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RESEARCH ARTICLE

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Efficiency in the Atlantic salmon futures market

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Abstract

In this study, we examine the efficiency and unbiasedness of Atlantic salmon futures prices. Market participants use the Fish Pool futures market to hedge the increasingly volatile salmon spot price. We further examine the futures market's predictive accuracy, comparing it to a variety of proprietary prediction models. Our results show that futures prices are efficient and unbiased in the long-run, while being biased and inefficient in the short-run. Moreover, we find that futures prices provide an adequate price discovery function for most contracts, while suffering from magnified risk premiums due to few noncommercial traders.

KEYWORDS

commodity markets, financial forecasting and simulation, futures pricing, information and market efficiency

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 (Guttormsen, 1999; Oglend, 2013). The ever-growing price risk has intensified 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 However, due to thin trading, the financial options were withdrawn within a few years, leaving futures contracts as the only remaining hedging tools (Fish Pool ASA, 2019c).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 markets, leaving its hedging efficiency subject to question.

In this study, we examine the efficiency and unbiasedness of Atlantic salmon futures prices, both in the long-run and short-run. 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 generalized autoregressive heteroscedastic (ECM-GARCH) components in the assessment of short-run efficiency and unbiasedness. We also examine the price discovery role of the futures market employing causality tests for both long-run and short-run causality. We further assess the futures market's predictive power by comparing the predictions provided by the market, to out-of-sample predictions provided by several comprehensive prediction models, which were specifically developed for the purpose of our analysis.

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 the long- and short-run, whereas out-of-sample predictions produced by our prediction models were consistently outperforming the futures market, possibly indicating exploitable inefficiencies. In terms of the salmon market's characteristics, our results indicate that a short-run bias partly reflects underlying market risk factors, while also revealing potential excess risk-adjusted return, presumably due to the sparse number of speculative traders in the market.

Our findings should be of particular interest to any market participants, both commercial and noncommercial. For commercial market participants, the findings indicate that the risk premium paid to hedge the salmon price is relatively high over time, meaning that risk preferences and financial solidity is of great importance when determining whether futures contracts should be applied for hedging or not. Consequently, for any noncommercial participants, the findings indicate that there is an opportunity for risk-adjusted excess return from speculative futures trading in the Fish Pool futures market.

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., 2016b; Fisher & Lai, 2016; Yeboah et al., 2016). We provide an updated market review, applying an extended data set covering the time period from January 2007 to December 2018. Furthermore, we develop a substantially more comprehensive framework than what has previously been applied, accounting for essential features of the salmon market. In conclusion, the combination of familiar methodology on market efficiency and a number of sophisticated prediction models, yields novel insights into the characteristics of both the futures market and the entire value chain of the Atlantic salmon 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 our analysis, whereas theory on market efficiency as well as the methodology is outlined in Section 4. We present results from our analysis in Section 5, followed by conclusive remarks in Section 6.

2 | LITERATURE REVIEW

There are relatively few studies on the Atlantic salmon futures market, 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. (2016b) perform efficiency testing on monthly observations spanning the time period from 2006 to 2014, involving monthly contracts with 1–6 months to maturity. Using 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 nonstationary and cointegrated for all maturities. 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 also fail to reject that spot prices are *exogenous* in the spot-futures relation, suggesting that the futures prices do not perform a price discovery role, an important feature of a mature futures market (Garbade & Silber, 1983; Hansen & Hodrick, 1980).

Fisher and Lai (2016) perform 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. (2016b), they perform tests of stationarity and cointegration. In addition to 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 ECM, testing for both long- and short-run efficiency. They fail to reject unbiasedness based on the the Engle-Granger parameters, for all maturities. However, based on the Johansen cointegrating parameters, unbiasedness is rejected for some of the contracts. These differing results clearly highlight the problems imposed by the use of the Engle-Granger procedure, in terms of efficiency and unbiasedness testing. Contrary to Asche et al. (2016b) they conclude that the futures market does, in fact, provide a price discovery function. Looking closer at their test results on weak exogeneity however, 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. They find that the unbiasedness hypothesis holds 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. (2016b) and Fisher and Lai (2016). They reveal that the futures contracts do provide the expected price discovery role for 3-, 4-, 5-, 9- and 12-month futures contracts, but simultaneously that this is not the case for 1-, 2- and 6-month futures contracts. They conclude that the futures market does exhibit properties of a maturing market, but that hedging efficiency is better for longer contracts than for contracts closer to maturity. Moreover, they find 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 with the salmon market. A broad range of recent studies follows a conventional approach, finding nonstationary properties for both spot and futures prices, and testing for long-run cointegrating relations. Also, these studies impose restrictions on the parameters of a fitted ECM, yielding conclusions of both long- and short-run market efficiency and unbiasedness. Following this methodology, Kellard 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 and 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, using 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 modeling 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 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

[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, which we will further discuss in subsequent sections.

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 on a superior framework. Using state-space modeling on salmon price forecasting, Vukina and Andersen (1994) amply demonstrate that 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 A. 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 provides mixed findings in terms of both efficiency, unbiasedness, and the price discovery function. These partially contradicting findings should be carefully assessed, acknowledging the fact that the small size of available data sets, might cause inconsistencies across different methodologies. The majority of existing papers were published in 2016, typically assessing the market based on 10 years of monthly data, which is a relatively short time span compared with studies on well-established markets. Brorsen and 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 we emphasize 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 and Holt (2002), we account for the existence of ARCH effects in the ECM residuals 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, we compare the predictive power of a variety of models to the predictive power of futures prices, giving additional insights into market efficiency of both the 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 | DATA

In this section, we describe the most important data used in the analysis of the Atlantic salmon futures market. As we will further explain in subsequent sections, we have developed multiple prediction models as part of the market analysis, incorporating extensive data on exogenous factors affecting the salmon spot price. As the predictions models as such are outside the main scope of this study, descriptions and details on prepossessing the data employed by these models are found in Appendix A.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 futures market is the *Fish Pool Index*™ (FPI). The FPI is a synthetic

[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.

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

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, 2019b). 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, 2019a). The settlement price for, for example, January 2018 is calculated as the average of the FPI over Weeks 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 futures 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 most frequently traded. A review of all the completed trades clearly demonstrates that certain contracts are superior in terms of trading volume. Moreover, we found that the front-month,[4] half-year, and quarterly contracts, as well as monthly contracts with 1 and 2 months to expiration, were the most reasonable contracts to analyze. Based on this review, we chose to examine monthly contracts with 1–6 months to expiration, indirectly assessing the upfront quarter and half-year contracts as well. Throughout this study, the prices of the monthly contracts at time t, expiring in 1–6 months, are referred to as $F_{t,1}$, $F_{t,2}$, ..., $F_{t,6}$, 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), 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 transformation. Next, the daily futures prices are transformed into monthly prices by averaging monthly observations. That is, the price of, for example, $F_{t,1}$ 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.

In the assessment of futures contracts, one may experience issues from overlapping observations, including autocorrelation and the spurious appearance of inefficiency (Hansen & Hodrick, 1980). To curtail such effects, futures contracts with unequal time to expiration are treated separately in the analysis. Moreover, only nonoverlapping observations are included in the time series of each futures contract. As demonstrated by (Kellard et al., 1999), an effective way of dealing with autocorrelated residuals is to apply sampling intervals equal to the forecast interval. This approach would give a sampling interval of 6 months for contracts expiring in 6 months, which would imply that the number of observations for these contracts would be reduced from 144 to 24. Due to the already short sampling period, this approach is found not to be favorable for this study, although the applied sampling intervals could potentially lead to spurious appearance of inefficiency from autocorrelated residuals.

3.3 | Unit root testing

To examine whether the data exhibits non-stationarity, we apply the ADF test (Dickey & Fuller, 1979) to the time series in both log levels ($s_t = \log S_t, f_t = \log F_{t,T}$) 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 nonstationary and integrated of the first order, as depicted in Table 1.

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

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***

Note: The ADF was conducted with and without a deterministic trend. The number of lags was chosen based on the Akaike information criteria.
*** indicates rejection of the null hypothesis (H_0: A unit root is present in the time series) at 1% level.
Abbreviation: ADF, augmented Dickey–Fuller.

3.4 | Seasonality

The Atlantic salmon spot and futures prices are previously found to exhibit seasonal properties (Asche et al., 2016a), 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, that is, 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 C. 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 suggests 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 repeatedly 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, we found that the risk premia exhibit seasonal patterns for all the futures contracts we examined. Eventually, we further applied this method to the seasonal prediction model proposed in Section 4.2.

3.5 | Descriptive statistics on the risk premia

Table 2 exhibits the most important statistics on the risk premia, as well as relevant test results. The positive mean for all contracts indicates a possible overweight of traders wishing to hedge their exposures 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, that is, 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 C).

TABLE 2 Descriptive statistics on the risk premia

Contract	N	Descriptive statistics				Tests		
		Mean	SD	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***

Note: ***, **, and * indicates rejection of the null-hypotheses at a 1%, 5%, and 10% level, respectively.

Abbreviation: ADF, augmented Dickey–Fuller.

4 | THEORY AND METHODOLOGY

The majority of studies on efficiency in futures markets are built on the theoretical *efficient market hypothesis* (EMH), presented by Fama (1970). Conceptually, the EMH assumes that the present futures price F_t in an efficient market equals the expected spot price at expiration, given the information-set Φ_t. This implies that the futures price is the best possible forecast of the spot price at expiration. In terms of the price of a futures contract at time t, expiring at time $t + 1$, this is formally expressed as

$$F_{t,1} = \mathbb{E}[S_{t+1}|\Phi_t]. \tag{1}$$

The information-set on which the expectations are based is, however, highly relevant. Fama (1970) and Roberts (1967) consider 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, that is, 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, that is,

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

where the residuals, u_t, are assumed i.i.d. $\sim N(0, \sigma^2)$. Market *inefficiencies* are then found by rejecting 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 represented by an equal number of short and long hedgers. In reality, however, this is rarely the case. Under the *Keynes–Hicks* hypothesis (Hicks, 1939; Keynes, 1927), 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 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:

$$F_{t,1} = RP_{t+1} + \mathbb{E}[S_{t+1}|\Phi_t]. \tag{3}$$

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 demonstrated by Byrne et al. (2013), most commodity prices are nonstationary 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 ordinary least squares (OLS) linear regression may therefore lead to spurious regression results. Methods have been presented to bypass the problem of nonstationary properties, by first-differencing Equation (2) with respect to the spot and futures price

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

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

4.1 | Long- and short-run analysis

As outlined in Section 3.3, both the spot price and the futures prices are all nonstationary 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

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

where j represents the months ahead expiry of the futures contracts being assessed.

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.

