Bendik Persch Andersen

Efficiency in the Atlantic Salmon Futures Market

Master's thesis in Industrial Economics and Technology Management
Supervisor: Petter Eilif de Lange
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ABSTRACT

The global production volume of farmed Atlantic salmon has experienced tremendous growth over the last few decades, becoming a considerable part of the global aquaculture sector. However, due to severe production risk and fluctuating demand, the salmon spot price has been increasingly volatile alongside the production growth. As a direct consequence, the need for financial risk management tools became more evident, leading up to the establishment of the *Fish Pool* futures market in 2005. Due to thin trading, however, the market's efficiency has been subject to question ever since its inception. The aim of this study is to provide a thorough review of current market characteristics and their implications. By the use of an extensive model framework, we assess efficiency and unbiasedness of the futures prices, both in the long- and short-run. Further, the futures market's ability to provide adequate price predictions is examined by the use of causality tests, and by comparing its predictive accuracy to a variety of comprehensive prediction models, specifically developed as part of this market review. Our results show that the Fish Pool futures market is efficient and unbiased in the long-run while exhibiting inefficiencies and biases in the short run. Moreover, we find that the futures prices do provide an adequate price discovery function for most contracts, while suffering from somewhat magnified risk premia, due to the sparse number of non-commercial traders. Interpreted in the context of the salmon market's attributes, our results provide evidence of the futures market being attractive for any market participants, both hedgers and speculators alike.

SAMMENDRAG

Vi har gjennom de siste tiårene vært vitne til en formidabel vekst i den globale produksjonen av atlantisk oppdrettslaks, som i dag utgjør en betydelig del av den globale havbrukssektoren. Grunnet omfattende produksjonsutfordringer og fluktuerende etterspørsel, har imidlertid lakseprisen blitt stadig mer volatil, parallelt med produksjonsveksten. Som en direkte konsekvens ble også behovet for finansielle risikostyringsverktøy sterkt økende, frem til etableringen av derivatmarkedet *Fish Pool* i 2005. Grunnet relativt lavt handelsvolum har det imidlertid blitt stilt spørsmålstegn ved markedets effisiens. Formålet med dette studiet er å gi en omfattende vurdering av dagens markedskarakteristika, og hvilke implikasjoner disse har for aktører i markedet. Ved bruk av et bredt modellrammeverk analyserer vi både effisiens og hvorvidt futuresprisene innehar biaser, både på kort og lang sikt. Videre vurderer vi markedets evne til å forutsi fremtidige prisbevegelser. Vi undersøker dette ved både å innlemme kausalitetstester og ved å sammenlikne futuresprisenes prediksjonser over en lengre periode mot prediksjoner fra omfattende prediksjonsmodeller, spesifikt utviklet for denne markedsanalysen. Resultatene våre indikerer at futuresprisene er effisiente på lang sikt, samtidig som de innehar både ineffisiens og biaser på kort sikt. Vi finner også at futuresprisene innehar tildels gode prediksjonsegenskaper, samtidig som det ser ut til å lide av noe forhøyet risikopremie, som følge av en relativt lav andel spekulative markedsaktører. Sett i sammenheng med laksemarkedets egenskaper tyder resultatene våre på at Fish Pool futuresmarked er et attraktiv marked for både minimering av prisrisiko og for spekulative formål.

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ACRONYMS

ADF	Augmented Dickey-Fuller
AIC	Akaike information criteria
ANN	Artificial neural network
ARIMA	Autoregressive integrated moving average
DGP	Data generating process
ECM	Error correction model
EMH	Efficient market hypothesis
EWMA	Exponentially weighted moving average
FPI	Fish Pool Index^{TM}
GARCH	Generalized autoregressive conditional heteroscedasticity
GQARCH-M	Generalized quadratic autoregressive conditional heteroscedasticity in-mean
MoM	Month-over-Month
RMSE	Root mean squared error
YoY	Year-over-Year

1 INTRODUCTION

Ever since the first net-pen production facilities for Atlantic salmon were established in 1969, the Norwegian salmon industry has experienced tremendous growth, becoming a substantial contributor to Norwegian exports figures (Aarset 1998). However, due to considerable production risk and fluctuating demand, the salmon price has been highly volatile, imposing a significant price risk on any market participant (Oglend 2013, Guttormsen 1999). The ever-growing price risk has substantiated the need for adequate risk management tools, initially seen as traditional forward contracts initiated by market participants on both sides of the transactions. In 2005, a growing desire for a financial derivatives market was accommodated, with the establishment of the *Fish Pool* futures market. In the years following its inception, Fish Pool provided both futures contracts and financial options. However, due to thin trading, the financial options were withdrawn within a few years, leaving futures contracts as the only provided hedging tools (Fish Pool ASA 2019c). Today, the Fish Pool futures market is the exclusive trading platform for salmon derivatives. Nevertheless, the futures market's trading volume is rather thin in comparison to other commodity futures market, leaving its hedging efficiency subject to question.

Existing literature on the subject of efficiency in the Fish Pool futures market is both relatively scarce, and to some degree contradicting. Moreover, the most recent studies were published in 2016, examining data sets covering time periods up until 2014, 2015 and mid-2016, respectively (Asche et al. 2016*c*, Yeboah et al. 2016, Fisher & Lai 2016). Applied in this study is an extended data set, covering the time period from January 2007 to December 2018, evidently providing an updated market review. Furthermore, we provide a more comprehensive framework than what is previously applied, accounting for the essential features of the salmon market.

Initially, we perform a long-run analysis of the market by conventional likelihood-ratio tests on the restriction of cointegration parameters. Moreover, we perform a more extensive analysis of short-run efficiency by initially utilizing a prototypical error correction model (ECM), conventionally applied in the assessment of cointegrated time series. Residuals analysis does, however, reveal that the ECM exhibits shortcomings in the assessment of a market such as the salmon market, which to a large extent is subject to severe fluctuations. We account for this by applying an extended ECM with GARCH components (ECM-GARCH) in the assessment of short-run efficiency and unbiasedness. Furthermore, the price discovery role of the futures market was examined by causality tests for both long- and short-run causality. The predictive power was further assessed by comparing the predictions provided by the futures market to out-of-sample predictions provided by several comprehensive prediction models, specifically developed for the purpose of this market review.

The results of our long-run analysis indicate both efficiency and unbiasedness in the long-run, in line with previous findings. The short-run analysis does, on the other hand, provide less convincing results, indicating both inefficiencies and biases in the futures prices. Moreover, the results on the predictive power are rather twofold. The tests of causality indicate that the futures do, to some extent, perform price discovery in both long- and short-run, whereas out-of-sample predictions of our prediction models were consistently outperforming the futures market, possibly indicating exploitable inefficiencies. Seen in the context of the salmon market's characteristics, our results indicate that a short-run bias is partly reflecting underlying market risk factors, while also revealing potential excess risk-adjusted return, presumably due the sparse number of speculative traders acting in the market.

The remainder of this study is organized as follows: In section 2 we provide a thorough review of existing literature, related to the assessment of the Atlantic salmon futures market. In section 3 we present the most vital data applied in the analysis, whereas theory on market efficiency as well as the methodology is outlined in section 4. The results of our assessment are presented in section 5, followed by conclusive remarks in section 6.

2 LITERATURE REVIEW

Existing studies on the salmon futures market is rather scarce, and previous findings are not entirely consistent. However, the literature on other futures markets is rich and may provide valuable insights, both in terms of common market properties and useful methodological techniques. Therefore, the following literature review contains relevant literature on the salmon market as well as other commodity markets exhibiting similar properties.

2.1 LITERATURE ON EFFICIENCY IN THE ATLANTIC SALMON FUTURES MARKET

The Fish Pool futures market has been subject to only a few studies ever since its inception in 2005. The most recent studies on the efficiency and unbiasedness of the salmon futures market provide somewhat conflicting results, partly due to differences in both methods and data preprocessing. Asche et al. (2016*c*) performs efficiency testing on monthly observations spanning the time period from 2006 to 2014, involving monthly contracts with 1-6 months to maturity. By the use of the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller 1979) and Johansen's test for cointegration (Johansen 1988, 1991), they find that the spot and futures prices are non-stationary and cointegrated for all maturity lengths. Based on restrictions on the cointegrating parameters, they fail to reject the null hypothesis of long-run market efficiency and unbiasedness, suggesting that the market does provide effective hedging. However, they fail to reject that spot prices are exogenous in the spot-futures relation, suggesting that the futures prices do not perform any price discovery role, an important feature of a mature futures market (Garbade & Silber 1983).

Fisher & Lai (2016) performs a similar study on weekly observations covering the time period from June 2006 to June 2016, involving monthly contracts with 1-12 months to maturity. Similar to Asche et al. (2016*c*), they perform tests of stationarity and cointegration. In addition to the Johansen's test for cointegration, they apply the conventional Engle-Granger (Engle & Granger 1987) cointegration procedure. As emphasized by Stock (1987), the cointegrating parameters incurred by the Engle-Granger procedure do not follow standard limiting distributions, and market efficiency testing by restrictions on the given parameters is not appropriate. Conversely, the results of this procedure are redundant, at best. Ultimately they incorporate a prototypical error correction model, testing for both long- and short-run efficiency. They fail to reject unbiasedness based on the the Engle-Granger parameters, for all maturity lengths. However, based on the Johansen's cointegrating parameters, unbiasedness is rejected for some of the contracts. These differing results clearly highlights the problems imposed by the use Engle-Granger procedure, in terms of efficiency and unbiasedness testing. Contrary to Asche et al. (2016*c*) they conclude that the futures market does, in fact, provide a price discovery function. Looking closer at their test results on weak exogeneity, their results might be interpreted differently, questioning their contradicting conclusion.

Yeboah et al. (2016) examine the salmon futures market by utilizing monthly data from 2006 to 2015, confirming previous findings on stationarity and cointegrating relations. Furthermore, the unbiasedness hypothesis is found to hold for monthly futures contracts with 1-6 and 9 months to maturity. Furthermore, they examine the price discovery role in a similar manner as Asche et al. (2016*c*) and Fisher & Lai (2016). They find that the futures contracts do provide the expected price discovery role for 3-, 4-, 5-, 9- and 12-months futures contracts, but simultaneously that this is not the case for 1-, 2- and 6-months futures contracts. They conclude that the futures market does exhibit properties of a maturing market, but that hedging efficiency is better for farmost contracts than for contracts closer to maturity. Moreover, they found strong support for the Samuelson hypothesis, stating that futures price volatility increases as the futures contract approaches maturity.

2.2 Literature on Efficiency in Other Commodity Futures Markets

The literature on other commodity futures markets is extensive, compared to the salmon market. A broad range of recent studies follows a conventional approach, finding non-stationary properties for both spot and futures prices, followed by a test for long-run cointegrating relations. Ultimately, restrictions on the parameters of a fitted error correction model (ECM) is carried out, yielding a conclusion on both long- and short-run market efficiency and unbiasedness. Following this methodology, Keillard et al. (1999) fail to reject long-run efficiency in a range of commodity markets but find evidence for short-run inefficiencies. Similarly, Beck (1994) finds several agricultural futures markets to be sporadically inefficient in the short-run. When investigating some of the same agricultural futures markets, McKenzie & Holt (2002) acknowledge the fact that the futures risk premium is time-varying, and that the conventional ECM does not provide sufficient insight. This is confirmed by the existence of significant autoregressive heteroscedastic (ARCH) effects in the ECM residuals. These effects are captured by complementing the ECM model with a generalized quadratic ARCH in-mean component, in what is referred to as a GQARCH-M-ECM model. Once again, the cattle, hogs and corn futures markets were found to be efficient in the long-run, while simultaneously exhibiting short-run inefficiencies and pricing biases. The salmon market has an important common denominator with the markets considered in all of these studies, namely that they are all subject to seasonal effects, which to a large extent is explained by periodic harvesting patterns. With this in mind, the findings of the previously mentioned studies are highly relevant when examining the salmon futures market.

2.3 Literature on Modelling Atlantic Salmon Spot Price

When assessing a futures market's ability to serve as an adequate hedging tool, its predictive power is of key importance. Existing literature on the salmon futures market examines weak-form market efficiency, exclusively, which we further discuss in section 4. For any market participants, however, semi-strong form efficiency is of major concern. The existence of a model, comprising all publicly available information[1], significantly outperforming the futures market would imply semi-strong form market inefficiencies, which would be of great concern to both hedgers and speculators. The literature on modeling salmon spot price is rather scarce and does primarily cover models predicting the *direction* of future price movements. Guttormsen (1999) applied a variety of prediction models[2] but was unable to conclude upon a superior framework. Using state-space modeling on salmon price forecasting, Vukina & Andersen (1994) amply demonstrate that

[1] In terms of semi-strong market efficiency, the available information set comprises all relevant and publicly available information, including information on exogenous factors affecting the spot price, further described in subsequent sections

[2] Models applied in the study include *autoregressive moving average* (ARMA), *Holt-Winters exponential smoothing* (HW) *Classical Additive Decomposition* (CAD), *Vector Autoregression* (VAR), as well as two naïve techniques.

the salmon price exhibits considerable seasonal properties. Sandaker et al. (2017) model the distribution of the Atlantic salmon spot price using quantile regression, thoroughly studying factors affecting the salmon spot price, including factors affecting both demand and supply. Although the findings in the existing literature are not directly transferable to the evaluation of market efficiency, these empirical findings were highly valuable to our development of prediction models, which we further explain in section 4.2 and appendix B. Broadly speaking these findings are key insights on seasonal effects and exogenous factors affecting the salmon spot price.

2.4 Contribution to Existing Literature

Existing literature on the Atlantic salmon futures market exhibits mixed findings in terms of both efficiency, unbiasedness and price discovery function. The partially contradicting findings should be carefully assessed, acknowledging that the small size of available data sets might cause inconsistencies across different methodologies. The majority of existing literature was published in 2016, typically assessing the market based on 10 years of monthly data, which is a relatively short time span compared to studies on well-established markets. Brorsen & Fofana (2001) found that the majority of newly established futures markets fail to acquire the hedging properties of a mature market, and are abolished within a few years of inception, implying that consecutive reviews over the first few decades of inception are of particular interest. By incorporating extended data sets, this study captures the evolution of the Atlantic salmon futures market over the last few years, providing an updated review of market characteristics.

Furthermore, existing literature does not fully account for some of the important proprieties of the salmon market, possibly leaving the basis for conclusions somewhat inadequate. As amply outlined in subsequent sections, seasonal effects on the spot price are reflected in the realized futures *risk premium*[3]. This implies that neither the existence of cointegrating relations nor the application of an ECM is sufficient to conclude on short-run unbiasedness. Inspired by the work of McKenzie & Holt (2002), the existence of ARCH effects in the ECM residuals is incorporated in an extended ECM model, allowing for a time-varying risk premium. Failure to reject market efficiency does not rule out the existence of market inefficiencies, and the strive for an adequate model is crucial. Ultimately, the predictive power of a variety of models is compared to the predictive power of futures prices, giving additional insights into market efficiency, both weak and semi-strong form variety. The results of these models provide further intuition in the assessment of current market features, knowledge which should be of great interest to market participants, both hedgers and speculators alike.

[3]The risk of futures contract is defined as the difference between contractual price and realized spot price, often referred to as the basis.

3 DATA

In this section, we will describe the most vital data used in the analysis of the Atlantic salmon futures market. As we will further elaborate upon in subsequent sections, the development of multiple prediction models has been carried out as part of the market analysis, incorporating extensive data on exogenous factors affecting the salmon spot price. Acknowledging that the predictions models them self are outside the main scope if this study, however, descriptions and details on prepossessing of this data are found in appendix B.1.

3.1 THE FISH POOL INDEX™

In this study, we examine the Fish Pool futures market and its characteristics. The underlying price for financial settlement of all futures contracts on the Fish Pool future market is the *Fish Pool Index*™ (FPI). The FPI is a synthetic spot price, reflecting the current market price of 1 kg of fresh Atlantic salmon. It is based on a weighted average of sizes of 3-6 kg, superior quality, head-on-gutted salmon, and comprises data from the Nasdaq Salmon Index, Statistics Norway (SSB) and the Fish Pool European Buyers Index (Fish Pool ASA 2019*b*). The prices are reported on a weekly basis, whereas the underlying settlement prices of futures are calculated as their monthly average. These calculations are based on schedules published in the *Fish Pool Rulebook* (Fish Pool ASA 2019*a*). The settlement price for e.g. January 2018 is calculated as the average of the FPI over week 1-5 2018. Following this schedule, the weekly spot prices are transformed into monthly prices, comprising 144 observations over the time period January 2007 - December 2018.

3.2 FUTURES PRICES

Fish Pool ASA provides daily updated futures prices, reflecting the latest market trades. The futures prices are ultimately highly dependent on the participants risk preferences as well as the total trading volume. A necessity for an efficient and unbiased futures market is, therefore, a sufficient number of participants taking both long and short positions. Thus, when assessing the efficiency of a future market, it is of primary interest to assess contracts that are frequently traded. The total trading volume on the Fish Pool futures market is thin, relative to a number of global and mature markets. It is, therefore, of particular interest to examine the contracts that are traded most frequently. A review of all the completed trades clearly demonstrates that certain contracts are superior in terms of trading volume. As amply exhibited in appendix A.2, the front-month,[4] half-year and quarterly contracts, as well as monthly contracts with 1 and 2 months to expiration, are evidently the most reasonable contracts to assess. Based on the this review, we chose to assess monthly contracts with 1-6 months to expiration, indirectly assessing the upfront quarter and half-year contracts as well. Throughout the rest of this study, the prices of the monthly contracts at time t, expiring in 1-6 months, are referred to as $F_{t,1}, F_{t,2}, \ldots, F_{t,6}$, respectively.

