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Joint estimation of technology choice and technical efficiency: an application to organic and conventional dairy farming

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Abstract This paper proposes an econometric framework for joint estimation of technology and technology choice/adoption decision. The procedure takes into account the endogeneity of technology choice, which is likely to depend on inefficiency. Similarly, output from each technology depends on inefficiency. The effect of the dual role of inefficiency is estimated using a single-step maximum likelihood method. The proposed model is applied to a sample of conventional and organic dairy farms in Finland. The main findings are: the conventional technology is more productive, ceteris paribus; organic farms are, on average, less efficient technically than conventional farms; both efficiency and subsidy are found to be driving forces behind adoption of organic technology.

Keywords Production function · Inefficiency · Endogeneity · Maximum likelihood

JEL Classifications C23 · D24 · D83 · O30 · Q12

1 Introduction

Productivity differential between alternative production systems such as organic and conventional farming has raised debates in the literature. In principal, this differential can arise either from technological differences (meaning that the conventional or organic (frontier) production technology can produce the same output with fewer inputs or lower cost) or differences in technical efficiency or both. Organic production is largely based on more restricted use of specific inputs than conventional production, which tends to increase production costs. If organic farms are less productive their profitability will be lower unless the output price differential is high enough to compensate for lower productivity. If not, organic farming is not able to attract new entrants or to keep current farmers in the business.

In order to promote organic farming, the Finnish government has offered some subsidies for switching from conventional to organic farming. Since subsidies are often justified on the ground of productivity differential, it is necessary to examine the sources of the possible productivity differences, i.e., how much of it comes from technological differences and how much is from technical inefficiency. One might argue that even if the organic production technology is inferior and the productivity differential (controlling for expenses in inputs) is not compensated by higher prices of marketable organic products, organic production is still worth promoting because of its positive non-marketable effects.[1] Technically efficient organic farmers should be compensated, if

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[1] It is worth noting that organic farming might have other effects (positive or negative) for example, on the environment, which are not taken into account due to lack of reliable farm level data. Nielsen and Kristensen (2005) conclude that N and P surpluses are larger on conventional dairy farms in Denmark. Grönroos et al. (2006) have suggested that the use of non-renewable energy is higher per unit produced on conventional farms. Hole et al. (2005) also suggest that biodiversity is larger in organic farming systems than in conventional ones. Thus, we are able to clarify the question only with respect to traditional inputs and outputs.

the productivity differential is due to technology. Subsidies should be designed in a way that does not promote inefficiency.[2] Using Finnish data Pietola and Oude Lansink (2001) have suggested that policies promoting organic farming may have suffered from adverse selection problems because subsidies associated with organic farming might have attracted less productive conventional farmers to organic farming. Tzouvelekas et al. (2001) argued that the use of subsidies might lead to increased technical inefficiency, especially if subsidies attract farmers who are more interested in additional support than developing efficient organic farming practices.

Several other studies have suggested that organic dairy farms are less efficient technically compared to conventional farms (Oude Lansink et al. 2002; Ricci Maccarini and Zanoli 2004). Since inefficiency is an important factor behind low productivity, one might wonder whether less efficient farmers are indeed more likely to participate in organic farming. Thus, in the evaluation of various technologies it is necessary to recognize that technology choice might be endogenous with respect to inefficiency. Ignoring this choice problem is likely to introduce bias in the parameters of the production technologies. Consequently, the estimates of inefficiency are likely to be inappropriate. Furthermore, if inefficiency affects the adoption decision, one cannot use standard binary choice models (probit, logit, etc.) to estimate the choice probabilities without first estimating inefficiency.

To address the afore-mentioned issues we consider a model that recognizes endogeneity of the technology choice problem, and apply it to the Finnish dairy farm data. We allow production technology of organic and conventional farms to be different.[3] Since inefficiency is likely to appear in both the production and adoption/choice functions, the standard selectivity correction that takes into account endogeneity of technology choice does not work. Consequently, we use a system approach to estimate the production technologies and the choice equation simultaneously. The system approach in which full information maximum likelihood method is used solves both the problems.

Empirical results from the Finnish dairy farms show that subsidy is positively related to adoption, thereby meaning that subsidies might have attracted farms to organic production, ceteris paribus. On the other hand, inefficiency is found to decrease the probability of adopting organic farming. Thus, we cannot find support for the adverse selection problem with respect to technical inefficiency. However, we find that, on average, organic farmers could have produced 5.3% more had they used the conventional technology, *ceteris paribus*. Similarly, on average, organic farms are found to be about 5% less efficient than conventional farms. Because subsidy is attracting efficient farmers, one might hope that in the long run subsidy will be necessary only if productivity shortfall of organic farms is not compensated by the price premium they receive.

The rest of the paper is structured as follows. In Sect. 2 we introduce the econometric model. First, we consider the two-step procedure and explain why this strategy does not work for the problem at hand. We then develop the single step procedure to estimate technical efficiency and technology choice jointly. Section 3 describes the data of Finnish dairy farms. Empirical results are presented in Sect. 4. The last section summarizes the main findings.

