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CROSS-NATIONAL COMPARISON OF DYNAMIC INEFFICIENCY FOR EUROPEAN DIETETIC FOOD MANUFACTURING FIRMS

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Abstract. Food health and wellness has become increasingly important for consumers, and this has inevitably caused growth in the dietetic food manufacturing sector. This paper examines the technical inefficiency of dietetic food manufacturing firms in five major dietetic food producing European countries (France, Italy, Norway, Poland and Spain) for the period 2009–2017. To account for the sluggish adjustment of capital, we employed a dynamic production framework within the nonparametric method of Data Envelopment Analysis. Furthermore, we used the concept of a metafrontier to compare inefficiency between countries and analyzed three inefficiency measures: estimated with regard to a metafrontier (pooled dynamic inefficiency), computed with reference to country-specific frontier (managerial dynamic inefficiency), and the gap between these two frontier measures (program dynamic inefficiency). The results indicate that firms in Poland were the least dynamically inefficient among countries analyzed, while companies in Norway were at the opposite end of the spectrum. Managerial inefficiency was the largest source of pooled inefficiency for firms in France and Italy, while program inefficiency was the main reason of pooled inefficiency for firms in Norway, Poland and Spain. The results also reveal that investments were the most inefficient factor, followed by output, materials and employees.

Keywords: efficiency, food manufacturing industry, dietetic food industry, Data Envelopment Analysis.

JEL Classification: C61, D24, L66.

Introduction

The food manufacturing industry plays a significant role in the economies of European countries, producing approximately 13 per cent of the total value of output in the manufacturing sector and being the largest manufacturing sector in terms of employment (Eurostat, 2020a).

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It is the largest sector within bioeconomy that refers to economic activities that use renewable biological resources from land and sea to produce food, materials and energy, leading to a more resource-efficient and sustainable economy (Ramcilovic-Suominen & Pülzl, 2018). Within the European food manufacturing sector, the dietetic food sector is gaining popularity and importance as consumer health and wellness awareness towards food continues to grow (Herath et al., 2008; Domínguez Díaz et al., 2020). This development comes with the increasing availability of health information, together with ageing populations and growing risk of lifestyle-related diseases (Kearney, 2010; El Bilali et al., 2019). Adopting healthy diets and increased cautiousness about food ingredients is linked to growing attention to maintaining healthy lifestyles and preventing diseases or serious and life-threating food allergies and intolerances (such as gluten intolerance) (European Commission, 2016; Afshin et al., 2019). This is all related to sustainability and corporate social responsibility (CSR), as healthy food choices are often sustainable choices (Health Council of the Netherlands, 2011; Esteve-Llorens et al., 2020). In fact, sustainable diets are defined as being beneficial to health, ensuring food safety, and being economically affordable and respectful of ecosystems (Food and Agriculture Organization, 2010). In addition, among firms' CSR activities one can find business practices related to product safety and healthiness (Auer & Schuhmacher, 2016).

The dietetic food manufacturing industry is part of other food manufacturing and concerns the production of dietetic foods or foods for particular nutritional use. Dietetic foods comprise foodstuffs whose composition and manufacturing process are designed to meet special nutritional purposes (European Parliament and the Council, 2009)[1]. Examples of dietetic foods include food for infants and young children, slimming foods, dietary food for special medical uses, sports foods, food for people with gluten intolerance, low-sodium foods and food for people suffering from diabetics (Eurostat, 2008; Bragazzi et al., 2017)[2]. Dietetic foods are also closely related to functional foods, which are foods consumed as a part of the usual diet and providing health effects that go beyond traditional nutritional benefits (Stein & Rodríguez-Cerezo, 2008; Küster-Boluda & Vidal-Capilla, 2017). The growing consumer attention towards healthy foods becomes evident by looking at statistics on the European dietetic food manufacturing sector, which show that between 2011 and 2016 the number of firms and employment in this industry increased by 51 per cent and 24 per cent, respectively, while its value added grew by 11 per cent between 2013 and 2016 (Eurostat, 2020a).

Despite the growing popularity of dietetic food and the increasing importance of this industry, the academic literature has devoted very limited attention to the performance of firms comprising this industry. In particular, no research has been undertaken into the (in) efficiency of this industry[3]. Efficiency or inefficiency measures analyze technological and

[1] In the European classification of economic activities (NACE Rev. 2), dietetic food manufacturing is a subsector labelled as "Manufacture of homogenized food preparations and dietetic food".

[2] It is worth pointing out that, in Europe, the term "dietetic food" is currently being replaced by the term "food for specific groups" (European Parliament and the Council, 2013). However, as the NACE Rev.2 classification still uses the term "dietetic food" and our study follows this classification, we refer in this paper to the industry under study as the dietetic food sector.

[3] We note that the only related study referring to performance of dietetic food is Gołaś and Bieniasz (2016), which analyzed the relationship between inventory management and financial performance of food manufacturing in Poland, including the subsector of dietetic food. However, their analysis focuses on financial ratios such as ROA rather than on efficiency.