As emphasized by Ma et al. (1992), traders tend to roll over their positions in expiring contracts to other back-month contracts, causing rollover effects in the futures prices. Following Bloznelis (2018*b*), the futures prices are therefore adjusted by transforming the time series to log-returns, replacing the rollover return by the return on the underlying, and subsequently undoing the log

[4]Front-month contracts refers to the contracts with expiration date closest to the current date

transformation. Next, the daily futures prices are transformed into monthly prices by averaging monthly observations. That is, the price of e.g. $F_{t,1}$ contracts with expiration in June 2018 is calculated as the averaged price of this actual contract, observed over the entire month of May 2018. As for the spot price, this study comprises 144 observations of $F_{t,1}$ - $F_{t,6}$, covering the time period January 2007 - December 2018.

3.3 Unit Root Testing

In order to examine whether the data exhibits non-stationarity, we apply the augmented Dickey-Fuller test (Dickey & Fuller 1979) to the time series in both log levels ($s_t = logS_t$, $f_t = logF_{t,T}$) and first difference log levels. The number of lags was chosen based on the Akaike Information Criteria (AIC). As would be expected from previous findings in the literature, both the spot price and futures prices for all contract lengths were found to be non-stationary and integrated of the first order, tabulated in table 1.

Table 1: Results from ADF unit root testing

	Log levels		First difference log levels	
	Without trend	With trend	Without trend	With trend
Spot	0.554	-3.365	-7.197***	-7.178***
$F_{t,1}$	0.695	-3.274	-6.609***	-6.642***
$F_{t,2}$	0.880	-3.145	-6.083***	-6.146***
$F_{t,3}$	1.066	-2.991	-5.189***	-5.282***
$F_{t,4}$	1.141	-2.814	-5.673***	-5.786***
$F_{t,5}$	0.934	-3.158	-6.723***	-6.837***
$F_{t,6}$	0.957	-3.122	-6.328***	-6.456***

The ADF was conducted with and without a deterministic trend. The number of lags was chosen based on the Akaike Information Criteria (AIC). (***), (**) and (*) indicate rejection of the null hypothesis (H_0: A unit root is present in the time series) at 1% and 5% and 10 % level, respectively.

3.4 Seasonality

The Atlantic salmon spot and futures prices are previously found to exhibit seasonal properties (Asche et al. 2016*b*), reflecting deterministic patterns in both supply and demand. Of primary interest in the assessment of market efficiency, is the occurrence of deterministic seasonal patterns on the realized futures risk premia, i.e. the difference between futures and spot price at expiration ($RP_{t,T} = S_T - F_{t,T}$). The *a priori* belief was that such a pattern would be seen by visually examining the occurrence of any autocorrelation of the risk premia with lags of up to 12 months, depicted in the autocorrelation plots in appendix D. Although all the risk premia seem to be somewhat autocorrelated, the plots do not reveal any considerable autocorrelation for lags of exactly 12 months. This does, however, not rule out the existence of annual seasonality, but suggest that any seasonal effects are either found within only a few months of the year or coinciding with demand driving factors not constantly occurring at the same time of the year, such as certain holidays. The seasonal components were further investigated by composing 12 monthly dummy variables, $DE_{m,t}$ for months $M = \{Jan, Feb, ..., Dec\}$, as well as dummy variables for both the Chinese New Year and the Easter holidays, formally expressed as DE and DC, respectively. Noting that neither of these holidays are occurring constantly at the same time of the year, their occurrence where manually preassigned. The seasonal coefficients were found by regressing the observed values on each dummy variable. In order for the coefficients not to be collinear, one of the dummy variables were manually omitted before the regression. The Chinese New Year, which is found to have an impact on other aquaculture markets such as *shrimp* and *mud crab* (Lee. 1991), was found to be negligible in terms of seasonal effects, and its dummy variable, *DC*, was omitted for further analysis. Besides the insignificance of the Chinese New Year holidays, the risk premia were found to exhibit seasonal patterns for all the assessed futures contracts. Eventually, this method was further applied in the seasonal prediction model proposed in section 4.2.

3.5 Descriptive Statistics on the Risk Premia

We provide the most important statistics on the risk premia as well as relevant test results in table 2. The positive mean for all contracts indicates a possible overweight of traders wishing to hedge their position by taking short positions in futures contracts, i.e. an overweight of market participants on the supply side. Moreover, the risk premium of all contracts except the front-month contracts are positively skewed. Furthermore, all risk premia are found to be leptokurtic, i.e. heavy-tailed, reflecting the volatile nature of the underlying spot price. The *Jarque Bera* test rejects normally distributed risk premia for the front-month contracts, only. We check for stationarity and autocorrelation using the ADF and *Ljung Box*-tests, respectively. Neither stationarity nor the existence of autocorrelation in the risk premium can be rejected for any of the contracts (for visual inspection please refer to the plots in appendix D).

Table 2: Descriptive statistics on the risk premia

		Descriptive Statistics				Tests		
Contract	N	Mean	Std.dev.	Skew	Ex.kurt.	JB	ADF	Ljung.Box
$F_{t,1}$	144	0.424	4.34	-0.03	0.95	6.13**	-4.86***	40.94***
$F_{t,2}$	144	0.870	5.72	0.12	0.56	2.58	-4.38***	83.38***
$F_{t,3}$	144	1.305	6.62	0.23	0.48	2.93	-4.32***	106.14***
$F_{t,4}$	144	1.664	7.08	0.28	0.51	3.8	-3.76**	138.08***
$F_{t,5}$	144	1.957	7.30	0.24	0.42	2.69	-3.44*	182.70***
$F_{t,6}$	144	2.353	7.44	0.23	0.37	2.35	-3.56**	233.67***

(***), (**) and (*) indicates rejection of the null-hypotheses at a 1% , 5% and 10% level, respectively

4 Theory and Methodology

The majority of literature on efficiency in futures markets is built on the theoretical *efficient market hypothesis* (EMH), presented by Fama (1970). Conceptually, the EMH necessitates the present futures price F_t in an efficient market to equal the expected spot price at expiration, given the information-set Φ_t, and hence the futures price to be the best possible forecast of the spot price at expiration. Considering the price of a futures contract at time t-1, expiring at time t, this is formally expressed as

$$F_{t-1} = \mathbb{E}[S_t|\Phi_{t-1}] \tag{1}$$

The information-set on which the expectations are based is, however, highly relevant. Fama (1970) and Roberts (1967) considered market efficiency in three separate forms; *weak*, *semi-strong* and *strong form efficiency*. Weak-form efficiency implies that all historical price information is fully incorporated in the futures prices, i.e. that equation 1 holds for an information-set containing historical prices. Similarly, for the semi-strong and strong form efficiency, the information-set consolidates all publicly available and publicly unavailable information, respectively, including information on exogenous factors affecting the underlying. The classical approach, utilized in a number of studies (e.g. Bigman et al. (1983)), is simply to regress the futures price on the spot price at maturity, i.e.

$$S_t = A + BF_{t-1} + u_t \tag{2}$$

where the residuals, u_t, are assumed i.i.d. $\sim N(0, \sigma^2)$. Market inefficiencies are then found by the rejection of the null hypothesis $H_0 : A = 0$ and $B = 1$. Strictly speaking, this hypothesis can be viewed as a joint hypothesis of both market efficiency ($B = 1$) and unbiasedness ($A = 0$). The unbiasedness hypothesis is based on the assumption of fully risk-neutral market participants which are equally represented by the number of short and long hedgers. In reality, however, this is rarely the case. Under the *Keynes-Hicks* hypothesis (Keynes 1927, Hicks 1939), short hedgers are willing to sell futures contracts below the expected spot price, paying a risk premium to participants willing to offset the position. Conversely, long hedgers are willing to buy futures contracts above the expected spot price. Unless the market is perfectly balanced by the number of long and short hedgers, we would, therefore, expect to find a risk premium incorporated in the futures prices, ultimately causing the null hypothesis to be rejected. Under this theory, a hedge dependent risk premium can then be introduced into equation 1 as follows

$$F_{t-1} = RP_t + \mathbb{E}[S_t|\Phi_{t-1}] \tag{3}$$

Note that when we are evaluating storable commodities, the difference in futures price and realized spot price, generally referred to as the futures' basis, may be encountered as a convenience yield, rather than a risk premium. However, due to the limited storability of fresh salmon, the risk premium theory presented above seems more suitable for the interpretation of any price bias. Independent of the expected risk premium, the regression method in equation 2 does, however, yield limited or even misleading insights when evaluating most futures market. As found by Byrne et al. (2013), most commodity prices are found to be non-stationary with one unit root, which was also found to be the case for both salmon spot and futures prices in section 3.3. The use of OLS linear regression may, therefore, lead to spurious regression results. Methods have been presented to bypass the problem of non-stationary properties, by first-differencing equation

2 with respect to the spot and futures price

$$S_t - S_{t-1} = A + B(F_{t-1} - F_{t-2}) + u_t \tag{4}$$

once again implying a joint hypothesis of efficiency and unbiasedness by $A = 0$ and $B = 1$. However, also this approach has its pitfalls. If the time series are cointegrated, the regression is once again misspecified.

4.1 Long- and Short-Run Analysis

As outlined in section 3.3, both the spot price and the futures prices are all non-stationary and integrated of first order and, presumably, so are the residuals in equation 2 for most combinations of A and B. However, if the spot price and futures prices are cointegrated, they can not move too far away from each other in the long-run. If that is the case, there exist one or more combinations of cointegrating parameters, α and δ, leaving the residuals in equation 5 stationary. Formally, the cointegrating relationship is expressed as

$$S_t = \alpha + \delta F_{t-1} + u_t \tag{5}$$

We employ the Johansen multivariate cointegration test (Johansen 1988), and likelihood ratio tests on the cointegrating parameters, α and δ, testing for long-run efficiency ($\delta = 1$) and unbiasedness ($\alpha = 0$). Note that the broadly applied Engle-Granger (Engle & Granger 1987) procedure does not follow standard limiting distributions, meaning that hypothesis testing on the given parameters can not be performed by the use of conventional statistical tests. This procedure is, therefore, not applied to our study.

Error Correction Model

For a futures market to be efficient and unbiased, the futures prices need to be cointegrated with the underlying spot price. Cointegration does, however, only imply that the two time series do not move too far apart in the long-run, and is not sufficient evidence for short-run efficiency. The conventional approach for testing short-run efficiency in a cointegrated futures market, also applied in this study, is to formulate the cointegrated system as an error correction model (ECM) first introduced by Granger (1986). Formally, the ECM applied in this study is given by

$$\Delta S_t = -\rho u_{t-1} + \beta \Delta F_{t-1} + \sum_{i=2}^{m} \beta_i \Delta F_{t-i} + \sum_{j=1}^{k} \psi_j \Delta S_{t-j} + \upsilon_t \tag{6}$$

where u_t is the residual from equation 5 at time t. The futures market is weak-form efficient and unbiased in the short-run if all previous price information is incorporated into the futures prices, thus lagged versions of the spot and futures prices do not improve the forecast. Formally, efficiency implies not violating the following restrictions on equation 6.

$$\rho = 1, \beta \neq 0 \text{ and } \beta_i = \psi_j = 0 \quad [i, j] \in [M, K] \tag{7}$$

Similarly as for the long-run analysis, the short-run analysis on price bias may be divided into separate hypothesises, representing different scenarios. In order to better understand the implication of the scenarios, the ECM may be rewritten as

$$S_t = (1-\rho)S_{t-1} + \beta F_{t-1} + (\rho\delta - \beta)F_{t-2} + \rho\alpha + \sum_{i=3}^{m} \beta_i \Delta F_{t-i} + \sum_{j=1}^{k} \psi_j \Delta S_{t-j} + \upsilon_t \tag{8}$$

The first and, presumably, the least realistic scenario is a market with a zero risk premium in the short-run. This would indicate fully unbiased futures prices, in short necessitating an adequate balance of market participants in both long and short positions. Formally, this scenario means not violating neither the long-run restrictions ($\alpha = 0, \delta = 1$) nor the following short-run restrictions imposed on equation 6 above

$$\rho = \beta = 1, \beta_i = \psi_j = 0 \quad [i, j] \in [M, K] \tag{9}$$

implying that equation 8 is reduced to $S_t = F_{t-1} + u_t$. Another, and presumably more plausible, scenario is the finding of a market with a constant risk premium in the long-run. Such a finding would suggest an averaged overweight of hedgers in either short or long positions, depending on the risk premium's *signum*. Unlike the first scenario, this scenario implies that $\alpha \neq 0$, yielding a reduced form of equation 8 given by $S_t = \alpha + F_{t-1} + u_t$.

Error Correction Model with GARCH Component

The ECM outlined in equation 6 does however exhibit a shortcoming in that it does not encounter a time varying risk premium on the futures prices. Commodity markets with periodic harvest volumes are particularly likely to exhibit both seasonality and autocorrelation in the risk premia, which we already have found to be the case for the Atlantic salmon market. Further, the sporadic blossoms of sea lice and diseases[5], are likely to cause temporary volatility peaks on the spot price, yielding heteroscedastic properties of both the spot price and risk premia. This is confirmed by the existence of ARCH-effects in the ECM residuals outlined in section 5.1, suggesting that an extended version of the conventional ECM model would be more appropriate. McKenzie & Holt (2002) did similar observations when assessing agricultural futures markets, leading to the utilization of an extended ECM with a generalized quadratic ARCH-in-mean component, referred to as a GQARCH-M-ECM model. Inspired by their work, we extended the prototypical ECM to incorporate autocorrelated residuals. Consecutive residual analysis indicated that an ECM-GARCH(1,1) model was able to capture the ARCH-effects found in the ECM-residuals for all contracts, and was, therefore, applied to the short-run analysis. Formally, the model is expressed as

$$\Delta S_t = -\rho u_{t-1} + \beta \Delta F_{t-1} + \sum_{i=2}^{m} \beta_i \Delta F_{t-1} + \sum_{j=1}^{k} \psi_j \Delta S_{t-j} + \theta\sqrt{h_t} + \upsilon_t \tag{10}$$

where

$$h_t = w + \sum_{i=1}^{r} \gamma_i h_{t-i} + \sum_{j=1}^{s} a_j \upsilon_{t-j}^2 \quad \text{and} \quad \upsilon_t = e_t\sqrt{h_t}, e_t \sim IN\{0, 1\} \tag{11}$$

where h_t is the conditional variance of spot price changes for period t. Once again, short-run efficiency implies not violating the restrictions

$$\rho = 1, \rho\delta = \beta \neq 0, \beta_i = \psi_j = 0 \quad [i, j] \in [M, K] \tag{12}$$

[5] See appendix A.1 for further background information on the farming industry, including the occurrence of dreadful diseases.

and conversely, short-run unbiasedness along with efficiency and unbiasedness in the long-run ($\alpha = 0, \delta = 1$ from the cointegrating relation in equation 5) is given by the additional fulfillment of the stricter restriction, $\beta = 1$.

4.2 Predictive power

In a final assessment of the futures market, we examine its predictive power. This part of the analysis is twofold: We assess the futures market's price discovery role, as well its historical prediction accuracy in comparison to a variety of models, testing for both weak and semi-strong market efficiency.

Price Discovery Role

If the spot and futures prices are found to be cointegrated, we know that the two time series will not move too far apart in the long-run. When assessing long- and short-run market relations, we examine whether the spot or the futures price is the driving force towards equilibrium, i.e. which of the two prices perform a price discovery function. In a mature and efficient futures market, we would expect to find bidirectional causalities where both the spot and the futures prices contribute to price changes. The analysis of long- and short-run causality was performed by establishing a bivariate vector error correction model (VECM), similar to the ECM in equation 6 for both the spot and futures prices, given by

$$\Delta s_t = -\rho_1 u_{t-1} + \sum_{i=1}^{n} \beta_i \Delta f_{t-i} + \sum_{j=1}^{m} \psi_j \Delta s_{t-j} + \upsilon_{1,t} \tag{13}$$

$$\Delta f_t = -\rho_2 u_{t-1} + \sum_{k=1}^{m} \psi_k \Delta f_{t-k} + \sum_{l=1}^{n} \beta_l \Delta s_{t-l} + \upsilon_{2,t} \tag{14}$$

The long-run price dynamics are assessed by running a conventional t-test on the coefficients of the error correction term, i.e. ρ_1 and ρ_2. A statistically significant coefficient implies causality in the long-run. The analysis of short-run causality is performed by block exogeneity tests on the respective ECM models, excluding the lagged price information on the endogenous variable. That is, forcing $\beta_i = 0, i \in [1,n]$ in equation 13 and $\psi_k = 0, k \in [1,m]$ in equation 14. A Wald-type χ^2 test on the restricted and unrestricted models reveals whether the excluded variables have any statistically significant explanatory power, and thereby if there exists any short-run causality. These procedures are often referred to as long- and short-run *Granger causality tests* (Granger 1988, Alzahrani et al. 2014).

Out-of-Sample Prediction Accuracy

The second part of the assessment of predictive power was performed by dividing the complete time series into two separate parts, for an in- and out-of-sample analysis, comprising 108 and 36 monthly observations, respectively. The two models outlined above were then re-estimated in-sample, and their respective out-of-sample forecasts were re-transformed into price levels. The predictive performances of the re-estimated models were then compared to that of the futures prices, out-of-sample. The metric for goodness-of-fit used for assessment of prediction accuracy was the out-of-sample root mean squared error (RMSE). The futures markets' primary purpose is to serve as a tool to hedge price risk, inevitably testifying to the existence of risk-averse market participants in an efficient market, i.e. market participants with non-linear concave utility functions. Such risk preferences are reflected in the use of RMSE which is disproportionately penalizing large errors.

