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Opportunity Costs of Providing Crop Diversity in Organic and Conventional Farming

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Abstract

Targeted environmental policies for farmlands may improve the cost-efficiency of conservation programs if one can identify those farms that produce public goods with the least cost. We derive shadow values of producing crop diversity for a sample of Finnish conventional and organic crop farms in the period 1994-2002 in order to examine their opportunity costs of conservation. Our results of Data Envelopment Analysis show that there is variation in the shadow values between farms and between the technologies adopted. The degree of cost heterogeneity and farms' potential for specialization in the production of environmental outputs determine whether voluntary programs such as auctions for conservation payments are economically reasonable.

Keywords: biodiversity, Shannon index, DEA, distance functions, shadow values, Finland

JEL Classification: C21, D24, H41, Q12, Q24

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1. Introduction

Biodiversity conservation on farmland is increasingly recognized as an important environmental goal in agricultural policies (see, e.g., Wossink and van Wenum, 2003). Nevertheless, the general public largely views agri-environmental policies as subsidy programs that compensate farmers for the costs of conservation measures but have yet to provide convincing evidence that they have resulted in a better environment (Feng 2007). One of the challenges in designing environmental policies is measuring the benefits of environmental improvements. An additional concern is that, due to asymmetric information, the regulator does not necessarily know the costs of conservation on farmland (Sheriff 2009). In any event, policy design in agriculture needs to be evaluated with respect to its environmental targets.

Calls have been heard for better incentives and market-like mechanisms for conservation - such as auctions – that would improve the effectiveness and impact of policies designed to enhance biodiversity in agriculture (e.g., Pascual and Perrings, 2007). The US Department of Agriculture has the longest experience with auctions through its Conservation Reserve Program, into which farms are accepted based on an environmental benefits index (Latacz-Lohman & Van der Hamsvoort 1997, Kirwan, Lubowski and Roberts 2005). In contrast, the European Common Agricultural Policy has focused on dictating farming practices and offering fixed-rate payments rather than providing incentives for creating actual environmental benefits. This orientation may be changing, for there is growing interest in using auctions as a means to deliver payments for environmental services in agriculture. However, given the limited use of auctions in European agriculture, the bulk of the research evaluating such policy instruments is based on pilot studies or experiments and simulations carried out to test auction theory in alternative settings (e.g., Bastian et al. 2008, Glebe 2008). Owing to the hypothetical approach used in experimental auctions, the bids do not necessarily reflect farmers' opportunity costs of conservation.

We analyze agricultural production within the frame of economic theory by taking crop diversity into account as a positive non-market output of farms. Trade-offs in the production of market and non-market outputs are made explicit, since the opportunity costs of conservation measures ultimately determine the costs of the agri-environmental policies implemented. To gain insight into those costs, we apply the framework provided by Färe and Grosskopf (1998) to estimate shadow values for non-market environmental amenities. Variants of estimation methods within this framework have been used to price negative externalities in European agriculture (e.g., Huhtala and Marklund 2008, Piot-Lepetit and Le Moing 2007); rather less work has been carried out on pricing the effects of agriculture on biodiversity conservation. The analysis of biodiversity most closely related to ours is an application by Färe, Grosskopf and Weber (2001) which prices the non-market characteristics of conservation land in the United States.

Our analysis uses crop diversity as a non-market output; this is measured by a farm-level value for the Shannon Diversity Index, which captures both the richness and evenness of the crops cultivated. The index is a typical landscape diversity indicator, one that can be seen as reflecting the esthetic value of a diverse agricultural landscape from a social point of view. On the other hand, in the literature on risk management in agriculture, crop diversity has been attributed a private value as an option whereby risk-averse farmers can hedge against uncertainty (Di Falco and Perrings 2005). On these grounds, the trade-off between market output (crop yield) and non-market ecological by-products (crop diversity) can be considered relevant for farmers' decision making.

Lastly, it is important to bring out how the European agricultural policies are reflected in choices of farming practices and the corresponding (ecological) benefits. Compared to conventional farming, organic production can be seen as a more restricted – or even an alternative – technology that has been promoted for environmental reasons[1]. We estimate distance functions and efficiency scores for conventional and organic crop farms, but our main interest lies in determining shadow values of crop diversity for each technology. These values can be interpreted as the opportunity costs of crop diversity in terms of forgone crop output. This information reveals whether there is heterogeneity in costs between types of farms and, accordingly, room for improving the cost-efficiency of policies that target the conservation of crop biodiversity in agriculture.

The paper is organized as follows. Section 2 introduces the crop biodiversity index applied in the empirical study. In section 3, we present models of distance functions for the case where there are multiple outputs and, alternatively, where one of the outputs is held as a minimum constraint; we then derive shadow values for crop diversity using these alternative models. Section 4 presents how distance functions, efficiency scores and shadow values are estimated by applying Data Envelopment Analysis (DEA), and discusses the interpretation and robustness of the DEA results. Section 5 presents the data for the period 1994 – 2002, obtained from cross-sections of Finnish crop farms participating in the bookkeeping system of the Farm Accountancy Data Network (FADN). The results are reported in section 6. The concluding section discusses several findings on variation in the shadow values between farms and between the technologies adopted.

2. Crop biodiversity

In addition to yielding marketable output such as food and fiber, agricultural systems may produce biodiversity, a positive by-product. Crop rotation, the application of chemical inputs, and similar choices by the farmer may have various impacts on biodiversity. Biodiversity is a complex concept with several dimensions and choosing proper measures of (or indicators for) it poses a challenge.

