Efficiency of Egyptian Organic Agriculture: a Local Maximum Likelihood Approach

Bouali Guesmi*[1,2], Teresa Serra[3], Amr Radwan[4,5] and José María Gil[1]

[1] Centre de Recerca en Economia i Desenvolupament Agroalimentari (CREDA-UPC-IRTA).
Parc Mediterrani de la Tecnologia, Edifici ESAB, Avinguda del Canal Olímplic s/n, 08860 Castelldefels, SPAIN. Tel.: +34935521209; Fax: +34935521121. bouali.guesmi83@gmail.com, chema.gil@upc.edu

[2] Department of Agricultural Economics, University of Carthage, Mograne Agricultural High School- 1121 Zaghouan , Tunisie Tél.: (+216) 72 660 283; Fax : (+216) 72 660 563.

[3] Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, Illinois. 335 Mumford Hall, 1301 West Gregory Drive, Urbana, IL 61801. tserra@illinois.edu

[4] Facultad de Ciencias Económicas y Administrativas, Universidad Tecnológica IndoAmérica, Ambato, Ecuador. amrradwan2010@yahoo.com

[5] Department of Agricultural Economics, Faculty of Agriculture, Cairo University, Cairo, Egypt.

*Corresponding author, E-mail address: bouali.guesmi83@gmail.com

Abstract

Productive efficiency analysis is a relevant tool that can be used to evaluate differences in performance between conventional and organic farms. Such study is important for the assessment of the economic viability of these two agricultural systems. While the existing research has widely used the stochastic frontier methodology and the DEA nonparametric approach to assess farming performance, the use of the local maximum likelihood (LML) approach proposed by Kumbhakar et al. (2007) is scarce. This study represents the first analysis that compares the efficiency levels of organic and conventional farms in Egypt. To do so, we apply LML methods to cross sectional, farm-level data collected from a sample of 60 Egyptian farms. Results suggest that performance of organic farmers is slightly better than performance of their conventional counterparts. Further, we find a positive relationship between technical efficiency and farm size.

[EconLit citations : C14; Q12; D24]

1. Introduction

Although with a declining trend, Egyptian agriculture accounts for about 17 per cent of gross domestic product and 20 per cent of total exports and foreign-exchange revenues. In addition, agriculture-related industries, such as processing, marketing and input supplies, account for another 20 per cent of the gross domestic product. Agriculture is therefore a key sector in the Egyptian economy, providing the livelihood for 55 per cent of the population (UNDP, 2011). A very important pillar for the modernization of the Egyptian agriculture involves promoting exports of high value added products such as organic produce.

The Center of Organic Agriculture in Egypt (COAE), the entity in charge of certifying organic agriculture, awarded its first certification more than 20 years ago to a 17 hectares farm (SEKEM, http://www.sekem.com/), located in the eastern desert and devoted to produce medicinal herbs for the export market. While expansion of organic farming was quite slow until 1988, it experienced a rapid growth in the vegetables, fruits, cereals, and cotton sectors thereafter. This rapid growth was initiated mainly by SEKEM and some other growers in Fayum and Kalubia governorates. Currently, organic agriculture in Egypt is expanding very fast due to public awareness of the advantages associated to this farming practice, as well as the increasing demands for organic food and fibers in both local and export markets. As a result, organic farming has rapidly grown from 15 thousand hectares farmed by 460 organic farms in 2006 to 56 thousand hectares managed by 909 producers in 2009 (FiBL & IFOAM, 2011). Almost half of the Egyptian organic farms are located in the middle Nile, in the region of El Fayoum, 100 Km south of Cairo. Organic farms in Egypt are generally small holdings whose size usually ranges from 4.5 to 20 hectares. A few farm enterprises are larger than 400 hectares, but they account for 20% of all organic farmland and are located in the Nile delta and in Upper Egypt (Kledal et al., 2008).

The major organic producers in Africa are Uganda (227 thousand hectares) and Tunisia (168 thousand hectares) that concentrate around 40% of total organic area in Africa. Egypt is among the leading African countries in terms of organic area, occupying the eighth position (FiBL & IFOAM, 2011). Despite its relevant growth, the organic area share over the total utilized agricultural area is still low at around 1%. Organic farming mainly relies on the use of less chemical inputs than conventional agriculture. Because this restricted input use, organic practices are likely to be less productive than conventional agriculture. This lower productivity however does not necessarily affect farms' profits once their product is certified organic, due to the high market price for organic produce. During the early stages of conversion, however, farms may face economic hardships for not being yet able to receive the organic produce price premium.

Technical efficiency (TE) is a prerequisite for economic efficiency, which in turn is a necessary condition for the economic viability and sustainability of a firm (Tzouvelekas et al., 2001). Knowledge about productivity and efficiency differences between conventional and organic farms is a relevant tool for economic agents considering alternatives to improve the performance of organic agriculture, and designing suitable policies to support the expansion of organic agriculture within Egypt. Using robust methodologies for TE analysis is important to derive unbiased efficiency estimates that allow monitoring the impacts of policy and better targeting policy measures. Despite the relevant growth of organic agriculture in Egypt, up to date there is no study that assesses the performance of organic farms in this country. Unlike previous mainstream literature on organic farming TE, which has widely relied on either the Stochastic Frontier Analysis (SFA) or the Data Envelopment Analysis (DEA), we use a new methodology recently introduced by Kumbakhar et al. (2007) based on local maximum likelihood techniques. In order to achieve the aforementioned objective, a survey was conducted for a sample of organic and conventional farms mainly specialized in horticulture and cereal production and located in the Upper Egypt area. More specifically, the survey was conducted in Suhag, Assiut and Fayum governorates.

The rest of the paper is organized as follows. In the next section, a literature review and the contribution of this work to previous literature is presented. Then, we describe the methodology used in our empirical application. The fourth section presents the data and results of the empirical implementation. Finally, the paper ends with some concluding remarks.

2. Literature review

While analyses on the adoption of organic farming practices have proliferated (Fairweather, 1999; Lohr & Salomonson, 2000; Pietola & Oude Lansink, 2001; Acs et al., 2007, Padel, 2001; Parra et al., 2007; Radwan et al., 2011), the literature on TE performance of organic farming is still small, which may be due to the scarcity of organic farming data necessary to conduct such analyses (Oude Lansink et al., 2002). Parametric SFA and non-parametric DEA methods constitute the mainstream of the efficiency literature assessing the differences in TE between conventional and organic farms. Results are not conclusive and differ across sectors, regions and methodologies.

Oude Lansink et al. (2002) used DEA techniques to compare organic and conventional crop and livestock farms in Finland. They found that organic farms are more technically efficient than conventional farms (0.96 *vs.* 0.72), though they tend to be less productive. Different results were achieved by another DEA-based study by Bayramoglu and Gundogmus (2008), who found that conventional raisin-producing farms in Turkey are more efficient than organic producers (0.90 *vs.* 0.86). Tzouvelekas et al. (2001; 2002a, b) used the SFA approach to assess the TE performance of Greek organic and conventional farms. They suggested that organic farmers are operating closer to their frontier than their conventional counterparts. In contrast, Madau (2007) applied a SFA model and found that Italian conventional cereal farms tend to be more efficient than organic farms (0.90 *vs.* 0.83). In another SFA-based study, Guesmi el al. (2012) suggested that the Catalan organic grape producers are more efficient than conventional growers (0.80 *vs.* 0.64, respectively).