In addition to the already stated models, we constructed a seasonal prediction model on the risk premia, directly incorporating historical in-sample seasonal effects on the risk premia. This was done by introducing seasonal dummies for each month of the year, as well as for the Easter holiday, in line with the approach outlined in section 3.4. Formally, the model is expressed as

$$\hat{S}_T = F_{T,t} + \sum_{m=1}^{12} \omega_{t,m} DM_{m,T} + \phi_t DE_T + \upsilon_t \tag{15}$$

where $\omega_{t,l}$ is a binary variable taking on the value 1 if time t coincides with month of the year l, $DM_{m,T}$ is the historical seasonal risk premium components of contracts expiring in T months, for the calendar month $m \in \{Jan, \ldots, Des\}$. Similarly, for the Easter holiday effect, ϕ_t is a preassigned value between 0 and 1, reflecting the portion of the Easter holiday effect affecting the respective month, whereas DE_T is the in-sample seasonal effect on the risk premium for the Easter holiday.

Thus far, this study has dealt with the futures markets weak-form efficiency, exclusively. For any market participants, however, semi-strong efficiency is equally important. Considerable effort was, therefore, put into the construction of additional models, comprising publicly available information on exogenous factors affecting the spot price, thoroughly described in appendix B. This includes a vector autoregressive (VAR) model, as well an artificial neural network (ANN) model. As for the weak-form models above, these models were estimated in-sample, and their out-of-sample predictive power was then compared to that of the futures prices. In the context of this study, the results of the models are of primary interest, rather than the actual model development. Descriptions of the development procedures of the VAR and ANN models are, therefore, found in appendices B.3 and B.4, respectively.

5 RESULTS

The following sections provide empirical findings based on the methodologies previously presented. We start by presenting long-run properties of the futures market, followed by a more comprehensive short-run analysis. Next, we evaluate the predictive power of Atlantic salmon futures markets, both in terms of the price discovery role and the out-of-sample predictions. Finally, we discuss our findings and interpret our results in the context of the properties of the salmon market.

5.1 LONG- AND SHORT-RUN ANALYSIS

Already knowing that both the spot and futures price series are non-stationary with one unit root, the first part of the long-run analysis was the assessment of cointegration. The Johansen's test reveals that the prices for all the assessed contracts are cointegrated with the spot price. In table 3 we show both the trace and eigenvalue statistics for $r = 0$ and $r = 1$ cointegrating relations, both rejecting $r = 0$ for all contracts at a 1% level of significance. We also list the parameters, α and β, for cointegration without trends.

Table 3: Results from Johansen's bivariate cointegration test

$$\lambda_{trace} = -T\sum_{i=r+1}^{n} log(1-\hat{\lambda}i), \quad \lambda_{max} = -Tlog(1-\hat{\lambda}+1) \quad r \in [0, n-1]$$

	r = 0		r ≤ 1		Parameters	
	λ_{trace}	λ_{max}	λ_{trace}	λ_{max}	α	δ
$s_t; f_{t,1}$ [3]	30.76***	28.74***	2.02	2.02	0.118	0.967
$s_t; f_{t,2}$ [9]	47.11***	44.34***	6.67	2.77	0.109	0.972
$s_t; f_{t,3}$ [5]	30.95***	28.69***	2.26	2.26	0.130	0.965
$s_t; f_{t,4}$ [9]	48.52***	43.98***	2.95	2.95	0.100	0.972
$s_t; f_{t,5}$ [10]	47.43***	44.38***	3.44	3.44	0.151	0.958
$s_t; f_{t,6}$ [9]	50.15***	47.43***	2.72	2.72	0.192	0.947

Number of lags are shown in brackets, and were chosen based on the Akaike Information Criteria (AIC) from the corresponding VAR model. (***), (**) and (*) indicates rejection of null hypothesis at 1%, 5%and 10% level, respectively. H_0 : There exists r cointegrating relations.

Table 4: Test of restrictions on parameters for long-run efficiency

	$H_0 : \alpha = 0$		$H_0 : \delta = 1$		$H_0 : \alpha = 0, \delta = 1$	
$s_t; f_{t,1}$ [3]	1.102	(0.765)	1.107	(0.766)	0.343	(0.706)
$s_t; f_{t,2}$ [9]	1.472	(0.810)	1.451	(0.808)	1.875	(0.153)
$s_t; f_{t,3}$ [5]	0.808	(0.716)	0.757	(0.706)	1.520	(0.217)
$s_t; f_{t,4}$ [9]	0.876	(0.729)	0.845	(0.723)	0.626	(0.531)
$s_t; f_{t,5}$ [10]	1.333	(0.795)	1.286	(0.790)	1.081	(0.337)
$s_t; f_{t,6}$ [9]	1.372	(0.799)	1.313	(0.793)	1.516	(0.218)

P-values are shown in parentheses. (***), (**) and (*) indicates rejection of the null hypothesis at 1%, 5%and 10% level, respectively.

The analysis of long-term relationship of the spot and futures prices proceeds with hypothesis testing on the cointegrating parameters, incorporating the restrictions for efficiency and unbiasedness outlined in section 4.1. As depicted in table 4, neither of the restrictions on individual coefficients, $\alpha = 0$ and $\delta = 1$, are rejected for any of the assessed futures contracts. Moreover, the joint hypothesis of simultaneous fulfillment of the two restrictions, $\alpha = 0$ and $\delta = 1$, implying long-run market efficiency and unbiasedness, can not be rejected. Evidently, the findings entail that all contracts exhibit the properties of an efficient market in the long-run.

Table 5: ECM parameters

$$\Delta s_t = -\rho u_{t-1} + \beta \Delta f_{t-1} + \sum_{i=2}^{m} \beta_i \Delta f_{t-i} + \sum_{j=1}^{k} \psi_j \Delta s_{t-j} + \upsilon_t$$

Parameter	$F_{t,1}$	$F_{t,2}$	$F_{t,3}$	$F_{t,4}$	$F_{t,5}$	$F_{t,6}$
ρ	0.337	0.004	0.211	0.061	0.138	0.037
β	0.546	0.333	0.376	0.264	0.613	0.667
β_2	-0.323	–	–	0.340	–	–
β_3	–	–	0.191	–	-0.412	–
β_4	–	0.302	–	-0.433	–	-0.444
β_5	–	–	–	0.268	–	0.372
β_7	–	0.397	–	–	0.469	–
β_8	–	-0.309	–	–	0.379	–
β_9	–	0.246	–	-0.302	–	–
ψ_1	0.369	–	0.292	0.128	0.175	–
ψ_2	-0.143	–	0.113	–	0.182	–
ψ_3	–	-0.262	–	–	–	–
ψ_5	–	–	–	-0.154	–	–
ψ_6	–	-0.218	–	-0.185	-0.228	-0.140
ψ_7	–	-0.153	–	–	–	–
ψ_9	–	–	–	–	0.131	–
Q(12)	52.782*	27.593**	32.684	32.524***	32.052***	31.515***
	(0.069)	(0.024)	(0.384)	(0.006)	(0.001)	(0.001)
$H_0 : \rho = 1$	(0.066)*	(0.065)*	(0.038)**	(0.045)**	(0.048)**	(0.033)**
$H_0 : \beta = 1$	(0.113)	(0.101)	(0.109)	(0.087)*	(0.161)	(0.177)
Efficiency	3.506**	2.295*	2.573*	2.577**	3.455***	3.113***
	(0.031)	(0.0788)	(0.063)	(0.031)	(0.002)	(0.008)
Unbiasedness	32.779***	7.005***	16.417***	6.636***	6.765***	5.582***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Tabulated are coefficients significant at a 10% level only. Q(12) indicates portmanteau test results with 12 lags (H_0: No residual autocorr. up to 12 lags). *Efficiency* and *unbiasedness* indicate test results on hypothesis of efficient and unbiased futures prices, respectively. P-values are found in parentheses. (***), (**) and (*) indicates rejection of the null hypothesis at a 1%, 5% and 10% level of significance, respectively.

Unable to reject efficiency in the long-run, we proceed with the assessment of short-run properties. The prototypical error correction model outlined in section 4.1 was estimated for all the futures prices, followed by tests on the presented restrictions for both efficiency and unbiasedness in the short-run. The tests were performed by imposing F-tests on the residuals of both the restricted and the unrestricted models. In table 5 we depict the coefficients of explanatory variables found to be statistically significant. We also show the test result for efficiency and unbiasedness, indicating that short-run efficiency is rejected at a 5% level of significance for contracts with 1, 4, 5 and 6 months to expiration. Similarly, for contracts with 2 and 3 months until expiration, efficiency is rejected at a 10% level of significance. The joint hypothesis of efficiency and unbiasedness in the short-run is, however, strongly rejected ($p \ll 1\%$) for all the futures contracts, suggesting the existence of a risk premium in the short-run. A *pormanteau* (Castle & Hendry 2010) test for autocorrelation in the residuals with lags of up to 12 months does, however, reveal that the ECM-residuals exhibits ARCH effects for all contracts except contracts expiring in 3 months. These findings suggest that the prototypical ECM is somewhat misspecified. To capture the ARCH-effects, we incorporate the extended error correction model with GARCH-components, previously referred to as the ECM-GARCH model presented in section 4.1.

Table 6: ECM-GARCH parameters

$$\Delta s_t = -\rho u_{t-1} + \beta \Delta f_{t-1} + \sum_{i=2}^{m} \beta_i \Delta f_{t-1} + \sum_{j=1}^{k} \psi_j \Delta s_{t-j} + \theta \sqrt{h_t} + \upsilon_t$$

Parameter	$F_{t,1}$	$F_{t,2}$	$F_{t,3}$	$F_{t,4}$	$F_{t,5}$	$F_{t,6}$
ρ	0.369	0.004	0.223	0.062	0.138	0.017
β	0.508	0.333	0.352	0.264	0.613	0.667
β_2	-0.340	–	–	0.341	–	–
β_3	–	–	0.196	–	-0.412	–
β_4	–	0.302	–	-0.433	–	-0.444
β_5	–	–	–	0.269	–	0.372
β_7	–	0.398	–	–	0.468	–
β_8	–	-0.310	–	–	0.380	–
β_9	–	0.246	–	-0.302	–	–
ψ_1	0.397	–	0.295	0.128	0.173	0.089
ψ_2	-0.129	–	0.119	–	0.184	–
ψ_3	–	-0.264	–	-0.105	–	–
ψ_5	–	–	–	-0.153	–	–
ψ_6	–	-0.217	–	-0.185	-0.228	-0.140
ψ_7	–	-0.152	–	–	–	–
ψ_9	–	–	–	–	0.133	–
θ	0.227	0.248	0.004	0.248	0.351	0.225
w	0.002	0.002	0.002	0.001	0.002	0.006
γ_1	0.594	0.981	0.657	0.977	0.988	0.123
a_1	0.071	0.052	0.068	0.029	-0.043	-0.133
Q(12)	48.132	27.591	31.682	32.525	32.052	35.139
	(0.467)	(0.992)	(0.967)	(0.957)	(0.963)	(0.917)
$H_0 : \rho = 1$	(0.064)*	(0.063)*	(0.041)**	(0.042)**	(0.046)**	(0.032)**
$H_0 : \beta = 1$	(0.109)	(0.094)	(0.101)	(0.091)*	(0.163)	(0.176)
Efficiency	2.960*	2.096	2.288*	2.416**	3.293***	2.943***
	(0.053)	(0.117)	(0.097)	(0.046)*	(0.003)	(0.012)
Unbiasedness	32.779***	4.577***	16.417***	6.636***	6.765***	5.582***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Tabulated are coefficients significant at a 10% level only. Q(12) indicates Portmanteau test results with 12 lags (H_0: No residual autocorr. up to lag 12). *Efficiency* and *unbiasedness* indicate test results on hypothesis of efficient and unbiased futures prices, respectively. P-values are found in parentheses. (***), (**) and (*) indicates rejection of the null hypothesis at a 1%, 5% and 10% level of significance, respectively.

Examining the ECM-GARCH coefficients, the efficiency hypothesis is rejected at a significance level of 5% for contracts expiring in 4, 5 and 6 months, and at a 10% level of significance for contracts expiring in 1 and 3 months. Efficiency of contracts with 2 months until expiration can, however, not be rejected. The joint hypothesis of efficiency and unbiasedness is, on the other hand, once again strongly rejected for all contracts. The minor changes in the test statistics and probabilities, as compared to the ECM-results, are partly due to changes in the degrees of freedom imposed by the increased number of restricted parameters. They do, however, also confirm our previous findings of autocorrelated risk premia, which we will discuss further in section 5.3.

5.2 Predictive Power

Price Discovery Role

In table 7, we show results on the price discovery role of both spot and futures prices from employing the methodology for causality testing, outlined in section 4.2. The long-run analysis reveals that a bidirectional causality can only be rejected for the front-month contracts and contracts expiring in 3 months, implying that the futures contracts expiring in 2, 4, 5 and 6 months, do indeed exhibit a price discovery role in the long-run. Generally speaking, this is an indication of well informed market participants, with adequate knowledge on long-term market prospects. In practice, this can be viewed as market participants' updated view on the long-term prospects of the salmon market being consecutively reflected in the futures prices. For a better intuition on why this is, it is worth noting that the word *causality* could be somewhat misleading in the assessment of the price discovery function. If the futures price is indeed *Granger causing* the spot price, it does not imply that a change in the futures price itself causes a change in the spot price, acknowledging that the spot price is in essence a direct reflection of supply and demand in the market. Rather, such a causality implies that any change in the market prospects is reflected in the futures prices prior to the spot price, further elaborated upon shortly.

Table 7: Results on long- and short-run causality

Contract	Cause	Long-run[a]		Short-run[b]	
$F_{t,1}$	Δs_t	4.220	(0.999)	84.095	(0.000)***
	$\Delta f_{t,2}$	-2.388	(0.009)***	7.216	(0.000)***
$F_{t,2}$	Δs_t	6.342	(1.000)	26.181	(0.000)***
	$\Delta f_{t,2}$	0.019	(0.507)	0.176	(0.839)
$F_{t,3}$	Δs_t	5.470	(0.999)	13.495	(0.000)***
	$\Delta f_{t,3}$	-2.189	(0.015)**	1.123	(0.340)
$F_{t,4}$	Δs_t	6.218	(1.000)	7.239	(0.000)***
	$\Delta f_{t,4}$	-0.461	(0.323)	1.489	(0.206)
$F_{t,5}$	Δs_t	6.216	(1.000)	6.845	(0.000)***
	$\Delta f_{t,5}$	-1.039	(0.150)	2.391	(0.029)**
$F_{t,6}$	Δs_t	6.752	(1.000)	0.796	(0.373)
	$\Delta f_{t,6}$	-0.369	(0.356)	7.1829	(0.008)***

The number of lags in the Granger causality test were chosen based on Akaike Information Criteria (AIC).
[a] The presented p-value and test statistics indicate the significance level ρ from the VECM in equation 13 and 14. This may be translated to $H_0 : \Delta X$ causes ΔY in the long-run
[b] The presented p-value indicates the p-value of rejection of the null hypothesis, H0: ΔX does *not* Granger cause ΔY in the short-run. (***), (**) and (*) indicates rejection of the null hypothesis at a 1%, 5% and 10% level of significance, respectively.

Shifting focus to the short-run analysis, the impression of a somewhat fulfilled price discovery function is further strengthened. As evident in table 7, the null hypothesis of the short-run Granger causality test ($H_O : \Delta x$ do not Granger-cause Δy in the short-run) was rejected for both the front-month and the contracts expiring in 5 and 6 months. For the front-month and contracts expiring in 5 months, the short-run causality was found to be bidirectional, whereas unidirectional causality was found to be the case for the contracts expiring in 6 months, with the futures price performing the price discovery. A necessity of no-arbitrage is that the futures' basis[6] is approaching zero as we get closer to expiration. For the front-month contracts, this basis is ultimately relatively small. Acknowledging that salmon is neither a particularly liquid nor a storable asset, and that the spot price underlying the futures contracts is not directly tradable in the market, the finding of a bidirectional causality close to expiration is not surprising. For the futures contract expiring in 2-4 months, however, the short-run price impacts are unidirectional with the spot price as the driving force. To see how these findings can be interpreted in the context of the salmon market, we will present an example: Following the blossom of a fatal alga in the Northern parts of Norway, in May 2019, the overall market view was that such an outbreak would lead to an increased harvest volume in the short-term due to preventive harvest peaks in areas nearby the affected farming facilities, followed by a long-term supply decrease proportional to the overall biomass reduction. Knowing that the harvest volume is negatively correlated with the spot price (see table 9 in appendix B.2), one would expect a momentary price drop, and a simultaneous positive shift in the distant parts of the forward curve. Examining the price of a monthly futures contract expiring in October 2019, the price as of May 15, 2019 was 55.90 NOK/kg. One week later, on May 22, the price of a similar contract had increased to 57.20 NOK/kg, presumably due to the fatal algae which caught global media's attention on May 16 (iLaks 2019).