economic relationships between output production and input consumption (Morrison-Paul & Siegel, 2006) and provide information on how well a company transforms its inputs into outputs in relation to benchmark of best practice companies[4]. In contrast, many studies have analyzed the inefficiency of gross food manufacturing sector (e.g., Setiawan et al., 2012; Giokas et al., 2015; Gardijan & Lukač, 2018; Kedžo & Lukač, 2021), or several subsectors within food manufacturing (e.g., Ali et al., 2009; Shee & Stefanou, 2015; Boyd & Doolin, 2021). A vast amount of research has also been devoted to the inefficiency analysis of specific subsectors of food processing, such as meat processing (Kapelko, 2017; Kapelko & Oude Lansink, 2018), dairy processing (Soboh et al., 2014; Kapelko & Oude Lansink, 2017; Čechura & Žáková Kroupová, 2021), oils (Dios-Palomares & Martínez-Paz, 2011; Niavis et al., 2018), or sugar (Mulwa et al., 2009; Carlucci et al., 2021). Inefficiency studies of several subsectors of food manufacturing have also analyzed other food industries, but without distinguishing the manufacturing of dietetic food (see, e.g., Rezitis & Kalantzi, 2016; Rudinskaya, 2017; Kapya et al., 2018)[5]. The aforementioned papers for the assessment of efficiency applied both Data Envelopment Analysis (DEA) of Charnes et al. (1978) and Banker et al. (1984) (e.g., in the studies by Setiawan et al., 2012 or Giokas et al., 2015) and Stochastic Frontier Analysis (SFA) of Aigner et al. (1977) (e.g., in the studies by Rudinskaya, 2017 or Shee & Stefanou, 2015), with one study that relied on both techniques (Mulwa et al., 2009). Within the papers that relied on DEA, various efficiency measures are used that operationalize the paths to the frontier of best practice firms for inefficient firms, with the vast majority being radial models (e.g., in the studies by Setiawan et al., 2012; Rezitis & Kalantzi, 2016 or Kedžo & Lukač, 2021). Only few papers considered directional efficiency measures (Kapelko, 2017) or slack-based directional efficiency measures (Kapelko & Oude Lansink, 2017, 2018). Furthermore, all papers assumed input- or output-orientation in the DEA models, focusing on the ability of firms to minimize input use in the production of a given set of outputs or the ability to maximize output from a given set of inputs. None of the papers, however, applied DEA models in the full input-output-investment space, allowing for a simultaneous increment in outputs and investments, and a reduction of inputs. Furthermore, all papers made some assumptions of the DEA model such as that of convexity and returns to scale without appropriate testing if these assumptions hold.

As no research has been devoted to the analysis of the inefficiency of food manufacturing firms that engage in the production of dietetic food, the present paper aims to fill this gap in the literature and contributes by studying the inefficiency of these firms in the European context. The measurement of firms' inefficiency is a relevant topic for managers and policy makers. It can provide important insights into the performance of the sector and its competitiveness, as well it can support the design of firms' strategies and government policies targeted at improvement of performance. The food manufacturing industry is relatively capital-intensive, so the capital and investment changes require appropriate modelling of

[4] The literature uses both the terms "efficiency" and "inefficiency". Because the mathematical measures we apply define firms' performance in terms of inefficiency, to be consistent we use the term "inefficiency" throughout the paper.

[5] The well-established and large body of research analyses the efficiency and productivity at the farm level (e.g., Lambarraa et al., 2016; Namiotko & Baležentis, 2017; Li et al., 2018; Hansson et al., 2020).

the inefficiency accounting for sluggish responses and capital adjustment costs related to learning curves, training and education (Morrison-Paul, 1997). This can be achieved via a recent method of the measurement of dynamic inefficiency (Silva et al., 2015, 2021; Kapelko et al., 2014) that represents adjustment cost technology. Hence, in the present study, the evidence on the inefficiency of dietetic food industry is provided using the dynamic method. Furthermore, in differentiation to previous research, we apply the dynamic model in the full input-output-investment space that allows to optimize on these three dimensions with the aim to measure firms' inefficiency. In the empirical implementation of dynamic inefficiency measures we apply DEA. For the unbiasedness of our results, we use recently developed statistical results to test the convexity assumption of the DEA model, as well to test the returns to scale (Kneip et al., 2016; Simar & Wilson, 2020).

The empirical analysis of this paper focuses on the recent dataset of the firms that represent five European countries (France, Italy, Poland, Norway and Spain) engaged in the production of dietetic foods over the period 2009–2017. In general, the inefficiencies for the countries included in the analysis cannot be directly compared between them due to differences in technologies. In order to be able to appropriately model the differences in inefficiency between these countries, we further apply the concept of a metafrontier (Battese et al., 2004; O'Donnell et al., 2008) and compute two inefficiency measures – one with regard to a metafrontier calculated for all firms in the sample regardless of the country, and one with reference to a country-specific frontier assessed separately for firms in each country – and then calculate a gap between the metafrontier and the country-specific frontier.

The paper contributes to the literature in several ways. Firstly and most importantly, it is the first study that analyzes the performance and inefficiency of firms representing the manufacturing of dietetic food. We believe this is an important contribution as so far no research has been devoted to the assessment of the performance of firms comprising this sector. Given the growth of this sector and increasing popularity of dietetic food among consumers, it is important to know if it goes in line with improving firms' performance and efficiency. Secondly, in contrast to most existing papers on the measurement of firms' inefficiency in other sectors of food manufacturing that focused on the input-oriented or output-oriented measurements (e.g., Kapelko & Oude Lansink, 2017; Gardijan & Lukač, 2018; Kedžo & Lukač, 2021), the present paper looks at efficiency appraising due to the changes in three dimensions of inputs, outputs and investments simultaneously. In most of practical situations it is desirable to use the inefficiency measures in the full input-output-investment space, in which units are able to optimize inputs, outputs and investments, as it is assumed in this study. Thirdly, this study differs from the papers on the measurement of firms' inefficiency in other sectors of food manufacturing in terms of exploiting the new statistical results that have been recently developed on testing the convexity and returns to scale in DEA (Kneip et al., 2016; Simar & Wilson, 2020).

The paper proceeds as follows. The measures of dynamic inefficiency are presented in the next section. The data used are described in Section 2, and empirical results are discussed in Section 3. Conclusions are given in the last Section.

1. Measuring dynamic inefficiency of the European dietetic food firms – within-country dynamic inefficiency and country gap

The literature distinguishes two main approaches to the measurement of efficiency: (1) a static framework (Farrell, 1957; Varian, 1984) that does not take into account the intertemporal linkages of firms' production decisions and in which firms are assumed to instantaneously adjust inputs and outputs to their optimal levels; and (2) a dynamic framework (Silva & Stefanou, 2003, 2007) that considers that current production possibilities constrain or enhance future production decisions and models the sluggish adjustment of quasi-fixed inputs to their optimal levels. We have opted for the dynamic approach to the measurement of efficiency because the static one is too restrictive and, in the presence of dynamic interdependence and sluggish adjustment, might result in a misleading estimation of efficiency (Kapelko et al., 2014; Aparicio & Kapelko, 2019). In the dynamic approach, the gradual adjustment of quasi-fixed factors occurs by imposing adjustment costs. Adjustment costs are transaction or reorganization costs that are inevitably incurred when investing in quasi-fixed factors, such as the costs of searching for new equipment or learning to use this equipment[6].

