# VOLATILITY IN THE SALMON MARKET 

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## Summary

Research has shown that volatility in the salmon market is high and increasing, which can have negative economic consequences for both the producers and buyers of farmed salmon. Knowledge of how salmon price volatility varies over time is important, especially if fish farmers want to reduce their exposure to salmon price risk. The purpose of this article is to examine how volatility in the salmon market varies over time. We document that volatility in the salmon market has largely grown since the mid-1980s, which is 20 years longer than previously assumed. Despite the ever-increasing price uncertainty, farmers do not show much interest in price hedging of market risk.

Keywords: salmon prices, volatility, spot prices, risk, price uncertainty, risk management, price shocks, salmon farming, aquaculture
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## Introduction

This article examines price uncertainty (volatility) in the market for farmed Norwegian fresh salmon. Since price uncertainty can have major economic consequences for producers, traders, and buyers of salmon, it is important to have an understanding of what causes volatility in the salmon market, and how uncertainty varies over time. The purpose of the study is to investigate how volatility varies over time, both seasonal variation in a year, and from year to year.

Figure 1 shows that salmon prices, measured in NOK per kg, have changed considerably since 1980. However, observations of price levels do not provide good information about price variation. If we examine changes in prices, we get a far better impression of price uncertainty (Chart 2).

Figure 1. Monthly salmon prices 1980-2017


Note to the figure. Nominal monthly prices in USD/kg (source: IMF) and translated into NOK/kg at monthly exchange rates (source: Norges Bank), and at real prices (2015=100) using the monthly consumer price index (source: Statistics Norway).

We see that there have been relatively large monthly price changes in the salmon market over the past 25-30 years. The largest changes have been about 20 per cent up or down over the course of a month, a level corresponding to annual changes of formidable +/- 240 per cent. Furthermore, we see that price variation has increased over time, which is in line with research by Asche et al. (2018), Oglend (2013) and Bloznelis (2016), both of which show that salmon price volatility has risen sharply since 2006.

Chart 2. Log yields 1980-2017


Note to the figure. Changes in salmon prices are calculated as log yields on monthly salmon prices (source: IMF).

It is well known from the literature that commodity prices are very uncertain, and that uncertainty varies over time (Pindyck, 2004). This is also the case in the salmon market where studies report high and stochastic volatility (Oglend and Sikveland, 2008; Solibakke, 2012; Oglend, 2013, Dahl and Oglend, 2014; Asche, Dahl and Steen, 2015; Bloznelis, 2016; Dahl, 2017; Asche et al., 2018).

Drivers of changes in volatility over time is crucial knowledge for a buyer or seller of salmon. High or increasing volatility will increase the need for price hedging instruments such as forward contracts, futures, and options. Volatility is particularly important for pricing options on salmon prices, as volatility is a key assumption in the valuation formula. A cost-effective risk management strategy is therefore dependent on good estimates of future volatility.

One limitation of previous research on salmon price volatility is that the studies only use observations from the mid-1990s, since weekly prices are only available after 1995. However, monthly salmon prices date back to 1980, which opens for investigation of volatility in a significantly longer time perspective. This is especially important since several studies point out that there has been a growth trend in volatility, a phenomenon that cannot last forever. A relevant research question is therefore whether the trend of increasing volatility observed since the mid-2000s is only limited to this period, or whether we can identify other periods of growth in volatility.

The extent of the seasonal variation in volatility is another area where knowledge is lacking. It is known from other commodity markets that volatility varies over seasons (Suenaga et al., 2008; Misund and Oglend, 2016). Although several studies suggest that seasonal volatility fluctuations may also be present in the salmon market (e.g., Bloznelis, 2016), no one has explicitly examined it or modeled it. There is therefore limited knowledge as to whether there is seasonal variation in salmon price volatility and its extent. This is the second research question we ask in this article.

We use monthly salmon prices from 1980 to 2017, a total of 450 observations. Volatility is estimated using an Autoregressive Moving Average - Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) model. To investigate trends and seasonal variation, we are selecting STL (SeasonTrend decomposition by Loess) (Cleveland et al., 1990). The method allows for a decomposition of monthly volatilities into three components: seasonal, trend and residual.

Our results show that the trends identified in previous studies extends further back in time than previously thought. In fact, we find that the growth in volatility began as early as the mid-1980s, and that since then volatility has more than doubled. Furthermore, the results show that volatility peaked at the end of 2013, followed by a significant drop in the period 2014-2017. The latter period has been characterized by a significant salmon price increase due to scarcity of the commodity, suggesting a kind of 'leverage effect' between price changes and volatility in this last period.

Although we manage to identify clear seasonal variations in volatility, the effect of seasonal variation on total volatility appears to be very moderate. The results also suggest that there is an asymmetry that is not captured in an ARMA-GARCH model. Further studies should investigate this further.

