INVESTIGATING SALMON PRICE VOLATILITY

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ABSTRACT

An understanding of the structure of price volatility is of great interest since this is a major contributor to economic risk in the salmon industry. The volatility process in salmon prices was analyzed based on weekly price data from 1995 to 2007. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was used to test for volatility clustering and persistence of volatility for prices. We find evidence for and discuss the degree of persistence and reversion in the salmon price volatility. We further find that the usual assumption of an independent zero mean normally distributed error term is not satisfactory when describing the salmon price process.

Keywords: Price risk, salmon aquaculture, salmon prices, volatility.

Introduction

In general, producers face two main types of risk, production risk, which influences how much is produced with a given input factor combination, and price risk, which influences obtained from the quantity produced (Just and Pope 1978; Sandmo 1971). A number of studies have recognized that salmon farming is a risky (Asche and Tveterås, 1999; Tveterås, 1999; 2000, Kumbhakar, 2002 and Kumbhakar and Tveterås, 2003). However, production risk is the main focus of these studies. Despite substantial volatility in prices that also seems to be one main source for cycles in profitability, price risk in salmon aquaculture has received little focus. In this paper we will investigate the price volatility for Norwegian salmon, and thereby obtain information with respect to the nature of the price risk that salmon farmers are facing.

For the salmon industry providing information on the volatility of prices is potentially valuable. There is substantial variability in industry profit levels (Tveterås, 1999), and an important part of this variability is due to fluctuating prices. Not only the first hand sellers, the farmers, experience the economic costs of highly fluctuating prices. The costs of price volatility are transferred to the entire value chain. Retailers and consumers increasingly demand stability of price and supply, and often have little understanding for biological and other mechanisms driving the formation of prices in the market. Modern value chains for food products are organized and have capital-intensive technologies that are geared towards predictability and stability of supplies and prices. From the fluctuating first-hand prices to the relative stable retail prices many intermediary agents in the value chain, such as fish processors, can experience substantial variability of capacity utilization and profits, as prices fluctuate.

Revealing information on the volatility term of the price process also contributes to the literature on price processes in aquaculture. Studies of price forecasting (Guttormsen, 1999; Gu and Anderson, 1995; Vukina and Anderson, 1994) rely on precise knowledge of the noise generating part of prices. The question of how precise we can expect price forecasts to be is highly related to the volatility term. Also studies of market integration (Asche, Bremnes, and Wessells, 1999; Asche, Gordon, and Hannesson, 2004) rely on knowledge of the volatility term. If markets for comparable goods are integrated, which imply that we can describe them through one price measure, this should also include the integration of the volatility processes of the comparable goods.

Previous research on salmon prices has been predominantly concerned with issues such as price forecasting and market integration, and as such has for the most part focused on the price levels and the drift term of the price process. As far as we know little work has been done on examining the volatility properties of salmon prices. Thus this paper contributes to the study of salmon prices by analytically and descriptively investigating the volatility term of the price process. In essence we will look for indications that the volatility term cannot be described by a, generally assumed, independent zero-mean normally distributed random variable. We do this econometrically by applying the GARCH model (Bollerslev 1986) to our price time-series. The GARCH model allows us to model the variance term of the price process as a regression equation dependent on some explanatory variables, where the lagged variance and squared error term of the price process is assumed as default variables. This in essence allows us to empirically model any heteroskedasticity in the process. The result from the analysis of this process will reveal information on the volatility term in the form of bringing to light attributes such as volatility clustering[i] and the degree of persistence of volatility. This again allows us to discuss how volatility reverts after a shock, and as such reveal predictive powers of the volatility. The persistence of any volatility shock will also provide an indicator on the level of efficiency in the market; how fast prices revert to a conceived equilibrium following a shock. In addition we will investigate the distributional properties of the error term in the price structure in order to reveal non-normality attributes such as leptokurtosis and skewness. In estimating the distributional form of the error term we apply the kernel density estimation method.

The paper starts by descriptively trying to analyse the behaviour of price volatility. We apply some measures of volatility to our time series in order to apprehend indications of the properties of volatility that will in turn direct our further analysis. Following the descriptive analysis we apply the GARCH model to our time series so as to more rigorously investigate the properties suggested by the descriptive analysis. Our results reveal that the volatility term is not independent and that persistence and clustering is present in the short term dynamics of the price structure. As such the investigation provides valuable information on the salmon price path for any risk averse market participant.