[1] Organic farming emphasizes environmental protection. It avoids, or substantially reduces, the use of synthetic fertilizers, pesticides and additives. Crop rotation, mechanical weed control and the protection of beneficial organisms are also important (Organic Farming in the EU: Facts and Figures, 2005). These restrictions most likely have an impact on the production technology and economic performance of organic farms.

We rely on a relatively simple measure of diversity known as the crop diversity index, which can be described as a measure of landscape diversity. Callicott, Crowder and Mumford (1999) classify the crop diversity index as a compositional measure of species diversity.

Species-level diversity is quantified as the number of species in a given area (richness) and how evenly balanced the abundances of each species are (evenness) (Armsworth, Kendall and Davis, 2004). This is only one of the measures that can be used in analyzing biodiversity. For example, community-level biodiversity describes the interactions of species in their natural habitats. The spatial scale is also important since richness increases with area. Typically a choice is made to use either an economically or an ecologically meaningful scale. We choose to study the diversity of agricultural land use at the farm level within the framework of production theory. [2] At the farm level, the number of crops cultivated and the area under each crop are available for use by government authorities for implementing policy based on crop diversity indices. In fact, the cultivation of local crops and crop diversification have been included among the voluntary conservation measures eligible for specific support in the Finnish agri-environmental program, but the measures have not gained wide popularity among farmers. (Horisontaalinen maatalouden kehittämisohjelma 2006)

In this study, richness is measured by the number of cultivated crops, such as barley, grass silage, potato, or by the area lying fallow. Evenness refers to how uniformly the arable land area of a farm is distributed among different crops and uses. Evenness and richness can be quantified using the Shannon Diversity Index (SHDI) (Armsworth, Kendall and Davis, 2004), and the following formula:

[2] For further discussion on farmland biodiversity, see e.g., Jackson, Pascual and Hodgkin (2007).

$$SHDI = -\sum_{i=1}^{J}(P_i \times \ln P_i), \quad (1)$$

where J is the number of cultivated crops, P_i denotes the proportion of the area covered by a specific crop, and *ln* is the natural logarithm.[3] The index in equation (1) equals zero when there is only one crop, indicating no diversity. The value increases with the number of cultivated crops and when the cultivated areas under various crops become more even. The index reaches its maximum when crops are cultivated in equal shares, that is, when $P_i = 1/J$.

We use the SHDI to approximate the diversity produced by farms, that is, a good output within the frame of production theory. This can be motivated by the fact that greater crop diversity is likely to increase the number of different habitats. In conventional farming, a monoculture may be successful, whereas organic production technology requires at least some crop rotation, ruling out single-crop cultivation. Thus, organic farming is likely to produce higher crop diversity. Moreover, studies have shown that crop rotation conserves soil fertility (Watson et al., 2002), improves nutrient and water use (Karlen et al., 1994), and increases yield sustainability (Struik and Bonciarelli, 1997).

3. Production technology

Technology is typically described by production functions defining output as a function of inputs. In contrast to scalar-valued production functions, distance functions allow multiple outputs and multiple inputs (Shephard 1970). In principle, there are two extreme options that may be applied, an

[3] The index has its origin in information theory (Shannon 1948); for applications in environmental economic studies, see, e.g., Pacini et al., 2003; Miettinen, Lehtonen and Hietala-Koivu, 2004; Di Falco and Perrings, 2005. Sometimes the index is presented in the form exp(SHDI). At the maximum, this form indicates the number of species corresponding to a uniform distribution (maximum entropy).

input or an output distance function[4]. For any input-output combination $(x,y) \in R_+^{N+M}$, the Shephard output distance function $D_o(x,y)$ is such that $D_o(x,y) = \min \{\lambda > 0: y/\lambda \in P(x)\}$, where P(x) is the output (producible) set.[5] The output distance function calculates the largest expansion $(1/\lambda)$ of y along the ray through y as far from 0 as possible while staying in output set (P(x)), which means that y belongs to P(x) if and only if $D_o(x, y) \leq 1$. The distance function takes the value one only if the output vector belongs to the frontier of the corresponding input vector. Therefore, the output distance function completely characterizes the technology, which inherits its properties from P(x).

Färe (1975) showed a connection between Shephard distance functions and (Debreu)-Farrell input- and output-oriented measures of technical efficiency. The Farrell (1957) measure of output-oriented technical efficiency (F_o) is the reciprocal of the value of output distance function, that is $F_o(x,y) = (D_o(x,y))^{-1}$. One property of the Farrell measure is that it is invariant with respect to the units of measurement in the inputs and outputs. Furthermore, the evaluation of input and output efficiency provides equal, albeit reciprocal, values for distance function/technical efficiency when constant returns to scale prevail.

Färe and Primont (1995) have shown that there is a dual relationship between input (output) distance functions and cost (revenue) functions. This duality can be utilized when we consider which orientation would be appropriate in our case; it is also an important property that can be used in determining shadow prices.

[4] Directional distance functions provide a more general representation of technology than do the proportional distance functions discussed by Shephard. Chambers, Chung and Färe (1998) have shown that the proportional distance function is a special case of the directional distance function. In spite of the generality of directional distance functions, it is problematic that the direction vector has to be defined a priori. Therefore, proportional functions are preferred as a starting point in the present case.

[5] Input (x) and output (y) combinations consist of N non-negative inputs and M non-negative outputs. Alternatively, the input distance function $D_i(x, y)$ can be presented as $D_i(x, y) = \max \{\gamma > 0: x/\gamma \in V(y)\}$, where V(y) is the input (requirement) set.

