reveals that a 1% change in the natural logarithm of the salmon price will change the natural logarithm of our index value by 3.33%.

5.5 Result with VECM

The final step of our analyze is to include a vector error correction model. VECM is built on the basis of VAR, the only difference is that VECM include an error correction component. However, from earlier results, the information criterions suggest three lags as the optimal lag-length in our analysis. The specific VECM is based on Equation 13 and Equation 14:

$$\Delta lnINDEX_t = \beta_{1,0} + \sum_{i=1}^{3}(\beta_{1,i}\Delta lnINDEX_{t-i} + \alpha_{1,i}\Delta lnFRESH_{t-i}) + \gamma_1\hat{u}_{t-1} + u_{1,t,} \tag{21}$$

$$\Delta lnFRESH_t = \beta_{2,0} + \sum_{i=1}^{3}(\beta_{2,i}\Delta lnINDEX_{t-i} + \alpha_{2,i}\Delta lnFRESH_{t-i}) + \gamma_2\hat{u}_{t-1} + u_{2,t.} \tag{22}$$

The first step is to determine the number of cointegrated vectors. From the ECM section of this thesis, we already found evidence for cointegrated variables. We include the Johansen test to improve our model and strengthen our evidence for cointegrated variables.

Max rank	Parms	LL	Eigenvalue	Trace	5% value
0	14	3122.42	-	15.6168	15.41
1	17	3129.93	0.0155	0.6016*	3.76
2	18	3130.23	0.0006	-	-

Table 13 Johansen test for cointegration.

From Table 13, we see the results from Johansen test for cointegration. The maximum rank tells us how many cointegrations there are between our variables. They are also our null hypothesis. However, since we only have two variables in our model the highest number of cointegrations we might obtain is one. If we first look at the maximum rank of 0, the null hypothesis says there are no cointegration among our variables, while our alternative hypothesis says there is at least one cointegration. To determine if we can reject the null hypothesis or not, we look at the trace statistics and the 5% critical value. If the trace statistics is more than the 5% critical value, we can reject the null hypothesis. If the maximum rank equal to 0, we can see that our trace statistics is more than a 5% critical value, 15.6168 > 15.41. We may therefore reject the null hypothesis and accept the alternative hypothesis. We know that we have cointegration, but we have not determined how many. If we now look at the maximum rank of 1, our null hypothesis says that there is one cointegration between our variables, while our alternative hypothesis still says at least one cointegration. Here, our trace statistics is less than the 5% critical value, 0.6016 > 3.76, which means that we may not reject our null hypothesis. This indicates that we have one cointegrating relationship between our variables. In other words, there exists a long-term relationship. This takes us to the next step where we estimate a VECM including a trend term, where the trend term was required in the ECM to achieve stationary residuals.

	ΔlnINDEX		ΔlnFRESH	
Variable	Coefficient	p-value	Coefficient	p-value
$\hat{u}_{t-1}$	-0.0040**	0.026	0.0046***	0.000
$\Delta lnINDEX_{t-1}$	0.0690**	0.033	0.0911***	0.000
$\Delta lnINDEX_{t-2}$	0.0673**	0.039	0.0098	0.639
$\Delta lnINDEX_{t-3}$	0.0679**	0.037	0.0212	0.308
$\Delta lnFRESH_{t-1}$	0.0327	0.523	0.1579***	0.000
$\Delta lnFRESH_{t-2}$	0.0126	0.801	-0.2252***	0.000
$\Delta lnFRESH_{t-3}$	-0.0444	0.381	0.0583*	0.071
$\text{WEEK}_{\text{Trend}}$	0.0000	0.282	0.0000	0.140
$\text{Intercept}_{\text{Short-term}}$	-0.0027	0.492	-0.0023	0.353

Cointegrating equation	Coefficient	p-value
lnINDEX	1	
lnFRESH	-7.5658***	0.000
$\text{WEEK}_{\text{Trend}}$	0.0039	
$\text{Intercept}_{\text{Long-term}}$	19.9699	

Table 14 Vector error correction model – short run and long run estimates.
*1%*** significance level, 5%** significance level, 10%* significance level.*

Table 14 represents the short-term and long-term estimates we got from constructing the VECM. This model includes three lagged differences of the variables and one cointegrating equation. The two $\hat{u}_{t-1}$ coefficients creates the long-term adjustment vector for our model. The short-term coefficients can be found in the first part of the table and are given by the lagged differences of the variables. The cointegrating equation, which represents the long-term equilibrium, can be found at the bottom of the table. The last coefficients of interest are the constant vectors, which is given by both of the intercept coefficients.

