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Non-Parametric Production Analysis of Pesticides Use in the Netherlands

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Abstract

Many previous empirical studies on the productivity of pesticides suggest that pesticides are under-utilized in agriculture despite the general held believe that these inputs are substantially over-utilized. This paper uses data envelopment analysis (DEA) to calculate non-parametric measures of the value of the marginal product of pesticides. Furthermore, the effect of pesticides on the value of the marginal product of productive inputs is investigated in order to analyze technical interdependence between pesticides and productive inputs. Results suggest, in general, substantial under-utilization of pesticides, which is consistent with earlier findings of parametric specifications.

JEL Classification: C6, Q0, Q1

Keywords: pesticides, DEA, shadow prices, efficiency

1. Introduction

Pesticides are playing an important role as an output quantity- and quality-increasing input in much of the world's agriculture. However, environmental and food safety concerns have encouraged the introduction of policies aiming at a reduction of the use and dependence of agriculture on pesticides in many western countries.

The measurement of the marginal productivity of pesticides has been the subject of a continuous debate among agricultural economists. There is, in general, a discrepancy between econometric results and perception concerning pesticide productivity. A number of previous studies generated empirical results suggesting that pesticides are under-utilized in agriculture despite the general perception of over-utilization of this input.

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Previous empirical studies have analyzed pesticides use in agriculture using parametric approaches. One of the central issues in these studies is the functional specification of the role of damage control inputs in the production process. Lichtenberg and Zilberman (1986) hypothesized that earlier estimates of the value of the marginal product of pesticides (e.g., Headley, 1968; Carlson, 1977) were biased upward since they do not account for the role of a damage abatement input that pesticides play in the production process. Based on agronomic evidence that demonstrates pesticides are damage reducing rather than a productivity increasing input, Lichtenberg and Zilberman (1986) proposed an asymmetric treatment of productive inputs and damage abatement inputs. Damage abatement inputs are defined in general as inputs that reduce damage rather than increase output. Typical examples of damage abatement inputs are costs of surveillance and electronic monitoring to reduce theft in shops and pesticides and veterinary costs to reduce damage from pests and diseases to crops and livestock.

The output damage abatement specification developed by Lichtenberg and Zilberman (1986) was applied by Babcock et al. (1992), Carrosco-Tauber and Moffit (1992), Lin et al. (1993), and Chambers and Lichtenberg (1994). The results of empirical applications of asymmetric functional forms are mixed. Some of the empirical studies indicated over-utilization of pesticides (e.g., Babcock et al., 1992), while others reported estimates of the value of marginal product of pesticides that exceed marginal factor cost (e.g., Carrasco-Tauber and Moffit, 1992). Furthermore, the estimates of the value of the marginal product are sensitive to the parametric functional form specified for the damage abatement function (e.g., Carrasco-Tauber and Moffit, 1992).

The asymmetric functional specification proposed by Lichtenberg and Zilberman (1986) is questioned by Carpentier and Weaver (1997), since this specification imposes implicit restrictions on the production technology (e.g., homothetic separability of the input vector in the partition of inputs into productive inputs and damage abatement inputs). Based on theoretical grounds, Carpentier and Weaver (1997) proposed an input damage abatement approach that treats damage abatement inputs and productive inputs symmetrically. Oude Lansink and Carpentier (2001) used the Generalized Maximum Entropy method to estimate a quadratic input damage abatement specification and found evidence for different technical interactions between pesticides and productive inputs, which violates the assumption of homothetic separability.

This paper contributes to the literature on the economics of pesticides by investigating the technical interdependence between productive inputs and pesticides and measuring the shadow price (or the value of the marginal product) of pesticides using a non-parametric approach.[1] A non-parametric approach is more flexible than a parametric approach, since it allows implicitly for technical interactions between damage abatement and productive inputs without imposing a specific functional form to represent the production technology. The essence of the non-parametric approach employed in this study can be found in Färe et al. (1994). The shadow price of pesticides is generated according to the procedure proposed by Ball et al. (1994, 2000) and is elaborated in detail later in the paper.

Although the approach used in this study has the advantage of being non-parametric, it has the drawback of being deterministic. Consequently statistical noise may affect the measurement of the shadow price of pesticides, though in an unknown direction. This study employs a sensitivity analysis to investigate the impact of outliers on the shadow prices of inputs.

The objectives of this paper are twofold. First, this paper calculates the shadow price of pesticides using data envelopment analysis (DEA). The DEA approach adopted treats productive inputs and damage abatement inputs symmetrically. The shadow price of pesticides is generated using four input-oriented models. Second, the effect of pesticides on the value of the marginal product of productive inputs is investigated in order to analyze the technical interdependence between damage abatement and productive inputs.

The remainder of this paper is structured as follows. Non-parametric models of production in the presence of damage abatement and productive inputs are presented in the next section. This is followed by a discussion of the data and the empirical results. The paper concludes with comments.

