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# Risk Preferences and Technology: A Joint Analysis

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**Abstract** *This paper deals with derivation and estimation of the risk preference function in the presence of output price uncertainty. The derivation depends neither on a specific parametric form of the utility function nor on any distribution of output price. The risk preference function is flexible enough to test different types of risk behavior (e.g., increasing, constant, and decreasing absolute risk aversion). We also test for asymmetry in the distribution of output price, which appears in the risk preference function. Moreover, we allow heterogeneity in production technology. Parameters of production technology and risk preference function are jointly estimated using the system of equations derived from the first-order conditions of expected utility of profit maximization and the production function. The estimated parameters of the risk preference function are used to calculate absolute, relative, and downside risks for each producer. A panel data on salmon farming from Norway is used as an application.*

**Key words** Price uncertainty, risk preference function, joint estimation, expected utility, absolute risk aversion, downside risk aversion, Norwegian salmon.

## Introduction

The theoretical literature on the effect of risk associated with output price uncertainty on producers' decisions regarding input demand and output supply is well developed. There is, however, a paucity of models that are easy to estimate and yet flexible enough to accommodate the sufficiently general form of risk behavior of producers. Flexibility in risk behavior is important from an empirical point of view because risk preferences of producers affect estimates of input demand, output supply, technical change, total factor productivity growth, and returns to scale (Chambers 1983).

Since the risk preference function depends on the utility function, $u(\pi)$ ($\pi$ being profit), and the distribution of output prices, the choice of utility functions and distributions of output price that yield a closed form solution are severely limited. This paper proposes an alternative approach to derive the risk preference function. The derivation depends neither on a specific parametric form of the utility function nor any distribution of output price. It is based on a second order approximation of $u'(\pi)$ [instead of assuming a parametric form of $u'(\pi)$] and a specific probability distribution for the output price variable. The risk preference function can be made flexible enough to test different types of risk behavior (*e.g.*, increasing, constant, and decreasing absolute risk aversion). The model also allows one to test for asymmetry in the distribution of output price, which appears in the risk preference function. The main advantage of the approach proposed here is that all the parameters of the risk

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preference function are identified and estimated when a parametric form of the absolute risk aversion function is assumed.

In this paper, our focus is on estimation of the production technology and risk preference functions when farmers face output price uncertainty. For empirical application we use data on a panel of Norwegian salmon farmers to estimate and test several types of risk specifications. This particular application is interesting, since producers in the salmon industry are subject to considerable price risk. There are several sources of uncertainty in prices of farmed salmon. High volatility of salmon prices is due to uncertainty associated with both demand and supply. These sources are market driven as well as political. Supply of wild-caught Pacific salmon and supply of farmed salmon are examples of market-driven risk that contribute to price uncertainty. Political factors such as trade policy (*e.g.*, tariffs and price restrictions imposed by importing countries) and actions by private groups (*e.g.*, boycott of Norwegian salmon to protest Norwegian whaling, blockade of fishing trucks by protesting fisherman in some importing countries, *etc.*) have contributed to salmon price uncertainty in the past. In recent years, the European Union has imposed restrictions on the quantity of salmon Norway can export to the member countries. Productivity gain, reduction in input cost, public R&D investment, *etc.*, contributed to a decline in salmon prices (Asche 1997). The Norwegian Fish Farmers' Association (NFF), which represents most of the fish farms in Norway, has stated several times that risk reduction in fish farming is a high priority task (see NFF 1990, p. 10).[1]

We estimate the model using a parametric form of the production technology. The first-order conditions of expected utility maximization, which bring risk preferences into the analysis, are also used in estimation along with the production technology. These equations are estimated jointly thereby taking endogeneity of variable inputs into account. From the estimated risk preference function, one could obtain estimates of absolute, relative, and downside risk aversion functions for each producer. Empirical results show the presence of decreasing absolute risk aversion and symmetric distribution of output price in Norwegian salmon farming.

## Modeling Risk Preferences

We assume that the objective of firms is to maximize expected utility of anticipated profit, $u(\pi)$, where $u(\pi)$ is a continuous and differentiable function $\pi$. Anticipated profit, $\pi$, is defined as:

$$\pi = p^e y - w \cdot x - C_f, \tag{1}$$

where $p^e$ is anticipated price of output, $y$. Firm production technology is represented by $y = Af(x, z, t)$ in which $x$ and $z$ are variable and quasi-fixed input vectors, and $t$ is the time trend variable. Heterogeneity in the production technology is introduced through the firm-specific parameter $A$. The parameters in $f(.)$ are common to all firms. The vector of variable input price is $w$, and $C_f$ denotes cost of fixed/quasi-fixed inputs. Following Zellner, Kmenta, and Dreze 1966), we assume that $p^e = pe^n$, which implies that $E(p^e) = pE(e^n) = p$ when $E(e^n) = 1$ and $p$ is the observed output price. Variance of $e^n$ is assumed to be constant.

The first-order conditions of expected utility of profit maximization can be written as:

[1] Furthermore, a number of stochastic biophysical factors make the production process in salmon farming risky. Salmon farming is more risky than most other types of meat production due to the salmon's high susceptibility to the marine environment it is reared in. Kumbhakar and Tveterås (2001) addressed these issues in a paper in which production risk and risk preferences are modeled.

$$E\left[u'(\pi)\left\{Af_j(\cdot)p^e - w_j\right\}\right] = 0,$$

which can be expressed as:

$$Af_j(\cdot) = (w_j/p) \cdot \left[1/1(1+\theta)\right] \equiv w_j/p^s \,, \tag{2}$$

where $\theta = Cov\{u'(\pi), e^n/E[u'(\pi)]\}$is the risk preference function,[2] $p^s = p(1 + \theta)$, and $f_j(\cdot) = [\partial f(\cdot)/\partial x_j]$. If producers were risk neutral, θ would be zero. In such a case, maximization of expected utility of profit would be identical to maximization of expected profit.

