Schweizerische Gesellschaft für Agrarwirtschaft und Agrarsoziologie
Société Suisse d'Economie et de Sociologie rurales
Swiss Society for Agricultural Economics and Rural Sociology

Journal of Socio-Economics in Agriculture

Comparison of the Economic Performance between Organic and Conventional Dairy Farms in the Swiss Mountain Region Using Matching and Stochastic Frontier Analysis

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This study evaluates and compares the economic performance across organic and conventional dairy farms in the Swiss mountain region. To mitigate possible self-selection bias, matched groups of organic and conventional dairy farms with similar production possibilities are determined using exact and propensity score matching. Stochastic frontier analysis is then applied to estimate productivity differentials and technical efficiencies. Results reveal that organic farms are more productive converting input (labour, land, intermediate costs, capital) into output (revenues) while there are no significant differences in technical efficiencies. These findings suggest that the organic milk price overcompensates for lower yields in organic production leading to higher incomes. Thus switching into organic farming in the low intensive mountain region can improve the economic situation of conventional dairy farmers.

Keywords: *Stochastic Frontiers, Technical Efficiency, Productivity, Propensity Score Matching, Self Selection, Dairy, Organic*
JEL classifications: *D24, Q12, Q16*

1 Introduction

Agriculture in Switzerland underwent a significant structural change since the 1980s. This is especially true for the low intensive mountain region. Between 1999 and 2012, every fourth farm in this region was abandoned while the average size of the farms increased by 30%. This change can be explained by the depopulation of rural regions and the low incomes of farmers compared to the second or third sector (BfS, 2013).

In the same time we observed a growing demand for organic food products explained by growing concerns about food quality and climate change issues in the last two decades (Lairon, 2011). As a result, organic farming experienced a continuous expansion between 1997 and 2005 particularly in the low intensive mountain region. However, since 2005, the rate of conversion declined as expectations of an improved economic situation often were not fulfilled (Ferjani et al., 2010).

Organic farms usually have lower yields per hectare compared to conventional technology due to the restrictive use of certain inputs and restrictions concerning animal breeding (Mayen et al., 2010). On the other hand, they receive a price premium for certified organic food products paid by the consumer that compensates for lower yields in production. If the organic output price premium is too low to compensate lower yields, it is necessary to support organic farmers with additional payments in order to prevent reconversion.

But organic farmers can have higher incomes compared to conventional farmers even without additional direct payments. This is the case when the organic output price overcompensates for lower yields in production. In this case, it can be reasonable to make additional direct payments thus create financial incentives for conversion in order to promote organic farming for its positive external effects (e.g. lower impact on the environment, higher biodiversity) (Kumbhakar et al., 2009).

However, Pietola & Lansink (2001) found that organic farmers in Finland showed lower technical efficiency compared to their conventional counterparts. These findings indicate adverse selection problems in the promotion of organic farming. The least efficient conventional farmers participate in organic farming programs in expectation of higher direct payments. In such cases, direct payments do not lead to the desired effects and are thus not justified (Kumbhakar et al., 2009). The findings of Pietola & Lansink (2001) were later confirmed for the Italian context by Madau (2007). These studies show that a high number of conversions from conventional to organic farming does not necessarily mean that the policy framework leads to its desired effect.

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This work tries to compare the two production technologies with respect to income, productivity and technical efficiency. The aims of this study are twofold. First, differences in farmer's incomes give recommendations for farmers which technology might lead to a better economic situation. In order to prevent rural depopulation and preserve the alpine landscape, it is essential to prevent farm abandonment for economic reasons and to find ways to improve the overall financial situation of the farmers. Second, this study can help designing effective agricultural policies as it reveals whether we observe the problem of adverse selection in Switzerland too.

This article is organized as follows. The next section introduces the concepts of matching and stochastic frontier analysis. The following section presents and discusses the results. The article ends with some concluding remarks.

2 Theoretical Background & Methods

Comparing productivity and technical efficiency between conventional and organic farming systems has gained considerable attention (Lakner et al., 2012) in the agricultural economic literature as governments are increasingly interested in the economic performance of the production systems to design effective policies.

