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Economic inefficiency and environmental impact: An application to aquaculture production

Frank Asche *, Kristin H. Roll, Ragnar Tveteras

Department of Industrial Economics, University of Stavanger, N-4036 Stavanger, Norway

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ABSTRACT

In industries characterized by frequent innovation and high productivity growth, substantial variation in produced quantity and input use may occur, leading to increased costs. An effect that has received little attention is that inefficiency can exacerbate environmental impacts. This effect is particularly important if environmentally damaging inputs are overused. In addition to increasing firms' costs, such inefficiency can also increase the environmental impact of the firm's activity. This makes the degree of inefficiency in an industry an issue for environmental regulators. In this paper, we estimate technical and allocative efficiency for a sample of Norwegian salmon farmers. Our results show that both technical and allocative inefficiency on average are significant in explaining the level and variation in farm costs, and that the main environmental impact due to inefficiency from the Norwegian salmon aquaculture industry has its origin in technical inefficiency.

1. Introduction

Firms that exploit natural resources interact with the environment, which can cause negative environmental externalities. While the effect of externalities is well understood in theory, analyses of externalities from production processes in the literature are limited to firm behavior in equilibrium. There is however, a significant literature that argues inefficiency is not uncommon (see [23] for a survey). Technically inefficient firms use more inputs than necessary to produce a given quantity of output. When externalities are associated with the input use, this will exacerbate the externality. Another important source of inefficiency is a suboptimal input factor mix given the prices of inputs and technology in place. Known as allocative inefficiency, this describes the case where some factors are overused while other factors are underused. In industries that cause environmental externalities, a suboptimal input mix can increase negative environmental externalities if environmentally damaging inputs are overused, and vice versa if they are underused. For an inefficient firm, the effect of measures aimed at correcting the externality can therefore be reduced, implying that regulatory agencies and public managers should be concerned with how firms in environmentally sensitive industries utilize their technology.

In this study, we investigate technical and allocative inefficiency in an aquaculture industry—salmon aquaculture. Aquaculture is currently the world's fastest growing food production technology, and four of the six most consumed seafood species in the US are primarily derived from aquaculture [2]. Because aquaculture production closely interacts with the environment, the growth, mortality and quality of the fish are sensitive to changes in the environment and influence

* Corresponding author. Fax: +47 51 83 17 50.
E-mail address: Frank.Asche@uis.no (F. Asche).

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the environment where production takes place. Moreover, production practices also influence the environmental effects of the industry [25]. The overuse of feed, for instance, can lead to organic emissions that may increase eutrophication and thereby be harmful to the environment. Furthermore, technological innovation may influence the environmental effects of production. An example is the development of formula-based feed, which is utilized more efficiently by the fish and therefore reduces the environmental impact.

During recent decades, farmed salmon has been one of the most successful aquaculture species as measured by production growth. Production has increased from a few thousand tonnes in 1980 to 1.8 million tonnes by 2007. The main forces behind this rapid growth are technological progress and improved efficiency [1,3]. Several studies have documented the rapid productivity growth and the corresponding decrease in production costs that have followed [3,17,22,28,29].

As salmon farming is a relatively young industry that has experienced rapid change in production technology, the industry is particularly interesting from the perspective of productivity and efficiency analysis. Frequent innovations, biased technological change, and changes in factor prices have created substantial challenges for producers and additional complexity for regulatory agencies in aquaculture as they influence both the production technology and the input factor mix. Because frequent innovation makes it difficult to keep up with a fast-moving production frontier, and given the fact that biased technological change alters the optimal input mix, variations in both produced quantity and input use might have occurred, and led to efficiency differences among farms.

Furthermore, government regulations may have significantly influenced the productive efficiency of the industry. Regulations have played an important role in determining the spatial distribution of farms along the Norwegian coast, farm size and the ownership structure of farms. Behind these regulations, there is a mix of environmental, regional, and economic policy considerations. However, regulations can often produce a spatial farm distribution that would not have emerged with free entry and production that is not economically optimal. One possible effect may be the location of farms at sites with low biophysical productivity (as determined by temperature, topography, currents, waves, etc.), thus leading to technical inefficiency. Another possible effect is that the government, by influencing the composition of human and financial capital entering the industry, has created a nonoptimal input mix. Allocative inefficiency could therefore be attributed to either managerial skill, because of the slow adjustment to past changes in input prices and technology, or government intervention, as pointed out by Bjørndal and Salvanes [10].

Our empirical analysis concerns a sample of Norwegian salmon farms spanning the period 1985–2004. To investigate the effects of technological change and inefficiency, a shadow cost model based on a system consisting of a translog cost function and its factor share equations is specified and estimated [6,7,19,20,21,23]. Previous studies on economic inefficiency in Norwegian aquaculture estimated technical efficiency using the stochastic frontier approach [22,29]. By using the alternative shadow price approach, computational difficulties associated with the decomposition of economic efficiency are remedied [23]. In particular, this approach allows us to decompose overall cost inefficiency into its technical and allocative components. Because salmon aquaculture is a relatively young industry where the technical frontier is moving rapidly, it is necessary to control for time variability. Building on earlier work [8,12], the shadow cost system is therefore modified to account for time-varying efficiency by letting allocative efficiency change over time.

2. Aquaculture and the Norwegian salmon farming industry

Aquaculture is an old production technology. Although it has its roots in China more than a thousand years ago, a revolution took place beginning in the 1970s as a number of technological innovations yielded increased control of the production process. These new technologies allowed a significant increase in the scale and intensification of production, leading to productivity growth and increased production.

Since 1970, aquaculture has been the world's fastest growing food production technology with an annual growth rate of 8.8% as compared with 2.8% for animal protein from agriculture and 1.2% for fisheries [15]. Aquaculture production has increased from 3.6 million tonnes in 1970 to 62.9 million tonnes in 2005. Moreover, its share of the total seafood supply has increased from 5% in 1970 to 40% in 2005. The rapid increase in aquaculture production has ensured that global seafood supply has increased on a per capita basis, despite the fact that supplies from wild fisheries have remained stagnant.

Salmon is one of the most successful aquaculture species, as measured by the quantity produced, and is the technologically leading species in many areas. Commercial salmon farming was pioneered in the 1970s, and the industry has grown from producing a few thousand tonnes in 1980 to about 1.6 million tonnes by 2004. Globally, the two largest salmon-producing countries are Norway (38%) and Chile (34%).