In addition to yielding crops that can be sold on the market, agricultural production provides other, non-market outputs as by-products. Some of these non-market outputs are desirable and others are not, a fact that has to be taken into account when production technology is modelled. When two outputs are both desirable, as in our case, it is reasonable to assume a production technology of multiple desirable outputs (and multiple inputs), which are strongly disposable.

The assumption as to whether different farm types have or do not have access to the same technology is critical in the measurement of the distance function if the technological frontiers differ by technology. As Dyson et al. (2001) have pointed out, a comparison of firms assumes that the firms compared have access to a similar set of inputs, that is, production technology. This is not the case when organic and conventional technologies are analyzed. An additional challenge when applying DEA is that if the number of observations differs markedly between samples representing two types of technology, the average efficiency scores of the samples are also likely to deviate from one another because of the difference in dimensionality. Another concern is the robustness of non-parametric results. How these challenges are met in the estimations will be discussed in section 4.

Approaches using traditional output distance functions assume that the distance is calculated as a possibility for an equiproportionate increase in outputs, given inputs and reference units. The direction is chosen without taking into account the preferences of society with regard to these different outputs. In principle, the optimal product mix in terms of Pareto optimality is produced when the marginal rate of transformation, or the slope of the transformation curve, equals the marginal rate of substitution, or the slope of the (utility) indifference curve for the society. In practice, we do not know the preferences of society. Therefore, the direction of the distance function is a critical assumption in the case of non-market outputs, which do not have a market price. We may assume that socially optimal proportions of the two outputs are already being produced but that the objective of society is to produce more of both. We might also think that society chooses between alternative policy goals by seeking to increase either crop diversity (given the inputs and traditional output) or the traditional crop output (given the inputs and crop diversity). This would be conceivable where a socially optimal level of one of the outputs is already being produced but the aim is to evaluate the possibilities to increase the other output. This kind of directional distance function is similar to that employed in calculating technical subvector efficiency by Färe, Grosskopf and Lovell (1994) and applied to variable inputs by Oude Lansink, Pietola and Bäckman (2002). Figure 1 illustrates the traditional radial output distance function (solid line) and the specific directional distance functions (broken lines: vertical for crop, horizontal for crop diversity[6]). These three directions are considered in our empirical analysis and, as discussed above, the directions reflect society's potential policy goals.

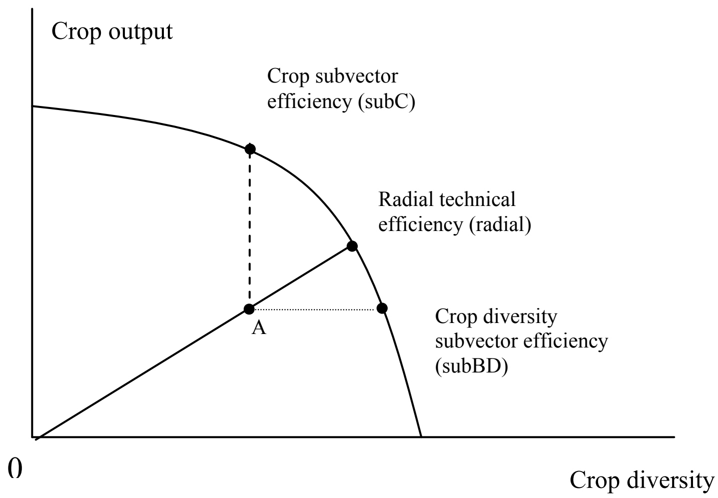

Figure 1. Traditional (radial) and sub-vector (crop and crop diversity) technical efficiencies.

[6] An obvious alternative would be to think that society seeks to reduce the cost/input use of production but to still preserve current output quantities. This would lead us to an input orientation coinciding with the farm-level objective of cost minimization.

Although non-market goods have no market price, the current product mix of each farm reflects the marginal rate of transformation (MRT) between crop output and crop diversity. It is possible to derive a shadow value for crop diversity from the known price of crop output and the current output mix, that is, the MRT between market and non-market outputs. It can be claimed that farmers do not in fact aim at producing crop diversity; rather, it is a by-product of their production process. However, there may be differences between farms in their location on the transformation curve (different shadow values), for example because of unobserved heterogeneity in resources or heterogeneous risk preferences. This variation provides an opportunity to target policy actions such that they serve the aims of enhancing or preserving crop diversity.

4. Methods of analysis

The most frequently used approaches for estimating distance functions/efficiency scores are mathematical programming and econometric estimation of stochastic frontiers. Charnes, Cooper and Rhodes (1978) extended the piecewise linear frontier function to multiple inputs and outputs and referred to the method as Data Envelopment Analysis (DEA). The benefits of DEA are that no functional form (except the scale, disposability, and convexity properties) of the production technology has to be assumed prior to analysis and that the method can easily handle multiple inputs and outputs. One drawback is that no error component is incorporated into the analysis. Stochastic frontier analysis requires specific assumptions about functional forms and efficiency distributions but also accounts for statistical noise.[7]

[7] For a methodological development, see e.g., Daraio and Simar (2007), Kuosmanen and Johnson (2010).

