

The relation between technical farm performance and antimicrobial use of broiler farms¹

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ABSTRACT The aim of the present study was to explore the relation between both farm performance and antimicrobial use (AMU) of broiler farms. Farm performance was expressed as technical efficiency, obtained by using a bootstrap data envelopment analysis. AMU was expressed as treatment incidence. Cluster analysis is used to obtain groups of farms with similar characteristics regarding technical farm performance and AMU. Results indicate that the farms within the different clusters combine different technical farm performance and different levels of AMU. Between the clusters, significant differences were found in technical farm performance, AMU, the resource intensity of the number of animals at set-up, the number of

antimicrobial treatments, the number of antimicrobial treatments related to either gut health or combined problems, and the number of antimicrobial treatments with either yellow or orange active substances. Farmers who combine high levels of AMU with high technical farm performance are likely to overestimate the real economic value of AMU. Proper coordination between the farmer and the veterinarian can be crucial in that case for reducing AMU. Farms with low performance are likely to have poor farm conditions. Improving those farm conditions can help reducing the need for AMU on this kind of farms. The farm-specific conditions have to be considered in future policies aimed at reducing AMU in livestock production.

Key words: broiler production, antimicrobial use, technical farm performance

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INTRODUCTION

Antimicrobial agents have been widely used in veterinary medicine for therapeutic treatment, metaphylaxis, prophylaxis, and growth promotion (van den Bogaard and Stobberingh, 1999; McEwen and Fedorka-Cray, 2002). The advantages generated from veterinary antimicrobial use (AMU) exceed more than just animal health and welfare, as it has resulted in economic benefits for food animal producers through increased production efficiency and a more secure health for the general public (Hao et al., 2014). Although AMU provides clear benefits, it simultaneously results in clear risks because of the enrichment of antimicrobial-resistant

microorganisms. There is a broad consensus that excessive and inappropriate AMU enriches the development, selection, and spread of antimicrobial resistance (AMR). Subsequently, resistant microorganisms can be transferred from agricultural settings to humans (Aarestrup and Wegener, 1999; Singer et al., 2003; Aarestrup et al., 2008). This has resulted in increased societal and political pressure to reduce AMU.

Given the link between AMU and AMR, the use of antimicrobial growth promoters was banned in the European Union (Landers et al., 2012). Several European countries (including Denmark, France Norway, and The Netherlands) have introduced general policies aimed at reducing nonhuman AMU with formal reduction targets expressed as percentage of previous use (Rushton et al., 2014). These reduction targets were not based on any evidence-based dosage (AMU) – effect (AMR) relation. However, faced with increasing public pressure and concerns, the focus of national and supranational governments is on further reducing AMU (Speksnijder et al., 2015). The generic policies already picked up the low-risk, high-yield opportunities regarding AMU such as reducing obvious overuse of AMU (e.g., the use of antimicrobial growth promoters). To go beyond these opportunities, the focus needs to be

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shifted from generic measures toward farm-specific conditions. From that perspective, insights into the relation between technical farm performance and AMU of individual farms are needed.

The aim of the present study was therefore to explore the relation between technical farm performance and AMU. Some studies already investigated the link between AMU and technical farm performance. [Collineau et al. \(2017\)](#) conducted a cross-sectional study among farrow-to-finish pig farms in Belgium, France, Germany, and Sweden in which “top farms” were allocated and compared with “regular farms” in terms of farm characteristics, biosecurity, and health status. Top farms were ranked based on the combination of their level of AMU and their level of technical performance (expressed by the number of weaned pigs per sow and per year), and a group of farms that combined both high technical farm performance and low AMU was found. In addition, other studies did not find any significant associations between technical performance indicators and AMU in broiler and pig farms (e.g., [Chauvin et al., 2005](#); [van der Fels-Klerx et al., 2011](#)).

This study differs from previous studies in the sense that a multidimensional performance indicator of technical farm performance is used instead of a one-dimensional performance indicator, such as the number of weaned pigs per sow and per year used by [Collineau et al. \(2017\)](#). The multidimensional indicator used in this study includes all inputs that are needed to produce a defined level of output. A widely used concept in economics to address technical farm performance is technical efficiency. Technical efficiency reflects the ability of a farmer to produce maximum output with a given bundle of inputs or the minimum input needed to produce a given level of outputs ([Farrell, 1957](#)). In the remainder of this study, the terms technical efficiency and technical farm performance are used interchangeably. AMU was expressed as treatment incidence, and these terms are also used interchangeably in this study.

In the present study, multiple flock observations per farm were used to provide an appropriate assessment of both technical farm performance and AMU instead of using single flock or herd observations. In addition, specific differences between farms with respect to various indicators related to technical farm performance and AMU are tested. The aim of this study was to examine the relation between technical farm performance and AMU and to show how insights into this relation can be deployed in policy aimed at reducing AMU.

