LEARNING IN ORGANIC FARMING – AN APPLICATION ON FINNISH DAIRY FARMS

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Abstract

Organic farming technology may be relatively unknown to farmers at the time when they switch from conventional into organic farming. Therefore, experience gained over time and learning by doing may be important determinants in the efficiency of organic farming. It may also take time to reach the optimal nutrient stock of soil and optimal nutrient supply for arable crops under organic farming. Thus, efficiency of organic farming can either grow or decrease over time depending on the nature of the technology and the learning process.

This paper estimates technical efficiency of organic farming and its development over time. We control for possible selection bias and regional heterogeneity when estimating a stochastic frontier distance functions for a sample of conventional and organic dairy farms in Finland. The results suggest that organic dairy farms are less technically efficient than conventional farms. Technical efficiency at first diminishes when the conversion towards organic production starts. After 6 years from the switch, technical efficiency starts to increase again. The estimates signal that the length of the conversion and learning process of organic farming is in average 6-7 years.

Key words: technical efficiency, technical change, output distance function, SFA

JEL Codes: C23, D24, D83, O30, Q12

1. Introduction

Promotion of organic farming has widely been seen as a way to improve food safety and environmental quality of food production in Europe. The share of organic production in the EU has increased but remained relatively small although well-defined and controlled standards related to the use of mineral fertilizers and other chemicals like pesticides provide efficient means for product differentiation and increase consumers' information about organic products.

Until recent years, the organic farming technology has developed with only little input from scientific research institutions (Lampkin et al. 1999). Even the number of studies comparing conventional and organic farming is still small. Offerman and Nieberg (2000) have compared the economic performance of organic and conventional farms in different countries. According to them, organic farms have lower yields, higher output prices and slightly lower unit costs. In addition, deviations of average profitability of organic farms from average profitability of comparable conventional farms range between about plus and minus 20 per cent of profit of conventional farms. Ricci Maccarini and Zanoli (2004) found that organic livestock farms were technically less efficient compared to the common production frontier but more efficient compared to their own frontier. They suggest that this lower average performance may be partially explained by underestimated difficulties related to conversion from conventional to organic production. Oude Lansink et al. (2002) studied the efficiency and productivity of organic and conventional farms using DEA. Their results indicate that productivity of organic farms is considerably lower than that of conventional farms concluding that conventional technologies more efficiently use scarce resources. In particular, productivity of capital, but also productivity of land and labour were found to be low in organic farming.

In spite of preceding fairly uniform results, the existing studies on performance of organic and conventional farms provide contradictory results on how efficient organic farming technology is in using natural resources – especially if other aspects than conventional inputs and outputs are considered. Stoltze et al. (2000) conclude that organic farming comprises fewer detrimental effects to the environment and to resource use than conventional farming systems. This conclusion is partially contradicted by the results of Grönroos and Seppälä (2000). Hole et al. (2005) have concluded on the basis of an extensive literature review about biodiversity that there are still considerable knowledge gaps preventing a full appraisal of the potential role of organic farming in biodiversity conservation in agro-ecosystems.

Organic farming methods are relatively unknown to farmers when they switch to organic farming. Therefore it may be possible to observe learning effects, which may take several forms: technical change may be different on organic and conventional farms but also the technical efficiency may change over time in a different way. In some sector level studies the change in technical efficiency is linked to diffusion of innovations when technical progress is linked to adoption of innovations. Learning-by-doing literature suggests that education and management experience can lead to productivity gains when the knowledge increases with the results of experiments (Arrow 1962). There are several studies that have assessed the effect of experience on technical or allocative efficiency. Kumbhakar et al. (1991) and Rougoor et al. (1998) have used age, experience and education when describing the ability of the farm manager (technical efficiency). Reinhard and Thijssen (2000) also in addition, analysed the role of milk output per cow although this indicator also represents different feeding strategies. Stefanou and Saxena (1988) used age and experience as explanatory variables of varying price distortions. Kumbhakar and Bhattacharrya (1992) applied years of education and farm size for the same purpose.

This paper tests for the presence of learning effects in organic farming, i.e. organic farmers may be expected to increase their efficiency as they gain experience with organic farming. Learning is a special case of adjustment costs that are caused by investments, technology switches etc. When a firm switches to a new technology, it may require time to learn on how to apply the new technology optimally. Thus, the productivity of the new technology (such as organic farming) may increase gradually over time. Learning plays an important role in the productivity of new technologies and as such it has been accounted for in innovation adoption studies (Luh and Stefanou 1993).

Agricultural processes are stochastic. Therefore, the choice of stochastic frontier analysis (SFA) seems natural, in spite of its limitations. Technical efficiency effect models developed by Kumbhakar et al. (1991) and Battese and Coelli (1995) provide a tool to simultaneously analyse whether some learning effects (an increase in technical efficiency) appears in the process of switching to organic farming. Consequently, SFA is used in this study to compute overall and input specific technical efficiencies. Model restrictions are used to test whether frontier functions differ between organic and conventional farms. Statistical tests are performed to test whether efficiency and productivity differences between conventional and organic farms are significant.

The results of Pietola and Oude Lansink (2001) suggest that policies promoting organic farming may suffer from adverse selection problems since they found that subsidised organic farming is more attractive to farmers with lower productivity in conventional systems. Farmer switches towards organic technologies may have been encouraged by premium subsidies granted to organic farms rather than by high productivity and input use efficiency of the organic technology. Thus, there seems to be observable factors like intensity of production, location of the farm, age of the farmer that should be controlled when the performance of organic and conventional farms are compared. Therefore one of the first steps is to construct a self selection model for controlling the possible selection bias.

This article applies SFA approach and output distance functions to a sample of conventional and organic dairy farms. We control for possible selection bias and regional heterogeneity and provide an estimate for the effect of experience in organic farming on technical efficiency. Still, our analysis is limited to conventional inputs and outputs. In addition to output oriented technical efficiencies we estimate input specific efficiencies for both organic and conventional farms.

The structure of the paper is as follows. Section 2 defines the framework of stochastic output distance function and the general model to identify factors influencing technical efficiency and discusses how to correct for self-selectivity bias in models estimated for organic and conventional farms. Next, the sample of Finnish dairy farm is described and the specification of the empirical model is presented. Results of organic and conventional farms are presented next, and the paper concludes with comments.

2. Method

Derivation of parametric output distance function

This section describes the stochastic output distance function. Assume that the production technology is defined by an output set Y(x), representing the vector of outputs $y \in R_{+}^{M}$ that can be produced by an input vector $x \in R_{+}^{N}$. That is $Y(x) = \{y \in R_{+}^{M} : x \text{ can produce } y\}$. The output distance function is given by $D_O(x, y) = \min\{\theta : y/\theta \in Y(x)\}$. $D_O(x,y)$ is non-decreasing, positively linearly homogenous and convex in y, and decreasing in x (see Färe and Primont 1995). 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. 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):

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

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. The output distance function is by definition linearly homogenous in outputs which is imposed by dividing all outputs by one of the outputs.

