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Technical efficiency of organic pasture farming in Germany: The role of location economics and of specific knowledge

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Abstract

We analyze the efficiency of organic pasture farming in Germany using data from 1994/95 to 2005/06. Five inputs and one output are analyzed by means of a stochastic frontier production function, allowing for heteroscedasticity and technical effects. Five sets of possible determinants of technical efficiency are considered in the model. These include: (1) farm structure and resources; (2) human capital and management capacities; (3) institutional choice; and (4) subsidies. To these factors that are commonly included in technical effects models, we add (5) a set of variables that capture localization and urbanization economies such as the share of organic farms in a region and the regional share of votes for the Green Party in recent elections. These regional effects are found to have a significant impact on the technical efficiency of organic farms. The evolution of efficiency on farms that are converting from conventional to organic farming is also analyzed.

Key words: efficiency analysis, organic farming, location economics, specific knowledge

Introduction

The importance of organic farming has increased rapidly in the EU and especially Germany in recent years. The share of organic farmers in Germany grew from 1.3% in 1996 to 5.9% in 2010[1]. Currently, 7.9 million hectares or 4.5% of the agricultural area in the EU is under organic production[2]. As concerns rise about agriculture's contribution to climate change, its influence on biodiversity, and issues such as animal welfare and food safety, EU and member state policy-makers can be expected to direct more attention and probably support toward organic farming.

Designing appropriate policies requires a solid understanding of the factors, such as technical efficiency (TE) that influence the competitiveness of organic farming. Due to the regulations that define and govern organic farming, organic production systems differ from conventional systems, and are subject to different relative scarcities. For example, since synthetic fertilizer use is not permitted in organic farming, nitrogen scarcity forces organic farmers to make efficient use of organic manure or nitrogen fixed, for example, by clover or other leguminous plants[3]. The greater dependence of organic production systems on the availability of natural resources could lead to a higher variance of TE scores in organic farming[4].

The organic production regulation promotes more integrated farming systems. A study on organic dairy farms in the USA shows that on organic dairy farms the vertical integration produces substantial economies of scope (in contrast to conventional dairy farms). There seems to be a systematic incentive toward an integrated farming and against a high degree of specialization[5], which is a special characteristic of organic farming systems too.

These issues warrant a closer look at efficiency in organic farming, and at the possible determinants of differences in efficiency between organic farms. Besides the standard determinants that are usually considered in efficiency analysis—such as farm structure or the age and educational status of the farm manager—we highlight two factors that have received little attention in the literature on the efficiency of organic farming to date.

The first of these factors is a *farm's conversion status*. Nieberg[6] shows that grain yields fall to 53% of their starting level after 4 years on German farms that are converting from conventional to organic farming, and then recover slightly to 72% of the starting level by the sixth year. Farmers in conversion have to acquire specific

knowledge and expertise for managing a new technology. Hence, one might expect TE to fall on a farm that has begun to convert, but to increase thereafter as the farmer acquires knowledge and expertise. This has implications for policy, if increasing the number of organic farms or the share of organic food production is a policy goal and policy-makers wish to design appropriate support packages for converting farms.

The second factor that has received little attention is *location*. In the past century, organic farming in Germany emerged in several distinct regional centers. The 'Demeter' movement influenced by Rudolf Steiner (1861–1925) started in the 1920s on east German farms. In the 1960s and 1970s, many small farms in southern Germany and Switzerland followed the ideas of Hans Müller (1891–1988) and Hans-Peter Rusch (1906–1977). Finally, after German reunification, many farms in the former German Democratic Republic converted to organic farming with the support of EU agri-environmental schemes that were introduced with the 'MacSharry Reform' of 1992[7]. The emergence of organic farming in distinct geographic regions suggests that location effects such as localization and urbanization economies effects might have played a role in the development of the sector[8] via their impact on farm-level efficiency.

In this paper, we analyze the determinants of the efficiency of organic pasture farms in Germany. Extending existing studies, we address two important questions for organic farming in Germany and elsewhere; whether location has a significant impact on TE and whether TE follows a distinct path over the course of the conversion period from conventional to organic farming. We proceed as follows: in the 'Background/Literature Survey' section, we provide a short overview of the recent literature on the impact of conversion and location effects on TE, and we propose a framework that includes location effects among the determinants of TE on organic pasture farms. In the 'Methods and Data' section, we present the methods and the data used in our empirical analysis. In the 'Results and discussion' section, we present and discuss the results, and the 'Conclusion' section concludes.

Background/Literature Survey

An extensive literature deals with the determinants of TE in farming in general[4,9–14]. This literature has identified the following four categories of determinants of TE:

1. farm structure and available natural resources;
2. management capacities and human capital;
3. institutional choice (legal form and tax options); and
4. market orientation and policy support.

Several studies investigate the TE of organic farms specifically[4,15–20]. The development of TE during the conversion period from conventional to organic farming is addressed in some of these studies. Lohr and Park[19] studied the influence of the organic farm manager's experience in the USA by splitting the sample into farms with more than 5 years of experience in organic farming, and farms with less than 5 years. The authors found that efficiency grows with years of experience in organic production. According to Sipiläinen and Oude Lansink[17], the learning process in organic dairy farms in conversion in Finland takes about 6–7 years following the decision to convert.

Initial studies of the location of organic farming in the 1980s and 1990s hypothesized that organic farms would cluster in the neighborhoods of cities with high population densities and therefore a high potential for direct marketing[21]. After the introduction of per-hectare payments for organic farming by EU regulation 2078/92 in 1993, many farms converted in parts of east Germany where agro-climatic conditions are less favorable[21]. One determinant of the spatial distribution of organic farming might therefore be lower opportunity costs due to less profitable conditions for conventional farming.

Bichler et al.[8] confirmed that there is a higher concentration of organic farms in German regions with less favorable soil quality. They also found a higher prevalence of organic farming in regions in which the difference between the subsidies provided for organic and for conventional pasture is large, and in regions in which greater shares of land have been designated as water protection or nature conservation areas. In some west German regions, local per capita income and farm size were also found to have a positive influence on the share of organic farms. Finally, Bichler et al.[8] also provide evidence that the spatial distribution of organic farms tends to be more concentrated in proximity to big cities with high population densities. In Figure 1, we can see the local share of organic farms in the total number of farms at the county level in 2007, which in general shows the local concentration of organic farming, which is in the south, center-west and north-east of Germany.

A number of studies have analyzed the role of information spillovers on the spatial distribution of organic farming. Farmers in the UK who are converting from conventional to organic production receive most of their information from other organic farmers in the same region[24]. Studies in Germany[7] and Wales[25,26] confirm that neighboring organic farmers are the main source of information for converting and converted organic farms. Regional networks of farmers and support groups encourage the regional concentration of organic farms in Wales and England[27]. The importance of information exchange between farmers is probably greater for organic than for conventional farming, because until recently there were relatively few specialized extension and education/training services for organic farmers. This is generally true for the western European countries that we have studied, and certainly for Germany. Therefore, most knowledge and information had to be generated by organic farmers themselves and was disseminated via local working groups[7]. Where specialized extension services exist, they were found to have a positive impact on organic conversion rates[28].

