Learning and Technology Spillover: Productivity Convergence in Norwegian Salmon Aquaculture

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Abstract

An econometric analysis of productivity convergence in Norwegian salmon aquaculture is undertaken. We also test for the effects of learning and external industry infrastructure capital. Empirical evidence for reduction in productivity differentials is found, but the estimated models also provide indications of more permanent differences in productivity and their underlying sources.

1. Introduction

This paper provides an econometric analysis of productivity convergence in the Norwegian salmon farming industry, which is a particularly interesting case study for several reasons. First, it is a young industry where large scale production started in the late 1970s and most firms were established during the 1980s. Second, it has experienced major changes in the production technology during its short lifetime due to innovations in e.g. production equipment, feed technology, salmon genetics, and medical treatment.[1] Third, different coastal regions entered the industry at different stages and faced different technological and institutional opportunities and obstacles when they entered.

Through production practice farms accumulates knowledge, and older farms are expected to be more efficient than new farms due to longer production experience. Another factor is the rate of acquisition of new capital equipment by new and older farms. New farms may use more recent technologies due to high replacement costs for physical capital. The effect of own production experience may also be mitigated by knowledge spillover, if knowledge capital has a public goods property in aquaculture. In this paper it is argued that intra-regional knowledge spillovers dominate inter-regional spillovers because, in addition to historical differences and geographical barriers, industry infrastructure such as farmer organizations and public extension services are organized at the regional level. These factors leads to higher costs associated with transmitting knowledge across regions than within regions. Hence, they should act as an impediment to rapid productivity convergence across regions. Furthermore, it has been asserted that spatial clustering of producers facilitates the development of a regional industry-specific infrastructure, which allows the firms to exploit external economies of scale. The degree of spatial clustering should consequently be taken into account in models of productivity convergence.

The results from this analysis also has implications for the public regulation of the industry, since the Norwegian government has regulated the regional distribution of salmon farms. Spatial regulation of production is present in many countries, for example in the agricultural sector in the European Union, as a central element in regional income redistribution policies. One may ask if this spatial regulation has lead to efficiency losses in salmon aquaculture. In the early years of the data period one observed substantial differences in average productivity between regions. Were these differences, and hence efficiency losses, transitory or permanent? Biophysical conditions may give rise to permanent productivity differences. However, there may also have been more transitory productivity differentials in earlier years due to differences in production experience and technology, which can be eliminated through learning and replacement of capital equipment. Finally, sharing of industry infrastructure capital may give rise to external economies of scale. The presence of external effects suggests a role for government regulation, provided that regulators have sufficient knowledge about the nature of the externalities.

We employ an unbalanced panel data set with a total of 2738 observations on 577 farms observed during the 1985-1995 period. The farms are 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 translog production model specifications are estimated to test the hypotheses on productivity convergence. An extension of the standard time trend model that allows for region-specific rates of technical change is estimated. We also estimate a more flexible time dummy model that allows for discontinuous region-specific technical change.

Finally, we estimate model specifications with internal and external factors which can influence productivity. Farm age is implemented to capture potential learning-by-doing effects. The external factors we account for is regional industry size (measured by employment), and farm density in the region. We assert that the possibility for sharing of industry infrastructure capital and exploiting external economies of scale is closely linked with these two regional industry indicators.

2. Discussion of Issues Related to Industry Infrastucture and Learning

In the empirical analysis we compare the performance of eight regions. These regions are listed according to their location on the north-south axis, from the southernmost county of Rogaland (R) to the northernmost counties of Troms and Finnmark (T&F). There are several reasons for using a regional division for the Norwegian salmon farming industry. First, regions have different *biophysical* conditions. This applies particularly to the sea temperature and the water exchange - 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.

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[1] See Dietrichs (1995) for a discussion of the process of technological change in the industry.

Industry-specific infrastructure is too 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 which affect farm performance. The fish farmers' own industry association has also been organized in regional units. This organization is involved in training programs and dissemination of knowledge to fish farmers.