4.1 Non-parametric efficiency analysis

We prefer non-parametric DEA-based models because of the minimal assumptions required for estimation. Moreover, it is possible to derive farm-specific shadow prices for crop diversity, not just one socially optimal value for all farms. In DEA, estimation is carried out using linear programming (LP) models which have to be solved for each decision-making unit (farm) separately. In the case of constant returns to scale, we define the model with M outputs, y_m, and N inputs, x_n, and with K decision-making units forming the reference set and each unit, *k'*, being compared in turn to that set. In our notation, $F_o(CRS, S)$, or ϕ, denotes technical output efficiency under constant returns to scale (CRS) and strong disposability (S) assumptions. Radial output efficiency can be conveniently used in the estimation, inasmuch as the measure is the reciprocal of the output distance function, that is, $(D_o(x, y))^{-1}$ (Färe, Grosskopf and Lovell, 1994).

$$\begin{aligned}
&F_o(CRS, S) = (D_o(x, y))^{-1} = \max \phi \\
&s.t.\ \ \phi y_{k'm} \le \sum_{k=1}^{K} z_k y_{km}, m = 1, \ldots, M, \\
&\sum_{k=1}^{K} z_k x_{kn} \le x_{k'n}, n = 1, \ldots N, \\
&z_k \ge 0, k = 1, \ldots, K.
\end{aligned} \tag{2}$$

When the non-negative intensity variables z_k are not constrained, the scaling of reference units up and down is unlimited, a condition which reflects CRS.

4.2 Efficiency scores

The DEA method for efficiency scores suffers from two limitations: sensitivity, meaning that outliers may significantly affect the location of the non-stochastic frontier, and the curse of dimensionality, meaning that the number of observations affects the level of efficiency. This precludes comparing the scores of the two samples, conventional and organic, directly, in particular when the samples differ in size. There are alternative solutions to overcome this obstacle.

First, one has to determine which observations should be regarded as outliers. We have applied the approach put forward in Charnes et al. (1985) by removing the most influential observations in the DEA.[8] In several sequential runs of the analysis, we removed observations that were peers for more than one-third of the observations; we left out the observations that were peers only for themselves and for a few other farms; and lastly we removed the most inefficient farms, defined as those with efficiency scores of less than one-third.

Second, we tackle the curse of dimensionality in alternative ways. In order to compare different groups, we apply the metafrontier approach and pool all the farms into one data set (Battese, Rao and O'Donnell 2004). The efficiency of all units is assessed against the same pooled set of reference observations. The efficiency levels are therefore more readily comparable than they would be in separate samples. One drawback here is that the method cannot account for the fact that one production method may be more restrictive than another in the use of inputs, for example, a condition we may well assume when comparing organic and conventional farms. Thus, metafrontier results should be interpreted with care in comparisons, but they do bring additional information about the robustness of efficiency scores and shadow values.

As the choice of the reference set for technology is crucial in the efficiency analysis, the small number of observations for organic farms poses a challenge for analyzing the organic technology separately. Accordingly, we perform sensitivity analysis of efficiency scores following the procedure described by Simar and Wilson (2000). The procedure takes into account the fact that DEA scores are based on finite samples and that efficiency scores may be sensitive with respect to the estimated efficient frontier because of sampling variation. It provides bias-corrected estimates

[8] De Witte and Marques (2010) describe several ways to search and test for outliers in data; one of the tests presented is the one proposed by Charnes et al. (1985).

and confidence intervals for efficiency scores.[9] Yet, these confidence intervals are fairly wide; despite fairly large differences in the efficiency scores of specific units, the differences often do not turn out to be statistically significant.

4.3 Shadow values

Relative shadow values or prices (relative weights) for inputs and outputs can be obtained from the dual (primal in Charnes, Cooper and Rhodes, 1978) solutions of the linear equation system above (equation 2). The dual form for a regular model (CRS) is as follows:

$$\begin{aligned} &F_O(CRS, S) = \min \sum \mu_{k'n} x_{k'n} \\ &\quad s.t. \ \sum \nu_{k'm} y_{k'm} = 1 \\ &\sum \nu_{k'm} y_{km} - \sum \mu_{k'n} x_{kn} \leq 0 \quad \forall k \\ &\nu, \mu \geq 0 \quad \forall m, n. \end{aligned} \tag{3}$$

The non-negative multipliers μ_n and ν_m can be interpreted as the relative shadow prices of inputs x_n and outputs y_m. As the equations show, the prices are farm (k') specific. We apply these relative shadow prices, estimated from the above dual formulation of DEA, when determining the value of crop diversity. When we have estimates for the relative shadow prices and know the true price of one of the outputs (crop output), we may solve for the shadow value of crop diversity for the current product mix and MRT for each farm.

To assess the influence on the shadow values of the direction chosen for the evaluation, we introduce the LP model of subvector efficiencies with a slightly different set of constraints[10]. In particular, we first assume that only the traditional output is adjusted; crop diversity is treated as an

[9] For bias correction, the R package FEAR was used. (Wilson 2008)
[10] In practice, in the primal (output-oriented) formulation the distance/efficiency coefficient is minimized/maximized with respect to only one output, the other output being an ordinary constraint. See online Appendix.

ordinary constraint, indicating that the crop diversity in any feasible solution should be at least as large as in our decision-making unit (the vertical direction in Figure 1, henceforth denoted by _subC). Technical output efficiency is thus only measured in relation to traditional output, given inputs and crop diversity. Second, we evaluate the efficiency with respect to crop diversity, given traditional output and inputs (the horizontal direction in Figure 1, _subBD).

Finally, we want to gain insight into the factors that influence shadow values. This is not necessarily a straightforward task. It has been debated whether the second-stage regression on efficiency scores can be estimated with consistency (e.g., Simar and Wilson 2007), and similar concerns can be raised where identifying determinants for shadow values is concerned. Having said this, the results of a second-stage regression of non-parametric efficiency scores have proven to be fairly robust with respect to the estimation method used. Following McDonald (2009), we use ordinary least squares in our regressions for shadow values.

