

DP 2004/3

**Sources of Productivity
Growth and Stochastic
Dominance Analysis of
Distribution of Efficiency**

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June 2004

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June 11, 2004

Abstract

The objective is to examine sources of productivity change on Finnish dairy farms in the 1990s. The decomposition of productivity change into technical change and technical efficiency change is widely recognized but it neglects the price and scale effects. The generalized decompositions incorporating all four components are calculated in a sample of Finnish dairy farms for 1989-2000. The period is of interest because of the drastic change in agricultural policy when Finland joined the European Union (EU) in 1995. The results show that productivity growth has been on average low, approximately 1% per year. Technical change is identified to be the most important source of productivity growth. Technical efficiency change does not vary systematically over time. The role of scale is also minor in productivity change. Cumulative price effects are small but considerable price distortions could be observed at the time of EU accession. In the detailed analysis of efficiency, the extended Kolmogorov-Smirnov tests of first and second order stochastic dominance in distribution of inefficiency were employed. Partial control for time and many farm-specific attributes, such as size, location and production factor intensities by comparing group cells were offered. A number of strong second order rankings between groups was found.

JEL Classification Numbers: C14; C23; D24; L25; Q12

Keywords: Malmquist index; technical efficiency; technical change; scale effect; price effect; SFA; stochastic dominance, bootstrap, inefficiency distribution, testing.

Suggested citation: Sipiläinen, T. & Heshmati, A. 2004. Sources of Productivity Growth and Stochastic Dominance Analysis of Distribution of Efficiency. MTT Economic Research, Agrifood Research Finland. Discussion Papers 2004/3.

1. Introduction

In measuring productivity, a ratio between output(s) and input(s) is computed. In the case of single output and single input, this is trivial but when the number of inputs and outputs increases, a method of aggregation is needed to compute productivity. In the latter case, we could employ some index numbers like the Fisher (1922) ideal or Törnqvist (1936) superlative productivity indices (see Diewert and Nakamura 2003 for a detailed discussion). Both of these indices require price and quantity data but no modelling and estimation are needed. In addition, assumptions about technology and behaviour of the decision-maker have to be made. Indices like the Fisher and Törnqvist indices can be used to show whether the quantity index of outputs changes at a different rate compared to the quantity index of inputs, *i.e.* to show the rate of productivity change. The problem is that we cannot separate the sources of productivity change in these indices (Kumbhakar and Lovell 2000).

Productivity measures may encompass several components the identification and quantification of which are crucial to different economic decision makings. If we assume constant returns to scale and efficiency of production, productivity growth equals technical change, *i.e.* the shift of production frontier (or production function). Technical change over time is realized as improvements in output-input relationship. In practice, it is possible that there exists increasing economies of scale¹ such that proportional increase in output is more than corresponding proportional changes in inputs. Thus, technical change and the increase in farm size may be related. Technical change may also be biased towards some inputs so that the share of certain inputs (*e.g.* capital) increases compared to others (*e.g.* labour) over time. Output bias is also possible. In this case technical change, effects the efficient allocation of inputs and outputs.

If we allow for technical inefficiency (and constant returns to scale) but assume allocative efficiency, then productivity growth equals the change in technical efficiency multiplied by the rate of technical change (Nishimizu and Page 1981). By the term technical efficiency, we follow Farrell's (1957) definition of technical efficiency.² If we allow for allocative inefficiency, the farm may be technically efficient lying on the isoquant but it is not producing the output by minimum cost (or producing maximum revenue by given inputs). Inefficiency in allocation of inputs effects the cost shares (return shares) which are often utilized in the aggregation of inputs and outputs to construct the quantity indices.

In principle, we can decompose the productivity change to four components: technical change, technical efficiency change, scale effect and price (allocative) effect.

In the case of several inputs and outputs, it is possible to apply the Malmquist productivity index (1953) to measure total factor productivity. The Malmquist index serves also our purpose in identifying various sources of productivity change since

¹ If we are talking about economies of size, the minimum cost combination of inputs is dependent on the size of operation.

² Efficiency is measured the ratio between observed and potential output using the best practice technology as reference. The ratio indicates possible equiproportional increase in outputs keeping inputs constant or equiproportional decrease in inputs keeping outputs constant by using frontier technology.

several decompositions for this index have been proposed (Färe *et al.* 1994, Orea 2002, Lovell 2003). This index has the advantage that it does not require price information or behavioural assumptions, however a representation of the production technology is needed in the form of distance functions, which is applicable to cases with multiple inputs and outputs. In case of only single output (or input), the analysis is similar to production function analysis. The index can be calculated or estimated using nonparametric or econometric techniques³. The distance function applications were at first almost entirely based on nonparametric data envelopment analysis (DEA) models. Recently several authors have developed parametric counterparts for those distance functions (see *e.g.* Coelli *et al.* 1999 and Brümmer *et al.* 2002 and references there).

The advantage of the nonparametric techniques is the minimum requirements needed about the technology for the calculation of distance functions but on the other hand, only an econometric approach may allow for stochastic circumstances affecting production and productivity. On the other hand, econometric techniques require assumptions to be made about the functional form, which despite limited testing possibilities may not be correctly chosen.

In earlier Finnish studies of productivity change, both econometric estimation (Hemilä 1982, Ylätaalo 1987, Ryhänen 1994, Sipiläinen and Ryhänen 2002) and index numbers (Ihamuotila 1972, Sims 1994, Myyrä and Pietola 1999) have been applied. The majority of these studies is relatively old. One exception is Myyrä's and Pietola's (1999) research in which they used data covering almost the entire 1990s and applying index number techniques. Sipiläinen (2003) has studied the productivity growth on dairy and cereal farms applying nonparametric methods and the Malmquist index. No recent research on Finnish data has been conducted applying up-to-date econometric techniques on productivity and efficiency analysis.

The 1990s are a period of interest since Finland joined the European Union (EU) in the middle of the decade. When Finland became a member in the EU at the beginning of 1995, there followed a fundamental change in national agricultural policy, resulting in drastically lower output prices as well as somewhat lower input prices.⁴ The immediate threat of a corresponding fall in agricultural income was softened by an increase in direct payments. A five-year transition period with decreasing support and a range of investment subsidies were applied to help farmers adjust to the changes following on EU membership. In addition, prior to membership, several restrictions on agricultural production were already introduced. Therefore, an evaluation of the effects of EU membership and restrictions imposed on agricultural production is highly desirable.

The aim of this paper is to investigate the sources of productivity change by decomposing the Malmquist productivity index. This paper provides a detailed analysis of productivity changes for a sample of specialized Finnish dairy farms in the 1990s. We present a decomposition, which can recognize all essential productivity change

³ Important links between index number and econometric estimation techniques have been shown to exist. For instance, Nadiri (1970) showed that the underlying function for the Laspeyres total factor productivity (TFP) index is constant elasticity of substitution (CES) production function. Diewert (1976) also showed that the Törnqvist total factor productivity (TFP) index is exact for a linearly homogeneous translog function. Later, Diewert (1992) states that Fisher TFP index (geometric mean of Laspeyres and Paasche index) is exact for a flexible variable profit function.

⁴ The cereal and beef prices were cut to half and even more.

effects like technical change (both neutral and non-neutral) and technical efficiency change, but also price effects. The latter may be important in restrictive production conditions (milk quotas, set-aside, *etc.*) and in cases of considerable regime changes (EU accession). Technical efficiency changes and factors affecting technical efficiency are also carefully tested. The efficiency is estimated both when data is measured per farm and per cow levels. We employ the extended Kolmogorov-Smirnov tests of first and second order stochastic dominance in distribution of inefficiency by controlling for the time period and several farm-specific attributes. This allows for the statistical comparison of the whole distribution rather than points of inefficiency.

The structure of the paper is the following. First, in Section 2, we present the concept of productivity, in general, and the Malmquist productivity index, in particular, and introduce different ways to decompose the index. Then, we show how these indices can be calculated applying parametric distance functions. The data is described in Section 3. Empirical specification of the parametric distance function is outlined in Section 4. In Section 5, we discuss results from identification of the sources of productivity and the decomposition of the productivity index. The analysis of dominance in the distribution of inefficiency by various farm attributes is discussed. The final Section concludes.

2. The Methodology

In this paper, we apply econometric methods for measurement and analysis of total factor productivity (TFP). Let's assume that the production technology can be presented using output set $Y(x)$, which defines the set of output vectors $y \in \mathbb{R}_+^M$ that can be produced by an input vector $x \in \mathbb{R}_+^N$. That is $Y(x) = \{y \in \mathbb{R}_+^M : x \text{ can produce } y\}$. The output distance function can be defined as $D_O(x, y) = \min\{\theta : y/\theta \in Y(x)\}$. $D_O(x, y)$ is non-decreasing, positively linearly homogenous and convex in y , and decreasing in x . The value of the distance function is less than or equal to one for all feasible output vectors. On the outer boundary of the production possibilities set, the value of $D_O(x, y)$ is one. Thus, the output distance function indicates the potential radial expansion of production to the frontier. Stochastic frontier production function analysis can be extended to stochastic output distance function analysis if there are several outputs. Assuming a translog specification and technical change represented by a time trend, it can be written as (Coelli *et al.* 1999, Fuentes *et al.* 2001):

$$\begin{aligned} \ln D_O^t(x_i^t, y_i^t) &= \beta_0 + \sum_{k=1}^h \beta_k \ln x_{ki}^t + \frac{1}{2} \sum_{k \leq j}^h \sum_{j=1}^h \beta_{kj} \ln x_{ki}^t \ln x_{ji}^t + \sum_{m=1}^p \beta_m \ln y_{mi}^t \\ (1) \quad &+ \frac{1}{2} \sum_{m \leq n}^p \sum_{n=1}^p \beta_{mn} \ln y_{mi}^t \ln y_{ni}^t + \sum_{k=1}^h \sum_{m=1}^p \beta_{km} \ln x_{ki}^t \ln y_{mi}^t + \beta_t t + \frac{1}{2} \beta_u t^2 + \sum_{k=1}^h \beta_{kt} \ln x_{ki}^t t \\ &+ \sum_{m=1}^p \beta_{mt} \ln y_{mi}^t t \end{aligned}$$

where x :s are inputs, y :s outputs, t is time, β :s are coefficients to be estimated and D_O is the output distance function. The symmetry of coefficients is also assumed.

It is not possible to estimate the function in (1) in its current form unless the property of linear homogeneity in outputs is applied. The output distance function is by definition

linearly homogenous in outputs. Dividing the outputs by one of the outputs imposes the linear homogeneity in outputs. This follows by the following constraints:

$$(2) \quad \sum_{m=1}^p \beta_m = 1; \sum_{m=1}^p \beta_{mn} = 0; \sum_{m=1}^p \beta_{km} = 0 \text{ and } \sum_{m=1}^p \beta_{mt} = 0$$

Homogeneity in output implies that:

$$(3) \quad D'_O(x'_i, y'_i / y'_{mi}) = D'_O(x'_i, y'_i) / y'_{mi}$$

Transforming the variables in logarithms and rearranging the equation gives the translog functional form (TL is an abbreviation):

$$(4) \quad -\ln y'_{mi} = TL(x'_i, y'_i / y'_{mi}, t; \beta) - \ln D'_O(x'_i, y'_i).$$

Setting $u_{it} = \ln D'_O(x_{it}, y_{it})$ and adding a stochastic error term, our presentation is similar to that of a parametric stochastic frontier with a decomposed error term:

$$(5) \quad -\ln y'_{mi} = TL(x'_i, y'_i / y'_{mi}, t; \beta) + u_{it} + v_{it}$$

where u_{it} are time-varying inefficiency effects. The estimated parameters can now be used to construct the output oriented Malmquist productivity index for each production unit in the analysis.

At early stages of development of the productivity analysis methodology, productivity change was considered identical with technological change. Technological change describes how the sets of feasible input-output combinations expand or contract. Later on, technical efficiency change has been invented as an important factor in productivity growth. When technological change is related to shifts of the frontier, efficiency change shows if the firm is getting closer to or further away from the frontier. The use of the Malmquist index enables us to combine these changes. However, according to Balk (2001, p. 160) there remain two problems: first, whether to use actual or artificial technology and secondly, how to take scale effect (scale efficiency) into account. The scale of production may affect the productivity (in the sense of output-input relation), and thus also the productivity changes, even if the firm operates on the frontier but in a different scale (or size). Therefore, we define also scale effect as a part of productivity change.

In addition to changes in levels of inputs and outputs, in a multiple input multiple output case, input and output mixes may change over time. These changes may also affect productivity change. In this regards *e.g.* Kumbhakar and Lovell (2000) emphasize that also price or market effects should be taken into account when TFP changes are evaluated.

In order to measure productivity change, time has to be incorporated. Let's denote t and $t+1$ two adjacent periods. Thus, $D^t(x^t, y^t)$ refers to the evaluation of the firm's distance in the period t from the frontier of the same period. When evaluated against the technology of the period t , the Malmquist productivity index is:

$$(6) \quad M^t = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}$$

but, when evaluated against the technology of the period t+1 it is written as:

$$(7) \quad M^{t+1} = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}.$$

However, the choice of the time period is arbitrary. Caves *et al.* (1982) presented that under the assumption of technical and allocative efficiency (s.t. translog functional form) productivity change is equal to a geometric mean of these two indices:

$$(8) \quad M = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \right]^{1/2}.$$

Recently Orea (2002) suggested a generalized Malmquist productivity index. Starting from Diewert's (1976) quadratic identity lemma he derived a natural logarithmic productivity index that can be defined as the difference of the weighted average rates of growth of outputs and inputs. The weights are output and (negative) input distance elasticities (Orea 2002, p. 10). After some rearrangements the index is written as follows:

$$(9) \quad \ln M_o = \left[\ln D_o(x^{t+1}, y^{t+1}, t+1) - \ln D_o(x^t, y^t, t) \right] - \frac{1}{2} \left[\frac{\partial \ln D_o(x^{t+1}, y^{t+1}, t+1)}{\partial t} + \frac{\partial \ln D_o(x^t, y^t, t)}{\partial t} \right]$$

The first term in (9) corresponds to technical efficiency change and the second term to technical change. Structurally this corresponds to the traditional output-oriented Malmquist productivity index (Färe et al 1994):

$$(10) \quad M_c = \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)} \left[\frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^{t+1}, y^{t+1})} \frac{D_c^t(x^t, y^t)}{D_c^{t+1}(x^t, y^t)} \right]^{1/2}.$$

Thus $\ln M_o$ is a parametric counterpart to M_c when the output-oriented distance function is translog but here the subscript c indicates that the frontier is defined under the assumption of constant returns to scale. The decomposition can be extended to allow also non-constant returns to scale. This is possible if scale effect will be taken into account.