Although both SFA and DEA methods entail several methodological advantages, they are also criticized for their shortcomings that may conduct to biased efficiency estimates. The main difference between these two approaches is that the SFA accounts for the stochastic component of production and measurement errors and that these are separated from the inefficiency effects. In contrast, DEA methods do not allow disentangling inefficiency from stochastic effects (Sharma et al., 1999; Wadud & White, 2000). Further, SFA permits conducting conventional statistical tests of hypotheses. SFA, however, relies on restrictive assumptions regarding the functional form representing the production frontier, as well as the distributional assumption for the random noise and inefficiency error components. DEA, in contrast does not require specification of any functional form. TE estimates have been shown to be sensitive to estimation techniques and functional form specifications (Ferrier & Lovell, 1990; Coelli & Perelman, 1999; Ruggiero & Vitaliano, 1999; Chakraborty et al., 2001). Both functional form and error distribution misspecifications, as well as ignoring stochastic component of production can lead to inaccurate efficiency estimates (Kumbhakar et al., 2007; Martins-Filho & Yao 2007; Serra & Goodwin, 2009).

To overcome the shortcomings of both methods without foregoing their advantages, Kumbhakar et al. (2007) recently developed a new methodological approach based on local modeling techniques. This model allows the parameters representing both production and error distribution to be localized with respect to the covariates. Hence, in contrast to standard SFA models, parameters representing production characteristics are allowed to change from firm to firm according to each firm particularities. In addition, as opposed to DEA nonparametric techniques, this approach allows for stochastic variables and variable measurement errors when deriving TE scores. Furthermore, an important feature of this method is that it addresses heteroscedasticity by estimating observation-specific variances of the inefficiency and noise components of the error term (Serra & Goodwin, 2009). The local modeling approach proposed by Kumbhakar et al. (2007) relies upon local maximum likelihood (LML) principles (Fan & Gijbels, 1996).

In spite of the relevant features of LML techniques, there are few empirical studies in the literature (Kumbhakar et al., 2007; Martins-Filho & Yao 2007; Serra & Goodwin, 2009) relying on these methods. Only Serra and Goodwin (2009) have used LML to compare the efficiency performance of organic and conventional arable crop farming in Spain. Our work contributes to the efficiency literature as it constitutes the first study that compares TE levels for organic and conventional farms in Egypt. Productivity differences between the two farm types are also studied by determining the output elasticity of different inputs used in the production process.

3. Methodology

TE studies can constitute a useful tool to improve a firm’s economic performance. For such purpose, it is necessary to choose a robust method that produces unbiased efficiency estimates. We choose the LML approach to consistently estimate TE. As noted above, LML methods overcome the most relevant limitations that have been attributed to DEA and SFA methods, without giving up their advantages. LML techniques are used to compare the TE with which Egyptian organic and conventional farms operate.

Aigner et al. (1977) and Meeusen and Van den Broeck (1977) specified the general stochastic frontier model as follows $Y_i = \beta_0 + \beta^T X_i - u_i + v_i$, where Y_i represents the observed output level produced by firm $i = 1, ..., N$, $X_i \in \mathbb{R}^d$ is a vector of input quantities used in the production process, the betas are unknown parameters to be estimated, $u_i > 0$ is a non-negative inefficiency term and v_i is a random noise term. The parametric estimation of stochastic frontier models is usually based on maximum likelihood techniques. The joint pdf of (Y, X) is decomposed into a marginal pdf for X, $pdf(x)=p(x)$ and a conditional pdf for Y given x, $pdf(y|x) = g(y, \theta(x))$, where $\theta(x) \in \mathbb{R}^k$ is the vector of parameters to be estimated.

Based on the parametric model developed by Aigner et al. (1977), the conditional pdf for Y given $X = x$ can be defined as: $Y = r(X) - u + v$, where $r(x)$ is the production frontier, $u | X = x \sim \left|N(0, \sigma_u^2(x))\right|$, $v | X = x \sim N(0, \sigma_v^2(x))$, and u and v are assumed to be independently distributed, conditional on X. Following Kumbhakar et al.' (2007) approach, the 3-dimensional local parameter vector is defined as $\theta(x) = \left(r(x), \sigma_u^2(x), \sigma_v^2(x)\right)^T$ and is derived using local polynomials. The conditional log-likelihood function $L(\theta) = \sum_{i=1}^{N} \log g(Y_i, \theta(X_i))$ is locally approximated by the following mth order local polynomial function:

$$L_N(\theta_0, \theta_1, ..., \theta_m) = \sum_{i=1}^{N} q\left(Y_i, \theta_0 + \theta_1 (X_i - x) + ... + \theta_m (X_i - x)^m\right) K_H(X_i - x), \quad (1)$$

where x represents a fixed interior point in the support of $p(x)$, $q = \log g$, $\theta_j = \left(\theta_{j1}, ..., \theta_{jk}\right)^T$ for $j = 0,1,...,m$, and $K_H(u) = |H|^{-1} K(H^{-1}u)$, where K represents a multivariate kernel function and H is assumed to be a positive definite and symmetric bandwidth matrix. The local polynomial estimator is determined by $\hat{\theta}(x) = \hat{\theta}_0(x)$ where

$$\left(\hat{\theta}_0(x), ..., \hat{\theta}_m(x)\right) = \arg \max_{\theta_0, ..., \theta_m} L_N(\theta_0, \theta_1, ..., \theta_m). \quad (2)$$

To empirically derive the LML estimator, Kumbhakar et al. (2007) propose using a local linear technique. The random noise and inefficiency terms are assumed to be distributed following a local normal and a half normal distribution, respectively, and the conditional probability density function of $\varepsilon = v - u$ is expressed as:

$$f(\varepsilon \mid X = x) = \frac{2}{\sigma(x)} \varphi\left(\frac{\varepsilon}{\sigma(x)}\right) \Phi\left(-\varepsilon \frac{\lambda(x)}{\sigma(x)}\right) \tag{3}$$

where $\sigma^2(x) = \sigma_u^2(x) + \sigma_v^2(x)$, $\lambda(x) = \sigma_u(x) / \sigma_v(x)$ and $\varphi(.)$ and $\Phi(.)$ represent the probability and the cumulative distribution functions of a standard normal variable, respectively. The local linear parameter is given by $\theta(x) = \left(r(x), \sigma^2(x), \lambda(x)\right)^T$ and the conditional pdf of Y given X is specified as:

$$g(y; \theta(x)) = \frac{2}{\sigma(x)} \varphi\left(\frac{y - r(x)}{\sigma(x)}\right) \Phi\left(-\left(y - r(x)\right) \frac{\lambda(x)}{\sigma(x)}\right) \tag{4}$$