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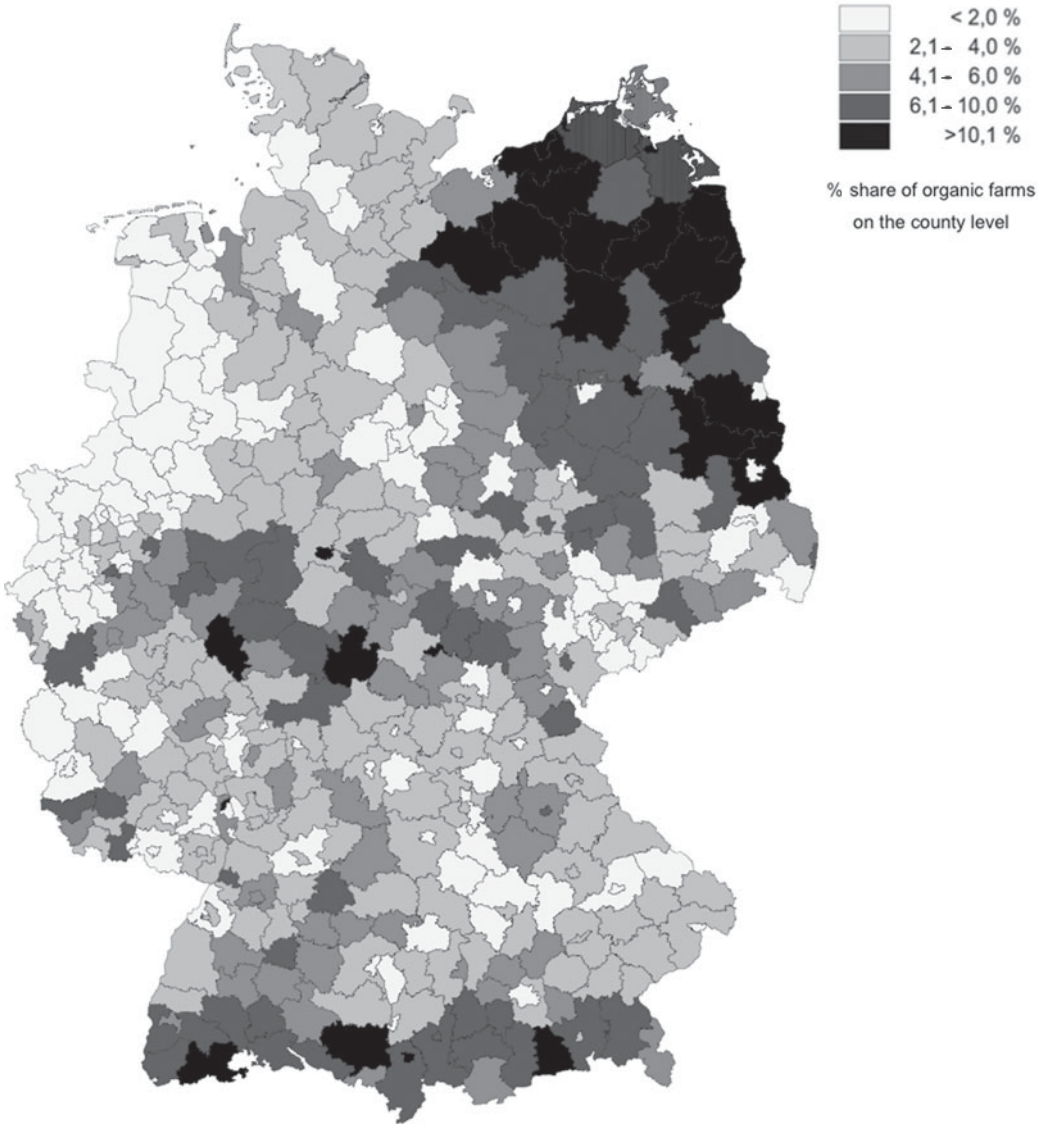

Figure 1. Regional concentration of organic farms in Germany in 2007. Source: Own calculation. Data on the county ('Landkreis') level from the German Federal Statistical Office[22], Regional Database 2005 and 2007[23]. Due to administration reforms, in 15 of 457 counties there were no data in the regional statistics for the year 2007. For the missing data in 2007, we took data from the previous years 2005 or 2003, assuming that the organic sector is constantly growing and we get a 'minimum number' of organic farms from 2003/2005 for the year 2007.

If information spillovers between organic farms are important, it is reasonable to expect that location will have an impact on farm-level efficiency. While we are aware of no studies on the impact of location on the efficiency of organic farms, the impact of location on efficiency has been studied in other agricultural contexts. For example, according to one study, a high regional concentration of aquaculture farms in Norway is associated with lower output but higher efficiency[29]. In other studies, the total sales per employee increase with the number of organic processors and traders located in a county in the USA[30], and regional concentration, distance to the nearest slaughterhouse, and the population density in neighboring regions influence the TE of pig farms in western France[31]. There is also evidence of spatial-efficiency clusters in Ukrainian dairy farming, with proximity to other efficient farms and to dairy processors exercising a positive effect on efficiency and total factor productivity[32].

Based on this review of the literature, we propose to consider—in addition to the four 'traditional' categories of factors that influence efficiency mentioned above—variables that account for location effects. First, a large share of organic farmers in a region might create external advantages that are referred to as *localization economies* in location theory[33]. Localization economies arise when many firms from the same industry are located in a region. They include access to pooled markets for skilled labor, the regional emergence of firms that provide specific intermediate inputs, and ease of communication leading to technological spillovers. All of these factors are expected to

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have a positive impact on TE as the number of organic farmers in a region increases.

Second, the efficiency of organic farming might also benefit from *urbanization economies*[34]. Urbanization economies are the effects on a firm's economic performance that arise from regional economic activity in other sectors. At first glance, it may seem incongruous to discuss urbanization in connection with a distinctly rural activity such as organic farming. However, in a densely populated and comparatively decentralized country such as Germany, rural and urban areas lie close together and are strongly interlinked. It is reasonable to expect that organic farms will perform better in regions that are characterized by local communities that are sensitive to environmental concerns and willing to pay higher prices for organic products. Such regions will provide sufficient demand to sustain direct marketing, specialized retail outlets such as organic farmers' markets and restaurants that specialize in organic food, and processors such as organic bakers and dairy enterprises that benefit from a dependable local supply of organic farm products. Such regions will also be able to sustain special advisory services for organic farms, and service providers that cater to the needs and preferences of organic farmers (e.g., a Waldorf school for children, practitioners of alternative medicine). We capture urbanization effects with two variables. Since we study organic pasture farms, we use a farm's distance from the nearest organic dairy processor as an indicator of local-demand conditions. In addition, we use recent local election results of the Green Party as a measure of the overall local level of acceptance for organic farming. The Green Party in Germany has traditionally championed environmental issues and organic farming, and most organic farmers and their supporters come from a socio-economic background that is associated with support for the Green Party[7].

