Technical Change and Productive Inefficiency Change in Norwegian Salmon Farming: The Influence of Regional Agglomeration Externalities

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Abstract. This paper analyses the factors explaining productivity and efficiency differences across salmon aquaculture farms, with an emphasis on agglomeration externalities. We specify a stochastic frontier production model with agglomeration indexes included in both the frontier production function and the technical inefficiency model. The frontier model is estimated on a rich panel data set with 2,738 observations on 577 farms. Our results confirm the importance of agglomeration externalities for the productivity and technical inefficiency of salmon farms. Both frontier output and technical efficiency increase with increasing regional industry size. There is a negative relationship between overall productivity and regional farm density, suggesting the presence of negative biological congestion externalities. These results have implications for the Norwegian government's regulation of the industry, since the government, to a large extent, has determined the spatial distribution of salmon production through a licence system.

1. INTRODUCTION

During the 1990s, several empirical studies of agglomeration externalities have appeared in the literature.[1] These studies hypothesized that there is a positive relationship between the size of an industry, or industry agglomeration, in a region, and externalities among firms belonging to the regional industry that lead to increased productivity. Such externalities can be among competing firms, among firms and their vendors, or among firms and their customers.

Our empirical analysis focuses on a primary production sector – salmon aquaculture. The notion that primary production sectors (e.g., agriculture and aquaculture) are technologically less sophisticated than manufacturing and certain service sectors has become obsolete with the increasing use of computer-based technologies and bio-technologies in the former sectors. This development may have lead to the emergence of external economies that were previously not present in primary production sectors.

Our study of Norwegian salmon aquaculture extends the empirical literature on agglomeration economies in three directions. First, we measure agglomeration externalities, or "localization" economies, using firm-level panel data instead of aggregate industry data.[2] Hence, we avoid aggregation biases associated with internal returns to scale and the assumption of cross-industry homogeneity for input parameters of the production function, which also influence the estimates of external returns to scale (Burnside, 1996). Second, we separate the effects of agglomeration externalities on the production frontier and technical inefficiency. Previous studies have estimated average production functions. Third, we provide empirical evidence for a primary production sector. Although, empirical analysis of external effects have generally been undertaken for manufacturing sectors, there are also pervasive reasons to hypothesize the presence of such effects in primary sectors due to technological sophistication, specialization and indivisibilities associated with both physical capital and labor. We assert that this is the case for the salmon aquaculture industry.

[1] See, for example, Caballero and Lyons (1992), Ciccone and Hall (1996), Paul and Siegel (1999), and other studies cited in Eberts and McMillen (1999).

[2] Localization economies are external to the firm but internal to the industry. Another category of agglomeration economies, which is external to both the firm and the industry, is termed "urbanization economies". See Eberts and McMillen (1999, pp. 1460-63) for a discussion of different types of agglomeration economies.

We employ an unbalanced panel data set with 2,738 observations on 577 salmon aquaculture farms observed during the years, 1985 to 1995. The farms were observed from one to eleven years. Information on the age of the farm, regional location, production level, input levels, costs and revenues are included in the data set. Several econometric production model specifications are estimated to test hypotheses on productivity convergence.

Finally, we estimate model specifications with internal and external factors that can influence productivity. The external factors we consider are regional industry size (measured by employment) and farm density in the region. We assert that the possibilities for the sharing of industry infrastructure capital and exploiting external economies of scale are closely linked with these two regional industry indicators.

The paper is organized as follows: Section 2 provides a further discussion of some of the issues raised in the introduction. The empirical models are presented in Section 3. Section 4 presents the empirical analysis. A summary and conclusions are provided in Section 5.

2. MODEL SPECIFICATION ISSUES

This section discusses agglomeration externalities and other issues that have implications for the specification of the production models in this paper.

In the empirical analysis, we compare the performance of salmon aquaculture producers in eight Norwegian regions. There are substantial cross-regional differences in the size of the salmon aquaculture industry and the spatial concentration of production. This is important if there are external economies of scale.[3] Sources of external economies are indivisibilities associated with tangible and intangible capital inputs, such as physical industry infrastructure capital, research and development, knowledge spillovers (i.e., learning from others) and specialized human capital. Firms sharing these types of capital inputs have savings on materials and labor inputs, and a reduced need for internal investments in certain types of capital equipment.

Salmon aquaculture is a capital-intensive industry. Several types of capital equipment used by the industry are characterized by lumpiness, where full capacity utilization requires that several farms demand their services.[4] The industry is also a heavy user of advanced computer-based technologies for different operations in the production process (Dietrichs, 1995). Moreover, it demands specialized expertise in management, export marketing, production monitoring, veterinary services, biology, etc. Provision of specialized services to the industry requires a certain minimum market size. Since the Norwegian industry is spread over a long coastline, with high transportation costs for factors of production, the relevant input market is generally the regional market. It can be asserted that an increase in the size of the regional salmon aquaculture industry will lead to the provision of more productive specialized physical and human capital inputs.