Of the studies comparing technical efficiencies of conventional and organic farms, only three controlled for self-selection bias. Sipiläinen & Oude Lansink (2005) used the Heckman correction while Kumbhakar et al. (2009) jointly estimated production frontiers and choice of technology. However, Heckman correction is unsuitable for stochastic frontier models as it assumes linearity of the model. Mayen et al. (2010) controlled for self-selection bias using propensity score matching with the nearest neighbouring technique and then compared the subsample of matched conventional with the organic farms.

For the unbiased estimation of productivity and technical efficiency in this work, two methodological procedures are performed; (i) exact and propensity score matching to control for possible self-selection bias and (ii) stochastic frontier analysis to estimate productivity differentials and technical efficiency.

2.1 Matching

The decision whether to produce organically or conventionally belongs to each individual farmer thus there is no control for the assignment over a specific observation group (organic vs. conventional). If organic and conventional farms are different with respect to production conditions and farm characteristics (e.g. size, region, zone, production conditions, farm type), estimates from the stochastic frontier model would be biased and productivity and technical efficiency scores of the two technologies would be incorrect (Sipiläinen & Oude Lansink, 2005).

To overcome self-selection bias, exact and propensity score matching techniques proposed by Rosenbaum & Rubin (1985) are applied. The aim of this first step is to generate a quasi-experimental situation where we compare organic farms which are as similar as possible to a group of conventional farms. Thus this approach mitigates potential biases associated with observed characteristics (Rosenbaum und Rubin 1983).

For nominally scaled covariates propensity score matching is inappropriate. Therefore, all conventional farms are first matched to an organic farm with one-to-one exact matching. One-to-one propensity score matching is then applied to this subsample.

Since the aim of the approach is to create a hypothetical situation where each pair of conventional and organic farm has the same potential for production independent of their technology, covariates used for matching must be independent of production technology (organic vs. conventional) (Offermann & Nieberg, 2000).

Nieberg et al. (2007) proposed a framework for comparison studies between organic and conventional farms that uses "non-system determined" factors. The authors suggest four areas that have to be covered by such variables; (i) similar natural production conditions, (ii) same geographical region, (iii) similar endowment of production factors and (iv) identical farm type (Nieberg et al., 2007). Based on these guidelines the variables used for matching are presented in table 1.

To calculate propensity scores, which is equal to the probability of producing organically based on a given set of covariates, a binary choice model is used (probit model). Using the PSM-covariates of table 1, the probit model takes the form:

$$P(y_i = 1) = \Phi\,(\beta_0 + \beta_1\, steep + \beta_2\, land + \beta_3\, dairy + \beta_4\, para.agri)$$

2.2 Stochastic Frontier Analysis

In this study, technical efficiency is the ratio of the produced output of a farm over the maximal possible output with a given set of inputs. For the estimation of technical efficiency in order to compare farms against the "best practice" farm, frontier analysis models are used in benchmarking literature. There are two main approaches to estimate a production possibility frontier function: non-parametric Data Envelope Analysis (DEA) first proposed by Charnes et al. (1978) and parametric stochastic frontier analysis (SFA) independently proposed by Aigner et al. (1977) and Meeusen & van den Broeck (1977).

While both methods have their advantages and disadvantages, the decision for one or the other depends on the setting of a study. The main disadvantages of stochastic frontier models are the assumptions about the functional form of the frontier function (linear, quadratic, cobb-douglas, translog) and the distribution of the error terms that have to be made in advance (Bogetoft & Otto, 2011). Inadequate assumptions lead to biased estimates of the parameters.

Table 1: Covariates used for exact and propensity score matching (PSM)

	Description	Name	Matching type
	Year of observation	year	exact
(i)	**Natural production conditions**		
	(1) MZ II, (2) MZ III, (3) MZ IV[a]	zone	exact
	% steep slope payments over total direct payments	steep	PSM
(ii)	**Geographic location**		
	(1) SW, (2) Jura, (3) C & NE, (4) SE[b]	region	exact
(iii)	**Production factor endowment**		
	Agricultural land in ha	land	PSM
(iv)	**Farm type**		
	1: silage-free production, 2: silage-based production	silage free	exact
	1: owner of farm, 0: tenant of farm	ownership	exact
	% dairy production in total agricultural revenues	dairy	PSM
	% para-agricultural revenues in total farm revenues	para.agri	PSM