Homogeneity in outputs implies that

$$D_O^t(x_i^t, y_i^t / y_{mi}^t) = D_O^t(x_i^t, y_i^t) / y_{mi}^t \quad (2)$$

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

$$-\ln y_{mi}^t = TL(x_i^t, y_i^t / y_{mi}^t, t; \beta) - \ln D_O^t(x_i^t, y_i^t). \quad (3)$$

Setting $\mathrm{u_{it}} = -\ln \mathrm{D_O^t}(\mathrm{x_{it}}, \mathrm{y_{it}})$ and adding a stochastic error term (v_{it}), our presentation is similar to that of a parametric stochastic frontier with a decomposed error term:

$$-\ln y_{mi}^t = TL(x_i^t, y_i^t / y_{mi}^t, t; \beta) + u_{it} + v_{it} \quad (4)$$

where u_{it} are time-varying inefficiency effects.

The ratio form in (4) has been discussed in the literature. Kumbhakar and Lovell (2000) argued that the outcome of a normalisation is not independent of the choice of the numeraire output. Moreover, Brümmer *et al.* (2002) state, that the use of the norm model leads to 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.[1] 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).

Kumbhakar, Ghosh and McGuckin (1991) and Reifschneider and Stevenson (1991) proposed a stochastic frontier model in which the inefficiency effects (u_i) are expressed as an explicit function of a vector of firm-specific variables and a random error. This model was adapted by Battese and Coelli (1995) to account for panel data, and this model is also applied in our study. 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:

$$\mu_{it} = \delta_0 + \sum_{s=1}^{r} \delta_s x_s \quad (5)$$

The parameters δ are regression coefficients capturing the effect of the independent variables *x* on inefficiency. The inefficiency effects part of the equation makes it possible to test whether technical efficiencies differ for example by some background variables.

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}

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1 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.

(ε_{it}.= v_{it} - u_{it}; Battese and Coelli 1988)[2]. The level of technical efficiency is by definition between 0 and 1, and varies across farms, and over time.

Input specific efficiencies

Results of Oude Lansink et al. (2003) suggest that input specific efficiencies may differ between conventional and organic farms. This is because organic farms are ruled by a different set of restrictions concerning the application of fertilizers and chemicals. The estimation of input specific efficiencies requires a solution of this efficiency for each observation, given predicted output and actually applied quantities of other inputs. When calculating input specific efficiencies we follow the approach in Reinhard et al. (1999). The logarithmic value of technically efficient production is obtained when we set $u_{it} = 0$ in Equation 4. The logarithmic value of the input specifically efficient output can be estimated by replacing the observed input values of this input by the optimal one (x_{kei}) and setting $u_{it} = 0$. Setting Equation 4 equal to the latter we get Equation 6:

$$TL(x_{ki}^t, y_i^t / y_{mi}^t, t; \beta) + v_{it} + u_{it} = -\ln \hat{y}_{mi}^t + v_{it} \tag{6}$$

where -ln $\hat{y}_{mi}^t$= $TL(x_{kei}^t, x_{j\neq ki}^t, y_i^t / y_{mi}^t, t; \beta)$ and x_{kei} the efficiently applied quantity of input x_{ki}. The logarithm of the stochastic input specific efficiency ($\ln XE_{kit} = \ln x_{keit} - \ln x_{kit}$) can be defined and calculated applying the solver equation of the second order polynomial as follows

$$\ln XE_{kit} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}, \text{ where}$$

$$a = \tfrac{1}{2}\beta_{kk}\ ;\ b = \beta_k + \sum_{j\neq k} \beta_{jk} \ln x_{ij}^t + \beta_{kk} \ln x_{ik}^t + \sum_{m=1}^{p} \beta_{mk} \ln y_{im}^t + \beta_{kt} t \text{ and } c = u_{it}. \tag{7}$$

Since technically output efficient farm also has to be input efficient we apply only the positive option of the formula (Reinhard et al. 1999).

Selectivity bias

We may assume that the farmers choose organic or conventional production because they from benefit the choice. This may cause self selection bias. Possible selection bias between organic and conventional production can be taken into account by applying Heckman's (1979) two step procedure where in the first step a probit model is estimated in order to model the choice, which in our case is a choice between organic and conventional farming (see Maddala 1983, p. 22; Hsiao 2003, p. 225-227). In the binomial probit model the data is pooled and an unobserved latent variable z^* is set as a function of *x* affecting the choice:

$$z_i = ß'x_i + \varepsilon_i\ ,\ \varepsilon_i \sim N(0,1). \tag{8}$$

What we actually observe is z (the binary choice either 0 or 1), not the continuous variable z^*. We may, however, set threshold values for *z* such that

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2 For the estimation purpose we reverse the signs of Equation (4). Thus, the interpretation of TE terms is as in the production function.

$$z_i = 1 \text{ if } z_i^* > 0 \text{ and } z_i = 0 \text{ otherwise}.$$

Thus, we are estimating an expected value of the latent variable given x:s $E(z_i \mid x_i)$ instead of *z*. The above relationships yield

$$P(z_i = 1) = P(\varepsilon_i > -\beta' x_i) = 1 - F(-\beta' x_i), \tag{9}$$

where *F* is a cumulative distribution function for ε_i. For the binomial process the likelihood function can be written in the case of standardized normal distribution, i.e. a probit model, as follows:

$$L = \prod_{i=1}^{n} [\Phi(\beta' x_i)]^{z_i} [1 - \Phi(\beta' x_i)]^{1-z_i} \tag{10}$$

the logarithmic form of which is applied in maximum likelihood estimation. Inverse Mill's ratio can be obtained for z=1 by $IMR_i = \phi(\beta' x_i) / \Phi(\beta' x_i)$, where Φ cumulative normal distribution function and ϕ is normal density function. Inverse Mill's ratio (IMR) obtained on the basis of probit models is introduced in the frontier models to capture possible selectivity bias in the separate models of organic and conventional farms. The final IMR estimates were calculated by the random effects binary probit model[3].

3. Data and model

The dairy farm data are collected from bookkeeping farm data base of MTT Economic Research. The data include a detailed farm level data on production and costs over the period from 1995 to 2002 (8 periods). Altogether the panel includes 459 farms. Dairy farms are a subsample of this sample. Due to the changes in the main production line farms may entry or exit the sample of dairy farms during the period. In addition, because of the small number of organic farms we complemented the sample by all organic dairy farms in the bookkeeping data set. Less than one tenth of farms are following organic production rules. Also only part of the farms classified as organic dairy farms produce organic milk since the classification to organic and conventional farms is based on subsidies paid for organic crop production. The data are an unbalanced panel of 279 farms. The total number of observations is 1921, the number of organic farms being 49 (159 observations).