5. Data

We use a data set of bookkeeping farms that constitutes a sample of Finnish crop farmers from the Farm Accountancy Data Network (FADN) of the EU in the period from 1994 to 2002. Because of the small number of organic farms, the original panel was complemented by adding organic farms that had participated in the bookkeeping system for at least two years as well as the farms that had changed over from other forms of production (e.g., milk production) to crop production. Thus, the final panel is unbalanced. Farms were classified as crop farms if their animal density was less than 0.1 animal units per hectare and the share of cereals in total sales return was at least 20 percent.[11] In total, about 1,000 farms in Finland submit their bookkeeping records to FADN. Farms receiving aid

[11] This is to guarantee that the return from animal production is low but that, at the same time, the farm is allowed to have a limited amount of such production. Farms that specialize solely in sugar beet and potato cultivation are eliminated, because the production technology of such farms differs significantly from that of the majority of less-specialized crop farms. See Oude Lansink, Pietola and Bäckman (2002).

for organic farming are considered farms engaged in organic production. Summary statistics for the final data set used in the analysis are presented in Table 1. [12]

Table 1. Descriptive statistics of conventional and organic farms.

	Conventional		Organic	
Number of observations	662		136	
	Mean	St.dev.	Mean	St.dev.
Crop output, € (constant 2000 prices)	32,776	23,856	14,758	20,565
Crop diversity, SHDI	1.31	0.37	1.40	0.32
Labour, hours	1,823	983	1,497	1,075
Land, ha	65	36	48	42
Energy, € (constant 2000 prices)	5,516	3,430	4,263	5,254
Other inputs, € (constant 2000 prices)	20,152	13,866	11,866	17,765
Capital, € (constant 2000 prices)	63,589	44,030	50,693	57,848

We use crop returns as a proxy of the quantity of aggregate marketable crop output, measured at constant prices of the year 2000. For both organic and conventional farms, output at constant prices is obtained by dividing crop returns by the respective price indices of conventional outputs published by Statistics Finland. The main reason for using only price indices for conventionally produced goods is that no reliable prices or price indices for organic products are available. Consequently, any price premium for organic products would increase our proxy of the output quantity[13]. Then again, the average traditional crop output is considerably lower on organic than on conventional farms (see Table 1).[14] All subsidies (direct payments) paid on the basis of the arable land area of the farms are excluded.

[12] It should be noted that the average arable land area (size) of farms in FADN is larger than the average in Finland. In 2000, the number of crop farms in FADN by size class was as follows: 32 farms were smaller than 30 ha in size, 42 between 30 and 50 ha, 36 between 50 and100 ha and 15 over 100 ha. (Riepponen, 2003)
[13] The same applies to other positive quality differences that cause higher prices.
[14] The market share of organic products was at most two percent in Finland, and anecdotal evidence suggests that price premiums did not increase over the study period, but, at best, the prices followed the pattern for conventional products.

We use the Shannon Crop Diversity Index (SHDI) to measure the desirable environmental by-product of the farms in the study – crop diversity. As Table 1 indicates, the index is on average larger on organic farms.[15] Even though the SHDI was chosen as an indicator, because it takes into account the evenness and richness of land use, there is a strong correlation between the index and the number of crops cultivated on a farm. The distribution of the number of crops for organic farms is slightly skewed such that the share of farms having seven or more crops is larger among the organic than the conventional farms.

Five inputs are used for the outputs. Labour is measured in hours as a sum of family and hired labour input. Land is measured in hectares representing the total arable land area of the farm. Input variables accounted for at constant prices of 2000 are energy, including both fuel and electricity; other variable input, consisting of purchased fertilizers, seed, etc.; and capital, including the value of buildings and machinery. The respective input price indices are obtained from Statistics Finland. The average arable land area of conventional farms is about 15 hectares larger than that of organic farms, a difference that is statistically significant (t-test statistics 4.41, p-value < 0.001).

We observed some very low or fairly high crop output values in the original data set. As emphasized above, in non-stochastic models it is important to search for possible outliers, since low (high) output relative to inputs also yields a low (high) technical efficiency score for a farm. After a careful analysis of possible outliers (Charnes et al. 1985), we removed 27 conventional farms and 6 organic farms from the data set. The total number of observations used is 798, of which 662 are conventional and 136 organic farms (Table 1).

[15] The t-test statistics for differences in output and crop diversity index were 9.04 (p-value < 0.001) and -2.91 (p-value < 0.001), respectively.

6. Results

6.1 Efficiency scores for conventional and organic farms

The mean values and confidence intervals for the efficiency scores from the alternative models are summarised in Table 2. The large difference in the distributions of efficiency scores for organic farms by number of outputs is reflected in the summary statistics for efficiency scores from the metafrontier model. Table 2 shows that the mean (confidence interval) one-output efficiency score for organic farms is 0.33 (0.30-0.36), whereas the mean two-output efficiency score is 0.63 (0.60-0.66). A similar comparison among the conventional farms shows that the mean one-output efficiency score is 0.54 (0.53-0.57), whereas the mean two-output efficiency score is 0.61 (0.60-0.63). For two-output metafrontier models, no differences in efficiency scores between the farm types exist and the confidence intervals also overlap in the models with bias correction.

Table 2. Radial technical efficiency scores.

