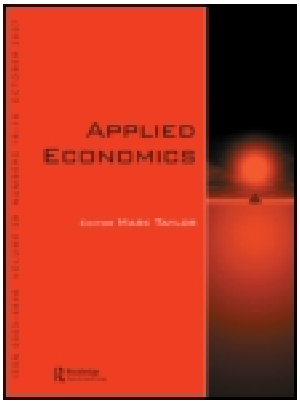

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Technical and environmental efficiencies and best management practices in agriculture

Lota D. Tamini [a], Bruno Larue [b] & Gale West [b]

[a] Institut de Recherche et Développement Agroenvironnemental et Center of Research on the Economics of Agri-food, Laval University, Québec, Canada

[b] Center of Research for the Economics of Agri-food, Laval University, Québec, Canada

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Technical and environmental efficiencies and best management practices in agriculture

Lota D. Tamini[a], Bruno Larue[b,*] and Gale West[b]

[a]*Institut de Recherche et Développement Agroenvironnemental et Center of Research on the Economics of Agri-food, Laval University, Québec, Canada*
[b]*Center of Research for the Economics of Agri-food, Laval University, Québec, Canada*

An Input Distance Function (IDF) is estimated to empirically evaluate and analyse the technical and environmental efficiencies of 210 farms located in the Chaudière watershed (Quebec), where water quality problems are particularly acute because of the production of undesirable outputs that are jointly produced with agricultural products. The true IDF is approximated by a flexible translog functional form estimated using a full information maximum likelihood method. Technical and environmental efficiencies are disaggregated across farms and account for spatial variations. Our results show that there is a significant correlation between the two efficiencies. The IDF is used to compute the cumulative Malmquist productivity index and the Fisher index. The two indices are used to measure changes in technology, profitability, efficiency and productivity in response to the adoption of two selected Best Management Practices (BMPs) whose objective is to reduce water pollution. We found significant differences across BMPs regarding the direction and the magnitude of their effect.

Keywords: environmental efficiency; distance function; phosphorus runoff; productivity; profitability; technical efficiency

JEL Classifications: Q25; Q52

I. Introduction

Typically, farmers produce good outputs such as crops and livestock (‘*goods*’ henceforth), but also undesirable outputs (‘*bads*’ henceforth) such as excessive phosphorus or sediments. The analysis of Technical Efficiency (TE) in agricultural production has a long and rich history (e.g. Farrell, 1957), but its linkage to Environmental Efficiency (EE) is fairly recent (Reinhard *et al*., 1999; Cuesta *et al*., 2009). Concerns about climate change, biodiversity and water pollution have boosted interest in mitigating the environmental consequences of agriculture through Beneficial Management Practices (BMPs). Hence, the extent by which BMPs may impact on measured efficiencies and other aspects of economic performance has important public policy implications.

*Corresponding author. E-mail: Bruno.Larue@eac.ulaval.ca

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Barbera and McConnell (1990)[1] analyse economic performance of firms producing good and bad outputs by estimating a cost function. Their approach entails disaggregating a subset of inputs into abatement and nonabatement components to calculate their effect on costs. However, this approach usually does not consider the abatement components of other inputs. Another approach is to introduce one or more bad outputs along with good outputs in a multi-product production function. Each choice of the base unconstrained emission rate thus creates a different nonlinear transformation of the original variables conditioning agricultural production and hence a new model with different elasticities, returns to scale and test statistics. Stochastic Frontier Analysis (SFA) has also been applied to cost functions and is most useful when production processes are subject to random shocks (Coelli *et al*., 2003).[2]

Fernandez, Koop and Steel (FKS, 2000, 2002), introduced good and bad outputs in a stochastic production frontier, estimated with Bayesian methods, to disentangle TE and EE. FKS (2002) made the assumption that the frontier for the '*goods*' depends only on input quantities, whereas the frontier for the '*bads*' is determined by the amount of good outputs produced.

The direct estimation of a cost frontier can be impractical or in some cases inappropriate because of systematic deviations from cost-minimizing behaviour. In such cases, the duality between cost and production functions vanishes and cost frontier estimates are biased (Coelli *et al*., 2003). A solution is the use of a shadow cost function, which explicitly models systematic deviations. This can be a complex exercise even when simplifying assumptions are made to obtain a tractable model. Reinhard and Thijssen (2000) base their analysis of EE on a system of equations estimating shadow input costs. The authors compute nitrogen efficiency through technical and allocative components.[3] Another solution is to obtain a direct estimate of the primal production technology, and then derive the implicit cost frontier. Bravo-Ureta and Rieger (1991) use this approach and assume that input quantities are decision variables. As mentioned by Coelli *et al*. (2003), this approach is not widely adopted because of a simultaneity bias. Finally, based on Färe *et al*. (2005), Huhtala and Marklund (2005) develop an empirical framework to estimate the shadow prices for '*bads*' based on the opportunity cost of production. They assume that abatement is only possible by adjusting agricultural production. Atkinson and Dorfman (2005) use an Input Distance Function (IDF) approach to characterize a polluting technology. The IDF can be interpreted as a multi-input output-requirement function that allows deviations from a frontier.[4] Distance function approaches allow for the computation of measures reflecting the output and input relationships indicative of performance. As such, they are ideally suited to analyse efficiency at the watershed level.

In this article we estimate TE and EE as well as indices of productivity and profitability and assess the impact of BMPs on them. We follow Atkinson and Dorfman (2005) in relying on an IDF with a '*bad*' modelled as a technology shifter to compute our performance indicators. We also rely on an IDF with an aggregate '*goods*' modelled as a technology shifter to compute our environmental performance indicators. A constrained maximum likelihood estimator is used to estimate our three-equation systems. We found that farms that are technically inefficient tend to be environmentally inefficient and that there are significant differences across BMPs regarding the direction and the magnitude of their effect on profitability, efficiency and productivity. Our analyses have focused on a limited number of BMPs and only one bad output. Even though BMP implementation and bad output reductions are costly, BMP adoption increases profitability for one of the BMPs considered.

The remainder of this article is structured as follows: the next section describes our methodological approach while the third section discusses some aspects of the survey from which our data originates. The fourth section presents estimation results, performance indicators and how the latter are affected by BMPs. The last section concludes the article.

[1] Färe *et al*. (1993) treated environmental effects of an undesirable output and an undesirable input using parametric mathematical programming and nonparametric mathematical programming known as Data Envelopment Analysis (DEA). The DEA approach has been used extensively in studies of SO_2 emission in electric utilities and for nitrogen and phosphorus runoff in agriculture.

[2] Schmidt and Lovell (1979) described how one could estimate a Cobb–Douglas stochastic cost frontier and then use duality to derive the implicit production frontiers. With these two frontiers, one could measure cost efficiency and technical efficiency, and hence allocative efficiency residually.