2. Specifications of DEA Models with Damage Abatement Inputs

This section presents different DEA models of production incorporating damage abatement and productive inputs. Four input-oriented models are used to generate the shadow price of pesticides. These models measure efficiency in different directions and provide radial and non-radial (i.e., subvector and a type of Russell) efficiency measures. Although these models provide different efficiency scores, the main purpose is to generate the shadow price of pesticides at four different points on the production frontier. The models also provide information on the technical interdependence between productive and damage abatement inputs.

2.1. DEA Models Incorporating Damage Abatement Inputs

Let $\mathbf{x} = (x_1, x_2, \ldots, x_S) \in R^S_+$ and $\mathbf{z} = (z_1, z_2, \ldots, z_A) \in R^A_+$ denote the quantity vectors of productive inputs and damage abatement inputs to produce a single output $\mathbf{y} \in R_+$. A production technology can be fully characterized by the input requirement set $V(\mathbf{y}) = \{(\mathbf{x}, \mathbf{z}) : (\mathbf{x}, \mathbf{z}) \text{ can produce } \mathbf{y}\}$. A nonparametric representation of $V(\mathbf{y})$ can be given as:

$$V(\mathbf{y}) = \{(\mathbf{x}, \mathbf{z}) : Y'\lambda \geq \mathbf{y}_i, X'\lambda \leq \mathbf{x}_i, Z'\lambda \leq \mathbf{z}_i, I'\lambda = 1, \lambda \geq 0\},$$

where $\mathbf{Y}$ is the $(N \times 1)$ vector of observed outputs, $\mathbf{y}_i$ is the observed output level of firm i, X is the $(N \times S)$ matrix of observed productive inputs, $\mathbf{x}_i$ is the vector of productive inputs used by firm i, Z is the $(N \times A)$ matrix of observed damage abatement inputs, $\mathbf{z}_i$ is the vector of damage abatement inputs (pesticides) used by firm i; λ is a $(N \times 1)$ vector of intensity variables (firm weights) and $\mathbf{I}$ is the $(N \times 1)$

unitary vector. This technology satisfies convexity, strong disposability of the output and all inputs and variable returns to scale (VRS).[2]

Efficiency is measured relative to production possibilities characterized by $V(\mathbf{y})$. Four input-oriented models are constructed measuring efficiency in four different directions.

The first model measures efficiency radially in the full input space indicating the potential to scale down all (productive and damage abatement) inputs, keeping the output constant.

$$\begin{aligned} \min_{\gamma_{1i},\lambda} \quad & \gamma_{1i} \\ \text{s.t.} \quad & Y'\lambda \geq \mathbf{y}_i, \\ & \gamma_{1i}\mathbf{x}_i \geq X'\lambda, \\ & \gamma_{1i}\mathbf{z}_i \geq Z'\lambda, \\ & I'\lambda = 1, \\ & \lambda \geq 0. \end{aligned} \tag{1}$$

The second model measures efficiency radially in the productive input subspace in terms of the ability of the firm to contract all productive inputs equiproportionately, given the damage abatement inputs and output.

$$\begin{aligned} \min_{\gamma_{2i},\lambda} \quad & \gamma_{2i} \\ \text{s.t.} \quad & Y'\lambda \geq \mathbf{y}_i, \\ & \gamma_{2i}\mathbf{x}_i \geq X'\lambda, \\ & \mathbf{z}_i \geq Z'\lambda, \\ & I'\lambda = 1, \\ & \lambda \geq 0. \end{aligned} \tag{2}$$

The third model measures efficiency radially in the damage abatement input subspace indicating the potential to contract all damage abatement inputs with an equal proportion, given the productive inputs and the output level.

$$\begin{aligned} \min_{\gamma_{3i},\lambda} \quad & \gamma_{3i} \\ \text{s.t.} \quad & Y'\lambda \geq \mathbf{y}_i, \\ & \mathbf{x}_i \geq X'\lambda, \\ & \gamma_{3i}\mathbf{z}_i \geq Z'\lambda, \\ & I'\lambda = 1, \\ & \lambda \geq 0. \end{aligned} \tag{3}$$

The fourth model is a variation of the Russell efficiency measure (Färe and Lovell, 1978). The Russell measure allows for non-proportional contractions in each positive input. The efficiency measure in (4) allows for non-proportional reductions in each subset of inputs, allowing for different efficiency scores of productive inputs and damage abatement inputs.

$$
\begin{aligned}
&\min_{\gamma_{3i}\lambda,\gamma_{5i}} \ (\gamma_{4i}+\gamma_{5i})/2\\
&\text{s.t.}\quad Y'\lambda \geq \mathbf{y}_i,\\
&\qquad \gamma_{4i}\mathbf{x}_i \geq X'\lambda,\\
&\qquad \gamma_{5i}\mathbf{z}_i \geq Z'\lambda,\\
&\qquad I'\lambda = 1,\\
&\qquad \lambda \geq 0.
\end{aligned}
\tag{4}
$$

The efficiency measures from models (1)–(4) are demonstrated graphically in Figure 1, representing a situation with one damage abatement input (z) and one productive input (x). Given observation A, model m, $m = 1, \ldots, 4$, projects the observed input combination on point m, $m = 1, \ldots, 4$, in the figure.