## Derivation of the Risk Preference Function

Since we are interested in estimating the risk preference function, the most important task is to derive an algebraic form of θ that is easy to implement econometrically and imposes minimum restrictions on the structure of risk preferences of the individual producers. In general, the risk preference function, θ defined in equation (2), is a function of the parameters of the utility function, probability distribution of η, and data on inputs and output quantities. It is possible to derive an explicit form of θ if (*i*) some particular forms of $u(\cdot)$ are chosen and (*ii*) some specific distributions on η are assumed. Choices of (*i*) and (*ii*) are very much limited in practice.[3] Here we propose an alternative solution, which requires specification of neither any utility function (at least directly) nor any distributional assumption on η.

**Proposition 1:** If $u(\cdot)$ is continuous and differentiable, and $u'(\pi) = u'(\mu_\pi + \sigma_\pi z)$ is approximated by a second order polynomial around $z = 0$, then the risk preference function θ is:[4]

$$\theta = \frac{AR \cdot \beta^2 \cdot py + \frac{1}{2} DR \cdot \beta^3 \cdot \gamma \cdot (py)^2}{1 + \frac{1}{2} DR.\beta^2 \cdot (py)^2}. \tag{3}$$

In the above formulation, $\pi = pye^\eta - w \cdot x - C_f$ is rewritten as $\pi = \mu_\pi + \sigma_\pi \cdot z$, where the mean and standard deviation of profit are $\mu_\pi = \{py - w \cdot x - C_f\}$ and $\sigma_\pi = py.\beta$. The random variable $z = (e^n - 1)/\beta$ has a zero mean and unit variance where $\beta^2 = \text{var}(e^n)$. AR is the Arrow-Pratt measure of the absolute risk aversion coefficient [*i.e.*,

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[2] The first-order conditions in equation (2) are somewhat different from those derived and presented in Kumbhakar and Tveterås (2001). Although the risk preference function has the same interpretation, it's driven by production risk in Kumbhakar and Tveterås. Consequently, the effect of output price uncertainty and output risk on input demand is different. By comparing the two sets of first-order conditions, one can easily see this difference.

[3] Following Love and Buccola (1991), if one assumes $u(\cdot)$ to be exponential and η normally distributed, or $u(\cdot)$ expo-power and η follow the weibull distribution (Saha, Shumway, and Tolpaz 1994), it is possible to derive an analytical form for θ. Estimation is, however, a problem in both cases. The approach by Chavas and Holt 1996) does not require specification and estimation of θ directly. It does assume parametric utility and production functions. The method relies heavily on numerical methods, and therefore, estimation can be a real burden if one wants to try more than one form of utility and production functions.

[4] Kumbhakar and Tveterås (2001) derived a similar result based on a model that includes Just-Pope (1978) type production risk.

$AR = -u''(\pi)/u'(\pi)$], and DR is the downside risk aversion coefficient [*i.e.*, $DR = u'''(\pi)/u'(\pi)$]. Finally, $\gamma$ measures the skewness of $e^{\eta}$ [*i.e.*, $\gamma = E(z^3)$].

From an empirical point of view, the main advantage of the above result is that one needs to specify only the AR function to estimate $\theta$ [since $DR = (\partial AR/\partial \mu_{\pi}) + AR^2$]. Consequently, a wide variety of parametric forms for AR can be used without knowing the exact form of the underlying utility function. It is to be noted that all the parameters in $\theta$ can be identified, except when AR is a constant and $DR \approx 0$.

Several important features of $\theta$ and some special cases of interest are:

(*i*) $\gamma = 0$, which means that the distribution of output price is symmetric. Such a hypothesis can be empirically tested.

(*ii*) Constant absolute risk aversion (CARA), decreasing absolute risk aversion (DARA), and increasing absolute risk aversion (IARA) hypotheses can be tested by specifying an appropriate form of AR. For example, if $AR = c_0 + c_1\,\mu_{\pi}$ then $c_1 = 0$, positive, negative, will imply CARA, IARA, and DARA, respectively. Finally, if $c_1 = c_0 = 0$ then producers are risk neutral. Some other non-linear functional forms on AR can also be used to parameterize and test different forms of risk references. Although the AR function is linear, the risk preference function is highly non-linear.

(*iii*) Since $DR = (\partial AR/\partial \mu_{\pi}) + AR$ it is not necessary to specify any functional form on $DR$, and no additional parameters are involved in $DR$. If AR is firm-specific, so is $DR$.

(*iv*) Relative risk aversion function ($RR = AR.\mu_{\pi}$) is firm-specific with or without AR being firm-specific. (*v*) All the parameters in $\theta$ are identified, including $\beta$ and $\gamma$. This is also true even if $\gamma = 0$. When $DR$ is close to zero so that $\theta = -AR.\beta^2.py$ , then $\beta$ is not identified.

(*iv*) It is possible (*a*) to accommodate higher order terms in the approximation of $u'(\pi)$ around $z = 0$, and (*b*) specify a variety of functional forms for $AR$. Although a functional form on $AR$ indirectly implies some functional forms for the utility function, it is not necessary to have an analytical solution for the underlying utility function for every specification of $AR$.

If a firm is risk averse, then $\theta < 0$ , which, in turn, implies that the relevant output price is less than observed price (*i.e.*, $p^s < p$). Consequently, the presence of output price uncertainty reduces demand for inputs and supply of output for a risk adverse firm (Blair and Lusky 1975). More generally, it can be seen from equation (2) that input demand, and hence output supply, will depend on risk preferences, $\theta$, as well as firm-effects, $A$. Thus, if firm-effects are assumed to be random, input variables in the production function cannot be independent of the random firm components (in a one-way error component panel data model) of the production function. Consequently, the parameter estimates obtained from a single equation production function will be biased and inconsistent.

