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Converting to organic farming in France: Is there a selection problem?

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Abstract

Using a sample of French crop farms during the 1999-2006 period, we test whether less technically efficient farmers are more likely to engage in organic farming in order to benefit from conversion subsidies. Despite some limitations in our data, we find no evidence of such selection effect. On the contrary, our estimation results indicate that more technically efficient farmers are more likely to convert to organic farming. This finding is found to be robust to the method of calculation of efficiency scores, either parametric or non-parametric. This study also confirms that farm's characteristics (education, farm size and legal status) and farmers' practices under conventional farming do impact the probability of conversion to OF.

Keywords: Organic farming; technical efficiency; subsidies; selection; France

1. Introduction

A number of food-safety events along with increasing concerns for sustainability of ecosystems make organic farming (OF) an appealing option for both governments and consumers. As a consequence, most governments, particularly in the United States (US) as well as in the European Union (EU), have encouraged farmers to convert to OF by distributing conversion subsidies. In an era of falling income in the agricultural sector, this subsidy scheme may have attracted “subsidy-hunters” into OF, who are also likely to be less productive (and hence less efficient) than conventional farmers. This “selection problem” has been discussed by Pietola and Oude Lansink (2001) and Tzouvelekas et al. (2001) but tested only once, as far as we know: Kumbhakar et al. (2009), on a sample of Finnish farms, estimate simultaneously technical efficiency (TE) and organic adoption, and find that inefficiency did not increase the probability of adoption. In this article we test the selection hypothesis on a sample of French crop farms by assessing the impact of past TE on the decision to convert to OF.

This article adds to the growing literature linking adoption of OF and farmers’ efficiency measures. A number of articles report TE scores for organic and conventional farmers. However, the comparison of their respective TE scores does not tell whether one group is more efficient than the other since they likely operate under different technologies. Also, it does not inform on whether technical efficiency before conversion plays a role or not. The only evidence so far is found in Kumbhakar et al. (2009) for a sample of Finnish farms. We propose to address a similar question through a different approach. By contrast to Kumbhakar et al. (2009) who perform a joint estimation, we employ a two-stage approach by estimating the influence of several determinants, including TE calculated in a first stage, on the probability to convert to OF. In order to draw robust conclusions, technical efficiency scores are calculated using both parametric methods (stochastic frontier) and non-parametric methods (bias-corrected Data Envelopment Analysis (DEA), and Free Disposal Hull (FDH)). In addition we take into account that French farmers operate in very different agro-climatic conditions when calculating the TE scores.

Our article also provides the first comprehensive analysis of factors driving the adoption of OF in France, a country which lies behind other European partners in terms of organic food production.[1] Our results can be useful to policy makers who are "under pressure" since the French government (through the *Grenelle de l'Environnement*) has set as an objective a threefold increase of the area under OF between 2007 and 2012 (i.e., an increase from 2% to 6%). At the end of 2008, only 2.1% of the national utilized agricultural area (UAA) were under OF.

Section 2 explains the modeling framework. In Section 3, we describe the data and discuss our hypotheses regarding the role of the main variables of interest on OF adoption. In Section 4, we present the methodology for calculating TE scores and estimating the probability of conversion to OF. The results are commented in Section 5. Section 6 concludes.

2. Modeling framework

We assume that a representative crop farmer (currently using conventional practices) takes the decision to adopt organic technology (OT) or to continue with the conventional technology (CT) based on the comparison of his/her expected profit under the two technologies during the next five years. In France this duration corresponds to the period during which the farmer receives subsidies for conversion after the conversion occurred. Since the conversion to OF is not an irreversible decision, the farmer may decide, at the end of the five-year period, to switch back to conventional farming.

For simplicity, we assume that the farmer owns one unit of land, and that all this land is converted to OF in case of adoption of this technology. In addition, we assume that converting to OT does not alter the crop pattern on the farm. We also assume that the farmer is risk-neutral and we neglect the discount factor. A farmer will adopt OT in year t if and only if

$$\sum_{t+1}^{t+5} E\left(\Pi_t^{\mathrm{OT}}\right) > \sum_{t+1}^{t+5} E\left(\Pi_t^{\mathrm{CT}}\right) \tag{1}$$

with $\Pi_t^{\mathrm{OT}} = p_t^{\mathrm{OT}} y_t^{\mathrm{OT}} - w_t^{\mathrm{OT}} x_t^{\mathrm{OT}} + s_t^{\mathrm{OT}}$ and $\Pi_t^{\mathrm{CT}} = p_t^{\mathrm{CT}} y_t^{\mathrm{CT}} - w_t^{\mathrm{CT}} x_t^{\mathrm{CT}} + s_t^{\mathrm{CT}}$, the t-th period profit under the OT and CT, respectively. Variables p, y, w, x, and s denote respectively output prices, output levels (and in our case, yields), input prices, input quantities, and subsidies received by the farms. The underlying technology is assumed to be different for

[1] Among others, with 2% of the total arable land under OF in 2007, France lies behind Italy (9%), Spain (4%), Germany (5%), Sweden (10%), and Portugal (6%).

Source: Agence Bio, document available at http://www.agencebio.org/upload/pagesEdito/fichiers/bioUE.pdf.

organic and conventional farming: $y_t^{\mathrm{OT}} = f^{\mathrm{OT}}\left(x_t^{\mathrm{OT}};\theta_t^{\mathrm{OT}}\right)$ and $y_t^{\mathrm{CT}} = f^{\mathrm{CT}}\left(x_t^{\mathrm{CT}};\theta_t^{\mathrm{CT}}\right)$ where θ_t^{OT} and θ_t^{CT} represent farmer's TE under OT and CT, respectively. Although most of the machinery can be used in both technologies, the ban of applying synthetic fertilizers and plant protection in OF suggests that both technologies and production practices are different.

In general, we expect the price of organic products to be higher than the price of conventional products once the production has been organically certified: $p_t^{\mathrm{OT}} = p_t^{\mathrm{CT}}$ in $t+1$ and $t+2$ and $p_t^{\mathrm{OT}} > p_t^{\mathrm{CT}}$ from $t+3$ onwards, as the farmer cannot sell products under organic labeling before three years of conversion have passed[2]. The price differential should compensate (at least partly) for the loss in productivity since yield under OT is expected to be lower than yield under CT $\left(y_t^{\mathrm{OT}} < y_t^{\mathrm{CT}}\right)$. Input prices are assumed to be the same $\left(w_t^{\mathrm{OT}} = w_t^{\mathrm{CT}}\right)$.[3] The impact of converting to OT on input costs is ambiguous *ex ante* since we expect a decrease in the use of fertilizers and plant protection under OT but an increase in the use of labor and machinery costs. Finally, under the assumptions of unchanged crop pattern on the farm and similar agricultural policy over the period considered, subsidies received by the farm are higher under OT due to the specific subsidies received by the farmer during the period of conversion $\left(s_t^{\mathrm{OT}} > s_t^{\mathrm{CT}}\right)$. Subsidies are provided to compensate the loss in revenues due to technical difficulties implying lower yields during the conversion period, and to the impossibility for the farmer to sell at the organic price during the first years of the conversion period.