In the analysis we distinguish two outputs (milk and other output (excluding subsidies)) and five inputs (labour, land, energy, material and capital). Milk, labour and land are measured in physical units. Milk output is the annual milk production of the farm. The differences in composition of milk are not possible to take into account since this information is missing since 1998. In those cases when output quantity is not recorded the quantity is derived from the milk return using the regional milk price as a proxy of the actual milk price at the farm level. Labour input is the sum of working hours of the farm family and hired labour on the farm. The land area covers both own and rented arable land. Other output, energy, materials (fertilizers, seeds, purchased feed) and capital have been calculated as

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[3] Random effects binary probit model takes the panel property of the data into account as follows (see Nlogit user's manual):

$$z_{it}^* = \beta^{*\prime} x_{it} + u_i + v_{it}, \text{ where } i=1,...,N;\ t=1,...,T;\ \beta=\beta^*/\sigma(v_{it}),$$

$$z_{it} = 1 \text{ if } z_{it}^* > 0 \text{ and } 0 \text{ otherwise},$$

$$\mathrm{Var}[u_i + v_{it}] = \mathrm{Var}[\varepsilon_{it}] = \left[\sigma^2(u_i) + \sigma^2(v_{it})\right].$$

the ratio of the monetary value and their price index. This procedure assumes that farmers face equal prices and differences in the composition of the input or output or quality differences are reflected in the implicit quantity. Capital input is measured as a sum of machinery and building capital stock. Table 1 presents the descriptive statistics of the farms.

Table. 1. Descriptive statistics – pooled, conventional and organic farm data for 1995-2002.

	n	All farms Mean	Std Dev[b]	n	Convent-ional Mean	Std Dev	n	Organic Mean	Std Dev
Output									
Milk (ltr) [a]	1921	139347	73646	1762	140563	71382	159	125871	94441
Other output (€)[a]	1921	10224	10993	1762	10011	10616	159	12248	15341
Input									
Labour (h)	1921	5033	1485	1762	5045	1474	159	4895	1604
Land (ha) [a]	1921	39.2	21.5	1762	38.5	19.8	159	46.9	34.2
Energy (€)	1921	4671	2625	1762	4657	2617	159	4821	2718
Material (€)	1921	32668	19606	1762	32547	18808	159	33998	26955
Capital (€)	1921	85174	67693	1762	84420	67184	159	93527	72801
Livestock units [a]	1921	31	16	1762	31	15	159	34	22
Age of farmer [a]	1921	44	9.0	1762	45	9.0	159	42	7.8

[a] According to t-test, the means of conventional and organic farms differ significantly at least at 5% risk level.
[b] Std Dev refers to standard deviation.

Table 1 shows that organic farms have, on average a significantly larger land area and number of animal units than conventional farms. However, their average milk output is 10 percent smaller than the output of conventional farms. On the other hand, the other output is significantly larger on organic farms indicating that they are more diversified. In the input side there are no significant differences in other inputs than arable land area.

Organic farmers are significantly younger than conventional farmers. The logarithm of the age of farmer is also used as an indicator of experience in general in the technical efficiency effect model. Farmers' experience in organic farming is introduced in the technical efficiency effect model to account for possible learning by doing effects.

Table 2. Number of conventional and organic farms by year.

	1995	1996	1997	1998	1999	2000	2001	2002	Sum
Conventional	242	231	234	223	222	218	209	182	1762
Organic	18	22	17	21	21	19	19	22	159
Sum	260	253	251	244	243	237	228	204	1921

Table 2 presents the number of conventional and organic farms in the sample. The number of organic farms stays relatively stable but the number of conventional farms decreases. The average experience in organic farming is 4.3 when the first year is coded as 1. Table 3 shows that the average experience at first decreases but starts then to increase. When in the first year in the sample the experience is on average 4 years, at the end of the research period it is 5.5 years.

Table 3. Average experience in years of organic farmers in organic farming.

year	n	Mean	Std Dev	Min	Max
1995	18	4.06	2.41	1	8
1996	22	3.27	2.64	1	9
1997	17	3.00	2.37	1	10
1998	21	3.43	2.44	1	11
1999	21	4.81	2.77	1	12
2000	19	5.32	2.71	1	13
2001	19	5.21	2.62	1	11
2002	22	5.55	3.05	1	12

Milk output and the use of most inputs have increased on dairy farms. The other output increased relatively faster than milk output but this is partially related to the devaluation of animal capital in years after the EU accession in 1995. Thus, initially low output levels are reflected by in relative terms a large increase in the other output. On the input side, the growth has been the fastest in the capital input per farm, which has almost doubled during the period. The use of materials has increased by the same rate as milk output but the use of land has increased less and use of energy has even decreased. Labour input has remained at the same level for the whole research period, in spite of the increase in output. Changes in capital and labour input suggest a substantial substitution of capital for labour in the period under study.

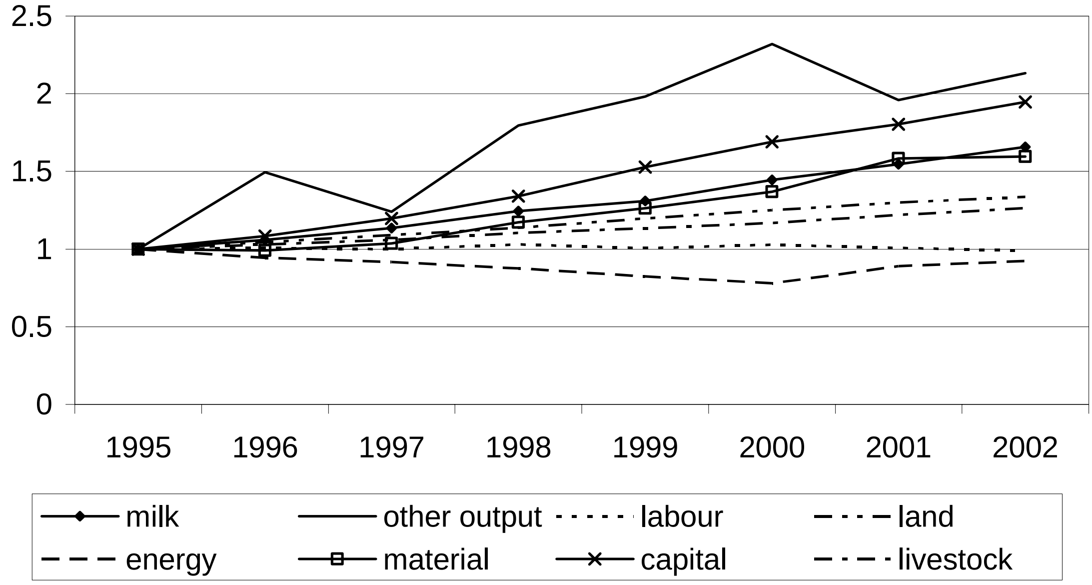

Figure 1. Relative use of inputs and production of outputs in 1995 - 2002 (annual average of all farms. The quantity in 1995 equals 1).