[3] The materials balance condition of the nitrogen cycle ensures that the nitrogen surplus of output-constrained dairy farms is minimized if farm is nitrogen efficient in the inputs.

[4] The Output Distance Function (ODF) identifies the largest set of outputs possible given a set of inputs while the IDF identifies the smallest set of inputs necessary to produce a set of outputs. The ODF can thus be interpreted as a multi-output production function allowing deviations (distance) from the frontier.

II. Methodological Approach

Input distance function of 'goods' with 'bads' as technological shifters

Let us define $\mathbf{x}=(x_1,\ldots,x_N)\in R_+^N$ as a vector of inputs and $\mathbf{y}=(y_1,\ldots,y_M)\in R_+^M$ a vector of good outputs. Treating the '*bads*' as exogenous shifters of the technology set allows us to write an IDF as (Atkinson and Dorfam, 2005)

$$D^I(\mathbf{y},\mathbf{x}\mid\mathbf{b})=\sup_{\lambda}\left\{\lambda:(\mathbf{x}/\lambda,\mathbf{y}\mid\mathbf{b})\in L(\mathbf{x},\mathbf{y}\mid\mathbf{b})\right\} \quad (1)$$

The IDF is monotonically nondecreasing in inputs $(\partial D^I/\partial x_n\geq 0)$ and the '*bads*' $(\partial D^I/\partial b\geq 0)$[5] and monotonically nonincreasing in outputs $(\partial D^I/\partial x_y\geq 0)$. This specification of the distance function enables us to compute technological efficiencies and other measures of performance conditioned on levels of bad outputs. Since the IDF is dual to the cost function, we can write

$$C([\mathbf{y},\mathbf{b}],\mathbf{x})=\min_{\mathbf{x}}\left\{\mathbf{px}:D^I([\mathbf{y},\mathbf{b}],\mathbf{x})\geq 1\right\} \quad (2)$$

where $\mathbf{p}=(p_1,\ldots,p_N)\in R_+^N$ is the vector of input prices and $C([\mathbf{y},\mathbf{b}],\mathbf{x}])$ is a cost function. Equation 2 implies that unless inputs are used at their cost-minimizing proportions and levels, the IDF measure will be greater than one.

Input distance function of the 'bads'

In FKS (2002), the frontier for the '*bads*' is conditioned by the amount of '*goods*'. Consequently, the frontier of the '*bads*' depicts the cleanest possible technology to produce a given bundle of '*goods*'. This is convenient, but it might be too restrictive.[6] In the following, the '*goods*' are treated as exogenous shifters in the technology set of the '*bads*'. Conditional on the level of '*goods*', efficiency measures over the '*bads*' and the inputs are well-defined. Following FKS (2000), we model the production technology of the '*goods*' using a constant elasticity of transformation aggregator:

$$G=\left(\sum_{m=1}^{M}y_m^{(1+q)/q}\right)^{q/(1+q)} \quad (3)$$

with $q>0$. If q is zero, products cannot be substituted while a value of infinity implies perfect substitution. In this 'reverse' SFA framework, any systematic negative deviation is interpreted as *environmental inefficiency*. Treating the '*goods*' as exogenous shifters of the technology set allows us to define the IDF of the '*bads*' as

$$\overset{\leftrightarrow}{D}^I(\mathbf{b},\mathbf{x}\mid\mathbf{y})=\sup_{\iota}\left\{\iota:(\mathbf{x}/\iota,\mathbf{b}\mid\mathbf{y})\in L(\mathbf{x},\mathbf{b}\mid\mathbf{y})\right\} \quad (4)$$

This specification allows us to estimate EE conditioned on levels of good outputs.

Empirical specification and estimation

The IDF in (4) is approximated by a translog functional form. For farms $f=1,\ldots,F$ the technology is

$$\begin{aligned}0=&\alpha_0+\alpha_\kappa\ln\bar{\kappa}_{if}+\sum_j\alpha_j r_{jf}+\sum_i\alpha_i\hbar_{if}+\sum_z\alpha_z\ln b_{zf}\\&+\sum_m\alpha_m\ln y_{mf}+\sum_n\alpha_n x_{nf}\\&+(1/2)\sum_m\sum_{m'}\alpha_{mm'}\ln y_{mf}\ln y_{m'f}\\&+(1/2)\sum_z\sum_{z'}\alpha_{zz'}\ln b_{zf}\ln b_{z'f}\\&+(1/2)\sum_n\sum_{n'}\alpha_{nn'}\ln x_{nf}\ln x_{n'f}\\&+(1/2)\alpha_{\kappa\kappa}\ln\bar{\kappa}_{if}\ln\bar{\kappa}_{if}+\sum_n\sum_n\alpha_{mn}\ln y_{mf}\ln x_{nf}\\&+\sum_n\sum_{m'}\alpha_{zm}\ln b_{zf}\ln y_{mf}+\sum_k\sum_m\alpha_{\kappa m}\ln\bar{\kappa}_{if}\ln y_{mf}\\&+\sum_i\sum_m\alpha_{im}\ln\hbar_{if}\ln y_{mf}\\&+\sum_z\sum_n\alpha_{zn}\ln b_{zf}\ln x_{nf}\\&+\sum_k\sum_n\alpha_{\kappa n}\ln\bar{\kappa}_{if}\ln x_{if}+\ln h(\varepsilon_f)\end{aligned} \quad (5)$$

where y_{mf} represent quantities of '*goods*' m, b_{zf} stand for quantities of '*bads*' z, x_{nf} are quantities for the n variable inputs, $\bar{\kappa}$ is the level of capital (treated as a quasi-fixed input). External variables, introduced to account for heterogeneity, appears in two different ways in Equation 5. Some of them (r_{jf}) act only as external effects while others $(\hbar_{if})$ act as production

[5] To get this result, Atkinson and Dorfman (2005) assume that the '*bads*' can only be decreased and that, following Pittman (1983), with constant '*goods*' and technology, '*bads*' can be reduced only by increasing one or more inputs.

[6] As mentioned by FKS (2002, p. 433), one could construct a single frontier defined as the maximal combinations of good outputs, given quantities of bad outputs and inputs. Under a separability assumption, this approach essentially reduces to treating the two types of outputs differently in the same aggregator and it does not allow for a natural separation of technical and environmental efficiencies because a single frontier is generated. The implication is that a fully technically efficient farm is also fully environmentally efficient.

shifters (first-order polynomial and in interaction with the outputs).[7] Finally,

$$h(\varepsilon_f) = \exp(v_f - u_f) \tag{6}$$

is an additive error with a symmetric noise component, v_f with zero mean and a half-normal distribution component u_f.