	All farms		Conventional		Organic	
	Mean	CiL-CiU	Mean	CiL-CiU	Mean	CiL-CiU
Metafrontier (MF)						
MF_1O	0.51	0.49-0.52	0.54	0.53-0.57	0.33	0.30-0.36
MF_2O	0.62	0.60-0.63	0.61	0.60-0.63	0.63	0.60-0.66
MF_2Obc	0.56	0.55-0.57	0.56	0.55-0.57	0.55	0.53-0.58
Separate frontiers (SF)						
SF_1O			0.54	0.53-0.56	0.50	0.46-0.54
SF_2O			0.67	0.66-0.69	0.69	0.68-0.71
SF_2Obc			0.61	0.60-0.63	0.61	0.58-0.64

Note: 1O – one output, 2O – two outputs, 2Obc - two outputs bias corrected;
CiL – confidence interval (lower 95%), CiU – confidence interval (upper 95%).

In the lower panel of Table 2, the efficiency scores estimated separately for each technology show that the estimates for organic farms in the case of one output are slightly lower than in the conventional case but that the confidence intervals overlap. In the two-output case, the efficiency of conventional and organic farms is significantly higher than in the one-output case but bias correction reduces the scores of both farm types.

Due to the relatively wide confidence intervals, there is only limited statistical evidence that the estimation method has an impact on efficiency scores in the two-output case. Table 2 shows that the models using separate frontiers produce systematically higher scores for organic farms than the metafrontier approach does. This is true also for conventional farms, except for the very similar one-output estimates obtained for the separate frontier and the metafrontier. A natural explanation for the lower efficiency scores of organic farms in the metafrontier approach is the crucial impact of the reference set in DEA: organic farms, which are fewer in number and, on average, have smaller traditional crop output, account for fewer close-to-frontier observations than the more numerous conventional farms.[16]

All models show that there is room for improvement in efficiency for both conventional and organic farms. There is variation in the efficiency scores and, as will be seen, there is also variation in the estimates of shadow values.

6.2 Shadow values, or opportunity costs, of crop diversity

We apply the dual formulation of DEA to calculate shadow values for crop diversity. It should be noted that an increase of one unit in the index is quite considerable, whereby we report the shadow

[16] In fact, we estimated technical efficiencies also applying order-m which is more robust with respect to the number of observations and extreme values than standard DEA (Cazals, Florens and Simar, 2002 and Daraio and Simar, 2007). The estimations were carried out using FEAR (Wilson 2008). The results of separate frontiers (assuming m=20 and input orientation) show that in the one-output case conventional farms (mean technical efficiency 0.835 and standard deviation 0.243) are more efficient than organic farms (mean technical efficiency 0.805 and standard deviation 0.206). However, when two outputs are considered, organic farms (mean technical efficiency 0.825 and standard deviation 0.182) are more efficient than conventional farms (mean technical efficiency 0.786 and standard deviation 0.222). The differences are significant at least at the 5 % risk level.

prices, or marginal values, for an increase of 0.1 unit of the SHDI. This is an increase that an average farm in the data set might achieve by adding one crop, for example.

Since the shadow values reflect the opportunity costs to farms of increasing crop diversity, they provide important information for policy design. Indeed, it is meaningful to compare the shadow values also between organic and conventional technologies, because the shadow values - the opportunity costs - may be technology driven and, given their technological constraints, the farms supply crop diversity as an output to the same "policy-driven market" of environmental outputs.

Table 3. Shadow values of crop diversity (SHDI) per hectare in Euros.

Direction of	Conventional		Organic	
distance function	Mean	CiL-CiU	Mean	CiL-CiU
MF_radial	21	19-23	56	46-66
SF_radial	44	39-48	41	31-51
SF_subBD	66	60-72	53	42-63
SF_subC	23	21-25	18	14-22

Note: Shadow values based on directional distance functions, constant returns to scale. Metafrontier (MF) and separate frontiers (SF) for conventional and organic farms: radial (_radial), crop diversity sub-vector (_subBD) and crop sub-vector (_subC); CiL – confidence interval (lower 95%), CiU – confidence interval (upper 95%)

Table 3 summarizes statistics for the shadow values of a marginally increasing SHDI based on the alternative models for organic and conventional technologies. In addition to the Farrell-type radial direction, two subvector efficiency models are applied using the two directional distance functions, that is, crop subvector efficiency (_subC) and crop diversity subvector efficiency (_subBD). For comparison purposes, the shadow values from the metafrontier model in the radial direction are also presented.

Interestingly, the differences in the mean shadow values between technologies do not prove to be statistically significant in the technology specific, separate estimations. The large deviation in shadow values leads to large confidence intervals (also for individual units when bootstrapped), and the confidence intervals for the shadow values for organic and conventional farms overlap. Comparison of the separate frontiers shows that the shadow values derived from the crop subvector (SF_subC) are the lowest for both farm types. However, when compared to the use of separate frontiers, the metafrontier approach (MF_radial) generates the lowest shadow values for conventional farms and the highest shadow values for organic farms. This pattern can be attributed to the fact that the reference group determining the frontier is different in the models with separate frontiers and a metafrontier and that the reference set affects shadow prices. Given that organic farms have on average smaller crop output and larger crop diversity than conventional farms, their opportunity costs in terms of forgone output are larger in the pooled data set, which is dominated by observations representing conventional technology.

One is naturally inclined to explain the variation in shadow values with reference to variables describing the farm characteristics. A second-stage OLS regression on the shadow values of crop diversity is estimated separately for organic and conventional farms. The dependent variable is the estimated shadow value of crop diversity per hectare, based on the radial direction.