[a] MZ: Mountain Zone according to Swiss FADN data
[b] SW: South-West, C: Central, NE: North-East, SE: South-East

On the other hand, deterministic models like DEA lack a stochastic error term representing measurement errors of unobservable variables (Bogetoft & Otto, 2011). In DEA models, all deviations from the production frontier are explained by technical inefficiency. This assumption is inappropriate for most agro-economical study settings because there is a stochastic component in agriculture (e.g. weather, luck, diseases, farmer's motivation) that has to be taken into account (Coelli & Battese, 1996). One of the main advantages of SFA over DEA models is that hypothesis can be tested with conventional statistical tests (Singh et al., 2001). In most agroeconomical studies estimating efficiency scores, the SFA method is favoured and thus is also used for this study.

Unlike ordinary least square (OLS) models, stochastic frontier models consist of two error components: one representing the stochastic effect related to statistical noise *(v)* and the other related to technical inefficiency of the farms *(u)*.

Aigner et al. (1977) and Meeusen & van den Broeck (1977) were the first to propose a stochastic frontier model in order to account for statistical noise. The error term consists of a stochastic error term v_{it} and an inefficiency error term u_{it}. The model takes the form:

$$\ln(y_{it}) = \ln(f(x_{it})) + v_{it} - u_{it} \text{ with } u \geq 0$$

v_{it} is either positive or negative and is assumed to be normally distributed while u_{it} is non-negative and either assumed to be half-normal or truncated normally distributed (Coelli & Battese, 1996).

Four input variables are included in the production frontier function. These are *land* (total agricultural land area), *labour* (including family and hired labour), *capital* (including machinery and building's depreciation value) and *interm. cost* (intermediate input costs for plant and animal production as well as costs associated with para-agricultural income). These are used to produce the output y_{it} defined by the total revenue generated at the farm (not including direct payments). To find the model that best fits the data, different model specifications are tested. For clarity, the following model specifications are only presented for cobb-douglas production frontier although different functional forms were tested (e.g. translog).

The stochastic frontier model with the cobb-douglas specification and the mentioned dependent and explanatory variables takes the form:

$$\ln(y_{it}) = \beta_0 + \beta_1 \ln(land_{it}) + \beta_2 \ln(labour_{it}) + \beta_3 \ln(interm.\ cost_{it}) + \beta_4 \ln(capital_{it}) + v_{it} - u_{it}$$

For this study, the stochastic error term v_{it} is assumed to be normally distributed with zero mean and constant variance σ_v^2 as it represents an unsystematic stochastic effect related with measurement errors and random influences (e.g. weather, luck).

The inefficiency error term u_{it} is assumed to be positive half-normally distributed. Furthermore, u_{it} and v_{it} are assumed to be independent (Coelli et al., 2005). These assumptions were proposed by several authors (Aigner et al., 1977; Battese & Corra, 1977; Meeusen & van den Broeck, 1977):

$$v_{it} \sim i.i.d.N(0, \sigma_v^2)$$
$$u_{it} \sim i.i.d.N^{+}(0, \sigma_v^2)$$

To estimate productivity differentials when switching technology, the approach of Kumbhakar et al. (2009) is applied. In a first step, the highest possible output for all observations using the given inputs of every farm is calculated both with organic and conventional stochastic production frontier ($\widehat{y}_o, \widehat{y}_c$). In a second step, differences between these two estimates are calculated with respect to their technology, thus:

for organic farms: $\Delta_{\widehat{yo}} = \widehat{y}_o - \widehat{y}_c$
for conventional farms: $\Delta_{\widehat{yc}} = \widehat{y}_c - \widehat{y}_o$

This approach does not account for stochastic error and the technical inefficiency of the farms. However, these two error components can be assumed to be the same if a farmer switches technology because stochastic errors are random and farmer's inefficiency is specific to the individual.

Technical efficiency can be derived for each farm. It is the ratio of the output y_{it} over the stochastic frontier output when $u_{it} = 0$. The resulting technical efficiency has then a value between 0 and 1 and gives information about the distance from the data point to the production frontier at a given scale:

$$TE_{it} = \frac{y_{it}}{\exp(x_{it}\beta + v_{it})} = \frac{\exp(x_{it}\beta + v_{it} - u_{it})}{\exp(x_{it}\beta + v_{it})} = \exp(-u_{it})$$

2.3 Statistics
The analysis is performed using the open-source software R (Team, 2012). The matching is done with the MatchIt package by Ho et al. (2011) using the nearest neighbour method and probit distance measure. Stochastic frontier analysis is performed using the frontier package by Coelli & Henningsen (2013).

