TECHNICAL, ALLOCATIVE, AND ECONOMIC EFFICIENCY IN SWEDISH DAIRY FARMS: THE DATA ENVELOPMENT ANALYSIS VERSUS THE STOCHASTIC FRONTIER APPROACH

Helena Johansson, Swedish University of Agricultural Sciences (SLU), PO-Box 7013, SE-75007, Uppsala, Sweden. Tel: +46(0)18-671714. E-mail: Helena.Johansson@ekon.slu.se

Poster background paper prepared for presentation at the XI:th International Congress of the European Association of Agricultural Economists (EAAE), Copenhagen, Denmark, August 24-27, 2005

Abstract

Technical, allocative, and economic input efficiency scores were estimated for an unbalanced panel of Swedish dairy farms, using data envelopment analysis (DEA) and the stochastic frontier approach (SFA). By comparing the results it was concluded that when the entire dairy farm is studied the DEA is more appropriate to use since it does not require any particular parametric form to be chosen. The average DEA technical, allocative and economic efficiency indices were eventually found to be 0.77, 0.57, and 0.43 respectively. The influence of size on the efficiency scores was analyzed and significant evidence indicating a positive relationship between size and efficiency was found. Finally it was concluded that the main challenge facing the Swedish dairy farms is to enhance their cost minimizing skills.

Keywords: Technical efficiency, allocative efficiency, economic efficiency, data envelopment analysis, stochastic frontier approach

JEL classification: C14, C23, C24

1 Introduction

Efficiency in production is a way to ensure that products of firms are produced in the best and most profitable way. To prevent waste of recourses, efficiency is of great importance for every sector in the economy, but for the agricultural sector, the up-coming Mid Term Review will radically increase the already high need of efficiency. In addition, in Sweden the dairy farms are undergoing huge structural changes which implies that they are becoming fewer and larger. This means that they have to face new kinds of problems, like having employees and greater debt, implying that the sensitivity to slacks due to inefficiencies will become more severe. Also, the seemingly constant low profitability in dairy production stresses the importance of efficiency.

Following Farrell (1957) one can describe technical and allocative efficiency of firms. (The latter is referred to as price efficiency in Farrell's seminal article). From the output perspective, technical efficiency measures the potential increase in output, keeping the inputs constant. Allocative efficiency from the output perspective is simply the revenue maximizing problem. Technical efficiency from the input perspective measures the ability of the firms to produce a given output using the smallest set of inputs. Allocative efficiency in this case measures the firm's ability to allocate the input bundle in the cost minimizing way. Combining measures of technical and allocative efficiency yields a measure of economic efficiency. The output and input perspective will coincide when measuring technical efficiency under constant returns to scale. The allocative and economic efficiency measures however are completely different in nature and are not likely to coincide for other reasons than by chance.

As was pointed out in Alvarez (2004) various degrees of inefficiency in production seems to be the rule rather than the exception. Bravo-Ureta and Rieger (1991) studied technical, allocative, and economic efficiency of a sample of New England dairy farms, using the stochastic frontier approach (SFA) and a Cobb-Douglas production function. They found overall economic inefficiencies of on average 30 %. However it was little difference between mean technical (83.0%) and mean allocative efficiency (84.6%). Lansink et al (2002) studied technical efficiency of Finnish farms, using the data envelopment analysis (DEA), and found that the conventional livestock farms had technical efficiency scores of 69 %. Heshmati and Kumbhakar (1994) examined the technical efficiency of four panels of Swedish dairy farms, during the period 1976 – 1988, excluding 1985, using the stochastic frontier approach and a translog production function. They found that the mean technical efficiency indices were located between 0.81 and 0.83 for all four panels. This indicates technical inefficiencies of almost 20 % in the Swedish dairy farms. Jonasson (1996) measured various output efficiencies of a sample of Swedish farms during 1989 – 1991, using (DEA). He found that the average technical and allocative output efficiencies where 0.95 and 0.92 respectively. A possible reason for the great difference between the two studies in Sweden is that Jonasson didn't aggregate output in DEA. Adding an extra output or input in DEA will never cause a reduction of the efficiency scores and a greater number of outputs and inputs compared to the total number of observations will always cause greater efficiency scores. (Coelli et al, 2002). Thus, the difference is much likely to depend on the differences in the methods. Although data envelopment indices should not be used for comparison between different studies (Coelli et al, 2002), since the scores only measure the relative efficiency within the sample, there are evidence of technical, allocative, and economic inefficiencies in dairy farms.

Farm size is a parameter which has revealed significant influence on efficiency. For example Bravo-Ureta and Rieger (1991) found a significant positive relationship between technical efficiency and farm size in the sample of New England dairy farms. However, the relationship between economic efficiency and allocative efficiency and size was found to be significantly negative. Bailey et al. (1989), who estimated technical, allocative and economic efficiency on a sample of Ecuadorian dairy farms, also found a positive relationship between size and technical efficiency. In contrast to the New England study, medium-sized Ecuadorian farms were found to be as allocatively efficient as large farms.