The literature on measuring dynamic efficiency within adjustment cost framework has developed following two approaches: one involving SFA in the studies by Rungsuriyawiboon and Stefanou (2007), Serra et al. (2011) or Minviel and Sipiläinen (2021), and one based on DEA in the studies by Silva et al. (2015), Kapelko et al. (2014) or Baležentis and Oude Lansink (2020). In the present study, we have used DEA due to its flexibility as it does not impose restrictive assumptions on the specification of the technology. In addition, the main assumptions of DEA can be now tested following recent statistical results (Kneip et al., 2016; Simar & Wilson, 2020). The literature has proposed several measures to determine the technical efficiency of decision making units (DMUs) in the DEA context. In this study, we rely on the directional distance function (Chambers et al., 1998) and, in particular, its dynamic representation (Silva et al., 2015) due to its relevant properties such as flexibility, duality, units invariance and translation invariance[7]. Dynamic directional distance function can assume input orientation, in which a decision maker seeks to minimize variable inputs and maximize investments; output orientation, in which maximization of outputs is pursued; or graph orientation, which combines input- and output-oriented models by aiming for simultaneous contraction of variable inputs, and expansion of outputs and investments (in this case, inefficiency is determined in the full input-output-investment space). The present paper seeks to determine dynamic technical inefficiency in the full input-output-investment space, as it is reasonable to assume that firms in the industry under study focus on all three of these dimensions in their production decisions.

Let us now provide the mathematical representation of dynamic directional distance function in the full input-output-investment space. Let us assume a data series ($\mathbf{y}$, $\mathbf{k}$, $\mathbf{x}$, $\mathbf{I}$)

[6] A further strand of dynamic efficiency studies models the network structure of firms' production systems (for example, output in one stage of production in one period is used as input in the second stage for the next period or quasi-fixed inputs are used as outputs in the current period and as inputs in the next period). The studies include, for example, Färe and Grosskopf (1996), Nemoto and Goto (2003), Chen (2009), Tone and Tsutsui (2014) or Fukuyama and Weber (2017).

[7] Directional distance function is a version of the shortage function by Luenberger (1992a, 1992b).

that represents $j = 1, .., n$ DMUs that produce s outputs (denoted as **y**), using f quasi-fixed inputs (denoted as **k**), m variable inputs (denoted as **x**), and f gross investments in quasi-fixed inputs (denoted as **I**). The variable inputs could comprise of labor and materials, quasi-fixed inputs could be capital, investments could be undertaken in the capital, and all of these factors are used in the production of revenues, as in the context of our empirical analysis of the dietetic food industry in European countries. The dynamic directional distance function in the full input-output-investment space is defined as follows (Silva et al., 2021):

$$\begin{aligned} &\vec{D}(\mathbf{x},\mathbf{I},\mathbf{y},\mathbf{k};\mathbf{g}^x,\mathbf{g}^I,\mathbf{g}^y) = \max\left\{\beta \in \Re : (\mathbf{x}-\beta\mathbf{g}^x, \mathbf{I}+\beta\mathbf{g}^I, \mathbf{y}+\beta\mathbf{g}^y) \in P(\mathbf{y}:\mathbf{k})\right\} \\ &\text{if } (\mathbf{x}-\beta\mathbf{g}^x, \mathbf{I}+\beta\mathbf{g}^I, \mathbf{y}+\beta\mathbf{g}^y) \in P(\mathbf{y}:\mathbf{k}) \text{ for some } \beta \\ &\vec{D}(\mathbf{x},\mathbf{I},\mathbf{y},\mathbf{k};\mathbf{g}^x,\mathbf{g}^I,\mathbf{g}^y) \to -\infty \quad \text{if} \quad (\mathbf{x}-\beta\mathbf{g}^x, \mathbf{I}+\beta\mathbf{g}^I, \mathbf{y}+\beta\mathbf{g}^y) \notin P(\mathbf{y}:\mathbf{k}), \end{aligned} \tag{1}$$

where $\mathbf{g}^x$, $\mathbf{g}^I$ and $\mathbf{g}^y$ are non-zero vectors determining the direction for variable inputs, investments and outputs, β is a measure of dynamic technical inefficiency, and $P(\mathbf{y}:\mathbf{k})$ is the input requirement set (representing the dynamic production technology). The dynamic directional distance function measures dynamic technical inefficiency for each firm, given the input-output-investment space, and represents the maximum contraction in variable inputs in the direction of $\mathbf{g}^x$ and, simultaneously, the maximum expansion in gross investments in the direction of $\mathbf{g}^I$ and in outputs in the direction of $\mathbf{g}^y$.

Dynamic production technology, which transforms variable inputs and gross investments into outputs at a given level of quasi-fixed inputs, is defined as follows (Silva & Stefanou, 2003):

$$P(\mathbf{y}:\mathbf{k}) = \{(\mathbf{x},\mathbf{I}) \text{ can produce } \mathbf{y}, \text{ given } \mathbf{k}\}. \tag{2}$$

Based on Silva et al. (2021) and Aparicio and Kapelko (2019), the dynamic directional distance function in the full input-output-investment space to evaluate firm 0 can be determined using DEA as follows:

$$\begin{aligned} \vec{D}\left(x_0, I_0, y_0, k_0; g_0^x, g_0^I, g_0^y\right) = \ & \text{Max}\ \beta \\ \text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0} - \beta g_{i0}^x, && i = 1, ..., m \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0} + \beta g_{r0}^y, && r = 1, ..., s \\ & \sum_{j=1}^{n} \lambda_j \left(I_{hj} - \delta_h k_{hj}\right) \ge \left(I_{h0} - \delta_h k_{h0}\right) + \beta g_{h0}^I, && h = 1, ..., f \\ & \sum_{j=1}^{n} \lambda_j = 1, \\ & \lambda_j \ge 0, && j = 1, ..., n \end{aligned} \tag{3}$$

in which δ_h denotes depreciation rates and λ is the intensity vector of firm weights. Dynamics are incorporated in Eq. (3) through constraint on investments; the model imposes convexity (which implies that points on the frontier used to evaluate observations are constructed using the linear combinations of actual data points) and assumes variable returns to scale (VRS).

