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The Behaviour of Salmon Price Volatility

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Abstract *Salmon prices exhibit substantial volatility. An understanding of the structure of 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 analysed 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 salmon price volatility. Further, we find increased volatility in periods of high prices. For the industry this means that larger expected profits more often than not come at a tradeoff of greater price risk.*

Key words Price risk, salmon aquaculture, salmon prices, volatility.

JEL Classification Codes C22, Q21, Q22.

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 the revenue one will obtain from the quantity produced (Just and Pope 1978; Sandmo 1971). A number of studies have recognized that salmon farming is a risky industry (Asche and Tveteras 1999; Tveteras 1999, 2000; Kumbhakar 2002; Kumbhakar and Tveteras 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.

To put the salmon industry into a broader perspective, we can compare it with meat-producing sectors in agriculture. From 1995 to 2007 the standard deviation of monthly salmon prices around their linear trend was 14.9%. For US beef and pork the standard deviation in the same time period was 11.9% and 24.9%, respectively. One particular distinguishing factor with salmon is that as it approaches harvest-ready sizes, it also approaches sexual maturation, which causes a significant decline in quality and growth. Salmon farmers will often have a relatively short time window for harvesting and will consequently be concerned about week-to-week variation price dynamics during that time window.

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For the salmon industry, providing information on the volatility of prices is potentially valuable. There is substantial variability in industry profit levels (Tveteras 1999), and an important part of this variability is due to fluctuating prices. Figure 1 shows the average operating margin and its standard deviation from 1985 to 2002. Not only first-hand sellers 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 of 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 relatively 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 rely on precise knowledge of the noise-generating part of prices (Guttormsen 1999; Gu and Anderson 1995; Vukina and Anderson 1994). The question of how precise we can expect price forecasts to be is highly related to the volatility term. Studies of market integration rely also on knowledge of the volatility term (Asche, Bremnes, and Wessells 1999; Asche, Gordon, and Hannesson 2004). If markets for comparable goods are integrated, which implies that they can be described through one price measure, this should also include the integration of the volatility processes of the comparable goods.

In addition, the volatility of prices is important in establishing the value of contingent claims. Forward and futures markets for salmon are now under establishment in Norway and Switzerland, although they have not been successfully established on a large scale. This is due to many factors outside the scope of this paper, but since the value of a contingent claim is dependent on the underlying asset (in this case the salmon price), it is important to establish the true properties of the volatility gener-

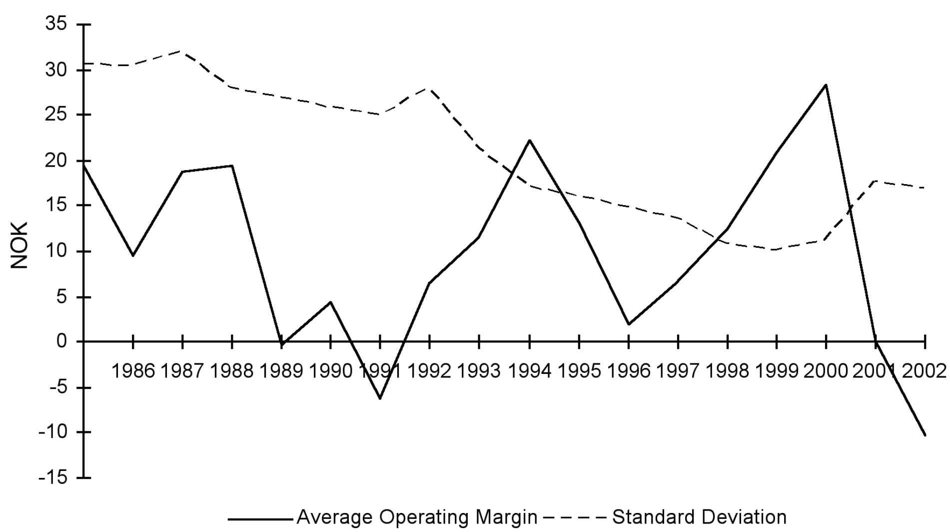

Figure 1. Average and Standard Deviation of the Export Margin for Norwegian Salmon Exports, 1985–2002

Source: The Norwegian Directorate of Fisheries.

ating part of the price process. Simply assuming an independent zero-mean normally distributed term for describing volatility can be costly if the price process contains properties and connections diverging from a random walk. For instance, assuming normality if the distribution displays fat tails can lead to underestimation of extreme events and consequently to severe losses, as many speculators and investors on the world's stock markets have experienced. For example, the probability of a trading loss as that incurred from the Black Monday stock market crash has been estimated using a normal distribution to occur with a probability of 1 in 10^{157} per day (James and Zetie 2002).

Previous research on salmon prices has been predominantly concerned with issues such as price forecasting and market integration, and as such has mainly 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 to our price time-series (Bollerslev 1986). 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 are 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 reveals information on the volatility term by bringing to light attributes such as volatility clustering[1] and the degree of persistence of volatility. This again allows us to discuss how volatility reverts after a shock and, as such, reveals 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 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 article starts by providing a short overview of the aquaculture industry and some of the processes generating price risk. After this, we start our analysis 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 volatility properties 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.