## Data

The model outlined in the previous section is estimated using panel data on 28 Norwegian salmon farms observed during 1985–92. Norway has long been the world leader in farmed salmon production (Bjørndal 1990; Asche 2001). Salmon farming is a relatively young industry. Small-scale salmon farming started in the 1970s, but

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[5] I am grateful to R. Tveterås for allowing use of some of his data presented in his doctoral dissertation. Details on the sample and construction of the variables used here can be found in Tveterås (1997).

most farms were established in the 1980s.

Since 1982, the Norwegian Directorate of Fisheries has compiled salmon farm production data. In the present study, we use a balanced panel of 28 such farms observed during 1985–92.[5] The output variable ($y$) is sales (in 1,000 kilograms) of salmon and the change in stock of fish (in 1,000 kilograms). The input variables are: feed, stock of fish, labor, and capital. Feed is a composite measure of salmon feed measured in thousand kilograms. Fish input is the stock of fish (measured in thousand kilograms) at the beginning of the year (January 1st). The stock of fish is measured as the total biomass of live fish in the pens on the first of January. Labor is total hours of work (in 1,000 hours). Capital is the replacement value (in real terms) of pens, buildings, feeding equipment, *etc.* Price of salmon is the market price of salmon per kilogram in real NOK. The wage rate (in real NOK) is obtained by dividing labor cost by hours of hired labor. Price of feed is similarly obtained by dividing expenditure on feed by the quantity. Summary statistics of these variables are given in table 1 by year. Production of salmon increased, while prices decreased during this period. Labor hours declined after attaining a peak in 1990. Real wages increased very little during this period. Capital use increased substantially up to 1990. It then declined in the last two years. The fish input figures show a decline in the last year. In the present study, we are treating labor and feed as variable inputs. Fish and capital are treated as quasi-fixed inputs ($z$), primarily because it is difficult to construct price data for fish stock and capital from the information in the data set.

## Estimation and Results

### *Model Specification and Estimation*

We assume that the production technology is represented by a Cobb-Douglas function, viz.,

$$\ln y = \ln A + \sum_{j}^{J} \alpha_j \ln x_j + \sum_{q}^{Q} \beta_q \ln z_q + \alpha_T t, \tag{4}$$

where $A = \exp(\mu)$, $\mu$ being fixed firm-effects (constant over time). Using the production function in equation (4), the first-order conditions of expected utility of profit maximization in equation (2) can be expressed as:

**Table 1**
Summary Values

| Year | Output | Labor | Feed | Fish | Capital | Price | Feed Price | Wage |
|---|---|---|---|---|---|---|---|---|
| 1985 | 195.634 | 7.770 | 201.277 | 82.146 | 2,231.900 | 60.553 | 15.610 | 108.188 |
| 1986 | 222.840 | 8.124 | 206.015 | 105.511 | 2,718.350 | 47.309 | 10.119 | 109.622 |
| 1987 | 251.491 | 7.835 | 242.425 | 100.151 | 3,023.600 | 47.765 | 9.974 | 115.200 |
| 1988 | 352.403 | 8.930 | 370.264 | 123.365 | 3,467.320 | 44.642 | 8.933 | 122.079 |
| 1989 | 470.981 | 9.175 | 459.975 | 197.841 | 4,007.350 | 35.872 | 10.486 | 128.556 |
| 1990 | 472.233 | 9.389 | 455.276 | 232.955 | 4,133.470 | 32.389 | 10.982 | 110.939 |
| 1991 | 457.234 | 8.226 | 390.690 | 216.216 | 3,731.270 | 29.460 | 9.731 | 122.180 |
| 1992 | 467.072 | 8.165 | 471.699 | 206.639 | 3,408.810 | 29.784 | 9.612 | 136.219 |
| Mean | 361.236 | 8.452 | 349.703 | 158.103 | 3,340.259 | 40.972 | 10.681 | 119.123 |
| Std. Dev. | 121.585 | 0.623 | 116.175 | 60.963 | 650.651 | 10.958 | 2.082 | 9.939 |

$$\ln y - \ln x_j = \ln(w_j / p) - \ln(1 + \theta) - \ln \alpha_j, \; j = 1, \ldots, J. \tag{5}$$

These equations can be used, in principle, to solve for ln $y$ and ln $x_j$. In equations (4) and (5), we have a system of ($J$ + 1) equations in ($J$ + 1) endogenous variables $y$, $x_1$, …, $x_j$). Since θ is a highly non-linear function of $y$ and $x$, analytical solutions of input demand and output supply functions are not possible, even for the Cobb-Douglas case. It is, however, clear that input demand and output supply will be reduced if $\theta < 0$.

It is worth noting here that the risk-preference function does not appear directly in the production function in equation (4). Thus, direct estimation (single equation technique) of the production function in equation (4) does not yield any information on risk-preference behavior of firms. In fact, direct estimation of the production function in equation (4) might be inappropriate, given that some of the inputs appearing on the right-hand side of the equation are endogenous.

Depending on the specification of $AR$, a variety of risk-preference behavior can be tested in the model outlined in equations (4) and (5). Here, we report results from five models. Each of these models consists of the production function in equation (4) and the first-order conditions in equation (5). Models 1-4 take risk into account, while Model 5 assumes that salmon farmers are risk neutral. In Model 1, we specify $AR$ as $AR = c_0 + c_1\mu_\pi$, and rewrite θ in equation (3) as:

$$\theta = \frac{AR \dfrac{1}{py} + \dfrac{1}{2} DR.h_2}{h_1 \dfrac{1}{(py)^2} + \dfrac{1}{2} DR},$$

where $DR = -c_1 + AR^2$, $h_1 = 1/\beta^2 = 1/\text{var}(e^\eta)$, $h_2 = \beta\gamma$. Symmetry in $e^\eta$ can be tested from $\gamma = 0 \Rightarrow h_2 = 0$. Risk neutrality can be tested from $c_0 = c_1 = 0$. Finally, CARA, DARA, and IARA hypotheses can be tested from $c_1 = 0, < 0$, and $> 0$, respectively.

