Assessing managerial performance using non-parametric distance functions compared to technical and accounting ratio analysis: an application to French farms in Nord-Pas-de-Calais specialized in field crops

Stéphane Blancard, Jean-Philippe Boussemart, Michel Debruyne, . Cnrs Lem Lille Economie & Management Umr 8179

▶ To cite this version:

Stéphane Blancard, Jean-Philippe Boussemart, Michel Debruyne, . Cnrs Lem Lille Economie & Management Umr 8179. Assessing managerial performance using non-parametric distance functions compared to technical and accounting ratio analysis: an application to French farms in Nord-Pas-de-Calais specialized in field crops. 2006. hal-02819975

HAL Id: hal-02819975
https://hal.inrae.fr/hal-02819975

Preprint submitted on 6 Jun 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Document de travail du LEM
2006-13

Assessing managerial performance using non-parametric distance functions compared to technical and accounting ratio analysis: an application to French farms in Nord-Pas-de-Calais specialized in field crops

Stéphane Blancard*, Jean-Philippe Boussemart, Michel Debruyne*****

* *CESAER, INRA-ENESAD, Dijon, France*

** *LEM-CNRS, IESEG and Université Lille 3, France*

*** *Université Lille 3, France*

Assessing Managerial Performance Using Non-Parametric Distance Functions Compared to Technical and Accounting Ratio Analysis: An Application to French Farms in Nord-Pas-de-Calais Specialized in Field Crops

Stéphane Blancard*

Jean-Philippe Boussemart**

Michel Debruyne***

December 2006

First draft

Abstract

This paper highlights the operational possibilities of applying non-parametric distance functions to diagnose farm performance. An empirical application on 178 farms in the Pas de Calais region specialized in field crops and observed over the period 1994-2001 establishes the coherence of this method compared to the usual approaches based on technical and accounting ratios. In addition, our results highlight the relevance of the additional information which is being generated by dissociating the technical and scale components of total factor productivity levels.

Keywords: agriculture, data envelopment analysis (DEA), distance function, production technology, ratio analysis, total factor productivity.

* CESAER, INRA-ENESAD, Dijon, France

** LEM-CNRS, IESEG and Université Lille 3, France

*** Université Lille 3, France

1. Introduction

Managerial performance evaluation is a central objective for organizations. The information provided from measure of performance allows managers to make strategic plans and track their progress relative to the firm's goals. These measures can usually be obtained from technical and accounting ratios, but today must go further than the simple study of partial productivities or ratio analysis (Smith 1990). It can refer to the concept of distance functions which evaluate the gap between the assessed decision making unit and its optimal situation located on the production frontier considered as a benchmark to reach. More precisely, with given resources, it determines the maximum level of output which a unit can produce, or alternatively, with a defined quantity of output, it assesses the minimal quantities of inputs which can be spent.

Various methods to estimate this distance have already been proposed and applied to many fields or types of organization (Fried *et al.* 1993). Unfortunately the majority of these approaches remain of academic interest, as they are still seldom applied by managers to complement the other methods which are more frequently used (e.g. ratio analysis or credit scoring). However, some papers on performance evaluation by distance functions, and their operational and complementary aspects compared to using the usual accounting methods, do exist. Most of these studies agree that distance functions provide additional information to analysts to complement their traditional analyses. Furthermore, it is then possible to overcome certain problems inherent in the latter. In a paper, Fernandez-Castro and Smith (1994) highlight many problems which can arise in applying conventional methods to accounting ratios[1] For instance, Athanassopoulos and Ballantine (1995) examine the use of alternative methodologies for assessing the corporate performance of the grocery industry in the UK. They argue that the ratio analysis in itself is insufficient for assessing performance and that other techniques like Data Envelopment Analysis (DEA) should be used. In the oil and gas industry, Feroz *et al.* (2003) demonstrate that DEA can provide a consistent and reliable measure of the managerial or operational efficiency of a firm. Thus, their results show clearly how financial analysts can

[1] Less subjective than accounting approaches, distance functions also avoid problems of interpretation sometimes raised when several ratios do not vary in the same direction. Moreover, ratios provide little help when considering the effects of economy scale and the estimation of total performance measures of firm

employ a non-parametric distance function like DEA as a complement to the ratio approach. Emel *et al.* (2003) apply DEA to current data for 82 manufacturing firms comprising the credit portfolio of one of Turkey's largest commercial banks. Using financial ratios, they synthesize a firm's overall performance into a single financial efficiency score. Their results were validated by regression analyses and expert judgments based on current knowledge of the firms. As for the specific field of agriculture, few papers relative to the linkage between ratio analysis and efficiency scores based on a non-parametric method exist to our knowledge, although we can mention Featherstone *et al.* (1997) study. For a sample of Kansas beef cow farms, they showed that enterprise profitability measured by usual ratios was correlated positively with the efficiency measures.

