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Structure and Performance of Agriculture and Agri-products industry Network

Technical Efficiency, Environmental Efficiency, Productivity and Beneficial Management Practices [1]

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Abstract: An input distance function (IDF) is estimated to empirically evaluate and analyze 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 technical and environmental efficiencies. Farms that are technically efficient tend to be environmentally efficient. We used the cumulative Malmquist productivity index and the Fisher index to measure changes in technology, profitability, efficiency, and productivity in response to the adoption of 2 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 on profitability, efficiency and productivity.

Résumé: Une fonction de distance est estimée empiriquement pour évaluer les efficiences technique et environnementale de 210 fermes localisées dans le bassin Chaudière (Québec) où des problèmes avec la qualité de l'eau, découlant de la production d'outputs indésirables qui accompagnent les productions agricoles, ont été observés. Nous estimons une forme fonctionnelle Translog par la méthode de maximum de vraisemblance à information complète. Les mesures d'efficience, qui sont calculées pour chaque ferme, prennent en compte les variations spatiales. Nos résultats indiquent qu'il y a une corrélation positive entre les efficiences techniques et environnementales. Les fermes qui sont plus efficientes techniquement sont aussi plus efficientes au niveau environnemental. Les indices cumulatif Malmquist et Fisher sont utilisées pour faire des inférences sur la profitabilité, la productivité et les changements technologiques en réponse à l'adoption de pratiques bénéfiques à l'environnement. Nos résultats diffèrent d'une pratique à une autre en ce qui concerne les effets des pratiques sur la profitabilité, l'efficience et la productivité.

Keywords: Environmental efficiency, distance function, phosphorus runoff, productivity, profitability, technical efficiency.

J.E.L. Classification: Q25, Q52.

Technical Efficiency, Environmental Efficiency, Productivity and Beneficial Management Practices

1. Introduction

Typically, farmers produce good outputs such as milk and maize ("*goods*" henceforth), but also undesirable outputs ("*bads*" henceforth) such as excessive phosphorus or sediments. They must allocate marketable inputs efficiently to be competitive, and are increasingly under pressure to reduce environmental damages. The analysis of technical efficiency in agricultural production has a long and rich history (e.g., Farrell, 1957; Timmer, 1971), but its linkage to environmental efficiency is fairly recent (Reinhard, Lowell and Thijssen, 1999). Concerns about climate change, biodiversity and water pollution have boosted interest in mitigating the environmental consequences of agriculture through Best 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.

Atkinson and Dorfman (2005)[1] analyze 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 non-abatement components to calculate their effect on costs. However, this approach usually does not consider the abatement components of other inputs (see Barbera and McConnell, 1990). Another approach is to introduce one or more bad outputs along with good outputs in a multiproduct production function. Each choice of the base unconstrained emission rate thus creates a different nonlinear

[1] Färe et al. (1993) treated environmental effects of an undesirable output and an undesirable input using parametric mathematical programming and non-parametric 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 the agricultural sector.

transformation of the original variables conditioning agricultural production and hence a new model with different elasticities, returns to scale and test statistics (Atkinson and Dorfman, 2005). Stochastic frontier analysis (SFA) has also been applied to cost functions and is most useful when production processes are subject to random shocks (Coelli, Singh and Fleming, 2003).[2]

Following Fernandez, Koop and Steel (2000), Fernandez, Koop and Steel (2002) (FKS henceforth), introduce good and bad outputs in a stochastic production frontier, estimated with Bayesian methods, to disentangle technical and environmental efficiencies. Technical efficiency is the ratio of actual output and the maximum possible output predicted by an estimated frontier. FKS's (2002, p. 433) definition of environmental efficiency aims to answer the following question: "How much pollution could be reduced, without sacrificing good outputs, by adopting best-practice technology?" (p. 433). 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. A key assumption of FKS (2002) is that of a separable technology allowing for the aggregation of inputs and outputs.

The direct estimation of a cost frontier is impractical in some cases (e.g. when input prices do not vary much across firms) or is inappropriate because of systematic deviations from cost-minimizing behavior. This is the case in an industry where regulatory factors cause shadow prices to deviate from market prices in a systematic way. In these situations, the duality between cost and production functions vanishes, and the resulting bias in the cost frontier estimates makes the efficiency calculation and

[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.

decomposition biased as well (Coelli, Singh and Fleming, 2003). A possible solution is the use of a shadow cost function, which explicitly models systematic deviations from allocative efficiency. This can be a complex exercise even when simplifying assumptions are made to obtain a tractable model (Coelli, Singh and Fleming, 2003). Reinhard and Thijssen (2000) base their analysis of environmental efficiency on a system of equations estimating shadow input costs. In effect, firms minimize shadow costs (or behavioral costs) rather than actual 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, Singh and Fleming (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 environmentally detrimental outputs based on the opportunity cost of production. They implicitly assume that abatement is only possible by adjusting agricultural production, or output/value added at the farm level. Using this approach, a directional output–input distance function can be defined and estimated. Atkinson and Dorfman (2005) also 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

[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.

reflecting the output and input relationships indicative of performance (Paul and Nehring, 2005). As such, they are ideally suited to analyze efficiency at the watershed level.

In this paper we estimate technical and environmental efficiency scores 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 a distance function with a "*bad*" modeled as a technology shifter to compute our performance indicators. Monotonicity with respect to all inputs, "*goods*" and the "*bad*" (i.e., phosphorus), is imposed on our system of equations derived from a translog distance function. A constrained maximum likelihood estimator is used to estimate our three-equation system. 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 the paper 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 paper.

2. Methodological approach

2.1. 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 let $\mathbf{y} = (y_1,\ldots,y_M) \in R_+^M$ be a vector of good outputs. Disregarding the "*bads*", the production technology is:

(1) $$L(\mathbf{x},\mathbf{y}) = \{(\mathbf{x},\mathbf{y}) : \mathbf{x} \text{ can produce } \mathbf{y}\}$$

This representation is a multi-output, multi-input specification of the technology set that allows for interactions among these netputs. We define the "*bads*" as:

(2) $$\mathbf{b} = b(\mathbf{x},\mathbf{y})$$

The production of "*bads*" is a function of the inputs, the "*goods*" and the state of technology b. Symmetric treatment of "*bads*" and "*goods*" using an input distance function can be specified as in Färe and Primont (1995):

(3) $$D^I([\mathbf{y},\mathbf{b}],\mathbf{x}) = \sup_l \{l \ : ([\mathbf{y},\mathbf{b}],\mathbf{x}/l\ ) \in L(\mathbf{x},\mathbf{b},\mathbf{y})\}$$

Here, the "*goods*" and the "*bads*" are held constant and inputs are proportionally scaled downward to their minimum required level. Since the input distance function in (3) is dual to the cost function, we can write:

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

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 (4) implies that unless inputs are used at their cost-minimizing proportions and levels, the input distance measure will be greater than one. Taking the first order conditions, the shadow value of each input is given by:

(5) $$\mathbf{p} = C([\mathbf{y},\mathbf{b}],\mathbf{p})\nabla_x D^I([\mathbf{y},\mathbf{b}],\mathbf{x})$$

where $C([\mathbf{y},\mathbf{b}],\mathbf{p})$ is the value of the Lagrange multiplier[5] and $\nabla_x D^I([\mathbf{y},\mathbf{b}],\mathbf{x}) \equiv \left[\partial D^I([\mathbf{y},\mathbf{b}],\mathbf{x})/\partial x_1,\ldots,\partial D^I([\mathbf{y},\mathbf{b}],\mathbf{x})/\partial x_n\right]$. Treating the "*bads*" as exogenous shifters of the technology set allows us to write (3) as:

(6) $$D^I(\mathbf{y},\mathbf{x}\,|\,\mathbf{b}) = \sup_l \left\{ l : (\mathbf{x}/l, \mathbf{y}\,|\,\mathbf{b}) \in L(\mathbf{x},\mathbf{y}\,|\,\mathbf{b}) \right\}$$

The input distance function is monotonically non decreasing in inputs $\left(\partial D^I/\partial x_n \geq 0\right)$ and the "*bads*" $\left(\partial D^I/\partial b \geq 0\right)$[6] and monotonically non increasing in outputs $\left(\partial D^I/\partial y_m \leq 0\right)$. This specification of the distance function enables us to compute technological efficiencies and other measures of performance conditioned on levels of bad outputs.