In the case where data is normally distributed, it is expressed as mean with standard deviation (SD) as well as median for unbalanced variables. The latter is the case for technical efficiency scores because the assumptions made about the error structure. Differences in means are compared with t-tests. Differences in technical efficiency scores between conventional and organic farms are initially tested with the Mann-Whitney-U test because it does not imply normal distribution of the variable of interest.

To test the goodness of fit of the different model specification, the log-likelihood ratio test is used. The test statistics is calculated with:

$$\lambda = -2\left(\ln \frac{L(H_0)}{L(H_A)}\right)$$

where L(H_0) is the log-likelihood of the model with null-hypothesis and L(H_A) is the log-likelihood of the alternative hypothesis. The statistics λ has χ^2-distribution with degrees of freedom equal to the differences in parameters of the models. If test statistics are lower than the critical value at the 5 % significance level, null-hypothesis is accepted.

2.4 Data
For this study, accountancy data from the Swiss Farm Accountancy Data Network (FADN) is used. The data collection occurs according to very strict standards available in Hausheer Schnider (2010). The Swiss government has divided the country into three production regions (lowland, hill and mountain) based on their topography and thus production conditions. The mountain region is characterised by a short growing season, small farms and large market distance leading to lower economic performance compared to the lowland and hill region (Schmid & Roesch, 2012).

The number of farms used is 1305 where 23 % being organic (n=296) and 77 % conventional (n=1009) respectively. Observations from the three periods (2009–2011) are combined into an unbalanced panel, thus variables that are expressed in monetary terms have to be deflated with price indexes of the specific observation period. Price indexes are taken from Swiss agricultural statistics (Schmid & Roesch, 2012).

3 Results & Discussion

This chapter discusses the main results and findings of the work. In the first section differences in the farmer's incomes of the two subgroups are discussed. The second part addresses productivity differentials and technical efficiencies of the farmers derived from the technology specific stochastic production frontiers.

3.1 Matching
After all farms are exactly matched to the nominally scaled variables *year*, *zone*, *region*, *silage-free* and *ownership*, the probit model is estimated. Table 2 shows the estimated coefficients of the probit model which is used to calculate propensity scores. Three of the four variables have a significant influence on the choice of production technology (organic vs. conventional).

The variable *steep* indicates that organic farms show a higher share of steep agricultural land. This suggests that organic farms are more likely to be located where production conditions are unfavourable. With increasing production difficulties due to steep agricultural land the dairy production becomes more extensive. There are no significant differences in agricultural land area between the two production technologies *(land)*. Organic farms show a higher degree of specialisation in milk production *(dairy)*. This finding might be explained by the rigid restrictions on organic farming in Switzerland. Therefore, it is easier to convert a farm with a high degree of specialisation. Farms with a higher share of para-agicultural activities tend to produce organically *(para.agri)*. This might indicate that organic farmers diversify their income to improve the economic situation.

With the probit model, a propensity score for each farm is estimated. Each organic farm is then matched to a conventional farm with the closest propensity score (one-to-one propensity score matching). After building these subgroups with similar production possibilities and farm characteristics, the farmer's income (work income per family work unit) of the two subgroups are compared (including direct payments). The work income per family work unit of organic farms is on average 29 % higher compared to their conven-

Table 2: Estimates of the probit model

Variable	Coefficient	SD	T-value
Constant	–2.251	0.264	–8.52
Steep	0.001***	0.001	3.99
Land	0.006	0.004	1.54
Dairy	0.013***	0.003	4.69
Para.agri	0.013**	0.004	3.24

Statistically significant: * p<0.05 ** p<0.01 ***p<0.001

tional counterparts. This finding indicates that switching from conventional to organic dairy farming in the mountain region can lead to a higher income and could thus potentially improve the economic situation of the conventional farmers. It might also explain why the share of organic farms is much higher in the mountain region (20 %) compared to the lowland region (4.5 %) (BfS, 2013). The share of direct payments received from total revenues in the data set is 39.9 % for conventional and 40.6 % for organic farms. Thus, the observed differences in farmers' incomes cannot be explained by the direct payments for organic production.