The large increase in salmon production has been accompanied by a substantial decline in production costs, and the real cost of salmon production per kilo in 2004 was about one quarter of the cost in the mid-1980s. Lower production costs have contributed to making the salmon industry more competitive as the decline in the price has induced greater consumption of salmon. Exploitation of scale economies has also contributed to a reduction in production costs. For instance, the average size of a Norwegian salmon license increased from a production of 47 tonnes per farm in 1982 to 652 tonnes by 2004 [13].

While the substantial growth in the aquaculture industry has made it possible for aquaculture to become an important food source, it has also been responsible for creating some significant environmental challenges [25]. It is conventional wisdom among many consumers and environmental nongovernment organizations in North America and Europe that farming practices for salmon and shrimp, two of the most important aquaculture species, are harmful to the environment.

Environmental concerns go in several directions [25]. One concern is the emissions from the farms in the form of unused feeds, feces, antibiotics, and other emissions that can lead to substantial local environmental changes, in the form of both eutrophication and damage to surrounding ecological systems. There are also land use issues. For example, shrimp farming has had significant negative impact on mangrove forests [14]. Finally, the impact on wild fish stocks has been a concern, either because fingerlings are harvested from the wild, or because the increased demand for fish feed leads to increased fishing pressure for species used to produce feed, or because the genetic pool of wild fish is polluted through the escape of farmed fish. If the producers' input mix is inefficient, these environmental impacts are exacerbated.

The environmental issues that arose in intensive salmon farming during the 1980s and 1990s must be seen in relation to the introduction of salmon farming as a new technology that uses the environment as an input. The higher the production and the more intensive the production process, the greater is the potential for environmental damage

While an intensive production process on one side may increase the potential for environmental damage, a greater degree of control of the production process also makes it easier to address these issues and therefore to avoid the negative effects on the environment and the repercussions of negative productivity [4]. In salmon farming the main sources of organic pollution are unused feed and feces which sink through the bottom of the fish cage [30]. Besides consuming oxygen and thus competing with the salmon for the limited amount of oxygen available in the cage, this organic waste produces toxic by-products (such as ammonia) and can therefore hamper productivity growth in general and increase production costs. As these negative feedback effects reveal, farmers attempt to adopt cultivation practices to avoid negative repercussions on productivity. An indication of this is development in the feed conversion ratio (FCR), which is the quantity of feed measured in kilos used per kilo of salmon produced. This is the most commonly used physical measure of feeding efficiency as well as for organic emissions as these increase with a higher FCR [30]. The FCR has significantly improved as feed efficiency has increased. The FCR fell from 2.8 in 1980 to 1.2 in 1995. Thereafter, the feed conversion ratio has stabilized around 1.2. Given that salmon are now able to utilize feed much more efficiently, there has been a dramatic reduction in the organic emissions from farms relative to production volumes.

Conversely, if there are no or small negative feedbacks on expected profitability, it is unlikely that the industry will internalize detrimental environmental effects. In this case, the government has to regulate the industry if the effects are to be reduced. Environmental considerations have also been a rationale for the regulation of salmon production through licensing by the Norwegian government since 1973.[1] When salmon farming became economically viable in the early 1980s, many entrepreneurs applied to the Norwegian government for licenses to establish farms. The central government determined the number of licenses awarded to each region, while regional/local authorities determined which entrepreneurs should obtain licenses and the location of the farms in their region. License owners could not move their farm to another location or region, or sell their license without a permit from the authorities. Besides spatial location, production volume was also limited for each license. Most of the licenses that have been and are still in operation were awarded during the 1980s.

3. Efficiency decomposition

Following earlier studies in the aquaculture economics literature, a cost function is used to represent the underlying technology:

$$C(y,w) = Min\{w'x; y\}, \tag{1}$$

where w is a vector of input prices, y a given output and x a vector of inputs.[2] While the cost function describes the minimum cost required to produce a given quantity of salmon, producers do not always succeed in minimizing the cost required to produce the output, or in allocating their inputs in a cost-effective manner. A number of technologies and skills are involved in the different operations that are undertaken. Despite generally improved knowledge about the central features of the production process and the introduction of innovations, salmon farmers have had, and still have, an incomplete understanding of the production process. Because of an incomplete understanding of interactions in the fish culture environment, it has been difficult to isolate and measure the effects of new production practices, procedures, and technologies. It is therefore desirable to use a theory of producer behavior where minimum costs are not guaranteed for any given output level and input prices.

Efficiency measurement began with Farrell [16] who proposed an input-oriented cost efficiency (CE) measure, defined as the ratio of minimum production cost to actual observed cost ($w'x$):

$$CE(y,x,w) = \frac{C(y,w)}{w'x}. \tag{2}$$

[1] Besides environmental considerations, regional policy aimed to promote industrial activity and employment in rural regions has also been a motive for regulation.

[2] The argument for choosing cost minimization to represent the technology draws on the heavy regulation of the Norwegian salmon industry. Government licenses have regulated the Norwegian salmon industry since 1973. A salmon farming license specifies the sea location for the farm as well as the maximum size of the farms in terms of m^3 pen volume. Farmers' opportunities to adjust output levels are consequently severely limited, and output can be considered exogenous.

As cost efficiency consists of both technical and allocative efficiency, expression (2) can be decomposed into the product of a technical efficiency (*TE*) index and an allocative efficiency (*AE*) index, as follows:

$$CE(y,x,w) = TE(y,x) \times AE(y,x,w), \tag{3}$$

where the *TE* index is defined as the ratio of technically efficient cost and actual cost:

$$TE(y,x) = \frac{C^{te}(y,x)}{w'x} \tag{4}$$

and the *AE* index is defined as the ratio of minimum cost to the technically efficient cost:

$$AE(y,x,w) = \frac{C(y,w)}{C^{te}(y,x)}. \tag{5}$$

Thus, for producers to achieve minimum cost, it is necessary and sufficient that they be technically efficient and employ the correct mix of inputs in the production process. Failure to achieve either of these outcomes results in higher costs. Evidence of allocative inefficiency indicates that a reduction in costs would be possible by correcting the input mix, whereas technical inefficiency implies that the farm's manager should direct his/her attention to enhancing productivity such that the farm is operating on the efficient production frontier. In addition to any empirical rationale for investigating both technical and allocative inefficiency, methodological reasons also exist, as ignoring either technical or allocative inefficiency may seriously bias the estimates of the modeled efficiency [7].