A set of dual variables for each observation is obtained from each model measuring the effect on efficiency (the optimal value of the objective) of a change of each technological constraint. These dual variables are used to generate the shadow value of each input using the procedure suggested by Ball et al. (1994, 2000).

The marginal product of each input is given by[3]

$$
\begin{aligned}
MP_{si}^{m} &= \frac{\partial y_i}{\partial x_{si}} = -\frac{\partial\gamma_{mi}/\partial x_{si}}{\partial\gamma_{mi}/\partial y_i}, \quad m = 1, \ldots, 4;\ s = 1, \ldots, S; i = 1, \ldots, N;\\
MP_{ai}^{m} &= \frac{\partial y_i}{\partial z_{ai}} = -\frac{\partial\gamma_{mi}/\partial z_{ai}}{\partial\gamma_{mi}/\partial y_i}, \quad m = 1, \ldots, 4;\ a = 1, \ldots, A; i = 1, \ldots, N;
\end{aligned}
\tag{5}
$$

where MP_{si}^{m} is the marginal product of the productive input s for observation i estimated from model m, MP_{ai}^{m} is the marginal product of the damage abatement input a for observation i estimated from model m and γ_{mi} is the efficiency score for the ith observation in model $m\,(= 1, \ldots, 4)$. The variables $\partial\gamma_{mi}/\partial x_{si}, \partial\gamma_{mi}/\partial z_{ai}$ and

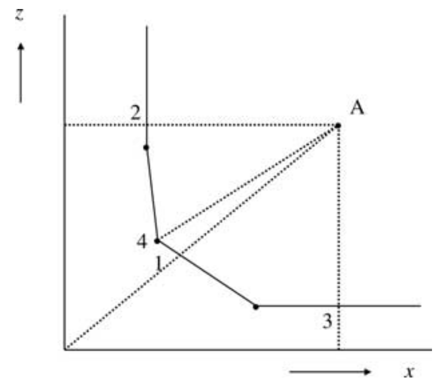

Figure 1. Input oriented technical efficiency measures.

$\partial \gamma_{mi}/\partial y_i$ are calculated using the dual variables in model m ($m = 1, \ldots, 4$) associated with the constraints on the productive input s, the damage abatement input a and the output.

The shadow value (or the value of the marginal product) of each input is obtained as

$$SV_{si}^m = pMP_{si}^m, \\ SV_{ai}^m = pMP_{ai}^m, \tag{6}$$

where p is the output price (Ball et al., 1994, 2000). Each model provides an "estimate" of the shadow price of each input at a particular point on the frontier, being the projection point of the observed input vector (models 1 and 4) or the observed input subvector (models 2 and 3). Figure 1 illustrates the different points on the frontier where the shadow price of each input is evaluated. Model 1 (2) generates the shadow price of each input at point 1 (2). Similarly, models 3 and 4 measure the shadow value of each input at points 3 and 4, respectively. Thus, four shadow values are generated for each input and each firm from models (1)–(4). Comparing the shadow price of each input across models is equivalent to comparing the shadow price of the input at different points on the frontier. *A priori*, it is expected that the shadow values of productive inputs (damage abatement inputs) generated from model 2 (model 3) are larger than those "estimated" using the other models. This follows from the convexity property of the input requirement set. Considering the points illustrated in Figure 1, the shadow value of the productive input x is larger at point 2 than at the other points. Also, the shadow value of the damage abatement input z is larger at point 3 than at points 1, 2 and 4.

The extent to which damage abatement inputs are under- or over-utilized is inferred from a comparison of the shadow prices and the market prices. Profit maximization implies that shadow prices equal market prices. Shadow prices are greater (lower) than market prices for inputs that are under-utilized (over-utilized).

Technical interdependence between damage abatement inputs and productive inputs is investigated using the four previous models. First, a set of shadow prices of the productive inputs is generated for each model. Second, one damage abatement input constraint is increased by one unit and new shadow values of the productive inputs are generated for each model. This constraint perturbation is done A times where A is the number of damage abatement inputs. Comparison of the new shadow values of the productive inputs and the original set of shadow values provides information on the local (i.e., at the projection point of the frontier) technical interdependence between these inputs and a particular damage abatement input. If the increasing a damage abatement input increases (reduces) the shadow value of another input, then both inputs are locally technically complementary (competitive). Furthermore, increasing the pesticides constraint is expected to decrease the shadow value of pesticides.

3. Data

Data on specialized arable farms[5] in the South West clay area, covering the period 1989–1992, were obtained from a stratified sample of Dutch farms which kept accounts on behalf of the farm accounting system of the Agricultural Economics Research Institute (LEI).[6] Farms stay in the sample to a maximum of four years, where some farms are represented in the sample for only one year. The data set used for all models contained 293 observations on 111 farms. Table A1 in Appendix A reports the mean values of the data.

