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# Micro-data efficiency evaluation of agricultural companies: The case of Germany and neighbouring countries

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**Abstract:** This study uses micro-financial data to examine the efficiency of agricultural enterprises in Germany and its neighbouring countries. The aim of the study is to introduce a model for the agricultural sector and conduct an efficiency analysis using these data, interpreting the results with specific knowledge in the management of an agriculture company. Both technical and allocative efficiencies were determined, and the companies were ranked. Possible correlations between company size, measured by turnover, and the determined efficiency were analysed. At present, there is a lack of studies in the agricultural sector with high aggregated financial data, which are the basis and necessity for well-founded decision support to increase efficiency. The data envelopment analysis method was used, as a non-parametric procedure from operations research and economics field. Both the constant returns to scale (CCR) and variable returns to scale (BCC) models were used to calculate the efficiency values. The results showed that large and very large companies achieved the highest levels of efficiency. Interestingly, very large companies lost efficiency compared to large companies, suggesting that the optimal efficiency level lies with the latter. Furthermore, the Netherlands was the absolute efficiency leader, while the other countries achieved similar lower efficiencies. This study contributes to the literature by providing a comprehensive efficiency analysis in the agricultural sector based on financial data, thus offering a basis for future studies and political decisions.

**Keywords:** bioeconomy; company size; data envelopment analysis; efficiency analysis; non-perennial crop

Agriculture plays a central role in Germany and its neighbouring countries, influencing various societal and environmental aspects. Although its share of total economic output is declining, as the country's largest land user it is largely responsible for soil, water, air quality, climate, and biodiversity. Analysing the efficiency of this sector is considered crucial for securing the basis of human existence. A distinction is made between technical and allocative efficiency, with the former describing a production facility's ability to achieve maximum yield using given resources and production methods, while the latter describes the optimal use of resources, taking into account their prices (Moutinho et al. 2018).

The agricultural sector is facing various challenges that affect its profitability, as well as environmental and social aspects. Economic profitability in agriculture holds crucial importance, as farmers are faced with price fluctuations for their products and rising production costs. To remain financially stable, they are forced

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to use efficient production methods that minimise costs while ensuring the quality of their produce. Profitability affects not only the individual farm but also the entire agricultural economy and rural communities, reflecting a complex balance between income, expenditure, and sustainable management. Fluctuations in market prices for agricultural products can affect the profitability of growing non-perennial crops and jeopardise farmers' income security. Due to the current geopolitical situation, market prices are subject to significant fluctuations and the market conditions for different crops change within a very short period as a result of political decisions.

The environmental aspect relates to soil health, water management, climate change, and the use of fertilisers and crop protection products. Intensive cultivation methods can lead to soil erosion, nutrient depletion, and soil compaction, impairing the soil's long-term productivity. Strauss et al. (2023) name seven suggestions for sustainable soil management: structural landscape elements, organic fertilisation, diversified crop rotation, permanent soil cover, conservation tillage, reduced soil loads, and optimised timing of wheeling.

Agriculture often requires considerable amounts of water, and water shortages or inefficient water management can lead to crop failures. Water management is an important component of efficient production in many areas; Chebil et al. (2015) used the amount of water used in wheat production in Tunisia as an input factor in data envelopment analysis. Breeding of new varieties with high drought tolerance holds particular interest.

Changes in climate conditions can affect the growing season, pest pressure, and crop yields, leading to uncertainty for farmers, who are also focused on measuring and reducing their carbon footprint (Toma et al. 2017). Climate change is also a particularly prevalent issue in agriculture due to the susceptibility of crops to various pests and diseases, whereby the use of pesticides can have an environmental impact and promote resistance. In particular, the political and societal pressure to reduce the use of pesticides will pose challenges for farmers in the future, as they will have to maintain an efficient and sustainable farm structure even without these crop protection products. The use of mineral fertilisers will also be further regulated and reduced by political requirements.

The potential of data envelopment analysis (DEA) estimates for policymakers to obtain significant results relating to agricultural production patterns and, consequently, planning for sustainable development has already been recognised in the EU context (Bojnec et al. 2014).

Efficiency in overcoming these challenges is a key factor in running a successful company. Hollingsworth (2003) outlined two approaches to efficiency analysis, namely the parametric approach of stochastic frontier analysis (SFA) and the non-parametric approach of DEA. Based on the analysis of Staňková et al. (2022) and the established correlation between SFA and DEA, only DEA is used in this paper. The number of publications in the field of DEA has sharply risen since the development of Charnes et al. (1978), whereby the method is now used extensively for efficiency analysis in agriculture.

The heterogeneity in the development and productivity of Europe's agricultural regions justifies the relevance of analysing technical efficiency in this sector (Moutinho et al. 2018). Traditional technical efficiency in the field of agronomy using DEA (for example) is determined using various specific input parameters, including the usage of pesticides, seeds, fertilisation, mechanical tillage, labour, and the consumption of water. The classically selected output parameter is the yield of the respective crop, either in quantity or financial terms. In this context, Piot-Lepetit et al. (1997), Gocht and Balcombe (2006), Bojnec et al. (2014), Chebil et al. (2015), and Shkodra et al. (2022) are among various publications in the field of DEA analysis.

However, the overarching comparison is not trivial due to the heterogeneous nature of the companies. In order to do justice to the different specialisations of the individual companies, Atici and Podinoski (2015) suggested introducing specialisation indices into the DEA framework. In this paper, the focus lies on an overarching efficiency analysis, whereby the analyses are carried out using the normal DEA models. Given the lack of efficiency assessments using financial company data in the literature, this paper used data from the Orbis database of Bureau van Dijk (2024) to carry out an efficiency analysis for Germany and its neighbouring countries.