One of the coefficients in the adjustment vector $\hat{u}_{t-1}$ is negative and significant, which implies a correction to the equilibrium. The adjustment parameter of lnINDEX is negative and significant with a p-value at 0.026, with an estimated coefficient at -0.004, which is a result of $\Delta lnINDEX_{t-1} < (\beta_0 + \beta_1 \Delta lnFRESH_{t-1})$. This implies that when the spot price of salmon is too high, our portfolio index attempts to adjusts down to the equilibrium. The adjustment parameter for the lnFRESH is significant with a p-value at 0.00, with a positive estimated coefficient at 0.0046. This is a result of $\Delta lnFRESH_{t-1} > (\beta_0 + \beta_1 \Delta lnINDEX_{t-1})$, and implies that when the value of our portfolio index is high, the spot price of salmon adjusts upwards to match our portfolio index.

From the short-term coefficients, the only variable which has a significantly short-term effect on $\Delta lnINDEX_t$ is its own three lagged values with estimated parameters at 0.0690, 0.0673 and 0.0679. This implies that its own lagged values up to three lags has a significantly positive effect on the first difference of lnINDEX at time t. When we look at $\Delta lnFRESH_t$ as the endogenous variable, $\Delta lnINDEX_{t-1}$, $\Delta lnFRESH_{t-1}$, $\Delta lnFRESH_{t-2}$ and $\Delta lnFRESH_{t-3}$ has estimated parameters at 0.0911, 0.1579 , -0.2252 and 0.0583. This means that these variables have a significantly effect on the first difference of lnFRESH at time t. The rest of the estimates are not significantly different from zero.

The cointegrating equation represents and explains the long-term relationship between our portfolio index and the spot price of salmon. From Table 18, we see that all of the coefficients in the cointegrating equation are all significantly different from zero, and we may summarize the long-term relationship as:

$$lnINDEX_t = 7.5658 lnFRESH_t + 0.0039\text{WEEK} - 19.9699 + \hat{u}_t. \qquad (23)$$

6 Discussion

We have now analyzed the relationship between the spot price of salmon and a portfolio index with three different models. The reason why we have included all three models is because they have different approaches when estimating the data, and therefore they might have different results. We believe that salmon price has a huge impact on salmon farming companies, therefore we restricted our analysis with only these two variables.

From our first model with VAR, we estimated the short-term relationship between our variables, which indicated a unidirectional causal relationship. Our portfolio index may not be predicted by previous values of the spot price of salmon, but on the other hand, it indicated that the spot price of salmon may be predicted by previous values of our portfolio index. We wanted to investigate if this statement has support from the Granger causality test. Our findings from the Granger causality test gave us stronger evidence for the one-way causal relationship we obtained from the VAR. We find these results not intuitive because we expected a two-way causal relationship, or at least the opposite direction, where our portfolio index could be predicted by previous values of the spot price of salmon. Based on these results, we believe that the market does not respond to changes in the spot price of salmon quick enough on a short-term basis. In other words, the elasticity is low in the short-term, which is why our portfolio index does not respond to changes in the salmon price. We can compare these results with Andersen, Roll and Tveterås paper, where they investigated the supply elasticity, and suggested that salmon producers have limited power to respond to price changes in the short-term. This result has similarities with our findings. These findings only represent the short-term relationship between our variables. To look at the long-term relationship, we use the ECM and the VECM.

Based on the results from the ECM, we found that there exists a common unit-root between the variables, which implies that these variables are cointegrated. This indicates that there is a long-term relationship between the spot price of salmon and our portfolio index. The error correction term is in principle the same for both directions, and therefore we have an ECM in only one direction. This long-term relationship was something we expected based on relationships between commodities and corresponding stock price of a company that operates in other industries. Our findings support our initially thought, that the salmon price and our portfolio index have a positive correlation. This is also supported by statements of several analysts who predicted that increasing spot price is positively reflected over to salmon companies which we mentioned in the introduction. Now that we have evidence for a long-term relationship between our variables, we wanted to include a VECM to investigate this relationship in detail.

