What is my optimal technology? A metafrontier approach using Data Envelopment Analysis for the choice between conventional and organic farming

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Abstract

We analyse the relative competitiveness between organic and conventional farming under different policy scenarios using a DEA-based non-convex metafrontier model. This model allows us to identify a farm's *ex post* optimal technology based on input-output observations. Results for Bavarian dairy farms indicate that more than two-thirds of the farms in both technologies – organic and conventional – have chosen their optimal farming system. The remaining farmers could increase their productivity by roughly 5% on average by switching to the other technology. Assuming away the existence of the EU milk quota, reduces the number of sample farms for which organic farming is the optimal technology by more than three fourth. This finding suggests that *ceteris paribus* organic dairy farms may lose competitive advantage with the abolition of the EU's milk quota regime in 2015.

Keywords: organic farming, EU milk quota, Data Envelopment Analysis, metafrontier analysis

1 Introduction

Over the past ten years, the number of organic farms in the European Union has more than tripled to about 150,000 certified organic farms in 2005 (Eurostat, 2008), representing a significant share of farms and agricultural land. On the other hand, there is evidence of organic farmers reverting to conventional farming methods (DEFRA, 2002). As a consequence, organic and conventional farmers may wonder whether they have chosen their optimal farming technology or farming system. In particular, dairy farmers are confronted with this decision because EU dairy market policies will face substantial changes in the future.

In EU agriculture, profits from dairy farming are heavily influenced by two policy instruments: subsidy payments for organic and conventional farming as well as the so-called milk-quota in the EU. The quota restricts the milk quantity an individual farmer can sell on the market. Since the subsidy scheme is expected to be changed and the quota will be abandoned in 2015 some farmers' choice between conventional and organic dairy farming will probably change in the future. Policy makers may want to know how farmers' choices may be affected by the policy changes because an increase of organic farming is in line with main political objectives in the EU.

For farmers, we identify the *ex post* most productive technology for each farm in our sample given the political framework of subsidy payments and milk quota restrictions. We also compute the increase in productivity that a farmer could have reaped had he chosen his optimal (= most productive) technology. In a second step, we change the policy instruments and identify each farm's optimal technology within this new environment. Comparing the number of farms who should prefer organic dairy farming over conventional dairy farming in the different policy environments we assess a potential impact of policy changes on the relative competitiveness between both farming systems. Our analysis is based on data of more than 1,000 conventional and more than a hundred organic farmers in the Federal State of Bavaria in Germany. The lack of reliable studies on the future of organic dairy farming after the end of the milk quota in the EU makes our empirical analysis valuable for policy makers although it is based on one European region only. Nevertheless, we discourage from extrapolating our quantitative estimates for Bavaria to the EU milk sector as a whole.

We first reveal the conceptual framework for comparing productivities of different technologies (Section 2), before presenting our empirical procedure (Section 3). The empirical study comparing the productivity of conventional and organic dairy farming under different policies follows in Section 4. The last section concludes with a discussion of conceivable policy implications.

2 Conceptual Framework

From a real-world perspective, we wish to: (1) determine for each individual farm the *ex post* optimal technology – organic or conventional dairy farming – under different policy scenarios, and (2) estimate a farm's productivity increase had it used the optimal instead of its actual technology. We define and explain graphically the optimal technology of two competing technologies while we refer to the different policy scenarios in the sequent chapter. By our definition, a firm has chosen the optimal technology if it is 'technologically efficient'. We define technological efficiency in two ways: A firm is technologically efficient <u>by output orientation</u> if it uses a technology out of the set of applicable technologies that allows for the highest possible output with a given input bundle. Or, in terms of efficiency analysis, the firm uses the technology with the highest frontier output for the given level of inputs.

Alternatively, a firm is technologically efficient by input orientation if it uses a technology out of the set of applicable technologies that allows for the lowest input bundle for a given output level.

Obviously, a firm can be technologically efficient by means of the input-oriented definition, while it is technologically inefficient following the output-oriented definition, and vice versa. This raises the question of which orientation is most appropriate. For common efficiency analyses, Coelli *et al*. (2005) argue that 'one should select the orientation according to which quantities (inputs or outputs) the managers have most control over' (page 180). For example, it is hard to increase the output of hospitals when people are healthy and, thus, inefficient hospitals should focus on input (and thus cost) reductions. In this article, we choose the output-oriented approach for comparing the productivity of organic and conventional dairy farms. We consider the output-oriented view more appropriate because it would be difficult to argue that inefficient farmers should scale down the use if inputs such as family labour or buildings. It is more realistic for most farmers to increase output, given these inputs. However, we shall conduct an input-oriented efficiency analysis as well to check for the robustness of results.

As Tzouvelekas *et al.* (2001) point out, common efficiency analysis – assuming the same production system for all sample farmers – is not appropriate to conventional and organic farming. Therefore, our methodological approach is based upon a metafrontier concept in efficiency analysis touched on by O'Donnell, Rao, and Battese (2008) (ORB) and implicitly applied by Kumbhakar, Tsionas, and Sipiläinen (2009) (KTS) to estimate productivity differences among competing technologies. Neither ORB nor KTS are interested in evaluating a single firm's technology choice.