2.2. Input distance function of the "*bads*"

In FKS (2002), the frontier for the "*bads*" is conditioned by the amount of "*goods*" produced as some "goods" must be sacrificed to lower the "bads". Consequently, the frontier of the "*bads*" depicts the cleanest possible technology to produce a given bundle of "goods". The firms' environmental efficiencies are defined as the ratio of the minimum bad aggregate output and the observed bad aggregate output.[7] The assumption that "goods" are function only of inputs and "*bads*" are function only of "goods" is convenient, but it might be too restrictive. An alternative is to treat the "*goods*" as

[5] For more details, see Rodriguez-Alvarez, del Rosal and Bonanos-Pino (2007).

[6] 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 only be reduced through increased usage of at least some inputs.

[7] 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.

exogenous shifters in the technology set of the "*bads*". Conditional on the level of good outputs, efficiency measures over the "*bads*" and the inputs are well defined. The frontier for the "*bads*" being measured for given levels of "*goods*" requires that we aggregate our good outputs into a single aggregate metric. To this end, we follow FKS (2000) and model the production technology of the "*goods*" using the following aggregator:

$$(7) \qquad G = \left(\sum_{m=1}^{M} y_m^{(1+q)/q} \right)^{q/(1+q)}$$

with $q > 0$. This constant elasticity of transformation aggregator was first developed by Powell and Gruen (1968) to analyze agricultural supply. If q is zero, products cannot be substituted while a value of infinity implies perfect substitution in production. 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:

$$(8) \qquad \vec{D}^I\left(\mathbf{b}, \mathbf{x} \mid \mathbf{y}\right) = \sup_i \left\{ i : \left(\mathbf{x} / i, \mathbf{b} \mid \mathbf{y} \right) \in L\left(\mathbf{x}, \mathbf{b} \mid \mathbf{y} \right) \right\}$$

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

2.3. Empirical specification and estimation

We assume that the IDF in (6) and (8) can be approximated by a translog functional form with capital, denoted by $\bar{k}$, treated as a quasi-fixed input. Following Paul and Nehring (2005) we use farms' and farmers' specific characteristics denoted by vector $\mathbf{r}$ to account for heterogeneity. Thus for farms $f = 1, \ldots, F$ the technology can be depicted as follows:

$$0 = a_0 + a_k \ln \bar{k}_{if} + \sum_j a_j r_{jf} + \sum_i a_i \hbar_{if} + \sum_z a_z \ln b_{zf} + \sum_m a_m \ln y_{mf} + \sum_n a_n x_{nf} +$$

$$(1/2)\sum_m \sum_{m'} a_{mm'} \ln y_{mf} \ln y_{m'f} + (1/2)\sum_z \sum_{z'} a_{zz'} \ln b_{zf} \ln b_{z'f} +$$

(9) $$(1/2)\sum_n \sum_{n'} a_{nn'} \ln x_{nf} \ln x_{n'f} + (1/2) a_{kk} \ln \bar{k}_{if} \ln \bar{k}_{if} + \sum_m \sum_n a_{mn} \ln y_{mf} \ln x_{nf}$$

$$+ \sum_z \sum_m a_{zm} \ln b_{zf} \ln y_{mf} + \sum_k \sum_m a_{km} \ln \bar{k}_{if} \ln y_{mf} + \sum_i \sum_m a_{im} \ln \hbar_{if} \ln y_{mf}$$

$$+ \sum_z \sum_n a_{zn} \ln b_{zf} \ln x_{nf} + \sum_k \sum_n a_{kn} \ln \bar{k}_{if} \ln x_{nf} + \ln h(e_f)$$

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, $\bar{k}$ is the level of capital and r_{jf} and $\hbar_{if}$ are respectively external farm specific variables j and i. Finally,

(10) $$h(e_f) = \exp(v_f - u_f)$$

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

External variables appears in two different ways in equation (9). Some of them (r_{jf}) act only as external effects while others $(\hbar_{if})$ act as production shifters (first order polynomial and in interaction with the outputs).[8] This introduces some flexibility in the IDF which will be useful in our analysis of the impacts of BMPs on productivity and profitability.

Taking logs and deriving with respect to input quantities, equation (5) can be written as:

(11) $$\partial \ln D^I / \partial \ln x_n = w_n x_n / C$$

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[8] We follow Paul and Nehring (2005) with their external or shift factors. Fuentes, Grifell-Tatjé and Perelman (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.

where w_n is the price of input x_n and C is the total cost of variables inputs.[9] Using (9) and (11) the cost minimisation condition is (Färe and Primont, 1995):

$$\text{(12)} \qquad \frac{w_n x_n}{C} = a_n + a_{kn} \ln \bar{k} + (1/2)\sum_{n'} a_{nn'} \ln x_{n'} + \sum_m a_{mn} \ln y_m + \sum_z a_{zn} \ln b_z + x_n$$

We assume that costs are being systematically minimized and that the error terms x_n have zero mean. Parametric restrictions are imposed when estimating (9).[10] Symmetry requires that:

$$\text{(13)} \qquad \begin{array}{ll} a_{mm'} = a_{m'm}, & \forall m, m', \ \ m \neq m', \\ a_{zz'} = a_{z'z}, & \forall z, z', \ \ z \neq z', \\ a_{nn'} = a_{n'n}, & \forall n, n', \ \ n \neq n', \\ a_{kk'} = a_{k'k}, & \forall k, k', \ \ k \neq k' \end{array}$$

In addition, linear homogeneity in variables input quantities implies: $\sum_n a_n = 1$;

$\sum_n a_{nn'} = \sum_{n'} a_{nn'} = \sum_n \sum_{n'} a_{nn'} = 0$; $\sum_n a_{mn} = 0, \forall m$; $\sum_n a_{zn} = 0, \forall z$ and $\sum_n a_{kn} = 0, \forall k$.

The estimated distance system consists of n equations: the distance function represented by equation (9) estimated subject to (10), 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 $x \square N_{f(n-1)}\left(0_{f(n-1)}, \Sigma \otimes I_f\right)$ where Σ is a $(n-1)\times(n-1)$ covariance matrix, $v_f \square N\left(0, s_v^2\right)$ and $u_f \square N^+\left(z_f' d, s_u^2\right)$ (i.e., u follows a half-normal distribution). z represents a set of

[9] Under the assumption that capital is quasi-fixed, our analysis focuses on the sub-cost function with non-capital inputs i.e. labour, fertilizers and herbicides.

[10] These constraints can be imposed by normalizing the function by one of the outputs (Paul, Johnston and Frengley, 2000; Cuesta, Lovell and Zofio, 2009) or by one input (Paul and Nehring, 2005). As mentioned by Atkinson, Färe and Primont (2003), a direct estimation with linear homogeneity imposed via parametric restriction has the advantage of automatically generating the fitted distance function, and the partial derivatives of its log.

variables that conditions differences in technical efficiency across farms and d is a vector of corresponding coefficients as in Kumbhakar, Ghosh and McGuckin (1991) and Battese and Coelli (1995). Given the above distributional assumptions and following Battese and Corra (1977), the likelihood function of the model is:

$$
\begin{aligned}
(14)\qquad \ln L = & -\frac{F(n-1)}{2}\ln(2p) - \frac{F}{2}\ln\left(s^{2}\right) - \frac{F}{2}\ln|\Sigma| \\
& + \sum_{f=1}^{F}\ln\Phi\left(-\frac{e_f}{s}\sqrt{\frac{g}{1-g}}\right) - \frac{1}{2}\sum_{f=1}^{F}\left[x_f'\Sigma^{-1}x_f + e_f^2 s^{-2}\right]
\end{aligned}
$$

where $e_f \equiv u_f - v_f$, $\Phi(\cdot)$ is the cumulative distribution function of a standard normal random variable, $s^2 \equiv s_v^2 + s_u^2$ and $g \equiv s_u^2 / s^2 \in [0,1]$. If $g = 0$, then all deviations from the frontier are due to noise, while $g = 1$ means all deviations are due to technical inefficiency. The model is estimated with a constrained maximum likelihood estimator.[11]

2.4. General performance measures

The above IDF specification is used to compute several performance measures pertaining to technical efficiency, productivity, profitability and environmental efficiency. Index numbers are used to analyze the impact of BMPs on the performance measures. This requires the estimation of distance functions on samples of farms that have adopted a given BMP and on farms that have not and rejection of the null of parameter equality to validate that adopters and non-adopters have different technologies.

[11] Outputs and inputs may be endogenous. Rodrıguez-Alvarez and Lovell (2004), Atkinson, Cornwell and Honerkamp (2003) and Atkinson and Dorfman (2005) use instrumental variables techniques to deal with this endogeneity issue. In their application featuring electricity power plants, Atkinson and Dorfman (2005) examine identification issues using Hansen's (1982) J test in a GMM framework. However, given that Coelli and Perelman (2000) and Rodriguez-Alvarez et al. (2007) define the input distance function 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).