We contribute to the literature by showing that there are significant time variations in salmon price volatility, over a longer period of time than found in previous research. Although we find seasonal variations, it does not seem to be very important. Knowledge of trends in volatility is potentially very useful information for companies in their risk management decisions. Since salmon markets have become significantly more risky since the mid-1980s, it is important that buyers and sellers of salmon consider how they can manage this risk. Although fish farmers have had the opportunity to use futures contracts for risk management over the past ten years, it seems that interest in risk management tools limited among fish farmers (Bergfjord, 2007; Asche et al., 2016b). Fish farmers are therefore facing a significant and increasing market risk, without showing a willingness to reduce it.

The article is organized as follows. The next chapter describes how volatility arises in commodity markets, and especially in seafood markets exemplified by fresh salmon. It also describes why knowledge of volatility is important for producers and buyers of salmon. After this, the data set and methodology are described. Then the results are presented and discussed before the final chapter concludes.

## Volatility in the salmon market

How does volatility arise in commodity markets? Volatility is a measure of price variation, and one must therefore start from the actual formation of prices. Price formation is a complex process and is the result of an interaction between endogenous factors related to the properties of the raw material, supply and demand factors, and exogenous factors such as weather.

According to economic theory of market efficiency, prices will at all times reflect the information held by market participants. In a perfect competition market, price changes will only reflect systematic components such as seasonal fluctuations in price. But when the market receives new information, e.g. about changes in supply or demand, prices will change to reflect the value of the new information. It is precisely the assimilation of the new, unexpected information that leads to price shocks (Tomek and Kaiser, 2014), and that creates the price uncertainty we measure as volatility.

The extent to which the new information affects volatility depends on the economic context in which the information originates (Tomek and Kaiser, 2014). If there are signals of increased demand, this information will have little price effect if the raw material can be stored and there are large stocks of finished products, the production cycle is short, there is high price elasticity on the supply side, and there is no shortage of the raw material. Volatility will change little in these situations.

The opposite is true in salmon production and may substantiate that there is relatively high volatility in the salmon market. First, there is low price elasticity on the supply side (Andersen et al., 2008; Asheim et al., 2011), especially in the short term, which is important as volatility is mostly a shortterm phenomenon. The main reason for the low price elasticity is the long production cycle of salmon and biological limitations, which make it difficult for producers to adapt production to price signals. A variable growth in demand for salmon may also contribute to high volatility (Brækkan, 2014; Brækkan and Thyholt, 2014).

Furthermore, it is well known that there is a negative relationship between stocks of commodities and volatility (Pindyck, 2001). Fresh salmon has a short shelf life and cannot be stored to any great extent, which indicates a high volatility.

In addition to the endogenous factors mentioned above, there may also be exogenous factors that also affect volatility. There is a significant production risk in aquaculture (Asche and Tveterås, 1999; Tveterås, 1999; Kumbhakar and Tveterås, 2003). Disease outbreaks are widespread (Asche et al., 2009; Hansen and Onazaka, 2011; Torrisen et al., 2011; 2013). Furthermore, algal outbreaks have occasionally reduced production in several countries (Haigh and Esenkulova, 2014; Cabello and Godfrey, 2016). In addition, salmon lice problems can increase variability in production (Abefiola et al., 2017).

The factors described above may explain the high volatility in the salmon market compared to other commodities. But what can lead to increasing volatility over time? Oglend (2013) has several explanations. The most important of these are increased food prices, stricter regulations, as well as increased use of contracts in the salmon industry.

Oglend (2013) found a positive correlation between increased food prices and salmon price volatility. He explains this by saying that there is at least one channel where food prices can affect salmon volatility. First, the use of non-marine raw materials in salmon feed has increased significantly over time (Asche and Oglend, 2016; Misund et al., 2017), which may help explain the increased feed and production costs in aquaculture we have seen over the past 10 years. An increased correlation between agricultural raw materials and salmon prices has recently been documented (Asche and Oglend, 2016). This, in turn, can reduce the short-term price elasticity of demand (Oglend, 2013), which will increase volatility.

As regards the effect of increased regulations in the aquaculture industry and increased use of contracts, these factors affect volatility by increasing the scarcity of the raw material. Several articles have discussed regulations in aquaculture (Kinnucan and Myrland, 2002; Tveterås, 2002; Asche and Bjørndal, 2011). Since 2005, a cap has been set on how much biomass fish farmers can have at any given time (Maximum Allowable biomass, MAB). Since 2012, there has been little growth (Figure 3). A
levelling off of production, both in Norway and in other producing countries, combined with continued growth in demand, will increase the degree of shortages and thereby increase volatility.

Figure 3. Maximum permitted biomass (MAB) and production of salmon in Norway.