2 Econometric model

Here we assume availability of panel data[4] where the i subscript refers to each farm and t is the time trend variable. The production function for organic farming is assumed to be different from that of conventional farming. These production functions in log form are

$$y_{it} = f_{I_{it}}(x_{it}, \beta) + v_{it} - u_{it}, \tag{1}$$

where y is output (scalar) and x is a vector of inputs. The parameter vector is β, the inefficiency term is $u_{it} \geq 0$ and the noise term is v_{it}. The production technologies $f(\cdot)$ are assumed to be log-linear (although they can easily be generalized to accommodate nonlinear functions). They as well as the u_{it} and v_{it} terms depend on I_{it} which is the observed binary indicator variable defined as

$$I_{it} = \begin{cases} 0, & \text{for conventional farming, } I_{it}^* \leq 0 \\ 1, & \text{for organic farming, } I_{it}^* \geq 0, \end{cases}$$

[2] To capture differences in input and output prices the comparison should be based on profitability.

[3] Most of the technical efficiency comparisons between organic and conventional farms are based on traditional inputs (labor, land, materials) and outputs (milk, grain etc.) in which the technology is assumed to be the same (e.g., Tzouvelekas et al. 2001). Although most of the machinery can be used in both technologies the ban of applying synthetic fertilizers and plant protection in organic farming suggest that the organic farmer has to learn new production practices and has to take a somewhat long-term perspective. In addition, changes are required when it comes to animal production, animal welfare, feeding and treatment of sick animals. Organic farmers are required to have larger space per animal in the cowshed, restrictions in the percentage of purchased (especially conventional) feeding stuffs and the use of medicines. In view of these, we assume that organic and conventional production technologies are different.

[4] It is worth noting here that the model developed in this section works with cross-sectional data as well. Since panel data is used in the application, we decided to write down the model in terms of panel data.

where

$$I_{it}^{*} = z_{it}'\gamma + \delta u_{it} - e_{it}. \tag{2}$$

That is, the "inclination" towards organic farming (measured via the latent indicator function I^*) is determined by a vector of covariates (z_{it}) and technical inefficiency (u_{it}). The error term in the indicator function is e_{it}. Note that the inefficiency and noise terms (u_{it} and v_{it}) are random. These random terms are assumed to be from the same family of distributions for both the conventional and organic farms.

In particular, we assume that $v_{it}|I_{it} \sim iid\, N(0, \sigma^2_{v,I_{it}})$, $u_{it}|I_{it} \sim iid\, N(0, \sigma^2_{u,I_{it}})$, $e_{it} \sim iid\, N(0,1)$ and are all independent given x_{it} and z_{it}. With these assumptions, the probability of choosing conventional farming is given by $P(I_{it} = 1|u_{it}) = P(I_{it}^{*} \geq 0|u_{it}) = \Phi(z_{it}'\gamma + \delta u_{it})$, where Φ denotes the standard normal cumulative distribution function (cdf).[5] In this form the model is equivalent to a mixture model, where the mixing probability is a function of the covariates z_{it}, technical inefficiency u_{it}, and the previous period's choice $I_{i,t-1}$. Furthermore, since we are dealing with organic and conventional farming the number of technologies is known a priori.[6]

The presence of technical inefficiency (an unobserved latent variable) is what distinguishes this model from standard mixture models. If the adoption decision does not depend on technical inefficiency, then the model for I_{it} is a standard binary choice model for panel data. In such a case one needs to correct for the selectivity problem (that arises due to non-random adoption) in estimating the production technologies. However, the present model is much richer in the sense that we take both endogeneity of the technology choice and the simultaneity problem by estimating both I_{it} and the two production functions jointly. A model that combines production frontiers with binary dependent variables (where technical inefficiency plays a non-trivial role) is not common in the literature.[7] It should be noted here that technical inefficiency measures cannot be obtained from the production function alone but must exploit the equation that determines choice of technology (organic versus inorganic farming). This is because the technology choice is endogenous. Consequently, exploiting the choice equation could prove crucial for obtaining meaningful and more precise estimates. This is the main innovation of the paper.

The model can be extended to allow past decision to play a role in the present technology choice decision. For this we specify the latent inclination function as

$$I_{it}^{*} = z_{it}'\gamma + \varphi I_{i,t-1} + \delta u_{it} - e_{it}. \tag{3}$$

Thus, past experience in organic farming increases (decreases) the probability of being engaged in organic farming if φ is positive (negative), ceteris paribus. Under the normality assumption[5] on e_{it} the model for I_{it} is a dynamic probit model for panel data, conditional on the technical inefficiency term u_{it}. Note that u_{it} plays a dual role. It affects output via (1) and the technology choice through (2) or (3). Furthermore, u_{it} is technology-specific.

2.1 A two-step procedure

Before discussing the full fledged maximum likelihood method, we first examine whether there are simpler alternatives, namely, a two-step procedure that can give consistent estimates of the technology. Since the technology choice is not random, i.e., $E(v_{it} - u_{it}|I_{it} = 1 \text{ or } 0)$ is non-zero (depends on the z variables) even if v and e are independent, the estimates of the production function parameters in (1), after assuming a functional form on it, are likely to be inconsistent (Heckman type selectivity bias). In such a case, one can perform the Heckman-type sample selectivity correction (Sipiläinen and Oude Lansink 2005) to correct for endogeneity in the technology choice decision. However, the choice equation cannot be estimated using probit/logit because of the presence of the unknown inefficiency term (u_{it}). Thus, the two-step procedure (estimating the adoption equation first and then using the inverse Mill's ratio in the production functions) is problematic in the present situation.