The directional vector adopted in the empirical analysis for inputs ($\mathbf{g}^x$), for investments ($\mathbf{g}^I$) and for outputs ($\mathbf{g}^y$) are the actual quantity of variable inputs, 20 per cent of the size of the capital stock and the actual quantity of outputs, respectively.

Model (3) allows for the estimation of dynamic technical inefficiency of firms comprising the dietetic food industry in Europe. To be able to directly compare the technical inefficiency of these firms classified into groups, as defined by different European countries, we use the concept of a metafrontier introduced by Battese et al. (2004) and O'Donnell et al. (2008), and empirically applied elsewhere (e.g., Walheer & He, 2020). The metafrontier is a frontier that envelops all group-specific frontiers, in our case frontiers of countries. It allows the calculation of comparable efficiencies of firms operating under different technologies, as in our case the technologies in different countries. To measure dynamic technical inefficiency with relation to the metafrontier, we run Model (3) with a pooled sample of all firms in all countries. The score obtained can be called pooled (or overall) dynamic technical inefficiency. We can next explore the sources of pooled dynamic inefficiency by decomposing it into two components. The first component measures the distance from the firm to its country-specific frontier (and how close a firm is operating to this frontier), reflecting the spread in inefficiency within the country; therefore, it can be called within-country dynamic technical inefficiency. It is calculated by running Model (3) for firms in each country separately. The second component measures the distance (gap) between the country-specific frontier and the metafrontier (and how close a country-specific frontier is to the metafrontier) and can be called the country gap. This component reflects the restrictive nature of the production environment (O'Donnell et al., 2008) and can be viewed as a measure of whether a firm has chosen the best available technology (Kerstens et al., 2019). It is calculated as a difference between the pooled and within-country dynamic technical inefficiencies. Therefore, the decomposition is the following:

$$\text{Pooled dynamic inefficiency} = \text{Within-country dynamic inefficiency} + \text{Country gap}. \quad (4)$$

All three performance indicators take values larger or equal to 0. For pooled and within-country dynamic technical inefficiency, a unit is efficient if the values of indicators are equal to 0, and the larger the values, the more inefficiency a firm has; therefore, these indicators are measures of firm inefficiency. For the country gap, an increase in indicator involves an increase in the gap between the country-specific frontier and the metafrontier. The decomposition shown by Eq. (4) is in line with the idea of Charnes et al. (1981), who proposed measuring inefficiency in relation to the group-specific frontier in order to assess managerial inefficiency, and to measure the difference between the group-specific frontier and the frontier consisting of all observations in all groups to assess program inefficiency. This decomposition is further used in the empirical analysis.

Recently, Kerstens et al. (2019) questioned the convexity assumption in metafrontier analysis. In particular, they concluded that a convexification strategy for metafrontiers can lead to erroneous results. Also recently, however, Kneip et al. (2016) and Simar and Wilson (2020) provided a statistical test to assess the convexity assumption. The test was derived for Farrell efficiency measures (Farrell, 1957) and relies on central limit theorems developed by Kneip et al. (2015) and convergence rates for DEA and free disposal hull (FDH) estimators, as calculated by Kneip et al. (1998) and Park et al. (2000), respectively. Therefore, this test cannot be applied directly in our context of inefficiency measures based on dynamic directional distance function. However, we applied this test indirectly, based on the fact that directional distance function encompasses the Shephard distance function (Shephard, 1953) (which is the inverse of Farrell efficiency measures) when the directional vector equals the actual values of inputs and outputs (Chambers et al., 1998)[8]. The results of the test show that the null hypothesis of convexity (that is, that both FDH and DEA estimators are consistent) cannot be rejected for our data. Furthermore, knowing that the convex estimator should be consistent in our case, we also tested for the specific assumption of returns to scale: constant returns to scale (CRS) versus VRS following Kneip et al. (2016) and Simar and Wilson (2020), applying the similar reasoning as for the convexity test. The results of the test suggested that, in some years of the analysis, only the VRS estimator is consistent (hence, the null hypothesis of both CRS and VRS being consistent is rejected) and for some years both CRS and VRS are consistent (hence, the null hypothesis of both CRS and VRS being consistent cannot be rejected). Therefore, in the present study, based on the results of all tests described, Model (3), which assumes VRS, was used to calculate dynamic inefficiencies and decomposition of pooled inefficiency into within-country inefficiency and country gap.

Finally, based on Kapelko et al. (2017), the model (3) might be modified in order to allow for nonradial improvements in inputs, outputs and investments:

$$\vec{D}\left(x_0, I_0, y_0, k_0; g_0^x, g_0^I, g_0^y\right) = \mathrm{Max}_{\beta_i, \theta_r, \gamma_h,}\left(\sum_{i=1}^{m}\beta_i + \sum_{r=1}^{s}\theta_r + \sum_{h=1}^{f}\gamma_h\right)$$

$$\begin{aligned}
\text{s.t.}\quad & \sum_{j=1}^{n}\lambda_j x_{ij} \le x_{i0} - \beta_i g_{i0}^x, && i = 1, \ldots, m \\
& \sum_{j=1}^{n}\lambda_j y_{rj} \ge y_{r0} + \theta_r g_{r0}^y, && r = 1, \ldots, s \\
& \sum_{j=1}^{n}\lambda_j\left(I_{hj} - \delta_h k_{hj}\right) \ge \left(I_{h0} - \delta_h k_{h0}\right) + \gamma_h g_{h0}^I, && h = 1, \ldots, f \\
& \sum_{j=1}^{n}\lambda_j = 1, \\
& \lambda_j \ge 0, && j = 1, \ldots, n \quad (5)
\end{aligned}$$

where β_i, θ_r and γ_h measure the degree of input i-, output r- and investment h-specific inefficiencies.