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 of farms. The industry has experienced that disease losses are not evenly distributed along the Norwegian coast, but has been concentrated in certain regions.

Regions entered the industry at different stages, which means that there are cross-regional differences in average farm age. If there are learning-by-own-experience effects present then age differences may lead to productivity differences.

There are substantial differences in the size of the regional industries and the spatial concentration of production. This is important if there is potential for sharing industry infrastructure capital or external economies of scale.[23] Sources of external economies of scale are indivisibilities or nonexclusiveness associated with tangible and nontangible capital inputs, such as physical industry infrastructure capital, R&D, knowledge spillovers (i.e. learning from others), and specialized human capital. For the firm sharing of these types of capital leads to savings on materials and labor inputs, and a reduced need for internal investments in capital equipment.

In this paper we are concerned about the effects of learning on productivity differentials. We use farm age to capture the effect of own learning from own production experience. However, the age variable may also account for other influences upon productivity. If replacement of old capital equipment is costly the farm age variable may also capture capital vintage effects. For this particular industry there is probably also a negative relationship between farm age and the quality of the farm site, since older farms tended to be located at more sheltered sites which had lower bioproductivity(Johannessen *et al.*).

Producers may not only learn from own production experiences, but also from other producers. The extent of external knowledge spillovers should be increase with farm density,

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[2] See Caballero & Lyons (1990), Baltagi & Pinnoi (1995) Morrison & Scwartz (1996), Morrison & Siegel (1998) and Segoura (1998) for discussions of these issues, and for empirical testing of the contribution of public capital and external economies of scale.

[3] External economies of scale is present for an industry with constant internal (or private) economies of scale if a doubling of inputs by all firms together more than doubles their output.

which is implemented in one of the model specifications. Finally, producers may learn from other agents which is a part of the industry infrastructure. In the case of salmon farming feed manufacturers, veterinarians, salmon fingerling producers and researchers may be sources of knowledge on different aspects of the production process.

3. Empirical Model Specifications

In this paper we estimate production functions to test for convergence and the effects of different industry characteristics on productivity.[4] In one class of models the specification of technical change is an extension of Cornwell, Schmidt & Sickles' (CSS) specification.[5] We denote this class CSSE models:

$$\ln y_{it} = \alpha_r + \sum_k \alpha_k \ln x_{k,it} + \sum_j \sum_k \alpha_k \ln x_{j,it} \cdot \ln x_{k,it} + \sum_k \alpha_{kt} \ln x_{k,it} \cdot t$$
$$+ \sum_r \alpha_{rt} D_r \cdot t + \sum_r \alpha_{rt2} D_r \cdot t^2 + \sum_r \alpha_{rt3} D_r \cdot t^3 + h(\mathbf{FC}, \mathbf{RC}; \boldsymbol{\alpha}_{FC}, \boldsymbol{\alpha}_{RC})\text{'}$$

y is salmon output, x_k is input k (k = capital, fish, feed, labor, materials), t is a time trend variable (t = 1 in 1985), and D_r is region-specific effects (region-dummies), r = (R, H, SF, MR, ST, NT, N, T&F). Subscripts i and t denotes farm and time, respectively. A term h(**FC**, **RC**) is also added, where **FC** is a (vector of) farm characteristics and **RC** is region characteristics which influences productivity. The technical change specification in the CSS model is a special case of the above model with the terms involving the third-order time trend variable excluded (i.e. $\alpha_{rt} = 0\ \forall r,t$).