Among the explanatory variables, the capital-labour and land-labour ratios measure the relative intensity of input use. In general, these shares change according to farm size, but they are also dependent on the kinds of crops being cultivated. These variables have been used in Latruffe, Davidova and Balcombe (2008), for example, as explanatory variables for efficiency scores. Dummy variables are used as indicators for size.[17] The region variable includes two regions:

[17] These four size classes were used in Riepponen (2003).

southern Finland and the rest of Finland. Climatic conditions are best in the south, where most of the farms are located. Region in the models is a dummy variable receiving a value of 0 for southern Finland and 1 otherwise. The observations are from several time periods, or years. The period variable captures a possible linear trend in shadow value over time. The share of cereal output of total output is a measure of specialization in cereal farming. The effects of interactions between size dummies and number of crops and region have been included in the model.

The results of a regression analysis on the shadow values from separate frontiers are presented in Table 4. The model diagnostics indicate that all the models are significant although their coefficients of determination (R^2) are fairly low, varying between 0.25 and 0.45. The directions of effects are mainly similar, but the significance levels of coefficients vary. In the regression for organic farms, the only significant variables (at least at the 10 % risk level) are the regional and land area dummies, as well as their interactions. The estimated shadow values of crop diversity tend to be higher on average in the rest of Finland than in the south. However, farm size counteracts regional impact: it is less costly to increase diversity on large than on small farms.

Table 4. Ordinary least squares regression on shadow value of crop diversity

Explanatory variables, X	Conventional Coeff.	p-value	Mean (X)	Organic Coeff.	p-value	Mean (X)
Constant	43.85***	0.0029		54.36*	0.0602	
Period	-0.03	0.9568	5.13	0.92	0.6430	5.60
Nr of crops, NC	11.80***	0.0002	5.27	-0.45	0.8858	5.98
Regional dummy, R	28.48*	0.0795	0.12	61.03***	0.0004	0.34
Land-labour ratio	-202.86***	0.0095	0.04	-58.12	0.8086	0.04
Capital-labour ratio	0.12**	0.0298	41.27	0.24	0.2250	47.46
Share of cereal output	21.06***	0.0006	0.76	-17.51	0.4140	0.60
Size dummy[a], S1	-43.34***	0.0053	0.35	-18.55	0.2250	0.37
Size dummy[a], S2	-39.89***	0.0078	0.41	-44.86**	0.0394	0.14
Size dummy[a], S3	-46.92***	0.0078	0.15	-61.19***	0.0095	0.14
Interaction R*S1	-15.03	0.3862		-68.46***	0.0055	
Interaction R*S2	-44.66**	0.0215		-64.95***	0.0383	
Interaction R*S3	-34.54*	0.0636		-55.02	0.2093	
Interaction NC*S1	-1.21	0.7453				
Interaction NC*S2	-10.37***	0.0025				
Interaction NC*S3	-11.55***	0.0013				
Model diagnostics						
Number of observations		641				125
Parameters		16				13
Degrees of freedom		625				112
R-squared		0.458				0.325
Adjusted R-squared		0.445				0.252
F(prob)		35.3(.0000)				4.5(.000)
Log likelihood		-3165				-667
Restricted(b=0)		-3362				-692
Chi-sq(prob)		393.1(.000)				49.1(.000)

[a] For size dummies, S1=between 30 and 50 ha, S2= between 50 and100 ha, and S3 = over 100 ha; the reference class is a farm smaller than 30 ha in size.
Note: Mean value of a dummy variable indicates the share of the farms in the dummy category.
Asterisks denote significance at * 10% level, ** 5% level, *** 1% level.

For the shadow values of conventional farming, all other explanatory variables are significant except period. The shadow value per hectare is higher on average in the rest of Finland than in the south, and the impact of size is negative and highly significant. As in the case of organic farms, the regional and size dummies counteract each other. A high capital-to-labour intensity raises but a high land-labour ratio reduces the shadow price of crop diversity. The number of crops and the share of cereal output have a positive effect on the shadow value of crop diversity. The effect of the number of crops on the shadow value decreases with farm size, and it is negligible in the largest size class. All in all, the results make economic sense, since one could expect capital-intensive, specialized farms that are close to practicing a cereal monoculture to have high opportunity costs of increasing crop diversity.

6.3 Policy implications

Because there is strong variation in the shadow values, we identify the shadow values of the least-cost farms to see how large a proportion of each sample they represent. We order the farm observations (given their land area) by the estimated shadow values, or opportunity costs (per hectare) of increasing crop diversity (SHDI) by a marginal value of 0.1 unit. The opportunity costs in Figure 2, presented in order from lowest to highest, can be interpreted as supply curves for crop diversity, provided that the samples can be considered representative of active farms in Finland.