The short term dynamics of salmon prices

Our data set is provided by the Norwegian Seafood Export Council and consists of 650 weekly observations of salmon prices in Norwegian Kroners from the start of 1995 to week 21 in 2007. One observation of price at time *t* will be denoted as X_t. As a starting point we decompose the price path as such.

$$dX_t = \mu X_t + \sigma X_t dB_t \tag{1}$$

The above Stochastic Differential Equation breaks the price movement down in two parts. One predictable, or trend part μX_t, and one noise part, $\sigma X_t dB_t$ accounting for the uncertainty of the price movement. The uncertainty of price movements σ is driven by the Brownian motion B_t, which in its increments is normally distributed with mean zero and variance equal to the size of the time increment. Note that the price decomposition contains two information terms, namely the drift term and a constant volatility term. The Brownian motion is pure noise and contains no information.

This basic way of modelling price movements is much applied in financial economics. We will argue that the price process in the salmon industry may be described by the same process. The selling and buying of salmon is motivated by the same incentive for utility maximization as any financial asset investment. The sale of salmon does not have to occur at the exact moment the fish reaches sellable size; the profit maximizing policy of sellers is a dynamic problem, they might hold the salmon and wait for price to change or sell it immediately. This strengthens the speculative forces underlining the price of salmon. Since uncertainty is a fundamental attribute of the salmon production process we know that the price of salmon is volatile. A hypothesis concerning salmon prices is therefore that the price process is very much explained by the Brownian motion, and that long term predictability is limited. In our time series the long term predictability, or drift term, is linked to any trend observed in the given time domain.

The relative difference in price levels, or return, from week to week is denoted as $R = X_t / X_{t-1}$. To account for proportional changes in returns we apply a logarithmic transformation of the price difference such that $Y_t = \ln X_t - \ln X_{t-1}$. The logarithmic transformation is also applied to the price process; transforming both the variables and the shape and moments of the probability distribution

$$dY_t = (\mu - \tfrac{1}{2}\sigma^2)dt + \sigma dB_t \tag{2}$$

The log return Y_t is normally distributed with mean $(\mu - \frac{1}{2}\sigma^2)\Delta t$ and variance $\sigma^2 \Delta t$. This simple model, in the case of zero drift, assumes that log returns are independent. For the Black-Scholes option pricing formula, for example, the pricing equation does not contain a local mean rate of return. Generally this seems like a strict assumption, and as such the seminal work done by Black and Scholes has been criticized for this independence assumption. In fact, empirical analysis of stock returns indicates that non-linear functions of returns are autocorrelated (Jones, 2003). The non-zero correlation between different powers of return gives rise to volatility clustering. Thus log-returns, at least for stocks, often seem to be connected not only through a drift term but also through a non-zero conditional variance.

If the noise term σ is equal to zero, the price movement is completely predictable and described by the linear relationship $Y_0 + \mu t$. Thus we see that volatility is the term describing the divergence of prices from its predictable level. In relation to salmon prices we might expect that the price will often diverge from any assumed predictable level. From 1996 to 2007 we observe that the trend line in prices (figure 1) is weakly declining. Increasing industry productivity subsequently explains the decline in prices over time[ii]. In our figure prices are nominal so that the downward effect from increased productivity on prices is counteracted by inflation.