VECM investigates both short-term and long-term relationship between our variables, where both variables are listed as endogenous variables. The short-term coefficients we obtained in the VECM model suggested quite comparable results with similar estimates in the coefficients from the VAR model. These coefficients also indicated that our portfolio index could only be predicted by its own previous values, but the spot price of salmon may be predicted by two of its own previous values in addition to one lagged value of our portfolio index. The short-term results from the VECM supports the findings we obtained from VAR and the Granger-causality test. If we now look at the long-term relationship from VECM, we found some interesting evidence. However, if we first go back to our introduction section under "Salmon market in Norway", we could see that the salmon price exported increased by 11% in February 2019 if we compare it to the same month last year. At the same time, salmon companies could show an increase in stock price. Several analysts suggested that this increase in stock price is caused by an increase in salmon price, and it is this relationship we believe we have found evidence for, both in ECM and VECM.

When we look at the error correction terms from the VECM, both of them were significant. As expected, the coefficient of the first error correction is negative since a negative residual is a result of $\Delta lnINDEX_{t-1} < (\beta_0 + \beta_1 \Delta lnFRESH_{t-1})$. Therefore, when the error term is negative, we need our portfolio index to increase to converge towards the equilibrium. The coefficient of the second error correction term is positive and is a result of $\Delta lnFRESH_{t-1} > (\beta_0 + \beta_1 \Delta lnINDEX_{t-1})$. This implies that when the error term is positive, we need the spot price of salmon to decrease to get back to the equilibrium. However, we find positive coefficients in the error correction term surprisingly because it implies that the model does not converge towards the equilibrium in the long-term. Usually this an indication of misspecification in our model.

The cointegrating equation describes the long-term relationship between the variables, and it indicates a positive correlation. Based on the equation, we could expect an increase of 7.57% in the log of our portfolio index when the log of spot price increases by 1%. This result was something that was expected. It is known that a commodity price in most cases, affects the companies connected to this commodity. When the commodity price increases, the companies will increase its profit, which makes it more desirable for investors. If we look at our example, an increase in spot price of salmon will perhaps generate an optimism for the companies in our portfolio index, which may result in an increase in share price. This has previously been argued for by analysts, but they have not supported this by any empirical evidence as background.

As mentioned earlier, our research question was to investigate if there exists a relationship between the variables of interest. However, we could expand our model for further research. There are a lot of other factors that may have a significant effect in our model that we could include. We believe that a majority of the transactions are done with future contracts where prices are fixed several months in advance. Therefore, we assume that future prices would have a significant impact in our VECM.

7 Conclusion

In this master thesis we have investigated how the spot price of fresh farmed salmon and the returns from an equally weighted portfolio index consisting of salmon farming companies listed on Oslo Stock Exchange affects each other, both in a short-term and long-term. We have not found any research papers concerning this issue, which gave us a huge motivation to investigate this relationship. To achieve this, we have used three different models. First, we included a VAR model which investigates the short-run relationship. On the contrary, our findings reveal that our initial thought, where we at first believed that our portfolio index could be predicted by previous values of the spot price of salmon, was not supported by any evidence. Our findings suggested the opposite where we got evidence for a unidirectional relationship, where our spot price of salmon could be predicted by previous values of our portfolio index. Since VAR models only investigates the short-term relationship, we included an ECM and a VECM. These two models analyses the relationship between the variables, both in short-term and long-term, and includes an error correction term which corrects for disequilibrium from previous periods. With these procedures we achieved cointegrated relationship between the variables of interest, and we have evidence for both in short-term and long-term relationship.

To sum up, the relationship between the spot price of salmon and our portfolio index behave differently when we look at short-term and long-term relationships. In short-term, our evidence from VAR and causality test suggest that the relationship is unidirectional. On the other hand, when we investigated the long-term relationship with ECM and VECM, they suggest a two-way direction. This means that we have provided evidence with advanced methodology, that the spot price of salmon is a driving force for our portfolio index, that several analysts have predicted, but with no research paper as background. We believe this thesis can help analysts and investors to achieve a better understanding about how the relationship between the spot price and a portfolio index of salmon companies behaves both in short-term and long-term.