4. The shadow cost model

Several previous studies have made use of a stochastic frontier approach when estimating inefficiency in Norwegian aquaculture [22,29]. In the stochastic frontier approach, efficiency is modeled by constructing a composed error term, where efficiency estimates are identified separately from the usual white noise stochastic term. There are two drawbacks to this approach. First, while estimating technical *or* economic efficiency is not complicated, the process of decomposing economic inefficiency into its technical *and* allocative efficiency components is less straightforward [23]. Second, the stochastic frontier approach assumes the usual random error term and the half-sided error term, are independent, which can be problematic. For example, a good manager may be better able to cope with exogenous shocks. Thus random shocks might be correlated with technical and allocative efficiency of the firm.

The computational difficulties involved in the decomposition of economic efficiency in the stochastic frontier approach can be resolved by using the alternative shadow price approach to estimate and decompose economic efficiency. Utilization of the shadow price approach allows us to model allocative inefficiency explicitly and further to derive the exact relationship between allocative efficiency and cost. Both types of inefficiencies are modeled parametrically, and hypothesis tests concerning the magnitude and direction of inefficiency are based on the estimated values of these additional parameters. Technical inefficiency is modeled as a fixed effect, and allocative inefficiency is modeled through shadow prices. Shadow prices are those prices that force the technically efficient input vector to be the minimal cost solution for producing a given output, and the observed input mix is allocatively inefficient when some inputs are perceived more or less valuable than their market value.

Formally, the shadow cost function is formulated as follows[3]:

$$C^*\left(y, \frac{w^*}{\phi}\right) = \min_{\phi x}\left\{\left(\frac{w^*}{\phi}\right)(\phi x) : f(\phi x) = y\right\} = \left(\frac{1}{\phi}\right)C^*(y, w^*), \tag{6}$$

where *f* is a neoclassical production function common to all firms, ϕ $(0<\phi<1)$ is a firm-specific parameter measuring the extent to which actual and minimal input usages differ, and w^* is a vector of shadow prices parametrically related to market prices as $w^* = (\theta_1 w_1, \theta_2 w_2, \ldots, \theta_J w_J)$, with $\theta_j > 0$. Because we can only measure relative efficiency using a cost function, shadow and market prices have to be normalized. By choosing the first input as the numeraire and redefining $w^* = [w_1, (\theta_2/\theta_1)w_2, \ldots, (\theta_J/\theta_1)w_J] = [w_1, \theta_{21}w_2, \ldots, \theta_{J1}w_J]$, it is possible to estimate input price distortions relative to the first input: $\theta_{j1} > 1$ implies underuse of input *j* relative to input 1, whereas $\theta_{j1} < 1$ implies overuse.

While firms are assumed to minimize total shadow cost, we do observe only actual cost and input shares. On the other hand by using the relationship between observed prices and shadow prizes, actual cost are related to shadow cost and actual cost shares are related to shadow cost shares [23]:

$$C = \sum_j w_j x_j = \sum_j w_j \frac{C^* S_j^*}{w_j^*} = C^* \sum_j \frac{S_j^*}{\theta_j}, \tag{7}$$

$$S_j = \frac{w_j x_j}{C} = \frac{w_j^* x_j}{C^*} \frac{C^*}{C} \frac{w_j}{w_j^*} = \frac{C^*}{C} \frac{S_j^*}{\theta_j} = \frac{S_j^* \theta_j^{-1}}{\sum_k S_k^* \theta_k^{-1}}. \tag{8}$$

[3] The last equality in the shadow cost function is a consequence of the linear homogeneity in shadow input prices.

To estimate the model, a functional form has to be chosen for the shadow cost function. The translog functional form is a appropriate choice, which is frequently applied in other studies [7,20,21]. When choosing the translog functional form for the shadow cost function, the corresponding actual cost is given by

$$\begin{aligned}\ln C_{it} = & \sum_{i=1}^{I} \ln \frac{1}{\phi_i} D_i + \sum_j \beta_j (\ln \theta_{j1i} w_{jit}) + \frac{1}{2} \sum_j \sum_k \beta_{jk} (\ln \theta_{j1i} w_{jit})(\ln \theta_{k1i} w_{kit}) \\ & + \beta_y \ln y_{it} + \frac{1}{2} \beta_{yy} (\ln y_{it})^2 + \sum_j \beta_{jy} \ln y_{it} \ln(\theta_{j1i} w_{jit}) \\ & + \beta_t t + \frac{1}{2} \beta_{tt} t^2 + \beta_{yt} \ln y_{it} t + \sum_j \beta_{jt} \ \ln(\theta_{j1i} w_{jit}) t \\ & + \ln \left\{ \sum_j \theta_{j1i}^{-1} \left[\beta_j + \sum_k \beta_{jk} \ln(\theta_{k1i} w_{kit}) + \beta_{jy} \ln y_{it} + \beta_{jt} t \right] \right\}, \end{aligned} \tag{9}$$

where subscript i relates to firms and subscripts j and k relate to input factors. Firm-specific technical inefficiency is modeled as a fixed effect through firm-specific dummies (D_i). Firm- and input-specific allocative inefficiency are captured by the price distortion parameters (θ_{j1i}) that measure allocation biases in the input factors relative to the first input. Symmetry and homogeneity of degree one in input prices are imposed through the parameter restriction $\beta_{jk} = \beta_{kj}$ for $j \neq k$, $\sum_j \beta_j = 1$, $\sum_j \beta_{jy} = 0$, $\sum_j \beta_{jt} = 0$, and $\sum_j \beta_{jk} = \sum_k \beta_{jk} = \sum_j \sum_k \beta_{jk} = 0$. The last term in function (9) is the difference between the actual cost function and the corresponding shadow cost function. The corresponding input cost share can be written as

$$S_{jit} = \frac{[\beta_j + \sum_j \beta_{jk} \ln(\theta_{k1i} w_{kit}) + \beta_{jy} \ln y_{it} + \beta_{jt} t] \theta_{j1i}^{-1}}{\sum_j [\beta_j + \sum_k \beta_{jk} \ln(\theta_{k1i} w_{kit}) + \beta_{jy} \ln y_{it} + \beta_{jt} t] \theta_{j1i}^{-1}}. \tag{10}$$

Over time, innovation and adoption of new technology may lead to shifts in the cost frontier, which necessitates accounting for technological progress in the model. Hicks-neutral technological change is represented by a quadratic function of time, and nonneutral change is represented by interaction terms between the right-hand side variables and a trend variable. A primary drawback of this specification is that it restricts technical efficiency to being time invariant, as the time trend cannot appear as a regressor in both technological change and technical efficiency change [24]. On the other hand, time-invariant technical efficiency can be a reasonable assumption as estimated firm differences to a large extent are believed to reflect differences in biophysical conditions, and moving a farm to improve its location and biophysical conditions is difficult as production licenses specify the sea location for each individual farm.