Another source of external economies is knowledge spillovers. Producers may not only learn from their own production experiences, but also from those of others. The extent of external knowledge spillovers should increase with farm density, which is considered in one of the model specifications below. Finally, producers may learn from other agents in the industry infrastructure. Feed manufacturers, veterinarians, salmon fingerling producers and researchers may be sources of knowledge on different aspects of the production process for salmon farming.

Industry-specific infrastructure is, to a large extent, organized in regional units. This is the case for government agencies that monitor and assist fish farms on disease treatment, environmental issues (e.g., farm location) and other matters that affect farm performance. The *Norwegian Fish Farmers' Association*, which is organized in regional units, is involved in training programs and dissemination of knowledge to fish farmers.

There are several other reasons for using a regional division for the Norwegian salmon farming industry. First, regions have different biophysical conditions. This applies particularly to sea temperature and water exchange, which are two important determinants of salmon growth and mortality. The average sea temperature is significantly lower in the northern counties than in the southern counties. The growth rate of salmon increases with sea temperature. On the other hand, due to tidal currents, the water exchange is higher in the northern regions than in the southern regions, implying that the supply of clean water and oxygen is higher in northern regions. Biophysical shocks, such as disease outbreaks and algae blooms, tend to be spatially correlated. Diseases are usually first transmitted to neighboring farms, and the probability of contagion is positively related to the density

[3] For discussions of these issues, and for empirical testing of the contribution of external economies, see Caballero and Lyons (1990), Basu and Fernald (1997), and Paul and Siegel (1999). For an industry with constant internal (or private) economies of scale, external economies of scale are present if a doubling of inputs by all firms more than doubles their outputs.

[4] Examples of lumpy capital inputs are vessels which transport salmon fingerling and salmon feed to the farms, vessels which transport live fish from the farms, and slaughter facilities.

of farms. Density-dependent disease externalities can be regarded as a special type of congestion externalities. In this paper, we explore whether positive or negative density-dependent externalities dominate in salmon aquaculture. Historically, disease losses have not been evenly distributed along the Norwegian coast, but were concentrated in certain regions. In our econometric production model, we use region-specific effects to account for differences in biophysical conditions.

Regions also entered the industry at different stages, which means that there are cross-regional differences in average farm age. If learning-by-doing effects are present then age differences may lead to productivity differences. We include farm age in the production model to account for age-dependent effects.

Government regulations have played an important role in determining the spatial distribution of farms along the Norwegian coast. When salmon farming became economically viable in the early 1980s, a large number of entrepreneurs applied to the Norwegian government for licences to establish farms. The central government decided the number of licences that should be awarded to each region, while regional/local authorities determined which entrepreneurs should obtain licences and the location of farms in the region. Licence owners could not move the farm to another location or region, or sell the licence without a permit from the authorities. It can be asserted that the government regulations produced a spatial farm distribution that would not have emerged with a national licence auction system or free entry. It is natural to ask what effects regulation has had on the productivity of the industry. Are there welfare losses due to higher marginal production costs associated with the current spatial industry configuration?

There are some conceptual problems associated with the specification of external effects in a production frontier model. The literature that deals with external economies, or, more specifically, agglomeration effects, generally includes an external economy index in the production function and ignores inefficiency. For example, Caballero and Lyons (1990) specify the production function, $y = f(\mathbf{x}; E, t)$, where $\mathbf{x}$ includes inputs; E is an external economy index; and t is a productivity index. Inefficiency has been a less relevant issue for most empirical studies of external economies, since they, unlike this study, test hypotheses using aggregate industry data. Important questions are the following. Do external effects, in the form of information spillovers among firms, only lead to the transmission of existing knowledge which is already embodied in the frontier (best-practice) production technology? If this is the case, then knowledge spillovers lead to a reduction in firms' technical inefficiency relative to the production frontier that represents efficient input use with the best-practice technology. On the other hand, could information spillovers be of a nature and processed in a way that leads to the creation of new knowledge which is not already embodied in the frontier production technology? In this case, the production frontier will shift in a positive direction, leading to an increase in maximum output conditional on a given level of inputs. Finally, to what extent are information spillovers and new knowledge creation from this localized? With localized information spillovers and knowledge creation the production frontier becomes region-specific, conditional on an index representing locally generated knowledge.

A general specification of the production model that accounts for the technical inefficiency and other factors discussed above is

$$y = f(\mathbf{x}, D_r, E, t)\cdot\exp(V - U),$$

where $f(\cdot)$ is now the production frontier function; D_r is a region-specific effect (regional dummy), capturing regional biophysical conditions (e.g., temperature and tidal water) and other more or less time-invariant factors influencing productivity; E is an external economy index; t is a time-trend variable, representing technical change; V is a traditional random error term; and U is a *non-negative* random variable associated with technical inefficiency of production. In its most general form, U is defined by

$$U = U(\mathbf{x}, AGE, E),$$

where AGE is the farm age; and $U(\cdot)$ represents a function of the variables, $\mathbf{x}$, AGE and E. With the above specification, the production model allows agglomeration effects to influence both the production frontier and the level of technical inefficiency.