The cost minimization condition is (Färe and Primont, 1995)

$$\frac{w_n x_n}{C} = \alpha_n + \alpha_{\kappa n} \ln \bar{\kappa} + (1/2) \sum_{n'} \alpha_{nn'} \ln x_{n'} + \sum_m \alpha_{mn} \ln y_m + \sum_z \alpha_{zn} \ln b_z + \xi_n \tag{7}$$

We assume that costs are being systematically minimized and that the error terms ξ_n have zero mean. Symmetry requires that

$$\begin{aligned} \alpha_{mm'} &= \alpha_{m'm}, & \forall m, m',\ m \neq m' \\ \alpha_{zz'} &= \alpha_{z'z}, & \forall z, z',\ z \neq z' \\ \alpha_{nn'} &= \alpha_{n'n}, & \forall n, n',\ n \neq n' \\ \alpha_{kk'} &= \alpha_{k'k}, & \forall k, k',\ k \neq k' \end{aligned} \tag{8}$$

In addition, linear homogeneity in variables input quantities implies

$$\sum_n \alpha_n = 1; \quad \sum_n \alpha_{nn'} = \sum_{n'} \alpha_{nn'} = \sum_n \sum_{n'} \alpha_{nn'} = 0;$$
$$\sum_n \alpha_{mn} = 0, \quad \forall m; \quad \sum_n \alpha_{zn} = 0, \quad \forall z \quad \text{and}$$
$$\sum_n \alpha_{kn} = 0, \quad \forall k$$

The estimated distance system consists of n equations; the IDF in (5) is estimated subject to (6), and $n-1$ input shares first order conditions. Following Kumbhakar and Tsionas (2005), we assume that v and u are mutually independent and independent of the explanatory variables. We also assume that $\xi \sim N_{f(n-1)}\left(0_{f(n-1)}, \sum \otimes I_f\right)$, where $\sum$ is a $(n-1) \times (n-1)$ covariance matrix, $v_f \sim N(0, \sigma_v^2)$ and $v_f \sim N^+(z_F'\delta, \sigma_u^2)$ (i.e. u follows a half-normal distribution). z represents a set of variables that conditions differences in technical efficiency across farms and δ is a vector of corresponding coefficients.[8]

General performance measures

The above IDF specification is used to compute several performance measures pertaining to TE, productivity, profitability and EE.

Performance impacts of the farms' and farmers' characteristics. The farms' and farmers' characteristics can be construed as fixed effects. The distance function elasticities for these external factors are given by

$$-\varepsilon_{D^I, r_j} = -\partial \ln D^I / \partial r_j \quad \text{and} \quad -\varepsilon_{D^I, \hbar_j} = -\partial \ln D^I / \partial \hbar_j \tag{9}$$

Input compensation for increasing 'goods'. The variable input elasticity measures the input expansion required to achieve a 1% increase in Y_m.

$$-\varepsilon_{D^I,\, Y_m} = -\partial \ln D^I / \partial \ln Y_m \tag{10}$$

Output jointness or complementarily is measured by $\varepsilon_{D^I Y_m, Y_{m'}} = \partial \varepsilon_{D^I Y_m} / \partial \ln Y_{m'} = \beta_{mm'}$. Output complementarity implies $\varepsilon_{D^I Y_m, Y_{m'}} < 0$, which means that input use does not have to increase as much to expand y_m when the level of y_n is higher.

Scale economies. The sum of first-order netput elasticities defines the extent of scale economies. In our multi-output context, our measure indicates how much overall input use must increase to support a 1% increase in all (good) outputs. Therefore, an elasticity less than unity indicates increasing returns.

$$-\varepsilon_{D^I, Y} = -\sum\nolimits_m \partial \ln D^I / \partial \ln Y_m \tag{11}$$

This measure, developed by Baumol *et al.* (1982) for a multiple-output technology, is similar to a cost function's elasticity of size.

Technical efficiency. Farm f's TE level is given by $TE_f = \exp(-\hat{u}_f)$, where $\hat{u}_f$ is as in Jondrow *et al.* (1982)

$$\hat{u}_f = u_f^* + \sigma_* \left[\frac{\phi(u_f^*/\sigma_*)}{\Phi(u_f^*/\sigma_*)} \right] \tag{12}$$

[7] We follow Paul and Nehring (2005) with their external or shift factors. Fuentes *et al.* (2001) introduce the time trend in the same way and interaction effects with the inputs. This approach is also close to the one applied by Rodriguez-Alvarez *et al.* (2007) who treat some external factors as quasi-fixed inputs in their description of the production process.

[8] Outputs and inputs may be endogenous. Rodriguez-Alvarez and Lovell (2004), Atkinson *et al.* (2003) and Atkinson and Dorfman (2005) use instrumental variables techniques to deal with this issue. In their application featuring electricity power plants, Atkinson and Dorfman (2005) examine identification issues using Hansen's (1982) J test in a Generalized Method of Moments (GMM) framework. Because, Coelli and Perelman (2000) and Rodriguez-Alvarez *et al.* (2007) define the IDF as the radial (proportional) expansion of all inputs (given the output level), the endogeneity problem does not arise if the random disturbance affecting production processes changes all inputs in the same proportion (Roibas and Arias, 2004).

and $u_f^* \equiv D^I(\mathbf{y}, \mathbf{x}, \hat{\theta}) \cdot \hat{\gamma}, \sigma_*^2 \equiv \hat{\gamma} \cdot \sigma_v^2$, $\phi(\cdot)$ and $\Phi(\cdot)$ are respectively the probability density function and the cumulative distribution function of a standard normal random variable.

BMPs adoption impact measures

Malmquist input-based productivity index. We are interested in the comparison of performances of more than two groups. In this instance, 'circularity' is a crucial property for a bilateral productivity index.[9] Pastor and Lovell (2005) show that the contemporaneous Malmquist productivity index is not circular and can give conflicting signals. Following Camanho and Dyson (2006), we compute a Malmquist-based performance index that satisfies the circularity property and can be used for the comparison of more than two groups. The index is computed as follows

$$M_{adj}^{PB} = \frac{\left[\prod_{f=1}^{F_B} D_B^I(\mathbf{y}_f^B, \mathbf{x}_f^B)\right]^{1/F_B}}{\left[\prod_{f=1}^{F_P} D_P^I(\mathbf{y}_f^P, \mathbf{x}_f^P)\right]^{1/F_p}} \cdot \left[\prod_{i=1}^{N} \frac{\left[\prod_{f=1}^{F_i} D_P^I(\mathbf{y}_f^i, \mathbf{x}_f^i)\right]^{1/F_i}}{\left[\prod_{f=1}^{F_i} D_B^I(\mathbf{y}_f^i, \mathbf{x}_f^i)\right]^{1/F_i}}\right]^{1/N} \tag{13}$$

where parameter P represents the pooled dataset and F_i the number of farms in each group i ($i = l, \ldots, N$). Let MF_{adj}^{PB} be the product of ratios in the second bracket and ME^{PB} the first bracket. A value of ME^{PB} below one indicates that there is greater structural efficiency in group B than in the pooled dataset P.[10] A value of MF_{adj}^{PB} below one indicates superior productivity of the technological frontier of group B compared to group P. And finally, a value of M_{adj}^{PB} below (above) unity indicates a superior (inferior) productivity of group B compared to group P.