Aquaculture Production and Risk

The salmon farming industry is experiencing rapid growth. From 1996 to 2006 the volume of salmon sold from Norwegian farms more than doubled (from 298 to 626 thousand metric tonnes). This development has transformed what was once a relatively small-scale periphery of the biological production sector into a multi-billion

[1] Volatility clustering is the property that prices are correlated in higher powers; 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.

dollar industry. For the biological production sector, the breeding and cultivation of salmon has been one of the most commercially successful endeavours. Today Norway is the leading producer of salmon, accounting for around 40% of world production. Most of the industry growth is due to a substantial growth in productivity which over time has substantially reduced unit costs (Asche 2008). The reduction of production costs is due to two main factors. Firstly, fish farmers are able to produce more with a given amount of inputs, and secondly, improved input factors have made the production process cheaper (for example the development of better feed and feeding technology). The reduction in unit costs has led the price of salmon to decrease over time, providing a long-term trend for the general direction of the salmon equilibrium price (figure 2). In Norway, most of the salmon farms were established during the 1980s. The long Norwegian coastline provides a large array of potential farm locations and further provides the farmer with potential hedging of production risk as correlation of farm-specific risks, such as disease outbreaks and temperature fluctuations, decreases over geographical distance. At present, salmon farms are located along most of the Norwegian coastline.

We can define volatility as the fluctuations of prices above and below some preconceived long-term trend or equilibrium. These price movements are for the most part risky, as the direction and force of the motions are largely unknown on a short-term basis. For the salmon industry, the level of prices functions as the target for which production is evaluated. When prices increase, the farmers seek to increase profits by increasing the amount of salmon produced and sold; when prices decline, the farmers might choose to reduce the intensity of production and the amount of

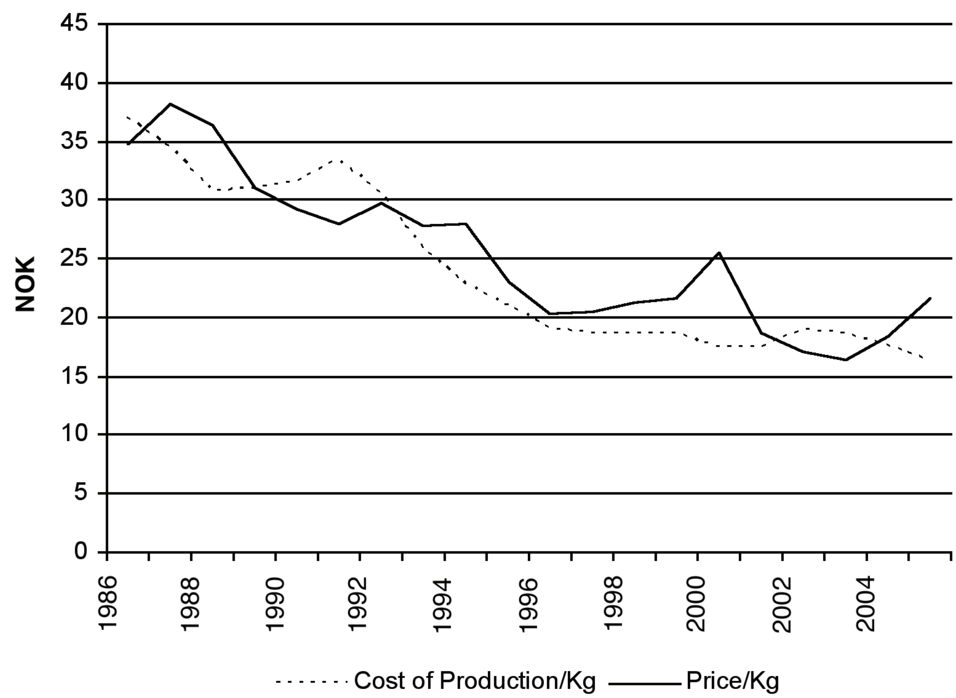

Figure 2. Cost of Fish Production and Price Per Kilo for the Norwegian Salmon Farming Industry 1986–2005

Source: The Norwegian Directorate of Fisheries.

fish sold in an attempt to wait for prices to increase. The biological nature of the production process implies that the desired production output does not always meet its target. Disease, escape of fish, and water temperature conditions are important factors that determine the final fish stock. As such, the possibility at any time to clear the market is not at unity. Andersen, Roll, and Tveterås (2008) have further shown that elasticity of supply is larger in the long run than in the short run. There will be periods of over and under supply which will cause prices to fluctuate. In particular, the market for fresh fish will be subject to volatility as inventory space is limited, although some flexibility is allowed through the stocking of fish in pens. This inventorying is limited because the fish eventually reach sexual maturity, and when they do, their quality deteriorates rapidly. Salmon in Norway have the largest probability of reaching sexual maturity during August-September. Thus one would expect seasonal differences in the flexibility available for the farmers in exploiting profit probabilities. Further on the demand side, factors such as seasonality and changes in preferences (*e.g.*, caused by information on animal diseases and potentially harmful and beneficial substances) and changing exchange rates in different markets will also contribute to the volatility of prices.[2] If salmon farmers are risk averse, they will use the volatility of prices, in addition to the level, as a target to evaluate the amount of salmon produced and sold in the market at a given time. Information on the short-term dynamics of volatility can provide valuable information, since on a short-term basis farmers have some level of flexibility in realising an optimal utility of profits.