2. Dataset and variable specification

In this study, we calculated the dynamic indicators for 2155 observations for 363 firms in European dietetic food manufacturing industry (NACE Rev. 2 code 1086) from 2009 to 2017 (unbalanced panel). The data were obtained from AMADEUS, a database prepared by

[8] In particular, in the application of this test we assumed two inputs and two outputs (i.e., regular output and investments) for Farrell efficiency measures. The test was applied separately for each year of the sample data. It was implemented in FEAR (Wilson, 2008).

Bureau van Dijk (Belgium). The firm-level data cover five European countries – France, Italy, Norway, Poland and Spain. The choice of these countries is given by the importance of the industry under analysis of a given country in the whole European dietetic food production, the representativeness of countries for each European region as well as the data availability. Firstly, these countries account for the largest percentage of the total production, turnover and value added within European dietetic food industry. Also, these countries have the largest number of companies for dietetic food industry in Europe. For example, when looking more closely at the variable value added, the five countries considered account for more than 78 per cent of the total value added of this industry in Europe, with France hitting 35.2 per cent, Italy 19 per cent, Spain 16.8 per cent, Poland 5.8 per cent, and Norway 1.4 per cent. Secondly, with these countries we are able to represent each geographical region with its main dietetic food-producing countries: Eastern Europe (Poland), Southern Europe (Italy and Spain), Western Europe (France) and Northern Europe (Norway). Thirdly, the choice of these countries is given by the data availability. In particular, firms in Germany and the UK also provide a considerable fraction of production, turnover and value added for the European food dietetic industry (for example, value added for Germany is 14.7 per cent, while for the UK it is 2.2 per cent). However, due to the poor data availability on the variables of interest for this study, we are not able to include these countries in the analysis[9,10]. The final sample was obtained through elimination of firms with missing data as well as outliers, following the procedure of Simar (2003). Hence, our level of analysis (DMU) is a firm from the dietetic food industry, and we aggregate firm-level results to country level in order to be able to compare inefficiencies between countries[11].

In the DEA model we specify one output (revenues), two variable inputs (material costs and employee costs) and one gross investment in capital (gross investments in fixed assets). This is a common input-output configuration used in the research, including the studies on the dynamic inefficiency and the studies on food manufacturing efficiency (e.g., Setiawan et al., 2012; Soboh et al., 2014; Kapelko et al., 2014; Kapelko & Oude Lansink, 2017; Martínez-Victoria et al., 2019; Čechura & Žáková Kroupová, 2021)[12]. The output, inputs and investment were downloaded from AMADEUS in local currencies and current prices, and adjusted using the purchasing power parity (PPP) of the local currency to the US dollar and deflated with appropriate price indexes (constant prices of 2008). Revenue is a profit and loss account item that includes total sales and other operating revenues; they were deflated by

[9] In particular, for Germany there are too few firms available in the dataset (which is connected with weak disclosure obligations for German small firms), while for the UK material costs are not available (only costs of goods sold are provided which, however, do not allow to disentangle material and labor costs).

[10] In addition, all other European countries (not considered in the study and besides Germany and the UK) represent less than 1 per cent of the total value added produced by the dietetic food industry. For example, the next country for Eastern Europe is Czech Republic with only 0.9 per cent representation of the value added, for Southern Europe it is Portugal with only 0.5 per cent of the value added fraction, for Western Europe it is Belgium with only 0.9 per cent of the value added, and finally for Northern Europe it is Finland with only 0.3 per cent of the total value added. Hence, their contribution can be considered as negligible.

[11] The number of firms per country and year satisfies the popular rule of thumb as suggested by Dyson et al. (2001).

[12] The inputs and output we used are the most important in the firms' production process, given the limitation related to accounting data. Basic inputs of employees and materials are converted into single output of revenues. Capital enters through investments that form dynamics of firms' production process.

the producer price index for food manufacturing. Material costs are also extracted from the firms' profit and loss account in AMADEUS and they reflect the expenses on raw materials; they were deflated using the producer price index for intermediate goods. Employee costs (profit and loss account item) represent all wages and costs of employee benefits and payroll taxes paid by an employee, and they were deflated by the labor cost index in food manufacturing. Gross investments in fixed assets in year t, computed as the beginning value of fixed assets in year $t+1$ minus the beginning value of fixed assets in year t plus the value of depreciation in year t, were deflated by the producer price index for capital goods. The values of depreciation for each firm were taken directly from the firms' profit and loss accounts. Fixed assets are a proxy for firms' capital and are a balance sheet item that comprise the value of tangible assets such as buildings and machinery, and intangible assets such as goodwill and patents, as well as financial investments. All price indices were specific for each country and were obtained from Eurostat (2020b). By computing the ratios of inputs and outputs that are expressed as values to their corresponding price indices, implicit quantity indices are obtained (Oude Lansink et al., 2015; Silva et al., 2015). The usage of input-output data in monetary terms is very common approach in the efficiency literature (e.g., Baležentis et al., 2013; Titko et al., 2014; Hsu, 2015; Setiawan, 2019; Čechura & Žáková Kroupová, 2021).