The model applied in the study is specified as follows:

$$
\begin{aligned}
-\ln y_{oi}^{t} &= \beta_0 + \sum_{k=1}^{5}\beta_k \ln x_{ki}^{t} + \tfrac{1}{2}\sum_{k\le}^{5}\sum_{j=1}^{5}\beta_{kj}\ln x_{ki}^{t}\ln x_{ji}^{t} + \beta_m \ln y_{mi}^{t} \\
&+ \tfrac{1}{2}\beta_{mm}\ln y_{mi}^{t}\ln y_{mi}^{t} + \sum_{k=1}^{5}\sum_{m=1}^{1}\beta_{km}\ln x_{ki}^{t}\ln y_{mi}^{t} + \beta_t t + \tfrac{1}{2}\beta_{tt}t^2 + \sum_{k=1}^{5}\beta_{kt}\ln x_{ki}^{t} t \\
&+ \beta_{mt}\ln y_{mi}^{t} t + \sum_{r=2}^{7}\beta_r D_r + \beta_{IMR} IMR + u_{it} + v_{it}
\end{aligned}
\tag{11}
$$

where

$y_{oi}^{t} = milk\ output,\ y_{mi}^{t} = other\ output / milk\ output,$

$x_{ki}^{t} = labour,\ land,\ energy,\ materials\ and\ capital\ input,$

$t = time\ trend,\ D_r = regional\ dummy, IMR = inverse\ Mill's\ ratio,$

$\beta = estimated\ regression\ coefficients.$

Neutral technical change is specified as a time trend. Biased technical change is defined by interactions of time trend and respective inputs and outputs. In addition to the first order terms of inputs and outputs, our full translog model includes second order and cross terms of inputs and outputs. Different production potential of different regions was taken into account by regional dummies. Inverse Mill's ratio (IMR) was also introduced in the separate organic and conventional farming models to capture possible selection bias.

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 (output) 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 follows:

$$\mu_{it} = \delta_0 + \delta_{\exp} Exp + \delta_{\exp^2} Exp^2 + \delta_{age}\ln(Age) + \delta_{age^2}\ln(Age)^2, \tag{12}$$

where Exp and Exp^2 refer to first and second order terms of years of experience in organic farming. ln(Age) and $\ln(Age)^2$ refer to the first and second order logarithmic terms of farmer's age. The δ :s are regression coefficients of respective efficiency effects. The inefficiency effects part of the equation makes it possible to test whether technical efficiencies differ by experience and age. Estimations are performed by Frontier 4.1 (Coelli, 1996).

4 Results

We estimate three models: an organic, a conventional and a pooled model. In separate organic and conventional models we also have to consider for controlling for possible self selectivity bias. We may assume that samples of organic or conventional dairy farms are not a random selection of dairy farms since the decision whether to produce organic or conventional products is up to the farmer. The intensity and extent of production, the location of the farm and farmer's age were used as explanatory variables in the probit model where the indicator of organic/conventional production was the choice variable.

The binomial probit model suggests that the time period, regional dummies and the age of the farmer affect significantly the choice of between organic or conventional farming (see Appendix A). The probability to choose organic farming is also larger on dairy farms with larger arable land area. Older farmers are less likely to farm organically. Increasing milk output per livestock unit decreases the probability of choosing organic farming but labour intensity (input per livestock unit) has an opposite effect. In the random effects binary probit model the significant intensity variables are slightly different. In this case labour intensity is no more a significant contributor in the prediction of the choice but more land per livestock unit increased the probability to choose organic farming. In the case of energy intensity the effect was the opposite. None of the above mentioned models was good in predicting the actual choice of organic farming correctly, although the model was fairly good in predicting the choice of conventional farming.

The probit models produce an inverse Mill's ratio that is used in the distance function of organic (and conventional) farms to test and capture possible selection bias between organic and conventional farms. In the second stage we apply IMRs from the random effect probit model.

Parameter estimates and model specification

In Model 1 of Table 4 organic and conventional farms are pooled in the same data set. According to the likelihood ratio test, the best fit of those considered is obtained by the translog specification without cross terms of inputs and output (inputs are weakly separable from output; see likelihood ratio tests in Appendix B). Instead, the hypothesis of unbiased technical change could not be accepted. Translog functional form also outperforms Cobb-Douglas type function. The value of the log likelihood function is 20.11. The inefficiency is also highly significant when the likelihood ratio value exceeds considerably the critical value.

The coefficients of the translog function cannot be interpreted as elasticities but they are different at each point of observation. The first order coefficient of neutral technical change does not differ significantly from zero. The sign is negative indicating slightly progressive but over time slower neutral technical change. The non-neutral technical change components were significant for energy and capital. The regional dummies were also significant for most regions and they were included in the model. They indicate that in general output decreases when going from south to north. Altogether 20 of 36 parameters of the frontier model were statistically significant at the 5 percent risk level.

Mean technical efficiency is 0.812. The inefficiency is on average larger on organic than conventional farms. In technical efficiency effect explanatory variables are the experience in organic farming in years and the logarithm of farmer's age. We also added their second order terms to show possible non-linear changes of the effects over time. The results indicate that the inefficiency is lower on the farms after the conversion and inefficiency increases for several years (6-7) but at a decreasing rate. On the other hand, inefficiency decreases with the farmer's age but this rate of change is also decreasing. On the sample farms inefficiency decreases until the farmer is approximately sixty years old.

Model 2 is similar to Model 1 but we have added slope dummies that allow different elasticities for conventional and organic farms in the same distance function. Together these dummies were not significantly different from zero at 10 percent risk level, according to the likelihood ratio test (10.9 versus the critical value of 12.0). Only the coefficients of energy and neutral technical change differed significantly between conventional and organic farms. The effects of experience and age are similar in both models.

Model 3 is estimated separately for conventional farms. In this case the best fit is obtained using the full translog specification (see likelihood ratio tests in Table B2, Appendix B). Likelihood ratio test shows also that in this case IMR receives a significant value (22.496 vs. critical value of 3.84). Inefficiency is also significant (LR test of the one-sided error = 684.40 with four restrictions when the critical value of generalized likelihood ratio test is 8.76).

Altogether 25 of 43 parameters are statistically significant at the 5 percent risk level. The first order component of neutral technical change does not differ significantly from zero but the second order term is highly significant. Non-neutral technical change components are significant for energy, materials and capital. The regional dummies are also significant for almost all regions, and they were included in the model.

Mean technical output efficiency is 0.827. In technical efficiency effect model only farmer's age is used as an explanatory variable. In this case the result is the same as in the pooled model: inefficiency decreases by age but at a falling rate. According to this estimate, inefficiency decreases until the farmer is approximately 61 years old.

