Technical efficiency and conversion to organic farming: the case of France

Laure Latruffe

INRA, UMR 1302 SMART, F-35000 Rennes, France
Agrocampus Ouest, UMR 1302 SMART, F-35000 Rennes, France

Céline Nauges

Toulouse School of Economics (LERNA-INRA), France

Working Paper LERNA n°10.23.329, Toulouse (France)

December 2010

Available at http://www2.toulouse.inra.fr/lerna/

Technical efficiency and conversion to organic farming: the case of France

Laure Latruffe [a, b] and **Céline Nauges** [c]

[a] INRA, UMR 1302 SMART, F-35000 Rennes, France

[b] Agrocampus Ouest, UMR 1302 SMART, F-35000 Rennes, France

[c] Toulouse School of Economics (LERNA), France

Abstract

Using a sample of French crop farms during the 1999-2007 period, we test whether farmers' technical efficiency under conventional practices is a significant driver of conversion to organic farming. An important issue is whether subsidies to organic farming could encourage inefficient farmers to convert. We find that the probability of conversion does depend on technical efficiency preceding the conversion, but that the direction of the effect depends on farm size. This result 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, indebtedness) and farmers' practices under conventional farming do impact the probability of conversion to OF.

Keywords: Organic farming; technical efficiency; subsidies; adverse 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 the EU the first national subsidization programs started in a few countries like Denmark and Austria at the end of the 1980s, while the EU-wide recognition arrived with the Council Regulation 2092/91 and the inclusion of support to OF in agri-environmental measures (Stolze and Lampkin 2009). The rationale behind subsidies to OF is that farmers internalize negative externalities on the environment, without being paid for it on the market.

Although there exist claims that agricultural subsidies in general have rather favored conventional systems to the detriment of organic systems (e.g. Nemes 2009), the provision of specific support to OF may be the main motivation to adopt the organic technology (OT) for some farmers. In her literature review Padel (2001) noted for example that the adoption of OT had been higher in those European countries where the support program for OF was more favorable. If conversion to OF has historically been based on ideological motives and other non-economic factors, a shift to financial motivation has been observed since the late 1990s when payments for OF started to be introduced (Rigby et al. 2001; Darnhofer et al. 2005; McCarthy et al. 2007). Farmers adopting OT based on economic aspects are identified in the literature as “pragmatic”, in opposition to “committed” converters. The possibility of OF specific subsidy programs attracting “subsidy-hunters” has been discussed by Pietola and Oude Lansink (2001) and Tzouvelekas et al. (2001), but seldom tested.

If the objective of the policy is to support agricultural activity and farmers’ income, then attracting “subsidy hunters” into OF may not be a problem per se. However, if the policy is aimed at maximizing organic production at the least possible cost, then it may be worth checking who is attracted by the subsidy program. Indeed, if “subsidy-hunters” make their production choices based on the maximization of subsidies received, they are likely to be less efficient than farmers who search for the best combination of outputs and inputs based on prices and available technology. In this particular situation, the subsidy program could induce some *adverse selection effect* that may not be considered desirable by the policy makers.

The main purpose of this paper is to investigate whether less efficient farmers are more likely to convert. This test has been made 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. They do not find any evidence of an adverse selection effect since, on their sample, inefficiency did not increase the probability of conversion to OF. In this article we test the adverse selection hypothesis on a sample of French crop farms by assessing the impact of past TE on the decision to convert to OF. By contrast to Kumbhakar et al. (2009) who perform a joint estimation, we employ a two-stage approach. We estimate 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, TE 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. The data used cover several years, enabling us to investigate the influence of several farm characteristics, including TE, in past periods, on the decision to adopt OF.

There exist a number of articles comparing TE of organic producers and conventional producers. Such comparisons are an indication of how close to the production frontier each group of farmers operates. But because organic and conventional production technologies are different in most cases (Mayen et al. 2010), such a comparison cannot be used as evidence for or against the adverse selection hypothesis. We argue that such evidence can only be obtained by estimating simultaneously production choices and decision to convert to OF (Kumbhakar et al. 2009) or by investigating the role of past characteristics, including TE, on the probability to adopt OT (this paper).

Another contribution of this paper is to provide 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. Only 2% of the total arable land in France was under OF in 2007, a figure lower than what is observed in most European countries, e.g. Spain (4%), Germany (5%), Portugal (6%), Italy (9%) and Sweden (10%) (Agence Bio 2010). In 2007 the French government launched a broad reflection on the state of the environment in the country (the *Grenelle de l'Environnement*) and on measures to improve the condition of the environment. In particular, the government has set an objective of a threefold increase of the national area under OF between 2007 and 2012 (i.e., an increase from 2% to 6%), and an increase to 20% in 2020. Some crucial policy steps are necessary to attain this objective, since at the end of 2008 only 2.1% of the national utilized agricultural area (UAA) were under OF. Understanding the determinants of conversion to OF and in particular the effect of past performance (as measured by technical efficiency) will provide valuable information for designing successful policy programs.

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

For comparability purposes, we focus our analysis on crop farming and disregard livestock farming, for which requirements for converting to OF are more complex. 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 (Ministère de l’Agriculture 2001). 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 the period under consideration, there was no support scheme for organic farmers in France after the conversion period had ended.

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 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. The price differential may compensate (at least partly) for the loss in productivity since yield under OT is expected to be lower than yield under CT $\left(y_t^{\mathrm{OT}} < y_t^{\mathrm{CT}}\right)$. As the farmer cannot sell products under certified organic labeling before the end of the transition period, that is to say before three years of conversion have passed[1], the following relationships apply: $p_t^{\mathrm{OT}} = p_t^{\mathrm{CT}}$ in $t+1$ and $t+2$ and $p_t^{\mathrm{OT}} > p_t^{\mathrm{CT}}$ from $t+3$ onwards. The price differential in favor of organic products has for example been given evidence by McBride and Greene (2009). The authors have shown that, for US soybean producers, the commodity price per bushel was on average more than USD 9 higher for organic than for conventional soybean in 2006. By contrast, average organic soybean yields were 16 bushels per acre lower than yields of conventional soybean. Oelofse et al. (2010) also report lower yield (differential of 279 kg per hectare (ha)) but higher price (differential of USD 0.05 per ha) for organic soybean than conventional soybean for a Chinese farmers sample. Unfortunately, official statistics on the price of organic products do not exist in France.

In our modeling framework, input prices are assumed to be the same $\left(w_t^{\mathrm{OT}} = w_t^{\mathrm{CT}}\right)$.[2] The impact of converting to OT on input costs is ambiguous *ex ante* since we expect, on the one hand, a decrease in the use of fertilizers and plant protection under OT, but, on the other hand, an increase in the use of labor and machinery costs. Sainte-Beuve (2010) reports such discrepancies for French farms in 2007.