4.1.1 | ECM

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 ECM first introduced by Granger (1986). Formally, the ECM applied in this study is given by

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

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, such that lagged versions of the spot and futures prices do not improve the forecast. Formally, efficiency implies not violating the following restrictions on Equation (6):

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

Similar to the long-run analysis, the short-run analysis on price bias may be divided into separate hypotheses, representing different scenarios. To better understand the implication of the scenarios, the ECM may be rewritten as

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

One scenario, and presumably the least realistic, is a market with a zero risk premium in the short-run. This would indicate fully unbiased futures prices, reflecting 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:

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

implying that Equation (8) is reduced to $S_t = F_{t-1} + v_t$. 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 $S_t = \alpha + F_{t-j,j} + v_t$.

4.1.2 | ECM with GARCH component

The ECM outlined in Equation (6) does however exhibit a shortcoming in that it does not include 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 have already found to be the case for the Atlantic salmon market. Further, the sporadic blossoms of sea lice and diseases 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 and 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 this model was therefore applied to the short-run analysis. Formally, the model is expressed as

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

where

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

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

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

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) assume that the stricter restriction $\beta = 1$ is fulfilled.

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 as its historical prediction accuracy in comparison to a variety of models, testing for both weak and semi-strong market efficiency.

4.2.1 | 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 toward 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. We analyze long- and short-run causality establishing a *bivariate vector error correction model* (VECM), similar to the ECM in Equation (6) for both the spot and futures prices, given by

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

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

The long-run price dynamics are assessed by running a conventional *t-test* on the coefficients of the error correction term, that is, 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).

4.2.2 | 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 with that of the futures prices, out-of-sample. The metric for goodness-of-fit used for assessing prediction accuracy, was the out-of-sample root mean squared error (RMSE). The futures markets' primary purpose is to serve as a tool for hedging price risk, inevitably testifying to the existence of risk-averse market participants in an efficient market, that is, market participants with nonlinear 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

$$\hat{S}_t = F_{t-j,j} + \sum_{m=1}^{12} \omega_{m,t} DM_{m,j} + \phi_t DE_t, \tag{15}$$

where $\omega_{m,t}$ is a binary variable taking on the value 1 if time t coincides with month of the year l, and $DM_{m,j}$ is the in-sample seasonal risk premium components of contracts expiring in j months for the calendar months $m \in \{Jan, ..., Des\}$. 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 at time t, 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 A. 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 with that of the futures prices. In the context of this study, the results of the models are of primary interest rather than the technical details of the actual models. Further details on the VAR and ANN models are therefore found in Appendices A.3 and A.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 nonstationary with one unit root, the first part of the long-run analysis is the assessment of cointegration. The Johansen 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.

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 futures contracts we examined. 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, our findings imply that all contracts exhibit the properties of an efficient market in the long-run.

Unable to reject efficiency in the long-run, we proceed with the assessment of short-run properties. The prototypical ECM outlined in Section 4.1.1 was estimated for all futures prices, followed by tests on 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 results 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 ECM with GARCH-components, previously referred to as the ECM-GARCH model presented in Section 4.1.2 (Table 6).

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 with 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.

TABLE 3 Results from Johansen's bivariate cointegration test

	$r = 0$		$r \leq 1$		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

Note: $\lambda_{\text{trace}} = -T\sum_{i=r+1}^{n}\log(1-\hat{\lambda}i)$, $\lambda_{\max} = -T\log(1-\hat{\lambda}+1)$ $r \in [0, n-1]$. The number of lags shown in brackets were chosen based on the Akaike information criteria from the corresponding VAR model. *** indicates rejection of null hypothesis at 1% level. 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)

Note: *p* Values are shown in parentheses.

TABLE 5 Error correction model parameters

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)

Note: $\Delta s_t = -\rho u_{t-1} + \beta \Delta f_{t-j,j} + \sum_{i=j+1}^{m} \beta_i \Delta f_{t-i,j} + \sum_{l=1}^{k} \psi_l \Delta s_{t-l} + \upsilon_t$. The depicted coefficients are significant at a 10% level only. Q(12) indicates portmanteau test results with 12 lags (H_0: No residual autocorrelation up until 12 lags). *Efficiency* and *unbiasedness* indicate test results on the hypothesis of efficient and unbiased futures prices, respectively. *p* Values are shown in parentheses. ***, **, and * indicate rejection of the null hypothesis at a 1%, 5%, and 10% level of significance, respectively.

TABLE 6 Error correction model-generalized autoregressive heteroscedastic parameters

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)

Note: $\Delta s_t = -\rho u_{t-1} + \beta \Delta f_{t-j,j} + \sum_{i=j+1}^{m} \beta_i \Delta f_{t-i,j} + \sum_{l=1}^{k} \psi_l \Delta s_{t-l} + \theta\sqrt{h_t} + \upsilon_t$. The depicted coefficients are significant at a 10% level only. Q(12) indicates Portmanteau test results with 12 lags (H_0: No residual autocorrelation up to lag 12). *Efficiency* and *unbiasedness* indicate test results on the hypothesis of efficient and unbiased futures prices, respectively. p Values are found in parentheses. ***, **, and * indicate rejection of the null hypothesis at a 1%, 5%, and 10% level of significance, respectively.

5.2 | Predictive power

5.2.1 | 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

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)***

Note: The number of lags in the Granger causality test were chosen based on Akaike information criteria.

[a]The presented p-value and test statistics indicate the significance level ρ from the vector error correction model in Equations (13) and (14). This may be translated to H_0: ΔX causes ΔY in the long-run.

[b]The presented p value indicates the p value of rejection of the null hypothesis, H_0: 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.

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 of long-term market prospects. In practice, this can be viewed as if market participants' updated view on the long-term prospects of the salmon market are being consecutively reflected in the futures prices. For a better intuition on why this is the case, 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, this does not imply that a change in the futures price itself causes a change in the spot price, since 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 before the spot price, a phenomenon we will further discuss shortly.

Turning now to the short-run analysis, the presence of a price discovery function is further strengthened. In Table 7 we show that the null hypothesis of the short-run Granger causality test (H_O: Δx 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 for the contracts expiring in 6 months, with the futures price performing the price discovery role. A necessity of no-arbitrage is that the futures' basis[5] is approaching zero as we get closer to expiration. For the front-month contracts, this basis is ultimately relatively small. In view of the fact 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 A1), one would

[5]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.

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 prices. 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, which we found to be the case for the front-month contracts, assuming that market participants are adequately but not perfectly informed on the short-term harvest volumes. Similarly, for the longest 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 in the market than both front-month and the longest 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 minor changes in market expectations. Thus, findings of price discovery in the front-month and longest contracts are indications of no-arbitrage and well-informed marked participants, acting on the basis of updated market prospects respectively. The finding of an inadequate price discovery role for intermediate contracts may, on the other hand, be an indication of few speculative traders willing to speculate on the more risky and less predictable intermediate effects of an event, such as the alga outbreak.

5.2.2 | Out-of-sample predictions

The last part of our assessment of the futures market's price discovery abilities, is the analysis of its *out-of-sample prediction accuracy*. In Table 8 we present the RMSE-figures for both futures prices and the models previously outlined, 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 unable to provide the best possible predictions[6]. 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 including data on exogenous factors improves the prediction results, implying that there might be speculative opportunities for risk-adjusted return in the futures market. Note, however, that the Diebold–Mariano test of prediction accuracy indicates that the prediction accuracy is statistically different from that of the futures prices, primarily for the front-month forecasts. Although these findings could to some degree be explained by the low number of out-of-sample observations, the prediction results should be interpreted as no more than indications of the futures prices failing to provide the best predictions possible. In the following, we will evaluate these findings in the context of our previously reported results.

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

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

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)
	0.022	*0.301*	*0.434*	*0.105*	*0.544*	*0.422*
ECM-GARCH	5.788** (3)	8.639 (3)	9.664 (3)	9.384 (3)	10.311 (3)	10.804 (4)
	0.017	*0.280*	*0.408*	*0.107*	*0.317*	*0.338*
Seasonal	6.603** (5)	8.666 (5)	9.818 (4)	10.402 (5)	10.606 (4)	10.698 (3)
	0.264	*0.278*	*0.354*	*0.415*	*0.288*	*0.263*
VAR	5.428** (1)	8.483 (2)	8.886 (1)	9.043 (1)	9.115 (1)	9.748 (1)
	0.039	*0.158*	*0.167*	*0.189*	*0.205*	*0.171*
ANN	5.554** (2)	7.608* (1)	9.571 (2)	9.629 (2)	9.637 (2)	9.976 (2)
	0.017	*0.066*	*0.288*	*0.210*	*0.190*	*0.172*

Note: Root mean squared errors of out-of-sample predictions. Ranks in parentheses. *p* Values from the Diebold–Mariano test in italic, indicating the probability of the prediction accuracy being statistically different from that of the futures prices. ***, **, and * indicates rejection of the null-hypotheses at a 1%, 5%, and 10% level, respectively.

function. Such predictability and biases would not be found in an unbiased futures market in the framework of the 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 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[7] 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, as shown in Figure 1b.

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, we employed the absolute values of the risk premia in the regression, reflecting price risk on both sides of the hedge. The volatility was initially found as the exponentially weighted moving average (EWMA)[8] 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 conclusions based on the results. If there is a relation, however, the regression suggests that a higher risk premium is, to some degree, reflecting valid expectations of price risk.

The observed risk premia should be of particular interest for major market participants, occupying positions making up considerable parts of the overall trading volume. Investors in illiquid markets who want to liquidate or offset their positions, often discover that there is no way out at the current market price. In such cases, an offsetting position is likely to disrupt the price severely, effectively reducing the risk-reward trade-off considerably. Moreover, commodities are often found to be more volatile than other asset classes, making liquidity even more of an issue.

[7]The correlation figures in Table A1 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.