This paper aims to transfer the model used in Staňková et al. (2022) to the agricultural sector and carry out the efficiency assessment using company financial data. In addition, the determined efficiencies were analysed, and a ranking of companies in the countries under consideration was created. In addition, the aim is to explore potential correlations between company size (measured in turnover) and the efficiency determined.

## MATERIALS AND METHOD

This study employed the DEA methodology (Charnes et al. 1978). The DEA SolverPro was used for the DEA so-

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lutions (Cooper et al. 2007). The radial constant returns of scale (CCR) and variable returns of scale (BCC) were used. The efficiency score $E_H$ results from the weighted sum of the outputs to the weighted sum of the inputs:

$$E_{CCR} = \frac{\sum_{j=1}^{n} u_j \times y_j}{\sum_{i=1}^{m} v_i \times x_i} \tag{1}$$

where: $u_j$ – weights for the outputs of the decision making unit (DMU), $u_j \geq 0$, $j = 1, 2, \ldots, n$; $y_j$ – actual output values of the DMU; $v_i$ – weights for the inputs of the DMU, $v_j \geq 0$, $i = 1, 2, \ldots, m$; $x_i$ – actual input values of the DMU.

The DEA model maximises the efficiency score on the condition that all efficiency scores are less than or equal to 1:

$$\frac{\sum_{j=1}^{n} u_j \times y_{jk}}{\sum_{i=1}^{m} v_i \times x_{ik}} \leq 1,\ k = 1, 2, \ldots, K \tag{2}$$

The extended BCC model allows variable returns to scale by inserting an additional term in both the objective function and the constraint representing the extent of the deviation from constant returns to scale (Banker et al. 1984):

$$E_{BCC} = \frac{\sum_{j=1}^{n} u_j \times y_j - \mu_o}{\sum_{i=1}^{m} v_i \times x_i} \tag{3}$$

$$\frac{\sum_{j=1}^{n} u_j \times y_{jk} - \mu_o}{\sum_{i=1}^{m} v_i \times x_{ik}} \leq 1,\ k = 1, 2, \ldots, K \tag{4}$$

where: $\mu_o$ – unconstrained in sign.

Kyrgiakos et al. (2023) conducted a systematic literature review of DEA applications in the field of agriculture under the prism of sustainability, finding that 76% of all publications were input-oriented. However, those publications focused on sustainability and the reduction of input factors, such as crop protection, fertilisation and energy. By contrast, in this study, we focused on the output-oriented view, which means that the aim of DEA was to maximise output rather than minimise inputs. The background to this was the use of financial indicators, and the aim was not to downsize the company but rather become increasingly efficient by making sensible adjustments to output.

In DEA, scale efficiency refers to whether a company is operating at its optimal size. If a firm is not at the optimal scale, further comparisons using varying returns to scale can determine whether it is 'too large' or 'too small'. Downsizing or adjusting the scale can lead to efficiency gains.

Since both the CCR model with constant returns and the BCC model with variable returns of scale were calculated, it was also possible to calculate the scale efficiency:

$$E_{SE} = \frac{CCR - efficiceny}{BCC - efficiency} \tag{5}$$

If the scale efficiency is 100%, the DMU has the optimal scale and cannot be more productive by changing the scale. If the scale efficiency is below 100%, the DMU can adjust its scale to a more optimal setting, thereby improving efficiency.

A gap to the efficient margin was also calculated for each DMU by calculating the efficiency margin during the DEA, resulting in the efficiency score. In addition, so-called slacks could also be considered as input and/or output variables that lead to efficiency through disproportionate changes. This means that a proportional increase in all variables is not necessary. For output parameters, a slack indicates that an increase by the described value is necessary. Regarding input factors, the slack value needs to be decreased to become an efficient DMU

In the DEA base model, the efficient margin is developed through all DMUs, and the efficiency can therefore be a maximum of 1 for a DMU. In order to identify outstanding or super-efficient DMUs, the DMUs are removed individually from the entire data set. If the value of the DMU under consideration is now above the efficient frontier, it is super-efficient. The model was originally developed by Andersen and Petersen (1993) and was described in further detail by Cooper et al. (2007).

It was not possible to analyse the Malmquist index because only very few companies provided financial data to Orbis over the entire period under review. Overall, only 49 companies were consistently represented over the entire time horizon.

The financial key figures used in this publication were sourced from Orbis, a comprehensive and global database that collects and provides company information. It is operated by Bureau van Dijk (2024), a Moody's Analytics company. Orbis provides detailed data on companies worldwide, including financial data, company hierarchies, M&A activity, risk ratings and other factors. Company data from category 011 'growing of non-perennial crop' was used for this publication.