Model 2 restricts $\gamma = 0$ thereby imposing symmetry restrictions on the distribution of output price. On the other hand, Model 3 assumes CARA, but allows γ to be non-zero. Finally, Model 4 assumes $\gamma = 0$ as well as $AR$ constant (CARA). Consequently, Model 4 is a special case of Models 2 and 1. Since Models 2-4 are nested in Model 1, we use the likelihood ratio (LR) test to select the best model. Finally, Model 5 assumes farmers to be risk neutral. Thus, Model 5 becomes a special case of Models 1-4.

To estimate Models 1-5, we append error terms to the production function and each of the $J$ first-order conditions. The error term in the production function specified in equation (4) is assumed to have zero mean and constant variance, while those in the first-order conditions [given in equation (5)] are allowed to have non-zero mean (varying across farms) but constant variances.[6] The error terms in equations (4) and (5) are, however, freely correlated among themselves. Since the equations in equations (4) and (5) constitute a simultaneous equation system in which the output and some inputs are endogenous, we used a system approach to estimate each of the models. Each model is estimated using both nonlinear iterative 3SLS and the FIML methods. The FIML results are not much different from the 3SLS results. We report the FIML results in table 2.

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[6] The hypothesis that the error vector in equation (5) has zero mean for all farms is accepted in each model by the likelihood ratio test at the 5% level of significance.

### *Results*

In table 2, we first report the production function parameters (input coefficients) followed by the parameters of the risk preference function. Estimates of input coefficients (elasticities) in Models 1-4 are quite similar. However, these coefficients are somewhat different from those in Model 5, which is estimated based on the assumption that the farmers are risk neutral. Thus, Model 5 ignores the risk terms in equation (5) — the first order conditions. The labor and feed coefficients in Model 5 are lower compared to those from Models 1-4. On the other hand, the capital coefficient in Model 5 is too big compared to those in Models 1-4. The coefficient on the time trend variable (which is interpreted as exogenous technical change) is found to be almost identical in all five models.

Since we used a Cobb-Douglas production function in all models, returns to scale (RTS) results are constant over time and across farms. RTS estimates are quite stable across Models 1-5 (0.806, 0.826, 0.824, 0.825, and 0.816, respectively). Thus, we find evidence of decreasing returns to scale in salmon farming from all five models.

We now examine the parameters of the risk preference function θ. These parameters are: $c_0$ and $c_1$ in the AR function (in Models 1 and 2) and β, and γ (in Models 1 and 3). In Model 1, all of these parameters are significant at the 1% level of significance, except γ. Although the distribution of output price is found to be positively skewed, the hypothesis that $\gamma = 0$ (meaning the distribution of output price is symmetric) is accepted at the 5% level of significance using the asymptotic t and LR tests. Both the $c_0$ and $c_1$ coefficients are significantly different from zero at the 1*u*″% level of significance. Since $c_1 < 0$ and statistically significant, we find evidence in support of DARA hypothesis. In Model 2, we restrict $\gamma = 0$. Both the $c_0$ and $c_1$ coefficients are significantly different from zero at the 1% level of significance. Furthermore, $c_1 < 0$ and is statistically significant. This result supports the DARA hypothesis as well. Model 3 assumes constant absolute risk aversion (*i.e.*, $c_1 = 0$), but allows asymmetry in the distribution of output price (*i.e.*, $\gamma \neq 0$). The γ coefficient is found to be positive, but not significantly different from zero at the 5% level of significance. However, the LR test ($c_1 = 0$) rejects Model 3 when tested against Model 1. Finally, in Model 4 we use a CARA specification with $\gamma = 0$. The LR test accepts $\gamma = 0$ when comparing between Models 3 and 4. Thus in Model 4, the CARA hypothesis is rejected but the symmetry hypothesis ($\gamma = 0$) is not. Finally, Model 5 assumes risk-neutrality, which is rejected by the LR test against Models 1-4 at the 1% level of significance. In view of these results, we find Model 2 to be the preferred model.

**Table 2**
Parameter Estimates

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Parameter | Estimate | t-value | Estimate | t-value | Estimate | t-value | Estimate | t-value | Estimate | t-value |
| $\alpha_L$ | 0.082 | 7.589 | 0.087 | 10.141 | 0.082 | 7.515 | 0.082 | 9.739 | 0.063 | 11.302 |
| $\beta_K$ | 0.075 | 2.800 | 0.069 | 2.795 | 0.084 | 3.170 | 0.083 | 3.350 | 0.123 | 3.705 |
| $\beta_F$ | 0.333 | 8.170 | 0.356 | 16.068 | 0.332 | 8.103 | 0.333 | 14.257 | 0.242 | 21.825 |
| $\beta_{FS}$ | 0.315 | 15.717 | 0.313 | 16.398 | 0.326 | 16.380 | 0.326 | 16.955 | 0.388 | 19.061 |
| RTS | 0.806 | 10.203 | 0.826 | 13.152 | 0.824 | 12.671 | 0.825 | 13.047 | 0.816 | 15.096 |
| $\alpha_T$ | 0.052 | 9.402 | 0.051 | 10.299 | 0.051 | 9.236 | 0.051 | 10.083 | 0.053 | 7.624 |
| $c_0$ | 4.481 | 2.557 | 5.920 | 6.096 | 5.6033 | 1.990 | 5.715 | 4.567 | — | — |
| $c_1$ | –1.392 | –2.141 | –1.842 | –3.722 | — | — | — | — | — | — |
| $\beta^2$ | 0.848 | 2.869 | 0.704 | 4.026 | 0.452 | 2.399 | 0.448 | 3.384 | — | — |
| γ | 0.159 | 0.743 | — | — | 0.011 | 0.036 | — | — | — | — |

The estimated values of the risk preference function, θ, are found to be negative in all four models at every data point. This means that all salmon farmers are risk averse. However, the degree of risk-aversion (magnitude of θ) varies among farms, as well as over time. Instead of reporting the θ values, we report the absolute, relative risk, and downside risk aversion for each farm (whenever applicable).

