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Innovative Applications of O.R.

Estimating shadow prices and efficiency analysis of productive inputs and pesticide use of vegetable production

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ABSTRACT

This paper analyzes technical efficiency and the value of the marginal product of productive inputs vis-a-vis pesticide use to measure allocative efficiency of pesticide use along productive inputs. We employ the data envelopment analysis framework and marginal cost techniques to estimate technical efficiency and the shadow values of each input. A bootstrap technique is applied to overcome the limitations of DEA and helps to estimate the mean and 95 percent confidence intervals of the estimated quantities. The methods are applied to a sample of vegetable producers in Benin over the period 2009–2010. Results indicated that bias corrected technical efficiency scores are lower than the initial measures and the former estimates are statistically significant. The application results show that vegetable producers are less efficient with respect to pesticide use than other inputs. Also, results suggest that pesticides, land and fertilizers are overused.

1. Introduction

Unlike productive inputs (e.g. fertilizers or improved crop varieties) which have a more straightforward relationship with higher productivity and for which there are well-established methods and models that can be used to predict their effect on crop yields, pesticides do not have a direct impact on crop yields, other than limiting the possible adverse effects of pests, and are extremely diverse with nearly a thousand active ingredients currently in use. Vegetable production is impacted by the presence of large range of insects, implying increasing use of pesticides. Williamson, Ball, and Pretty (2008) indicated that the relative costs of pesticides have risen sharply in recent years, implying that farmers continuously need to adapt the use of pesticides in order to avoid over- or under use. Insights in the value of the marginal product (VMP) of pesticides in vegetable production and the impact of other inputs on the VMP of pesticides can help in determining the optimal use of pesticides.

Parametric and non-parametric approaches have been used to study the value of the marginal product of pesticides. Oude Lansink and Carpentier (2001) and Skevas, Stefanou, and Oude Lansink (2013) adopted a parametric approach to measuring the VMP of pesticides, distinguishing damage abatement inputs and productive inputs. Both studies report overuse of pesticides. Non-parametric approaches are an attractive alternative to parametric approaches, since a functional form of the distance or production function does not have to be assumed. Furthermore, the non-parametric Data Envelopment Analysis (DEA) approach allows for simultaneous measurement of technical efficiency and the VMPs of inputs. However, despite their clear advantages, non-parametric approaches have rarely been used in the literature to address this question. Oude Lansink and Silva (2004) used DEA to estimate the VMP of pesticides and to investigate the impact of productive inputs on the VMP of pesticides. Skevas, Oude Lansink, and Stefanou (2012) use DEA to represent a production technology that considers both pesticides' dynamic impacts and production uncertainty (accounted through variability in climatic conditions) in their effort to investigate the performance of Dutch arable farms. Their results show that ignoring the effects of variability in production conditions may lead to an overestimation of farmers' inefficiency. A shortcoming of previous nonparametric approaches is their failure to perform statistical inference on the estimated VMP's of pesticides. Recently bootstrap methods (Simar & Wilson, 2008) have been proposed in the literature to enable statistical inference in DEA models. However, these methods have not yet been applied in the estimation of VMPs from DEA models.

Against the background of the foregoing, the objective of this study is to estimate technical efficiency and the shadow price values (VMP)

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of pesticides and other inputs in vegetable production. The VMPs are estimated from different DEA models, each determining technical efficiency and VMP on a different part of the frontier. Statistical inference on technical efficiency and VMPs is obtained using a smooth bootstrap procedure. Also, the impact of different inputs on the VMP of pesticides is investigated. This paper contributes to the literature by being the first to employ a bootstrap method for performing statistical inference of technical efficiency and for the value of marginal products (VMPs) in order to overcome the main drawback of DEA approach. The method is applied to vegetable production in Benin.

The remainder of this paper is organized as follows. Section 2 presents the DEA models and the bootstrap technique to perform statistical inference on the VMPs of pesticides and other inputs. The case study of vegetable production in Benin is described in Section 3, followed by the presentation of the empirical results in Section 4. Concluding remarks follow in the last section.

2. Input distance function with damage abatement inputs

2.1. DEA models incorporating damage abatement inputs

Consider a sample of N farms which produce Q outputs from P purchased productive inputs and A purchased damage abatement inputs (pesticides). Let $y \in \Re_+^Q$, $x \in \Re_+^P$, and $z \in \Re_+^A$ denote vectors of non-negative outputs, non-negative productive inputs and non-negative damage abatement inputs, respectively. The production technology for a decision making unit (DMU) is fully represented by the input requirement set:

$$L(\boldsymbol{y}) = \{(\boldsymbol{x}, \boldsymbol{z}) \in \Re_+^P \times \Re_+^A \,|\, (\boldsymbol{x}, \boldsymbol{z}) \text{ can produce } \boldsymbol{y}\} \tag{1}$$

which represents the set of all feasible combinations of vectors of productive and damage abatement inputs given a vector of outputs $\boldsymbol{y}$. A non-parametric representation of $L(\boldsymbol{y})$ is:

$$L(\boldsymbol{y}) = \left\{(\boldsymbol{x}, \boldsymbol{z}) : \boldsymbol{Y}'\lambda \geq y_i,\ \boldsymbol{X}'\lambda \leq x_i, \boldsymbol{Z}'\lambda \leq z_i,\ \mathbf{I}'\lambda = \mathbf{1},\ \lambda \geq \mathbf{0}\right\} \tag{2}$$