Note to figure. Source: White Paper 16 (2014-2015), www.regjeringen.no

Another factor that can affect volatility is the use of sales contracts. There has been an increase in the use of sales contracts in the aquaculture industry over time (Kvaløy and Tveterås, 2008; Larsen and Asche, 2011; Straume, 2014; 2017). Increased use of sales contracts will reduce the volume of salmon sold in the spot market, which will lead to increased scarcity of salmon, and therefore increased volatility.

## Risk management: the fight against volatility

Before we go any further, it may be appropriate to explain why knowledge of volatility is important. Salmon farming is considered to be a very risky industry characterized by large fluctuations in profitability (Asche and Sikveland, 2015). Since the revenues from salmon farming are equal to the product of volume sold salmon and the price achieved in the market, there are mainly two sources of variation in profitability, namely volume uncertainty and market risk. The literature tells us that there is significant production risk (volume risk) in salmon farming (Asche and Tveterås, 1999; Tveterås 1999; Kumbhakar and Tveterås 2003), in addition to a high (Guttormsen, 1999; Oglend and Sikveland, 2008; Solibakke, 2012; Dahl, 2017; Misund and Oglend, 2017), and increasing market risk (Oglend, 2013; Bloznelis, 2016).

There are several disadvantages of high price risk. A fish farmer has limited opportunity to postpone the slaughter of salmon. When salmon grow larger, the likelihood of sexual maturation increases, which entails a significant deterioration in quality and financial loss. The breeder must therefore make a decision on slaughter within a relatively short period of time. High volatility will therefore contribute to economic uncertainty for the producer. Operational planning also becomes difficult over long periods of time, since volatility will also increase the variance of the prediction error when calculating the expected salmon price (Guttormsen, 1999).

In the event of high market risk, market participants will often need price hedging. A common way to reduce market price exposure is to use derivative contracts, either futures contracts or options contracts (Hull, 2015). High volatility will lead to increased costs associated with price hedging, both with futures contracts and with options contracts.

If one wishes to use futures contracts for hedging, one must calculate how many futures contracts are needed to minimize risk. For this purpose, we can calculate the optimal hedge ratio ( $h^{*}$ ), a ratio that minimizes variance and is calculated as follows:

$$
\begin{equation*}
h^{*}=\rho \frac{\sigma_{S}}{\sigma_{F}} \tag{1}
\end{equation*}
$$

where $\rho$ is the correlation between the spot price and the futures price and $\sigma_{S}$ is the standard deviation (volatilite) of the spot and $\sigma_{F}$ futures price respectively. We see that the optimal ratio $h^{*}$ is increasing in spot price volatility. This means that one needs to use more futures contracts when the spot price volatility of salmon is high than when it is low. Hedging costs increase with increased transaction costs. Furthermore, the spot price volatility of salmon also affects the price of options where the salmon price is the underlying asset. Starting from a simple Black-Scholes model of a European call option (assuming that the salmon price behaves like a stock that pays no dividend), and deriving the value of the option in terms of volatility, we get the measure vega, which tells us how changes in volatility affect the value of an option:

$$
\begin{equation*}
\frac{\partial c}{\partial \sigma}=S \sqrt{T} N^{\prime}\left(d_{1}\right) \tag{2}
\end{equation*}
$$

where $c$ is the option price. On the right side of the equation, $S$ is the spot price of salmon, $T$ is the time to maturity of the option, and $N^{\prime}\left(d_{1}\right)$ is the density function of the variable $d_{1}$. All the variables on the right are greater or equal to 0 , which tells us that there will be a positive correlation between the option price and volatility. Thus, the higher the volatility, the higher the option price. All else being equal, a higher volatility will make it more expensive to use options to hedge the price of salmon. In addition to the fact that a high price risk increases the need for derivative contracts, they also have a direct influence on how many contracts to choose, in addition to the pricing of the contracts.

If derivatives are to be used, it is important to know whether the derivative contracts that exist on the market place fulfil their roles as risk transfer mechanisms and arenas for price discovery. Fish Pool, established in 2005, is the only marketplace in the world for price hedging of salmon price risk. However, there are few players in the market who have expressed concern about the liquidity of Fish Pool. Only about 10 per cent of salmon turnover is price-hedged with Fish Pool futures contracts (Asche et al., 2016b), which can be explained by the fact that fish farmers are only moderately risk averse (Bergfjord, 2009), even though they are exposed to significant market risk. Low liquidity is not necessarily worrisome since futures contracts can still fulfill their roles (Adämmer et al. , 2016). Recent research on Fish Pool derivatives also supports this (eg. Bergfjord, 2007; Ewald, 2013; Ewald et al., 2016a, 2016b; Ewald and Ouyang, 2017; Asche et al 2015; Ankamah-Yeboa et al., 2016; Asche et al. 2016a, 2016b, 2016c; Misund and Asche, 2016; Misund, 2017; Bloznelis, 2017; Schütz and Westgaard, 2017). These studies suggest that Fish Pool is maturing and that futures contracts have an adequate, albeit moderate, risk reduction capability.