Starting from the ideas of Denny *et al.* (1981) Orea (2002) proposed a generalized output-oriented Malmquist productivity index where he aggregated growth in inputs by distance elasticity shares instead of distance elasticities:

$$(11)$$

$$\ln G_o = \ln M_o +$$

$$\frac{1}{2} \sum_{k=1}^n \left[\left(-\sum_{k=1}^n \frac{\partial \ln D_o(x^{t+1}, y^{t+1}, t+1)}{\partial \ln x_k} - 1 \right) \cdot e_k(t+1) + \left(-\sum_{k=1}^n \frac{\partial D_o(x^t, y^t, t)}{\partial \ln x_k} - 1 \right) \cdot e_k(t) \right] \cdot \ln \left(\frac{x_k^{t+1}}{x_k^t} \right)$$

where

$$(12) e_k(t) = \frac{\partial \ln D_o(x^t, y^t, t) / \partial \ln x_k}{\sum_{k=1}^n \partial \ln D_o(x^t, y^t, t) / \partial \ln x_k}.$$

The scale effect is determined by scale elasticities and changes in input quantities. The effect vanishes under constant returns to scale and/or constant values of inputs. In this case, the scale effect is defined without the concept of scale efficiency, which is Central for example for Balk's (2001) method of decomposition.

The scale effect presented by Orea (2002) is formally similar to that in the Brümmer *et al.* (2002) decomposition. The Brümmer *et al.* decomposition is actually an extension of Kumbhakar and Lovell (2000)'s production function approach to distance functions. Their decomposition of TFP growth includes in addition to the above mentioned effects also output price and input price effects. They are related to allocative effects. These allocative effects are derived from violations of the first-order conditions of profit maximization. As Brümmer *et al.* (2002) have stated these effects are not connected to the technology as technical change, technical efficiency change or scale effect. They claim that allocative effects are caused by market and behavioural conditions. In spite of this, they are components of technological productivity measure but connected to market. Formally their decomposition can be presented as follows:

$$(13) \ln AG_o = \ln G_o + \frac{1}{2} \sum_{k=1}^n [(-e_k(t+1) - S_k^{t+1}) + (-e_k(t) - S_k^t)] \cdot \ln \left(\frac{x_k^{t+1}}{x_k^t} \right) + \frac{1}{2} \sum_{m=1}^q \left[(R_m^{t+1} - \frac{\partial \ln D_o(x^{t+1}, y^{t+1}, t+1)}{\partial \ln y_m}) + (R_m^t - \frac{\partial \ln D_o(x^t, y^t, t)}{\partial \ln y_m}) \right] \cdot \ln \left(\frac{y_m^{t+1}}{y_m^t} \right)$$

where

$$(14) e_k(t) = \frac{\partial \ln D_o^t(x^t, y^t) / \partial \ln x_k}{\sum_{k=1}^n \partial \ln D_o^t(x^t, y^t) / \partial \ln x_k}$$

S_k is the observed cost share of the input x_k , ($S_k = \frac{w_k x_k}{\sum_{k=1}^n w_k x_k}$), R_m is the observed revenue

share, ($R_m = \frac{p_m y_m}{\sum_{m=1}^q p_m y_m}$), p and w are the price vectors of inputs and outputs.

According to Kumbhakar and Lovell (2000, p. 284), the allocative inefficiency component described above may represent either allocative inefficiency or scale inefficiency.

3. The Data

Our unbalanced panel data from 1989-2000 consist of 72 Finnish bookkeeping farms specialized in milk production. From 1992, the panel is complete. The panel includes, overall, some 812 observations over 12 years. The number of observations of a given

farm varies from 9 to 12. In 1989-1994, the sample farms were chosen following the principle that at least 60% of the sales return of the farm be generated from milk production in each year. Since 1995, the share has varied due to a considerable change in price relations but the target group has remained the same. This way, we were able to focus our analysis on farms, which had made a strategic choice for specialising in milk production. Thus, we could follow the changes of productivity in a relatively homogeneous group.

The main reason for concentrating the analysis in specialised farms was that it was not possible to separate inputs used in milk production from those used jointly in other production lines. Keeping the share of other production small gives an opportunity to get a more detailed picture about the development in milk production. The disadvantage is that the number of farms in the analysis becomes relatively small. Naturally, dairy farms produce also products other than milk for sale. These products are mainly animal products. In addition to this, it is common for farms to produce most of their feed locally. The self-sufficiency in roughage is typically the minimum requirement. Arable farming is therefore an essential part of the Finnish dairy farming system.

The Malmquist productivity index does not require data on input and output prices. However, prices are used to aggregate inputs and outputs to a smaller number. In our analysis, we apply two outputs: Milk output per farm (Y_m) is measured as the quantity of fat-corrected milk produced within a year. Other output (Y_o) covers outputs other than milk. The latter is measured in current values but deflated by respective indices to the fixed 1990-prices. Direct payments are excluded. The inputs used in the analysis include labour, land, material, and capital. Labour (L) and land (A) are measured in physical quantities, hours and hectares, while material (M) and capital (K) are measured in monetary values and transformed to fixed 1990-prices. The capital variable is an aggregate of machinery, building and animal capital. Machinery, buildings and animals (K) are measured as stock variables. Material input consists of purchased feed, fertilisers, energy and miscellaneous expenditures. The costs are measured in real 1990 price level. Table 1 presents the descriptive statistics of the data set.

Table 1. Descriptive statistics, 812 observations.

Variables	Measure	Mean	Std dev	Minimum	Maximum
<u>Outputs:</u>					
Milk (Y_m)	Litres	143,977	50,203	48,702	371,690
Other outputs (Y_o)	€	17,039.29	10,569.43	105.96	80,680.25
<u>Inputs:</u>					
Labour (L)	Hours	5,129	1,316	2,143	11,459
Land (A)	Hectares	28.6	11.2	10.2	79.5
Materials (M)	€	38,230.46	16,529.51	4,928.58	130,903.19
Capital (K)	€	101,838.97	59,521.37	20,865.90	484,059.15
Cows (C)	Numbers	19	6	8	50

Finnish farms are typically small. Table 1 shows that the mean arable land area of the sample farms was 28.6 hectares, with the number of cows being 19. Milk output was on average 144,000 litres. In 1990, milk output per farm has increased almost by 55% but the quantity of other outputs increased only slightly (Figure 1a). In fact, it decreased after EU accession. The fall is probably partially induced by the value changes in inventories and the need to use more animals for reproduction when the number of cows

was increased. Partially, this indicates that specialised dairy farms have become even more specialised in milk production.

Milk output per farm started to grow more rapidly a couple of years before the Finnish EU accession in 1995 when milk quotas became tradable. Finland had introduced milk quotas in 1984. The quotas became an effective constraint for milk production slowing down structural development. Only administrative transfers of quotas were allowed. This involved partial transfer of the quota of farmers who stopped milk production to active producers. The quota system met its objective in preventing the increase in production and the total production decreased considerably. The quota system became more flexible in 1993-1994 when part of the quotas became tradable or could be leased among milk producers.

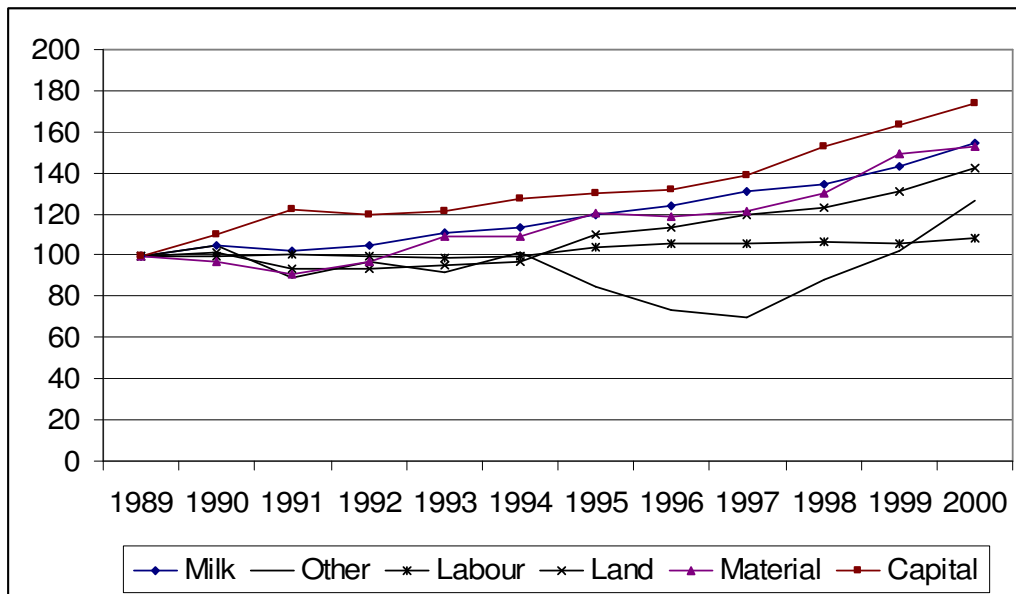


Figure 1a. Development of mean inputs and outputs by average farm (1989 = 100).

EU accession has speeded up the ceasing of milk production, but simultaneously investment aid has since 1996–1997 boosted the building and renovating of cowsheds on surviving farms. Milk output has increased faster than the number of cows per farm. The average number of cows per farm has increased by a little more than 30% from 17 to almost 23 cows. Simultaneously, milk yield per cow has increased by 17%. The changes in output measured in per unit of cow are presented in Figure 1b.

In relative terms, capital stock per farm has increased more rapidly than milk output, 73.4% (see Figure 1a). Investment in agriculture was at the record high level in 1989-1990. Since then, investment activity has dropped and was at its lowest in the middle of 1990s, at the time of the Finnish EU accession. After EU accession, considerable public investment aids have boosted investment activities, and in dairy farming as well. In the middle of 1990s, a large share of investment in animal farms was made in the renovation and enlargement of manure storage areas. The average size of farms has started to grow more rapidly not before the late 1990s. However, structural change in Finnish agriculture is still slower than in many other western European countries.

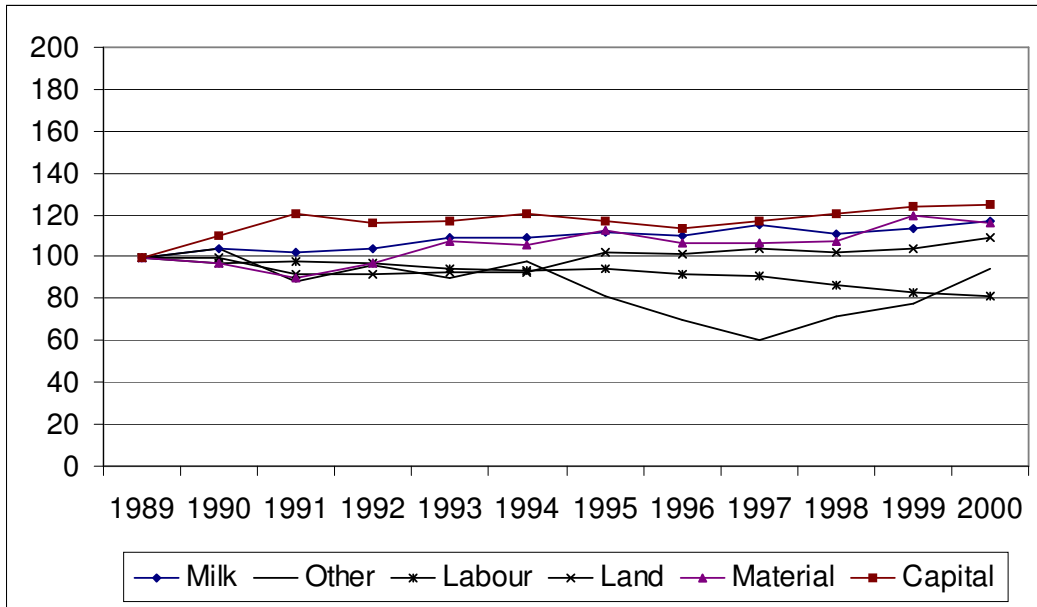


Figure 1b. Development of mean inputs and outputs by cow (1989 = 100).

Capital stock per cow has remained almost unchanged since 1991. Capital has also substituted for labour, since the growth of labour input is only 8% during the time period under study. This follows that the labour input per cow has dropped by almost 20% during the research period. Although the total labour input in agriculture has decreased because of the decreasing number of farms, simultaneously, farms increasing in size have had to increase their total labour input, but relatively less than other inputs.

The arable land area on sample farms has increased by 40%. Up to 1995, there was almost no growth in cultivated arable land area. This is largely due to the extensive set-aside programs in early 1990s. A mandatory set-aside system came into effect in 1991. According to the system, the farmer had to leave fallow 15% of his arable land area. Through increased premiums and stricter obligations for large farms the set-aside area increased by up to 500,000 hectares, which covered more than 20% of the arable land area. During EU membership, the proportion of fallow land has been less than half of that. The use of materials per farm has also increased by approximately 50% during the sample period. The growth rate per cow has been less than 17%. This rate is similar to the increase in per cow milk yield.

For regression analysis, it is important that the regressors correlate with the dependent variable but the collinearity among independent variables may make the parameters insignificant, confounded and unstable. When we are interested in, for example, the elasticity of specific inputs as we have to use estimated coefficients which may be unreliable due to problems of collinearity. The correlation coefficients by per farm and per cow are reported in Table 2. In general, correlations are higher in the case per farm than per cow. The Table shows that measured per cow the input variables with the exception (of cows and labour, 0.63) do not correlate highly significantly among themselves. The correlations between the milk output and inputs are higher except in the case of labour and land, but they are relatively low. The correlations between inputs

and the other output are even less significant. The correlation is higher among the two outputs (0.27) than in the per farm model (0.15). When the farm level data is used, multicollinearity is probably a less significant problem since the within-group correlations among the different groups of outputs and outputs are considerably smaller than the between-groups of inputs and outputs. Thus, results based on per farm level data are expected to be more reliable.

Table 2. Pearson correlation matrix of variable measured in per farm (upper triangle) and per cow (lower triangle), p-values in parenthesis (NT=812).