MATERIALS AND METHODS

Data

The data used in the present study were collected in the context of a European project regarding AMR, called EFFORT (Ecology from Farm to Fork Of microbial drug Resistance and Transmission). The data used in this study are a subset of the data collected at 1 of the European countries that participated in the EFFORT project. Within the consortium of the EFFORT project,

it was agreed to anonymize the data. The broiler farms included in this study are conventional farms. Hence, the intended slaughter age is lower than 60 D and the average gain per day is higher than 55 g per day. In addition, the stocking density is 10 birds or more per square meter, and each poultry house contains between 10,000 and 40,000 birds. In total, data were collected from 251 flocks from 39 broiler farms. First, the data were screened for the availability of data regarding the number of animals delivered to the slaughterhouse (including their mean weight measured in kilograms), the number of animals at set-up (calculated by correcting the number of animals slaughtered via mortality) and the total amount of feed used (consisting of concentrate feed and wheat). In total, information with respect to feed was (partly) missing for 17 broiler farms including 104 flock observations. Consequently, these observations were considered in subsequent analyses. Within the data from the remaining 22 broiler farms, information about the mean weight at slaughter was missing for the second flock of farm 3 and mortality was missing for the seventh flock of farm 16. Hence, these observations were not taken into account in subsequent analyses. The large number of missing data is explained by the fact that the design and collection of the data were not specifically designed for the present study.

The data were provided and screened by project partners. Additional screening resulted in 18 potential outliers (i.e., potential experimental errors) as these values deviated significantly from other parameters both within and between farms. The project partners responsible for collecting the data were contacted. Additional checks were performed based on the correctness of the parameters. For example, the quantity of feed was checked by using the feed conversion rate. Afterward, 10 outliers were observed and removed from the data. Details regarding the screening of the (potential) outliers are provided in [Supplementary Table 1](#). After removing the flock observations with missing data and outliers, a data set with 134 flock observations from 22 broiler farms remained.

Technical Farm Performance

The literature distinguishes 2 main approaches toward measuring technical efficiency of decision-making units (DMU). One approach is the parametric Stochastic frontier analysis (SFA) and the other 1 is the nonparametric method data envelopment analysis (DEA) ([Coelli et al., 2005](#)). The strength of DEA vs. SFA is that it does not require assumptions about the functional form and the distribution of the inefficiency term. However, a limitation of the DEA method is that it is a deterministic approach assuming that there are no random factors that affect the location of the frontier when assessing performance ([Horta et al., 2012](#)). Hence, the DEA method is sensitive to potential outliers. In this study, bootstrapping is applied to remove the (potential) sample bias. The present study used the method as

outlined in [Simar and Wilson \(1998\)](#) for obtaining bias-corrected efficiency scores and CIs.

The DEA method was introduced by [Charnes et al. \(1978\)](#) who built on the seminal work of [Farrell \(1957\)](#). For a given a sample of farms, efficiency scores are measured for each flock relative to an efficiency frontier which is a benchmark of the best performing flocks ([Ray, 2004](#)). It was assumed that the production technology deployed by the farms exhibits variable returns to scale. This implies that each farm is compared with farms on the frontier that have a similar size. In addition, short-term effects are preferred rather than long-term effects. This study uses an input-oriented method, which implies that farms aim at reducing the use of inputs to produce a given quantity of output. The input orientation was used because it was expected that farmers more easily adjust their input use rather than the production of outputs, as the latter is limited by the production capacity. The

DMU *E* and DMU *F* are inefficient DMUs. The technical efficiency score of DMU *E* is calculated by the ratio of 2 distances, that is, distance O–E' and distance O–E.

In this study, a DMU represents a flock and 1 frontier is estimated for all flock observations. The technical efficiency of each flock is computed relative to that frontier using the package Benchmarking, which runs under R (R Foundation, Vienna, Austria).

Quantification of AMU

AMU was quantified in a standardized manner using the treatment incidence (TI) as described by [Persoons et al. \(2012\)](#). The TI for broilers is defined as the number of chickens per 1,000 that are treated daily with one defined daily dose (DDD_{VET}). The DDD_{VET} is defined as average maintenance dose per day and per kg chicken of a specific drug ([Jensen et al., 2004](#)). The following formula was used to calculate the $TI_{1,000}$ (equation 6):

$$TI_{1,000} = \frac{\text{total amount of antimicrobial administered (mg)}}{\text{DDD}_{VET}(\text{mg/kg}) \cdot \text{number of days at risk, kg chicken}} \cdot 1,000 \text{ animals at risk} \quad [6]$$

input-oriented DEA model used in this study is a linear programming model as reflected in equation 1–5:

