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Abstract

It can be argued that the competitiveness of an industry consists of two main parts: The production conditions and the utilization of these. The production conditions are largely determined by factors exogenous to the firms comprising the industry, including the economic environment, regulatory framework, etc. The utilization of the production conditions corresponds to the classic economic notion of structural efficiency. We here argue that it is crucial for policy analysis to be able to quantify each of these two aspects separately, since the production conditions are partly in the hands of the policy makers, whereas the utilization is mainly the responsibility of firm management. In this paper we define two new bilateral indicators; the Bilateral Industry Utilization (BIU) indicator, and the Bilateral Production Conditions (BPC) indicator. These are applied to a large data set of dairy farms across 19 European countries provided by the Farm Accountancy Data Network (FADN). With focus on the competitiveness of Danish dairy farms we show that dairy farms in most other

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countries have significantly better production conditions than those in Denmark while Sweden is the only country with significantly better utilization. Finally, we asses potential causes behind the differences and discuss possible remedies.

Keywords: Competitiveness indicators; Production conditions; Structural efficiency; Bilateral indicators; Dairy farms; Efficiency; Frontier analysis; Jackknifing.

JEL classification: C61, D04, E23, O47, Q12

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1 Introduction

Problem: Although economic theory has no formal definition of *competitiveness* there seems to be widespread agreement that it comprises some aspect of productivity. For instance, World Economic Forum's Global Competitiveness Report 2016-17 "*define competitiveness as the set of institutions, policies, and factors that determine the level of productivity of a country*" (Schwab and Sala-i-Martin, 2016, page 4). Specifically, we here argue that the competitiveness of an industry, comprising a set of individual firms, consists of two parts; *production conditions*, that are largely determined by factors exogenous to the individual firms, such as the economic environment, regulatory framework etc.; and the industry's overall *utilization* of these production conditions (as in the "structural efficiency" concept of Farrell, 1957). A similar viewpoint, where competitiveness is determined by "factors controllable by firms" and "factors non-controllable by firms", can be found in the OECD report by Latruffe (2010). From a policy perspective, it is crucial to evaluate these two parts separately because policy makers can likely influence production conditions, whereas the utilization thereof is mainly the responsibility of firm management.

In the present paper we formulate indicators to evaluate both these aspects of industry competitiveness. Measurement of the utilization of production conditions within a given industry has been debated at least since the 1950s (e.g., Farrell, 1957, Aigner and Chu, 1968, Førsund and Hjalmarsson, 1979). However, the arguably more policy relevant question of quantifying differences in production conditions between countries has received surprisingly little attention. A possible explanation might be that it is difficult to quantify the overall impact of various differences in conditions: for instance, country A may have higher wages than country B, but more favorable environmental regulations, so does this imply that the overall production conditions in country A are better or worse than those of country B? We here address this question and also propose an indicator for bilateral comparisons of production conditions based on well established frontier concepts from production economics (Färe et al., 1994a).

We provide: Bilateral indicators capable of evaluating differences in production conditions for a given industry in different competitive environments as well as in the utilization of the conditions. While generally applicable, the method will here be used to investigate differences in the competitive conditions between large dairy farms in different European countries. This was made possible by being granted access to farm-level data from the Farm Accountancy Data Network (FADN), comprising comparable farm-level accounting and production data for a large number of farms across 28 European countries.[1] Specifically we focus on Danish dairy farms, which are renowned for high technical efficiency (as indicated by KPIs such as "milk per cow") and find that they actually suffer from having basically the worst production conditions amongst their European counterparts from an economic perspective. Furthermore, we find that the Danish dairy farms are amongst the best in terms of utilization with only one country (Sweden) performing significantly better on this aspect. Noting that there has been a large number of failing Danish farms in recent years, it seems that the farms themselves have limited possibilities of improving their situation since they are showing better utilization of worse conditions than the farms in the other European countries. Understanding the distinction between conditions and utilizations thereof, and separately evaluating the extent of each, is crucial for the appropriate design of remedial policies. In the specific Danish context, recent political initiatives have in fact acknowledged that the productive conditions are limiting for the Danish farms and have subsequently loosened environmental regulations amongst other things.[2] In order to understand potential causes, we outline an approach to investigate factor specific differences in production conditions.

Method: From a theoretical viewpoint, comparing production conditions is a matter of comparing production functions between groups. In practice, however, such production functions have to be estimated. Frontier methods, providing estimates of *best practice*, are well established in the academic literature as representations of the unknown production functions.[3] We here

[1]See, FADN: http://ec.europa.eu/agriculture/rica/.

[2]See http://mfvm.dk/landbrug/vaekst-eksport-og-arbejdspladser/foedevare-og-landbrugspakke/ (in Danish)

[3]See, for example, Fried, Lovell and Schmidt (2008).

utilize approaches related to Data Envelopment Analysis (DEA) which can be used for identification and quantification of frontier differences, here interpreted as differences in production conditions. Unlike the more commonly used meta-frontier approaches, originating in the program efficiency idea of Charnes et al. (1981), we here advocate using a modification of the so-called global frontier difference index of Asmild and Tam (2007). In short, this has the advantage of avoiding the questionable assumption of convexity between groups underlying the meta-frontier approach. Indeed, the fundamental premise of our analysis is that firms in different countries operate under different production conditions. Assuming convexity between countries implies that it is reasonable to compare a firm to a convex combination of the performances of other firms belonging to different countries. Such constructed benchmarks are clearly meaningless in the present context where different production conditions do not co-exist and firms therefore operate under either one or the other set of conditions.