How about using the above two-step procedure in the reverse order? *Step 1*: Estimate the production function in (1) separately for the organic and conventional farms, and obtain estimates of technical inefficiency (u_{it}) using the Jondrow et al. (1982) formula. *Step 2*: Use the estimated inefficiency in the choice Eqs. 2 or 3 and estimate it using the standard binary choice models (probit or logit) regression. There are two problems associated with this procedure. First, since the technology choice is endogenous (not randomly assigned); estimates of the production function in (1) are likely to be inconsistent (Heckman type selectivity bias). That is, endogeneity of technology choice is completely ignored. Consequently, estimated inefficiencies based on these inconsistent parameter estimates are likely to be wrong. Second, although the purpose of this second stage regression is to analyze determinants of technology choice, this information is not used in the

[5] The normality assumption on e_{it} can be easily relaxed if we specify that $P(I_{it} = 1|u_{it}) = F(z_{it}'\gamma + \delta u_{it})$ where F is any cdf. We used two other distributions in the empirical application.

[6] Mixture models for production or cost frontiers are considered in Orea and Kumbhakar (2004) and Tsionas et al. (2006). For stochastic frontier models in general see Kumbhakar and Lovell (2000) and Greene (1993, 2001).

[7] See Tsionas and Papadogonas (2006) for a model where technical inefficiency is a determinant of exit.

estimation of the technology. Thus none of the two-step procedures work for the model at hand. To make use of endogeneity of technology choice in the estimation of the production functions we now move to the single-step maximum likelihood (ML) method.

2.2 The single-step ML procedure

Our analysis in this section is conditional on x_{it}, z_{it}, and the parameter vector, θ. Our objective here is to derive the joint distribution of y_{it} and I_{it}. To do so, we make the following assumptions:

$$y_{it}|I_{it}, u_{it} \sim N(x'_{it}\beta_{I_{it}} - u_{I_{it}}, \sigma^2_{v,I_{it}}),$$
$$P(I_{it}=1|u_{it}) = F(z'_{it}\gamma + \delta u_{it}),$$
$$u_{it}|I_{it} \sim N^+(0, \sigma^2_{u,I_{it}}).$$

The assumption that technical inefficiency depends on the choice between organic and conventional farming is critical and requires special care as we show later. Conditional on the latent inefficiency, the joint distribution of y_{it} and I_{it} can be expressed as

$$p(y_{it}, I_{it}|u_{it}) = p(y_{it}|I_{it}, u_{it})p(I_{it}|u_{it}) \tag{4}$$

which is expressed as

$$p(y_{it}, I_{it}|u_{it}) = f_N(y_{it}|x'_{it}\beta_{I_{it}} - u_{I_{it}}, \sigma^2_{v,I_{it}})F(z'_{it}\gamma + \delta u_{it})^{I_{it}} \times \left[1 - F(z'_{it}\gamma + \delta u_{it})\right]^{1-I_{it}}, \tag{5}$$

where $f_N(y|\mu, \sigma^2)$ denotes the density of normal distribution for the random variable y, with mean μ and variance σ^2. The unconditional density of the joint distribution of y_{it} and I_{it} is

$$p(y_{it}, I_{it}) = \int_0^\infty p(y_{it}, I_{it}|u_{it})p(u_{it})du_{it}, \tag{6}$$

where $p(u_{it})$ is the marginal distribution of the latent technical inefficiency. This integral cannot be computed in closed form. Furthermore, we have to deal with another complication because u_{it} and I_{it} are not independent, that is we allow for the possibility that conventional and organic farming do not have the same inefficiency distribution. The problem is how to obtain the marginal distribution of inefficiency to use in connection with (6).

To evaluate (6) we proceed as follows. Let

$$\varphi_{it} = P(I_{it}=1) = \int_0^\infty F(z'_{it}\gamma + \delta u_{it})p(u_{it})\mathrm{d}u_{it}, \tag{7}$$

which is the marginal probability of organic farming. The marginal distribution of inefficiency has density

$$p(u_{it}) = f_N^+(u_{it}|\sigma^2_{u,0})P(I_{it}=0) + f_N^+(u_{it}|\sigma^2_{u,1})P(I_{it}=1),$$

from which we obtain

$$p(u_{it}) = f_N^+(u_{it}|\sigma^2_{u,0}) + \varphi_{it}\left[f_N^+(u_{it}|\sigma^2_{u,1}) - f_N^+(u|\sigma^2_{u,0})\right], \tag{8}$$

where $f_N^+(u_{it}|\sigma^2_u) = \left(\pi\sigma^2_u/2\right)^{-1/2} \exp\left(-u^2_{it}/2\sigma^2_u\right), u_{it} \geq 0$, is the density of the half-normal distribution. Substituting this in (7) and solving for φ_{it} we get

$$\varphi_{it} = \frac{A_{it}(\sigma^2_{u,0})}{1 + A_{it}(\sigma^2_{u,0}) - A_{it}(\sigma^2_{u,1})}, \tag{9}$$

where

$$A_{it}(\sigma^2) = \int_0^\infty F(z'_{it}\gamma + \delta u_{it})f_N^+(u_{it}|\sigma^2)\mathrm{d}u_{it}. \tag{10}$$

Given the expression for φ_{it}, the marginal distribution of latent inefficiency can be obtained through (8). In turn, this must be substituted in (6) to obtain the joint distribution of observed endogenous variables.