---

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

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

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 $\left(s_t^{\mathrm{OT}} > s_t^{\mathrm{CT}}\right)$[3].

On an economic point of view, subsidies are justified by organic farmers' private internalization of social costs caused to the society from environmental pressures. On a practical point of view, subsidies may be seen as compensatory payments for 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. In France the level of conversion subsidies set by the government is calculated on the basis of the potential profit loss depending on the type of crop, and is provided per hectare of specific crop converted. For example cereals would be eligible to 366 euros per hectare in the first two years following conversion, 183 euro/ha in the following two years, and 122 euro/ha in the fifth year (Ministère de l'Agriculture 2001).

The decision of each farmer to convert to OF will thus depend, among other things, on production technology, organic price premium, costs differentials, conversion subsidies 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.

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 2007. 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, based on the FADN classification according to farm 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. This classification is the standard EU classification called Type of Farming (TF). The TF

[3] During the period analysed in our paper, French farmers could receive subsidies in the frame of the EU Common Agricultural Policy agri-environmental measures during the conversion period to OF. However, unlike all other EU Member States, France did not yet provide subsidies to remain in OF (Stolze and Lampkin 2009).

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 imprecision. 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, the first conversion period that is considered here is therefore 2003. The earlier years of data (1999-2002) are used to calculate TE scores of the farmers who are still present in the FADN sample during the 2003-2007 years.

Table 1 presents the number and share of farms having converted to OF during the period going from 2003 until 2007. The number of farms adopting OT is in general low, and this is partly due to the fact that we cannot consider partial conversions in our database. Overall 66 farms in our sample have converted to OF in the selected TFs, which represents 1.1% of the sampled farms. A higher rate of conversion is observed for TF38 (other grape production than high quality wine). Among the 66 farms, 14 have converted to OF in 2003, 7 in 2004, 17 in 2005, 17 in 2006, and 11 in 2007.

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

	Total number of farms	Number of farms having converted to OF	% of farms having converted to OF within the specific TF
TF13 (COP)	1,972	14	0.7%
TF14 (other field crops)	940	7	0.7%
TF28 (fruits and vegetables)	311	4	1.3%
TF29 (horticulture)	235	4	1.7%
TF37 (high quality wine)	1,127	16	1.4%
TF38 (other grape production)	344	8	2.3%
TF39 (permanent crops)	468	7	1.5%
TF60 (mixed crop farming)	433	6	1.4%
Total	**5,830**	**66**	**1.1%**

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. For example, 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, or previous experience) instead of being related to reduce grain surplus, market adjustment, better economy or support provided (Lohr and Salomonsson, 2000). Also Läpple (2010) finds that Irish drystock farmers who expressed a higher level of environmental concern were more likely to adopt OT in 2008. Similarly, Genius et al. (2006) indicate that in 1996-1997 Cretan farmers who expressed great concern about environmental problems were more likely to convert to OF. The same finding is reported by Burton et al. (2003) for horticultural farmers surveyed in 1996 in the United Kingdom. Our data do not contain any variable on farmer's opinion about issues related to environment, health and food quality. We 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 under conventional farming is more likely to convert to OF.

We also control for the farmer's level of education. 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”. For example, Genius et al. (2006) find that the number of years of education increased the probability to convert to OT by Cretan farmers in 1996-1997. Gardebroek (2003) also indicates a positive effect of education on the conversion probability for Dutch dairy farms in 1994-1999. Similarly, Koesling et al. (2008), for a survey of Norwegian farms in 2003, find a positive effect of education on the probability that a surveyed conventional farmer has indicated to potentially convert to OF in the future. Since better educated persons are often more sensitive to environmental problems but also because of the assumed positive link between education and knowledge regarding new technologies, we hypothesize better educated farmers to be more likely to adopt OT.

Farm’s structural characteristics

We expect the size of the farm at the time it was operated under conventional practices to influence the decision to convert to OF. 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. This reason is also proposed by Gardebroek (2003) to explain the positive effect of farm UAA on the probability to convert for Dutch dairy farms during 1994-1999. By contrast, Läpple (2010) finds that farm UAA has a negative effect on farmers’ decision to adopt OT for a sample of drystock farms in Ireland in 2008. McBride and Greene (2009) also report that the likelihood of choosing OT decreases with farm acreage for US soybean producers in 2006. They explain that small farms suffer from size diseconomies and consider OF as an alternative to improve farm returns. The situation may be similar in France 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 and less productive. 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) are 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 empirical 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 into OF less productive conventional farmers who are more "pragmatic" than "committed". 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. Lohr and Salomonsson (2000) report that 147 out of 234 Swedish organic producers who converted in 1990 following the introduction of the conversion subsidy scheme in the country in 1989, would not have converted in the absence of subsidies. Tzouramani et al. (2010), using a real option approach on a sample of dairy sheep farms in Greece, explain that organic farming is not a profitable option in the absence of organic subsidies even if farms can benefit from investment subsidies to adopt the new technology. In what follows, we will calculate the organic subsidy level 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 on the farm does not change after conversion.[4] We then use in the model the average conversion subsidy per ha of UAA per year. We hypothesize that a higher potential conversion subsidy per ha 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), and expect a positive effect as

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

public subsidies may reduce the farm's financial pressure. This effect was hypothesized and given evidence by Genius et al. (2006), who find that subsidies received in the context of the CAP by Cretan farmers in 1996-1997 increase their probability to convert to OF. The effect of non-organic subsidies on the probability to adopt the OT may also reflect the attitude of the farmer towards subsidies. However, this effect 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 CAP 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 products under conventional practices 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 products before adoption could also indicate farmers' environmental awareness and thus a higher probability to adopt OT. Also, conventional farmers who use a relatively low level of fertilizers and plant protection products are more likely to use a technology which is in fact similar to the OT, and may thus be more likely to adopt OT. The effect of the intensity of fertilizers' and plant protection products' use before conversion is therefore ambiguous but we expect the latter effect to dominate, that is to say low input use under conventional farming should increase the probability to convert to OF. McBride and Greene (2009) calculate farming cost under OT and CT for a sample of soybean producers in the US in 2006. The authors find that costs per bushel are on average USD 1 to USD 6 higher under OT than under CT. In particular, while chemical costs are lower under OT, capital and labor costs are much higher. Oelofse et al. (2010) report that total variable costs were higher for a sample of Chinese organic soybean producers compared to their conventional counterparts. The differential was USD 116 per ha, which is mainly due to a differential of USD 177 per ha in hired labor cost in disfavor of organic producers. Not using data from a sample of farms but with a case-study of one farm in England, Cobb et al. (1999) find that switching to OF induces higher labor costs and higher fixed costs (on this particular farm the conversion to organic agriculture required different machinery). Comparing one organic dairy farm with a conventional one with equivalent structure in 2003-2007, Shadbolt et al. (2009) indicate that the organic holding incurred higher fixed cost but lower cost per cow (veterinary, feed). 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, but we do not have a priori expectations on the sign of the effect.