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:

(15) $-e_{D^I,r_j} = -\partial \ln D^I \big/ \partial r_j$ and $-e_{D^I,\hbar_j} = -\partial \ln D^I \big/ \partial \hbar_j$

Input compensation for increasing "goods"

The variable input elasticity measures the input expansion required to achieve a 1 % increase in Y_m .

(16) $-e_{D^I,Y_m} = -\partial \ln D^I \big/ \partial \ln Y_m$

Output jointness or complementarily is measured by $e_{D^I y_m, y_{m'}} = \partial e_{D^I y_m} \big/ \partial \ln y_{m'} = b_{mm'}$. Output complementarity implies $e_{D^I y_m, y_{m'}} < 0$, 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 define the extent of scale economies or the increase in productivity resulting from increasing all variable inputs. In our multi-output context, our measure indicates how much overall input use must increase to support a 1 % increase in all outputs. Therefore, an elasticity less than unity is indicative of increasing returns.

(17) $-e_{D^I,Y} = -\sum_m \partial \ln D^I \big/ \partial \ln Y_m$

This measure, developed by Baumol, Panzar and Willig (1982) for a multiple-output cost model (Paul and Nehring, 2005), is similar to a cost function's elasticity of size which compares marginal and average costs to produce all outputs.

Technical efficiency

Farm f 's level of technical efficiency (*TE*) is given by $TE_f = \exp\left(-\hat{u}_f\right)$. We use Jondrow et al.'s (1982) predictor of u_f :

(18) $$\hat{u}_f = u_f^* + s_* \left[\frac{f\left(u_f^* / s_*\right)}{\Phi\left(u_f^* / s_*\right)} \right]$$

where $u_f^* \equiv D^I\left(\mathbf{y},\mathbf{x},\hat{q}\right)\cdot\hat{g}$, $s_*^2 \equiv g \cdot s_v^2$, $f\left(\cdot\right)$ and $\Phi\left(\cdot\right)$ are respectively the probability density function (pdf) and the cumulative distribution function (cdf) of a standard normal random variable. The normalization of $\hat{u}_f$ guarantees that $0 < TE_f \leq 1$. TE_f compares the input use by an efficient farm on the frontier to that of farm *f* to produce the same outputs: the lower TE_f, the less efficient farm *f* is.

2.5. BMPs adoption impact measures

Malmquist Input-Based Productivity Index

The Malmquist index is a measure of true productivity change accounting for "*bads*" and is defined by ratios of distance functions which can be interpreted as the product of an efficiency change index and the geometric mean of two indices measuring technological change or how the frontier changes when BMP are accounted for (Caves, Christensen and Diewert, 1982). Formally, the index is defined as (Färe, Grosskopf and Lovell, 1994, pp. 227-232):

(19) $$M = \left[\frac{D_{t+1}^I(\boldsymbol{y}_{t+1},\boldsymbol{x}_{t+1})}{D_t^I(\boldsymbol{y}_t,\boldsymbol{x}_t)}\right] \times \left[\frac{D_t^I(\boldsymbol{y}_{t+1},\boldsymbol{x}_{t+1})}{D_{t+1}^I(\boldsymbol{y}_{t+1},\boldsymbol{x}_{t+1})}\frac{D_t^I(\boldsymbol{y}_t,\boldsymbol{x}_t)}{D_{t+1}^I(\boldsymbol{y}_t,\boldsymbol{x}_t)}\right]^{\frac{1}{2}}$$

The product of ratios in the second bracket can be thought of as a measure of technological change; the first bracket captures the changes in efficiency between the two periods, as measured by the ratio of the two efficiencies. A value of M greater (less) than unity indicates an improvement (deterioration) in productivity. Given the objective of the study at hand, we are interested in the comparison of performances of more than two groups. In this instance, "circularity" is a desired property for a bilateral productivity index.[12] Pastor and Lovell (2005) show that the contemporaneous Malmquist productivity index is not circular and can give conflicting signals. Camanho and Dyson (2006) define a Malmquist-based performance measures for groups with the circularity property:

$$M^{AB} = \frac{\left[\prod_{f=1}^{F_A} D_A^I(\mathbf{y}_A, \mathbf{x}_A)\right]^{1/F_A}}{\left[\prod_{f=1}^{F_B} D_B^I(\mathbf{y}_B, \mathbf{x}_B)\right]^{1/F_B}} \cdot \left[\frac{\left(\prod_{f=1}^{F_A} D_B^I(\mathbf{y}_A, \mathbf{x}_A)\right)^{1/F_A}}{\left(\prod_{f=1}^{F_A} D_A^I(\mathbf{y}_A, \mathbf{x}_A)\right)^{1/F_A}} \cdot \frac{\left(\prod_{f=1}^{F_B} D_B^I(\mathbf{y}_B, \mathbf{x}_B)\right)^{1/F_B}}{\left(\prod_{f=1}^{F_B} D_A^I(\mathbf{y}_B, \mathbf{x}_B)\right)^{1/F_B}}\right]^{1/2} \tag{20}$$

where the parameter F represents the number of farms in a given subset of the database. The ratio inside square brackets evaluates the gap between the frontiers of the two groups while the ratio outside square brackets compares within-group efficiency spreads. Following Camanho and Dyson (2006), we compute an overall performance index that satisfies the circular relation and can be used for the comparison of more than 2 two groups. This index is obtained by pooling all the data and establishes a technology for this pooled set.[13] The index is computed as follows

[12] The circularity property posits that an index that compares productivity between units *k* and *f*, and between *l* and *f*, must be able to establish a productivity comparison between units *k* and *l* via the arbitrary third unit, *f*, that is independent of the chosen third unit, *f* (Førsund, 2002) .

[13] One could also choose one group as a base but in that case, the value of the index depends on the technology chosen. It implies that there are some reasons for picking a specific reference base. Examples are 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* technology and of *accumulating* technology.

$$M_{adj}^{PB} = \frac{\left[\prod_{f=1}^{F_B} D_B^I\left(\mathbf{y}_f^B, \mathbf{x}_f^B \right) \right]^{1/F_B}}{\left[\prod_{f=1}^{F_P} D_P^I\left(\mathbf{y}_f^P, \mathbf{x}_f^P \right) \right]^{1/F_P}} \cdot \left[\prod_{i=1}^{N} \frac{\left(\prod_{f=1}^{F_i} D_P^I\left(\mathbf{y}_f^i, \mathbf{x}_f^i \right) \right)^{1/F_i}}{\left(\prod_{f=1}^{F_i} D_B^I\left(\mathbf{y}_f^i, \mathbf{x}_f^i \right) \right)^{1/F_i}} \right]^{1/N} \tag{21}$$

where parameter P represents the pooled dataset and F_i the number of farm in each group i $\left(i = 1,\ldots,N\right)$. 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. 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 index in (21) provides a robust performance ranking of groups of farms operating under different conditions. Camanho and Dyson (2006, p.40) indicate that "The advantage of this index is that the comparison between frontiers is made for a larger number of points, covering a wider range of activity profiles … The additional information considered in the adjusted index guarantees its circularity."

The profitability change

Using Althin, Färe and Grosskopf's (1996) Fisher-based index, the profitability change when adopting a BMP can be expressed as:

$$\overleftrightarrow{F}^2 = ME^{PB} \times \left\{ \frac{e_{D^I,Y}^B\left(\boldsymbol{x}_B, \boldsymbol{y}_B\right)}{e_{D^I,Y}^P\left(\boldsymbol{x}_P, \boldsymbol{y}_P\right)} \right\} \tag{22}$$

where $e_{D^I,Y}$ is the primal input-based measure of elasticity of scale as defined before. There is an improvement when $\overleftrightarrow{F} < 1$ since Georgescu-Roegen's (1951) "return on the dollar" is higher for the BMP adopters (group *B*).[14] As in Althin, Färe and Grosskopf (1996), our analysis of the impacts of BMP adoption on productivity and profitability entails estimating separate distance function for each individual BMP.[15]

2.6. Environmental performances measures

Shadow price of the "bads"

The shadow price of the "*bads*" is:

(23) $$\frac{\partial C\left(\left[\mathbf{y},\mathbf{b}\right],\mathbf{p}\right)}{\partial \mathbf{b}}=-C\left(\left[\mathbf{y},\mathbf{b}\right],\mathbf{p}\right)\nabla_b D^I\left(\left[\mathbf{y},\mathbf{b}\right],\mathbf{x}\left(\left[\mathbf{y},\mathbf{b}\right],\mathbf{p}\right)\right)$$

We assume that the set of inputs $\mathbf{x}$ is a cost-minimizing solution and that $C\left(\left[\mathbf{y},\mathbf{b}\right],\mathbf{p}\right)$ is a function of shadow prices. We then assume that the observed price equals the shadow price for one input. Assuming that herbicide is this input, its shadow price is given by (5). By taking the ratio of the shadow price of the "*bads*" to the observed price of herbicide, the $C\left(\left[\mathbf{y},\mathbf{b}\right],\mathbf{p}\right)$'s cancel out and we can solve for the estimated shadow price of the "*bads*" in terms of ratios of estimated partial derivatives and the observed price of herbicide.