The above model can be divided into four parts. First, the region-specific effect (α_r) which gives rise to permanent output differences. Second, the pure input level effect (i.e. $\sum_k \alpha_k \ln x_{k,it} + \sum_j \sum_k \alpha_k \ln x_{j,it} \cdot \ln x_{k,it}$). Third, the input-biased technical change effect (i.e. $\sum_k \alpha_{kt} \ln x_{k,it} \cdot t$) which is influenced both by the input levels and the time period. Fourth, the region-specific technical change effect (i.e. $\sum_r \alpha_{rt} D_r t + \sum_r \alpha_{rt2} D_r t^2 \sum_r \alpha_{rt3} D_r t^3$). When we compare two regions r and s from time period t to t+1 relative output will be influenced both by relative changes in output levels $\mathbf{x}_r$ and $\mathbf{x}_s$ and the region-specific technical change effects.

The following time-dummy model provides a more flexible specification of technical change than the CSS time-trend model (hereafter denoted *TD*):

[4] Salvanes (1989; 1993) and Bjørndal and Salvanes estimate cost functions for the Norwegian salmon industry.
[5] However, Cornwell, Schmidt and Sickles specified a production frontier model with a half-normal random term in addition to the usual white noise error term.

$$\ln y_{it} = \sum_k \alpha_k \ln x_{k,it} + \sum_j \sum_k \alpha_k \ln x_{j,it} \cdot \ln x_{k,it} + \sum_k \sum_t \alpha_{kt} \ln x_{k,it} \cdot D_t$$
$$+ \sum_r \sum_t \alpha_{rt} D_r \cdot D_t + h(\mathbf{FC}, \mathbf{RC}; \boldsymbol{\alpha}_{FC}, \boldsymbol{\alpha}_{RC}),$$

where D_t is time-specific effects (time-dummies), t = 1985,…, 1995. The above model allows discontinuous shifts in technical change between years within a region. This seems plausible, since it is difficult to provide *a priori* support for the smooth technical progress function implied by the time trend model.

To capture the effects of farm-specific effects due to biophysical characteristics and quality of human capital an extension of the *CSSE* model specification with random farm-specific effects added was also estimated (denoted *CSSE-RE*).[6]

Farm age (*AGE*) is included in one model specification (denoted *CSSE-AGE*). Due to farms' learning-by-own-experience a positive relationship is expected between age and productivity. However, as mentioned earlier, there may also be capital vintage and farm site effects working in the opposite direction.

To account for density dependent external effects between farms the number of farms per square kilometer of sea area (*FSR*) in the region is included in one of the model specifications (denoted *CSSE-FSR*). 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, slaughter- and processing facilities. Hence, investments in capital equipment is expected to decline for each individual farm due to increased possibility 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, fish disease externalities between farms is expected to increase with higher farm density, leading to lower expected productivity.

Total regional industry employment (*RL*) is also included in one specification (denoted *CSSE-RL*). This variable may capture external economies of scale or the availability of industry-specific capital. It can be viewed as a proxy for human (intangible) capital in the regional industry, but is probably also correlated with the regional industry's physical capital.

White noise error terms are added to all models. Heteroskedasticity is adjusted for by means of White’s (1980) procedure.

[6] See e.g. Berge & Blakstad (1989) and Johannessen for documentation of the producer heterogeneity in salmon farming. Surveys of a large number of farm sites have shown that there are considerable differences in the biophysical productivity.

4. Empirical Results[7]

The largest farms are found in region H (see Table 2 for full region names), where the sample average salmon output is 534 tonnes, while the smallest farms are located in region NT, with an average production of 355 tonnes. The average age of the sample farms is 9.6 years. The longest average production experience in the sample is found in the regions ST (12.6 years), MR and H (both 11.2 years), while the farms in the northernmost regions of T&F and N have the shortest average production experience (6.6 and 7.9 years, respectively).

Region H has the highest employment - three times higher than region R, which has the smallest employment (1151.72 and 342.23 thousand man-hours, respectively). There are large cross-regional variations in farm density, as measured by the number of farms per square km of sea area. In the high-density region H there are 0.035 farms per square km, while the low-density regions N and T&F have only 0.005 and 0.004 farms per sq.km, respectively. This means that the farm density in region H is almost nine times higher than in N and T&F.