	MILK	OTHER	LABOUR	LAND	MATERIAL	CAPITAL	COWS	TIME
MILK	1	0.1494 (0.0001)	-0.5377 (0.0001)	-0.7004 (0.0001)	-0.7867 (0.0001)	-0.7165 (0.0001)	0.8705 (0.0001)	0.3680 (0.0001)
OTHER	0.2659 (0.0001)	1	0.0708 (0.0436)	0.0104 (0.7654)	-0.0234 (0.5044)	0.0940 (0.0073)	0.0193 (0.5833)	0.2632 (0.0001)
LABOUR	-0.0551 (0.1162)	0.1161 (0.0009)	1	0.5188 (0.0001)	0.4252 (0.0001)	0.4162 (0.0001)	-0.5693 (0.0001)	-0.1037 (0.0031)
LAND	-0.1411 (0.0001)	0.0668 (0.0569)	0.2443 (0.0001)	1	0.5542 (0.0001)	0.5824 (0.0001)	-0.7069 (0.0001)	-0.3036 (0.0001)
MATERIAL	-0.3896 (0.0001)	0.0124 (0.7239)	-0.0104 (0.7657)	0.0256 (0.4652)	1	0.5897 (0.0001)	-0.7060 (0.0001)	-0.3464 (0.0001)
CAPITAL	-0.1898 (0.0001)	0.1765 (0.0001)	-0.0683 (0.0515)	0.0976 (0.0054)	0.1057 (0.0026)	1	-0.7085 (0.0001)	-0.2673 (0.0001)
COWS	-0.0763 (0.0295)	0.0192 (0.5833)	-0.6301 (0.0001)	-0.1641 (0.0001)	-0.0228 (0.5163)	0.1016 (0.0037)	1	0.2670 (0.0001)
TIME	0.2954 (0.0001)	0.2632 (0.0001)	0.2196 (0.0001)	-0.1139 (0.0011)	-0.2246 (0.0001)	-0.1347 (0.0001)	0.2670 (0.0001)	1

4. Specification and Estimation of the Model

We assume that the following translog distance function defines the (milk) production process at the farm:⁵

$$\begin{aligned}
(15) \quad & -\ln y_{mi}^t = \beta_0 + \sum_{k=1}^4 \beta_k \ln x_{ki}^t + \frac{1}{2} \sum_{k \leq j=1}^4 \sum_{j=1}^4 \beta_{kj} \ln x_{ki}^t \ln x_{ji}^t + \sum_{p=1}^3 \beta_{op} D_p \ln y_{oi}^t \\
& + \frac{1}{2} \sum_{p=1}^3 \beta_{oop} D_p (\ln y_{oi}^t)^2 + \sum_{k=1}^4 \beta_{km} \ln x_{ki}^t \ln y_{oi}^t + \beta_t D_t + \sum_{k=1}^4 \beta_{kt} \ln x_{ki}^t \\
& + u_{it} + v_{it}
\end{aligned}$$

where i represents the farm ($i=1, \dots, 72$) and t the year of observation ($t=1, \dots, 12$). The output variables applied in the analysis are: milk output (y_m) measured in litres of milk and other outputs (y_o) measured in monetary terms divided by the milk output. The input variables denoted as x_1 to x_4 are: labour (L) input in hours, arable land area (A) in hectares, capital stock (K) in euro, and materials (M) in euro. The variables expressed in monetary values are transformed to fixed 1990 prices.

⁵ The distance translog function differs from a standard translog production function in the way the left hand variable is defined and normalized. The sign of the coefficients are also reversed. The differences in the formulation have no implication for the properties and estimation procedure.

The variables denoted as D_t are time dummies to capture year-to-year neutral technical change and D_p is the time interval for the regression coefficient of other output representing years 1989-1994, 1995-1997 and 1998-2000. The interaction of D_p and y_o allows for heterogeneity in slopes associated with other outputs due to the effects of changes in policy over time and its implications for composition of outputs produced by individual farms. Non-neutral technical change is defined as a cross term of inputs or the other output and the time trend.

The error term is decomposed into two components. The first component, v_{it} , is a standard random variable capturing effects of unexpected stochastic changes in production conditions, measurement errors in milk output or the effects of left-out explanatory variables. It is assumed to be independent and identically distributed with $N(0, \sigma_v^2)$. The second component, u_{it} , is a non-negative random variable, associated with the technical inefficiency in production, given the level of inputs. The u_{it} s are independently distributed with a truncation at zero of $N(\mu_{it}, \sigma_u^2)$, where μ_{it} is modelled in terms of determinants of inefficiency as:

$$(16) \quad \mu_{it} = \delta_0 + \sum_{sc=1}^3 \delta_{sc} D_{sc} + \sum_{re=1}^3 \delta_{re} D_{re}$$

where D_{sc} refers to size class dummy variables and D_{re} to regional dummies. Farms were classified as small if they belonged, according to the number of cows, to the lower quartile in a specific year. Farms were classified as large ones if they belonged to the upper quartile in a specific year. Middle sized farms were those farms whose size was between lower and upper quartiles. The size classification of a farm may thus change from year to year due to structural change. In the analysis, the reference size was that of small farms. The region refers to the geographic location - Southern, Central and Northern Finland - of the farm, Central Finland being the reference group. The δ :s are respective efficiency effects regression coefficients. The inefficiency effects part of the equation makes it possible to test whether technical efficiencies differ by size class and regional location.

The parameters of the model are estimated by the method of maximum likelihood. We applied the computer program Frontier 4.1 (Coelli 1996). The variance parameters are defined as $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma_s^2$ where γ takes the value between 0 and 1. Parameters of the stochastic frontier model can be tested using the generalised likelihood ratio statistics. Given the translog stochastic frontier specification of output distance function, technical efficiency of production can be obtained from the conditional expectation of $TE_{it} = \exp(-U_{it})$, given the random variable ε_{it} ($\varepsilon_{it} = v_{it} - u_{it}$; Battese and Coelli 1988). The level of technical efficiency is by definition between 0 and 1, and varies across farms, and over time.

It should be noted that prior to the estimation the inputs and outputs are transformed to deviations from their sample means since each variable has been divided by its own mean. Thus, the first order coefficients are the distance elasticities at the sample mean. Linear homogeneity of outputs is imposed by dividing the two outputs by milk output. This ratio form as an explanatory variable has been discussed in the literature. Kumbhakar and Lovell (2000) have argued that the outcome of a normalisation is not independent of the choice of specific normalising output variable. Brümmer *et al.*

(2002) state, however, that the use of the norm model would lead to increasing multicollinearity and, thus, unstable estimates. Another related question is the possible endogeneity of output ratios. Coelli and Perelman (1999) have stated that transformed output variable in the ratio model are actually measures of output mix which are more likely exogenous than the variables in the norm model.⁶ Furthermore, according to Mundlak (1996), in the case of expected profit maximisation, the ratio variables in the production function do not suffer from endogeneity. This result can be generalised to output ratio variables in output distance functions (Brümmer *et al.* 2002).

5. Empirical Results

5.1 The parameter estimates

Farm level estimated parameters of the output distance function described above are presented in Table 3. Several nested model specifications for the translog distance functions were estimated and tested prior to the selection of the final model. Nested likelihood ratio tests for various model specifications showed that the Cobb-Douglas specification was not a sufficient representation to describe the input-output technical relationship on Finnish dairy farms. The neutral technical change specification was also rejected against the non-neutral technical change specification (see Table 4). The hypothesis of the presence of inefficiency in the operation of farms could not be rejected either. Likelihood ratio test value for one-sided error is 111.983 indicating that the variance of inefficiency effects is a significant part of the error term variances. We could also observe that the coefficients in the model explaining inefficiency were not jointly zero.

Farm level estimation results suggest that efficiency increases by size class and those farms located in the middle of Finland are technically among the most efficient farms. Thus, analyses of the result presented below are based on the specification and estimation of a stochastic frontier translog distance model incorporating both non-neutral representation of technical change and the technical efficiency effect model.

Respective estimation results per cow are presented in Appendix A. Nested likelihood specification tests showed that the full translog specification is the best specification of those considered. In the per cow case, technical efficiency increased by size class but by location, there was no significant differences.

Although the nested tests showed that the non-neutral technical change stochastic frontier translog specification is the best representation of the technology of those considered, 13 of the 39 coefficients in the regression model were not statistically significantly different from zero in the per farm model (with 18 of 39 in the per cow model).

⁶ In the norm model, all outputs are divided by Euclidean norm of outputs $\|y\| = \sqrt{\sum_i y_i^2}$. In the ratio model, one of the outputs serves as denominator for all outputs.

Table 3. Estimated (farm level) parameters of the translog distance function, NT=812 observations.

Variable	Param	Coeff.	Std err	t-ratio	Variable	Param	Coeff.	Std err	t-ratio
Constant	β_0	0.0660	0.0232	2.8428	$\ln(L)^2$	β_{LL}	0.1102	0.0728	1.5153
$\ln(Y_o)_{89-94}$	β_{o1}	0.1734	0.0205	8.4514	$\ln(A)^2$	β_{AA}	0.1493	0.0588	2.5373
$\ln(Y_o)_{95-97}$	β_{o2}	0.1203	0.0166	7.2455	$\ln(M)^2$	β_{MM}	-0.1348	0.0288	-4.6879
$\ln(Y_o)_{98-00}$	β_{o3}	0.1340	0.0206	6.4962	$\ln(K)^2$	β_{KK}	0.0564	0.0262	2.1548
$\ln(L)$	β_L	-0.2472	0.0569	-4.3454	$\ln(L)\ln(A)$	β_{LA}	-0.1417	0.0976	-1.4518
$\ln(A)$	β_A	-0.2550	0.0501	-5.0933	$\ln(L)\ln(M)$	β_{LM}	0.0652	0.0803	0.8122
$\ln(M)$	β_M	-0.3035	0.0383	-7.9356	$\ln(L)\ln(K)$	β_{LK}	-0.0002	0.0801	-0.0030
$\ln(K)$	β_K	-0.1038	0.0363	-2.8611	$\ln(A)\ln(M)$	β_{AM}	0.1979	0.0572	3.4574
D1990	β_{t2}	-0.0406	0.0258	-1.5727	$\ln(A)\ln(K)$	β_{AK}	-0.1889	0.0581	-3.2524
D1991	β_{t3}	-0.0215	0.0270	-0.7940	$\ln(M)\ln(K)$	β_{MK}	0.0566	0.0502	1.1276
D1992	β_{t4}	-0.0525	0.0252	-2.0872	$\ln(L)T$	β_{Lt}	-0.0158	0.0076	-2.0605
D1993	β_{t5}	-0.0384	0.0254	-1.5113	$\ln(A)T$	β_{At}	-0.0115	0.0061	-1.8759
D1994	β_{t6}	-0.0561	0.0254	-2.2070	$\ln(K)T$	β_{Kt}	0.0046	0.0049	0.9513
D1995	β_{t7}	-0.0122	0.0263	-0.4628	$\ln(M)T$	β_{Mt}	0.0133	0.0048	2.7388
D1996	β_{t8}	-0.0116	0.0264	-0.4378	Dsc1	β_{sc1}	0.0705	0.0451	1.5619
D1997	β_{t9}	-0.0282	0.0275	-1.0255	Dsc2	β_{sc2}	0.2108	0.0224	9.4209
D1998	β_{t10}	-0.0500	0.0274	-1.8251	Dre1	β_{reg1}	-0.0880	0.0301	-2.9178
D1999	β_{t11}	-0.0486	0.0274	-1.7749	Dre2	β_{reg2}	-0.7340	0.3491	-2.1024
D2000	β_{t12}	-0.1146	0.0276	-4.1500		σ^2	0.0240	0.0025	9.6306
$\ln(Y_o)^2_{89-94}$	β_{oo1}	0.0256	0.0287	0.8893		γ	0.4165	0.0853	4.8820
$\ln(Y_o)^2_{95-97}$	β_{oo2}	0.0262	0.0069	3.7952					
$\ln(Y_o)^2_{98-00}$	β_{oo3}	0.0680	0.0175	3.8912					

Log likelihood test value is 519.423.

Table 3. Generalised likelihood ratio tests for parameters of the translog stochastic frontier model.

Null hypothesis	Test statistics ^a	Critical value
Cobb Douglas – no TC vs. neutral TC (d.f. 11)	50.020	19.675
Cobb Douglas – neutral TC vs. Translog – neutral TC (d.f. 13)	81.986	22.362
Translog – neutral TC vs. non-neutral TC (d.f. 4)	121.080	9.488
No technical inefficiency (d.f. 5) ^b	111.983	14.325
No technical efficiency effect (d.f. 4)	111.506	9.488

^a Log likelihood ratio test $-2(\log L(H_0) - \log L(H_1))$

^b The critical value is obtained from Table 1 in Kodde and Palm (1986) which shows the statistics for a mixed Chi-square distribution with degrees of freedom equal to 5.

5.2 The distance elasticities

The first order coefficients as expected show that, at the sample mean, the output distance function is decreasing in inputs and increasing in outputs. In the per farm model, the distance elasticities are highest for labour, land and materials. The per cow model is largest for materials. The elasticity of capital is always the lowest. However, input elasticities should be negative at every point.⁷ Otherwise the scale elasticity will

⁷ Due to the functional form and negative sign on the front of dependent variable, the sign of the coefficients are reversed. Here, a negative input elasticity is interpreted as output is increasing in inputs.

be biased. Therefore, Table 5 shows the number of positive and negative point elasticities.

In the upper part of the Table, per farm results show that input elasticities for labour, land and materials are negative at every point of observation. For capital input, the monotonicity fails to hold in 41.5% of observations. Thus, we can conclude that the effect of scale economies cannot be measured accurately for the whole sample. The magnitude of bias should however be very small as the capital elasticity is the smallest, only -0.058 and insignificant.

In the lower part of Table 5, per cow results indicate monotonicity violations in other elasticities except materials, the elasticity of labour being the most often violated. The number of violations is approximately equal both in per farm and per cow models. In the per cow case, the magnitude of bias is probably larger since the mean elasticities of land and labour are higher and more significant than that of capital.

Table 5. Monotonicity of elasticities in the per farm and per cow model formulations.

Elasticities per farm	Mean	Std error ^a	t-value	Positive	Negative
Milk output (Ym)	0.852			812	0
Other output (Yo)	0.148	0.016	9.250	810	2
Labour (L)	-0.354	0.106	-3.336	0	812
Land (A)	-0.333	0.090	-3.704	0	812
Materials (M)	-0.272	0.069	-3.925	0	812
Capital (K)	-0.058	0.068	-0.855	337	475
Returns to scale				Decreasing RTS	Increasing or constant RTS
Scale elasticity ^b	-0.967	0.099	-9.748	323	152

Elasticities per cow	Mean	Std error ^a	t-value	Positive	Negative
Milk output (Ym)	0.892				
Other output (Yo)	0.108	0.013	8.438	812	0
Labour (L)	-0.146	0.072	-2.042	87	725
Land (A)	-0.144	0.077	-1.860	163	649
Materials (M)	-0.229	0.064	-3.561	0	812
Capital (K)	-0.077	0.058	-1.334	110	702
Returns to scale				Decreasing RTS	Increasing or constant RTS
Scale elasticity ^b	-0.590	0.125	-4.724	543	6

^a Standard errors calculated at the sample mean.

^b Includes only observations not violating monotonicity.