Following these diverse studies mainly made in the area of the manufacturing or service industries, this paper aims to provide empirical evidence that a non-parametric distance function enables one to draw up an operational diagnosis of farm efficiency, and how it refines results from the accounting analyses. Based on linear programming which allows a more intuitive interpretation for professionals than econometric models, this approach measures the productive efficiency and the optimal size for each decision making unit. Its main advantages are: *i)* it does not require to define with precision a functional form between outputs and inputs, *ii)* it is interested in individual observations rather than in averages over a sample, *iii)* it produces a synthetic measurement for each unit, *iv)* it quantifies achievable economies on each input and possible gains of output and *v)* on these potential productivity gains, it separates those which concern technical inefficiency from the bad scale of activity (scale inefficiency). From an application on a sample of 178 farms specialized in field crops and located in the Nord-Pas-de-Calais region over the period 1994-2001, this paper compares the coherence of the diagnosis of this approach with that given by advisers in agricultural management based on technical and accounting ratios (Purdy and Langemeier 1995; Barry *et al.* 1999; Kay *et al.* 2004). Then it reveals the relevance of additional information which can be obtained when corrective and preventive actions are needed to improve the farm's financial position and profitability.

This paper is structured as follows. The next section defines the various efficiency concepts using distance functions and presents the DEA method developed by Charnes *et al.* (1978). Section 3 discusses the sample and introduces the basic empirical efficiency results. Lastly, the diagnoses of efficiency are compared with the criteria used by the advisers to evaluate the performance of a farm specialized in field crops. Conclusions appear in the final section.

2. The Productive Efficiency: Definitions and Measures Using Distance Functions

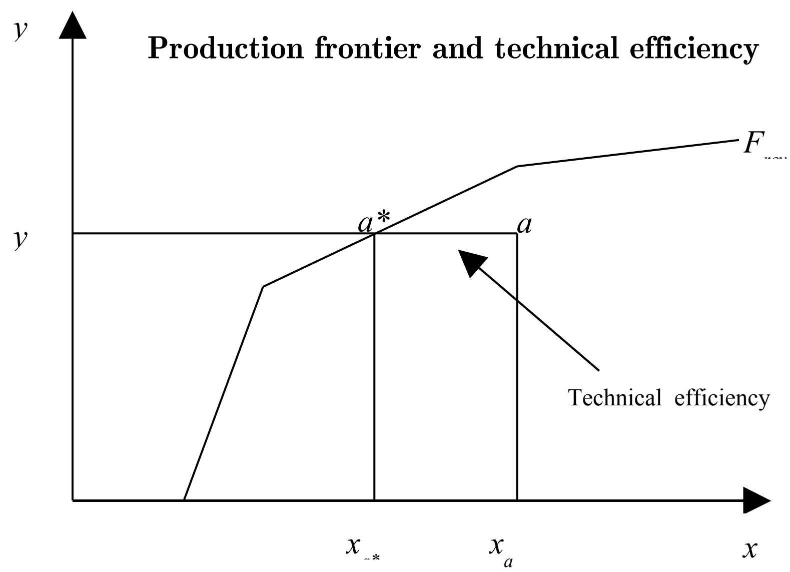
In this section, we define the various types of productive efficiency (2.1). Lastly, we present its measurement using distance function framework (2.2).

2.1 Definitions of the various types of productive efficiency

The concept of technical efficiency is connected to a particular interpretation of the production function. Coupled to the technically possible frontier of the assessed unit, this function specifies the minimal level of inputs necessary to reach the observed level of outputs. Based on the best practices of the considered group, this benchmark defines a concept of relative efficiency which is not an absolute standard. As shown in Figure 1, the efficiency is given by the distance from the observed position of the entity, or more commonly, of the decision making unit (DMU), to its production frontier.

Figure 1

Production frontier and technical efficiency



According to this figure, if DMU a adopted the best practices of the group determined by the production frontier under variable return to scale assumption (F_{rev}), it could reduce its inputs x_a to x_{a^*} maintaining its production quantity y_a. Its level of relative inefficiency($1\text{-}f_a$) measures the percentage of achievable economies on its total expenditure with:

$$\frac{x_{a^*}}{x_a} = f_a .$$

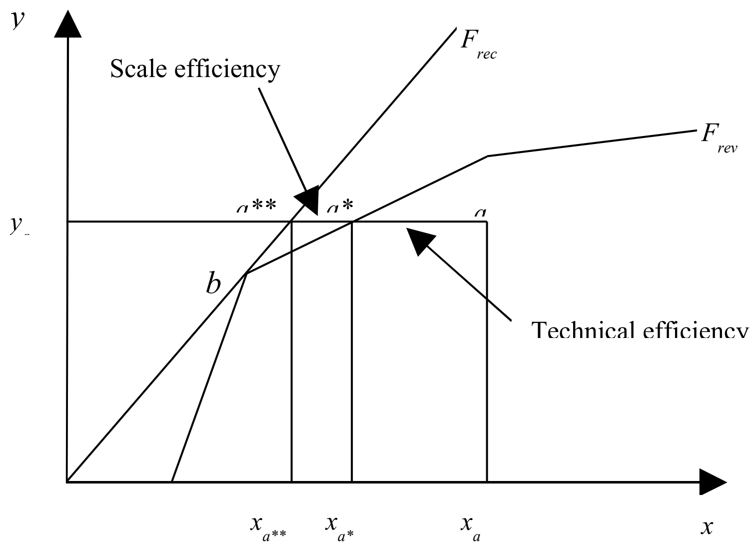
To determine the maximum level of productivity of DMU a, a production frontier with constant return to scale (F_{rec}) tangent to the previous production function (F_{rev}) must be added.

In Figure 2, we can note that in spite of the efforts of good input management in a^*, DMU a suffers from too big a size to obtain the maximum level of productivity observed with DMU b which is its optimal size. To reach such a level of productivity, it is necessary to reduce the inputs to $x_{a^{**}}$ and to project DMU a to a^{**} on F_{rec}. The total efficiency is given by the ratio $g_a = (x_{a^{**}}/ x_a)$, (1-g_a) measures the percentage of feasible economies on the whole of its inputs to reach the maximum level of productivity. Following Banker *et al.* (1984), this total technical inefficiency breaks down into two components, the technical inefficiency measured as previously by (1-f_a) and the scale inefficiency (1-h_a) such that:

$$\frac{x_{a^{**}}}{x_a} = g_a, \quad \frac{x_{a^*}}{x_a} = f_a, \quad \frac{x_{a^{**}}}{x_{a^*}} = \frac{g_a}{f_a} = h_a .$$

Figure 2

Return to scale and decomposition of the total efficiency



2.2 Measuring productive efficiency

Econometrics methods and mathematical programs allow the measurement of the various types of efficiency defined above[2]. In this paper, we used a non-parametric determinist distance function based on the linear programs developed by Charnes *et al.* (1978) and initially proposed by Farrell (1957). This method, widely known as Data Envelopment Analysis (DEA), consists in measuring the gaps between observations and a benchmark (here the production frontier). This approach involves constructing a piecewise linear frontier that connects the set of the best practices, and is particularly adapted to modeling a primal multi-outputs/multi-inputs technology.

Moreover, DEA requires few assumptions. Thus, only the free disposal of inputs and outputs and convexity assumptions are imposed for the production possibility set (Färe *et al.* 1985). It does not require any functional form of the production frontier. However, contrary to stochastic approaches, the totality of the distance to the frontier is allocated to inefficiency; there is no random error term.

In the general case of S outputs and M inputs, the production possibility set is defined by:

$$P = \left\{ \left(x, y \right) \in R_{+}^{M+S} : x \text{ can produce } y \right\}$$

where y and x are an output vector of dimension S and an input vector of dimension M, respectively. The Farrell input distance function D^I relative to technology P can be defined as:

$$D^I : \mathbb{R}_{+}^{M+S} \to \mathbb{R}_{+} \cup \left\{ -\infty, \infty \right\}$$
$$D^I(x, y) = \inf \left\{ f : (f.x, y) \in P \right\}$$

$D^I(x, y)$ can be interpreted as the contraction of the input vector with the output vector held fixed. More precisely, at each year t, set P groups the pairs (x_t, y_t) corresponding to the annual data of the farms. With the above assumptions, constant returns to scale and variable returns to scale production frontiers can be built for each t. These benchmarks are determined using the best practices of the sample. Consequently, the input distances of each farm to the two annual frontiers are

[2] The reader interested in the development of these methods can refer to e.g. Badillo and Paradi (1999) or Coelli *et al.* (2002).

calculated with linear programs which measure the levels of total, technical and scale efficiency scores illustrated by Figure 2.

The diagnosis of technical efficiency (under the variable returns to scale assumption) of DMU a among N farms belonging to set P is given by the following linear program:

$$\begin{aligned}
&\underset{(f_a,\lambda)}{\text{Min}}\ f_a \\
&\text{subject to:} \\
&i)\sum_{n=1}^{N} \lambda_n . y_n^i \geq y_a^i, \forall\ i \in \{1,2,\ldots,S\} \\
&ii)\sum_{n=1}^{N} \lambda_n x_n^j \leq f_a . x_a^j, \forall\ j \in \{1,2,\ldots,M\} \qquad \textit{[PL1]} \\
&iii)\sum_{n=1}^{N} \lambda_n = 1 \\
&iv)\ \lambda_n \geq 0, \forall\ n \in \{1,2,\ldots,N\}
\end{aligned}$$

where y_n^j is the *j*th output of the *n*th farm and x_n^i is the *i*th input of *n*th farm. λ is the intensity vector which enables the benchmark or best practice frontier to be constructed.

