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DETERMINANTS OF INEFFICIENCY IN NORWEGIAN SALMON AQUACULTURE

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□ *This article builds on the literature investigating productivity and efficiency in the Norwegian salmon farming industry. The objective of this article is to investigate the determinants of inefficiency. We use a stochastic frontier approach that allows the estimation of a production function and an inefficiency function. The sources of inefficiency can be separated into temporary shocks and factors that lead to permanent efficiency differences. The results indicate an improvement in technical efficiency over time. This improvement can partly be explained by a restructuring of the industry, with firms becoming bigger and more specialized, as well as by improvements in government regulations. The inefficiency that is still present is mainly the result of temporary shocks. Disease outbreaks seem to be the most important of these temporary shocks, as disease problems lead to early harvesting or destruction of the fish and thereby, obviously, increase inefficiency.*

Keywords efficiency, Norway, Salmon farming, stochastic frontier approach

INTRODUCTION

Aquaculture is the world's fastest growing food production technology (Food and Agricultural Organization [FAO], 2010). The key drivers for this development are the innovations and productivity growth enabled by increased control with the production process (Asche, 2008). Salmon has been one of the most successful aquaculture species in terms of production growth, with production growth of 16% per year since 1985. Furthermore, as salmon is increasing its share of total aquaculture production, productivity growth for salmon is more rapid than for aquaculture in general. Norway is the largest salmon-producing country in the world, with a production share of over 50%. Atlantic salmon is the dominant species in Norway, but salmon trout is also produced.[1]

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Commercialized salmon farming in Norway commenced in the mid-1970s and, in many ways, the industry can still be characterized as an immature industry. The first salmon producers were mainly small-scale farmers producing a relatively limited quantity of fish. During the last 30 years, the industry has grown substantially, and more than 1 million tons of salmon and salmon trout was produced in 2011. Several articles have documented the productivity growth and the subsequent reduction of cost and output prices that have been the main driver for this growth (Asche & Tveteras, 1999; Tveteras, 1999; Guttormsen, 2002; Kumbhakar, 2002; Tveteras & Heshmati, 2002; Tveteras & Batteese, 2006; Andersen et al., 2008; Asche, 2008; Asche, Roll & Tveteras, 2009; Vassdal & Holst, 2011).[2] Also of relevance are the results of Nilsen (2010), who investigates the capital vintage and learning-by-doing hypothesis and finds evidence of learning by doing, implying different productivity levels for different firms. The focus of most of these studies is productivity growth and technical change and, with the exception of Tveteras and Batteese (2006), Asche, Roll and Tveteras (2009) and Roll (2013), none of these studies investigates technical inefficiency. Roll (2013) investigates technical inefficiency on a regional basis and provides evidence of regional differences.

In this article, we use a stochastic frontier approach to investigate not only technical inefficiency, but also the determinants of the inefficiency.[3] Several factors can influence the efficiency of Norwegian salmon farms. Some of the factors are likely to be one-off events, some factors change slowly over time, while other factors will maintain differences in efficiency over time. Examples of factors that occur from time to time that can have serious consequences for the efficiency of a farm are disease outbreaks and escapes (Tveteras, 2002; Torrissen et al., 2011). Both these issues create major problems for the farms in the years in which they occur. Asche (1997) shows that diseases can have a direct impact on production cost and one would expect that a significant loss of fish due to escapes also reduces productivity.

A more slowly changing factor that is also expected to influence efficiency is the gradual restructuring of the industry. To stay competitive, it is important for farmers to keep pace with technological developments and not fall behind. During the last two decades, there has been a major restructuring of the industry. Although previously the industry was made up of many small owner-operated farms, consolidation has created fewer and larger companies (Kvaløy & Tveteras, 2008; Olson & Criddle, 2008).

Over the years, Norwegian salmon farms have also become more and more specialized. Economic theory indicates that specialization in production can lead to higher efficiency if there are cost anti-complementarities (Squires, 1987). The age of the farm is also hypothesized to influence efficiency, but the direction of the effect is not clear. The frequent innovations in the salmon industry may be advantageous for young farms that use the newest technology but, on the other hand, these farms may lack the experience that older farms often have (Nilsen, 2010). Development of technical efficiency over time can also be influenced by the regulatory environment, which is often a key factor in the development of salmon aquaculture (Bjørndal & Salvanes, 1995; Chu et al., 2010).

Another factor that can influence technical efficiency is the market conditions for salmon. For instance, if firms increase production in response to high prices, this can reduce technical efficiency as the farm moves along the marginal cost schedule. Oglend and Sikveland (2008) and Solibakke (2012) provide evidence of highly volatile salmon prices, while Andersen et al. (2008) and Aasheim et al. (2011) indicate that short-run supply is highly inelastic and Larsen and Asche (2011) show how contracts contribute to this development.[4]

Understanding the drivers of productivity growth and inefficiency is important for several reasons. First, it is central to further development of the salmon aquaculture industry. This is particularly important because there is evidence that productivity growth is slowing (Vassdal & Holst, 2011), and that demand growth is now as high as productivity growth (Asche et al., 2011). It can also be important to reduce environmental externalities (Asche et al., 2009).[5] Second, understanding the driving forces behind the successful development of the salmon industry provides important knowledge relevant to new and upcoming species. Although conditions will vary in the production of other species, some of the knowledge and experience acquired in developing the successful salmon industry might be transferred to other species. Sharma and Leung (2003) provide a review and find evidence of the importance of productivity growth for a range of species. Recent examples of productivity studies relating to shrimp are Gordon et al. (2008) and Gordon and Bjørndal (2009), along with studies by Binh et al. (2010) on pangasius and Gillespie et al. (2012) on crawfish.