The decision of each farmer to convert to OF will thus depend, among other things, on production technology, organic price premium, costs differentials, and farmer's characteristics including technical efficiency. Since all these factors may differ across crops and geographical areas, the decision to convert to OF remains an empirical question.

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[2] In France farmers are allowed to sell their products under the organic label after two years of conversion for field crops and three years for permanent crops. For simplicity, we used the duration of three years in our model.

[3] This may be a strong assumption since seeds and authorized fertilizers may indeed be more expensive than those used in conventional farming. Unfortunately, we do not have any statistical evidence to support this claim.

3. Description of the data and variables used in the analysis

3.1. Database

We use farm-specific data extracted from the French Farm Accountancy Data Network (FADN) database between 1999 and 2006. These data have been combined with NUTS2 and NUTS3 regional data from the French Institute for Environment (IFEN) and the French Observatory for Rural Development (*Observatoire du Développement Rural* (ODR).[4]

The FADN database includes accounting data for a sample of professional farms above a specific size threshold, with a five-year rotating sampling system. Only crop farms are considered here. In the FADN database farms are classified according to their production specialization based on their products' gross margin: at least 66 percent of the gross margin must come from a specific crop or group of crops. The classification is the standard EU classification called Type of Farming (TF). The TF considered here include farms specialized in cereal, oil- and protein-seeds (COP) (TF13), in other field crops (TF14), in fruits and vegetables (TF28), in horticulture (TF29), in high quality wine (TF37), in other grape production (TF38), in permanent crops (TF39) and in mixed crop farming (TF60). All values relating to production were deflated by the national price index of agricultural output with base 2000. Values relating to capital were deflated by the national price index of inputs contributing to investment in agriculture, and values relating to variable inputs were deflated by the national price index of inputs currently consumed in agriculture, both with base 2000.

Within the FADN database, information on whether the farm has engaged in OF is available since 2002 only. The specific variable enables to identify farms that are fully operating under CT, and farms that are fully operating under OT. Farms that are partially operating under CT and OT are not considered here due to data unreliability. Therefore, we consider that a farm has converted to OF in period *t* if it was fully operating under CT at year *t-1* and fully operating under OT at year *t*. Since information on OF practices is available since 2002 only,

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[4] The EU Nomenclature of Territorial Units for Statistics (NUTS) defines standard territorial units in the EU (http://ec.europa.eu/eurostat/ramon/nuts/home_regions_en.html). In France, NUTS1 level corresponds to the national territory, NUTS2 regions are the 22 French administrative regions ("régions") and NUTS3 regions are the 96 French administrative sub-regions ("départements").

Data from IFEN and ODR are available through the following websites:
http://www.stats.environnement.developpement-durable.gouv.fr/bases-de-donnees.html, and
http://esrcarto.supagro.inra.fr/, respectively.

the first conversion period that is considered here is therefore 2003. The earlier years of data (1999-2002) will be used to calculate TE scores of the farmers still present in the FADN sample during the 2003-2006 years.

Table 1 presents the number and share of farms having converted to OF during the period from 2003 until 2006. The number of farms adopting the OT is in general low, and this may be due to the fact that we cannot consider the partial conversions in our database. Overall 56 farms in our sample have converted to OF in the selected TFs, which represents 0.9% of the sampled farms. A higher rate of conversion is observed for TF38 (other grape production). Among the 56 farms, 15 have converted to OF in 2003, 7 in 2004, 17 in 2005, and 17 in 2006.

Table 1: Number of farms having converted in the sample per TF

	2003-2006
TF13	10 (0.6%)
TF14	8 (0.9%)
TF28	4 (1.4%)
TF29	4 (1.9%)
TF37	13 (1.3%)
TF38	6 (1.9%)
TF39	6 (1.4%)
TF60	5 (0.3%)
Total	**56 (0.9%)**

Note: the figures in brackets represent the number of farms having converted given as a share of the TF sample over the period 2003-2006.

3.2. Factors hypothesized to influence OF adoption

Farmer's characteristics

It is commonly acknowledged that non-economic factors such as political and ideological perspectives, sensitivity to environmental problems, health and food quality considerations may induce a farmer to convert to OF. In a survey of 550 organic farmers made in Sweden in 1990, 79% responded that the primary reason for converting was non-economic (i.e. enjoyment, environment, health, food quality, ergonometric or previous experience) instead of being related to reduce grain surplus, market adjustment, better economy or support provided

(Lohr and Salomonsson, 2000). Our data do not contain any variable describing the farmer's opinion about issues related to environment, health and food quality. However we will control for the farmer's level of education. Since better educated persons are often more sensitive to these issues but also because of the assumed link between education and knowledge regarding new technologies, we hypothesize better educated farmers to be more likely to adopt OT. In a review of factors influencing the adoption of conservation agriculture practices (including, but not restrained to, OT), Knowler and Bradshaw (2007) find that "education, be it specific or general, commonly correlates positively with the adoption of conservation agriculture practices; however, some analyses have found education to be an insignificant factor or even to negatively correlate with adoption". Finally, we will introduce in our model a variable measuring the share of agri-environmental subsidies in total operating subsidies received by the farmer, as a proxy for his/her environmental awareness and environmental practices. We hypothesize that a farmer getting more agri-environmental subsidies is more likely to convert to OF.

Farm's characteristics

We will control for farm size. Pietola and Oude Lansink (2001), for a sample of Finnish farms, find that farmers with large land areas and, consequently, good opportunities for practicing extensive farming technologies, are more likely to switch to OF. The marginal effect of land area on the probability to adopt OT was estimated at 0.5. The situation may be different in France, though, since the largest farms, which are commonly located in plains, are usually the most productive ones (in terms of yields). On the contrary, farms in less favored areas are usually smaller. Hence the yield differential between organic and conventional farming $\left(y^{ot}-y^{ct}\right)$ is expected to be lower for smaller farms, which should then have a higher probability to adopt OT. For the particular case of France, we thus hypothesize that larger farms (as measured by the farm UAA) will be less likely to adopt OT.