If DMU a is efficient then $f_a = 1, \forall\ n \neq a$, $\lambda_n = 0$ and $\lambda_a = 1$. DMU a will be positioned on the best practice frontier. In P, it is not possible to find another farm or a combination of farms producing as much (or more) of each output (to respect constraints *i*) and using a lower quantity of inputs (to respect constraints *ii*) than DMU a. Coefficient f_a is applied to the whole of the input vector and is assimilated to a coefficient of resources as a radial measurement of efficiency (Farrell 1957).

Under the assumption of constant returns to scale, it is possible to measure total factor productivity combining the pure technical and the scale efficiencies of DMU a. For that, it is necessary to remove constraint *iii* in program *[PL1]*. Thus, the CRS linear program is given by:

$$\begin{aligned}
&\underset{(g_a,\lambda)}{\text{Min}}\ g_a \\
&\text{subject to:} \\
&i)\sum_{n=1}^{N} \lambda_n . y_n^i \geq y_a^i, \forall\ i \in \{1,2,\ldots,S\} \qquad [PL2] \\
&ii)\sum_{n=1}^{N} \lambda_n x_n^j \leq g_a . x_a^j, \forall\ j \in \{1,2,\ldots,M\} \\
&iv)\ \lambda_n \geq 0, \forall\ n \in \{1,2,\ldots,N\}
\end{aligned}$$

The successive resolutions of linear programs *[PL1]* and *[PL2]* refine the diagnosis and enable one to measure three efficiency scores:

- g_a: total efficiency score corresponding to the ratio of maximum productivity of DMU a projected to a^{**} over F_{rec} (cf. Figure 2),
- f_a: technical efficiency score corresponding to the distance between DMU a and its projection a^* over F_{rev} (cf. Figure 2),
- h_a: scale efficiency score equal to ratio g_a/f_a

The optimal size is calculated with the values obtained from left hand side members of constraints i) and ii) of [*PL2*] and divided by $\sum_{n=1}^{N} \lambda_n$.

3. An Application to the Field Crops Farms in Nord-Pas-de-Calais Region

This third section gives the results of an application carried out in collaboration with the professional advisers[3] of the "Centre d'Economie Rurale du Pas de Calais" during the year 2002. From the main accounting and technical data of 178 farms observed over the period 1994-2001, we calculated total, technical and scale efficiency scores for each one, as well as optimal size thanks to the linear programs detailed above. The farms in this balanced panel are specialized in cash crops (grain, sugar beets, colza, etc.). Livestock is of little or no importance for them.

Firstly, we describe the panel and specify the technology as well as the usual indicators used by professional advisers as comparators for the DEA-based measures of efficiency (3.1). Secondly, we present and discuss the results of efficiency scores (3.2). From the comparison with the usual practice of farm evaluation it will highlight the operational and complementary aspects of the distance functions (3.3).

3.1 The technology Specification and the Technical and Accounting Ratios Selected

Selecting proper input and output variables is perhaps the most important issue in using DEA to measure the efficiency of any type of firms, since it determines the

[3] We thank in particular Mr. Heroguelle and Mr. Choquet for their advice and always finding time for us.

evaluating context of the comparison. Following the recommendations of professional advisers, the technology specification retains one output and four inputs:

- Output is measured by total sales.
- Number of hectares or surface area.
- Number of Full-Time Employees (FTEs) on the farm[4].
- Cost of immobilizations includes mechanization and building expenses (tools, equipment and building depreciations, rent, maintenance and repairs).
- Intermediate consumption includes operational expenses (fertilizer, seeds, pesticide) and other costs (fuel, lubricants, water, gas, electricity).

Monetary data are deflated using their price indices and expressed in constant 1994 Euros, to neutralize strong price variations over time (especially for the outputs)[5].Descriptive statistics of the variables used to provide efficiency measures are detailed in Table 1. On average, the farms tally a turnover of 225 000 € on an area of 112 hectares with 1.8 FTEs. The sample contains some heterogeneity in size for some variables, but in general the spread is rather low. The coefficients of variation are less than one. Over the period, the annual growth rate was faster for turnover (2.59%) than for hectares (1.11%) and for total worked hours (0.73%). Thus, the volume of sales per hectare or per FTE increased. Also let us note that output increases faster than intermediate consumption (2.04%) but more slowly than the expenditure relating to immobilizations (4.97%).

Table 1

Descriptive statistics of the variables (period 1994-2001)

	Mean	**Std. dev.**	**Coefficient of variation**	**Min**	**Max**	**Annual growth rate**
Sales (€ 1994)	225 343	138 343	0.61	24 678	937 601	2.59%
Intermediate consumption (€ 1994)	51 350	31 438	0.61	6 162	185 931	2.04%
Cost of immobilizations (€ 1994)	38 863	30 100	0.77	1 612	268 997	4.97%
Surface area (ha)	112.24	60.52	0.54	20.80	340.00	1.11%
Full-Time Employees	1.80	0.95	0.53	0.50	6.50	0.73%

[4] An FTE represents 2 400 hours of labor per year. This indicator is an approximation of the real quantity of available hired and family labor. It is extremely difficult to know the exact number of full time workers if several members of the family work part-time during the year.