One output, five productive inputs (N-fertilizer, other variable inputs, land labor and capital) and three damage abatement inputs (herbicides, fungicides and other pesticides) are distinguished. Output mainly consists of potatoes, sugar beets and winter wheat. Other variable inputs consist of services, fertilizers, seed and planting materials, purchased feed input, energy and other variable inputs. Land represents the total area under crops and is measured in hectares; labor is measured in quality-corrected man-years and includes family as well as hired labor; capital includes capital invested in machinery and livestock and is measured at constant 1990 prices.

Tornqvist price indices were calculated for outputs, other variable inputs and other pesticides (prices were obtained from the LEI-DLO/CBS). For outputs and most inputs (except land and labor), the available data contain information about the revenues and expenses, respectively and no information about physical quantities. Implicit quantity indexes (i.e., in 1,000 guilders of 1990) were obtained for output, N-fertilizer, other variable inputs and all pesticides as the ratio of value to the Tornqvist price index. The price indices vary over the years but not over the farms, implying that differences in the composition of inputs/output and quality differences are reflected in the quantity (Cox and Wohlgenant, 1986).[7]

4. Results

The mathematical programming problems in (1)–(4) are run for each farm in the sample in each year. Empirical results are reported in Tables 1–4.

Table 1 presents average technical efficiency scores in each year and for the whole time period 1989–1992. The efficiency scores generated in the four models indicate,

Table 1. Average technical efficiency scores.

					Model 4	
Year	# observations	Model 1	Model 2	Model 3	Productive	Pesticides
1989	70	0.753	0.734	0.521	0.790	0.583
1990	74	0.798	0.778	0.599	0.831	0.645
1991	75	0.782	0.766	0.584	0.821	0.638
1992	74	0.902	0.889	0.793	0.926	0.821
1989–1992	293	0.810	0.792	0.625	0.843	0.673

Table 2. Annual averages of the shadow values of inputs.

	1989	1990	1991	1992	1989–1992
Model 1					
N-Fertilizer	3.607	9.472	5.641	5.654	6.126
Other variable inputs	1.051	0.985	1.019	1.452	1.127
Land	4.037	6.313	5.036	3.884	4.829
Labor	96.598	123.000	132.008	93.972	111.349
Capital	0.170	0.220	0.634	0.305	0.369
Herbicides	2.472	3.795	3.528	4.446	3.575
Fungicides	8.279	8.805	9.901	9.957	9.251
Other Pesticides	11.386	37.779	40.373	42.732	33.388
Model 2					
N-Fertilizer	4.789	10.047	6.830	7.443	7.309
Other variable inputs	1.428	1.409	1.294	1.761	1.473
Land	4.375	10.810	5.072	2.860	5.818
Labor	90.474	112.071	116.454	67.868	96.870
Capital	0.191	0.420	0.380	0.440	0.358
Herbicides	0.206	0.233	0.398	2.789	0.914
Fungicides	3.770	5.763	5.393	3.228	4.552
Other Pesticides	5.577	6.300	10.458	28.798	12.874
Model 3					
N-Fertilizer	1.173	5.119	2.392	4.997	3.447
Other variable inputs	0.024	0.125	0.083	0.171	0.102
Land	0.260	0.518	1.264	1.237	0.829
Labor	26.949	47.418	56.658	47.861	45.00
Capital	0.138	0.350	0.069	0.12	0.169
Herbicides	34.498	22.494	20.372	18.718	23.866
Fungicides	14.712	29.947	13.919	14.872	18.397
Other Pesticides	26.085	28.387	56.502	27.568	34.827
Model 4					
N-Fertilizer	2.322	5.227	3.473	6.038	4.289
Other variable inputs	0.398	0.409	0.311	0.549	0.417
Land	1.572	1.495	2.729	1.674	1.875
Labor	92.709	98.753	105.123	66.038	90.677
Capital	0.165	0.220	0.122	0.130	0.160
Herbicides	16.482	14.757	14.133	13.519	14.697
Fungicides	12.687	10.345	11.591	12.010	11.644
Other Pesticides	19.308	18.357	56.115	23.429	29.530

in general, a significant amount of inefficiency in each year. Improvements in efficiency are achieved in 1992 relative to previous years as shown by the values of the efficiency scores in each model. The efficiency scores of model 3 indicate a higher amount of inefficiency than models 1 and 2. Since model 3 measures efficiency in the use of pesticides, this suggests that the farms in the sample are less efficient in the use of these inputs.[8] Also, the efficiency scores of model 4 indicate, on average, a higher amount of inefficiency in the use of pesticides than in the use of productive inputs, given the output level. The results from models 3 and 4 suggest that the application

Table 3. Percentage of farmers that under-utilize pesticides.