Although we find Model 2 to be the preferred model, we report different measures of risk aversion for all five models to check robustness of results due to model misspecification. We report predicted values of the AR function by farm in table 3. These are the mean values (over time) of AR. The AR values are all positive, thereby indicating that all farms are risk averse. The larger values of AR imply stronger aversion to risk. It can be seen from the table that in each model the AR values are not much different among farms. Part of the reason is that these values are the mean values of AR (over time) for each farm. The minimum and maximum values of the AR function are 0.30 and 6.42 (in Model 1) and 0.39 and 8.47 (in Model 2). The overall mean values of AR in Models 1 and 2 are 3.22 and 4.25, respectively. Thus, there are substantial variations in the degree of salmon producers' attitudes towards risk aversion.

Predicted values of the relative risk aversion (RR) function are reported by farm in table 4. Again, a positive value of RR indicates risk aversion, and larger values of

**Table 3**

Predicted Values of Absolute Risk Aversion (AR) Function by Farm

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| No. | AR | t-value | AR | t-value |
| Farm 1 | 3.25 | 13.74 | 4.29 | 13.72 |
| Farm 2 | 3.25 | 13.73 | 4.28 | 13.71 |
| Farm 3 | 3.53 | 14.91 | 4.65 | 14.89 |
| Farm 4 | 2.57 | 10.85 | 3.38 | 10.83 |
| Farm 5 | 2.39 | 10.09 | 3.15 | 10.07 |
| Farm 6 | 3.15 | 13.33 | 4.16 | 13.31 |
| Farm 7 | 3.49 | 14.75 | 4.6 | 14.73 |
| Farm 8 | 3.54 | 14.96 | 4.67 | 14.94 |
| Farm 9 | 2.69 | 11.39 | 3.55 | 11.37 |
| Farm 10 | 2.75 | 11.61 | 3.62 | 11.59 |
| Farm 11 | 3.14 | 13.27 | 4.14 | 13.25 |
| Farm 12 | 3.32 | 14.06 | 4.39 | 14.04 |
| Farm 13 | 3.17 | 13.41 | 4.18 | 13.39 |
| Farm 14 | 3.64 | 15.38 | 4.8 | 15.36 |
| Farm 15 | 3.02 | 12.77 | 3.98 | 12.75 |
| Farm 16 | 3.51 | 14.85 | 4.63 | 14.83 |
| Farm 17 | 3.67 | 15.52 | 4.84 | 15.5 |
| Farm 18 | 3.44 | 14.54 | 4.54 | 14.52 |
| Farm 19 | 3.62 | 15.31 | 4.78 | 15.29 |
| Farm 20 | 2.79 | 11.78 | 3.67 | 11.76 |
| Farm 21 | 3.69 | 15.61 | 4.87 | 15.59 |
| Farm 22 | 2.98 | 12.58 | 3.92 | 12.56 |
| Farm 23 | 2.88 | 12.19 | 3.8 | 12.17 |
| Farm 24 | 3.65 | 15.45 | 4.82 | 15.43 |
| Farm 25 | 2.97 | 12.56 | 3.92 | 12.54 |
| Farm 26 | 3.43 | 14.49 | 4.52 | 14.47 |
| Farm 27 | 3.62 | 15.29 | 4.77 | 15.27 |
| Farm 28 | 3.06 | 12.93 | 4.03 | 12.91 |
| Mean | 3.22 | | 4.25 | |

RR imply a stronger degree of risk aversion. The main difference between the RR and the AR measure is in the scale. Another difference between the AR and the RR values is that the RR values are both farm- and time-specific, even if the AR values are firm- and time-invariant. The RR measure might be preferred because it is a unit-free measure. Similar to the AR measure, we do not see much difference in the RR values among farms, primarily because these values are mean (over time) for each farm. The mean values of RR for the entire sample in Models 1-4 are: 2.55, 3.36, 5.08, and 5.19, respectively.

Predicted values of the downside risk aversion (DR) function corresponding to Models 1 and 2 are reported in table 5. Producers are averse to downside risk if they " ... generally avoid situations which offer the potential for substantial gains but which also leave them even slightly vulnerable to losses below some critical level" (Menezes, Geiss, and Tressler 1980, p. 921). Alternatively, when there is a choice between two profit distributions with the same mean and variance, they will prefer the profit distribution that is less skewed to the left. Thus, a positive value of DR would indicate that individual producers are averse to downside risk. In both models, the DR values are found to be positive and statistically significant. A positive value of DR indicates averse to downside risk. This result is expected, since we find