In contrast to the case for technical efficiency, it is possible to account for time-varying allocative efficiency. Replacing the time-invariant allocative inefficiency measure with a firm-specific quadratic function of time,

$$\theta_{j1it} = \eta_{j1i} + \eta_{j1it} t + \eta_{j1itt} t^2, \tag{11}$$

makes the allocative price distortion input, firm and time specific [8,12]. The parameter η_{j1i} captures the time-invariant but firm- and input-specific effect, whereas η_{j1it} and η_{j1itt} capture the input-, firm-, and time-varying effects.

5. Data

Production data are provided by the Norwegian Directorate of Fishery and originate from an annual profitability survey of Norwegian salmon farms. Each year, all firms with aquaculture licenses receive two detailed questionnaires from the Directorate of Fisheries. Together with cost, revenue, production, and input levels, the data set includes a farm identification code, that allows us to track farms over time. These farms are located in nine different coastal regions along the Norwegian coast, covering the entire Norwegian salmon production area from the southernmost region of Rogaland to the northernmost region of Finmark. The survey format of the data collection generates an unbalanced panel, as few firms are represented across all years. Our panel contains data on 25 Norwegian salmon farms observed from 1985 to 2004. For each firm we have at least 16 observations, giving a total of 439 observations. To estimate the model, we employ data on real output, prices and cost shares for feed, labor, and capital. Table 1 provides summary statistics of these variables.

Output is the salmon harvest in kilos, adjusted for the change in stock of live fish in the pens and the change in frozen holdings during the year.[4] The price of feed is the total cost of feed divided by the quantity of feed.[5] The price of labor is total labor costs divided by labor inputs, measured by the hours of work at the farm by owners and workers. The price of capital is the depreciation cost plus a user cost calculated as 7% of total capital [28].

[4] The output is live fish delivered to a processing plant. Hence, farms do not produce different product forms. However, the market does distinguish between different sizes of fish and can be regarded as a segmented market. Whether this is the case has been tested by Asche and Guttormsen [5]. As they find that the generalized composite commodity theorem holds, one can analyze the generic commodity salmon.

[5] For the period 1985–1993, the quantity of feed is not given directly but is calculated as the product of output and the feed conversion ratio [26].

Table 1
Summary statistics for the variables in the analysis.

	Mean	Std. dev.	Min.	Max.
Cost (C)	9,771,909	9,155,868	766,809	67,012,886
Output (y)	841,693	879,552	40,696	5,794,797
Feed price (w_f)	7.2622	2.0108	3.0103	23.2844
Labor price (w_l)	164.89	74.91	37.96	596.87
Capital price (w_c)	0.1331	0.0407	0.0455	0.4192

Cost and prices are in NOK.

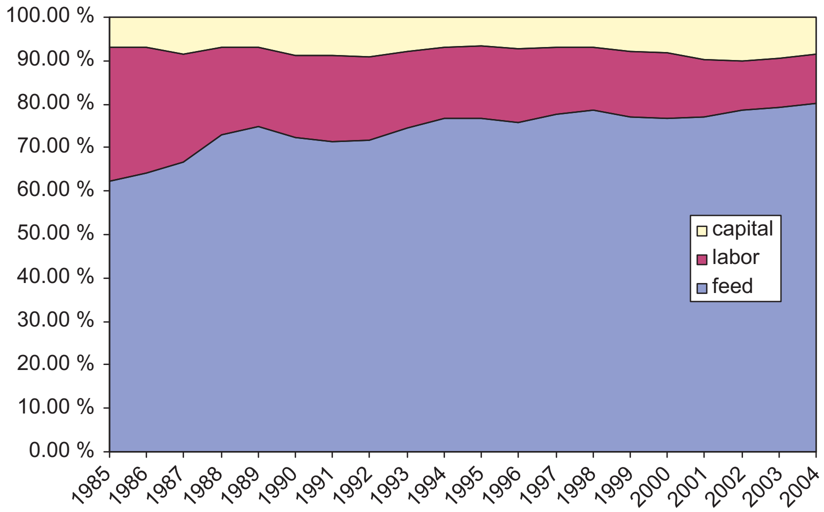

Fig. 1. Cost shares in Norwegian salmon farming. *Source*: Norwegian directorate of fisheries.

Production costs are the sum of feed, labor, and capital costs. As previously discussed, salmon farming production costs have decreased substantially over time. Moreover, along with the substantial general reduction in production cost, cost shares have shifted dramatically over time [17]. This is illustrated in Fig. 1, where the production cost of the Norwegian salmon farm industry is divided into feed, labor, and capital costs. As shown, feed is the most important input in salmon farming. While feed cost per kilo of salmon produced has fallen since 1980, its share of costs has increased substantially during the same period. This is mainly because technical change has led to even greater savings in other inputs. However, the cost share of labor has decreased. This is explained by the substitution of manual labor with capital equipment and information technologies in several tasks, including fish feeding and monitoring. The share of capital costs has been relatively stable over time. This has occurred despite automation of the production process. One reason for this may be that the new equipment makes the production process less costly for all factors, including the cost of the capital itself. Furthermore, higher production at each farm has led to the greater utilization of capital equipment.

6. Empirical analysis

The translog cost function in Eq. (9), together with labor and feed cost share Eq. (10) form a system of equations estimated after an additive random error is appended to each equation.[6] Because of the nonlinear model specification, a nonlinear generalized least squares method is required to estimate the parameters. With a highly nonlinear model, there may be several local maxima for the likelihood function. We therefore first estimated a restrictive cost frontier to obtain the first sets of starting values; these are then varied in new estimations. The reported parameters are the estimates associated with the highest value of the likelihood function. It is worthwhile to note that the estimated elasticities of scale and input demand are similar to estimates from a linear translog cost function [17,28]. This gives further evidence that our model has converged to a global maximum. Because of the long time series involved, we test for serial correlation. The Durbin–Watson test statistic is 1.54, and therefore the hypothesis of no autocorrelation is not rejected.

Table 2 presents the full set of technology parameters (the parameters associated with technical and allocative inefficiency are reported and commented upon below). The parameter subscripts relate to y: output, f: feed price, l: labor

[6] The share equation of capital was removed from the system to avoid singularity.

Table 2
Estimated technology parameters.