## Data

The data sample consists of nominal salmon prices, measured in US dollars per kilo of fresh salmon sourced from the International Monetary Fund (IMF). We then calculate monthly log yields on the salmon price, which are used further in the volatility calculations. Descriptive statistics for salmon prices, log yields and volatility are given in Table 1. We check if the variables are stationary with the augmented Dickey-Fuller test (ADF), and the outcome of the tests is reported along with the volatility in the results chapter.

Table 1. Descriptive statistics (nominal price and return)

| Variable | Mean | Standard | Min | 25th | Median | 75th | Max |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
|  |  | deviation |  | percentile |  | percentile |  |
| Price | 35.833 | 10.006 | 17.496 | 27.401 | 34.807 | 41.981 | 73.259 |
| Return | 0.0002 | 0.0590 | -0.2112 | -0.0292 | 0.0023 | 0.0309 | 0.2103 |

The average nominal price is approx. NOK $36 / \mathrm{kg}$, with a standard deviation of NOK $10 / \mathrm{kg}$, which gives coefficient of variation of 28 per cent. Based on the nominal prices, one may get the impression that there has only been a moderate price level variation in the last 35-40 years (min: 17.5 and maximum NOK $73.3 / \mathrm{kg}$ ). The picture is different if you look at real prices (min: 23.2 and max $149.4 \mathrm{kr} / \mathrm{kg}$ ).

The average monthly return is 0.02 percent per month, equivalent to an 0.22 percent annual price change, which is relatively low. The reason for the low nominal return (and correspondingly negative real return) is because production costs have fallen significantly over time (even around the turn of the century) as a result of substantial productivity growth in aquaculture (Asche et al., 2013). The fall in costs led to a fall in real salmon prices, which is also evident in Figure 1. The standard deviation of monthly log yields is 5.9 percent, which equates to 20.4 percent annual volatility. With daily or weekly data, volatility will be higher than with monthly observations. By comparison, Oglend (2013) reports weekly volatilities equivalent to between 30-70 percent on an annual basis. The difference between annual volatility calculated from weekly or monthly data is because producers and consumers have more time to adapt to new information in a month than they have over a day or abroad, so that the price effect of new information is lower on a monthly basis. In addition, Oglend (2013) has examined a time period with higher volatility than in the 1980s and 1990s.

## Method

There are several methods for calculating volatility. In practice, a simple method with a rolling window is often used, where one calculates standard deviation of price returns over a rolling period of, for example, 20 trading days (equivalent to 1 month). The disadvantage of this method is that it weights all price shocks equally, i.e. price shocks that took place several weeks or months back are weighted as much as yesterday's shock. Often, it will be more appropriate to be able to weight recent price shocks in volatility differently from historical shocks. Other, more advanced, methods allow us to do this.

One of the most well-known volatility models is GARCH. The starting point for GARCH can be found in the work of Engle (1982), who showed that serial correlation in quadratic returns (i.e. shock, also referred to as conditional heteroskedasticity), can be modeled as an autoregressive conditioned heteroskedastisity model (Autoregressive Conditional Heteroskedasticity, ARCH) as follows

$$
\begin{gather*}
r_{t}=E_{t-1}\left(r_{t}\right)+\varepsilon_{t}  \tag{3}\\
\varepsilon_{t}=z_{t} \sigma_{t}  \tag{4}\\
\sigma_{t}^{2}=a_{0}+a_{1} \varepsilon_{t-1}^{2}+\cdots+a_{p} \varepsilon_{t-p}^{2} \tag{5}
\end{gather*}
$$

where is return, is shock in return, is $r_{t}$ an $\varepsilon_{t}$ expectation operator at time $E_{t-1} t-1$, () is the standard deviation (variance) in log yields, $p$ is the number of lags, and $\sigma_{t} \sigma_{t}^{2}$ is $a$ the coefficients of the shocks. Bollerslev (1986) further developed the ARCH model converting Equation 5 from being an autoregressential model $A R(p)$ to an autoregressive moving average model (ARMA ( $p, q$ )), as follows:

$$
\begin{equation*}
\sigma_{t}^{2}=\omega+\sum_{i=1}^{p} \alpha_{i} \varepsilon_{t-i}^{2}+\sum_{i=1}^{q} \beta_{i} \sigma_{t-i}^{2} \tag{6}
\end{equation*}
$$

where $\omega$ is the long-term average of the variance, $\alpha$ is the parameters of the shock in the return (from about 1 to $p$ ), and $\beta$ are the parameters of the lagged variance (from about 1 to $q$ ). Equation (6) tells us that conditional volatility consists of three links, a long-term average that volatility returns to after shocks, and that this process is driven by an ARCH term (second term on the right side), and a GARCH joint (last term). Alpha tells us how much emphasis is placed on price shocks, beta what impact lagging variances have on the conditional variance. Equation 6, along with 3-4, gives us the well-known GARCH $(p, q)$ model. The simplest form of this is a GARCH (1.1) model:

$$
\begin{equation*}
\sigma_{t}^{2}=\omega+\alpha_{1} \varepsilon_{t-1}^{2}+\beta_{1} \sigma_{t-1}^{2} \tag{5}
\end{equation*}
$$