Policies

Even if the theory indicates that the higher the subsidies to OF, the greater the probability of adoption should be, there is little evidence on the magnitude of the effect. Pietola and Oude Lansink (2001) find that the probability of switching to OF increases at an increasing rate with increasing premium subsidies to the OF for Finnish farms during 1994-1997. They estimate that a 1% increase in the premium subsidy rate for OF increases the probability of choosing OT by 0.2%. Interestingly, the elasticity of the probability of conversion to the non-organic specific subsidy rate for land is the same. This latter result may suggest that the subsidy to support conversion may be seen by some farmers as a way to increase their revenues, at least during the period of conversion. Hence policies promoting OF may suffer from selection problems because subsidies may attract less productive conventional farmers to OF. Tzouvelekas et al. (2001), in a study of the olive-growing sector in Greece, make a similar analysis. They assess that a “loose” eligibility criterion for receiving the conversion subsidy has attracted “subsidy-hunters” not truly interested in producing organically but rather in absorbing the “organic” financial aid. Kumbhakar et al. (2009), for a sample of Finnish dairy farms (followed during the period from 1995 to 2002), also find evidence that higher subsidies increase the probability of OT adoption.

In what follows, we will estimate the subsidy that each farmer would get over the next five years if converting to OF in the next year. This calculation is based on the assumption that the whole area is converted to OF and that the crop pattern does not change.[5] We hypothesize that a higher expected subsidy will increase the probability to convert to OF.

We will also introduce in the model the total amount of Common Agricultural Policy (CAP) subsidies received by the farm (as a ratio of its total output) to control for the dependency of farmers upon subsidies in general. Finally, some specific subsidies may be distributed by local administrations to encourage adoption of OF. Because we do not have such information, we will use as a proxy the average amount of subsidies received per farm in the *département* where each farm of our sample is located. The effect of the non-organic subsidies on the probability to adopt the OT may reflect the attitude of the farmer towards subsidies but may be ambiguous. On the one hand, “subsidy-hunters” may be interested in both non-organic and organic subsidies, implying a positive effect. On the other hand, farmers receiving a large amount of subsidies may find it sufficient and may not be interested in getting additional subsidies.

Potential change in input costs

Farmers who make an intensive use of fertilizers and plant protection may experience a larger reduction in input costs after adoption of OT, and may thus be more likely to adopt. However, a non-intensive use of fertilizers and plant protection (before adoption) could also indicate farmers’ environmental awareness and thus a higher probability to adopt. Also, farmers who use (before adoption) a relatively low level of fertilizers and pesticides are more likely to use

[5] Crop-specific conversion subsidies were obtained from Ministère de l’Agriculture (2001).

a technology which is more similar to the OT and may thus be more likely to adopt OT. The effect of the intensity of fertilizer and plant protection use (before conversion) is therefore ambiguous but we expect the latter to dominate. In the forthcoming empirical application, we will use the ratio of fertilizer expenditure over the standard gross margin as a measure of intensity of fertilizer use.[6]

Potential change in revenues

We would expect that farms for which the expected loss in revenue after conversion from CT to OT is lower to be more likely to adopt OT. The revenue differential will depend on both yield and price differentials between OT and CT. In regions where yield has been historically high we expect a lower probability of conversion.

The price differential between OT and CT also has an impact on expected revenues. Official statistics regarding the price of organic products do not exist in France. We therefore make use of the information available in our FADN sample to compute a price index for organic products and build a variable that measures the price premium that farmers could get if they were switching to OF. Again, this calculation is made under the assumption that the cropping pattern remains unchanged and that the entire crop area is converted.[7] We are not aware of any study using such a variable to explain adoption. Pietola and Oude Lansink (2001) find that a 1% output price decrease increases the probability of choosing OT by 0.4%, but output price in their model is the same for both organic and conventional products. We expect farmers with a higher expected price premium to have a higher probability to adopt OT.

Technical efficiency

As mentioned earlier, there exists a number of studies comparing the TE of organic producers and conventional producers but few of which try to assess the influence of TE (before adoption) on the decision to convert to OF. Some studies suggest that organic farmers are more efficient technically compared to conventional farmers (Tzouvelekas et al. 2001 applying stochastic frontier to data on olive-growers in Greece; Oude Lansink et al. 2002

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[6] As far as we know, there is no study comparing the cost of organic versus conventional farming with an empirical analysis on a sample of farms. Cobb et al. (1999), with a case-study of one farm in England, find that switching to OF induces higher labor costs and higher fixed costs (in this particular farm the conversion to organic agriculture required different machinery).

[7] The price index for organic products was calculated from the FADN data, using the quantities and values of products sold by farmers fully engaged in organic production.

applying DEA on data from crop and livestock farms in Finland). Other studies suggest the opposite: Serra and Goodwin (2009), using the local maximum likelihood method introduced by Kumbhakar et al. (2007), find that (Spanish) organic farms have efficiency levels that are below conventional farms. These authors argue that disparities between their results and results from other studies could be due to the difference in methodology. Sipiläinen and Oude Lansink (2005), in an unpublished paper, find that organic dairy farms are less technically efficient than conventional farms in Finland, using stochastic frontier distance functions. Strictly speaking, the difference between average technical efficiencies between organic and conventional farmers cannot be interpreted to suggest that one group is more efficient than the other one since production frontiers are different for organic and conventional holdings. Differences in efficiency simply indicate that farms belonging to the group with the higher average TE operate closer to their production frontier than farms from the other group do to theirs. In a recent article Mayen et al. (2010), using formal testing, reject the hypothesis that organic and conventional farms employ a single, homogeneous technology using data on US dairy farms. They also find that organic dairy technology is 13% less productive than that used by conventional farms and find little difference in TE across the two groups.

To our knowledge, the only study which considers TE as a potential factor driving adoption of OT is Kumbhakar et al. (2009). They propose a joint estimation where TE drives both technology choice and output. Using a sample of Finnish dairy farms (over the period from 1995 to 2002), their results suggest that inefficiency is not a driving force behind adoption of OT (inefficiency has a negative effect on the probability of adoption). They also find that on average, organic farms are about 5% less efficient than conventional farms.

In the forthcoming empirical application, we consider four-year average of TE (before adoption for future OF adopters) in order to smooth for climate shocks.

Risk

OF is generally perceived to be riskier than conventional farming, as organic farmers are restricted in the use of pesticides and artificial fertilizers that may help the farmer in reducing production risk (Gardebroek et al., 2010). Also, as it is the case with any new technology, a farmer willing to adopt OT has to face uncertainty regarding expected revenues and costs since it may take some time for him/her to learn about this new technology. Sipiläinen and Oude Lansink (2005), using data on Finnish dairy farms, estimate the length of the conversion and learning process of OF to be on average 6-7 years.

Gardebroek et al. (2010) estimate the Just-Pope stochastic production function using panel data of Dutch organic and conventional specialized arable farms covering the period 1990–1999. They find evidence that manure and fertilizers are risk-increasing inputs on organic farms but risk-decreasing inputs on conventional farms. Capital and land are found to reduce production risk while labor and other variable inputs are found to increase production risk in both farm types. However, unobserved differences in risk management or soil types are found to be much more important in explaining output risks on both farm types than variations in inputs used.