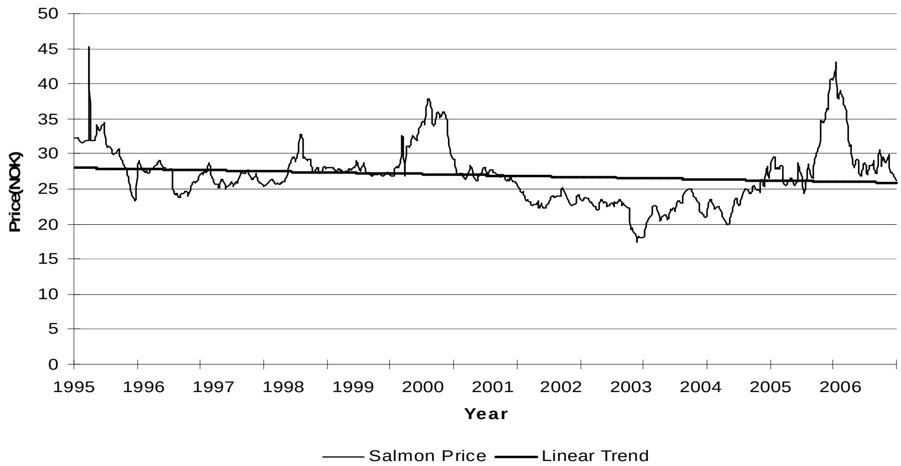

Figure 1. Weekly salmon prices from 1995 to 2007 with fitted trend line.

If the market for salmon is completely efficient, meaning that all relevant information concerning the future value of salmon is incorporated in its price, the predictable part of the price movement approximates to zero; more precisely, any trend observed in the price in the case of an efficient market is due to inflation. Thus the change in price from week to week should be completely described by the noise term $\sigma X_t dB_t$. The parameter σ in the price process is the fundamental measure of volatility, and is in this simple description assumed to be constant. From figure 3 it is hard to argue that the predictable factor μ is very dominant, there seems to be little drift in the price process and the dominant part of the given price movement seems to be given by the Brownian motion. If this holds then no patterns in prices can be found, and thus for the market participants they would be unable to acquire any information on the future price movements. The best prediction on future prices would simply be today's price levels, where the volatility term would be a simple white noise term.

In order to examine the noise term of the production process, we now apply a historical rolling volatility measure in which we measure the divergence of prices from a 20 week moving average.

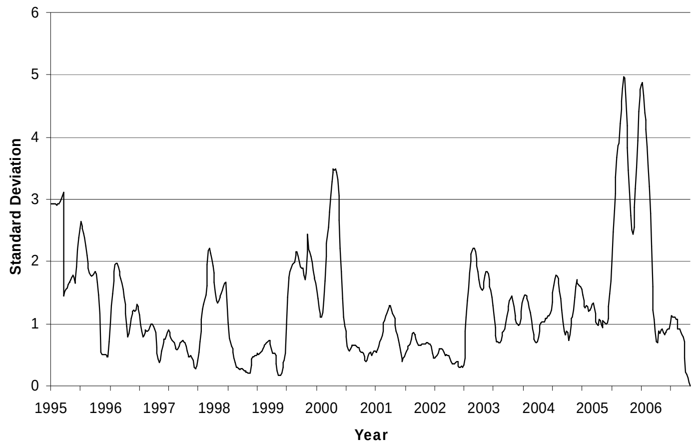

Figure 2. Twenty weeks moving average of salmon price volatility

As indicated in Figure 2 volatility is displaying variation over time. In addition volatility seems to “spike” in some time intervals. There seems to be significant positive jumps in the volatility process. This suggests that the volatility σ in our price process is itself stochastic, and that the assumption that volatility σ is fixed seem insufficient in describing the price process. When modelling stochastic volatility to incorporate spikes the Ornstein-Uhlenbeck process for volatility has been applied (Zerili 2005). The Ornstein-Uhlenbeck process allows for autocorrelation in volatility.

For discrete time the counterpart of the Ornstein-Uhlenbeck process can be implemented by the GARCH model. The indication that volatility is stochastic process opens up for the possibility that volatility is connected across time and such that a GARCH model is suitable to describe the price process for the discrete time approach.

We might also incorporate the moving average measure of volatility in the level chart of salmon prices.