where $\boldsymbol{Y}$ is the $(N \times Q)$ matrix of observed outputs, y_i is the vector of observed outputs of farm i, $\boldsymbol{X}$ is the $(N \times P)$ matrix of observed productive inputs, x_i is the vector of productive inputs used by farm i, $\boldsymbol{Z}$ is the $(N \times A)$ matrix of observed damage abatement inputs, z_i is the vector of damage abatement inputs used by farm i; λ is a $(N \times 1)$ vector of intensity variables (farm weights) and I is the $(N \times 1)$ unit vector. We assume that (1) satisfies the standard regularity conditions: possibility of inactivity, no free lunch, strong input and output disposability,[1] closedness of $L(\boldsymbol{y})$ and variable returns to scale (VRS) (Färe, 1988, p. 35; Färe & Grosskopf, 1990; Fukuyama & Weber, 2002). The VRS condition ($\mathbf{I}'\lambda = 1$) ensures that increased amounts of inputs do not necessarily lead to a proportional increase of the amount of outputs. Technical efficiency is defined as the ability of a farm to use the minimum feasible amounts of productive and/or damage abatement inputs to produce a given level of output. Hence technical efficiency is measured relative to production possibilities characterized by $L(\boldsymbol{y})$. The Shephard input distance function is defined as:

$$D^I(x, z, y) = \sup\left\{\gamma > 0 : (x/\gamma, z/\gamma) \in L(y)\right\} \tag{3}$$

where γ is the input sub-vector space technical efficiency scores for the DMU. The input distance function can reflect joint production of multiple outputs, while duality between the input distance function and the cost function allows retrieval of the input shadow prices. In order to compute the technical efficiency of an individual input, sub-vector technical efficiency measures are introduced to generate technical efficiency measures of a subset of inputs rather than for the entire vector of inputs, holding all other inputs and outputs constant. Four input-oriented models are constructed for measuring technical efficiency, i.e. they contract inputs in four different directions.

The first model (Model 1) measures technical efficiency by radially contracting all productive inputs (fixed and variable inputs) and damage abatement inputs equiproportionately, while keeping outputs constant. In this model, we assumed that producers can adjust all inputs. This standard radial measure is incapable of identifying the technical efficiency of individual input use, since such a measure treats the contribution of productive and abatement inputs to technical efficiency equally. The technical efficiency score obtained from this model is a radial measure and is restrictive in that it assumes that inefficient producers can be brought to the frontier only by shrinking all inputs. In other words, this model assumes that a technically inefficient producer will have the same degree of input overuse for all inputs. The second model (Model 2) measures technical efficiency by radially contracting only variable productive inputs equiproportionately, given the fixed inputs, the damage abatement inputs and outputs. The third model (Model 3) measures technical efficiency by radially contracting all damage abatement inputs in equal proportions, given the productive inputs (variable and fixed inputs) and the output level. The fourth model (Model 4) is a variation of the Russell technical efficiency measure that allows for non-proportional contractions in each input. This model allows for non-proportional reductions in each subset of inputs, allowing for different technical efficiency scores of productive inputs and damage abatement inputs. This is equivalent to the non-radial notion of input technical efficiency, as discussed by Kopp (1981). The main purpose of having four different input-oriented models (radial and non-radial) is to have four separate sets of shadow price calculations of pesticide and productive inputs at four different points on the production frontier. This procedure was also applied by Ball, Lovell, Nehring, and Somwaru (1994) and Oude Lansink and Silva (2004). It helps to show the variation in the results according to each point on the frontier. The general form of the four models is given by:

$$\begin{aligned}
&\min_{\gamma_i,\lambda} \gamma_{ji} \\
&\text{s.t.} \\
&Y\lambda \geq y_i \\
&X\lambda \leq \gamma_{ki}x_i \\
&Z\lambda \leq \gamma_{li}z_i \\
&\mathbf{I}\lambda = 1 \\
&\lambda \geq 0
\end{aligned} \tag{4}$$

where γ_k and γ_l are the input sub-vector space technical efficiency scores for farm $\boldsymbol{i}$. The specification of each of the four models is summarized in Table 1.

Table 1
Specification of the models.

Models	Technical efficiency for choice variables	Objective function
Model 1:		
Radial technical efficiency in the full input space	$\gamma_{ki} = \gamma_{li} = \gamma_{1i}$	$\min_{\gamma_{1i},\lambda} \gamma_{1i}$
Model 2:		
Radial technical efficiency in the productive input subspace	$\gamma_{ki} = \gamma_{2i}, \gamma_{li} = 1$	$\min_{\gamma_{2i},\lambda} \gamma_{2i}$
Model 3:		
Radial technical efficiency in the damage abatement input subspace	$\gamma_{ki} = 1, \gamma_{li} = \gamma_{3i}$	$\min_{\gamma_{3i},\lambda} \gamma_{3i}$
Model 4:		
Non-radial technical efficiency measure	$\gamma_{ki} \neq \gamma_{li}$	$\min_{\gamma_{ki},\gamma_{li},\lambda} (\gamma_{ki} + \gamma_{li})/2$

[1] Since we applied our models to small scale farms we maintain strong disposability assumption for fixed inputs because strong disposability implies weak disposability, but the converse does not hold (see Färe, Grosskopf, & Lovell, 1994, p. 38 for details). We experimented by assuming weak disposability of fixed inputs as in Skevas et al. (2012) and found that the technical inefficiency scores are relatively close but greater than or equal to the ones obtained from imposing strong disposability.