In the case of a considerable harvest peak, such as the one following the alga outbreak, a natural short-term effect is a sudden price drop, both in spot and futures price. Knowing that the spot price is reflecting the actual market price in the preceding week, the effect of a sudden harvest peak would be somewhat lagged in the spot price, which is not necessarily the case for the futures price. Under the no-arbitrage argument outlined above, the causality needs to be bidirectional close to expiration, as was found to be the case for the front-month contracts, assuming the market participants to be adequately but not perfectly informed on the short-term harvest volumes. Similarly, for the farmost contracts such as contracts expiring in 6 months, the most obvious effect of the alga outbreak is an increase in futures price proportional to the biomass reduction. For an intermediate horizon, however, such as contracts expiring in 2-4 months, the effect is not that obvious. No one can really tell for how long the alga outbreak is going to last, nor the exact magnitude of the event. If the algae will keep forcing farmers to harvest for another month, it is likely that the spot price will keep declining or at least be kept at a minimum level for a longer period of time. Likewise, it is difficult or even impossible to conclude when the effect of the alga outbreak will turn from negative to positive, in terms of spot price changes. Under all circumstances, eligible anticipations on the effect in 2-4 months require substantially more accurate insights on the market than both front-month and the farmost contracts. Although the example of an alga outbreak of this magnitude is an extreme event in the context of price changes, the intuition is the same for

[6]Note that the basis is not referred to as a risk premium in this context, as any deviation from the long-run equilibrium is not exclusively described by a risk-adjust price premium, acknowledging that the long-run equilibrium would include an appropriate long-run risk premium.

minor changes in the market expectations. Thus, findings of price discovery in the front-month and farmost contracts are indications of no-arbitrage and well informed marked participants acting on the basis of updated market prospects, respectively. The finding of inadequate price discovery of intermediate contracts may, on the other hand, be an indication of sparse number of speculative traders willing to speculate on the more risky and less predictable intermediate effects of an event, such as the alga outbreak.

Out-of-Sample Predictions

The last part of our assessment of the futures market's ability to provide the best possible price forecast, is the analysis of its out-of-sample prediction accuracy, compared to the models previously outlined. In table 8 we present the RMSE-figures for both futures prices and the models, covering prediction horizons of 1-6 months. It turns out that all models outperform the futures prices for all horizons, indicating that the futures market is, in fact, unable to provide the best possible predictions[7]. Appreciating the previous findings of both inefficiencies and biases in the short-run, it is not surprising to see that both the ECM and the more comprehensive ECM-GARCH models were able to slightly outperform the futures market. Moreover, the fact that also the seasonal model was able to outperform the market on all horizons indicates that the short-run bias is, at least to some degree, deterministic and reflecting a time-varying spot price risk, which we will discuss further in the following section. The prediction results also show that the included data on exogenous factors is, in fact, improving the prediction results, implying that there might be speculative opportunities for risk-adjusted return in the futures market. In the following, we will evaluate these findings in the context of our previously reported results.

Table 8: Out-of-sample prediction results

Model	1 mo.	2 mos.	3 mos.	4 mos.	5 mos.	6 mos.
Futures	6.814 (6)	8.836 (6)	10.096 (6)	10.794 (6)	11.075 (6)	11.340 (6)
ECM	5.815 (4)	8.653 (4)	9.915 (5)	9.651 (4)	10.609 (5)	11.089 (5)
ECM-GARCH	5.788 (3)	8.639 (3)	9.664 (3)	9.384 (3)	10.311 (3)	10.804 (4)
Seasonal	6.603 (5)	8.666 (5)	9.818 (4)	10.402 (5)	10.606 (4)	10.698 (3)
VAR	5.428 (1)	8.483 (2)	8.886 (1)	9.043 (1)	9.115 (1)	9.748 (1)
ANN	5.554 (2)	7.608 (1)	9.571 (2)	9.629 (2)	9.637 (2)	9.976 (2)

Tabulated are the root mean squared errors (RMSE) of out-of-sample predictions. Ranks in parentheses.

5.3 Interpretations

In this section, we further discuss and interpret our findings of short-run bias in the context of relevant features of the salmon market, as well as the results on predictive power. Throughout the study, we have presented results indicating time-varying and somewhat predictable risk premia exhibiting seasonal patterns, despite an adequate price discovery function. Such predictability and biases would not be found in an unbiased futures market in the framework of the efficient market hypothesis (EMH). We appreciate that the EMH is a theoretical framework subject to criticism for its tendency of characterizing well established and apparently efficient markets, as both inefficient

[7] Note that transaction costs are excluded from the analysis, in favor of the prediction models

and biased (Malkiel 2003). Thus, there might be natural causes explaining both predictability and bias, which would be of great interest to market participants utilizing the futures market as a risk management tool.

A remark on the finding of somewhat predictable risk premia is that the risk premia are likely to reflect one or more underlying risk factors also exhibiting seasonality. In figure 1A we depict the monthly components applied in the seasonal prediction model for a forecast horizon of 1 month (excluding the Easter-component), as well as the additive inverse[8] of the seasonal components of the monthly harvest volume in Norway over the same time period. Evidently, the plot shows that the risk premium has in general been relatively high in conjunction with months with low harvest volumes, indicating an overweight of hedgers on the supply side. Similarly, for months with high seasonal components on the harvest volume, the risk premium is significantly lower, indicating a relative increase in the number of hedgers on the demand side. To further examine whether the risk premium is a direct reflection of time-varying price risk, the realized risk premia of all the contracts over the 144 months are regressed on the spot price volatility at the time of expiration, depicted in figure 1B.

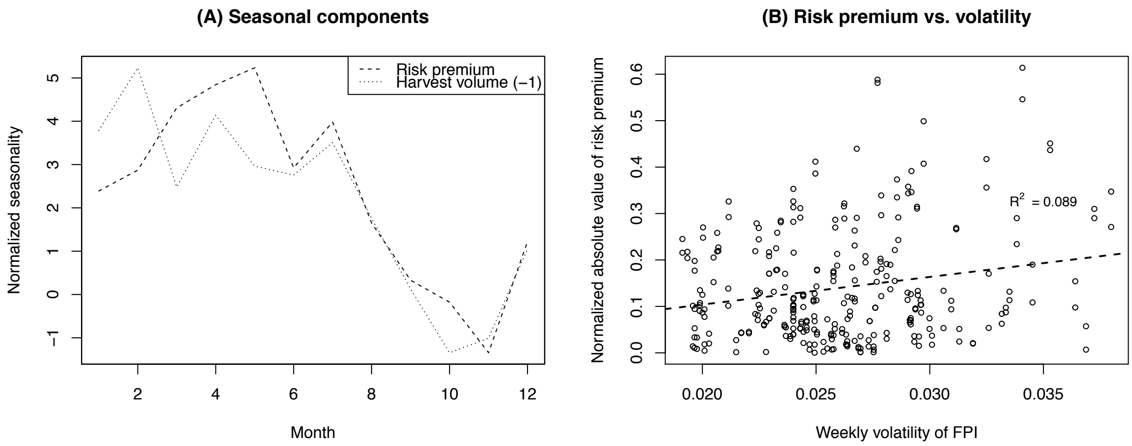

Figure 1: Plot (A) depicts the annual seasonal decomposition of salmon spot price, upfront monthly futures contracts and the additive inverse of harvest volume. Plot (B) depicts observations on normalized risk premium regressed on weekly spot price volatility.

The risk premia were normalized to make them comparable across contract lengths, acknowledging that the risk premium is expected to approach zero as we get closer to expiration. Furthermore, applied in the regression are the absolute values of the risk premia, reflecting price risk on both sides of the hedge. The volatility was initially found as the exponentially weighted moving average (EWMA)[9] of the log-returns of weekly updated spot prices (FPI). The volatility assigned to each contract was the average of the weekly volatility figures within the contract month. The regression shows a low degree of explained variance ($R^2 = 0.089$), and one should be careful in drawing an inference based on the results. If any relation, however, the regression do indicate that higher risk premium is, at least to some degree, reflecting eligible expectations of price risk.

[8] The correlation figures in table 9 reveals that the harvest volume is negatively correlated with the spot price, and it is therefore more illustrative to plot the risk premium on the additive inverse of the harvest volume

[9] The EWMA-parameter was estimated by MLE using the log-likelihood of the observed weekly log-returns. $\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1-\lambda) r_{t-1}^2, \quad \lambda = 0.92.$

Knowing that all salmon futures contracts are thinly traded, as compared to futures contracts on other commodity markets, the bias is also likely to reflect illiquidity in the market. If so, the risk premium is not only reflecting the underlying spot price risk, both also a liquidity risk. Such a liquidity premium can be further interpreted in different ways. First, the liquidity premium of an illiquid market could be considered a proportional premium on both sides of the hedge, reflecting a scarce number of traders willing to enter an offsetting position. If such liquidity premium makes up a considerable part of the observed short-run bias, we should expect the realized risk premium to decrease in conjunction with increased trading volumes. To assess whether that has been the case in the salmon futures market over the last decade, we derive the 12 mos. moving average of the realized risk premia of monthly contracts expiring in 1-6 months, once again applying normalized absolute values under the same argument as above. In figure 2A we show the derived figures, as well as the annual contract values of traded contracts on the Fish Pool futures market, covering the time period of 2008-2018. Despite the fact that the futures market has experienced substantial growth over the last decade, this has not led to a reduction in the overall risk premium level, rather the opposite. This does, however, not rule out the existence of liquidity premia, appreciating that the salmon price has become increasingly volatile over the last couple of decades (Oglend 2013), presumably reflected in the increased risk premium.

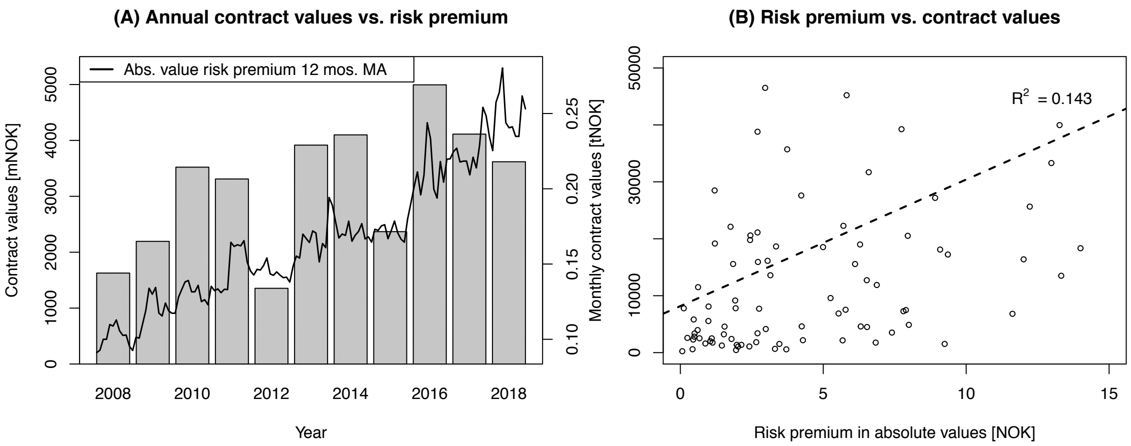

Figure 2: Plot(A) depicts 12 mos. moving average of the normalized risk premia over the total contract values on Fish Pool futures market. Plot (B) shows an OLS regression of trading volumes on realized risk premia.

To further investigate the existence of liquidity premia in the futures market, we perform a review of all the individual trades on monthly contracts on the Fish Pool futures market ever since its inception. By regressing the total contract values of each monthly contract (usually comprising a number of transactions each) on the absolute value of the realized risk premia, we wish to determine whether low trading volume on individual contracts tend to imply an increased liquidity premium. Once again, we obtain an OLS which is unable to explain a satisfactory part of the total variance ($R^2 = 0.143$). The regression does, however, indicate the complete opposite of an additional liquidity premium in case of low trading volumes on individual contracts. Once again, this does, however, not rule out the existence of a liquidity premium, but rather emphasizes previous findings of the risk premium reflecting actual price risk. In case of high expected price risk, the desire to hedge a vulnerable position increases. Assuming the market participants' expectations of high price risk to be valid, the relation found by the OLS in figure 2B indicates that the risk premium is, in fact, reflecting the actual price risk, partly explaining the bias found in the short-run analysis of unbiasedness. That being said, the fact that our prediction models were consistently able to outperform the futures market, is an indication of opportunities of excess risk-adjusted return in the market. During the time period of 2010-2013, speculative traders made up about 30% of the total number of market participants on the Fish Pool futures market (Fish Pool ASA 2014)[10], which is rather low in comparison to e.g. crude oil futures, on which speculators make up more than 50% (Smith 2009). The prediction results, as well as the lack of price discovery for the intermediate contracts, are presumably indications of magnified risk premia due to a sparse number of speculators.

[10]Current figures on the number of speculators are not known.

6 Conclusion

The salmon spot price is known to by highly volatile, creating an obvious need for financial risk management tools, such as financial futures contracts. Following its inception in 2005, the Fish Pool futures market has experienced considerable growth. However, despite being the exclusive financial market providing salmon derivatives, the trading volumes are relatively scarce, in comparison to other commodity markets. As a consequence, the hedging efficiency is ever so often subject to question. The objective of this study was to assess efficiency and unbiasedness of the Fish Pool futures market. Subject to analysis were the monthly contracts expiring in 1-6 months, covering the time period from January 2007 to December 2018.

The augmented Dickey-Fuller test rejected stationarity for both spot price and futures prices on all the monthly contracts, whereas the Johansen's cointegration procedure was incorporated, showing that all futures contracts are cointegrated with the spot price. By the application of likelihood ratio tests on the cointegration parameters, we were unable to reject both efficiency and unbiasedness in the long-run, in line with existing research (Asche et al. 2016*c*, Yeboah et al. 2016). Furthermore, we initiated a short-run analysis by the use of a prototypical ECM. Residuals analysis did, however, reveal ARCH-effects in the ECM-reciduals, reflecting the autocorrelated nature of the risk premia found in the initial data analysis in section 3.5. An extended ECM-GARCH model was implemented, capturing autocorrelation and heteroscedasticity. By imposing various restrictions on parameters of the ECM-GARCH model, the hypothesis of short-run efficiency was only rejected at a 5% level of significance for the contracts expiring in 4, 5, and 6 months, indicating that futures contracts closer to expiration are more likely to be efficient. The hypothesis of short-run unbiasedness was, on the other hand, rejected for all contracts. Knowing that unbiasedness in the long-run could not be rejected, the rejection of short-run unbiasedness indicates a time-varying risk premium, partly seen as seasonal effects. Our findings on time-varying risk premia conform well with previous findings by Asche et al. (2016*a*) and Konjhodzic & Narmo (2017), all of which found seasonal effects when assessing determinants of the salmon futures risk premium.

Furthermore, we assessed the price discovery role of the futures market by the incorporation of long- and short-run Granger causality tests. The two tests revealed that both front-month and the farmost contracts do perform the price discovery role of an efficient and mature market, indicating no-arbitrage and well-informed traders, respectively. Intermediate contracts expiring in 2-4 months, however, fails to perform the desired price discovery, presumably as a consequence of sparse number of speculative traders acting in the Fish Pool futures market. The absence of numerous speculative traders could possibly imply unexploited excess risk adjusted return. The suspicion of such a market characteristic was further strengthened by the futures prices' low prediction accuracy, in comparison to out-of-sample predictions of a variety of models. Applied in the analysis were the out-of-sample prediction performances of both the ECM and the ECM-GARCH models, as well as a seasonal model, a vector autoregressive (VAR) model and an artificial neural network (ANN) model. The root mean squared error of the out-of-sample predictions showed that all of our models were able to consistently outperform the futures market for the horizons of 1-6 months over a time period of 36 months, amply depicting speculative trading opportunities.

Our results indicate that Fish Pool exhibits some of the characteristics of an efficient futures market, while still suffering somewhat by the sparse trading volume and number of speculative traders. We demonstrate that the time-varying risk premium is to a large extent reflecting time variation in the actual price risk. For any risk averse market participant utilizing the futures market for risk management purposes, our results indicate that the futures contracts provide adequate hedging efficiency, but that the risk premium is likely to be somewhat higher than what the actual price risk of an offsetting position would suggest.

6.1 Further Research

Provided evidence of salmon futures exhibiting adequate hedging properties, albeit limited by thin trading, an obvious way to proceed the market review would be to assess hedging strategies and optimal hedge ratio, previously performed by Bloznelis (2018*a*). Further, the finding of short-run bias should be further examined to determine whether the pricing bias involves opportunities of excess risk adjusted return from a speculative point of view. Appreciating that the salmon price is not only highly volatile, but also subject to sporadic jumps in either directions, the historical return should not only be adjusted for volatility estimated by the use of week-over-week (WoW) spot price changes. Rather, the historical returns should be further assessed in a Value-at-Risk (VaR) and Expected Shortfall (ES) framework.

We have shown that the risk premia exhibit seasonal patterns reflecting underlying risk factors. Further research on determinants of the salmon futures risk premium, should incorporate traders' non-static risk preferences, as well as the prevailing price level. Any market participant's desire to hedge its position is likely to be highly dependent on its ability to handle a substantial downside loss, i.e. its financial solidity. Over the last decade, actors within the salmon market and farmers, in particular, have experienced tremendous economic growth (Misund 2018), yielding substantial solidity, presumably reducing the need to hedge price risk. Moreover, looking back only a few years, the farmers were far more leveraged than they are today. By locking in its profit via futures contracts, a leveraged company becomes more attractive in the bond market, and is presumably offered lower interest rates on its bonds. Thus, the farmers' decreased leverage ratios over the last decade have not only affected their risk preferences, but also reduced their financial incentives to lock in future profits at a certain price level. Further, appreciating that the spot price is generally fluctuating within a certain price range, the potential downside for a supplier is certainly reduced in the case of temporally low spot prices, presumably reducing the willingness of financially solid short-hedgers to pay a disproportional risk premium for the hedge.

A Appendix A - Background Information

The following section provides valuable insights into the farming industry, including an overview of the global Atlantic salmon market as well as a brief summary of the production cycle. Subsequently, follows an introduction to the Fish Pool futures market as well as a review of historical trading data.