The integral in (10) has to be evaluated twice, for $\sigma^2 = \sigma^2_{u,0}$ and $\sigma^2 = \sigma^2_{u,1}$. This integral is not available in closed form so it must be evaluated by numerical integration. Subsequently, once (8) has been evaluated, it must be substituted in (6) and evaluate the integral numerically. The final expression becomes

$$\begin{aligned} p(y_{it}, I_{it}) &= \int_0^\infty f_N(y_{it}|x'_{it}\beta_{I_{it}} - u_{it}, \sigma^2_{v,I_{it}})F(z'_{it}\gamma + \delta u_{it})^{I_{it}} \\ &\quad \times \left[1 - F(z'_{it}\gamma + \delta u_{it})\right]^{1-I_{it}} \cdot \Big\{f_N^+(u_{it}|\sigma^2_{u,0}) \\ &\qquad + \varphi_{it}\left[f_N^+(u_{it}|\sigma^2_{u,1}) - f_N^+(u_{it}|\sigma^2_{u,0})\right]\Big\}\mathrm{d}u_{it}, \end{aligned} \tag{11}$$

where φ_{it} is evaluated numerically using (9) and (10). Since φ_{it} does not depend on u this integral can be evaluated as

$$\begin{aligned} p(y_{it}, I_{it}) = \varphi_{it} &\int_0^\infty f_N(y_{it}|x'_{it}\beta_{I_{it}} - u_{it}, \sigma^2_{v,I_{it}})F(z'_{it}\gamma + \delta u_{it})^{I_{it}} \\ &\times \left[1 - F(z'_{it}\gamma + \delta u_{it})\right]^{1-I_{it}} f_N^+(u_{it}|\sigma^2_{u,1})\mathrm{d}u_{it} \\ &+ (1 - \varphi_{it}) \int_0^\infty f_N(y_{it}|x'_{it}\beta_{I_{it}} - u_{it}, \sigma^2_{v,I_{it}}) \\ &\times F(z'_{it}\gamma + \delta u_{it})^{I_{it}}\left[1 - F(z'_{it}\gamma + \delta u_{it})\right]^{1-I_{it}} \\ &\times f_N^+(u_{it}|\sigma^2_{u,0})\mathrm{d}u_{it} \end{aligned} \tag{12}$$

If we define

$$J_{it}(\sigma^2) = \int_0^\infty f_N(x_{it}'\beta_{I_{it}} - u_{it}, \sigma^2_{v,I_{it}}) F(z_{it}'\gamma + \delta u_{it})^{I_{it}} \times \left[1 - F(z_{it}'\gamma + \delta u_{it})\right]^{1-I_{it}} f_N^+(u_{it}|\sigma^2) \mathrm{d}u_{it}, \quad (13)$$

then (12) can be expressed in a simpler form, viz.,

$$p(y_{it}, I_{it}) = \varphi_{it} J_{it}(\sigma^2_{u,1}) + (1 - \varphi_{it}) J_{it}(\sigma^2_{u,0}), \quad (14)$$

which shows that the joint distribution is, in fact, a mixture of distributions. The expression for $J_{it}(\sigma^2)$ in (13) can alternatively be expressed as

$$J_{it}(\sigma^2) = \left(2\pi\sigma^2_{v,I_{it}}\right)^{-1/2} \left(\pi\sigma^2/2\right)^{-1/2} \times \int_0^\infty F(z_{it}'\gamma + \delta u_{it})^{I_{it}} \left[1 - F(z_{it}'\gamma + \delta u_{it})\right]^{1-I_{it}} \times \exp\left[-\frac{(u_{it} + \varepsilon_{it})^2}{2\sigma^2_{v,I_{it}}} - \frac{u_{it}^2}{2\sigma^2}\right] \mathrm{d}u_{it}, \;\; \varepsilon_{it} = v_{it} - u_{it} \quad (15)$$

As we mentioned before, the integral that appears above has to be evaluated by numerical integration techniques. Since the integrals involved are univariate, we use the quadrature method which is more efficient and economical than the simulated maximum likelihood estimation procedure.[8]

2.3 Estimation of inefficiency

Next, we address the issue of inefficiency measurement given the observed data. In standard stochastic frontier models technical inefficiency measurement can be performed using the Jondrow, Lovell, Materov and Schmidt (1982) estimator, viz., $E(u_{it}|\text{data, parameters})$. For this, we need to derive $p(u_{it}|y_{it}, I_{it})$, i.e., the conditional probability density function $u_{it}|$data, parameters), viz.,

$$p(u_{it}|y_{it}, I_{it}) = \frac{p(u_{it}, y_{it}, I_{it})}{p(y_{it}, I_{it})} = \frac{p(y_{it}|u_{it}, I_{it}) p(u_{it}|I_{it}) p(I_{it})}{p(y_{it}, I_{it})}, \quad (16)$$

which can be rewritten as

$$p(u_{it}|y_{it}, I_{it}) \propto p(y_{it}|u_{it}, I_{it}) p(u_{it}|I_{it}) = f_N(y_{it}|x_{it}'\beta_{I_{it}} - u_{it}, \sigma^2_{v,I_{it}}) f_N^+(u_{it}|\sigma^2_{u,I_{it}}). \quad (17)$$

The normalizing constant of the distribution and its moments are then obtained using numerical integration. More, specifically, we use (17) to compute $E(u_{it}|y_{it}, I_{it})$, which is used as a measure of inefficiency.

[8] See Greene (2003) for details on the use of simulated maximum likelihood procedure in estimating inefficiency using the stochastic frontier approach.

3 Data

The dairy farm data are collected from the bookkeeping farm database of MTT Economic Research. The data include detailed farm level information on production and costs on various items over the period from 1995 to 2002. Our sample consists of an unbalanced panel of 279 farms of which 49 farms (17.56%) are organic. The total number of observations is 1921. During the period of this sample, more than 20% of sample farms were organic producers for at least 1 year.