$$\min \theta \quad [1]$$

subject to

$$\sum_{n=1}^N \lambda_n x_{jn} \leq \theta x_{jp} \quad j = 1, \dots, m \quad [2]$$

$$\sum_{n=1}^N \lambda_n y_{kn} \geq y_{kp} \quad k = 1, \dots, r \quad [3]$$

$$\sum_{n=1}^N \lambda_n = 1 \quad n=1, \dots, N \quad [4]$$

$$\lambda_n \geq 0 \quad [5]$$

where θ represents the (input-oriented) technical efficiency score of the DMU under analysis; N represents the number of DMU in the sample; λ is a vector of weights of the DMU that identify the benchmarks for inefficient units; x_{jn} is the quantity of input j used by DMU n ; x_{jp} is the j^{th} input for DMU p ; y_{kn} is the quantity of output k provided by DMU n ; and y_{kp} is the k^{th} output for DMU p .

[Figure 1](#) illustrates how a production frontier of efficient DMU is established. Decision-making units *A–D* are on the production frontier, which indicates that their technical efficiency scores equal 1. Within this example,

Cluster Analysis

The present study used cluster analysis to identify farms with similar technical farm performance and AMU. The farms are clustered based on the standardized values of both the average bias-corrected efficiency scores and the average treatment incidence of the farms. [Milligan \(1980\)](#) has shown the strong dependence of the *K*-means algorithm on initial clustering and suggests that good final

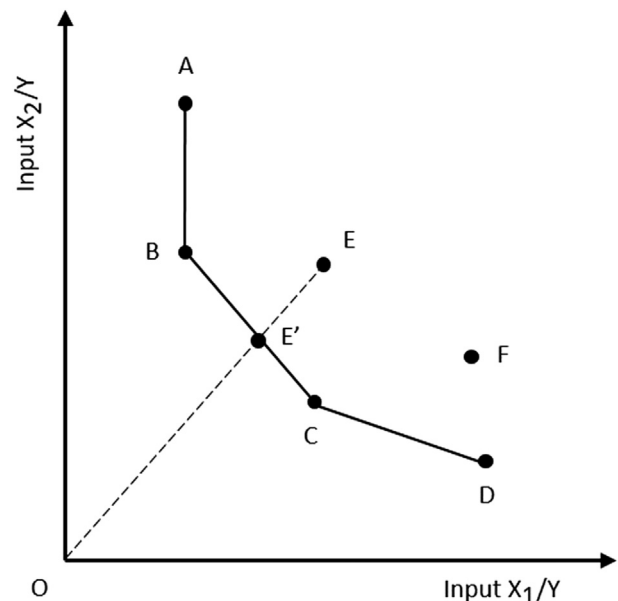


Figure 1. Schematic representation of an input-oriented data envelopment analysis model.

cluster structures can be obtained by using Ward's hierarchical method (Ward, 1963) to provide the *K*-means algorithm with an initial number of clusters. The optimal number of clusters is therefore chosen based on the hierarchical Ward's minimum variance method, which minimizes the sum of squared distances between farms within a cluster and maximizes the square distance between the various clusters. Both the dendrogram and the agglomeration schedule from Ward's method and the level interpretability of the obtained solutions are used to establish the most meaningful number of clusters. In that decision process, the latter criterion has been decisive in the present study. After selecting an appropriate number, a nonhierarchical *K*-means cluster method is applied to cluster the farms. *K*-means clustering minimizes the distance between the data and the corresponding cluster centroid. The squared Euclidean distance (i.e., the sum of the squared differences between the values of the clustering variables) is selected to measure the distance between the farms in the cluster analysis.

After the clustering, the groups of farms are compared by using the flock observations and looking at technical efficiency, AMU, the resource intensity of the 2 selected inputs, the number of antimicrobial treatments, the number of antimicrobial treatments related to different categories of clinical disorders, the type of active substance used, and the day of the first antimicrobial treatment. Resource intensity is a measure of the resources required for the provision of a kilogram of meat delivered to the slaughterhouse. The clinical disorders for which antimicrobials are mostly used include gut health problems, respiratory diseases, and locomotion-related disorders (EMA and EFSA, 2017). Additional categories are first-week problems and other disorders. The present study used a color system for ranking the type of active substance. The Belgian Center of expertise on Antimicrobial Consumption and Resistance in Animals introduced this system to determine the conditions of use for each active substance, based on their importance for animal and human health as classified by the World Health Organization and the World Organisation for Animal Health. Yellow, orange, and red are the color codes used in the color system. Yellow active substances can be used with no additional conditions (but laboratory testing is recommended). Orange active substances require at least a diagnosis based on laboratory testing. Use of red active substances is only allowed when diagnosis is based on laboratory testing and the pathogen is resistant to first-, second-, or third-choice antimicrobials color coded yellow or orange.