A.1 Background Information on the Salmon Farming Industry

The Atlantic salmon (*Salmo salar*), hereafter simply referred to as *salmon*, is a fish in the *Salmonidae* family. Over the last few decades, salmon farming has experienced tremendous growth, outperforming the growth of the majority of other food sectors, including other aquaculture sectors (FAO 2019, Brækkan & Tyholdt 2014). Although being a global industry in terms of demand, the current supply-side on salmon is dominated by a few countries only. Several conditions need to be fulfilled to achieve satisfactory production circumstances, precluding production in the majority of the world. The most crucial condition is low seawater temperatures, leaving Norway, Chile, Canada, Scotland and the Faroes as the dominating producers (Solibakke 2012). In an attempt to achieve adequate conditions, both land-based and closed-containment facilities are in the pipeline, and particularly in countries not suited for traditional salmon farming. Although such facilities are yet to prove profitable in competition with traditional farming, they are likely to improve in the years to follow, possibly becoming a substantial industry providing locally produced food (Bjørndal & Tusvik 2007).

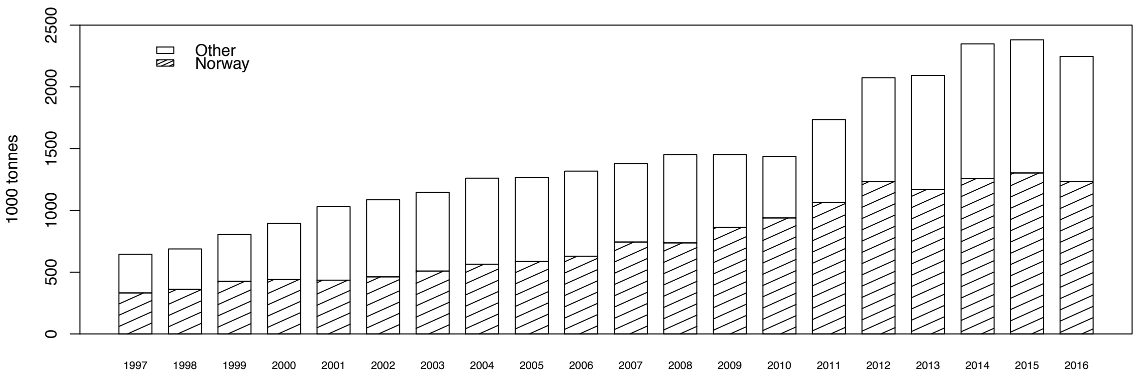

Figure 3: Shown are the annual harvest figures over the last two decades, both globally and in Norway exclusively. Following an ISA outbreak in Chile in 2007, the global harvest volume experienced a minor reduction up until 2010, despite considerable growth in Norway.

Data source: Food and Agriculture Organization of the United Nations (FOA) and Statistics Norway (SSB)

In conjunction with market growth and a strive for profitability, the industry has been subject to an increasingly frequent occurrence of sea lice and diseases. This became particularly visible in 2007 when Chile experienced a serious outbreak of sea lice and the viral disease *infectious salmon anemia* (ISA), eradicating about two-thirds of the harvest in the subsequent production cycles (World Bank Group 2015). More recently, in the spring of 2019, a handful of farmers in the Northern parts of Norway were hit by the blossoming of a natural but fatal alga, wiping out more than 13,000 tonnes of salmon within a few days (Fiskeridirektoratet 2019). The problems of parasites and diseases have partially been stifled by considerable and efficacious use of antibiotics and vaccines. Of major concern is, however, the emergence of drug resistance in sea lice and bacteria (Aaen et al. 2018), becoming an ever-growing threat to traditional salmonid aquaculture and simultaneously enforcing the search for profitable closed containment facilities. In an attempt to further control the prevalence of sea lice and diseases, strict regulations have been introduced over the preceding decades, including comprehensive licensing systems.

Production Cycle

The production cycle of salmon is a rather tedious process normally lasting for two to three years. Initially, eggs are spawned and kept in freshwater over a period of 6-12 months, gradually growing to become what is defined as *smolts*. Whereas historically there has been a tradition for separate smolt suppliers, the majority of today's smolts are produced ”in-house” for own use by full-scaled salmon farmers, proven to be a more cost-effective and less disease exposed production method (Marine Harvest 2018). Once the smolts are found to be robust enough, usually weighing about 60-100 grams, they are released into seawater cages. The final seawater stage typically lasts for 14-24 months, primarily depending on water conditions and desired harvest weight. In order to limit the risk of sea lice and other threatening outbreaks, the producers are now generally prolonging the *smoltification* period as compared to what has traditionally been the case, conversely reducing the time spent in seawater cages (Usher et al. 1991, Lysfjord et al. 2004).

A.2 Background Information on the Fish Pool ASA Futures Market

Fish Pool ASA serves as an international market place for financial salmon contracts. Licensed by the Norwegian Ministry of Finance, it provides risk management tools for market participants subject to salmon price risk. After its inception in 2005, both futures contracts and diverse financial options have been offered. Due to scarce trading volumes, however, options have been withdrawn from the product line for an indefinite period of time (Fish Pool ASA 2019c), leaving futures contracts with diverse features as the only available products. The futures contracts do not involve any physical delivery of salmon, but rather financial settlements on the difference between the contractual price and the realized spot price referred to as the basis. The underlying is a synthetic spot price, the *Fish Pool Index™* (FPI), reflecting the trailing market price.[11] The final clearing services are operated by NASDAQ OMX, providing sufficient payment security in case of a counterparty's failure to fulfill its financial obligations.

Although being the leading provider of futures contracts on salmon, the futures trading volume is rather limited relative to the size of the salmon market as a whole. The underlying harvest volume of the futures contracts settled in 2017 was 67 521 tonnes of salmon, equaling about 2.8 % of the total harvest volume of salmon over the same time period (Fish Pool ASA 2018). There might be several reasons for scarce trading figures. Illiquid markets are usually subject to high spreads and inefficiencies, often reflected in substantial liquidity premiums. The occurrence of such risk premia is in itself limiting the hedgers' desire to take part in the futures market. Ultimately, a certain trading volume is necessary to achieve the hedging efficiency needed for market participants to take part in the trades. Thus, illiquid markets are likely to stay illiquid, causing the majority of commodity futures markets to fail within a few years of inception (Brorsen & Fofana 2001). Furthermore, Jacobsen & Mokkelbost (2014) emphasises that limited knowledge on financial instruments among farmers and other market participants is likely to hamper the utilization of the available risk management tools. With this in mind, the subsequent review of the historical trading data on the Fish Pool futures market provides valuable insights in the assessment of market efficiency and unbiasedness.

Historical Trading Data

In the assessment of a futures market, the choice of contracts to examine is a vital first step. A prototypical choice, often seen in a lot of empirical studies on commodity futures markets is to simply assess the front-month monthly contracts only, i.e. contracts covering one month with delivery in the subsequent month. In this study, the choice of monthly contracts with time to expiration of 1-6 months is based on the trading figures depicted in figures 4 and 5, both visualizing the number of completed trades over the time period of June 2006 to December 2018. As can be seen in figure 4, contracts covering delivery over 1, 3, 6 and 12 months are by far the contracts with the highest trading figures, independent on time to expiration. In order to make the contract descriptions more coherent, an arbitrary contract is selected for illustrative purposes.

On the 27.10.2017 a futures contract was agreed upon with the delivery of 14 tonnes of salmon each month for 6 months starting in January 2018, with a settlement price of 60.25 NOK/kg. The

[11] The FPI spot price and the settlement price are described in detail in section 3.1

average FPI spot price in January 2018 turned out to be 54.63 NOK/kg. Similarly, the spot price for the remaining five months were 58.83, 71.08, 71.61, 76.24 and 60.77 NOK/kg. This implied an average delivery price over the contract period of 65.53 NOK/kg, yielding a basis of 5.28 NOK/kg. With a delivery of 14 tonnes per month for six months, this implied a settlement transaction of 443 520 NOK.

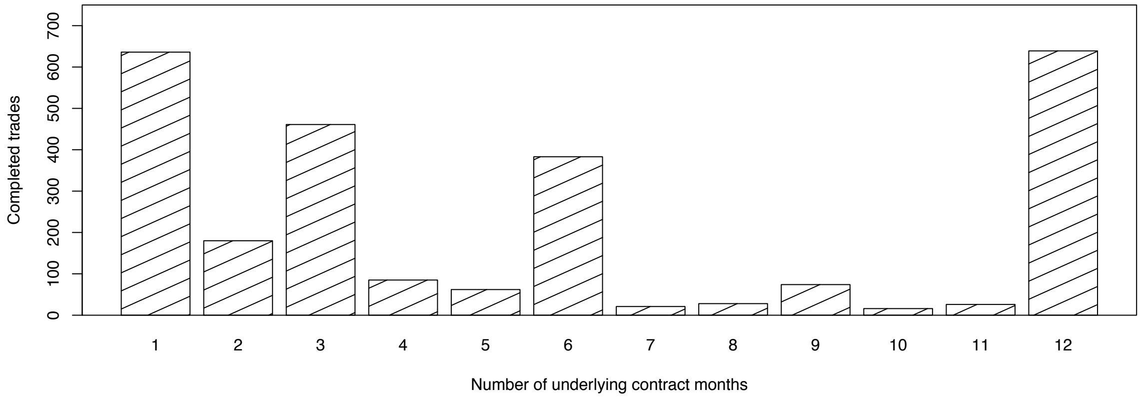

Figure 4: Trading volume on contracts with varied number of underlying contract months.
Data source: Fish Pool ASA; salmonprice.com

The contract described in the example above is referred to as a contract covering 6 months, with 3 months until the first delivery. Figure 5 depicts the historical trading figures on contracts covering 1, 3 and 6 months, with 0-6 months until the first delivery. Contracts with 0 months until delivery are contracts traded within the contract period, and are not further considered in this assessment. Ultimately, contracts with 1 and 2 months until the first delivery are the contracts that historically traded the most. A review of individual contracts reveals no arbitrage opportunities, by e.g. taking simultaneous long positions in monthly contracts with 1-3 months until the first delivery and a short position in a quarterly contract with 1 month until the first delivery, *ceteris paribus*. The absence of such arbitrage opportunities implies that the trading on contracts covering 3 and 6 months provide further liquidity to justify the assessment of monthly contracts with 1-6 months until delivery, despite the scarce trading of monthly contracts with delivery in more than 2 months.

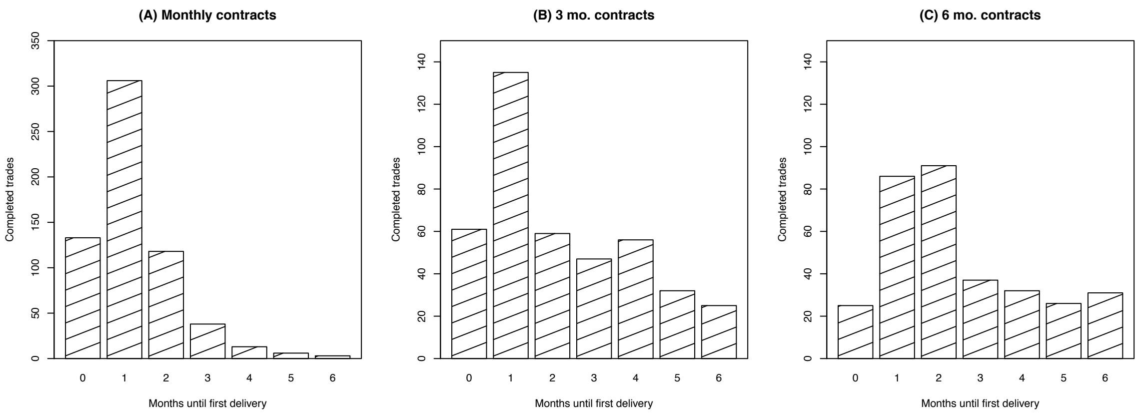

Figure 5: Number of completed trades on futures contracts with 0-6 months until the first delivery. The trading figures are provided for contracts covering 1 (A), 3 (B) and 6 (C) months.
Data source: Fish Pool ASA; salmonprice.com

B Appendix B - Spot Price Predictions

Vital in the assessment of semi-strong market efficiency, are prediction models comprising publicly available observations on exogenous factors affecting the salmon spot price. A conventional approach in the modeling of the spot price is a simple linear regression of the year-over-year (YoY) change of harvest volume on the YoY change in the spot price. More sophisticated models include a variety of input factors, usually comprised as year-over-year or month-over-month (MoM) changes, depending on whether the time series exhibits annual seasonality or not (e.g. Sandaker et al. (2017)). An alternative approach, utilized in this study, is to model irregular observations on both a range of explanatory variables and the spot price. The irregularities are extracted by thorough prepressessing, predominantly involving detrending and deseasonalization. Subsequent sections provide descriptions of exogenous[12] variables applied in the modeling of the spot price, as well as the preprocessing performed on each variable. Note that the futures prices are not included in the models as input variables, due to the inadequate price discovery function, tabulated by Granger causality in table 7. Subsequently follows the description of a *Vector Autoregressive* (VAR) model and an *Artificial Neural Network* (ANN) model, both comprising the exogenous variables.

B.1 Factors Affecting the Salmon Spot Price

Harvest Volume

When assessing trailing changes on the salmon spot price, the preceding harvest volume of salmon is unarguably among the factors with the highest explanatory power, partly reflected by the correlation figures in table 9. As depicted in figure 6, the harvest volume of salmon in Norway exhibits considerable seasonal patterns. The seasonality is both due to natural causes such as salmon growth rate, sea lice occurrence and sea temperature, as well as seasonal demand variations. Moreover, the harvest volume has had a substantial positive trend over the last decade, reflecting the overall market growth. The time series on harvest volume was, therefore, both detrended and deseasonalized, emulating deviations from the detrended seasonal expectations. The data was deseasonalized by introducing both an annualized pattern, as well as an Easter dummy reflecting the demand growth in conjunction with the Easter holiday.

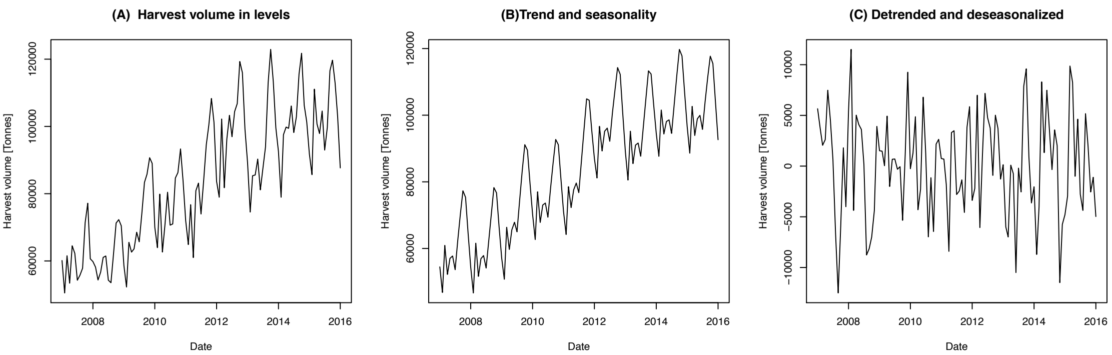

Figure 6: The harvest volume was both detrended and deseasonalized. The seasonal component comprises both monthly dummies as well as an Easter dummy.

Data source: Fisheries Monitoring Centre (FMC), the Norwegian Directorate of Fisheries

[12]Note that all the subsequent factors are referred to as exogenous, although a few of them such as harvest volume and biomass are likely to be somewhat affected by the spot price.

Smolt Release

As described in section A.1, smolts are released into seawater cages weighing about 60-100 grams. In order to reduce mortality rates over the first few months of release, the smolt release figures are peaking in spring and autumn, coinciding with optimal water temperatures, causing significant seasonal patterns. Moreover, the amount of smolts released in Norway has increased in a similar manner as the salmon market as a whole. Thus, the time series on smolt individuals released was both detrended and deseasonalized.

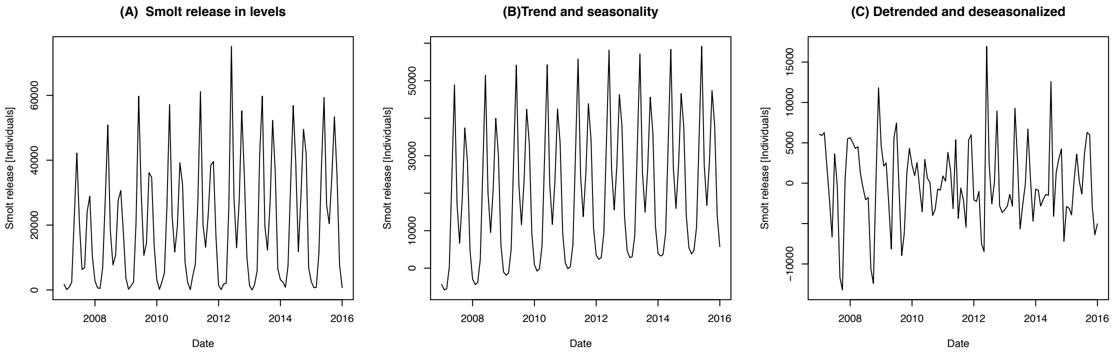

Figure 7: The smolt release was both detrended and deseasonalized on an annual basis.
Data source: Fisheries Monitoring Centre (FMC), the Norwegian Directorate of Fisheries

Standing biomass

The standing biomass of salmon (in tonnes) is directly linked to smolt release and growth rate on one side of the production cycle, and harvest volume on the other. As a direct consequence of the seasonalities on both input and output, the standing biomass is also subject to substantial seasonal patterns. Moreover, the time series exhibit a substantial trend, once again reflecting the overall market growth. The time series was, therefore, both detrended and deseasonalized. The Easter effect found in the harvest volume is, however, negligible in the assessment of standing biomass and was omitted from the preprossessing.