As has already been indicated, the results of an efficiency study can be sensitive to the method selected to estimate the efficiency scores. The two most popular techniques used to measure farm efficiency are the DEA (Charnes et al. 1978) and the SFA (Aigner et al. 1977; Meeusen and van den Broeck 1977). The former uses mathematical linear programming methods, whereas the latter uses econometric methods. The choice of which method to use is in no way obvious, but has to be decided in every case. The quality of the data, the appropriateness of various functional forms, and the possibility of making behavioural assumptions will heavily influence the relative appropriateness of DEA and SFA. For example, the DEA approach, compared to the SFA doesn't require any specific functional form to be selected, neither are any behavioural assumptions needed as long as allocative efficiency is not considered. However, DEA is a deterministic approach, meaning that it doesn't account for noise in the data. All deviations from the frontier will thus be accounted for as inefficiencies. Therefore the DEA efficiency scores are likely to be sensitive to measurements errors and random errors. The SFA on the other hand accounts for random errors and has the advantage of making inference possible. (Coelli et al, 2002). However, SFA is sensitive to the choice of functional form.

Obviously, choosing between parametric and nonparametric methods is a delicate matter and some studies comparing the results of two approaches have been done. An example outside the agricultural sector is Coelli and Perelman (1999) who compared technical efficiency scores on a sample of European railways. They found that the choice of method should not have much influence on the results. Resti (1996) compared cost efficiency scores on a sample of Italian banks. She found that there was not much difference between the two methods. In agriculture, an example is Iráizoz et al (2003) who compared technical efficiency results on a sample of Spanish vegetable producers, and found correlation between the parametric and nonparametric approach. As far as we are aware of the only study that compares the decomposition of economic efficiency into its technical and allocative parts under parametric and nonparametric approaches is Sharma et al (1999) who studied swine producers in Hawaii. In their study the SFA the technical efficiency was measured against a Cobb-Douglas production function. They found that, on average, the estimated technical and economic efficiencies were significantly higher in the SFA compared to the DEA under the assumption of constant returns to scale (CRS). Under the assumption of variable returns to scale (VRS) however, the measures were quite similar. Allocative efficiency was found to be generally higher in DEA. The efficiency ranking of the farmers in the sample was positively correlated, indicating that the two approaches assess relative efficiency to the same farms.

As DEA reports all deviations from the frontier as inefficiency, and thus should report lower efficiency scores compared to SFA it is possible to assume that DEA is the better choice whenever the reported scores are higher under DEA. Higher DEA results is an indication of miss specification of the functional form used in SFA. When analysing the technical and allocative parts of economic efficiency, as in the example of Sharma (1999), a dual functional form (i.e Cobb-Douglas) has to be chosen. Higher scores under DEA implies that restrictions of functional form under SFA is inappropriate.

The issue of which method to use when analysing technical, allocative and economic efficiency in dairy farms is still unexplored. A direct analogy to the study by Sharma (1999) would not be possible since dairy farms are characterised by multiple output in a more complicated way than swine farms. Producing milk without producing beef in one way or the other would be impossible. Furthermore, usually a higher proportion of the harvested crops and all forage is used as intermediate products at dairy and beef farms. Neither would an analogy to Irázoz et al (2003) be possible, since the results are likely to differ when allocative and economic efficiencies are also considered. An analogy to the studies outside the agricultural sector is not possible for the same reason, but also because agriculture is likely to differ much from other sectors in the economy. One reason is the strong connection to and dependence on the farm family. The multiple output situation of dairy farms is a fact that was neglected in the study by Bravo-Ureta and Rieger (1991) referred to above. They used the produced amount of milk in hundredweights as output. It was also neglected in Bailey (1989) who only accounted for the milk production. As the economic situation of the farmers is determined by the entire production, it is important to incorporate the whole production in the analysis. Efficiency in one part of the production is no guarantee for efficiency in an other part. Actually, it may well be the case that efficiency in one part makes the farmer feel that inefficiency in other parts of the production can be "afforded".

The aim of the present paper is twofold. First, we want to compare the relative appropriateness of DEA and SFA in estimating technical, allocative, and economic efficiency scores in dairy production. Second, we want use the results from this evaluation to establish measures of technical and allocative efficiency to analyse the economic input efficiency of Swedish dairy farms, and how the efficiency measures are influenced by farm size. Considering the changing structure and market situation of these farms, studies of the economic input efficiency is of high importance to understand the challenges facing the dairy farmers. As the trend in the Swedish dairy farms seems to be towards bigger herds it will also be interesting to investigate the relationship between efficiency and farm size. This study would give us un idea about the orientation of the problems facing the dairy farms on their way to becoming more economically efficient.

2 Methodology

The idea behind efficiency studies is to measure a firm's position relative to an efficient frontier, resulting in an efficiency score of the firm. The efficiency scores will be bounded between zero and one, where a score of one indicates full efficiency. A consequence of this and the fact that the economic efficiency is the product of the technical and allocative efficiencies, is that the technical efficiency can never be smaller than the economic efficiency, since this would lead to allocative efficiency scores greater than one. Measurement of efficiency requires knowledge of the efficient production function, which thus has to be estimated from the sample data.

As was pointed out in the previous section, DEA and SFA are two techniques of estimating a firm's relative position to the frontier. When using SFA, estimation via the production, cost or profit function is possible. The cost and profit functions are both dual to the production function, and thus they can be derived from the estimates. Cost and profit functions have the advantage of allowing for multiple output, but if we want to limit the behavioural assumptions, as we do in this study, the production function is probably a better choice. (Coelli, 1995) We also believe that our data on inputs have higher quality than our price data, making the production function a more suitable choice. (See section 3.1) Below follows a description of the two techniques employed in this article for measuring the efficiency indices.

2.1 DEA

The idea behind DEA is to use linear programming methods to construct a surface, or frontier around the data. Efficiency is measured relative to this frontier, where all deviations from the frontier are assumed to be inefficiency.