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

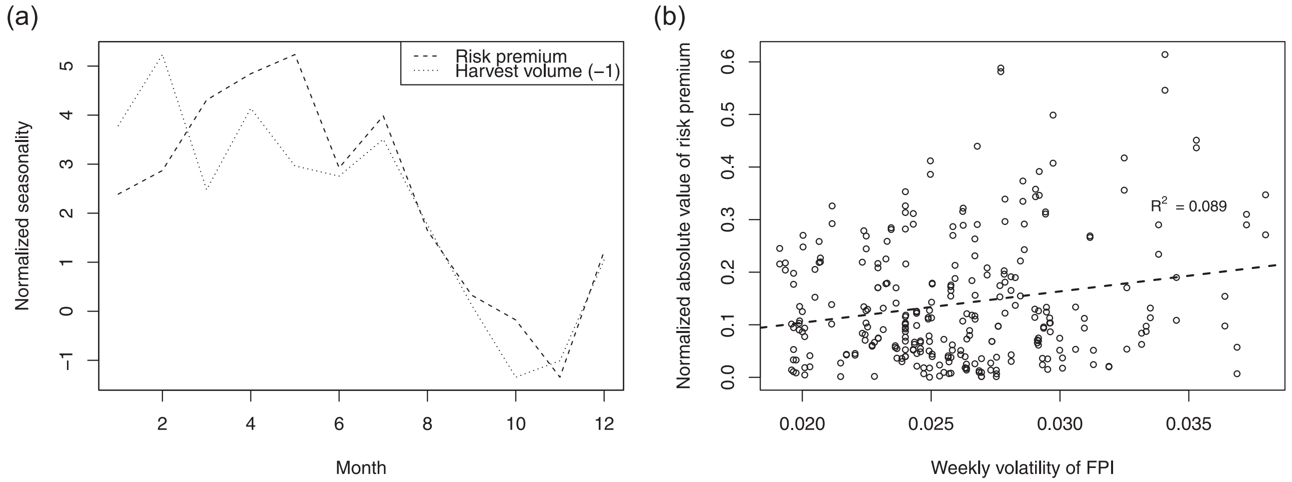

FIGURE 1 (a) Seasonal components and (b) risk premium versus volatility. (a) depicts the annual seasonal decomposition of salmon spot price, upfront monthly futures contracts, and the additive inverse of harvest volume. (b) depicts observations on normalized risk premia regressed on weekly spot price volatility

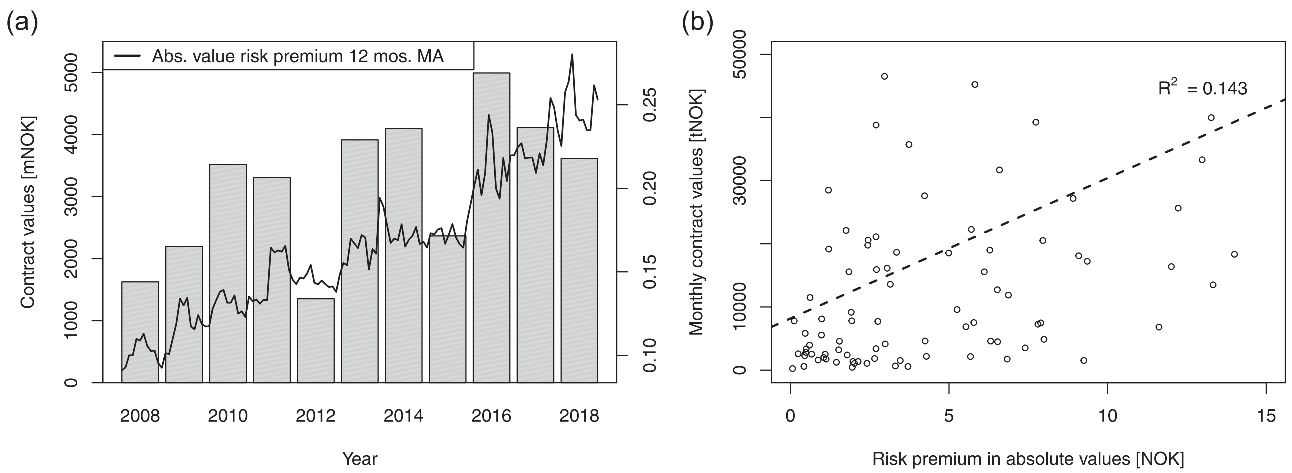

FIGURE 2 (a) Annual contract values versus risk premium and (b) risk premium versus contract values. (a) depicts 12 months moving average of the normalized risk premia over the total contract values on Fish Pool futures market. (b) shows an ordinary least squares regression of trading volumes on realized risk premia

Consequently, investors in such illiquid markets generally expect a higher premium than in other comparable markets with higher liquidity (Cho et al., 2019). Knowing that all salmon futures contracts are thinly traded compared with futures contracts on other commodities, the observed bias is also likely to reflect poor market liquidity. If so, the risk premium is not only reflecting the underlying spot price risk, both also a liquidity risk. This liquidity premium can be interpreted in different ways. Obviously, the liquidity premium could be considered a proportional premium on both sides of the hedge, reflecting a scarce number of traders willing to enter into an offsetting position.

If the 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 months moving average of the realized risk premia of monthly contracts expiring in 1–6 months, applying normalized absolute values under the same argument we offered above. We display the results in Figure 2, including 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, rather the opposite. This does not, however, rule out the existence of liquidity premia. The increase in the overall risk premium could simply reflect the fact that the salmon price has become ever more volatile over the last couple of decades (Oglend, 2013).

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 seek to determine whether low trading volume on individual contracts tends to imply an increased liquidity premium. From this regression we obtain an OLS, which is unable to explain a satisfactory part of the total variance ($R^2 = 0.143$). The regression output does, however, suggest the complete opposite of an additional liquidity premium in case of low trading volumes on individual contracts. Nevertheless, this does not rule out the existence of a liquidity premium, but rather confirms our 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 are valid, the relation found by the OLS in Figure 2b indicates that the risk premium is, in fact, reflecting actual price risk, partly explaining the bias found in the short-run analysis of unbiasedness.

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)[9], which is rather low in comparison with, for example, the market for crude oil futures, of 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.

6 | SUMMARY AND CONCLUSIONS

The salmon spot price is highly volatile, creating a 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, its hedging efficiency has often been questioned. In this study, we assess the efficiency and unbiasedness of the Fish Pool futures market. We examine monthly futures contracts expiring in 1-6 months, covering the time period from January 2007 to December 2018.

The ADF test rejected stationarity for both spot price and futures prices on all the monthly contracts, whereas the Johansen cointegration procedure showed that all futures contracts were cointegrated with the spot price. Applying 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., 2016b; Yeboah et al., 2016). Furthermore, we initiated a short-run analysis by the use of a prototypical ECM. Residual analysis did, however, reveal ARCH-effects in the ECM-residuals, 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 4–6 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 due to seasonal effects. Our findings on time-varying risk premia conform well with previous findings by Asche et al. (2016a) and Konjhodzic and 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 employing long- and short-run Granger causality tests. The two tests revealed that both the front-month and the longest contracts perform a price discovery role of an efficient and mature market, indicating no-arbitrage and well-informed traders. Intermediate contracts expiring in 2–4 months, however, fail to perform the desired price discovery role, presumably as a consequence of sparse numbers of speculative traders acting in the Fish Pool futures market. The absence of numerous speculative traders could imply unexploited excess risk-adjusted return. Our suspicion of such a market characteristic was further

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

strengthened by the futures prices' low prediction accuracy, in comparison to out-of-sample predictions by a variety of models. We computed out-of-sample predictions of ECM and ECM-GARCH models, as well as a seasonal model, a VAR model and an ANN model. The RMSEs of the out-of-sample predictions showed that all of our models were able to *consistently* outperform the futures contracts maturing in 1–6 months over a time period of 36 months, suggesting that there might be speculative trading opportunities in these contracts.

Our results indicate that the Fish Pool exchange exhibits some of the characteristics of an efficient futures market, while still suffering somewhat from the sparse trading volume and low number of speculative traders. Although the observed inefficiencies could be partly explained by autocorrelated risk premia, due to the shorter sampling intervals discussed in Section 3.2, 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.

CONFLICT OF INTERESTS

The authors declare that there are no conflict of interests.

DATA AVAILABILITY STATEMENT

All data included in the analysis is publicly available, and can be accessed from the data sources listed subsequent.

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APPENDIX A: 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 YoY or month-over-month (MoM) changes, depending on whether the time series exhibit 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 preprossessing, predominantly employing detrending and deseasonalization. Subsequent sections provide descriptions of exogenous[10] 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, demonstrated by Granger causality in Table 7. We also develop a *Vector Autoregressive* (VAR) model and an *ANN* model, both comprising the exogenous variables.

A.1 Factors affecting the salmon spot price

Harvest volume

Examining trailing changes on the salmon spot price, the preceding harvest volume of salmon is one of the factors with the highest explanatory power, partly reflected by the correlation figures in Table A1. As depicted in Figure A1, 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. The data was deseasonalized by introducing both an annualized pattern and an Easter dummy, reflecting the demand growth in conjunction with the Easter holiday.

Smolt release

Weighing about 60–100 g the salmons, usually referred to as *smolts*, are released into seawater cages. 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 and causing significant seasonal patterns. Moreover, the amount of smolt released in Norway has increased in a similar manner to the salmon market as a whole. Therefore, the time series on smolt individuals released was both detrended and deseasonalized.

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.

Seawater temperature

Seawater temperature has a direct influence on feed consumption and growth rates, and ultimately the harvest volume. Temperatures are collected for a number of Norwegian counties.[11] 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 and should not be removed. The time series was therefore deseasonalized with an annual pattern.

[10]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.

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

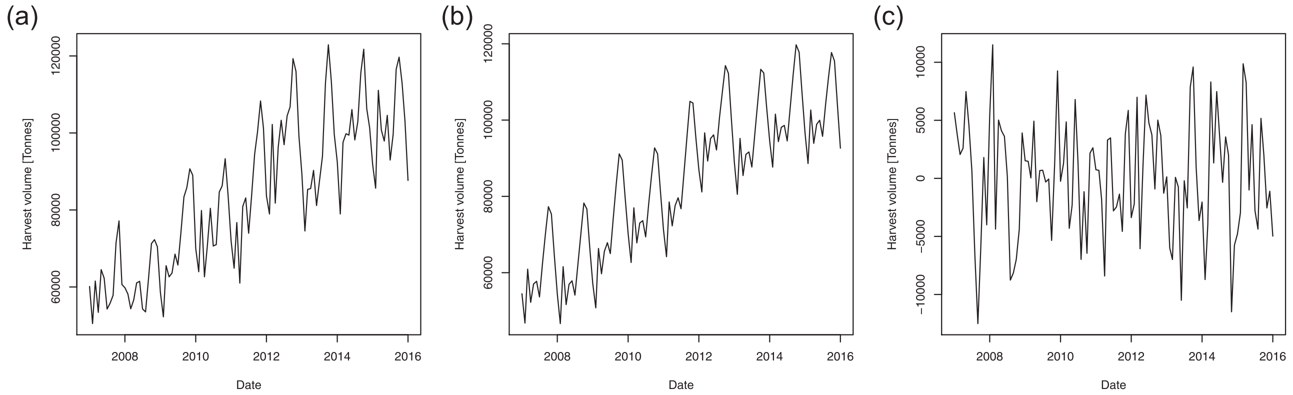

FIGURE A1 (a) Harvest volume in levels, (b) trend and seasonality, and (c) detrended and deseasonalized. The harvest volume was both detrended and deseasonalized. The seasonal component comprises both monthly dummies as well as an Easter dummy. *Source*: Fisheries Monitoring Centre (FMC) and the Norwegian Directorate of Fisheries