Methods and Data

Methods

The field of empirical efficiency analysis in economics has grown very rapidly over the past roughly two decades, with applications not only in agriculture but also in many other areas such as health care provision and energy generation. Two main empirical approaches have been developed; so-called Data Envelopment Analysis (DEA) based on programming techniques and Stochastic Frontier Analysis (SFA) based on econometric estimation of production functions. We employ SFA in this paper. A brief explanation of this method follows; for a detailed exposition of SFA and DEA, see Coelli et al.[35] and Kumbhakar and Lovell[36].

SFA estimates a producer's (in the following we will refer to farms) TE by measuring the distance between its observed input–output combination and the best-feasible input–output combination that it could obtain if it were located on the so-called '*production frontier*'. This production frontier defines the highest possible amount of output that can be obtained from any given amount of input ('*output oriented approach*'). Alternatively, the frontier can be defined in terms of the lowest amount of input that is required to produce a given amount of output ('*input oriented*'). In agriculture, where many key inputs such as land, machinery and buildings are given, at least in the short run, the output-oriented approach is often favored.

Deviations between individual farms' observed output and the frontier output could occur for two reasons. The first reason is *technical inefficiency*—the fact that some farmers are more successful than others at putting the inputs at their disposal to the best possible use, i.e., at feeding cows to produce milk or at tending crops. The second reason is due to *stochastic effects* such as weather, luck or measurement errors. It is important to allow both components in order to avoid confounding the technical inefficiency estimates with purely random errors. The SFA approach accomodates this requirement by using a composed error structure, where one one-sided error component captures technical inefficiency, and a second error, symmetric error component, captures random deviations from the frontier. This basic SFA model is illustrated in Figure 2.

Due to the presence of stochastic effects, the production frontier is refered to as '*stochastic*', and for Farms A and B with input levels x_a and x_b we see how its observed output deviates from its '*frontier output*' y_b^* due to inefficiency and stochastic effects. Note that with a large positive stochastic effect v the observed output can lie above the frontier. Econometric SFA techniques estimate the location of the stochastic production frontier from data on the input use and output production of a set of farms, and decompose the deviation of each individual farm's actual production from the frontier into its inefficiency and stochastic components. Of course, in reality, farms use many inputs to produce more than one output, but the SFA model depicted in Figure 2[37,38] can be generalized to deal with the multi-input/multi-output case.

Formally, this generalized SFA model that we employ can be written as

$$y_{it} = f(x_{jit};\beta)^* \exp\{w_{it}\} \quad \text{with} \quad w_{it} = v_{it} - u_{it}, \qquad (1)$$

$$y_{it} = f(x_{jit};\beta)^* \exp\{v_{it} - u_{it}\}. \qquad (2)$$

In these equations, y_{it} is the output of farm i in year t measured as its total agricultural revenue, and x_{jit} measures the use of input j by farm i in year t. In our application, there are $j = 5$ inputs:

x_1: intermediate inputs (such as feed and electricity);

x_2: other operating expenses (such as repairs to buildings and machinery, insurance premia and fees for membership in professional organizations);

x_3: the depreciation of fixed assets (buildings and machinery);

x_4: labor, measured as total labor in agricultural working units per year; and

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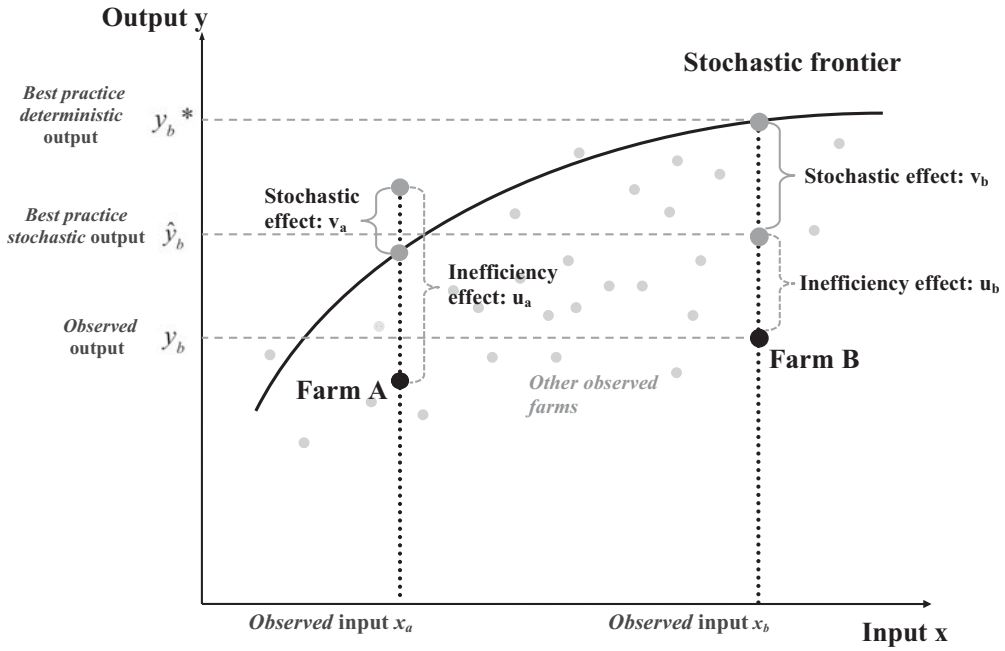

Figure 2. The estimation of the stochastic frontier model. Source: Own presentation based on Coelli et al.[35] p. 244.

x_5: land, measured as utilized agricultural area in hectares.

β denotes a vector of parameters to be estimated that describe the specific mathematical form of the function $f(\cdot)$ that relates input use x_{jit} to output y_{it}. In most applications of the SFA method, including ours, a functional form called the 'translog' is used. The translog function broadly satisfies the requirements of economic-production theory but is at the same time sufficiently flexible to allow the data to 'speak for themselves' and permit subsequent testing of conditions such as decreasing marginal returns to individual inputs and whether or not returns to scale in production are constant.