To determine whether a firm is technologically efficient one needs a metafrontier. For our problem, a metafrontier represents the hull of different technology sets; this hull represents maximum output for a given input bundle among different technologies. In accordance with the literature, we refer to the frontier output for a single technology as 'group frontier'. Except KTS, former empirical studies are based on convex metafrontiers that are constructed from a convex set of production possibilities.[1] A convex metafrontier – such as the one represented

[1] Like ORB in their empirical analysis, Gunaratne and Leung (2001), Sharma and Leung (2000), Oude Lansink et al. (2002), Battese and Rao (2002) pool their observations from different technologies or producer groups to construct a (convex) metafrontier, while Battese and Rao (2002) and Battese et al. (2004) fit 'virtual' (convex) metafrontiers by enveloping the group frontiers with a function of minimum average distance to the group frontiers.

by the dotted line in Graph 1 – exhibit segments based on combinations or averages of technologies.

Graph 1 about here

The dotted line in Graph 1 is constructed by pooling the input-output observations of all firms in the sample, irrespective of the technology chosen. It is constructed by linear combinations of efficient firms. The vertical line up to I1 follows from technology I only. Equivalently, the part of the dotted line to the right of II2 is constructed from data points from technology II only. By contrast, the line between I1 and II2 represents linear combinations of I1 and II2. This part of the frontier implies the assumption that technologies are combinable in one firm, that is, one firm can use combinations of different technologies. In determining the optimal technology, a segment such as I1 to II2 can be misleading if it represents a benchmark that is not actually feasible. We therefore refer to this segment as a 'virtual' part of a metafrontier.

To overcome the problem of virtual benchmarks, we prefer a 'non-convex metafrontier'. In contrast to the convex metafrontier, it encloses the segment I1-S-II2 instead of I1-II2. Interval I1-S is constructed from linear combinations of firms I1 and I2 which use technology 1 only. Likewise, interval S-II2 is constructed from linear combinations of the input-output data of firms II1 and II2, both of which apply technology II. The remaining segments of the convex metafrontier are also part of the non-convex metafrontier. Consequently, all points on our non-convex metafrontier represent linear combinations of input-output observations from firms which use the same technology. At the costs of losing the convex hull, this metafrontier consists only of benchmarks that are technically feasible without need for the assumptions that technologies are combinable in one firm. ORB make reference to this type of metafrontier in a graphical representation under the proviso that the observed technologies are 'exhaustive' (p. 235).

For our empirical case, we make the assumption that organic and conventional farming technologies or systems are mutually exclusive and we, thus, apply the non-convex metafrontier. Organic dairy farmers are more restricted in their production than conventional farmers. For example, organic farmers can only keep fewer animals per hectare than conventional farmers because they cannot produce as much feed as conventional farmers: on one hand their yields are smaller because mineral fertilizer and chemical pesticides are not applied and on the other hand purchasing feed from other sources is heavily restricted. In general, organic dairy is not allowed to use common veterinary drugs, either. Consequently, some arbitrary 'hybrid' technology of organic and conventional farming is only allowed for non-organic, i.e. conventional farmers. If such 'hybrid' input-output observations were efficient we should observe them for conventional farmers. In this sense, 'hybrid' technologies are part of the production set conventional farmers may apply and we should not represent them by virtual parts of the metafrontier.[2]

Following the non-convex metafrontier, the (output-oriented) technological efficiency of firm I3 in Graph 1 is unity because the firm uses technology I and is benchmarked against I3` which lies on the part of the metafrontier that is spanned by firms which also apply technology I. More general, output-oriented technological efficiency represents the output of a group frontier relative to the metafrontier output for a given input vector. Thus, it represents the production potential in the observed technology relative to the maximum output in the optimal technology. For firm I3, technological efficiency based on the convex metafrontier amounts to approximately 0.8 because I3`` belongs to the convex metafrontier which is above the non-convex benchmark I3`. A firm thus is technologically efficient if the technological efficiency score is unity. We refer the reader to the appendix for a more formal definition of the non-convex metafrontier and 'technological efficiency'.

Instead of technological efficiency, Battese and Rao (2002) use the term 'technology gap ratio', which was also used in Battese *et al.* (2004). ORB refer to technological efficiency as 'metatechnology ratio'. We prefer the term 'technological efficiency' along the lines of 'technical efficiency'. In our view, 'technology gap' is more appropriate to describe 'technological inefficiency' since the technology gap increases with the level of technological inefficiency. In addition, 'technological efficiency' is more descriptive than 'metatechnology ratio'.