To explain the differences between the farm clusters, a Shapiro–Wilk test was performed to test the normality of the data (i.e., the standardized residuals should be normally distributed). In addition, the Levene's test was carried out to test the homogeneity of variance. For the normally distributed data with equal variances for all groups of farms, a one-way ANOVA including the Tukey Honestly Significant Difference post hoc test was applied. For the non-normally distributed data with equal variances, a Kruskal–Wallis test with Dunn's pairwise tests was used.

RESULTS

Descriptive Statistics

One output and 2 inputs were selected to determine technical farm performance. Output (*Y*) corresponds to the total quantity of meat delivered to the slaughterhouse per flock, measured in kilograms. The total energy value of the total amount feed used per flock and the number of day-old chicks at set-up per flock are selected as inputs. These 2 inputs are considered as the main inputs in broiler production because feed costs and the costs for day-old chicks are the main production costs of broilers in euros per kilogram live weight in the European Union (van Horne, 2017). Regarding feed use, distinction is made between concentrate feed and wheat. The energy value for concentrate feed is considered 12.65 MJ (mega joules) per kilogram and 12.47 MJ per kg for wheat (van Duinkerken and Spek, 2016). See equation 7:

$$\begin{aligned} \text{Total energy value of feed used} &= \text{kilograms concentrate} \\ &\text{feed used} \cdot \text{energy value of concentrate feed} \\ &+ \text{kilograms wheat used} \cdot \text{energy value of wheat} \end{aligned} \quad [7]$$

The second input selected consists of the number of day-old chicks used at set-up (X_2). AMU is quantified in a standardized manner using $TI_{1,000}$. When the $TI_{1,000}$ for overall antimicrobial consumption equals 300, it means that on average per day, 300 broilers out of 1,000 animals were treated with one DDD_{VET} . A $TI_{1,000}$ of zero indicates that no treatment was recorded for this flock.

Table 1 shows the descriptive statistics of the selected output, inputs, and AMU including the mean, the SD, and the minimum and maximum of all flock observations.

Technical Farm Performance and AMU

Results of the DEA are shown in Table 2. The first column of the table shows the farm ID followed by the number of flock observations per farm, which differs among the farms included in the sample. Thereafter, Table 2 shows the average original efficiency scores, the average bias-corrected efficiency scores, the bias, the CI, and the variance. The bootstrap DEA results show that the bias-

Table 1. Descriptive statistics of output *Y*, inputs X_1 and X_2 , and AMU.

Abbreviation	Unit	Mean	SD	Min	Max
<i>Y</i>	kg	96,740	56,199	39,146	232,914
X_1	MJ	2,121,327	1,380,726	801,899	6,221,609
X_2	AU	40,467	23,588	17,317	100,796
AMU	$TI_{1,000}$	145	110	0	557

Abbreviations: AMU, antimicrobial use expressed as treatment incidence ($TI_{1,000}$); X_1 , total energy value in mega joules (MJ) of the total amount of feed used; X_2 , total number of day-old chicks at set-up measured in animal units (AU); *Y*, total kilograms (kg) of meat delivered to the slaughterhouse.

Table 2. The average input-specific technical efficiency scores (including the bias-corrected efficiency scores, the bias, and the 95% CI) and antimicrobial use (AMU).

Farm ID	Number of flocks	Efficiency scores	Bias-corrected efficiency scores	Bias	95% CI		AMU
					Lower limit	Upper limit	
1	6	0.925	0.916	0.009	0.903	0.924	114.39
2	7	0.913	0.900	0.013	0.886	0.912	185.65
3	3	0.968	0.932	0.037	0.883	0.966	71.54
4	6	0.934	0.926	0.008	0.916	0.932	116.25
5	6	0.892	0.880	0.012	0.869	0.890	133.59
6	7	0.968	0.945	0.024	0.915	0.966	29.43
7	3	0.909	0.893	0.016	0.877	0.906	223.35
8	2	0.977	0.968	0.009	0.956	0.976	59.58
9	6	0.957	0.942	0.015	0.929	0.955	133.77
10	7	0.987	0.972	0.015	0.957	0.985	178.88
11	6	0.947	0.934	0.013	0.916	0.945	318.24
12	8	0.916	0.908	0.008	0.899	0.915	203.84
13	6	0.899	0.892	0.006	0.883	0.898	150.37
14	7	0.959	0.950	0.009	0.939	0.958	324.86
15	8	0.993	0.967	0.027	0.938	0.991	117.72
16	3	0.948	0.935	0.013	0.920	0.947	168.07
17	8	0.962	0.936	0.025	0.895	0.960	78.67
18	7	0.854	0.843	0.011	0.827	0.852	16.74
19	6	0.948	0.932	0.016	0.913	0.946	168.29
20	8	0.937	0.928	0.010	0.915	0.936	124.18
21	7	0.913	0.905	0.009	0.894	0.912	88.76
22	7	0.918	0.909	0.009	0.898	0.916	169.55

corrected efficiency scores are within relatively narrow CIs, that is, the lower bound and the upper bounds are relatively close. Furthermore, the bias-corrected estimates are preferred to the original estimates, as described by [Fried et al. \(2008\)](#), because the estimated bias is much larger than the SD (i.e., the square root of the variance as presented in [Table 2](#)). In the last column of the table, the average AMU is shown.