Different measures have been used for the external agglomeration effect, E. Caballero and Lyons (1992) employed aggregate manufacturing output as agglomeration index when analyzing data from a two-digit manufacturing sector. Ciccone and Hall (1996) used a spatial density of employment index as the external-effects index to explain differences in labor productivity across US states.[5] In our analysis of firm-level salmon aquaculture data, we employ both the size of the regional industry and the spatial concentration of production activity as regional agglomeration indexes.

3. EMPIRICAL MODEL SPECIFICATIONS

Three different empirical models, denoted A, B and C, are estimated in this paper. These models are specified with both a stochastic frontier production function and a technical inefficiency model, following Battese and Coelli (1995). The models differ with respect to the specification of agglomeration effects.

[5] Eberts and McMillen (1999, pp. 1480-1483) discuss the measurement of agglomeration economies in urban areas.

The specification of the stochastic frontier production function is:

(1) $\ln y_{it} = \beta_0 + \Sigma_r \beta_r D_r + \Sigma_k \beta_k \ln x_{kit} + \Sigma_j \Sigma_{k \geq j} \beta_{jk} \ln x_{jit} \ln x_{kit} + \beta_t t + \beta_{t2} t^2 + \beta_{t3} t^3 + \Sigma_k \beta_{kt} \ln x_{kit} t + E_r + (V_{it} - U_{it}),$
$i = 1,\ldots, N;\ t = 1,\ldots, T,$

where $\ln y_{it}$ is the natural logarithm of salmon output of farm i in year t; D_r is the dummy variable for region r ($r = H, SF, MR, ST, NT, N, T\&F$); $\ln x_{kit}$ is the logarithm of input k, where $k = F, I, K, L, M$ represent the five inputs, fish feed, fish stock at the beginning of the year, capital, labor, and materials, respectively; E_r is an agglomeration index to be defined below; and the βs are parameters to be estimated. The intercept for region r is $\beta_0+\beta_r$, where β_0 is the intercept for the base region, Rogaland. The production frontier may shift over time according to the values of the parameters, β_t, β_{t2}, β_{t3} and β_{kt}. The V_{it}s are random variables that are assumed to be independent and identically distributed and have $N(0,\sigma_V^2)$-distribution. The translog form for the terms involving the input levels, x_{kit}, implies that we do not impose any *a priori* restrictions with respect to the internal returns to scale. The U_{it}s are non-negative random variables, which account for technical inefficiency in production, and are assumed to be independently distributed, such that U_{it} is the truncation (at zero) of the $N(\mu_{it},\sigma^2)$-distribution, where μ_{it} is a function of observable explanatory variables and unknown parameters, as defined below. It is assumed that the V_{it}s and U_{it}s are independent random variables.

Different specifications of the external economy index, E_r, in the production frontier (1) are estimated. These are defined as follows:

Model A: $E_r = \beta_{RL} \ln RL + \beta_{RL2} (\ln RL)^2$,

where RL is regional industry size (measured by employment).

Model B: $E_r = \beta_{FSR} \ln FSR + \beta_{FSR2} (\ln FSR)^2$,

where FSR is farm density in the region (farms per square kilometer).

Model C: $E_r = \beta_{RL} \ln RL + \beta_{RL2} (\ln RL)^2 + \beta_{FSR} \ln FSR + \beta_{FSR2} (\ln FSR)^2$,

to account for regional industry size and farm density, simultaneously. The rationale for these external economy indexes RL and FSR are discussed later in this section.

Next, we turn to the specification of the technical inefficiency model. The means of the technical inefficiency effects, the U_{it}s, the μ_{it}s, are assumed to be a function of farm and regional characteristics:

(2) $\mu_{it} = \mathbf{z}_{it}\delta$

where $\mathbf{z}_{it}$ is a vector of values of observable variables explaining the inefficiency; and δ is a vector of parameters to be estimated. A positive parameter value for a coefficient of the kth z-variable, i.e., $\delta_k>0$, implies that the mean technical inefficiency increases as the value of this z-variable increases.