The conditional local log-likelihood function is defined as:

$$L(\theta) \propto \sum_{i=1}^{N} -\frac{1}{2} \log \sigma^2(X_i) - \frac{1}{2} \frac{\left(Y_i - r(X_i)\right)^2}{\sigma^2(X_i)} + \log \Phi\left(-\left(Y_i - r(X_i)\right) \frac{\lambda(X_i)}{\sqrt{\sigma^2(X_i)}}\right) \tag{5}$$

In the present study, we use a local linear model for the frontier $r(x_i)$ and a local constant model for the parameters of the error term. As a result, expression (5) is rewritten as:

$$L_N(\theta_0, \Theta_1) \propto \sum_{i=1}^{N} -\frac{1}{2} \log \sigma_0^2 - \frac{1}{2} \frac{\left(Y_i - r_0 - r_1^T (X_i - x)\right)^2}{\sigma_0^2} + \log \Phi\left(-\left(Y_i - r_0 - r_1^T (X_i - x)\right) \frac{\lambda_0}{\sqrt{\sigma_0^2}}\right) K_H(X_i - x) \tag{6}$$

where $\theta_0 = \left(r_0, \sigma_0^2, \lambda_0\right)^T$ and $\Theta_1 = r_1^T$. The local linear estimator of the model is given by $\hat{\theta}_0$:

$$\left(\hat{\theta}_0(x), ..., \hat{\Theta}_1(x)\right) = \arg \max_{\theta_0, \Theta_1} L_N(\theta_0, \Theta_1) \tag{7}$$

Jondrow et al. (1982) proposed to obtain the efficiency measure for a particular sample observation as follows:

$$\hat{u}_i = \frac{\hat{\sigma}_0(X_i)\hat{\lambda}_0(X_i)}{1+\hat{\lambda}_0^2(X_i)}\left[\frac{\varphi\left(-\hat{\varepsilon}(X_i)\hat{\lambda}_0(X_i)/\hat{\sigma}_0(X_i)\right)}{\Phi\left(-\hat{\varepsilon}(X_i)\hat{\lambda}_0(X_i)/\hat{\sigma}_0(X_i)\right)}-\frac{\hat{\varepsilon}(X_i)\hat{\lambda}_0(X_i)}{\hat{\sigma}_0(X_i)}\right], \tag{8}$$

where $\hat{\varepsilon}(X_i) = Y_i - \hat{r}_0(X_i)$. When variables are measured in logs, the efficiency level is given by $\hat{eff}_i = \exp(-\hat{u}_i) \in [0,1]$. The maximization problem in (7) is resolved by specifying starting values following Kumbhakar et al. (2007). We start with the local linear least squares estimator of $\hat{r}_0(x)$ and $\hat{r}_1(x)$ and the global ML estimators of $\hat{\sigma}^2$ and λ. By using the parametric Modified Ordinary Least Squares (MOLS) estimator, the local intercept $\hat{r}_0(x)$ is corrected. For this purpose we follow Kumbhakar et al. (2007) and we use the following specification $\hat{r}_0^{MOLS}(x) = \hat{r}_0(x) + \sqrt{2\hat{\sigma}_u^2/\pi}$, where $\hat{\sigma}_u^2 = \hat{\sigma}^2\hat{\lambda}^2 / (1+\hat{\lambda}^2)$. Hence, starting values for solving (7) are derived from $\theta_0 = \left(\hat{r}_0^{MOLS}, \hat{\sigma}^2, \hat{\lambda}\right)^T$ and $\Theta_1 = \hat{r}_1(x)^T$.

Regarding the multivariate kernel, we choose the following expression $h^{-d}\prod_{j=1}^{d} = K\left(h^{-1}\left(x_j\right)\right)$, where $K(.)$ is the Epanechnikov Kernel and d represents the number of covariates. The bandwidth is defined as: $h = h_{base} s_x N^{-1/5}$, where s_x represents the vector of empirical standard deviations of the covariates and N represents the number of observations. The cross validation criterion (CV) proposed by Kumbhakar et al. (2007) is used to obtain the optimal value for h_{base}. The CV, for a given value of h_{base}, is defined by minimizing the following expression:

$$CV(h_{base}) = \frac{1}{N}\sum_{i=1}^{N}\left[\left(Y_i - \left(\hat{r}_0^{(i)}(x) - u_i^{(i)}\right)\right)\right]^2, \tag{9}$$

where $\hat{r}_0^{(i)}$ and $u_i^{(i)}$ are the leave-one-out versions of the local linear estimators defined above.

4. Empirical application and results

The empirical analysis uses cross sectional, farm-level data collected from a survey designed and conducted in Upper Egypt, specifically in Suhag, El Fayum and Assiut Governorates during the year 2010. These three governorates concentrate almost half of the organic area in Egypt (Kledal et al., 2008). Data were collected by face-to-face questionnaires during the period from March to June 2010 in these three governorates. The identification of the main organic production areas was based on a list of certified organic farmers obtained from COAE. Collected data include details on farm production and input use, financial and socio-economic characteristics (age, gender, education, family size, relevance of family labor, total farm income, output, subsidies, etc.), as well as information on farm structural characteristics (farm size, tenure regime of land).

Our final sample consists of 30 organic farmers and 30 neighboring conventional farms mainly specialized in fruit crops, cereal and horticulture.[1] The neighboring criteria allows obtaining a relatively analogous composition of the two subsamples, organic and conventional, avoiding unobserved regional differences in land quality, farm management skills, or agricultural production techniques (Tzouvelekas et al., 2001; Madau, 2007; Kopke, 2009; Guesmi et al., 2012; Seufert et al., 2012). The reduced number of observations makes it advisable to pool organic and conventional data for the empirical application. On the other hand, conventional and organic farms use different technologies. The resulting heterogeneity of the sample makes it specially useful to use LML techniques[2].

For the purpose of our efficiency analysis, we define the following variables. Farm output (y_i) is expressed in currency units, euros, and represents total farm income. The use of

[1] In order to promote participation and accuracy of the responses, farmers received economic incentives. This limited the number of farms that could be included in the analysis. This is a shortcoming in that the small number of units included may not fully reflect the existing variability within the population of farms.
[2] It is important to recall the robustness of LML to compositional differences in the sample (Kumbhakar et al., 2007).

a single aggregate output instead of a multi-output vector is common in productive efficiency analyses, requires measurement of output in monetary units, and reduces dimensionality problems (e.g. Färe et al., 1994; Brümmer, 2001; Chavas, 2008; Serra el al., 2010; Nauges et al., 2011). While prices are very likely to be exogenous and homogeneous within the conventional and organic farming groups, they are likely to be different across groups. The price premium received by organic farms may lead to overestimation of the efficiency of organic farmers. Possibly higher input prices paid by organic farms may compensate this problem. Furthermore, it is worth noting that the LML method is likely to minimize the price difference problem between organic and conventional farms by choosing a homogeneous farms' reference set.