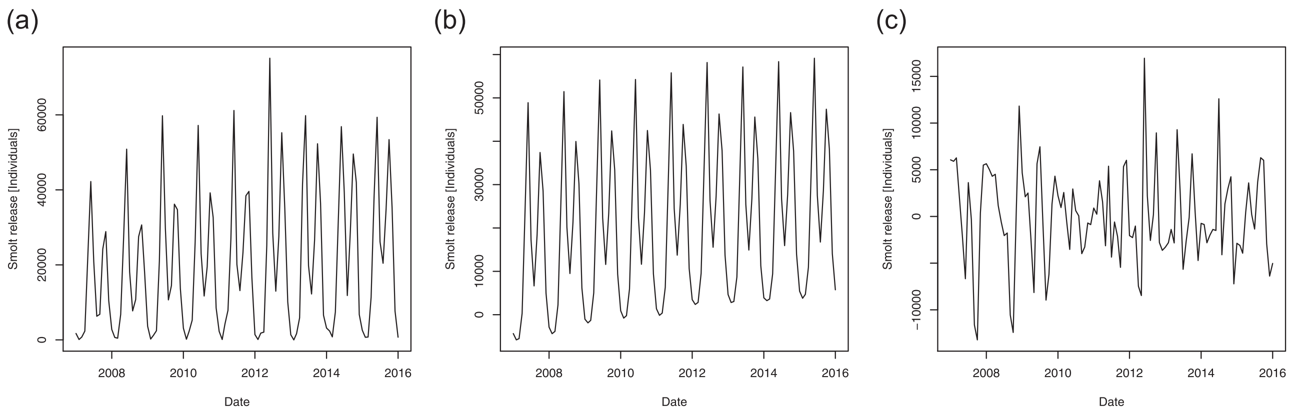

FIGURE A2 (a) Smolt release in levels, (b) trend and seasonality, and (c) detrended and deseasonalized. The smolt release was both detrended and deseasonalized on an annual basis. *Source*: Fisheries Monitoring Centre (FMC) and the Norwegian Directorate of Fisheries

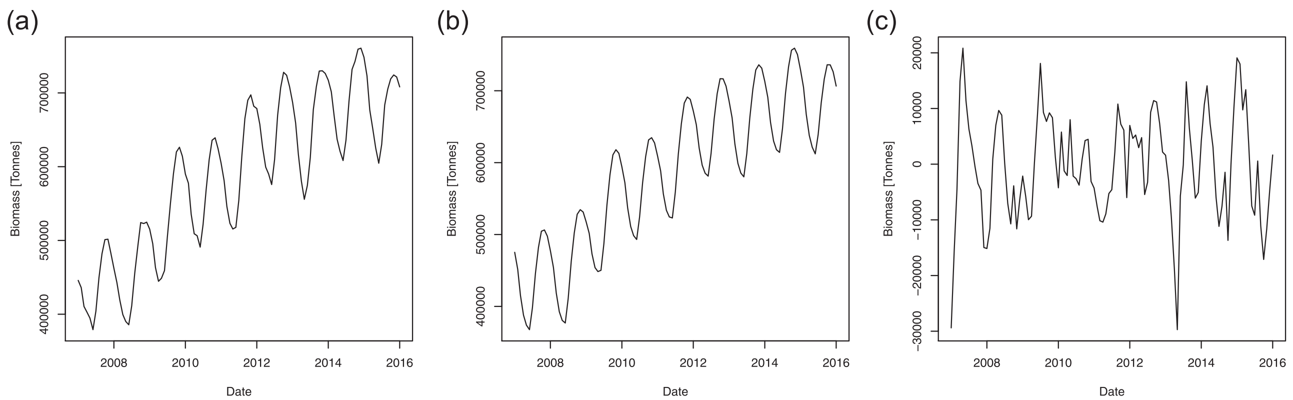

FIGURE A3 (a) Biomass in levels, (b) trend and seasonality, and (c) detrended and deseasonalized. The amount of standing biomass was both deseasonalized and detrended. *Source*: Fisheries Monitoring Centre (FMC) and the Norwegian Directorate of Fisheries

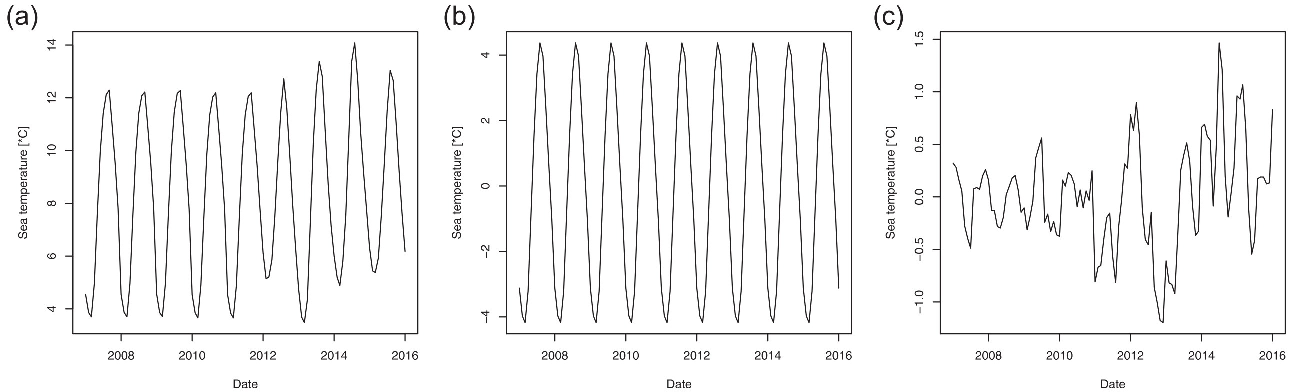

FIGURE A4 (a) Sea temperature in levels, (b) seasonality, and (c) deseasonalized. The seawater temperature was deseasonalized on an annual basis. *Source*: The Norwegian Food Safety Authority [Lusedata.no]

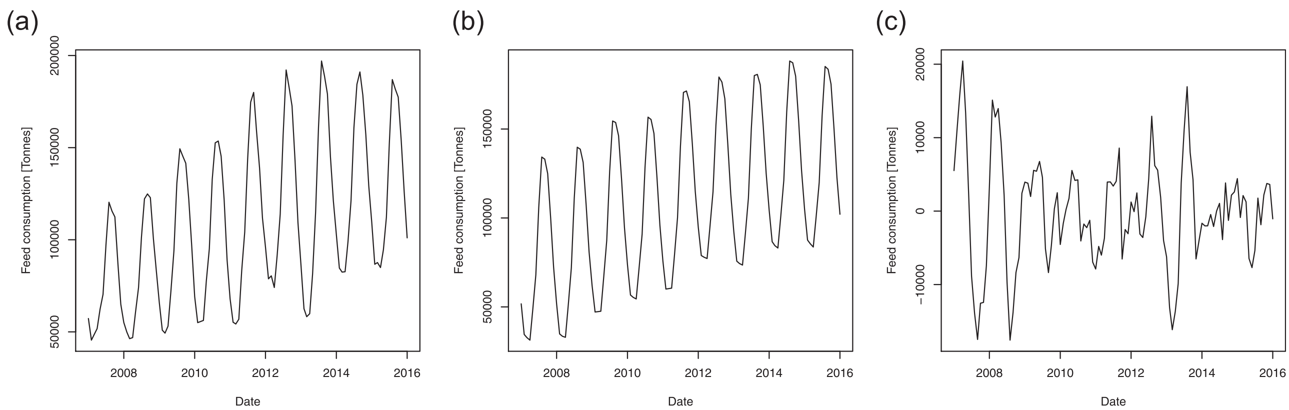

FIGURE A5 (a) Feed consumption in levels, (b) trend and seasonality, and (c) detrended and deseasonalized. The figures on feed consumption were both deseasonalized and detrended. *Source*: Fisheries Monitoring Centre (FMC) and the Norwegian Directorate of Fisheries

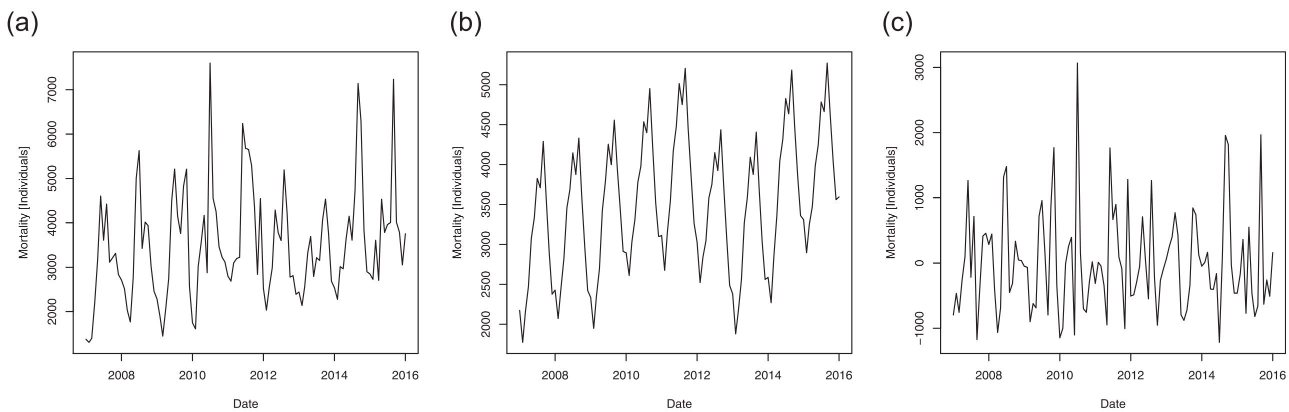

FIGURE A6 (a) Mortality in levels, (b) trend and seasonality, and (c) detrended and deseasonalized. The mortality rates were both detrended and deseasonalized. *Source*: Fisheries Monitoring Centre (FMC) and the Norwegian Directorate of Fisheries

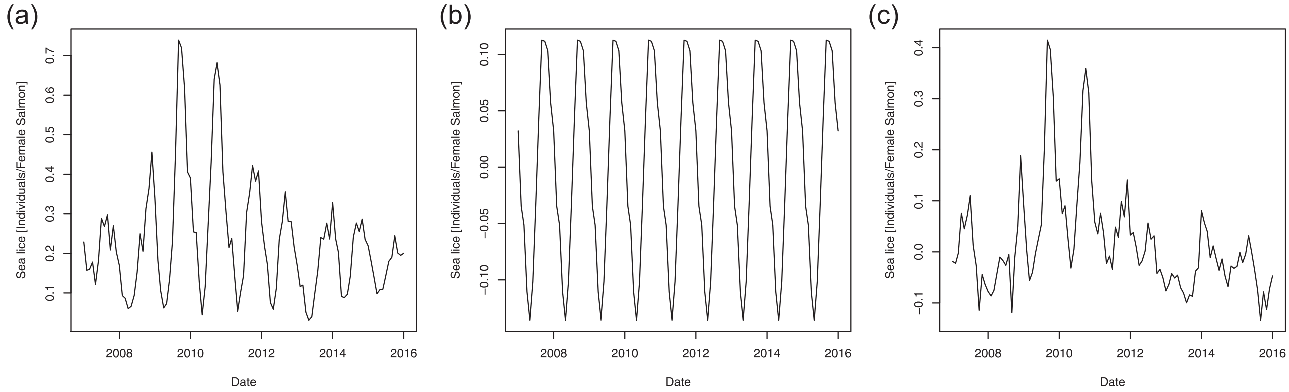

FIGURE A7 (a) Sea lice occurrence in levels, (b) seasonality, and (c) deseasonalized. The relative occurrence of sea lice is highly seasonal and was, therefore, deseasonalized. *Source*: The Norwegian Food Safety Authority [Lusedata.no]