[5] These price indices are collected from the regional and national agricultural accounting framework and are not specific to each farm.

With regard to the technical and accounting ratios, a wide variety is commonly calculated to assess farm's performance[6]. It is custom in this literature to identify several categories of variables when assessing managerial performance: profitability, liquidity, solvency, financial efficiency, etc. To compare these with DEA-based measures of efficiency, we have retained the:

Corn yield (*WYIELD*) expressed in quintals per hectare,

Sugar beet yield (SBYIELD) in tons per hectare,

Sales / surface area in euros (*SALELAND*),

Added value / sales (AVRATE),

Added value / own capital (AVOCAP),

Gross margin / gross product (GMGP),

Operating profit before depreciation and amortization/gross product (OPBDAGP),

Internal financial self-sufficiency / sales (*IFSALE*),

Structural costs / sales (COSTSALE).

The first two yields (*WYIELD* and *SGYIELD*) are technical performance indicators of the two main products. The sales per hectare (*SALELAND*) give a synthetic measurement of the economic productivity of land. It attempts to provide a measure of the ability of farms to utilize their surface to generate sales revenue. The added value rate (*AVRATE*) estimates the enhancer of the output. Furthermore, within the context of our specialized farms focusing mainly on cereals and sugar beet, this ratio can only improve by also cultivating at least some higher value-added crops (e.g. endives, cauliflower). Therefore, in our context of almost monoculture farming, it can reveal a strategy of diversification. It is well-known that the simultaneous existence of a variety of technologies allows farms to select a suitable scale of operations and that economies of scope are substantial, but seem to diminish with size (Chavas, 2001). The following three ratios (*AVOCAP, GMGP* and *OPBDAGP*) approximate economic profitability. The rate *IFSALE* is the share of the current capacity of self-financing which is assigned to the farm, and which allows an increase in the working capital. *IFSALE* approximates the financial independence and is defined as follows: current financial self-sufficiency minus amortization of loans and household expenses to gross product. Finally, the structural cost rate (*COSTSALE*),

[6] See e.g. Barry *et al.* (1999) and Kay *et al.* (2004) for a list of ratios.

entering through the numerator the non variable operating expenses (e.g. fixed equipment, tools, building), measures the relative level of the fixed costs.

Table 2 provides a summary of the statistics for the technical and accounting ratios. Over the whole of the period, the yield averages are respectively 87 quintals per hectare and 68 tons per hectare for corn and sugar beet. $GMGP$ and $OPBDAGP$ account for 63% and 33% of the gross product, respectively. Except for $AVOCAP$ and $IFSALE$ which are very widely spread, the other ratios are relatively closed to their mean.

Table 2

Descriptive statistics of the ratios (period 1994-2001)

	Mean	Std. Dev.	Coefficient of variation	Min.	Max.
$WYIELD$	86.74	12.29	0.14	27.00	125.00
$SGYIELD$	67.67	10.09	0.15	34.00	99.00
$SALELAND$	1775.94	531.01	0.30	0.00	6089.70
$AVRATE$	0.74	0.05	0.07	0.48	1.00
$AVOCAP$	0.36	15.05	41.44	-522.74	49.79
$GMGP$	0.63	0.09	0.14	0.00	0.99
$OPBDAGP$	0.33	0.10	0.32	-0.33	0.67
$IFSALE$	0.06	0.26	4.42	0.00	1.83
$COSTSALE$	0.47	0.11	0.22	0.00	1.02

3.2 Efficiency Scores: Results and Interpretations

To take into account a climatic effect, we preferred to calculate a different technology per year which implicitly integrates this risk in the time dimension of our analysis instead of computing a common benchmark on the whole of accumulated sample (178 farms over 8 years). Therefore, two production frontiers were estimated each year. They correspond to the constant and variable returns to scale assumptions, respectively. We measure total efficiency or technical efficiency levels using the linear programs, presented in subsection 2.2 and deduce the scale efficiency level. These three scores enable one to compare each farmer with the others and with his own previous performance. If a farm improves its relative position (rise of the efficiency score) over time, its distance to the production frontier decreases and thus catches up with the performance of the most efficient farms defining the benchmark.