Finally, the combined error-term w_{it} in Equation 1 is split into the two components introduced above, as depicted in Equation 2. v_{it} captures stochastic effects for farm i in year t and is assumed to be normally distributed. u_{it} measures the inefficiency of farm i in year t; u_{it} is greater than or equal to zero because a farm's input–output combination can only lie below the production frontier (in which case u_{it} is positive and is a measure of the farm's inefficiency) or exactly on the frontier (in which case u_{it} equals zero and the farm is perfectly efficient). The non-negative part of a normal distribution u_{it} is frequently used in SFA applications, and we follow this practice. Hence, denoting by μ the mean and by σ_u^2 the variance of the underlying normal distribution, the inefficiency related errors u_{it} are modeled by truncation from below as $u_{it} \sim N^+(\mu, \sigma_u^2)$. The mean and the variance of the truncated distribution u_{it} itself will differ from μ and σ_u^2, the mean is

$$E(u) = \mu + \sigma \frac{\varphi(-\mu/\sigma)}{1-\Phi(-\mu/\sigma)}, \tag{3}$$

and the variance is

$$\mathrm{VAR}(u) = \sigma^2 \left(1 - \frac{\varphi(-\mu/\sigma)}{1-\Phi(-\mu/\sigma)} \left(\frac{\varphi(-\mu/\sigma)}{1-\Phi(-\mu/\sigma)}\right) + \mu/\sigma\right). \tag{4}$$

TE_{it} is defined as the ratio of empirically observed output $\hat{y}_{it}$ to the maximum feasible output $y_{it}^{\max} = f(x_{jit};\beta)\exp(v_{it})$ so that

$$\mathrm{TE}_{it} = \frac{\hat{y}_{it}}{y_{it}^{\max}} = \exp(-u_{it}). \tag{5}$$

Jondrow et al.[39] outline the econometric techniques that are used to decompose the error term w_{it} into its inefficiency and stochastic components u_{it} and v_{it}, respectively[39]. Econometric estimation of the model in Equation 1 hinges on the assumption that both these error components are homoscedastic, in other words they have constant variances[36]. However, this may not be the case. In particular, the inefficiency term u_{it} is likely to vary with the size of a farm, since a farm with a large input endowment (and therefore high output capacity) might exhibit substantially more variation, and therefore more scope for inefficiency than a smaller farm[40]. To account for this possibility, we estimate the following modification of the SFA model[10,40].

$$\sigma_{u_{it}} = \exp(x_{jit}\rho_j). \tag{6}$$

In Equation 6, the variance of the inefficiency term is a function of the j inputs x_{it} for farm i in year t introduced above, and ρ_j is a corresponding set of j parameters to be estimated. A positive estimate of ρ_j implies that the corresponding input x_j leads to a larger variance of the inefficiency term. This in turn indicates that the input has a negative impact on TE.

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Table 1. Description of the variables in the production function.

Variable description		Unit	Minimum	Mean	Maximum	Standard deviation
Sum of agricultural revenue	y	€	586	91,752	931,220	72,162
Intermediate inputs	x_1	€	915	38,845	527,230	41,135
Other operating expenses	x_2	€	902	21,037	187,050	15,714
Depreciation	x_3	€	140	22,622	234,620	16,336
Labor	x_4	AWU/year[1]	0.13	1.81	15.16	1.09
Land	x_5	hectares	0.70	65.75	1,041.80	82.96

Source: Own calculations.
[1] AWU, standardized agricultural work units.

The influence of additional potential determinants of TE can be estimated in terms of the parameter μ of the truncated normal distribution[9] as specified in Equation 7:

$$\mu_{it} = z_{kit}\delta_k + e_{it}, \quad (7)$$

where z_{kit} is a setof k determinants of TE for farm i in period t, and δ_k is a corresponding set of k parameters to be estimated. A positive estimate of δ_k indicates that the corresponding variable z_k increases the distance between a farm's input/output combination and the production frontier, and therefore has a negative impact on TE.

In order to see the regional distribution of efficiency scores, we applied a standard cluster analysis with the 'partitioning around medoids (PAM)' algorithm[41]. The idea is to cluster the farms according to their geographical location information, which are given as 'Universal Transverse Mercator (UTM)' values. We used the x and y values of the UTM value, which are the north–south- and the west–east-coordinates, as input to the algorithm to produce 15 regional cluster.

Data

We use accounting data for organic pasture farms in Germany from 1994/1995 to 2004/2005. Pasture farms are defined as '*specialized pasture farms*' that derive more than 66% of their agricultural revenue from products based on pasture, or '*mixed farms with a focus on pature farming*' that derive at least 33% of their revenue from such products. While some production of sheep, goats and suckler cows is pasture-based, the majority of the pasture in Germany is used in dairy production, and milk is the most important pasture-based output of the farms in our sample. The data were collected according to the agricultural accounting standard of the German Federal Ministry for Nutrition, Agriculture, and Consumer Protection, and made available by LAND DATA, which is a private firm that offers professional services with respect to bookkeeping and official tax declarations for farms. The dataset, therefore, covers farms that use the services provided by LAND DATA for their accounting, and hence is not the product of a representative sampling effort.

Since organic farming in Germany has been expanding rapidly over the past roughly 15 years, the characteristics of a representative sample have been changing as well. While the regional distribution of the farms in the sample is similar to that reported in official statistics[42], two types of organic pasture farms are under represented. The first group comprises very small farms. Many of these farms have no detailed accounting, and most are part-time and can be considered non-commercial or hobby enterprises. These farms will presumably be of below-average efficiency (for example, because they have no accounting that could be used as a management tool), but their omission from the dataset is not critical because their share of pasture production in Germany is small, and they are not the farms that will shape the future of organic pasture farming in Germany. The other group of farms that is under represented are large former collective farms in eastern Germany that have converted to organic pasture production. Some of these farms are large enough to have their own accounting specialists and, hence, they do not engage the services of LAND DATA. Despite the fact that this type of farm is under represented, we do have a number of east German farms (62) in our sample, and there is no reason to expect any systematic differences between these farms and those that are not in the sample. Overall, we are confident that the sample provides a robust basis for analyzing the determinants of TE in German organic pasture farming, for a detailed discussion of the sample and its representativity, see Lakner[42].

The subset of this data that we analyze consists of an unbalanced panel with 1717 observations from $i = 396$ organic pasture farms over $t = 11$ years. Observations with obvious inconsistencies or missing values were deleted from the sample, and monetary variables were deflated using the official price indices for agricultural products and for agricultural inputs that are provided annually by the German Federal Office for Statistics[22]. All input variables were normalized by dividing by sample means, except for the linear trend that enters in deviations from the sample mean.Table 1 describes the input and output variables in the production function.

We use the following set of z variables as potential determinants of TE in the estimation of Equation 7 (variable names in *italics*, descriptive statistics in Table 2):

Management capacity and human capital. Farmers with *No Agricultural Education* from a university, technical college or agricultural school are expected to be less technically efficient. However, earlier studies find that

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Table 2. Variables used as determinants of TE.