The average input-specific bias-corrected technical efficiency score for farm 1 ([Table 2](#)) equals 0.916, indicating that this farm is efficient for 91.6% and input use can be reduced on average with 8.4% to obtain the same level of output. The low margins and high volumes in broiler meat production explain the high overall

efficiency scores, through which farms are forced to operate in an efficient way to survive.

Cluster Analysis

[Figure 2](#) shows the results of the nonhierarchical K-means cluster method. In total, 3 different clusters are distinguished. The distribution of the farms over the clusters is unbalanced. The 3 clusters include 12, 6, and 4 broiler farms with 70, 38, and 26 flock observations, respectively.

[Table 3](#) shows the mean and SD of the selected variables in the 3 clusters and the comparison among the different variables between them. A Kruskal–Wallis

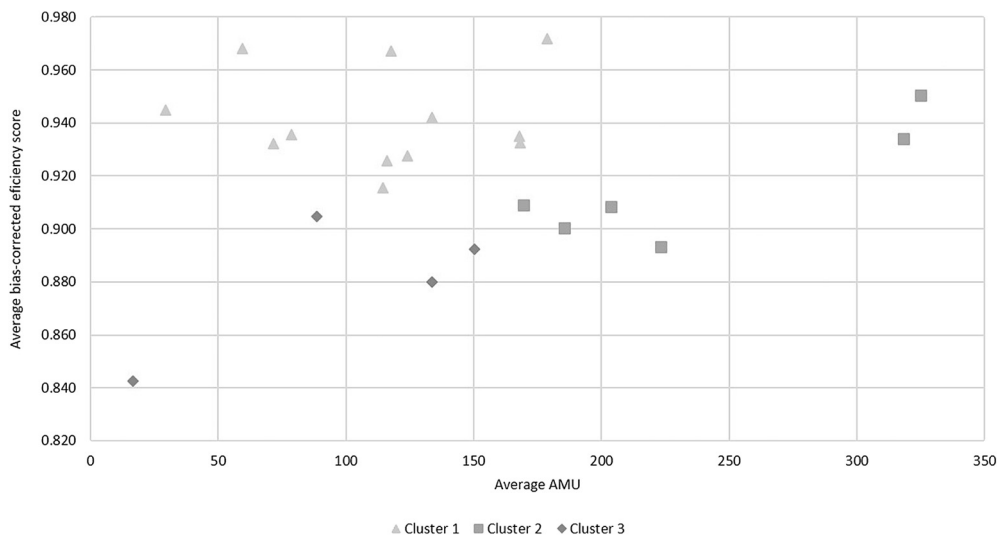


Figure 2. Results hierarchical cluster analysis. Abbreviation: AMU, antimicrobial use.

Table 3. Mean and SD for the selected variables in 3 clusters and the comparison between them.

Variables	Cluster 1 (n = 70)		Cluster 2 (n = 38)		Cluster 3 (n = 26)	
	Mean	SD	Mean	SD	Mean	SD
BCE	0.941 ^{b,c}	0.033	0.918 ^{a,c}	0.034	0.879 ^{a,b}	0.040
AMU	115.098 ^b	76.001	236.069 ^{a,c}	132.402	93.936 ^b	71.024
RI(x ₁)	21.306 ^c	2.686	20.573 ^c	1.563	23.243 ^{a,b}	2.474
RI(x ₂)	0.413 ^{b,c}	0.024	0.425 ^a	0.024	0.431 ^a	0.021
TRE	2.586 ^c	1.198	2.632 ^c	1.217	1.885 ^{a,b}	0.816
GUT	1.414 ^c	1.014	1.368 ^c	0.913	0.577 ^{a,b}	0.578
RES	0.029	0.168	0.079	0.359	0.077	0.272
LOC	0.057	0.234	0.026	0.162	0.038	0.196
FIR	0.829	0.613	0.921	0.539	0.692	0.618
OTH	0.229	0.487	0.237	0.490	0.192	0.491
COM	0.029 ^c	0.168	0.000 ^c	0.000	0.308 ^{a,b}	0.618
YEL	0.229	0.423	0.079	0.273	0.077	0.272
ORA	2.214	1.075	2.447 ^c	1.224	1.654 ^b	0.745
RED	0.143	0.352	0.105	0.311	0.154	0.368
DT1	6.304	9.077	5.079	9.012	11.077	13.314

^{a,b,c}Superscripts indicate significant difference ($P < 0.05$) compared with cluster 1 (a), cluster 2 (b), or cluster 3 (c).