Three parameters were selected for the input variables, namely fixed assets, shareholder funds and the

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Table 1. Number of companies per country and year

| Year | Germany | Denmark | Netherlands | Belgium | France | Austria | Czech Republic | Poland | Total |
|---|---|---|---|---|---|---|---|---|---|
| 2010 | 18 | 1 | 12 | 64 | 256 | – | 346 | 248 | 945 |
| 2011 | 16 | 1 | 18 | 76 | 251 | – | 362 | 170 | 894 |
| 2012 | 21 | 1 | 16 | 65 | 229 | 2 | 375 | 245 | 954 |
| 2013 | 34 | 1 | 16 | 51 | 236 | 3 | 396 | 307 | 1 044 |
| 2014 | 50 | – | 23 | 53 | 301 | 5 | 355 | 253 | 1 040 |
| 2015 | 146 | 6 | 23 | 49 | 271 | 4 | 440 | 247 | 1 186 |
| 2016 | 175 | 13 | 15 | 47 | 236 | 3 | 384 | 229 | 1 102 |
| 2017 | 186 | 17 | 15 | 47 | 200 | 3 | 364 | 842 | 1 675 |
| 2018 | 168 | 22 | 10 | 41 | 150 | 3 | 191 | 757 | 1 342 |
| 2019 | 96 | 21 | 11 | 43 | 106 | 1 | 50 | 720 | 1 048 |

Source: Own calculations based on Orbis data (2010–2019) (Bureau van Dijk 2024)

Table 2. Statistical data from 2010 to 2019 on input and output parameters per country, total assets, capital and turnover in thousands of EUR, and number of employees

| Country | | Number of employees | Total assets | Shareholder funds | Turnover |
|---|---|---|---|---|---|
| Germany | mean | 75 | 21 943 | 11 379 | 16 729 |
| | min | 1 | 27 | –1 968 | 50 |
| | max | 5 147 | 2 114 953 | 963 547 | 1 182 822 |
| | SD | 442 | 139 503 | 74 059 | 106 592 |
| France | mean | 99 | 46 921 | 25 585 | 16 916 |
| | min | 1 | 6 | –7 166 | –34 |
| | max | 21 073 | 9 362 083 | 4 757 584 | 2 358 400 |
| | SD | 956 | 479 595 | 270 609 | 129 629 |
| Denmark | mean | 188 | 55 592 | 27 903 | 31 204 |
| | min | 1 | 107 | –2 355 | 1 |
| | max | 1 506 | 609 108 | 185 961 | 246 074 |
| | SD | 396 | 105 259 | 47 573 | 59 406 |
| Austria | mean | 20 | 3 860 | 1 813 | 1 879 |
| | min | 1 | 75 | –247 | 2 |
| | max | 64 | 26 422 | 25 832 | 5 348 |
| | SD | 22 | 5 425 | 5 266 | 1 509 |
| Netherlands | mean | 265 | 89 672 | 51 141 | 88 444 |
| | min | 1 | 246 | –5 131 | 80 |
| | max | 3 012 | 1 017 976 | 796 250 | 488 803 |
| | SD | 524 | 165 828 | 138 622 | 94 643 |
| Czech Republic | mean | 16 | 1 918 | 1 108 | 1 346 |
| | min | 1 | 0 | –1 633 | –48 |
| | max | 375 | 56 543 | 42 283 | 21 803 |
| | SD | 26 | 3 120 | 2 281 | 1 965 |

Table 2 to be continued

| Country | | Number of employees | Total assets | Shareholder funds | Turnover |
|---|---|---|---|---|---|
| Belgium | mean | 31 | 5 457 | 2 023 | 6 860 |
| | min | 1 | 27 | –1 129 | 8 |
| | max | 537 | 58 230 | 37 111 | 134 719 |
| | SD | 70 | 9 299 | 4 413 | 17 449 |
| Poland | mean | 17 | 2 942 | 1 601 | 1 427 |
| | min | 1 | 0 | –11 512 | –110 |
| | max | 1 027 | 99 946 | 52 115 | 89 237 |
| | SD | 39 | 5 673 | 3 612 | 3 742 |

Source: Own calculations based on Orbis data (2010–2019) (Bureau van Dijk 2024)

number of employees. Turnover was selected as the output parameter.

Bobitan et al. (2023) conducted a comprehensive analysis of financial indicators in the area of sustainability and agriculture, with the specific key figures also coming from Orbis. However, due to data availability issues, fewer than 100 DMUs could be analysed in this context. This publication uses the identical input and output parameters as Staňková (2022), which increased the number of DMUs with accessible data to an average of 1 123 per year.

The number of data records per country and year is shown in Table 1, while the statistical data for input and output parameters broken down by country used is shown in Table 2.

In 2017, one DMU from Switzerland was included in the data set, which will not be considered further

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Table 3. Number of companies per country and size for all years

| Country | Size | | | |
|---|---|---|---|---|
| | small | medium | large | very large |
| Belgium | 296 | 168 | 58 | 14 |
| Denmark | 51 | 6 | 10 | 16 |
| Germany | 514 | 312 | 47 | 37 |
| France | 1 512 | 495 | 146 | 83 |
| Netherlands | 2 | 22 | 51 | 84 |
| Austria | 14 | 10 | – | – |
| Poland | 3 337 | 615 | 62 | 4 |
| Czech Republic | 2 712 | 514 | 37 | – |
| Total | 8 438 | 2 142 | 411 | 238 |
| Total (%) | 75 | 19 | 4 | 2 |

Source: Own calculations based on Orbis data (2010–2019) (Bureau van Dijk 2024)

below. Denmark up to 2010–2015 and Austria are also partly excluded from the further analysis as the number of companies considered is too small.

Most of the considered companies were located in the Czech Republic and Poland, followed by Germany and France. The number of companies analysed in the Netherlands was comparably low, while the number of Belgian companies was still comparably high. In 2011, only data records for 894 DMUs were available, whereas in 2017, a total of 1 675 DMUs were analysed.

The largest companies in terms of the parameters considered were located in the Netherlands, followed at some distance by Denmark and then Germany and France. The Belgian companies were again significantly smaller, but the significantly smallest companies considered are located in Poland and the Czech Republic. The mean value for these DMUs in terms of turnover was around 60 times smaller than in the Netherlands. Table 3 shows the grouping of companies into small (≤ EUR 2 million), medium (≤ EUR 10 million), large (≤ EUR 50 million), and very large companies (> EUR 50 million turnover). The proportion of large and very large companies was highest in the Netherlands. Overall, 75% of the companies considered are classified as small companies, followed by 19% medium-sized companies. The proportion of companies with a turnover of more than EUR 10 million is only 6%.