Potential change in revenues

In France, a farmer converting to OF will usually experience a decrease in revenue, at least during the first years of conversion. We expect that farmers for whom the expected decrease in revenue after conversion from CT to OT is lower to be more likely to adopt OT. This is confirmed for example by the study by Gardebroek (2003) for Dutch dairy farms in 1994-1999, who finds that past year profit has a negative effect on the choice of adopting OT. Farms with higher past profit may indeed incur higher decrease in revenue if they converted to OT. It may also be the case that a positive shock on profit may encourage to continue with the current technology whereas a negative shock may encourage switching. The revenue differential depends 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 has also an impact on expected revenues, as motivated in the modeling section. 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. This calculation is made under the assumption that the cropping pattern remains unchanged on the converting farm and that the entire crop area is converted.[5] 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. In our analysis 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 try to assess the influence of TE before adoption on the decision to convert to OF. Some studies suggest that organic farmers are more technically

---

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

efficient compared to conventional farmers: e.g. Tzouvelekas et al. (2001) applying stochastic frontier to data on olive-growers in Greece, and Oude Lansink et al. (2002) applying DEA on data from crop and livestock farms in Finland. Other studies suggest the opposite: e.g. 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. Similarly, 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. Based on a sample of Finnish dairy farms (over the period 1995-2002), their results suggest that inefficiency is not a driving force behind adoption of OT as the inefficiency score has a negative effect on the probability of adoption. The level of TE achieved under CT may have an ambiguous effect on the decision to adopt OT. On the one hand, farmers who are already technically efficient under CT, that is to say who have rationalized their use of inputs, may adopt more easily a technology that is complex and that uses low levels of inputs. On the other hand, conversion implies a decrease in yields, and this may reduce incentives to convert for technically efficient farmers who obtain high yields under CT. The ambiguity is reinforced by the allocation of conversion subsidies. Indeed, conversion subsidies may compensate for the loss in revenue during the conversion period, and thus may reduce the negative influence of TE on the decision to convert to OF; it may in turn motivate highly efficient farmers to convert. However, if there is no obligation or no financial incentives to remain under OT after the conversion period, as it was the case in

France during the period studied here, then this may attract low efficient farmers in the organic sector, who may revert to CT once the compulsory conversion period has ended.

In the forthcoming empirical application, in order to test for the effect of TE under CT on the decision to convert to OF, we consider four-year average of TE calculated before adoption for future OF adopters. By contrast to Kumbhakar et al. (2009) who use data from the same period to estimate TE and the probability to convert, we use data from the period before conversion to OT. Moreover, we use an average over several years in order to smooth for climate shocks that may affect TE levels.

Risk

OF is generally perceived to be riskier than conventional farming, as organic farmers are restricted in the use of chemical pesticides and fertilizers that could help them in reducing production risk (Gardebroek et al., 2010). Organic farmers are therefore more exposed to disease or parasite outbursts, and to harsh weather conditions. 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 other 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 it in both farm types.

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). Gardebroek (2006), using a Bayesian random coefficient model, finds that organic arable farmers were less risk averse than conventional arable farmers in the Netherlands during the period 1990-1999. Regarding the link between risk attitude and conversion to OF, Acs et al. (2009) simulate the adoption of OT by a typical farm in the Netherlands with mathematical programming model. The authors find that the degree of risk aversion influences the adoption decision. In particular, it is optimal for a risk-averse farmer to adopt OT only in the scenarios of pesticide tax or conversion subsidies. Kerselaers et al. (2007) explain that one reason to low OT adoption in Belgium is the perception that farmers have of the production risks in OF, which influences in turn their perception of higher economic potential under OF. This implies that risk-averse farmers would have a lower willingness to convert. Using a sample of Irish drystock farms surveyed in 2008, Läpple (2010) finds that risk aversion, proxied by component scores calculated from several attitudinal statements, decreases the probability to adopt OT. Similarly, Kallas et al. (2010) find that Spanish grape producers surveyed in 2008 who took risky management decisions, were more likely to convert to OF.

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, farms under partnership management, and companies. In the latter, private assets are separated from professional assets and therefore we would expect farms run as companies to be less risk averse than individual farms. We will also control for the ratio of farm debt to assets and hypothesize 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 extensively studied yet. It is recognized that information provided about new technologies (by other farmers, media, meetings, farmers' unions, extension officers, etc) usually positively correlates with adoption of these technologies (Knowler and Bradshaw 2007). Moreover, observing successful organic farmers could give incentives to conventional farmers to convert (Lohr and Salomonsson 2000). Lohr and Salomonsson (2000) find for example that, for a sample of Swedish farmers in 1990, the number of organic farms in a farmer's district increases his/her probability to convert. 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. Unfortunately we do not have any information on the total number of farms engaged in OF in the neighborhood of the farms surveyed in our sample.

3.3. Descriptive statistics of the data

Table 2 presents descriptive statistics of the FADN sample French farms during the years 1999-2007. Overall, 7,946 farms were included in the FADN 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 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; farm averages for the whole period 1999-2007

Type of farming	Number of farms	UAA (ha)	Total output (euros)	On-farm labor (AWU)	Total operational subsidies (euros)
TF13 (COP)	2,592	142	112,263	1.6	53,092
TF14 (other field crops)	1,338	111	187,623	2.4	36,679
TF28 (fruits and vegetables)	409	14	259,828	4.9	6,461
TF29 (horticulture)	283	4	252,026	4.7	2,058
TF37 (high quality wine)	1,482	23	226,841	3.4	3,478
TF38 (other grape production)	536	41	128,880	2.6	7,943
TF39 (permanent crops)	628	33	197,173	5.2	15,525
TF60 (mixed crop farming)	678	82	152,881	2.6	28,759

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

A summary description of all variables that will be used as explanatory factors in the OF adoption model is available in Appendix A1 and some descriptive statistics of these variables are presented in Appendix A2. The summary statistics indicate that farmers who convert to OT have (on average) lower TE scores (how TE scores are calculated is explained below), operate a smaller farm, are more educated, receive a higher share of agro-environmental subsidies, and are less indebted than farmers who continue to operate under CT.

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 2007. 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 a specific year as a function of a set of farm and farmer characteristics before conversion, including the farmer's average TE score computed over the four years preceding the conversion. The second-stage estimation is made on a selected sample of farms: those farms that are present at least one year during the 2003-2007 period and for which the TE score could be calculated over the four years preceding conversion. 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 shortcoming of the dataset will not induce selection bias in the second-stage estimation.