Correlations between inputs of materials and employees vary between countries, ranging from rather low for Norway (0.66) to rather high for Spain (0.99), with rather high values on average across all countries (0.98). Nevertheless, both materials and employees are conceptually different inputs and both are indispensable in the firms' production set, hence we believe we cannot omit any of these two variables in our calculations. Also, previous research considered both materials and employees as important inputs in the efficiency assessment (e.g., Soboh et al., 2014; Kapelko & Oude Lansink, 2017; Čechura & Žáková Kroupová, 2021). Furthermore, we found that the correlations between inputs and output are relatively high (on average across countries there is 0.99 of correlation between output and employees and 0.98 of correlation between output and materials) and as López et al. (2016) concluded when correlation between inputs and outputs is relatively high, the correlation between inputs is not relevant: it does not affect efficiency scores or at the most it might cause the slightly lower average efficiency scores. Therefore, given the evidence by López et al. (2016), we believe that both materials and employees should be maintained in our computations.

Table 1 provides the averages and standard deviations for input, output and investment variables, as well as information on the sample composition for the data pooled over the years 2009–2017. It shows that French and Spanish companies have, on average, the highest values of revenues, material and employee costs, and investments, while the opposite is observed for Norwegian firms, which tend to be small with regard to input and output variables. The statistics in Table 1 also show that the largest number of firms' observations in the sample are by Italian, Spanish and French companies, which generally reflect the statistics on the composition of the number of companies within dietetic food in Europe (Eurostat, 2020a).

Table 1. Averages and standard deviations of firm input-output variables, reported per country and for the whole sample, 2009–2017 (millions of PPP, as of 2008)

Country	No of firms	Revenues	Material costs	Employee costs	Investments
France	397	48.502	18.043	5.846	1.978
		(143.748)	(46.693)	(16.850)	(6.572)
Italy	737	8.368	3.997	1.113	0.749
		(21.689)	(11.522)	(2.743)	(4.483)
Norway	121	5.798	3.223	1.267	0.298
		(4.209)	(2.942)	(0.968)	(0.870)
Poland	166	21.823	11.147	1.919	1.720
		(50.451)	(25.590)	(4.372)	(6.477)
Spain	734	41.754	21.226	6.397	2.418
		(265.812)	(140.649	(37.380)	(16.316)
Total	2155	28.025	12.960	3.855	1.593
		(168.831)	(85.380)	(23.194)	(10.453)

Note: Standard deviations are in parentheses. Number of firms in France: 46 (2009), 51 (2010), 53 (2011), 49 (2012), 51 (2013), 43 (2014), 41 (2015), 33 (2016), 30 (2017). Number of firms in Italy: 60 (2009), 69 (2010), 68 (2011), 73 (2012), 81 (2013), 85 (2014), 88 (2015), 103 (2016), 110 (2017). Number of firms in Norway: 12 (2009), 12 (2010), 13 (2011), 13 (2012), 13 (2013), 14 (2014), 15 (2015), 15 (2016), 14 (2017). Number of firms in Poland: 11 (2009), 16 (2010), 16 (2011), 15 (2012), 19 (2013), 25 (2014), 22 (2015), 23 (2016), 19 (2017). Number of firms in Spain: 67 (2009), 79 (2010), 73 (2011), 82 (2012), 85 (2013), 85 (2014), 89 (2015), 89 (2016), 85 (2017).

3. Empirical results

Table 2 and Figure 1 present the average values of dynamic technical inefficiency estimates for dietetic food firms in the sample countries: pooled and within-country inefficiency and country gap, for the entire period 2009–2017, that is for solving Eqs (3) and (4). Based on these results, the following observations can be made. Firstly, analyzing the results when firms are assessed with regard to country frontier, we should note that average dynamic inefficiency ranges from a minimum of 0.076 for Norway to a maximum of 0.380 for France. Therefore, given the country frontier, firms in Norway could reduce their variable inputs and increase their outputs and investments by 7.6 per cent of the values of the directional vectors, while for firms in France the reductions and increments are required in a much larger amount: 38 per cent when using the own country technology. Also, firms in Poland score relatively low on their country-specific dynamic inefficiency, reaching the level of 0.106. This indicates that firms in Norway and Poland have relatively low levels of managerial inefficiency related to shortcomings in managerial practices, while the opposite is observed for firms in France. This also suggests that firms in Norway and Poland are more homogenous in terms of their performance, while companies in France are less homogenous than firms in other countries. As no previous studies were undertaken to analyze the efficiency of the dietetic food industry, the only closest point of comparison for our results are papers on other food manufacturing industry, albeit in a different geographical setting to ours. In particular, Rezitis and Kalantzi (2016) found relatively large efficiency scores of 0.987 for Greek industry, Rudinskaya (2017) reported a moderate value of 0.787 for the Czech Republic, and Kapya et al. (2018) rather low efficiency of 0.447 for Zambia. Hence, our results are more in line with the findings of Rezitis and Kalantzi (2016) and Rudinskaya (2017) than of Kapya et al. (2018). In particular, our average inefficiency results for Norway and Poland approximate these of Rezitis and Kalantzi (2016), while our average findings of inefficient performance for France, Italy and Spain are consistent with these reported by Rudinskaya (2017).