Using data from a sample of Spanish farms specialized in the production of arable crops, Serra et al. (2008) find evidence that both conventional and organic farmers are risk averse. Both groups are found to exhibit decreasing absolute risk aversion (DARA) but organic farmers have preferences that are very close to constant absolute and relative risk aversion (CARA and CRRA). The authors explain that these differences may come from the fact that organic farmers in the sample considered are wealthier than conventional growers (and may thus be willing to take more risk).

The measurement of risk aversion goes beyond the scope of this article. However, we will consider explanatory variables that may be linked to unobserved risk aversion. We include a categorical variable to control for the legal status of the farm which distinguishes between farms managed through a sole proprietorship, partnership management, and companies. In the latter, private assets are separated from professional assets so we would expect farms run as companies to be less risk averse than individual farms, in particular if there is no partnership in farm management.

We will also control for the ratio of debt to assets and assume that farms with a higher share of debt will be less likely to convert to OF due to their current financial vulnerability.

Social learning / neighborhood effects

As far as we know, the role of social learning and neighborhood effects on the adoption of OT has not been studied yet. However, it is recognized that information provided about new technologies (by other farmers, media, meetings, extension officers) usually positively correlates with adoption of these technologies (Knowler and Bradshaw 2007). Thus we should expect CT farmers neighboring OT farmers to learn more quickly about the technology and to have a higher probability to adopt OT. We will use the share of UAA under OT in the *département* where the farmer is located as a proxy for neighborhood effects in our regression models.

3.3. Descriptive statistics of the data

Table 2 presents descriptive statistics of the surveyed French farms during the years 1999-2006. Overall, 7,702 farms were included in the survey over this period. The largest farms in our sample are those specialized in COP (TF13) and other field crops (TF14), with an average UAA of 142 hectares (ha) and 111 ha respectively. These farms receive the highest amount of operational subsidies, on average, and are the least labor-intensive farms.

Table 2: Descriptive statistics of the data used; averages for the whole period 1999-2006

Type of farming	Number of farms	UAA (ha)	Total output (euros)	On-farm labor (AWU)	Total operational subsidies (euros)
TF13	2,505	142	109,193	1.6	52,939
TF14	1,298	111	186,270	2.4	36,063
TF28	412	14	261,059	4.8	6,647
TF29	275	4	255,058	4.7	2,031
TF37	1,441	23	231,215	3.4	3,477
TF38	517	41	128,975	2.5	7,860
TF39	603	32	196,269	5.2	15,356
TF60	651	81	151,978	2.6	28,457

Note: 1 AWU (Annual Working Unit) corresponds to a full-time equivalent of 2,200 hours of labor per year.

A summary description of the variables that will be used as explanatory factors in the OF adoption model is available in Appendix A1.

4. Methodology

4.1. A two-stage approach

We proceed in two steps. In the first step, we calculate the TE scores of all farms present in the FADN sample between 1999 and 2006. As it will be explained below, we use three competing methods to obtain TE scores and take into account that farmers operate in different agro-climatic conditions. In the second step, we estimate the probability of a farm converting to OF in the next year as a function of a set of farm and farmer characteristics including the farmer's average TE score computed over the past four years. The second-stage estimation is made on a selected sample of farms: those farms that are present at least one year during the 2003-2006 period and for which the TE score could be calculated over the four past years. Since our sample is a rotating sample, we are not able to control for entry and exit of farms over time. We believe that this procedure will not induce selection bias in the second-stage estimation.

We chose to calculate the average TE score over the past four years in order to get a "robust" measure of TE for each farmer. Indeed, farmers may exhibit lower TE scores when facing adverse weather conditions. A four-year average allows smoothing such effects. Going further than four years would have entailed the loss of too many observations at the second-stage of the analysis. Further details on the methodology are provided in the following.

4.2. First stage: calculation of TE

In the literature two main approaches compete to calculate TE: parametric methods, in particular stochastic frontier (SF), and non-parametric methods, in particular DEA and FDH. The SF approach relies on estimating a production function with a double error term, including a random error term and a term representing the technical inefficiency (Aigner et al. 1977; Meeusen and van den Broeck 1977). This method enables to account for noise, but may give rise to misspecification errors. By contrast, DEA is a deterministic method but does not rely on specification assumptions (see Farrell 1957; Charnes et al. 1978). The idea behind DEA is to construct, with linear programming, a piece-wise frontier that envelops all observations of the sample used. The distance of an observation to the frontier represents its technical inefficiency, with observations on the frontier being fully technically efficient and with a TE score of 1. FDH relies on the same idea, except that the convexity assumption of the frontier is relaxed, and thus the frontier is step-wise and envelops the observations more closely than DEA does (see Tulkens 1993).

In order to draw robust conclusions, the three approaches, namely SF, DEA and FDH, are used here. In each case the model includes one single output, namely total output in value, and four inputs, namely UAA (ha), total labor used in Annual Working Units (AWU; 1 AWU corresponds to one full-time equivalent that is to say 2,200 hours of labor per year), intermediate consumption in value, and the value of assets. The Translog function is specified for the SF approach. An input-oriented model is assumed for DEA and FDH. The assumption of variable returns to scale (VRS) is made for the DEA model. Separate frontiers are constructed per TF. In addition, in the case of DEA and FDH, yearly frontiers are constructed, while a single frontier on the merged period is estimated with SF, including a trend in the production function.

Farmers' TE may be affected by agro-climatic conditions, and the efficiency scores calculated may not reflect only farmers' management practices but may also incorporate some inefficiency component due to unfavorable natural conditions if the latter are not controlled for in the efficiency model. In our case, this may in turn affect the influence of TE on the probability to convert. For this reason, TE frontiers are constructed separately for groups of farms, depending on their agro-climatic conditions. Farms are firstly classified into two or three groups within each TF with a hierarchical agglomerative clustering procedure based on annual municipality data relating to slope, altitude, average monthly minimal temperatures, average monthly maximal temperatures, average water deficits and average monthly climatic indices (calculated with sunshine and frost durations and evapotranspiration). Then TE is calculated with separate frontiers for each cluster in each TF.

Non-parametric methods are sensitive to outliers. For this reason, in addition to cleaning manually inconsistent data, outliers were removed before efficiency computations with DEA and FDH based on Wilson's (1993) outlier detection method that relies on comparing geometric volumes spanned by subsets of data. Moreover, efficiency results from the DEA method may be affected by sampling variation. This problem, inherent to the method, implies that distance from the frontier (and thus inefficiency) may be underestimated if the most performing units of the population are not included in the sample at hand. To correct for this problem, bootstrapping followed by bias-correction or confidence interval construction is the only method available (Simar and Wilson 2000a). Here the smooth homogenous bootstrap proposed by Simar and Wilson (1998, 2000b) is used to provide bias-corrected technical efficiency scores for DEA.