Derived elasticities from the estimated models are presented in Table 1. In all models fish feed (*F*) turns out to be the most important input as measured by the feed elasticity, which ranges from 0.48 to 0.51 across the models. Fish input (*I*) is the second most important input in terms of output elasticity, which ranges from 0.304 to 0.311. Labor (*L*), materials (*M*), and particularly capital (*K*) are much less important. The output elasticity with respect to these inputs is generally around or less than 1/10 of the feed elasticity.The mean returns to scale (RTS) is very similar across models; it ranges from 0.92 to 0.93. This implies that the mean farm in the panel operated at a sufficiently large scale to exhaust economies of scale.

The first model to be estimated is the CSS production function. According to both t-ratios and joint tests the use of region-specific technical change parameters is appropriate. The standard production function specification with pooled intercept and technical change is firmly rejected at conventional significance levels by a likelihood-ratio test, with an estimated test statistic of 101.40 (21 degrees of freedom). A production function with heterogeneous intercepts but pooled technical change parameters is also rejected with an L-R test statistic of 57.32 (14 df).

Next, the extended CSS model (CSSE) was estimated. The addition of third-order region-specific technical change parameters turns out to be appropriate. An L-R test of the

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[7] Due to space restrictions several tables in the full paper version is not presented here, but available from the author upon request.

CSSE versus the restricted CSS model provides a test statistic of 60.48 (8 df), thus rejecting the restricted model at conventional significance levels.

To account for farm-specific effects the CSSE model was extended to include a random farm-specific error component (model CSSE-RE). The estimates of the observation- and firm-specific variance in the CSSE-RE model are $\hat{\sigma}_u^2$ = 0.4146 and $\hat{\sigma}_\eta^2$ = 0.0947, respectively. From Table 2 one can see that the inclusion of a random effect lead to some changes in elasticity estimates, although not dramatic.

Next, we examine the estimated CSSE-AGE model, where a first- and second-order logarithmic transformation of farm age is added to the CSSE model. An L-R test of CSSE-AGE versus CSSE supports the extension of the model, with a test statistic of –2(806.10-814.64)=17.08 (2 df). The inclusion of an age effect in the model only lead to small changes in the elasticity estimates. However, the parameter estimates associated with the age terms did not provide support for a positive learning effect on productivity, as both terms had negative signs. The elasticity of output with respect to farm age is -0.023 for the sample mean farm. This leads to the conclusion that negative capital vintage and farm site effects discussed in the previous section dominate the learning effect.

We then turn to the models with regional characteristics included. First we examine the model with total regional salmon industry employment terms added (CSSE-RL). This extension of the model is also supported by an L-R test, with a test statistic of –2(806.10-826.91)=41.62 (2 df). According to the estimated model industry size has a significant positive impact on productivity. For the sample average farm the elasticity of output with respect to regional industry employment is 0.299 (!).

Regional farm density also has a significant impact on productivity, according to the estimated model (CSSE-FSR). Two farm density terms are added to the CSSE model in this specification, ln *FSR* and $(\ln FSR)^2$. The L-R test supports the inclusion of the farm density terms with a test statistic of –2(806.10-817.58)= 22.96 (2 df). The elasticity of output with respect to farm density is 0.152 for the sample mean farm. However, the effect is ambiguous, since the second order farm density term ($(\ln FSR)^2$) has a negative coefficient. This may indicate that for low values an increase in farm density is beneficial for farm productivity, possibly due to increased sharing of capital equipment, human capital and knowledge, while for higher values a further increase in farm density is harmful due to negative disease externality effects.

Next, we estimated a model with region-specific time dummies (model TD) to allow for higher flexibility in the rate of technical change. According to both estimated t-ratios and joint tests this specification is appropriate. A Wald test firmly rejects identical time-specific effects across regions with a test statistic of 328.4 (80 df) and p-value of 0.000.

Farm age was also added to the time dummy model in one specification (TD-AGE). As for the CSSE model we find a significant negative age effect, thus reinforcing the above conclusions.