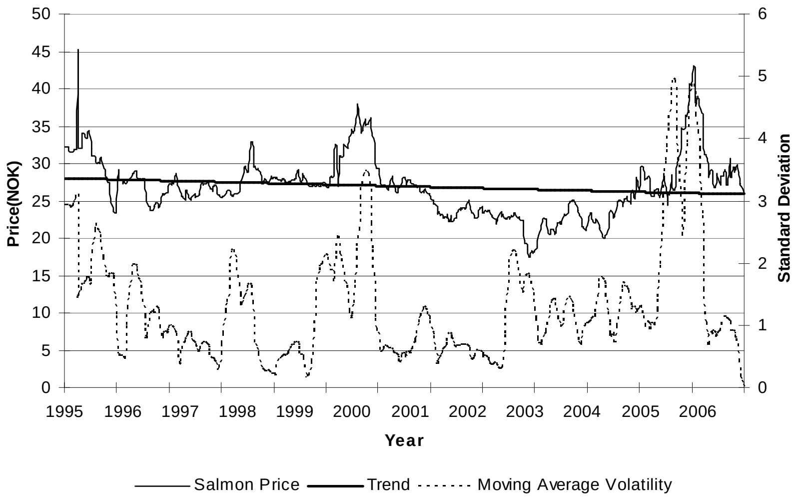

Figure 3. Salmon Price and Volatility

By examining Figure 3 another pattern in the volatility process seems to emerge. The figure suggests that volatility is larger in periods of relative high prices, that there is positive correlation between price and volatility. In the theory of commodity prices it has been conjectured that this relationship should exist (Deaton and Laroque, 1992; Chambers and Bailey, 1996). In periods with scarce availability of goods; for example due to a streak of bad harvests, the price is allowed to persist above the long run equilibrium level. As inventories are emptied the producers reach a state where excess demand can not be satisfied. This gives rise to the characteristic price spikes observed in commodity markets; and as such larger than average volatility. In order to examine this property we divide our data-set in two; one set where price is below the trend and one where it is above. Thus this functions as a proxy for a high and low price data set. Further we test, using both the Levene (1960) and Brown and Forsythe (1974) test, whether the standard-deviation of the two price sets are significantly different, as shown in Table 1. We note that the standard deviation of the "high price" and "low price" series are 3.47 and 2.27, respectively. Both the Levene and the Brown and Forsythe test strongly indicate that the standard deviations are different. As such this approach supports the suspicion that volatility is larger in periods of high prices. For the market participants this means that larger expected profits generally come at a trade-off of larger price risk.

Table 1. Levene/Brown and Forsythe test for equality of variance

Dummy	Mean	St.Dev.	Freq.
Low price	24.33	2.27	360
High price	30.19	3.47	290
Total	26.95	4.08	650

w0 = 40.14 df(1,648) Pr > F = 0.0000000

w50 = 13.26 df(1,648) Pr > F = 0.0002914

w10 = 24.15 df(1,648) Pr > F = 0.0000011

*****The term w0 reports Levene's statistic, and w50(median) and w10(10 percent trimmed mean) replaces the mean with the two alternative location estimators as proposed by Browne and Forsythe.

Next we move to the log-space where we apply our measures of volatility to the log-return of prices. By examining returns instead of levels we are able to say something about the short term dynamics of the price movements; that is the corrective movements in prices. The return movement indicates how the market price converges to the equilibrium price. If the equilibrium price level is constantly changing, as we would assume in a market with much uncertainty, this would lead to large volatility in returns as prices constantly "catches up" to the equilibrium price. Moreover, if drift is absent from the return process we should observe that the log returns are independent and (in the case of a constant volatility term) fluctuate unsystematically around zero according to the Brownian motion (the Brownian motion is as stated independent and normally distributed in its increments).

Figure 4 depicts the moving average with and without drift. The figure supports the hypothesis that drift is largely absent in the salmon return process. There seems to be little divergence between a drift and a zero drift process. The difference between the two moving average measures is a mean adjustment term to the log-returns in the case of the drift measure. If there were significant drift in the price process this would lead to a notable difference between the two measures since log-returns would over time diverge from zero. This figure also suggests that volatility displays clustering. The indication of volatility clustering further strengthens our suspicion that the volatility term of the price process is itself stochastic, meaning that both the Brownian motion and the stochastic volatility might shift prices, and such that variance is not independent of other previous week(s) variance. Moreover, assuming that volatility fully follows a random walk does not seem satisfactory in describing the volatility term in the price process.

It is also necessary to determine the time series properties of the variables in order to avoid the problem of nonstationarity. We do this by testing for nonstationarity by applying the augmented Dicky-Fuller (ADF) test. We included a constant in all our variables that do not appear to be trending, and included a trend, in addition, in the ADF test on volume. The results are shown in table 2. Lag length was chosen to minimize Akaike Information Criterion. The most important tests are the tests on log returns and log volume change (log-diff.-volume). The ADF tests reject the null of nonstationarity on both of these variables at the five percent level.