The article is organized as follows: next we present a theoretical approach, followed by an empirical specification section and a discussion of the data and the variables for the expected effect on efficiency. Results and some concluding remarks are provided in the final section.

THEORY

The methodological starting point to investigate the technical inefficiency in Norwegian salmon farming is the stochastic frontier production function model of Aigner et al. (1977). The approach assumes that, at a given point in time, there exists a production frontier, which represents the means of best-practice production, given the existing technology and input levels. The frontier is specified as:

$$\ln y_i^* = f(x_i; \beta) + v_i, \tag{1}$$

where $\ln y_i^*$ represents this stochastic frontier for observation i, $f(x_i;\beta)$ is the technology, x_i is a vector of input variables and β is the corresponding coefficient vector. The zero-mean stochastic noise is represented by v_i. This frontier gives the fully efficient level of output, or the best-practice production.

Efficiency is introduced into the model by constructing a new composite error term, where efficiency estimates are identified separately from the usual white-noise stochastic terms. The stochastic production frontier with output-oriented inefficiency is specified as:

$$\ln y_i = f(x_i;\beta) + \varepsilon_i \tag{2}$$

$$\varepsilon_i = v_i - u_i, \tag{3}$$

where ε_i is the composed error term, which consists of v, the zero-mean random error, and u, denoting the effect of production inefficiency. u_i is bounded between 0 and 1, where a value of 1 implies fully efficient production, whereas a value below 1 implies inefficiency. As $u_i \geq 0$, the observed output, ($\ln y_i$), is bounded below the production frontier ($\ln y_i^*$).

The two random variables are identified by imposing a parametrical distribution function on v_i and u_i. v_i is assumed to follow a zero-mean normal distribution, whereas u_i must follow a nonnegative distribution. Half-normal, exponential, truncated normal and gamma distributions are all used in the literature. Following Aigner et al. (1977) and Meeusen and van den Broeck (1977), in this article we assume u_i follows a half-normal distribution [$u_i \sim N^+(0, \sigma^2)$]. We also assume that v_i and u_i are independently distributed. Although a half-normal distribution lacks the flexibility of some of the other distributions, an advantage is that it has only a single parameter and is therefore relatively easy to estimate.

To find the determinants of technical inefficiency, u_i can also be a function of exogenous variables (Battese & Coelli, 1995). As u_i is supposed to follow a half-normal distribution, (i.e., $\mathrm{u_i} \sim N^+(0, \sigma^2)$), σ^2 is the only parameter to be parameterized, and the heteroskedasticity problem of u_i can be translated to indicate the determinants of inefficiency. The parameterization is formally stated as:

$$\sigma_i^2 = \exp(z_i; w), \tag{4}$$

where z_i represents variables that are likely to affect inefficiency and w is a corresponding parameter vector. The exogenous determinants of inefficiency (z_i) can be unique variables or the same as in the frontier (x_i). The sign of the coefficient reveals the direction of the impact of z_i on $E(u_i)$. A negative coefficient of the exogenous variable in the regression indicates that firms with larger values of the variables tend to have a lower level of inefficiency, whereas a positive value indicates a higher level of inefficiency. Although the sign of the coefficient reveals the direction of impact of z_i on $\mathrm{E}(u_i)$, the slope coefficients of w are not the marginal effects of z_i. This is because the relationship between $E(u_i)$ and z_i is non-linear.

DATA AND EMPIRICAL SPECIFICATION

A data panel describing the production activities of Norwegian salmon farms from 1985 to 2008 is used for the empirical analysis. As commercialized salmon farming did not start until the early 1980s, our data cover almost the entire period of industrialized/intensive salmon production in Norway. The data are provided by the Norwegian Directorate of Fisheries (DoF), which annually collects data for all Norwegian salmon farms. Each year, all firms with an aquaculture license receive two detailed questionnaires from the DoF, which they are obliged by law to complete and return, together with their annual accounts.[6]

Roughly 80 variables are reported for each farm, including the age of the farm, regional location, production level, input level, cost and revenues. It should, however, be noted that not all responses are accepted into the database by DoF and, accordingly, the panel is unbalanced. The sample available for our use is still rather extensive, covering more than 50% of the total Norwegian salmon production for most years, and the entire Norwegian salmon-producing area. In total, there are 4,901 observations in the data set. However, we do not have data for all variables in all years. For several of the explanatory variables in the inefficiency function, we only have data until 1995, as the collection of these variables was discontinued from this time. We therefore specify and estimate two models: one model where all variables are included, but for the subsample period 1985–1995; and one model covering all years but with fewer explanatory variables in the inefficiency function. The production function is specified in the same way in both these models.

To estimate the production function, a translog functional form is specified.[7] This allows for complete specification of substitution patterns among the included variables. Given the panel data, the translog production function is given by:

$$\begin{aligned}\ln y_i = \sum_r \alpha_r D_r + \sum_k \beta_k \ln x_{ki} + 0.5 \sum_k \sum_l \beta_{kl} \ln x_{ki} \ln x_{li} \\ + \beta_t t + 0.5\beta_{tt} t^2 + \sum_k \beta_{kt} \ln x_{ki} t + (v_i - u_i),\end{aligned} \tag{5}$$

where the dependent variable, y_i, is the harvest of salmon in kilograms, adjusted for the changes in the stock of living fish in the pens and frozen holdings during the year of observation i.[8] The vector of inputs is x_{ki}, where k and l reflect the different inputs, t is a time trend included to control for technological changes and innovations, and D_r denotes region-specific dummy variables included to account for differences in biophysical factors among the sample farms. Some larger firms cannot be assigned a regional dummy, as they operate in several regions. For these firms, the category "several counties" is used. This group mainly consists of firms established after 1992, because before November 1992 the government restricted the major ownership interest to a maximum of one license. However, there were also a few larger companies that were established before the ownership regulations were implemented in 1973.