**Table 4**
Predicted Values of Relative Risk Aversion (RR) Function by Farm

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| No. | RR | t-value | RR | t-value | RR | t-value | RR | t-value |
| Farm 1 | 2.45 | 5.90 | 3.23 | 5.89 | 4.97 | 5.23 | 5.07 | 5.23 |
| Farm 2 | 2.51 | 6.03 | 3.31 | 6.03 | 4.98 | 5.24 | 5.08 | 5.24 |
| Farm 3 | 2.08 | 5.01 | 2.75 | 5.01 | 3.86 | 4.06 | 3.94 | 4.06 |
| Farm 4 | 3.25 | 7.83 | 4.29 | 7.82 | 7.71 | 8.12 | 7.87 | 8.12 |
| Farm 5 | 2.34 | 5.64 | 3.08 | 5.63 | 8.44 | 8.88 | 8.60 | 8.88 |
| Farm 6 | 2.92 | 7.02 | 3.85 | 7.02 | 5.36 | 5.64 | 5.47 | 5.64 |
| Farm 7 | 1.44 | 3.45 | 1.89 | 3.45 | 4.01 | 4.22 | 4.09 | 4.22 |
| Farm 8 | 2.39 | 5.74 | 3.15 | 5.74 | 3.81 | 4.01 | 3.88 | 4.01 |
| Farm 9 | 3.32 | 8.00 | 4.38 | 7.99 | 7.20 | 7.58 | 7.35 | 7.58 |
| Farm 10 | 2.82 | 6.78 | 3.71 | 6.77 | 6.99 | 7.36 | 7.13 | 7.36 |
| Farm 11 | 2.93 | 7.05 | 3.86 | 7.05 | 5.41 | 5.70 | 5.52 | 5.70 |
| Farm 12 | 2.56 | 6.17 | 3.38 | 6.17 | 4.67 | 4.91 | 4.76 | 4.91 |
| Farm 13 | 2.91 | 6.99 | 3.83 | 6.99 | 5.28 | 5.56 | 5.39 | 5.56 |
| Farm 14 | 2.13 | 5.12 | 2.81 | 5.12 | 3.41 | 3.59 | 3.48 | 3.59 |
| Farm 15 | 2.98 | 7.18 | 3.93 | 7.17 | 5.89 | 6.20 | 6.01 | 6.20 |
| Farm 16 | 2.28 | 5.49 | 3.01 | 5.49 | 3.91 | 4.12 | 3.99 | 4.12 |
| Farm 17 | 2.10 | 5.06 | 2.78 | 5.06 | 3.28 | 3.45 | 3.35 | 3.45 |
| Farm 18 | 2.48 | 5.97 | 3.27 | 5.97 | 4.21 | 4.43 | 4.29 | 4.43 |
| Farm 19 | 2.10 | 5.05 | 2.77 | 5.05 | 3.47 | 3.66 | 3.54 | 3.66 |
| Farm 20 | 3.35 | 8.05 | 4.41 | 8.05 | 6.84 | 7.19 | 6.97 | 7.19 |
| Farm 21 | 1.97 | 4.73 | 2.59 | 4.73 | 3.19 | 3.36 | 3.25 | 3.36 |
| Farm 22 | 3.05 | 7.35 | 4.03 | 7.35 | 6.07 | 6.39 | 6.19 | 6.39 |
| Farm 23 | 2.30 | 5.53 | 3.03 | 5.52 | 6.44 | 6.78 | 6.57 | 6.78 |
| Farm 24 | 2.10 | 5.06 | 2.77 | 5.06 | 3.35 | 3.52 | 3.41 | 3.52 |
| Farm 25 | 3.04 | 7.31 | 4.00 | 7.30 | 6.09 | 6.41 | 6.21 | 6.41 |
| Farm 26 | 2.38 | 5.73 | 3.14 | 5.73 | 4.26 | 4.48 | 4.34 | 4.48 |
| Farm 27 | 2.13 | 5.13 | 2.81 | 5.13 | 3.50 | 3.68 | 3.57 | 3.68 |
| Farm 28 | 3.02 | 7.27 | 3.98 | 7.27 | 5.74 | 6.04 | 5.85 | 6.04 |
| Mean | 2.55 | | 3.36 | | 5.08 | | 5.19 | |

**Table 5**
Predicted Values of DR Coefficients by Farm

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| No. | DR | t-value | DR | t-value |
| Farm 1 | 12.56 | 8.27 | 21.26 | 8.04 |
| Farm 2 | 12.47 | 8.21 | 21.10 | 7.98 |
| Farm 3 | 14.31 | 9.43 | 24.32 | 9.19 |
| Farm 4 | 8.37 | 5.51 | 13.97 | 5.28 |
| Farm 5 | 8.84 | 5.82 | 14.79 | 5.59 |
| Farm 6 | 11.47 | 7.55 | 19.36 | 7.32 |
| Farm 7 | 15.05 | 9.91 | 25.61 | 9.68 |
| Farm 8 | 13.95 | 9.19 | 23.68 | 8.95 |
| Farm 9 | 8.85 | 5.83 | 14.80 | 5.59 |
| Farm 10 | 9.79 | 6.45 | 16.44 | 6.21 |
| Farm 11 | 11.39 | 7.50 | 19.23 | 7.27 |
| Farm 12 | 12.74 | 8.39 | 21.57 | 8.16 |
| Farm 13 | 11.57 | 7.62 | 19.54 | 7.39 |
| Farm 14 | 14.75 | 9.72 | 25.09 | 9.48 |
| Farm 15 | 10.79 | 7.10 | 18.17 | 6.87 |
| Farm 16 | 13.98 | 9.20 | 23.73 | 8.97 |
| Farm 17 | 14.93 | 9.83 | 25.39 | 9.60 |
| Farm 18 | 13.36 | 8.80 | 22.67 | 8.57 |
| Farm 19 | 14.72 | 9.69 | 25.03 | 9.46 |
| Farm 20 | 9.22 | 6.07 | 15.46 | 5.84 |
| Farm 21 | 15.22 | 10.03 | 25.90 | 9.79 |
| Farm 22 | 10.48 | 6.90 | 17.65 | 6.67 |
| Farm 23 | 11.13 | 7.33 | 18.77 | 7.10 |
| Farm 24 | 14.86 | 9.78 | 25.27 | 9.55 |
| Farm 25 | 10.49 | 6.91 | 17.66 | 6.67 |
| Farm 26 | 13.45 | 8.86 | 22.82 | 8.63 |
| Farm 27 | 14.65 | 9.65 | 24.90 | 9.41 |
| Farm 28 | 10.91 | 7.18 | 18.39 | 6.95 |
| Mean | 12.30 | | 20.81 | |

evidence in support of DARA hypothesis that implies $u'''(\cdot) > 0$, thereby indicating that producers are averse to downside risk (Pratt 1964). The magnitude of DR values differs among farms within and between models. The DR values in Model 2 (the preferred model) are much higher compared to those in Model 1. The overall mean of DR values in Models 1 and 2 are 12.30 and 20.81, respectively.