Consider n firms producing m different output using h different inputs. Thus, Y is an m*n matrix of outputs and X is an h*n matrix of inputs. Both matrices contains data for all n firms. The technical efficiency (TE) measure under the assumption of constant returns to scale (CRS), can be formulated as follows:

$$\begin{array}{ll} & \min_{q,l} q \\ \textit{Subject to} & -y_i + Yl \geq 0, \\ & qx_i - Xl \geq 0, \\ & l \geq 0 \\ & q \in (0,1] \end{array} \tag{1}$$

and solved for each firm in the sample. q_i is firm i’s index of technical efficiency relative to the other firms in the sample. y_i and x_i represents the output and input of firm i respectively. Yl and Xl are the efficient projections on the frontier. A measure of $q_i = 1$ indicates that the firm is completely technically efficient. Thus, $1-q_i$ measures how much firm i’s inputs can be proportionally reduced without any loss in output. However, the assumption of CRS is correct only as long as firms are operating at an optimal scale (Coelli et al, 2002). Various constraints on inputs like financing, and the goals of the owner may cause the firm to operate at a non-optimal scale. Using the CRS DEA model when firms are not operating at their optimal scale will cause the TE-measures to be influenced by scale efficiencies and thus the measure of technical efficiency will be incorrect. By adding a convexity constraint to the model above VRS is instead assumed:

$$\begin{array}{ll} & \min_{q,l} q \\ \textit{Subject to} & -y_i + Yl \geq 0, \\ & qx_i - Xl \geq 0, \\ & N1' l = 1 \\ & l \geq 0 \\ & q \in (0,1] \end{array} \tag{2}$$

The new constraint is $N1' l = 1$ where N1 is a n*1 vector of ones. This constraint makes the comparison of firms of similar size possible, by forming a convex hull of intersecting planes, so that the data is enveloped more tightly. The technical efficiency measures under VRS will always be at least as great as under the CRS-assumption.

In order to derive the economic efficiency of the firm, the following model is solved:

$$\begin{array}{ll} \textit{Subject to} & \min_{l,x_i^*} w_i' x_i^* \\ & -y_i + Yl \geq 0 \\ & x_i^* - Xl \geq 0 \\ & N1' l = 1 \\ & l \geq 0 \\ & q \in (0,1] \end{array} \tag{3}$$

where w_i represents firm i’s vector of input prices and x_i^* is the cost-minimizing input bundle faced by firm i. The economic efficiency for firm i is then solved by the following computation:

$$EE_i = \frac{w_i ' x_i^*}{w_i ' x_i} \tag{4}$$

that is, the observed cost is compared to the minimum cost the firm would face if using the optimal input bundle. Furthermore, the allocative efficiency (AE) of firm i can calculated as follows:

$$AE = \frac{EE}{TE} \tag{5}$$

which measures firm i's relative ability to allocate the input-bundle in the cost-minimizing way, given the estimated technology.

Panel data will be used in the present study. However, as far as we are aware of, there are no methods for estimating allocative and economic efficiency using DEA and panel data. Therefore equation 2 and 3 will be solved once for each farm and year. This means that each year is treated as a cross section dataset. To estimate technical efficiency there are panel data methods for the DEA (the Malmqvist index), but it is not possible to use here as all efficiency indices must be measured against the same frontier production function.

2.2 SFA

Following Battese and Coelli (1992) we consider a stochastic production function for unbalanced panel data:

$$Y_{it} = f(x_{it}; b) + e_{it} \tag{6}$$

where Y_{it} is the natural logarithm of the production of the i:th firm in the t:th period of time, $f(x_{it}; b)$ is a function of a logged input vector x_{it} for the i:th firm in the t:th period of time and the parameters to be estimated. The error term e_{it}, is defined as follows:

$$e_{it} = v_{it} - u_{it} \tag{7}$$

and

$$u_{it} = (u_i \exp(-h(t - T))) \tag{8}$$

where the v_{it} represents the random errors, assumed to be independent and identically distributed $N(0, s_v^2)$ and the u_{it}'s, which represents the technical inefficiency, are assumed to be identically and independently distributed non-negative truncations at zero of the $N(m, s^2)$ distribution. h is a time parameter to be estimated and t is time. Thus, technical efficiency is allowed to change over time. This model do not impose any firm specific effects, which means that it doesn't account for possible heterogeneity between farms in the sample. This makes comparison with DEA easier since there are no firm effects in the DEA model.

Maximum likelihood estimation of equation (6) provides estimates of b and the variance parameters, $s^2 = s_v^2 + s_u^2$ and $g = \frac{s_u^2}{s^2}$. Mean technical efficiency is defined as

$$TE_t = E\left[\exp(-h_t U_i)\right] \tag{9}$$

where

$$h_t = \exp\left[-h(t-T)\right] \tag{10}$$

As in Bravo-Ureta and Rieger (1991) and in Sharma et al (1999) we follow the Kopp and Diewert (1982) cost decomposition procedure which yields measures of economic efficiency and allocative efficiency. Subtracting v_{it} from both sides of equation (6) gives

$$Y_{it}^{*} = Y_{it} - v_{it} = f(\mathbf{x}_{it}; b) - u_{it} \tag{11}$$

where Y_{it}^{*} is the observed output of firm i in period t, adjusted for the white noise, v_{it}. The technically efficient input vector $(\mathbf{x}_{it}^{te})$ for a given level of output Y_{it}^{*}, is obtained by simultaneously solving equation (11) and the input ratios $\frac{x_{1t}}{x_{it}} = k_{it}$ $(i > 1)$, where k_{it} is the ratio of the observed inputs at the output level Y_{it}^{*} in period t.