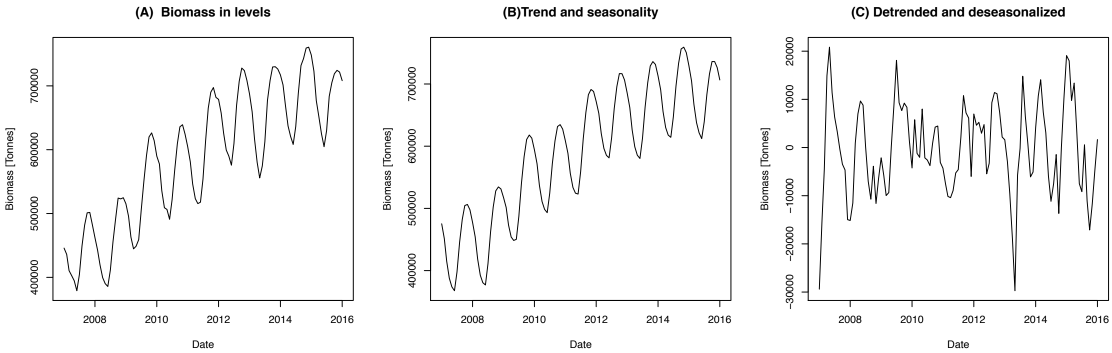

Figure 8: The amount of standing biomass was both deseasonalized and detrended.
Data source: Fisheries Monitoring Centre (FMC), the Norwegian Directorate of Fisheries

Seawater Temperature

Seawater temperature has a direct influence on the feed consumption and growth rate, and ultimately the harvest volume. The temperatures are collected for a collection of Norwegian counties [13]. The measure used in this study is computed as a weighted average based on the trailing harvest volume in each county. Although the time series does exhibit a somewhat positive trend over the last few years of in-sample observations, this trend is not caused by market growth or similar trends and should not be removed. The time series was therefore deseasonalized with an annual pattern.

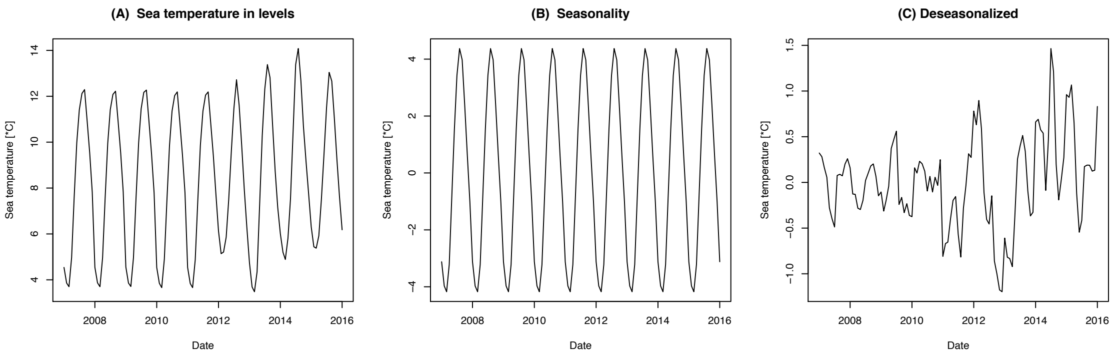

Figure 9: The seawater temperature was deseasonalized on an annual basis.
Data source: The Norwegian Water Resources and Energy Directorate

Feed Consumption

The feed consumption per salmon is a non-linear function of both average salmon size and water temperature. During the winter the feed consumption drops due to low water temperatures, whereas too high temperatures during the summer may have the same effect, partly due to reduced oxygen levels in the water negatively affecting the salmon (Handeland et al. 2008). Thus, the figures on feed consumption (tonnes) exhibit a similar trend and seasonal components as most of the previously described factors. Therefore, the time series was detrended and deasonalized.

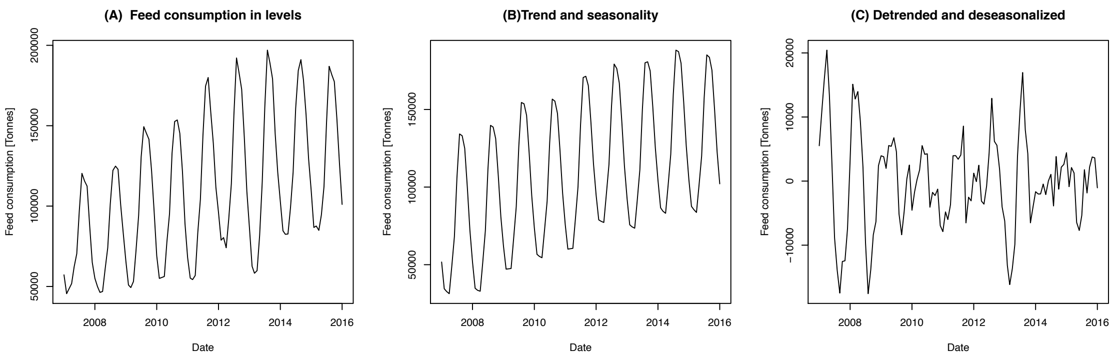

Figure 10: The figures on feed consumption were both deseasoalized and detrended.
Data source: Fisheries Monitoring Centre (FMC), the Norwegian Directorate of Fisheries

[13] Finnmark, Troms, Nordland, Trønderlag, Møre og Romsdal, Sogn og Fjordane, Hordaland and Rogaland

Mortality

Mortality rates are usually observed to peak during the first 2 months after smolts are released into seawater (Marine Harvest 2018). Furthermore, farmers may experience minor mortality peaks due to external factors such as sea lice occurrence or reduced oxygen levels in the seawater, both frequently observed in conjunction with high water temperatures. The mortality figures do, therefore, exhibit seasonal patterns, reflecting seasonality in both smolt release as well as other factors. Moreover, the mortality figures exhibit a somewhat positive trend, obviously reflecting the growth in standing biomass over the last in-sample time period. Therefore, the time series on mortality was both detrended and deseasonalized.

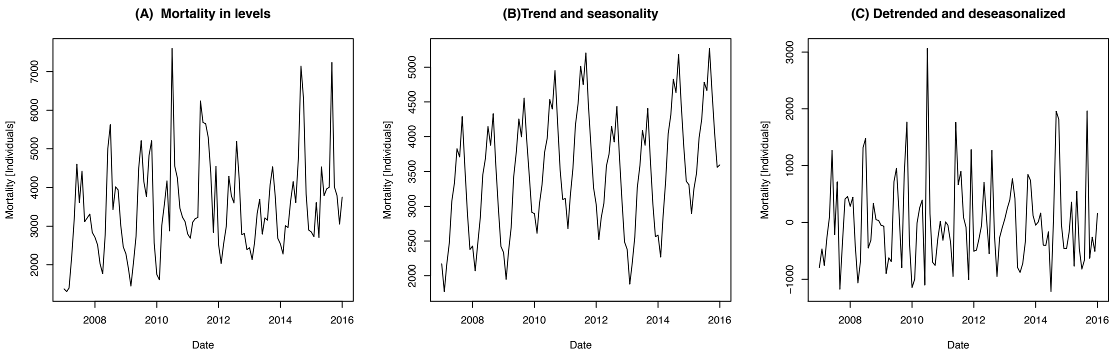

Figure 11: The mortality rates were both detrended and deseasonalized.
Data source: Fisheries Monitoring Centre (FMC), the Norwegian Directorate of Fisheries

Sea lice Occurrence

The occurrence of sea lice does occasionally have a major impact on the salmon market as a whole. Due to strict regulations, farmers may be forced to harvest significant amounts of salmon in case of immense sea lice rates. Applied in this study is not a measure of the absolute number of lice in the Norwegian farming sites, but rather a number of female sea lice per salmon. Thus, one should not expect to find any natural trend despite significant market growth, and the time series should not be detrended. The occurrence is, however, somewhat correlated with the water temperature, yielding peaks during the summer. The time series was, therefore, deseasonalized with an annual seasonal pattern.

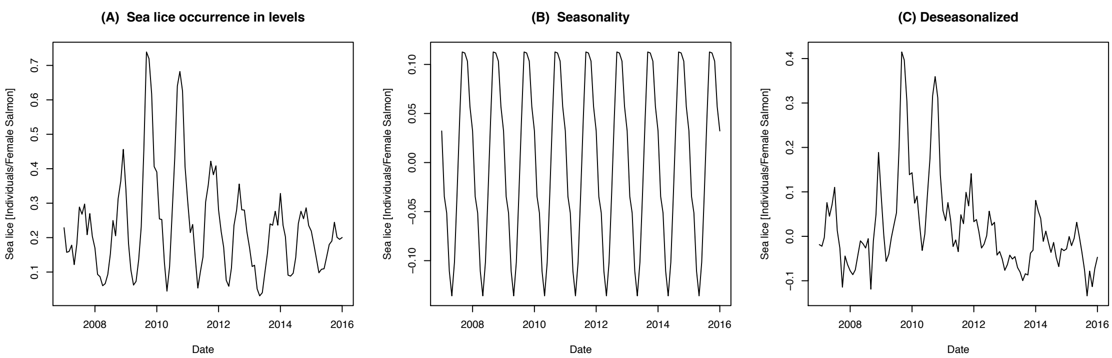

Figure 12: The relative occurrence of sea lice is highly seasonal and was, therefore, deseasonalized.
Data source: The Norwegian Food Safety Authority [Lusedata.no]

Meat Price

The demand for fresh salmon is found to be price elastic (Lohdi 2015) suggesting that alternative proteins serve as substitutes, ultimately affecting the spot price of salmon. Included in this analysis is, therefore, the *FOA Meat Price Index* reflecting international price quotations of pork and bovine meats on a monthly basis. The index exhibits both a significant trend and seasonal patterns and was, therefore, both detrended and deseasonalized.

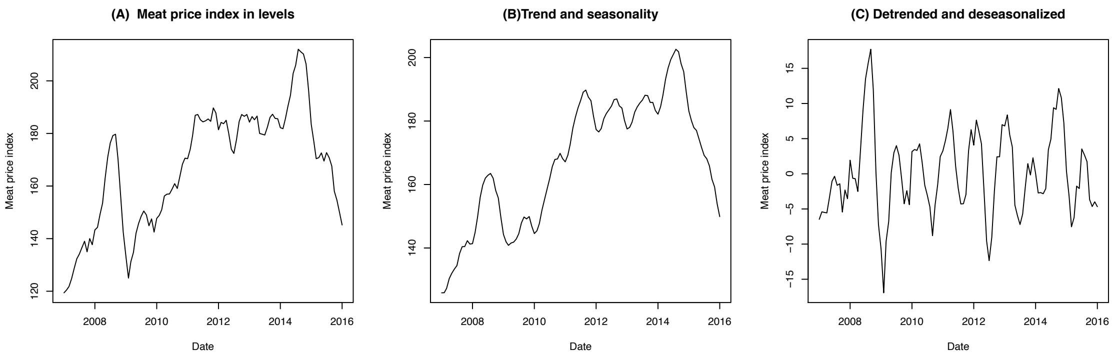

Figure 13: The FOA Meat Price Index was both detrended and deseasonalized.
Data source: The Food and Agriculture Organization of the United States (FAO)

Currency Index; NOK/USD and NOK/EUR

Only for a minority of the Norwegian salmon export, the invoicing currency is, in fact, Norwegian Krone (NOK). Over the time period 2003-2009 this was the case for only 20.1% of the fresh and frozen salmon combined. The euro (EUR) was by far the dominating currency, making up about 51%, whereas the US dollar (USD) was the invoicing currency for about 17.5% of the exported tonnes (Straume 2014). As the spot price (FPI) is denoted in NOK, both the NOK/EUR and NOK/USD exchange rates are likely to have a substantial impact on the spot price. A currency index was therefore constructed, comprising trailing exchange rates and invoice volume for both currencies. The index was then included in the models as MoM first differences.

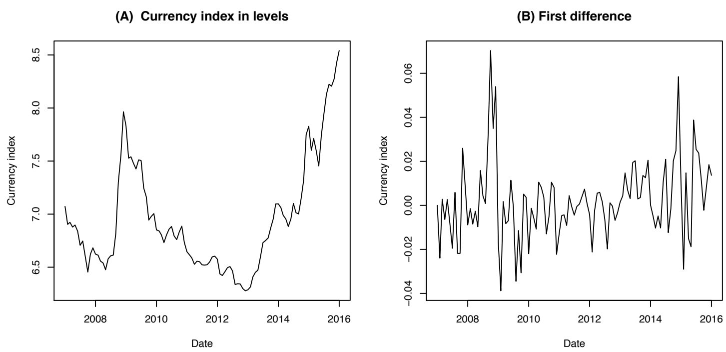

Figure 14: The currency index reflects trailing exchange rates as well as salmon invoice value for EUR and USD. Applied in the models was the MoM first differences.
Data source: The Central Bank of Norway

B.2 Descriptive Statistics

Table 9: In-sample descriptive statistics on preprossessed exogenous factors

		Descriptive Statistics				
Time series	N	Mean	Std.dev.	Skew	Ex.kurt.	FPI corr.
FPI	108	-0.047	3.75	0.43	0.43	1.00
Harvest volume	108	119.381	5548.44	-0.04	-0.6	-0.62
Smolt release	108	0.000	5138.22	0.29	0.19	-0.15
Biomass	108	0.000	9503.81	-0.14	0.50	0.02
Temperature	108	0.092	0.50	-0.02	-0.10	0.06
Feed consumption	108	0.000	7341.69	0.18	0.16	-0.23
Mortality	108	0.000	962.25	0.74	0.42	0.02
Sea lice	108	0.000	0.10	1.63	3.92	0.04
Meat price	108	0.000	5.51	0.33	0.66	0.22
Currency Index	108	0.002	0.02	0.84	2.42	0.11

		Tests		
Time series	N	JB	ADF	Ljung.Box
FPI	108	5.94*	-6.57***	99.32***
Harvest volume	108	1.98	-6.38***	32.38**
Smolt release	108	2.44	-7.40***	38.55***
Biomass	108	2.30	-5.21***	82.89***
Temperature	108	0.04	-3.41*	123.10***
Feed consumption	108	1.08	-7.97***	211.48***
Mortality	108	14.85***	-3.95**	54.61***
Sea lice	108	161.55***	-4.14***	199.73***
Meat price	108	5.74*	-4.79***	218.99***
Currency Index	108	54.89***	-3.96**	22.64***

Descriptive statistics for time series, preprossessed as previously described. (***), (**) and (*) indicates rejection of the null-hypotheses at a 1% , 5% and 10% level, respectively.

B.3 Vector Autoregressive (VAR) Model

A vector autoregressive VAR(p) model was constructed, comprising the preprocessed time series on exogenous factors introduced in appendix B.1. The number of lags was chosen based on AIC and BIC criteria and was set to $\rho = 6$ months for all variables except for the smolt release, which was lagged 14-24 months. Formally, the model is expressed as

$$\mathbf{Y}_t = \alpha + \beta_1 \mathbf{Y}_{t-1} + \beta_2 \mathbf{Y}_{t-2} + \cdots + \beta_6 \mathbf{Y}_{t-6} + \varepsilon_t \tag{16}$$

where

$$\boldsymbol{\beta_1} = \begin{pmatrix} \beta_{1,11} & \cdots & \beta_{1,1n} \\ \vdots & \ddots & \vdots \\ \beta_{1,n1} & \cdots & \beta_{1,nn} \end{pmatrix}, \boldsymbol{\beta_2} = \begin{pmatrix} \beta_{2,11} & \cdots & \beta_{2,1n} \\ \vdots & \ddots & \vdots \\ \beta_{2,n1} & \cdots & \beta_{2,nn} \end{pmatrix}, \quad \ldots, \quad \boldsymbol{\beta_6} = \begin{pmatrix} \beta_{6,11} & \cdots & \beta_{6,1n} \\ \vdots & \ddots & \vdots \\ \beta_{6,n1} & \cdots & \beta_{6,nn} \end{pmatrix} \tag{17}$$

As for the majority of the included factors, also the spot price exhibits substantial seasonal patterns. A conventional approach is therefore to assess YoY-change of the spot price. However, the assessment of YoY-change has its limitations in the fact that irregularities in the previous observations, such as shocks caused by factors outside the model, may cause significant errors in the subsequent predictions. Therefore, the approach chosen in this study is to only assess irregularities in both explanatory factors as well as in the spot price, i.e. the observed deviation from seasonal expectations. This is achieved by detrending and deseasonalizing the spot price in-sample. The trend is simply the annual moving average of the time series, whereas the seasonal component comprises both annual seasonal patterns, as well as an Easter holiday dummy accounting for the fact that the Easter holiday week is not consistently occurring at a particular time of the year. This preprocessing is depicted in figure 15, where the detrended and deseasonalized spot price is shown in the rightmost plot. The VAR model was estimated in-sample, restricted only to include parameters significant at a 5% level, presented in table 10. Based on the estimated models, trailing out-of-sample forecasts of the deviations were made for horizons of 1-6 months. The predictions were then reseasonalized and retrended by including the price level at the time of prediction and the in-sample seasonal patterns, ultimately yielding spot price predictions in levels. Out-of-sample predictions for all horizons are depicted in figure 19 in appendix C, whereas figures on the predictive power are tabulated in table 8 in section 5.2.

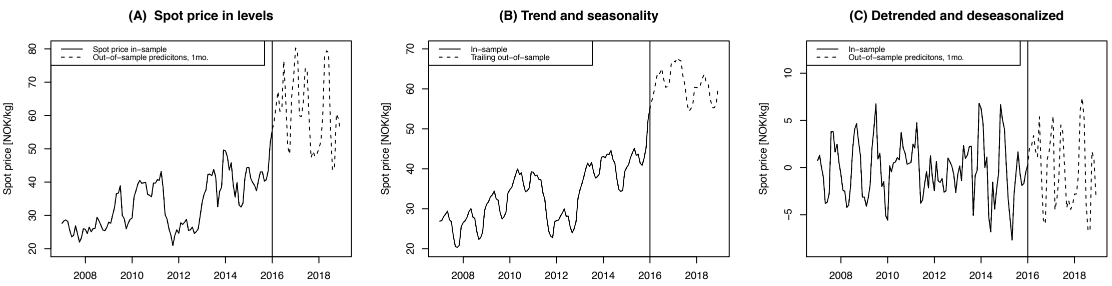

Figure 15: The leftmost figure shows the in-sample spot price in levels, as well as the trailing 1 mo. predictions. The plot in the middle depicts the trend and seasonal component in the price series, whereas the rightmost plot shows the in-sample and out-of-sample predictions of the price deviations from the detrended and deseasonalized expectations.