Parameter	Coefficient	t-value
β_y	0.9878	13.9616[a]
β_{yy}	0.0911	2.6907[a]
β_f	0.8793	68.1151[a]
β_l	0.0980	9.4432[a]
β_c	0.8041	38.7503[a]
β_{ff}	0.0427	7.1911[a]
β_{fl}	−0.0344	−6.1225[a]
β_{fc}	−0.0083	−4.8039[a]
β_{ll}	0.0439	7.1825[a]
β_{lc}	−0.0094	−5.3475[a]
β_{cc}	0.0177	5.1509[a]
β_{fy}	0.0500	7.6631[a]
β_{ly}	−0.0385	−6.7855[a]
β_{cy}	−0.0116	−4.4631[a]
β_t	−0.0915	−7.7232[a]
β_{tt}	0.0058	6.5827[a]
β_{yt}	−0.0084	−1.6475
β_{ft}	−0.0046	−5.6720[a]
β_{lt}	0.0017	3.4650[a]
β_{ct}	0.0029	4.6182[a]
Log-likelihood value	2486.84	
R^2 of cost function	0.979701	
R^2 of feed share equation	0.830484	
R^2 of labor share equation	0.866081	

[a] Indicates that the coefficient is significant at the 1% level.

Table 3
Derived demand and Morishima elasticity estimates.

Elas.	Derived demand elasticities		Morishima elasticities	
	Estimate	t-value	Estimate	t-value
ε_{ff}	−0.1951	−24.5883[a]		
ε_{ll}	−0.5733	−16.2056[a]		
ε_{cc}	−0.6980	−16.1681[a]		
ε_{fl}	0.1266	16.8390[a]	0.7435	18.4820[a]
ε_{fc}	0.0685	29.8193[a]	0.8392	33.1739[a]
ε_{lf}	0.5485	16.8390[a]	0.6999	16.4165[a]
ε_{lc}	0.0249	2.43183[b]	0.6273	12.8460[a]
ε_{cf}	0.6441	29.8193[a]	0.7666	16.8696[a]
ε_{cl}	0.0539	2.43183[b]	0.7229	13.5657[a]

[a] Indicates that the coefficient is significant at the 1% level.
[b] Indicates that the coefficient is significant at the 5% level.

price, c: capital price, and t: time trend. Most of the slope parameters are statistically significant at the 1% level, and the R^2 values for the cost and the share functions are high.

As the interpretation of the individual parameters of a translog function may not be particularly meaningful, the own-price and cross-price elasticities of the conditional factor demands are calculated. The input-compensated own- and cross-price elasticities are together with their t-statistics reported in columns 1 and 2 in Table 3 for the sample average farm. All elasticities are statistically significant at the 1% level, except the cross-price elasticities between labor and capital that are significant at the 5% level. All the inputs have price inelastic demand. However, as expected the own-price elasticity is less elastic for feed than for labor and capital. This result is consistent with [17], who found that the substitution possibilities for feed have diminished because of the increasing cost share of feed. Furthermore, all of the cross-price elasticities are positive, indicating that the input factors are substitutes.

Because one is sometimes interested in a more direct measure of the technical rate of substitution, we also report the Morishima elasticities of substitution. In some ways, the Morishima elasticities are more meaningful measures of pairwise input substitution than standard input demand elasticities as they provide an accurate indication of the curvature of the

Table 4
Test of technical and allocative inefficiency.

	Null hypothesis	χ^2-value	Decision
(i)	$TE_i = 1\forall i$	112.926	Reject H_0
(ii)	$\theta_{lft} = 1\forall i$	14140.284	Reject H_0
(iii)	$\theta_{cft} = 1\forall i$	85621.016	Reject H_0

isoquant, unlike the one-price, one-factor input-compensated, demand elasticities [11]. Defined in terms of the cost function, the Morishima elasticity of substitution is derived as the logarithmic derivative of an input quantity ratio with respect to the corresponding input price ratio, which can be written as $MES_{jk} = \varepsilon_{kj} - \varepsilon_{jj}$. The derived Morishima elasticities and associated t-statistics are shown in columns 3 and 4 in Table 3. All of the Morishima elasticities of substitution are significant at the 1% level, and similar to the conditional cross-price elasticities, the Morishima elasticities of substitution are positive, indicating that the input factors are substitutes.

Returns to scale (RTS) are given by the inverse cost elasticity of output, which is given by

$$RTS = \left[\begin{array}{c} \beta_y + \beta_{yy}\ln y_{it} + \sum_j \beta_{jy}\ln(\theta_{j1rt}w_{jit}) + \beta_{yt}t \\ + \left[\sum_j \beta_{jy}\theta_{1j}^{-1}\right] \times \left\{\sum_j \theta_{j1rt}^{-1}\left[\beta_j + \sum_k \beta_{jk}\ln(\theta_{k1rt}w_{kit}) + \beta_{jy}\ln y_{it} + \beta_{jt}t\right]\right\}^{-1} \end{array}\right]^{-1}. \tag{12}$$

The sample average RTS is calculated as 1.20, thereby indicating increasing RTS. This is in accordance with [28], who found the estimated RTS to be 1.206. The elasticity is fairly stable from 1988, but were higher in the earlier years [26].

Technological change has shifted the cost frontier over time. The rate of technological change is given by the cost elasticity with respect to the time trend variable:

$$\begin{aligned} TC_t = \frac{\partial \ln C_{it}}{\partial t} &= \beta_t + \beta_{tt}t + \beta_{yt}\ln y_{it} + \sum_j \beta_{jt}\ln(\theta_{j1rt}w_{jit}) \\ &+ \left[\sum_j \beta_{jt}\theta_{1j}^{-1}\right] \times \left\{\sum_j \theta_{j1rt}^{-1}\left[\beta_j + \sum_k \beta_{jk}\ln(\theta_{k1rt}w_{kit}) + \beta_{jy}\ln y_{it} + \beta_{jt}t\right]\right\}^{-1}. \end{aligned} \tag{13}$$

The calculated sample mean technological change is highly significant with an average yearly cost saving effect of 2.27%. Several factors help explain this considerable technological progress: Large innovations in the genetic quality of the salmon, the quality of fish feed and feeding equipment, disease treatment and vaccines, and sea cage systems all took place during the sample period.

The main focus of this paper is on the magnitude of technical and allocative inefficiency. In Table 4, Wald test statistics are reported for the null hypotheses of (i) absence of technical inefficiency and the absence of allocative inefficiency for (ii) labor and (iii) capital. As all of the null hypotheses are rejected, we conclude that both technical and allocative inefficiency are present in the Norwegian aquaculture industry and are important when estimating efficiency.

