Measuring Sustainability Efficiency At Farm Level :

A Data Envelopment Analysis Approach

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1. Introduction

The Committee on Twenty-First Century Systems Agriculture (NRC, 2010, p. 4) characterizes sustainable agriculture as the one satisfying human food, feed, fiber and biofuel needs; enhancing the quality of the environment and resource base; ensuring the economic viability of the agricultural sector; and improving the quality of life of farmers, farm workers and society. Sustainability can be pursued both at the aggregate (i.e. country or region) and at the individual (firm) level on which we focus. Through the concept of corporate social responsibility (CSR) the business model has embraced sustainability. Firms have progressively taken responsibility for their impact on society and on the environment, becoming better corporate citizens (CC) who adopt CSR strategies (Bowen, 1953; Carroll, 1999). Agricultural policies in developed countries have promoted adoption of such strategies among agricultural holdings. The European Union's Common Agricultural Policy (CAP) has been no exception. Since its inception, it has undergone different reforms that reflect changing political priorities over time. While initially the CAP essentially aimed at guaranteeing food security by stimulating agricultural production and protecting farmers' quality of life, a succession of changes have reformulated the CAP into a policy that embraces food safety, animal welfare, land management, rural development, environmental development and pollution control. In short, the CAP has leaned towards promoting a more sustainable agricultural sector. Consistently, farm payments have been progressively remodeled to reward those farms that meet different economic, environmental and territorial criteria. Noteworthy is the proposal to redistribute farm payments to better align the CAP with sustainability principles and objectives.

Sound implementation of farm payment schemes requires appropriate tools to measure farms' success in achieving policy goals. Since the pioneering work by Farrell (1957), the production economics literature has developed efficiency indices that can be used to assess this success. While the literature on efficiency measurement was initially focused on the desired output production technology, as sustainability of economic activities became relevant, firm-performance studies were extended to include environmental concerns (Coelli, Lauwers, & Van Huylenbroeck, 2007; Färe, Grosskopf, Noh, & Weber, 2005; Murty, Russell, & Levkoff, 2012; O'Donnell & others, 2007; Oude Lansink & Van Der Vlist, 2008; Reinhard, Lovell, & Thijssen, 1999). Only recently, have these measures been extended to quantify the social dimension of firm performance (Chambers & Serra, 2016). By providing quantitative guidelines for benchmarking firm performance, efficiency measures can be very relevant in assisting public payment redistribution schemes. By building on the method proposed by Chambers & Serra (2016), this article is the first to derive farm-level productive, environmental and social efficiency measures by allowing for the stochastic nature of agricultural production. Assessing the environmental and social dimensions of performance requires data that are not usually available, especially at farm-level. We elicit this information through a survey conducted to a sample of Catalan farms.

Extension of production efficiency measures to allow for the environmental dimension of economic activities has not been without debate. Late articles (Førsund, 2009; Murty et al., 2012) have criticized previous approaches because they fail to address the material balance principle. Murty et al. (2012) and Coelli et al. (2007) have led the development of environmental efficiency measures based on the materials balance concept. Serra, Chambers, & Oude Lansink (2014) extend Murty's approach by incorporating the state-contingent framework to model the stochastic nature of production. We use this proposal to measure farm performance in minimizing nitrogen and pesticide pollution. We also take the literature one-step further by extending Serra, Chambers, & Oude Lansink (2014) to allow for the social output of firms.

Substantial ambiguity surrounds the operationalization of the social dimension of sustainability (Dempsey, Bramley, Power, & Brown, 2011; Vifell & Soneryd, 2012; Dixon, Colantonio, & Lane, n.d.; Murphy, 2012; Thin, 2002), which has received much less attention than the other two pillars of sustainability (Cuthill, 2010; Vavik & Keitsch, 2010). An essential question is which indicators should be used to reflect the social outputs of a business. Lebacq et al. (2013) suggest taking a set of indicators that revolve around labor, including workload, employment quality and health. Our research focuses on one particular indicator that reflects worker exposure to different health and safety issues (Ridley, 2010; Myers, Layne, & Marsh, 2009): fatal and non-fatal injuries suffered by farmers and farm workers. A second indicator that we use to represent farm social outputs is the generation of farmers' satisfaction, which we measure using a Likert scale (Bacon, Getz, Kraus, Montenegro, & Holland, 2012; Pissourios, 2013).

Ignoring the stochastic nature of an economic activity may lead to biased efficiency results (O'Donnell, Chambers, & Quiggin, 2010). Most empirical studies on efficiency have relied on the realized output to measure firm performance. These analyses, however, can confound poor outcomes related to the stochastic nature of production, with an inefficient use of the technology. As a result, it is relevant to model efficiency by allowing for the stochastic conditions in which production takes place. Our article follows the proposal by Chambers & Quiggin (1998, 2000) and models risk using the state-contingent approach. Our farm-level survey elicits ex-ante production data to empirically represent the state-contingent technology of sample farms.