Variable	Unit	Minimum	Mean	Maximum	Standard deviation
Management capacities and human capital					
In conversion	0/1	0	0.1	1	0.3
No agricultural education of the farmer	0/1	0	0.1	1	0.3
Age of the farmer	Years	20	43.5	70	8.4
Expenses for legal advice	€	0	58.3	6572	329.6
Farm structure and available natural resources					
Soil quality	EMZ/ha	25	3344.5	9877	1256.0
Equity share	%	0	77.8	100	24.0
Sum of land rent	€	0	6428.4	111,290	9242.1
Volume of milk quota	kg/yr	0	8645.6	307,430	19,135.0
Intensity of livestock production	VE/ha[1]	0	1.0	2.4	0.4
Pasture share	%	0	61.2	100	28.1
Institutional choice (legal form, tax options)					
Legal status = *GbR* (civil law association according to the German civil code)	0/1	0	0.2	1	0.4
Part-time farm	0/1	0	0.1	1	0.3
Market orientation and policy support					
Volume of subsidies	€	0	12,588	163,990	10,659
Regional variables					
Share of organic farmers	%	0.3	4.2	16.4	2.8
Eastern Germany[2]	0/1	0	0.07	1	0.3
Northern Germany	0/1	0	0.05	1	0.2
Western Germany	0/1	0	0.08	1	0.3
Share of votes for the Green Party	%	2.4	6.6	18.4	2.2
Distance to the nearest organic dairy	km	4.9	38.4	154.4	26.3

Source: Own calculations.
[1] VE = 'Vieheinheiten', which are standardized animal units. [2] The reference regional dummy variable is for southern Germany.

education has no impact on the success of organic farms[18,43], and it may be that the education provided in most Germany universities, technical colleges and agricultural schools to date does not address the specific needs of organic farming. A farm manager's *Age* captures the impact of both education and experience. The literature includes studies with positive[44] and negative[10] impacts of age on TE. The impact of *Expenses for Legal Advice* is ambiguous: taking legal advice could lead to more efficient enterprise organization and management, but it might also reflect entanglement in disputes that bind resources and distract from other management tasks. As discussed above, farms in *Conversion* are expected to be less technically efficient.

Farm structure and resources. *Soil Quality* (EMZ/ha) is expected to exert a positive impact on TE[18]. Soil quality is measured in '*Ertragsmesszahl*' (*EMZ*) according to the German soil classification system. EMZ/ha ranges from 25 (poorest) to 10,000 (best) and reflects characteristics such as soil texture (percentage of clay, silt and sand) and water retention capacity as well as climatic aspects such as temperature patterns. A high *Share of Pasture Area* in total agricultural area and a high *Intensity of Livestock Production* (measured in animal-units per hectare) are indicators of specialization that both can be expected to lead to higher efficiency. Financial management variables such as *Share of Equity* could affect TE in either direction[13], depending on whether agency theory (monitoring) or credit-evaluation issues (lender aversion to risky credits) dominate. In the European Union, the milk production is limited by a *milk quota* that allows farmers to deliver milk to the dairies and that was originally distributed to the farms in 1984. Since 2004 quota can be traded within different German regions, which makes allocation of quota to growing farms possible, but which is also a cost factor. The *Volume of Milk Quota* owned by the farm might therefore have a positive impact on efficiency, since farms that own quota do not have to rent it. Furthermore, this variable captures the difference between milk producers and other pasture farms in the sample that do not produce milk (suckler cows, sheep and goats). Farmers who rent land are obliged to pay a market price for the use of this land, whereas those who farm their own land can hide a lack of efficiency behind low-imputed rental payments for this land. Hence, we expect that as a farm's *Total Expenditure for Land Rental* increases, so will its TE.

Institutional choices. Farms with the legal status of a *Gesellschaft bürgerlichen Rechts* (*GbR* or 'civil law association' according to the German Civil Law section 705) face high set-up costs and internal transaction costs. The *GbR* is frequently observed when two or more farmers establish a partnerhsip. We therefore expect that the establishment of a *GbR* will be associated with strategic

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Table 3. Coefficient estimates for the production function.

	Coefficient	*t*-value		Coefficient	*t*-value
β_0	0.3250	10.10	β_{14}	−0.0402	−0.93
β_1	0.3327	14.90	β_{15}	−0.0086	−0.30
β_2	0.1777	7.18	β_{1t}	0.0008	0.17
β_3	0.0798	4.25	β_{23}	0.0705	1.94
β_4	0.1832	6.15	β_{24}	−0.0339	−0.78
β_5	0.1772	5.46	β_{25}	0.1158	3.10
β_t	0.0121	4.30	β_{2t}	−0.0005	−0.11
β_{11}	0.2179	8.40	β_{34}	−0.1459	−4.48
β_{22}	0.0004	0.01	β_{35}	−0.0149	−0.40
β_{33}	0.0666	1.70	β_{3t}	−0.0014	−0.34
β_{44}	0.0389	0.75	β_{45}	0.0895	1.73
β_{55}	−0.0646	−1.65	β_{4t}	0.0040	0.69
β_{tt}	−0.0067	−4.20	β_{5t}	−0.0028	−0.50
β_{12}	−0.1064	−3.29	ln σ_v	−2.0170	−36.90
β_{13}	−0.0504	−1.31			

Source: Own calculations.

restructuring efforts and, thus, increased TE. *Part-Time Farms* might be less efficient because a part of the family income is derived from other activities and the family therefore relies less on the efficiency of farm operations.

Market orientation/policy support. The impact of the *Volume of Subsidies* that a farm receives for organic production is ambiguous. Organic farms receive per hectare premium payments from EU agri-environmental programs (see EU-VO 2078/92 and EU-VO 1257/99). Many publications point to the negative impact that subsidies have on efficiency by weakening managerial efforts[45,46]. However, subsidies can lead to increased investment and thus efficiency, as for example reported in a study on dairy farms in Denmark, Sweden and Finland[47]. Hence, we formulate no expectations for this variable.

Location. The regional variables discussed above (*Regional Share of Organic Farmers* and *Local Election Results of the Green Party*) are provided by the German Federal Office for Statistics that provides data at the county level every 2 years[23]. Election results for the Green Party are taken from national elections. The results of state or local elections might better depict local voter preferences, but voter participation is much lower and more variable in these elections. The *Distance to Nearest Organic Dairy* was calculated using ArcView 10. We also include a set of dummy variables to capture regional differences in production systems in Germany. Analysis by the International Farm Comparison Network (IFCN) shows that the large milk producers that emerged from the former collective farms in eastern Germany are very competitive internationally[48]. Hence, we expect the dummy for *eastern Germany* (the omitted reference dummy is for *southern Germany*; dummies for *northern* and *western Germany* are also included) to have a significant positive impact on TE.

We estimated the model with *Oxmetrics 6.0* and the program package *sfamb for ox*[49].

Results and Discussion

The estimation results for the *production function model* (Eqn 2) are presented in Table 3. Most of the estimated coefficients are significantly different from zero at the 5% level. Because all variables have been normalized by their respective sample mean prior to taking logarithms, the first-order estimates β_j can be interpreted as partial production elasticities at the sample mean that shows how much the output would increase in percentage terms if the use of the respective input was increased by 1%. Of the five inputs, intermediate inputs have the largest partial production elasticitiy ($\beta_1 = 0.33$). The estimated elasticity of labor ($\beta_4 = 0.18$) is larger than that found for conventional dairy farms[10]. This is plausible since the labor share is higher on organic than on conventional farms. The other inputs play less important roles. The estimated annual rate of technological progress (indicated by β_t) is 1.2%.