3 Methods for Empirical Implementation

In order to estimate technological efficiency (or inefficiency) scores for individual firms, one must derive the non-convex metafrontier shown in Graph 1. The most common methods for such frontier analyses are SFA (Stochastic Frontier Analysis) and DEA (Data Envelopment Analysis). We consider DEA to be more appropriate than SFA for evaluating individual dairy

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[2] Even if one does not follow our assumption that organic and conventional farming are different technologies the non-convex metafrontier approach is much more appropriate for evaluating the relative competitiveness between organic and dairy farming than assuming a common benchmark (e.g. convex metafrontier) for them. A common benchmark may lead to the conclusion that a farm can increase its productivity to the level of a linear combination among organic and conventional dairy farms. But this conclusion may be of little help for the farmer because such a virtual benchmark may mix up organic price premiums with the use of (conventional) mineral fertilizer and pesticides.

farmers' choice between organic and conventional technology for two reasons. First, the restrictions on milk sales owing to the EU quota regime cannot be easily represented in a standard SFA approach. The marginal impact of milk quota on output would hardly be interpretable in a regression framework because the *ceteris paribus* assumption does not necessarily hold. In general, a farmer cannot increase his milk production by means of more milk quota without changing the bundle of other inputs at the same time. Second, our sample farms differ substantially in size. In our view, using a frontier benchmark which is influenced by 'large' farms (by Bavarian standards) with, say, over 100 cows is not appropriate for evaluating the performance of a 'small' farm with only 8 cows. However, this exactly happens in the SFA framework via estimating the frontier's parameters. We argue with KTS that SFA is appropriate if one is interested in average measures of performance of the sample farms, such as the (average) productivity difference between conventional and organic farming. But if the objective is to determine whether a specific farm is technologically efficient, we prefer benchmarks constructed from frontier farms with similar input levels. We thus compute a non-convex metafrontier such as KTS, but instead of using SFA we apply DEA.

The construction of a non-convex metafrontier by means of DEA proceeds in two steps. We first estimate a DEA frontier for each technology separately and, second, choose the group technologies which represent sectors of the non-convex metafrontier. The DEA approach can be traced back to Charnes, Cooper, and Rhodes (1978). They were the first to construct a non-parametric piece-wise linear frontier for the analysed firms by means of linear programming. The frontier is built up by efficient firms, i.e. those which produce the highest output for a given input combination, and by convex linear combinations of these firms.

We use a common (i.e. for a homogenous technology) output-oriented[3] DEA assuming variable returns-to-scale to compute the technical efficiency of a firm. Each firm j out of N firms can produce s outputs with m inputs. Efficiency scores are then computed by running linear programming model (1) for each firm in the data set:

(1) $$\underset{\phi_j, \lambda}{Max} \quad \phi_j$$

s.t.

[3] We show the input-oriented approach in the appendix.

$$\mathbf{Y\lambda} \geq \phi_{\mathbf{j}} \mathbf{y}_{\mathbf{j}}$$
$$\mathbf{X\lambda} \leq \mathbf{x}_{\mathbf{j}}$$
$$\mathbf{e}'\boldsymbol{\lambda} = 1$$
$$\boldsymbol{\lambda} \geq 0$$

For each firm *j*, the model aims at maximising a scalar $\phi_j \geq 1$ which is multiplied by the observed output $\mathbf{y_j}$ ($s\times 1$ vector) to represent the maximum output that is feasible for firm *j*. Thus, the higher ϕ_j the less efficient is firm *j*. The maximum output is represented by a convex linear combination of the observed outputs of all other firms $\mathbf{Y\lambda}$ ($s\times N$ matrix) where $\boldsymbol{\lambda}$ is a $N\times 1$ vector of non-negative weights which must sum to one (assumption of a variable returns-to-scale technology), and **e** is a $N\times 1$ vector of ones. The maximum output must be produced with no more input than observed for firm *j*. In other words, the inputs corresponding to the maximum output are represented by a convex linear combination of inputs $\mathbf{X\lambda}$ ($m\times N$ matrix) of all firms that do not exceed the observed input $\mathbf{x_j}$ of firm *j*. The technical efficiency of firm *j* becomes $TE_j = \phi_j^{-1}$.

We extend (1) to estimate technological efficiency. For this purpose, we integrate multiple (*K*) technologies into the model, one of which is termed *k*. A firm's *j* observed technology is denoted *p*. We apply two steps to solve (2) for firm *j* and to derive its technological efficiency score.

$$(2) \qquad \underset{\phi_{\mathrm{j}},\lambda}{Max} \quad \phi_{\mathbf{j}}^{\mathbf{k}} = \underset{\mathbf{k}}{max}\left\{\phi_{\mathbf{j}}^{\mathbf{k}}\right\} \text{ for all } k = 1, 2, \ldots, p, \ldots, K$$

s.t.

$$\mathbf{Y^k\lambda^k} \geq \phi_{\mathbf{j}}^{\mathbf{k}} \mathbf{y}_{\mathbf{j}}^{\mathbf{p}}$$
$$\mathbf{X^k\lambda^k} \leq \mathbf{x}_{\mathbf{j}}^{\mathbf{p}}$$
$$\mathbf{e}'\boldsymbol{\lambda}^{\mathbf{k}} = 1$$
$$\boldsymbol{\lambda}^{\mathbf{k}} \geq 0$$