The technical inefficiency models are specified as follows:

(3a) $\mathbf{z}_{it}\delta = \delta_0 + \Sigma_k \delta_k \ln x_{kit} + \delta_{LNAGE} \ln AGE + \delta_{LNAGE2} (\ln AGE)^2 + \delta_{RL} \ln RL + \delta_{RL2} (\ln RL)^2 + \Sigma_r \delta_{rt} D_r t + \Sigma_r \delta_{rt2} D_r t^2$ (Model A)

(3b) $\mathbf{z}_{it}\delta = \delta_0 + \Sigma_k \delta_k \ln x_{kit} + \delta_{LNAGE} \ln AGE + \delta_{LNAGE2} (\ln AGE)^2 + \delta_{FSR} \ln FSR + \delta_{FSR2} (\ln FSR)^2 + \Sigma_r \delta_{rt} D_r t + \Sigma_r \delta_{rt2} D_r t^2$ (Model B)

(3c) $\mathbf{z}_{it}\delta = \delta_0 + \Sigma_k \delta_k \ln x_{kit} + \delta_{LNAGE} \ln AGE + \delta_{LNAGE2} (\ln AGE)^2 + \delta_{RL} \ln RL + \delta_{RL2} (\ln RL)^2 + \delta_{FSR} \ln FSR + \delta_{FSR2} (\ln FSR)^2 + \Sigma_r \delta_{rt} D_r t + \Sigma_r \delta_{rt2} D_r t^2.$
(Model C)

The input levels, x_k, are included to account for the relationships between scale of operation and the level of technical inefficiency. Managerial ability, which is unobserved, is expected to be positively correlated with the size of the farm, since larger farms can afford to hire better-educated managers.

The variable, *AGE*, is included as a determinant of technical inefficiency in all model specifications. A negative relationship is expected between technical inefficiency and the logarithm of farm age, due to learning-by-doing. However, there may also be forces working in the opposite direction with respect to farm age. If replacement of physical capital is costly, a negative capital vintage effect, which is positively correlated with farm age, may be present. Furthermore, early entrants tended to be located at more sheltered sites with lower bioproductivity than farms that entered the industry later. According to studies of salmon farms, the marine environment around a farm also tends to become more disease prone over time, due to the accumulation of organic sediments below the cages, leading to oxygen loss and increased risk of fish diseases.[6] Since it may be difficult to obtain a government licence to relocate at a new site with higher bioproductivity, and relocation of farms is costly, farm age may be positively correlated with technical inefficiency. Finally, due to changes in the recruitment process to the industry over time, it may also

[6] These findings have been documented in a large number of scientific reports by Johannessen (with different co-authors) during the 1985-1992 period. See Johannessen, P.J. *et al*. (1985-92), *Studies of Recipient Capacity at Fish Farm Sites* (In Norwegian: "Resipientundersøkelser på oppdrettslokaliteter"), Report, Institute of Fisheries and Marine Biology, University of Bergen.

be the case that the early cohorts of entrepreneurs were less competent than those entering at a later stage.[7]

The models assume that the technical inefficiency is a function of time, t, and allows the rate of adjustment to vary across regions by interacting the time variable with the regional dummy variables, D_r. Through the region-specific time variables, we try to capture technology and knowledge-diffusion processes that lead to reductions in technical inefficiency differentials across regions. By including both farm age and the time effect, we distinguish between the effects of learning-by-own-doing and diffusion processes on the inefficiencies of firms.

Total regional industry employment (*RL*) is included in models A and C. This variable may capture external economies of scale or the availability of industry-specific capital. It can be viewed as a proxy for human capital in the regional industry, but it is probably also correlated with the physical capital of the regional industry.

To account for density-dependent external effects among farms, the number of farms per square kilometer of sea area (*FSR*) in the region is included in models B and C. The proximity of farms can influence productivity in several respects. High farm density should enhance knowledge transmission. It should also lead to a more efficient use of industry capital equipment, such as vessels for transportation of live fish, and fish-processing facilities. Hence, investments by individual farms in capital equipment are expected to decline due to increased opportunities for sharing. This implies that there are external economies of scale associated with an increase in the number of farms in a region. On the other hand, there may be congestion externalities of a biological nature. Fish disease externalities among farms are expected to increase with higher farm density, leading to lower technical efficiency (and productivity).

All inputs and the externality indexes were normalized by their respective sample means prior to estimation.

The parameters of the model are estimated using the program, FRONTIER 4.1, written by Coelli (1996), such that the variance parameters are defined by $\sigma_S^2 = \sigma_V^2 + \sigma^2$ and $\gamma = \sigma^2 / \sigma_S^2$, originally recommended by Battese and Corra (1977). The log-likelihood function of this model is presented in the appendix of the working paper, Battese and Coelli (1993). When the variance associated with the inefficiency term, U_{it}, converges towards zero (i.e., $\sigma^2 \to 0$) then the ratio parameter, γ, approaches zero. When the variance of the random error, V_{it}, (σ_V^2) decreases in size, relative to the variance associated with the U_{it}s, the value of γ approaches one.

4. EMPIRICAL RESULTS

In the presentation of the empirical results, we first discuss the results for the frontier production function and the technical inefficiency model separately, before we present overall results from our estimated models.