The production function is specified with three input variables: feed, labor and capital. Feed has consistently been the most important input in salmon farming over the years, and represented 55% of the production cost in 2008. For the years 1985–1993, the feed usage is not given directly, but is calculated by feed cost divided by feed price, where feed price is the price of "Edel," one of the most popular salmon feeds at the time. Labor is measured by the hours worked at the farm by owners and workers, and capital by the real replacement value of capital equipment such as pens, buildings, feeding equipment, etc. Summary statistics for the variables are given in Table 1.

TABLE 1 Summary Statistics for the Variables in the Production Function

	Mean	Standard Deviation
Production (y)	1, 207, 849	3, 188, 355
Feed (x_1)	1, 513, 600	3, 851, 757
Labor (x_2)	10, 226	15, 879
Capital (x_3)	92, 169	294, 830
County dummies (D_r)		
• Vest Agder	0.01571	0.1244
• Rogaland	0.06101	0.2394
• Hordaland	0.17405	0.3792
• Sogn og Fjordane	0.08937	0.2853
• Møre og Romsdal	0.11243	0.3159
• Sør Trøndelag	0.06203	0.2412
• Nord Trøndelag	0.06264	0.2423
• Nordland	0.14528	0.3524
• Troms	0.07345	0.2609
• Finnmark	0.02244	0.1481
• Several counties	0.18160	0.3856

The inefficiency function is specified as linear in the logarithm of its variables and is given as:

$$\begin{aligned}\sigma_i^2 &= \omega_0 + \sum_a \omega_a\, activety_{ai} + \omega_{oa}\, otheractivety_i + \omega_b\, broodstock_i \\ &\quad + \omega_s\, smolt_i + \omega_{pc}\, productioncapasaty_i + \sum_c \omega_c\, companytype_{ci} \\ &\quad + \omega_d\, disease_i + \omega_i\, insurance + \omega_{age}\, age_i + \omega_p\, price_i, \end{aligned} \tag{6}$$

where σ_i^2 is the variance of the nonnegative error term, u_i, in Equation (1). The inefficiency function is specified with a number of explanatory variables. Summary statistics for these variables are given in Table 2. The second column reports the summary statistics for the years 1985 to 2008 (all sample years), while the third column reports the summary statistics for the years 1985 to 1995. As seen from the table, a number of variables were only collected until 1995, and two different models are therefore specified for the inefficiency function: one model where all variables are included but on the subsample 1985–1995, and one model for all years but with fewer explanatory variables. In the following, we will discuss the expected effect on efficiency of the different variables.

The $activity_a$ variables are dummy variables that indicate whether the farm is a pure salmon producer, a pure trout producer, or if it produces

TABLE 2 Summary Statistics for the Variables in the Inefficiency Function

	1985–2008	1985–1995
Main activity		
Salmon producer	0.7758 (0.4171)	0.7399 (0.4388)
Trout producer	0.0141 (0.1178)	0.0040 (0.0632)
Salmon and trout producer	0.2102 (0.4075)	0.2561 (0.4366)
Other activity	0.1132 (0.3169)	0.0741 (0.2619)
Own brood stock		0.0142 (0.1185)
Lack of smolt		0.1259 (0.3318)
Utilized production capacity		0.6439 (0.4789)
Company Type		
Limited company		0.8734 (0.3326)
Owner-operated business		0.1018 (0.3024)
Other types of company		0.0248 (0.1556)
Disease		0.4615 (0.4986)
Insurance disbursement	0.1961 (0.3971)	0.2284 (0.4199)
Age		8.5808 (6.1134)
Obtained price	24.663 (12.646)	28.635 (14.804)
Number of observations	4901	2741

Standard deviation in parentheses.

both salmon and trout. If the salmon or trout producers are found to be more efficient than the producers of both salmon and trout, this is considered to be an indication of the economies of specialization, whereas if the opposite is true, it indicates economies of scope.

Over the years, the degree of specialization in production has increased, as more farmers have become pure salmon producers. This is illustrated in Figure 1, which shows the distribution of producers of salmon, trout, and both salmon and trout over time. In the early years of salmon production, more than 50% of the farms produced both salmon and trout, but by the end of the eighties this had fallen to less than 20%, and by the end of the nineties it was below 10%. Since then, we have seen a decrease in specialization, whereby fewer farms are pure producers of salmon. The share of farmers producing only trout has been marginal compared with the producers of salmon, but here there has also been an increasing degree of specialization, with the share of pure trout producers increasing over time.

The *other activity* variable is another measure of specialization. This variable specifies if the farm is registered for an activity apart from salmon production. We also investigate if vertical specialization affects efficiency by testing if a farm that keeps its own brood stock has higher or lower efficiency. In discussions with farmers, the quality of smolt has been mentioned repeatedly as a cause of high mortality rates in the industry. If the smolt produced on a farm has a lower mortality rate, it will positively affect efficiency, or if a specialized smolt producer keeps the higher-quality smolt, the opposite will be true.

As well as the differences in smolt quality, several farms have explained that, especially in the early years, it could be a problem obtaining enough smolt, which would have meant that production capacity would not be fully utilized and efficiency would decrease. To control for this, a dummy variable indicating whether farms have had problems obtaining enough smolt is included (*smolt*). We also test for this by including in the model a dummy variable that reflects whether production capacity is fully utilized (*production capacity*).