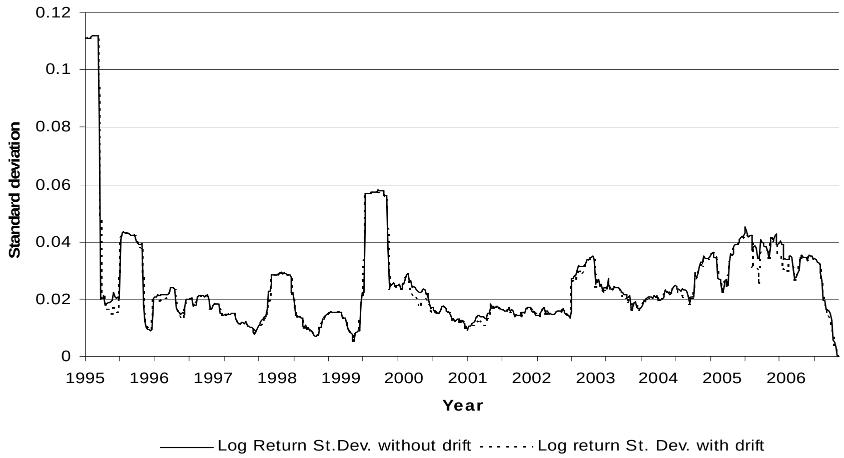

Figure 4. Twenty weeks moving average of log returns with and without drift

Table 2: Unit root tests (ADF)

Series	t-adf	Lag lenght	Options included
Salmon price	-2.748	2	Constant
Log-Return	-26.84**	0	Constant
Volume	-12.10**	1	Constant and trend
Log.-diff.-volume	-10.75**	14	Constant

We also tested for "ARCH effects" (Engle 1982) on both log return and log-diff.-volume We regressed the dependent variable (log return and log-diff.-volume sequentially) on a constant, and saved the residuals, squared them, and regressed them on five own lags to test for ARCH of order 5. We obtained R^2 and multiplied with the number of observations. This test statistic is distributed as Chi-square. The test statistic (table 3) for both log return and log-diff.-volume shows that the series show evidence of ARCH effects. A test for autocorrelation in the data was also performed. The Ljung-Box test suggests that autocorrelation is present in all series except log returns.

Table 3: Autocorrelation and ARCH tests

Price Series	Autocorrelation	ARCH
	Ljung-Box (25)	Chi^2
Salmon Price	8405**	
Log-Return	24	220**
Volume	6096**	
Log-diff.-volume	114**	265**

The analysis so far suggests that long term predictability is severely limited; that drift in the price process is largely absent in our time frame, and such that the volatility movements is important in describing the price process.

Further, the existence of spikes and clustering of volatility suggests that volatility is itself described by a stochastic process and that it is not independent across time. This further suggests that, despite a lack of predictability arising from an approximately zero drift term, the log returns still might display correlations arising from a non zero conditional volatility. Thus the natural extension of the analysis is to apply the GARCH model to our price process.

Econometric approach

If we simulate an ARCH(1) series, we can see that the ARCH(1) error term u_t has clusters of extreme values. This is a consequence of the autoregressive structure of the conditional variance. That the variance is dependent on the squared variance of the previous period leads to the possibility of higher power correlations between log-returns. If the realized value of u_{t-1} is far from zero, h_t (the conditional variance of u_t) will typically be large. Therefore, extreme values of u_t are followed by other extreme values, and thus we observe the clustering seen in financial market returns.

There have been some difficulties implementing the ARCH model. A problem is that often a large number of lagged squared error terms in the equation for the conditional variance are found to be significant on the basis of pre-testing. In addition, there are problems associated with a negative conditional variance, and it is necessary to impose restrictions on the parameters in the model. Consequently in practice the estimation of ARCH models is not always straight forward. Bollerslev (1986) extended the ARCH model and allowed for a more flexible lag structure. He introduced a conditional heteroskedasticity model that includes lags of the conditional variance (h_{t-1}, h_{t-2},…, h_{t-p}) as regressors in the model for the conditional variance in addition to lags of the squared error term $(u_{t-1}^2, u_{t-2}^2, ..., u_{t-q}^2)$, which leads to the generalized ARCH (GARCH) model. In a GARCH(p,q) model, u_t is defined as:

$$u_t = \varepsilon_t (\alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j})^{1/2} \tag{4}$$

where ε_t ~NID(0, 1); $p \geq 0, q \geq 0; a_0 > 0, a_i \geq 0, i = 1,..., q$ and $\beta \geq 0$, j = 1, 2,…, p.