Unlike other studies (e.g. Kumbhakar et al. (2009); Lansink et al. (2002); Tzouvelekas et al. (2001)) revenues *(output)* from organically operated farms are on average 8 % higher compared to conventional farms being significant at the 5 % level. This is surprising as no significant differences in production factor endowment can be found between technologies while organic farms have on average a 12 % lower milk production per hectare. The lower yields per hectare in organic farming are caused by the less intensive production (Milk intensity & Livestock intensity). Although only significant at the 10 % level (p-value: 0.09), the capital endowment of organic farms is on average 7 % higher compared to their conventional counterparts. This confirms the findings of other studies on the subject (Mayen et al., 2010; Kumbhakar et al., 2009; Sipiläinen & Oude Lansink, 2005).

3.2 Stochastic Frontier Analysis

Different model specifications for the stochastic frontier model are estimated and statistically tested to find the specification best describing the observations. Table 3 summarises the performed statistical tests.

A first test is conducted to examine whether production technology between organic and conventional farming is different. A log-likelihood test rejects the null hypothesis for homogeneous technology ($D_{org}=0$) with a p-value of 0.003. The dummy variable D_{org} is positive (0.067) and significantly different from 0 (p-value: 0.002) indicating higher productivity of organic technology.

The second test concerns production function specification. The cobb-douglas production function is tested against translog specification. Results favour translog over cobb-douglas specification. However, with the translog production function, the monotonicity condition is violated in too many observations, thus technical efficiency estimated out of the model could be misinterpreted. For this reason, cobb-douglas production function is used for further analysis.

A third test addresses stochastic effects of the model. For both technologies, the stochastic frontier model should clearly be preferred in favour of an ordinary-last square (OLS) model.

Table 3: Hypothesis testing for model specification

Model	H_0	λ	λ^2_{crit}	Decision
Technological homogeneity	$D_{org} = 0$	8.88	3.84	Rejected
Organic technology				
Cobb-douglas vs. translog	$\beta_{ij} = 0$	24.82	18.31	Rejected
No stochastic effects	$v_{it} = 0$	150.37	6.00	Rejected
No technological change	$t = 0$	2.44	3.84	Accepted
Conventional technology				
Cobb-douglas vs. translog	$\beta_{ij} = 0$	23.69	18.31	Rejected
No stochastic effects	$v_{it} = 0$	62.14	6.00	Rejected
No technological change	$t = 0$	1.53	3.84	Accepted

Critical values are significant at 5% level

The last likelihood ratio test is performed to see whether an additional variable t accounting for technological change improves the goodness of fit. The null hypothesis indicates that there has been no technological change over the three years of observation.

These test results lead to the following model specification: For the stochastic frontier analysis of conventional and organic farms different production frontier functions are assumed. Cobb-douglas specification is used. Technical efficiency is estimated using the stochastic frontier model with time-varying efficiencies of the farmers but without technological change in accordance with the model specification for panel-data proposed by Battese & Coelli (1992).

With these specifications, the estimated coefficients of the stochastic frontier models for the matched subsample of organic and conventional technology are presented in table 4.

The estimated stochastic production frontiers show that differences in production technology are relatively small between organic and conventional dairy farms in the mountain region. These findings might be explained by the fact that production is extensive in both technologies because of the difficult production conditions.

Table 4: Coefficient estimates of the stochastic frontier analysis

	Organic			Matched Conventional		
Parameters	Coefficient	SD	T-value	Coefficient	SD	T-value
Constant	2.920***	0.388	7.53	2.597***	0.458	5.66
Labour	0.039	0.055	0.71	0.122**	0.044	2.76
Land	0.190***	0.047	4.05	0.146***	0.043	3.37
Interm. cost	0.544***	0.035	12.03	0.562***	0.044	12.80
Capital	0.213***	0.035	6.06	0.224***	0.028	8.14
Time	–0.023	0.023	–1.02	–0.043	0.029	–1.46
σ_v	0.179***	0.029	6.23	0.151***	0.024	6.41
γ_u	0.940***	0.013	70.55	0.933***	0.019	48.54
Log-Likelihood	95.26			63.07		