The estimated ratio of the inefficiency variance to the total error variance, $\gamma = \sigma_u^2/\sigma_u^2 + \sigma_v^2$, is 0.95. Hence, most of the variation in the composite error term is due to the inefficiency component. The average TE score is 0.74, with a standard deviation of 0.21; this indicates that the average farm in the sample is producing 74% of the maximum feasible output for its level of input use.

Table 4 presents the results of selected *specification tests* for the production function model with technical effects.

H^1 tests the hypothesis that every farm in the sample is fully efficient and that the introduction of an 'inefficiency term' is therefore not justified. This hypothesis is rejected, which indicates that inefficiency effects play a significant role. The hypothesis of linear homogeneity (H^2) is rejected, which means that the assumption of globally constant returns to scale is not supported by the data. The mean scale elasticity is 0.93 and we find decreasing returns to scale on about 79.1% of the farms, meaning that if the use of all inputs was increased by some proportion X on each of these farms, their output would increase by less than proportion X. This result contrasts with results for dairy farms in the USA, which show increasing returns to scale for both organic and conventional farms[14]. The rejection of H^3 indicates that the z variables in Equation 7 have a significant joint impact on technical efficienty, and the rejection of H^4 indicates that the subset of z variables that capture location effects also has a significant joint impact on TE. Other specification tests (available from the authors) favor the translog functional form of the frontier production function over the simpler Cobb–Douglas form. Overall, the results in Table 4 support the specification of the SFA model proposed above, including variables that capture location effects as determinants of TE.

The results from the 'heteroscedasticity model' (the parameter estimates for the x-variables presented in Eqn 6) show that efficiency is significantly affected by different factor endowments on the farms. For example, farms with higher levels of intermediate inputs, labor and land use

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Table 4. Results of tests for model quality.

Test	Null hypothesis	Test value	Critical value[1]	Result
H^1: no inefficiency	$\gamma = 0$; $\rho = 0$; $\delta = 0$	1,312.70	30.81	Reject
H^2: linear homogeneity	$\sum\beta_j = 1$; $\sum\sum \beta_{jk} = 0$	33.06	12.59	Reject
H^3: no technical effects	$\delta_0 = \delta_1 = \ldots = \delta_{19} = 0$	560.29	31.41	Reject
H^4: no location effects	$\delta_{14} = \delta_{15} = \ldots = \delta_{19} = 0$	53.13	12.59	Reject

Source: Own calculations.
[1] Critical value for H^1 from Kodde and Palm[50]; the test statistics for H^2 through H^4 follow χ^2 distributions. The critical values are significant at the 5% level of error probability; all test values are significant at the 1% level.

Table 5. Estimated coefficients for the technical effects model.

Variable	Parameter	Coefficient	*t*-value	Marginal effect
Constant	δ_0	−0.073	−0.35	.
In conversion	δ_1	0.133***	2.58	−0.004
No agricultural eduction of the farmer	δ_2	−0.069	−0.72	0.002
Age of the farmer	δ_3	0.0004	0.25	−0.000
Expenses for legal advice	δ_4	0.008*	1.82	−0.0002
Soil quality	δ_5	−0.100**	−2.52	0.003
Equity share	δ_6	−0.001	−0.18	0.000
Sum of land rent	δ_7	−0.031***	−3.87	0.001
Volume of milk quota	δ_8	−0.012***	−2.87	0.0004
Intensity of livestock production	δ_9	−0.441***	−4.75	0.014
Pasture share	δ_{10}	−0.068**	−2.10	0.002
Legal status = *GbR*	δ_{11}	−0.171**	−2.04	0.003
Part-time farm	δ_{12}	−0.085	−1.26	0.002
Volume of subsidies	δ_{13}	0.015**	2.32	−0.001
Regional variables				
Regional share organic farmers	δ_{14}	−0.130**	−1.98	0.004
Eastern Germany	δ_{15}	0.221**	2.27	−0.004
Northern Germany	δ_{16}	−0.363***	−2.73	0.006
Western Germany	δ_{17}	−0.346***	−3.27	0.006
Share of votes for the Green Party	δ_{18}	−0.099*	−1.76	0.003
Distance to the nearest organic dairy	δ_{19}	0.108**	2.52	−0.003

Source: Own calculations.
*Estimated results with 10% error-probability, **estimated results with 5% error probability, ***estimated results with 1% error probability.

tend to have a smaller σ_u, in other words to be less inefficient.

Table 5 presents the parameter estimates and marginal effects for the *determinants of TE* (the z variables in Eqn 7). Marginal effects measure the change in TE in percentage points due to a small change in the corresponding determinant[51]. These are estimated for the continuous variables by numerical differentiation at the sample mean, and for dummy variables, they measure the impact on TE of a unit change (from zero to one) in the corresponding variable.

Among the management variables, we find that farms in *Conversion* to organic production are less technically efficient than converted organic farms, a result that we discuss in more detail below. Farmers with *No Agricultural Education* are neither more nor less technically efficient than others, and *Age* also has no significant influence on efficiency. The first of these results confirms the results from other studies in organic farming[14,18,43]. It suggests that agricultural education in German universities, technical colleges and agricultural schools has, at least to date, not imparted knowledge and skills that contribute to technically efficient organic farming. *Expenses for Legal Advice* do not have a significant impact on TE.

As a farm's *Soil Quality*, *Pasture Share* and *Volume of Milk Quota* increase, so does its TE. A farm's *Equity Share* has no significant impact on its TE. As expected, the *Total Expenditure for Land Rent* has a positive impact on TE, and this impact is highly significant. Mayen et al.[14] argue that renters of land might have lower incentives to use rented land efficiently. This might be true in the USA and in general for markets where rental prices of land are low. But as competition on the landmarket and rental prices for land increase (as in west Germany), the incentives to use land efficiently should increase as well, resulting in higher-efficiency scores (as estimated here).