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Appendix

```
//Set time
gen t=_n
tsset t, w
gen WEEK = tw(2000w01) + t - 1
tsset WEEK, w
drop t

// Generate log. scale
gen lnINDEX=ln(INDEX)
gen lnFRESH=ln(FERSK)

//Graphical inspection of variables at level
twoway tsline (lnINDEX lnFRESH)

//test for stationarity
dfuller lnINDEX
dfuller lnFRESH

//Generate first order differences
gen dlnINDEX = lnINDEX - L1.lnINDEX
gen dlnFRESH = lnFRESH - L1.lnFRESH

//Graphical inspection of variables in first differences
twoway tsline (dlnINDEX dlnFRESH)

//Test first differences for stationarity
dfuller dlnINDEX
dfuller dlnFRESH

//----------VAR------------------

//lag-order selection
varsoc lnINDEX lnFRESH
var dlnINDEX dlnFRESH, lags (1/3)

//-----------ECM------------------

reg lnINDEX lnFRESH
predict resi,r
dfuller resi
//Nonstaionary – try to include trend term

reg lnINDEX lnFRESH WEEK
predict resi2,r
dfuller resi2 //cointegrated
```

```
//ECM
reg dlnINDEX dlnFRESH L1.resi2

//-------------VECM-----------------

vecrank lnINDEX lnFRESH, lags(4)
vec lnINDEX lnFRESH, trend(trend) lags(4)
```

Reflection paper

Tord Magnus Hopsdal

The main theme in our thesis has been assembling and analyzing data from the salmon market. We used a lot of time just gather the data we needed for our analyze and choose what kind of data that was relevant. We have used different empirical models where some have been more challenging than others, however, since I have throughout the master had different kind of lectures in financial economics, my background in this subject was very good. Our main goal of our master thesis was to find a relationship between the spot price of salmon and a portfolio of salmon farming companies. We looked at both short-term and long-term. In the short-term our evidence suggested that our spot price of salmon could be predicted by previous values of our portfolio index. In other words, the relationship was unidirectional, meaning only one direction. However, when we look at the long-term, we have a relationship that goes both ways, meaning that they affect each other. The short-term evidence was a bit surprising, that our portfolio index could not be predicted by previous values of spot price of salmon. There could be some model misspecification, or that the market, in the short-term, does not respond to changes fast enough.

Norway holds a big part of the salmon market, and the growth has been tremendous the last ten years, especially after sushi was introduced all around Europe. This trend has increased the demand and may be a factor of why the salmon companies in Norway can show such an increase in profit. Atlantic salmon is known to be one of the best in the market, but biological factors like stable sea temperature, makes it hard to find the perfect location for production. Luckily, Norway´s coastline is perfectly suited for breading Atlantic salmon. This is why Norway takes 50% of the global market, and why the companies in Norway have generated high profit, job opportunities and high knowledge about technology when it comes to fishing facilities. For example, Argentina has asked Norwegian companies to help them to implement fishing facility. In other words, Norway is a big international leader in all part of the value chain when it comes to salmon. Especially when it comes to technology, which may be the biggest trend the world right now, Norway is far ahead of competition.

It has been proven historically, that companies who always have the desire to think innovation, and always think about how they can improve their company, will stay ahead of competition.

Norwegian salmon companies are a perfect example of this. They always think of new methods of how they can produce salmon in fishing facilities, and if it works, international companies seeks help from Norwegian companies. The reason why innovation is important in the salmon market is because of the fishing facilities. Salmon is an animal that needs good conditions like any other animal. Over the years of salmon production, there have been some problems like salmon lice. Salmon lice has caused a lot of problems, and a lot of salmon have died because of it. This is one of the reasons why innovation is important, that conditions in the farming facilities are improved, and salmon gets a better life. Another trend that has increased over the years is the environment issue. Environmental issues are getting more and more attention and may have an effect when the population are deciding what kind of protein source they want to consume. The protein from salmon is produced at a very efficient way if we compare it to for example chicken or pork. By efficient we mean how much animal protein that is produced per unit compared to how much protein they are fed. These examples may be one of the reasons why salmon has a high demand in the world. As a healthy, climate friendly and resource efficient product, it fits well with the global trends.