When standard errors of some regression coefficients are large, the standard errors⁸ of calculated elasticities also become large. The elasticity of capital is the only insignificant elasticity among the inputs. Another problem related to input elasticities

⁸ The standard errors for individual input elasticities are obtained using the delta method. It gives the distribution of a function of random variables for which one has a distribution. In our case, standard errors

for elasticities of x_k are obtained from the square root of the diagonal elements of $(\frac{\partial y}{\partial x_k}) \text{cov}(y, x) (\frac{\partial y}{\partial x_k})'$

(Heshmati 2001).

and the decomposition of productivity changes is that the correlations between several variables are high. This multicollinearity in inputs may also affect the reliability of individual coefficients and associated input elasticities.

The average scale elasticity in the per farm model is less than 1.0 indicating on the average decreasing returns to scale (RTS). In 68% of observations, RTS is decreasing, while in 32% it is increasing. In the per cow model, RTS is increasing only in 1% of cases and the average scale elasticity is less than 0.6. Thus, a 1% growth in all inputs per cow produces a 0.6 percent increase in output. In Table 5, scale elasticity is calculated only for those observations where the monotonicity condition is not violated. An inclusion of the violating observations in the calculation will bias upward (less negative) the scale measure.

The sample mean scale elasticity based on the per farm model with the exception of 1989, 1990 and 1995 does not differ significantly from constant returns to scale in any of the observed years. Over time, the sample average RTS has increased slightly but we have to take into account that the number of valid observations decreases at the same time. In the per cow case, RTS is in every year significantly less than one but the scale elasticity is steadily increasing over time.

Table 6. Mean distance elasticities over time per farm and per cow models.

Year/Model	Milk	Other output	Labour	Land	Materials	Capital	RTS
<u>Per farm</u>							
1989	0.818	0.182	-0.263	-0.258	-0.311	-0.100	-0.928
1990	0.818	0.182	-0.283	-0.291	-0.297	-0.086	-0.952
1991	0.823	0.177	-0.290	-0.346	-0.292	-0.069	-0.973
1992	0.820	0.180	-0.304	-0.333	-0.298	-0.057	-0.977
1993	0.823	0.177	-0.317	-0.322	-0.304	-0.049	-0.966
1994	0.821	0.179	-0.334	-0.340	-0.294	-0.044	-0.971
1995	0.881	0.119	-0.353	-0.322	-0.278	-0.050	-0.951
1996	0.888	0.112	-0.374	-0.337	-0.263	-0.041	-0.973
1997	0.897	0.103	-0.394	-0.350	-0.249	-0.042	-0.980
1998	0.878	0.122	-0.411	-0.364	-0.239	-0.045	-1.017
1999	0.872	0.128	-0.424	-0.349	-0.242	-0.036	-0.976
2000	0.861	0.139	-0.448	-0.355	-0.221	-0.025	-0.985
Average	0.852	0.148	-0.354	-0.333	-0.272	-0.058	-0.967
<u>Per cow</u>							
1989	0.892	0.108	-0.108	-0.142	-0.210	-0.070	-0.510
1990	0.891	0.109	-0.118	-0.144	-0.220	-0.070	-0.530
1991	0.888	0.112	-0.126	-0.138	-0.253	-0.079	-0.574
1992	0.890	0.110	-0.140	-0.147	-0.244	-0.081	-0.586
1993	0.887	0.113	-0.153	-0.151	-0.234	-0.085	-0.583
1994	0.889	0.111	-0.156	-0.134	-0.241	-0.083	-0.597
1995	0.922	0.078	-0.152	-0.122	-0.225	-0.077	-0.560
1996	0.917	0.083	-0.148	-0.139	-0.229	-0.073	-0.584
1997	0.910	0.090	-0.148	-0.150	-0.229	-0.072	-0.605
1998	0.866	0.134	-0.163	-0.156	-0.232	-0.079	-0.628
1999	0.871	0.129	-0.164	-0.147	-0.217	-0.082	-0.647
2000	0.881	0.119	-0.151	-0.156	-0.214	-0.072	-0.635
Average	0.892	0.108	-0.146	-0.144	-0.229	-0.077	-0.590

In the per farm case, distance elasticities are on average highest for labour, with land followed by materials. In the per cow model, the elasticities are in general lower but the elasticity of materials is the highest, and it is almost as high as in the per farm model. Elasticities of capital are very low and do not differ significantly from zero. Table 6 shows how the elasticities evolve over the time period under investigation. The elasticities in the per cow case stay relatively stable. The only exception is the increase in the elasticity of labour. There are larger changes in the per farm case. Elasticities of labour and land increase considerably but those of materials and capital have been decreasing. At the beginning of the period, the partial elasticity of materials is the highest but, at the end, the highest elasticity is related to labour. The pattern of change indicates the presence of substantial substitution and complementarity among the inputs in milk production. Despite increased capital intensity in production, the role of capital is declining. The elasticity of capital has been decreasing steadily and, especially at the end of the period, the monotonicity assumption is often violated. The distance elasticity of other output has also decreased indicating a transformation of technology to a higher degree of specialisation on sample farms over time.

Table 7 shows whether the distance elasticities differ between size classes and regions. The elasticity of materials is a decreasing function of the farm size. In the per farm model, this concerns also land but in the per cow model the elasticity of land increases by farm size. There is a similar qualitative difference when RTS is considered. Only for the group of small farms does the average RTS exceeds one in the per farm case. However, RTS is the highest on large farms in the per cow case. When looking at mean values by location, the biggest differences are in elasticities of land and materials. The elasticity of land decreases when moving from the South to the North in both models. Instead, the elasticity of materials is the highest in the northern part of Finland when the per farm model is considered but in the per cow model the direction is the opposite. Returns to scale has a tendency to fall in going from South to North.

Table 7. Distance elasticities by farm size class and regional location of farms.

	Milk	Other output	Labour	Land	Material	Capital	RTS
<u>Farm size classes:</u>							
<u>Per farm model</u>							
Small	0.851	0.149	-0.349	-0.351	-0.328	-0.055	-1.019
Medium	0.854	0.146	-0.358	-0.337	-0.270	-0.053	-0.978
Large	0.848	0.152	-0.352	-0.311	-0.232	-0.068	-0.920
<u>Per cow model</u>							
Small	0.893	0.107	-0.153	-0.104	-0.257	-0.077	-0.559
Medium	0.890	0.110	-0.144	-0.126	-0.229	-0.077	-0.576
Large	0.896	0.104	-0.144	-0.198	-0.208	-0.077	-0.626
<u>Regional location:</u>							
<u>Per farm model</u>							
South	0.855	0.145	-0.346	-0.392	-0.272	-0.067	-1.013
Central	0.848	0.152	-0.357	-0.340	-0.262	-0.062	-0.973
North	0.860	0.140	-0.352	-0.288	-0.296	-0.046	-0.933
<u>Per cow model</u>							
South	0.890	0.110	-0.171	-0.213	-0.272	-0.090	-0.745
Central	0.894	0.106	-0.139	-0.144	-0.231	-0.075	-0.589
North	0.887	0.113	-0.151	-0.115	-0.205	-0.076	-0.536

5.3 Technical efficiency

In the per farm model, technical efficiency (TE) on the sample farms was on average 0.933 and the standard deviation being 0.053. This would mean that the farms should on average be able to increase their outputs by 6.7% without increasing their input use. The per cow model indicates slightly smaller efficiency: TE is 0.904 and standard deviation 0.052. The average efficiencies are relatively high compared to the efficiency scores obtained by other model specifications (*e.g.* Sipiläinen 2003). Sipiläinen used data envelopment analysis (DEA) to obtain efficiency scores. The DEA does not distinguish between inefficiency and random error terms. A composed effect is labelled as inefficiency which explains the lower efficiency resulted from the use of DEA based on the same data. However, in this study, the efficiency scores are not directly comparable to those of Sipiläinen since different methods and models are used. Empirical evidence suggests that the level of efficiency is not independent of the estimation or computation method. The maximum technical efficiency (TE) is 0.990 and the minimum 0.674 in the per farm case. The respective values in the per cow model are 0.980 and 0.543.

The point efficiency estimates do not have a standard error. Therefore we cannot infer about their significance levels. Confidence intervals for individual point estimates of technical efficiency scores were obtained using the approach proposed by Horrace and Schmidt (1996) and applied by Hjalmarsson *et al.* (1996) and Battese *et al.* (2000). For details on the construction of confidence intervals for the efficiency point estimates, see Appendix B.

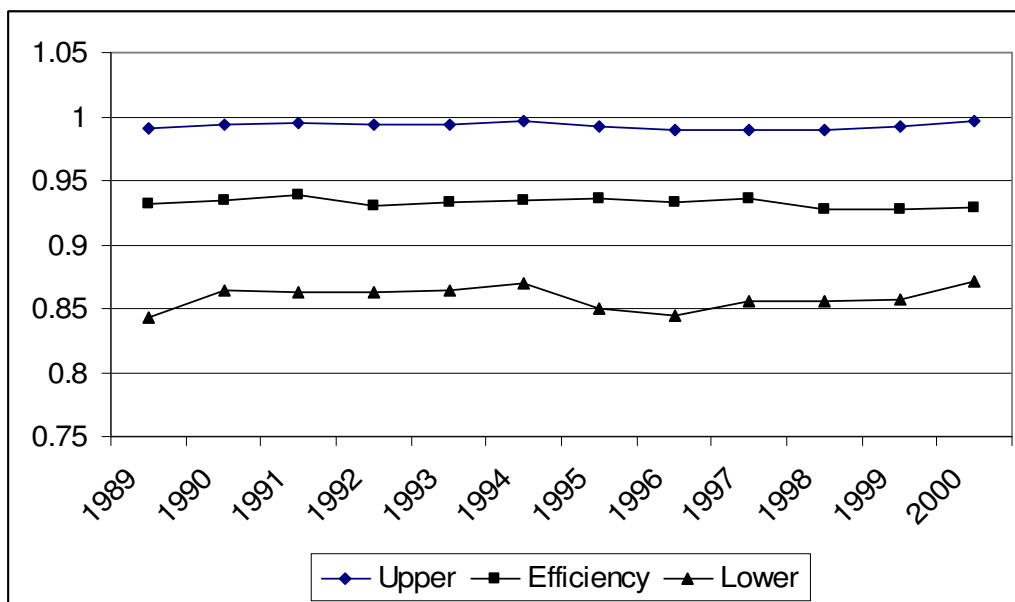


Figure 2. Average technical efficiencies and 95 % confidence intervals for 1989–2000 (per farm).

In Figure 2, we present the annual confidence intervals for average technical efficiency of the sample farms for 1989–2000. The average efficiency remains relatively stable

over the period. The confidence interval does not change much either. The interval is wider in 1989 and at the time of the EU accession as well as post the accession period. In 2000, the interval becomes narrower and it is as large as that found before EU accession.

Table 8 presents technical efficiencies and confidence intervals by farm size class and regional location of farms. The results suggest a positive association between efficiency and size of farms when per farm results are considered. It shows that the efficiency of small farms is on average the lowest and also the range of lower and upper limits of confidence intervals is the highest among the three groups of farms. Technical efficiency of large farms is significantly higher than that of medium sized farms, and it has a small dispersion round its mean value. It should, however, be noted that in the per cow model, we do not observe much efficiency differences between the three farm size classes. This contradicts the result of the technical efficiency effect model in the per cow model.

The average technical efficiency of farms is as expected the lowest in the northern region in both models. The width of the confidence interval is also the largest. In the per cow case, regional averages deviate less from each other than in the per farm case. It should be kept in mind as Battese *et al.* (2000) have stated that these confidence interval predictions may be conservative in measuring the confidence and dispersion in efficiency.

Table 8. Average technical efficiencies and 95% confidence intervals by size class and regional location of farms.

Farm size classes:	Lower	Mean	Upper	Range
<u>Per farm model</u>				
Small	0.786	0.883	0.981	0.195
Medium	0.841	0.925	0.994	0.153
Large	0.953	0.986	1	0.047
<u>Per cow model</u>				
Small	0.826	0.898	0.981	0.155
Medium	0.849	0.909	0.989	0.139
Large	0.853	0.898	0.988	0.135
<u>Regional location of farm:</u>				
<u>Per farm model</u>				
South	0.859	0.935	0.996	0.136
Central	0.883	0.953	0.998	0.115
North	0.799	0.882	0.980	0.181
<u>Per cow model</u>				
South	0.851	0.896	0.988	0.137
Central	0.858	0.916	0.991	0.133
North	0.811	0.878	0.977	0.165

The cumulative frequency distributions of technical efficiencies in the per farm model are presented in Figure 3 for all observations and the entire period. There are no shifts in efficiency distributions over time but between size classes and regions the cumulative distributions differ. Table 8 already shows that average efficiencies are lowest on small farms and highest on large farms. Almost all large farms do, in fact, belong to the highest efficiency class, that is, between 0.975–1.0, although none of those are fully

efficient. On the contrary, none of the smaller farms was evaluated as highly efficient. It should be noted that the current sample consists of relatively small dairy farms and the frontier is build on the sample best practice farms, which might differ from the population best practice technology.

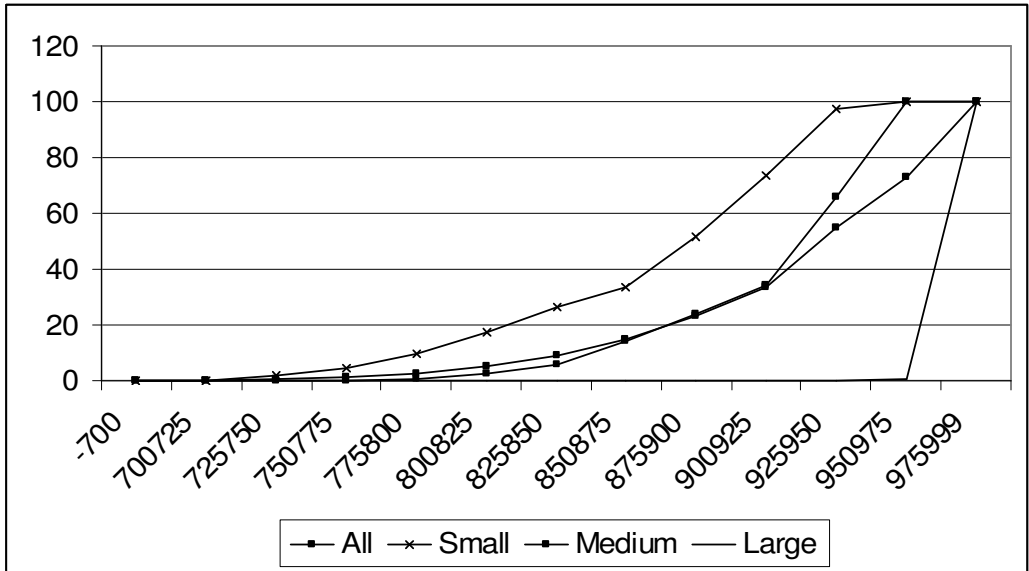


Figure 3. The cumulative distribution of technical efficiencies by size class (per farm; e.g. 700725 stands for technical efficiency of 0.700 – 0.725).