Farm-effects often reflect differences in either managerial ability (Mundlak 1961) or technical efficiency (Schmidt and Sickles 1984) among farms. Some unmeasured fixed effects can also explain the inter-farm productivity differential. These effects might contribute to heterogeneity in farm production technology. We report the farm-effects in Appendix A. Although the magnitude of these farm-effects is quite similar, the hypothesis that there is no farm-heterogeneity ($\mu_i = \mu, \forall i$) is rejected at the 5% level of significance. Farm-effects are found to be almost identical in Models 3 and 4. To the extent these farm-effects reflect technical efficiency, one can, following Schmidt and Sickles (1984), calculate relative efficiency of these farms (treating the best farm 100% efficient). These relative efficiencies are reported in Appendix B. The mean efficiency levels are in the range of 80% (Model 5) to 86% (Models 1-2). The same farm (No. 5) is identified as the best in every model. This is also true for the worst farm (No. 27). Correlation coefficients of efficiency rankings among models (in pairs) are found to be very high (the minimum being 0.96 and the maximum 0.99).

## Summary and Conclusions

This paper introduces a new approach to derive the risk preference function in the presence of output price uncertainty. The distinguishing feature of the present approach is that we do not use any parametric form of the utility function, yet the model is quite flexible in accommodating different types of risk behavior. All the parameters of the risk preference function are identified and estimated when a parametric form of the absolute risk aversion (AR) function is assumed. Although an assumption on the form of the AR function implies some underlying utility function, the main advantage of the approach used in the paper is that one does not have to specify a parametric form of AR function for which there is an explicit analytical form of the underlying utility function. Consequently, a variety of functional forms for risk preferences can be estimated and tested. From the estimated risk preference function, one can easily obtain predicted values of absolute, relative, and downside risk aversion functions.

In estimating the risk preference function, we take into account heterogeneity in production technology and use a system of equations consisting of the production function and the first-order conditions of expected utility of profit. Thus, endogeneity of the variable inputs is explicitly taken into account. The resulting system of equations, mainly those derived from the first-order conditions of expected utility of profit maximization, is nonlinear and can be estimated either using the 3SLS or FIML technique. The model is estimated using a panel of 28 Norwegian salmon farms observed during 1985–92. Four separate variants of the risk preference function with a different specification of AR functions (Models 1-4) are considered. We find that all salmon farms are risk averse. Furthermore, we find that farmers' risk preferences exhibit decreasing absolute risk aversion. The hypothesis of risk neutrality is rejected by the data in all four models. All three risk aversion measures (absolute, relative, and downside) are found to vary substantially among farms. We also find evidence of farm heterogeneity in the production technology. Farm-efficiency rankings across different models are found to be highly correlated. This result might be used to assert that the estimates of risk aversion functions are not driven by the choice of a particular form of the production function.