4.2. Second stage: estimation of the determinants of the conversion to OF

Following (1), we assume that farmer *i* decides to convert to OF in period *t* if the expected net benefit of this decision is positive, that is if

$$d_{it}^{*} \equiv \sum_{t+1}^{t+5} E\left(\Pi_{it}^{\mathrm{OT}}\right) - \sum_{t+1}^{t+5} E\left(\Pi_{it}^{\mathrm{CT}}\right) > 0 \,. \qquad (2)$$

The latent variable, d_{it}^{*}, is not observed; only the decision to adopt OT or not is known to the econometrician. We assume that farm *i*'s expected net benefit from converting to OF can be modeled as follows: $d_{it}^{*} = \mathbf{X}_{it}^{'}\boldsymbol{\beta} + \varepsilon_{it}$, where the vector $\mathbf{X}_{it}$ includes characteristics of the farm and its environment. The decision model at time t is thus written as

$$d_{it}^{*} = \mathbf{X}_{it}^{'}\boldsymbol{\beta} + \varepsilon_{it} \geq 0 . \quad (3)$$

And the probability that farmer i adopts OT in year t is estimated using the following Probit model:

$$d_{it} = F\left(\mathbf{X}_{it}^{'}\boldsymbol{\beta}\right) + \nu_{it} , \quad (4)$$

where d_{it} equals 1 if the expected net benefit d_{it}^{*} is positive, and 0 otherwise. Function F is the cumulative distribution of the ε_{it} error term, assumed standard normal. Maximum-likelihood provides consistent estimates of the parameter vector $\boldsymbol{\beta}$.

Our purpose is to model the decision to convert to OF. In the data used farms that do adopt OT take the decision to convert to OF only once. Therefore, in our adoption model, a farm that converts to OF is included in the sample only once, in the year that the conversion is made, and excluded from the sample in the subsequent years (Khanna and Damon 1999 followed a similar approach). Since it is likely that the decision to adopt OT is made a year before the actual conversion, and in order to eliminate simultaneity bias, all explanatory variables are measured in year *t-1*.

The number of farms adopting OT is quite small in our sample (see Table 1), which makes it necessary, first, to estimate a unique adoption model with all TF merged and, second, to estimate the conversion model on a choice-based sub-sample in order to get a more balanced proportion of adopters and non-adopters (see Greene 2003). At this stage, 25 farms that converted to OF during the 2003-2006 period are included in our final sample along with 147 non-adopters randomly drawn from the entire population of non-adopters over the period. The random draw is designed such that non-adopters appear only once in the final sample. In order to correct the bias induced by over-sampling one group of farms, we estimate the model using the weighted endogenous sampling maximum likelihood (WESML) estimator derived by Manski and Lerman (1977). The log-likelihood function is written as follows:

$$\ln L = \sum_{i,t} \rho_{it} \left\{ d_{it} \ln F\left(\mathbf{X}_{\mathbf{it}}^{'}\boldsymbol{\beta}\right) + \left(1 - d_{it}\right) \ln\left[1 - F\left(\mathbf{X}_{\mathbf{it}}^{'}\boldsymbol{\beta}\right)\right]\right\} \quad (5)$$

where d_{it} describes the adoption decision ($d_{it} = 0$ or $d_{it} = 1$), $\rho_{it} = d_{it}(\kappa_1/\zeta_1) + (1 - d_{it})(\kappa_0/\zeta_0)$, with κ_1 and κ_0 the true population proportions (obtained from the representative sample of farms), and ζ_1 and ζ_0 the proportions of adopters and non-adopters in the choice-based sample.[8]

Three regression models will be estimated, differing in the TE score used as an explanatory variable: one regression including the average (over the past four years) TE score calculated with DEA under VRS and corrected for sampling bias; one regression including the average TE score calculated with FDH; one regression including the average TE score estimated with SF.

5. Results

5.1. Technical efficiency

Table 3 presents technical efficiency averages per TF calculated with the three different methods, with *ex ante* clustering of farms depending on the agro-climatic conditions. We distinguish farmers who converted to OF and farmers who use a CT during the years 2003-2006. For farmers who converted to OF, we report the average TE score before conversion. For each of the three TE scores (DEA-based, FDH-based, SF-based), we performed mean comparison tests between the two groups of farmers with the same TF (under the assumption that the variances in the two sub-samples are unequal). We indicate in the table when the null assumption that the two means are equal is rejected. We present graphs of the distribution of the TE scores for both groups of farmers in Appendix A2.

The average TE scores by TF vary depending on the computation method. For all TFs, the average TE score obtained using FDH is higher than the TE score calculated from the SF, itself being higher than the TE score obtained with DEA under VRS assumption.

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[8] The first and second derivatives of the log-likelihood function are weighted likewise and the asymptotic covariance matrix is corrected (Greene 2003).

Table 3: Technical efficiency results [a]: averages over the period 1999-2006

	Bias-corrected DEA-based TE score		FDH-based TE score		SF-based TE score	
	Farms under CT	Farms under future OT [b]	Farms under CT	Farms under future OT [b]	Farms under CT	Farms under future OT [b]
TF13	0.73	0.74	0.90	0.92	0.79	0.82(**)
TF14	0.71	0.75(*)	0.91	0.98(***)	0.81	0.78(*)
TF28	0.69	0.75	0.94	0.94	0.80	0.77
TF29	0.78	0.77	0.97	0.97	0.81	0.81
TF37	0.56	0.51(**)	0.78	0.70(***)	0.71	0.67(***)
TF38	-	-	-	-	0.68	0.62(**)
TF39	0.65	0.63	0.89	0.91	0.71	0.71
TF60	0.72	0.75	0.92	0.93	0.78	0.83(***)
Total number of farms	5,778	63	5,778	63	6,152	69

[a] Larger scores indicate higher TE.

[b] (*), (**), (***) respectively indicates that the null assumption that the two means are equal is rejected at the 10%, 5%, and 1% level of significance.

The mean comparison tests based on TE scores calculated with DEA indicate that farmers in TF14 (field crops) who will convert to OT have higher average TE scores than farmers who will keep operating with CT. The same conclusion is reached from the mean comparison test applied to FDH-based TE scores but we get the opposite result from the SF-based TE scores. The mean comparison tests provide consistent results across the three types of TE scores for TF37 (high quality wine): farmers who will convert to OT have significantly lower TE scores than farmers who will remain with CT. Finally, mean comparison tests indicate significantly different SF-based TE scores between farmers who decide to convert to OF and farmers operating under CT in TF13 (COP), TF38 (other grape production) and TF60 (mixed cropping).