In the first step, we compute a firm's technical efficiency score by benchmarking it against the frontier of its own technology *p*. In the second step, we insert firm *j*'s input-output data into each of the other technology groups and rerun the model. We thus compute *j*'s efficiency by benchmarking its input-output combination against each of the other group frontiers. By so doing we obtain technical efficiency scores ϕ_j^k for firm *j* in each of the *K* alternative technologies. Thus, (1) is computed *K* times. $\mathbf{Y^k}$ ($\mathbf{X^k}$) are the observed outputs (inputs) of all firms using technology *k*, while the observed input $\mathbf{x_j}$ and output set $\mathbf{y_j}$ of firm *j* is the same in each of the *K* computations. We obtain { ϕ_j^k } with $k = 1, 2, \ldots, K$ and determine the maximum of { ϕ_j^k }. The technology which represents the metafrontier for firm j is T^{k^*} such that k^* maximises { ϕ_j^k }. The product of $\phi_j^{k^*}$ and $\mathbf{y_j}$ represents the maximum frontier output (among the different technologies) achievable for j. T^{k^*} thus is the optimal technology for firm j, and the output-oriented technological efficiency score of firm j becomes $TLE_j^o = \phi_j^p / \phi_j^{k^*}$. The relative output increase from switching to the optimal technology, i.e. the vertical distance between the frontiers of technology k^* and technology p relative to the observed output, is represented by $\phi_j^{k^*} - \phi_j^p$. It is assumed that the inputs observed for firms in different technologies are sufficiently similar to reach the same level of technical efficiency in each technology.

As a benchmark we also construct a convex metafrontier by DEA such as in ORB. This is done to check whether empirical results differ significantly between the two metafrontier approaches.

4 Technological efficiency of organic and conventional farms

After presenting the data, we first ask whether dairy farmers have chosen the optimal farming technology: organic versus conventional. Second, we estimate for technologically inefficient farmers the productivity gain that could have been reaped had they used the optimal instead of their actual technologies. Third, we vary the assumptions about policy scenarios determined by public subsidies and the milk quota.

4.1 Data and policy scenarios

The small to medium sized family farms are all located in Bavaria, in the south of Germany, and data are taken from the farms' profit-and-loss accounts and balance sheets for financial year 2004/2005. We have included in the analysis only farms that generate at least two-thirds of their output from milk and milk product sales. The sample contains 102 dairy farmers who had been applying organic farming methods for at least three years prior to 2004/2005. Thus, all organic farmers have finished their compulsory conversion period to organic farming. On average, their farms are slightly smaller than the 1239 conventional farms in the sample (Table 1).[4] The average organic dairy farm has a milk quota of 224,000 kilograms per year,

[4] We restrict our analysis to Bavaria to reduce problems following from regional heterogeneity. Our DEA benchmarks would be inappropriate if the benchmark for a farm in the Alps is another farm near the North Sea. Although the farm inputs may be identical climate, soil, and market conditions might be quite different.

while the conventional average is 312,000 kilograms per year. Due to lower per-cow milk yields in organic farming, herd sizes are similar for both technologies: between 40 to 60 cows.

Table 1 about here

Total farm output comprises the value of agricultural production, including agricultural services and subsidy payments, but except investment aid.[5] We include subsidies in the output figure because we search for the optimal technology from an individual farmer's point of view. The inputs are labour (measured as full-time equivalents per year), capital (depreciations on machinery and buildings), expense for intermediate inputs, and land (measured in hectares of arable and pasture land). In general, organic farms use slightly less input on average than conventional farms. The mean labour input is nearly identical while the use of intermediate inputs is approximately 30% lower for organic farms due to limitations on the use of pesticides and mineral fertilisers. The minimum and maximum values show that both subsamples span a similar range of farms as measured by their input and output quantities. In the organic sample, some large farms skew the distributions of most variables to the right.

The different policy scenarios are implemented in the following manner. Under 2004/2005 policies some subsidies can clearly impact the relative competitiveness between organic and conventional dairy because they are (partly) coupled to production, in particular for organic farming. We, thus, add them to the market revenues for the DEA. Milk quota can be seen as an input necessary to sell milk and we, thus, include it as in input in the DEA. In Germany quota can be sold and bought only on official quota auctions for specified regions, leasing is not permitted. Bavaria had seven different trading regions in the time of analysis and interregional trade was not allowed. In a hypothetical scenario milk quota is abandoned and we compute the DEA without milk quota. In another hypothetical scenario subsidies are not paid (which is equivalent for the relative competitiveness to fully decoupling subsidies from production) and we use market revenues only as output variable. Finally we combine both hypothetical scenarios to an extreme policy without milk quota and subsidies.