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

[14] This measure suggested by Georgescu-Roegen (1951) is a simplified measure of profitability change because it omits mixed terms (see Althin, Färe and Grosskopf, 1996).

[15] We expect that adoption of a BMP would 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 different inputs. Using a Chow test (see Greene, 2008), we test the hypothesis that the coefficient vectors are the same for the subset of adopters and non-adopters. Consistent with our expectations, we reject the null hypothesis of equal coefficients for herbicides controls and manure injection BMPs (see table A4 in appendix). The size of our data set prevented us from doing estimation on sub-samples of farmers adopting more than one BMP.

Because of the log representation of the distance function, we can compute the elasticity that measures the percentage increase in the shadow price of the bad in response to a 1% decrease in bad output.

Environmental Efficiency Scores

We use Reinhard, Lowell and Thijssen's (1999, 2002) approach to derive a stochastic measure of producers' environmental efficiency (*EE*). The log of the IDF of an environmentally efficient producer is obtained by replacing b_{zf} with $t\,b_{zf}$ where $t \leq 1$ and by setting $\hat{u}_F = 0$. Setting the production function for farm f equal to the production function of an environmentally efficient farm, we can solve for $\ln EE_f = \ln t\, b_f - \ln b_f = \ln t$:

$$(25) \qquad \ln EE_{zf} = a_{zz}^{-1} \left[\begin{array}{l} -\left(a_z + a_{zz} \ln b_{zf} + \sum_n a_{zn} \ln x_{nf} + \sum_m a_{zm} \ln y_{mf} \right) \\ \pm \left\{ \left(a_z + a_{zz} \ln b_{zf} + \sum_n a_{zn} \ln x_{nf} + \sum_m a_{zm} \ln y_{mf} \right)^2 - 2a_{zz} u_f \right\}^{0.5} \end{array} \right]$$

In (25), we use the predictor $\hat{u}_f$ given by equation (18) . Environmental efficiency is calculated using the positive root in (25)[16] and is used to compute the environmental efficiency score (*EES*) for each farm as $EES_{zf} = \min\left(EE_{zf}\right) / EE_{zf}$.

Inputs compensation for reducing "bads"

Our objective is to measure the input expansion required to compensate for a 1% decrease in the "*bads*" b_z while producing the same level of "*goods*".

$$(26) \qquad -e_{D^I, b_z} = \partial \ln \vec{D}^I / \partial \ln b_z$$

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

Environmental Efficiency

Firm f 's level of Environmental Efficiency (*EE*) is computed using Jondrow et al.'s (1982) results (see equation (18)) with the IDF of the "*bads*" with an aggregate "*good*" used as a technological shifter. This *EE* measure of environmental efficiency is an alternative to the *EES* measure previously described. The degree of consistency between the two measures can be ascertained by computing the level of correlation. A strong positive correlation would be indicative of robust results.

3. The data

Our sample consists of 210 observations. Agricultural production consists of good outputs, namely livestock and crops, and bad outputs associated with runoff and leaching of chemicals and sediments.

The "goods"

Crops (y_C) and animal (y_A) production are measured in thousands of dollars. The percentage of producers claiming to raise beef cattle and dairy cows account for 59.5% and 52.9% of all producers in our sample as many are engaged in both productions. Hog producers make up a smaller share at 20.8%, but they marketed a total of 197,000 hogs compared to 8,700 heads for beef producers. The dairy producers owned a total of 5,600 dairy cows. Finally, the total acreage cultivated with crops (hay, alfalfa, pulses, maize and other cereals) amounted to 33,380 acres.

The "bads"

Agricultural production is also assumed to generate "*bads*". They are identified by the levels of emission (kilograms) of nitrogen (b_N), phosphorous (b_P) and sediments (b_S).

Chemicals' runoff levels are computed through a simulation program that identifies the amount of chemical leached from individual *Relatively Homogeneous Hydrological Units* (RHHUs).[17] The correlation coefficients between these "*bads*" are so high[18] that only phosphorus runoff is considered in the empirical application.

Variables inputs

Quantities of labor (x_L) are in working hour while the quantities of fertilizers (x_F) and herbicides (x_H) are in kg per acres.

Quasi-fixed input

Capital $\bar{k}$ is assumed to be quasi-fixed in the short run. It is proxied by owned and rented machinery and equipment estimated value.

BMPs variables

There are four binary 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 $(\hbar_{manure})$ in the soil within 24 hours of the initial spreading and herbicide control and reduction measures $(\hbar_{herbcont})$. Crop rotation is considered to be practiced if it covers over half of the cultivated land and we merged the herbicide control and reduction practices because of their high correlation. The establishment and

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[17] RHHUs correspond to small sub-watersheds whose drainage structures are derived from a relatively high resolution Digital Elevation Model (DEM). In some cases, two or more farms were located on the same RHHU and therefore were associated with the same level of bad output.

[18] 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.

maintenance of a riparian buffer zone larger than one meter (r_{buffer}) is used as an external effect.

Farm characteristics

Other variables that reflect "environmental sensibility" are added. We hypothesize that having a certificate for biological/organic production $(r_{organic})$ and belonging to an agro-environmental club $(r_{envclub})$ also condition the IDF.

Farm and producer's attributes

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 $(Education)$ is specified through an ordered variable. It takes the value of 0 when secondary school is attained and 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 $age \leq 55$ and a value of one if $age > 55$ years. Land use (Use) and farm size $(Size)$ are added to reflect the potential relationship between efficiencies and agricultural production. The variable *Use* equals 1 if the value of crops produced is higher than the value of livestock and dairy l productions and 0 otherwise. Finally, another variable, the level of annual expenditure on telecommunication services$(Telcom)$, is used to capture a producer's exposure to information. Then, technical inefficiency is modelled as:

(27) $$u_f = d_1 Age_f + d_2 Gender_f + d_3 Education_f + d_4 Use_f + d_5 Size_f + d_6 Resfarm_f + d_7 Telcom_f$$

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

4. Results

4.1. 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 non-decreasing in inputs and non-increasing in "*goods*" as well as quasi-concave in variable inputs.[19] The monotonicity condition of the "*bad*s" is also met. The input cross-effects coefficients are predominantly significant and positive, thus indicating complementarities between fertilizers, herbicides and labor. The "*goods*" cross-effect coefficient is positive and significant, reflecting substitution between the two outputs. The cross-effect coefficient of the two "*goods*" and the "*bads*" are non-significant, indicating that the link between "*goods*" and "*bads*" is noisy. Output mix, including the "*bads*" seems to be less fixed across farm types than the input composition as in Paul and Nehring (2005).[20] Generally, these results suggest that diversification at the farm level does not contribute significantly to overall economic performance. The cross output-input terms are not significant for animal production, which is consistent with the separability hypothesis between outputs and inputs. However, this is not the case for the crop output.

The performance impacts of the farms and farmers' characteristics are given by the estimated coefficient in table 2. Adopting a riparian buffer tends to have a positive

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

[20] Just and Pope (1978) and Paul and Nehring (2005) contend that the impact of input use on risk may induce a correlation between outputs that would be independent without risk. The idea is that uncertainty causes variations in the marginal products or contributions of inputs across products.

impact on the overall performance of the farm - a negative impact on the value of the distance function- while having an organic product certificate tends to have a negative impact on overall performance. The mean of the performance impacts of the farm– and farmer-specific variables that can interact with the level of production $(\hbar)$ is shown in table 4. The computed means of the overall impact of the three variables are negative implying a reduction of the IDF.

The mean value of the predicted distance function is 1.413. We estimate the same distance function without taking into account the "*bads*" as a technological shifter. The mean value of the predicted IDF is 1.430 when the "*bads*" are not considered as a technological shifter. This difference confirms that the potential to increase production with the given bundle of inputs decreases when farms are not allowed to freely dispose of phosphorus emissions. The two mean values are statistically different at the 5% level, as expected.