In the present analysis, we use one output (which is a composite measure of milk and other outputs) and five inputs (labor, land, energy, material and capital). Labor input is the sum of working hours on the farm (family and hired labor). The land area covers both own and rented arable land. Energy, materials (fertilizer, seed and purchased feed) and capital are expressed in monetary values. Capital input is measured as a sum of machinery and building capital stock. Since we do not have access to farm specific prices, we have converted monetary values of outputs and inputs to implicit quantities by deflating those using price indices of respective input and output categories published by Statistics Finland. Thus, quality differences are reflected in input and output quantities. This is important because organic farms may receive a price premium for their products. On the other hand, input prices for example for certified seeds in organic farming are in Finland higher than the prices of conventionally produced seeds. Table 1 presents the descriptive statistics of all farms and conventional and organic farms separately.

It can be seen from Table 1 that the average farm size in Finland is small (the average arable land area is slightly more than 39 ha). The average number of animal units is approximately 31. Organic farmers cultivate, on average, a significantly larger land area and possess a larger number of animals compared to conventional farmers. However, the average milk output on organic farms is 10% smaller compared with conventional farms. On the other hand, organic farms produce a wider array of products indicating that they are more diversified than conventional farms. There are no significant differences in the usage of other inputs except in the arable land area although the capital input is larger on organic farms. Livestock densities do not differ significantly either but milk output per hectare is significantly higher on conventional farms. On the contrary, support per hectare is significantly higher on organic farms. This support measure includes all subsidies except investment aids. The average age of farmers in our sample is 44 years. Organic farmers are significantly younger than conventional farmers.

Usage of inputs and production of outputs have increased steadily over time. On the input side, the growth has been the fastest for the capital input, which has almost doubled

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

	All farms (N = 1,921)		Conventional (N = 1,756)		Organic (N = 165)	
	Mean	Std[b]	Mean	Std	Mean	Std
Output (€)	60,716	29,864	60,983	29,114	57,875	36,897
Input						
Labor (h)	5,033	1,485	5046	1,477	4897	1,566
Land (ha)[a]	39.2	21.5	38.5	19.8	46.9	33.6
Energy (€)	4,671	2625	4,652	2,620	4,868	2,682
Material (€)	32,668	19,606	32,559	18,829	33,827	26,547
Capital (€)	85,174	67,693	84,508	67,274	92,265	71,834
Livestock units[a]	31	16	31	15	35	22
Livestock-intensity	0.87	0.33	0.87	0.33	0.84	0.34
Milk-intensity[a]	3,903	1,686	3,971	1647	3181	1,917
Support (€/ha)[a]	515	129	500	120	669	125
Age of farmer[a]	44	9	45	9	43	7.7

[a] According to t-test, the means of conventional and organic farms differ significantly at least at the 5% level of significance

[b] Std refers to standard deviation

during the period. The use of materials has increased by the same rate as milk output (60%) but the arable land area has increased less (25%) and use of energy has even decreased slightly. Labor input has remained at the same level for the whole sample period in spite of the increase in output. Changes in input shares suggest a substantial substitution of capital for labor and energy during this period.

Table 2 shows how the experience in organic farming (measured in years) has developed during the sample period. The average experience in years has increased from four to five and a half years. Experience has been used as a proxy for managerial experience in several studies (Stefanou and Saxena 1988; Weersink et al. 1990; Bravo-Ureta and Rieger 1991; Reinhard 1999).

We used organic farming experience as a covariate in the adoption decision process, viz., whether to continue to be in organic farming, because the more experienced a farmer is in organic farming, the more likely that he will continue. In addition, the data includes the information about the location of the farm. Because of geographical differences, the country is divided into seven so called agricultural support regions. The regions reflect climatic conditions and differences between southern, central and northern Finland. When moving from south to north the growing period becomes shorter. In southern Finland the effective temperature sum is close to 1,300°C while it is less than 700 in the north. These climatic differences naturally affect productivity. Even the size of field plots and their location are less favorable in the northern than southern parts of the country. Shorter growing and grazing period also increase the need for larger feed and manure storages as well as better insulated buildings against severe cold during the winter. Regional dummy variables have therefore been used in the models to capture the differences in physical environment (Kumbhakar et al. 1991; Hallam and Machado 1996; Reinhard 1999; Tzouvelekas et al. 2001). Physical differences of the regions may also affect the competitiveness and choices made in relation to the use of available technologies. Therefore, the same regional dummy variables are also included in the technology choice model.

Production intensity is likely to affect the adoption of technologies. Farmers used to high intensity farming technique are less likely to shift to organic technology that is less intensive (such as lower feed output per hectare). We also used two intensity variables: milk intensity and animal density are indicators of how specialized a farm is. These intensity variables are related to production conditions because in less specialized and poor production conditions these intensity variables are lower. Higher intensities also usually reflect more intensive use of purchased feeding stuffs. Organic production is largely based on home grown forage.