The parameter estimates for our stochastic frontier production functions are not presented here.[8] The hypothesis that the average production function is an adequate representation of the data, given the specifications of the stochastic frontier model of equations (1)-(2), is rejected for all three models at the one per cent level of significance. For example, the likelihood-ratio (LR) statistic, for testing that the inefficiency effects in Model A are not present, is equal to 439.60, which exceeds, 46.96, the upper one per cent point for the Chi-square distribution with 27 degrees of freedom.[9]

Table 1. Frontier Elasticity Estimates*

Model	A		B		C	
	Mean	St. Err.	Mean	St. Err.	Mean	St. Err.
E_{Feed}	0.455	0.014	0.455	0.015	0.452	0.015
E_{Infish}	0.269	0.010	0.274	0.010	0.275	0.010
$E_{Kapital}$	0.0212	0.0088	0.0183	0.0091	0.0194	0.0089
E_{Labor}	0.024	0.016	0.023	0.016	0.024	0.016
E_{Mater}	0.0585	0.0089	0.0596	0.0087	0.0621	0.0087
RTS	0.828	0.027	0.830	0.027	0.833	0.027
TC	0.0441	0.0038	0.0563	0.0032	0.0464	0.0035
E_{RL}	0.187	0.041			0.293	0.051
E_{FSR}			-0.002	0.030	-0.139	0.038

- Elasticities are evaluated at the sample mean level of the regressors. *Symbols*: E_k = Elasticity of frontier output with respect to input k (k = F, I, K, L, M); *RTS* = Returns To Scale; *TC* = rate of Technical Change; E_{RL} = Elasticity of frontier output with respect to regional industry employment; E_{FSR} = Elasticity of frontier output with respect to regional farm density.

[7] The Norwegian government awarded licences to new farms, and, in the early stages, it tended to put less emphasis on the qualifications of applicants and more on their regional affiliation.

[8] Available from the authors upon request.

[9] The correct critical values for testing the hypothesis that the parameter, γ, is equal to zero, should be obtained from Table 1 of Kodde and Palm (1986). These values are less than the upper per cent points for the Chi-square distribution. For Model A, the correct value is 39.53. However, if the LR statistic exceeds the Chi-square value, then the null hypothesis that γ=0 should obviously be rejected.

4.1. The Frontier Production Function

The estimates for the *frontier elasticities*, evaluated at the sample mean levels of the variables, are presented in Table 1. Later, in Table 3, we present the elasticities of mean output with respect to the inputs, where the *elasticity of the technical efficiency* is added to the elasticity of frontier output. These elasticity estimates are discussed later.

In all three models, fish feed (F) turns out to be the most important input, as measured by the frontier feed elasticity (E_F) with values 0.45-0.46 across the models for the frontier function (cf. Table 1). Fish stock (I) is the second most important input in terms of frontier output elasticity, with values around 0.27. Labor (L), materials (M), and capital (K) are much less important. The frontier output elasticity with respect to materials is about 13 per cent of the feed elasticity. The frontier output elasticities with respect to capital and labor are about five per cent of the feed elasticity. The returns-to-scale (RTS) parameter, which is the sum of the input elasticities, is very similar across the three models, with a mean value around 0.83. This implies that farms with inputs at the mean levels operate at a sufficiently large scale to exhaust economies of scale.

Models A and C include regional industry size (RL) as a proxy for agglomeration externalities, causing shifts in the regional production frontier. According to the parameter estimates, the production frontier increases with industry size, but at a decreasing rate. The elasticity of frontier output with respect to regional employment (E_{RL}) is 18.7 and 29.3 per cent in Models A and C, respectively (see Table 1). These estimates suggest that an increase in regional industry size has a substantial impact on the regional production frontier.

The other index for agglomeration externalities, regional farm density (FSR), has no statistically significant effect on frontier output in Model B, according to the standard errors of the estimators for the parameters, β_{FSR} and β_{FSR2}. The frontier output elasticity with respect to FSR is estimated to be very small in Model B, namely –0.2%. However, in Model C, the most general model, regional farm density is significant in both statistical and economic terms. The frontier elasticity with respect to FSR is estimated to be –13.9 per cent, meaning that the frontier output is lower for farms that are closely located. Our interpretation of this result is that biological congestion effects, mainly through fish diseases, dominate any positive externalities from spatial proximity.

The rate of technical change (TC) of the production frontier exhibits some variation across models; technical progress is estimated to be 4.4, 5.6 and 4.6 per cent using Models A, B and C, respectively. The discrepancy in TC estimates seems to be due to different specifications of regional agglomeration effects in the models.

The coefficients associated with the regional dummies suggest that there are statistically significant differences in frontier output of a more permanent character, and that these differences are fairly large. It is reasonable to attribute these differences to varying biophysical conditions and services from regional public infrastructure capital.