In addition, there are many different variants in the GARCH family (see Bollerslev (2009) for an overview).

The speed of volatility when it returns to its long-term average can be calculated with half-lives. For a GARCH (1.1) model, the half-life is given by $K=\ln (0.5) / \ln (\alpha+\beta)$. Furthermore, the sum of the parameters will say something about $\alpha$ the $\beta$ duration of volatility (persistence). The closer this number is to 1 , the longer it takes for the variance to return to its long-term average. A number above 1 is undesirable as it would imply that volatility grows explosively.

Often it may also be appropriate to come up with a ARMA model, to also capture how the conditional average of returns behaves.

$$
\begin{equation*}
r_{t}=\mu+\sum_{i=1}^{n} \theta_{i} r_{t-i}+\sum_{i=1}^{o} \gamma_{i} \varepsilon_{t-i}+\varepsilon_{t} \tag{6}
\end{equation*}
$$

A combined ARMA $(n, o)-\operatorname{GARCH}(p, q)$ model is then described by Equations 2,4 and 6 .

## Diagnostic tests on the fault link in the ARMA-GARCH model

There are potentially many possible GARCH models given the choice of $n, o, p$, and $q$. The resulting models will vary according to ability to capture the characteristics of the conditional return and variance. To find the best model that captures all the ARCH and GARCH effects in the data, the literature recommends a series of tests. One tests the error term for whether heteroskedasticity exists using standard tests such as Jarque-Bera and Shapiro-Wilk. If the null hypothesis of homoskedasticity is rejected, the standard errors must be made robust. An LM-ARCH test (Engle, 1982) is used to investigate the relevance of using a GARCH model at all. To investigate whether there are still ARCH effects that are not captured by the model, a Ljung-Box and a Li-Mak test of the squared and standardized error terms. The null hypothesis is the absence of ARCH effects. In addition, one also examines the standardized error terms for the presence of serial correlation using a Ljung-Box test. The null hypothesis is that there is an absence of serial correlation in the standardized error terms. Finally, an information criteria (e.g., AIC) is used to select the best of several possible models, determined by the one that minimizes the value of the information criterion.

## Results and discussion

This section presents and discusses the results of the volatility modelling. First, we analyze how well the model captures the serial correlation in the data, both for the conditional return and for the conditional variance. This is followed by a description of the volatility, and how the decomposed volatility in trend and season, can answer the research questions asked initially. Furthermore, regression analysis is used to examine whether seasonal variation, and trends in volatility are statistically significant.

We start by estimating a $\operatorname{GARCH}(1,1)$ model and expand with autoregressive algs of the conditional average of returns. Three of the information criteria tell us that we should use 6 lags in the autoregressive part of the model (Table 3). Neither the use of MA layers nor expansion to GARCH (2.1), GARCH (1.2), or GARCH (2.2) resulted in a better model than GARCH (1.1). Our chosen model form will then be $\operatorname{AR}(6)-G A R C H(1,1)$.

Table 2. Selection of the number of lags using information criteria.

|  | AIC | BIC | SIC | HQIC |
| :--- | :--- | :--- | :--- | :--- |
| MA(0) and GARCH (1,1)* |  |  |  |  |
| AR(0) | -2.933 | -2.896 | -2.933 | -2.919 |
| AR(1) | -3.029 | -2.984 | -3.030 | -3.011 |
| AR(2) | -3.032 | -2.977 | -3.032 | -3.010 |
| AR(3) | -3.036 | -2.972 | -3.036 | -3.011 |
| AR(4) | -3.034 | -2.961 | -3.035 | -3.005 |
| AR(5) | -3.053 | -2.971 | -3.054 | -3.020 |
| AR(6) | $-3,057$ | -2.965 | -3.058 | -3.021 |
| AR(7) | -3.053 | -2.952 | -3.054 | -3.013 |
| AR(8) | -3.049 | -2.939 | -3.050 | -3.006 |
| AR(9) | -3.046 | -2.927 | -3.048 | -2.999 |
| AR(10) | -3.043 | -2.915 | -3.045 | -2.993 |

Note to the table. * Neither the use of MA lags nor the expansion of GARCH to GARCH (2.1), GARCH (1.2), or GARCH (2.2) led to a better model in GARCH (1.1). Lowest value in bold.