It follows from manipulation of the above equation that h_t (the conditional variance of u_t) is a function of lagged values of u_t^2 and lagged values of h_t:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{5}$$

Earlier in the paper we noted that volatility is larger in periods of higher prices, as such it seems reasonable that the volatility process is asymmetric and positively skewed. In order to incorporate asymmetric volatility it is normal to apply the EGARCH (exponential GARCH) rather than GARCH model. In describing our price series we have not found this to be a suitable approach. Under leptokurtic distributions such as the Student-t distribution, the unconditional variance does not exist for EGARCH. The exponential growth of the conditional variance changes with the level of shocks, this leads to the explosion of the unconditional variance when extreme shocks are likely to occur. In empirical studies it has been found that EGARCH often overweighs the effects of larger shocks on volatility and thus results in poorer fits than standard GARCH models[iii].

Econometric results and discussion

In this section, we present the results from our GARCH estimation. A normality test (Doornik and Hansen, 1994), which is presented in Table 4, on our price series indicate non-normality, which is not surprising considering many large residuals. Non-normality is an inherent feature of the errors from regression models of financial data, and hence robust standard errors are calculated. Further the price level series displays kurtosis (1.6361) and skewness (0.8663). Concerning log returns the distribution displays excess kurtosis (45.324) but as opposed to the price level series skewness (0.094122) is to a large degree eliminated. Furthermore the large kurtosis in log returns means that more of its variance is explained by infrequent extreme deviations from its mean. This illustrates the uncertainty and risk underlying the return process in the industry. Corresponding results for both volume and log-diff.-volume can be seen in table 4 below. Applying kernel density estimation with a Gaussian distribution term we can estimate the distribution of the price series and log-returns.

Table 4. Summary Statistics for Salmon Price, log returns, volume and log-diff.-volume

Price Series	Mean	Std.Dev.	Skewness	Kurtosis	Normality Chi^2
Salmon Price	26.946	4.0835	0.8663	1.6361	67.858**
Log-Return	-0.00032165	0.031898	0.094122	45.324	3607**
Volume	5305.9	1954.6	0.84598	1.0401	81.885**
Log-diff.-volume	0.0023095	0.49352	0.03005	129.11	9449.3**

As figure 10 shows the skewness is to a large extent eliminated when looking at log-returns. The low level of skewness suggests that in the short term there is little possibility of any reliable excess return. Furthermore the high kurtosis in log returns means that more of its variance is explained by infrequent extreme deviations from its mean. This would suggest that large returns are generated by unpredictable shocks. The distributional analysis indicates that assuming a normally distributed error term in the price structure of salmon is non trivial, and that any research on salmon prices should account for the distributional form of the price series in their time domain.

In the volatility equation we will include the stationary time series of log volume differences. This series illustrates the growth pattern in volume of salmon sold. The reason for including volume can be found in the relationship between inventorying and short term price dynamics in commodity prices (Deaton and Laroque, 1992; Chambers and Bailey, 1996). The theory states that inventorying allows the smoothing of short term price fluctuations. In production of goods with limited durability; such as fresh salmon, the possibility for inventorying is limited. One might conjecture that the only possibility for inventorying of fresh fish in aquaculture is through a continuation of cultivation. As such there exists an inverse relationship between the growth in volume sold and the availability of inventories to smooth future prices; or alternatively that the growth in volume indicates the utilization of inventories. The relationship between volatility and volume is also investigated in financial markets (c.f. Bessembinder and Seguin 1993).

We estimate the GARCH model with Student-t distributed errors, as proposed by Bollerslev (1987)[iv]. The distribution tends to the standard normal when degrees of freedom go to infinity. From table 5 below we observe that the optimal number of lags in our model is five.