## RESULTS

Figure 1 shows the development of efficiencies in the CCR and BCC models examined over the entire period under review. As each year is evaluated individually in the DEA, a direct comparison of the trend was not appropriate. However, the figure shows an overall correlation between CCR and BCC and a slight downward trend over the period examined. In 2010 and 2011, the general efficiency in the CCR model was still around 20%. In the last two years examined, 2018 and 2019, it was only around 15%. This reduction is visible in almost all results shown below.

The difference between the CCR and BCC models is that the former represents overall efficiency. This means that the DMU under consideration was not only technically optimal but also optimal in terms of size. In the BCC model, only the technical efficiency was considered due to the variable return of scale approach. Therefore, the difference between the two models was scale efficiency. This is examined separately below, whereby the other results were calculated using the CCR model.

Figure 2 shows the mean values for efficiency per individual country. According to the chosen model, the most efficient companies were in the Netherlands, followed by Belgium, France and Germany. Denmark, Poland and the Czech Republic showed the lowest efficiency values. Although Denmark also had a high proportion of larger companies, the calculated efficiency was very low, compared to the Netherlands.

Figure 3 shows the development of the mean efficiency values grouped by company size over time. Unsurprisingly, small companies have the lowest efficiency.

Companies with a turnover of more than EUR 2 million were already significantly more efficient. Table 4 shows the average efficiency values and the number of DMUs considered over the entire period. Medium-sized companies were around 70% more efficient than small companies (10% *vs.* 17%). Large and very large companies significantly increased their efficiency to an average value of 30% and 24%, respectively. It is noticeable that very large companies lost efficiency compared to large companies, suggesting that the optimum lies with large companies.

Given that small companies account for considerably the largest group analysed, this group was analysed in more detail in Table 5. The efficient farms (> 50% efficiency score) were compared with the other farms (≤ 50% efficiency score) in the respective country.

For Belgium, all input factors for the efficient companies were significantly lower than the average for the other companies, whereas turnover was around twice as high. France was comparable in this respect, displaying a similar trend, although the reduction in input factors was not as drastic as the increase in turnover.

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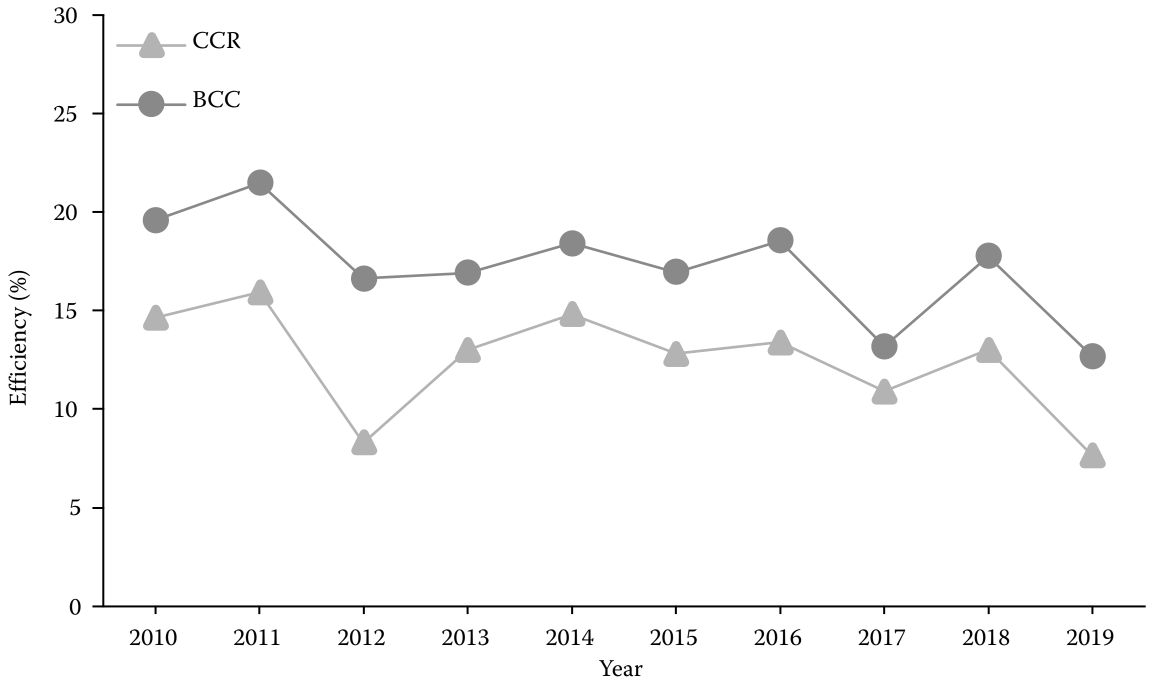


Figure 1. Median efficiency individually for the CCR and BCC models from 2010 to 2019

CCR – constant returns to scale; BCC – variable returns to scale
Source: Own processing based on Orbis data (2010–2019) (Bureau van Dijk 2024)