4.2. Technical efficiency (*TE*)

Table 2 also reports on the parameters conditioning the level of technical efficiency of farms. The level of education and the size of the farm have a significant and positive impact on *TE*. Bigger farms and producers who hold a technical school, college or university degree are generally more efficient. The log-likelihood is parameterized in terms of $g \equiv s_u^2 \big/ \left(s_v^2 + s_u^2\right)$. 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. This is similar to the estimated value of 0.58 found in Reinhard, Lowell and Thijssen's (1999) analysis of Dutch dairy farms. The mean of the predicted *TE* is 0.426.[21] Overall the estimated mean value of the predicted *TE* is low.[22] Figure 1 plots the density distribution of predicted technical efficiency within the dataset. The mean of the predicted *TE* scores 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. This wide range in technical efficiencies is consistent with the fact that the number of farms is decreasing in spite of generous farm programs.

4.3. Scale elasticities

The measure of scale elasticity is 0.644 which suggests that there are significant economies of scale (see table 3). The scale elasticity has a value of 0.682 when only farms involved in crop production are considered and a value of 0.625 for farms involved only in animal production. The difference between these two values is significant at the 5% level. These elasticities are quite close to the 0.65 obtained by Paul and Nehring for the United States (2005). A value of 1 is consistent with constant return to scale

Individual output contributions embodied in the overall scale elasticitiy are presented in table 3. The results show that more variable input are needed to increase crop production by 1% than to increase livestock production by the same level. The

[21] 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.

[22] Coelli, Singh and Fleming (2003) get a predicted mean technical efficiency 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. Fernandez, Koop and Steel (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.

coefficients have the correct sign and are significant at the 5%.level. The values of labor and fertilizer elasticities are respectively -0.621 and -0.291. The value of the shadow share of labor is smaller than the observed mean share (72.38%). This finding is indicative of low labor productivity.

4.4. The impact of best 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. In some cases, new machinery may be needed that may increase or decrease the demand for other inputs like labour. We relied on a Chow test (see Greene, 2008), with a null hypothesis of equal coefficient vectors for estimations done on subsamples of adopters and non-adopters, to determine whether BMP adopters actually use a different technology. Consistent with our expectations, we rejected the null hypothesis of equal coefficients for herbicides controls and manure injection BMPs (see table A4 in appendix).[23] Accordingly, we restricted our analyses regarding the potential impact of BMPs to the two aforementioned BMPs.

Figures 5-8 present the impacts of BMP adoption on efficiency, productivity and profitability. The methods used to compute the productivity change as well as the profitability change look at marginal changes represented by the adoption of the BMP. In order to make figures 5-8 as illustrative as possible, we represent the inverses of MF_{adj}^{PB}, ME^{PB}, M_{adj}^{PB} and $\vec{F}$. As a result, a value greater (less) than one represents an improvement (a deterioration).

[23] The size of our data set prevented us from doing estimation on sub-samples of farmers adopting more than one BMP.

Farms that have adopted herbicides control are technically less efficient (0.939<1), but enjoy a -very small- technological advantage (1.008>1). In this case, the overall effect is a decline in productivity (0.947>1). However, the adoption of herbicide control also tends to slightly decrease economies of scale, as indicated by the profitability index (1.054<1). This net impact on the profitability index implies an important change in scale elasticity and then, in the best practice frontier. In contrast, the technical efficiency of farms that have adopted manure injection tends to be higher. These farms also have a technological advantage over farms that have not adopted this BMP. The net positive effect on productivity is 1.142>1. Furthermore, profitability increases sharply when manure injection within 24 hours is adopted (1.136>1), indicating an increase in returns to scale. Our results uncovered positive environmental effects, namely a reduction of pollutant induced by the adoption of the BMP, and positive private effects. Ambec and Lanoie (2007) and Horbach (2008) suggest that the positive private gains can be attributed to reductions in the cost of regulations and to the fact that environmental management tools provide incentives to develop new cost saving practices (specifically material and energy savings). These innovations induced by the adoption of environmentally-friendly practices are at the heart of the Porter-hypothesis (Porter, 1991; Porter and van der Linde, 1995).[24] Piot-Lepetit and Le Moing (2007) also found a gain in productivity resulting from the relationship between efficiency and environmental regulation in the French pig sector, but Managi (2004) did not find evidence in support of the Porter-hypothesis when analyzing the US agricultural sector.

[24] 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."

4.5. 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 a standard deviation of 0.001. The shadow price of the "*bad*" for farms primarily involved in livestock production is 0.0652, which is higher than the value of 0.062 for farms involved in crop production. The difference between these two estimates is significant at the 5% level. As in Ball et al. (2002), reducing a "*bad*" output is costly.[25] A 10% reduction in phosphorus induces a 0.628 % increase in cost, evaluated at the mean values of the data. 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.[26] The effect of the scale of crop and animal production on the marginal abatement cost can also be estimated. These coefficients have a negative sign, but are not significant at 5 %. This suggests that the marginal abatement cost of runoff weakly increases with the scale of production. There is a small difference between animal and crop productions. 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

The mean of the computed *EES* is 0.486. Figure 2 plots the density distribution of computed *EES* within the dataset and figure 3 the density distribution of the estimated

[25] Our estimate is higher than Ball et al. (2002)'s 0.09% and 0.08% for leaching and runoff.

[26] 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 non point 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.

EE. The mean of the *EES* for farms specialized in animal production is smaller than its crop production counterpart: 0.380 versus 0.504. The difference is significant at the 5% level. The correlation between the two sets of environmental efficiencies *EES* and *EE* is high. This Spearman rank correlation between the two efficiencies is 0.71.

Table 5 reports the Spearman rank correlation between technical and environmental efficiencies. In this table, the dataset is subdivided into subsets based on the predicted *TE*. Table 5 shows that the correlation is strongest for the 75th percentile to the maximum of the *TE* within the dataset and that there is no statistically significant correlation between *EE* and *TE* when the latter lies between the median and the 75th percentile. Overall there is a tendency for farms that are technically inefficient to also be environmentally inefficient. A similar finding was reported by Reinhard, Lowell and Thijssen (1999) and FKS (2002).[27] 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.

The input compensation for reducing "bads"

Figure 4 plots the distribution of the "*bads*" elasticity using a model where "*goods*" are introduced as technological shifters in the production frontier of phosphorus. This elasticity tells us about the percentage increase in all inputs necessary to decrease the level of phosphorus emissions by 1%. The mean value of the input share of the "*bads*" is -0.048 which implies that overall inputs use must decrease by 4.8% to decrease phosphorus emission by 1% while keeping the good outputs at the same levels. However,

[27] 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 0.40.

because of the values spanned by the plot in Figure 4, we divided our sample in two groups to gain more insights about the elasticity of the "*bads*". In the first group, reducing the level of inputs "suffices" to reduce the level of "*bads*" without altering the level of "*goods*" outputs. The mean value of predicted "*bads*" elasticity of these farms that have to reduce the level of inputs is -5.09% for a 1% decrease in the "*bads*". In the second group, the "*bads*" 's elasticity is positive implying that input use must increase for at least one input. Input costs must increase by 1.80% to implement a 1% reduction in "*bads*" output. This subset of our sample includes only 10 farms.

5. Conclusion

The variability in farmers' technical efficiency is likely to influence observed environmental performance, as does the adoption or non-adoption of Best Management Practices (BMPs). A distance function approach is implemented to empirically analyze technical and environmental efficiencies. In the context of multiple good and bad outputs, two types of input distance function (IDF) are estimated. For the first type, a bad output is modeled as a technological shifter in an IDF for good outputs. For the second type, good outputs are aggregated into one good output which is introduced as a technological shifter in an IDF for the bad output. Systems of equations accounting for the monotonicity property (inputs, outputs and undesirables) are estimated. The IDF 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 and livestock and crop production intensive. Data on phosphorus, nitrogen and sediment loads have been simulated through a hydrological model. These simulations identify the amount of chemical leached from individual Relatively Homogeneous Hydrological Units (RHHUs) that are then matched with the location of individual farms.