Assuming that the production function is self-dual, i. e. Cobb-Douglas, the corresponding cost function can be derived algebraically and written in its general form as follows:

$$C_{it} = f(w_{hit}, y_{it}^{*}) \tag{12}$$

where c_{it} is the minimum cost associated with production y_{it}^{*} of firm i in period t and w_{ht} is the price of the h:th input in period t. Applying Shephard's lemma we obtain

$$\frac{dc_{it}}{dw_{hit}} = x_{hit}(w_{it}, y_{it}^{*}), \quad h = 1,2,\ldots,h \text{ inputs} \tag{13}$$

which is a system of minimum cost input demand equations.

The economically efficient input demand vector (x_{it}^{ee}) is obtained by substituting the firm's input prices and output level from equation (11) into equation (13).

The technically and economically efficient input vectors are used to calculate the cost of the technically and economically efficient input combination of firm i in the time period t, $w_{it}' x_{it}^{te}$ and

$w_{it}'x_{it}^{ee}$, respectively. Combined with the observed cost $w_{it}'x_{it}$, the economic efficiency measures can be computed as follows:

$$EE_{it} = \frac{w_{it}'x_{it}^{ee}}{w_{it}'x_{it}} \tag{14}$$

Realizing that technical efficiency can be described as follows

$$TE_{it} = \frac{w_{it}'x_{it}^{te}}{w_{it}'x_{it}} \tag{15}$$

and following Farrel (1957), these measures can be combined to yield a measure of allocative efficiency:

$$AE_{it} = \frac{EE_{it}}{TE_{it}} = \frac{w_{it}'x_{it}^{ee}}{w_{it}'x_{it}^{te}} \tag{16}$$

3 Data and empirical specification

Data from the Farm Economic Survey from Statistics Sweden was used in this study. Statistics Sweden collects numerous data from different kinds of farms, and the main purpose for the data is to be the base of the Farm Accounting Data Network (FADN). The basic data is used in this study, not the FADN variables, because the basic data is more detailed. The basic data consists of the balance sheets, the income statements and some additional information like harvest and time worked, reported for each farm. Information on prices of the inputs came from a database consisting of gross margin budgets for different agricultural production lines and regions in Sweden (www.agriwise.org).

A dairy farm is defined as a farm selling milk, and thus our sample consists of the farms in the basic data delivering milk to a dairy plant processor. The time period of the study is from 1998 through 2002. The reason for this choice is that the data before 1998 was presented in a very different way compared to 1998 and after, and the data for the years after 2002 was not yet reported when the study was started.

Statistics Sweden uses a rotating panel for the basic data. This means that the panel used in the present study is unbalanced and thus all farms will not be studied during the entire period. The number of dairy farms in the panel 1998 through 2002 was 428, 417, 394, 350 and 351 respectively, which means that the total number of observations in the econometric analysis was 1940. In total there were 543 individual farms participating in the panel.

3.1 Variables

Since we choose to estimate the SFA efficiency scores against the production function (See section 2) we have to aggregate all inputs of the farms into a single output index (Y); revenues adjusted to the price level in 1998 by a production price index. The revenues consists mainly of income from milk, beef and crops. A similar approach was employed in Heshmati and Kumbhakar (1994) and in Kumbhakar and Heshmati (1995). This way of treating the outputs of the farms makes it possible to aggregate otherwise completely different products like beef and milk in an easy way. The average share of income from milk compared to all income is 77%. If all income from beef is also included the income share is 89 %. The median observation is 81 % and 93 % respectively.

Inputs are aggregated into six categories; fodder (X_1), labour (X_2), capital (X_3), energy (X_4), seed (X_5), and fertilizer (X_6) which are considered as the main inputs of a dairy farm. The fodder variable consists of purchased fodder, mainly concentrate and mineral fodder. Labour consists of the number of hours worked at the farm by both family and hired labour. Capital is a measure of production rights, inventories and buildings. A more complete measure of capital would include a measure of land but due to limitations in our dataset it was not possible to do this. Energy is a measure of the amount used of oil and electricity. Seed and fertilizer measure the amount used of each. The fodder, energy, seed, and fertilizer variables were calculated by use of the income statement and prices. All relevant costs were divided by its corresponding price to get a measure in relevant units. In this way the amount of each input was derived. The total reported costs of the respective variables were divided by the amount calculated earlier. In this way a weighted price, mirroring the differences in use, was obtained. For the price of labour, the average price of hired labour was calculated and used as an approximation of the price of family labour and for the cases when data on wages were otherwise missing. The cost of capital was calculated by dividing total financial costs by total debt. Where this gave an unrealistically small capital cost (below the relevant interest rate) it was substituted with the 2-year interest rate offered by one of the leading banks in Sweden (www.foreningssparbanken.se). Table 1 shows summary statistics of the variables in the study.

Table 1
Summary statistics of the variables in the study. The figures represents the mean use and standard error on year basis.