Abbreviations: AMU, antimicrobial use; BCE, bias-corrected efficiency scores; COM, the number of antimicrobial treatments related to combined problems; DT1, day first antimicrobial treatment; FIR, the number of antimicrobial treatments related to the first-week problems; GUT, the number of antimicrobial treatments related to gut health problems; LOC, the number of antimicrobial treatments related to locomotion problems; ORA, the number of antimicrobial treatments with orange active substances; OTH, the number of antimicrobial treatments related to other problems; RED, the number of antimicrobial treatments with red active substances; RES, the number of antimicrobial treatments related to respiratory problems; RI(x₁), resource intensity of input x₁; RI(x₂), resource intensity of input x₂; TR, the number of antimicrobial treatments; YEL, the number of antimicrobial treatments with yellow active substance.

test was conducted to compare the clusters with respect to all variables except for the resource intensity of input X_2 for which a Welch test with a Games–Howell post hoc test was conducted. The Kruskal–Wallis test indicated a significant difference in the mean ranks of at least 1 pair of cluster for the bias-corrected efficiency scores ($P = 0.000$). Dunn’s pairwise comparison test indicate a significant difference in the mean ranks of cluster 1 and 2 ($P = 0.003$), cluster 1 and 3 ($P = 0.000$), and cluster 2 and 3 ($P = 0.006$). This indicated a significant higher technical farm performance of farms in cluster 1 than that of the farms in cluster 2 and 3. In addition, the farms in cluster 2 performed significantly better than the farms in cluster 3.

With respect to AMU, the Kruskal–Wallis test indicated that there was a significant difference in the mean ranks of at least 1 pair of cluster ($P = 0.000$). Dunn’s pairwise comparison test indicates a significant difference in the mean ranks of cluster 1 and 2 ($P = 0.000$) and cluster 2 and 3 ($P = 0.000$). This indicated a significant higher AMU of farms in cluster 2 than that of the farms in cluster 1 and 3.

The Kruskal–Wallis test indicated that there was a significant difference in the mean ranks of at least one pair of clusters with respect to the resource intensity of input x_1 ($P = 0.000$). Dunn’s pairwise comparison test indicates a significant difference in the mean ranks of cluster 1 and 3 ($P = 0.001$) and cluster 2 and 3 ($P = 0.000$). This indicates a significant higher resource

intensity of input x_1 of the farms in cluster 3 than that of the farms in cluster 1 and 2. This might be an explanation for the significant lower technical farm performance of the farms in cluster 3 than that of the farms in cluster 1 and 2.

The Welch test indicated that there was a significant difference in the mean difference of the resource intensity of input x_2 (Welch’s $F(2, 64.323) = 7.925$, $P = 0.001$) between the clusters. Games–Howell post hoc comparisons showed a significance between cluster 1 and 2 ($P = 0.026$) and cluster 1 and 3 ($P = 0.001$). This indicated a significant lower resource intensity of x_2 of the farms in cluster 1 than that of the farms in cluster 2 and 3. This might indicate lower mortality rates and higher average daily growth because the farms in cluster 1 need less day-old chicks at set-up to obtain a relatively high output.

With respect to the number of antimicrobial treatments, the Kruskal–Wallis test indicated a significant difference in the mean ranks of at least 1 pair of clusters ($P = 0.022$). Dunn’s pairwise comparison test indicates a significant difference in the mean ranks of cluster 1 and 3 ($P = 0.030$) and cluster 2 and 3 ($P = 0.044$). This indicates that the number of antimicrobial treatments was significantly lower in the farms of cluster 3 than in the farms in cluster 1 and 2.

In addition, the Kruskal–Wallis test indicated that there was a significant difference in the mean ranks of at least 1 pair of clusters for the number of antimicrobial treatments related to gut health problems ($P = 0.000$).

Dunn's pairwise comparison test indicates a significant difference in the mean ranks of cluster 1 and 3 ($P = 0.000$) and cluster 2 and 3 ($P = 0.001$). This indicates that the number of antimicrobial treatments related to gut health problems was significantly lower at the farms of cluster 3 than at the farms within cluster 1 and 2.

Regarding the number of antimicrobial treatments related to combined problems, the Kruskal–Wallis test indicated a significant difference in the mean ranks of at least 1 pair of the clusters ($P = 0.000$). Dunn's pairwise comparison test indicates a significant difference in the mean ranks of cluster 1 and 3 ($P = 0.001$) and cluster 2 and 3 ($P = 0.000$). This indicates that the number of antimicrobial treatments related to combined problems was significantly higher at the farms of cluster 3 than at farms within cluster 1 and 2.