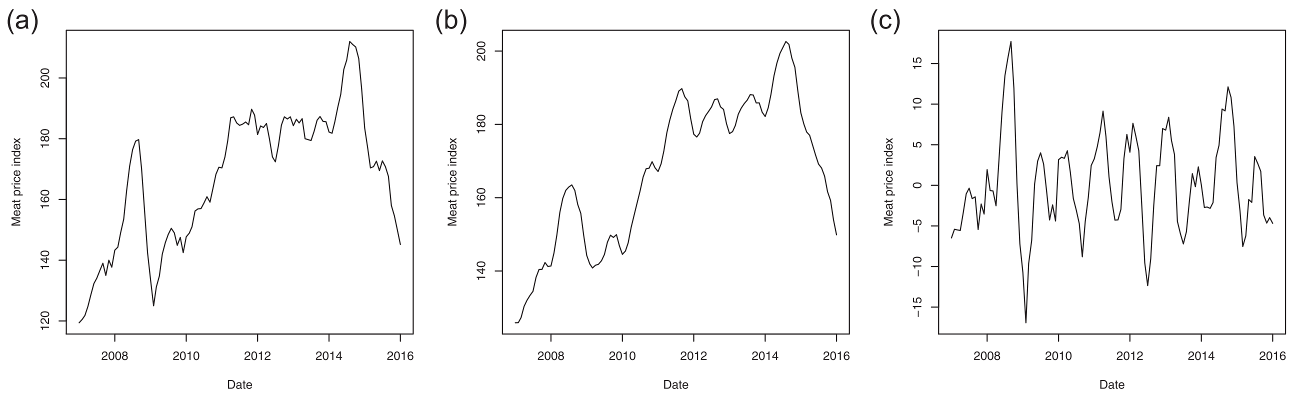

FIGURE A8 (a) Meat price index in levels, (b) trend and seasonality, and (c) detrended and deseasonalized. The FOA meat price index was both detrended and deseasonalized. *Source*: The Food and Agriculture Organization of the United States (FAO)

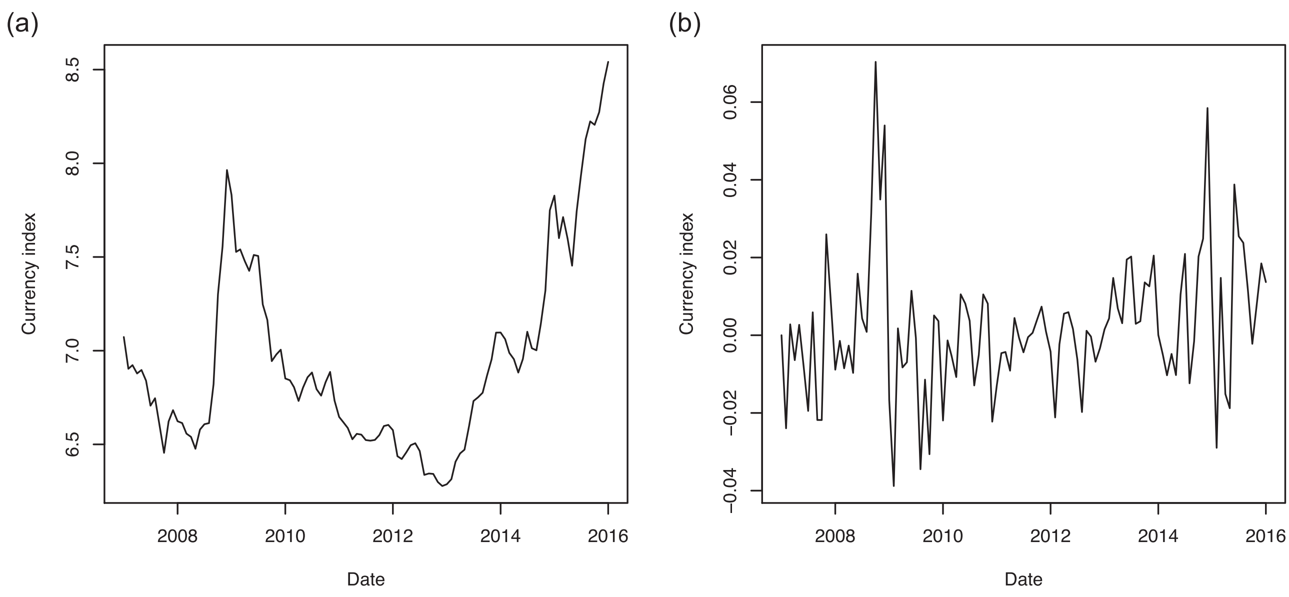

FIGURE A9 (a) Currency index in levels and (b) First difference. The currency index reflects trailing exchange rates as well as salmon invoice value for EUR and USD. Applied in the models was the MoM first differences. *Source*: The Central Bank of Norway

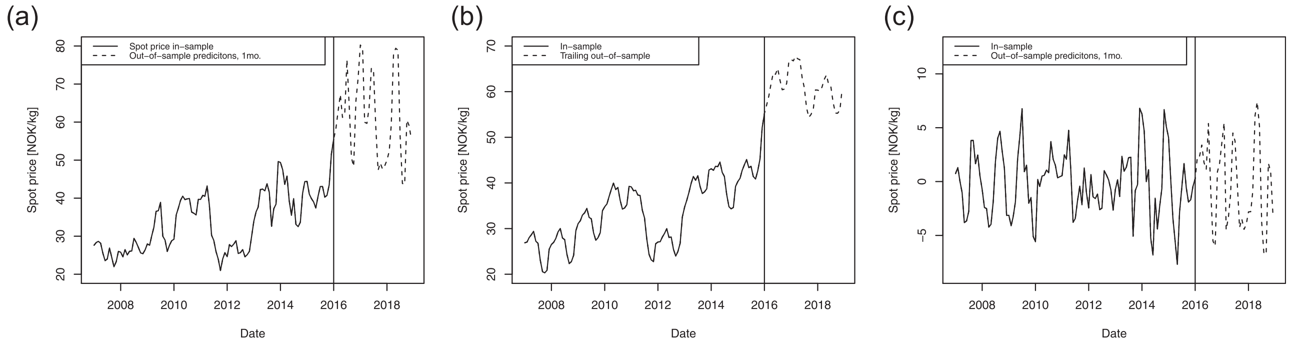

FIGURE A10 (a) Spot price in levels, (b) trend and seasonality, and (c) detrended and deseasonalized. The leftmost figure shows the in-sample spot price in levels, as well as the trailing 1-month predictions. The plot in the middle depicts the trend and seasonal component in the price series, whereas the rightmost plot shows the in-sample and out-of-sample predictions of the price deviations from the detrended and deseasonalized expectations

Feed consumption

Feed consumption per salmon is a nonlinear function of both average salmon size and water temperature. During the winter the feed consumption drops due to low water temperature. Also, 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.

Mortality

Mortality rates are usually observed peaking during the first 2 months after smolts have been 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 and 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.

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 cases of high sea lice rates. In this study, we apply a measure of the 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. Lice 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.

Meat price

The demand for fresh salmon turns out to be price elastic (Lohdi, 2015), suggesting that alternative proteins serve as substitutes affecting the spot price of salmon. In this study we include 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.

Currency indices; Norwegian krone (NOK)/US dollar (USD) and NOK/euro (EUR)

The NOK is used as invoicing currency in only a minority of Norwegian salmon export transactions. Over the time period 2003–2009 the NOK was used in contracts comprising 20.1% of the combined fresh and frozen salmon export. The EUR was by far the most frequently used currency, as contracts comprising 51% of exported tonnes were denominated in euros. The equivalent figure for the USD was 17.5% (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. We therefore constructed a currency index, comprising trailing exchange rates and invoice volume for both currencies. The index was employed in the models as MoM first differences.

A.2 Descriptive statistics

TABLE A1 In-sample descriptive statistics on preprossessed exogenous factors

	Descriptive statistics					
Time series	***N***	**Mean**	***SD***	**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***

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

Abbreviations: ADF, augmented Dickey–Fuller; FPI, Fish Pool Index™.

A.3 Vector autoregressive (VAR) model

A vector autoregressive VAR(p) model was constructed, comprising the preprocessed time series of exogenous factors introduced in Appendix A.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

$$\mathbf{Y}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}_1\mathbf{Y}_{t-1} + \boldsymbol{\beta}_2\mathbf{Y}_{t-2} + \cdots + \boldsymbol{\beta}_6\mathbf{Y}_{t-6} + \epsilon_t, \tag{A1}$$

where

$$\boldsymbol{\beta_1} = \begin{pmatrix} \beta_{1,11} & \cdots & \beta_{1,1n} \\ \vdots & \ddots & \vdots \\ \beta_{1,n1} & \cdots & \beta_{1,nn} \end{pmatrix}, \boldsymbol{\beta_2} = \begin{pmatrix} \beta_{2,11} & \cdots & \beta_{2,1n} \\ \vdots & \ddots & \vdots \\ \beta_{2,n1} & \cdots & \beta_{2,nn} \end{pmatrix}, \quad \cdots, \quad \boldsymbol{\beta_6} = \begin{pmatrix} \beta_{6,11} & \cdots & \beta_{6,1n} \\ \vdots & \ddots & \vdots \\ \beta_{6,n1} & \cdots & \beta_{6,nn} \end{pmatrix} \tag{A2}$$

TABLE A2 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)

(Continues)

TABLE A2 (Continued)

	5 mos	Coefficient		6 mos	Coefficient
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)

Note: Standard errors are shown in parentheses. Note that lags are denoted from the time of forecast, that is, $t = 0$. When the lag is less than the time to expiration, lagged FPI values are substituted with the respective FPI forecast. Only parameters significant at a 5% level are included in the forecast models. ** and *** indicate significance at a 5% and 1% level, respectively.

Abbreviations: ADF, augmented Dickey–Fuller; VAR, Vector autoregressive.

As for the majority of the included factors, also the spot price exhibits substantial seasonal patterns. A conventional approach is therefore to examine YoY-change of the spot price. However, the assessment of YoY-change has its limitations in the sense that irregularities in previous observations, such as shocks caused by factors outside the model, may cause significant errors in the predictions. Therefore, the approach chosen in this study is to assess irregularities in both explanatory factors as well as in the spot price, that is, 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 A10, 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 A2. 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 B4, whereas figures on the predictive power are shown in Table 8 in Section 5.2.