We now start our analysis of salmon price volatility. We do this with the assumption that the volatility term is approximated by a random process, an assumption that seems reasonable in light of the large degree of uncertainty inherit in the market. As we will see, this assumption will soon break down; the analysis will show that the volatility term itself contains valuable information.

The Short-term Dynamics of Salmon Prices

Our data set was 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 into 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

[2] Kinnucan and Myrland (2002, 2001) provide a discussion of the impact of exchange rates.

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:

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

The log return, Y_t, is normally distributed with mean $[\mu - (1/2)\sigma^2]\Delta t$ and variance $\sigma^2\Delta t\sigma^2\Delta t$. 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 (1973) 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 their 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 is weakly declining (figure 3). Increasing industry productivity subsequently explains the decline in prices over time.[3] In our figure prices are nominal so that the downward effect from increased productivity on prices is counteracted by inflation. 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 price trend observed 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 the market participants would be unable to acquire any information on the future price movements. The best prediction of 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 two empirical measures of volatility on the salmon price series, a standard deviation measure, and a historical rolling volatility measure. The standard deviation measure

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[3] See Asche (1997) and Asche and Tveteras (2002).

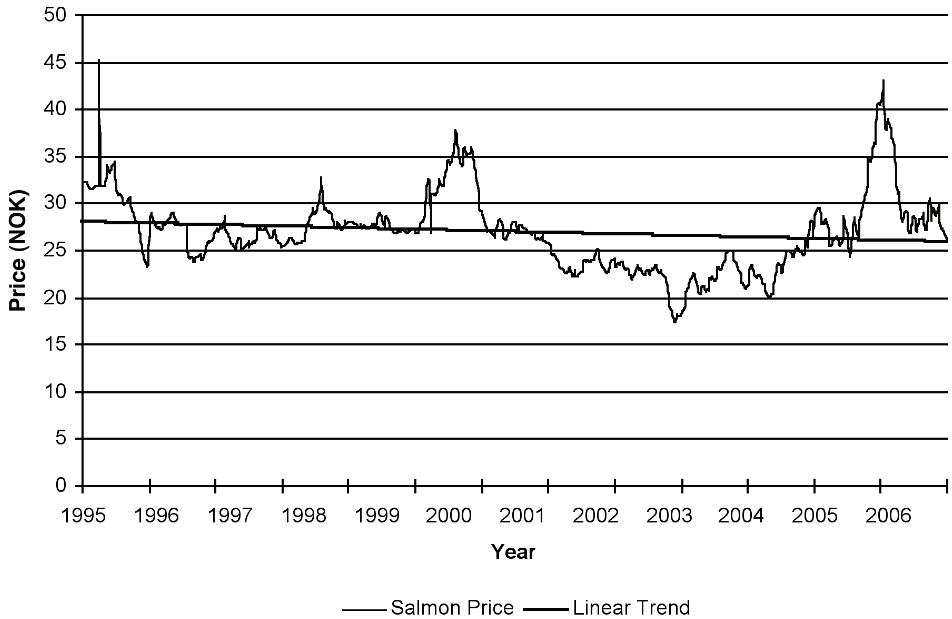

Figure 3. Weekly Salmon Prices from 1995 to 2007 with Fitted Trend Line

in figure 4 gives us the annual average variation of prices from its mean. This simple measure gives us our first indication that volatility fluctuates. The annual standard deviation only gives one observation per year, and it does not contain much information. To give a more detailed picture of volatility, we expand on the annual standard deviation measure by using a rolling measure in which we measure the divergence of prices from a 20-week moving average.

As indicated in figures 4 and 5, the 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 stochastic and that the assumption that volatility σ is fixed seems insufficient in describing the price process. When modelling stochastic volatility to incorporate spikes, the Ornstein-Uhlenbeck process for volatility has been applied (Zerilli 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 a stochastic process opens the possibility that volatility is connected across time and 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. By examining figure 6, another pattern in the volatility process seems to emerge. The figure suggests that volatility is larger in periods of relative high prices and 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 cannot be satisfied. This gives rise to the characteristic price spikes observed in commodity markets and