We chose to calculate the average TE score over the four years preceding the conversion 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 and avoid peaks or drops in TE that would be only artifacts of specific years. 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 farmers' technical inefficiency (see 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).

Non-parametric methods are sensitive to outliers as they construct the frontier with observations at hand. 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.

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 Cobb-Douglas function is specified for the SF approach.[6] An input-oriented model is assumed for DEA and FDH. The assumption of variable returns to scale (VRS) is made for the DEA model.

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 and maximal temperatures, average monthly water deficits and average monthly climatic indices (calculated with sunshine, frost durations and evapotranspiration).[7] Then TE is calculated with separate frontiers for each cluster in each TF and in each year of the period.

[6] When using a Translog specification for the stochastic frontier, convergence could not be achieved in some cases.

[7] Details on the clustering procedure are available upon request.

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

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

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 farmer and its environment. The decision model at time *t* is thus written as

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

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

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

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 farmers who 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). For consistency, and to avoid the presence of repeated observations over time, a random draw is designed such that non-adopters also appear only once in the final sample. Since it is likely that the decision to adopt OT is made (at least) a year before the actual conversion, and in order to eliminate simultaneity bias, all explanatory variables are measured in year *t-1*, except for the TE proxy that is measured as the average of TE scores calculated in years *t*-4, *t*-3, *t*-2 and *t*-1, with *t* being the year of conversion for farmers who convert and being the year of observation for farmers who remain in conventional farming.

Three regression models will be estimated, differing in the TE score used as an explanatory variable: one regression including the average (over the four years preceding conversion of the converting farm or preceding observation of the conventional farm) 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 their agro-climatic conditions. We distinguish farmers who converted to OF between 2003 and 2007, and farmers who continued to use a CT during the years 2003-2007. For farmers who converted to OF, we report the four-year average TE score before the conversion period. For farmers who remained in conventional farming, we report the four-year average TE score before the year of observation. For each of the three TE scores (DEA-based, FDH-based, SF-based), we performed mean comparison tests between the two groups of farmers within the same TF (under the assumption that the variances in the two sub-samples are unequal). We indicate in Table 3 when the null assumption that the two means are equal is rejected.

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.

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 remaining under CT	Farms under future OT [b]	Farms remaining under CT	Farms under future OT [b]	Farms remaining under CT	Farms under future OT [b]
TF13 (COP)	0.73	0.74	0.90	0.92	0.80	0.85 (***)
TF14 (other field crops)	0.71	0.74	0.91	0.98 (***)	0.81	0.79
TF28 (fruits and vegetables)	0.69	0.73	0.94	0.93	0.82	0.80
TF29 (horticulture)	0.78	0.77	0.97	0.97	0.84	0.85
TF37 (high quality wine)	0.56	0.50 (**)	0.78	0.70 (***)	0.72	0.72
TF38 (other grape production)	0.63	0.60	0.82	0.77	0.69	0.63 (*)

TF39 (permanent crops)	0.65	0.63	0.89	0.91	0.72	0.75
TF60 (mixed crop farming)	0.72	0.74	0.93	0.93	0.84	0.90 (**)
Total number of farms	6,096	65	6,096	65	6,156	65

[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 indicate that farmers growing field crops (TF13, 14, and 60) and who will convert to OT have higher average TE scores than farmers who will keep operating with CT (except for TF14 with SF). The difference in average TE scores is statistically significant for SF-based TE scores in TF13 and TF60, and for FDH-based TE scores in TF14. For farmers engaged in wine and grapes production (TF37 and TF38), the average TE scores for farmers who will convert to OT are lower than the average TE scores for farmers who will remain with CT. The difference between average TE scores is statistically significant for DEA-based and FDH-based TE scores in TF37 and for SF-based TE scores in TF38. Finally, for farmers growing fruits and vegetables (TF28) or engaged in horticulture (TF29), there is no clear pattern and no statistically significant difference between TE scores of the two groups of farmers.

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 3,761 farmers, including 43 OT adopters. The number of farms adopting OT is quite small in our sample (see Table 1), which makes it necessary to estimate a unique adoption model with all TFs merged. 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. In this model, the TE score has been interacted with the size of the farm (UAA).[8]

[8] In particular, farmer's age and regional dummies were tested as well as terms interacting TE score 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).

Table 4: Results of the estimation of the probability to convert to OF (3,761 farmers)

Probability of conversion to OF in the next year	Model with DEA-based TE score		Model with FDH-based TE score		Model with SF-based TE score	
	Coef.	P>z	Coef.	P>z	Coef.	P>z
TE score (past four-year average)	**-1.490**	**0.027**	**-1.517**	**0.026**	**-1.491**	**0.062**
UAA	**-0.010**	**0.041**	**-0.014**	**0.043**	**-0.021**	**0.039**
EDUC = 1 (ref.)	-	-	-	-	-	-
EDUC = 2	0.113	0.458	0.108	0.476	0.098	0.520
EDUC = 3	**0.455**	**0.008**	**0.453**	**0.008**	**0.417**	**0.014**
STATUS = 1 (ref.)	-	-	-	-	-	-
STATUS = 2	-0.053	0.716	-0.021	0.885	-0.003	0.981
STATUS = 3	0.167	0.452	0.212	0.333	0.242	0.268
SH_ENVSUBS	**0.011**	**0.000**	**0.010**	**0.000**	**0.011**	**0.000**
DEBTTOASSET	-0.010	0.817	-0.006	0.848	-0.008	0.818
FERT_SGM	-1.030	0.313	-1.063	0.297	-1.010	0.322
SUBTOOUT	0.198	0.750	0.104	0.865	0.118	0.850
POTDIFPRICE	0.003	0.260	0.003	0.235	0.002	0.496
POTCONVSUBS	0.000	0.793	0.000	0.816	0.000	0.717
TE × UAA	**0.014**	**0.053**	**0.015**	**0.054**	**0.024**	**0.042**
Year 2003 (0/1)	0.144	0.531	0.172	0.451	0.156	0.495
Year 2004 (0/1)	**0.368**	**0.080**	**0.389**	**0.061**	**0.401**	**0.053**
Year 2005 (0/1)	0.272	0.204	0.296	0.161	0.289	0.173
Year 2006 (0/1)	0.103	0.642	0.137	0.528	0.132	0.545
Constant	-1.439	0.022	-1.109	0.137	-1.206	0.125
N	3,761		3,761		3,761	
Pseudo R2	0.0865		0.0865		0.0856	
Log-pseudolikelihood	-214.67697		-214.6904		-214.89524	

Note: in bold, significant effects. Definition of explanatory variables in Appendix A1.