Table 4. Parameter estimates and their significance.

	Model 1		Model 2		Model 3		Model 4	
Parameter	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
β_0	-23.5660	-8.017	-22.4875	-7.306	-23.8808	-7.111	-30.7847	-4.493
β_Y	0.2157	26.206	0.2156	24.779	0.3391	5.022	0.3619	14.857
β_{YD}			-0.0087	-0.760				
β_L	-5.0518	-8.078	-4.8616	-7.596	-4.6611	-6.961	-5.5749	-3.314
β_{LD}			0.0018	0.021				
β_A	1.7787	3.050	1.7237	3.068	1.4348	2.464	-1.4118	-0.916
β_{AD}			-0.0159	-0.301				
β_E	-0.3140	-0.647	-0.1429	-0.295	0.1472	0.310	-3.2893	-2.505
β_{ED}			-0.1323	-2.056				
β_M	-2.2108	-4.893	-2.3084	-5.223	-2.7586	-5.673	1.1768	1.083
β_{MD}			0.1039	1.799				
β_K	0.4996	1.478	0.5049	1.536	0.4130	1.242	-0.1403	-0.150
β_{KD}			0.0160	0.322				
β_{R2}	0.0999	3.985	0.0970	3.907	0.1219	4.552		
β_{R3}	0.0463	1.818	0.0445	1.782	0.0602	2.221		
β_{R4}	0.0810	3.400	0.0812	3.476	0.1102	4.316		
β_{R5}	0.1695	5.367	0.1813	5.733	0.2207	6.631		
β_{R6}	0.1865	6.929	0.1883	7.048	0.2117	7.461		
β_{R7}	0.2256	6.187	0.2258	6.257	0.2413	6.358		
β_T	-0.0932	-0.972	-0.0537	-0.565	0.0062	0.064	-0.0707	-1.381
β_{TD}			-0.0255	-1.971				
β_{TT}	0.0074	5.447	0.0076	5.501	0.0075	5.404	0.0035	0.654
β_{YY}	0.0161	26.589	0.0161	25.324	0.0152	23.018	0.0300	13.963
β_{LL}	0.1561	2.848	0.1515	2.700	0.1465	2.542	-0.0060	-0.031
β_{AA}	0.1858	5.101	0.1901	5.363	0.1321	3.404	-0.0152	-0.135
β_{EE}	-0.0203	-0.820	-0.0195	-0.791	-0.0185	-0.807	0.0083	0.061
β_{MM}	-0.0221	-0.824	-0.0102	-0.382	0.0131	0.466	-0.2170	-2.505
β_{KK}	0.0113	0.920	0.0098	0.812	0.0093	0.745	0.0944	1.781
β_{YL}					-0.0167	-2.015		
β_{YA}					0.0181	2.609		
β_{YE}					-0.0077	-1.203		
β_{YM}					0.0047	0.753		
β_{YK}					-0.0024	-0.526		
β_{LA}	-0.2867	-4.416	-0.2732	-4.231	-0.2176	-3.350	-0.1200	-0.549
β_{LE}	0.1532	2.561	0.1497	2.482	0.1234	2.118	0.0519	0.182
β_{LM}	0.1442	2.345	0.1364	2.228	0.1375	2.242	0.4182	2.248
β_{LK}	-0.0147	-0.316	-0.0168	-0.367	-0.0244	-0.512	0.0138	0.077
β_{AE}	-0.0749	-1.656	-0.0746	-1.658	-0.0543	-1.189	-0.0703	-0.447
β_{AM}	0.0228	0.488	0.0122	0.263	0.0325	0.690	0.4685	3.270
β_{AK}	-0.0207	-0.630	-0.0186	-0.572	-0.0340	-0.992	-0.1887	-1.535
β_{EM}	0.0647	1.546	0.0520	1.265	0.0275	0.692	0.1332	0.759
β_{EK}	-0.0958	-3.224	-0.0952	-3.226	-0.0864	-2.911	0.0960	0.695
β_{MK}	0.0270	0.829	0.0300	0.930	0.0398	1.200	-0.2324	-1.708

Continues

Table 4. Continues.

Parameter	Model 1 Estimate	t-value	Model 2 Estimate	t-value	Model 3 Estimate	t-value	Model 4 Estimate	t-value
β_{YT}	-0.0005	-0.566	-0.0003	-0.373	-0.0014	-1.305		
β_{LT}	0.0192	1.648	0.0177	1.532	0.0184	1.545		
β_{AT}	-0.0081	-0.922	-0.0053	-0.605	-0.0062	-0.686		
β_{ET}	0.0278	3.188	0.0265	3.039	0.0299	3.461		
β_{MT}	-0.0138	-1.729	-0.0164	-2.073	-0.0275	-3.410		
β_{KT}	-0.0193	-3.590	-0.0186	-3.477	-0.0158	-2.924		
β_{IMR}					-0.3910	-4.915		
δ_0	65.3616	9.610	65.6994	10.270	85.6276	9.133	-29.5661	-1.611
δ_{exp}	2.6457	14.118	2.7696	12.442			1.2390	1.657
δ_{exp2}	-0.2042	-18.588	-0.2020	-12.081			-0.0952	-1.624
δ_{age}	-38.8263	-9.654	-39.2170	-10.312	-49.3887	-9.144	5.4571	1.349
δ_{age2}	4.7113	9.485	4.7883	10.142	6.1119	9.035	-0.2531	-0.779
σ^2	3.1840	11.208	3.1749	11.941	2.9801	10.490	3.0078	1.828
γ	0.9947	1491.946	0.9949	1540.576	0.9947	1812.361	0.9905	154.772
LLF		20.113		25.563		104.894		-31.949
LR test of the one-sided error		698.938		698.938		684.395		624.174

Y, L, A, E, M, K refer to other output, labour, land, energy, materials and capital
T, exp, age refer to time trend, experience in organic farming and farmer's age
LLF – log likelihood function, LR one-sided – likelihood ratio test value of one-sided error term

Model 4 was estimated separately only for organic farms. In this case selectivity bias was insignificant (2.26 versus the critical value of 3.84 according to the likelihood ratio test at 5 percent risk level) and we may leave it out of the list of explanatory variables. Because of a relatively small number of observations we also drop out regional dummies. The best fit of the model is obtained using the translog specification without biased technical change components and assuming that output shares do not affect input use (see likelihood ratio tests in Appendix B). In this case the value of log likelihood function is -31.994.

Neutral technical change components do not differ significantly from zero but their signs indicate progressive although slowing down technical change. The non-neutral technical change components are not significant either (LR test 0.94 vs. critical value of 3.84). Only 8 of 25 parameters are statistically significant at 5 percent risk level but we could not accept the null hypothesis of second order and cross terms of inputs and outputs being zero. A large number of insignificant coefficients raises concerns about large standard errors of elasticities in this case.