4.2 Results and Discussion

While we focus on results from the output-oriented efficiency analysis, we report results based on input-orientation at the end of this section to see by how much they diverge. We start with results on the farms' technical efficiency to place our analysis into the context of the

[5] Although we include subsidies in the output for most analyses, we use the term 'productivity' as output relative to input.

empirical literature. The average technical efficiency of the conventional farms is 80%; it is 3 per cent points higher for organic farms (first row in Table 2). By contrast, KTS report average technical efficiencies of around 86% (76%) for conventional and 80% (74%) for organic dairy farms, respectively, assuming normal or logistic (extreme value) distributions of the error term in the selection equation.[6] However, KTS do not include subsidies in their output measure. On the other hand, Oude Lansink *et al*. (2002) report average technical efficiencies based on input-oriented DEA for conventional arable and livestock farms of around 70%, while the organic counterparts reach technical efficiencies of 96% (arable) and 93% (livestock) on average. The high average efficiency of organic arable farms may have been caused by the small sample of only 45 organic farms in Oude Lansink *et al.*'s analysis.

Table 2 about here

Using the non-convex metafrontier and measuring output-oriented, the average technological efficiency score comes out at 99% for the sample of organic farms and 98.5% for the sample of conventional farms (second row in Table 2). Closer inspection of the result reveals that every fifth organic farm and nearly every third conventional farm should have chosen the other technology (fourth row). Finally these farms, on average, could have increased their productivity by between 5% and 7% had they chosen the optimal technology. This increase is substantial in terms of profit because the profit margin is small for many farms. We conclude that (1) conventional dairy farming does not ensure the highest productivity (including subsidies) for all sample farms. Whether organic or conventional farming is optimal for a farmer depends on a farm's input bundle, including its endowment with quasi-fixed production factors. (2) More than two-thirds of the farms in both technologies apply their optimal technology. (3) There are, however, substantial productivity differences between both technologies, as can be observed by the potential productivity gains from switching to the optimal technology.

To what extend do these findings differ from results derived from previous research? First, we compare our results with ORB's convex metafrontier. As set out above, we implemented ORB's convex metafrontier by pooling the data and estimating, by means of DEA, the convex hull encompassing the two technology sets. As expected, average technological efficiency based on the non-convex metafrontier is higher than that based on ORB's convex metafrontier approach (Table 3). The differences between both metafrontier approaches are substantial at the farm level. For more than 50% of the farms in the sample, the difference between both

[6] KTS conduct a SFA conditioned on the choice between organic and conventional farming. This choice is modeled as a Heckman sample selection problem.

approaches is more than 2 per cent points. Non-convex metafrontier results have indicated that more than two-thirds of the farms in each sample have chosen the optimal technology. By contrast, the convex metafrontier identifies more than 78% of the farmers as technologically inefficient, implying that they could have increased their productivity by changing their technology (third and fourth rows in Table 3). But which technology should a farmer choose? According to Table 3 (bottom row), the convex metafrontier identifies virtual benchmarks for more than 78% (93%) of the organic (conventional) farms. Such virtual benchmarks are combinations of organic and conventional farms. But these are not necessarily permissible for organic producers, as spelled out above. The convex metafrontier suggests that only 1% of both conventional and organic farmers should switch to the other technology, respectively. Consequently, the convex metafrontier fails to identify the 22% (32%) of organic (conventional) farmers who should change over to the other farming system (Table 2).

Table 3 about here

We now turn to the impact of different policy assumptions on the relative competitiveness between organic and conventional farming. The first row of Table 4 reveals that under the current system 31.6% of conventional farmers and 78.4% of organic farmers, respectively, should have produced organically. We start with the extreme policy scenario: that is, we excluded subsidies from the output measure and did not account for the milk quota. Results are quite sensitive to these changes: only 1.5% of the conventional farmers in the sample should switch to organic farming and only 45% of the organic farmers should stay in their farming system (second row in Table 4).

Table 4 about here

These findings may have important policy implications. Under the current system, organic farming is the optimal technology for 472 (35%) of the sample farms. Without milk quota and subsidies – but everything else being equal – only 65 should choose organic farming. On the one hand, this is a clear indication that organic dairy farming has gained competitive advantage over conventional dairy farming due to agricultural subsidies and the milk quota system. On the other hand, even without subsidies and milk quota, organic farming remains the more productive technology for nearly 5% of the sample farms. However, this percentage is likely to increase if one accounted for the rise in the price for organic milk resulting from the fall in supply due to fewer organic dairy farms.

We proceed with a less extreme scenario. If agricultural subsidies were abandoned for both organic and conventional dairy farms while keeping the quota in place, the relative competitiveness of the organic system would decline, too. Organic farming would remain the optimal technology for only 318 farms compared to 472 under the current system. However, even without subsidies for either of the two technologies, 70% of organic farmers would generate higher productivity in organic farming (third row in Table 4).

We used the model also to analyse the impact of abolishing the milk quota on the relative competitiveness of organic and conventional dairy farming. The last row in Table 4 shows the portion of farmers for whom organic production remains the optimal technology if milk quota restrictions were removed but subsidies kept. Under these circumstances, organic farming is the optimal choice for only 107 of the sample farms, and 40% of the farms currently in organic production should revert to conventional farming. One can thus expect that the abolition of the milk quota regime increases the relative competitiveness of conventional dairy farming, assuming that subsidies for organic and conventional dairy farms remain unchanged.[7] Again, this effect is likely to be attenuated by the relative price increase for organically produced milk in response to a drop in supply of organic milk.