Statistically significant: * p<0.05 ** p<0.01 ***p<0.001

The production factor *labour* is not found to be significant in organic production. This finding is contra-intuitive as organic farming is thought to be more labour-intensive than conventional farming because of the additional restrictions on organic farming. However, this result is consistent with several studies performed on the subject. Madau (2007); Kumbhakar et al. (2009); Ferjani & Flury (2009); Karagiannias et al. (2006) also found lower elasticity of *labour* in organic technology. The second variable to differ between organic and conventional technology is *land*. From all four estimated input variables, only the elasticity of *land* is higher in organic production. This might be explained by the fact that organic technology is more land-intensive because of restrictions regarding organic farming. The production factor *land* is found to be less important compared to *interm. cost* and *capital* for organic and conventional farming. This finding contradicts the result of Madau (2007) who found *land* to be the most important production factor. However, Mamardashvili & Bokusheva (2012) found that the elasticity of land decreases from lowland to mountain region in Switzerland. This can be explained by the fact that in the mountain region the agricultural land cannot be seen as "quasi-fixed" input factor because the production is extensive.

Based on the stochastic production frontiers, productivity differentials from switching technology are estimated using the approach described above. If the productivity differentials ($\Delta\hat{y}_o$ respective $\Delta\hat{y}_c$) are positive, switching technology would lead to a decrease of revenues because the technology is superior prior to switching. If the difference is negative, the used technology is inferior and switching technology would increase the farm's revenues.

Figure 1 shows the boxplots of the productivity differentials between organic and conventional technology. If organic farmers would have switched to conventional farming, they would on average have 8.0 % less revenues with the same amount of input and therefore less profit. On the other hand, conventional farmers would have generated on average 8.8 % more revenues with the given amount of inputs, if they would have switched to organic technology and thus have increased their profits. The results show that all organic farms use the superior technology ($\Delta\hat{y}_o > 0$) while all conventional farms use the inferior one ($\Delta\hat{y}_c < 0$).

Higher productivity in organic technology is surprising because organic farms produce 12 % less milk output per hectare compared to their conventional counterparts. The two technologies use similar input endowments and have similar production conditions but organic farms on average attain 8 % higher revenues (not including direct payments). This indicates that the organic output milk price overcompensates the lower yields of production. This finding points out that the organic technology can compete with the con-

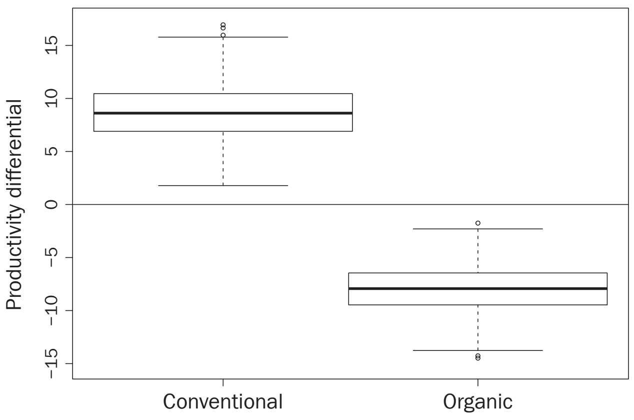

Figure 1: Productivity differentials from switching

ventional one and organic farmers would thus have no incentive to reconvert to conventional practices even if they are not supported with additional payments. In that sense subsidies for organic farming are primarily economic incentives for conventional farmers to converse. However, the fact that the share of organic farms in the mountain region stagnates indicates that these financial incentives for conversion are not strong enough to overcome conversion barriers such as high investment costs or missing organic networks in some mountain areas.

It is important to mention here that the observed productivity differences between conventional and organic farming are highly dependent on the milk price. If the number of farmers producing organically increases, the additional supply of organic milk could lead to a decrease in the organic milk prices and an increase in conventional milk prices.

Figure 2 shows the results from estimation of technical efficiency of the individual farms. Since production technology is not homogenous and hence organic and conventional farms have different production frontiers, differences in technical efficiency between organic and conventional technology can only be examined in relation to their technology specific production frontiers.