Among the inputs considered is crop land (x_1) measured in hectares. Total labor input (x_2) expressed in euros and comprising both family[3] and hired labor. Chemical inputs (x_3) represent the expenditures (in euros) in fertilizers and pesticides. Other inputs (x_4) include irrigation, energy, fuel and seed expenses and are also measured in monetary units. Table 1 provides summary statistics for the variables used in the analysis.

Organic and conventional farms differ in terms of both inputs used and outputs produced. Conventional farms' cultivated area more than triples the area planted by organic farms. The majority of land is cultivated by small farmers (farm average size is about 5 ha and 16 ha for organic and conventional groups, respectively) who often diversify their income sources. Conventional and organic farms are mainly specialized in the production of fruit crops, cereals and vegetables, which together represent on average 96% and 70% of total agricultural income, respectively. However, organic farms are more diversified and also embrace the production of aromatic and medicinal crops, which represent about 30% of their

[3] Family labor was priced using actual payments to family labor when these were made. In case that farm labor was not compensated, opportunity costs were used, i.e., the market price of labor in the region was used.

income. Differences in value of output may be thus be attributed to different reasons such as the composition of agricultural production, farming yields and price premiums received by organic farmers. The average value of conventional farm output (27,242 Euros) more than doubles the average output of their organic counterparts (11,319 Euros). This is in line with previous literature that has generally shown that conventional farms are usually larger than organic farms (Oude Lansink et al., 2002; Serra & Goodwin, 2009; Guesmi el al., 2012). Yields, however, are superior in organic farms, which may be due to the organic produce price premium and is in line with previous studies (Offermann & Nieberg, 2000; Oude Lansink et al., 2002; Oude Lansink & Jensma, 2003). Conventional (organic) farms spend 1,440 (1,052) Euros annually in labor input. On a per unit of land, organic farms are much more labor intensive than conventional farms (427 *vs.* 142 Euros per ha). Given the restrictions faced by organic farms regarding the use of chemical inputs, labor becomes much more relevant in these farms. Relative to organic farms, conventional farms spend quite a lot of money to ensure immunity against pests and diseases (5,899 Euros *vs.* only 589 Euros). On a per ha basis, these expenses show that conventional farms are much more intensive in fertilizers and crop protection applications (477 Euros per ha) than organic farms (240 Euros per ha). This is not surprising given the legal regulations that substantially restrict the use of chemical inputs by Egyptian organic farms. On a per ha basis, organic farms are less intensive in energy, fuel and seed use (511 Euros per ha) than conventional farms (631 Euros per ha). Expenses in other inputs are rather low in organic farms compared to their conventional counterparts (1,575 Euros *vs.* 8,147 Euros). Variation in climatic conditions for our sample farms is scarce due to the cross sectional nature of our data and the fact that sample farms are all located in Upper Egypt. Precipitation is the most influential climatic condition for our sample farms and changes in precipitation will imply changes in the use of irrigation systems. As a result, the variable other inputs also reflects weather conditions[4].

Using the aforementioned variables and based on Kumbhakar et al.'s (2007) approach, the parametric frontier model is specified as a Cobb-Douglas function:

$$\log Y = \beta_0 + \beta_1 \log x_1 + \beta_2 \log x_2 + \beta_3 \log x_3 + \beta_4 \log x_4 - u + v \tag{10}$$

It is worth noting that estimating the frontier for each observation in the sample allows overcoming any functional form misspecification. It also provides enough flexibility to capture the differences in production behavior across sample farms. The CV procedure defined above is used to select the bandwidth parameter required to derive the LML estimator of (10). Final results indicate that the bandwidths h_1, h_2, h_3 and h_4 take values of 4.45, 8.50, 5.12 and 5.65, respectively. Once the adequate bandwidth for our data is selected, the local parameter estimates are derived.

Table 2 shows the descriptive statistics for the variation in the local estimates of σ_u^2 and σ_v^2. These statistics support the presence of heterogeneity in the sample indicating an important degree of variability among observations regarding the proportion of the inefficiency volatility to the noise term volatility ($\lambda = \sigma_u^2 / \sigma_v^2$). The noise term however usually dominates the inefficiency term, which is compatible with efficiency levels being derived from relatively homogeneous subsets of data, which reduces σ_u^2. Figures 2 and 3 illustrate the variation of the estimates of the input coefficients for conventional and organic farms, respectively. Since a Cobb–Douglas functional form is assumed for our model, the coefficients represent input elasticities. The variation in the localized estimates supports that

[4] To the extent that remaining variables influencing production are observed by the firm but are not observed by the econometrician, faulty measures of efficiency and productivity may be derived. Recent papers have proposed alternative solutions to the problem (Quiggin and Chambers, 2006; Mutter et al., 2013; Tran and Tsionas, 2013; Shee and Stefanou, 2015).

it is not advisable to assume the same input elasticities for all observations[5]. For conventional farms, variation is especially important for land, with an elasticity that ranges from 16% to 75%, followed by chemical inputs, labor and other inputs, that have an elasticity fluctuating from 10% to 50%, 15% to 45% and 10% to 40%, respectively. In the case of organic farms, variation is relevant for land with an elasticity that ranges from 20% to 43%, followed by other inputs (20% to 40%), labor (20% to 38%) and chemical inputs (3% to 18%).

Input elasticities indicate that both conventional and organic farms operate under decreasing returns to scale with a mean scale elasticity equal to 0.835 and 0.749, respectively (table 3). Hence, it is not recommendable to increase farm size for the purpose of increasing productivity. The localized elasticity estimates for both types of farms have the expected positive sign. On average, production elasticity estimates indicate that labor is the most productive input in conventional farming, followed by land, fertilizers and crop protection products. In organic farming, other inputs present the highest contribution to output increases followed by land, labor and crop protection inputs. The restrictions faced by organic farmers regarding the use of conventional inputs may be behind the low productivity of crop protection inputs, i.e., the authorized crop protection inputs may not be as productive as conventional ones. The fact that labor is more productive in conventional than in organic farming is compatible with the more restrictive use that conventional farms make of this input. Further, the lower intensity with which organic farms use other inputs also explains the higher productivity of this input in organic produce.

The distribution of the localized efficiency estimates is shown in Table 4. Our empirical findings suggest high and similar TE performance for both farm types. Organic farmers, on average, are slightly more efficient than their conventional counterparts (97.5% and 96.4%, respectively), indicating that organic (conventional) farmers achieve 97.5%

[5] Kumbhakar et al. (2007) conducted simulation exercises that prove that the LML approach is preferred to ML methods.

(96.4%) of their maximum potential output. High TE performance contributes to the firm's economic viability. This high level of efficiency is motivated by the scarcity of agricultural resources such as land and water which compels farmers to optimize their use. It also indicates that there is small scope, for both types of farms, to improve their economic results by reducing input use. Hence, in light of increasing input costs, both types of farms are likely to face reduced economic profits: organic (conventional) farms would only be able to increase their output by 2.5% (3.6%) if they were in the efficient frontier (i.e., by holding input level constant).