Table 2 Average experience in organic farming

Year	N	Mean	Std	Min	Max
1995	18	4.06	2.41	1	8
1996	22	3.27	2.64	1	9
1997	24	3.96	2.66	1	10
1998	21	3.38	2.48	1	11
1999	21	4.85	2.85	1	12
2000	19	5.26	2.75	1	13
2001	19	5.16	2.63	1	11
2002	22	5.55	3.05	1	12

4 Results

Because of the problems associated with the two-step procedures mentioned in Sect. 2.1, we are not discussing results based on these models in details. We find evidence in favor of two separate technologies based on the standard likelihood ratio test. The parameters associated with organic and conventional technologies ignoring endogeneity of technology choice (first-step of the two-step procedure) are reported in the Appendix (Table A1). The second-stage estimators (parameters of the adoption equation) are reported in Table A2 under three different distributions on the noise term (e) in the adoption Eq. 3, viz., normal, logistic and extreme value. We used regional dummies in the adoption equation as well as in the production functions. The coefficients associated with the regional dummies are not reported in these tables to save space. Most of the coefficients associated with organic and conventional technologies as well as the inefficiency parameters are found to be statistically significant. The time trend variable is found to be negative (though not significant for the organic technology), which indicate that both organic and conventional farms experienced technical regress. Technical regress for the conventional farms is much higher (perhaps due to increased regulations over time). Negative technical change during this relatively short period of time is likely to be related to the Finnish EU-accession in 1995, which caused a marked change in prices and subsidies. The weather conditions in the late 1990s were also very poor. Technical change is also found to be low in other Finnish dairy farm studies.

So far as adoption is concerned experience, past adoption, subsidy provision and animal density are found to increase the probability of adopting/continuing organic farming. These results are quite intuitive. The positive and significant coefficient associated with a subsidy shows that organic farmers may be lured by subsidies. Inefficiency is, however, found to decrease the probability of adopting/continuing organic farming. That is, we do not find any evidence to support that inefficiency is a driving force behind adoption of organic farming technology. This finding makes sense. The efficient farmers can make a profit by switching because by doing so they are entitled to get an additional subsidy. Milk intensity is found to decrease the probability of adopting/continuing organic farming. When milk intensity is high, it is not possible to produce the feed for cows on their own fields, which is a prerequisite for organic farming. Intensive dairy farms are also highly specialized in milk. Thus, the switch from conventional production is often handicapped by ‘home grown’ feeding stuff. The coefficient of animal density is positive. Therefore, dairy farms that are less specialized in milk production but produce a relatively wide array of animal products are more likely to adopt organic farming practices.

Table 3 Productivity differential between conventional and organic farms

Productivity differential	Normal CDF	Logistic CDF	Extreme value CDF
Mean	21%	33%	37%

The parameter estimates from the single-stage ML approach are reported in Table A3.[9] The signs on the parameters associated with the organic and conventional technologies are robust across different models, although their magnitudes differ. The coefficients associated with the basic inputs (land, labor, capital, energy and material) are all positive and most of them are statistically significant. The trend variable (for the organic farms) has a negative coefficient (technical regress), except for the logistic distribution. However, the coefficient is not significant under any distribution. This is, however, not the case for the conventional farms. We find significant technical regress under all three distributions. So far as returns to scale (given by the sum of the input coefficients) is concerned, we do not find much difference between the conventional and organic farm technologies (1.036 vs. 1.052). Similar to the two-stage model, experience, past adoption and animal density are found to increase the probability of adopting/continuing organic farming. On the other hand, the opposite is true for inefficiency and milk intensity.

To examine whether the conventional technology is better than the organic technology, we compare the productivity differential between organic and conventional farming. Since the technologies use multiple inputs we compute productivity from that ratio $\hat{Y}/\hat{X}$ where $\hat{Y}$ is the predicted frontier output and $\hat{X}$ is a measure of aggregate input constructed from the estimated coefficients of individual inputs as weights (i.e., $\ln \hat{X} = \sum_j \hat{\alpha}_j \ln X_j$ where $X_j =$ land, labor, capital, energy and material). Differences in productivity between conventional and organic farms can then be computed from the log difference in $(\hat{Y}/\hat{X})$. Note that this measure is free from noise as well as inefficiency. It can be seen from Table 3 that, on average, conventional farms are more productive. The difference also depends on distributional assumption on the noise term in the adoption equation. As argued before, these differences can be used to justify subsidy to the organic farmers.

In the productivity comparison above, we did not control for input usage. Since input levels used by organic and conventional farms are different, we can make the comparison more meaningful by computing technology gap in the following manner. First, we compute output levels

[9] The coefficients on the regional dummies are not reported here to conserve space.

using the estimates of conventional and organic technologies (denoted by $\hat{Y}_c$ and $\hat{Y}_o$) and take the maximum value of $\hat{Y}_c$ and $\hat{Y}_o$ (i.e., $\hat{Y}_m = \max\{\hat{Y}_c, \hat{Y}_o\}$) at each data point. Then we compute the difference between $\hat{Y}_m$ and $\hat{Y}_o$ at each data point. If the difference is positive and the farm is using conventional technology, there will be no productivity gain in switching to organic farming, because the conventional technology is superior. On the other hand, if the difference is positive and the farm is using the organic technology (viz., an organic farmer), the difference can be viewed as output loss because the organic technology is inferior (produces less with the same input quantities). Alternatively, a positive difference means that if an organic farm decides to use the conventional technology with his input levels, he should be able to produce more. Unless this difference is positive for all organic farms we cannot say that the organic technology is inferior. In such a case, one could argue that unless the output loss is compensated by a higher output price the organic farmers cannot compete with the conventional farmers and will be out of business.

Our result on productivity differential (reported in Table 4) is sensitive to distributional assumptions on the error term in the adoption equation. For example, under the normality assumption we find that for 75% of the organic farms the technology is inferior. On average, they could have produced 5.3% more had they used the conventional technology, *ceteris paribus*. However, for the remaining 25% of the organic farms there would have been no gain had they moved to conventional farming. Thus, we cannot say that the technology is inferior for all organic farms. Only the extreme value distribution predicts that for 99% of the organic farms, output is lower because the technology they are using is inferior.