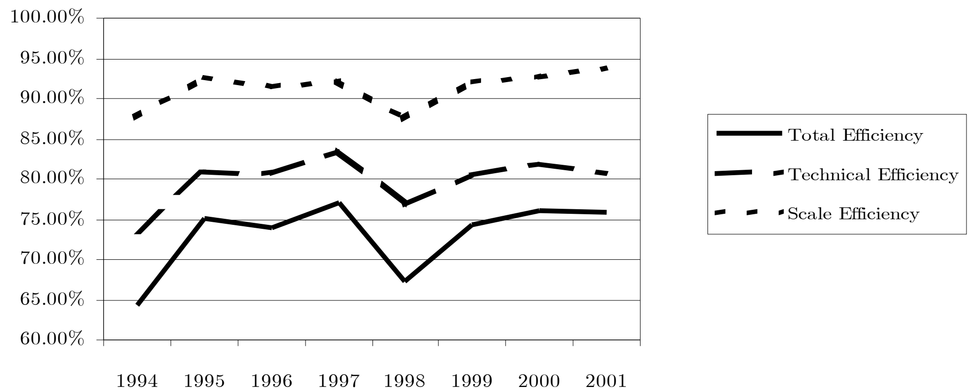
Figure 3 presents the various scores of efficiency. Over the period, the average of total efficiency was around 73.0%. In other words, the potential gains in total factor productivity would be about 27.0% if farms were aligned on the observable best practices. Better technical management of the inputs (technical efficiency) would account for a progression of 20.0% while the adaptation of the structures to their optimal size (scale efficiency) would improve it by 8.7%[7].

Over the years 1994-1997, the farms productive performance improved gradually then underwent a substantial deterioration in 1998 before approaching once more their benchmark between 1999 and 2001. In fact, this rupture in 1998 can be explained partly by the abundance of cereals which caused a depreciation in their prices, and partly by the variation in the corn and beet yields which were accentuated.

Apart from these average scores, the method enables one to diagnose the performance of each farm, and to treat on a hierarchical basis the efforts to improve productivity between technical and scale components. Table 3 illustrates the various scores and the returns to scale indicator for the first five of the 178 DMUs observed in 2001. For example, farm 1 obtains a total efficiency score g of 52.0% which is composed of a technical efficiency of 57.6% and of a scale efficiency score of 90.3%. In other words, to reach its best level of productivity, it should save approximately 42.6% of its input quantity and increase its size by a factor of 1.8 ($1/\Sigma\lambda$). Farm 5 is both technical and scale efficient and is thus located on its benchmark, and constitutes one of the best observable practices.

Figure 3

Evolution of average efficiency scores



[7] The decomposition of total efficiency scores being multiplicative ($g_a=f_a.h_a$), the gains in productivity points per technical and scale components are not exactly equal to 100%.

Table 3
Efficiency scores (in percent) and returns to scale indicator for five farms (year 2001)

	Total efficiency	Technical efficiency	Scale efficiency	$\Sigma\lambda$
Farm 1	52.0	57.6	90.3	0.5451
Farm 2	81.8	87.5	93.5	0.5135
Farm 3	69.0	69.0	100.0	1.0347
Farm 4	74.2	81.1	91.4	1.5659
Farm 5	100.0	100.0	100.0	1.0000

3.3 Comparison of Efficiency Scores with Technical and Accounting Ratios

We compare the DEA diagnosis with the technical and accounting ratios in two steps. Firstly, we calculate non-parametric tests on the Spearman rank correlation coefficients to establish a significant link of order between the efficiency scores and the accounting ratios. Secondly, we regress the latter on the efficiency scores and on the returns to scale indicator. By dissociating the technical and scale components of total factor productivity implicitly contained in these ratios, the DEA method should be a better evaluate farm performances than that carried out by professional advisers. The results associated with the rank correlations are reported in table 4. One can note that for almost all of the ratios, the classifications which result from them are significantly related to DEA-based measures of efficiency. Although there are generally statistically significant at the 1 or 5% level, none has an absolute value above 0.6. In particular, for *WYIELD* and *SGYIELD* (rank coefficients are below 0.15), the weak positive connection can be explained by the fact that these agronomic performance indicators give a partial view of performance based on only one input. DEA scores contain more information since they take into account the performance of the DMU over several inputs and outputs simultaneously. But, with indicators which offer a more complete evaluation of the performance (e.g. *AVRATE* and *OPBDAGP*), one can mention stronger rank correlations. However, as we will show it, these indicators cannot separate the scale component and the technical efficiency from the total factor productivity level. This suggests that if we use technical or financial ratios to assess the performance of units, we will not generally capture all the dimensions of the global performance (Thanassoulis *et al.* 1996).

Except for *COSTSALE*, the other ratios are positively correlated with efficiency scores in accordance with intuition. We may conclude that the higher the level of productive efficiency the higher the level of yields and profitability ratios, and the lower the level of productive efficiency, the higher the level of structural costs. In other words, these results confirm that farms with higher productive efficiency are more profitable (Featherstone *et al.* 1997).