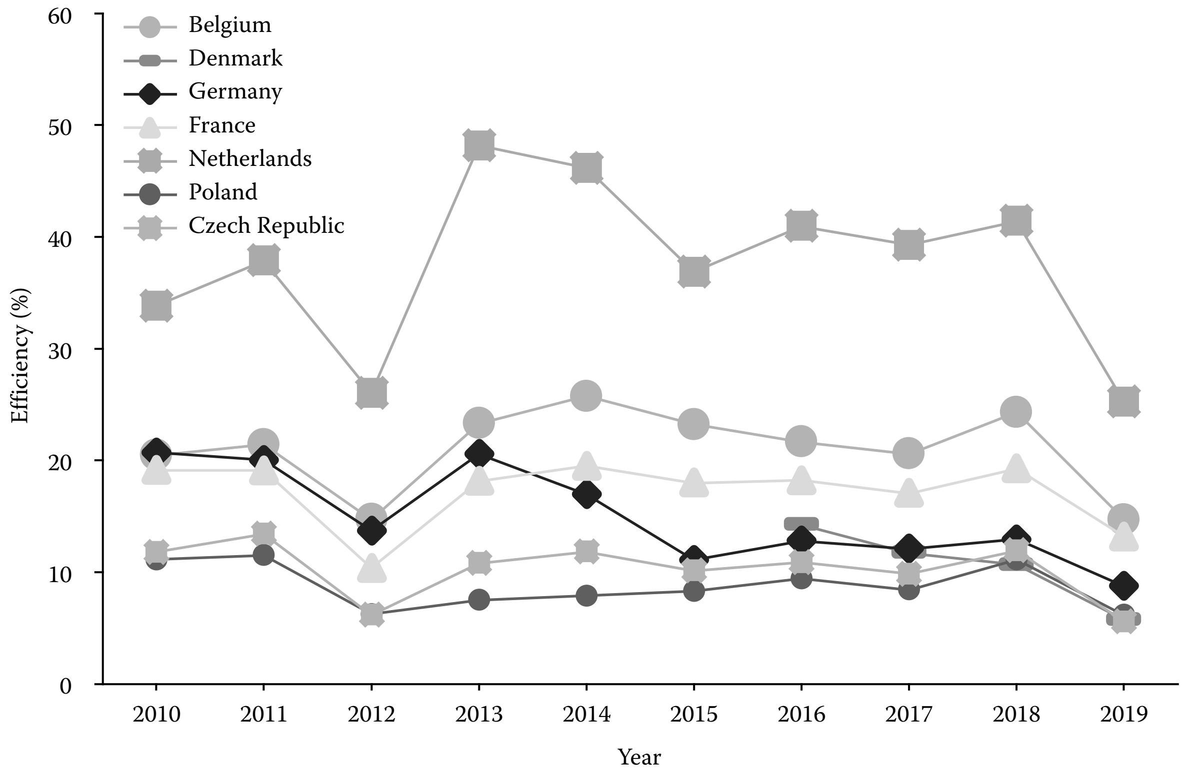


Figure 2. Median efficiency (CCR model) individually for Belgium, Denmark, Germany, France, the Netherland, Poland, and Czech Republic individually by country from 2010 to 2019

CCR – constant returns to scale
Source: Own processing based on Orbis data (2010–2019) (Bureau van Dijk 2024)

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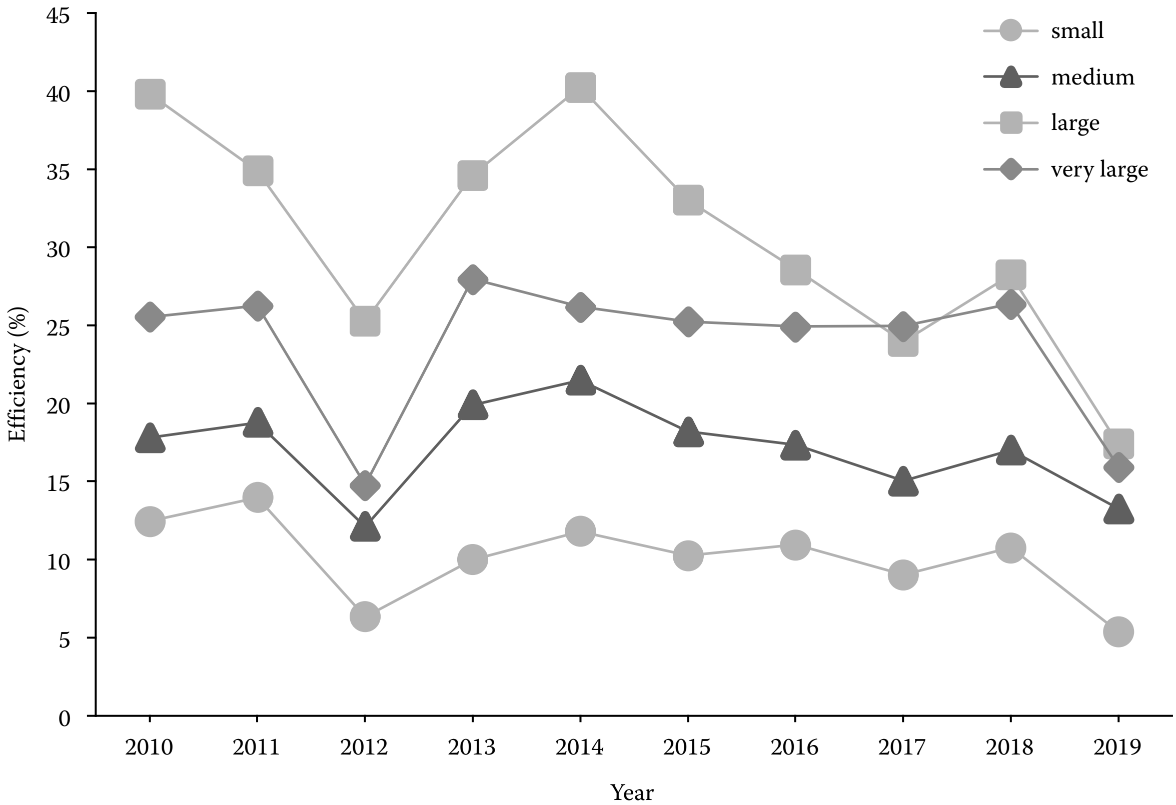


Figure 3. The median efficiency (CCR model) individually for small (dot), medium (triangle), large (square) and very large (diamond) companies from 2010 to 2019.