The parameters of the $A R(6)-G A R C H(1,1)$ model are presented in Table 3. We see that lags $1,3,5$, and 6 are statistically significant in the pricing model. This tells us that returns are affected by changes over a period of half a year. This is longer than found in research on volatility with weekly observations.

Both Oglend and Sikveland (2008), Oglend (2013), and Bloznelis (2016) find significant parameters on AR lags of the conditional average yield of respectively 5,3 , and 3 weeks. Our results therefore indicate that the return on salmon prices is more affected by returns further back in time when viewed over a longer period of time. This may indicate that there has been a change in dynamics over time. In other words, it has become more difficult to predict future salmon prices based on historical prices over the past 20 years than in the previous two decades.

Table 3. AR (6) - GARCH (1.1) model estimation results.

| Coefficient | Estimate | Standard errors | t-value | $p$-value |
| :---: | :---: | :---: | :---: | :---: |
| Price function (AR (6)) |  |  |  |  |
| $\mu$ | -0.0019 | 0.0025 | -0.7320 | 0.4644 |
| AR(1) | 0.3219 | 0.0507 | 6.3540 | <0.001 |
| AR(2) | -0.0536 | 0.0478 | -1.0210 | 0.2623 |
| AR(3) | -0.1086 | 0.0553 | -1.9650 | 0.0495 |
| AR(4) | 0.0256 | 0.0487 | 0.5260 | 0.5986 |
| AR(5) | -0.1304 | 0.0480 | $-2.7140$ | 0.0066 |
| AR(6) | -0.0858 | 0.0513 | -1.6720 | 0.0945 |
| Variance function (GARCH (1,1)) |  |  |  |  |
| $\omega$ | $3.650 \mathrm{x}^{10-5}$ | $2.672 \mathrm{x}^{10-5}$ | 1.3660 | 0.1719 |
| $\alpha_{1}$ | 0.0597 | 0.0185 | 3.2340 | 0.0012 |
| $\beta_{1}$ | 0.9335 | 0.0208 | 44.9600 | <0.001 |

When we move to the volatility model, we can see that omega is relatively low. This parameter represents the base level of volatility over time (long-term mean). A value of $3.650 \times{ }^{10-5}$ (in variance
form) corresponds to 2.09 percent annual volatility ${ }^{1}$, which is significantly lower than the figure of around 20.40 percent that we could read out of Table 1. It may therefore appear that there is a longterm average to which volatility returns. This conclusion is supported by the fact that the coefficient is not statistically significant. The model has therefore not captured a long-term average. One reason may be that volatility has grown significantly over time. Bloznelis finds higher values of omega, but that it has also increased significantly over time. The long-term average increased almost tenfold between the period 1996-2005 and the period 2006-2013, which in turn may be an effect of growing volatility over time. The question may therefore be raised as to whether it is appropriate to model a long-term average as a constant. Further studies of salmon price volatility should consider using alternative models that capture this trend as a deterministic link.

The sum of $\alpha$ and $\beta$ gives us a measure of the duration of volatility, and thus also a measure of market efficiency. A low value implies a high degree of market efficiency in that a price shock is rapidly corrected in the market. Conversely, a high value implies a low degree of market efficiency, which we find in our analysis. The value is at almost $1(0.060+0.938)$, which suggests that it takes a relatively long time to turn back to a long-term average, and that the market takes a long time to correct shocks. High values are also found by others. Oglend (2013) reports figures of 0.96 for weekly volatility and 0.99 for monthly volatility. Since Oglend (2013) only looks at data after 1995, this suggests that that duration has not changed over time. The results also reflect that the time variation in omega is not captured by a constant.

The half life is 34.3 months $(K=\ln (0.5) / \ln (\operatorname{lambda})=34.3)$, which means that it takes almost three years for the distance between current conditional variance and its long-term average to be closed . However, given that we could not find a significant measure of the long-term average, one should not put so much into this number.

[^0]After we have chosen the GARCH model, we examine the terms for error specification (Table 5). We see from the Jarque-Bera and Shapiro-Wilk tests that the error terms are not normally distributed and not in line with a prediction of normally distributed residuals. Table 4 therefore contains robust standard errors. Furthermore, there is no serial correlation in the conditional mean at a 5 percent significance level. We also see that we can retain the hypotheses that the model has captured all the ARCH effects. We can therefore conclude that the model is well specified.