Figure 1 plots the predicted output by region over the 1985-1995 time period for farms employing sample mean input levels based on the TD model estimates. We see that the flexible TD specification is able to capture the volatility of productivity growth in Norwegian salmon farming. For example. the region Sør-Trøndelag (ST) experienced an outbreak of the fish disease *Furunculosis* in 1985-86, which lead to huge losses. From the figure one can see that this is captured by the TD model.

According to figure 1 productivity seems to converge from 1985-86 to the middle of the data period. But thereafter productivity differentials seem to have stabilized or possibly diverged again. To analyze this issue further we examine the relative productivity estimates in table 2. According to the estimates based on the TD model the standard deviation of productivity was 5.94 in the first data year, 1985. Relative productivity differentials peaked in 1986, with a standard deviation of 10.52. Thereafter relative productivity differences declined, although not monotonously, and reached a minimum in 1991. Since then the relative productivity differentials seem to have stabilized at lower levels than in the first half of the data period.

5. Summary and Conclusions

This paper has examined whether productivity converged across regions in Norwegian salmon aquaculture from 1985 to 1995. Several competing primal models of technical change were estimated. According to the most credible model productivity differentials have declined during the data period. However, there are still substantial differences in productivity as the mean farm in the least productive region (Rogaland) was 10 % less productive than the mean farm in the most productive region (Nord-Trøndelag) in 1995. One cannot find a consistent productivity pattern along the north-south axis, as the southernmost region is the least productive, followed by the two northernmost regions in 1995.

We do not find a positive relationship between production experience as measured by farm age and productivity. On the contrary, older farms seems to be less productive, suggesting that negative capital vintage and site effects dominate positive learning effects. Hence, it seems like farms which entered the industry at later stages were not severely disadvantaged due to lack of own production experience, but compensated for this by learning from other industry agents and investing in the newest technologies.

Evidence is found for the contribution of industry-specific infrastructure capital to farm productivity. The size of the regional industry and farm density both have a significant positive effect. However, the empirical results suggest that for farm density negative fish disease externalities may dominate with high densities.

The Norwegian government has influenced the regional distribution of salmon farms through its regulations. This paper has shown that regional location of farms may influence the industry’s marginal cost curve. There exists is a potential for spatial redistribution of farms that can lead to a downward shift in the industry’s supply curve. However, based on the findings here one should also take into account density-dependent effects of relocation and effects on regional external economies of scale. According to our results shifting production between two regions will affect the productivity in both regions, but in opposite directions. Although government regulation may have lead to an average productivity which 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 will not be fully internalized by private decision makers, leading to inefficient outcomes. Hence, there is a role for government regulation which takes these externalities into account.

This paper has provided new evidence on productivity convergence and the effects of learning and industry infrastructure on productivity in Norwegian salmon aquaculture. Future analyses should aim to decompose and measure further the effects of biophysical differences, farm-specific factors and regional industry infrastructure on productivity differentials.