5.2. Determinants of the conversion to OF

We present below the estimation results of the three Probit regression models, which differ only by the method of calculation of the TE scores (DEA-based, FDH-based, and SF-based) used as an explanatory variable. The three models are estimated on a sample of 172 farmers. A number of models were estimated differing on the explanatory variables' combination, and we kept the one which provided the best fit to our data.[9] In this model, the TE score has been interacted with the size of the farm (UAA), with the potential conversion subsidy that the farmer could receive if converting next year (POTCONVSUBS) and with the potential difference in price between organic and convention products (POTDIFPRICE). Standard errors have been corrected following the method described earlier. Some descriptive statistics of the explanatory variables used in the final model are presented in Appendix A3. In order to control for the representativity of our final sample of non-organic farmers, we perform mean comparison tests for each explanatory variable between the 147 non-organic farmers randomly drawn and the entire sample of non-organic farmers. The means are not statistically different except in one case: the second category of the education variable. Based on these findings, we are confident that the randomly drawn sample of non-organic farmers is representative of the entire population of non-organic farmers.

Results of the Probit estimations are presented in Table 4. Interestingly, only the TE score calculated from SFs is found to have a significant impact on the probability of conversion directly as well as indirectly through its cross effects with farm size ($\text{TE} \times \text{UAA}$) and potential subsidies from conversion ($\text{TE} \times \text{POTCONVSUBS}$). However, the marginal effect of past TE on the probability to convert to OF is found to be positive in the three models. In all three cases, the predicted probability of conversion is positively related to average past TE (see Figure 1). Our findings thus support those of Kumbhakar et al. (2009).

[9] In particular, farmer's age and regional dummies were tested.

Table 4: Results of the estimation of the probability to convert to OF

Probability of conversion to OF in the next year	DEA-based TE	P>z	FDH-based TE	P>z	SF-based TE	P>z
Constant	-7.137	0.036	-12.876	0.065	3.987	0.140
TE score (past 4-year average)	7.116	0.150	11.428	0.119	**-8.736**	**0.022**
UAA	0.000	0.993	0.013	0.447	**-0.043**	**0.011**
EDUC = 1 (ref.)	-	-	-	-	-	-
EDUC = 2	0.106	0.685	0.068	0.808	0.187	0.499
EDUC = 3	**0.706**	**0.028**	**0.602**	**0.070**	**0.742**	**0.038**
STATUS = 1 (ref.)	-	-	-	-	-	-
STATUS = 2	0.208	0.403	0.094	0.708	0.154	0.528
STATUS = 3	**0.838**	**0.017**	**0.883**	**0.019**	**0.923**	**0.013**
SH_ENVSUBS	**0.015**	**0.062**	**0.015**	**0.069**	0.007	0.241
DEBTTOASSET	-0.054	0.760	-0.123	0.557	0.039	0.797
FERT_SGM	-1.339	0.265	-1.635	0.208	-1.296	0.400
SUBTOOUT	0.109	0.918	0.519	0.623	1.326	0.250
POTDIFPRICE	0.021	0.570	0.017	0.769	-0.073	0.116
POTCONVSUBS	0.013	0.166	0.024	0.177	**-0.017**	**0.033**
TE x UAA	-0.002	0.874	-0.016	0.394	**0.049**	**0.011**
TE x POTCONVSUBS	-0.021	0.145	-0.028	0.156	**0.023**	**0.052**
TE x POTDIFPRICE	-0.021	0.745	-0.008	0.903	0.101	0.125
REG_SH_UAAOT	-8.174	0.301	-6.286	0.506	-11.611	0.214
REG_FARMSUBS	0.000	0.945	0.000	0.882	0.000	0.673
REG_N_FERTAREA	0.000	0.898	0.001	0.823	-0.001	0.890
Year 2003 (0/1)	-0.011	0.980	0.053	0.901	0.131	0.768
Year 2004 (0/1)	0.315	0.379	0.443	0.216	0.319	0.318
Year 2005 (0/1)	**0.714**	**0.033**	**0.766**	**0.020**	**0.622**	**0.057**
Log-pseudolikelihood	-7.527		-7.378		-7.577	
Pseudo R2	0.147		0.164		0.142	

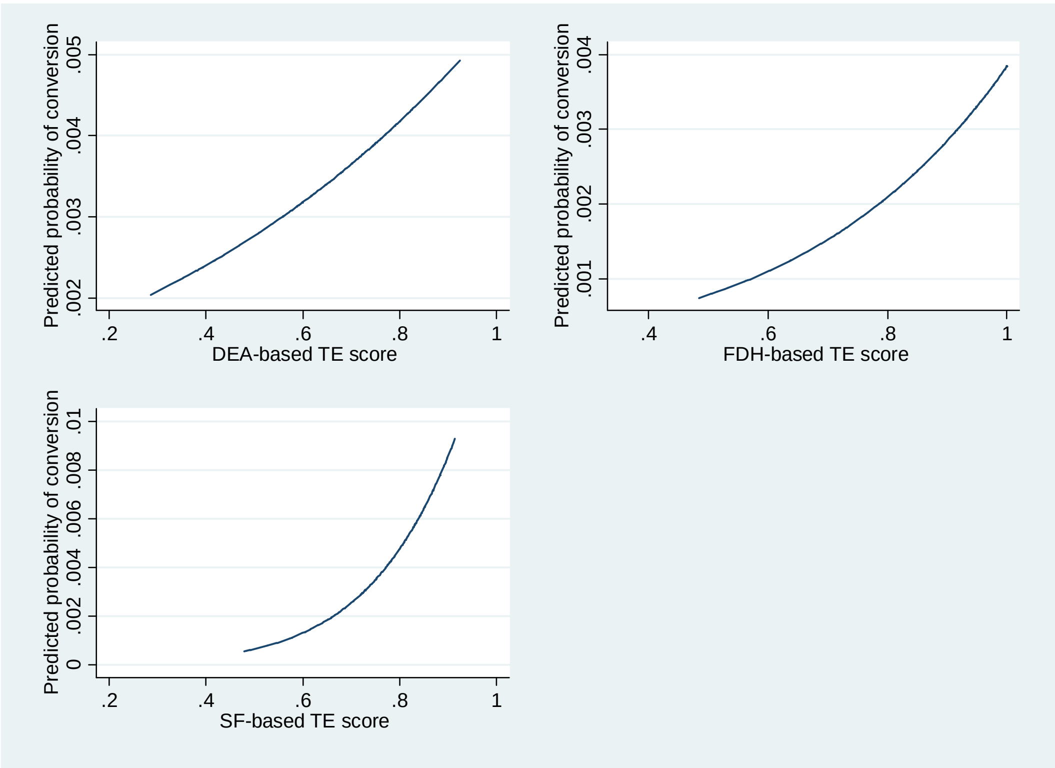
Note: in bold, significant effects.