When examining the utilization of production conditions we maintain a bilateral approach and define an indicator as the ratio between the output-weighted mean utilization of the production conditions within the two groups being compared. This indicates whether the structural efficiency within one group is higher than that within another, i.e., whether firms in the former are better at utilizing their given conditions than firms in the latter.

However, it is important to realize that both these bilateral indicators are sensitive to differences in samples size of the two groups. This is because the frontiers estimated using DEA cannot regress when more observations are included, *ceteris paribus*. To control for this bias we suggest the use of jackknifing (e.g., Efron, 1982) which results in empirical distributions for the indicators had the groups been of identical size.

Related literature: Within the economic growth literature it is common to measure and compare productivity at the industry level (see e.g., Jorgenson, 2011). Typical quantifiers are Total Factor Productivity (TFP) measures, which are closely related to DEA efficiency scores under the assumption of constant returns to scale (see e.g. Färe et al., 1994c, Färe et al., 1997). A general characteristic of these analyses is that they do not distinguish between differences in production conditions and in the utilization thereof. However, distinguishing between intra- and inter-group differences is not a novel idea. For example, Acemoglu and Dell (2010) consider differences between municipalities as well as between countries when analyzing income and productivity differences. In particular they note that productive efficiency, within countries, depend on local institutions. Comparisons of such productive conditions is exactly the purpose of our suggested approach. However, our empirical illustration considers firms making up a given industry which is subsequently compared between countries.

Closest to our suggested approach is the work by Camanho and Dyson (2006) who define indices of group performance related to the two elements of production conditions and their utilization. Their starting point is the classic Malmquist index and its decomposition (Färe et al., 1994b). However, where the Malmquist index is designed for measuring productivity changes over time, the application in terms of group differences makes the interpretation of the index and its components somewhat questionable. Furthermore, their construction of the index for efficiency spread (resembling utilization) is at odds with the conventional aggregation of firms into an industry.

Specifically for agricultural productivity there are plenty of studies on productivity growth typically using TFP measures (e.g., Ball, 1985, Jorgenson and Gollop, 1992, Brümmer et al., 2002). For dairy farms, Serra et al. (2011) is but one example of a recent study of productivity growth.

Content: The rest of this paper is organized as follows: In section 2 the two new bilateral indicators, the Bilateral Industry Utilization (BIU) indicator and the Bilateral Productions Conditions indicator (BPC) are defined, together with a description of the jackknifing procedure used to control for sample size biases. Section 3 provides the empirical illustration focused on comparing dairy farms in Denmark to those in the other European countries. It also outlines, and provides selected results from, an approach to further investigations of factor specific differences. Finally, section 4 concludes.

2 Methodology

As mentioned in the introduction we argue that competitiveness comprises both *production conditions* and *utilization* of these production conditions, and we here propose ways in which to quantify both these elements. By separating production conditions from utilization we implicitly assume that these are independent to a certain degree. This means that if production conditions improve we expect improved performance as well, since the utilization will not be directly affected.

We submit that a suitable analytical technique for quantifying both production conditions and utilization is related to estimation of empirical production frontiers representing best practice amongst observed firms. For quantification of differences in production conditions the relevant analysis relates to differences between estimated production frontiers, whereas utilization is related to actual performance relative to the groups' estimated production frontier. In contrast, classic regression type models, through estimation of average relationships, capture a combination of the production conditions and their utilization.

Empirical production frontier estimation can be carried out using either parametric or non-parametric approaches for which the main methodologies are Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) respectively (Fried, Lovell and Schmidt, 2008). Arguments can be made in favor of either approach. For the present analysis we have chosen to use the non-parametric (DEA) models. In standard DEA, a score for the technical efficiency of each firm is computed as the relative distance from an actual production plan to the estimated production frontier, typically using the radial Farrell index (Farrell, 1957) as distance measure.

Our model simultaneously includes multiple inputs and multiple outputs, since we are modeling a production process consuming various resources in order to produce several outputs. The variables are all measured in monetary terms, which means that the production model captures aspects of economic decision making rather than a narrow managerial focus on physical production. Differences in cost levels reflect differences in input quantities, but also in prices and the economic environment in general, for instance regulatory requirements. In this sense our model is richer than a traditional technical production function focusing on the transformation of quantities of physical production factors into quantities of physical outputs.

2.1 Estimating Production Frontiers

Consider a set of firm-level data belonging to a number of different groups (here countries). Formally, let $N = \{1, \ldots, n\}$ be a total set of firms which can be partitioned into m groups: $N = G^1 \cup \cdots \cup G^m$. For every firm $i \in N$ data consists of input-output vectors $(x_i, y_i) \in \mathbf{R}^s_+ \times \mathbf{R}^t_+$; that is, for a given firm i, s inputs, x_i, are used to produce t outputs, y_i.