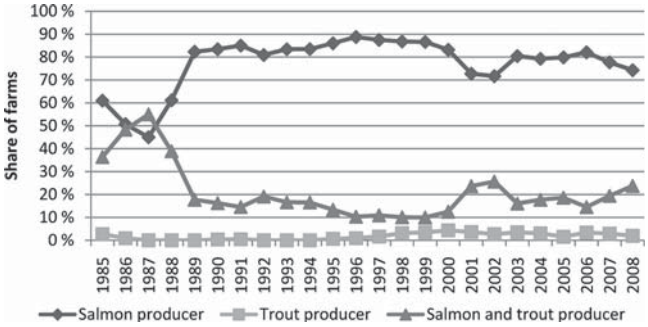

FIGURE 1 The distribution of producers of salmon, trout, and both salmon and trout over time.

The trends in these three variables are illustrated in Figure 2. As shown in the figure, a lack of smolt was only a problem in the earlier salmon-producing years. Over time, a smaller fraction of the farms have kept their own brood stock, indicating vertical specialization over time. On the other hand, we observe an increasing number of farms occupied in activities apart from salmon or trout production over time. The reason for this pattern might be a tendency toward larger multi-industry firms. Over the last few decades, there has been a reorganization of the structure of the industry. Where previously the industry was made up of many small family-run farms occupied mainly with fish production, consolidation activity has created fewer and larger companies.

The effect of the reorganization is illustrated in Figure 3, which shows the development of different types of companies over time. We distinguish between limited responsibility companies, owner-operated companies and companies registered with other organizational forms. We can see from the figure that there are an increasing number of limited responsibility companies compared with owner-operated businesses over time. In the model, we test for efficiency differences between the different types of companies by including dummy variables for *company type*, which distinguishes between the three company types illustrated in Figure 3.

Other factors that might explain the high losses in salmon farming are diseases, escapes and site breakdowns. Although insurance usually covers equipment failures and subsequent escapes caused by the failures, it does not cover farms against losses because of diseases. We have therefore included dummy variables that indicate if a farm has had disease problems over the year (*disease*) and a dummy variable that indicate if a farm has had any insurance disbursement (*insurance*).

Figure 4 illustrates the share of farms with diseases and insurance disbursements over the years. The share of farms with insurance disbursements

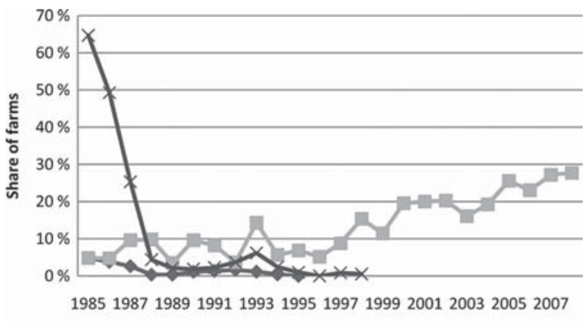

FIGURE 2 The share of farms with their own smolt production, the share of farms engaging in activities additional to fish production, and the share of farms affected by lack of smolt.

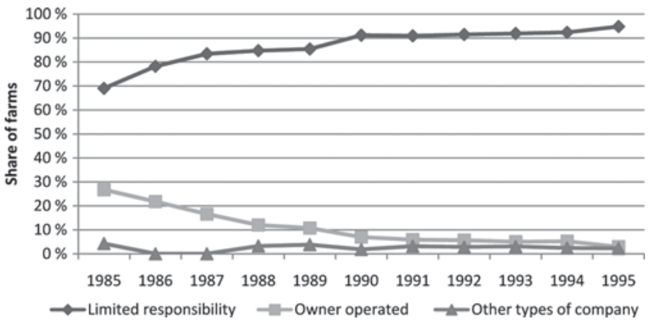

FIGURE 3 The development of different types of companies from 1985 to 1995.

over the years varies from almost 40% in 1986 to below 10% in the mid-1990s. In the last years of the sample period, this share remained relatively stable, with 14% to 19% of the sample farms receiving insurance disbursements over the years 2003–2008. The share of farms that have had disease problems over the years varies even more. As expected, there are large variations in this variable, because diseases are often contagious and come in waves.[9] The drop in the number of farms with disease problems that can be seen between 1993 and 1996 is a consequence of the development of vaccines against the diseases *furunculosis* and *infectious salmon anemia*, which were a major problem in the early 1990s.

To test if the age of a salmon farm influences efficiency, a variable measuring the age of the farm is included in the model (*age*). Age can affect efficiency in two possible ways. On the one hand, age may be related to a capital vintage effect that causes a reduction in technical efficiency as the age of the farm increases, whereas on the other hand, age may be related to experience and "know-how," with the oldest farms acquiring knowledge and experience that newer farms often do not have.

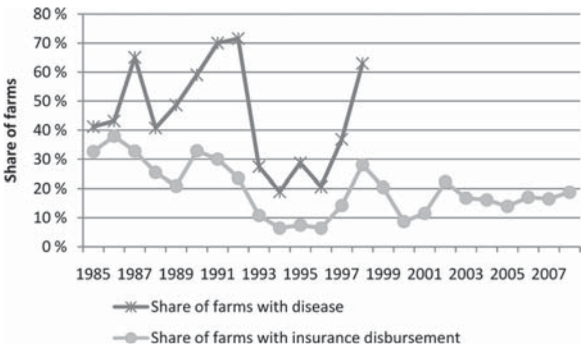

FIGURE 4 The share of farms with diseases and insurance disbursements over the years.