2. Methods

Our theoretical framework builds on the papers by Murty et al. (2012), Chambers & Serra (2016) and Serra et al. (2014). The three articles contribute to the academic debate on how to properly model byproducts from production technologies. Murty et al. (2012) model a company's production technology as the interaction of two sub-technologies; an intended output and an unintended output technology. Serra et al. (2014) extend Murty et al. (2012) by incorporating the state-contingent approach to modelling production risk. Chambers & Serra (2016) study the social dimension of firm performance by considering a third sub-technology in which social outputs are production netputs. Our work takes Chambers & Serra (2016) one-step further by modelling production risk.

Production of our sample farms is the result of the interaction of five different sub-technologies that shed light on firm's economic, environmental and social outputs. The first sub-technology models the production of intended agricultural outputs. The second and third sub-technologies reflect unintended pollution caused by nitrate and pesticide, herbicide and insecticide (PHI). The fourth and fifth sub-technologies reflect farm social outputs and focus on the generation of farmers' satisfaction and the minimization of work-related accidents.

The production technology is defined as a function of different netputs. Desired agricultural production is represented by $\tilde{y}_h$ for $h = 1, \ldots, H.$, where H is the number of stochastic desired outputs, and assumed to depend on crop growing conditions. A farmer's overall satisfaction with her professional activity (s) is considered as another good output. Three types of unintended byproducts are considered: environmental impacts of PHI, fertilizer pollution and worker injuries. Nitrogen pollution is assumed to be contingent on the state of nature and denoted by $\tilde{z}_k$ for $k =$

$1, \ldots, K$. Due to data constraints, farmer's satisfaction (s), environmental impacts of PHI pollution (p) and worker injuries (i) are treated as non-stochastic outputs. Outputs are generated using several inputs. We consider a set of N nonpolluting productive inputs, denoted by $x \in \mathbb{R}^N$ for $n = 1, \ldots, N$. In our empirical application, variable x_1 represents land planted to crops and x_2 measures the capital replacement value. Variable x_3 represents paid and unpaid family work. Inputs x_4 and x_5 measure, respectively, the costs of energy and seeds. Organic and chemical fertilizers applied are denoted by $r_k \in \mathbb{R}^K$ for $k = 1, \ldots, K$. PHI applications, measured in liters of active ingredients, are denoted by $c_d \in \mathbb{R}^{\mathrm{D}}$ for $d = 1, \ldots, D$. Working conditions are considered as an input and denoted by $w_a \in \mathbb{R}^A, a = 1, \ldots, A$, with better working conditions being represented by higher values of w_a.

T, the general production technology, is assumed to be composed by an intended output sub-technology T^Y, a PHI pollution sub-technology T^P, a fertilizer runoff sub-technology T^Z, a work satisfaction sub-technology T^S, and a work injuries sub-technology T^I. The general production technology, integrated by the different sub-technologies, can be expressed as follows:

$$T = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i) : (x_n, r_k, c_d, w_a) \text{ can produce } (\tilde{y}_h, \tilde{z}_k, p, s, i)\} \tag{1}$$

Following previous research (Coelli et al., 2007; Serra et al., 2014), our representation of T meets material balance conditions requirements. In this regard, the applications of the runoff inputs (organic and chemical fertilizers – r_k and PHI – c_d) equal the quantity absorbed in the production of intended outputs plus the runoff byproducts. Fertilizer runoff is state-contingent since the quantity of fertilizer absorbed by plants depends on plant growth and can be represented by $r_k = \tilde{q}_k + \tilde{z}_k$, where $\tilde{q}_k$ is the quantity of fertilizer input r_k absorbed by agricultural production, and $\tilde{z}_k$ represents the runoff. Only the quantity of fertilizer that remains on the crop ($\tilde{q}_k$) has an impact on the quantity of crop produced (Serra et al., 2014). Pollution derived from the application of PHI is assumed to have environmental and health impacts (p), which can be computed as the product of c_d and an environmental impact quotient (EIQ) per unit of active ingredient ($\varepsilon_d \in \mathbb{R}^D$). Since PHI are damage abatement inputs that do not contribute to crop growth, runoff coincides with the amount applied $p = \sum_d \varepsilon_d \, c_d$.

The specification of the intended output technology is:

$$T^Y = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i) : (x_n, r_k - \tilde{z}_k, c_d, w_a) \text{ can produce } \tilde{y}_h\}. \tag{2}$$

Following Serra et al. (2014), fertilizer runoff could be affected, for example, by the quality of the fertilizer applicator. Hence, fertilizer pollution is assumed to depend on productive inputs (x_n) such as labor and capital. To the extent that working conditions (w_a) can influence labor performance, they could also influence farmers' judgement regarding the need to apply fertilizers and consequently nitrogen runoff. As a result, the fertilizer runoff byproduct technology is expressed by:

$$T^Z = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i) : (x_n, r_k, w_a) \text{ can produce } \tilde{z}_k\} \tag{3}$$

The PHI pollution technology models the environmental impact derived from PHI application. Since we do not observe the environmental impact, we construct an estimate (p) by weighting the amount of active ingredients applied by an EIQ. We assume that an increase in conventional inputs (x_n) such as quantity of land sprayed, will increase the environmental impact of PHI. An exception is the amount of seeds, as a larger quantity of seed implies a higher crop density, thus less space for weeds which should reduce the need for herbicides. The PHI pollution technology is thus:

$$T^P = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i) \colon (c_d, x_{n\neq 5}, x_5) \text{ can produce } p\} \tag{4}$$