Finally, the Kruskal–Wallis test indicated a significant difference in the mean ranks of at least 1 pair of the clusters with respect to the number of antimicrobial treatments with orange active substances ($P = 0.022$). Dunn's pairwise comparison test indicates a significant difference in the mean ranks of cluster 2 and 3 ($P = 0.022$). This indicates that the number of antimicrobial treatments with orange active substances was significantly higher at the farms in cluster 2 than at the farms in cluster 3.

DISCUSSION

The aim of this study was to explore the relation between technical farm performance and AMU. A multidimensional performance indicator, combining 1 output and 2 inputs, was used to assess the technical farm performance of 22 broiler farms and their corresponding AMU. DEA with bootstrapping was used to obtain the technical farm performance, and a cluster analysis was used to compare clusters of farms with similar farm characteristics with respect to technical farm performance and AMU. In total, 3 clusters of farms that combine different levels of both technical performance and AMU were distinguished in this study. The findings are line with those of other studies, including [Collineau et al. \(2017\)](#), which indicated that farms can combine low AMU with high technical farm performance.

The results of this study showed that farms have unique combinations of technical farm performance and AMU. The need for AMU in the cluster of farms that combines high technical farm performance and low AMU appears to be relatively low. High levels of AMU combined with high technical farm performance indicate that the farmer overestimates the real economic value of AMU. If so, coordination between the farmer and the veterinarian can be crucial for reducing AMU. The importance of the relation between the farmer and the veterinarian was addressed by [Currie et al. \(2018\)](#), who conducted a Delphi study to identify veterinary behaviors, which UK-based experts believe to contribute to AMR and antimicrobial stewardship. Their findings indicated that interactions between the farmer and the

veterinarian are a major influencing factor. Hence, proper monitoring and regular contact with the veterinarian can help maintaining the high technical farm performance while keeping AMU low or reducing AMU.

Poor farm conditions can result in farms with low technical farm performance. In such situations, antimicrobial agents are used as a cheap substitute for improving farm conditions. Interventions targeting the farm and the animals might improve the technical farm performance and reduce AMU at the same time ([Roskam et al., 2019](#)). On the one hand, the farmer can ensure that the animals become less susceptible to disorders, for example, by improving biosecurity or through vaccination. On the other hand, the farmer can ensure that the impact of a disorder becomes less significant through an early detection of clinical signs to enable quick counter measures (including nonantimicrobial alternatives). The introduction of precision livestock farming offers a management tool that enables a farmer to monitor animals automatically by using sensors, cameras, and microphones ([Armstrong et al., 2014](#)).

The category of farms that combines low technical farm performance and high AMU was not observed. However, this seems plausible because it would be difficult for this category of farms to survive in practice, especially because these farms require major improvements and investments that appear to affect both the variable and the fixed costs.

Further research is needed to validate the findings of this study in larger and more representative samples, as well as among broiler farms and other species in other countries and different parts of the world. Future research should also take into account other inputs, such as animal welfare and environmental issues, when estimating technical farm performance.

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SUPPLEMENTARY DATA

Supplementary data associated with this article can be found in the online version at <https://doi.org/10.1016/j.psj.2019.10.054>.

REFERENCES

- Aarestrup, F. M., and H. C. Wegener. 1999. The effects of antibiotic usage in food animals on the development of antimicrobial resistance of importance for humans in *Campylobacter* and *Escherichia coli*. *Microbes. Infect.* 1:639–644.
- Aarestrup, F. M., H. C. Wegener, and P. Collignon. 2008. Resistance in bacteria of the food chain: epidemiology and control strategies. *Expert Rev. Anti-infective Ther.* 6:733–750.