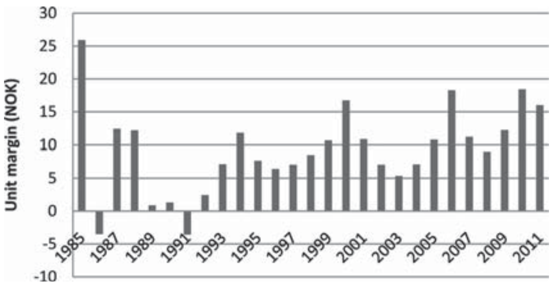

FIGURE 5 Trends in unit margins.

Finally, a price variable is included to test whether the market condition impacts efficiency. Compared with crop production and traditional land-based livestock production, aquaculture production is very volatile. Figure 5 illustrates the average profit margin in Norwegian salmon production over time. As seen in the figure, some years have been more profitable than others. In particular, the margins were narrow in 1996, 1998–1992 and 1997, and were especially wide in the intervening years. This structure is commonly seen in biological industries, with a substantial lag between the decision to increase production and the entry of the increased production onto the market. It takes, for instance, 16–22 months to grow a salmon. By including the salmon price variable in the model, we investigate how the variation in profit has affected efficiency.

EMPIRICAL RESULTS

As the stochastic frontier model is a relatively complex model, a test for the presence of technical efficiency should always be conducted as a first step. Therefore, an OLS residual test was first conducted to check for the validity of the model's stochastic frontier specification. This test is performed by estimating the OLS that correspond to the stochastic frontier model and testing for negative skewness. With a skewness value of -1.2967 and a *P*-value of less than 0.001, we found support for a left-skewed error distribution. As negative skewness can be regarded as evidence of technical inefficiency, we proceed to estimate the stochastic frontier model with the composed error term.

To achieve efficient estimates, Equations (5) and (6) were estimated in a single-step procedure (Schmidt & Wang, 2002).[10] Convergence was obtained using a sequential estimation procedure, where restrictive models provided starting values for less restrictive models. The model fit is relatively good, with a Wald $\chi^2(24)$ statistic of 21,850.83 and a *P*-value of less than 0.001 in the full model estimated on the subsample 1985–1995, and a $\chi^2(10)$ statistic of 178,819.98 with a *P*-value of less than 0.001 in the model estimated on the full sample, but with limited explanatory variables in the inefficiency function. Estimated output elasticities (ε_k) are presented in Table 3. As expected, output elasticity is positive for all inputs, but it is only the elasticity for feed that is statistically significant. This is, however, in accordance with the previous literature that found diminishing substitution possibilities between feed and other inputs as the industry grew (Guttormsen, 2002).

The sample average return to scale (RTS) is 1.0795, which indicates increasing economies of scale. However, the 95% confidence interval lies between 0.7180 and 1.4410, implying that we cannot reject the null hypothesis of constant returns to scale. The yearly technical change (TC) is found to be 3%, which is in accordance with the findings of previous research (Asche, Roll, & Tveteras, 2009). During the sample period, there have been large innovations in the quality of fish feed, feed equipment, disease treatment and vaccines, and in the robustness of the sea-pen systems.

Figure 6 presents the estimates that measure productivity differences (PD_r) between regions, together with the size of the regions measured by number of observations in a region.[11] The PD_r scores are derived relative to the region with the highest effect, and are calculated as follows:

$$PD_r = \frac{e^{\alpha_r}}{e^{\alpha_e}}, \tag{7}$$

where α_e is the region-specific effect of the most efficient region (region e) and $0 < PD_r < 1,\ r \neq e$. This normalization ensures that the PD_r measures provide a direct measure of the relative differences between regions. As illustrated in Figure 6, Hordaland is found to be the most productive region, and hence the productivity of the other regions is measured relative to that of Hordaland. Besides being the most productive, Hordaland is also the largest region, with 853 observations.

TABLE 3 Output Elasticities, Returns to Scale and Technological Change

	Elasticity	95% Confidence Interval
$\varepsilon_{\text{feed}}$	0.8559**	0.8351–0.8767
$\varepsilon_{\text{labor}}$	0.1012	−0.1208–0.3232
$\varepsilon_{\text{capital}}$	0.1224	−0.0380–0.2829
RTS	1.0795	0.7180–1.4410
TC	0.0309**	0.0285–0.0334

**Significant at the 1% level.

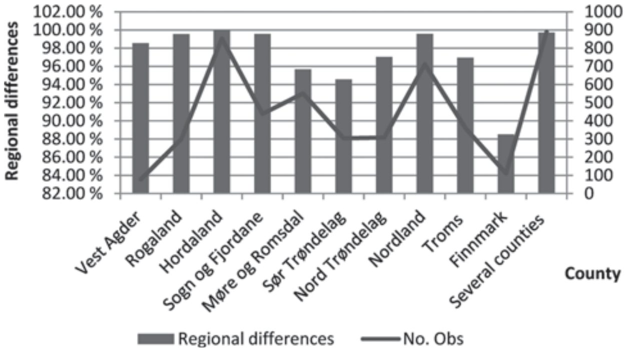

FIGURE 6 The relationship between productivity differences in regions and the size of the regions.

Although Hordaland is given the highest productivity score, we do not find the regions Vest Agder, Rogaland, Sogn og Fjordane, Nordland or the firms operating in several counties to be significantly different from Hordaland.[12,13] All of these regions except Nordland are located in the southernmost regions. Our finding that the southernmost regions are more productive than the northernmost regions is expected, because the southern regions have more favorable growing conditions due to higher water temperatures.