To draw further conclusions from our results, an ANOVA analysis is used to examine the relationship between farm size and several production characteristics including input use per hectare, output generated per hectare and technical efficiency (table 5). Three conventional (organic) categories of farms are defined as follows: the first group is integrated by farms cultivating less than 10 (2) ha, representing 43% (47%) of the subsample of conventional (organic) farms. The second cluster consists of farms that cultivate between 10 and 20 (2 and 5) ha, representing 33% (30%) of the subsample. The third cluster is integrated by holdings with an area larger than 20 (5) ha, representing 23% (23%) of the subsample (table 5). Results show that, on per hectare basis, input costs are much higher in small farms than those borne by larger ones, implying that larger farms tend to rely on more extensive production techniques. Accordingly, output per hectare is bigger in smaller farms. Larger and more extensive farms are found to operate closer to their production frontier than smaller farms. On average, the first, second and third conventional (organic) groups have an efficiency level of 92.9% (96.3%), 98.8% (97.9%) and 99.4% (99.5%), respectively. Differences in efficiency levels across farm size groups appear to be statistically significant (at the 10% significance level) for the conventional farm group, but not for the organic farm group. Thus, increased conventional farm size measured as the extension of cultivated land, may lead to higher efficiency levels.

Serra and Goodwin (2009) found that organic arable crop farming in Spain has efficiency levels slightly below conventional farms (0.94 *vs.* 0.97). In any case, average efficiencies are close to the ones derived in our work. Comparison with other studies that use different methodologies can be conducted to provide a reference for our findings. Guesmi et al. (2012) used SFA and obtained TE scores of 0.80 and 0.64 for organic and conventional grape farms in Catalonia, respectively. These efficiency scores are very distant from ours and are likely due to heterogeneity in the sample. In another study, Oude Lansink et al. (2002) used DEA to compare organic and conventional crop and livestock farms in Finland and found that organic crop producers have higher efficiency than conventional farms 0.96 and 0.72, respectively. Our findings are also consistent with Tzouvelekas et al.'s results (2001; 2002a, b), who used the SFA approach to evaluate the TE levels achieved by Greek organic and conventional farms. They found organic producers to be more efficient than conventional ones for five types of farms, namely, wheat, olives, raisins, grapes and cotton (0.84 *vs.* 0.79, 0.69 *vs.* 0.54, 0.76 *vs.* 0.70, 0.68 *vs.* 0.62 and 0.75 *vs.* 0.71, respectively). However, our results are different from those derived by Bayramoglu and Gundogmus (2008), who assessed the efficiency of the Turkish grape sector using DEA techniques and suggested that conventional farms operate closer to their frontier than organic producers (0.90 *vs.* 0.86). In contrast with our findings, Madau (2007) used a SFA model and concluded that Italian conventional cereal farms are more efficient than organic farms (0.90 *vs.* 0.83). Differences in TE estimates found in the literature of productive efficiency of organic farming can be attributed to either the use of different methodologies or different production systems.

Technical efficiencies range from a minimum of 69% (81%) to a maximum of 100% (100%) for conventional (organic) farmers, indicating important heterogeneity within sample farms. However, a lower dispersion is found among organic farms: almost two thirds of organic farmers have efficiency ratings between 99% and 100%, whereas one half of conventional farmers display these high performance levels. This result is expected as the organic Egyptian farms are rather homogeneous regarding managing practices and area cultivated, while conventional farms are more diverse ranging from very small farms to huge commercial ones.

5. Concluding remarks

Despite the relevant growth in organic farming in Egypt, there is no study that focuses on the performance of organic farming in this country. Ours contributes to the scarce literature by conducting a comparative study of technical efficiency ratings for organic and conventional farms in Egypt. As well known, both parametric SFA and nonparametric DEA approaches present some shortcomings that may conduct to derive biased efficiency estimates. A new approach introduced by Kumbhakar et al. (2007) based on LML techniques allows to overcome these drawbacks by locally estimating the parameters of the deterministic and stochastic components of the frontier. Since using a robust methodology is important for sound decision making, LML methods are used in this article.

Our analysis is based on farm-level dataset which consists of 60 organic and conventional farms in Egypt. Empirical findings indicate substantial variation in efficiency estimates across observations. Results suggest that our sample farms operate with high mean efficiency scores and that organic farmers, on average, achieve higher technical efficiency levels than their conventional counterparts (0.97 and 0.96, respectively). Further, we find a positive relationship between technical efficiency and farm size for conventional farms, suggesting that large sized farms are found to be more technically efficient compared to small scale categories.

Our results allow deriving some interesting policy implications. Since high technical efficiency is a prerequisite for economic viability, knowledge that organic farms are at least as efficient as conventional farms may encourage more farmers to adopt organic practices. The low productivity of authorized organic fertilizers and crop protection inputs in organic farming, may be attributed to the lack of necessary information on how to adequately use these inputs. Specialized extension and training services providing technical assistance could improve production performance.

Our research can be extended in different ways. Given the increasing relevance of the environmental impacts of agriculture, correcting the technical efficiency estimates with environmental considerations would provide very useful information. Consideration of risk issues in our efficiency analysis may refine research results. As is well known, agriculture is affected by both output and price risks that usually determine production decisions, which in turn can affect production efficiency.

References

Acs, S., Berentsen, P.B.M., & Huirine, R.B.M. (2007). Conversion to organic arable farming in the Netherlands: A dynamic linear programming analysis. Agricultural Systems, 94, 405-415.

Aigner, D., Lovell, C.A.K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production functions models. Journal of Econometrics, 6, 21-37.

Bayramoglu, Z., & Gundogmus, E. (2008). Cost Efficiency on organic farming: A comparison between organic and conventional raisin-producing households in Turkey. Spanish Journal of Agricultural Research, 6, 3-11.

Brümmer, B., (2001). Estimating confidence intervals for technical efficiency: the case of private farms in Slovenia. European Review of Agricultural Economics, 28, 285-306.

Chakraborty, K., Biswas, B., & Lewis, W.C. (2001). Measurement of technical efficiency in public education: A stochastic and non-stochastic production function approach. Southern Economic Journal, 67, 889-905.

Chavas, J. P., (2008). A cost approach to economic analysis under state-contingent production uncertainty. American Journal of Agricultural Economics, 9, 435-446.

Coelli, T.J.,& Perelman, S., (1999). A comparison of parametric and non-parametric distance functions: With application to European railways. European Journal of Operational Research, 117, 326-339.

Fairweather, J.R. (1999). Understanding how farmers choose between organic and conventional production: Results from New Zealand and policy implications. Agriculture and Human Values, 16, 51-63.

Fan, J., & Gijbels, I. (1996). Local polynomial modeling and its applications. London: Chapman & Hall.

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z., (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. American Economic Review, 84, 66-83.

Ferrier, R.S., & Lovell, C.A.K. (1990). Measuring cost efficiency in banking: An econometric and linear programming evidence. Journal of Econometrics, 46, 229-245.