Inefficiency is also significant (LR test of the one-sided error = 16.7, with six restrictions the critical value at 5 % risk being 11.91). Mean technical output oriented efficiency is 0.783. The experience in organic farming could at 10 percent risk level significantly contribute in explaining technical efficiency differences among organic dairy farms. Technical inefficiency increases with years of experience in organic farming but at a decreasing rate. Inefficiency is at the lowest approximately after six years and starts then to grow. The age of the farmer could not significantly contribute in explaining the efficiency differences. Even the signs of the coefficients of age were opposite compared to other models.

Elasticities

Average distance elasticities are presented in Table 5. In the translog model elasticities are point elasticities that are different at each data point. The results are calculated only for those data points which do not violate the monotonicity assumption. Especially in the case of energy violations are common. We should also note that negative values of distance elasticities and returns to scale (RTS) are in accordance with the assumptions of the output distance function.

In general the differences in elasticities and returns to scale are relatively small. In addition, elasticity differences should be interpreted with care because of a large number of insignificant coefficients in distance functions. However, we can observe some tendencies but also mixed results. The results show that the share of other output is on average generally bigger on organic than conventional farms. Thus, organic farms are less specialized. The models give mixed results for labour but for land the elasticity tends to be larger on organic farms, except in Model 4. The elasticity of energy is low in all models but it tends to be larger on organic farms. In Model 2 of organic farms and in Model 4 elasticity of materials is considerably smaller than in other models. The elasticity of capital is larger in the translog models for organic farms but in Model 4 it is the lowest.

Table 5. Distance elasticities of specified models.

	Model 1 TL, Homog.slopes All	 Convent.	 Organic	Model 2 TL, Heterog. slopes Convent.	 Organic	Model 3 TL Convent.	Model 4 Organic
Other output	0.161	0.160	0.174	0.160	0.166	0.153	0.289
Labour	-0.257	-0.253	-0.303	-0.254	-0.299	-0.262	-0.403
Area	-0.164	-0.164	-0.170	-0.163	-0.177	-0.154	-0.071
Energy	-0.081	-0.080	-0.092	-0.076	-0.169	-0.074	-0.105
Materials	-0.498	-0.498	-0.501	-0.514	-0.416	-0.499	-0.444
Capital	-0.135	-0.134	-0.142	-0.133	-0.136	-0.133	-0.084
RTS	-1.054	-1.050	-1.101	-1.053	-1.112	-1.033	-1.107
TC	-2.75 %	-2.80 %	-2.60 %	-2.50 %	-4.80 %	-2.44 %	-3.88 %

TL - Translog type, RTS – returns to scale, TC – technical change

Table 6 describes the direction of changes in distance elasticities over time for conventional and organic farms in different models. The tendencies are similar: the output share of other output is increasing, elasticities of labour and energy inputs are decreasing. Instead, the elasticities of materials and capital are increasing. The elasticity of land decreases or remains the same.

Table 6. Changes in distance elasticities (absolute values) over time.

	Model 1 Convent.	 Organic	Model 2 Convent.	 Organic	Model 3 Convent.	Model 4 Organic
Output	+	+	+	+	+	+
Labour (L)	-	-	-	-	-	--
Land (A)	+/-	+/-	-	+/-	-	-
Energy (E)	-	-	-	-	-	-
Materials (M)	+	+	+	+	+	++
Capital (K)	+	+	+	+	+	+/-

-- substantially decreasing, - decreasing, +/- no change, + increasing, ++ substantially increasing absolute elasticity.

The sum of input distance elasticities provides the RTS measure. In Translog models the average RTS is in all models slightly smaller than -1 indicating increasing returns to scale. As input distance elasticities are evolving over time so does the RTS measure. These changes are presented in Table 7.

The absolute value of RTS is slightly decreasing over time in all models for conventional farms. In the group of organic farms the annual variation is larger.

Table 7. Average returns to scale over time.

	Model 1 Convent.	Organic	Model 2 Convent.	Organic	Model 3 Convent.	Model 4 Organic
1995	-1.056	-1.057	-1.062	-1.101	-1.039	-1.261
1996	-1.072	-1.101	-1.075	-1.109	-1.069	-1.062
1997	-1.068	-1.213	-1.074	-1.163	-1.052	-1.126
1998	-1.037	-1.169	-1.033	-1.175	-1.014	-1.129
1999	-1.031	-1.082	-1.031	-1.087	-1.009	-1.109
2000	-1.009	-1.027	-0.989	-1.134	-0.976	-1.107
2001	-0.999	-1.070	-0.988	-1.034	-0.967	-1.030
2002	-1.031	-0.916	-1.018	-1.094	-0.983	-1.054

RTS is calculated only for the observations not violating monotonicity constraint

When the absolute value of RTS is larger than one it is able to contribute productivity growth since the input output relation improves also due to scale effect. In most years the effect is slightly productivity increasing on average.

Technical change

Technical change including both neutral shift of the frontier and some inputs increasing or decreasing effects (biased technical change) is often the main contributor of productivity growth. The specification of the model also follows that the more negative value technical change receives the faster is technical change. Average technical change tends to be slightly faster on organic than on conventional farms, as Table 5 shows. In all models technical change is slowing down over time because of lower neutral technical change (the second order terms of time are positive). On conventional farms technical change slows down slightly faster than on organic farms. Technical change on conventional farms' group turns even from progress to regress in the last years of the research period.

Table 8. Technical change (%) over time in different models.

	Model 1 Convent.	Organic	Model 2 Convent.	Organic	Model 3 Convent.	Model 4 Organic
1995	-6.31	-6.23	-6.23	-8.59	-5.86	-6.37
1996	-5.22	-4.94	-5.05	-7.32	-4.77	-5.67
1997	-4.13	-3.74	-3.91	-6.05	-3.64	-4.97
1998	-3.34	-3.03	-3.06	-5.27	-3.05	-4.27
1999	-2.36	-2.41	-2.04	-4.54	-2.09	-3.57
2000	-1.30	-1.41	-0.93	-3.54	-1.12	-2.87
2001	0.29	-0.43	0.65	-2.57	0.40	-2.17
2002	1.72	1.14	2.12	-0.93	1.87	-1.47
Average	-2.80	-2.60	-2.50	-4.80	-2.44	-3.88

The contribution of technical change on productivity growth is considerable on the sample farms.

Output oriented technical efficiency

Average technical efficiencies and their distribution over research period are presented in Table 9. Average technical efficiency is higher on conventional than on organic farm in all models. On conventional farms technical (output oriented) efficiency is on average 0.83. Thus, farmers should be able to increase their output by seventeen percent if they were efficient. In the pooled Models 1 and 2 the difference in average efficiency is approximately 10 percentage units. When compared separately to their own frontiers the difference in inefficiency of conventional and organic farms is less than half of that but still the organic farms are less efficient. The variation in average efficiency of organic farms is larger between years than in the group of conventional farms. Thus, the variation of efficiency in the group of organic farms is larger both within and between years than in the group of conventional farms.