Using a non-parametric envelopment approach (e.g., Charnes et al., 1978), for each group G with observations $\{(x_i, y_i)\}_{i \in G}$, estimate the production technology $T(G)$ under constant returns to scale, as:

$$T(G) = \{(x, y) \in \mathbf{R}^{s+t}_+ \mid \sum_{i \in G} \lambda_i x_i \leq x, \sum_{i \in G} \lambda_i y_i \geq y, \lambda_i \geq 0 \text{ for all } i\} \quad (1)$$

By the efficient frontier of $T(G)$ we mean the weakly Pareto efficient subset of $T(G)$ (cf. e.g. Färe et al., 1994a). The efficient frontier can be interpreted as an empirical estimate of the best practice of the firms in the industry.

2.2 Industry Utilization Indicator

The input efficiency of a given observation (x_{i^o}, y_{i^o}), relative to the technology $T(G)$, is measured using Farrell's input oriented radial index of technical efficiency (Farrell, 1957): $e^G_{i^o} = \min\{e \mid (ex_{i^o}, y_{i^o}) \in T(G)\} \in (0, 1]$. With the technology $T(G)$ given by (1) this can be formulated as a linear programming problem (Charnes et al., 1978):

$$
\begin{aligned}
& e^G_{i^o} = \min e \\
& s.t. \\
& \sum_{i \in G} \lambda_i x_i \leq e x_{i^o} \\
& \sum_{i \in G} \lambda_i y_i \geq y_{i^o} \\
& \lambda_i \geq 0 \text{ for all } i.
\end{aligned} \tag{2}
$$

Observe that any observation on the efficient frontier of $T(G)$ has efficiency score $e = 1$; the more inefficient the lower the score.

Based on the efficiency scores from program (2), we now define a weighted *Bilateral Industry Utilization* (BIU) indicator for the comparison of firms in G' resp. G'''s utilizations of their corresponding production conditions (given by the technologies $T(G')$ resp. $T(G'')$) as the ratio of the weighted averages of the firms' efficiency scores:

$$
BIU(G', G'') = \frac{\sum_{i' \in G'} w_{i'} e^{G'}_{i'}}{\sum_{i'' \in G''} w_{i''} e^{G''}_{i''}}, \tag{3}
$$

where w is a vector of observation specific weights summing to one within each group, i.e. $w \in \mathbf{R}^{|G|}_+, \sum_{i \in G} w_i = 1$.

A value $BIU(G', G'') > 1$ indicates that the firms in G' on average have a better utilization of their production conditions than the firms in G'' (and vice versa when $BIU(G', G'') < 1$). Both the numerator and the denominator in (3) are similar to one of Farrell's measures of *structural efficiency* of an industry: they indicate *"the extent to which an industry keeps up with the performance of its own best firms"* (Farrell, 1957, p. 262).

In our current application we use output-weights defined as the observation's share of the total output of the group, i.e. $w_i = \frac{\sum_{j=1}^t y_{ij}}{\sum_{i \in G} \sum_{j=1}^t y_{ij}}$ for every $i \in G$. This is well defined in our case since all outputs are revenues measured in monetary units.[4]

[4]If there is no natural weighting scheme, the observations can simply get equal weights.

2.3 A Bilateral Production Conditions Indicator

Next, we will make a series of bilateral comparisons of the groups' production conditions: for each comparison of two groups G' and G'', compute the efficiency score of each firm belonging to either of those two groups, relative to the efficient frontier of each group in turn (using (2)).

Consequently, for every bilateral comparison between groups G' and G'', a given firm $i^o \in G' \cup G''$ will have a pair of associated efficiency scores $(e_{i^o}^{G'}, e_{i^o}^{G''})$ relative to the efficient frontiers of G' and G'' respectively.

Now, we define the weighted *Bilateral Production Conditions* (BPC) indicator for groups G' and G'', $BPC(G', G'')$, as the weighted geometric mean of the ratios of the firms' efficiency scores (2) relative to the efficient frontiers of G' and G'', i.e.,

$$BPC(G', G'') = \Pi_{i \in G' \cup G''} \left(\frac{e_i^{G''}}{e_i^{G'}} \right)^{w_i}, \tag{4}$$

where w is a vector of observation specific weights summing to one across the two groups being compared, i.e. $w \in \mathbf{R}_+^{|G' \cup G''|}, \sum_{i \in G' \cup G''} w_i = 1$.

Note that $BPC(G', G'') \in (0, \infty)$. We say that the production conditions of group G' are better than those of G'' if and only if $BPC(G', G'') > 1$; and vice versa when $BPC(G', G'') < 1$. In the obvious case, where the technology of one group, G'', is imbedded in the technology of the other group G', it is clear that for each $i \in G' \cup G''$, the efficiency score $e_i^{G''} > e_i^{G'}$, and consequently $BPC(G', G'') > 1$. However, in other cases where the efficient frontiers of the two groups intersect, for some $i \in G' \cup G''$ we will have that $e_i^{G''} > e_i^{G'}$, whereas for other firms $e_i^{G''} < e_i^{G'}$. Taking the geometric mean results in an index for the overall comparison of production conditions.[5]

In our current application we again suggest using output-weights defined as the observation's share of the total output across the two groups, i.e. $w_i = \frac{\sum_{j=1}^{t} y_{ij}}{\sum_{i \in G' \cup G''} \sum_{j=1}^{t} y_{ij}}$, for every $i \in G' \cup G''$.