This research considers two outputs related to the social dimension of economic activities, the level of work satisfaction as perceived by farmers (s) and the number of work injuries (i). Satisfaction is assumed to depend on working conditions (w_a). Since the use of conventional inputs can ease the work burden of labor and affect farmers' overall satisfaction with the work, they are also considered in the definition of T^S as follows:

$$T^S = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i) \colon (x_n, r_k, c_d, w_a) \text{ can produce } s\} \tag{5}$$

The last sub-technology is related to preventing or reducing farmers' injuries and fatalities. In order to avoid zeros in the dataset, the injuries variable is transformed so that high positive values represent little or no injuries and small values represent numerous injuries (see next section for further details). Conventional agricultural inputs such as PHI, agricultural machinery, or labor hours are assumed to increase injuries. An improvement in w_a, in contrast, is likely to reduce injuries. The T^I sub-technology is thus specified as:

$$T^I = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i) \colon (x_n, r_k, c_d, w_a) \text{ can produce } i\} \tag{6}$$

The overall technology T is then defined as the intersection of these five production sets: $T = T^Y \cap T^Z \cap T^P \cap T^S \cap T^I$.

To empirically estimate the model, we use a nonparametric Data Envelopment Analysis (DEA). Constant returns to scale (CRS) and free disposability are assumed to characterize the intended output technology T^Y. The intended output technology can be expressed as follows:

$$\begin{aligned} T^Y(J) = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i) \colon & \\ x_n \geq \sum_j \beta^j x_n^j, n = 1, \dots, N & \\ r_k - \tilde{z}_k \geq \sum_j \beta^j \left(r_k^j - \tilde{z}_k^j\right), k = 1, \dots, K & \\ c_d \geq \sum_j \beta^j c_d^j, d = 1, \dots, D & \\ w_a \geq \sum_j \beta^j w_a^j, a = 1, \dots, A & \\ \tilde{y}_h \leq \textstyle\sum_j \beta^j \tilde{y}_h^j, h = 1, \dots, H, & \\ \beta^j \in R_+^N\} & \end{aligned} \tag{7}$$

where j indexes the number of observations.

T^P is approximated as follows. An increase in the quantity of PHI applied (c_d) increases the environmental impacts. We assume that PHI pollution cannot be disposed without additional cost, which implies weak disposability of the byproduct. Thus T^P can be approximated as follows:

$$T^P(J) = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i): \quad (8)$$
$$c_d \le \sum_j \alpha^j c_d^j, d = 1, \dots, D$$
$$x_{n\neq 5} \le \sum_j \alpha^j x_n^j, n \neq 5$$
$$x_5 \ge \sum_j \alpha^j x_5^j$$
$$p = \sum_j \alpha^j p^j, \alpha^j \epsilon\, R_+^N\}$$

T^Z, the nitrogen runoff technology, imposes free disposability on non-polluting inputs and costly disposability of $\tilde{z}_k$ (Serra et al., 2014)

$$T^Z(J) = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i): \quad (9)$$
$$x_n \ge \sum_j \gamma^j x_n^j, n = 1, \dots, N$$
$$r_k \le \sum_j \gamma^j r_k^j, k = 1, \dots, K$$
$$w_a \ge \sum_j \gamma^j w_a^j, a = 1, \dots, A$$
$$\tilde{z}_k \ge \sum_j \gamma^j \tilde{z}_k{}^j, k = 1, \dots, K, \gamma^j \epsilon\, R_+^N\}$$

Usually, adults spend much of their time working, which gives the workplace a very important dimension in people's life and impacts heavily on their well-being. The fourth sub-technology reflects satisfaction from work. As a qualitative factor, s is measured on a Likert scale. Traditional DEA models are not appropriate for non-continuous data. Cook et al. (1996, 1993) proposed the first modified DEA model including ordinal data. Cooper et al. (1999)'s imprecise DEA (IDEA) allows for imprecise measurements such as bounded data, ordinal data and Likert scales, into standard DEA. This results in a non-linear and non-convex DEA model. Cook & Zhu (2006) present a unified DEA structure allowing the integration of rank order or Likert scale information. As shown by Chen et al. (2015), however, in the radial DEA approach used by Cook & Zhu (2006), the projected points on the frontier do not necessarily correspond to Likert Scale information. We therefore adopt the adjusted DEA model proposed by Chen et al. (2015). As noted, we assume the use of conventional and good working conditions to ease the work burden of labor and thus increase work satisfaction. The approximation to T^S can be expressed as:

$$T^S(J) = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i): \quad (10)$$
$$c_d \ge \sum_j \delta^j c_d^j, d = 1, \dots, D$$
$$x_n \ge \sum_j \delta^j x_n^j, n = 1, \dots, N$$
$$w_a \ge \sum_j \delta^j w_a^j, a = 1, \dots, A$$

$$s \leq \sum_j \delta^j s^j, \qquad \delta^j \in R_+^N,$$

The last process concerns prevention of injuries at the farm level and assumes that increased input use such as pesticide, machinery, etc. tends to increase the number of injuries, while improved working conditions helps reducing them. By assuming free disposability of worker injuries, T^I can be expressed as:

$$T^I(J) = \{(x_n, r_k, c_d, w_a, \tilde{y}_h, \tilde{z}_k, p, s, i): \tag{11}$$
$$x_n \leq \sum_j \eta^j x_n^j, n = 1, \dots, N$$
$$c_d \leq \sum_j \eta^j c_d^j, d = 1, \dots, D$$
$$w_a \geq \sum_j \eta^j w_a^j, a = 1, \dots, A$$
$$i \leq \sum_j \eta^j i^j, \qquad \eta^j \in R_+^N, \}$$