The profitability change. Using Althin *et al.*'s (1996) Fisher-based index, the profitability change when adopting a BMP is

$$\overset{\leftrightarrow}{F}{}^2 = ME^{PB} \cdot \left\{ \frac{\varepsilon_{D^I,Y}^B(\mathbf{X}_B, \mathbf{Y}_B)}{\varepsilon_{D^I,Y}^P(\mathbf{X}_P, \mathbf{Y}_P)} \right\} \tag{14}$$

where $\varepsilon_{D^I,Y}$ is the primal input-based measure of elasticity of scale defined in Equation 10. There is an improvement when $\overset{\leftrightarrow}{F} < 1$.[11] As in Althin *et al.* (1996), our analysis of adoption's impacts on productivity and profitability entails estimating separate IDF for each individual BMP.[12]

Environmental performances measures

Shadow price of the 'bads'. The shadow price of the '*bads*' is

$$\frac{\partial C([\mathbf{y}, \mathbf{b}], \mathbf{p})}{\partial \mathbf{b}} = -C\big([\mathbf{y}, \mathbf{b}], \mathbf{p}\big) \nabla_b D^I\big([\mathbf{y}, \mathbf{b}], \mathbf{x}([\mathbf{y}, \mathbf{b}], \mathbf{p})\big) \tag{15}$$

We assume that the set of inputs $\mathbf{x}$ is a cost-minimizing solution and that $C([\mathbf{y}, \mathbf{b}], \mathbf{p})$ is a function of shadow prices. We then assume that the observed price equals the shadow price for one input, herbicides. By taking the ratio of the shadow price of the '*bads*' to the observed price of herbicide, the $C([\mathbf{y}, \mathbf{b}], \mathbf{p})$'s cancel out and we can solve for the estimated shadow price of the '*bads*'.

$$p_b = -p_{herbicide} \frac{\partial D^I([\mathbf{y}, \mathbf{b}], \mathbf{x}([\mathbf{y}, \mathbf{b}], \mathbf{p}))/\partial b}{\partial D^I([\mathbf{y}, \mathbf{b}], \mathbf{x}([\mathbf{y}, \mathbf{b}], \mathbf{p}))/\partial x_H} \tag{16}$$

Environmental efficiency scores. We use Reinhard *et al.* (1999) approach to derive a stochastic measure of EE

$$\ln EE_{zf} = \alpha_{zz}^{-1} \left[-\begin{pmatrix} \alpha_z + \alpha_{zz} \ln b_{zf} \\ + \sum_n \alpha_{zn} \ln x_{nf} \\ + \sum_m \alpha_{zm} \ln y_{mf} \end{pmatrix} \pm \left\{ \begin{pmatrix} \alpha_z + \alpha_{zz} \ln b_{zf} \\ + \sum_n \alpha_{zn} \ln x_{nf} \\ + \sum_m \alpha_{zm} \ln y_{mf} \end{pmatrix}^2 - 2\alpha_{zz} u_f \right\}^{0.5} \right] \tag{17}$$

[9] The circularity property posits that an index comparing productivity between units k and f, and between l and f, must be able to compare productivity between units k and l via the arbitrary third unit, f. The outcome must be unaffected by the choice of the third unit, f (Førsund, 2002).

[10] One could choose one group as the base, but in this case, the value of the index would depend on the technology chosen. Examples include Berg *et al.* (1993) and Camanho and Dyson (2006). As mentioned by Førsund (2002), in a time series context, this procedure is similar to the notions of *inter temporal* and *accumulating* technologies.

[11] This measure suggested by Georgescu-Roegen (1951) is a simplified measure of profitability change because it omits mixed terms (see Althin *et al.*, 1996).

[12] We expect the adoption of a BMP to induce a structural change in the IDF. For example, manure injection implies a modification – or a replacement – of machinery, an increase in the time used to spread the manure and then a possible reallocation of the use of inputs. Using a Chow test (Greene, 2008), we test the hypothesis that the coefficient vectors are the same for the subset of adopters and nonadopters. The size of our data set prevented us from doing estimation on sub-samples of farmers adopting more than one BMP.

where the predictor $\hat{u}_f$ is given by Equation 12. A measure of EE is calculated using the positive root in Equation 17[13] and is used to compute the environmental efficiency score (EES) for each farm as $EES_{zf} = \min(EE_{zf})/EE_{zf}$.

Environmental efficiency (EEJ). An alternative measure of firm f's EE level is computed using Jondrow *et al.*'s (1982) formula (see (12)) from the IDF of the '*bads*' with an aggregate '*good*' used as a technological shifter. A strong positive correlation between EES and EEJ would be indicative of robust results.

III. The Data

Our sample consists of 210 farms, most of them involved in the production of two '*goods*', crops (y_C) and animal productions (y_A), both measured in thousands of dollars. We have data on three '*bads*', measured as the emission levels (kilograms) of nitrogen (b_N), phosphorous (b_P) and sediments (b_S).[14] Because, the correlation coefficients between the '*bads*' are high,[15] we considered only phosphorus runoff in our empirical application. Variable inputs are labor (x_L), measured in hours, fertilizers (x_F) and herbicides (x_H), both expressed in kg. Capital $\bar{\kappa}$ is assumed to be quasi-fixed in the short run and is proxied by the estimated value of owned and rented machinery and other equipment.

There are four BMP variables that take a value of one when the BMP is implemented and zero otherwise. As mentioned before, some BMP variables act as production shifters and they are: crop rotation cycles ($\hbar_{rotation}$), injection of liquid and semi-liquid manure ($\hbar_{mamre}$) in the soil within 24 hours of the initial spreading and herbicide control and reduction measures ($\hbar_{herbamt}$). Crop rotation is considered to be practiced if it covers over half of the cultivated land. The establishment and maintenance of a riparian buffer zone larger than 1 m (r_{buffer}) is used as an external effect. We hypothesize that having a certificate for organic production ($r_{organic}$) and belonging to an agro-environmental club ($r_{envclub}$) also condition the IDF.