Table 1. Estimated Elasticities*

Model	CSS		CSSE		CSSE-AGE		CSSE-RA		CSSE-FSR		CSS-RL		TD		TD-AGE	
	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev	Mean	St.Dev
E_L	0.047	0.052	0.054	0.051	0.055	0.052	0.064	0.057	0.057	0.052	0.055	0.051	0.055	0.068	0.055	0.069
E_F	0.510	0.095	0.504	0.095	0.499	0.094	0.480	0.086	0.503	0.094	0.500	0.094	0.498	0.106	0.493	0.104
E_I	0.310	0.056	0.311	0.057	0.310	0.056	0.304	0.057	0.305	0.057	0.308	0.056	0.304	0.076	0.304	0.075
E_K	0.023	0.020	0.021	0.021	0.026	0.022	0.026	0.024	0.023	0.020	0.023	0.020	0.022	0.027	0.027	0.028
E_M	0.044	0.038	0.042	0.040	0.043	0.039	0.049	0.043	0.042	0.040	0.043	0.041	0.044	0.046	0.045	0.046
RTS	0.934	0.056	0.932	0.056	0.934	0.056	0.923	0.055	0.929	0.056	0.929	0.055	0.922	0.047	0.924	0.047
*TC***	0.025	0.037	0.037	0.048	0.039	0.048	0.040	0.050	0.030	0.053	0.022	0.048	0.051	0.096	0.052	0.095
*TC_PURE***	0.041	0.041	0.054	0.053	0.056	0.052	0.057	0.054	0.047	0.058	0.039	0.052	0.045	0.084	0.047	0.083
*TC_NONUT***	-0.017	0.019	-0.017	0.019	-0.017	0.019	-0.018	0.019	-0.016	0.019	-0.017	0.019	0.006	0.065	0.006	0.064
TFP	0.023	0.054	0.031	0.065	0.033	0.065	0.032	0.067	0.028	0.067	0.023	0.061	0.044	0.107	0.046	0.106

* E_k = Elasticity of output with respect to input k (k = F, I, K, L, M), *RTS* = Returns To Scale, *TC* = rate of Technical Change, *TC_PUR* = rate of input-neutral technical change, *TC_NONUT* = rate of input-neutral technical change, *TFP* = rate of Total Factor Productivity growth.

** Technical change estimates include 1985 for the CSS and CSSE models, but not for the TD models.

Table 2. Estimated Productivity of Each Region Relative to Most Productive Region 1985-95*,**

Year	CSSE model estimates										TD model estimates									
	R	H	SF	MR	ST	NT	N	T&F	Mean	St.dev.	R	H	SF	MR	ST	NT	N	T&F	Mean	St.dev.
1985	100.00	94.48	95.75	94.72	81.73	86.87	94.23	79.58	90.92	6.83	95.60	93.37	100.00	93.54	87.95	85.28	95.19	80.50	91.43	5.94
1986	100.00	94.01	93.43	92.11	81.20	87.62	90.78	71.19	89.79	6.45	100.00	89.76	80.35	85.15	63.27	81.84	83.93	70.44	81.84	10.52
1987	100.00	94.11	93.24	91.04	82.25	88.88	90.27	81.11	90.11	5.80	100.00	97.76	90.14	89.81	87.06	80.82	85.42	81.05	89.01	6.58
1988	100.00	94.72	94.64	91.20	84.56	90.61	91.91	84.76	91.55	4.84	100.00	95.18	94.36	93.83	83.87	86.39	89.80	74.14	89.70	7.60
1989	100.00	95.81	97.16	92.32	87.86	92.76	95.04	89.60	93.82	3.73	97.37	95.02	100.00	90.78	86.00	94.01	94.91	94.10	94.02	3.93
1990	99.69	97.03	100.00	93.90	91.58	94.99	98.72	94.66	96.32	2.83	94.30	87.13	100.00	90.35	87.24	91.87	98.96	94.02	92.98	4.52
1991	96.55	95.83	100.00	93.23	92.91	94.74	99.56	96.58	96.18	2.45	97.85	96.74	97.23	97.24	93.03	92.20	100.00	96.83	96.39	2.39
1992	93.94	95.38	99.90	93.17	94.47	95.08	100.00	97.53	96.18	2.48	89.06	91.26	89.90	88.74	90.93	85.05	95.69	100.00	91.33	4.30
1993	92.52	96.36	99.91	94.20	96.59	96.69	100.00	97.39	96.71	2.38	91.50	96.10	100.00	87.97	91.23	97.72	92.51	88.51	93.19	4.06
1994	92.68	99.22	99.93	96.50	99.33	100.00	99.21	95.78	97.83	2.44	93.09	100.00	96.25	95.70	98.63	97.01	96.06	89.74	95.81	2.99
1995	89.83	99.01	94.56	95.04	97.34	100.00	92.17	87.48	94.43	4.11	89.99	98.27	96.58	94.75	98.20	100.00	95.86	93.12	95.85	3.00

* For each year the predicted output of the sample mean farm of each region is divided by the output of the sample mean farm in the region with the highest productivity.