Input-oriented technical efficiency is defined as the ratio of a farm's input use to the frontier's input use [18]. It is only possible to measure relative technical efficiency, and the most efficient farm in the sample (farm e) is therefore assumed to be technically efficient, against which all other farms are compared. Consequently, technical efficiency is calculated by

$$TE_i = \frac{\phi_i}{\phi_e} = \frac{\exp[\ln(1/\phi_e)]}{\exp[\ln(1/\phi_i)]} = \exp[\ln(1/\phi_e) - \ln(1/\phi_i)]. \tag{14}$$

$TE_e = 1$ by definition, whereas $0<TE_i<1$, $i\neq e$, and measures a farm's degree of technical efficiency relative to the most efficient farm.

While technical efficiency measures the maximum equiproportional reduction in all inputs that still allows continued production of a given output, the reciprocal of expression (14) measures technical inefficiency (TI), or the magnitude of the consequent cost increase. Fig. 4 depicts the full sample range of TI estimates found. The potential cost reductions range from 0.5% to 23% across the farms, and the mean technical inefficiency is 10%. Thus, on average, the sample farms could reduce their costs by 10% by using their inputs more efficiently. In addition to increasing the production cost for the average framer, inefficient use of environmentally degrading inputs contribute to the environmental impact of the industry.

Table 5 provides the estimated price distortion parameters for allocative inefficiency in labor and capital. Price distortion parameters for feed are not available as feed is the numeraire and normalized to one. An estimate of $\theta_{j1}<1$ implies that input j is overused relative to feed, whereas $\theta_{j1}>1$ indicates that input j is underused relative to feed, where j represents labor and capital. The t-statistics are generally large, thereby indicating the presence of allocative inefficiency. Forty-three percent of the allocative inefficiency parameters are statistically significant at the 5% level. The firm-specific, input but time-invariant (η_{lfi} and η_{cfi}) effects are, however, more significant than the time-varying parameters (η_{lfit}, η_{lfitt}, η_{cfit}, and η_{cfitt}). For 66% of the time, the invariant parameters are different from one at the 5% level of significance, while for

Table 5
Price distortion parameters for labor and capital.

$\theta_{lfi}=$	$\eta_{lfi}+\eta_{lfit}\times t$	$+\eta_{lfitt}\times t^2$	$\theta_{cfi}=$	$\eta_{cfi}+\eta_{cfit}\times t$	$+\eta_{cfitt}\times t^2$
$\theta_{lf1}=$	$-0.005+0.105\times t$	$-0.002\times t^2$	$\theta_{cf1}=$	$-0.189+0.083\times t$	$-0.001\times t^2$
$\theta_{lf2}=$	$0.909-0.013\times t$	$+0.003\times t^2$	$\theta_{cf2}=$	$0.347+0.001\times t$	$+0.000\times t^2$
$\theta_{lf3}=$	$1.234-0.063\times t$	$+0.002\times t^2$	$\theta_{cf3}=$	$-0.990+0.334\times t$	$-0.013\times t^2$
$\theta_{lf4}=$	$0.316+0.158\times t$	$-0.006\times t^2$	$\theta_{cf4}=$	$0.891-0.056\times t$	$+0.003\times t^2$
$\theta_{lf5}=$	$0.182-0.011\times t$	$+0.004\times t^2$	$\theta_{cf5}=$	$0.789+0.130\times t$	$-0.006\times t^2$
$\theta_{lf6}=$	$-0.026+0.093\times t$	$-0.001\times t^2$	$\theta_{cf6}=$	$-0.055+0.080\times t$	$-0.002\times t^2$
$\theta_{lf7}=$	$0.077+0.026\times t$	$+0.000\times t^2$	$\theta_{cf7}=$	$1.806-0.110\times t$	$+0.003\times t^2$
$\theta_{lf8}=$	$0.347+0.080\times t$	$-0.005\times t^2$	$\theta_{cf8}=$	$0.812-0.063\times t$	$+0.003\times t^2$
$\theta_{lf9}=$	$0.387-0.015\times t$	$+0.002\times t^2$	$\theta_{cf9}=$	$0.524-0.014\times t$	$+0.001\times t^2$
$\theta_{lf10}=$	$0.173+0.047\times t$	$-0.002\times t^2$	$\theta_{cf10}=$	$0.086+0.020\times t$	$-0.001\times t^2$
$\theta_{lf11}=$	$0.413-0.030\times t$	$+0.002\times t^2$	$\theta_{cf11}=$	$0.329+0.056\times t$	$-0.002\times t^2$
$\theta_{lf12}=$	$0.189+0.068\times t$	$-0.001\times t^2$	$\theta_{cf12}=$	$0.561-0.012\times t$	$+0.002\times t^2$
$\theta_{lf14}=$	$1.499-0.210\times t$	$+0.011\times t^2$	$\theta_{cf13}=$	$-0.047+0.133\times t$	$-0.006\times t^2$
$\theta_{lf13}=$	$0.134+0.118\times t$	$-0.004\times t^2$	$\theta_{cf14}=$	$0.052+0.174\times t$	$-0.006\times t^2$
$\theta_{lf15}=$	$0.501+0.056\times t$	$-0.001\times t^2$	$\theta_{cf15}=$	$0.637-0.133\times t$	$+0.007\times t^2$
$\theta_{lf16}=$	$0.170+0.068\times t$	$-0.001\times t^2$	$\theta_{cf16}=$	$0.999-0.046\times t$	$+0.002\times t^2$
$\theta_{lf17}=$	$0.662-0.039\times t$	$+0.004\times t^2$	$\theta_{cf17}=$	$-0.001+0.112\times t$	$-0.002\times t^2$
$\theta_{lf18}=$	$0.103+0.149\times t$	$-0.006\times t^2$	$\theta_{cf18}=$	$0.977-0.033\times t$	$-0.001\times t^2$
$\theta_{lf19}=$	$0.379-0.013\times t$	$+0.005\times t^2$	$\theta_{cf19}=$	$0.996+0.018\times t$	$-0.002\times t^2$
$\theta_{lf20}=$	$0.266-0.056\times t$	$+0.007\times t^2$	$\theta_{cf20}=$	$0.525+0.011\times t$	$+0.000\times t^2$
$\theta_{lf21}=$	$0.116+0.253\times t$	$-0.009\times t^2$	$\theta_{cf21}=$	$0.701-0.129\times t$	$+0.007\times t^2$
$\theta_{lf22}=$	$0.204-0.012\times t$	$+0.002\times t^2$	$\theta_{cf22}=$	$0.466+0.025\times t$	$-0.001\times t^2$
$\theta_{lf23}=$	$1.047-0.105\times t$	$+0.005\times t^2$	$\theta_{cf23}=$	$3.333-0.291\times t$	$+0.009\times t^2$
$\theta_{lf24}=$	$0.894-0.128\times t$	$+0.008\times t^2$	$\theta_{cf24}=$	$2.266-0.264\times t$	$+0.008\times t^2$
$\theta_{lf25}=$	$1.878-0.215\times t$	$+0.010\times t^2$	$\theta_{cf25}=$	$-0.036+0.077\times t$	$-0.003\times t^2$