- Armstrong, D., T. W. Bennedsgaard, L. Boyle, D. Burch, B. Debski, J. Dewulf, C. Fablet, E. G. Manzanilla, J. Harlizius, and I. Henning-Pauka. 2014. EIP-AGRI Focus Group- Reducing Antibiotic Use in Pig Farming: Final Report. European Commission.
- Charnes, A., W. W. Cooper, and E. Rhodes. 1978. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* 2:429–444.
- Chauvin, C., I. Bouvarel, P.-A. Belœil, J.-P. Orand, D. Guillemot, and P. Sanders. 2005. A pharmaco-epidemiological analysis of factors associated with antimicrobial consumption level in Turkey broiler flocks. *Vet. Res.* 36:199–211.
- Coelli, T. J., D. S. P. Rao, C. J. O'Donnell, and G. E. Battese. 2005. *An Introduction to Efficiency and Productivity Analysis*. Springer Science & Business Media, New York, NY.
- Collineau, L., A. Backhans, J. Dewulf, U. Emanuelson, E. B. Grosse, A. Lehébel, S. Loesken, E. N. Okholm, M. Postma, and M. Sjölund. 2017. Profile of pig farms combining high performance and low antimicrobial usage within four European countries. *Vet. Rec.* 181:657.
- Currie, K., C. King, T. Nuttall, M. Smith, and P. Flowers. 2018. Expert consensus regarding drivers of antimicrobial stewardship in companion animal veterinary practice: a Delphi study. *Vet. Rec.* 182:691.
- EMA, EFSA 2017. EMA and EFSA Joint Scientific Opinion on measures to reduce the need to use antimicrobial agents in animal husbandry in the European Union, and the resulting impacts on food safety (RONAFA). *EFSA J.* 15:e04666.
- Farrell, M. J. 1957. The measurement of productive efficiency. *J. R. Stat. Soc.* 253–290. Series A (General).
- Fried, H. O., C. A. K. Lovell, and S. S. Schmidt. 2008. *The Measurement of Productive Efficiency and Productivity Growth*. Oxford University Press, New York, NY.
- Hao, H., G. Cheng, Z. Iqbal, X. Ai, H. I. Hussain, L. Huang, M. Dai, Y. Wang, Z. Liu, and Z. Yuan. 2014. Benefits and risks of antimicrobial use in food-producing animals. *Front. Microbiol.* 5:288.
- Horta, I. M., A. S. Camanho, and J. Moreira da Costa. 2012. Performance assessment of construction companies: a study of factors promoting financial soundness and innovation in the industry. *Int. J. Prod. Econ.* 137:84–93.
- Jensen, V. F., E. Jacobsen, and F. Bager. 2004. Veterinary antimicrobial-usage statistics based on standardized measures of dosage. *Prev. Vet. Med.* 64:201–215.
- Landers, T. F., B. Cohen, T. E. Wittum, and E. L. Larson. 2012. A Review of antibiotic use in food animals: perspective, policy, and potential. *Public Health Rep.* 127:4–22.
- McEwen, S. A., and P. J. Fedorka-Cray. 2002. Antimicrobial use and resistance in animals. *Clin. Infect. Dis.* 34:S93–S106.
- Milligan, G. W. 1980. An examination of the effect of six types of error perturbation on fifteen clustering algorithms. *Psychometrika* 45:325–342.
- Persoos, D., J. Dewulf, A. Smet, L. Herman, M. Heyndrickx, A. Martel, B. Catry, P. Butaye, and F. Haesebrouck. 2012. Antimicrobial use in Belgian broiler production. *Prev. Vet. Med.* 105:320–325.
- Ray, S. C. 2004. *Data Envelopment Analysis: Theory and Techniques for Economics and Operations Research*. Cambridge university press, Cambridge.
- Roskam, J. L., A. G. J. M. Oude Lansink, and H. W. Saatkamp. 2019. The technical and economic impact of veterinary interventions aimed at reducing antimicrobial use on broiler farms. *Poult. Sci.* 98:6644–6658.
- Rushton, J., J. P. Ferreira, and K. D. Stärk. 2014. *Antimicrobial Resistance: The Use of Antimicrobials in the Livestock Sector*. OECD Publishing, Paris, France.
- Simar, L., and P. W. Wilson. 1998. Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. *Manag. Sci.* 44:49–61.
- Singer, R. S., R. Finch, H. C. Wegener, R. Bywater, J. Walters, and M. Lipsitch. 2003. Antibiotic resistance—the interplay between antibiotic use in animals and human beings. *Lancet Infect. Dis.* 3: 47–51.
- Spekknijder, D. C., D. J. Mevius, C. J. M. Brusckke, and J. A. Wagenaar. 2015. Reduction of veterinary antimicrobial use in The Netherlands. The Dutch success model. *Zoonoses Public Health* 62:79–87.
- van den Bogaard, A. E., and E. E. Stobberingh. 1999. Antibiotic usage in animals - impact on bacterial resistance and public health. *Drugs* 58:589–607.
- van Duinkerken, G., and J. Spek. 2016. *Tabellenboek Veevoeding 2016: voedernormen pluimvee en voederwaarden voedermiddelen voor pluimvee (Dutch)*. Federatie Nederlandse Diervoederketen, Wageningen, The Netherlands.
- van der Fels-Klerx, H. J., L. F. Puister-Jansen, E. D. van Asselt, and S. L. G. E. Burgers. 2011. Farm factors associated with the use of antibiotics in pig production. *J. Anim. Sci.* 89:1922–1929.
- van Horne, P. L. M. 2017. Competitiveness of the EU poultry meat sector, base year 2015: international comparison of production costs. Wageningen, Wageningen Economic Research. Accessed Dec. 2019. <https://edepot.wur.nl/404949>.
- Ward, J. H. 1963. Hierarchical grouping to optimize an objective function. *J. Am. Stat. Assoc.* 58:236–244.