Results of the Probit estimations are presented in Table 4 (robust standard errors were calculated). The four-year average TE score is found to have a significant impact on the probability of conversion directly as well as indirectly through its cross effects with farm size (TE × UAA), whatever the method used to calculate the TE score. In all three models, the direct effect of the TE score on the probability of conversion is negative and statistically significant while the cross term with farm size has a negative effect. Hence, the effect of past performance on the probability of conversion to OF depends on farm size.

In our sample, the elasticity of the probability of conversion with respect to the TE score is found to be negative for low values of farm size and positive for high values of farm size. The turning point is calculated at 109 ha in the model using DEA-based TE scores, 101 ha in the model using FDH-based TE scores, and 61 ha in the model using SF-based TE scores. For the sample used for estimating the model, the average farm size is 87 ha, hence the elasticity of the probability of conversion to the four-year average TE score is negative for some farms and positive for others.

Because our sample gathers farms engaged in different production specializations (TF), it is important to check whether our main result, that the elasticity of the probability of conversion depends on farm size, holds for the entire group of farmers as a whole or if it could be driven by heterogeneous effects across different TFs. The number of adopters in each TF is too small to permit separate Probit estimations by TF. However, it is possible to interact TF dummies with the four-year average TE score and/or to add TF dummies in the model. We re-estimated the three Probit models under these different specifications. In any case do the TF dummies come out significantly. This indicates that our findings hold for all farmers in our sample whatever their TF. The main conclusion would thus be that "low-efficient" farmers operating a farm which size is below a certain threshold (61 ha to 109 ha depending on the model) are more likely to convert to OF while "high-efficient" farmers operating a farm which size is above this threshold are more likely to convert to OF.

In our sample though, the average size of farms growing field crops is higher than the threshold (in TF13 and TF14 the average farm size is 142 ha and 115 ha respectively, and the average farm size is 82 ha in TF60) while the average farm size for farms growing grapes, fruits, vegetables or flowers is lower than the threshold. Our findings thus may indicate that a higher past performance induces a higher probability of conversion to OF in field crops but a lower probability of conversion to OF in other TFs.

In order to assess the magnitude of the effect of TE on the probability of conversion to OF, we calculate, for each type of farming activity, the expected probability of conversion if all farmers were technically efficient (Table 5). In the second and third columns of Table 5, we report the current (observed) probability of conversion and the current number of organic farmers. We then show, for each of the three models (models with DEA-based, FDH-based, and SF-based TE scores) the predicted probability of conversion and the corresponding predicted number of organic farmers. These predicted probabilities have been calculated at the sample mean for each type of farming activity, and under the assumption that the average TE score is 1 (fully technically efficient farmers).

Table 5: Predicted probability of conversion and number of organic farmers if all farmers were technically efficient

			Model with DEA-based TE scores		Model with FDH-based TE scores		Model with SF-based TE scores	
Type of farming	Current probability of conversion	Current number of OF farmers	Predicted probability of conversion	Predicted number of organic farmers	Predicted probability of conversion	Predicted number of organic farmers	Predicted probability of conversion	Predicted number of organic farmers
TF13 (COP)	0.006	9	0.009	13	0.007	11	0.014	20
TF14 (other field crops)	0.012	7	0.007	4	0.008	4	0.012	7
TF28 (fruits and veg.)	0.011	2	0.004	1	0.010	2	0.007	1
TF29 (horticulture)	0.020	1	0.004	0	0.011	1	0.008	0
TF37 (high qual. wine)	0.015	12	0.002	2	0.005	4	0.005	4
TF38 (other grape prod.)	0.021	5	0.003	1	0.006	1	0.007	2
TF39 (permanent crops)	0.018	5	0.001	0	0.004	1	0.002	1
TF60 (mixed crop farm.)	0.010	2	0.006	1	0.008	2	0.011	2
Total		43		22		26		38

All three models predict an increase in the number of organic farmers producing COP (TF13). In the model using SF-based TE scores, the number of organic farmers more than doubles, while the magnitude of the effect is smaller in the other models. The number of organic farmers is found to decrease or remain constant in the other types of farming. This is because the elasticity of the probability of conversion is negative at the mean of the corresponding samples. All in all, if all farmers in our sample were technically efficient, the number of organic adopters would be lower. Depending on the model, it would vary from 22 to 38, which corresponds to a decrease in the number of adopters in the range of 12% to 50%.

The three models also provide consistent findings on the positive role of education (EDUC): 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. In the three models, smaller farms (when size is measured by UAA) are found to be more likely to adopt OT all other things equal, which may be explained by smaller farms generating lower yields under CT than larger farms (and thus expecting a lower yield loss if converting to OF). These two findings confirm our expectations.

In the three Probit regression models, we obtain the expected result that farmers receiving more agri-environmental subsidies (as a percentage of total subsidies) (SH_ENVSUBS) are more likely to convert to OF. Also, farmers who incur higher fertilizers expenditure (relatively to their standard gross margin) (FERT_SGM) are less likely to convert to OF (this variable is however not significant in any of the three models). The coefficients for the potential difference in prices (organic *versus* non-organic products) (POTDIFPRICE) and the potential conversion subsidies (POTCONVSUBS) that could be received annually if converting next year are positive as expected, but not significant. The variables representing risk, namely legal status (STATUS) and indebtedness (DEBTTOASSET) are not significant in any of the models, as well as the proxy for subsidy dependence (SUBTOOUT).

5.3 Robustness checks

Because the proportion of adopters is very small in the full sample, we re-estimated the three Probit models on a choice-based sample (see Greene 2003), that is a sample in which the proportion of adopters is made artificially higher (the non-adopters are randomly selected). Our choice-based sample contains 238 observations, among them 43 adopters and 195 non-adopters, hence the proportion of adopters has been increased to 18% compared to our original 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:

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

where d_{it} describes the adoption decision ($d_{it} = 0$ or $d_{it} = 1$), $\rho_{it} = d_{it}\left(\kappa_1/\zeta_1\right) + \left(1 - d_{it}\right)\left(\kappa_0/\zeta_0\right)$, 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.[9] The estimation results are shown in Appendix A3.

The results obtained for the choice-based sample are found to be very close to the ones obtained for the full sample. However some of the explanatory variables have become

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

significant in the models based on the choice-based sample, in particular the ratio of debt to asset (DEBTTOASSET) and the potential difference in prices between organic and conventional products that may be received by converting farmers (POTDIFPRICE). The ratio of debt to asset has the expected negative sign in the three models and is found significant in the models using the DEA- and FDH-based TE scores. This confirms that farms already indebted are less likely to take any risk in converting to OF. This result may also indicate that the farming assets are to some extent technology specific. Farmers who have recently invested (in technology specific assets) would incur higher switching costs and are, therefore, more reluctant to switch. A higher expected difference in prices between organic and conventional product is found to significantly increase the probability of adoption in the three models, which also confirms our intuition.