Variable	**Mean**	**Standard deviation**
Income from milk, beef and other products (SEK)	1 118 175	1 237 723
Fodder (kg)	176 654	221 890
Labour (hours)	4 747	2 789
Capital (SEK)	848 707	1 188 790
Energy (Units)	118 693	127 150
Seed (kg)	7 536	13 260
Fertilizer (kg)	6 979	11 943
Price of fodder (SEK)	1.61	0.48
Salary (SEK)	95.95	8.33
Interest (SEK)	0.065	0.021
Price of energy (SEK)	0.63	0.37
Price of seed (SEK)	2.80	0.20
Price of fertilizer (SEK)	7.93	0.55

3.2 Empirical specification

Under the DEA approach the variables described above are used to solve equations (2) and (3) to estimate the technical, allocative and economic efficiency. Although it is possible to divide the output into its different parts in DEA, and not keep it aggregated, the output index described in section 3.1 is used here. Otherwise it will not be possible to compare the results from DEA with those from SFA.

The functional form of the production function for the SFA approach is assumed to be Cobb-Douglas because it is self-dual and therefore possible to use to derive the corresponding cost function needed to calculate economic efficiency. The logged empirical production function can be written as follows:

$$\begin{aligned} \ln(Y_{it}) = b_0 + b_1 \ln(X_{1it}) + b_2 \ln(X_{2it}) + b_3 \ln(X_{3it}) + \\ + b_4 \ln(X_{4it}) + b_5 \ln(X_{5it}) + b_6 \ln(X_{6it}) + e_{it} \end{aligned} \tag{17}$$

where i represents the individual farm, and t the period in time. Y_{it} and the X_{it}:es were defined in the previous section. The b $:as$ are the parameters to be estimated. e_{it} is defined according to equation (7).

The corresponding cost function is derived analytically and defined as follows:

$$\begin{aligned} \ln C_{it} &= b_0 + b_1 \ln(Y_{it}^*) + b_2 \ln(w_{1it}) + b_3 \ln(w_{2it}) + b_4 \ln(w_{3it}) + \\ &+ b_5 \ln(w_{4it}) + b_6 \ln(w_{5it}) + b_7 \ln(w_{6it}) \end{aligned} \tag{18}$$

where i refers to the individual farm, and t the period in time. Y_{it}^* is the output corrected for the white noise (equation 11) and $w_{1it}, w_{2it}, w_{3it}, w_{4it}, w_{5it}, w_{6it}$ are the input price of fodder, labour, capital, energy, seed, and fertilizer respectively.

4 Results

In estimating the efficiency scores, we assume variable returns to scale. This is intuitively more appealing since constant returns to scale assumes that the farms are operating at their optimal scale. Because of various constraints like goals of the farmer and constraints on financing and land supply, it is not sure that all farms in our sample are operating at their optimal scale. To prevent the efficiency estimates from being influenced by scale effects, we assume variable returns to scale. Allowing for variable returns to scale is not a constraint on the model since the result would be the same as under CRS if firms are operating at their optimal scale.

4.1 Comparison between DEA and SFA

Maximum likelihood estimates of the parameters of the production function (equation 17) were obtained by the program FRONTIER 4.1 (Coelli, 1996). The results, together with the Ordinary Least Square estimates, are presented in table 2. All estimates except the estimate of eta are highly significant.

Table 2

OLS-estimates of the average production function and ML-estimates of the frontier production function. All numbers have been rounded to three decimals. All estimates, except the estimate for eta, are significant at the 0.5 % level

Variable	**OLS- estimates**			**ML-estimates**		
	coeff.	std. error	t-ratio	coeff.	std. error	t-ratio
Intercept	1.889	0.151	12.442	4.625	0.272	16.525
ln(Fodder)	0.219	0.009	24.621	0.120	0.008	15.444
ln(Labour)	0.464	0.025	18.629	0.469	0.027	17.287
ln(Capital)	0.207	0.010	20.039	0.214	0.012	18.495
ln(Energy)	0.179	0.013	13.681	0.110	0.012	9.174
ln(Seed)	0.034	0.004	7.816	0.014	0.004	3.625
ln(Fertilizer)	0.033	0.004	9.326	0.015	0.003	4.587
g	-	-	-	0.808	0.023	34.891
s^2	-	-	-	0.244	0.027	9.034
m	-	-	-	0.647	0.076	8.512
h	-	-	-	-0.010	0.007	-1.460

The estimate of gamma is significantly different from zero, which means there are inefficiencies in the production. The estimate of eta is not significantly different from zero, indicating that the level of technical inefficiency has not changed over the five years.

The dual cost frontier is derived from the stochastic production frontier. The result is as follows:

$$\ln C_{it} = -3.574 + 1.060 \ln Y_{it}^{*} + 0.127 \ln w_{1it} + 0.497 \ln w_{2it} + \\ 0.227 \ln w_{3it} + 0.117 w_{4it} + 0.015 w_{5it} + 0.016 w_{6it} \tag{19}$$

where C_{it} is the total cost of farm i in period t, Y_{it}^{*} is the white noise adjusted output of farm i in period t, w_{1it} through w_{6it} represents the price of the inputs.

Efficiency indices according section 2 were calculated. As was pointed out earlier, when calculating allocative and economic efficiency using the DEA it is not possible to make use of panel data. Therefore, DEA indices of technical, allocative, and economic efficiency were calculated once for each year, treating each year as a cross section dataset. In the SFA case panel data was used.

The average, minimum, and maximum technical, allocative and economic efficiency indices computed by both SFA and DEA are shown in table 3. The results are presented both for each year and for the entire period.