FiBL & IFOAM (2011). The World of Organic Agriculture, statistics & emerging trends 2011. Bonn & Ackerstrasse: Research Institute of Organic Agriculture (FiBL) & International Federation of Organic Agriculture Movements (IFOAM).

Guesmi, B., Serra, T., Kallas, Z., & Gil, J.M. (2012). The productive efficiency of organic farming: The case of grape sector in Catalonia. Spanish Journal of Agricultural Research, 10, 552-566.

Jondrow, J., Lovell, C.A.K., Materov, I.S., & Schmidt, P. (1982). On the estimation of technical inefficiency in stochastic frontier production models. Journal of Econometrics, 19, 233-238.

Kledal, P.R, El-Araby, A. & Salem, S.G. (2008). Country report: Organic food and farming in Egypt. Mediterranean region. In The World of Organic Agriculture, statistics & emerging trends 2008. Bonn & Ackerstrasse : FiBL & IFOAM.

Kopke, U. (2009). Influence of organic and conventional farming systems on nutritional quality of food In I. Cakmak & R.M. Welch (Ed), Impacts of agriculture on human health and nutrition (pp. 210-238). United kingdom: Eolss Publishers Co.Ltd.

Kumbhakar, S.C., Byeong, U.P., Simar, L., & Tsionas, E.G. (2007). Nonparametric stochastic frontiers: A local maximum likelihood approach. Journal of Econometrics, 137, 1-27.

Lohr, L., & Salomonson, L. (2000). Conversion subsidies for organic production: Results from Sweden and lessons for the United States. Agricultural Economics, 22, 133-146.

Madau, F.A. (2007). Technical efficiency in organic and conventional farming: Evidence form Italian cereal farms. Agricultural Economics Review, 8, 5-21.

Martins-Filho, C., & Yao, F. (2007). Nonparametric frontier estimation via local linear regression. Journal of Econometrics, 141, 283-319.

Meeusen, W., & Van Den Broek J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. International Economic Review, 18, 435-444.

Mutter, R. L., Greene, W. H., Spector, W., Rosko, M. D., & Mukamel, D. B. (2013). Investigating the impact of endogeneity on inefficiency estimates in the application of stochastic frontier analysis to nursing homes. Journal of Productivity Analysis, 39, 101-110.

Nauges, C., O'Donnell, C.J., & Quiggin, J., (2011). Uncertainty and technical efficiency in Finnish agriculture: a state-contingent approach. European Review of Agricultural Economics, 38, 449-467.

Offermann, F., & Nieberg, H. (2000). Economic performance of organic farms in Europe. Organic Farming in Europe. Economics and Policy, 5, 1-198.

Oude Lansink, A., Pietola, K.S., Backman, S. (2002). Efficiency and productivity of conventional and organic farms in Finland 1994-1997. European Review of Agricultural Economics, 29, 51-65.

Oude Lansink, A., & Jensma, K. (2003). Analysing profits and economic behaviour of organic and conventional Dutch arable farms. Agricultural Economics Review, 4, 19-31.

Padel, S. (2001). Conversion to organic farming: A typical example of the diffusion of an innovation. Socialogia Ruralis, 4, 40-61.

Parra López, C., De Haro Giminez, T., & Calatrava, R.J. (2007). Diffusion and adoption of organic farming in the Southern Spanish olive groves. Journal of Sustainable Agriculture, 30, 105-152.

Pietola, K.S., & Oude Lansink, A. (2001). Farmer response to policies promoting organic farming technologies in Finland. European Review Agricultural Economics, 28, 1-15.

Quiggin, J., & Chambers, R. G. (2006). The state-contingent approach to production under uncertainty. Australian Journal of Agricultural and Resource Economics, 50, 153-169.

Radwan, A., Gil, J.M., Diab, Y.A.A., & AboNahoul, M. (2011, April). Determinants of the adoption of organic agriculture in Egypt using a duration analysis technique. Paper presented at the 85th Annual Conference, Warwick University, Coventry, UK.

Ruggiero, J., & Vitaliano, D. (1999). Assessing the efficiency of public schools using data envelopment analysis and frontier regression. Contemporary Economic Policy, 17, 321-331.

SEKEM Organization. Available at : http://www.sekem.com.

Serra, T., & Goodwin, B.K. (2009). The efficiency of Spanish arable crop organic farms, a local maximum likelihood approach. Journal of Productivity Analysis, 3, 113-124.

Serra, T., Stefanou, S., & Oude Lansink, A., (2010). A dynamic dual model under state-contingent production uncertainty. European Review of Agricultural Economics, 37, 293-312.

Seufert, V., Ramankutty, N., & Foley, J. A. (2012). Comparing the yields of organic and conventional agriculture. Nature, 485, 229-232.

Sharma, K.R., Leung, P., & Zaleski, H.M. (1999). Technical, allocative and economic efficiencies in swine production in Hawaii: A comparison of parametric and nonparametric approaches. Agricultural Economics, 20, 23-35.

Shee, A., & Stefanou, S. E. (2015). Endogeneity corrected stochastic production frontier and technical efficiency. American Journal of Agricultural Economics, 97, 939-952.

Tran, K. C., & Tsionas, E. G. (2013). GMM estimation of stochastic frontier model with endogenous regressors. Economics Letters, 118, 233-236.

Tzouvelekas, V., Pantzios, C.J., & Fotopoulos C. (2001). Technical efficiency of alternative farming systems: The case of Greek organic and conventional olive-growing farms. Food Policy, 26, 549-569.

Tzouvelekas, V., Pantzios, C.J., & Fotopoulos, C. (2002a). Empirical evidence of technical efficiency levels in Greek organic and conventional farms. Agricultural Economics Review, 3, 49-60.

Tzouvelekas, V., Pantzios, C.J., & Fotopoulos, C. (2002b). Measuring multiple and single factor technical efficiency in organic farming: The case of Greek wheat farms. British Food Journal, 104, 591-609.

UNDP, (2011). Country Evaluation Egypt.

Wadud, A. & White, B. (2000). Farm household efficiency in Bangladesh: A comparison of stochastic frontier and DEA methods. Applied Economics, 32, 165-73.