The TE scores were calculated based on separate frontiers for each TF, each year, and each cluster (defined from agro-climatic conditions). These TE scores were then pooled together in the Probit model. One could argue that TE scores calculated under different frontiers are not directly comparable. However, estimating TE scores for all farmers considering a unique frontier would not be relevant either, since farmers in different TF are likely to operate under different technologies (in particular for farmers growing field crops and farmers growing fruits or vegetables). In order to test the robustness of our results, we use relative TE scores instead of absolute TE scores used for obtaining results of Table 4. The relative TE score for farmer *i* is defined as the percentage of farms that have a lower TE score than farmer’s *i* own TE score (in the group of farms that are used to define the frontier). We call these variables TE ranks. The three Probit models are then re-estimated on the full sample using TE ranks instead of TE scores. Estimation results are shown in Table 6.

Table 6: Results of the estimation of the probability to convert to OF using TE-ranks (3,761 farmers)

Probability of conversion to OF in the next year	Model with DEA-based TE rank		Model with FDH-based TE rank		Model with SF-based TE rank	
	Coef.	P>z	Coef.	P>z	Coef.	P>z
TE rank based on past four-year average score	**-0.009**	**0.013**	**-0.007**	**0.062**	**-0.007**	**0.029**
UAA	**-0.007**	**0.018**	-0.003	0.104	**-0.005**	**0.031**
EDUC = 1 (ref.)	-	-	-	-	-	-
EDUC = 2	0.111	0.467	0.111	0.463	0.121	0.430
EDUC = 3	**0.431**	**0.012**	**0.455**	**0.008**	**0.467**	**0.006**
STATUS = 1 (ref.)	-	-	-	-	-	-
STATUS = 2	-0.002	0.989	-0.050	0.732	-0.016	0.910
STATUS = 3	0.247	0.261	0.157	0.480	0.207	0.342
SH_ENVSUBS	**0.011**	**0.000**	**0.010**	**0.000**	**0.010**	**0.000**
DEBTTOASSET	-0.009	0.807	-0.010	0.809	-0.006	0.852
FERT_SGM	-0.926	0.362	-1.059	0.295	-1.087	0.286
SUBTOOUT	0.035	0.956	0.163	0.791	0.114	0.853
POTDIFPRICE	0.002	0.590	0.002	0.386	0.003	0.315
POTCONVSUBS	0.000	0.773	0.000	0.903	0.000	0.962
TE × UAA	**0.000**	**0.012**	**0.000**	**0.191**	**0.000**	**0.035**
Year 2003 (0/1)	0.161	0.485	0.178	0.437	0.160	0.487
Year 2004 (0/1)	**0.388**	**0.064**	**0.425**	**0.041**	**0.383**	**0.067**
Year 2005 (0/1)	0.302	0.157	0.338	0.111	0.302	0.153
Year 2006 (0/1)	0.153	0.484	0.174	0.423	0.143	0.510
Constant	-1.955	0.000	-2.202	0.000	-2.058	0.000
N	3,761		3,761		3,761	
Pseudo R2	0.0916		0.0826		0.0867	
Log-pseudolikelihood	-213.4851		-215.61392		-214.64052	

Note: in bold, significant effects. Definition of explanatory variables in Appendix A1.

Table 6 indicates that the three models provide results that are similar to the ones obtained using TE scores and presented in Table 4. The elasticity of the probability of conversion with respect to the TE score is still a function of farm size, with a negative value for small sizes and a positive value for large sizes. The turning point in the three models is as follows: 148 ha in the model using DEA-based TE ranks, 110 ha in the model using FDH-based TE ranks, and 93 ha in the model using SF-based TE ranks. Thus, the turning point is slightly higher when using TE ranks than when using TE scores, but not by a very large margin.

6. Conclusion

Using a sample of French crop farms over the 1999-2007 period, we test whether technical efficiency attained under conventional practices is a driver for conversion to OF. Despite some limitations in our data, we find that the probability of conversion does depend on technical efficiency preceding conversion but that the direction of the effect depends on farm size. More efficient farmers have a lower probability to convert if they operate small farms while they have a higher probability to convert if they operate large farms. The threshold that defines the sign of the elasticity of the probability of conversion to the average TE score has been estimated between 61 ha and 109 ha depending on the model. In our sample, the average size of farms engaged in field crops is higher than the threshold, while the average size of farms engaged in grape, fruits, vegetables or flower production is lower than the threshold. This finding is found to be robust to the method of calculation and definition of TE scores, either parametric (SF) or non-parametric (bias-corrected DEA or FDH). This study also confirms that farmer's and farm's characteristics (education, farm size, indebtedness) 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 and the impossibility to analyze partial conversions were the main limitations of our analysis. With a higher number of observations, we could have tested for heterogeneous responses across different types of farming or geographical areas.

Our results thus indicate that there may be an (adverse) selection effect, that is less efficient farmers being attracted by OF, in particular among the group of "small" farms in France. This is not a surprising finding given that small farms may suffer from financial problems due to their size (diseconomies of scale, difficulties to sell their small output to downward industries, credit constraints) which force them to consider production alternatives. One of them is OF, which enables small farms to produce high-value commodities, to obtain higher prices, to sell in short circuits, and thus to increase their profit. Hence, small inefficient farms are more likely to consider conversion to OF. However, with our results we cannot ascertain that such farms adopt OT in the main objective of receiving additional subsidies, nor that the selection effect is prompted by the subsidy program. Our findings would have to be confirmed with more recent data for two reasons. Firstly, the support scheme to OF has changed in 2008 with the introduction of payments to remain in OF, once the conversion period has ended. Thus, farmers adopting OT may now receive compensatory payments during and after the conversion. This may lower the rate of OF abandonment but may trigger the conversion of inefficient farmers who, under the conversion-subsidy only scheme, did not want to engage in the heavy conversion process fearing that they may not be able to remain in OF afterwards in the absence of subsidies at the end of the conversion. Secondly, the requirements under OF have changed in 2009 in France. The European Commission issued the first regulation governing OF standards EU-wide which applied in all member states from 1 January 2009 onwards. While on a competition point of view such regulation was welcome by French farmers who felt that they could not compete with imports of organic products from countries with less strict production rules, on a technical point of view the regulation largely lowers the national requirements that were in place in France. Hence, French farmers willing to convert to OF may find it easier now that the requirements are less tight, which may induce the conversion of less efficient farmers. Investigating the role of TE and organic payments on farmers' decision to convert is therefore necessary on more recent data.