Following Murty et al., (2012), the overall efficiency index is obtained by adding the five sub-technologies as follows:

$$E(x, r, c, w, \tilde{y}, \tilde{z}, p, s, i) = \frac{1}{5} \min_{\xi_1, \xi_2, \xi_3, \xi_4, \xi_5} \frac{\sum_\omega \xi_{1\omega}}{\Omega} + \xi_2 + \frac{\sum_\omega \xi_{3\omega}}{\Omega} + \xi_4 + \xi_5 \Bigg|$$
$$\langle x, r, c, w, \tilde{y} \emptyset \xi_{1\omega}, p \otimes \xi_2, \tilde{z} \otimes \xi_{3\omega}, s \emptyset \xi_4, i \otimes \xi_5 \rangle \in T \;) \tag{12}$$

where $\tilde{y} \emptyset \xi_1 = \langle y_1/\xi_{11}, \dots, y_\Omega/\xi_{1\Omega} \rangle$, $p \otimes \xi_2 = p\xi_2, \tilde{z} \otimes \xi_3 = \langle z_1\xi_{31}, \dots, z_\Omega \xi_{3\Omega} \rangle$, $s \emptyset \xi_4 = s/\xi_4$, $, i \otimes \xi_5 = i\xi_5$. In the following section a description of the data used is offered.

3. The Data

Our analysis is based on cross sectional, farm-level data collected from a sample of 173 Spanish holdings specialized in the production of cereal, oilseed and protein (COP) crops and located in the region of Catalonia.

As noted by Chambers & Quiggin (2000), the key challenge to construct empirical representations of state-contingent technologies is the lack of information on the ex-ante distribution of the random variables. We follow Chambers, Serra, & Stefanou (2015) and use survey-elicited ex-ante outputs to empirically represent the stochastic technology. For this purpose, we conducted the survey before the beginning of the agricultural season (October 2015) to collect point estimates of anticipated yields for three alternative states of the nature: bad, normal and ideal growing conditions $y = (y_1, y_2, y_3)$ (see Chambers et al., (2015) and Serra et al., (2014) for further details). Table 1 provides summary statistics for the variables considered in this study and shows COP output value per farm to fluctuate from less than 30 thousand to more than 63 thousand euros, depending on the state of nature, being 46 thousand euros the most common. We also collected detailed information from each farm on planned input use, which includes crop land (x_1 in hectares), capital (x_2 in replacement value), paid and unpaid labor (x_3 in hours), energy (x_4 in euros) and crop-specific inputs (crop protection products – c in liters, seeds - x_5 in euros, fertilizers

- r in kilos). On average, sample farms cultivate 72 ha, have a capital replacement value of 145 thousand euros, devote slightly less than 900 labor hours per year to the farm and spend around 4,4 thousand and 3,9 thousand euros on energy and seeds, respectively. In order to estimate the sub-technologies representing farm social outputs, farmers' degree of work satisfaction (s) and information on the accidents and work injuries (i) occurring in the farm was also collected.

On average, sample farms apply 80 liters of PHI, which corresponds to a rate of slightly more than 1 liter per hectare. PAN Germany (2003) places this value around 1.84 Kg/ha in Spain, which involves our sample farms are below the national average. We use the environmental impact quotient (EIQ) developed at Cornell University to provide an estimation of the environmental and health impacts derived from PHI (Eshenaur, B., Grant, J., Kovach, J., Petzoldt, C., Degni, J., & Tette, 2017; Kovach, Petzoldt, & Degni, 1992)[1]. The EIQ was developed to help farmers formulate informed decisions on pesticide selection. More specifically, to estimate pesticide pollution by farm, we multiply the amount of active ingredient applied in liters by the corresponding EIQ. The resulting quantity is taken as the estimate of p, the output of the PHI pollution technology. Noteworthy is the relatively small standard deviation of p for our sample farms (Table 1). In order to estimate pollution from fertilizers, we follow Serra et al. (2014). More specifically, our survey gathered information on the quantities of chemical and organic fertilizers applied and converted them into nitrogen quantities. While for chemical fertilizers the quantity of nitrogen can be easily found in the product specifications, we use Mercadé, Delgado, & Gil (2012) coefficients to approximate the quantity of nitrogen contained in organic fertilizers and the Spanish Ministry of Agriculture, Fisheries (2010) coefficients to quantify the nitrogen content in seeds. The nitrogen balance constraint requires estimation of crop nitrogen removal, which depends on yields, which in turn depend on the state of nature. Based on the Spanish Ministry of Agriculture, Fisheries (2010 information, we estimated three possible nitrogen removal quantities per farm (q_1, q_2, q_3) (see Serra et al. (2014) for further details). By computing the difference between nitrogen applied and removed, three possible nitrogen balances (one for each state of nature) were generated (z_1, z_2, z_3). The nitrogen balance fluctuates from 5,9 thousand to 3,5 thousand kilos in bad and good crop growing conditions, which is compatible with higher amounts of nitrogen being absorbed by crops under good crop growing conditions.