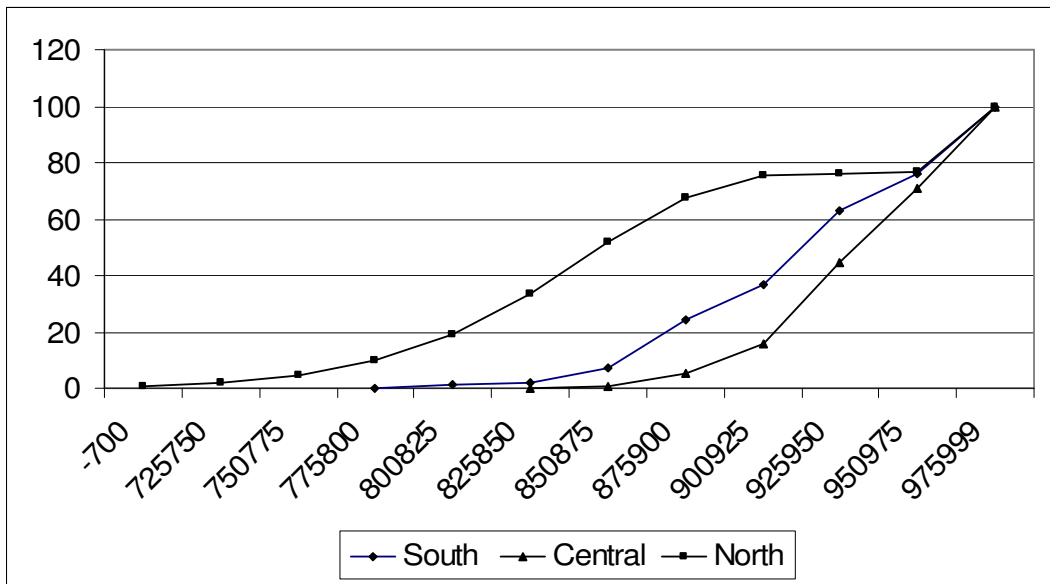


Figure 4. The cumulative distribution of technical efficiencies by region (per farm).

Cumulative distributions show clearly these systematic efficiency differences since there are no crossings in distribution curves. Those in the right hand side are dominating those to the left. The same concerns Figure 4 where cumulative distributions are

presented by the regional location. The latter figure shows that the efficiency scores of the cumulative distribution curve are in Central Finland at every point larger than in Southern Finland. It is important to compare distributions since two series with the same mean may have different distributions.

The frequency distributions discussed above despite of being very informative cannot determine whether the dominance of one distribution over another is statistically valid or not. In the next section, we perform first and second order dominance tests by using bootstrapping techniques. The test will consider dominance in the distribution of efficiency by a number of common characteristics, such as year of observation, size of farm, regional location, capital and labour intensities.

5.4 Evaluating dominance ranking of (in)efficiency by farm attributes

In this section, we examine the evolution of inefficiency, measured both at farm and at per cow levels. We employ the extended Kolmogorov-Smirnov tests of first and second order stochastic dominance as implemented by Maasoumi and Heshmati (2000). We offer partial control for many farm-specific attributes, such as size, location and production factor intensities by comparing group cells. This avoids having to specify and estimate models of dependence of inefficiency on these attributes, but lacks the multiple controls that is the promise of such techniques. We find a number of strong second order rankings between groups at the farm level but not over time or at the cow level.

5.4.1 Bootstrap procedure for dominance rankings

In recent years, methods have been developed to examine the existence of uniform weak orders between welfare outcomes measured by total real incomes. Partial *strong* orders are commonly used in evaluation on the basis of specific utility functions and their corresponding indices of such as inequality or poverty in welfare. Such strong orderings do not command consensus. Based on the expected utility paradigm, Stochastic Dominance (SD) relations of various orders attempt to resolve this problem. In evaluating distributed outcomes, average outcomes mask the differential impact on different participants and render index based assessments as blunt instruments for policy analysis. SD analysis reveals all of the distributional changes, especially amongst the target groups. For more details on these issues see Maasoumi and Heshmati (2004) and Appendix C.

In this paper, we follow an alternative bootstrap procedure for estimating the probability of rejection of the SD hypotheses with a suitably extended Kolmogorov-Smirnov (KS) test for first and second order stochastic dominance. Alternative simulation and bootstrap implementations of this test have been examined previously by several authors including McFadden (1989), Klecan, McFadden, and McFadden (1991), Barrett and Donald (2003) and Linton *et al.* (2003). They prove that the resulting test is consistent against all nonparametric alternatives.

5.4.2 Testing for SD among dairy farms

We compare 12 years of survey data on dairy production for the years 1989 to 2000. The data is defined in per farm and per cow levels. The efficiency in production is obtained from the estimation of a stochastic production function. For comparisons over time, we have chosen 1989, 1996 and 2000 covering both pre- and post-reform periods associated with Finland's accession to the European Union. The years were chosen to

be representative as well as sufficiently far apart so that reform policy would have time to produce measurable effects. It is to be noted that for the bootstrapping test we use percent inefficiency (100-efficiency) rather than percent efficiency. This implies that the cumulative distribution function (CDF) to the right (more inefficient) are dominated by those to the left (more efficient). In addition to unconditional comparison of the inefficiency distribution over time, inefficiency is compared conditional on a number of farm characteristics used in our previous analysis. The farm characteristics that we control for are: farm size, regional location of farms, and capital and labour factor intensity in production.

In defining farm size, we have divided the sample into three groups: small, medium and large. As to regional location, the sample is divided into South, Central and North. For the factor intensity, the sample is divided by intensity in the use of capital and labour in production into three groups: low, medium and high factor intensities. Small size and low factor intensity correspond to the first quartile, the medium to the second and third quartiles, while large size and high factor density to the fourth quartile of the distribution of size and factor intensities, respectively. Our analysis is carried out in two parts. Part one comprises unconditional tests for SD over the years for the entire distribution of inefficiency, with no controls for farm attributes. Part two comprises conditional tests by having controls for the above attributes. Summary statistics of the two inefficiency definitions by farm and by cow and various sub-groups of farms are given in the first parts of Appendix C, Table C1-C5. In the second part of the above Tables, the dominance test results including the means, standard errors and probabilities are reported. Graphs of the CDF by various sub-groups and data levels are found in Appendix C, Figure C1-C5.

All results are based on 1,000 bootstrap samples, with 5% inefficiency partitions. In comparing two distributions, the first group is denoted the X-distribution, and the second by Y-distribution. Thus, FSD_{xoy} denotes first order stochastic dominance of X over Y, and SSD_{xoy} is similarly defined for second order dominance of X over Y. The FOMax and SOMax denote the joint tests of X vs. Y and Y vs. X., referred to as maximality by McFadden (1989). The probability (denoted as “prob” in the Tables) rejects the null of no dominance when the statistics are negative.

5.4.3 The dominance test results

This first part of Table C1 summarizes our data by years of observation. The second part of the period is based on a balanced panel. The mean inefficiency does not change from 1989 (9.64) to 2000 (9.62) when inefficiency is based on cow level data. The corresponding inefficiency according to the farm level is increasing slightly from 6.85 to 7.08. The standard deviations are diminishing over time. In the second part of Table C1, our test statistics are summarized by their mean and standard errors, as well as the probability of the test statistic being negative or zero (the null hypothesis). None of the six test cases indicate presence of any first or second order dominance over time regardless of unit of observation. The distributions of inefficiency over time are not first and second order maximal (unrankable). The farm level inefficiency distributions dominate the cow levels (see Figure C1).

As mentioned previously, the farms are distinguished by the farm characteristics. Table C2 summarizes the results for different size classes, and separately for the two per farm and per cow units of measurement. The mean inefficiency and its dispersion measured

by per farm is a decreasing function of the farm size. No such relationship is found when the inefficiency is obtained by per cow data. The inefficiency is related to the optimality of the size of farm but not to the productivity of cows. The second part of Table C2 shows that there is no FSD or SSD between size classes when inefficiency measured by the cow level data. However, there is SSD when inefficiency is measured at the farm level where large farms SSD dominate the small and medium size farms (see also Figure C2). The distribution of inefficiency by size class is second order maximal.

Table C3 summarizes the results for different regional locations. The mean inefficiency measured at the farm level is not a clearly increasing function of the distance from the fertile South. The sub-sample of South is quite small. Farms located in Central Finland are better off in terms of inefficiency and its dispersion regardless of the level of measurement. When measured at the cow level, North weakly SSD dominates the Central location. However, when measured at the farm level North SSD dominates both Central and South regions (see Figure C3). The distributions of inefficiency by location measured at the farm level are second order maximal.

Comparisons of distribution by capital intensity are reported in Table C4. Unlike in the case of farm size, the inefficiency and its variation is increasing by degree of capital intensity when results are based on the cow level data. A low level of capital intensity is the most optimal when distribution is analyzed at the cow level. No such distinction is made at the farm level. The low and high intensity levels are second order maximal in both definition cases (see also Figure C4).

Table C5 provides a summary of the results for different labour intensities in production. At both units of measurement, inefficiency in production is positively associated with labour intensity. However, at the cow level no first or second order dominance is observed. The distributions at this level are not rankable. On the other hand, at the farm level higher labour intensity SSD dominates the lower levels of labour intensity (Figure C5). The distributions here are second order maximal. It is worth recalling that SD rankings are transitive.

In summary, the test results based on the sample of dairy farms over time are basically the same regardless of the farm or cow unit of observation. The average inefficiency and its dispersion are found to be quite constant over time. Based on our implementation of the KS type FSD and SSD tests, we were able to show a number of cases of dominance between conditional inefficiency distributions. These rankings are due to many other characteristics that may explain inefficiency differentials between subgroups of farms. Here the examination is offered by conducting SD tests for inefficiency of different groups identified by farm characteristics. Second order dominance is observed when the data is measured in per farm level but none when inefficiency is measured at the per cow level. The cows perform quite homogeneously at the farm level. The differences in performance seem to a high degree be related non-cow production factors or characteristics. The farms are rankable in performance by size, location and labour intensity, but not with respect to capital intensity in production. An alternative approach to the one presented above is to examine regression-based simultaneous controls for the multiple of characteristics. In a regression-based approach, as that in Maasoumi and Heshmati (2004), one avoids the problem of small cell sizes that would arise in current approach.

5.5 The Components of TFP growth

The productivity growth on the dairy farms in the sample is calculated applying the approach of Orea (2002). The productivity growth is decomposed to technical change, technical efficiency change and scale effect. The actual values are calculated on the basis of estimated per farm model coefficients in the translog model presented in Table 2. The TFP growth results are presented in Table 9.

Table 9. Average productivity change and its components (the decomposition of Orea, 2002).

Period (per farm)	Productivity % Change	Technical efficiency % Change	Neutral technical % Change	Non-neutral technical % Change	Scale % Effect ^a
1989/1990	2.92	0.38	4.06	-0.03	-1.49
1990/1991	-2.02	0.68	-1.92	-0.02	-0.76
1991/1992	2.83	-0.40	3.11	0.04	0.08
1992/1993	-1.76	-0.02	-1.41	0.05	-0.38
1993/1994	2.13	0.17	1.77	0.07	0.12
1994/1995	-3.85	0.11	-4.39	0.03	0.40
1995/1996	-0.50	-0.33	-0.06	-0.05	-0.06
1996/1997	1.87	0.29	1.67	-0.05	-0.04
1997/1998	1.22	-0.87	2.18	0.01	-0.10
1998/1999	0.05	-0.02	-0.15	0.10	0.12
1999/2000	6.83	0.21	6.61	0.12	-0.11
Per farm values:					
Cumulative	9.72	0.20	11.47	0.27	-2.23
Annual average	0.88	0.02	1.04	0.02	-0.20
Per cow unit values:					
Cumulative	8.60	0.19	9.38	0.05	-1.02
Annual average	0.78	0.02	0.85	0.00	-0.09

^a Calculated as a distance from 1 only for those observations, which do not violate monotonicity restriction.

According to the analysis, productivity growth on dairy farms has been low during the 1990s. The patterns are similar both in per farm and in per cow models. The average productivity growth is 0.9% (0.8% at the cow level) interpreted as the annual growth rate in output larger than the weighted average growth in inputs. High growth rates were observed both at the beginning and at the end of the decade. Before EU accession in 1995, productivity growth varied from positive to negative in sequential years. Slow productivity growth is probably a result of several production restrictions, which were in use or were introduced during that period. At the time of EU accession in 1995, the productivity declined significantly. This drop may partially be caused by data when the prices changed drastically, principally over a single night. After EU accession in 1995, productivity growth has been mostly positive. However, the growth rate has been relatively modest until the end of the research period. The annual cow level results are presented in Appendix D, Table D1.

The technical progress has mainly been based on pure (neutral) technical change. The most important sources for the progress are probably the relief of milk quota restrictions

and set-aside requirements. Both enlargements of the farms together with the adoption of modern production technology and good weather conditions at the end of the decade have contributed to productivity growth by shifting the production frontier upwards.

Technical efficiency change did not show any particular pattern and the changes between sequential years are found to be relatively small, as it was observed earlier. During the research period, there is practically no change in average technical efficiency as the previous chapter has already shown. The scale effect was almost negligible but its cumulative effect was negative over the research period. Even at the end of the period when milk production at the farm level increases most rapidly, the average scale effect is negative. We should also mention that the magnitude of the scale effect varies by farms. Monotonicity condition fails to hold in a large number of data points which is associated with the capital input variable in per farm case (the monotonicity in land and labour are also violated in the per cow model). The violated points are not considered in the calculation of returns to scale. Therefore, the number of observations when calculating scale effect is considerably smaller than the total number of observations in the sample.

Allocative inefficiency component is a result of the violations against the first-order condition of profit maximisation, for example, output elasticity shares of inputs deviate from their actual expenditure shares. Although the Malmquist index does not require any behavioural assumption to be made, we find it important to take into account the allocative effects. These violations may occur due to market imperfections like transactions costs, risk, quantitative restrictions, or imperfect information (Brümmer *et al.* 2002). Kumbhakar and Lovell (2000, p. 284) have stated that price data are required for calculating allocative inefficiencies. Aggregated cost and return data are actually sufficient for the analysis if uniform prices facing all farmers can be assumed.

Table 10 shows the input, output and their joint price effects. When evaluated over the whole period, the price effect is negligible but on average negative. At cow level, the average effect is larger than at farm level. However, in specific years the price effects (price distortions) can be considerably larger than technical change effect. The inputs distortions are found to be largest at the beginning of the research period and at the time of the EU accession. The main source of distortions has been the land input in the farm level model but capital and material inputs in the cow level model (see Appendix D, Table D2). In the first part of the research period, compulsory set-aside programs are a probable cause of land input price distortion at the farm level model. We should also keep in mind that the rental prices of land do not necessarily follow directly the productivity changes of land in the short run *i.e.* year-to-year variations in yield since the contracts have usually been made on a long-term basis covering several years and on the basis of fixed prices. The terms of such contracts in addition to productivity of land may also somehow reflect the expected output prices.