[5]Note that (4) is a slight modification of the global frontier shift (difference) index of Asmild and Tam (2007). In the present case we weigh the observations by their output share and furthermore only include observations from the two groups G' and G'' in the estimation of $BPC(G', G'')$ while Asmild and Tam (2007) includes all n observations.

2.4 Sample Size Bias

A non-parametric production frontier, as the one estimated by DEA, is a biased estimate of the unknown production function, since observed production is encompassed by the true, but unknown, production possibility set. For the bilateral comparisons employed here, this means that the efficient frontier for the group with the larger sample size is less biased than the efficient frontier for the smaller group. Therefore, when computing the $BIU(G', G'')$ indicators, as in (3), if $|G'| > |G''|$ this indicator will be underestimated.

Furthermore, when comparing the efficient frontiers of two groups, as in (4), the sample size bias means that the efficient frontier for the group with the larger sample size (G') is likely to dominate the efficient frontier for the group with the smaller sample size (G''), *ceteris paribus*.

To control for this sample size bias, we use a "delete ($|G'| - |G''|$) jackknife" resulting in empirical distributions for $BIU(G', G'')$ and $BPC(G', G'')$ had the groups been of similar sizes ($= |G''|$). In these distributions we can now assess whether there is a "significant" difference in utilization viz. production conditions depending on whether the value of 1 (indicating no difference) belongs to the empirical 95% confidence intervals around the mean.[6]

This jackknife procedure, defined formally below, relies on the implicit assumption that the bias between the jackknifed frontier for the larger group G', and its corresponding true, but unknown, production function on average is the same as the bias between the efficient frontier for the smaller group G'', and its corresponding (true, but unknown) production function. So therefore it becomes appropriate to compare the efficient frontier for G'' with the jackknifed frontier of G'.

Jackknife Procedure:
Input: Samples G' and G'' with $|G'| > |G''|$.

Step 1. Estimate efficiency scores for observations from G'' using (2) and denote these $e_i^{G''}$.

Step 2. Remove $|G'| - |G''|$ observations from G' without replacement, resulting in $\mathcal{G}'$ where $|\mathcal{G}'| = |G''|$.

[6] For details of jackknifing and related approaches see e.g. Efron (1982) and Shao and Tu (1995).

Step 3. Estimate jackknifed efficiency scores for observations from $\mathcal{G}'$ using (2), and denote these by $e_i^{\mathcal{G}'}$.

Step 4. Compute $BPC(\mathcal{G}', G'')$ using (4) and $BIU(\mathcal{G}', G'')$ using (3).

Repeat Steps 2-4, 1000 times.

Output: An empirical distribution over the jackknife replications for $BPC(G', G'')$ and for $BIU(G', G'')$ had G' been of the same size as G''.

Observation: *In every iteration of the jackknife procedure outlined above:* $e_i^{\mathcal{G}'} \geq e_i^{G'}$ *for all* $i \in \mathcal{G}'$.

Proof: Solving (2) for $G = \mathcal{G}'$ instead of $G = G'$ implies $e_o^{\mathcal{G}'} \geq e_o^{G'}$ since $\mathcal{G}' \subseteq G'$. □

3 Empirical Analysis

We consider the case of dairy farms in different European countries as an illustration of our methodological approach to quantifying differences in production conditions as well as utilization thereof. Specifically we show how the bilateral indicators defined in (3) and (4) can be applied together with the jackknife procedure outlined above, in order to compare the competitive conditions of Danish dairy farmers with those of the farms in other European countries.

Besides serving as an illustration of our suggested approach, the case of Danish dairy farms is of independent policy interest. Dairy farming has historically been an important, and highly export oriented, industry in Denmark. However, in recent years this industry has been under heavy economic pressure with many Danish dairy farms struggling to survive (according to data from Statistics Denmark[7]). Therefore, a formal analysis of whether this is actually caused by differences in production conditions, or instead simply by the farmers utilization of these, is imperative for policy makers.

The current analysis is focused on bilateral comparisons with Denmark, but could, of course, consider comparisons between all pairs of countries.

[7]See https://www.dst.dk/da/Statistik/bagtal/2018/ (in Danish)

3.1 The Data Set

Our empirical analysis is based on farm-level data from the Farm Accountancy Data Network (FADN), which collects production- and accountancy data from approximately 80.000 farms each year that, due to a three way stratification, is representative for 5 million EU farms covering approximately 90% of the total utilized agricultural area, and 90% of the total agricultural production in the EU.

Our model of dairy farm production comprises three inputs and two outputs defined as follows:

Inputs:

1. *Salary costs:* defined as the salaries paid to hired labor plus the hours worked by the farm owners multiplied by the average wage paid to hired labor.

2. *Variable costs:* defined as the costs of energy, fertilizers, feed, and other livestock-related costs, as well as current costs for buildings and machinery.

3. *Capital costs:* defined as 4% of asset value plus land rent, representing opportunity cost of capital.

Outputs:

1. *Milk revenue:* defined as the revenue from milk sales.