But why does the milk quota make organic dairying the optimal technology for many farms? We believe that milk quota has been the most limiting factor for many of our sample farms. In the German quota trading system, inter regional trade has long been prohibited. Consequently, purchasing additional milk quota has been very capital-intensive and expensive in some regions. In particular, German milk quota prices had been highest in Bavarian quota trading regions in 2004/2005 (BMVEL, 2005, p. 134). Assuming low opportunity costs for family labour and farm buildings, farmers act rationally by maximising their profits with respect to milk quota. Under these circumstances, organic milk production may be more profitable because it allows for a higher milk price per kilogram of milk quota than conventional farming. This is in line with an empirical finding of Gardebroek (2002).

4.3 Discussion

Our results are quite robust with respect to the orientation chosen for the efficiency analysis. The optimal technology based on the input-oriented and output-oriented approach, respectively, is quite consistent in our study. Both approaches result in the same optimal technology for 82.5% of the farms. Those that should switch technology can expect a productivity increase of about 5% on average following the input-oriented analysis (last row in Table 5). This is well in line with the results form the output-oriented analysis. Also, the

[7] However, one has to bear in mind that subsidies in the year of the analysis were partly linked to production, e.g. headage payments, e.g. for steer fattening and cattle slaughtering. The effect of decoupling on the relative competitiveness between organic and conventional dairy farming is not clear cut. Comprehensive theoretical or simulation-based analyses of the effect are missing in the literature.

sample averages of technical and technological efficiencies differ by less than 2% points between both orientations (Table 5).

Table 5 about here

We emphasise that our approach to choosing among competing technologies is only appropriate for evaluating technology choices *ex post*. Only to the extent that expectations of the technologies' potentials are appropriately reflected by historic data can our approach be used for making *ex ante* recommendations. One could then base the analysis on the 'expected' output for any planned input combination for each technology.

We finally discuss limitations of our empirical approach to evaluating technology choices. All *ex post* technology comparisons in the manner of KTS, ORB and our analysis suffer from the same basic problem: a technology's frontier output will be underestimated if firms that are not observed in this technology would be more productive with this technology than the firms that are actually applying it. If some of the very productive farmers have not chosen their optimal technology, the metafrontier output may be underestimated and the model fails to identify the technology correctly representing the metafrontier. However, one may expect that most such productive farmers would choose the technology that is optimal for them. If a farmer outperforms his peers in his own technology he can be expected also to recognise and adopt the technology that best suits his or her individual circumstances. However, the choice between conventional and organic farming is unlikely to be influenced by productivity considerations only. Risk considerations, the cost of switching technology or personal preferences may have a role to play as well. Our model does not cater for this complexity. In addition, our analysis is based on input-output observations from only one year. The relative competitiveness of both farming systems may change over time due to different price changes and different technical progress in both production systems.

Finally, a general problem with DEA-based metafrontier models can follow from too few observations in a technology. If one adds an observation the group frontier can only shift upwards (but never downwards). Thus, one underestimates the group frontier if the group's best farms are not observed. Then, the group's impact on the metafrontier might be underestimated, too. In our empirical analysis, however, this distorting effect is likely to be limited because more than one hundred organic farms have been included in the analysis. Therefore, we expect underestimation of the organic group frontier is not substantial for our analysis.

5 Concluding Remarks

We analyse the relative competitiveness between organic and conventional dairy farming under different policy scenarios using a DEA-based non-convex metafrontier model. This model allows us to identify a farm's *ex post* optimal technology based on input-output observations. In particular, we assess the potential impact of abandoning the EU milk quota on the relative competitiveness between organic and conventional dairy farming for a sample of Bavarian farms. The lack of reliable studies on the future of organic dairy farming after the end of the milk quota in the EU makes our empirical analysis valuable for policy makers although the analysis is based on one European region only.

Results indicate that more than two-thirds of the farms in both systems apply their optimal farming technology under current policies. The remaining farmers could increase their productivity (including subsidy payments) by around 5%, on average, by switching to the other technology, assuming that each farm's technical efficiency is equal in both technologies. In our analysis, organic farming turns out to be the optimal technology for 35% of sample farms. Results are sensitive to assumptions about agricultural policies. In the absence of the milk quota, organic farming would, *ceteris paribus,* remain the most productive technology for only 8% of sample farms. This finding suggests that organic dairy farming may lose relative competitiveness with the end of the milk quota system in the EU, assuming that prices and subsidies remain unchanged for organic and conventional farming. Assuming away both milk quota constraints and agricultural subsidies, organic farming remains the optimal technology for only 4.8% of sample farms. This effect will be attenuated by a likely increase in the price of organically produced milk relative to conventional milk following a slump in organic supply.