The results show that organic and conventional farms have on average the same relative potential for increasing their efficiency. The median of technical efficiency scores for organic dairy farms is 73 % and 74 % for conventional farms. The estimated technical efficiency is skewed towards 100 and thus not normally distributed. Because of this finding, a Mann-Whitney U-test is performed to compare the distribution of technical efficiency of organic and conventional farms. The left-skewness of technical efficiency is caused by the assumed distribution of the error term described in chapter 4 ($u_{it} \sim i.i.d.N^{+}(0, \sigma_v^2)$). The p-value of the Mann-Whitney U-test of 0.27 indicates that there are no significant differences in the distribution of technical efficiency between organic and conventional dairy farms in the Swiss mountain region. This means that both technologies use their available input resources with the same degree of efficiency.

This finding reveals that organic and conventional dairy farmers in the Swiss mountain region show no significant difference in the distribution of technical efficiencies. These findings confirm the results from Mayen et al. (2010) who used the same methodology as this study but contradict results from Kumbhakar et al. (2009) and Sipiläinen & Oude Lansink (2005) who both found lower technical efficiency in organic farms compared to their conventional counterparts. The result indicates that the Swiss agricultural policy promoting organic farming does not suffer from adverse selection problems in the mountain region. This implies that less efficient farmers are not disproportionately attracted by the additional direct payments for organic farming.

The study does not control for learning processes when switching technology. However, if conventional farms have converted to organic production technical efficiency would have been lower in the first few years after conversion be-

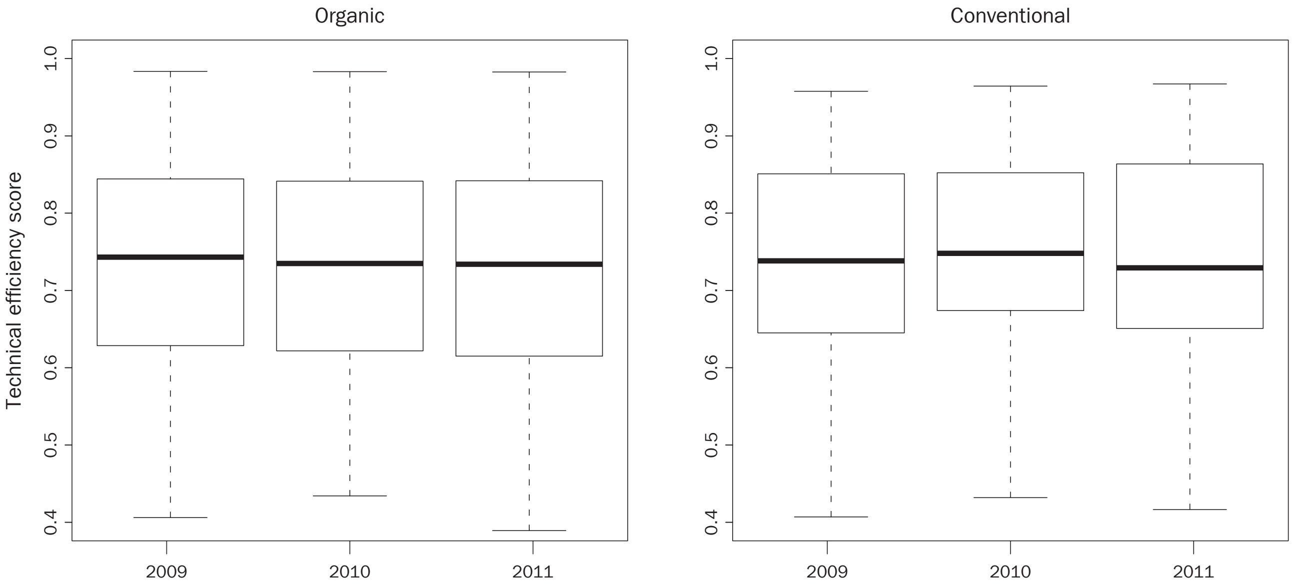

Figure 2: Technical efficiency scores

cause the farmer first would have to learn the organic production practices. Sipiläinen & Oude Lansink (2005) found that the average learning process when converting from conventional to organic farming takes 6–7 years. The median of organic farms with less than 6 years of organic farming experience is 0.71 compared to 0.74 of more experienced organic farmers (more than 5 years of experience).