The *Intensity of Livestock Production* also has a strong influence on TE, with a 1% increase in intensity boosting efficiency by nearly 1.4%. As expected, farms that have the

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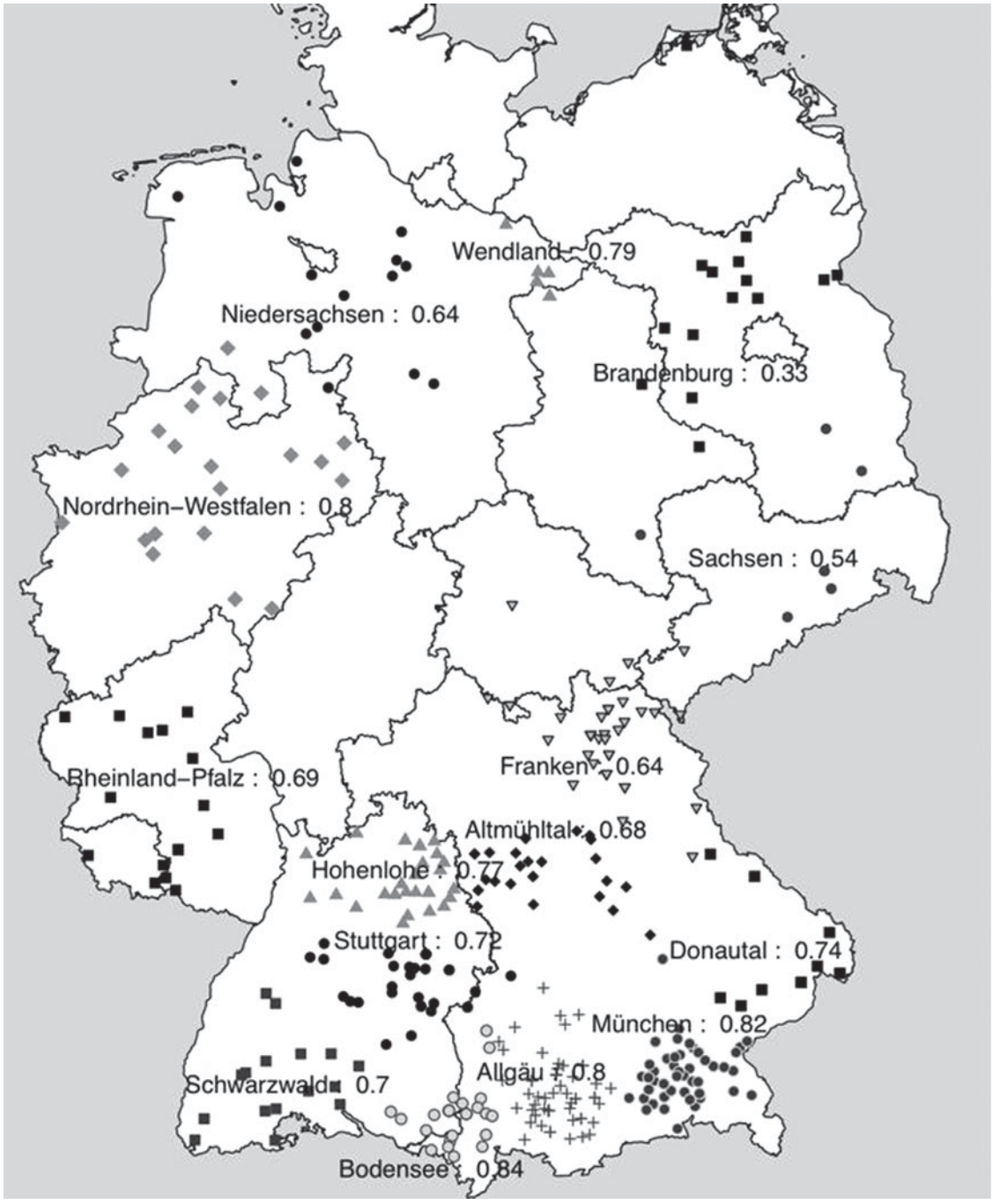

Figure 3. Average TE in 15 clusters of organic pasture farms in Germany. Source: Own presentation.

status of a *GbR* perform better than those that have adopted other legal forms. *Part-Time Farms* are more efficient, but this effect is not statistically significant. Farms that receive larger *Volumes of Subsidies* have lower-efficiency scores, although the impact is small. This may be evidence that subsidies for organic farms, which largely take the form of payments for agri-environmental services, lead farms to pursue other activities that detract from the core pursuit of efficient pasture-based production.

Most of the coefficients for variables that capture *location effects* are significant at the 5% level. There are distinct regional differences in TE. Compared with the reference region (southern Germany), the pasture farms in western and northern Germany are more efficient, other things being equal, while the pasture farms in eastern Germany are less efficient. This contradicts the findings of other studies[48], which find that organic milk producers are more competitive in eastern Germany than in other regions. However, the magnitude of the differences estimated here is small; farms in eastern Germany are on average 0.4% less efficient than those in southern Germany, and 1.0% less efficient than those in northern and western Germany. Furthermore, TE is only one component of competitiveness[52]; it could be that organic pasture farms

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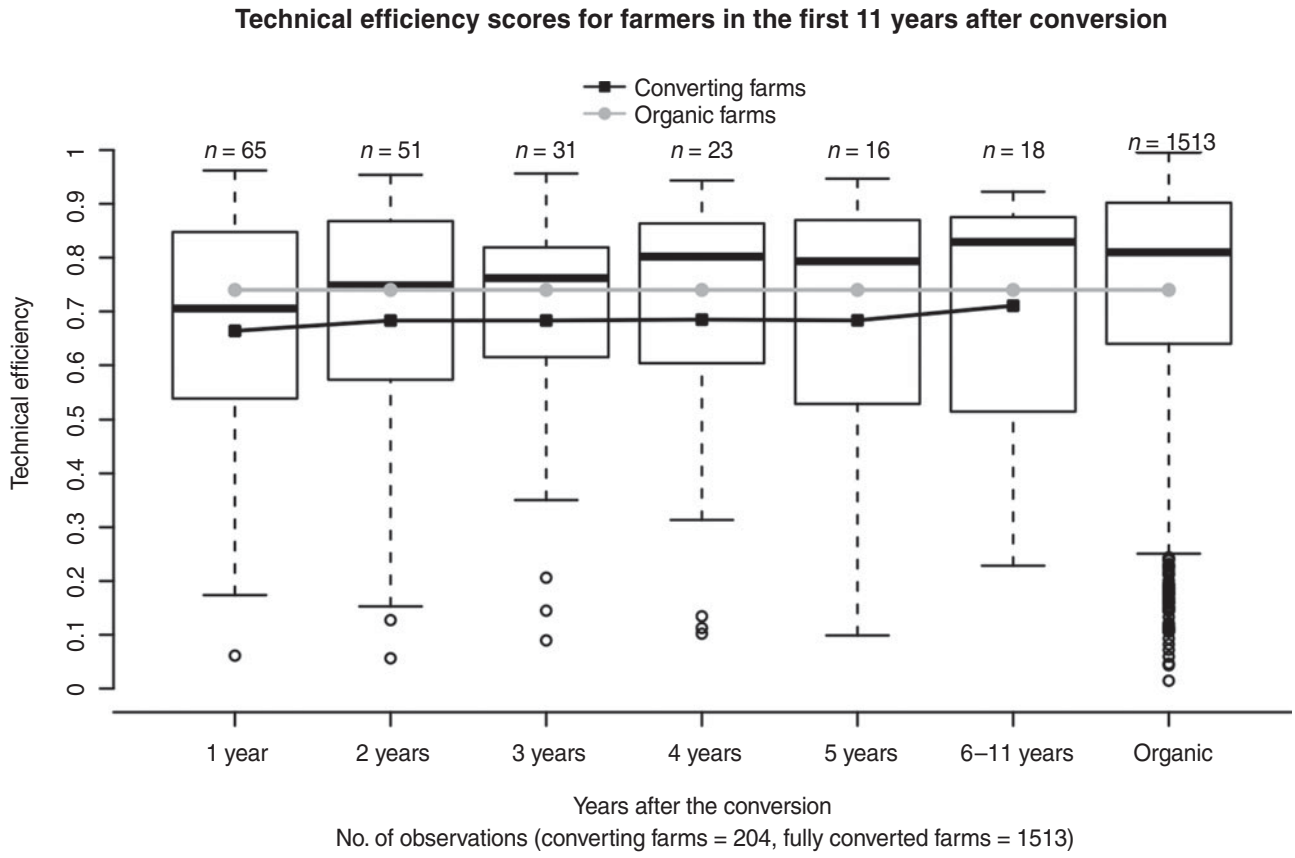