2. *Other revenue:* defined as all other revenues from farm production as well as subsidies.

Since we are modeling a production process consuming various resources to produce several outputs it is natural to utilize a multiple-inputs-multiple-outputs model formulation. However, instead of quantifying the variables in physical units they are here all measured in monetary units (Euro). We do this because differences in factor prices are an essential part of the differences in production conditions which we try to capture.

Regarding the included observations we only consider specialized dairy farms (according to the FADN 2008-classification) with more than 100 dairy cows (measured in livestock units). Due to the definition of total salary costs above, only farms with hired labor are included.

Countries with less than 20 observations based on the delineations above are excluded from the analysis. Furthermore, a few observations are excluded due to missing, faulty, or zero values on variables.

Data are from 2012. Descriptive statistics (means and standard deviation) for the variables in each country are provided in Table A1 and A2 in the Appendix.

3.2 Empirical Results

First we estimate the output-weighted BIU-indicator (3) for Denmark (DAN) compared to each of the other countries in turn. These results are furthermore jackknifed and the averages and 2.5th as well as 97.5th percentiles of the empirical distributions are shown in Table 1 below. Note that the number of observations for Denmark is 310.

Country	BGR	CZE	DEU	ESP	EST	FRA	HUN	IRE	ITA
$BIU(DAN, Country)$	1.05	1.16	1.12	1.04	0.95	0.95	0.95	0.94	1.24
Average jackknifed $BIU(DAN, Country)$	1.15	1.22	1.09	1.08	1.01	1.01	1.04	1.00	1.27
2.5th perc. jackknifed $BIU(DAN, Country)$	1.11	1.19	1.02	1.05	0.98	0.98	1.00	0.97	1.25
97.5th perc. jackknifed $BIU(DAN, Country)$	1.18	1.25	1.12	1.10	1.04	1.04	1.07	1.03	1.30
No. of obs.	26	72	455	98	57	49	27	51	136

Country, cont'	LTU	LVA	NED	POL	ROU	SUO	SVE	SVK	UKI
$BIU(DAN, Country)$	0.95	0.97	1.02	0.91	1.00	0.89	0.92	0.99	1.06
Average jackknifed $BIU(DAN, Country)$	1.06	1.04	1.05	1.00	1.09	0.98	0.96	1.05	1.06
2.5th perc. jackknifed $BIU(DAN, Country)$	1.02	1.00	1.03	0.97	1.05	0.94	0.94	1.02	1.06
97.5th perc. jackknifed $BIU(DAN, Country)$	1.09	1.06	1.07	1.03	1.12	1.00	0.99	1.08	1.07
No. of obs.	18	46	108	19	25	24	73	49	277

Table 1: The Bilateral Industry Utilization Indicator with jackknifing results.

In the first row of Table 1, we see the estimated BIU-indicator for Denmark with respect to each of the other countries in turn, where a value larger than 1 indicates that the farms in Denmark are better at utilizing their production conditions than those in the other country. Thus, at first glance, it appears that the utilization is better in Denmark than in around half of the other countries (and vice versa). However, these results are biased by the differences in sample sizes as explained in Section 2.4 above, since there are more observations in Denmark than in all the other countries except for Germany. Therefore consider instead the jackknifed averages in row 2 of Table 1, where we can see that the BIU-indicator has increased for all countries except for Germany (DEU) and United Kingdom (UKI) (where the indicator has decreased resp. is unchanged). A more detailed picture is provided by also considering the 2.5th and 97.5th percentiles of the jackknifed distribution. If the value of one is not included within this range we can conclude that the utilization in the respective country is significantly different from that of Denmark. Thus, we conclude that farms in Denmark have a significantly better utilization than those in most of the other countries (specifically 12 out of the 18 countries) and only significantly worse utilization than farms in Sweden (SVE).

Next, we estimate the output-weighted BPC-indicator (4) for Denmark compared to each of the other countries in turn. As before, these results are jackknifed and the averages and 2.5th as well as 97.5th percentiles of the empirical distributions are shown in Table 2 below.

Country	BGR	CZE	DEU	ESP	EST	FRA	HUN	IRE	ITA
$BPC(DAN, Country)$	0.67	0.79	0.58	0.77	0.92	0.78	0.74	1.11	0.60
Average jackknifed $BPC(DAN, Country)$	0.39	0.53	0.62	0.65	0.53	0.62	0.33	1.01	0.54
2.5th perc. jackknifed $BPC(DAN, Country)$	0.35	0.47	0.60	0.57	0.42	0.56	0.24	0.96	0.49
97.5th perc. jackknifed $BPC(DAN, Country)$	0.46	0.62	0.65	0.73	0.74	0.71	0.59	1.08	0.57
No. of obs.	26	72	455	98	57	49	27	51	136

Country, cont'	LTU	LVA	NED	POL	ROU	SUO	SVE	SVK	UKI
$BPC(DAN, Country)$	0.71	0.80	0.92	0.73	0.45	0.87	1.12	1.09	0.90
Average jackknifed $BPC(DAN, Country)$	0.53	0.52	0.81	0.55	0.34	0.68	0.84	0.39	0.89
2.5th perc. jackknifed $BPC(DAN, Country)$	0.48	0.44	0.77	0.48	0.30	0.60	0.72	0.30	0.88
97.5th perc. jackknifed $BPC(DAN, Country)$	0.60	0.66	0.85	0.66	0.38	0.79	1.02	0.67	0.90
No. of obs.	18	46	108	19	25	24	73	49	277

Table 2: The Bilateral Production Conditions Indicator with jackknifing results.