Based on the above mentioned findings, differences in economic performance between the two subgroups of conventional and organic farms can be explained. Organic technology has a higher productivity leading to higher incomes while there are no differences in technical efficiency.

4 Conclusion

From a farmer's perspective, the results of this work suggest that switching from conventional to organic production can improve the farm's income. However, this does not guarantee that switching from conventional to organic farming leads to an immediate improvement of the economic situation. This study indicates that switching to organic farming might improve the economic performance in the long run but not in the short run. This is explained by the fact that in the first few years after conversion, technical efficiency is lower due to the learning process which lasts 6–7 years (Sipiläinen & Oude Lansink, 2005) and thus farm's income might be lower during this period.

Between 1997 and 2010, a high number of farmers converted to organic production and reconverted shortly after because their economic situation did not improve as expected (Ferjani et al., 2010). This indicates that having other reasons to convert such as ecological conviction beside economic ones, might help farmers to endure the first years after conversion.

There is another important issue that has to be considered for the conversion decision. Some areas in the mountain region may not be well suited for organic production because of missing organic networks. In areas where the concentration of organic farms is very low, access to organic input products and food processors or traders may be difficult and represent a limiting factor for the expansion of this production form. Ferjani et al. (2010) showed that one reason for reconversion was the purchasing of organic feed and straw being either too expensive or not available in certain areas. Furthermore, information spillover plays an important role in organic farming (Burton et al., 1999). If there are no organic farmers in a certain location, gaining information about organic farming practices can be very expensive or prolong the learning process. Several studies show that technical efficiency is higher and learning process shorter in regions where the share of organic farms is higher (Lakner et al., 2012).

From a political perspective, this study found no problems of adverse selection such as the ones found by Pietola & Lansink (2001); Madau (2007); Kumbhakar et al. (2009) for the period of 2009 and 2011 in the observed study context. This means that under the current direct payment scheme in Switzerland, the promotion of organic farming in the mountain region does not attract least efficient farmers to organic production.

However, the findings in this study reveal that some policy adaptations should be considered when promoting organic farming in future policy reforms in order to effectively increase the share of organic farms and improve the economic situation of farmers in the mountain region. The high growth of organic farming between 1992–2005 shows that financial incentives can be powerful in encouraging conversion, however, since 2005 many farmers reconverted back to conventional technology because their expectations of improving the income were not fulfilled. The study shows that technical efficiency is lower in the first 5 years after conversion because new entrants need time to gain organic practices and competencies. Reconversions should be prevented in order to promote organic farming. During the learning process, additional subsidies for organic farming are important to at least partially compensate farmers for the lower income during this period. After the learning process is concluded, technical efficiency is similar to conventional technology. The price premium for organic products overcompensates for the lower yields in organic production and thus organic farming is competitive compared to conventional farming even without subsidies. Subsidies for organic farming then increase the income compensating farmers for prior investment but are not necessary to hold farmers in organic production. Future policy reforms might need to reconsider supporting experienced organic farmers (>5 years of organic farming) with the same amount of subsidies as inexperienced farmers (≤5 years of organic farming). Current subsidies for experienced farmers could be used for the improvement of the conversion process as well as the framework for organic farming in the mountain region. Such a support could focus on three aspects:

(1) Conversion from conventional to organic farming is linked to investment costs. As the economic situation of farmers in the mountain is weak and such costs could prevent them from conversion they should be supported.
(2) Professional training for new entrants or the coordination of organic farmers enhancing information spillover could shorten the learning process.
(3) The study shows that organic farming is highly concentrated in some mountain regions while it is rare in others due to the lack of input product vendors and organic milk processors or traders. Organic networks should be promoted in order to make organic production accessible for all farmers.

Acknowledgment

My utmost gratitude goes to my thesis advisors Dr Adrian Müller from ETH Zurich and FiBL, my supervisor Dr Pierrick Jan at Agroscope Tänikon and Prof Dr George

Sheldon at the University of Basel. I am very grateful to Dr Markus Lips and Dr Dierk Schmid for the provision of the FADN data set to perform this study and to Matthias Stolze from FiBL for further topical inputs. With this work, I hope to make a contribution to support the decision making of dairy farmers in the mountain region and preventing them from farm abandonment. I want to thank all of these farmers for their valuable work and their achievement in preserving the landscape of the Swiss alpine region.

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