The three models also provide consistent findings on the positive role of education: better educated farmers are found to be more likely to convert to OF than less educated farmers. More educated farmers may be more sensitive to environmental and food safety issues, they may also learn more quickly about new technologies, than less educated farmers. The legal status of the farm is also found to be a significant driver of conversion to OF. Farms with company-type status are more likely to convert to OF than farms with sole proprietorship. This result may be explained by farms in sole proprietorship being liable for all farm debts. These two findings confirm our expectation.

In the Probit model using SF-based TE, smaller farms (when size is measured by UAA) are found to be more likely to adopt OT, which is probably explained by smaller farms getting lower yields under CT than larger farms (and thus expecting a lower yield loss if converting to OF).

In two out of the three Probit regression models, we find the expected result that farmers receiving more agri-environmental subsidies (as a percentage of total subsidies) are more likely to convert to OF. Also, farmers who incur higher fertilizers expenditure (relatively to their standard gross margin) are less likely to convert to OF (this variable is however not significant in any of the three models). The role of the potential difference in prices (organic *versus* non-organic products) and the potential conversion subsidies that could be received annually if converting next year is indeterminate. We find a (non-significant) positive effect in two Probit regression models but a (non-significant) negative effect in one model. The variables observed at the aggregate level of NUTS2 and NUTS3 regions are not significant.

Figure 1: Predicted probability of conversion as a function of TE scores



In Table 5, we present the elasticity of the probability of conversion with respect to the four main variables of interest: 4-year average of TE score, UAA, potential difference in prices, and potential subsidies after conversion, for the three regression models. Elasticities have been computed at the sample mean.

Table 5: Elasticity of the probability of conversion

Elasticity of the probability of conversion with respect to:	Elasticity	Standard Error	p-value
Model with DEA-based TE scores			
TE score	0.891	1.597	0.577
UAA	-0.437	0.721	0.545
Potential difference in prices	-0.200	0.256	0.436
Potential conversion subsidies	-0.632	1.942	0.745
Model with FDH-based TE scores			
TE score	2.643	3.048	0.386
UAA	-0.122	0.763	0.873
Potential difference in prices	-0.269	0.282	0.341
Potential conversion subsidies	-0.029	2.276	0.990
Model with SF-based TE scores			
TE score	**4.740**	**2.702**	**0.079**
UAA	**-1.467**	**0.872**	**0.092**
Potential difference in prices	-0.109	0.197	0.580
Potential conversion subsidies	0.625	2.143	0.770

Note: in bold, significant elasiticities.

Elasticities of the probability of conversion with respect to TE scores are found to be positive in the three models, but significant only when TE scores are calculated using the SF approach. Elasticity with respect to farm size (UAA) is negative in the three models but significant only in the case of SF-based TE. The elasticities with respect to the potential difference in prices and with respect to the potential subsidies are not found significant. The low number of OT adopters in our sample probably explains the lack of significance of most elasticities.

The TE scores were calculated taking into account that farmers may operate in different agro-climatic conditions. In order to test for the role of such conditions on OT adoption, we re-calculated the TE scores without taking into account heterogeneity in agro-climatic conditions (i.e., without any clustering). The graphs showing how the predicted probability of conversion to OF varies as a function of TE scores are presented in Appendix A4. Interestingly, in two out of the three Probit models, the relationship is now found negative. Hence, not controlling for agro-climatic conditions when calculating TE scores may lead to the misleading conclusion that less efficient farmers have a higher probability to adopt the OT.

6. Conclusion

Using a sample of French farms over the 1999-2006 period, we test whether less technically efficient farmers are more likely to convert to OF in order to benefit from conversion subsidies. Despite some limitations in our data, we find no evidence of such selection effect and our findings support those of Kumbhakar et al. (2009) on Finnish farms. On the contrary, our estimation results indicate that more technically efficient farmers are more likely to convert to OF. This finding is found to be robust to the method of calculation of TE scores, either parametric (SF) or non-parametric (bias-corrected DEA or FDH). This study also confirms that farm's characteristics (education, farm size) and farmers' practices under the CT (as measured by the share of agri-environmental subsidies in total subsidies and expenditure in fertilizers) do impact the probability of conversion to OF.

The low number of OT adopters in our sample was the main limitation of our analysis and probably explains the lack of significance of a number of variables. With a higher number of observations, we could have tested for heterogeneous responses across different types of farming or geographical areas. We also expect in the future to be able to assess how TE has evolved for farmers who converted to OF.

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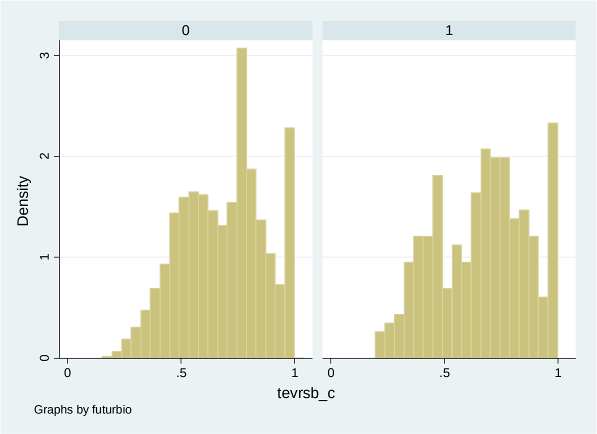
Appendices

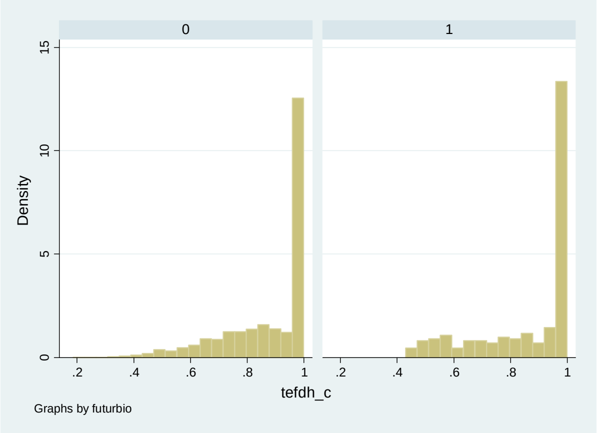
Appendix A1: Description of the explanatory variables used in the OF adoption model.