Table 10: In-sample coefficients of VAR-model for horizons of 1-6 months

	1 mo.	Coefficient		**2 mos.**	Coefficient
β_1	FPI, lag 1	0.38061***	β_1	Feed, lag 5	0.00021***
		(0.07465)			(0.00004)
β_2	Biomass, lag 5	-0.00011***	β_2	FPI, lag 1	0.35493***
		(0.00002)			(0.07523)
β_3	Harvest, lag 3	0.00017***	β_3	Biomass, lag 5	-0.00014***
		(0.00003)			(0.00003)
β_4	Feed, lag 1	-0.00016***	β_4	Feed, lag 1	-0.00016***
		(0.00003)			(0.00003)
β_5	Feed, lag 5	0.00017***	β_5	Sea lice, lag 5	12.66534***
		(0.00003)			(3.46952)
β_6	Biomass, lag 3	-0.00011***	β_6	Biomass, lag 5	-0.00009
		(0.00002)			(0.00002)
β_7	Sea lice, lag 5	5.42449***	β_7	Smolt, lag 20	0.00177***
		(1.71353)			(0.00054)
β_8	Smolt, lag 19	-0.00101***	β_8	Smolt, lag 21	-0.00176***
		(0.00032)			(0.00054)
	3 mos.	Coefficient		**4 mos.**	Coefficient
β_1	FPI, lag 1	0.46221***	β_1	FPI, lag 1	0.42840***
		(0.07268)			(0.09162)
β_2	Feed, lag 1	-0.00019***	β_2	Biomass, lag 2	-0.00015***
		(0.00004)			(0.00003)
β_3	Feed, lag 3	0.00017***	β_3	Biomass, lag 3	-0.00021***
		(0.00004)			(0.00021)
β_4	FPI, lag 4	-0.18826**	β_4	Feed, lag 2	0.00021***
		(0.07247)			(0.00005)
β_5	Biomass, lag 3	0.00008**	β_5	Meat price, lag 5	-0.20801***
		(0.00003)			(00107)
β_6	Mortality, lag 1	-0.00052**	β_6	Smolt, lag 5	-0.00292***
		(0.00025)			(0.00107)
β_7	Biomass, lag 3	-0.00007**	β_7	Mortality, lag 1	00069***
		(0.00004)			(0.00026)
β_8	-	-	β_8	Smolt, lag 16	-0.00365**
		-			(0.00150)
	5 mos.	Coefficient		**6 mos.**	Coefficient
β_1	FPI, lag 1	0.35641***	β_1	FPI, lag 1	0.38769***
		(0.07182)			(0.07004)
β_2	Feed, lag 1	-0.00013***	β_2	FPI, lag 6	-0.31552***
		(0.00003)			(0.07464)
β_3	FPI, lag 5	-0.32573***	β_3	Feed, lag 4	0.00014***
		(0.07385)			(0.00004)
β_4	Smolt, lag 23	0.00013***	β_4	Mortality, lag 4	-0.00075***
		(0.00004)			(0.00023)
β_5	Smolt, lag 21	-0.00154**	β_5	Smolt, lag 19	0.00171***
		(0.00061)			(0.00054)
β_6	Smolt, lag 22	0.00153**	β_6	Feed, lag 1	-0.00012***
		(0.00060)			(0.00004)
β_7	Smolt, lag 24	-0.00267**	β_7	Smolt, lag 18	0.00164***
		(0.00111)			(0.00054)
β_8	Smolt, lag 19	-0.00057**	β_8	Smolt, lag 17	0.00153***
		(0.00025)			(0.00052)

Standard errors in parentheses. Note that lags are denoted from time of forecast, i.e. t=0. Lagged FPI values when lag is less than the time to expiration is substituted with the respective FPI forecast. Only parameters significant at a 5% level are included in the forecast models. (**) and (***) indicates significance at a 5% and 1% level, respectively.

B.4 ARTIFICIAL NEURAL NETWORK (ANN) MODEL

The final model applied in the assessment of semi-strong market efficiency involves the use of a *multilayer perceptron* (MLP), a class of artificial neural networks (ANN). The number of hidden layers was set to one, and the numbers of neurons in each hidden layer were set to 2/3 of the number of input neurons. Utilizing normalized time series only, the applied activation function was the logistic sigmoid function, $f(x) = 1/(1+exp(-x))$. The applied solver algorithm was the *Broyden–Fletcher–Goldfarb–Shanno* (BFGS) algorithm, an iterative numerical optimization algorithm in the family of quasi-Newton methods. The applied learning rate of the model was an *Inverse Scaling* rate, which is gradually decreasing as the power of the model increases and can be seen as a trade-off between the computer processing time and the accuracy of the model.

The model inputs the preprocessed time series on exogenous factors and spot price, as described in sections B.1 and B.3, respectively. The exogenous factors were lagged 1-6 months except for the smolt release figures, which were lagged 14-24 months. All the time series were normalized before running the model on the in-sample subset. In order to reduce the consequences of both local optima and risk of overfitting in the model training procedure, the model was trained and evaluated 10 times. The average RMSE of these predictions was set as a benchmark, and the model was repeatedly trained until the RMSE was deviating from this benchmark with less than 5%. Utilizing the trained model, predictions were made out-of-sample. Ultimately, the predictions were denormalized and finally retrended and reseasonalized, reversing the preprocessing described in section B.3. This procedure was completed for spot price predictions 1-6 months ahead. Out-of-sample predictions for all horizons are depicted in figure 20 in appendix C, whereas figures on the predictive power are tabulated in table 8 in section 5.2. The described algorithm was specified as follows.

Algorithm 1 ANN-model

input *[exogenous factors, spot price deviations]*
normalize *time series*
  for *i in 1:10*
    train *MLP*
    $RMSE_{BM} \leftarrow RMSE_{BM} + RMSE_i$
  $RMSE_{BM} \leftarrow RMSE_{BM}/10$
  $RMSE_{train} \leftarrow 0$
while $abs(RMSE - RMSE_{BM})/RMSE_{BM} > 0.05$ **do**
    train *MLP*
    update $RMSE_{train}$
make *predictions out-of-sample*
denormalize, reseasonalize and retrend *out-of-sample predictions*
output *predictions*