The computed level of technical efficiency is disaggregated across farms. The level of education and the size of the farm have a significant and positive impact on the technical efficiency scores (*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 (*EE*) is relatively low and a positive correlation was found between 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 change, technical change and productivity change in response to the adoption of selected Best Management Practices (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. **Bibliography**

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Table 1. Summary statistics of variables used in the analysis

	Mean	Standard Deviation	Minimum	Maximum
"GOODS"				
Yield (x $1000)	103.09	325.41	0.15	2,696.16
Animal Production (x $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 (x $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 (x 100 acres)	1.29	1.47	<0.01	11.21
Animal Production (x 100 heads)	6.56	22.16	0.01	260
Crop production (binary variable)	1.24	1.41	<0.01	11.21
Telecommunication expenditures (x $1000)	1.33	1.73	0.05	15
TOTAL COST OF PRODUCTION (x $1000)	73.67	239.93	0.23	2011.62

Table 2. Estimated coefficients of the input distance function (full sample)

Parameters	Estimate	Standard Error	Parameters	Estimate	Standard Errors
a_{0}	0.817	0.152	$a_{herbicides\times fertilizers}$	-0.173	0.014
a_{ripbuf}	-0.024	0.035	$a_{crop\times labor}$	0.122	0.009
$a_{herbcont}$	-0.028	<0.001	$a_{crop\times fertilizers}$	-0.097	0.007
$a_{bioprod}$	0.482	0.112	$a_{crop\times herbicides}$	-0.025	0.004
$a_{envclub}$	0.025	0.035	$a_{animal\times labor}$	-0.001	0.006
a_{liqman}	-0.054	0.098	$a_{animal\times fertilizers}$	0.001	0.005
$a_{croprot}$	0.202	0.093	$a_{animal\times herbicides}$	0.001	0.002
$a_{phosphorus}$	-0.007	0.027	$a_{crop\times phosphorus}$	0.003	0.010
a_{crop}	-0.860	0.053	$a_{animal\times phosphorus}$	-0.006	0.005
a_{animal}	-0.102	0.033	$a_{crop\times capital}$	0.026	0.020
$a_{fertilizers}$	0.361	0.033	$a_{animal\times capital}$	-0.010	0.010
$a_{herbicides}$	0.192	0.012	$a_{crop\times croprot}$	-0.078	0.029
a_{labor}	0.447	0.041	$a_{animal\times croprot}$	0.011	0.023
$a_{capital}$	-0.033	0.049	$a_{crop\times liqman}$	0.007	0.023
$a_{animal\times animal}$	-0.017	0.008	$a_{animal\times liqman}$	-0.016	0.021
$a_{animal\times crop}$	0.074	0.019	$a_{crop\times contherb}$	-0.034	<0.001
$a_{crop\times crop}$	-0.071	0.017	$a_{animal\times contherb}$	0.018	0.021
$a_{phosphorus\times phosphorus}$	-0.012	0.007	$a_{phosphorus\times labor}$	0.009	0.009
$a_{capital\times capital}$	-0.013	0.027	$a_{phosphorus\times fertilizers}$	-0.007	0.007
$a_{labor\times labor}$	-0.173	0.014	$a_{phosphorus\times herbicides}$	-0.003	0.002
$a_{fertilizers\times fertilizers}$	0.027	0.009	$a_{capital\times labor}$	-0.006	0.012
$a_{herbicide\times herbicide}$	0.146	0.010	$a_{capital\times fertilizers}$	0.006	0.009
$a_{labor\times fertilizers}$	0.146	0.010	$a_{capital\times herbicides}$	0.001	0.003
$a_{labor\times herbicide}$	0.027	0.009			
Efficiency parameters					
$d_{education}$	-0.096	0.039	d_{use}	-0.018	0.078
d_{size}	-0.293	0.026	d_{gender}	0.049	0.088
d_{age}	0.014	0.044	$d_{resfarm}$	-0.022	0.053
$d_{telecom}$	0.016	0.057			
$g \equiv s_u^2 \left(s_v^2 + s_u^2\right)^{-1}$	0.583	0.117	s_v	0.474	0.034

Mean log-likelihood	3.186	**Number of observations**	210

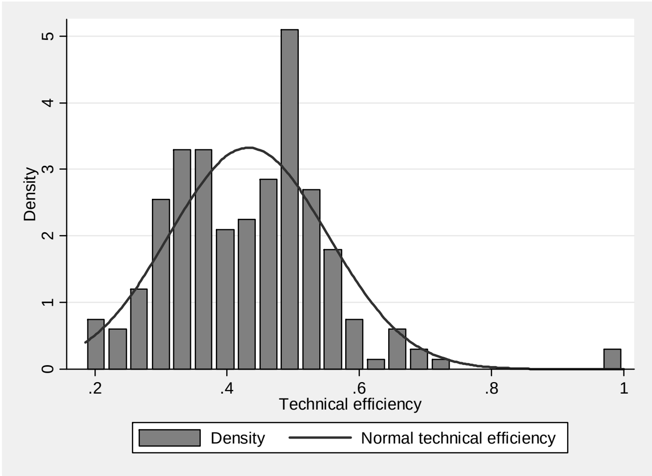

Figure 1. Predicted technical efficiency distribution

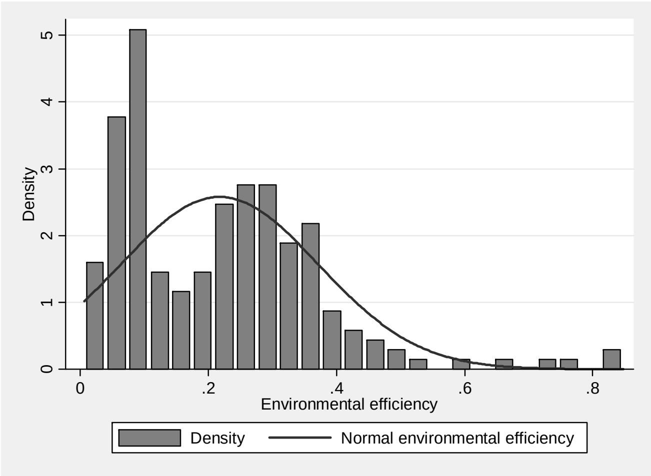

Figure 3. Predicted environmental efficiency (*EE*) distribution

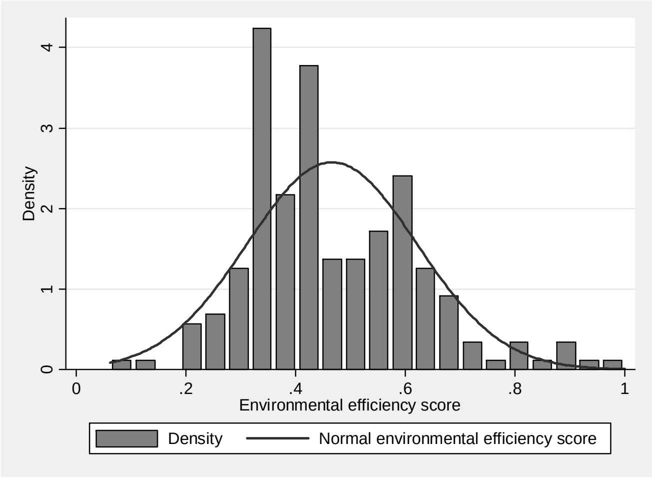

Figure 2. Predicted environmental efficiency score (*EES*) distribution

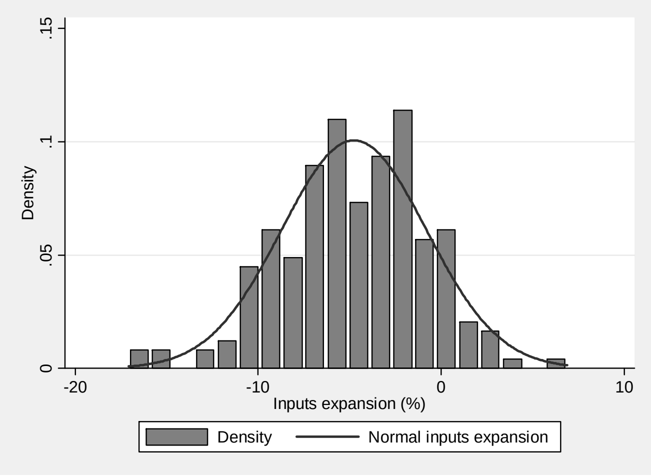

Figure 4. Inputs expansion (%) required for 1% reduction in phosphorus emission

Table 3. Economic performances measures

Parameters	Mean	Bootstrapped standard error 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]
Labor 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]

Table 4. Mean values of the overall impact of the external variables

Parameters	Mean	Bootstrapped standard error 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]

Table 5. Spearman correlation rank test between predicted technical efficiency and environmental efficiency measures