Producers' socio-economic attributes are used as explanatory variables in the decomposition of efficiency scores. The variable capturing whether the residence of the primary producer is on the farm or not (*Resfarm*) and gender (*Gender*) are modelled through binary variables. *Gender* takes a value of one when the primary producer is a woman. The level of education (*Education*) takes the value of 1 when the producer has a degree from a technical school, and/or a community college and/or a university. The age of the producer (*Age*) is introduced through a dummy variable taking a value of zero if $age < 55$ and a value of one if $age > 55$ years. Land use (*Use*) and farm size (*Size*) are added to assess the impact of specializing in cropping activities and farm size on efficiencies. The variable *Use* equals 1 if the value of crops produced is higher than the value of livestock and dairy productions and 0 otherwise. Finally, the level of annual expenditure on telecommunication services (*Telcom*), is used to capture a producer's exposure to information. Technical inefficiency is modelled as

$$u_f = \delta_1 Age_f + \delta_2 Gender_f + \delta_3 Education_f + \delta_4 Use_f + \delta_5 Size_f + \delta_6 \mathrm{Re}sfarm_f + \delta_7 Telcom_f \tag{18}$$

The summary statistics of the variables used in the distance function analysis are presented in Table 1.

IV. Results

General results

The coefficient estimates of the distance function system are displayed in Table 2. Many estimated coefficients are significant and have the expected sign. The model satisfies the curvature conditions, i.e. the distance function is monotonically nondecreasing in inputs and nonincreasing in '*goods*' as well as quasi-concave in variable inputs.[16] The monotonicity condition of the '*bads*' is also met. The input cross-effects coefficients are predominantly significant and positive, indicating complementarities between fertilizers, herbicides and labour. The '*goods*' cross-effect coefficient is positive and significant, indicating substitution between the two outputs. That result suggests that diversification at the farm level does not

[13] Reinhard *et al.* (1999) note that the *EE* measure adds independent information only if the outputs' elasticities are variable, a property of the translog IDF.

[14] 'Bads' levels are computed through simulations that estimate the amount of chemical leached from individual *Relatively Homogeneous Hydrological Units* (RHHUs). RHHUs correspond to small areas whose drainage structures are derived from a relatively high resolution Digital Elevation Model (DEM).

[15] The correlation coefficient between nitrogen runoff and phosphorus runoff was found to be 0.96. The correlation coefficients of the sediment runoff with nitrogen runoff and phosphors runoff were 0.82 and 0.87, respectively.

[16] Because we have imposed linear homogeneity, the input distance function must be quasi-concave.

Table 1. Summary statistics of variables used in the analysis

	Mean	SD	Minimum	Maximum
'Goods'				
Yield (×$1000)	103.09	325.41	0.15	2696.16
Animal production (×$1000)	6.55	22.16	0.00	260.00
'Bads'				
Nitrogen runoff (kilograms)	14.85	12.51	0.23	46.98
Phosphorus runoff (kilograms)	6.35	5.69	<0.01	20.55
Sediment runoff (kilograms)	1.53	1.39	<0.01	6.13
'Variable inputs'				
Labour				
Quantity (hours)	27.56	91.59	0.03	730.10
Share in total cost (%)	72.38	25.13	1.04	99.98
Fertilizers				
Quantity (kg/ha)	1.16	1.39	<0.01	10.91
Share of in total cost (%)	21.06	19.87	<0.01	77.33
Herbicides				
Quantity (kg/ha)	0.56	0.68	<0.01	4.99
Share in total cost (%)	6.56	6.90	<0.01	48.28
'Quasi-fixed inputs'				
'Quantity' of capital (×$1000)	137.77	115.10	1.79	784.50
BMP/Environmental variables (binary variables)				
Production shifter				
Crop rotation	0.70	0.46	0	1
Herbicide control	0.38	0.49	0	1
Manure control measures	0.41	0.49	0	1
Exogenous factors				
Riparian buffer	0.56	0.50	0	1
Biological/organic certificate	0.03	0.18	0	1
Belonging to an environmental club	0.62	0.49	0	1
Farm and producer's attributes				
Age (years)	49.23	9.95	17	81
Gender (binary variable)	0.04	0.21	0	1
Education (order variable)	2.31	1.04	1	5
Residence on farm (binary variable)	0.88	0.32	0	1
Size of farm				
Cultivated acres (×100 acres)	1.29	1.47	<0.01	11.21
Animal production (×100 heads)	6.56	22.16	0.01	260
Crop production (binary variable)	1.24	1.41	<0.01	11.21
Telecommunication expenditures (×$1000)	1.33	1.73	0.05	15
Total cost of production (×$1000)	73.67	239.93	0.23	2011.62

contribute significantly to overall economic performance. The cross-effect coefficient of the two '*goods*' and the '*bads*' are nonsignificant, indicating that a decrease in the bad does not impact on the increase in inputs needed to increase a 'good' by 1%. Output mix, including the '*bads*' seems to be less fixed across farm types than the input composition as in Paul and Nehring (2005).[17]

Adopting a riparian buffer tends to have a positive impact on the overall performance of the farm while having an organic product certificate tends to have a negative impact. The mean of the performance impacts of the external variables that can interact with the level of production ($\hbar$) *is* shown in Table 3. The computed means of the overall impact of the three variables are negative implying a reduction of the IDF.

[17] Just and Pope (1978) contend that the impact of input use on risk may induce a correlation between outputs that would otherwise be independent without risk. The idea is that uncertainty causes variations in the marginal products or contributions of inputs across products.