Table 4. Diagnostictests of ARMA-GARCH residuals

| Test | Residual | Type of | Test | p -value |
| :--- | :---: | :---: | :---: | :---: |
|  | form | statistics | statistics |  |
| Jarque-Bera | r | $\chi^{2}$ | 100.4379 | $<0.001$ |
| Shapiro-Wilk | r | W | 0.9790 | $<0.001$ |
| Ljung-Box | r | $\mathrm{Q}(10)$ | 0.8170 | 0.9999 |
| Ljung-Box | r | $\mathrm{Q}(15)$ | 22.2351 | 0.1018 |
| Ljung-Box | r | $\mathrm{Q}(20)$ | 28.8364 | 0.0910 |
| Ljung-Box | $\mathrm{r}^{2}$ | $\mathrm{Q}(10)$ | 6.0409 | 0.8118 |
| Ljung-Box | $\mathrm{r}^{2}$ | $\mathrm{Q}(15)$ | 10.4640 | $0.7,896$ |
| Ljung-Box | $\mathrm{r}^{2}$ | $\mathrm{Q}(20)$ | 11.3148 | 0.9376 |
| LM Arch | r | $\mathrm{TR}{ }^{2}$ | 9.2199 | 0.6840 |
| Li-Mak | $\mathrm{r}^{2}$ | $\mathrm{X}(6)$ | 1.3341 | 0.8281 |

Note. The Jarque-Bera and Shapiro-Wilk tests investigate whether there is heteroskedasticity in the residuals according to the ARMA-GARCH estimations. The null hypothesis of both tests is that the residuals are homoskedastic. Two types of Ljung-Box tests are done. The first three on the residuals, the last three on the square of the residuals. The LM ARCH test examines whether a GARCH model is relevant.

The next step is to use the $\operatorname{AR}(6)-\operatorname{GARCH}(1,1)$ model to calculate the historical conditional volatilities (Figure 3). Here we clearly see a strongly rising trend in the volatility of salmon prices over the entire time period. Previous studies have dated the start of the rising trend to around 2005, but in this study, we find that the growth in volatility has risen for a longer period than previously assumed, and that previous research has only revealed parts of the trend. Excluding the first year of the observations (which should be done since the AR-GARCH model uses several months of historical data to calculate volatility), volatility appears to have risen since the mid-1980s. This growth has been interrupted by at least two falls. The first period of volatility growth is found between medio-1982 and ultimo-1992. This period is characterized as one of the most troubled time periods in the Norwegian aquaculture industry. There were substantial disease problems (e.g. vibriosis, cold water vibriosis and furunculosis), and therefore a lot of uncertainty about produced volumes. In 1991, the US introduced punitive duties on Norwegian salmon, which reduced total demand. In November of the same year, the fish farmers' sales team went bankrupt, which led to some turmoil in the market.

Between 1993 and mid-2003, volatility dropped significantly. An important reason for this may be that the rules for ownership and size were changed in 1991 (Aarset et al., 2004), thus laying the foundation for considerable consolidation and stabilisation in the industry (Asche et al., 2013).

Figure 4. Salmon price volatility 1980-2017 (annualised)


Note to the figure. Volatility is estimated using the AR(7)-GARCH(1.1) model based on monthly logreturns, and annualized by the square root of 12 months.

Around 2000-2002, volatility peaked, which can be explained by a sharp fall in prices, with a subsequent wave of bankruptcy in the industry (Misund, 2017). In the ten-year period between 2003 and 2013, volatility increased significantly, as documented in several other studies (Oglend, 2013; Bloznelis, 2016). Oglend (2013) discusses several reasons for the rise in volatility during this period, including the introduction of MTB, increased use of sales contracts, as well as increased food prices. In 2014-2015, volatility fell, before it began to rise in 2016-2017 as a result of the scarcity of salmon in the market.

It is not easy to identify seasonal variation simply by inspecting Figure 4 . We therefore continue with a decomposition of volatility into seasonal, trend and residual components (Figure 4). The gray-colored columns on the right side of the figures tell us how important the three components are. The basis for comparison is the gray column of the top panel.

Figure 5. STL decomposition of volatility into season, trend and residual.


Note to the figure. Top panel (A) shows volatility over time estimated by $\operatorname{AR}(6)-\operatorname{GARCH}(1,1)$. This decomposes into (B) season, (C) trend, and (D) residual.

We can see that the most important part of volatility is the trend component. Volatility has generally been rising over the entire period, interrupted a couple of intervals of falling price uncertainty. We see that there is also a seasonal component, but that its extent is relatively insignificant. The residual component is relatively more important than the season, but less important than the trend. It may also appear that there are clusters in the residuals, suggesting that an AR-GARCH model does not adequately capture the behavior of the volatility. One possible option is to look at alternative models
in the GARCH family. For example, there may be asymmetric elements that are not captured in our model, e.g. a leverage effect. This is an area for future research

We see from the STL decomposition that we can break down total volatility by season and trend, but the analysis does not tell us about the statistical relevance of the various components. For that, we can use regression analysis. An easy way to do that is a regression of volatility on a trend variable and seasonal dummies. Before we can carry out the regression, we must test if the data is stationary. It is known from the literature that commodity prices are typically non-stationary, while returns are. The trend in volatility revealed earlier in the article raises suspicions that volatility is not stationary, but possibly trend-stationary. We therefore use an ADF test to examine the variables for stationarity, with and without constant and trend.