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## Appendix A

Estimates of Farm Effects

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| No. | Effects | t-value | Effects | t-value | Effects | t-value | Effects | t-value | Effects | t-value |
| Farm 1 | 2.69 | 5.32 | 2.48 | 6.20 | 2.45 | 5.04 | 2.44 | 6.20 | 2.44 | 5.05 |
| Farm 2 | 2.75 | 5.59 | 2.54 | 6.63 | 2.51 | 5.29 | 2.50 | 6.61 | 2.52 | 5.48 |
| Farm 3 | 2.70 | 5.59 | 2.50 | 6.63 | 2.47 | 5.30 | 2.46 | 6.64 | 2.48 | 5.51 |
| Farm 4 | 2.74 | 5.43 | 2.53 | 6.32 | 2.50 | 5.15 | 2.49 | 6.32 | 2.52 | 5.25 |
| Farm 5 | 2.81 | 5.34 | 2.60 | 6.21 | 2.58 | 5.08 | 2.57 | 6.24 | 2.63 | 5.20 |
| Farm 6 | 2.78 | 5.52 | 2.57 | 6.60 | 2.55 | 5.26 | 2.54 | 6.64 | 2.60 | 5.63 |
| Farm 7 | 2.61 | 5.13 | 2.41 | 5.90 | 2.37 | 4.84 | 2.37 | 5.89 | 2.34 | 4.74 |
| Farm 8 | 2.63 | 5.35 | 2.43 | 6.25 | 2.40 | 5.06 | 2.39 | 6.26 | 2.36 | 5.00 |
| Farm 9 | 2.59 | 5.07 | 2.39 | 5.87 | 2.35 | 4.77 | 2.35 | 5.85 | 2.37 | 4.82 |
| Farm 10 | 2.68 | 5.33 | 2.47 | 6.25 | 2.45 | 5.04 | 2.44 | 6.25 | 2.47 | 5.15 |
| Farm 11 | 2.62 | 5.37 | 2.42 | 6.25 | 2.39 | 5.07 | 2.38 | 6.23 | 2.35 | 4.97 |
| Farm 12 | 2.60 | 5.25 | 2.39 | 6.09 | 2.36 | 4.95 | 2.35 | 6.10 | 2.33 | 4.86 |
| Farm 13 | 2.62 | 5.19 | 2.42 | 6.07 | 2.39 | 4.90 | 2.38 | 6.09 | 2.40 | 5.01 |
| Farm 14 | 2.57 | 5.20 | 2.36 | 6.15 | 2.33 | 4.89 | 2.32 | 6.15 | 2.31 | 4.92 |
| Farm 15 | 2.60 | 5.19 | 2.40 | 6.09 | 2.37 | 4.88 | 2.36 | 6.06 | 2.36 | 4.94 |
| Farm 16 | 2.64 | 5.50 | 2.44 | 6.52 | 2.40 | 5.19 | 2.39 | 6.52 | 2.37 | 5.21 |
| Farm 17 | 2.67 | 5.66 | 2.46 | 6.79 | 2.44 | 5.37 | 2.43 | 6.80 | 2.42 | 5.58 |
| Farm 18 | 2.56 | 5.16 | 2.36 | 5.95 | 2.32 | 4.86 | 2.31 | 5.93 | 2.28 | 4.67 |
| Farm 19 | 2.61 | 5.24 | 2.40 | 6.13 | 2.38 | 4.96 | 2.37 | 6.17 | 2.37 | 5.00 |
| Farm 20 | 2.68 | 5.41 | 2.48 | 6.33 | 2.44 | 5.12 | 2.43 | 6.32 | 2.45 | 5.19 |
| Farm 21 | 2.74 | 5.70 | 2.54 | 6.83 | 2.50 | 5.40 | 2.49 | 6.82 | 2.46 | 5.51 |
| Farm 22 | 2.63 | 5.18 | 2.42 | 6.06 | 2.40 | 4.91 | 2.39 | 6.05 | 2.41 | 5.03 |
| Farm 23 | 2.67 | 5.22 | 2.46 | 6.02 | 2.43 | 4.93 | 2.42 | 5.96 | 2.44 | 4.93 |
| Farm 24 | 2.67 | 5.39 | 2.46 | 6.36 | 2.44 | 5.07 | 2.43 | 6.31 | 2.41 | 5.00 |
| Farm 25 | 2.64 | 5.27 | 2.44 | 6.11 | 2.40 | 4.99 | 2.39 | 6.10 | 2.37 | 4.91 |
| Farm 26 | 2.64 | 5.42 | 2.43 | 6.31 | 2.40 | 5.18 | 2.39 | 6.42 | 2.39 | 5.28 |
| Farm 27 | 2.47 | 4.97 | 2.27 | 5.73 | 2.23 | 4.65 | 2.22 | 5.70 | 2.14 | 4.42 |
| Farm 28 | 2.62 | 5.09 | 2.41 | 5.95 | 2.38 | 4.81 | 2.37 | 5.96 | 2.40 | 4.91 |
| Mean | 2.65 | | 2.45 | | 2.41 | | 2.41 | | 2.41 | |

**Appendix B**

Estimates of Relative Efficiency

| No. | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Farm 1 | 0.89 | 0.89 | 0.88 | 0.88 | 0.83 |
| Farm 2 | 0.94 | 0.94 | 0.93 | 0.93 | 0.90 |
| Farm 3 | 0.90 | 0.90 | 0.90 | 0.90 | 0.86 |
| Farm 4 | 0.93 | 0.93 | 0.92 | 0.92 | 0.90 |
| Farm 5 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Farm 6 | 0.97 | 0.97 | 0.97 | 0.97 | 0.97 |
| Farm 7 | 0.82 | 0.83 | 0.81 | 0.82 | 0.75 |
| Farm 8 | 0.84 | 0.84 | 0.84 | 0.84 | 0.76 |
| Farm 9 | 0.80 | 0.81 | 0.79 | 0.80 | 0.77 |
| Farm 10 | 0.88 | 0.88 | 0.88 | 0.88 | 0.85 |
| Farm 11 | 0.83 | 0.84 | 0.83 | 0.83 | 0.76 |
| Farm 12 | 0.81 | 0.81 | 0.80 | 0.80 | 0.74 |
| Farm 13 | 0.83 | 0.84 | 0.83 | 0.83 | 0.79 |
| Farm 14 | 0.79 | 0.79 | 0.78 | 0.78 | 0.73 |
| Farm 15 | 0.81 | 0.82 | 0.81 | 0.81 | 0.76 |
| Farm 16 | 0.84 | 0.85 | 0.84 | 0.84 | 0.77 |
| Farm 17 | 0.87 | 0.87 | 0.87 | 0.87 | 0.81 |
| Farm 18 | 0.78 | 0.79 | 0.77 | 0.77 | 0.70 |
| Farm 19 | 0.82 | 0.82 | 0.82 | 0.82 | 0.77 |
| Farm 20 | 0.88 | 0.89 | 0.87 | 0.87 | 0.84 |
| Farm 21 | 0.93 | 0.94 | 0.92 | 0.92 | 0.84 |
| Farm 22 | 0.84 | 0.84 | 0.84 | 0.84 | 0.80 |
| Farm 23 | 0.87 | 0.87 | 0.86 | 0.86 | 0.83 |
| Farm 24 | 0.87 | 0.87 | 0.87 | 0.87 | 0.80 |
| Farm 25 | 0.84 | 0.85 | 0.84 | 0.84 | 0.77 |
| Farm 26 | 0.84 | 0.84 | 0.84 | 0.84 | 0.79 |
| Farm 27 | 0.71 | 0.72 | 0.70 | 0.70 | 0.61 |
| Farm 28 | 0.83 | 0.83 | 0.82 | 0.82 | 0.79 |
| Mean | 0.86 | 0.86 | 0.85 | 0.85 | 0.80 |