Table 2. Estimated coefficients of the input distance function

Parameters	Estimate	SE	Parameters	Estimate	SE
α_0	0.817	0.152	$\alpha_{herbicides\times fertilizers}$	−0.173	0.014
α_{ripbuf}	−0.024	0.035	$\alpha_{crop\times labour}$	0.122	0.009
$\alpha_{Herbcont}$	−0.028	<0.001	$\alpha_{crop\times fertilizers}$	−0.097	0.007
$\alpha_{bioprod}$	0.482	0.112	$\alpha_{crop\times herbicides}$	−0.025	0.004
$\alpha_{envclub}$	0.025	0.035	$\alpha_{anima\times labour}$	−0.001	0.006
α_{liqman}	−0.054	0.098	$\alpha_{animal\times fertilizers}$	0.001	0.005
$\alpha_{croprot}$	0.202	0.093	$\alpha_{animal\times herbicides}$	0.001	0.002
$\alpha_{phosphorus}$	−0.007	0.027	$\alpha_{crop\times phosphorus}$	0.003	0.010
α_{crop}	−0.860	0.053	$\alpha_{animal\times phosphorus}$	−0.006	0.005
α_{animal}	−0.102	0.033	$\alpha_{crop\times capital}$	0.026	0.020
$\alpha_{fertilizers}$	0.361	0.033	$\alpha_{animal\times capital}$	−0.010	0.010
$\alpha_{herbicides}$	0.192	0.012	$\alpha_{crop\times croprot}$	−0.078	0.029
α_{labour}	0.447	0.041	$\alpha_{animal\times croprot}$	0.011	0.023
$\alpha_{capital}$	−0.033	0.049	$\alpha_{crop\times liqman}$	0.007	0.023
$\alpha_{animal\times animal}$	−0.017	0.008	$\alpha_{animal\times liqman}$	−0.016	0.021
$\alpha_{animal\times crop}$	0.074	0.019	$\alpha_{crop\times contherb}$	−0.034	<0.001
$\alpha_{crop\times crop}$	−0.071	0.017	$\alpha_{animal\times contherb}$	0.018	0.021
$\alpha_{phosphorus\times phosphorus}$	−0.012	0.007	$\alpha_{phosphorus\times labour}$	0.009	0.009
$\alpha_{capital\times capital}$	−0.013	0.027	$\alpha_{phosphorus\times fertilizers}$	−0.007	0.007
$\alpha_{labour\times labour}$	−0.173	0.014	$\alpha_{phosphorusher\times bicides}$	−0.003	0.002
$\alpha_{fertilizers\times fertilizers}$	0.027	0.009	$\alpha_{capital\times labour}$	−0.006	0.012
$\alpha_{herbicide\times herbicide}$	0.146	0.010	$\alpha_{capital\times fertilizers}$	0.006	0.009
$\alpha_{labour\times fertilizers}$	0.146	0.010	$\alpha_{capital\times herbicides}$	0.001	0.003
$\alpha_{labour\times herbicide}$	0.027	0.009			
Efficiency parameters					
$\delta_{Education}$	−0.096	0.039	δ_{use}	−0.018	0.078
δ_{size}	−0.293	0.026	δ_{gender}	0.049	0.088
δ_{age}	0.014	0.044	$\delta_{resfarm}$	−0.022	0.053
$\delta_{telecom}$	0.016	0.057			
$\gamma \equiv \sigma_u^2\left(\sigma_v^2+\sigma_u^2\right)^{-1}$	0.583	0.117	σ_v	0.474	0.034
Mean log-likelihood		3.186	Number of observations		210

Table 3. Mean values of the overall impact of the external variables

Parameters	Mean	Bootstrapped SE of the mean	Normal based 95% confidence interval of the mean
Herbicide control	−0.098	0.005	[−0.107; −0.089]
Manure injection	−0.062	0.002	[−0.067; −0.058]
Rotation cycle implementation	−0.015	0.010	[−0.034; −0.004]

The mean value of the predicted distance function is 1.413 (see Table 4). We estimate the same distance function without taking into account the '*bads*' and got a mean value of 1.430. The two mean values are statistically different at the 5% level and this confirms that the potential to increase production with a given bundle of inputs decreases when farms are not allowed to freely dispose of phosphorus emissions.

Technical efficiency

Table 2 also reports the parameters conditioning the level of *TE* of individual farms. Education and farm size have significant and positive impacts on *TE*. Bigger farms and producers who hold a degree from a technical school, college or university are generally more efficient. The log-likelihood is parameterized in terms of $\gamma = \sigma_u^2/(\sigma_v^2+\sigma_u^2)$.

Table 4. Economic performance measures

Parameters	Mean	Bootstrapped SE of the mean	Normal based 95% confidence interval of the mean
Technical efficiency	0.437	0.008	[0.422; 0.452]
Distance function	1.413	0.018	[1.379; 1.448]
Shadow value of bad	−0.063	0.001	[−0.064; −0.061]
'input share' of crop	0.618	0.014	[0.592; 0.645]
'input share' of animals	0.030	0.005	[0.020; 0.040]
Scale economies	0.644	0.014	[0.616; 0.671]
Labour elasticity	−0.621	0.011	[−0.644; −0.599]
Fertilizer elasticity	−0.291	0.010	[−0.311; −0.272]
Herbicide elasticity	−0.087	0.002	[−0.092; −0.083]

The significant estimate (i.e. 0.583) indicates that, about half of the variation in the composite error term is due to the noise component. The mean of the predicted *TE* scores is 0.426.[18] This is fairly low.[19] Figure 1 plots the density distribution of predicted technical efficiency within the dataset. The mean of the predicted *TE* of farms primarily involved in animal production is higher than the one for farms involved in crop production (i.e. 0.466 and 0.428 are statistically different at the 5% level of significance). The least efficient farm has a *TE* score of 0.186 while the most efficient farm has a *TE* score of 0.989.

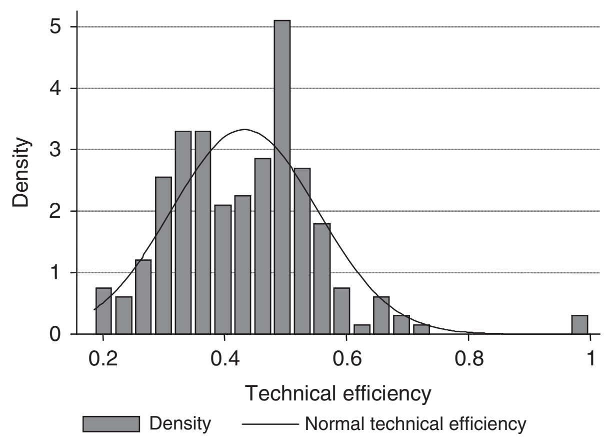

Fig. 1. Predicted technical efficiency distribution

Scale elasticities

The measure of scale elasticity is 0.644 which reveals the presence of large economies of scale (see Table 4). The scale elasticity has a value of 0.682 (0.625) when only farms predominantly involved in crop (animal) productions are considered. The difference is significant at the 5% level, but both elasticities are close to the 0.65 obtained by Paul and Nehring (2005) for the United States.

Individual output contributions embodied in the overall scale elasticity are presented in Table 4. The results show that more variable input are needed to increase crop productions by 1% than to increase animal productions by the same level. At −0.621, the value of the shadow share of labour (i.e. labour elasticity) is smaller than the observed mean share (72.38%) indicating a low labour productivity.

The impact of beneficial management practices

The adoption of a BMP is likely to induce a structural change in the IDF because some inputs are likely to interact in different ways when a BMP is implemented. We relied on a Chow test (Greene, 2008), with a null hypothesis of equal coefficient vectors for estimations done on subsamples of adopters and nonadopters, to determine whether BMP adopters actually use a different technology.[20] We rejected the null hypothesis of equal coefficients for herbicides controls and manure injection BMPs as the *p*-values for these BMPs, 0.001 and 0.000, fell well below the critical 0.05, while the *p*-value in the case of crop

[18] Without taking into account the '*bads*' as a technological shifter in the production process, the mean value of the predicted *TE* is 0.471. The null hypothesis of no significant difference between the means of *TE* with and without '*bads*' is rejected at the 5% level.