Over and under utilisation of resources typically varies a great deal over time and take out each other thereby the cumulative effect turns out to be relatively small. On the output side, the distortions are smaller than on the input side.

Table 11 presents the farm level joint productivity change, which consists of the sum of technical effects and price effects. Depending on the point of time these effects may accumulate or partially replace each other. The series shows that at the beginning of 1990s the productivity growth was relatively rapid but at the time of EU accession a

considerable regress could be observed. It was not before than at the end of the period when the productivity seemed to start to grow faster again.

Table 10. Input, output and joint price effects (PE).

	Inputs				Outputs			Joint	
	Labour (%)	Land (%)	Material (%)	Capital (%)	IPE (%)	Other (%)	Milk (%)	OPE (%)	PE (%)
By year:									
1989/1990	0.28	8.96	-2.06	-5.88	1.30	-2.39	2.19	-0.20	1.11
1990/1991	0.33	4.00	-0.78	0.39	3.95	0.41	0.11	0.52	4.47
1991/1992	-0.08	-0.13	-0.18	0.94	0.55	-0.35	0.13	-0.23	0.32
1992/1993	0.00	2.30	-0.07	-0.74	1.50	0.72	-0.07	0.65	2.15
1993/1994	-0.04	-0.25	-0.06	0.46	0.11	-0.37	-0.06	-0.43	-0.32
1994/1995	0.11	-3.76	0.30	0.35	-2.99	-0.06	-0.02	-0.08	-3.07
1995/1996	0.09	-1.19	-0.01	0.22	-0.89	-0.87	0.00	-0.87	-1.76
1996/1997	0.02	-1.29	-0.10	0.87	-0.51	1.21	-0.26	0.95	0.45
1997/1998	0.04	-1.07	0.47	1.25	0.69	-1.12	-0.19	-1.30	-0.62
1998/1999	-0.21	-1.45	1.05	0.48	-0.14	-0.65	-0.37	-1.02	-1.17
1999/2000	0.14	-2.59	0.24	1.10	-1.11	-1.00	-0.63	-1.64	-2.75
Per farm:									
Cumulative	0.68	3.54	-1.22	-0.55	2.45	-4.48	0.83	-3.65	-1.20
Average	0.06	0.32	-0.11	-0.05	0.22	-0.41	0.08	-0.33	-0.11
Per cow:									
Cumulative	-0.14	0.52	-1.40	-2.84	-3.87	-0.92	0.90	-0.02	-3.88
Average	-0.01	0.05	-0.13	-0.26	-0.35	-0.08	0.08	0.00	-0.35

Note: IPE, OPE and PE are inputs, outputs and joint price effects.

Table 11. Technical effect and price effects of productivity change (per farm).

Period	Price effects %	Technical effect %	Both effects %
1989/90	1.11	2.92	4.03
1990/91	4.47	-2.02	2.45
1991/92	0.32	2.83	3.15
1992/93	2.15	-1.76	0.39
1993/94	-0.32	2.13	1.81
1994/95	-3.07	-3.85	-6.92
1995/96	-1.76	-0.50	-2.26
1996/97	0.45	1.87	2.32
1997/98	-0.62	1.22	0.60
1998/99	-1.17	0.05	-1.12
1999/2000	-2.75	6.83	4.08
Cumulative	-1.20	9.72	8.52
Average	-0.11	0.88	0.77

Table 12 shows the respective price and technical components at the cow level. When comparing Tables 11 and 12, we can see that, although the average technical effects are almost similar both at farm and at cow level, annual averages may differ considerably. Even the signs of the effects may be the opposite. We can also observe that the negative price effect on productivity growth is considerably (three times) larger in the per cow

model than in the per farm model. This follows that the average annual productivity growth over the whole period is only 0.43% at the cow level when at the farm level a growth rate of 0.77% is shown. This indicates that the growth of farms in respect to the number of animals is an important source of productivity growth.

Table 12. Technical effect and price effects of productivity change (per cow).

Period	Price effect. %	Technical effect. %	Both effects. %
1989/90	-1.73	1.61	-0.12
1990/91	5.31	-7.28	-1.97
1991/92	-1.83	3.90	2.08
1992/93	1.15	3.05	4.21
1993/94	-0.40	0.80	0.40
1994/95	-3.01	0.92	-2.09
1995/96	0.33	-3.49	-3.17
1996/97	-0.36	3.32	2.97
1997/98	0.05	-1.32	-1.26
1998/99	-0.38	1.70	1.33
1999/2000	-3.02	5.37	2.35
Cumulative	-3.88	8.60	4.72
Average	-0.35	0.78	0.43

6. Discussion of the Results and Conclusions

In this paper, we have studied the productivity change applying the Malmquist productivity index. Several suggestions have been made to decompose the index in order to define the sources of productivity growth (*e.g.* Färe *et al.* 1994, Ray and Desli 1997, Lovell 2003). Many of the applications have been nonparametric. In our case, we have identified the components of productivity growth from the stochastic output distance function. We have applied the approaches suggested by Orea (2002), Brümmer *et al.* (2002) and Kumbhakar and Lovell (2000).

In Orea's (2002) decomposition of the Malmquist index, the specification of scale effect does not lean on the concept of scale efficiency and scale efficiency change as often is the case in nonparametric approach. It is possible to calculate also for Cobb-Douglas and ray-homogenous technologies. In our case, neither of the previously mentioned technologies are adequate representations of the production technology in Finnish dairy farming.

Productivity growth was relatively slow in the 1990s but it speeded up at the end of the study period. The growth related mostly to technical change. The result is reasonable when taking into account that the enlargement investments on dairy farms started to increase in 1996-1997 because of the introduction of state-sponsored investment subsidies and less restrictive policies. Simultaneously milk quota restrictions and set-aside requirements were relieved. Uncertainties related to EU accession in 1995 were also likely to postpone farmers' development strategies and their implementations.

Technical efficiency change does not show any systematic pattern over the research period. Technical efficiency varied over time, which was partially linked to weather conditions. The Finnish production system is largely based on on-farm produced feed. The quantity and quality of this feed depends on the weather, thus affecting the need to purchase externally produced inputs. The weather has also a direct effect on milk

production. Since the weather conditions may differ in different regions of the country within a year, it may influence the variation in the technical efficiency. The stochastic weather conditions may also affect the general shift of the frontier, *i.e.* technical change effect.

According to the analysis, EU accession did not seem to have a significant effect on technical efficiency. Instead, farm size and regional location could explain a significant share of the variation in technical efficiency among dairy farms at the farm level analysis. The test results for stochastic dominance over time are basically the same regardless of the unit of observation, per farm or per cow. However, we were able to show a number of cases of dominance between conditional inefficiency distributions. These rankings are due to many characteristics that may explain inefficiency differentials between sub-groups of farms. Second order dominance was observed when the data were measured in per farm level but none when using per cow level data. The farms are rankable in performance by size, location and labour intensity, but not with respect to capital intensity in production.

The average returns to scale at farm level models was smaller than one but not significantly, indicating on average decreasing returns to scale. Although RTS improved during the research period, the analysis showed that the role of the scale effect in productivity growth was small. The cumulative scale effect over the whole period was slightly negative. Thus, the input output relations did not improve despite the increase in the scale of production. The distance elasticity of capital was also very low. Even the monotonicity condition (an increase in inputs also increases output) was violated at several data points at the end of the research period in the farm level model. At the cow level analysis, violations were more evenly distributed over labour, capital and land inputs.

An important issue is that why the scale effect is so small? There might be several factors resulting in the absence of positive scale effects in Finnish agriculture. One is that capital has substituted for labour. It is evident that productivity of labour increases with the capital intensity. However, family labour is often a binding restriction to the scale of operation of farms. Increased capital input has made it possible to increase production with only a relatively small increase in labour input. We can conclude that the average size of dairy farms is such that an increase in farm size, combined with appropriate capital investments, may contribute markedly on labour productivity.

There seems also to be considerable substitution effect between land and materials inputs at the farm level. The elasticity of land has increased simultaneously with the decrease in the elasticity of materials. Over time land input has increased less than milk output, but the use of materials (*e.g.* purchased feed) has increased by the same proportion as milk output. Despite of the input substitution, in the cow level data elasticities of land, material and capital inputs have not diminished.

The farm level distance elasticities differ considerably from those presented by Brümmer *et al.* (2002) and Newman and Matthews (2003). In the above mentioned studies, the largest elasticities are related to intermediate inputs (materials) but, in Finland, the elasticities of land and labour are the highest followed by materials. In all other countries, the elasticity of labour is low compared to that of Finland. The differences are probably associated with differences in farming and dairy production systems in different countries. For example, in the Netherlands, elasticity of land was

almost as high as in Finland and the Polish elasticity of capital is approximately as low as that of Finland (Brümmer *et al.* 2002). In Finland, the share of purchased feed compared to on-farm produced feed has increased over time simultaneously with the increase in milk output per farm and per cow.

The results of our analysis on productivity change are similar to those based on the DEA analysis (Sipiläinen 2003). The nonparametric analysis also indicated that the main source of productivity change was a technical change. The only major difference was in the level of technical efficiency, which was considerably lower in the DEA based analysis. However, the effect of technical efficiency change on productivity change was minor. Thus, in both approaches, the level of technical efficiency was unchanged over time.

The allocative distortions were studied by comparing actual cost and return shares to those derived on the basis of elasticities. These differences can be interpreted as deviations from the first order conditions of profit maximisation. The largest distortions were observed in land input at the farm level model but in capital and materials at the cow level model. In general, output price distortions (the deviations from the optimum) were smaller than input distortions. Over and under utilisation of resources varied considerably over time and the cumulative effects were small. However, in specific years, the average price effect may be even larger than the technical effect. The highest distortions could be observed at the beginning and at the end of the research period. In addition, the Finnish EU accession caused a considerable peak in distortions. It should be kept in mind, however, that due to milk quota restrictions, an imposition of cost minimisation behaviour could be more applicable approach than profit maximisation.

Although at the time of EU accession the prices and relative prices changed dramatically and a large share of income started to come from direct payments, technical efficiency has remained unchanged on dairy farms. The process of the EU accession seems to have affected the productivity growth, at first, as reducing and postponing investment and then as boosting it. The changes in behaviour are related both to uncertainty and support measures like investment aids. Increased investment has led to growing herd sizes in the latter part of the 1990s. The growth of farms makes it possible to utilise modern technology and improve productivity but it is too early to say if the productivity growth will speed up from the low level of less than 1% per year. Productivity growth should be faster if Finnish dairy farms wanted to keep up with, or even catch up with, dairy farms in other countries.

The study provides a detailed decomposition of productivity change taking into account both technical and price effects. The applied distance function approach is a flexible method for analysis of factors causing productivity change. Identification and separation of such effects remain unobserved when TFP index numbers are applied. This approach can also be used when the variation in prices is insufficient for cost or profit function analysis of production.

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Appendix A. Estimated (per cow level) parameters of the translog distance function, NT=812 observations.

Table a. Estimated parameters of the translog distance function, NT=812 observations.

Variable	Param	Coeff.	Std err	t-ratio	Variable	Param	Coeff.	Std err	t-ratio
Constant	B_0	0.0698	0.0192	3.6270	$\ln(L)^2$	β_{LL}	0.0792	0.0485	1.6322
$\ln(Y_0)_{89-94}$	β_{o1}	0.1154	0.0162	7.1149	$\ln(A)^2$	β_{AA}	-0.0034	0.0488	-0.0692
$\ln(Y_0)_{95-97}$	β_{o2}	0.0769	0.0132	5.8389	$\ln(M)^2$	β_{MM}	-0.0987	0.0269	-3.6646
$\ln(Y_0)_{98-00}$	β_{o3}	0.1236	0.0165	7.5082	$\ln(K)^2$	β_{KK}	0.0102	0.0239	0.4249
$\ln(L)$	β_L	-0.0961	0.0399	-2.4089	$\ln(L)\ln(A)$	β_{LA}	-0.3485	0.0680	-5.1260
$\ln(A)$	β_A	-0.0830	0.0432	-1.9232	$\ln(L)\ln(M)$	β_{LM}	0.1812	0.0577	3.1387
$\ln(M)$	β_M	-0.1988	0.0353	-5.6373	$\ln(L)\ln(K)$	β_{LK}	0.0236	0.0533	0.4426
$\ln(K)$	β_K	-0.0699	0.0305	-2.2878	$\ln(A)\ln(M)$	β_{AM}	-0.1692	0.0641	-2.6391
D1990	β_{t2}	-0.0347	0.0202	-1.7156	$\ln(A)\ln(K)$	β_{AK}	-0.2028	0.0489	-4.1459
D1991	β_{t3}	-0.0037	0.0213	-0.1716	$\ln(M)\ln(K)$	β_{MK}	0.0697	0.0452	1.5398
D1992	β_{t4}	-0.0302	0.0200	-1.5125	$\ln(L)T$	β_{Lt}	-0.0042	0.0049	-0.8572
D1993	β_{t5}	-0.0486	0.0202	-2.4052	$\ln(A)T$	β_{At}	-0.0026	0.0052	-0.4965
D1994	β_{t6}	-0.0566	0.0200	-2.8339	$\ln(K)T$	β_{Kt}	-0.0045	0.0046	-0.9861
D1995	β_{t7}	-0.0373	0.0206	-1.8121	$\ln(M)T$	β_{Mt}	0.0010	0.0042	0.2375
D1996	β_{t8}	-0.0214	0.0207	-1.0306	Dsc1	β_{sc1}	0.0568	0.0297	1.9097
D1997	β_{t9}	-0.0609	0.0216	-2.8160	Dsc2	β_{sc2}	0.0986	0.0197	5.0014
D1998	β_{t10}	-0.0432	0.0215	-2.0088	Dre1	β_{reg1}	-0.0312	0.0266	-1.1726
D1999	β_{t11}	-0.0430	0.0212	-2.0324	Dre2	β_{reg2}	0.0066	0.0267	0.2457
D2000	β_{t12}	-0.0928	0.0214	-4.3285		σ^2	0.0201	0.0023	8.8260
$\ln(Y_0)^2_{89-94}$	β_{oo1}	0.0205	0.0225	0.9113		γ	0.7254	0.0614	11.8201
$\ln(Y_0)^2_{95-97}$	β_{oo2}	0.0201	0.0050	3.9924					
$\ln(Y_0)^2_{98-00}$	β_{oo3}	0.0559	0.0131	4.2819					

Log likelihood test value is 676.372.

Table b. Generalised likelihood ratio tests for parameters of the model.