Nordland, however, is an exception, as it is located in the far north and yet is one of the most productive areas. An interesting question, therefore, is what separates Nordland from the rest of the northern regions. Looking at the number of observations in each region, it is obvious that Nordland is a relatively large region in terms of salmon producers (712 observations). The size of the salmon-producing regions as measured by the number of observations in each region is reported in Figure 6. As seen in the graph, there is a strong correlation between the size of the region and productivity, and this is supported by a positive correlation coefficient of 0.551. This result may be interpreted as an indication of external economies of scale and agglomeration effects, and is in accordance with previous research, as several other articles have found a positive relationship between productivity and size of the salmon-producing region (Tveteras, 2002; Tveteras & Batteese, 2006).

Although the relationship between size and productivity is pronounced among the northern regions, it is weaker among the southern regions. The southernmost regions, Vest Agder and Rogaland, are found to be among the most productive regions, even though they are among the smallest. It therefore seems that the agglomeration effect is less important for regions that benefit from favorable temperature conditions, or that the positive biophysical effect offsets the lack of a positive agglomeration effect.

The main focus of this article is technical efficiency, and a plot of the efficiency scores, sorted from the least to the most efficient farm, is

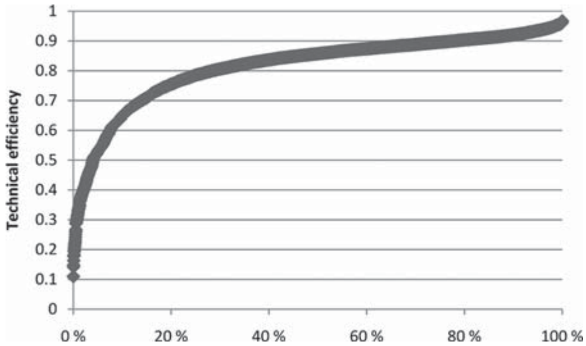

FIGURE 7 The estimated efficiency scores sorted from the least to the most efficient farm.

presented in Figure 7. The scores represent the degree of technical efficiency, where a score of 100% indicates full technical efficiency and a score below 100% represents the degree of efficiency. The closer the score is to 100%, the more efficient is the farm. Most farms are relatively efficient, and 80% of the farms have efficiency scores above 75%. The average technical efficiency score is found to be 81.5%, which indicates that the average farm could have increased its output by 18.5% using its inputs more efficiently.[14] There is, however, a large spread in efficiency, as a small number of farms were found to be very inefficient and, at the other extreme, a small number were almost fully efficient.

After identifying the degree of technical efficiency, the obvious next step is to try to explain the variation in efficiency: are there specific factors that characterize the efficient or inefficient farms? To answer this question, we look at the coefficients of the inefficiency function. These are reported in Table 4. A negative sign for a coefficient indicates that the variable reduces inefficiency, whereas a positive sign indicates that the variable increases inefficiency. The first two columns present the coefficient and *P*-values from the model estimated on the full sample but with limited explanatory variables, and the last two columns present the coefficient and *P*-values from the full model estimated on the subsample 1985–1995. A likelihood-ratio test was performed to test whether the variables in the efficiency function influenced technical inefficiency. This test was rejected with a log-likelihood value of 1535.63 and a *P*-value of less than 0.001 for the full sample model with limited explanatory variables. For the full model estimated on the subsample 1985–1995, we were not able to perform the test, because the restricted model would not converge.

There are some differences in the results between the two models, but essentially the estimates yield the same conclusion. As expected, both diseases and other farm problems leading to insurance disbursements have a negative effect on efficiency. Specialization has an effect on efficiency.

TABLE 4 The Coefficients of the Inefficiency Function

	1985–2008		1985–1995	
	Coefficient	P > |z|	Coefficient	P > |z|
Constant	−4.500	0.000	−4.138	0.000
Disease			0.335	0.000
Insurance disbursement	0.471	0.000	0.295	0.002
Trout producer	0.807	0.228	2.138	0.006
Salmon and trout producer	0.236	0.007	0.211	0.035
Other activity	−0.125	0.188	0.002	0.988
Own brood stock			−0.132	0.534
Owner-operated business			0.139	0.343
Other types of company			−0.256	0.104
Lack of smolt			0.386	0.003
Utilized production capacity			−0.384	0.000
Age			0.013	0.059
Achieved salmon price	0.065	0.000	0.054	0.000

The producers that produce both salmon and trout have a lower level of efficiency than those specializing in either salmon or trout. This is an indication of diseconomies of scope or economies of specialization. For the earlier years of salmon production, 1985 to 1995, it seems that trout producers were less efficient than salmon producers but, because there were only a few specialized trout producers during this period of time, this result is very uncertain. The other measures of specialization, whether a farm conducts activities in addition to salmon production (other activity) or whether a farm produces its own smolt (brood stock), were not found to have a significant effect on efficiency. We did not find any efficiency difference between different types of companies either. This is not surprising, given that we cannot reject the hypothesis of constant returns to scale.

Problems in getting enough smolt were found to have a negative effect on efficiency. This conclusion is supported by the full capacity variable that indicates that farms operating at full capacity have higher levels of efficiency on average.

Age was found to have a weak negative effect on efficiency. This result is not statistically significant at the 5% level, but a *P*-value of 0.059 can almost be regarded as significant. As efficiency is found to decrease with age, newer farms are generally the most efficient. This indicates that the negative capital vintage effect dominates the positive experience effect, which is in accordance with the result of Nilsen (2010).