Secondly, when comparing the dynamic inefficiencies between countries by looking at pooled inefficiencies, we observe that firms in Norway are the most inefficient, while firms in Poland are the most efficiently performing firms. In attempting to explain these findings, we should note that sample firms in Norway have the highest values of their inputs (materials and employees) relative to output (revenues) and are among the countries with the lowest investments with regard to output (Table 1). While firms in Poland use quite large values of materials relative to output, their employee costs relative to output are still very low and are among the countries that invest most with regard to output (Table 1). Being inputs the variables aimed to decrease and output and investments to increase, firms in Norway have to make much larger improvements in these dimensions of production set than firms in Poland. Therefore, the combination of inputs, outputs and investments can explain why firms are more or less dynamically efficient in the sample countries. Moreover, among the analyzed countries, as revealed by sectoral statistics, the dietetic food industry in Norway exhibited the lowest increments in turnover, production and value added in the analyzed period, while the Polish sector experienced the highest growth in all variables (Eurostat, 2020a). Hence, negligible growth of Norwegian dietetic food sector is accompanied by large values of firms' dynamic inefficiency. Dietetic food is not widespread in the Norwegian marketplace and Norwegians are highly skeptical of foods with health claims from manufacturing companies (Nystrand & Olsen, 2020), which could explain our results. The finding about Polish sector implies that the dietetic food industry's exceptional growth in Poland is combined with small values of dynamic inefficiency. In fact, Poland has observed increasing interest in healthy lifestyle and healthy nutrition in recent years, leading to rapidly growing emergence of firms suppling such products. That possibly lead to increased competition among dietetic food companies, and competitive pressures could force firms to perform more efficiently (Tan et al., 2021; Leibenstein, 1973). Also, the position of Polish producers of other food products in Europe is stronger than that of the food industry as a whole (Drożdż et al., 2014). Overall, based on this evidence, the extent of growth of dietetic food industry seems to be related to efficiency results of companies comprising this sector. Comparing country-specific and pooled inefficiencies, dietetic food firms from Norway and Spain show the largest increases in inefficiency, whereas those from France and Italy exhibit the smallest increases. Remarkably, the average inefficiency of dietetic food firms in Norway increased considerably from 0.076 to 0.611, when computed with regard to a country-specific frontier rather than a metafrontier.

Thirdly, the average values of the country gap vary from 0.100 for France to 0.535 for Norway, which indicates that country-specific frontier from France is closest to the pooled frontier, while the opposite applies for firms in Norway. The differences in the average values of the country gap between the analyzed countries also suggests differences in the technology employed by firms in each country and in their program inefficiency. In particular, the average country gap of 0.100 might suggest that French firms could use and produce 90 per cent of the output, inputs and investments that could be achieved using metatechnology. In other words, firms in France can improve their dynamic performance by 10 per cent, on average, by overcoming the limitations in the operational environment through accessing metatechnologies. An average country gap indicator of 0.535 could indicate that the maximum feasible combination of output, inputs and investments using Norwegian technology is only about 47 per cent of this combination that could be achieved using the technology represented by the pooled frontier. This is a very considerable gap between the group and metafrontiers, which suggests that firms in Norway could improve the dynamic performance by 53 per cent, on average, by discarding their within-country technologies and learning metafrontier technologies. The lowest country gap for France indicates that technology in this country is superior to technologies in other countries considered; the opposite is true for Norway.

Fourthly, the decomposition of pooled dynamic inefficiency into dynamic inefficiency within each country and the country gap in overall terms suggests that, on average, the factors embedded in the country are a slightly larger source of pooled inefficiency than firms' managerial practices (0.272 against 0.236). Hence, on average, the resources, technologies and other specific environmental constraints provide a larger potential for efficiency improvement than firms' internal practices. However, looking closely at different countries we can see that they have divergent profiles in their dynamic inefficiency indicators (Figure 1). For firms in France and Italy, the main source of pooled inefficiency is within-country inefficiency, which is due to shortcomings in managerial practices, while for firms in Norway, Poland and Spain this is a country gap that is inefficiencies due to country-related reasons and restrictive nature of the production environment. Therefore, countries differ in their sources for the potential of dynamic efficiency improvement by decreasing inputs and increasing output and investments. In particular, French and Italian firms could improve their efficiency by focusing on internal activities, that is the management of their resources. On the contrary, incentives for increasing efficiency of firms in Norway, Poland and Spain should focus on improving the technology employed by these firms. That could be done, for example, through investments in new technologies and educating the labor force.

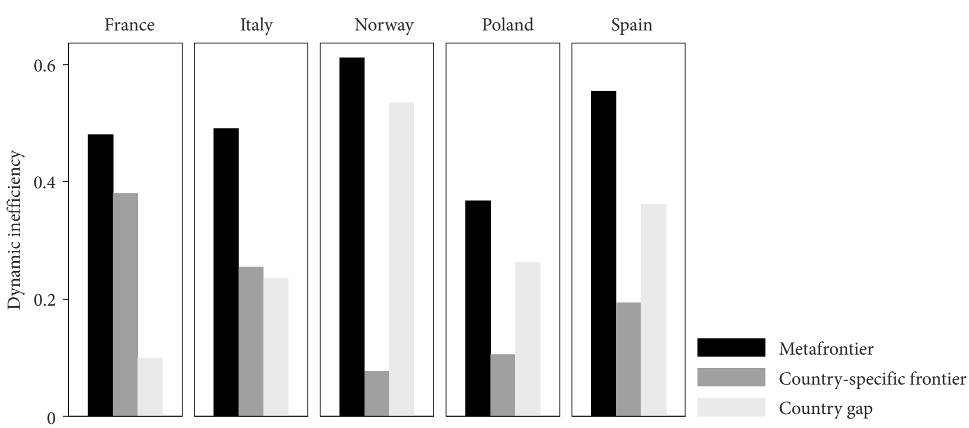

Figure 1. Inefficiency scores with respect to metafrontier and country-specific frontier, and country gap

Table 2. Firm inefficiency indicators (pooled and within-country inefficiency, and country gap), average values reported, 2009–2017

Country	Pooled inefficiency	Within-country inefficiency	Country gap
France	0.480	0.380	0.100
Italy	0.490	0.255	0.235
Norway	0.611	0.076	0.535
Poland	0.368	0.106	0.262
Spain	0.555	0.194	0.362
Overall	0.508	0.236	0.272

Figure 2 depicts the kernel distributions by country in each one of the inefficiency scores: computed with respect to metafrontier and country-specific frontier, and the difference between these two. When plotting these distributions, we follow the procedure proposed by Simar and Zelenyuk (2006). The comparison of pooled inefficiency between countries shows that for Norway, Spain and Italy the distributions are concentrated mostly around larger values of inefficiency of approximately 0.7; for France and Poland we observe the inefficiency scores being concentrated both around large and very small, close to zero values. Within-country inefficiency scores are evenly distributed between zero and 1 for France, Italy and Spain, while for Poland and Norway these scores are concentrated more around 0. Finally, the visualization of country gaps indicate their even distribution between zero and 1 for all countries except France, for which country gap for most of firms is close to 0. Overall, the visual inspection of the kernel distributions reveal that distributions of dynamic inefficiency scores are substantially different between countries.