4.2. The Technical Inefficiency Model

We now examine the results from the estimated technical inefficiency models. According to the estimated input parameters (δ_F, δ_I, δ_K, δ_L, δ_M), which are not reported here, the input use has a significant effect on mean technical inefficiency. For feed, fish input and labor, the coefficients are negative in all models, implying that efficiency increases as the quantity employed of these inputs increase. On the other hand, technical efficiency decreases as materials inputs increase. For the capital input the results are ambiguous across models, with models B and C indicating that technical efficiency increases with increasing capital. However, the estimates associated with capital are not significant for any of the three models. Table 2 provides the estimates of the *elasticity of technical efficiency* with respect to the inputs ($E_{\mu k}$). A positive estimate means that the level of technical efficiency is increased as the value of the associated variable increases. According to Table 2, the inputs have fairly small marginal effects. The effect of increasing the use of all inputs by the same magnitude is measured by the elasticity $TEI_\mu = \Sigma E_{\mu k}$ in Table 2. Depending on the model, a one per cent increase in all inputs leads to an increase in technical efficiency between 6.2 and 6.5 per cent.

Table 2. Estimates for Elasticities of Technical Efficiency*

Model	A		B		C	
	Mean	St. Err.	Mean	St. Err.	Mean	St. Err.
$E_{\mu Feed}$	0.0303	0.0039	0.0307	0.0041	0.0292	0.0040
$E_{\mu Infish}$	0.0286	0.0037	0.0251	0.0038	0.0258	0.0042
$E_{\mu Kapital}$	-0.001	0.0027	0.0029	0.0028	0.0024	0.0025
$E_{\mu Labor}$	0.0160	0.0049	0.0183	0.0048	0.0170	0.0044
$E_{\mu Mater}$	-0.011	0.0034	-0.012	0.0029	-0.013	0.0028
TEI_μ	0.0629	0.0084	0.0649	0.0084	0.0617	0.0082
$E_{\mu AGE}$	-0.001	0.0002	-0.001	0.0003	-0.001	0.0002
TEC_μ	0.0054	0.0009	0.0035	0.0010	0.0037	0.0010
$E_{\mu RL}$	0.0447	0.0091			0.0045	0.0082
$E_{\mu FSR}$			0.080	0.014	0.075	0.014

* This table provides elasticity estimates for technical efficiency, evaluated at the sample means of the regressors. The elasticities are defined as follows: $E_{\mu k}$ =

Elasticity of technical efficiency with respect to input k ($k = F, I, K, L, M$); $TEI_\mu = \Sigma E_{\mu k}$ = Total input elasticity of technical efficiency; TEC_μ = rate of change in technical efficiency (i.e. catch-up over time); $E_{\mu AGE}$ = Elasticity of technical efficiency with respect to age; $E_{\mu RL}$ = Elasticity of technical efficiency with respect to regional industry employment; $E_{\mu FSR}$ = Elasticity of technical efficiency with respect to regional farm density.

The effect of farm age on technical efficiency is of interest. Only very small values are estimated for the elasticity of technical efficiency with respect to farm age, being -0.1 per cent. for all models (see Table 2). This means that learning-by-doing contributes little to the catch-up of inefficient firms, or that learning-by-doing is counteracted by a farm site deterioration effect.[10]

Next, we investigate the change in technical efficiency over time, or the rate of catch-up of inefficient firms. Region-specific rates of catch-up are accounted for in the models.[11] A homogeneous rate of catch-up across regions (i.e., $\delta_{r,t} = \delta_t$ and $\delta_{r,t2} = \delta_t$ for all r) was rejected for all three models using a likelihood-ratio test, the test statistics being 23.98, 44.24 and 35.14 (exceeding the five per cent critical value, 23.68, for the Chi-square distribution with 14 df) for Models A, B and C, respectively.[12] Although estimates for the catch-up parameters, $\delta_{r,t}$ and $\delta_{r,t2}$, are statistically significant, the sizes of the estimates for the elasticity of technical efficiency with respect to time, TEC_μ , ranged from 0.3 per cent (for Model B) to 0.5 per cent (for Model A), indicating that differences in technical efficiencies over time are relatively small.

The relationship between technical efficiency and the agglomeration externalities indexes is now considered. The second-order coefficients, δ_{RL2} and δ_{FSR2}, are estimated to be negative across Models A, B and C, indicating that maximum values of the quadratic functions are involved. These coefficients are highly statistically significant, except for the estimate for regional industry size (RL) in Model C. The elasticity of technical efficiency with respect to regional industry size ($E_{\mu RL}$) is estimated to be 4.5 and 0.4 per cent for Models A and C, respectively (see Table 2). Furthermore, the elasticity of technical efficiency with respect to regional farm density is estimated to be 8.0 and 7.5 per cent for Models B and C, respectively. Hence, the models suggest that an increase in industry size and farm density lead to an increase in technical efficiency. For farm density, our results suggest that negative biological congestion externalities are captured by the production frontier function, while positive externalities (e.g., due to sharing of specialized input and knowledge spillovers) are captured by the technical inefficiency model.