On a policy point of view, such issue is crucial. Indeed, public authorities in industrialized countries have always been interested in the drivers of structural change and in whether the agricultural sector's competitiveness is constrained by the survival of inefficient farms. In general it is recognized that public support programs to agriculture enable inefficient farms to remain in the sector by covering their losses. However, inefficient farms may provide services to the society other than the production of food and fiber. The protection of environment is one of such services, whose provision is supposed to be realized by organic farms. In addition, higher labor employment on organic farms than on conventional farms may contribute to the socio-economic health of rural areas, in particular the remote ones.

Acknowledgements

The authors are grateful to Christophe Bontemps, Yann Desjeux and Fabrice Levert for technical assistance.

References

Acs, S., Berentsen, P., Huirne, R., van Asseldonk, M. 2009. Effect of yield and price risk on conversion from conventional to organic farming. *Australian Journal of Agricultural and Resource Economics* 53: 393-411.

Agence Bio. 2010. *L'Agriculture Biologique dans l'Union Européenne*. Paris, France. http://www.agencebio.org/upload/pagesEdito/fichiers/bioUE.pdf

Aigner, D., Lovell, C., Schmidt, P. 1977. Formulation and estimation of stochastic production function models. *Journal of Econometrics* 6: 21-37.

Burton, M., Rigby, D., Young, T. 2003. Modelling the adoption of organic horticultural technology in the UK using Duration Analysis. *Australian Journal of Agricultural and Resource Economics* 47(1): 29-54.

Charnes, A., Cooper, W., Rhodes, E. 1978. Measuring the efficiency of decision making units. *European Journal of Operational Research* 2: 429-444.

Cobb, D., Feber, R., Hopkins, A., Stockdale, L., O'Riordan, T., Clements, B., Firbank, L., Goulding, K., Jarvis, S., Macdonald, D. 1999. Integrating the environmental and economic consequences of converting to organic agriculture: Evidence from a case study. *Land Use Policy* 16: 207-221.

Darnhofer, I., Schneeberger, W., Freyer, B. 2005. Converting or not converting to organic farming in Austria: Farmer types and their rationale. *Agriculture and Human Values* 22: 39-52.

Farrell, M. 1957. The measurement of productive efficiency. *Journal of the Royal Statistical Society* 120(3): 253-281.

Gardebroek, C., Chavez, M.D., Oude Lansink, A. 2010. Analysing production technology and risk in organic and conventional Dutch arable farming using panel data. *Journal of Agricultural Economics* 61(1): 60–75.

Gardeboek, C. 2006. Comparing risk attitudes of organic and non-organic farmers with a Bayesian random coefficient model. *European Review of Agricultural Economics* 33(4): 485-510.

Gardebroek, C. 2003. Farm-specific factors affecting the choice between conventional and organic dairy farming. *Tijdschrift voor Sociaal wetenschappelijk onderzoek van de Landbouw* 18(3): 140-148.

Genius, M., Pantzios, C., Tzouvelekas, V. 2006. Information acquisition and adoption of organic farming practices. *Journal of Agricultural and Resource Economics* 31(1): 93-113.

Greene, W.H. (2003). *Econometric Analysis*. Prentice Hall, 5th Edition.

Kallas, Z., Serra, T., Gil, J.M. 2010. Farmers' objectives as determinants of organic farming adoption: The case of Catalonian vineyard production. *Agricultural Economics* 41: 409-423.

Kerselaers, E., De Cock, L., Lauwers, L., Van Huylenbroeck, G. 2007. Modelling farm-level economic potential for conversion to organic farming. *Agricultural Systems* 94: 671-682.

Khanna, M., Damon, L.A. 1999. EPA's Voluntary 33/50 Program: Impact on toxic releases and economic performance of firms. *Journal of Environmental Economics and Management* 37: 1-25.

Knowler, D., Bradshaw, B. 2007. Farmer's adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy* 32: 25-48.

Koesling, M., Flaten, P., Lien, G. 2008. Factors influencing the conversion to organic farming in Norway. *International Journal of Agricultural Resources, Governance and Ecology* 7(1/2): 78-95.

Kumbhakar, S.C., Park, B.U., Simar, L., Tsionas, E.G. 2007. Nonparametric stochastic frontiers: A local maximum likelihood approach. *Journal of Econometrics* 137: 1–27.

Kumbhakar, S.C., Tsionas, E.G, Sipiläinen, T. 2009. Joint estimation of technology choice and technical efficiency: an application to organic and conventional dairy farming. *Journal of Productivity Analysis* 31:151–161.

Läpple, D. 2010. Adoption and abandonment of organic farming: An empirical investigation of the Irish drystock sector. *Journal of Agricultural Economics* 61(3): 697-714.

Lohr, L., Salomonsson, L. 2000. Conversion subsidies for organic production: Results from Sweden and lessons for the United States. *Agricultural Economics* 22: 133–146.

Manski, C.F., Lerman, S.R. 1977. The estimation of probabilities from choice based samples. *Econometrica* 45(8): 1977–1988.

Mayen, C.D., Balagtas, J.V., Alexander, C.E. 2010. Technology adoption and technical efficiency: organic and conventional dairy farms in the United States. *American Journal of Agricultural Economics* 92(1): 181-195.

McBride, W., Greene, C. 2009. The profitability of organic soybean production. *Renewable Agriculture and Food Systems* 24: 276-284.

McCarthy, M., O'Reilly, S., O'Sullivan, A., Guerin, P. 2007. *An Investigation into the Determinants of Commitment to Organic Farming in Ireland*. 16th International "Farm Management Congress", University College Cork, Cork, Ireland, 15-20 June.

Meeusen, W., van den Broeck, J. 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review* 18: 435-444.

Ministère de l’Agriculture (2001). *Plan de Développement Rural National - Annexe B - Edition 2001*. Paris, France. pp127-129.

Oelofse, M ., Hogh-Jensen, H., Abreu, L., Almeida, G., Yu Hui, Q., Sultan, T., de Neergaard, A. 2010. Certified organic agriculture in China and Brazil: Market accessibility and outcomes following adoption. *Ecological Economics* 69: 1785-1793.

Oude Lansink, A., Pietola, K., Bäckman, S. 2002. Efficiency and productivity of conventional and organic farms in Finland 1994-1997. *European Review of Agricultural Economics* 29(1): 51–65.

Nemes, N. 2009. *Comparative Analysis of Organic and Non-Organic Farming Systems : A Critical Assessment of Farm Profitability*. Food and Agriculture Organization of the United Nations.

Padel, S. 2001. Conversion to organic farming: A typical example of the diffusion of an innovation? *Sociologia Ruralis* 41(1): 40-61.

Pietola, K., Oude Lansink, A. 2001. Farmer response to policies promoting organic farming technologies in Finland. *European Review of Agricultural Economics* 28(1): 1–15.

Rigby, D., Young, T., Burton, M. 2001. The development of and prospects for organic farming in the UK. *Food Policy* 26: 599-613.