CCR – constant returns to scale
Source: Own processing based on Orbis Data (2010–2019) (Bureau van Dijk 2024)

On the other hand, the turnover in Germany was similar for both comparison groups. The number of employees was higher on the efficient farms than on the other farms. The efficiency of companies was due to the extremely low employed capital, in terms of both total assets and shareholder funds. A similar picture emerged for the Czech Republic and Poland. Although turnover was slightly higher in the efficient companies in those countries, the main factor was capital investment.

Table 4. Median efficiency (CCR model) and numbers per company size for all years

| Company size | Average score (%) | Number |
|---|---|---|
| Small | 10.0 | 8 438 |
| Medium | 16.9 | 2 142 |
| Large | 29.8 | 412 |
| Very large | 23.8 | 238 |

CCR – constant returns to scale
Source: Own calculations based on Orbis data (2010-2019) (Bureau van Dijk 2024)

Table 6 shows the mean efficiency values across the respective countries and the size of the DMU for the analysis of the companies' scale efficiency. If there were fewer than ten observations per category, the values were removed from the overview due to the lack of statistical analysis capability. In general, the trend for all countries showed that scale efficiency decreased when the size of the company increased. This means that small and medium-sized companies were more likely to have already found the suitable size for their company compared to large and very large companies. This statement should be viewed in contrast to the previous results, as large and very large companies generally had a clear efficiency advantage. However, a similar result was also demonstrated for forest companies by Staňková et al. (2022).

Inefficient DMUs have slacks, with which inefficient companies can become efficient through non-proportional adjustments to the input or output parameters. Table 7 shows both the relative proportion of slacks occurring per country and the mean value

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Table 5. Median efficiency (CCR model) divided in two groups per country, mean values of employees, total assets, shareholder funds and turnover in thousands of EUR

| Country | | Number | Mean values | | | | |
|---|---|---|---|---|---|---|---|
| | | | number of employees | total assets | shareholder funds | turnover | efficiency score (%) |
| Belgium | score > 50 % | 10 | 2 | 633 | 28 | 1 488 | 71 |
| | score ≤ 50 % | 286 | 6 | 1 241 | 554 | 673 | 15 |
| Germany | score > 50 % | 11 | 16 | 186 | –37 | 1 158 | 64 |
| | score ≤ 50 % | 503 | 11 | 3 366 | 1 667 | 1 121 | 9 |
| France | score > 50 % | 26 | 3 | 483 | 117 | 1 123 | 63 |
| | score ≤ 50 % | 1 486 | 6 | 1 092 | 504 | 704 | 14 |
| Poland | score > 50 % | 35 | 11 | 179 | 29 | 1 071 | 69 |
| | score ≤ 50 % | 3 302 | 9 | 1 653 | 863 | 510 | 7 |
| Czech Republic | score > 50 % | 9 | 11 | 178 | 4 | 899 | 72 |
| | score ≤ 50 % | 2 703 | 9 | 1 052 | 558 | 652 | 10 |

CCR – constant returns to scale
Source: Own calculations based on Orbis data (2010–2019) (Bureau van Dijk 2024)

of the absolute level of slacks. For inputs, any slacks that occur must be reduced from the input. For the output, the occurring slacks must increase the turnover. Table 8 shows the same representation depending on the size of the company. The most frequent slacks occurred in the input area of shareholder funds and in the output area of turnover. In a country comparison, the relative frequency of slacks varied between the number of employees and total assets in the different countries. However, both input factors played a subordinate role in significantly increasing overall efficiency. The absolute slacks in the area of turnover clearly showed that almost all companies were significantly lacking in turnover to catch up with the best-performing companies. When analysing the slacks for Denmark, it became clear that both shareholder funds and total assets would have to be significantly reduced to become efficient in the selected model.

Table 6. Median efficiency (scale efficiency) per country and companies size for all years (in %)

| Country | Size | | | |
|---|---|---|---|---|
| | small | medium | large | very large |
| Belgium | 76 | 70 | 66 | 47 |
| Denmark | 77 | – | 41 | 29 |
| Germany | 85 | 74 | 64 | 29 |
| France | 81 | 78 | 57 | 25 |
| Netherlands | – | 69 | 76 | 41 |
| Austria | 75 | 79 | – | – |
| Poland | 85 | 69 | 51 | – |
| Czech Republic | 86 | 70 | 57 | – |

Source: Own calculations based on Orbis data (2010-2019) (Bureau van Dijk 2024)

A comparison of company size showed that shareholder funds and turnover were the determining slacks, although it is also evident that the input factor of employees had a higher relative frequency of slacks than the other input total assets. The larger the company structure, the higher the absolute slacks. In this statement, the focus was placed on the financial parameters of the input and output side. This only applied to a lesser extent to the number of surplus employees, which was 1 for small companies and 16 for very large companies. This ratio was significantly smaller than (for example) the shareholder funds of EUR 0.4 million to EUR 125 million (a factor larger than 300).