[10] Farms were located at sites that tended to become biologically exhausted over time due to the accumulation of organic sediments.

[11] In all regions, the region-specific estimated rate of change in technical efficiency (not reported here) is negative or zero, implying a reduction in the level of technical efficiency, except in the southernmost region, Rogaland. This is in line with *a priori* expectations, since Rogaland was considered to be the technically most efficient region in the beginning of the data period.

[12] The appropriateness of including time in the technical inefficiency functions was supported by LR tests of H_0: $\delta_{r,t} = 0$ and $\delta_{r,t2} = 0$, for all r, which provided test statistics of 30.42 for Model A and 54.08 for Model B (exceeding the critical value, 26.30, for the χ^2_{16} distribution).

4.3. Overall Results

We have estimated three competing models to test for the influence of agglomeration effects. It turns out that Model A and Model B are rejected by LR-tests, given the specifications of the more general Model C. We therefore put most emphasis on the results from Model C.

Table 3. Estimates of Elasticities of Mean Salmon Output With Respect to Inputs*

Model	A		B		C	
	Mean	St. Err.	Mean	St. Err.	Mean	St. Err.
EN_{Feed}	0.485	0.015	0.486	0.016	0.482	0.015
EN_{Infish}	0.298	0.010	0.299	0.011	0.301	0.011
$EN_{Kapital}$	0.0206	0.0092	0.0211	0.0095	0.0219	0.0093
EN_{Labor}	0.040	0.017	0.042	0.017	0.041	0.016
EN_{Mater}	0.047	0.010	0.0474	0.0092	0.0494	0.0092
$RTSN$	0.891	0.028	0.895	0.029	0.895	0.028
TCN	0.0495	0.0039	0.0598	0.0033	0.0501	0.0037
EN_{RL}	0.231	0.042			0.298	0.052
EN_{FSR}			0.078	0.034	-0.064	0.041

* This table provides non-neutral elasticity estimates, as proposed by Battese and Broca (1997), evaluated at the sample mean level of the variables. The elasticities are defined as follows (cf Table 1 and 2): $EN_k = E_k + E_{\mu k}$, $k = F, I, K, L, M$; $RTSN = RTS + TEI_\mu$; $TCN = TC + TEC_\mu$; $EN_{RL} = E_{RL} + E_{\mu RL}$; $EN_{FSR} = E_{FSR} + E_{\mu FSR}$.

In Table 3, we present the estimates for the *elasticity of mean output* with respect to the inputs obtained using Models A, B and C.[13] These elasticities involve both the elasticity of frontier output and the elasticity of technical efficiency, where the latter term is non-zero for a non-

[13] Other studies that have estimated elasticities for non-neutral frontier models are Huang and Liu (1994), Coelli and Battese (1996), Battese and Broca (1997), and Lundvall and Battese (2000).

neutral stochastic frontier model, which has input variables in the model for the inefficiency effects. The elasticities in Tables 1 and 2 are added, for the corresponding inputs, to obtain the elasticity of mean output with respect to the given input. Note that the estimated returns to scale (RTSN) is larger for all models.

According to Model C, the total effect of an increase in regional farm density on mean output is negative, with an elasticity of –6.4 per cent. This result suggests that negative biological congestion externalities more than outweigh positive externalities from higher farm density. On the other hand, all models with *RL* included provide support for positive externalities associated with increasing industry size. In the preferred model, Model C, the elasticity of output with respect to regional industry size is as high as 29.8 per cent. Inclusion of the agglomeration indexes is strongly supported by likelihood-ratio tests for all three models.[14]

5. CONCLUSIONS

In this paper, we examine the influence of regional agglomeration externalities on the productivity and efficiency of salmon farming in Norway. Our results support the presence of such externalities.

We estimate stochastic frontier production models on a large panel of salmon farms. These models allow us to distinguish the effects of different factors, such as inputs and external effects, on the production frontier and technical efficiency. We also control for unobservable region-specific effects, farm age and technical change in our models.

Internal returns to scale and agglomeration externalities are the main factors explaining differences in productive performance. Technical change is also an explanatory factor behind discrepancies when we compare productivity across time. Learning-by-doing, as measured by farm age, seems to be a less important factor.

Two external economy indexes are used in the models, namely regional industry size and regional farm density. In the most general specification, we use these indexes in both the frontier production function and the technical inefficiency model, because we hypothesize the agglomeration externalities influence both productivity and inefficiency of salmon farming. We found that an increase in regional industry size is associated with increases in both frontier output and the level of technical efficiency for farms in that region. An increase in regional farm density has a negative effect on frontier output, but is associated with a positive effect on the level of technical efficiency. Overall, the effect of increasing regional farm density on output is negative, implying that negative congestion externalities associated with fish diseases dominate positive externalities associated with knowledge spillovers and sharing of specialized inputs.