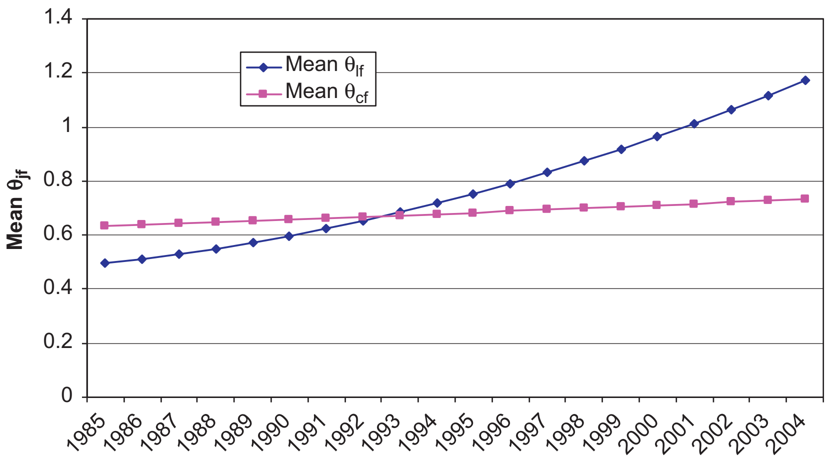

Fig. 2. Development of sample average price distortion parameters for labor (Θ_{lf}) and capital (Θ_{cf}).

the time-variant parameters, only 34% of the first-order and 30% of the second-order effects are statistically different from zero at the 5% level of significance. It also appears that the price distortion parameter is more significant for labor than for capital: 51% of the price distortion parameters are statistically significant for labor at the 5% level, while for capital, only 36% are significant.

There are considerable variations in the price distortion estimates among farms and over time. In many ways, this is expected because production shocks may alter the input factor use and cause substantial variations in the price distortion estimates among farms. Therefore, it is difficult to provide a simple description of the developments in allocative efficiency. A plot of the sample average price distortion factors over time may be useful to clarify the core of the matter.

Fig. 2 illustrates the development of the price distortions for labor and capital. The sample average price distortion factor for labor shows a gradual increment from 0.5 in 1985 to 1.2 in 2004. This indicates a yearly reduction in the overutilization of labor, until the average farm achieved full labor-feed allocative efficiency in 2001, after which a period of underutilization followed. In the same way as labor, the average price distortion for capital starts out significantly below one. However, compared with labor, the sample average price distortion parameters exhibit a very slow increase, and

Table 6
Number of significantly allocatively efficient and inefficient farms[a].

	1985	1990	1995	2000	2004
Labor					
$\theta_{lfi}<1$	18	18	12	7	3
$\theta_{lfi}=1$	7	7	12	17	21
$\theta_{lfi}>1$	0	0	1	1	1
Capital					
$\theta_{cfi}<1$	16	16	13	12	8
$\theta_{cfi}=1$	9	9	12	13	17
$\theta_{cfi}>1$	0	0	0	0	0

[a] Farms are significantly allocative efficient (at the 5% level) if $\theta_{lfi}=1$ or $\theta_{cfi}=1$, and inefficient if $\theta_{lfi}<1$, $\theta_{lfi}>1$, $\theta_{cfi}<1$, or $\theta_{cfi}>1$.

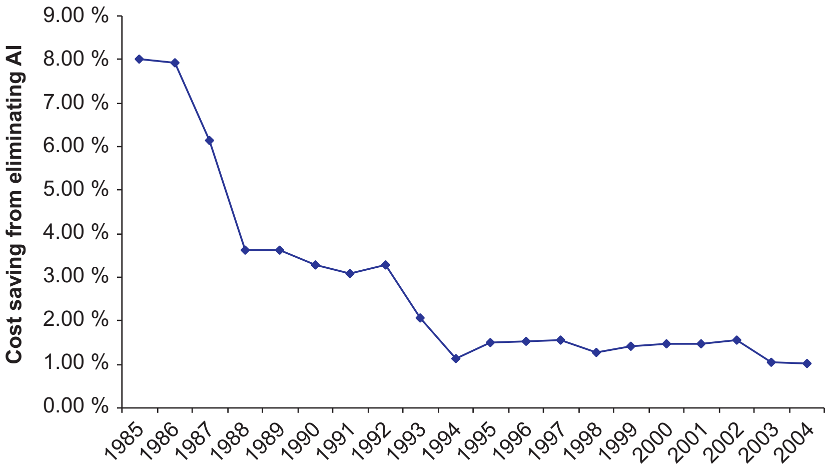

Fig. 3. Cost saving from eliminating allocative inefficiency.

capital is overused for the entire period. One reason for the slow change may be that it is often costly to adjust capital, especially if the capital has a long productive life.

To shed more light on the development of allocative efficiency, we report in Table 6 the number of farms that have price distortion factors significantly less than, equal to, and greater than one, for the years 1985, 1990, 1995, 2000, and 2004. Table 6 complements the information in Fig. 2. This clearly shows how more and more farms have become allocatively efficient for both labor and capital in the later years of the sample. Of particular interest is the price distortion of labor relative to feed. In 2004, the vast majority (21 of 25 farms) are allocatively efficient. Overall, Table 6 indicates that most of the sample farms are allocatively efficient at the end of the data period.

The percentage excess cost caused by allocative inefficiency can be calculated as one minus the ratio of the estimated cost function assuming allocative efficiency ($\theta_{lfi}=1$ and $\theta_{cfi}=1$) to the estimated cost without these restrictions. Fig. 3 illustrates the annual average costs for the period. The potential cost savings from eliminating allocative inefficiency have declined over time as allocative inefficiency has fallen. We find, as expected greater efficiency improvements in early years, as the potential for improvement is greater when the industry is young and farmers can increase efficiency by accumulating valuable production experience (or learning by doing). The average potential cost reduction from correcting allocative inefficiency declined from 8% in 1985 to 1% in 1994, then leveled out, remaining between 1% and 2% for the remainder of the sample period, a level that can be interpreted as the achievement of full allocative efficiency. Hence, the decline in the cost of allocative inefficiency indicates that while an inefficient input mix was an issue in Norwegian salmon aquaculture in the 1980s and early 1990s, this has largely disappeared.