Variable name	**Measurement unit**	**Description**	**Source**
Farm and farmer-specific data			
UAA	ha	Farm's UAA	FADN 1999 to 2006
EDUC	Categorical variable	Farmer's education level 1. No or primary education 2. Low secondary education 3. High secondary education	FADN 1999 to 2006
STATUS	Categorical variable	Farm's legal status 1. Sole proprietorship 2. Partnership 3. Companies	FADN 1999 to 2006
SH_ENVSUBS	%	Farm's share of agri-environmental subsidies in total operating subsidies	FADN 1999 to 2006
DEBTTOASSET	ratio	Farm's debt to asset ratio	FADN 1999 to 2006
FERT_SGM	ratio	Farm's fertilizers expenditure to standard gross margin	FADN 1999 to 2006
SUBTOOUT	ratio	Farm's total operating subsidies to total output	FADN 1999 to 2006
POTDIFPRICE	euro	Potential difference in prices between organic and conventional products, for the farm	Authors' own calculation based on FADN 1999-2006
POTCONVSUBS	euro/ha	Potential yearly conversion subsidies, for the farm if converting next year	Authors' own calculation based on FADN 1999-2006
NUTS3 ("département") region-specific data			
REG_SH_UAAOT	Ratio	UAA under OT to regional UAA	IFEN
REG_FARMSUBS	Euro	Average amount of CAP (pillar 1 and pillar 2) subsidies received by farm beneficiaries	ODR
NUTS2 ("région") region-specific data			
REG_N_FERTAREA	kg/ha	Average ratio of regional amount of nitrogen used to regional fertilizable area	IFEN

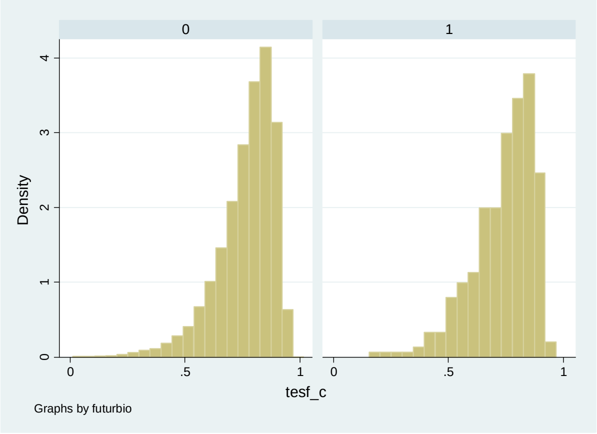
Appendix A2: Distribution of TE scores for farmers with CT (left graphs) and farmers who will convert to OT between 2002 and 2006 (right graphs)



TE scores computed from DEA



TE scores computed from FDH



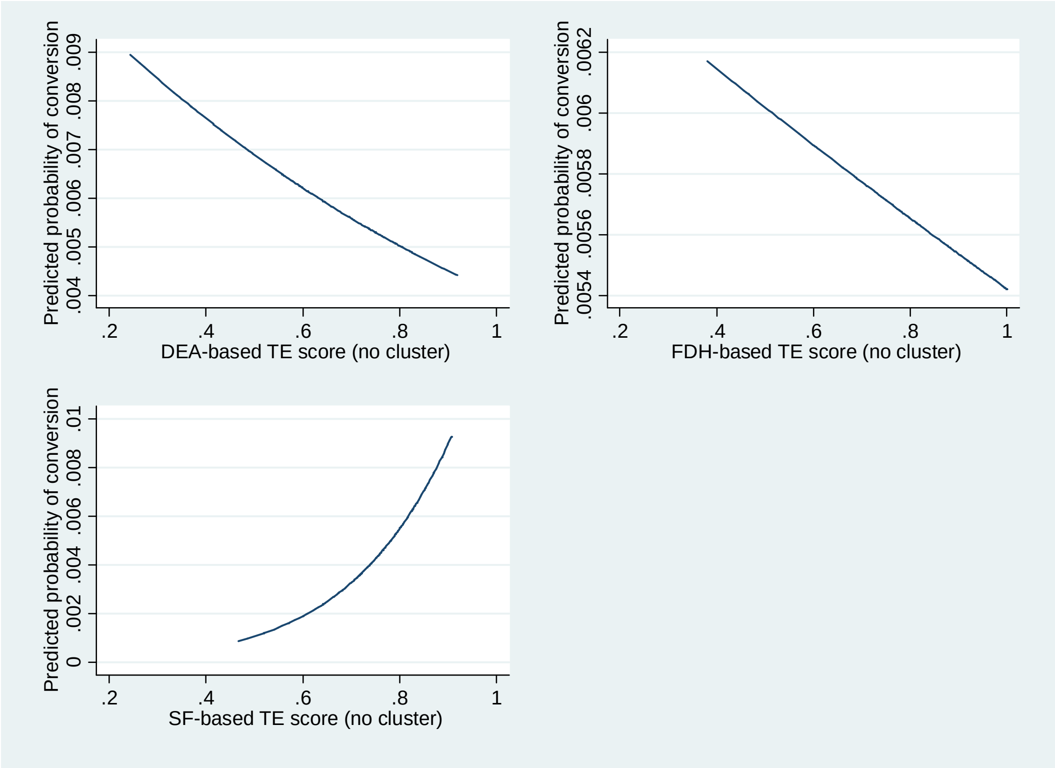
TE scores computed from SF

Appendix A3: Descriptive statistics of the explanatory variables in the Probit models (averages for the 2003-2006 period and mean-comparison test)

	Farmers with future OT Average (A)	Farmers with CT, random sample Average (B)	Farmers with CT, full sample Average (C)	Mean comparison test between (B) and (C) p-value
Number of farmers	25	147	2,755	
DEA-based TE score	0.64	0.65	0.66	0.40
FDH-based TE score	0.86	0.86	0.87	0.55
SF-based TE score	0.76	0.76	0.77	0.26
UAA	75	91	92	0.84
EDUC = 1	0.20	0.30	0.36	0.11
EDUC = 2	0.40	0.57	0.49	0.04
EDUC = 3	0.40	0.13	0.15	0.46
STATUS = 1	0.44	0.56	0.54	0.54
STATUS = 2	0.36	0.37	0.40	0.42
STATUS = 3	0.20	0.07	0.06	0.70
SH_ENVSUBS	6.0	3.4	2.9	0.59
DEBTTOASSET	0.96	0.80	2.00	0.69
FERT_SGM	0.10	0.13	0.13	0.90
SUBTOOUT	0.17	0.19	0.19	0.89
POTDIFPRICE	-9.17	-8.32	-10.25	0.49
POTCONVSUBS	328	320	329	0.46
REG_SH_UAAOT	0.02	0.02	0.02	0.75
REG_FARMSUBS	7,348	8,419	8,187	0.45
REG_N_FERTAREA	138	139	138	0.64

Appendix A4. Results when TE scores are calculated without taking into account that farmers operate in different agro-climatic conditions.

Predicted probability of conversion as a function of TE scores



Elasticity of the probability of conversion

Elasticity of the probability of conversion with respect to TE score:	Elasticity	Standard Error	p-value
DEA-based TE scores	-0.652	1.367	0.633
FDH-based TE scores	-0.171	2.017	0.933
SF-based TE scores	3.894	2.333	0.095