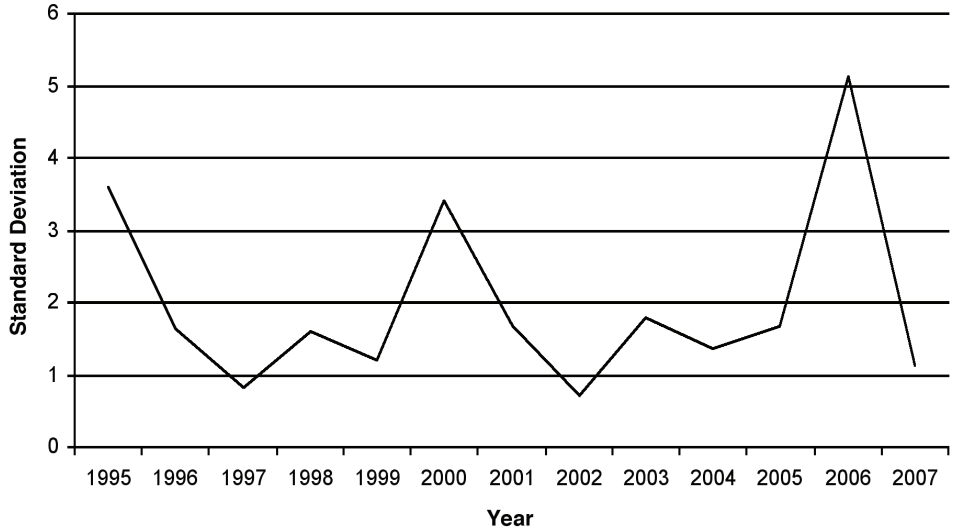

Figure 4. Annual Average of Weekly Standard Deviation of Salmon Prices

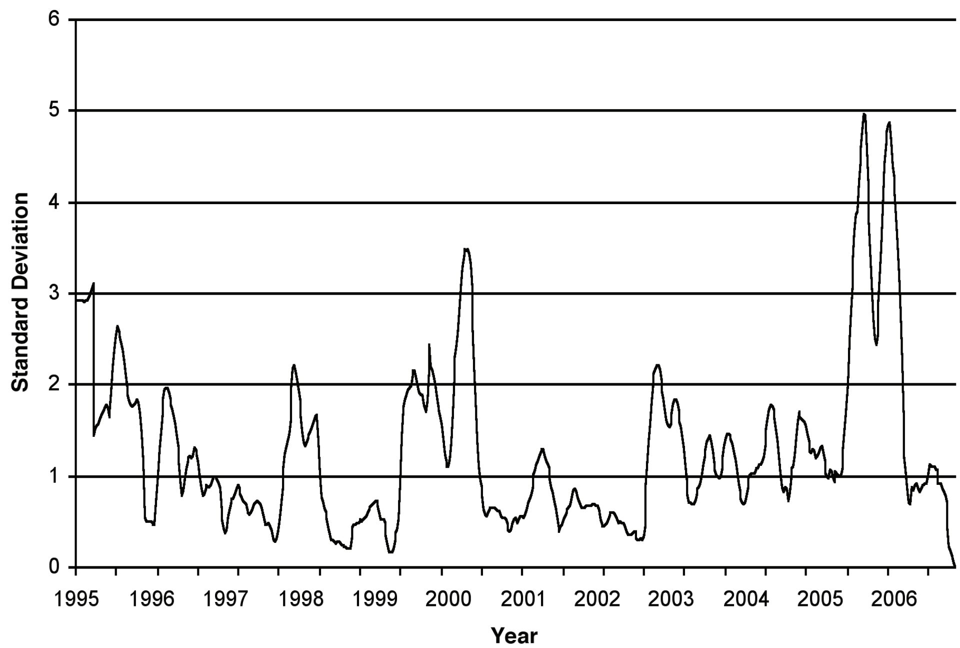

Figure 5. Twenty-week Moving Average of Salmon Price Volatility

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 whether the standard deviation of the two price sets are significantly different using both the Levene (1960) and Brown and Forsythe (1974) tests, as shown in table 1. We note that the standard deviation of the "high price" and "low price" series is 3.47 and 2.27, respectively. Both the Levene and the Brown and Forsythe tests strongly indicate that the standard deviations are different. As such, this approach supports the suspicion that volatility is greater in periods of high prices. For the market participants this means that larger expected profits generally come at a tradeoff of larger price risk.

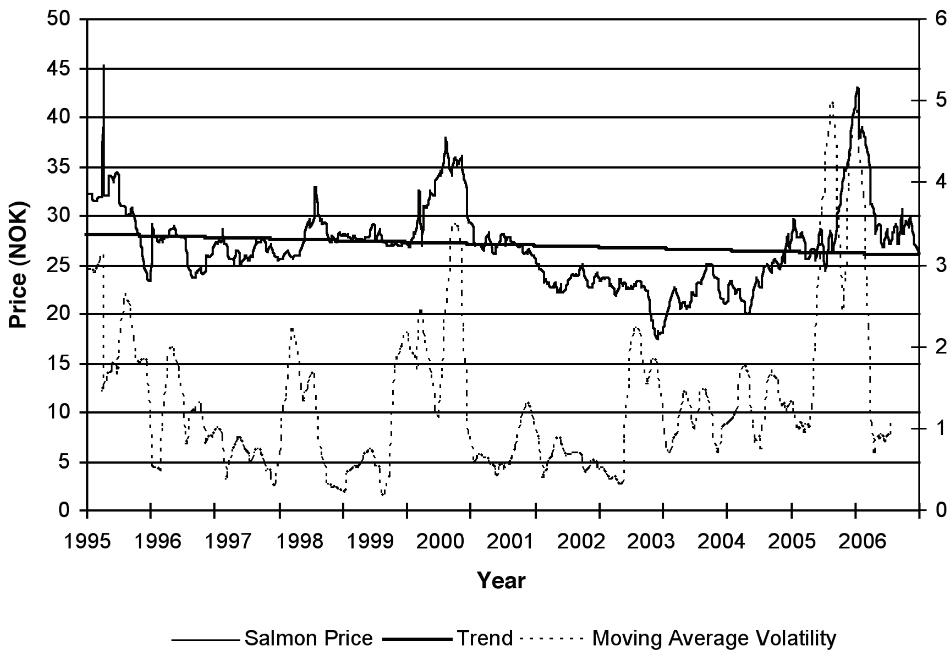

Figure 6. Salmon Price and Volatility

Table 1
Levene/Brown-Forsythe Tests 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	