	1989	1990	1991	1992
Model 1				
Herbicides	21.43	27.03	28.00	35.14
Fungicides	28.57	35.14	38.70	28.38
Other Pesticides	44.29	33.78	52.00	47.30
Model 2				
Herbicides	1.43	2.70	9.33	21.62
Fungicides	14.29	17.57	17.33	22.97
Other Pesticides	32.86	22.97	38.67	37.84
Model 3				
Herbicides	85.71	77.03	80.00	81.08
Fungicides	67.14	72.97	78.67	70.27
Other Pesticides	54.29	48.65	62.67	63.51
Model 4				
Herbicides	82.86	72.97	77.33	72.97
Fungicides	68.57	68.92	73.33	62.16
Other Pesticides	52.86	44.59	60.00	58.11

of pesticides is more difficult to manage than the use of productive inputs such as fertilizers, labor and capital. The efficiency of pesticides is generally more dependent on weather and soil conditions than the efficiency of productive inputs (Zadoks, 1993). The effect of herbicides is usually larger under conditions that are less beneficial for plant growth; winds during spraying also reduce the efficiency of most pesticides. Yet, another example is the incidence of hot and humid weather conditions reducing the efficiency of the use of fungicides that are applied against Phytophtora Infestans in potato production.

Although models 1–4 provide interesting insights in the efficiency of productive vis-à-vis damage abatement inputs, the main purpose of the paper is to generate shadow prices of damage abatement inputs at different points on the production frontier.[10] Table 2 reports the annual averages of the shadow values of all productive and damage abatement inputs for each model. Shadow values of productive inputs (pesticides) in model 2 are generally larger (smaller) than their values in models 1 and 3. All differences between the values of model 2 vis-à-vis those of either model 1 or 3 are significant at the critical 5% level, with the exception of the shadow values of land and capital in models 1 and 2. The differences between the shadow values of model 2 versus models 1 and 3 reflect the different points at the frontier at which the shadow prices are evaluated and are consistent with *a priori* expectations discussed in Section 2. The shadow price in model 2 is evaluated at the point on the frontier that reflects the minimum quantity of productive inputs required for producing a given bundle of outputs, given the quantity of pesticides. Shadow values in model 4 lie in the range spanned by the values of models 2 and 3, which is consistent with the observation

Table 4. Average differences in the shadow values of inputs when the herbicides, fungicides and other pesticides constraints change (sample period 1989–1992).

	Model 1		Model 2		Model 3		Model 4	
Input	Difference	*t*-value	Difference	*t*-value	Difference	*t*-value	Difference	*t*-value
Herbicides								
N-Fertilizer	0.01	0.04	– 0.03	– 0.25	0.25[b]	1.77	0.14	1.19
Other variable inputs	– 0.04[b]	– 1.69	– 0.05	– 1.33	0.05	0.78	0.02	0.64
Land	1.11	1.04	0.07	1.44	0.13[a]	2.66	0.06	1.54
Labor	2.83[a]	2.05	0.11	0.16	– 1.65[a]	– 2.65	– 0.32	– 0.29
Capital	– 0.01	– 0.16	– 0.01	1.09	0.04	1.01	0.03	1.14
Herbicides	– 0.49[b]	– 1.75	– 0.13[a]	– 2.44	– 3.61[b]	– 1.71	– 2.22[a]	– 3.71
Fungicides	0.75	1.20	0.16	1.08	1.97	1.39	0.64[b]	1.83
Other Pesticides	0.22	0.86	0.20	0.48	6.65[b]	1.78	1.59[a]	2.30
Fungicides								
N-Fertilizer	0.09	0.96	– 0.03	– 0.35	0.35[b]	1.71	0.37[b]	1.79
Other variable inputs	0.11	0.82	– 0.08	– 1.52	0.01	0.55	0.01	0.59
Land	– 0.01	– 0.42	– 0.01	– 0.30	– 0.03	– 0.81	0.00	0.00
Labor	1.37	1.20	– 0.19	– 0.16	– 0.42	– 0.21	0.00	0.00
Capital	0.05	0.88	– 0.07	– 1.29	– 0.06	– 1.26	0.00	0.00
Herbicides	0.22[a]	2.10	0.04	0.55	– 1.78	– 0.85	– 0.03	– 0.07
Fungicides	– 1.70[a]	– 2.74	– 1.69[a]	– 2.71	– 4.98	– 1.41	– 1.65[a]	– 4.36
Other Pesticides	8.47	1.17	8.36	1.16	0.75	0.34	3.81[b]	1.68
Other Pesticides								
N-Fertilizer	– 0.01	– 0.09	0.10	0.44	0.17	1.37	0.21[a]	2.09
Other variable inputs	– 0.05	– 0.94	– 0.05	– 1.41	– 0.01	– 0.82	– 0.04	– 1.28
Land	– 0.02	– 0.05	0.23	1.03	– 0.01	– 0.04	0.03	0.10
Labor	– 3.51	– 0.65	– 0.56	– 0.42	– 1.40	– 0.22	1.00	0.16
Capital	– 0.07	– 1.11	– 0.01	– 1.28	– 0.04	– 0.83	0.02	0.90
Herbicides	– 0.07	– 0.38	– 0.05	– 0.91	– 0.90	– 0.40	0.09	0.13
Fungicides	– 0.04	– 0.06	– 0.10	– 0.17	– 2.19	– 0.61	1.19[b]	1.83
Other Pesticides	– 8.18	– 1.54	– 1.63[a]	– 3.50	– 9.75[b]	– 1.64	– 7.46	– 1.32

[a]Significant at 5%

[b]Significant at 10%

that the evaluation point in model 4 is given by a non-radial contraction in the subspaces of productive and damage abatement inputs.