Table 9 shows the number of super-efficient companies per country for the entire period under consideration. The percentage of super-efficient DMUs compared to all DMUs in the respective country was also calculated. Again, the Netherlands had by far the best values, as more than 10% of all considered companies were not only efficient but also super-efficient. The Netherlands was followed by Belgium, where the percentage of super-efficient companies was around 3%. The company APLIGEER from Belgium was super-efficient in eight out of ten years under review. The company was characterised by a high turnover of approximately EUR 30 million with a low number of employees (approximate-

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Table 7. Median relative frequencies and median values of identified slacks by country, employee numbers, total assets, shareholder funds and turnover in thousands of EUR

| Country | Employees | | Total assets | | Shareholder funds | | Turnover | |
|---|---|---|---|---|---|---|---|---|
| | % | number | % | number | % | number | % | number |
| Belgium | 12 | 3 | 12 | 334 | 53 | 747 | 97 | 36 852 |
| Denmark | 8 | 22 | 28 | 5 012 | 70 | 14 467 | 100 | 334 178 |
| Germany | 9 | 2 | 4 | 184 | 58 | 3 715 | 99 | 154 756 |
| France | 12 | 2 | 6 | 1 683 | 54 | 11 283 | 99 | 210 133 |
| Netherlands | 7 | 23 | 10 | 1 588 | 46 | 24 564 | 89 | 519 764 |
| Austria | 13 | 2 | 21 | 1 077 | 38 | 1 372 | 96 | 18 957 |
| Poland | 22 | 3 | 5 | 135 | 66 | 804 | 100 | 21 784 |
| Czech Republic | 15 | 2 | 2 | 23 | 64 | 555 | 100 | 15 283 |

Source: Own calculations based on Orbis data (2010–2019) (Bureau van Dijk 2024)

Table 8. Median relative frequencies and median values of identified slacks by company size, employee numbers, total assets, shareholder funds and turnover in thousands of EUR

| Size | Employees | | Total assets | | Shareholder funds | | Turnover | |
|---|---|---|---|---|---|---|---|---|
| | % | number | % | number | % | number | % | number |
| Small | 17 | 1 | 5 | 102 | 61 | 392 | 100 | 9 826 |
| Medium | 13 | 4 | 4 | 249 | 65 | 1 565 | 98 | 47 042 |
| Large | 12 | 15 | 7 | 403 | 53 | 6 968 | 91 | 154 740 |
| Very large | 6 | 16 | 6 | 16 224 | 61 | 124 642 | 97 | 2 653 243 |

Source: Own calculations based on Orbis data (2010–2019) (Bureau van Dijk 2024)

ly ten) and low equity. The other companies that were rated as super-efficient at least four times are SARL BM PRODUCTION from France, RIJK ZWAAN DISTRIBUTION B.V. and SATTER PHALAENOPSIS B.V. from the Netherlands and RK NAKLO, S.R.O. from the Czech Republic. In the years of super-efficiency, this Czech company was run by one employee with stable turnover and low financial input. Both SARL BM PRODUCTION and SATTER PHALAENOPSIS B.V. had negative shareholder funds. RIJK ZWAAN DISTRIBUTION B.V. was a large company with very stable growth in both output and key financial figures of total assets and shareholder funds. The number of employees remained stable with an increasing turnover.

Table 9. Number and percentage of super-efficient DMUs in the entire data set

| Country | Number | Percentage |
|---|---|---|
| Belgium | 16 | 2.99 |
| Germany | 10 | 1.10 |
| France | 21 | 0.94 |
| Netherlands | 17 | 10.69 |
| Austria | 1 | 4.17 |
| Poland | 19 | 0.47 |
| Czech Republic | 8 | 0.25 |

DMU – decision making unit
Source: Own calculations based on Orbis data (2010-2019) (Bureau van Dijk 2024)

## DISCUSSION

In this publication, a DEA approach had been chosen to evaluate farms growing non-perennial crops in Germany and neighbouring countries using microfinance data. For this purpose, the labour input factors were the number of employees, the capital employed as shareholder funds and the fixed assets as total assets, while the selected output factor is the company's turnover. The selected parameters were chosen based on the availability of data to evaluate as many companies as possible and enable an overarching efficiency analysis of this economic sector. The results therefore represent an overarching view and are not a concrete recommendation for action on an individual basis.

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DEA assumes that all firms or decision-making units operate under similar conditions, which might not hold true in practice, particularly in sectors such as agriculture, where environmental, economic, and regulatory conditions can significantly vary across regions. In the context of our study, several specific limitations arise from the use of DEA for evaluating micro-data on agricultural companies. One major challenge is the availability and quality of data, particularly for smaller farms. While Eastern European countries tend to have more comprehensive micro-level data on smaller agricultural enterprises, data availability is significantly more limited in countries such as Germany. This creates a heterogeneous comparison group across different countries, as smaller farms might be underrepresented in some regions, potentially skewing the analysis towards larger companies.

In our analysis, we used turnover as the primary output factor. While maximising the advantages of the available data sources, this output choice limits the ability to assess profitability or financial health at the individual farm level, as turnover does not account for costs or other factors that influence profitability. As a result, the DEA model focuses on revenue generation rather than measures of farm performance, such as profit margins or sustainability practices. However, based on the data available, the study provides valuable insights into agricultural efficiency trends and helps to identify key performance drivers. By shedding light on the role of company size, scaling effects, and technological innovations, this research offers practical guidance for improving efficiency in the agricultural sector and serves as a foundation for future studies to address profitability and sustainability in further depth.