Figure 4. TE scores for farmers in the first 11 years after conversion. Source: Own calculations. Note that in the figure the efficiency of the farms 'in conversion' ($n = 204$, *in black*) is grouped according to the year after their conversion (i.e., 1 year, 2 years, . . .), whereas the performance of fully converted organic farms ($n = 1513$, *in grey*) is grouped altogether, denoted as 'organic'. The boxplots 1–6 are based on the data of the farms in the 11 years after the conversion (i.e., $n = 204$), boxplot 7 depicts the distribution of the fully converted organic farms (i.e., $n = 1513$).

in eastern Germany are able to compensate for their slightly lower TE by being larger and thus being able to negotiate better prices for their input purchases and output sales.

The significant negative coefficient on the variable *Regional Share of Organic Farmers* is evidence in favor of localization economies in organic pasture farming. The fact that TE decreases with increasing *Distance to the Nearest Organic Dairy* and increases with the *Share of Votes for the Green Party* suggests that urbanization economies also play a role. All other things being equal, a 1 km reduction in the distance to the nearest organic dairy is accompanied by a 0.3% increase in TE, while a 1% increase in the local Green election result increases TE by 0.3%.

Regional cluster (modeled as described in subsection 'Data') reveals that TE varies substantially across regions. Figure 3 shows 15 regional clusters with their mean TE score.

Especially in southern Germany we can find very efficient clusters ('Allgäu' with 0.8, Bodensee with 0.84 and the region of Munich with 0.82 average TE), whereas the clusters in east Germany show a relatively low performance (Saxony with 0.54 and Brandenburg with 0.33 average TE). Interestingly, especially the southern region with a very high share of organic farms in the south perform very well, whereas in the north-eastern regions, where we can also find high shares of organic farms (see Fig. 1), the efficiency performance is low.

Returning to the impact of *conversion* from conventional to organic farming, Figure 4 illustrates the development of TE over the course of conversion to organic farming. Figure 4 shows that converting farms have lower levels of average TE than converted farms, but that this gap closes over time. These results are as expected and coincide with the findings of Lohr and Park[19], who find lower TE scores in converting farms with less than 5 years of experience. Note that lower efficiency during conversion might be partly price-driven because the output of farms in conversion does not qualify as 'fully' organic, i.e., it has to be labeled differently and generally sells for lower prices. In a sample of organic farmers in Austria that had converted back to conventional production after 5 years, 58% reported converting back because they had only received conventional prices for their organic output[53]. Since we measure output in monetary terms in our application, lower prices could be showing up as reduced efficiency. However, closer examination of the data reveals no significant price differences between the converting and converted farms

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in our sample, which suggests that the lower TE of converting farms is not price driven.

The boxplots 1–6 in Figure 4 provide information on the distribution of efficiency scores for farms in the first 11 years after the conversion ($n = 204$), boxplot 7 shows the respective distribution for organic farms that are already converted ($n = 1513$). They show that in most years the distribution of TE is wider in the group of the converting farms than in the reference group of converted organic farms. They show that although converting farms are less technically efficient on average, the range of efficiencies is large and highly skewed toward lower-efficiency scores. The same is true of the efficiency distributions for converted farms.

Conclusions

We studied the TE of organic pasture farms in Germany using an unbalanced panel with 1717 observation from 396 farms over 11 years. TE is estimated using a stochastic translog production frontier that allows for the simultaneous estimation of the impact of specific variables on technical inefficiency. Along with the factors such as a farmer's age and education that are commonly used to explain TE in agriculture, we explicitly include variables that capture localization and urbanization effects.

The empirical results confirm that localization and urbanization effects do influence the TE of organic pasture farms in Germany. Specifically, TE increases with the regional share of organic farmers, with decreasing distance to the nearest organic milk processing plant, and with the regional share of votes for the 'Green Party' in federal elections. This suggests that future studies of TE in organic agriculture and also agriculture in general should take localization and urbanization effects into account or risk mis-specification. Our results also confirm that the conversion status of an organic farm can have a significant impact on its efficiency. As long as organic farming expands, samples of organic farms will include farms at different stages of the conversion process, and the results here suggest that empirical analysis should explicitly account for this.

The results of our analysis also have implications for policy. We find that organic farmers who have received no specific agricultural education are not less efficient than other organic farmers. While our binary measure of specific agricultural education is admittedly simple, this result matches the results of other studies and supports the supposition of many proponents of organic farming in Germany that agricultural education to date in Germany (which is almost exclusively publicly funded) has not been tailored to the needs of organic farming.

We also find that TE falls significantly with the volume of subsidies received, which was not expected *ex ante*. This might be evidence that the agri-environmental activites for which organic pasture farmers receive special subsidies are detracting from the efficient management of their core production activities. Of course, if farmers are volunteering to participate in these schemes, then presumably the subsidies that they are receiving in return must compensate for any resulting loss in efficiency. Nevertheless, if this explanation holds, German policy-makers might want to reconsider the types of subsidies that they have been providing to organic farming and design schemes that increase rather than decrease efficiency. However, this result might also reflect that the less efficient farmers are more likely to opt for participation in subsidy programs. Note that some of these programs require delivery of concrete environmental benefits, which from a broader perspective might compensate for lower TE. This links to the topic of 'environmental efficiency'[54], where more research seems to be necessary.

Finally, we find that farms that are converting to organic production are less efficient on average than converted farms, although the difference in efficiency between these groups of farms falls as conversion progresses. This finding could be used to justify temporary and phased support for converting farms[55]. In most German federal states, the special premia for farms converting to organic production were abolished in 2006/2007. However, our results also show that the distribution of TE among converting organic pasture farms is wide and skewed. Therefore, it would be difficult to determine an appropriate level of support and in particular avoid overcompensation of converting farms that are relatively efficient. How to dose and target support and what instruments should be used to provide it (e.g., per hectare payments, price supports and extension) are topics for further research.

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