In the first row of Table 2, we see the estimated BPC-indicator for Denmark with respect to each of the other countries in turn, where a value smaller than 1 indicates that the production conditions in Denmark are worse than those in the other country. Thus, we observe that, at first glance, the production conditions seems worse in Denmark than in most of the other countries except for Ireland (IRE), Sweden (SVE) and Slovakia (SVK). However, consider the jackknifed averages in row 2 of Table 2, where we can see that the BPC-indicator has decreased for all countries except for Germany (DEU) due to the fact that these countries have smaller sample sizes than Denmark. We note that all the countries except Ireland (IRE) actually have better production conditions than Denmark. Looking at the 2.5th and 97.5th percentiles of the jackknifed distribution we conclude that all countries except for Ireland and Sweden have significantly better production conditions than Denmark. It is here worth noting that the results for Slovakia are rather extreme since without correcting for sample size bias this country appeared to have worse conditions than Denmark, but after using jackknifing to control for the differences in sample size biases we in fact observe that the conditions in Slovakia are significantly better than those in Denmark.

Figure 1 shows smoothed density plots for the jackknifed BIU and BPC indicators for two selected countries: Germany (DEU) and Sweden (SVE). These countries are chosen to illustrate different scenarios. For Germany we see a bimodal distribution for the BIU indicator with most of the density located towards the right, which reinforces the conclusion that the BIU indicator value is larger than one, meaning that the farms in Denmark have significantly better utilization than those in Germany. For Sweden the jackknifed distribution of the BIU indicator is unimodal with low variance and almost all the density below one, showing that Sweden has significantly better utilization than Denmark.

For the BPC indicator, Germany shows a unimodal distribution, with a low variance, clearly located below the value of 1, so here it is clear that the production conditions in Germany are better than those of Denmark. For Sweden the distribution of the BPC index is actually tri-modal and with large variance. Thus, there is quite a big difference in the value of the

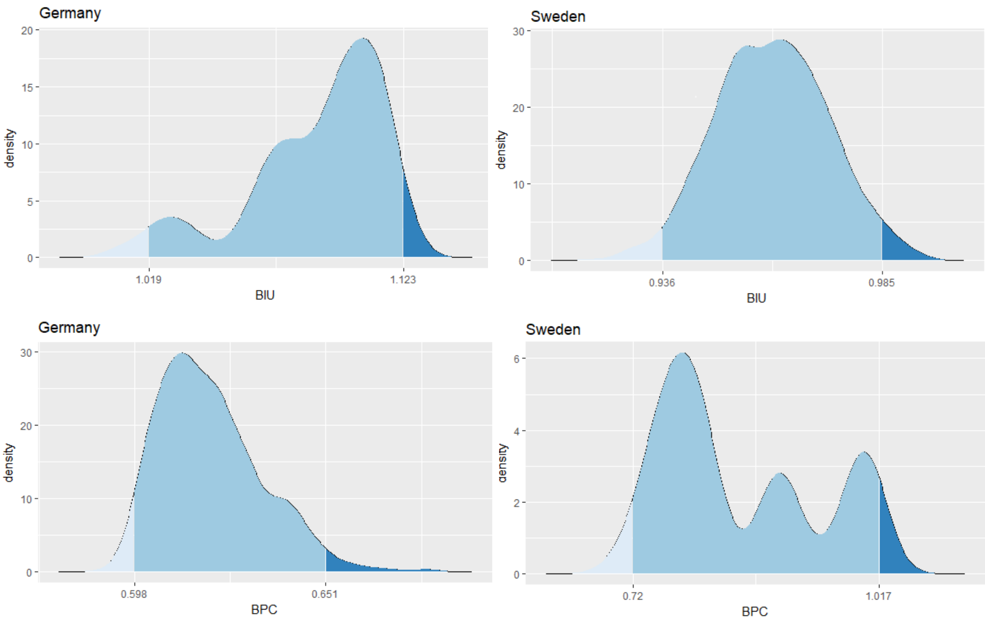

Figure 1: Smoothed density plots for jackknifed distributions of BIU and BPC indicators.

BPC-index depending on which observations from Denmark are included in a given jackknife sample. Since the value of 1 is between the 2.5th, and the 97.5th percentile we note that there is no significant difference between the production conditions in Denmark and Sweden even with a mean value of the jackknifed BPC-indicator of 0.84.

To summarize: no country has both significantly better production conditions and significantly better utilization than Denmark. Sweden is the only country with significantly better utilization than Denmark and most other countries have significantly better production conditions, yet significantly worse utilizations thereof.

Finally, it should be noted that the above results are robust to the choice of weighting scheme since performing the analysis with identical weights for all farms, or with weights used by FADN[8], yields the same conclusion as the output-weighted results above.