As expected, we see that the price level is non-stationary, but that the returns are (Table 5). As for the volatility, the ADF test tells us that the volatility is non-stationary. However, it is trend-stationary, but only at the 10 percent significance level. We therefore proceed with the regression analysis, knowing that the volatility variable is on the verge of being non-stationary. We defend the choice by including a trend in the model.

Table 5. Device root tests

| Test | Without drift and | With drift | With trend |
| :--- | :--- | :--- | :--- |
|  | constant |  |  |
| Prize level | $-0.359(18)$ | $-1.782(18)$ | $-1.389(18)$ |
| Log return | $-6.187(17)^{* * *}$ | $-6.179(17)^{* * *}$ | $-6.406(17)^{* * *}$ |
| Volatility | $0.259(1)$ | $-1.832(1)$ | $-3.139(1)^{*}$ |

Note to table. ADF test: The number of lags determined by the AIC criterion, and given in parantes. Significance is given with asterisks: ${ }^{*}: p<0.10,{ }^{* *}: p<0.05$, and ${ }^{* * *}: p<0.01$.

Table 6 presents the results of the regression of volatility on trend and monthly dummies. We see that both the constan and the trend are statistically significant. A strongly significant trend variable supports to the impression we received of the STL decomposition. The month dummies are nonsignificant (high p-values), which is also in line with the findings from the STL decomposition.

Table 6. Regression results

|  | Coefficient | Standard errors | t-value | p-value |
| :--- | :--- | :--- | :--- | :--- |
|  | $(\times 10-5)$ | $(\times 10-3)$ |  |  |
| Constant | 346.7 | 1.676 | 20.683 | $<0.001$ |
| trend | 8.859 | 0.00331 | 26.733 | $<0.001$ |
| Feb | $-3 . .638$ | 2.102 | -0.017 | 0.986 |
| Mar | -13.09 | 2.102 | -0.062 | 0.950 |
| Apr | -22.62 | 2.102 | -0.108 | 0.914 |
| May | -61.88 | 2.102 | -0.292 | 0.769 |
| Jun | -115.6 | 2.102 | -0.550 | 0.583 |
| Christmas | -92.78 | 2.116 | -0.438 | 0.661 |
| Aug | -42.43 | 2.116 | $0-0.201$ | 0.841 |
| Sep | -29.14 | 2.116 | -0.138 | 0.891 |
| Oct | 2.957 | 2.116 | 0.014 | 0.989 |
| Nov | -4.812 | 2.116 | -0.023 | 0.982 |
| Des | -40.05 | 2.116 | -0.189 | 0.850 |
| R | 0.6109 |  |  |  |

Note to the table. Feb, Mar, ... , Des are monthly dummies.

## Conclusion

Salmon farming is a very risky industry. In addition to significant operational risk, fish farmers are also exposed to a high price risk. Previous studies have shown that salmon price volatility has been on a rising trend, which is worrying for both fish farmers and buyers of salmon. Operational planning and investment analysis become more difficult when the sales price is uncertain. In addition, high and rising volatility will increase the need for risk management tools, such as futures and options contracts. However, a high volatility will also make it more expensive to use these risk management tools. It is therefore important for a fish farmer to possess knowledge of how salmon price volatility varies over seasons and over time.

This article examines the volatility of the salmon market since 1980, over a longer period of time than in previous studies. While previous research finds that volatility has only risen from the mid-2000s, we find that volatility has been on a rise three years since the mid-1980s, about 20 years longer than previously thought. This long period of volatility growth has been interrupted by shorter periods of falling price uncertainty. The results show that volatility in the salmon market is characterised by a high degree of trends, either rising or decreasing. Given the strong trend, it is difficult to find a 'normal level' for volatility. The volatility also shows a high duration, which means that shocks are corrected slowly in the market. This can be interpreted as low market efficiency.

Although we also find that there is a seasonal pattern in volatility, this is not statistically significant. The results indicate that seasonal variation is not a significant indication for risk management decisions. However, companies should be aware that volatility tends to trend, making it difficult to find a normal level of volatility.

The findings of this study suggest that volatility should be something producers, traders and buyers of salmon should be very concerned about. However, it may seem that the players in the industry regard
risk management of salmon price exposure as of little importance. Research shows that fish farmers are only moderately risk-averse, and that risk management tools such as derivatives are rarely used.

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[^0]:    ${ }^{1}$ Assume that variance increases proportionally with time by annualizing volatility.