The annual averages of the shadow values of fungicides and other pesticides are higher than their average market prices (presented in Table A1) in all models, indicating that fungicides and other pesticides are (on average) under-utilized. This means that farmers could increase their profitability by increasing the use of fungicides and other pesticides. Also, the annual average shadow values of herbicides are higher than the annual market prices for herbicides in models 1, 3 and 4, suggesting under-utilization of this damage abatement input. However, the overall average shadow value of herbicides in model 2 is lower than its market price suggesting over-utilization of this damage abatement input.

Table 3 reports the percentage of farmers that under-utilize pesticides in each model. The percentage of farmers that under-utilize pesticides is in general higher in model 3 than in the other models. This result is consistent with the results reported in Table 2 where the annual averages of the shadow values of pesticides are generally higher in model 3 than in the other models. The lower percentage indicated by model 1 and mainly model 2 is also consistent with the results reported in Table 2. The annual average of the shadow values of pesticides are in general lower in models 1 and 2 (substantially lower in model 2). Inspection of the shadow values of each pesticide in models 1 and 2 shows zero values for many farmers in each year. This occurs because the projected point for many farmers is a point on the horizontal segment of the frontier.

The large average values of the shadow prices of pesticides relative to their market prices may be a result of outliers due to, for example measurement errors of input and output quantities, causing extremely high shadow prices for individual observations. The sensitivity of the shadow prices to outliers is demonstrated by computing averages from truncated samples for each shadow price, i.e., samples that exclude shadow prices that are more than two, four and five standard deviations away from the untruncated mean. Results of this sensitivity analysis for pesticides are found in Tables A2–A4 in the Appendix; results for the productive inputs have been excluded because of space limitations, but can be obtained from the authors upon request. Most truncated means (four or five standard deviations) are substantially smaller than the untruncated means, implying the presence of outliers. However, the conclusions regarding over- or under-utilization of damage abatement inputs remain unchanged.

Oude Lansink and Carpentier (2001) using different parametric damage abatement specifications for the production function found shadow values for Herbicides in the range of 0.96–1.78, for Fungicides in the range of 2.22–2.94 and for other pesticides in the range of 2.94–9.14. Tables A2–A3 show that in particular the truncated means of models 1 and 2 are in line with results found by Oude Lansink and Carpentier (2001); shadow values obtained from models 3 and 4 are generally larger. Also, it can be seen that both the parametric and nonparametric models indicate that herbicides tend to have the lowest shadow price (among the damage abatement inputs), whereas other pesticides have the highest shadow price.

The effect of a change in each pesticide on the shadow values of all inputs is found by a perturbation procedure described before. Each pesticide constraint is increased separately by one unit and new shadow values of all inputs are generated for each model. A local "estimate" of technical interdependence between productive inputs and a particular pesticide is obtained by comparing the new shadow prices of productive inputs, found after perturbing a particular pesticide constraint, and the original shadow values (Table 2). Table 4 presents the differences in the shadow values (and the corresponding *t*-values) of productive and damage abatement inputs resulting from perturbing the herbicides, fungicides and other pesticides constraints.

The impact of an increase in each pesticide on the shadow value of a productive input varies, in general, from year to year. This variability may be explained by the fact that pesticides are generally dependent on weather and soil conditions; for example, the effect of herbicides is usually larger under conditions that are less beneficial for plant growth. Therefore, Table 4 and our discussion is based on the average differences for the whole time period 1989–1992.

Table 4 shows that, in line with *a priori* expectations, the shadow value of herbicides decreases when perturbing the herbicides constraint in each model. The same effects are found for fungicides and other pesticides when perturbing their constraints. The impact of an increase of herbicides on the shadow value of the productive inputs depends on the frontier point where it is evaluated. The impact on the shadow value of the N-fertilizer is positive in model 3 and insignificant in the other cases. This implies that the N-fertilizer and herbicides are complements at the point on the frontier that minimizes the use of pesticides, given the levels of productive inputs and outputs. Therefore, farmers that focus on minimizing the use of pesticides will likely benefit from a positive interaction between herbicides and N-fertilizer; at higher levels of pesticides application, the relation between N-fertilizer and herbicides is inconclusive as some models suggest they are substitutes whereas others suggest they act as complements.

Table 4 also shows that other variable inputs and herbicides are substitutes when all inputs are contracted radially (model 1). Furthermore, herbicides and labor are complements on farms minimizing the use of all (model 1) or only the productive inputs (model 2), and they are substitutes on farms minimizing the use of pesticides (model 3). These results reflect the possibility for farmers to substitute herbicides for more labor intensive mechanical or manual weeding when labor is available in sufficient amounts. On farms with limited availability of labor, substitution is not possible. Capital and herbicides are substitutes on farms minimizing the use of productive inputs and other pesticides and herbicides are complements at low application levels of pesticides.