Table 9. Average technical output oriented efficiency over time.

	Model 1		Model 2		Model 3	Model 4
	Convent.	Organic	Convent.	Organic	Convent.	Organic
1995	0.815	0.667	0.806	0.675	0.809	0.748
1996	0.850	0.787	0.843	0.783	0.845	0.830
1997	0.831	0.715	0.823	0.699	0.827	0.766
1998	0.850	0.729	0.843	0.706	0.845	0.802
1999	0.826	0.720	0.819	0.694	0.823	0.790
2000	0.834	0.747	0.829	0.711	0.830	0.792
2001	0.814	0.735	0.809	0.698	0.809	0.768
2002	0.829	0.745	0.827	0.699	0.827	0.759
Average	0.831	0.732	0.825	0.709	0.827	0.783

Figure 2 illustrates the pattern of changes in technical efficiency of different models as in Table 9. As the figure shows the pattern is similar in all models estimated for conventional farm. On these farms technical efficiency at first increased from 1995 to 1996 but started then to diminish. In 2001 the level of technical efficiency was the same as in 1995 but in 2002 it again slightly increased. Organic farms are on average less efficient in each year. In 1996 the gap is the smallest. The development of efficiency varies slight between models, escpecially from 2000 to 2002. Average technical efficiencies of organic farms are almost equal in Models 1 and 4 in 2002.

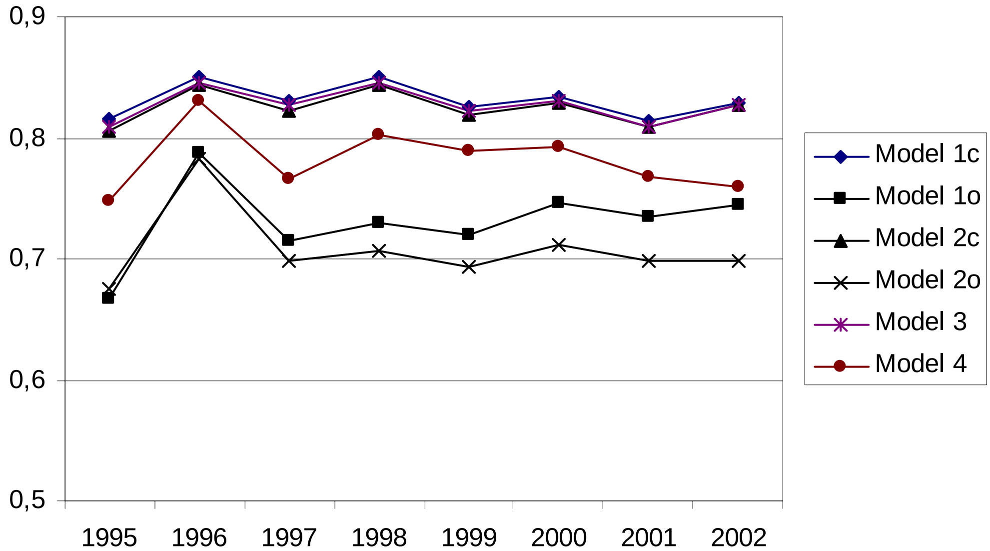

Figure 2. Average technical efficiencies for Models 1 – 4 in 1995 – 2002 (c and o refer to conventional and organic production).

Table 10 presents the 95 % confidence intervals of technical efficiencies for conventional and organic farms for different models. They are calculated following the procedure presented by Battese et al. (2000). The result shows that even if there are ten percentage unit's differences in average efficiencies of the groups the means still belong to the confidence interval of the other group. This indicates that the difference is not statistically significant at 5 percent risk level. The range is largest in Model 4 where only organic farms are included.

Table 10. Technical output efficiencies and their ranges at 5 % risk level.

		Mean	Lower	Upper	Range
Model 1	Convent.	0.831	0.677	0.953	0.277
	Organic	0.732	0.586	0.867	0.281
Model 2	Convent.	0.825	0.672	0.949	0.277
	Organic	0.709	0.567	0.846	0.279
Model 3	Convent.	0.827	0.676	0.948	0.273
Model 4	Organic	0.783	0.597	0.937	0.340

The distribution of efficiencies may also differ between models and groups. In our case the distributions in models for conventional farms are almost identical. In the group of organic farms the differences are bigger between models but the general feature is that the whole distribution has moved downwards when compared to the group of conventional farms. If we look at the distribution of technical efficiencies and experience in organic farming we can observe a similar pattern as the Models suggest: the average efficiency at first decreases but at a decreasing rate, and turns then after 6-7 years to an increase. We should, however, notice that the number of farmers having an experience of more than ten years is small.

Technical input specific efficiencies

Technical input specific efficiencies were estimated applying the method introduced by Reinhard et al. (1999). In our case, the method yields on average very low input specific efficiencies the average being at the level of 0.1. In general, conventional farms are also input specifically more efficient than organic farms but the absolute differences between the groups are minor. The differences are largest in land input followed by labour and materials. In capital input there were no differences.

5 Discussion and conclusions

This article has applied stochastic output distance function approach in analysing technical efficiency of organic and conventional dairy farms. The goal was to study whether some learning-by-doing effects can be observed. This was mainly analysed by investigating the relationship between technical efficiency and experience in organic farming. We tested for possible self-selectivity bias between organic and conventional farms. We also studied the differences in technical efficiency and technical change in the groups of conventional and organic farms in general.

When only traditional inputs and outputs are taken into account in the pooled data technical efficiency is on average 10 percentage units higher on conventional than on organic farms. Although the data suggest learning effects related to the experience in organic farming, differences in the development of organic and conventional farm groups were small. In our sample organic farms are less efficient even compared to their own frontier than conventional farms indicating that the variation is larger. This result contradicts that of Oude Lansink et al. (2002) and Ricci Maccarini and Zanoli (2004). The difference compared to Oude Lansink et al. (2002) may be caused by a different evaluation method. In the last mentioned articles the target group is also more heterogeneous than in our case of specialized dairy farms. Our result may indicate that organic production is more risky but it may also be partially caused by the sample where we had to include all organic dairy farms to guarantee the sufficient number of observations. Further analysis with respect to risk is, however, required.

We could observe significant change in technical efficiency by the experience in organic farming. According to our analysis, inefficiency increases at first after the switch to organic farming. Inefficiency increases for several years reaching the bottom after five to six years. Inefficiency starts to diminish not before than after 6 – 7 years of experience in organic farming. The result suggests that temporary premium schemes over a certain conversion period may be justified in promotion of organic farming. The result also suggests that this conversion period may take for a fairly long time.

Conventional production seems to be more technically efficient, i.e. more productive when only conventional inputs and outputs are taken into account. However, we have not considered possible external effects on the environment or landscape. These considerations might affect the relative performance of different production systems.