The salmon price variable, reflecting the state of the market, has a strong negative effect on efficiency. This indicates that farmers are generally less efficient when the salmon price is high.[15] This is also illustrated in Figure 8, in which the efficiency measure is plotted against the price parameter. There is a strong negative correlation, with a correlation coefficient

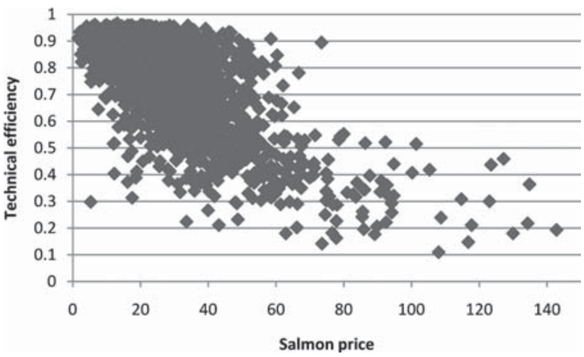

FIGURE 8 The relationship between the salmon price and technical efficiency.

of −0.7061. This may not be surprising, given that profitability in salmon farming has been highly variable, a feature that the industry has in common with many other industries that have a significant time lag between the decision to produce and the product being ready for the market (Andersen et al., 2008; Aasheim et al., 2011). This leads to a highly inelastic short-run supply and, thereby, a steep short-run marginal cost curve. In periods with high prices, the producers are provided with strong incentives to expand output. However, as they then deviate from the least-cost-production pattern, they are likely to become less efficient. This also implies that the apparent technical regress reported by Vassdal and Holst (2011) can be explained at least partly by the prolonged boom created for Norwegian salmon farmers by the Chilean disease crises (Asche et al., 2009).

In Figure 9, the efficiency scores are plotted over time. As is evident from the figure, the average efficiency has increased over time. The most efficient firms have been relatively stable over the years, but the least efficient have improved over time and managed to catch up with the best. This is particularly evident up to the mid-1990s. Since then, the average

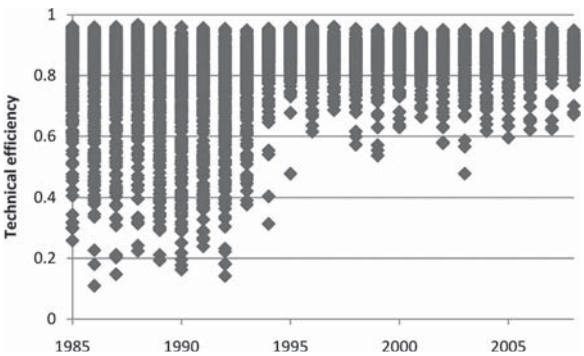

FIGURE 9 Trends in technical efficiency over time.

efficiency has been relatively stable, with only small variations from year to year. There seems to be a strong effect from 1992, when the ownership restrictions were abandoned. The main reason for this regulatory change was the lack of access to the capital market for many small companies in an increasingly capital-intensive industry. However, it also created new opportunities for economies of scale; for instance, a representative farm in 2010 typically operates four licenses, whereas the ownership restrictions prior to 1992 limited each farm to one license.

Having found this trend in technical efficiency, it is also interesting to look at the development in the explanatory variables over time. As illustrated in Figure 1, early on, many farmers produced both Atlantic salmon and salmon trout, while an increased degree of specialization took place from the late 1980s as more and more farmers become pure salmon producers. This contributed to the large increase in efficiency that can be observed in this period.

The problem of obtaining enough smolt is another variable that is found to reduce efficiency. As can be seen from Figure 2, lack of smolt was a problem in the earlier salmon-producing years. This corresponds to a period when the number of licenses for smolt producers was restricted. Although more than 60% of the farmers had problems getting enough smolt in 1985, this share was reduced to less than 5% in 1988 and to approximately zero in 1996. Deregulation of access to smolt licenses has therefore also contributed to the increased efficiency observed in the late 1980s and, given that the shortage was created by regulations, it highlights the unintended consequences and the many barriers to growth that poorly designed regulations can create. As such, it highlights the challenges raised by Chu et al. (2010).

Diseases and other farm problems leading to insurance disbursements are other factors that are found to affect efficiency negatively. Figure 4 shows the share of farms with diseases and insurance disbursements over the year. The share of firms that have had any insurance disbursement over the year varies significantly from year to year, but a downward trend can be discerned. Technological innovations that have improved the robustness of fish pens have contributed to this downward trend, but site breakdowns and escapes are still a problem in the industry today, and there remains room for improvement.

We only have farm-level data for the shares of farms with disease problems up to 1998. However, from 1994 to 2008, the Norwegian Directorate of Fisheries provides data on the industry average yearly loss, or the share of total stock that die in the Norwegian salmon industry. This is illustrated in Figure 10. As seen from the figure, a large share of the stock is lost every year. The determinants behind this loss are also given in the figure. Mortality is the main reason for this loss, followed by diseases. Therefore,

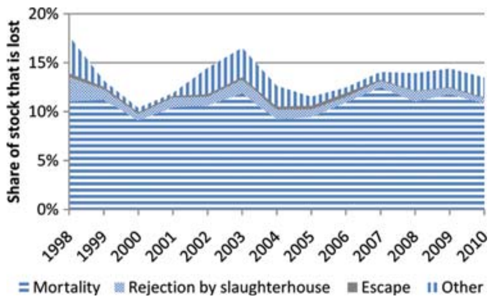

FIGURE 10 The share of total stock that die in the Norwegian salmon industry, separated by different causes. (Color figure available online.)

it is reasonable to conclude that diseases are one of the main causes of inefficiency that are present in the industry today. Hence, to improve efficiency and stay competitive, the current disease problem in Norwegian salmon aquaculture must be solved.