Results for fungicides show that fungicides have a small number of significant interactions with productive inputs. Fungicides and N-fertilizer are complements at low application levels of pesticides implying positive interactions between these inputs when farmers minimize pesticides use. Also, herbicides and other pesticides are locally complementary for fungicides in all models.

Other pesticides have a very low number of significant interactions with all other inputs. Only N-fertilizer and other pesticides show significant relationships in model 4, suggesting that these inputs are complements for non-radial contractions in each subset of inputs (productive and damage abatement inputs).

5. Conclusions

This paper presents a non-parametric production analysis of pesticides use on specialized cash crop farms in the Netherlands. Shadow prices of different pesticides are determined using four input-oriented models, each measuring these prices at different points of the frontier. Comparison of the shadow price of different pesticides with the corresponding market prices indicates whether pesticides are over- or under-utilized. Furthermore, special attention is paid to the technical interdependence between pesticides and productive inputs.

The empirical results indicate that almost all pesticides are, on average, under-utilized, which is in line with earlier findings in the literature. Technical interdependence between pesticides and productive inputs is investigated at different points on the frontier. The results indicate that technical interdependence between each pesticide and a particular productive input varies along the frontier. This result suggests that empirical studies using a parametric approach should not choose functional forms that impose a particular technical interdependence (e.g., the Cobb-Douglas production function assumes all inputs are substitutes).

This paper has contributed to the literature on the economics of pesticides by providing non-parametric "estimates" of shadow prices of different pesticides and investigating technical interdependence between pesticides and productive inputs using a non-parametric approach. Future research on the economics of pesticides should account for the effects of different outputs on the shadow prices and technical interactions between inputs. Another interesting avenue for future research is an investigation of non-convexities in the production technology that might occur due to the damage-reducing role of pesticides.

Appendix A

Table A1. Description of data and variability.

			Period: 1989–1992 Observations: 293	
Variable	Dimension/Base Year	Symbol	Mean	Standard Deviation
Prices				
Output	Base year 1990	p	0.94	0.14
Herbicides	Base year 1990	w_1	1.08	0.11
Fungicides	Base year 1990	w_2	1.12	0.09
Other Pesticides	Base year 1990	w_3	1.11	0.15
Quantities				
Output	1,000 guilders of 1990[a]	y	401.46	276.95
N-Fertilizer	1,000 guilders of 1990[a]	x_1	110.51	64.02
Other Inputs	1,000 guilders of 1990[a]	x_2	6.87	5.10
Land	Hectares	x_3	62.19	42.40
Labor	Man years	x_4	1.62	0.91
Capital	1,000 guilders of 1990[a]	x_5	510.47	402.99
Herbicides	1,000 guilders of 1990[a]	z_1	14.96	11.75
Fungicides	1,000 guilders of 1990[a]	z_2	10.41	8.76
Other Pesticides	1,000 guilders of 1990[a]	z_3	4.20	4.81

[a]1 euro is approximately 2.204 guilders.

Table A2. Untruncated and truncated averages of the shadow values of inputs—model 1.

Input	1989	1990	1991	1992
Herbicides				
untruncated mean	2.472	3.795	3.528	2.789
standard error	(5.919)	(8.801)	(9.612)	(9.182)
truncated mean 1[a]	1.212	2.023	2.309	2.440
truncated mean 2[b]	2.057	3.274	2.590	2.440
truncated mean 3[c]	2.472	3.795	2.590	2.789
Fungicides				
untruncated mean	8.279	8.805	9.901	3.228
Standard error	(20.480)	(22.616)	(38.241)	(53.238)
truncated mean 1[a]	4.116	4.342	5.736	3.228
truncated mean 2[b]	6.644	6.819	5.736	3.228
truncated mean 3[c]	6.644	6.819	5.736	3.228
Other Pesticides				
untruncated mean	11.386	37.779	40.373	28.798
standard error	(28.265)	(229.945)	(177.610)	(208.399)
truncated mean 1[a]	5.574	11.218	20.259	11.566
truncated mean 2[b]	9.157	11.218	20.259	20.198
truncated mean 3[c]	9.157	11.218	20.259	20.198

[a]Excludes observations more than two standard deviations away from the mean.
[b]Excludes observations more than four standard deviations away from the mean.
[c]Excludes observations more than five standard deviations away from the mean.