[19] Coelli *et al.* (2003) get a predicted mean *TE* of 0.86 from their sample of Indian dairy processing firms. Paul and Nehring's (2005) predicted mean *TE* is quite high at 0.93. Their IDF model was applied to US farm level data. FKS (2002) report a median *TE* of 0.67 for their sample of US dairy farms. The median for our study is 0.49. Finally, Atkinson and Dorfman (2005) report a weighted average *TE* of 0.55.

[20] Estimations results are available from the authors upon request.

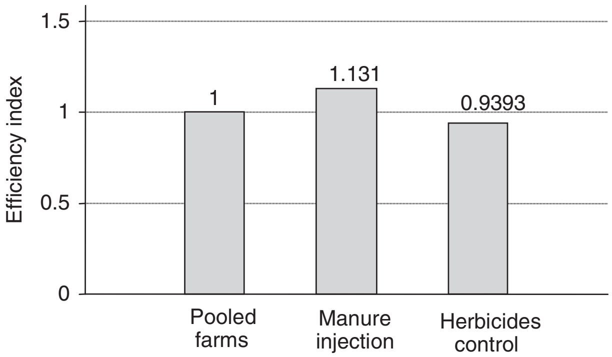

Fig. 2. Efficiency index, using pooled dataset as the reference

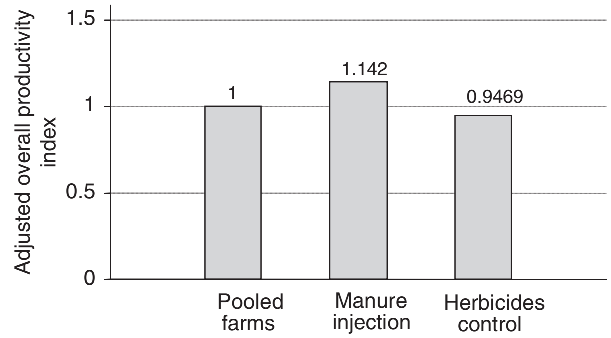

Fig. 4. Adjusted (overall) performance index, using pooled dataset as the reference

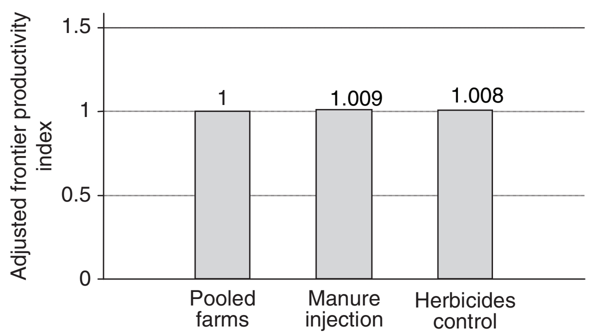

Fig. 3. Adjusted productivity index, using pooled dataset as the reference

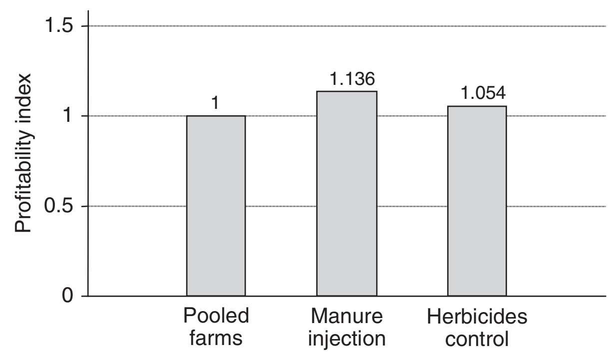

Fig. 5. Profitability index, using pooled dataset as the reference

rotation was 0.194. Accordingly, we restricted our analyses to the first two aforementioned BMPs.

Figures 2–5 present the impacts of BMP adoption on efficiency, productivity and profitability. In order to make Figs 2–5 as intuitive as possible, we computed the inverses of the Malmquist performance index M^{PB}_{adj}, its efficiency and productivity components MF^{PB}_{adj} and ME^{PB} and the profitability index $\overleftrightarrow{F}$. As a result, an index value greater (less) than one represents an improvement (a deterioration).

Farms that have adopted herbicides control are technically less efficient ($0.939 < 1$), but enjoy a very small productivity advantage ($1.008 > 1$). The combined effect is a decline in overall productive performance ($0.947 < 1$). However, the adoption of herbicide control also tends to slightly increase economies of scale, as indicated by the profitability index ($1.054 > 1$). Herbicide control probably frees up capital and labour which can then be used to produce more outputs. In contrast, farms that have adopted manure injection tend to be more technically efficient and more slightly productive than farms that have not adopted this BMP. The net positive effect on the overall Malmquist performance index is $1.142 > 1$. Furthermore, profitability increases sharply when manure injection is adopted ($1.136 > 1$), indicating an increase in returns to scale.

BMPs have positive environmental effects, as their adoption reduces the bad without affecting the goods. In the case of herbicide control, environmental gains do not imply a reduction in productive performance. Ambec and Lanoie (2008) and Horbach (2008) suggest that private gains from the adoption of environmentally-friendly technologies can be attributed to the fact that environmental management tools provide incentives to develop cost saving practices. These innovations induced by the adoption of environmentally-friendly practices are at the heart of the Porter-hypothesis (Porter and van der Linde, 1995).[21] Piot-Lepetit and Le Moing (2007) found a gain in productivity resulting from the relationship

[21] Horbach (2008, p. 172) concludes that '…An environmentally oriented research policy has not only to regard traditional instruments like the improvement of technological capabilities of a firm, but also the coordination with soft environmental policy instruments like the introduction of environmental management systems.'