Table 3
Mean, minimum and maximum technical (TE), allocative (AE), and economic (EE) efficiency indices. The figures in parenthesis are the standard deviations of the mean.

Period		Stochastic Frontier Approach			Data Envelopment Analysis		
		TE	AE	EE	TE	AE	EE
1998	mean	0.55	0.72	0.40	0.64	0.44	0.26
		(0.17)	(0.12)	(0.13)	(0.23)	(0.14)	(0.09)
	minimum	0.14	0.26	0.09	0.24	0.13	0.13
	maximum	0.95	1.00	0.889	1.00	1.00	1.00
Number of observations : 428							
1999	mean	0.55	0.75	0.41	0.64	0.57	0.34
		(0.17)	(0.15)	(0.15)	(0.24)	(0.17)	(0.12)
	minimum	0.14	0.16	0.05	0.26	0.16	0.16
	maximum	0.95	1.00	0.84	1.00	1.00	1.00
Number of observations: 417							
2000	mean	0.56	0.74	0.41	0.80	0.68	0.53
		(0.17)	(0.12)	(0.14)	(0.18)	(0.19)	(0.17)
	minimum	0.13	0.30	0.08	0.34	0.17	0.17
	maximum	0.95	1.00	0.91	1.00	1.00	1.00
Number of observations: 396							
2001	mean	0.54	0.76	0.42	0.83	0.77	0.62
		(0.17)	(0.12)	(0.15)	(0.17)	(0.17)	(0.16)
	minimum	0.13	0.17	0.08	0.32	0.25	0.24
	maximum	0.95	1.00	0.88	1.00	1.00	1.00
Number of observations: 350							
2002	mean	0.54	0.77	0.41	0.84	0.64	0.53
		(0.17)	(0.12)	(0.16)	(0.17)	(0.16)	(0.16)
	minimum	0.13	0.24	0.07	0.36	0.17	0.17
	maximum	0.95	1.00	0.87	1.00	1.00	1.00
Number of observations: 351							
98-02	mean	0.55	0.75	0.41	0.74	0.61	0.45
		(0.17)	(0.13)	(0.15)	(0.22)	(0.20)	(0.20)
	minimum	0.13	0.16	0.05	0.24	0.13	0.13
	maximum	0.95	1.00	0.91	1.00	1.00	1.00

When applying the stochastic frontier approach the mean technical, allocative and economic efficiency indices for the entire period are 0.55, 0.75, and 0.41 respectively. However, when applying the data envelopment analysis, the technical, allocative and economic efficency indices are 0.74, 0.61, and 0.45 respectively. Thus, the mean technical efficiency index is much higher under DEA than under SFA. Following the example of Sharma (1999) a paired t-test was conducted which shows that the measures of technical efficiency is significantly higher under the DEA approach. This is somewhat unexpected since DEA is deterministic and reports all deviations from the frontier as inefficiency. Thus, the measures are expected to be higher under SFA. As all three indices are measured against the same frontier, the measure of economic efficiency is consequently higher under the DEA approach. This was also confirmed by the paired t-test. However, the t-test showed that the measures of allocative efficiency were significantly higher under SFA. This is most likely a consequence of the low technical efficiency indices. A Kruskal-Wallis test was conducted to test for differences in efficiency rankings between SFA and DEA, which showed no evidence for different rankings.

As was pointed out in the beginning of the paper, an advantage of the DEA, compared to the SFA, is that no pre-specified functional form is required. Therefore the higher DEA technical efficiency scores could be and indication of inappropriate selection of the functional form. However, to derive the corresponding cost function from the production function it is necessary to assume a dual production function (i. e. the Cobb-Douglas production function), making other choices of production functions (like the Translog production function) inappropriate. The reported efficiency scores under both SFA and the deterministic DEA are thus likely to be underestimated. To avoid possible biases due to an inappropriate selection of production function, the following discussion will be based on the DEA results.

When considering the DEA results in table 3, the indices seem to increase over the years. This can be due to two things; actual improvements in efficiency or biases in the DEA measures because of unbalanced panels. To avoid measurement errors of the latter kind the DEA equations (2 and 3) were solved again. This time each firm was represented by its own average of its output, inputs, and prices. The results are shown in table 4:

Table 4
Mean, minimum, and maximum technical, allocative, and economic efficiency indices for the DEA case where each firm is represented by its own average. The figures in parenthesis are the standard deviations of the mean.

Period		Data Envelopment Analysis		
		TE	AE	EE
98-02	mean	0.77	0.57	0.43
		(0.17)	(0.13)	(0.11)
	minimum	0.37	0.22	0.14
	maximum	1.00	1.00	1.00

These DEA measures yielded technical, allocative and economic efficiency indices of 0.77, 0.57, and 0.43 respectively. As DEA is deterministic these indices will probably over estimate the real inefficiency a little, but still they indicate considerable inefficiency in Swedish dairy production. As is indicated by the efficiency scores the economic inefficiency is due both to technical and allocative inefficiencies. However, according to the results, the allocative inefficiency is much worse than the more modest technical inefficiency. This is also indicated in table 5 where the frequency distributions of the efficiency indices are shown:

Table 5
Frequency distribution of technical, allocative and economic efficiency.