Null hypothesis	Test statistics ^a	Critical value
Cobb Douglas – no TC vs. neutral TC (d.f. 11)	40.664	19.675
Cobb Douglas – neutral TC vs. Translog – neutral TC (d.f. 13)	90.016	22.362
Translog – neutral TC vs. non-neutral TC (d.f. 4)	10.074	9.488
No technical inefficiency (d.f. 5) ^b	52.698	14.328
No technical efficiency effect (d.f. 4)	22.278	9.488

^a Log likelihood ratio test $-2(\log L(H_0) - \log L(H_1))$

^b The critical value is obtained from Table 1 in Kodde and Palm (1986) which shows the statistics for a mixed Chi-square distribution with degrees of freedom equal to 5.

Appendix B. Confidence intervals for point estimates of technical efficiency

Given the distributional specification for u_i , it can be shown that upper and lower bounds of a confidence predictor for u_i at $(1-\alpha)$ confidence interval can be defined as:

$$(1) \quad U_i(\text{lower}) = \mu_i + \sigma \Phi^{-1} [1 - (1 - \alpha/2) \Phi(\mu_i / \sigma)] \text{ and}$$

$$(2) \quad U_i(\text{upper}) = \mu_i + \sigma \Phi^{-1} [1 - (\alpha/2) \Phi(\mu_i / \sigma)]$$

where $\Phi(\cdot)$ refers to the standard normal distribution function. The confidence predictor at $(1-\alpha)$ for $[\exp(U_i)-1]$ can be defined by:

$$(3) \quad \{ \exp[U_i(\text{lower})] - 1, \exp[U_i(\text{upper})] - 1 \}.$$

Horrace and Schmidt (1996, p. 261-262) have suggested that the confidence prediction should be based on conditional distribution of u_i , given $v_i - u_i$ in the context of a production function. However, the conditional distribution of u_i ($\varepsilon_i = v_i + u_i$) is the truncation at zero of the normal distribution with mean and variance:

$$(4) \quad \mu_i^* = \frac{-\varepsilon_i \sigma^2 + \mu_i \sigma_v^2}{\sigma^2 + \sigma_v^2}, \quad \sigma_*^2 = \frac{\sigma^2 \sigma_v^2}{\sigma^2 + \sigma_v^2}.$$

The variance of this distribution is smaller than the variance for u_i . The previous confidence interval predictors are likely to be conservative (Battese *et al.* 2000).

Appendix C. Bootstrap procedure for dominance rankings

Let X_1 and X_2 be two variables (such as efficiency in production) at either two different points in time or for different attributes like regional location. Let X_{ki} , $i = 1, \dots, N$; $k = 1, 2$ denote the not necessarily i.i.d. observations. Let U_1 denote the class of all von Neumann-Morgenstern type utility functions, u , such that $u' \geq 0$, (increasing). Also, let U_2 denote the class of all utility functions in U_1 for which $u'' \leq 0$ (strict concavity). Let $X_{(1p)}$ and $X_{(2p)}$ denote the p -th quantiles, and $F_1(x)$ and $F_2(x)$ denote the cumulative distribution functions, respectively. Following the notation in Maasoumi and Heshmati (2004) the first and second order SD are defied as follows.

X_1 First Order Stochastic Dominates X_2 , denoted $X_1 FSD X_2$, if any of the following equivalent conditions holds:

- (1) $E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_1$, with strict inequality for some u ; or
- (2) $F_1(x) \leq F_2(x)$ for all x with strict inequality for some x ; or
- (3) $X_{(1p)} \geq X_{(2p)}$ for all $0 \leq p \leq 1$, with strict inequality for some p .

X_1 Second Order Stochastic Dominates X_2 , denoted $X_1 SSD X_2$, if any of the following equivalent conditions holds:

- (4) $E[u(X_1)] \geq E[u(X_2)]$ for all $u \in U_2$, with strict inequality for some u ; or
- (5) $\int_{-\infty}^x F_1(t)dt \leq \int_{-\infty}^x F_2(t)dt$ for all x with strict inequality for some x ; or
- (6) $\Phi_1(p) = \int_0^p X_{(1t)}dt \geq \Phi_2(p) = \int_0^p X_{(2t)}dt$ for all $0 \leq p \leq 1$, with strict inequality for some value(s) p .

Weak orders of SD are obtained by eliminating the requirement of strict inequality at some point. When these conditions are not met, as when Generalized Lorenz Curves of two distributions cross, unambiguous First and Second order SD is not possible. Any strong ordering by specific indices that correspond to the utility functions U_1 and U_2 classes, will not enjoy general consensus.

This approach fixes the critical value (zero) at the boundary of our null, and estimates the associated significance level by bootstrapping the sample or its blocks. This renders our tests asymptotically similar and unbiased on the boundary. This is similar in spirit to inference based on p-values. This method could also be used to compare the two distributions up to any desired quantile, for instance, for performance rankings. The test statistics are as follows.

Suppose that there are 2 prospects X_1 , X_2 and let $A = \{X_k : k = 1, 2\}$. Let $\{X_{ki} : i = 1, 2, \dots, N\}$ be realizations of X_k for $k = 1, 2$. Let $F(x_1, x_2)$ be the joint c.d.f. of $(X_1, X_2)'$. Now define the following functionals of the joint distribution:

$$(7) \quad d = \min_{k \neq l} \sup_{x \in \mathcal{X}} [F_k(x) - F_l(x)]$$

$$(8) \quad s = \min_{k \neq l} \sup_{x \in \mathcal{X}} \int_{-\infty}^x [F_k(t) - F_l(t)] dt$$

where \mathcal{X} denotes a given set contained in the union of the supports of X_{ki} for $k=1,2$, that are assumed to be bounded. The hypotheses of interest are:

$$(9) \quad H_0^d : d \leq 0 \quad \text{vs.} \quad H_1^d : d > 0$$

$$(10) \quad H_0^s : s \leq 0 \quad \text{vs.} \quad H_1^s : s > 0$$

The null hypothesis H_0^d implies that the prospects in A are not first-degree stochastically maximal, *i.e.*, there exists at least one prospect in A which first-degree dominates the others. Likewise applies for the second order case.

In our applications, we report probabilities $\{d_N \leq 0\}$ and $\{s_N \leq 0\}$ and are able to identify which distribution dominates, if any. These are the maximum test sizes associated with our critical value of zero which is clearly the boundary of our null. Thus, we are reporting the critical level associated with this non-rejection region.

Appendix C. Bootstrapping test results.

Table C.1 Comparisons of mean inefficiency by YEAR of observation.

	By cow level data			By farm level data		
	N	Mean	Std dev	N	Mean	Std dev
1989	49	9.4224	4.9351	49	6.8522	5.0851
1996	72	9.5590	4.7583	72	6.7161	5.2800
2000	72	9.6223	4.3501	72	7.0755	5.1875
	Mean	Std err	Prob.	Mean	Std err	Prob.
1989 (x) vs 1996 (y)						
FSDxoy	0.1086	0.0680	0.000	0.1007	0.0520	0.000
FSDyox	0.1278	0.0582	0.000	0.1169	0.0722	0.000
F0max	0.0710	0.0392	0.000	0.0635	0.0375	0.000
SSDxoy	0.0066	0.3318	0.000	0.3291	0.4683	0.000
SSDyox	0.4595	0.4863	0.000	0.5130	0.5445	0.000
S0max	0.0529	0.0739	0.000	0.0418	0.0760	0.000
1989 (x) vs 2000 (y)						
FSDxoy	0.1432	0.0749	0.000	0.0894	0.0624	0.682
FSDyox	0.0897	0.0469	0.000	0.0936	0.0532	0.000
F0max	0.0660	0.0343	0.000	0.0488	0.0277	0.682
SSDxoy	0.5637	0.5325	0.000	0.3211	0.4581	0.345
SSDyox	0.2658	0.3765	0.000	0.4115	0.4860	0.000
S0max	0.0645	0.0718	0.000	0.0273	0.0774	0.345
1996 (x) vs 2000 (y)						
FSDxoy	0.1237	0.0599	0.000	0.1098	0.0654	0.018
FSDyox	0.0869	0.0411	0.000	0.0900	0.0488	0.005
F0max	0.0656	0.0275	0.000	0.0581	0.0340	0.023
SSDxoy	0.4428	0.4164	0.000	0.4899	0.4768	0.135
SSDyox	0.1830	0.2521	0.000	0.2712	0.4110	0.230
S0max	0.0492	0.0556	0.000	0.0357	0.0852	0.365

Note: First (Second) Order Stochastic Dominance of x over y FSDxoy (SSDxoy), First (Second) Order maximum F0max (S0max).

Figure C.1 CDF of inefficiency distribution measured per cow and per farm by year of observation.

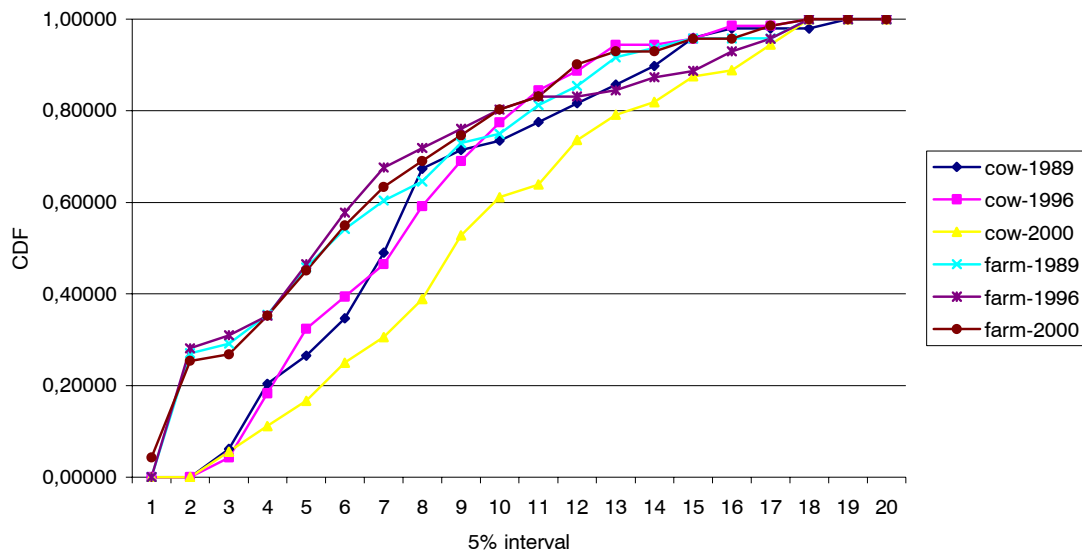


Table C.2 Comparisons of mean inefficiency by SIZE of farm.

	By cow level data			By farm level data		
	N	Mean	Std dev	N	Mean	Std dev
Small	175	10.2261	4.5852	175	11.6541	5.2507
Medium	418	9.0995	4.9756	418	7.4849	4.1227
Large	219	10.2224	5.8792	219	1.3921	0.3123
	Mean	Std err	Prob.	Mean	Std err	Prob.
Small (x) vs Medium (y)						
FSDxoy	0.0137	0.0096	0.000	0.0001	0.0001	0.000
FSDyox	0.1310	0.0369	0.000	0.4321	0.0317	0.000
FMax	0.0137	0.0094	0.000	0.0001	0.0001	0.000
SSDxoy	0.0066	0.0084	0.000	0.0000	0.0000	0.000
SSDyox	0.5176	0.1816	0.000	2.8071	0.2985	0.000
SMax	0.0063	0.0066	0.000	0.0000	0.0000	0.000
Small (x) vs Large (y)						
FSDxoy	0.0571	0.0259	0.000	-0.0056	0.0060	0.682
FSDyox	0.1073	0.0386	0.000	0.9975	0.0031	0.000
FMax	0.0509	0.0205	0.000	-0.0056	0.0060	0.682
SSDxoy	0.0721	0.1332	0.000	-0.4851	0.0336	1.000
SSDyox	0.3576	0.2040	0.000	7.9609	0.3086	0.000
SMax	0.0331	0.0544	0.000	-0.4851	0.0336	1.000
Medium (x) vs Large (y)						
FSDxoy	0.0969	0.0310	0.000	-0.0001	0.0001	0.344
FSDyox	0.0081	0.0136	0.000	0.9779	0.0072	0.000
FMax	0.0078	0.0126	0.000	-0.0001	0.0001	0.344
SSDxoy	0.5368	0.2107	0.000	-0.7818	0.0285	1.000
SSDyox	0.0070	0.0178	0.000	3.9517	0.1235	0.000
SMax	0.0065	0.0156	0.000	-0.7818	0.0285	1.000

Note: First (Second) Order Stochastic Dominance of x over y FSDxoy (SSDxoy), First (Second) Order maximum FMax (SMax).

Figure C.2 CDF of inefficiency distribution measured per cow and per farm by size of farm.

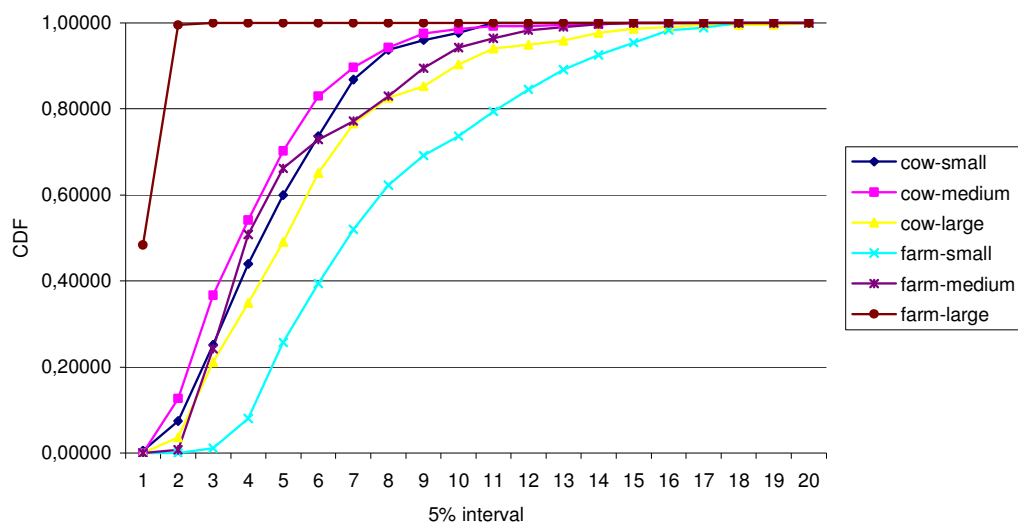


Table C.3 Comparisons of mean inefficiency by REGION of location.