More panel type studies are needed to confirm the existence of learning effects. In our analysis we have applied pooled data of an unbalanced panel. Still the number of organic farms is relatively small for a separate analysis.

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Appendix A1. The probit models.

Binomial Probit Model	
Maximum Likelihood Estimates	
Number of observations	1921
Log likelihood function	-472.7296
Restricted log likelihood	-548.4102
Chi squared	151.3612
Degrees of freedom	13
Prob[ChiSqd > value] =	.0000000
Hosmer-Lemeshow chi-squared =	11.69512
P-value= .16533 with deg.fr. =	8

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
	Index function for probability				
TIME	.07231954	.02375956	3.044	.0023	4.35346174
PELTO	.00684643	.00221608	3.089	.0020	39.2240968
DUM2	-.47468789	.17384262	-2.731	.0063	.20510151
DUM3	.10234074	.15317846	.668	.5041	.18427902
DUM4	-.41770795	.15333180	-2.724	.0064	.34617387
DUM5	.18398849	.20808471	.884	.3766	.05674128
DUM6	-.72167390	.23178218	-3.114	.0018	.11920875
MAIINTEN	-.00030036	.374330D-04	-8.024	.0000	4533.83555
TYOINTEN	.00174870	.00077682	2.251	.0244	184.269039
PELINTEN	-.02519516	.08596381	-.293	.7695	1.34198864
TARINTEN	-.157048D-04	.259624D-04	-.605	.5452	6307.46311
ENEINTEN	-.00010728	.00012958	-.828	.4077	961.220143
KAPINTEN	.183762D-05	.539083D-05	.341	.7332	16057.4743
IKA	-.01343344	.00418381	-3.211	.0013	44.3352421

Fit Measures for Binomial Choice Model
Probit model for variable LUOMU

Proportions P0= .917231 P1= .082769
N = 1921 N0= 1762 N1= 159
LogL = -472.72958 LogL0 = -548.4102
Estrella = 1-(L/L0)^(-2L0/n) = .08129

Efron	McFadden	Ben./Lerman
.10674	.13800	.86423
Cramer	Veall/Zim.	Rsqrd_ML
.10724	.20096	.07577

Information	Akaike I.C.	Schwarz I.C.
Criteria	.50675	1051.30758

Frequencies of actual & predicted outcomes
Predicted outcome has maximum probability.
Threshold value for predicting Y=1 = .5000

	Predicted		
Actual	0	1	Total
0	1754	8	1762
1	152	7	159
Total	1906	15	1921

Appendix A2. The probit models.

```
+---------------------------------------------+
| Random Effects Binary Probit Model          |
| Maximum Likelihood Estimates                |
| Number of observations              1921    |
| Iterations completed                  41    |
| Log likelihood function        -199.3224    |
| Restricted log likelihood      -472.7296    |
| Chi squared                     546.8143    |
| Degrees of freedom                     1    |
| Prob[ChiSqd > value] =          .0000000    |
| Unbalanced panel has     277 individuals.   |
+---------------------------------------------+
```

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
TIME	.26187083	.12515444	2.092	.0364	4.35346174
PELTO	.02508582	.01136932	2.206	.0274	39.2240968
DUM2	-9.38853682	2.59608803	-3.616	.0003	.20510151
DUM3	-2.03964528	1.19846621	-1.702	.0888	.18427902
DUM4	-2.77853798	1.11478099	-2.492	.0127	.34617387
DUM5	-1.91131770	1.30240319	-1.468	.1422	.05674128
DUM6	-5.76602944	2.34426941	-2.460	.0139	.11920875
MAIINTEN	-.00067622	.00014736	-4.589	.0000	4533.83555
TYOINTEN	.00496059	.00432029	1.148	.2509	184.269039
PELINTEN	1.01105816	.60464171	1.672	.0945	1.34198864
TARINTEN	.303731D-04	.00012606	.241	.8096	6307.46311
ENEINTEN	-.00139517	.00071448	-1.953	.0509	961.220143
KAPINTEN	.289553D-04	.539430D-04	.537	.5914	16057.4743
IKA	-.09668426	.02459530	-3.931	.0001	44.3352421
Rho	.97529251	.01056979	92.272	.0000	

```
+----------------------------------------+
| Fit Measures for Binomial Choice Model |
| Probit   model for variable LUOMU      |
+----------------------------------------+
| Proportions P0= .917231   P1= .082769  |
| N =     1921 N0=    1762   N1=     159 |
| LogL = -4024.60729 LogL0 =  -548.4102  |
| Estrella = 1-(L/L0)^(-2L0/n) =*******  |
+----------------------------------------+
|     Efron |  McFadden  |  Ben./Lerman |
|   -.05600 |  -6.33868  |       .91720 |
|    Cramer | Veall/Zim. |     Rsqrd_ML |
|    .03576 |   3.80193  |    -36.30598 |
+----------------------------------------+
| Information  Akaike I.C. Schwarz I.C.  |
| Criteria        4.20469    8155.06300  |
+----------------------------------------+
Frequencies of actual & predicted outcomes
Predicted outcome has maximum probability.
Threshold value for predicting Y=1 = .5000
            Predicted
------  ----------  +  -----
Actual      0    1  |  Total
------  ----------  +  -----
  0      1754    8  |   1762
  1       154    5  |    159
------  ----------  +  -----
Total    1908   13  |   1921
```

Appendix B.

Table B1. Likelihood ratio tests for parameters of Model 1.

Null hypothesis	Test statistics[a]	Critical value
Cobb Douglas – neutral TC vs. Translog – neutral TC (d.f. 16)	191.0	26.3
Translog – neutral TC vs. non-neutral TC (d.f. 6)	43.5	12.6
Translog – additively separable (d.f. 5)	3.11	11.1
No technical inefficiency (d.f. 6)[b]	698.94	11.91

Table B2. Likelihood ratio tests for parameters of Model 3.

Null hypothesis	Test statistics[a]	Critical value
Cobb Douglas – neutral TC vs. Translog – neutral TC (d.f. 16)	647.3	26.3
Translog – neutral TC vs. non-neutral TC (d.f. 6)	29.5	12.6
Translog – additively separable (d.f. 5)	12.8	11.1
No technical inefficiency (d.f. 4)[b]	684.40	8.76

Table B3. Likelihood ratio tests for parameters of Model 4.

Null hypothesis	Test statistics[a]	Critical value
Cobb Douglas – neutral TC vs. Translog – neutral TC (d.f. 16)	130.35	26.3
Translog – neutral TC vs. non-neutral TC (d.f. 6)	3.77	12.6
Translog – additively separable (d.f. 5)	6.04	11.1
No technical inefficiency (d.f. 6)[b]	16.70	11.91

[a] Log likelihood ratio test -2(log L(H0)-log L(H1))

[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 6.