Interval	Efficiency measure and number of firms		
	TE	AE	EE
< 0.1	0	0	0
0.1 – 0.2	0	0	1
0.2 – 0.3	0	17	48
0.3 – 0.4	5	41	164
0.4 – 0.5	19	83	218
0.5 – 0.6	69	165	88
0.6 – 0.7	104	167	17
0.7 – 0.8	121	63	3
0.8 – 0.9	70	3	0
0.9 - 1.0	155	4	4

The interval 0.9 – 1.0 is the most frequent interval of technical efficiency, whereas the most frequent interval of allocative efficiency is 0.6 – 0.7, indicating that the main problem of the Swedish dairy farmers is inability to allocate the inputs in the cost minimizing way, rather than inabilities in using the resources in the technically most efficient way.

4.2 Efficiency and size

As was pointed out earlier, the trend in Swedish dairy production is towards bigger herds. Following the example of Bravo-Ureta and Rieger (1991), an analysis of variance (ANOVA) and the Kruskal-Wallis test were conducted in order to determine the effect of size upon the efficiency indices. Size was measured as the amount of milk produced. The number of dairy cows would probably be a better measure of size, but no data on the number of cows was available in our dataset. However, the amount of milk produced ought to be a fairly good proxy of the number of dairy cows. A farm producing less than the 33rd percentile is considered as small. A farm producing between the 33rd percentile and the 66th is considered as medium sized. Finally the farms above the 66th percentile are considered as large. The ANOVA results, shown in table 6, show statistical significance for differences between small, middle sized and large farms for technical, allocative and economic efficiency. The results indicate that large farms are more allocatively and economically efficient than middle sized and small farms. Also, the results indicate that small farms are technically more efficient than larger farms, but medium sized farms shows the lowest technical efficiency score. However, the Kruskal-Wallis test gives no evidence for differences in technical efficiency, but strong evidence that there are differences in allocative and economic efficiency.

Table 6:
Statistical analysis of influence of farm size on technical, allocative, and economic efficiency.

Size	TE	AE	EE
Small	0.79	0.52	0.39
Medium	0.75	0.57	0.42
Large	0.78	0.61	0.47
Analysis of Variance			
	2.50*	27.52***	28.65***
Kruskal-Wallis test			
	-3.62	34.67***	55.31***

* Indicates statistical significance at the 10 % -level
*** Indicates statistical significance at the 1% -level

5 Discussion and conclusions

Basically, the present study has lead to two kinds of conclusions about efficiency studies and efficiency levels in dairy farms when the integrated production is considered. First, we draw some conclusions on methodology choice: The technical, allocative, and economic input efficiencies of Swedish dairy farms were measured using both the stochastic frontier approach and the data envelopment approach. The DEA measures for technical and economic efficiency were found to be significantly higher than the corresponding SFA measures. The allocative efficiency, however, was found to be significantly higher under the SFA approach. This is most probably a consequence of the lower SFA technical efficiency indices. As the DEA results were found to be higher than the SFA results, it is concluded that the Cobb-Douglas production function is not a satisfactory choice of frontier function when the farm is studied from the integrated perspective. However, to derive the allocative and economic efficiency of the farms it was necessary to assume a self dual production function (i.e. Cobb-Douglas). The DEA does not require any particular functional form to be chosen, thus it is concluded that in determining the efficiency of the sample of Swedish dairy farms the DEA is probably a better choice than the SFA. By using DEA all deviations from the frontier will be accounted for as inefficiency. Because of potential measurement errors and random errors the DEA efficiency scores may be an underestimation of the real inefficiency in the sample.

Second, we draw some conclusions about the efficiency scores and reasons for inefficiency: The average DEA technical, allocative and economic efficiency indices were eventually found to be 0.77, 0.57, and 0.43 respectively, meaning that there are considerable inefficiencies in Swedish average dairy production. The reported measure of technical efficiency is slightly lower than the findings of Heshmati and Kumbhakar (1994) referred to in section 1 of this article. The lower scores in this paper is probably due to the deterministic approach of DEA. Compared to the findings of Jonasson, also referred to in section 1, the results of technical efficiency in this study is much lower. A reason for the difference may be that DEA is sensitive to the number of outputs and inputs. We assumed single output while Jonasson assumed seven outputs. If the output index of this study is divided into its three main parts, income from milk procuction, income from beef, and income from other parts of the farm, and if the size of the farms is restricted to be the same as that of Jonasson's sample, we get a mean technical index of 0.88. This should be compared to the mean technical efficiency index of 0.77 which we got in this study, when outputs where aggregated into a single output. Even without the size restriction the technical efficiency index is much higher than in the case of aggregated output; 0.85.

Also the fact that Jonsson used the output perspective may cause some differences in technical efficiency if the farms are operating far from CRS. Regarding the scores of allocative and economic efficiency, they are not comparable to Jonasson's study at all, since the allocative and economic efficiency form the output perspective corresponds to the revenue maximizing problem.

The findings of this paper indicate that there is some spread of the efficiency scores within the sample. The reported standard deviations are 0.17, 0.13, and 0.11 for the technical, allocative, and economic efficiency respectively. Also the low mean efficiency scores and the fact that DEA always assess full efficiency to at least some farms indicates a spread of the efficiency scores.