Table 1. Summary statistics for the variables of interest

Variable	Organic (n=30)		Conventional (n=30)		T-test of mean difference Significance level[2]
	Mean	**Std. Dev.[1]**	**Mean**	**Std. Dev.[1]**	
Total output (€)	11,319.17	12,112.37	27,241.87	22,774.17	0.001***
Land (ha)	4.76	8.18	16.22	16.77	0.001***
Labor (€)	1,051.67	666.59	1,439.58	1,701.34	0.250
Chemical inputs (€)	589.38	483.70	5,898.54	7,118.34	0.000***
Other inputs (€)	1,574.76	1,874.08	8,147.42	1,0518.73	0.001***
Statistics on a per ha basis					
Total output (€/ha)	3,619.30	1,671.54	2,562.45	1,435.48	0.012*
Labor (€/ha)	426.65	307.48	141.50	150.51	0.000***
Chemical inputs (€/ha)	240.23	281.50	476.67	294.19	0.003**
Other inputs (€/ha)	511.03	376.23	630.78	366.46	0.221

[1]Std Dev: standard deviation. [2] ***, ** and * indicates statistical significance at the 1%, 5% and 10%, respectively

Table 2. Summary statistics for the local estimates of σ_u^2 , σ_v^2 and λ

Local estimates	σ_u^2	σ_v^2	λ
Maximum (100%)	0.183	0.093	30.117
Third quartile (75%)	4.895E-04	0.086	0.075
Median (50%)	7.610E-05	0.083	0.031
First quartile (25%)	1.130E-05	0.075	0.012
Minimum (0%)	1.458E-06	2.004E-04	0.004

Table 3. Input and scale elasticities for conventional and organic Egyptian Farms

Elasticities	**Conventional**		**Organic**	
	Estimate	**Std. Dev**	**Estimate**	**Std. Dev**
Land	0.239	0.158	0.237	0.048
Labor	0.271	0.117	0.202	0.091
Chemical inputs	0.161	0.094	0.062	0.044
Other inputs	0.164	0.108	0.248	0.068
Returns to scale	0.835	0.086	0.749	0.055

Table 4. Frequency distribution of technical efficiency scores

TE (%)	Conventional	Organic
<90	3	4
90-95	2	0
95-99	10	5
99-100	15	21
Mean	0.964	0.975
Standard deviation	0.075	0.045
Minimum	0.694	0.811
Maximum	0.998	0.999

Table 5. ANOVA analysis results

	Farm size			Test of difference between means (significance level)
	Small <10 ha	Medium 10-20ha	Big >20ha	
Conventional farms				
Total output (€/ha)	3498.55 (1159.53)	2390.72 (1112.75)	1069.31 (929.73)	0.000***
Labor (€/ha)	185.39 (159.87)	145.18 (170.86)	54.75 (40.13)	0.182
Chemical inputs (€/ha)	541.57 (177.36)	571.20 (338.88)	221.12 (287.97)	0.025**
Other inputs (€/ha)	802.87 (274.16)	586.69 (350.24)	374.17 (412.94)	0.034**
Technical efficiency	0.929 (0.105)	0.988 (0.022)	0.994 (0.005)	0.083*
Observations (%)	43.33	33.33	23.33	
Organic farms				
Total output (€/ha)	4538.59 (1516.01)	3854.17 (1109.16)	1610.09 (422.46)	0.000***
Labor (€/ha)	559.45 (324.91)	470.53 (245.80)	123.59 (35.39)	0.005**
Chemical inputs (€/ha)	335.03 (392.86)	218.46 (102.63)	92.14 (36.28)	0.180
Other inputs (€/ha)	(670.71) (494.79)	453.28 (140.81)	288.74 (163.08)	0.078*
Technical efficiency	0.963 (0.059)	0.979 (0.032)	0.995 (0.004)	0.309
Observations (%)	46.67	30.00	23.33	

Standard deviation in parenthesis. ***, ** and * indicate F-statistical significance at the 1%, 5% and 10%, respectively.