The average efficiency across all companies and years was 12%. However, there was a significant difference between both the various countries considered and the size of the companies. The Netherlands achieved the highest average efficiency score at 38%. In Nowak's (2015) study, the Netherlands also achieved the highest DEA score in terms of technical efficiency. In general, agriculture in the Netherlands was characterised by a high level of intensive use of technology, such as high-tech greenhouses, precise irrigation and modern animal husbandry. Dutch farms are also highly specialised and focused on the export of food, which enables them to be very large in the respective segment, whereby the chosen model confirms this fact. In addition to the Netherlands, the efficiency values of Danish farms stand out. The average efficiency was only 10%, which was below the average for all countries. Denmark also ranked with the highest score in Nowak et al. (2015) and Laurinavičius and Rimkuvienė (2017). The difference compared to this result is the focus on purely financial indicators. Danish farms are generally highly professional in the agricultural sector, the company structure is large, and the growing conditions are highly stable and effective due to the oceanic climate. However, as Danish companies are relatively conservative financially (with high shareholder funds and total assets) and mainly produce cereals with a low turnover, the farms in the selected model are rather inefficient. The financial yield per ha in Denmark was still above the average result in Europe, albeit three to four times lower than in the Netherlands.

Small companies had an average efficiency score of only 10%. Due to their low fixed assets, they were unable to use the most modern cultivation technology or had to purchase it at high costs. The lower efficiency of these companies was also to be expected in practice and was indeed confirmed by the model. Small farms are generally less efficient than larger ones due to limited access to technology and resources that enhance productivity. Larger farms benefit from economies of scale, allowing them to spread fixed costs over higher output and invest in advanced equipment and innovative practices. This technological edge enables larger farms to optimise operations and reduce costs, while small farms often lack the financial capacity to adopt such improvements. Consequently, larger farms can achieve higher efficiency and profitability compared to their smaller counterparts.

Efficiency-boosting measures for small businesses must be considered on a country-by-country basis. Whereas in Germany the clear recommendation is to use less capital, in other countries more measures to increase turnover and a critical review of the necessary headcount both make sense. The number of employees can be reduced by purchasing specialised agricultural services, and the performance of the work can be increased by competent and efficient specialist companies. However, the continuation of 'business as usual' (Janová et al. 2022) may prevent companies from adopting new technologies or processes, thereby decreasing their efficiency.

For very large companies, the calculated efficiency decreased again. Due to the lower number of DMUs in large and very large companies, the significance of the results is not high. In practice, the results could be explained by a lack of management expertise in very large structures at these companies.

In addition to increasing the turnover of the respective DMU, the proportion of shareholder funds was

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a second important factor for efficiency. To a certain extent, this parameter reflects the return on equity, which in particular is a crucial factor for the continued existence of a company. A reduction of this input factor to become efficient in this model should therefore be treated with caution. An exact recommendation for action in this area is not possible with the model developed without precise information regarding external financing and generated profit.

Large and very large companies achieved the highest efficiency score in this model. This result is also reflected in practice in Germany, as the number of agricultural enterprises in Germany is declining continuously and the remaining farms are growing in size. In practice, the chosen model reflects the reality in Germany very well, highlighting that small farms will have to increase their efficiency or most likely disappear from the market.

Only 49 out of a total of 3 519 surveyed companies were represented in all periods examined, which reflects the volatility in this economic sector. Reporting obligations change due to size adjustments, companies are closed or acquired, or new companies are created. Given that agriculture faces a variety of challenges in the future, an analysis of efficiency in this sector is therefore very helpful. The efficiency of the companies considered decreased over time, which clearly shows the challenges facing the sector and the need to address them. The efficiency map developed requires further research focused on the individual specialised segments of agriculture.

When building decision support systems, it is essential to balance necessary simplifications, such as those based on data limitations, with an accurate reflection of the real-world problems (Janová 2014). To improve this balance, further research should prioritise qualified surveys of companies due to the limited availability of financial and technical data. This approach will help obtain robust results and enhance the credibility and applicability of our findings.

## CONCLUSION

Our research highlights the varying levels of efficiency across six European countries' agricultural sectors, with the Netherlands emerging as the benchmark for best practices and technological innovations. The average efficiency of agricultural companies in Denmark was below the overall average for the countries considered, i.e. lower than expected. Although Danish farms rank highly in professional standards and benefit from stable growing conditions due to their oceanic climate, their conservative financial practices combined with a focus on low-turnover cereal production contribute to their relatively inefficient performance in the selected model. However, cross-country efficiency comparisons remain complex due to factors such as soil fertility, weather conditions, and national agricultural policies, all of which can influence performance.

The study demonstrated that large agricultural companies significantly benefit from economies of scale, enabling them to operate more cost-effectively by distributing fixed costs over higher production volumes. Our results confirm that small farms are generally less efficient than larger ones due to their limited access to technology and resources that enhance productivity. Additionally, the overall efficiency of the companies examined has declined over time, highlighting the challenges faced by the agricultural sector and emphasising the urgent need to address these issues.

To enhance agricultural efficiency across Europe, technological advancements and scaling up production are likely key strategies for improvement. Our results contribute to the growing knowledge of agricultural efficiency and provide a foundation for future studies in sustainable and efficient agricultural production. More research is necessary to explore the intersection of efficiency and sustainability, ensuring that future policies and practices can balance profitability with environmental responsibility. Given the challenges posed by the unavailability of comprehensive financial and technical data across numerous companies and countries, future research should prioritise the use of targeted, qualified surveys of companies to obtain robust results. This approach will allow for a more accurate assessment of the variables under study and enhance the credibility and applicability of the findings.

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