Note: The term w0 reports Levene's statistic; w50 (median) and w10 (10% trimmed mean) replace 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 high volatility in returns as price 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 7 shows the movements of log-returns. We observe that log-returns seem to fluctuate quite evenly around zero. The mean (variance) of log returns is estimated to –0.00032. As we will describe later in the article, skewness is eliminated when prices are transformed to log-returns. Thus this simple description seems to indicate that log-returns are reasonably approximated by the Brownian motion. But as we will see later, this simple analysis is incomplete, as it cannot isolate which part of the volatility is random and independent and which is correlated.

If we were to assume that log-returns are normally distributed and follow the price process stated above, we can reach an estimate on annual standard deviation of log returns based on the expression:

$$\bar{\sigma} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(Y_i - \bar{Y}_t)^2}\sqrt{\Delta T}, \tag{3}$$

where $\bar{Y}_t$ is the mean annual log-return, ΔT is the number of periods, here 52 weeks, and n is number of observations per year, also 52. Now, figure 8 as well as previous figures, suggest that the variance of salmon price is itself volatile, such that the volatility term σ is stochastic. Thus this simple estimate of annual standard deviation becomes unreasonable, since it assumes that returns are drawn from a fixed

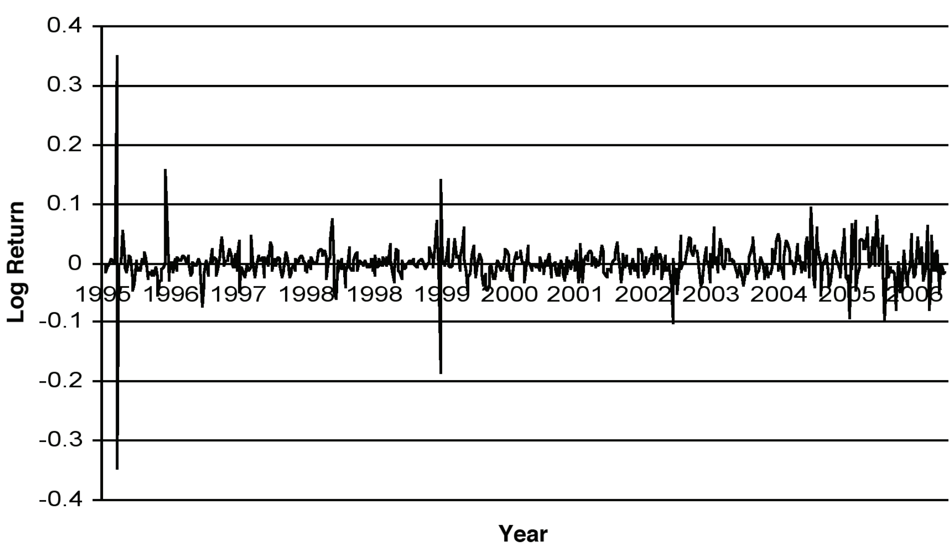

Figure 7. Log-Return of Salmon Prices

log-normal distribution in the sample interval. To obtain a more complete picture of the log-return volatility, we apply the dynamic moving average measure.

Figure 9 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

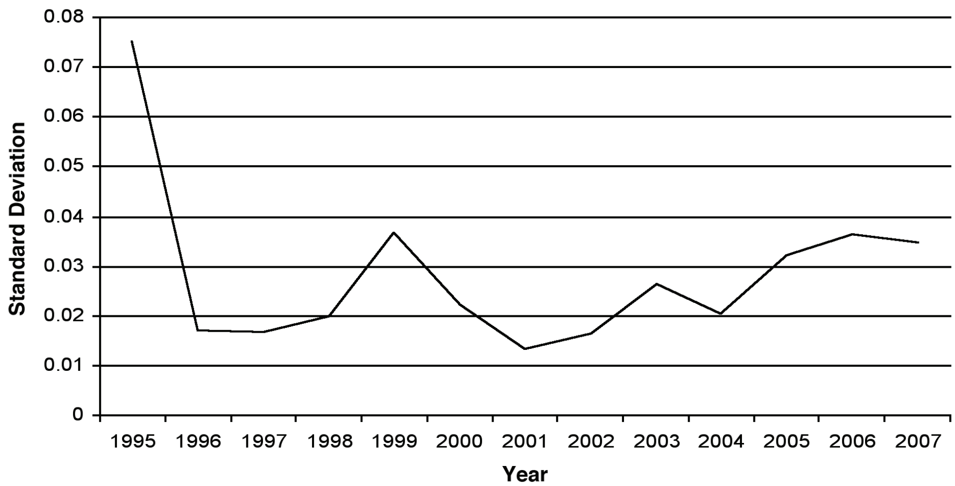

Figure 8. Estimation of Annual Volatility of Log Returns Based on Assumption of Log-normal Returns