Fig. 4 shows the average potential cost savings from eliminating technical and allocative inefficiency for the 25 sample farms. Even if technical and allocative inefficiency show substantial variations across farms, the correlation between them is positive, with an estimated correlation coefficient of 0.648. Thus, a technically inefficient farm also often exhibits a high degree of allocative inefficiency. This may indicate the existence of complementary technical and economic managerial skills, where some farmers are better managers than others, and more capable in terms of both adopting and using state-of-the-art production technologies and adjusting input use to the prevailing input prices vector.

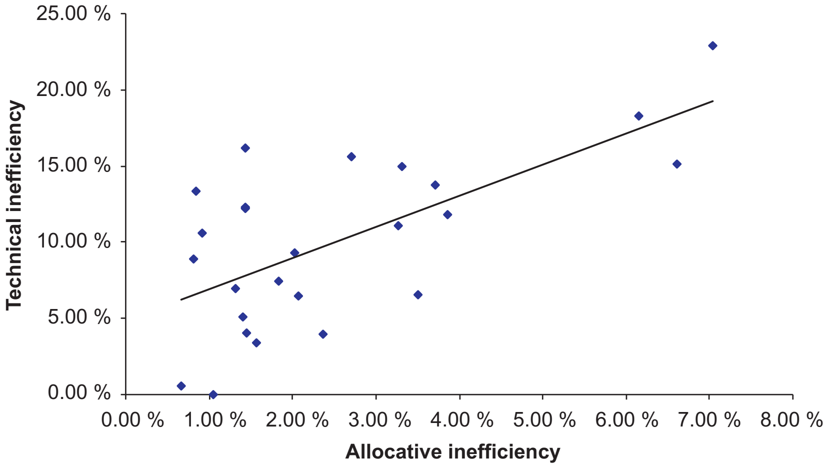

Fig. 4. Farm-specific technical and allocative inefficiency (in percentage of cost).

Although there is a positive correlation between the potential cost reductions from technical and allocative inefficiency, the size of the average potential cost reduction in the data period is not identical. The potential cost reduction from reducing the level of technical inefficiency is approximately three times the potential cost reduction from reducing the level of allocative inefficiency. That is, a greater reduction in cost is possible by improving technical efficiency, giving managers an incentive to enhance the productivity of all inputs so that the farms can operate on the efficient production frontier.

7. Conclusion

In industries with a high rate of innovation and rapid productivity growth, one often observes several different technologies employed at the same time, contributing to technical and allocative inefficiency. In biological industries where biophysical factors contribute to a complex production environment, the consequence of technical and allocative inefficiency can be even larger because both types of inefficiencies can contribute to the environmental impact of the industry. Technical inefficiency always lead to overuse of all input factors, while allocative inefficiency can lead to either over- or underuse use of specific environmentally degrading inputs.

Aquaculture in general, and salmon aquaculture in particular, is an industry with a biological production process that has experienced rapid technological progress. In salmon aquaculture, the industry average real production cost in 2004 was about a quarter of the cost in the mid-1980s but with a substantial variation of individual firm costs around the average each year [13]. Hence, it is challenging for firms in this industry to keep pace with the technological frontier and to use the correct input factor mix.

To investigate the effects of technical and allocative inefficiency, a shadow cost model based on a system consisting of a translog cost function and its factor share equations was specified and estimated. Because salmon aquaculture is a relatively young industry where the technical frontier is moving fast, we have accounted for time-varying efficiency by letting allocative efficiency change over time. We also estimated the rate of technological change, representing innovations in feed and feeding, disease treatment, and information technologies. Our results imply an annual rate of technical progress of 2.28% during the sample period. The positive development in the feed conversion ratio demonstrates the potential for technical progress to reduce environmental impacts.

Our results show that both technical and allocative inefficiency on average are significant in explaining the level and variation in farm costs. Although both technical and allocative inefficiency vary substantially between farms, our results indicate that they are positively correlated. Therefore, a technically inefficient farm will often also exhibit a high degree of allocative inefficiency. This may indicate the existence of managerial skills whereby some farmers are better managers than others, both in adopting and using state-of-the-art production technologies and in adjusting their input use to the prevailing input price vector. The mean technical efficiency level was estimated to be 90%, indicating that, on average, the sample farms could reduce their costs by 10%. The costs resulting from allocative inefficiency or an incorrect factor mix have been substantially reduced over time. From an estimated cost increase of 8% in the early sample years, the potential mean cost reduction declined to 1% by the end of the sample period. The decline in the cost of allocative inefficiency indicates that while an inefficient input mix was an issue in Norwegian salmon aquaculture in the 1980s and early 1990s, this has largely disappeared as fish farmers have increased their understanding.

The main environmental impact due to inefficiency from the Norwegian salmon aquaculture industry has its origin in the technical inefficiency. While, once an issue, allocative inefficiency concerns have largely disappeared. The technological progress and reduction in technical inefficiency also suggest that environmental impacts are falling over time.

Our results should also be considered in relation to the substantial technological progress that has characterized the industry. As with many new technologies, there may be unexpected side effects, and there will be a time lag from when a problem arises until it can be addressed. First, the impact and the causes must be properly identified. Second, the solution to the problems will require modification of existing technologies or practices, or perhaps entirely new technologies. In both cases, a reduction in pollution implies some form of induced innovation. Our results are therefore in accordance with the hypothesis that over time, an internalization process of externalities has resolved some of the major environmental issues in aquaculture [4]. Productivity in aquaculture depends crucially on an environment where farmed fish thrive. Fish farms with environmental practices that deteriorate the local environment will experience negative feedback effects, where poor water quality reduces on-farm productivity. The results are a reduced biomass growth through deteriorating fish health and, in a worst-case scenario, disease outbreaks that wipe out entire on-farm fish stocks. Consequently, one is concerned with cultivating management practices that avoid such negative repercussions on productivity.

What are the implications of our results for future growth and environmental impacts of the salmon aquaculture industry? Because the industry is largely allocatively efficient, there is limited scope for reducing future feed use per kilo of salmon produced. This implies that feed use should increase at the same rate as production.[7] However, there is still room for improvement in technical efficiency, as the cost associated with the mean technical efficiency is found to be 10%. Hence, by improving the technical efficiency both cost and the environmental impact could be reduced.

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[7] This does not mean that the industry will increase its demand for marine feed ingredients at the same rate in the future, because it still has considerable technical scope for changing the mix of ingredients in the feed; for instance, from marine to vegetable ingredients [9,27]. The global supply of marine feed ingredients is limited by fish stocks and is many times smaller than the vegetable substitutes. As marine ingredients become scarcer relative to vegetable ingredients, one would expect substitution away from fish oil and meal.

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