Few existing studies have considered the social dimension of firm performance. Contributing to this literature, we use two different sub-technologies that represent farm social outputs: the farmer's satisfaction level with working conditions (s) measured on four-point Likert scale and the number of work-related injuries (b). Since farms in our sample are mainly family-based farms employing a very small number of workers (mainly members of the manager's family), very few injuries have been reported (an average of 0.35 injuries per farm).

As noted by Sueyoshi & Sekitani (2009); Thompson, Dharmapala, & Thrall (1993), DEA models need to treat zeros in the data carefully. In order to avoid zero values in our dataset, the injuries variable is built as follows: we give a score of 100 for each farm, and for each minor injury we remove 5 points, while we remove 20 for a serious injury. For example[2], a farm with 1 minor injury and 1 serious injury will have a score of $i = 100 - \big((5) + (20)\big) = 75$.

[1] The coefficients have not been derived for Spanish agriculture and thus, they only represent and approximation.

[2] It should be noted that several combinations have been tried by the authors leading to the same results.

Table 1. Descriptive Statistics

	Variable description	Measurement Unit	Symbol	Mean	Std. Deviation
Inputs	Land	Hectares	x_1	72,33	55,25
	Capital	Euros	x_2	145,250.21	153,940.09
	Labor (paid and unpaid)	Hours	x_3	887,05	3 604,95
	Energy	Euros	x_4	4 428,08	4 313,45
	Seeds	Euros	x_5	3 861,27	3 076,19
	Pesticide active ingredients applied	Liters	c_d	81,23	85,09
	Nitrogen application through fertilizers and seeds	Kilograms	r_k	8 982,42	8 865,51
	Nitrogen absorbed by crops under bad conditions	Kilograms	q_1	3 235,65	2 679,60
	Nitrogen absorbed by crops under normal conditions	Kilograms	q_2	4 725,69	3 661,22
	Nitrogen absorbed by crops under ideal conditions	Kilograms	q_3	6 399,17	5 218,33
Outputs	Crop output value under bad conditions	Euros	y_1	29 413,51	25 151,39
	Crop output value under normal conditions	Euros	y_2	46 439,19	36 078,32
	Crop output value under ideal conditions	Euros	y_3	63 120,70	50 472,89
	Nitrogen balance under bad conditions	Kilograms	z_1	5 865,66	7 038,22
	Nitrogen balance under normal conditions	Kilograms	z_2	4 559,28	6 359,11
	Nitrogen balance under ideal conditions	Kilograms	z_3	3 471,60	5 569,09
	Injuries score	Score	i	97,28	6,37
	Farmer satisfaction level	Likert Scale	s	3,38	0,59
	Ecological impact of PHI	Liters	p	1 376,32	1 548,35

Redefinition of the injuries variable requires flipping the inequality sign in the last equation in (11). Farmers' satisfaction is obtained by asking farmers to value their overall degree of satisfaction with their work on a Likert Scale (from 1 to 4, being 1 the lowest and 4 the highest degree of satisfaction). The average is 3.4, showing a relatively high satisfaction level. To derive a quantitative measure of working conditions, farmers were asked to value, based on a four-point Likert scale, 17 items reflecting different dimensions of working conditions (workload, difficulty of the work, creativity, skills development, freedom in decision making, flexibility of schedules, work motivation). To reduce the number of netputs and improve the discriminatory ability of DEA, we perform a principal component analysis (PCA)[3]

4. Results

Efficiency scores are derived using the General Algebraic Modeling system (GAMS) software. Results obtained imply heterogeneity in farm performance in the different sub-technologies considered (Table 2). Overall efficiency averages 77.5%, a score that results from equation (12). This overall efficiency score can be decomposed into the technical, the environmental and the social measures. The environmental efficiency, on the order of 54.9%, is the lowest and measures the farm businesses performance in minimizing pollution caused by both PHI and nitrogen. The desired output technical performance of the firm is on the order of 89.1%. As will be explained below, this efficiency is however sensitive to the state of nature that is realized. Social output

[3] PCAs may contain negative values. Therefore all values were increased by the most negative value in the vector plus one, thus ensuring our data are strictly positive.

technologies display an efficiency level of 88.6%, which measures the performance of the farm business in minimizing work injuries, as well as in providing satisfaction to farmers.