As the measure of economic efficiency is the product of the technical and allocative efficiency measures, it is concluded that the main reason for the economic inefficiency is the allocative inefficiency, but also some technical inefficiency. This means that the average dairy farmers have to become better at choosing the cost minimizing input bundle. A reason why this is not already the case may be the inability to value one's own work or equity, or constraints on financing which prevents the farmer from using the inputs in the cost minimizing amounts. Also, significant evidence was found that large farms are more allocatively and economically efficient than their smaller counterparts. Reasons may be that the small and middle sized farms are so small that the farmers need to complement the family income with off-farm work. Blank (2005) maintained that small and middle sized farms maximise their family wealth rather than their farm income. This means that the family is not completely dependent on the farm in order to earn their living, but can afford to let the production be inefficient. An other reason may be that bigger farms have employees and greater debts. This means that they are more sensitive to slacks due to inefficiencies and thus have had to improve their management skills in order to make their farms survive. Yet an other reason for the greater efficiency in bigger farms can be technology. It is quite likely that the bigger farms have lose housing and milking robot which is less labour intensive. The Kruskal-Wallis test showed no evidence for differences in technical efficiency, as did the ANOVA. Together the results of this study implies that encouraging economics of size is one way to reduce the allocative, economic, and possibly even the technical inefficiencies.

Now that the relative appropriateness of DEA and SFA for analysing the technical and allocative parts of the economic efficiency of diary farms, when the whole production of the farm is included, has been analysed and it is clear that there is inefficiencies in our sample, it will be interesting to go on studying dairy farms. Research questions that deserve attendance are for example the impact of different choices of technology and management styles. (This paper is part of an ongoing research project intending to analyse in some detail the reasons for various inefficiencies in dairy farms.)

Acknowledgement
I am most grateful to my supervisors professor Bo Öhlmér and professor Hans Andersson for valuable comments and help. This study was financed by the Foundation of Agricultural Research (SLF), Stockholm, Sweden, to whom I also express my gratitude.

References

Agriwise: http://www.agriwise.org/
visited januari 10 – 11 2005

Aigner, D., Lovell, C. A. X., and Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. Journal of Econometrics. 6: 21-37.

Alvarez, A. and Arias, C. (2004). Technical efficiency and farm size: a conditional analysis. Agricultural Economics. 30: 241-250.

Bailey, D., Biswas, B, Kumbhakar, S. C., and Schulthies, B. K. (1989). An Analysis of Technical, Allocative, and Scale Inefficiency: The Case of Ecuadorian Dairy Farms. Western Journal of Agricultural Economics. 14: 30-37.

Battese, G.E. and Coelli T.J (1992). Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. The Journal of Productivity Analysis. 3: 153-169.

Blank, S. C. (2005) The Business of an Agricultural "Way of Life". Choices. 20: 161-166

Bravo-Ureta, B. and Rieger, L. (1991). Dairy Farm Efficiency Measurement Using Stochastic Frontiers and Neoclassical Duality. American Journal of Agricultural Economics. 73: 421-428.

Charnes, A., Cooper, W. W., and Rhodes, E., (1978). Measuring the Efficiency of Decision Making Units. European Journal of Operational Research. 2: 429-444.

Coelli, T. (1995). Recent Developments in Frontier Modelling and Efficiency Measurement. Australian Journal of Agricultural Economics. 39: 219-245.

Coelli, T. (1996). A Guide to FRONTIER Version 4.1:A Computer Program for Stochastic Frontier Production and Cost Function Estimation. Centre for Efficiency and Productivity Analysis, University of New England, Armidale, Australia.

Coelli, T. and Perleman, S. (1999) A comparison of parametric and non-parametric distance functions: With application to European railways. European Journal of Operational Research 117: 326-339

Coelli, T., Rao, P. D. S., and Battese, G. E. (2002). An Introduction to Efficiency and Productivity Analysis. Kluwer Academic Publishers, London.

Farrel, M. J. (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistical Society. Ser. A 120: 253-281

Föreningssparbanken: http://www.foreningssparbanken.se/
visited spring 2005

Heshmati, A. and Kumbhakar, S. C. (1994). Farm Heterogeneity and Technical Efficiency: Some Results from Swedish Dairy Farms. The Journal of Productivity Analysis. 5: 45-61.

Iráizoz, B., Rapún, M., Zabaleta, I. (2003). Assessing the technical efficiency of horticultural production in Navarra, Spain. Agricultural Systems 78: 387-403

Jonasson, L., (1996). Mathematical programming for sector analysis – some applications, evaluations and methodological proposals. Dissertations. Swedish University of Agricultural Sciences, Department of Economics.

Jordbruksverket (2004). Prisindex på jordbruks- och livsmedelsområdet 1966/67-2003. Sveriges Officiella statistiska meddelanden.

Kopp, R. J. and Diewert, W. E. (1982). The Decomposition of Frontier Cost Function Deviations into Measures of Technical and Allocative Efficiency. Journal of Econometrics. 19: 319-331.

Kumbhakar, S., C. and Heshmati, A. (1995). Efficiency Measurements in Swedish Dairy Farms: An Application of Rotating Panel Data, 1976-88. American Journal of Agricultural Economics. 77: 660-674

Lansink O. A., Pietola, K. and Bäckman, S. (2002) Efficiency and productivity of conventional and organic farms in Finland 1994-1997. European Review of Agricultural Economics. 29: 51-65

Meeusen, W. and van den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas production functions with composed errors. International Economic Review. 18: 435-444

Resti, Andrea (1997). Evaluating the cost-efficiency of the Italian Banking System: What can be learned from the joint application of parametric and non-parametric techniques. Journal of Banking & Finance. 21: 221-250.

Sharma, K. R, Leung, P., Zaleski, H. M. (1999). Technical, allocative and economic efficiencies in swine production in Hawaii: a comparison of parametric and nonparametric approaches. Agricultural Economics. 20: 23-35