Now we examine technical efficiency of organic and conventional farms under different distributional assumptions on the distribution of the error term in the adoption equation. The results are reported in Table 5 and Figs. 1–3.

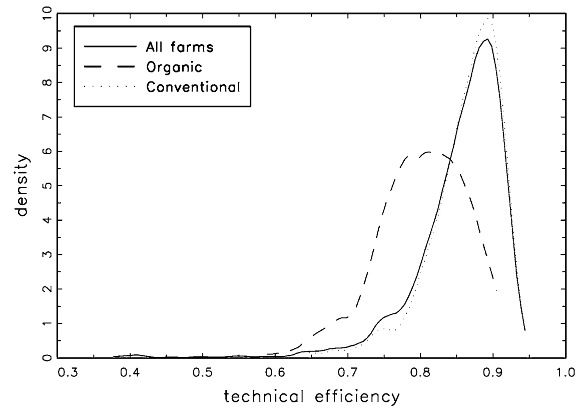

Fig. 1 Densities of technical efficiency –normal model

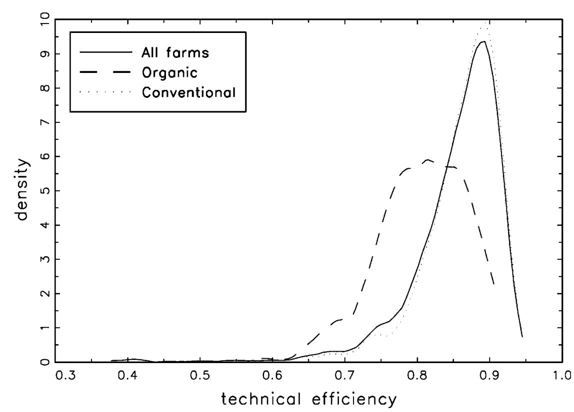

Fig. 2 Densities of technical efficiency –logistic model

It can be seen from Table 5 that (i) on average, organic farms are about 5% less efficient; and (ii) the mean efficiency is quite robust across different distributional assumptions. The extreme value distribution suggests higher relative inefficiency but a smaller difference between technologies. The density plot of the efficiency

Table 4 Productivity differential from switching

	Productivity differential	Normal CDF	Logistic CDF	Extreme value CDF
Conventional technology is better $\Rightarrow \hat{Y}_c - \hat{Y}_o > 0$	Mean (Median)	5.32% (4.24%)	7.73% (6.42%)	12.9% (12.12%)
	Percent of farms (organic)	75%	77%	99%

Table 5 Technical efficiency (single-stage ML) under different CDFs

	Normal CDF			Logistic CDF			Extreme value CDF		
	All	Organic	Conventional	All	Organic	Conventional	All	Organic	Conventional
Mean	0.854	0.796	0.859	0.853	0.798	0.858	0.759	0.744	0.761
Median	0.870	0.802	0.873	0.870	0.806	0.874	0.766	0.746	0.768
Std. dev	0.066	0.062	0.064	0.069	0.064	0.067	0.047	0.048	0.046
Min	0.374	0.587	0.374	0.374	0.584	0.374	0.396	0.595	0.396
Max	0.947	0.906	0.947	0.948	0.908	0.948	0.851	0.846	0.851

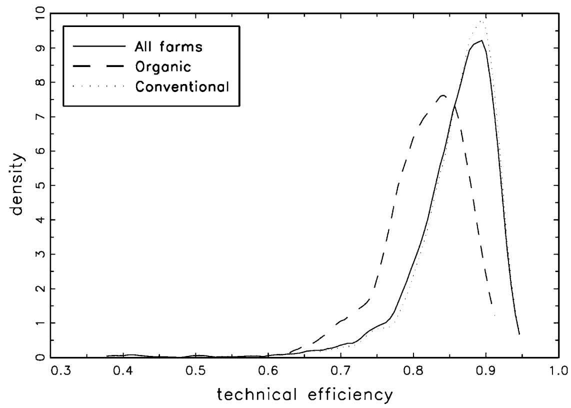

Fig. 3 Densities of technical efficiency –extreme value model

scores (Figs. 1–3) show that efficiency distributions are more concentrated for the conventional farms.

5 Discussion and conclusions

In recent years demand for organic products has increased tremendously due to consumers concern of health and safety of food products. In spite of this the percentage share of organic products in Europe as well as in the US has remained relatively small. Is it because productivity in organic farming is considerably lower than that of conventional farms? Are organic farms technically less efficient compared to the conventional farms? Is it subsidy that drives farmers in organic production? These questions are addressed in the present paper using dairy data from Finland. Following are the distinguishing features of the present study: (i) technologies of organic and conventional farms are allowed to be different, (ii) technology choice is endogenous, (iii) production efficiency (along with other exogenous covariates) affects technology choice decision. Since efficiency affects output as well as technology choice, we developed an econometric framework to estimate production technologies and technology choice/adoption decision simultaneously. Maximum likelihood method is used to estimate parameters of production technologies, which are then used to estimate efficiency of each organic and conventional farm. By doing so we could decompose productivity differentials into technology and efficiency components.

For example, under the normality assumption we find that for 75% of the organic farms the technology is inferior. On average, organic farmers could have produced 5.3% more had they used the conventional technology, *ceteris paribus*. Similarly, on average, organic farms are found to be about 5% less efficient. However, not all organic farms are inefficient. Finally, efficiency and subsidy are found to be driving forces behind adoption of organic technology (except for the logistic specification). Because subsidy is attracting efficient farms, one might hope that in the long run organic farms will be as efficient as the conventional ones. If so, in the long run subsidy will be necessary only if productivity shortfall of organic farms (pure technological not inefficiency) is not compensated by the price premium they receive.