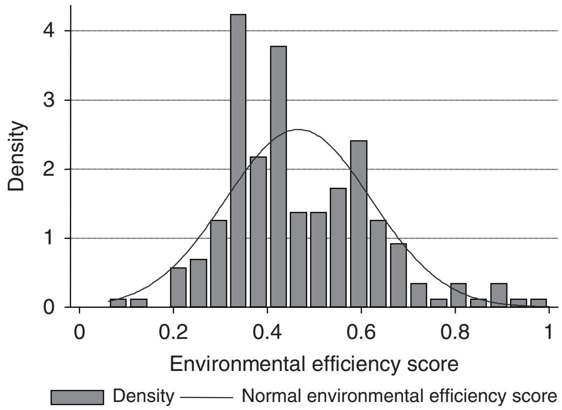

Fig. 6. Predicted environmental efficiency score (*EES*) distribution

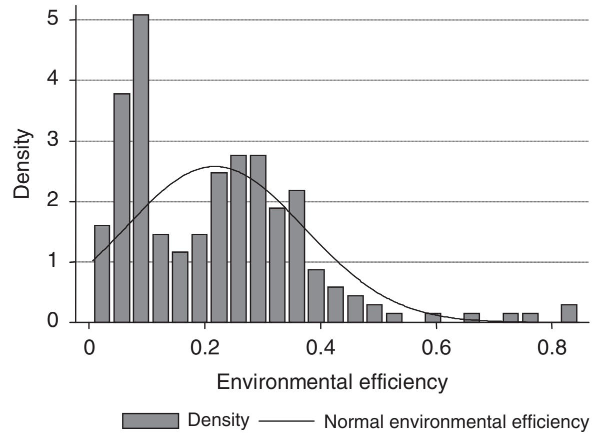

Fig. 7. Predicted environmental efficiency (*EEJ*) distribution

between efficiency and environmental regulation in the analysis of pig production in France, unlike Managi (2004) who did not find evidence in support of the Porter-hypothesis when analysing the US agricultural sector.

The 'bads'

The shadow value of the 'bads'. The estimated shadow value of phosphorus runoff (i.e. marginal abatement cost) has a mean value of 0.063 with an SD of 0.001. It is 0.0652 for farms primarily involved in animal productions, which is higher than the value of 0.062 for farms involved in crop productions. The difference between these two estimates is significant at the 5% level. As in Ball *et al*. (2002) and Ghazalian *et al*. (2010), reducing a '*bad*' output is costly.[22] A 10% reduction in phosphorus induces a 0.628% increase in the cost. In our sample, the average value for the sub-cost function is \$73 668, which implies that the cost of a 10% runoff reduction would be \$461.24.[23] The result also suggests that the marginal abatement cost of runoff weakly increases with the scale of production. The shadow value of the bad is higher for farms primarily involved in animal production than for farms specialized in crop production.

Environmental efficiency measures. We computed two sets of EE scores based on different methodologies. The mean of the computed *EES* is 0.486. Figure 6 plots the density distribution of computed *EES* within the dataset and Fig. 7 the density distribution of the estimated *EEJ*. The mean of the *EES* for farms specialized in animal productions is lower than its crop productions counterpart: 0.380 versus 0.504. The difference is significant at the 5% level. The Spearman rank correlation between *EES* and *EEJ* is high at 0.71 indicating robustness of the results.

Table 5 reports the Spearman rank correlation between technical and environmental efficiencies. In this table, the dataset is sub-divided into subsets based on the predicted *TE*s. The correlation is strongest for the most technically efficient farms (75th percentile to the maximum *TE*). There is no statistically significant correlation between *EE* and *TE* when only farms in the median-75th percentile subsample are considered. Overall there is a tendency for farms that are technically inefficient to also be environmentally inefficient. A similar finding was reported by Reinhard *et al*. (1999) and FKS (2002).[24] Because of the low level of predicted *TE*, our findings suggest that for many farms, pollution could be reduced at no cost in terms of good output foregone.

V. Conclusion

The variability in farmers' TE is likely to influence observed environmental performance, as does the adoption or nonadoption of BMPs. A distance

[22] Our estimate is higher than Ball *et al*.'s (2002) 0.09% and 0.08% for leaching and runoff.
[23] Using data covering the 2001–2003 period, Gangbazo and Le Page (2005) find that phosphorus runoff has to decrease by 30.8% in the Chaudière watershed to reach the target of 0.030 mg/l to prevent eutrophication at the water quality stations (Table 4.2, p. 26). These authors also find that 33.8% of the phosphorus runoff is a nonpoint source pollution generated to a large extent by agricultural activities (Table 4.3, p. 28). Clearly, discussing the cost of a 10% reduction is a sensible exercise.
[24] Reinhard *et al*. (1999) have found a positive Spearman rank correlation of 0.87 in their sample of Dutch dairy farms. A similar finding is reported for US dairy farms by FKS (2002) even if the correlation coefficient is noticeably lower than 0.40.

Table 5. Spearman correlation rank tests between predicted *TE* and *EE* measures

		EES		*EEJ*	
	Number of observations	Spearman correlation rank test	Probability > $\|t\|$	Spearman correlation rank test	Probability > $\|t\|$
Percentile distribution of predicted technical efficiency					
(0; p25(=0.343)[	52	0.349	0.011	0.321	0.020
[p25(=0.343);p50(=0.431)[	53	0.331	0.015	0.329	0.018
[p50(=0.431); p75(=0.509)[	51	0.177	0.206	0.330	0.0206
[p75(=0.509); p100)	54	0.590	<0.001	0.658	<0.001
Technical efficiency value					
(0; 0.25[	9	0.600	0.088	0.367	0.337
[0.25; 0.50[	139	0.625	<0.001	0.605	<0.001
[0.50; 0.75[	58	0.352	0.007	0.117	0.383
[0.75;1)	4	−0.316	0.684	−0.384	0.616
Overall sample	210	0.713	<0.001	0.757	<0.001

function approach is implemented to empirically analyse technical and environmental efficiencies. In the context of multiple good and bad outputs, two types of input distance function are estimated. For the first type, a bad output is modelled as a technological shifter in an IDF for good outputs. For the second type, good outputs are aggregated into one good output which is used as a technological shifter in an IDF for the bad output. The IDFs are approximated by a flexible translog functional form which is estimated using a full information maximum likelihood method. We rely on a unique data set covering 210 farms located in the Chaudière watershed, where water quality problems are acute. Data on phosphorus, nitrogen and sediment loads have been simulated through a hydrological model.

The computed level of *TE* is disaggregated across farms. The level of education and the size of the farm have a significant and positive impact on the *TE*. The mean of the predicted *TE* suggests that less than half of farm diversity is explained by the broad characterization of input and output relationships in the model. The mean of the computed environmental efficiency scores is relatively low and a positive correlation was found between scores of environmental and technical efficiencies. Our study also found that reducing phosphorus run off entails cost at the farm level.

The IDF of the good output is used to compute the cumulative Malmquist-based productivity index and we computed measures of efficiency and productivity changes in response to the adoption of selected BMPs. The Fisher productivity index was computed and, by exploiting the duality between cost and input distance functions, we obtained a measure of profitability change when farms adopt selected BMPs. Our results show significant differences across BMPs regarding the direction and the magnitude of their effect on profitability, efficiency and productivity. Even if BMP implementation and bad output reductions are costly, profitability increases for one of the implemented BMPs.

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