A.4 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 ANN. The number of hidden layers was set to one, and the numbers of neurons in each hidden layer was set to 2/3 of the number of input neurons. Utilizing normalized time series only, the applied activation function was the logistic sigmoid function, $f(x) = 1/(1 + exp(-x))$. We further employed the *Broyden-Fletcher-Goldfarb-Shanno* (BFGS) algorithm, an iterative numerical optimization algorithm in the family of quasi-Newton methods. The model's learning rate 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 A.1 and A.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. 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 A.3. This procedure was completed for spot price predictions 1–6 months ahead. Out-of-sample predictions for all horizons are depicted in Figure B5, whereas figures on the predictive power are shown in Table 8 in Section 5.2. The 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*

APPENDIX B: PREDICTION PLOTS

ECM predictions

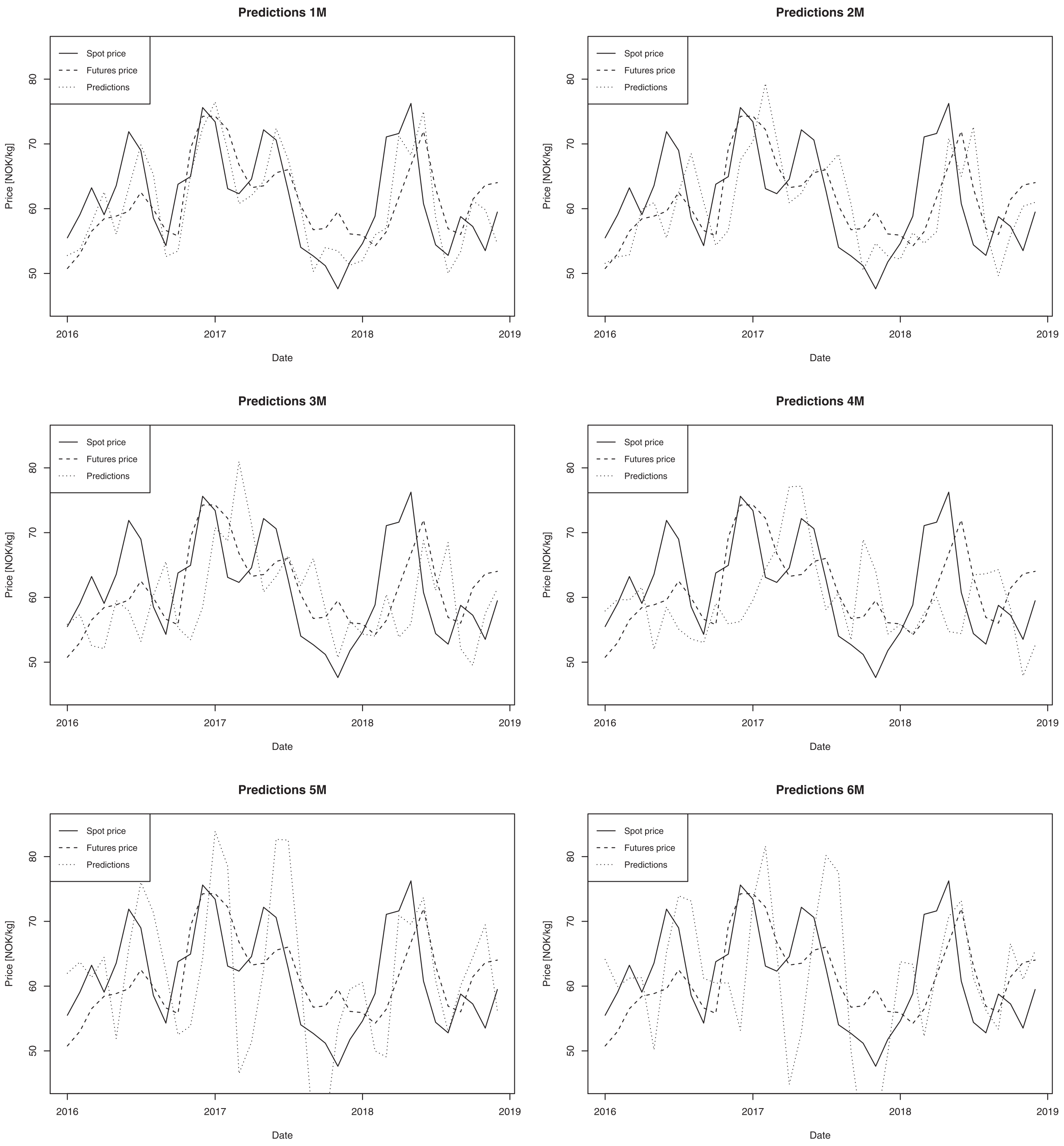

FIGURE B1 Predictions by the error correction model

ECM-GARCH predictions

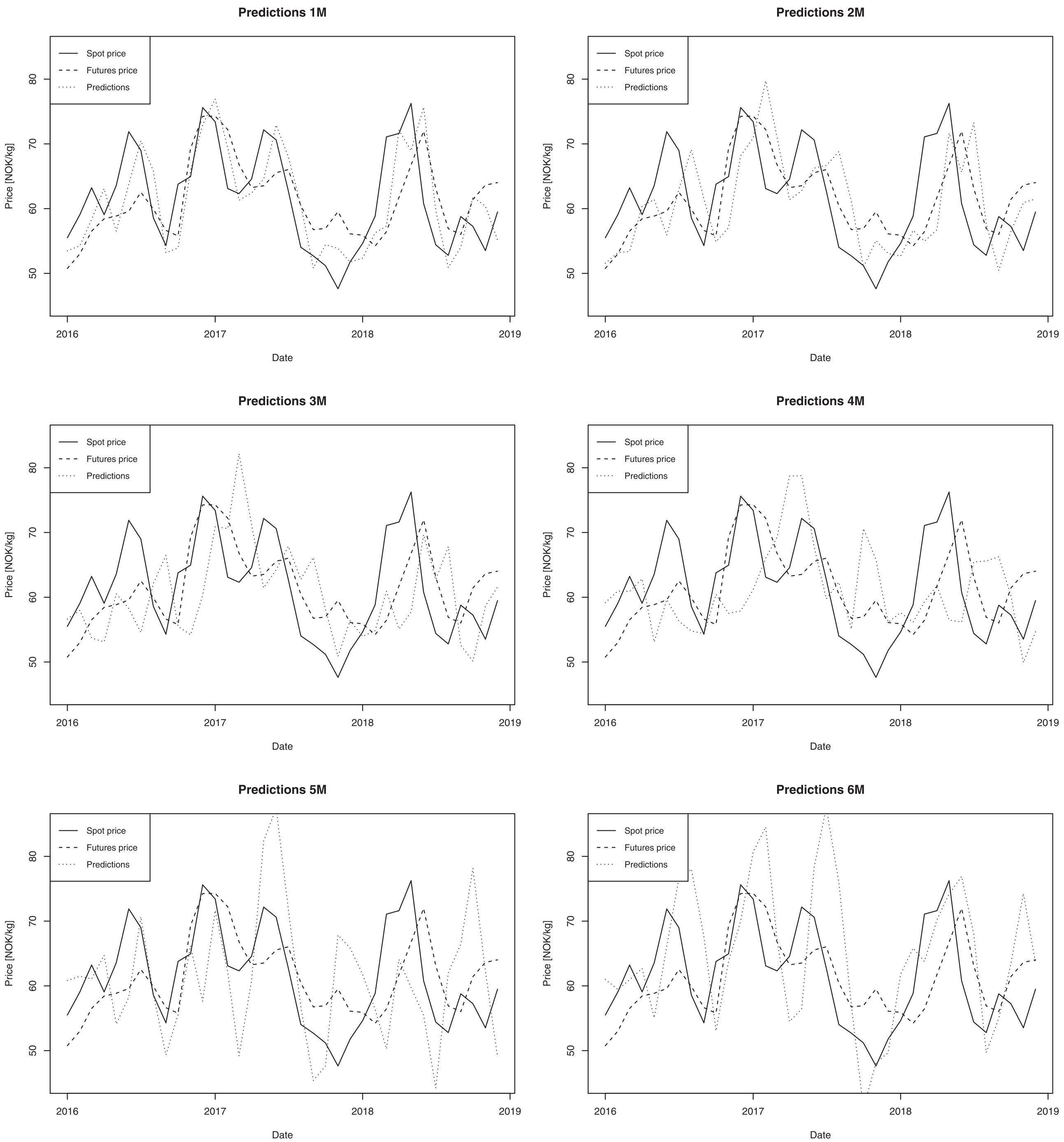

FIGURE B2 Predictions by the Error correction model-generalized autoregressive heteroscedastic model