** Full region names: R=Rogaland, H=Hordaland, SF=Sogn og Fjordane, MR= Møre og Romsdal, ST=Sør-Trøndelag, NT=Nord-Trøndelag, N=Nordland, T&F=Troms & Finnmark.

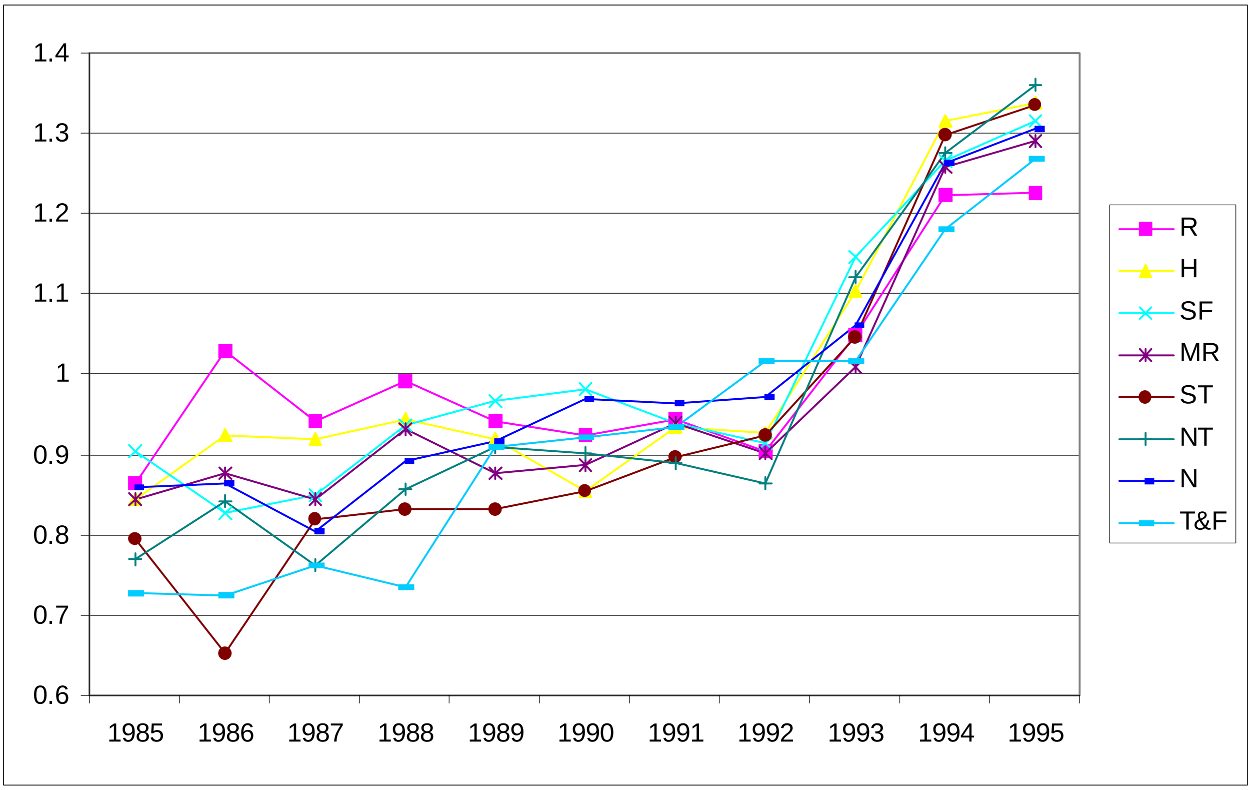

Figure 1. Predicted Output from Time Dummy Model (TD) by Region 1985-95 for Farm Employing Sample Mean Input Levels

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