Table 5. Akaike Information Criteria (AIC) and Bayesian Information Critaria (BIC)

GARCH(1,1) *	AIC	BIC
AR(1)	-3139.51	-3133.84
AR(2)	-3139.13	-3132.66
AR(3)	-3139.46	-3132.17
AR(4)	-3140.02	-3131.92
AR(5)	**-3146.11**	**-3137.21**
AR(6)	-3137.3	-3127.58
AR(7)	-3132.59	-3122.06

AR(8)	-3123.85	-3112.52
AR(9)	-3116.76	-3104.62
AR(10)	-3108.86	-3095.91

[*] Extending the GARCH terms to GARCH(2,1), GARCH(1,2) or GARCH(2,2) does not improve the fit over the GARCH(1,1) alternative

The model is estimated with a five week lag in the price equation and a one week lag in the GARCH and ARCH terms.

$$y_t = \mu + \sum_{i=1}^{5} \eta_i y_{t-i} + u_t \tag{6}$$

$$h_t = \alpha_0 + \gamma \Delta Volume + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{7}$$

Here $\Delta \mathrm{Volume}$ is along with return defined on log form. The model (6) – (7) was estimated sequentially using maximum likelihood[v].

Table 6. AR(5)-GARCH(1,1) estimation results

Parameter				
Price Function		**Coefficient**	**Robust Std.Dev.**	**t-value**
μ		-0.00024	0.00068	-0.358
η_1		0.35227**	0.04683	7.52
η_2		-0.02208	0.04079	-0.541
η_3		-0.06444	0.04129	-1.56
η_4		0.02923	0.03537	0.827
η_5		0.08648**	0.03061	2.83
Variance Function				
α_0		0.00018**	0.000003	2.81
γ		-0.00035*	0.00016	-2.13
α_1		0.44230**	0.1259	3.51
β_1		0.3694**	0.1214	3.04
Log likelihood	1581.8			

** implies significance on the one percent level, * implies significance on the five percent level

From table 6 we observe that both previous period variance and error term is significant on the 5% level on today's variance of price. Thus the large spiking and clustering in volatility indicated earlier can be explained by the conditional variance term. Intuitively the lag 1 structure of variance suggest that if price was very volatile last week it is more likely than not to be very volatile this week as well. After a period with high volatility, one can expect that the volatility reverts to a more stable level. For aquaculture firms this means that volatility last week has some predictive power concerning this week's volatility, and as such can offer information to a risk averse firm who values information on price volatility.

In the variance equation, we see that $\Delta Volume$ is negative and significant on the five percent level: the conditional variance of salmon prices is negatively (positively) related to positive (negative) changes in traded volume. Following the reasoning for including volume movements in the volatility equation, the results state that as the utilization of inventories increase volatility decreases. This supports the relationship that the availability of inventories helps smooth prices. However the utilization of inventories today comes at a trade-off of lower inventories tomorrow such that the option for smoothing prices in the future has decreased. We should note that although the difference in volume traded is statistical significant, it is less likely to be economically significant due to a low coefficient value.

In table 6 we observe how the conditional mean (return) is related to its previous values. Particularly, lag 1 and lag 5 are significant and positive. The return in week *t* depends on the return last week and return five weeks ago. Thus we might state that lag 1 and 5 of log returns offer some predictive powers on the log-returns.

Next we perform misspecification tests on the residuals from our model. The Portmanteau statistic for the scaled residuals returns a Chi square value of 15.453 (a *p*-value of 0.75). The Portmanteau statistic for squared residuals results in a Chi square value of 0.31328 (a *p*-value of 1). Hence, the Portmanteau tests reject autocorrelation in the residuals. We test for error ARCH from lags 1 to 2. With a *p*-value of 0.97 we reject ARCH 1-2 in the residuals. Lastly, a normality test is performed. A *p*-value of 0.00 implies serious non-normality. With regressions from speculative prices, we do not get normally distributed errors. We therefore report robust standard errors.

In a GARCH(1,1) model, the sum $(\alpha_1 + \beta_1)$ measures the degree of volatility persistence in the market; the speed at which the market dissipates a shock. Thus it tells us something about the degree of efficiency in the market, where the intuition is that if a market is completely efficient it should immediately correct to any shock. What this means is that the larger the persistence is the lower is the speed of correction in the market. We note that the value of volatility persistence in our model is estimated to 0,81. To put this in context we note that doomi, Hudson and Hanson (2003) found persistence values for catfish, corn, soybeans and menhaden equal to 0,98, 0,94, 0,88 and 0,38, respectively. Moreover, this suggests that the market for salmon displays a larger degree of efficiency than catfish, corn and soybeans products, but lower than menhaden.