Seasonal predictions

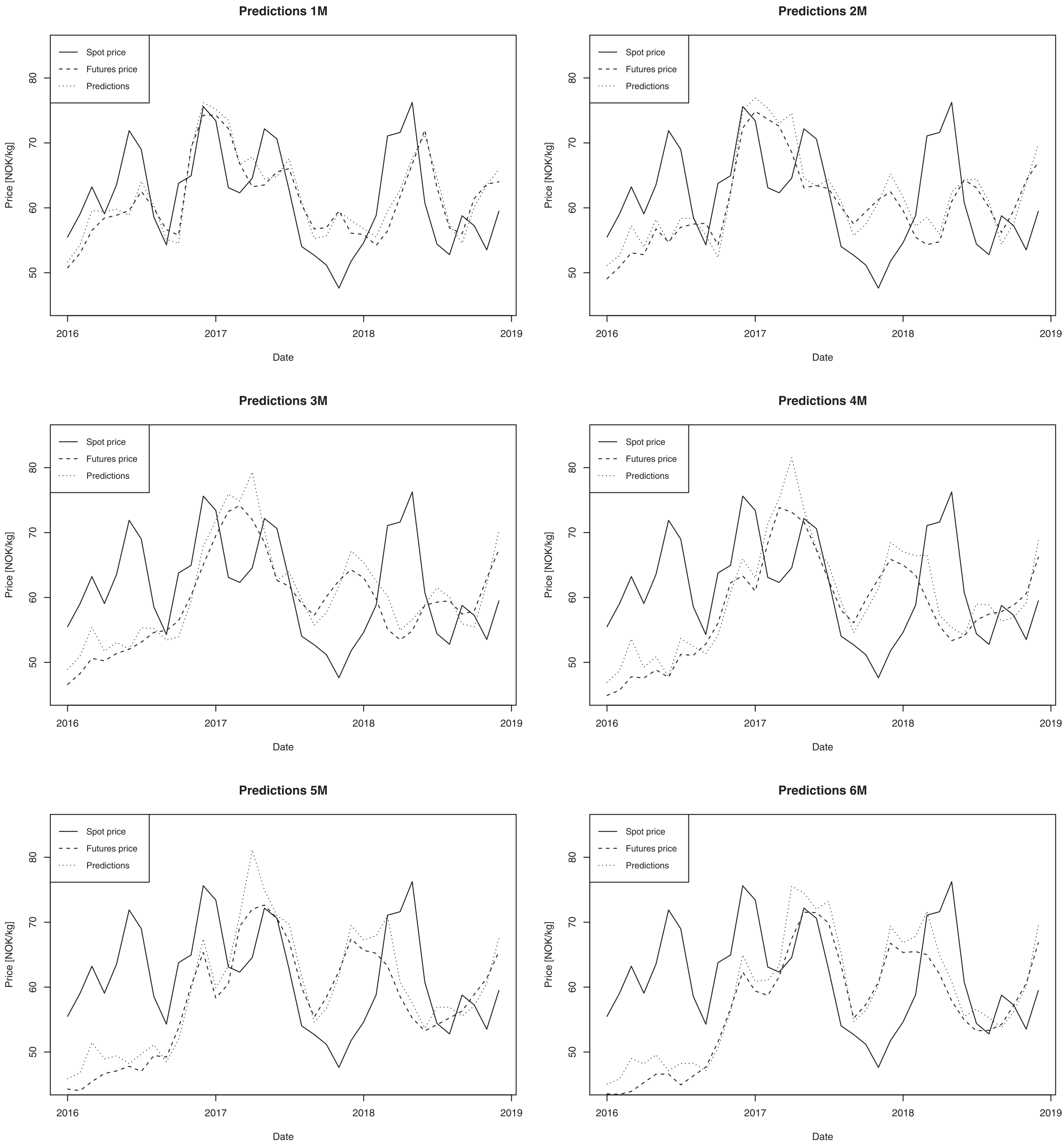

FIGURE B3 Predictions by the seasonal model

VAR predictions

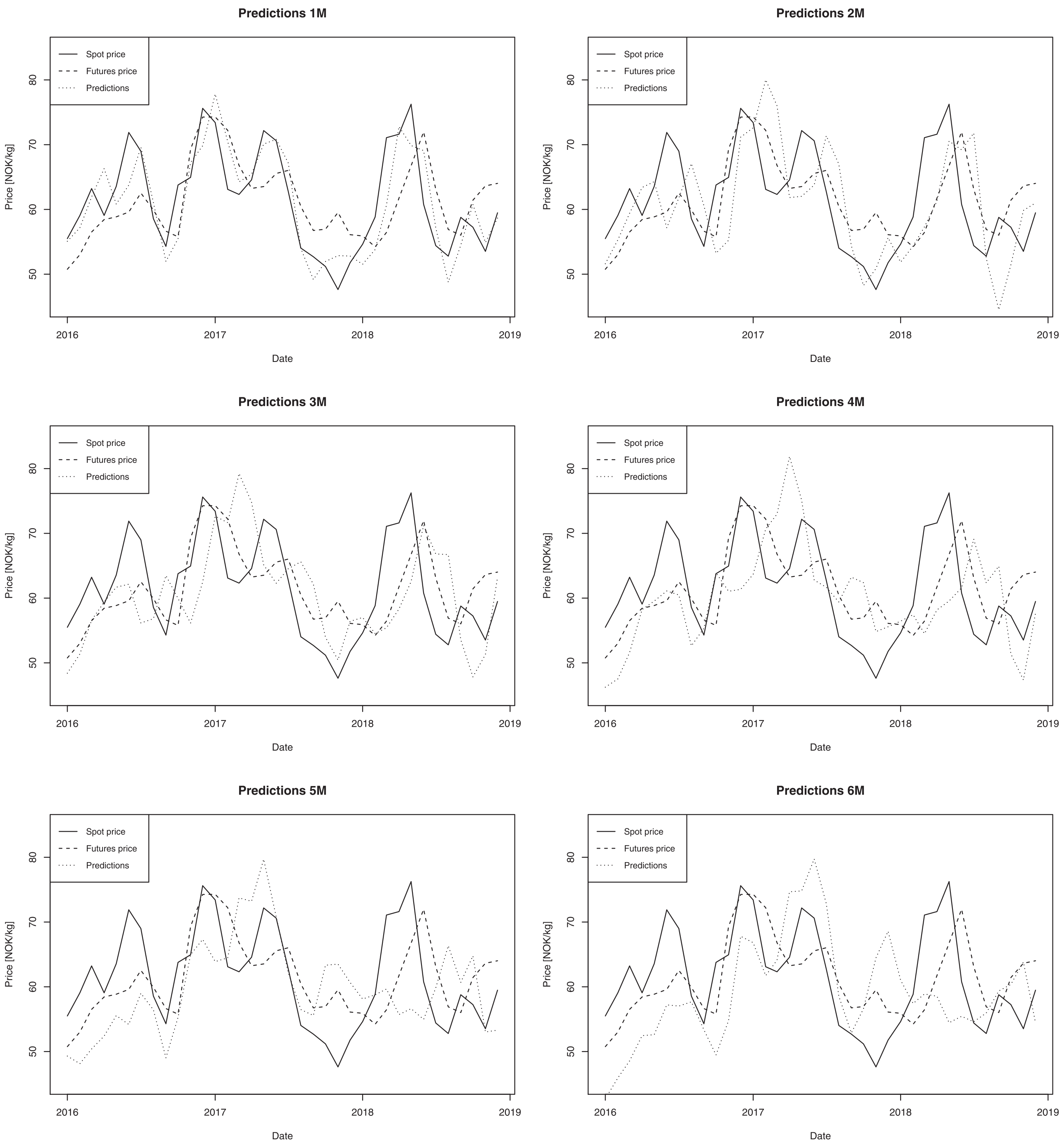

FIGURE B4 Predictions by the vector autoregressive model

ANN predictions

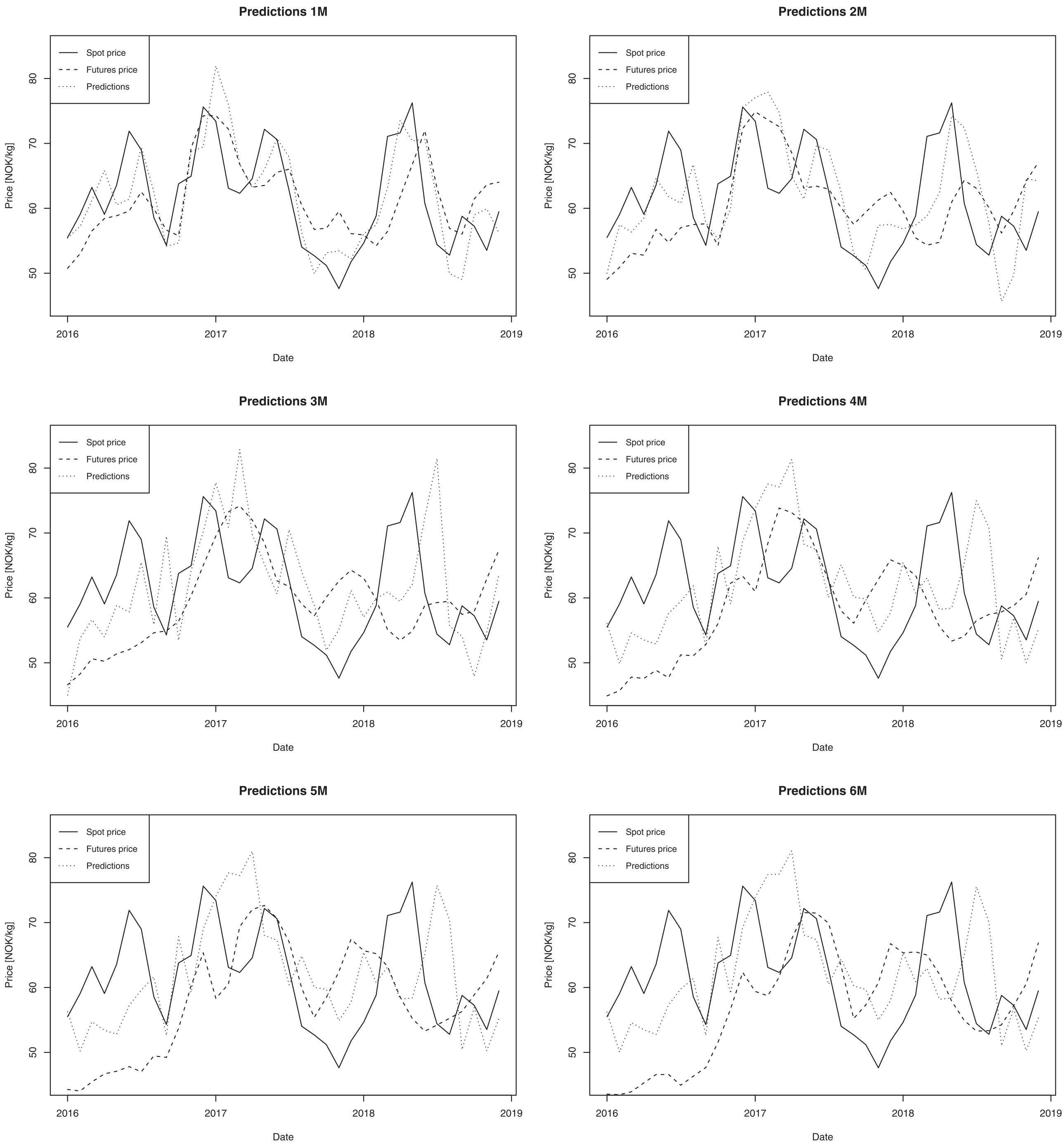

FIGURE B5 Predictions by the artificial neural network model

APPENDIX C: RISK PREMIUM PLOTS

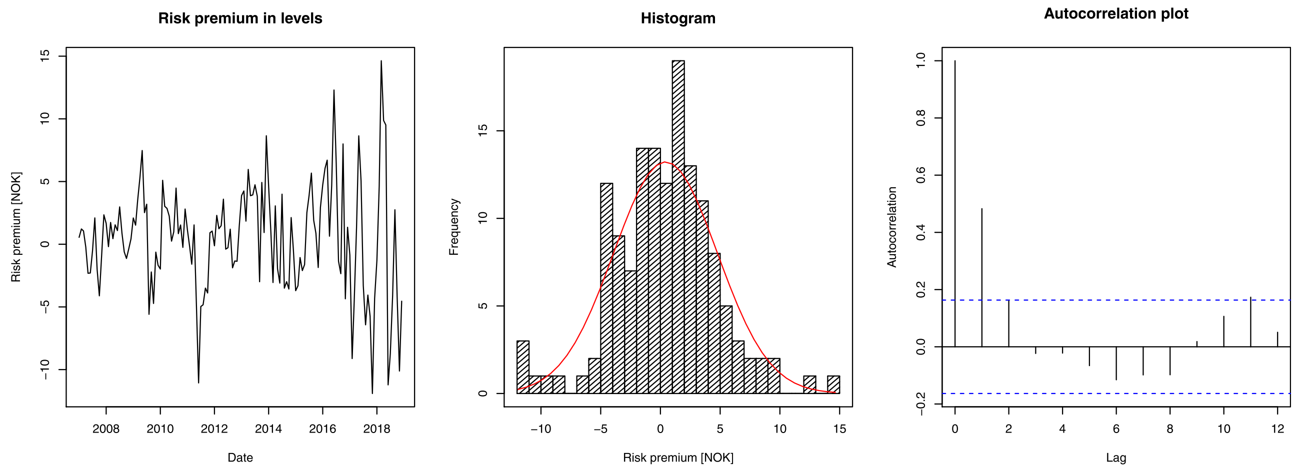

FIGURE C1 Risk premium for futures contracts with 1 month until expiration [Color figure can be viewed at wileyonlinelibrary.com]