C APPENDIX C - PREDICTION PLOTS

ECM Predictions

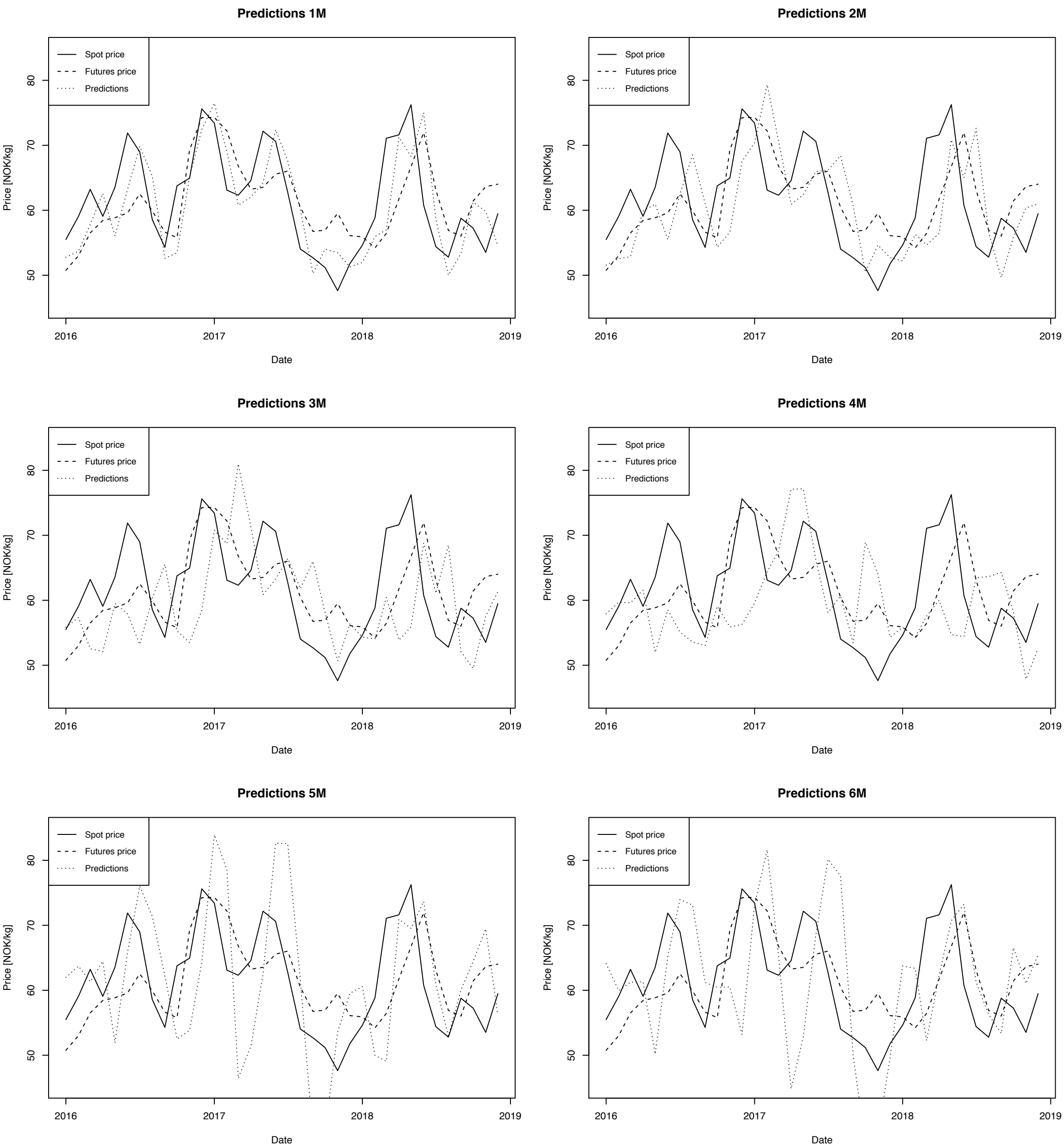

Figure 16: Predictions by the ECM model

ECM-GARCH Predictions

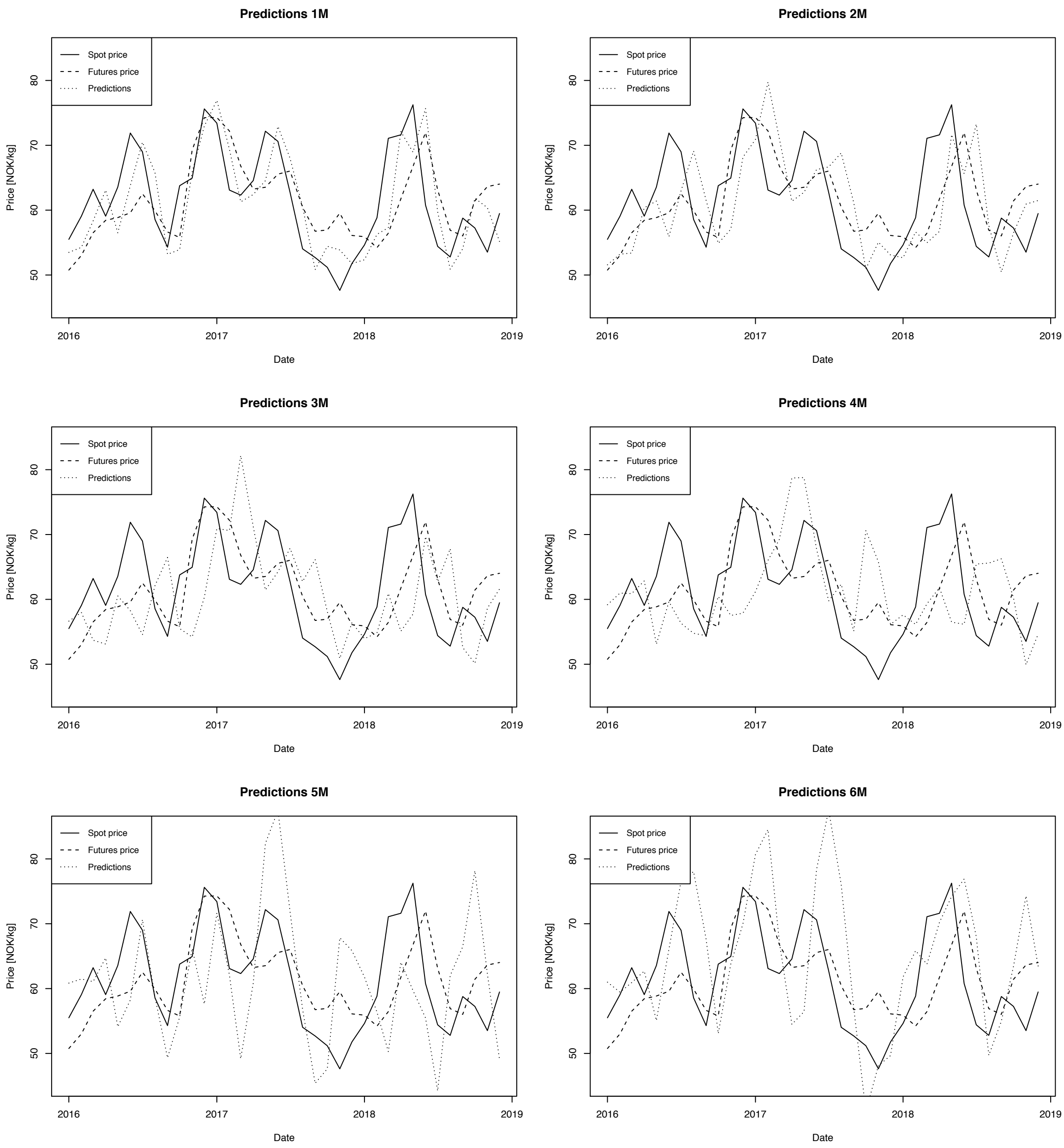

Figure 17: Predictions by the ECM-GARCH model

Seasonal Predictions

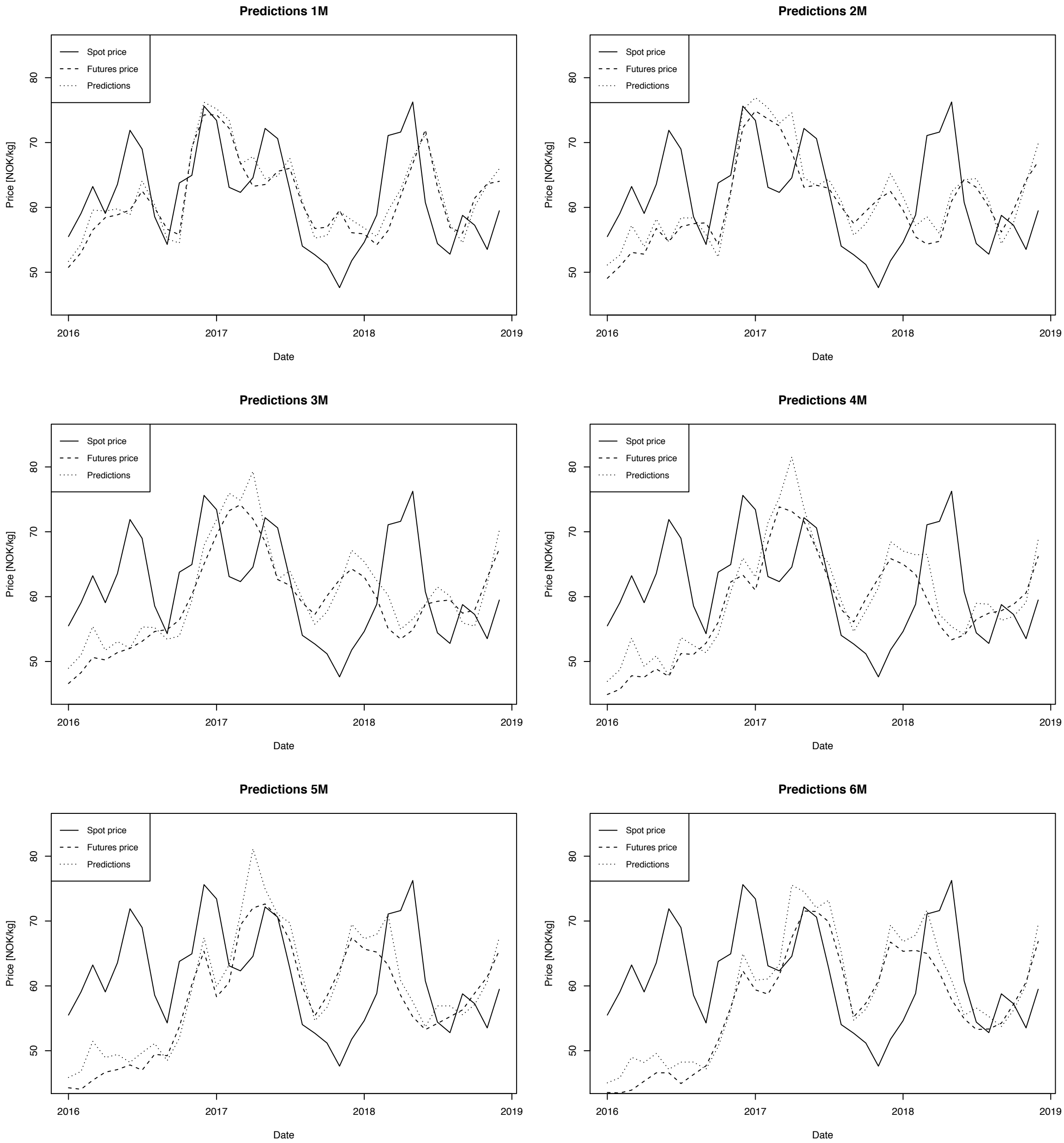

Figure 18: Predictions by the seasonal model

VAR Predictions

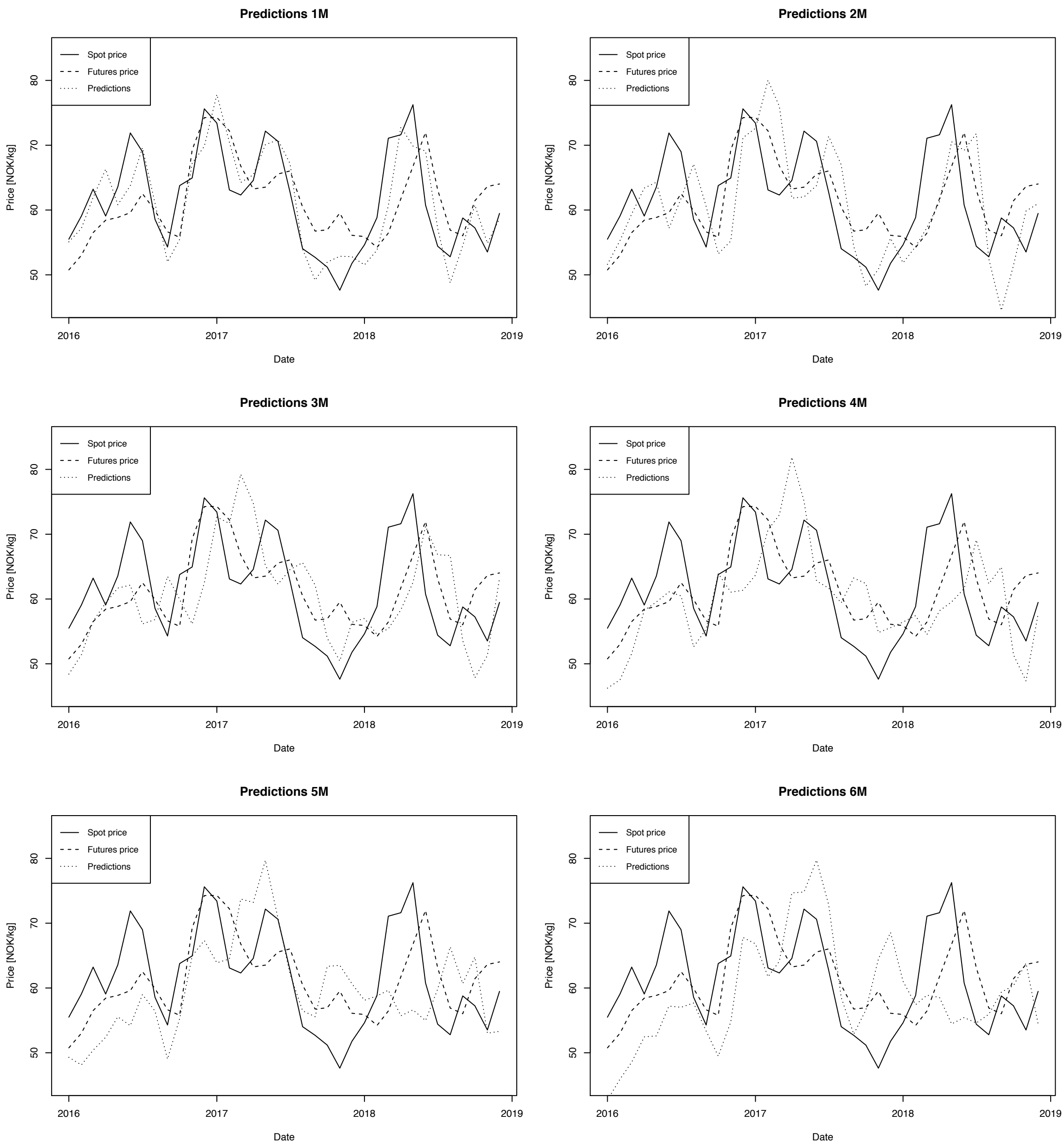

Figure 19: Predictions by the vector autoregressive (VAR) model

ANN Predictions

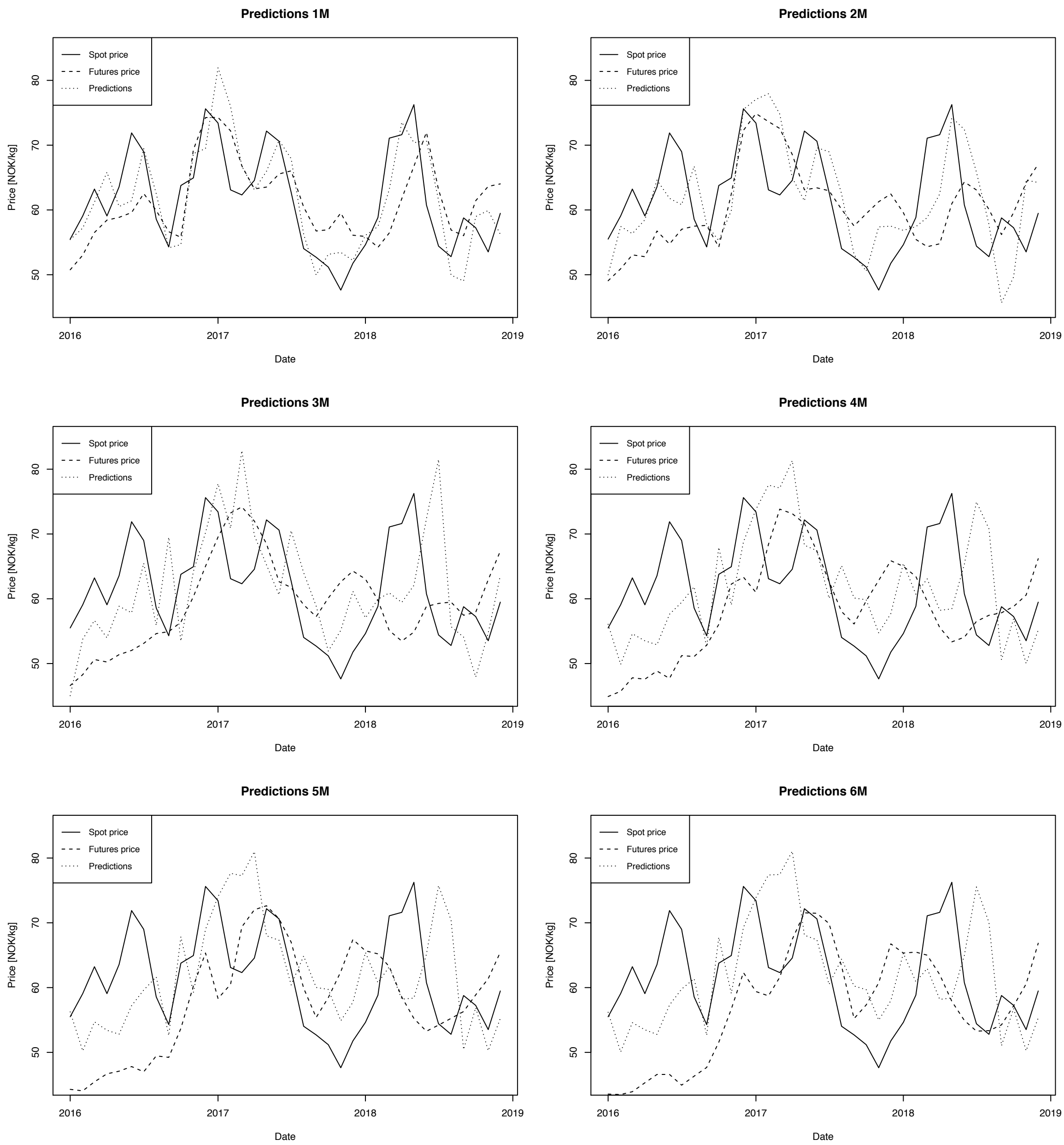

Figure 20: Predictions by the artificial neural network (ANN) model

D Appendix D - Risk Premium Plots

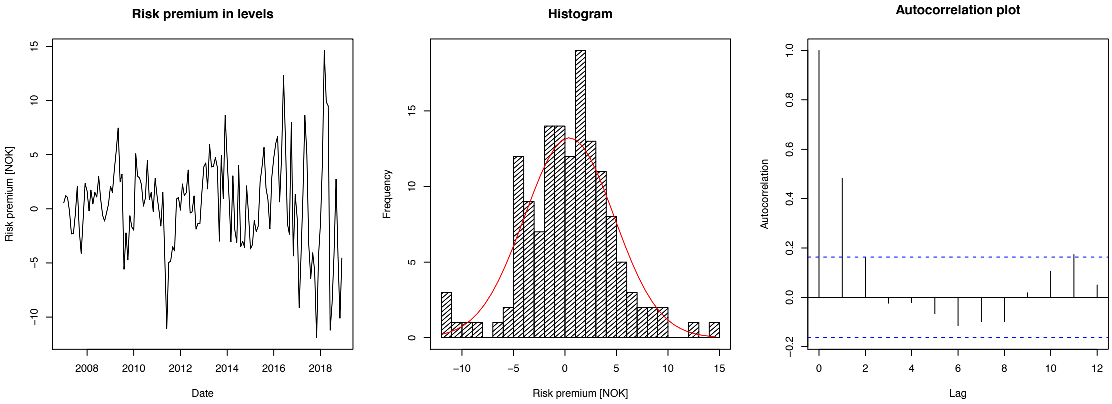

Figure 21: Risk premium for futures contracts with 1 month until expiration

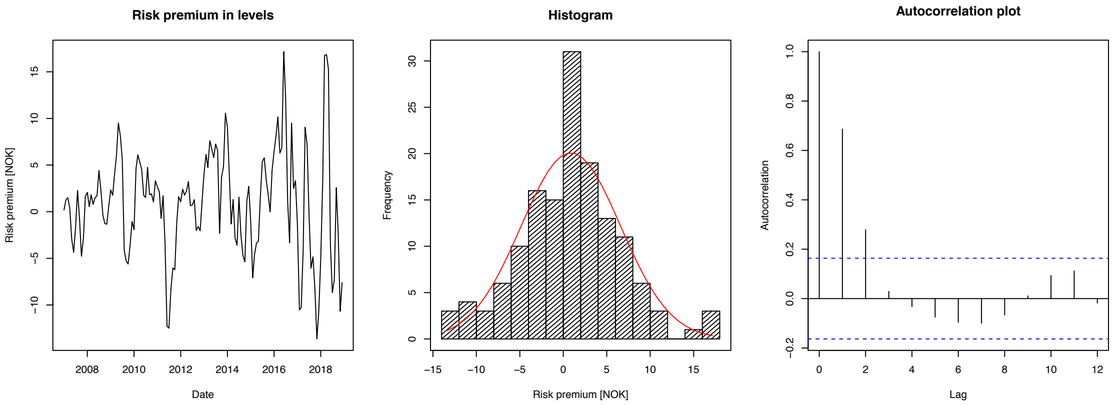

Figure 22: Risk premium for futures contracts with 2 months until expiration

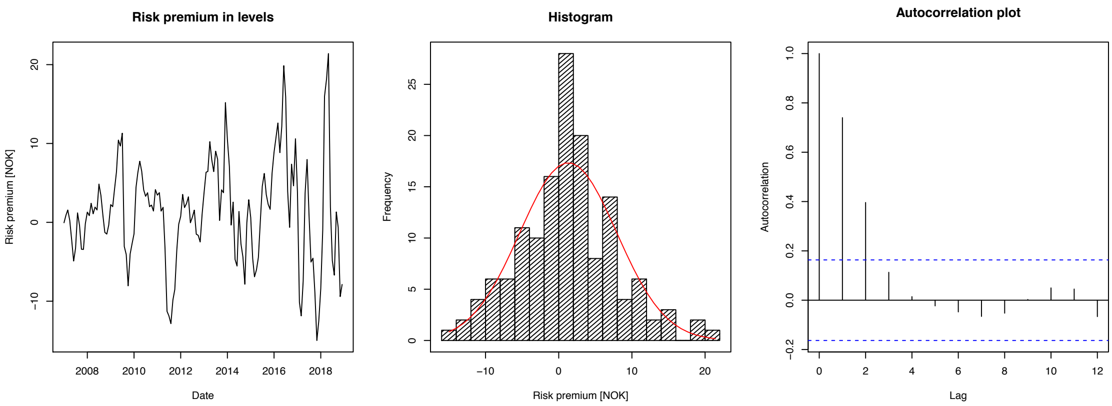

Figure 23: Risk premium for futures contracts with 3 months until expiration

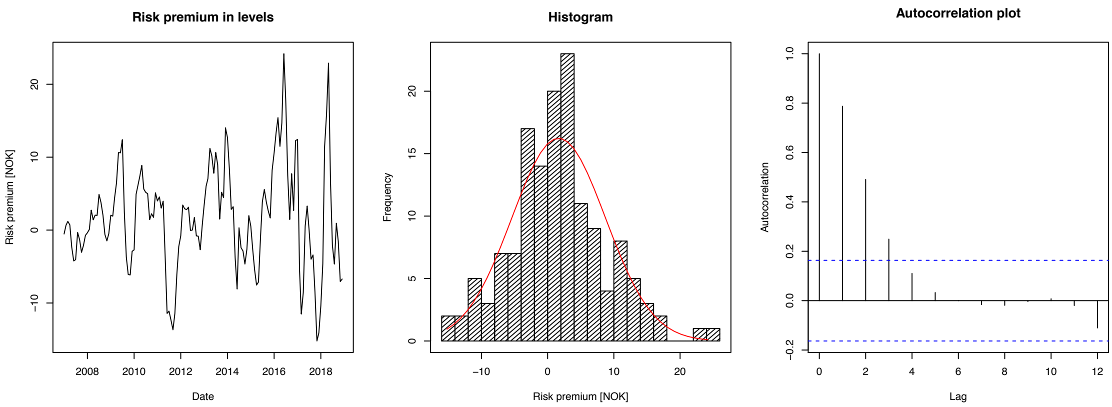

Figure 24: Risk premium for futures contracts with 4 months until expiration

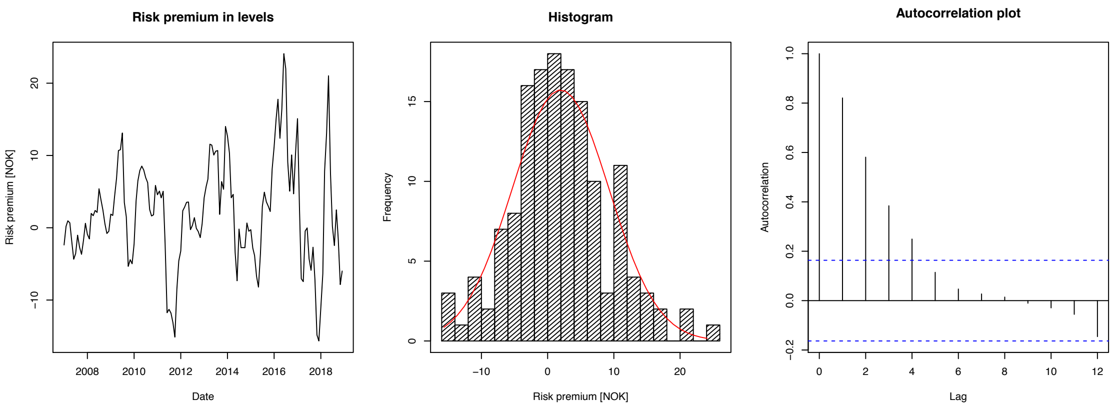

Figure 25: Risk premium for futures contracts with 5 months until expiration

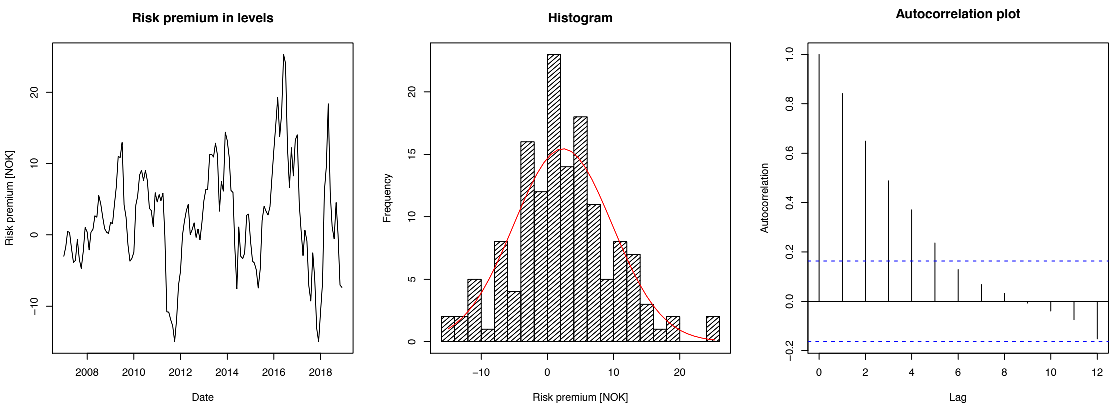

Figure 26: Risk premium for futures contracts with 6 months until expiration

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