Table A3. Untruncated and truncated averages of the shadow values of inputs—model 2.[a]

Input	1989	1990	1991	1992
Herbicides				
untruncated mean	0.206	0.233	0.398	2.789
standard error	(0.389)	(0.719)	(0.854)	(7.150)
truncated mean 1	0.018	0.0158	0.057	1.430
truncated mean 2	0.018	0.0158	0.203	2.238
truncated mean 3	0.018	0.0158	0.203	2.238
Fungicides				
untruncated mean	3.770	5.763	5.393	3.228
standard error	(11.573)	(20.572)	(22.793)	(7.951)
truncated mean 1	1.125	2.278	2.317	1.409
truncated mean 2	3.036	3.735	3.026	2.753
truncated mean 3	3.770	3.735	3.026	3.228
Other Pesticides				
untruncated mean	5.577	6.30	10.458	28.798
standard error	(15.430)	(19.030)	(23.349)	(195.872)
truncated mean 1	3.246	1.623	5.188	6.073
truncated mean 2	3.246	4.955	8.756	6.073
truncated mean 3	4.234	4.955	8.756	6.073

[a]See Table A2 for explanation.

Table A4. Untruncated and truncated averages of the shadow values of inputs—model 3[a].

Input	1989	1990	1991	1992
Herbicides				
untruncated mean	34.498	22.494	20.377	18.718
standard error	(74.863)	(28.946)	(19.165)	(19.503)
truncated mean 1	23.835	19.067	16.987	15.244
truncated mean 2	26.179	19.985	20.377	18.718
truncated mean 3	26.179	19.985	20.377	18.718
Fungicides				
untruncated mean	14.712	29.947	13.919	14.872
standard error	(16.606)	(121.003)	(12.204)	(35.295)
truncated mean 1	12.891	16.228	12.201	10.971
truncated mean 2	13.728	16.228	13.919	10.971
truncated mean 3	14.712	16.228	13.919	10.971
Other Pesticides				
untruncated mean	26.085	28.387	56.502	27.568
standard error	(41.288)	(69.203)	(199.595)	(82.1938)
truncated mean 1	16.084	21.449	33.986	18.621
truncated mean 2	26.085	21.449	33.986	18.621
truncated mean 3	26.085	21.449	33.986	18.621

[a]See Table A2 for explanation.

Table A5. Untruncated and truncated averages of the shadow values of inputs—model 4[a].

Input	1989	1990	1991	1992
Herbicides				
untruncated mean	16.482	14.757	14.133	13.519
standard error	(24.510)	(26.573)	(21.650)	(13.361)
truncated mean 1	13.258	11.240	10.422	10.755
truncated mean 2	14.031	12.142	12.656	13.519
truncated mean 3	14.031	12.142	12.656	13.519
Fungicides				
untruncated mean	12.687	10.345	11.591	12.010
standard error	(25.418)	(15.604)	(18.670)	(35.381)
truncated mean 1	9.333	6.832	8.753	8.071
truncated mean 2	10.224	10.345	10.051	8.071
truncated mean 3	10.224	10.345	10.051	8.071
Other Pesticides				
untruncated mean	19.308	18.357	56.115	23.429
standard error	(33.534)	(32.500)	(200.648)	(81.341)
truncated mean 1	13.257	12.994	33.593	14.425
truncated mean 2	19.308	18.357	33.593	14.425
truncated mean 3	19.308	18.357	33.593	14.425

[a]See Table A2 for explanation.

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Notes

1. Technical interdependence measures the impact of an input on the marginal productivity of another input. If the marginal productivity of an input increases (decreases) as the other input increases, then the two inputs are technically complementary (competitive). Two inputs are technically independent if the marginal productivity of one input is not affected by changes in the use of the other input (Beattie and Taylor, 1993).
2. This paper only considers models characterized by variable returns to scale (VRS) technologies, since the VRS formulation is *a priori* less restrictive in economic terms than the constant returns to scale (CRS). Imposing CRS requires the technology to satisfy this property globally. VRS allows the technology to satisfy increasing returns to scale, CRS and decreasing returns to scale locally.
3. In this paper, the marginal product of each input is calculated in a single-output context. However, the approach can be extended to the case of M outputs, i.e., by calculating a marginal product of an input for each of the M outputs. A weighted average can be calculated using revenue shares of the M outputs.
4. The non-uniqueness of the shadow price of an input is possible in the DEA models if the point of the frontier where it is evaluated is a vertex. In this case, GAMS picks one of the shadow values.
5. Farms with more than 80% of output coming from marketable crops. The average share of marketable crops in the output variable is 95%.
6. The willingness of the Agricultural Research Institute in the Hague to make the data available for this research is gratefully acknowledged.
7. Higher quality outputs or inputs are reflected by larger revenues and expenses, respectively. Therefore, implicit quantities calculated using the same prices for all farmers within one year are higher for farmers producing outputs or using inputs with a higher quality.
8. The results for model 3 are mainly methodological (reduced dimensionality). However, the lack of substantial difference in the average efficiency scores of models 1 and 2 suggest that reducing the three damage abatement inputs does not change the results. Thus, it is the productive inputs that are limiting for the efficiency scores and there is a lot more slack on the damage abatement inputs.
9. Differences in weather conditions between years do not have a large impact on the results here, since the production frontier is based on all observations of farms within one year. Local differences in weather conditions are also likely small since all farms are situated in the same region, i.e., the South-West clay area.
10. Also, shadow prices are being calculated at different points on the frontier since the projected point is not the same for each farm.

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