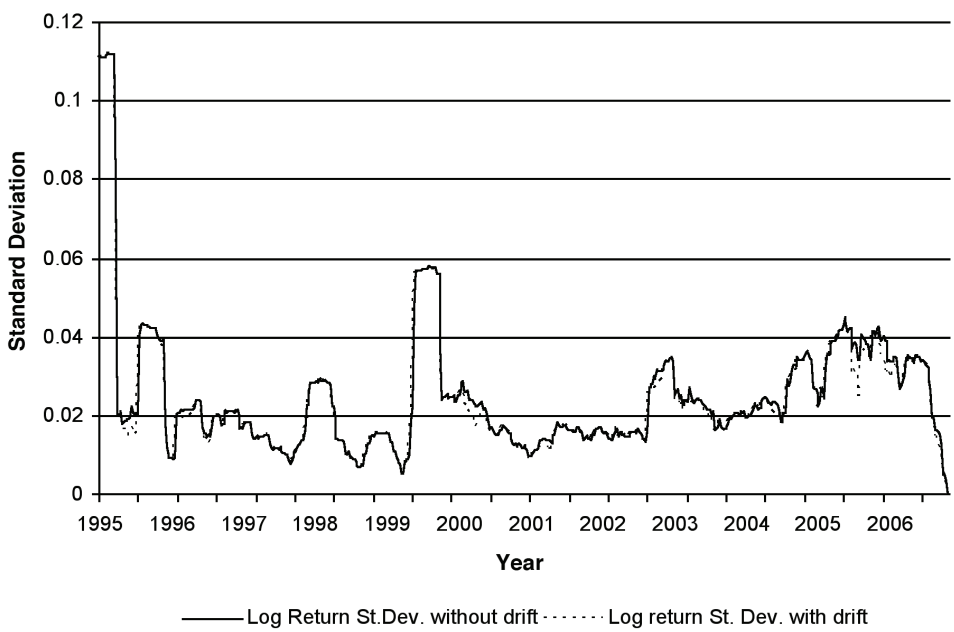

Figure 9. Twenty-week Moving Average of Log Returns with and without Drift

would diverge from zero over time. 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, such that variance is not independent of the variance of previous week(s). 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 test 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 5% level.

Table 2
Unit Root Tests (ADF)

Series	t-adf	Lag Length	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

** Indicates rejection of the unit root hypothesis at the 1% level.

We also tested for "ARCH effects" on both log return and log-diff.-volume (Engle 1982). 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 for both log return and log-diff.-volume shows that the series indicate evidence of ARCH effects (table 3). 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.

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

Table 3
Autocorrelation and ARCH Tests

Price Series	Autocorrelation Ljung-Box (25)	ARCH Chi^2
Salmon price	8,405**	
Log-return	24	220**
Volume	6,096**	
Log-diff.-volume	114**	265**

** Indicates rejection of the null hypothesis of no autocorrelation and no arch effects at the 1% level.

movements are important in describing the price process. Further, the existence of spikes and clustering of volatility suggest that volatility is 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. Since variance is dependent on the squared variance of the previous period, this 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 we observe the clustering seen in financial market returns.

There have been some difficulties implementing the ARCH model. One 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, the estimation of ARCH models is not always straightforward in practice. 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 ($h_{t-1}, h_{t-2}, \ldots, h_{t-p}$) as regressors for the conditional variance in addition to lags of the squared error term ($u_{t-1}^2, u_{t-2}^2, \ldots, u_{t-q}^2$), which leads to the generalized ARCH (GARCH) model. In a GARCH(p,q) model, u_t is defined as:

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

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

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 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 article we noted that volatility is greater 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 outweighs the effects of larger shocks on volatility and thus results in poorer fits than standard GARCH model.[4]

Econometric Results and Discussion

In this section, we present the results from our GARCH estimation. A normality test, which is presented in table 4, shows that our price series indicate non-normality, which is not surprising considering many large residuals (Doornik and Hansen 1994). Non-normality is an inherent feature of the errors from regression models of financial data; 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 largely eliminated. Furthermore, the high 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. Applying kernel density estimation with a Gaussian distribution term, we can estimate the distribution of the price series and log-returns.

As figure 10 shows, the skewness is mostly 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 high 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 any research on salmon prices should account for the distributional form of the price series in their time domain.

In the volatility equation we 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 fresh fish in aquaculture is through a continuation of cultivation. As such there exists an inverse relationship between the

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	3,607**
Volume	5,305.9	1,954.6	0.84598	1.0401	81.885**
Log-diff.-volume	0.0023095	0.49352	0.03005	129.11	9,449.3**

** Indicates rejection of the null hypothesis of a normal distribution at the 1% level.

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

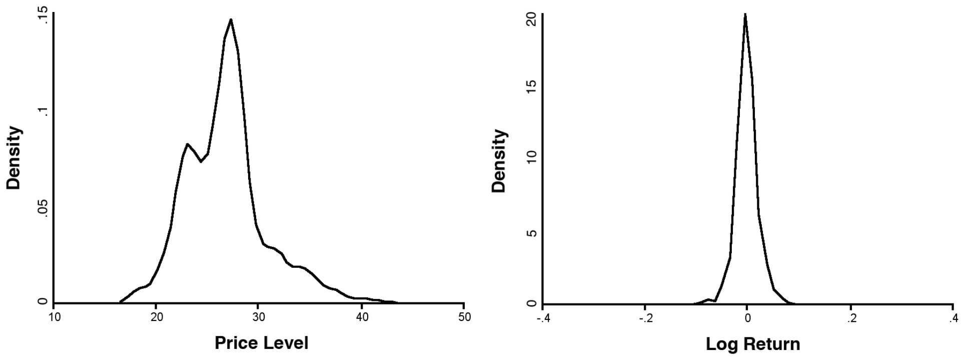

Figure 10. Kernel Density Estimates of Price Level and Log Return

growth in volume sold and the availability of inventories to smooth future prices or that the growth in volume indicates the utilization of inventories. The relationship between volatility and volume is also investigated in financial markets (Bessembinder and Seguin 1993).