Sainte-Beuve, J. 2010. *Etude des Déterminants de Conversion à l’Agriculture Biologique et Production de Références Economiques*. Master thesis. Institut Supérieur d’Agriculture, Lille, France.

Serra, T., Zilberman, D., Gil, J.M. 2008. Differential uncertainties and risk attitudes between conventional and organic producers: The case of Spanish arable crop farmers. *Agricultural Economics* 39: 219–229.

Serra, T., Goodwin, B.K. 2009. The efficiency of Spanish arable crop organic farms, a local maximum likelihood approach. *Journal of Productivity Analysis* 31: 113–124.

Shadbolt, N., Kelly, T., Horne, D., Harrington, K., Kemp, P., Plamer, A., Thatcher, A. 2009. Comparisons between organic and conventional pastoral dairy farming systems: Cost of production and profitability. *Journal of Farm Management* 13(10): 671-685.

Simar, L., Wilson, P. 1998. Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science* 44(1): 49-61.

Simar, L., Wilson, P. 2000a. A general methodology for bootstrapping in nonparametric frontier models. *Journal of Applied Statistics* 27(6): 779-802.

Simar, L., Wilson, P. 2000b. Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis* 13(1): 49-78.

Sipiläinen, T., Oude Lansink, A. 2005. *Learning in Organic Farming - An Application on Finnish Dairy Farms*. Manuscript presented at the XIth Congress of the European Association of Agricultural Economists (EAAE), Copenhagen, Denmark, August 17-24.

Stolze, M., Lampkin, N. 2009. Policy for organic farming: Rationale and concepts. *Food Policy* 34: 237-244.

Tulkens, H. 1993. On FDH efficiency analysis: Some methodological issues and applications retail banking, courts, and urban transit. *Journal of Productivity Analysis* 4: 183-210.

Tzouramani, I., Sintori, A., Liontakis, A., Alexopoulos, G. 2010. *Assessing Agricultural Policy Incentives for Greek Organic Agriculture: A Real Options Approach.* Manuscript presented at the 114th Seminar of the European Association of Agricultural Economists (EAAE), Berlin, Germany, April 15-16.

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.

Wilson, P. 1993. Detecting outliers in deterministic nonparametric frontier models with multiple outputs. *Journal of Business and Economic Statistics* 11(3): 319-323.

Appendices

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

Variable name	Measurement unit	Description	Source
UAA	ha	Farm's UAA	FADN 1999 to 2007
EDUC	Categorical variable	Farmer's education level 1. No or primary education 2. Low secondary education 3. High secondary education	FADN 1999 to 2007
STATUS	Categorical variable	Farm's legal status 1. Sole proprietorship 2. Partnership 3. Companies	FADN 1999 to 2007
SH_ENVSUBS	%	Farm's share of agri-environmental subsidies in total operating subsidies	FADN 1999 to 2007
DEBTTOASSET	ratio	Farm's debt to asset ratio	FADN 1999 to 2007
FERT_SGM	ratio	Farm's fertilizers expenditure to standard gross margin	FADN 1999 to 2007
SUBTOOUT	ratio	Farm's total operating subsidies to total output	FADN 1999 to 2007
POTDIFPRICE	euro	Potential difference in prices between organic and conventional products, for the farm if converting	Authors' own calculation based on FADN 1999-2007
POTCONVSUBS	euro/ha	Potential yearly conversion subsidies, for the farm if converting next year	Authors' own calculation based on FADN 1999-2007

Appendix A2: Descriptive statistics of the explanatory variables in the Probit models (averages for the 2003-2007 period).

	Farmers with future OT	Farmers remaining with CT
Number of farmers	43	3,718
DEA-based TE score	0.60	0.65
FDH-based TE score	0.83	0.86
SF-based TE score	0.75	0.78
UAA	62.27	87.62
EDUC = 1	0.23	0.36
EDUC = 2	0.42	0.48
EDUC = 3	0.35	0.15
STATUS = 1	0.51	0.56
STATUS = 2	0.37	0.37
STATUS = 3	0.12	0.06
SH_ENVSUBS	13.91	3.02
DEBTTOASSET	0.99	5.31
FERT_SGM	0.09	0.12
SUBTOOUT	0.14	0.18
POTDIFPRICE	-14.38	-9.97
POTCONVSUBS	381.10	345.53

Note: Definition of explanatory variables in Appendix A1.

Appendix A3: Results of the estimation of the probability to convert to OF (choice-based sample)

Probability of conversion to OF in the next year	Model with DEA-based TE score		Model with FDH-based TE score		Model with SF-based TE score	
	Coef.	P>z	Coef.	P>z	Coef.	P>z
TE score (past four-year average)	-1.231	0.114	**-1.278**	**0.092**	**-2.187**	**0.046**
UAA	-0.008	0.181	-0.014	0.216	**-0.022**	**0.081**
EDUC = 1 (ref.)	-	-	-	-	-	-
EDUC = 2	-0.014	0.939	-0.021	0.908	-0.049	0.785
EDUC = 3	**0.562**	**0.014**	**0.565**	**0.014**	**0.500**	**0.025**
STATUS = 1 (ref.)	-	-	-	-	-	-
STATUS = 2	-0.197	0.286	-0.165	0.365	-0.159	0.389
STATUS = 3	0.038	0.886	0.075	0.774	0.067	0.805
SH_ENVSUBS	**0.013**	**0.011**	**0.013**	**0.012**	**0.013**	**0.009**
DEBTTOASSET	**-0.136**	**0.090**	**-0.137**	**0.085**	-0.120	0.129
FERT_SGM	-1.587	0.170	-1.598	0.164	-1.148	0.331
SUBTOOUT	-0.359	0.591	-0.415	0.545	-0.723	0.350
POTDIFPRICE	**0.007**	**0.057**	**0.007**	**0.056**	**0.006**	**0.073**
POTCONVSUBS	0.000	0.948	0.000	0.832	0.000	0.960
TE × UAA	0.012	0.174	0.016	0.197	0.026	0.079
Year 2003 (0/1)	0.173	0.500	0.209	0.411	0.218	0.381
Year 2004 (0/1)	**0.440**	**0.040**	**0.464**	**0.029**	**0.497**	**0.024**
Year 2005 (0/1)	0.384	0.142	0.414	0.103	0.442	0.069
Year 2006 (0/1)	-0.009	0.970	0.010	0.967	-0.010	0.968
Constant	-1.386	0.048	-1.154	0.157	-0.497	0.610
N	238		238		238	
Pseudo R2	0.1057		0.1079		0.1107	
Log-pseudolikelihood	-13.299526		-13.267239		-13.225933	

Note: in bold, significant effects. Definition of explanatory variables in Appendix A1.