Appendix

Table A1 Parameter estimates (first-stage stochastic frontier model)

Parameters	Organic technology			Conventional technology		
	Estimates	Std. err.	*T*-value	Estimates	Std. err.	*T*-value
Constant	2.2181	0.9256	2.397	2.4817	0.2303	10.776
Land	0.1347	0.0577	2.335	0.1211	0.0178	6.817
Labor	0.1806	0.0882	2.047	0.2634	0.0263	10.019
Capital	0.0625	0.0463	1.349	0.1089	0.0102	10.720
Energy	0.1228	0.0670	1.834	0.0108	0.0153	0.708
Material	0.5523	0.0849	6.501	0.5344	0.0168	31.772
Time	−0.0132	0.0132	−1.001	−0.0213	0.0027	−7.894
σ_v	0.2220	0.0357	6.215	0.1223	0.0077	15.897
σ_u	0.2944	0.0763	3.856	0.3333	0.0262	12.712

Table A2 Parameter estimates (second-stage adoption model)

Parameters	Normal CDF			Logistic CDF			Extreme value CDF		
	Estimates	Std. err.	*T*-value	Estimates	Std. err.	*T*-value	Estimates	Std. err.	*T*-value
Constant	−2.5428	0.3676	−6.917	−4.4208	0.8027	−5.508	−1.8931	0.2433	−7.781
Experience	2.9490	0.3644	8.092	1.3929	1.4840	0.939	1.2161	0.4546	2.675
Milk intensity	−0.2722	0.1033	−2.635	−0.6039	0.2162	−2.794	−0.1832	0.0690	−2.657
Animal intensity	1.3478	0.6663	2.023	2.5959	1.5765	1.647	0.9542	0.4560	2.092
Lag adoption	1.3243	0.4313	3.071	5.4372	2.0936	2.597	3.5488	0.6695	5.301
Subsidy	0.4184	0.0728	5.747	0.8319	0.1424	5.841	0.3337	0.0604	5.523
Inefficiency	−1.1770	0.6589	−1.786	−2.8626	1.3220	−2.165	−0.7354	0.4040	−1.821

Table A3 Parameter estimates (single-stage ML) under different CDFs

Parameters	Normal CDF			Logistic CDF			Extreme value CDF		
	Estimates	Std. err.	*T*-value	Estimates	Std. err.	*T*-value	Estimates	Std. err.	*T*-value
Organic technology									
Constant	2.2536	0.8636	2.610	2.3204	0.8557	2.712	2.1882	0.9506	2.302
Land	0.1394	0.0550	2.533	0.1469	0.0560	2.622	0.1335	0.0598	2.234
Labor	0.1815	0.0873	2.078	0.1774	0.0852	2.083	0.1830	0.1010	1.811
Capital	0.0586	0.0449	1.305	0.0442	0.0447	0.989	0.0633	0.0459	1.379
Energy	0.1213	0.0653	1.858	0.1144	0.0666	1.718	0.1231	0.0687	1.790
Material	0.5512	0.0827	6.663	0.5599	0.0839	6.672	0.5523	0.0847	6.524
Time	−0.0107	0.0133	−0.804	0.0078	0.0147	0.527	−0.0133	0.0146	−0.914
σ_v	0.3390	0.0266	12.722	0.3476	0.0375	9.279	0.4713	0.0702	6.713
σ_u	0.3403	0.0593	5.738	0.2841	0.4734	0.600	0.2948	0.0552	5.341
Conventional technology									
Constant	2.4498	0.3319	7.382	2.4615	0.3979	6.187	2.4795	0.6008	4.127
Land	0.1254	0.0187	6.694	0.1409	0.0232	6.086	0.1211	0.0209	5.800
Labor	0.2642	0.0343	7.691	0.2616	0.0379	6.909	0.2636	0.0558	4.720
Capital	0.1085	0.0130	8.322	0.1050	0.0133	7.881	0.1088	0.0158	6.879
Energy	0.0047	0.0159	0.293	0.0059	0.0155	0.380	0.0109	0.0212	0.513
Material	0.5334	0.0221	24.127	0.5330	0.0254	21.015	0.5345	0.0379	14.098
Time	−0.0240	0.0028	−8.675	−0.0244	0.003	−8.780	−0.0213	0.0041	−5.128
σ_v	0.1876	0.0116	16.221	0.1857	0.0157	11.858	0.3721	0.1079	3.447
σ_u	0.3259	0.0586	5.565	0.0033	0.0001	31.410	0.3341	0.5842	0.572
Adoption									
Constant	−2.0022	0.3446	−5.809	−3.881	1.5044	−2.580	−0.6723	0.1963	−3.424
Experience	2.9776	0.3523	8.452	1.408	0.9811	1.436	1.1417	0.4696	2.431
Milk intensity	−0.4366	0.1163	−3.755	−0.913	0.3478	−2.625	−0.2801	0.0816	−3.431
Animal intensity	1.3909	0.7904	1.760	2.577	1.9151	1.346	0.8162	0.4882	1.672
Lag adoption	1.3471	0.4935	2.730	5.491	1.9755	2.780	4.0991	0.7101	5.773
Subsidy	0.4229	0.0711	5.945	0.918	0.1573	5.834	0.4132	0.0561	7.365
Inefficiency	−1.1354	0.4426	−2.565	−2.815	3.0705	−0.917	−0.5229	0.1735	−3.015

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