We estimate the GARCH model with Student-t distributed errors, as proposed by Bollerslev (1987).[5] From table 5 we observe that the optimal number of lags in our model is five. 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, $\Delta Volume$ is, along with return, defined on log form. The model (6) – (7) was estimated sequentially using maximum likelihood.[6] From table 6 we observe that both previous period variance and error term are significant at 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 can offer information to a risk-averse firm that values information on price volatility.

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[5] Likelihood Equation evaluated:

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

[6] 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.

In the variance equation, we see that Δ*Volume* is negative and significant at the 5% 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 indicate that as the utilization of inventories increases, volatility decreases. This supports the relationship that the availability of inventories helps smooth prices. However the utilization of inventories today comes at a tradeoff 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 statistically significant, it is less likely to be economically significant due to a low coefficient value. Figure 11 shows the relationship between log return standard deviation and changes in volume traded.

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

GARCH(1,1)*		
AR(1)	–3,139.51	–3,133.84
AR(2)	–3,139.13	–3,132.66
AR(3)	–3,139.46	–3,132.17
AR(4)	–3,140.02	–3,131.92
AR(5)	–3,146.11	–3,137.21
AR(6)	–3,137.3	–3,127.58
AR(7)	–3,132.59	–3,122.06
AR(8)	–3,123.85	–3,112.52
AR(9)	–3,116.76	–3,104.62
AR(10)	–3,108.86	–3,095.91

* 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.

Table 6
AR(5)-GARCH(1,1) Estimation Results

Parameter			
Price Function	Coefficient	Robust Std. Dev.	t-values
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		1,581.8	

* implies significance at the 5% level; ** implies significance at the 1% level .

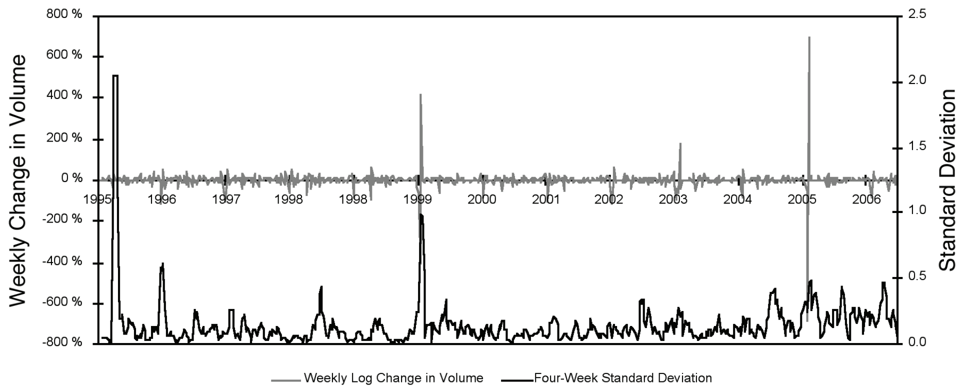

Figure 11. Change in Volume Traded and Four-week Standard Deviation of Log-returns

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 the 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, the lower 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 Buguk, 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 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 an 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 on the short-term dynamics. For studies of price forecasting this means that in periods of large shocks, we cannot expect forecasts to be as precise. In periods following the shocks, volatility will generally persist for some time as the market corrects. 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, and we should observe some volatility spill-over effects between comparable goods. For the relevant market participants the fact that volatility clustering exists offers some predictive information on price fluctuations in the market. More specifically, we find that the 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 high 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 higher in periods of high prices. For the industry this means that larger expected profits more often than not come at a tradeoff 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 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 one- and five-week lags 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 of 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 article has been on understanding price risk in salmon prices. Future research can be conducted on evaluating forecasting performance of different volatility models.

References

Andersen, T., K.H. Roll, and S. Tveterås. 2008. The Price Responsiveness of Salmon Supply in the Short and Long Run. *Marine Resource Economics* 23(4):425–37.

Asche, F. 1997. Trade Disputes and Productivity Gains: The Curse of Farmed Salmon Production? *Marine Resource Economics* 12:67–73.

___. 2008. Farming the Sea. *Marine Resource Economics* 23(4):527–47.

Asche, F., H. Bremnes, and C.R. Wessells. 1999. Product Aggregation, Market Integration and Relationships between Prices: An Application to World Salmon Markets. *American Journal of Agricultural Economics* 81:568–81.

Asche, F., D.V. Gordon, and R. Hannesson. 2004. Tests for Market Integration and the Law of One Price: The Market for Whitefish in France. *Marine Resource Economics* 19:195–210.

Asche, F., and R. Tveteras. 1999. Modeling Production Risk with a Two-Step Procedure. *Journal of Agricultural and Resource Economics* 24(2):424–39.