3.3 Disaggregating Production Conditions Differences

The results of Table 2 above highlight that the production conditions in Denmark are significantly worse than those in almost all the other countries. From a policy point of view it is therefore interesting to dig deeper into the nature of such differences. In particular, in order to design remedial policies it is important to assess which production factors are mainly responsible for the overall difference: for instance, knowing that Germany has better production conditions than Denmark, is that mainly explained by higher salary levels, or is the difference rather due to higher capital costs.

There is no obvious choice of methodological framework for this type of question. Within the non-parametric approach chosen in the present paper, problems arise because frontiers may be "intersecting" and consequently computing input specific measures of differences may not be well defined. In practice, and since we do pairwise comparisons, there will often be cases where the problem of undefined scores is inessential as we shall show in the case of Denmark and Germany.

[8]See http://ec.europa.eu/agriculture/rica/methodology3_en.cfm

To outline a potentially useful approach, we suggest to use input-oriented subvector scores (Färe et al., 1994a) to estimate input specific measures of frontier differences between two countries. Again we need to utilize jackknifing in order to acount for differences in sample sizes.

We illustrate the approach by comparing the Danish observations to the German frontier noting that there are fewer observations in the Danish sample (G') than in the German sample (G''). Specifically, for each of 1000 jackknife replications, subsample $|G'|$ observations from G'' resulting in the jackknifed sample $\mathcal{G}''$ where $|G'| = |\mathcal{G}''|$, and utilize the following stepwise procedure:

- We are interested in input specific frontier differences from the frontier of group G' to the frontier of group $\mathcal{G}''$. First move all observations in G' to the frontier of G' by multiplying each observation's input vector x_i with its input efficiency score, $e_i^{G'}$, computed using the program (2). This produces adjusted G' observations (x_i^*, y_i) where $x_i^* = e_i^{G'} x_i$.

- For all adjusted G'-observations, compute the subvector scores relative to the $\mathcal{G}''$-frontier, as follows:

  Given $(x_{i^0}^*, y_{i^0}) \in G'$, solve for each input $h = 1, \ldots, s$ the following program:

  $$\min \theta_{i^0 h} \; s.t. \sum_{i \in \mathcal{G}''} \lambda_i x_{ih} \leq \theta_{i^0 h}, \sum_{i \in \mathcal{G}''} \lambda_i x_{i(-h)} \leq x_{i^0(-h)}^*, \sum_{i \in \mathcal{G}''} \lambda_i y_i \geq y_{i^0}, \lambda_i \geq 0$$

  with optimal solution $(\hat{\lambda}, \hat{\theta}_{i^0})$. Note that subvector scores ≥ 1 implies that the G'-frontier is better than the $\mathcal{G}''$-frontier, and vice versa.

- The resulting distributions of input specific scores can be pairwise compared using robust Hotelling t^2-tests (Willems et al., 2002).

The average jackknifed input specific (sub-vector) scores are:[9]

- Salary costs: 0.54

[9] One Danish observation (out of 310) provided undefined scores because it is super-efficient compared to the German frontier and is therefore excluded in the calculation of the averages.

- Variable costs: 0.83
- Capital costs: 0.47

Thus, it appears that the largest difference between the the Danish and the German frontier is for capital costs and the smallest for variable costs. The robust Hotelling t^2-test is used within each jackknife replication for pairwise comparisons of the distributions of the sub-vector scores. These results reveal that all pairwise comparisons show significantly different distributions within *all* jackknifed replications. Therefore we can conclude that the above pattern is indeed strongly significant.

Looking at key performance indicators, as illustrated in Figure 2, reveals possible explanations for the above results, specifically for the comparison of Denmark and Germany. We first note that both assets per cow (panel A), variable costs per cow (panel B), and the paid wage rate (panel C), are generally higher in Denmark than in Germany.

The difference between Denmark and Germany is clearly largest for assets per cow and wage rate. This is consistent with the sub-vector scores that also show the largest differences for capital costs and salary costs. So the reason for higher salary costs in Denmark than in Germany is likely differences in the price of labor. With respect to capital costs Figure 2 reveals that Danish dairy farmers have larger capital base (per cow) than the German farmers which could be due to higher asset prices (e.g., land prices) and/or higher capital investments potentially due to regulatory requirements.

In terms of policy implications we have achieved two things. First the proposed method enables us to identify significantly worse production conditions in Denmark than in all the other countries considered (expect Ireland), but a significantly better utilization of the production conditions than in most of the other countries considered. Second, in a specific comparison between Denmark and Germany the outlined second-stage approach demonstrates that the largest differences are on capital costs and salary costs. These are likely explained by wage levels and asset prices and/or requirements. Thus, policy makers in Denmark need to be aware of the competitive disadvantage caused by the worse production conditions noting that the Danish dairy