The efficiency results of the state-contingent desired output technology show a small difference across the different states of nature, from 85.5% for the bad state of nature to 91% for the normal and ideal crop growing conditions. Our results are in line with previous studies (Serra et al. 2014), suggesting that technical farm performance is increasing with the improvement in crop growth conditions. Overall nitrogen pollution efficiency has an average of 71.9%, suggesting that there is significant room for efficiency improvements. Our sample farms display nitrogen application efficiency levels on the order of 0.6 in good states of nature, which contrasts with efficiency levels of 0.76-0.79 for the bad and normal crop growing conditions. These results are compatible with those obtained by Serra et al. (2014) and show that over-fertilization is specially problematic under ideal crop growing conditions. This is due to the fact that farms prepare for the worst conditions, which implies that under good conditions, fertilizer use is far from the best practice. Table 2 shows that while there are 24 farms with a nitrogen pollution efficiency of less than 50% in the bad state, the equivalent is 64 farms in the ideal state of nature. Serra et al. (2014) report an average nitrogen pollution efficiency larger than our results (80%), which can be explained by the fact that agricultural consumption of mineral nitrogen increased in Catalonia between 2011 and 2015 by more than 28% (MAPAMA, 2017).

The average efficiency score of the PHI sub-technology is around 38%, which leads to an efficiency distribution function with strong right skewness, suggesting that farms have the possibility to reduce the current amount of PHI-related pollution by an average of 62%. We observe a weak positive association between the state-contingent nitrogen pollution efficiencies and PHI pollution efficiencies, with the Spearman Rank correlation coefficients ranging between 0.35 and 0.45. Hence, to some extent, farmers who tend to overuse PHI may also tend to overuse fertilizers. The environmental impact of PHI does not depend exclusively on the amount used, the type of PHI may also play a major role. Zhu et al. (2014) reported relatively low eco-efficiency scores for some organophosphorus PHI such as Chlorpyrifos. These findings are in line with our results, as glyphosate and chlorpyrifos represent around 44% of the total amount of PHIs used by our sample farms. These active ingredients are characterized by their high environmental impact, which results in low efficiency scores. However, heterogeneity in our sample may also be responsible for the low ratings in PHI. Heterogeneity could come from the fact that while some farms may be placing greater weights on the environmental impacts of PHI use, others confer more relevance to yield improvement and crop loss prevention.

Very few researchers have ventured into quantifying the performance of firms as providers of social outputs (Lebacq et al., 2013). Our article is among the pioneers and extends Chambers & Serra (2016) model to allow for stochastic agricultural production conditions. The average score of social efficiency is around 88.6%, which implies that most of the farms are highly efficient in providing social outputs.

Table 2. Distribution of sustainability efficiency scores

Efficiency Interval	T^{Y_1}	T^{Y_2}	T^{Y_3}	T^{Z_1}	T^{Z_2}	T^{Z_3}	T^P	T^S	T^B
<0,1	0	0	0	8	13	27	44	0	0
0,1-0,2	0	0	0	5	4	12	26	0	0
0,2-0,3	0	0	0	4	6	5	24	0	0
0,3-0,4	1	0	0	4	7	11	14	0	0
0,4-0,5	10	1	1	3	5	9	13	0	0
0,5-0,6	2	0	0	6	0	17	8	1	2
0,6-0,7	13	5	3	14	14	19	10	5	0
0,7-0,8	28	21	21	14	14	8	5	35	34
0,8-0,9	34	38	48	30	22	7	1	51	42
0,9-1,0	85	108	100	85	88	58	28	81	95
Average	**0,855**	**0,910**	**0,908**	**0,792**	**0,765**	**0,599**	**0,380**	**0,883**	**0,899**
Average efficiency scores per sub-technology	Desirable output			Nitrogen pollution			PHI Pollution	Satisfaction	Injuries
	0,891			0,719			0,380	0,883	0,899
Average efficiency scores per sustainability dimension	Economic			Environmental				Social	
	0,891			0,549				0,886	
Overall score					**0,775**				

The social performance level includes two efficiency measures. First, the efficiency in generating farmer's satisfaction, with an average of 88.3%. Second, the efficiency in reducing work injuries, with an average of 89.9%. High T^S ratings can be due to people's tendency to think that they are happier than they actually are, which may lead farmers to overestimate their satisfaction with their work and working conditions (contentment) (Veenhoven, 1996, 1997).The high T^I ratings can be explained by the small number of work accidents occurring in sample farms.

Our efficiency analysis allows to characterize farms receiving direct payments according to their efficiency levels. With the green revolution, agricultural productivity soared in developed countries. Increases in productivity brought however significant costs such as groundwater pollution, soil depletion, or decline in the number of family farms and disintegration of rural communities. The CAP has progressively taken responsibility for these problems. The CAP rural development measures pay farmers for the provision of environmental goods and services. The CAP cross-compliance sets different rules that need to be respected by farmers in order to receive the CAP direct payments. These rules concern environmental preservation, animal welfare, plant health, food safety and maintenance of agricultural land in good agricultural and environmental conditions.