___. 2002. Economics of Aquaculture: Special Issue Introduction. *Marine Resource Economics* 17:73–5.

Bessembinder, H., and P.J. Sequin. 1993. Price Volatility, Trading Volume, and Market Depth: Evidence from Futures Markets. *Journal of Financial and Quantitative Analysis* 28:21–39.

Black, F., and Scholes, M. 1973. The Pricing of Options and Corporate Liabilities. *Journal of Political Economy* 81(3):637–54.

Bollerslev, T. 1986. Generalised Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics* 51:307–27.

___. 1987. A Conditional Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. *Review of Economics and Statistics* 69:542–47.

Brown, B.B., and A.B. Forsythe. 1974. Robust Tests for the Equality of Variances. *Journal of the American Statistical Association* 69(346):364–67.

Buguk, C., D. Hudson, and T. Hanson. 2003. Price Volatility Spillover in Agriculture: An Examination of U.S. Catfish Markets. *Journal of Agricultural and Resource Economics* 28(1):86–99.

Chambers, M.J., and R.E. Bailey. 1996. A Theory of Commodity Price Fluctuations. *The Journal of Political Economy* 104(5):924–57.

Deaton, A., and G. Laroque. 1992. On the Behaviour of Commodity Prices. *The Review of Economics Studies* 59(1):1–23.

Doornik, J.A., and H. Hansen. 1994. An Omnibus Test for Univariate and Multivariate Normality. Discussion Paper No. W4&91, Nuffield College, University of Oxford.

Engle, R.F. 1982. Autoregressive Conditional Heteroskedasticity, with Estimates of the Variance of United Kingdom Inflation. *Econometrica* 50:987–1007.

Engle, R.F., and V. Ng. 1993. Measuring and Testing the Impact of News on Volatility. *Journal of Finance* 48:1749–78.

Gu, G., and J.L. Anderson. 1995. Deseasonalized State-Space Time Series Forecasting with Applications to the US Salmon Market. *Marine Resource Economics* 10:171–85.

Guttormsen, A.G. 1999. Forecasting Weekly Salmon Prices: Risk Management in Fish Farming. *Aquaculture Economics and Management* 3(2):159–66.

James, J.E.M., and K.P. Zetie. 2002. Extreme Value Theory. *Physics Education* 37(5):381–83.

Jones, C.S. 2003. The Dynamics of Stochastic Volatility: Evidence from Underlying and Option Markets. *Journal of Econometrics* 16(1-2):181–224.

Just, R.E., and R.D. Pope. 1978. Stochastic Specification of Production Functions and Economic Implications. *Journal of Econometrics* 7:67–86.

Kalev, P., W. Liu, P. Pham, and E. Jarnecic. 2004. Public Information Arrival and Volatility of Intraday Stock Returns. *Journal of Banking and Finance* 28:1441–67.

Kinnucan, H.W., and Ø. Myrland. 2001. Optimal Promotion Expenditures for Salmon: The Importance of International Price Linkage. *Agriculture Economics and Management* 5(5/6):319–35.

___. 2002. The Relative Impact of the Norway-EU Salmon Agreement: a Mid-term Assessment. *Journal of Agricultural Economics* 53(2):195–219.

Kumbhakar, S.C. 2002. Specification and Estimation of Production Risk, Risk Preferences, and Technical Efficiency. *American Journal of Agricultural Economics* 84(1):8–22.

Kumbhakar, S.C., and R. Tveteras. 2003. Risk Preferences, Production Risk and Firm Heterogeneity. *Scandinavian Journal of Economics* 105(2):275–93.

Lamourex, C., and W. Lastrapes. 1990. Persistence in Variance, Structural Change, and the GARCH Model. *Journal of Business and Economic Statistics* 8(2):225–33.

Levene, H. 1960. Robust Tests for Equality of Variance, Contributions to Probability and Statistics. *Essays in Honor of Harold Hotelling*, pp. 278–92. Palo Alto, CA: Standard University Press.

Norwegian Directorate of Fisheries. Various years. *Profitability Survey of Fish Grow-out Farms*. Report. Norwegian Directorate of Fisheries, Bergen, Norway.

Norwegian Seafood Export Council (www.seafood.no/page?id=2950).

Pindyck, R. 2004. Volatility in Natural Gas and Oil Markets. *Journal of Energy and Development* 30(1):1–19.

Sandmo, A. 1971. On the Theory of the Competitive Firm under Price Uncertainty. *The American Economic Review* 61:65–73.

Tveteras, R. 1999. Production Risk and Productivity Growth: Some Findings for Norwegian Salmon Aquaculture. *Journal of Productivity Analysis* 12(2):161–79.

___. 2000. Flexible Panel Data Models of Risky Production Technologies with an Application to Salmon Aquaculture. *Econometric Review* 19(3):367–89.

Vukina, T., and J.L. Anderson. 1994. Price Forecasting with State-Space Models of Nonstationary Time Series: The Case of the Japanese Salmon Market. *Computers and Mathematics with Applications* 27:45–6.

Zerilli, P. 2005. Option Pricing and Spikes in Volatility: Theoretical and Empirical Analysis. Discussion Papers 07/08. Department of Economics, University of York.