	Number of observations	EES		EE	
		Spearman correlation rank test	Prob. >| t |	Spearman correlation rank test	Prob. >| 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

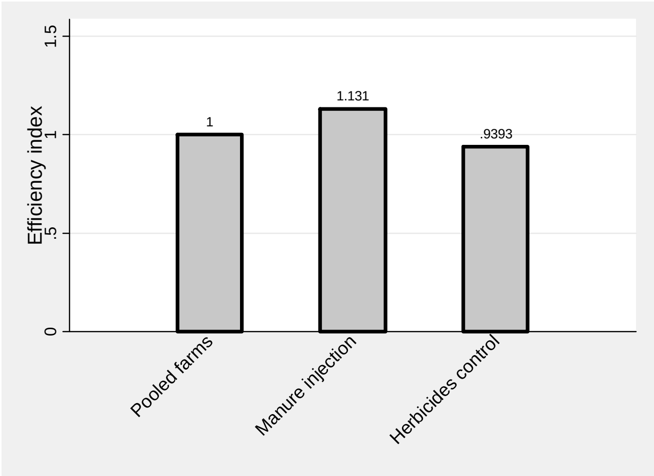

Figure 5. Index for the comparison of efficiency, using pooled dataset as the reference

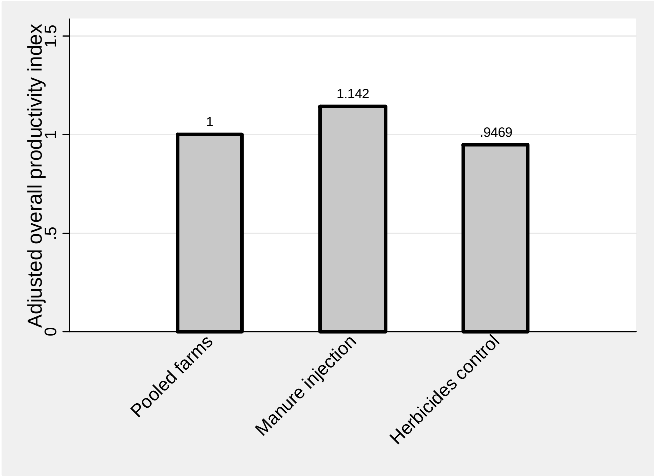

Figure 7. Adjusted (overall) index for the ranking of performance given the adopted BMPs, using pooled dataset as the reference

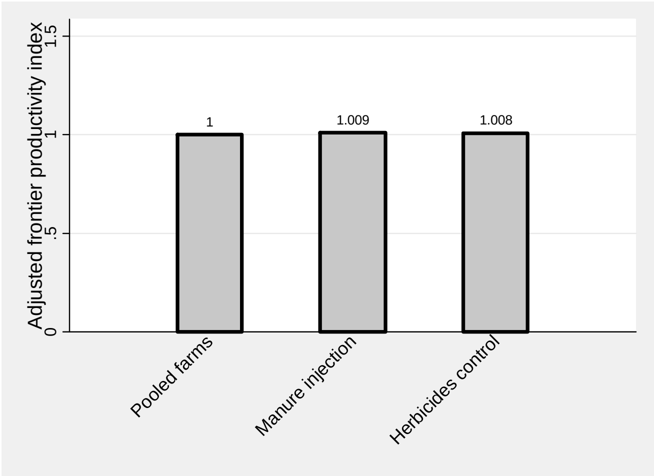

Figure 6. Adjusted index for the comparison of productivity of the farms best-practice frontiers, using pooled dataset as the reference

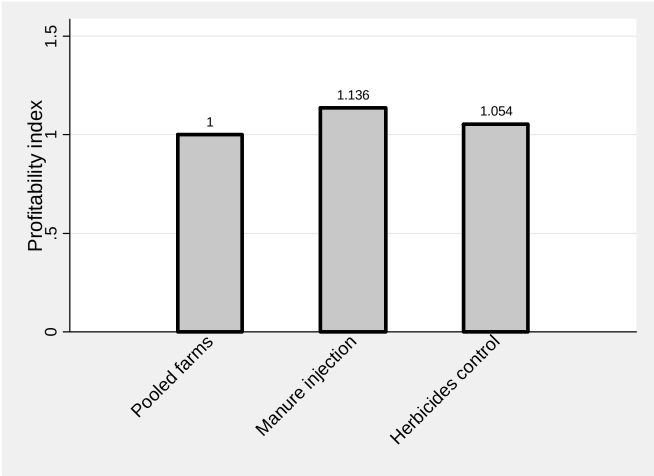

Figure 8. Index for the comparison of profitability given the adopted BMPs, using pooled dataset as the reference

Appendix

A1. Input distance function representation

Figure A1 provides an illustration of an input distance function. Two inputs are used to produce one output. The value of the distance will be equal to or greater than one if the input vector (x_1, x_2) is an element of the feasible input set $L(y)$. The isoquant SS' is the inner boundary of the input set, reflecting the minimum input combinations that may be used to produce a given output. The value of the distance function for the firm producing output, y, using the input vector defined by the point A is equal to the ratio OA/OB.

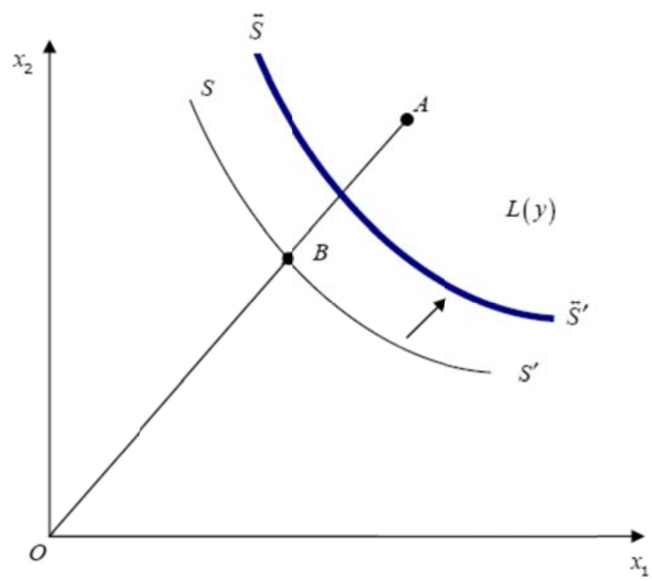

Figure A1. Input distance function representation

Treating the level of "*bads*" as a shifter of the technology set allows firms to be credited for reducing the level of "*bads*" that they produce. For the firm with the lowest level of bad, the isoquant shifts outward - $\vec{S}\vec{S}'$ - reflecting that more inputs are required to produce the same level of desirable output because some inputs are needed to reduce the production of the bad.

Table A1. Estimated coefficients of the IDF of farms that have adopted manure injection