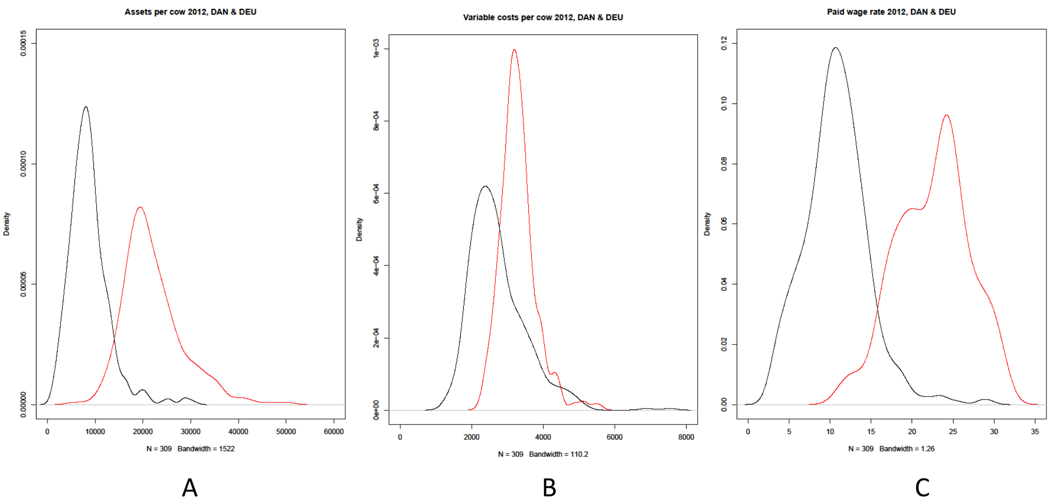

Figure 2: Comparison of key performance indicators between Denmark and Germany

farmers are in fact utilizing their existing conditions well. Furthermore, if policy makers want to improve the competitiveness of the Danish dairy farmers, it should be ensured that e.g., regulation does not lead to higher capital requirements in Denmark than elsewhere. With respect to factor prices, policies to increase labor supply might be relevant in order to reduce labor costs. Concerning land prices it is important that market forces are allowed to adjust asset prices to match earning potentials and therefore policies enhancing competitiveness should work in that direction.

4 Conclusion

In the present paper we argue that the overall notion of competitiveness should be thought of as two separate components: production conditions and the utilization thereof. While we are not the first to make this argument, we provide an operationalization of the idea such that both components can be measured and evaluated. Regarding the proposed method we argue that concepts from frontier analysis provide a natural starting point for defining suitable competitiveness indicators. Specifically, we define two bilateral indicators for the production conditions and for the utilization of conditions respectively.

By an empirical example of large specialized dairy farms in 19 European countries we demonstrate the potential usefulness and relevance of our approach. With particular focus on Danish dairy farmers we identify the overall conditions and further propose a second-stage approach to investigate underlying explanations relevant for remedial policies. Specifically we find that while the Danish dairy farmers have better utilization than the farmers in most of the other countries, they do, in fact, have worse production conditions than all the other countries except Ireland. If the Danish dairy farmers can, indeed, maintain their high utilization, they would benefit from seeking more favorable production environments, which is in fact what has been observed with a large number of Danish farmers settling in especially Eastern Europe (Hajderllari et al., 2012). Likewise we would not expect foreign farmers to move to Denmark given the current production conditions, unlike what happened in the 1980s where, for example, Dutch dairy farmers settled in Denmark due to lower prices on land and milk quotas.[10]

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[10]see e.g., `http://www.vimu.info/general_04.jsp?id=mod_27_1&lang=da&u=child&s` (in Danish).

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Appendix

MEANS	Salary	Var. costs	Capital	Milk rev.	Other rev.
BGR	61927	645446	1136458	494166	518072
CZE	543636	1202872	4699907	860496	1662039
DAN	160134	744729	4902686	711436	498383
DEU	296940	851023	2284527	786241	859418
ESP	94159	474909	1020564	514304	174442
EST	359122	1230218	2407313	1022448	1166282
FRA	73847	274205	744171	315904	248835
HUN	576428	1872859	951023	1436375	1884389
IRE	64608	221364	2330992	238311	147196
ITA	131326	541966	2637664	735769	310855
LTU	45658	309210	1009201	337781	312606
LVA	197331	640579	1493178	574739	624941
NED	108019	359443	5052383	541027	197601
POL	69591	392210	1352354	396901	292595
ROU	76655	324108	2177360	454424	439603
SUO	130067	478788	1639428	468800	431880
SVE	228887	825322	2238263	665234	572901
SVK	478957	1173862	1668531	689983	1408493
UKI	106454	436769	2168658	476550	215083

ST. DEV.	Salary	Var. costs	Capital	Milk rev.	Other rev.
BGR	77633	961319	1785351	563470	626668
CZE	313413	704747	3448119	486782	1250214
DAN	91857	406885	2738751	396568	335824
DEU	489812	1029391	2301053	814470	1394949
ESP	155552	317155	821444	351296	111494
EST	324924	1100213	2232525	874155	1282558
FRA	41738	59053	332387	98777	96586
HUN	1013601	2364546	3862667	1779304	3261636
IRE	30492	82362	928995	79160	65167
ITA	89550	460070	3439920	595757	308508
LTU	40966	176232	433124	160419	174159
LVA	221431	497043	1585489	450866	612569
NED	75787	202432	2645557	289801	247400
POL	96704	465375	590633	262768	516825
ROU	75825	212230	2226940	251104	328817
SUO	64790	122154	443099	72966	128984
SVE	179517	638334	1690901	579471	414872
SVK	376399	1183695	3093767	873252	1160694
UKI	64449	225185	1264222	242042	137939