Furthermore we might use the degree of volatility persistence in the market to estimate the half life of a volatility shock. The half life estimate measures the time it takes for a shock to fall to half of its initial value and is determined by (Pindyck 2004):

$$\text{Half-life time} = \log(.5)/\log(\alpha_1 + \beta_1) \tag{8}$$

We calculate a half life time of 3.3 weeks. Recent literature on volatility persistence suggests that the persistence in the conditional variance may be generated by an exogenous driving variable that is itself serially correlated. Hence the inclusion of such an exogenous variable in the conditional variance equation would reduce the observed volatility persistence (see Lamourex and Lastrapes, 1990; Kalev et al., 2004). We find that excluding the exogenous variable results in a half life time of 4.4 weeks.

Concluding remarks

While production risk in salmon aquaculture has received substantial attention, little focus has been given to price risk. It is important to understand price risk as this seems to be a main factor driving the cycles the industry is experiencing. Our results indicate that the assumption of an independent zero mean normally distributed error term is not trivial when modelling salmon prices. We find that the salmon prices and log-returns are non-normal, and display skewness and kurtosis for the former and kurtosis for the latter case. As such, assuming normality when modelling salmon prices is not supported by our study. Moreover, we find that a AR(5)-GARCH(1,1) process describes the salmon price process. Thus academic research applying salmon prices should account for the fact that there is persistence of volatility itself on the short-term dynamics. For studies of price forecasting, for example, this means that in periods of large shocks we cannot expect as precise forecasts, even in periods following the shock since volatility will generally persist for some time as the market corrects. Also for studies of market integration we note that if comparable salmon goods are to be aggregated they should also display some of the same volatility patterns, we should observe some volatility spill over effects between comparable goods. For the relevant market participants the fact that volatility clustering is existent offers some predictive information on the price fluctuations in the market. More specifically we find that previous week's volatility offers some indication of next week's volatility. This provides information to a market chronically missing stability and predictability. Risk averse market participants can avoid trading next week if they observe that volatility is large this week. This gives the market participants an additional hedging possibility; there is clear evidence that volatility reverts following a shock. We also find support for the hypothesis that volatility is larger in periods of high prices. For the industry this means that larger expected profits more often than not comes at a trade-off of larger price risk.

Our results also indicate that the degree of efficiency in the market for salmon aligns itself with a small sample of other agricultural goods. We also note that following a shock, the volatility will half in an estimated 3.3 weeks, which offers some planning information for the market participants. Concerning the predictability of prices we find that today's log-returns are dependent on a 1 and a 5 week lag of log-returns. This means that there is some level of short term predictability present in the market. To some degree this supports studies that claim to offer some level of short term predictions of salmon prices. Concerning long term predictions on price levels we find that the long term trend in prices is weakly declining. The decline is mostly due to increasing industry productivity. As such, any prediction on future price levels can, at least in the long run, be found in the continuation of the productivity increase. Short term price correlations offer no predictive powers on any long term price levels. The focus of this paper has been on understanding price risk in salmon prices. Future research can be conducted on evaluating forecasting performance of different volatility models.

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[i] Volatility clustering is the property that prices are correlated in higher powers, that in general large changes in prices(of either sign) are followed by large changes, and small changes (of either sign) are followed by small changes

[ii] See e.g. Asche (1997) and Asche and Tveterås (2002)

[iii] See the empirical study of Engle and Ng (1993)

[iv] Likelihood Equation evaluated

$$\ell(\Phi) = T\log\left\{\frac{\Gamma(\upsilon+1)/2}{\pi^{1/2}\Gamma(\upsilon/2)}(\upsilon-2)^{-1/2}\right\} - \left(1/2\right)\sum_{t=1}^{T}\log(h_t) - [(\upsilon+1)/2]\sum_{t=1}^{T}\log\left[1+\frac{\left(y_t-\mu-\sum_{i=1}^{5}\eta_i y_{t-1}\right)^2}{h_t(v-2)}\right]$$

[v] Akaike Information Criterion also confirms that log-diff-volume in the variance equation should be included. AIC with volume included is -4.88, and is -4.87 without log-diff-volume in the estimation.