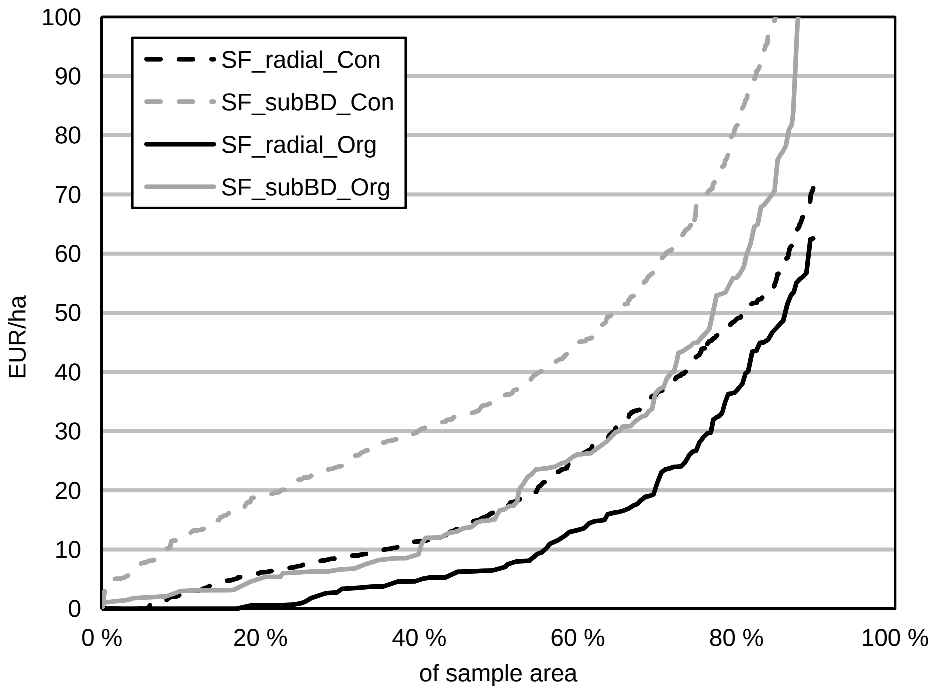

Figure 2. Observations of conventional (Con, broken lines) and organic (Org, solid lines) farms ordered by the estimated shadow values of increasing SHDI by 0.1 unit representing 90 % of total land area in each sample; separate frontiers (SF): radial (_radial, black lines) and crop diversity sub-vector (SF_subBD, grey lines).

Figure 2 shows that the shadow values for conventional farms derived from the radial model (black broken line) are rather close to the shadow values for organic farms derived from the crop diversity subvector model (grey solid line) but that the shadow values for organic farms increase faster. For both types of farms, the shadow values derived from the crop diversity subvector model give the highest estimates (grey lines), whereas the traditional radial distance function (black lines) produces shadow values that lie below the subvector estimates. This means that the opportunity costs of a policy that aims at increasing crop diversity at the current level of crop output will be higher than the costs of a policy that aims at increasing the current level of crop diversity while increasing traditional crop output.

Our findings provide interesting policy implications. The average opportunity costs of conservation do not reflect the variation in costs between farms and may bias the design of environmental policies. In addition to noting the absolute magnitudes of our shadow value estimates, one should recognize the heterogeneity between farms with respect to these costs. This causes the supply curves for crop diversity to become upward sloping, as illustrated in Figure 2. This in turn means that, for example, a discriminative-payment auction for crop diversity could generate cost savings in total payments compared to a fixed-payment scheme at any given payment level. Looked at in another way, for any proportion of a total budget allocated for conservation payments, a fixed-payment scheme would give society less crop diversity than a discriminative-payment scheme would. Stoneham et al. (2003) reached a similar finding on potential cost savings in a pilot auction of conservation contracts in Australia.

The least-cost farms would naturally be the most likely candidates for receiving conservation payments if auctions and competitive bidding were used to promote the conservation of crop diversity on farmland. Our analysis suggests that, of the two distinct technologies considered, organic rather than conventional farms are more likely to be among the least-cost farms. However, because conventional farms form a majority of farms, accounting for over 95% of arable land area, it is important to recognize that least-cost farms are not distinguished by farming technology alone. Our results suggest that the winners in auctions for conservation payments for crop diversity could be large-area farms in wealthier southern Finland. This can be a concern as regards distribution of income. Moreover, identification of low-cost farms using auctions for conservation payments should not increase the administrative costs of voluntary programs. On balance, further research is warranted on the issues of administrative burden and equity that come into play when implementing policies to achieve conservation targets for crop diversity in agriculture.

7. Conclusions

Consideration of the environmental benefits to be achieved is important for the design of agri-environmental policies. Our study integrates such benefits into the production process as a desirable output and compares conventional and organic technologies using the Shannon Crop Diversity Index. The index takes into account both richness and evenness, but one could focus on richness only and use number of crops as an ecological indicator.

In our sample, organic farms had slightly higher crop diversity on average than conventional farms did. A difference regarding crop diversity appeared in the analysis of the opportunity costs in that these costs were found to be higher on average for conventional than organic farms. Yet, it is important to recognize the heterogeneity in costs between the farms using the same technology, as the variation in the shadow values is strong. This means that the cost-efficiency of conservation programs could be improved generally by using discriminative payments and targeting low-cost farms: either cost savings could be realized in the total amount of payments or more crop diversity could be achieved with a given total budget for payments. Hence, targeted policies would make economic sense. However, our sample of farms and our analysis show that farms producing crop diversity at the lowest costs are not necessarily, nor even likely to be, those farms that policy makers ought to target under considerations of equity and opportunities to increase the incomes of small farms in areas less wealthy than southern Finland.

Even though our approach is only a first step towards analyzing the economic and environmental impacts of alternative farming technologies simultaneously, the thrust of our analysis is clear. Normally, there is a trade-off between several outputs, whereby multiple outputs, including environmental impacts, should be accounted for. It is important to identify the heterogeneity of farms in producing environmental benefits if tailored agri-environmental policies are to lead to cost-efficiency and savings in the use of taxpayers' money.

Further research is needed on elaborating other environmental benefit indices that can be calculated on the basis of the farm accountancy data available to regulators. If landscape values are evaluated, the scale of analysis should be extended beyond the borders of farm units. Studies incorporating aggregation over farms and time would enable better-informed policy assessments.

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