CONCLUSIONS

The technology used in Norwegian salmon aquaculture has changed rapidly throughout the industry's short history. It is, therefore, not unexpected that our results indicate substantial differences in technical inefficiency between firms and regions. Although there is a significant literature investigating technical change and productivity growth in salmon aquaculture, limited attention has been given to the sources of this inefficiency. In this article, we utilize a stochastic frontier to investigate the determinants of the observed inefficiency. These factors have varying impacts, as inefficiencies are caused by short-run shocks such as disease outbreaks and escapes, shocks that have an effect over longer periods, and permanent differences associated with such factors as regulations.

Two sources of inefficiency are particularly interesting; regulations and the economic conditions. The relaxation of access to smolt licenses and the abandonment of ownership regulations have both reduced inefficiency substantially. This underlines the argument of Chu et al. (2010) with respect to the importance of a well-designed regulatory system for any aquaculture industry. Given that Andersen et al. (2008) and Aasheim et al. (2011) have demonstrated that the supply of salmon is highly inelastic in the short run, it is not surprising that periods with high prices lead to inefficiency as farmers try to exploit the higher prices. The long experience of disease problems in Chile (Asche et al., 2009) may also partly explain the slower productivity growth observed by Vassdal and Holst (2011).[16] Although our results apply specifically to salmon aquaculture, most aquaculture producers in most regions are exposed to similar types of shocks. Therefore, our results should be relevant to other species.

The fact that the Norwegian salmon industry is, on average, only 81.5% efficient indicates that there remains substantial scope to increase the industry's competitiveness through catching up. However, our results also indicate that the degree of inefficiency has been reduced over time. Asche et al. (2011) noted that during the last decade, innovations in the supply chain that create demand growth have been as important as productivity growth for industry development. As the industry matures, there appears to be less scope for technological innovations to increase productivity by slowly improving existing technology. However, given that most innovations that have the potential to instigate radical changes, such as genetically modified salmon, are highly controversial (Smith et al., 2010), it will be important for the continued success of the industry to address the different sources of inefficiency to the greatest extent possible. The importance of maintaining competitiveness becomes more urgent as the seafood market becomes increasingly globalized (Tveterås et al., 2012).

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NOTES

1. Salmon trout (*Oncorhynchus mykiss*) is a large rainbow trout and is also known as steelhead.
2. Hassanpour et al. (2010, 2011) provide evidence of productivity development in trout farming in Iran.
3. A non-parametric data envelope analysis approach (DEA) could also have been used to investigate this issue. However, the DEA approach is deterministic, so any deviations from the production frontier are attributed to inefficiency. As salmon farmers are exposed to shocks from biophysical factors, allowing for stochasticity seems appropriate.
4. It is well documented that there is a global market for salmon (Asche et al., 2002; Asche et al., 2005; Tveteras & Asche, 2008; Asche et al., 2012; Tveteras et al., 2012) and there is no evidence of market power being exploited (Jaffry et al., 2003; Asche et al., 2011). Accordingly, the price can be regarded as exogenous for each individual farmer.
5. See Asche et al. (1999), Tveterås (2002), Liu and Sumaila (2010) and Torrissen et al. (2013) for discussions of environmental interactions from an economic perspective, and Oglend and Tveteras (2009) for a more risk-oriented perspective.
6. Since 1973, a license has been required to operate a salmon farm in Norway.
7. A likelihood-radio test was performed to test if a Cobb–Douglas specification could fit the model. This test is distributed as $\chi^2(20)$, and with a test statistic of 346.63 and a *P*-value of less than 0.001, the null hypothesis is clearly rejected.

8. A production function with a single output is specified, as several studies have shown that the generalized composite commodity theorem holds for different species of salmon (Asche & Guttormsen, 2001; Asche et al., 2005).
9. There is a long history of diseases in Norwegian and global salmon farming. Asche (1997) relates the main disease outbreaks to production costs in Norway up to 1997, while Asche et al. (2009) and Hansen and Onozaka (2011) discuss the main disease crises after the turn of the century, with particular focus on the major crises in Chile in 2009–2010.
10. Stata 11 was used for the estimation.
11. A likelihood-radio test was performed to test if the region-specific variables were superfluous. This test was rejected with a LR $\chi^2(10)$ statistic of 62.41 and a *P*-value of less than 0.001.
12. The category consisting of firms that have farms in several counties is not found to be significantly different from Hordaland. However, comparing this group to the rest of the regions is problematic, as the group consists of firms mainly established after 1992. Until 1992, the government restricted the major ownership to a maximum of one license.
13. These results also highlight the importance of the concerns raised by Hermansen and Heen (2012) in relation to potential climate effects.
14. It is of interest to note that this is very much higher than the efficiency score of the Norwegian fishing fleet, at 24.1% (Guttormsen & Roll, 2011). While productivity growth is higher in aquaculture than in traditional fisheries, it is important to note that also there productivity growth and inefficiency is highly important (Squires and Vetstergaard, 2013).
15. It is of interest to note that the volatility of the salmon price has been increasing over time (Oglend & Sikveland, 2008; Solibakke, 2012). This also has implications for the forecastability of the salmon price (Guttormsen, 1999) and optimal harvesting (Guttormsen, 2008), and is relevant for other species such as tuna (Shamshak, 2011).
16. It is interesting to note that this also benefited Alaskan wild salmon fishermen, as indicated by Williams et al. (2009) and Valderrama and Anderson (2010).

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