Nevertheless, the econometric results displayed in Table 5 seem to us better adapted to analyze this relation. On the one hand, they explicitly measure the respective influences of the technical and scale components on the ratios. On the other hand, the cross-section and time dimensions of our data allow us to explicitly take into account the heterogeneity of the farms by assigning a fixed individual effect to each one (within or LSDV model)[8]. According to Table 5, we note that efficiency scores and returns to scale indicator explain 17% (for IFSALE) to 84% (for AVOCAP) of the ratio variances. Most of the estimated coefficients are statistically significant and have a sign in conformity with the intuition. More precisely, the sugar beet and corn yields (agronomic performance indicators) are connected positively to the technical efficiency score, whereas they do not have any statistically significant relationship to the scale efficiency score and the returns to scale indicator.

Furthermore, the first six accounting ratios are all significantly and positively connected to the efficiency scores while it is a negative relation which prevails for the ratio relating to the structural costs. These ratios mix technical and scale components of total factor productivity without however being able to dissociate them. Lastly, the returns to scale play a role only in the equations relating to the rates of added value (*AVRATE*) and of gross margin (*GMGP*). The more the level of the returns to scale indicator increases, the more the ratios decrease. These results are due to the fact that the cash crop farms having a observed lower than their optimal size ($\Sigma\lambda <$ 1) generally have a small surface area. To earn a sufficient income, they must develop other types of activities with higher added value (e.g. endives, cauliflowers). By contrast, those which exceed their optimal size ($\Sigma\lambda > 1$) cultivate greater surface areas and can concentrate on production giving less added value or gross margin like cereals, sugar beet or colza.

[8] One can refer to the handbook of Sevestre (2001) for the various regression models on panel data: OLS, between, LSDV, within, GLS, etc.

Table 4

Spearman rank correlation tests between efficiency scores and ratios

	Total efficiency	**Technical efficiency**	**Scale efficiency**	**$\Sigma\lambda$**
WYIELD	0.1385**	0.1001**	0.0349	0.0540*
	0.0%	0.0%	18.7%	4.1%
SGYIELD	0.1417**	0.1002**	0.1013**	0.1312**
	0.0%	0.0%	0.0%	0.0%
SALELAND	0.4847**	0.3896**	0.2193**	0.3299**
	0.0%	0.0%	0.0%	0.0%
AVRATE	0.5786**	0.4497**	0.3484**	0.1896**
	0.0%	0.0%	0.0%	0.0%
AVOCAP	0.2638**	0.2210**	0.0739**	0.2053**
	0.0%	0.0%	0.5%	0.0%
GMGP	0.2573**	0.1749**	0.1744**	0.1154**
	0.0%	0.0%	0.0%	0.0%
OPBDAGP	0.3652**	0.2443**	0.2413**	0.1295**
	0.0%	0.0%	0.0%	0.0%
IFSALE	0.0897**	0.0936**	0.0149	0.0535*
	0.7%	0.4%	57.3%	4.3%
COSTSALE	-0.3215**	-0.2512**	-0.1519**	-0.0576*
	0.0%	0.0%	0.0%	3.0%

**, *: statistically significant test at 1%, 5% level; % : associated p-value

Finally the distances to the benchmark established by DEA method inform each assessed farm about technical improvements (better use of resources) and size adaptation (scale efficiency and returns to scale) to raise its level of productivity. In addition, these scores enable one to draw up a more precise diagnosis than those given by the usual ratio analyses used by professional advisers in agricultural management.

This study consolidates the results obtained by Athanassopoulos and Ballantine (1995), Thanassoulis *et al.* (1996) or Feroz *et al.* (2003) in manufacturing industries and services: distance functions based upon the DEA method given a better evaluation of total factor productivity.

Table 5

Regression of the ratios on the efficiency scores and on the returns to scale indicator

	Technical efficiency	**Scale efficiency**	**$\Sigma\lambda$**	**R^2**
WHEAT-YIELD	13.0895	5.4995	0.2241	0.40
	0.0%	28.5%	85.2%	
SUGBEET-YIELD	6.6273	6.4556	0.9730	0.38
	1.7%	13.4%	33.2%	
SALELAND	1079.3900	802.8720	-33.1448	0.79
	0.0%	0.0%	27.6%	
AVRATE	0.16378	0.1994	-0.0119	0.64
	0.0%	0.0%	0.4%	
AVOCAP	0.3134	0.5963	-0.0142	0.84
	0.0%	0.0%	76.2%	
GMGP	0.1569	0.1385	-0.0301	0.48
	0.0%	0.0%	0.0%	
OPBDAGP	0.2896	0.2984	-0.0131	0.55
	0.0%	0.0%	14.2%	
IFSALE	0.3017	0.2088	-0.0294	0.17
	0.0%	10.5%	32.8%	
COSTSALE	-0.2729	-0.1670	-0.0035	0.51
	0.0%	0.0%	70.8%	
1424 observations	N = 178	T= 8		