5. Concluding remarks

This study extends Chambers & Serra (2016) measure of firm-level sustainability to allow for the stochastic conditions under which production takes place using a state-contingent approach. The overall production technology is defined as a composite of several sub-technologies representing the economic, environmental and social dimensions of production. Our model is illustrated using a farm-level dataset from a sample of Catalan farms. Empirical findings suggest that our sample farms have overall efficiency scores on the order of 77.5%. The overall efficiency is specially penalized by the poor environmental performance. Overall nitrogen pollution efficiency is on the order of 71.9%, while PHI pollution efficiency scores are around 38%. Nitrogen pollution efficiency is found to decline as growing conditions improve, which suggests that farmers are risk-averse and prepare for the worse states of nature. At the social level, farms show high efficiency scores (on the order of 88%) when it comes to injury prevention and the generation of farmer satisfaction. Our measures of farm-level sustainability can be useful for policy purposes, such as the redistribution of CAP farm payments according to how well farms perform in the different sustainability dimensions. They also show that further efforts are required both by policy makers and farmers to find more environmentally friendly production processes. Specially worrisome is the low capacity of our sample farms to use PHI efficiently.

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References

Arrow, K. J. (1965). Aspects of the theory of risk-bearing (Yrjo Jahnsson Lectures). *Yrjo Jahnssonin Saatio, Helsinki*.

Bacon, C. M., Getz, C., Kraus, S., Montenegro, M., & Holland, K. (2012). The Social Dimensions of Sustainability and Change in Diversified Farming Systems. *Ecology and Society*, *17*(4), 41.

Bowen, H. R. (1953). Social responsibilities of the businessman. Harper & Row: NY.

Chambers, R. G., & Quiggin, J. (1998). Cost functions and duality for stochastic technologies. *American Journal of Agricultural Economics*, *80*(2), 288–295.

Chambers, R. G., & Quiggin, J. (2000). *Uncertainty, production, choice, and agency: the state-contingent approach*. Cambridge University Press.

Chambers, R. G., & Serra, T. (2016). The social dimension of firm performance: a data envelopment approach. *Empirical Economics*, 1–18.

Chambers, R. G., Serra, T., & Stefanou, S. E. (2015). Using ex ante output elicitation to model state-contingent technologies. *Journal of Productivity Analysis*, *43*(1), 75–83.

Chen, Y., Cook, W. D., Du, J., Hu, H., & Zhu, J. (2015). Bounded and discrete data and Likert scales in data envelopment analysis: Application to regional energy efficiency in China. *Annals of Operations Research*, 1–20.

Coelli, T., Lauwers, L., & Van Huylenbroeck, G. (2007). Environmental efficiency measurement and the materials balance condition. *Journal of Productivity Analysis*, *28*(1–2), 3–12.

Cook, W. D., Kress, M., & Seiford, L. M. (1993). On the use of ordinal data in data envelopment analysis. *Journal of the Operational Research Society*, *44*(2), 133–140.

Cook, W. D., Kress, M., & Seiford, L. M. (1996). Data envelopment analysis in the presence of both quantitative and qualitative factors. *Journal of the Operational Research Society*, *47*(7),

945–953.
Cook, W. D., & Zhu, J. (2006). Rank order data in DEA: A general framework. *European Journal of Operational Research*, *174*(2), 1021–1038.
Cooper, W. W., Park, K. S., & Yu, G. (1999). IDEA and AR-IDEA: Models for dealing with imprecise data in DEA. *Management Science*, *45*(4), 597–607.
Cuthill, M. (2010). Strengthening the “social”in sustainable development: Developing a conceptual framework for social sustainability in a rapid urban growth region in Australia. *Sustainable Development*, *18*(6), 362–373.
Debreu, G. (1959). *Theory of value: An axiomatic analysis of economic equilibrium*. Yale University Press.
Dempsey, N., Bramley, G., Power, S., & Brown, C. (2011). The social dimension of sustainable development: Defining urban social sustainability. *Sustainable Development*, *19*(5), 289–300.
Eshenaur, B., Grant, J., Kovach, J., Petzoldt, C., Degni, J., and Tette, J. (2017). www.nysipm.cornell.edu/publications/EIQ. Environmental Impact Quotient: “A Method to Measure the Environmental Impact of Pesticides.” New York State Integrated Pest Management Program, Cornell Cooperative Extension, Cornell University. 1992 – 2015.
Färe, R., Grosskopf, S., Noh, D.-W., & Weber, W. (2005). Characteristics of a polluting technology: theory and practice. *Journal of Econometrics*, *126*(2), 469–492.
Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, *120*(3), 253–290.
Førsund, F. R. (2009). Good modelling of bad outputs: pollution and multiple-output production. *International Review of Environmental and Resource Economics, Forthcoming*.
Frisch, R. (1965). *Theory of production. Theory of production.* Dordrecht: D. Reidel Publishing Co.
Hair, J. F. (2010). *Multivariate data analysis*. Prentice Hall. Retrieved from http://library.wur.nl/WebQuery/clc/1924429
INE. (2013). Instituto Nacional de Estadística. Encuesta sobre la estructura de las explotaciones agrícolas.
Kovach, J., Petzoldt, C., & Degni, J. (1992). A method to measure the environmental impact of pesticides. *New York’s Food and Life Sciences Bulletin (ISSN 0362-0069*, (139).
Lebacq, T., Baret, P. V, & Stilmant, D. (2013). Sustainability indicators for livestock farming. A review. *Agronomy for Sustainable Development*, *33*(2), 311–327.
MAPAMA. (2016). Spanish Ministry of Agriculture, Fisheries, Food and Environmental Affairs. Arable and industrial crops.
MAPAMA. (2017). MAPAMA. Retrieved May 25, 2017, from http://www.mapama.gob.es/es/estadistica/temas/estadisticas-agrarias/agricultura/estadisticas-medios-produccion/fertilizantes.aspx
Mercadé, L., Delgado, M., & Gil, J. M. (2012). Pr{à}ctiques de fertilitzaci{ó} a Catalunya. Enquesta 2010. Generalitat de Catalunya: Departament d’Agricultura, Alimentaci{ó} i Acci{ó} Rural.
Murty, S., Russell, R. R., & Levkoff, S. B. (2012). On modeling pollution-generating technologies. *Journal of Environmental Economics and Management*, *64*(1), 117–135.
Myers, J. R., Layne, L. A., & Marsh, S. M. (2009). Injuries and fatalities to US farmers and farm workers 55 years and older. *American Journal of Industrial Medicine*, *52*(3), 185–194.
NRC. (2010). *National Research Council;Toward Sustainable Agricultural Systems in the 21st Century*. Washington, D.C.: National Academies Press. https://doi.org/10.17226/12832
O’Donnell, C. J., Chambers, R. G., & Quiggin, J. (2010). Efficiency analysis in the presence of uncertainty. *Journal of Productivity Analysis*, *33*(1), 1–17.
O’Donnell, C. J., & others. (2007). Estimating the Characteristics of Polluting Technologies. In