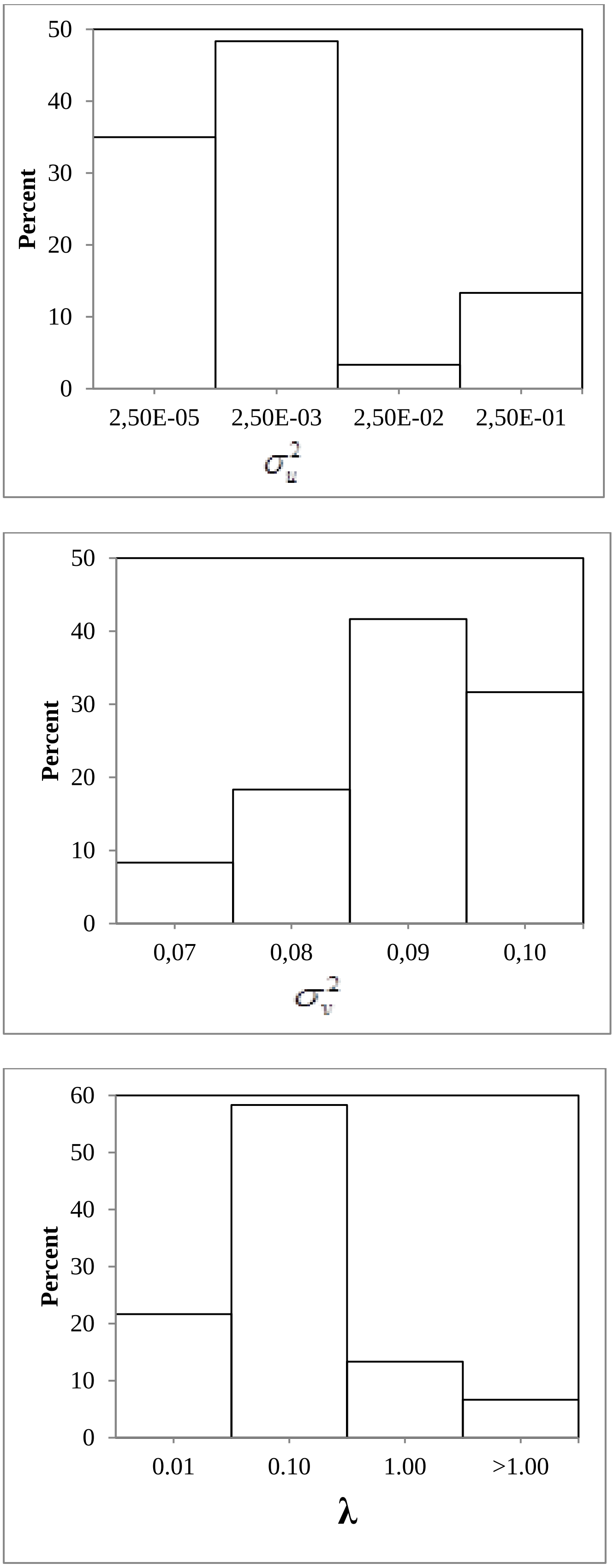

Fig. 1 Distribution of localized estimates of σ_u^2 , σ_v^2 and λ

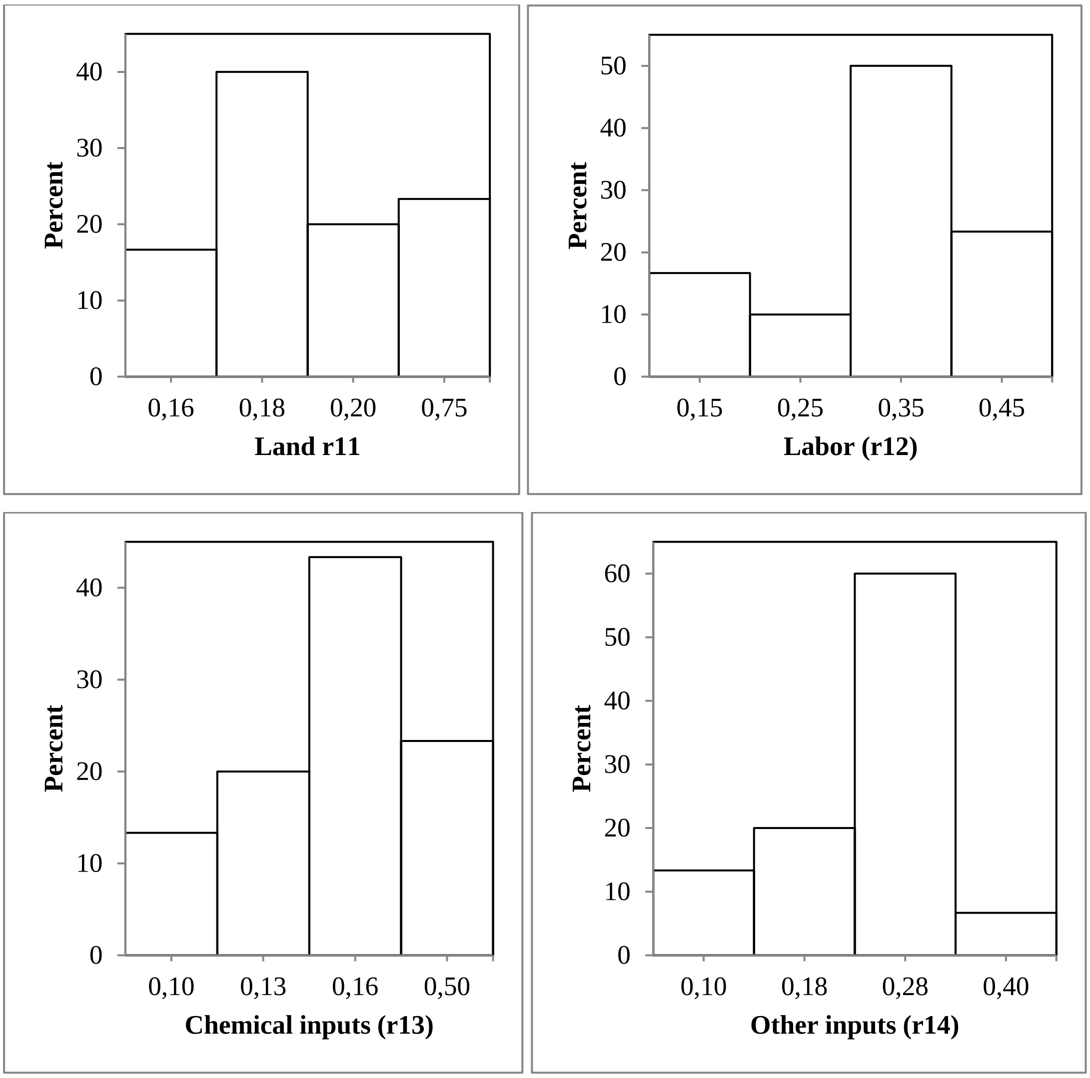

Fig. 2 Distribution of localized estimates of input elasticities: conventional farming

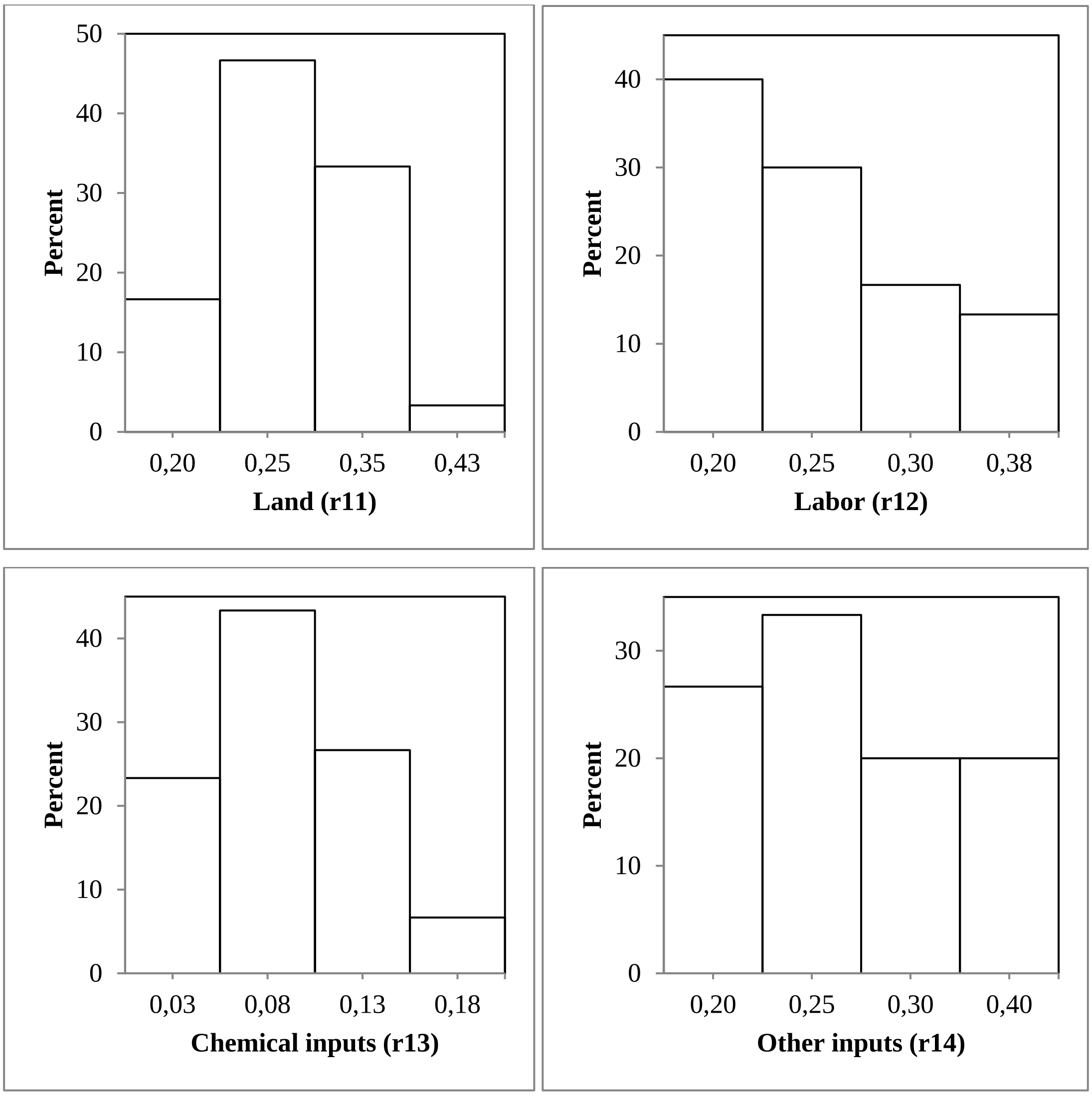

Fig. 3 Distribution of localized estimates of input elasticities: organic farming