+ or -: sign of estimated coefficients; %: associated p-value

4. Conclusion

This paper examined the contribution that distance function-based measures of efficiency as distance functions can provide in agricultural decision-making in comparison with ratio analysis. Indeed, despite the widespread use of ratio analysis for assessing managerial performance, the univariate nature of the method leads to some limitations. Ratios provide little help when considering the scale effects and the estimation of total performance measures of farms. In this way, we tested the validity of the total factor productivity measures based on distance functions when compared to the main technical and accounting indicators used by most experts in agricultural management. Thus, our study of 178 arable farms located in the Nord-Pas-de-Calais region and observed over eight years shows the operational range of this approach. With a relatively simple specification of the farm technology, it is possible to find information resulting from the main technical or accounting ratios and to measure the efficiency of each DMU. By separating technical and scale components, these measures build a diagnosis based on the identification of the best practices of a sample while respecting productive specificities of the assessed DMU. Thus, we hope to have illustrated the possibilities for the operational application of such a method to the productivity analyses of farms. Indeed, these measures could be used when corrective and preventive actions are needed to improve a farm's financial position. So authorities should promote the use of DEA-based scores and farmers should regard it as essential part of farm management. Combined with other countable and financial indicators such as rate of profitability, economic value added (EVA) or goodwill, DEA, or more generally, distance functions support a multidimensional approach to diagnose the valorization of farms. Therefore, it should take part in the revival of the methods generally adopted in financial analysis and become a referent tool of decision making aid for the farm-managers.

References

Athanassopoulos A., Ballantine J. (1995). Ratio and Frontier Analysis for Assessing Corporate Performance: Evidence from the Grocery Industry in the UK, *Journal of the Operational Research Society*, 46(4), 427-440.

Badillo Y., Paradi J. (1999). *La méthode DEA : analyse des performances*, Hermès, Paris, 366 p.

Banker R.D., Charnes A., Cooper W.W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science*, 30(9), 1078-1092.

Barry P.J., Ellinger P.N., Hopkin J.A., Baker C.B. (1999). *Financial Management in Agriculture*, Prentice Hall, New York, 682 p.

Charnes A., Cooper W.W., Rhodes E. (1978). Measuring the Efficiency of Decision Making Units, *European Journal of Operational Research*, 2(6), 429-444.

Chavas J.-P. (2001). Structural Change in Agricultural Production: Economics, Technology and Policy, In Gardner B. and Rausser G. (eds.), *Handbook of Agricultural Economics*, vol. 1a. Amsterdam: Elsevier, 263-285.

Coelli T., Rao D.S.P., Battese G. (2002). *An Introduction to Efficiency and Productivity Analysis*, Kluwer Academic Publishers, Boston, 275 p.

Emel A.B., Oral M., Reisman A., Yolalan R. (2003). A Credit Scoring Approach for the Commercial Banking Sector, *Socio-Economic Planning Sciences*, 37(2), 103-123.

Färe R., Grosskopf S., Lovell C.A.K. (1985). *The Measurement of Efficiency Production*, Kluwer-Nijhoff Publishing, Boston, 216 p.

Farrell M.J. (1957). The Measurement of Productive Efficiency, *Journal of the Royal Statistical Society*, Part 3, 120, 253-282.

Featherstone A.M., Langemeier M.R., Ismet M. (1997). A Nonparametric Analysis of Efficiency for a Sample of Kansas Beef Cow Farms, *Journal of Agricultural and Applied Economics*, 29(1), 175-184.

Fernandez-Castro A. and Smith P. (1994). Towards a General Non-Parametric Model of Corporate Performance, *Omega*, 22(3), 237-249.

Feroz E.H., Kim S., Raab R.L. (2003). Financial Statement Analysis: A Data Envelopment Analysis Approach, *Journal of the Operational Research Society*, 54(1), 48-58.

Fried H.O., Lovell C.A.K., Schmidt S.S. (1993). *The Measurement of Productive Efficiency: Techniques and Applications*, Oxford University Press, 427 p.

Kay R.D., Edwards W.M., Duffy P.A. (2004*). Farm Management*, McGraw-Hill, New York, 445 p.

Purdy B.M., Langemeier M.L. (1995). *Measuring Farm Financial Performance*, Working Paper, No. MF2148, Kansas State University, Manhattan.

Sevestre P. (2002). *Econométrie des données de panel*, Dunod, 211 p.

Smith P. (1990). Data Envelopment Analysis Applied to Financial Statements, *Omega*, 18(2), 131-138.

Thanassoulis E., Boussofiane A., Dyson R.G. (1996). A Comparison of Data Envelopement Analysis and Ratio Analysis as Tools for Performance Assessment, *Omega, International Journal of Management Science*, 24(3), 229-244.

Yeh Q.J. (1996). The Application of Data Envelopment Analysis in Conjunction with Financial Ratios for Bank Performance Evaluation, *Journal of the Operational Research Society*, 47, 980-988.