It should be noted that our results do not allow us to identify the sources or mechanisms that generate external economies. A more detailed case study of selected regions or farms could be a useful means to uncover the mechanisms that are at work.[15]

The Norwegian government has influenced the regional distribution of salmon farms through its regulations. This paper shows that regional location of farms may influence the industry's marginal cost curve. There exists a potential for spatial redistribution of farms that can lead to a downward shift in the industry's supply curve. Based on the findings here, one should take into account density-dependent effects of relocation and effects on regional external economies of scale. According to our results, shifting productive resources between two regions affects the productivity in both regions, but in opposite directions. Although government regulation may have lead to an average productivity that is lower than the potential, deregulation may not necessarily lead to an efficient spatial distribution of production. With a large number of independent farms, external economies of scale and disease externalities are not fully internalized by private decision makers, leading to inefficient outcomes. Hence, there is a role for government to account for these externalities.

This paper provides new evidence on the effects of learning and industry infrastructure on productivity in Norwegian salmon farming. Future analyses should try to decompose and measure the effects of biophysical differences, farm-specific factors and regional industry infrastructure on productivity differentials. Furthermore, models should be specified to allow testing whether individual farms have different abilities to capture positive externalities from the regional industry.

References

[14] The LR statistics associated with the null hypothesis, that all parameters involving the regional agglomeration indexes are zero, are 43.74 and 43.32 for Models A and B, which exceed the five per cent critical value, 9.49, for the χ^2_4 distribution). For Model C, the LR statistic is 83.90, which is greater than the critical value, 15.51, for the χ^2_8 distribution.

[15] The inability to precisely identify the underlying sources of agglomeration externalities is a common feature of empirical literature, cf. Bartelsman *et al*. (1994).

Bartelsman, E.J., Caballero, R.J., and Lyons, R.K. (1994), "Customer- and Supplier-Driven Externalities", *American Economic Review*, **84**(4), 1078-1084.

Basu, S., and Fernald, J.G. (1997), "Returns to Scale in U.S. Production: Estimates and Implications", *Journal of Political Economy*, **105**(2), 249-283.

Battese, G.E., and Coelli, T.J. (1993), "A Stochastic Frontier Production Function Incorporating a Model for Technical Inefficiency Effects", *Working Papers in Econometrics and Applied Statistics*, No. 69, Department of Econometrics, University of New England, 22 pp.

Battese, G. E., and S. S. Broca (1997), "Functional Forms of Stochastic Frontier Production Functions and Models for Technical Inefficiency Effects: A Comparative Study for Wheat Farmers in Pakistan", *Journal of Productivity Analysis*, 8, 395-414.

Batttese, G.E., and Coelli, T.J. (1995), "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data", *Empirical Economics*, **20**, 325-332.

Battese, G.E., and Corra, G.S. (1977), "Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia", *Australian Journal of Agricultural Economics*, **21**(3), 169-179.

Burnside, C. (1996), "Production Function Regressions, Returns to Scale, and Externalities", *Journal of Monetary Economics*, **37**(2), 177-201.

Caballero, R.J., and Lyons, R.K. (1990),"Internal Versus External Economies in European Industry", *European Economic Review*, **34**, 805-830.

Caballero, R.J., and Lyons, R.K. (1992),"External Effects in United States Procyclical Productivity", *Journal of Monetary Economics*, **29**, 209-225.

Ciccone, A., and Hall, R.E. (1996), "Productivity and the Density of Economic Activity." *American Economic Review*, **86**(1), 54-70.

Coelli, T.J. (1996), "A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation", *CEPA Working Papers*, No. 7/96, ISBN 1 86389 4950, Department of Econometrics, University of New England, Armidale, pp. 33.

Coelli, T.J., and Battese, G.E. (1996), "Identification of Factors which Influence the Technical Inefficiency of Indian Farmers", *Australian Journal of Agricultural Economics*, **40**, 103-128.

Dietrichs, E. (1995), "Adopting a 'High-Tech' Policy in a 'Low-Tech' Industry: The Case of Aquaculture", (Report No. 2). STEP Group, Oslo.

Eberts, R.W., and McMillen, D.P. (1999), "Agglomeration Economies and Urban Public Infrastructure", In E.S. Mills and P. Cheshire (Eds.), *Handbook of Regional and Urban Economics* (pp. 1455-1495), Elsevier Science B.V.

Huang, C.J., and Liu, J.T. (1994), "Estimation of a Non-Neutral Stochastic Frontier Production Function", *Journal of Productivity Analysis*, **5**, 171-180.

Lundvall, K., and Battese, G.E. (2000), "Firm Size, Age and Efficiency: Evidence from Kenyan Manufacturing Firms", *Journal of Development Studies*, 36 (No.3), 146-163.

Paul, C.J.M., and Siegel, D.S. (1999), "Scale Economies and Industry Agglomeration Externalities: A Dynamic Cost Function Approach", *American Economic Review*, **89**(1), 272-290.