Parameters	Estimate	Standard Error	Parameters	Estimate	Standard Errors
a_{0}	0.487	0.493	$a_{\text{herbicides}\times\text{fertilizers}}$	-0.130	0.015
a_{ripbuf}	0.151	0.080	$a_{\text{crop}\times\text{labor}}$	0.114	0.014
a_{herbcont}	-0.095	4.538	$a_{\text{crop}\times\text{fertilizers}}$	-0.093	0.011
a_{bioprod}	0.262	0.214	$a_{\text{crop}\times\text{herbicides}}$	-0.022	0.004
a_{envclub}	-0.072	0.080	$a_{\text{animal}\times\text{labor}}$	0.013	0.011
a_{liqman}	-	-	$a_{\text{animal}\times\text{fertilizers}}$	-0.011	0.009
a_{croprot}	-0.552	0.305	$a_{\text{animal}\times\text{herbicides}}$	-0.002	0.002
$a_{\text{phosphorus}}$	0.410	0.155	$a_{\text{crop}\times\text{phosphorus}}$	-0.089	0.034
a_{crop}	-0.590	0.151	$a_{\text{animal}\times\text{phosphorus}}$	-0.021	0.013
a_{animal}	-0.068	0.108	$a_{\text{crop}\times\text{capital}}$	0.035	0.054
$a_{\text{fertilizers}}$	0.191	0.073	$a_{\text{animal}\times\text{capital}}$	-0.049	0.032
$a_{\text{herbicides}}$	0.138	0.017	$a_{\text{crop}\times\text{croprot}}$	0.128	0.081
a_{labor}	0.672	0.087	$a_{\text{animal}\times\text{croprot}}$	0.023	0.047
a_{capital}	0.199	0.200	$a_{\text{crop}\times\text{liqman}}$	-	-
$a_{\text{animal}\times\text{animal}}$	0.035	0.022	$a_{\text{animal}\times\text{liqman}}$	-	-
$a_{\text{animal}\times\text{crop}}$	0.023	0.036	$a_{\text{crop}\times\text{contherb}}$	-0.096	0.539
$a_{\text{crop}\times\text{crop}}$	-0.122	0.042	$a_{\text{animal}\times\text{contherb}}$	0.005	0.041
$a_{\text{phosphorus}\times\text{phosphorus}}$	-0.025	0.019	$a_{\text{phosphorus}\times\text{labor}}$	0.009	0.017
$a_{\text{capital}\times\text{capital}}$	-0.032	0.101	$a_{\text{phosphorus}\times\text{fertilizers}}$	-0.008	0.014
$a_{\text{labor}\times\text{labor}}$	-0.130	0.015	$a_{\text{phosphorus}\times\text{herbicides}}$	-0.001	0.003
$a_{\text{fertilizers}\times\text{fertilizers}}$	0.014	0.008	$a_{\text{capital}\times\text{labor}}$	-0.069	0.028
$a_{\text{herbicide}\times\text{herbicide}}$	0.116	0.011	$a_{\text{capital}\times\text{fertilizers}}$	0.060	0.024
$a_{\text{labor}\times\text{fertilizers}}$	0.116	0.011	$a_{\text{capital}\times\text{herbicides}}$	0.009	0.006
$a_{\text{labor}\times\text{herbicide}}$	0.014	0.008			
Efficiency parameters					
$d_{\text{education}}$	-0.041	0.105	d_{use}	0.092	0.163
d_{size}	-	-	d_{gender}	0.001	0.144
d_{age}	0.135	0.090	d_{resfarm}	0.066	0.134
d_{telecom}	0.069	0.126			
$g \equiv s_u^2\left(s_v^2 + s_u^2\right)^{-1}$	0.831	0.175	s_v	0.379	0.243
Mean log-likelihood		3.529	**Number of observation**		89

Table A2. Estimated coefficients of the IDF of farms that have adopted crop rotation

Parameters	Estimate	Standard Error	Parameters	Estimate	Standard Errors
a_{0}	0.890	0.194	$a_{herbicides\times fertilizers}$	-0.174	0.018
a_{ripbuf}	-0.021	0.046	$a_{crop\times labor}$	0.127	0.015
$a_{herbcont}$	-0.072	0.844	$a_{crop\times fertilizers}$	-0.101	0.009
$a_{bioprod}$	0.567	0.145	$a_{crop\times herbicides}$	-0.027	0.005
$a_{envclub}$	0.002	0.045	$a_{animal\times labor}$	0.002	0.009
a_{liqman}	-0.119	0.137	$a_{animal\times fertilizers}$	-0.002	0.008
$a_{croprot}$	-	-	$a_{animal\times herbicides}$	<0.001	0.003
$a_{phosphorus}$	0.037	0.037	$a_{crop\times phosphorus}$	0.007	0.013
a_{crop}	-0.882	0.072	$a_{animal\times phosphorus}$	-0.013	0.007
a_{animal}	-0.171	0.057	$a_{crop\times capital}$	0.011	0.027
$a_{fertilizers}$	0.383	0.049	$a_{animal\times capital}$	-0.004	0.018
$a_{herbicides}$	0.197	0.017	$a_{crop\times croprot}$	-	-
a_{labor}	0.420	0.062	$a_{animal\times croprot}$	-	-
$a_{capital}$	0.011	0.092	$a_{crop\times liqman}$	0.027	0.031
$a_{animal\times animal}$	-0.006	0.012	$a_{animal\times liqman}$	-0.024	0.028
$a_{animal\times crop}$	0.088	0.025	$a_{crop\times contherb}$	-0.026	0.845
$a_{crop\times crop}$	-0.087	0.021	$a_{animal\times contherb}$	0.015	0.030
$a_{phosphorus\times phosphorus}$	-0.010	0.008	$a_{phosphorus\times labor}$	-0.005	0.011
$a_{capital\times capital}$	-0.014	0.047	$a_{phosphorus\times fertilizers}$	0.005	0.009
$a_{labor\times labor}$	-0.174	0.018	$a_{phosphorus\times herbicides}$	<0.001	0.003
$a_{fertilizers\times fertilizers}$	0.028	0.012	$a_{capital\times labor}$	-0.001	0.021
$a_{herbicide\times herbicide}$	0.146	0.013	$a_{capital\times fertilizers}$	0.001	0.017
$a_{labor\times fertilizers}$	0.146	0.013	$a_{capital\times herbicides}$	<0.001	0.006
$a_{labor\times herbicide}$	0.028	0.012			
Efficiency parameters					
$d_{education}$	-0.103	0.046	d_{use}	-0.067	0.101
d_{size}	-0.305	0.031	d_{gender}	0.053	0.110
d_{age}	0.001	0.052	$d_{resfarm}$	-0.032	0.067
$d_{telecom}$	-0.023	0.068			
$g \equiv s_{u}^{2}\left(s_{v}^{2}+s_{u}^{2}\right)^{-1}$	0.530	0.161	s_{v}	0.491	0.036
Mean log-likelihood		3.075	**Number of observations**		147

Table A3. Estimated coefficients of the IDF of farms that have adopted herbicides control

Parameters	Estimate	Standard Error	Parameters	Estimate	Standard Errors
a_{0}	3.101	0.565	$a_{herbicides\times fertilizers}$	-0.183	0.027
a_{ripbuf}	-0.053	0.081	$a_{crop\times labor}$	0.164	0.017
$a_{herbcont}$	-	-	$a_{crop\times fertilizers}$	-0.127	0.013
$a_{bioprod}$	0.381	0.142	$a_{crop\times herbicides}$	-0.037	0.008
$a_{envclub}$	-0.059	0.092	$a_{animal\times labor}$	-0.002	0.013
a_{liqman}	-0.507	0.199	$a_{animal\times fertilizers}$	0.001	0.010
$a_{croprot}$	-0.139	0.223	$a_{animal\times herbicides}$	0.001	0.004
$a_{phosphorus}$	-0.408	0.127	$a_{crop\times phosphorus}$	0.073	0.032
a_{crop}	-1.405	0.147	$a_{animal\times phosphorus}$	0.019	0.017
a_{animal}	-0.148	0.088	$a_{crop\times capital}$	0.248	0.053
$a_{fertilizers}$	0.207	0.057	$a_{animal\times capital}$	0.020	0.034
$a_{herbicides}$	0.164	0.024	$a_{crop\times croprot}$	0.103	0.069
a_{labor}	0.629	0.073	$a_{animal\times croprot}$	-0.082	0.075
$a_{capital}$	0.145	0.146	$a_{crop\times liqman}$	0.169	0.051
$a_{animal\times animal}$	0.065	0.031	$a_{animal\times liqman}$	-0.034	0.045
$a_{animal\times crop}$	-0.008	0.039	$a_{crop\times contherb}$	-	-
$a_{crop\times crop}$	-0.157	0.035	$a_{animal\times contherb}$	-	-
$a_{phosphorus\times phosphorus}$	0.006	0.024	$a_{phosphorus\times labor}$	0.014	0.018
$a_{capital\times capital}$	-0.356	0.097	$a_{phosphorus\times fertilizers}$	-0.008	0.014
$a_{labor\times labor}$	-0.183	0.026	$a_{phosphorus\times herbicides}$	-0.005	0.005
$a_{fertilizers\times fertilizers}$	0.033	0.017	$a_{capital\times labor}$	-0.106	0.029
$a_{herbicide\times herbicide}$	0.150	0.018	$a_{capital\times fertilizers}$	0.085	0.022
$a_{labor\times fertilizers}$	0.150	0.018	$a_{capital\times herbicides}$	0.022	0.009
$a_{labor\times herbicide}$	0.033	0.017			
Efficiency parameters					
$d_{education}$	-0.012	0.077	d_{use}	0.309	0.145
d_{size}	-	-	d_{gender}	-	-
d_{age}	0.109	0.097	$d_{resfarm}$	-0.116	0.106
$d_{telecom}$	-	-			
$g \equiv s_u^2 \left(s_v^2 + s_u^2\right)^{-1}$	0.134		s_v	0.521	0.022
Mean log-likelihood		2.995	**Number of observations**		80

Table 4A. Statistics of the Chow test

Parameters	$F\left[51,108\right]$	Prob.>F
Herbicide control	2.571	<0.001
Manure injection	4.528	0.000
Rotation cycle implementation	1.219	0.194