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Table and Graphs

Table 1. Descriptive statistics

Organic farms (n=102)		Mean	Standard deviation	Min	Max
Output	€	134,255	67,814	13,744	384,325
of which Subsidies	€	21,936	11,648	2,761	70,896
Land	ha	48.1	21.1	11.6	122.2
Labour (persons)	FTE	1.70	0.50	0.46	4.44
Capital	€	31,605	16,169	1,442	87,496
Intermediate inputs	€	44,101	31,592	5,359	178,046
Milk quota	kg	223,743	121,203	32,366	700,000

Conventinal farms (n=1239)		Mean	Standard deviation	Min	Max
Output	€	165,571	43,465	29,249	343,004
of which Subsidies	€	20,423	8,321	1,039	60,320
Land	ha	54.1	18.3	9.5	125.4
Labour (persons)	FTE	1.72	0.45	0.50	3.82
Capital	€	36,760	13,673	2,771	102,367
Intermediate inputs	€	68,431	16,576	8,884	162,373
Milk quota	kg	311,703	92,089	56,991	684,450

Table 2. Results from the output-oriented non-convex metafrontier model

	Observed technology	
	Organic	Conventional
Average technical efficiency	83.3%	79.8%
Average technological efficiency	99.1%	98.5%
Portion of farms that should maintain technology	78.4%	68.4%
Portion of farms that should switch technology	21.6%	31.6%
Average output increase by changing technology for technologically inefficient farms	5.0%	6.7%

Table 3. Results from the output-oriented convex metafrontier model

	Observed technology	
	Organic	Conventional
Average technological efficiency	96.5%	96.0%
Portion of farms that should maintain technology	21.6%	6.5%
Portion of farms that should switch technology	1.0%	0.9%
Portion of farms with 'virtual' benchmarks	77.5%	92.7%

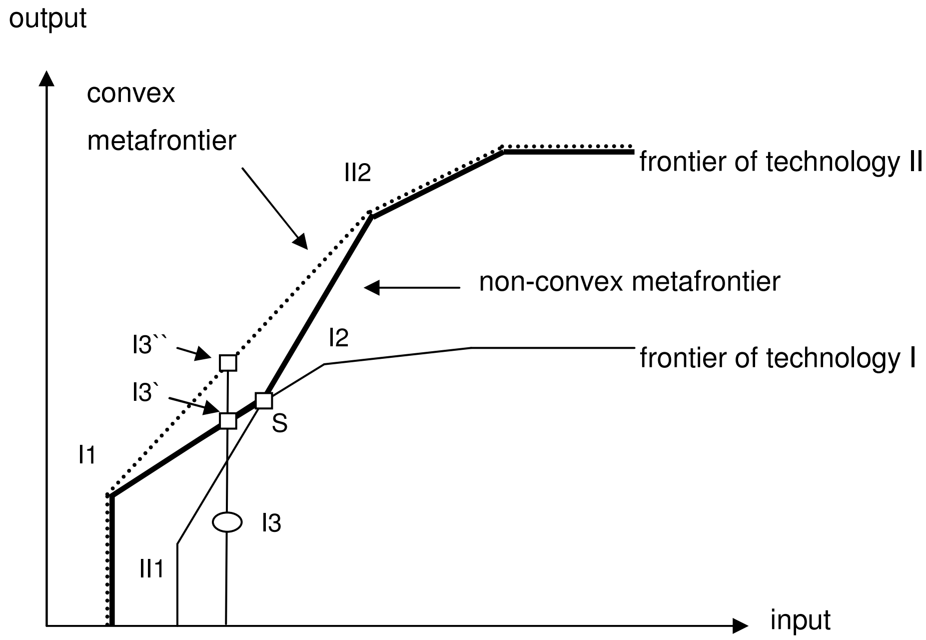
Table 4. Portion of farms that should produce organically in different policy scenarios

	Observed technology		Overall
Policy scenario	Organic	Conventional	
1. With subsidy and milk quota	78.4%	31.6%	35.2%
2. Without subsidy and milk quota	45.1%	1.5%	4.8%
3. Without subsidy but with milk quota	69.6%	19.9%	23.7%
4. With subsidy but without milk quota	59.8%	3.7%	8.0%

Table 5. Results from the input-oriented non-convex metafrontier model

	Observed technology	
	Organic	Conventional
Average technical efficiency	84.4%	79.7%
Average technological efficiency	99.0%	97.4%
Portion of farms that should maintain technology	79.4%	64.2%
Portion of farms that should switch technology	20.6%	35.8%
Average input reduction by changing technology for technologically inefficient farms	4.6%	5.6%

Graph 1. Convex and non-convex metafrontiers based on DEA



Appendix

Definition of the non-convex metafrontier

We now proceed with a more formal definition of the non-convex metafrontier. Following ORB (2008), we assume different technologies (defined by their technology sets) for each of *K* groups of firms. Each group's distinct technology set T^k consists of all possible input-output combinations for the firms in the *k*-th group:

(3) $$T^k = \{(x, y) : x > 0; y \geq 0; x \text{ can be used by firms in group } k \text{ to produce } y\},$$

where x (y) is a vector of non-negative inputs (outputs) and $k = 1, 2, \ldots, K$. The output set $P^k(x)$ for a given vector x using technology k is given by

(4) $$P^k(x) = \{y : (x, y) \in T^k\}.$$

The boundary of this output set is called group frontier or frontier of technology *k*. For each group's technology we assume some common properties of production technologies following Färe and Primont (1995):

1. $0 \in P^k(x)$ representing the possibility of not producing;
2. If (x, y) $\in T^k$ then (θx, y) $\in T^k$ for $\theta > 1$, representing the possibility of wasting inputs (weak disposability);
3. $P^k(x)$ is a closed and bounded set; and
4. $P^k(x)$ is a convex set.