2007 Conference (51st), February 13-16, 2007, Queenstown, New Zealand.

Oude Lansink, A., & Van Der Vlist, A. (2008). Non-Parametric Modelling of CO2 Emission Quota. *Journal of Agricultural Economics*, *59*(3), 487–497.

PAN Germany. (2003). *Pesticide Use Reporting: Options and Possibilities for Europe. Hamburg, Germany: PAN Germany.< http://www. pan-germany. org/download/pur_optionsEU. pdf> Accessed* (Vol. 21). Retrieved from http://www.pan-germany.org/download/pur_optionsEU.pdf

Patton, A. J. (2012). Copula methods for forecasting multivariate time series. *Handbook of Economic Forecasting*, *2*, 899–960.

Pissourios, I. A. (2013). An interdisciplinary study on indicators: A comparative review of quality-of-life, macroeconomic, environmental, welfare and sustainability indicators. *Ecological Indicators*, *34*, 420–427.

Reinhard, S., Lovell, C. A. K., & Thijssen, G. (1999). Econometric estimation of technical and environmental efficiency: an application to Dutch dairy farms. *American Journal of Agricultural Economics*, *81*(1), 44–60.

Ridley. (2010). Ridley, K., 2010. Farm Workers Suffer the Most from Pesticide Exposure. Sustainable Food. Published on-line June 24, 2010. http://food.change.org/blog/view/farm_workers_suffer_the_most_from_pesticide_exposure.

Serra, T., Chambers, R. G., & Oude Lansink, A. (2014). Measuring technical and environmental efficiency in a state-contingent technology. *European Journal of Operational Research*, *236*(2), 706–717.

Spanish Ministry of Agriculture, Fisheries, F. and E. A. A. and industrial crops. (2010). *Balance del nitrógeno en la agricultura española (año 2008) - criterios utilizados*. Retrieved from http://www.ruralcat.net/c/document_library/get_file?uuid=0f426950-264e-461e-9acf-5cce03ce9d3f&groupId=10136

Sueyoshi, T., & Sekitani, K. (2009). An occurrence of multiple projections in DEA-based measurement of technical efficiency: Theoretical comparison among DEA models from desirable properties. *European Journal of Operational Research*, *196*(2), 764–794.

Thin, N. (2002). *Social Progress and Sustainable Development*. Rugby, Warwickshire, United Kingdom: Practical Action Publishing. https://doi.org/10.3362/9781780441399

Thompson, R. G., Dharmapala, P. S., & Thrall, R. M. (1993). Importance for DEA of zeros in data, multipliers, and solutions. *Journal of Productivity Analysis*, *4*(4), 379–390.

Vavik, T., & Keitsch, M. M. (2010). Exploring relationships between universal design and social sustainable development: some methodological aspects to the debate on the sciences of sustainability. *Sustainable Development*, *18*(5), 295–305.

Veenhoven, R. (1996). Developments in satisfaction-research. *Social Indicators Research*, *37*(1), 1–46.

Veenhoven, R. (1997). Progr{č}s dans la compr{é}hension du bonheur. *Revue Qu{é}b{é}coise de Psychologie*, *18*, 29–74.

Vifell, Å. C., & Soneryd, L. (2012). Organizing matters: how “the social dimension”gets lost in sustainability projects. *Sustainable Development*, *20*(1), 18–27.

Zhu, Z., Wang, K., & Zhang, B. (2014). Applying a network data envelopment analysis model to quantify the eco-efficiency of products: a case study of pesticides. *Journal of Cleaner Production*, *69*, 67–73. https://doi.org/10.1016/j.jclepro.2014.01.064