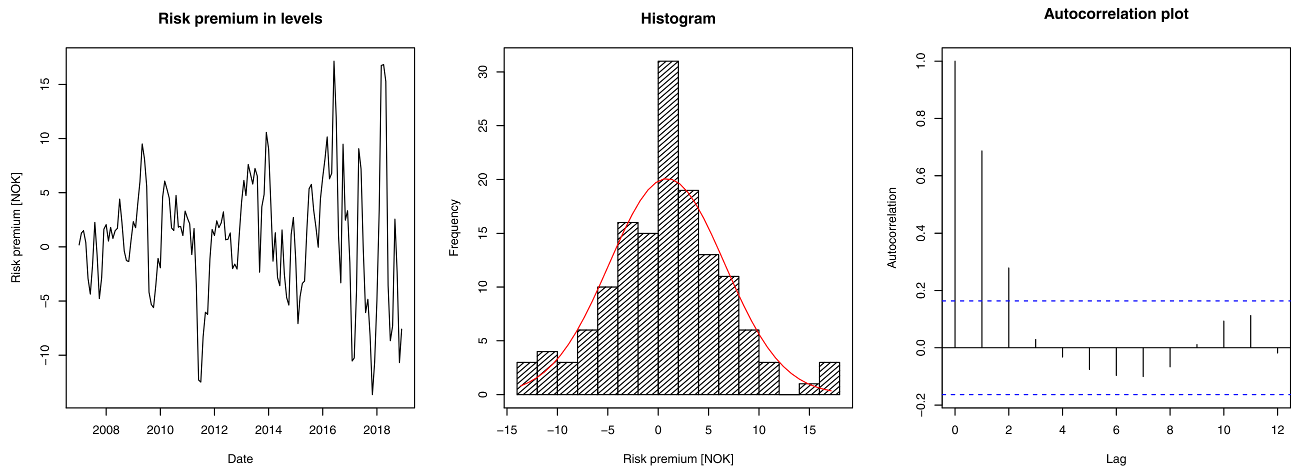

FIGURE C2 Risk premium for futures contracts with 2 months until expiration [Color figure can be viewed at wileyonlinelibrary.com]

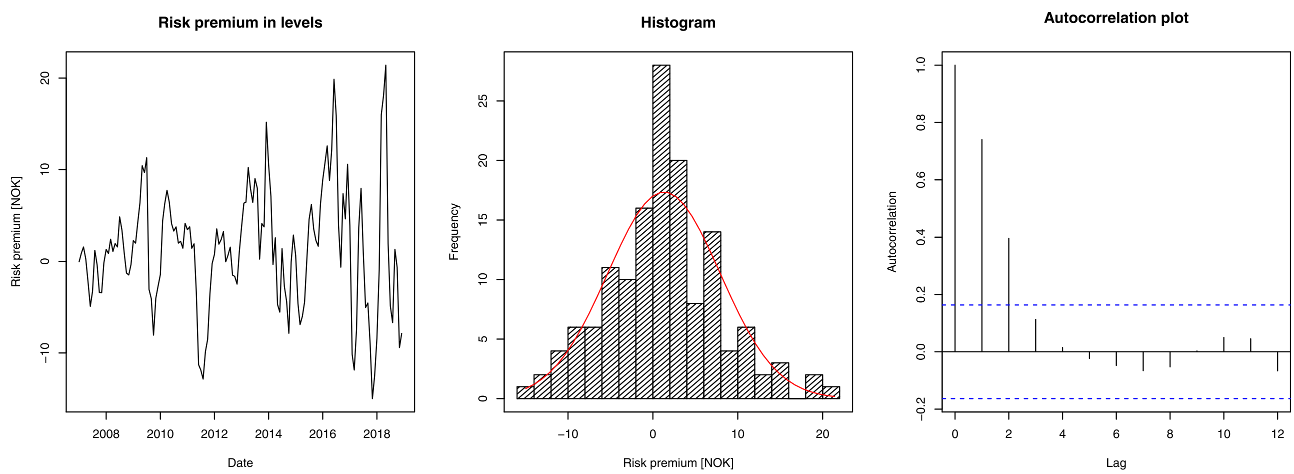

FIGURE C3 Risk premium for futures contracts with 3 months until expiration [Color figure can be viewed at wileyonlinelibrary.com]

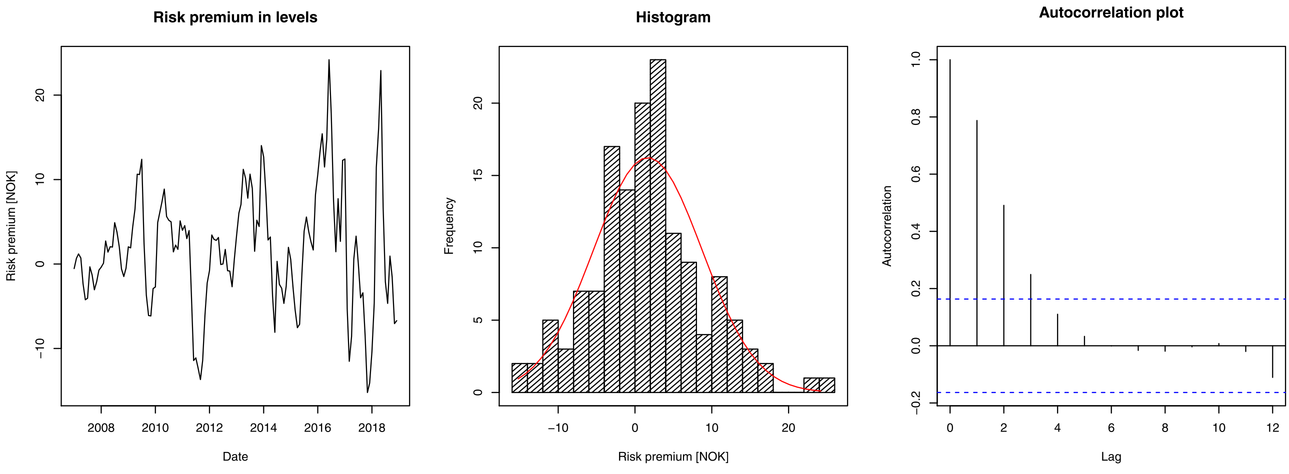

FIGURE C4 Risk premium for futures contracts with 4 months until expiration [Color figure can be viewed at wileyonlinelibrary.com]

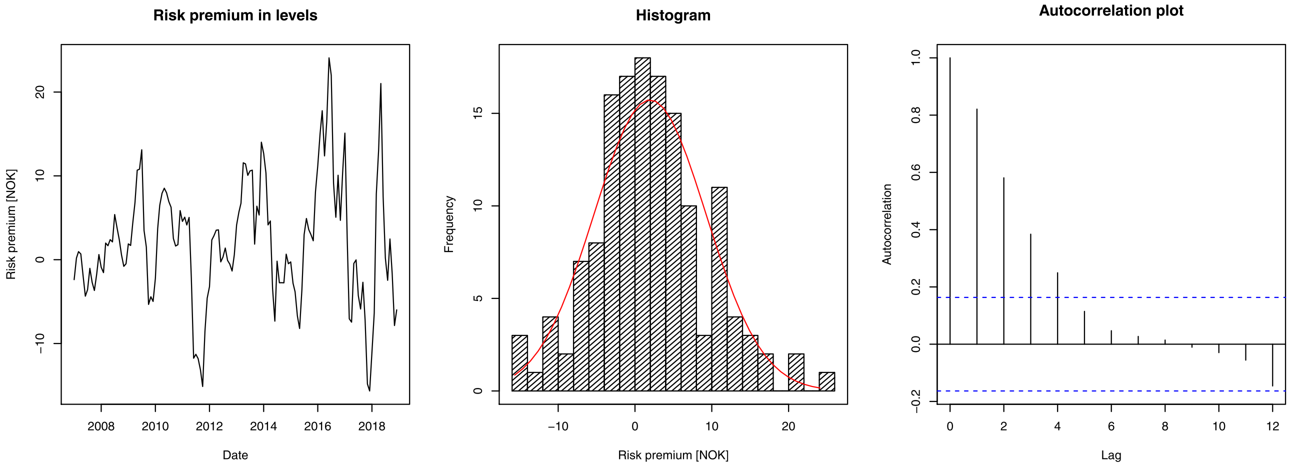

FIGURE C5 Risk premium for futures contracts with 5 months until expiration [Color figure can be viewed at wileyonlinelibrary.com]

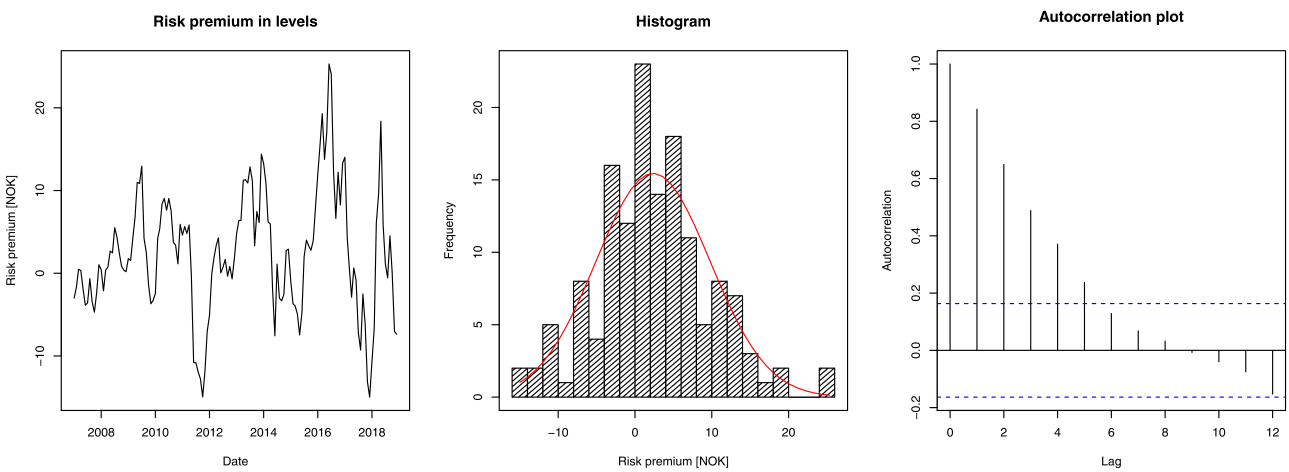

FIGURE C6 Risk premium for futures contracts with 6 months until expiration [Color figure can be viewed at wileyonlinelibrary.com]