	By cow level data			By farm level data		
	N	Mean	Std dev	N	Mean	Std dev
South	100	10.4491	5.6848	100	6.5060	4.1221
Central	505	8.4355	4.4701	505	4.7109	2.8871
North	207	12.2077	5.5479	207	11.8041	6.7376
	Mean	Std err	Prob.	Mean	Std err	Prob.
South(x) vs Central(y)						
FSDxoy	0.0067	0.0073	0.000	0.0055	0.0147	0.000
FSDyox	0.1857	0.0454	0.000	0.2293	0.0480	0.000
F0max	0.0067	0.0073	0.000	0.0055	0.0147	0.000
SSDxoy	0.0022	0.0077	0.000	0.0117	0.0343	0.000
SSDyox	1.1596	0.3367	0.000	1.9254	0.4957	0.000
S0max	0.0022	0.0077	0.000	0.0117	0.0343	0.000
South(x) vs North(y)						
FSDxoy	0.2707	0.0554	0.000	0.4668	0.0445	0.000
FSDyox	0.0290	0.0285	0.000	0.0182	0.0280	0.280
F0max	0.0289	0.0282	0.000	0.0182	0.0280	0.000
SSDxoy	0.7818	0.2480	0.000	3.3718	0.3813	0.000
SSDyox	0.0016	0.0169	0.000	-0.1971	0.0661	0.993
S0max	0.0015	0.0148	0.000	-0.1971	0.0661	0.993
Central(x) vs North(y)						
FSDxoy	0.3729	0.0376	0.000	0.6299	0.0033	0.000
FSDyox	0.0052	0.0034	0.025	0.0002	0.0022	0.507
F0max	0.0052	0.034	0.025	0.0002	0.0022	0.507
SSDxoy	1.6826	0.1784	0.000	4.5354	0.2936	0.000
SSDyox	-0.0019	0.0019	0.645	-0.2562	0.0232	1.000
S0max	-0.0019	0.0019	0.645	-0.2562	0.0232	1.000

Note: First (Second) Order Stochastic Dominance of x over y FSDxoy (SSDxoy),
 First (Second) Order maximum F0max (S0max).

Figure C.3 CDF of inefficiency distribution measured per cow and per farm by regional location.

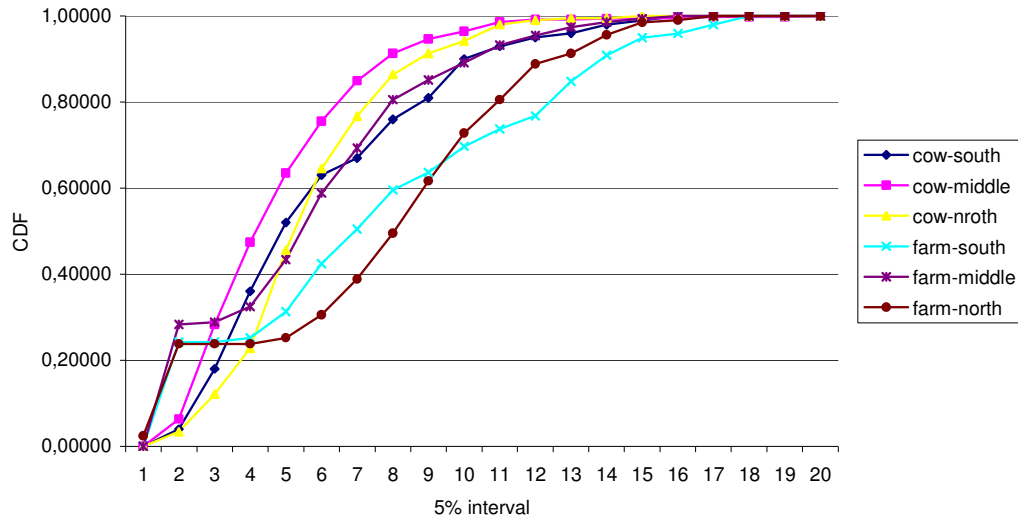


Table C.4 Comparisons of mean inefficiency by CAPITAL intensity.

	By cow level data			By farm level data		
	N	Mean	Std dev	N	Mean	Std dev
Low	200	7.6609	3.9661	200	6.0557	4.4543
Medium	408	9.9455	4.8794	408	6.9657	5.6354
High	204	10.9897	6.1828	204	6.9604	5.2660
	Mean	Std err	Prob.	Mean	Std err	Prob.
Low(x) vs Medium(y)						
FSDxoy	0.2590	0.0399	0.000	0.1070	0.0315	0.000
FSDyox	0.0004	0.0021	0.000	0.0450	0.0325	0.052
FMax	0.0004	0.0021	0.000	0.0414	0.0271	0.052
SSDxoy	1.5225	0.2490	0.000	0.6586	0.3250	0.020
SSDyox	0.0000	0.0000	0.000	0.0482	0.0809	0.268
SMax	0.0000	0.0000	0.000	0.0355	0.0590	0.288
Low(x) vs High(y)						
FSDxoy	0.2680	0.0449	0.000	0.1417	0.0490	0.000
FSDyox	0.0001	0.0001	0.240	0.0264	0.0254	0.113
FMax	0.0001	0.0001	0.240	0.0249	0.0230	0.113
SSDxoy	1.4002	0.2269	0.000	0.4639	0.2785	0.039
SSDyox	-0.0052	0.050	0.649	0.0142	0.0775	0.506
SMax	-0.0052	0.0050	0.649	-0.0026	0.0451	0.545
Medium(x) vs High(y)						
FSDxoy	0.0813	0.0263	0.000	0.0683	0.0360	0.004
FSDyox	0.0288	0.0288	0.000	0.0626	0.0237	0.000
FMax	0.0248	0.0224	0.000	0.0453	0.0204	0.004
SSDxoy	0.3879	0.2022	0.000	0.1755	0.1463	0.103
SSDyox	0.0111	0.0297	0.000	0.1771	0.2083	0.283
SMax	0.0085	0.0209	0.000	0.0387	0.0785	0.386

Note: First (Second) Order Stochastic Dominance of x over y FSDxoy (SSDxoy), First (Second) Order maximum FMax (SMax).

Figure C.4 CDF of inefficiency distribution measured per cow and per farm by capital intensity.

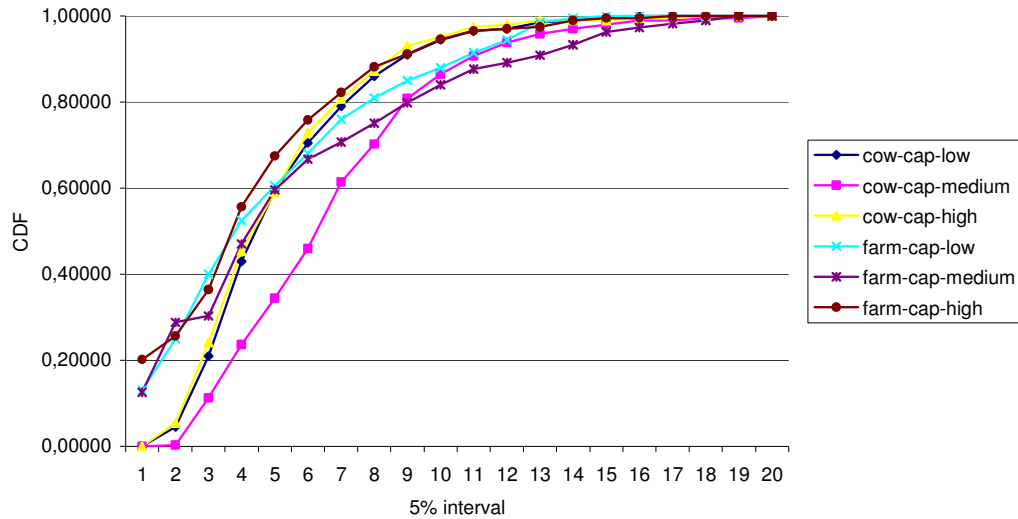
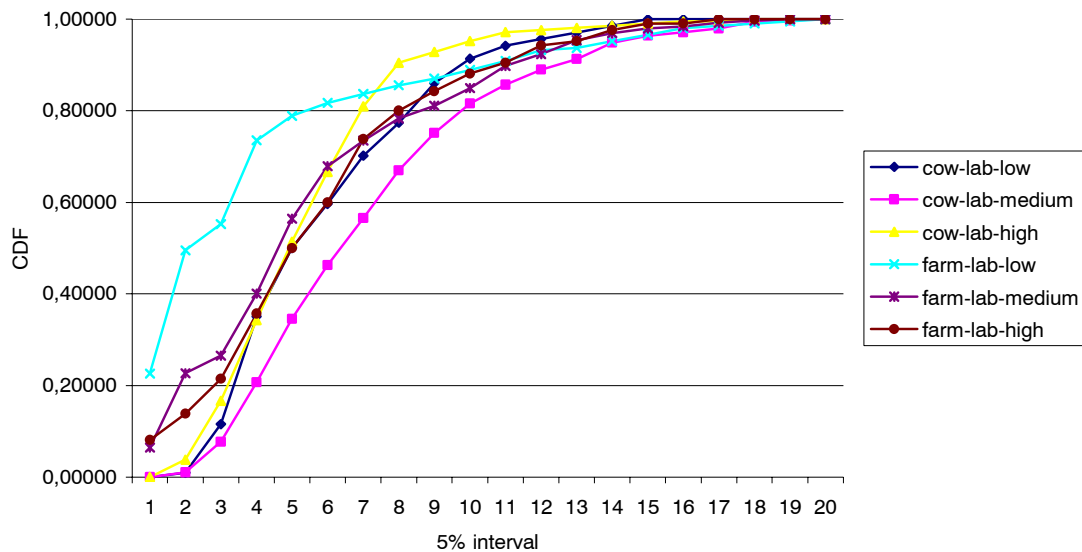


Table C.5 Comparisons of mean inefficiency by LABOUR intensity.

	By cow level data			By farm level data		
	N	Mean	Std dev	N	Mean	Std dev
Low	208	7.7976	3.8448	208	4.6145	4.9879
Medium	393	9.5624	4.9594	393	6.6247	4.6924
High	211	11.6203	5.9905	211	9.0508	5.6797
	Mean	Std err	Prob.	Mean	Std err	Prob.
Low(x) vs Medium(y)						
FSDxoy	0.1682	0.0387	0.000	0.3355	0.0401	0.000
FSDyox	0.0043	0.0059	0.000	0.0242	0.0153	0.008
F0max	0.0043	0.0059	0.000	0.0242	0.0153	0.008
SSDxoy	1.2452	0.2735	0.000	1.7167	0.3012	0.000
SSDyox	0.0046	0.0067	0.000	-0.1618	0.0328	1.000
S0max	0.0046	0.0067	0.000	-0.1618	0.0328	1.000
Low(x) vs High(y)						
FSDxoy	0.3204	0.0401	0.000	0.5113	0.0427	0.000
FSDyox	0.0001	0.0001	0.000	0.0010	0.0034	0.171
F0max	0.0001	0.0001	0.000	0.0010	0.0034	0.171
SSDxoy	1.6903	0.2154	0.000	2.7761	0.3279	0.000
SSDyox	0.0000	0.0000	0.000	-0.3510	0.0387	1.000
S0max	0.0000	0.0000	0.000	-0.3510	0.0387	1.000
Medium(x) vs High(y)						
FSDxoy	0.1774	0.0355	0.000	0.2403	0.0395	0.000
FSDyox	0.0102	0.0143	0.096	0.0007	0.0028	0.276
F0max	0.0102	0.0143	0.096	0.0007	0.0028	0.276
SSDxoy	0.8244	0.1984	0.000	1.4350	0.2770	0.000
SSDyox	-0.0026	0.0025	0.650	-0.0813	0.0275	0.999
S0max	-0.0026	0.0025	0.650	-0.0813	0.0275	0.999

Note: First (Second) Order Stochastic Dominance of x over y FSDxoy (SSDxoy), First (Second) Order maximum F0max (S0max).

Figure C.5 CDF of inefficiency distribution measured as per cow and per farm by labor intensity.



Appendix D.

Table a. Average productivity change and its components (the decomposition of Orea, 2002).

Period (per cow)	Productivity	Technical	Pure technical	Non-neutral	Scale
	% Change	Efficiency		technical	
1989/1990	1.61	-0.03	3.47	0.00	-1.83
1990/1991	-7.28	-0.04	-3.04	0.03	-4.23
1991/1992	3.90	0.60	2.69	0.06	0.55
1992/1993	3.05	-0.36	1.83	0.02	1.56
1993/1994	0.80	0.11	0.81	0.00	-0.13
1994/1995	0.92	-0.08	-1.93	-0.02	2.95
1995/1996	-3.49	0.03	-1.59	-0.03	-1.90
1996/1997	3.32	-0.72	3.95	-0.01	0.10
1997/1998	-1.32	-0.05	-1.77	0.01	0.50
1998/1999	1.70	0.49	-0.01	0.00	1.22
1999/2000	5.37	0.24	4.97	-0.01	0.17
Cumulative (per cow)	8.60	0.19	9.38	0.05	-1.02
Annual average (per cow)	0.78	0.02	0.85	0.00	-0.09

^a Calculated as a distance from 1 only for those observations, which do not violate monotonicity restriction.

Table b. Input, output and joint price effects (PE) at the cow level.

Period	Inputs					Outputs		Joint	
	Labour (%)	Land (%)	Material (%)	Capital (%)	IPE (%)	Other (%)	Milk (%)	OPE (%)	PE (%)
1989/1990	0.87	1.10	1.00	-3.92	-0.96	-2.19	1.42	-0.78	-1.73
1990/1991	-0.02	2.46	1.05	0.08	3.57	1.66	0.08	1.74	5.31
1991/1992	-0.56	-0.27	-0.34	0.40	-0.76	-1.14	0.07	-1.06	-1.83
1992/1993	-0.04	0.45	-0.38	-0.04	-0.02	1.74	-0.57	1.17	1.15
1993/1994	0.30	-0.37	0.51	0.03	0.47	-0.83	-0.03	-0.87	-0.40
1994/1995	0.02	-2.08	-1.60	-0.21	-3.87	0.96	-0.11	0.86	-3.01
1995/1996	-0.49	0.57	1.09	-0.34	0.83	-0.74	0.24	-0.50	0.33
1996/1997	-0.04	-0.43	-0.50	0.29	-0.67	0.69	-0.38	0.32	-0.36
1997/1998	0.16	0.26	-1.26	0.52	-0.32	0.04	0.34	0.37	0.05
1998/1999	0.06	-0.46	-0.49	0.32	-0.56	0.04	0.14	0.19	-0.38
1999/2000	-0.40	-0.71	-0.49	0.04	-1.56	-1.15	-0.31	-1.46	-3.02
Cumulative	-0.14	0.52	-1.40	-2.84	-3.87	-0.92	0.90	-0.02	-3.88
Average	-0.01	0.05	-0.13	-0.26	-0.35	-0.08	0.08	0.00	-0.35

Note: IPE, OPE and PE are inputs, outputs and joint price effects.