As I mentioned above, there are some challenges when it comes to salmon lice. Salmon companies has some responsibility when it comes to living conditions for salmon. Innovation of salmon facilities is difficult and may be expensive to implement. Therefore, they have an ethical problem. Should they spend a lot of money on fishing facilities so that salmon gets better conditions, or should they save the money and by that increase the risk for salmon lice? Throughout our master thesis, we have the impression of Norwegian salmon companies that they always strive for better conditions for salmon. The health of salmon is more important than saving money. I believe that Norwegian salmon companies take their responsibilities very seriously, and that they always try new innovation to see if it may be an improvement.

Reflection paper

Shandy Carl A. Nilsen

In our master thesis our main topic is the salmon market. We investigated the causal relationship between the spot price of fresh farmed salmon and the value of an equally weighted portfolio index. This portfolio index consists of salmon farming companies listed on Oslo Stock Exchange. We investigated and described the relationship both in short-term and long-term. We had an econometric approach to achieve satisfying findings and results. The main econometric models we used were the vector autoregressive (VAR) model, the error correction model (ECM), and the vector error correction model (VECM). The VAR model describes the short-term causal relationship, and the ECM and VECM finds a cointegrating equation and describes the relationship in the long-term.

At first, we expected that our portfolio index could be predicted by previous values of the spot price of salmon, but we did not find any evidence for our expectations. However, we found evidence for that the spot price of salmon could be predicted by our portfolio index. We find these results we obtained in the short-term surprising in the way that we found a unidirectional causal relationship, where the direction was opposite of what we expected. The results we obtained in the long-term was interesting but expected. We found evidence for a long-term relationship between the variables of interest, where we found one cointegrating equation that describes the equilibrium in the long-term.

International Trends

In the industry of salmon there are several forces that may influence the firms that operates in this environment. There are environmental factors such as the food production level, where there are difficulties to produce enough food to the world's population. Salmon is one of the most efficient protein sources humans can eat. Salmon is efficient in the way that it has a high level of output ratio of protein compared to cattle, chicken and pork. With the protein output ratio, I mean the ratio of how much animal protein that is produced per unit compared to how much protein they are fed. In addition to the efficiency of producing salmon, we also have health advantages from having salmon in our diet. In salmon we get several nutrients as omega-3, vitamin A and D. In the last decade, consuming fish has had an upward trend and I believe the trends is caused by these factors mentioned above.

Innovation

Salmon farming companies needs to be innovative to maintain their competitive advantage, hold their position in the market and increase their profit. Earlier, these companies had land-based salmon farming facilities, and they moved these facilities to the ocean where they had the fish in cages. This move made salmon farming more profitable, and they could produce more fish to a lower cost. However, there are biological boundaries that limits the production level. Salmon needs a water temperature between 8° C to 14°C, and at the same time there has to be a certain current of water through the cages that provides a high water quality. Salmon lice is also a threat for the salmon farming companies. At this point, there is not enough feasible coastline for the demand in the salmon production. When the fish is living close to each other in cages, the risk of lice is high, and the salmon might die. These biological factors forces the salmon farmers to think innovative, and now they are researching the opportunities to produce salmon on land again.

Responsibility

Again, I want to mention the hunger challenges in the world and biological boundaries in this section of responsibility. As I mentioned earlier in this reflection note, salmon farming is a very efficient way to produce proteins compared to cattle, chicken and pork. Therefore, if the salmon farming companies evolves the land-based production, the population could eat more fish in countries without coastline and serve food to countries with hunger challenges. In addition to the worlds hunger challenge, salmon farming companies has a responsibility of sustainable food production. If we want the next generations to have the same opportunities that we have today, we, especially these food producing companies, have to think sustainability. Salmon that escapes their cages may affect the wild salmon. Another challenge is the agent they use against the salmon lice. The waste from this agent affects the environment, and species such as shrimps and crabs suffer. Therefore, these salmon farming companies has a responsibility of the environment, and they need to produce food in a sustainable way.