The output-oriented technical efficiency relative to the group frontier $TE^{k,o}$ is defined by the output distance function $D^{k,o}(x,y)$:

(5) $$TE^{k,o} = D^{k,o}(x, y) = \inf\{ \phi^{-1} > 0 : (\phi y) \in P^k \}).$$

For a given input, this function gives the fraction of the observed output relative to the maximum output using technology *k*. One can also define an input distance function in order to compute input-oriented technical efficiency scores (see, for example, Färe and Primont, 1995).

The same characteristics of a metatechnology $T^* = \{T^1 \cup T^2 \cup \ldots \cup T^K\}$ follow from the properties of the group technologies, with the exception of the convex output set. ORB assume that the metatechnology's output set is also convex. However, a convex metafrontier output set does not necessarily imply convex group output sets, and vice versa. A convex metafrontier output set may encompass input-output combinations that are not part of the convex groups' output sets. Thus, a convex metafrontier can contain 'virtual' benchmarks which are not consistent with the properties of the group technologies (as we have shown in Graph 1).

To avoid this inconsistency, we assume the metaproduction output set to be

$$(6) \qquad P(x) = \{ y : (x, y) \in T^* \}$$

The boundary of output set (4) is the non-convex metafrontier, which is depicted by the bold line in Graph 1. The output-oriented technological efficiency TLE^o represents the output of a group frontier relative to the non-convex metafrontier output for a given input vector. It is calculated from

$$(7) \qquad TLE^o = TE^{*,o} \big/ TE^{k,o}$$

with $TE^{*,o}$ being computed as per (3).

Input-oriented approach

Analogous to the output-oriented approach, the technical inefficiency of firm *j* can be measured input-oriented. The input-oriented technical inefficiency describes how much input firm *j* can save without reducing its output. Solving linear program (8) yields the input-oriented technical efficiency score $\theta_j \leq 1$.

$$(8) \qquad \underset{\theta_j, \lambda}{Min} \quad \theta_j$$

s.t.

$$\begin{aligned} \mathbf{Y\lambda} &\geq \mathbf{y}_j \\ \mathbf{X\lambda} &\leq \theta_j \mathbf{x}_j \\ \mathbf{e}'\boldsymbol{\lambda} &= 1 \\ \boldsymbol{\lambda} &\geq 0 \end{aligned}$$

θ_j times $\mathbf{x}_j$ represents an input bundle which is not larger than the observed input bundle. Along the lines of the output-oriented approach, convex linear combinations of firms represent input bundle $\theta_j \mathbf{x}_j$ given output level $\mathbf{y}_j$. Thus, 1 – θ_j represents the percentage by which all inputs of firm *j* can be reduced without reducing the level of outputs.

To calculate the input-oriented technological efficiency the input-oriented technical efficiency

$\theta_{\mathbf{j}}^{\mathbf{k}}$ is computed for firm *j* with respect to the frontier of each technology *k*.

$$(9) \qquad \underset{\theta_j, \lambda}{Min} \quad \theta_{\mathbf{j}}^{\mathbf{k}} = \underset{\mathbf{k}}{min}\left\{\theta_{\mathbf{j}}^{\mathbf{k}}\right\} \text{ for all } k = 1, 2, \ldots, \text{p}, \ldots, K$$

s.t.

$$\begin{aligned} \mathbf{Y}^{\mathbf{k}}\boldsymbol{\lambda}^{\mathbf{k}} &\geq \mathbf{y}_{\mathbf{j}}^{\mathbf{p}} \\ \mathbf{X}^{\mathbf{k}}\boldsymbol{\lambda}^{\mathbf{k}} &\leq \theta_{\mathbf{j}}^{\mathbf{k}}\mathbf{x}_{\mathbf{j}}^{\mathbf{p}} \\ \mathbf{e}'\boldsymbol{\lambda}^{\mathbf{k}} &= 1 \\ \boldsymbol{\lambda}^{\mathbf{k}} &\geq 0 \end{aligned}$$

From (8) we obtain the smallest $\theta_{\mathbf{j}}^{\mathbf{k}}$ which we call θ_j^{k*}. It follows from technology T^{k*} which forms the metafrontier benchmark for firm *j*. Since $1-\theta_j^{k*}$ represents the highest (relative) reduction of inputs at constant output, the respective technology T^{k*} is the optimal technology for firm *j*.

The input-oriented technological efficiency becomes $TLE_j^i = \theta_j^{k*} / \theta_j^p$. All inputs of firm *j* can be scaled down in relative terms by $\theta_j^p - \theta_j^{k*}$ for the given output level when switching to the optimal technology.