We used the test proposed by Simar and Zelenyuk (2006) to test for the significance of the differences in the inefficiencies between countries reported in Table 2 and visualized on Figure 2[13]. As discussed in Simar and Zelenyuk (2006), the test is based on an adaptation of the Li (1996) test of the equality of two densities to the context of efficiency scores estimated via DEA. In particular, Simar and Zelenyuk (2006) show that the best performing approach to testing is based on computation and bootstrapping Li statistic, with efficiency estimates for firms on the efficient boundary smoothed by adding an uniform noise. We followed this procedure in our testing. The results of the tests outlined in Table 3 show that there are significant differences in inefficiencies between countries, for pooled, country-specific and country gap indicators (except for the differences in pooled inefficiency between Norway and Spain). Hence, the differences shown by kernel distributions are now confirmed with the values and significance of the tests. Therefore, these results provide clear and statistically precise evidence that, when assessed with regard to a metafrontier, firms in Norway and

[13] Kneip et al. (2016) and Simar and Wilson (2020), in addition to convexity and returns to scale tests, also proposed a test to assess the differences in average efficiencies. We did not apply this test because it has been developed specifically for Farrell efficiency measures and not for directional distance functions, relying on the asymptotic properties and convergence rates of Farrell efficiency measures. Simar and Zelenyuk's (2006) test allows for testing of the differences for directional distance functions directly, as it is more general and does not rely on these specific statistical results. In this way, we do not need to apply such an approximated version of Kneip et al. (2016) and Simar and Wilson (2020) test, as we did with convexity and returns to scale tests.

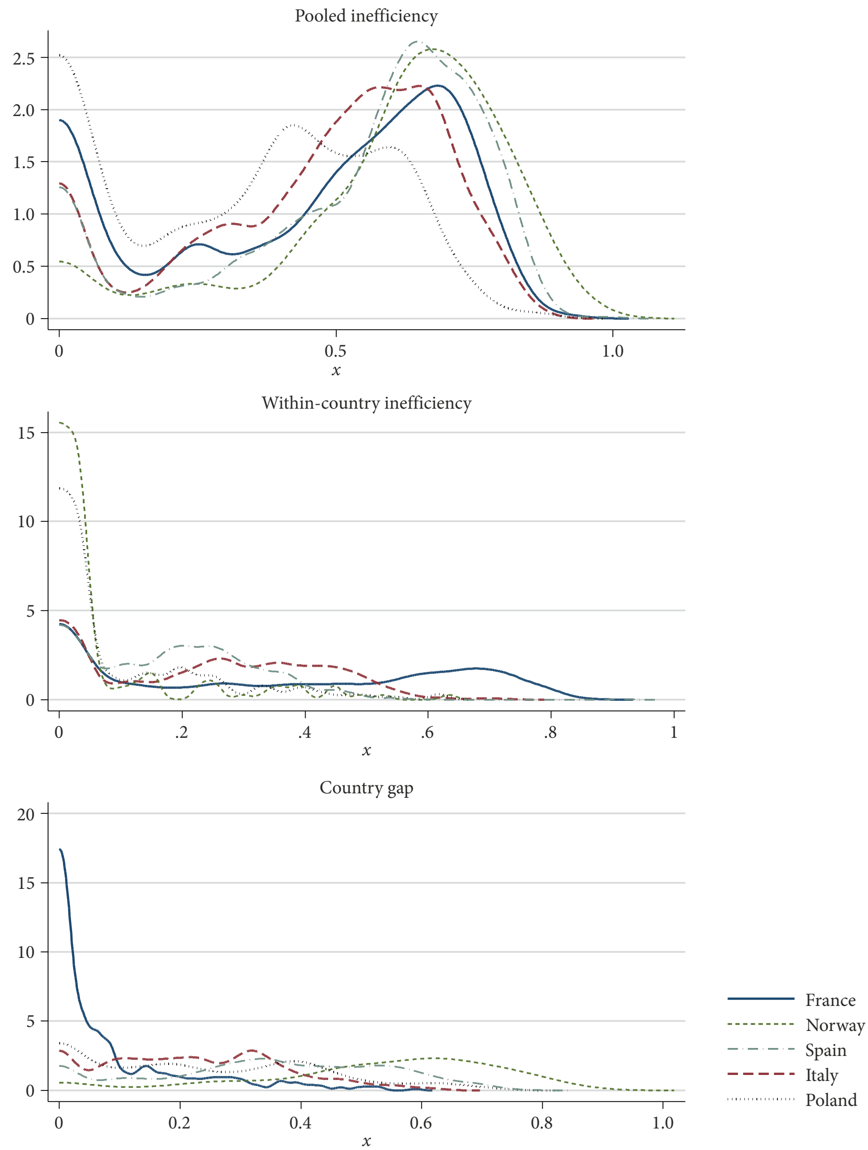

Figure 2. Kernel distributions by country for inefficiency scores with respect to metafrontier and country-specific frontier, and country gap

Spain are the most inefficient, while companies in Poland are the most efficient. When firms are assessed with respect to country frontiers, French companies present the largest values of inefficiency and Norwegian the smallest. Consequently, Norwegian firms have the largest values of country gap in the sample of considered countries.

The results presented so far provide clear evidence of the sources of dynamic inefficiencies in dietetic food industry over the entire period analyzed. To gain further insights, we investigate the changes in average inefficiency over the years represented in the sample. Tables 4, 5 and 6 summarize the evolution of pooled and country-specific inefficiencies and the country gap, respectively, over the period 2009–2017. These results suggest that dynamic pooled inefficiency increased substantially over time until 2014 for all countries in the sample and then dropped in 2015, with small fluctuation thereafter (Table 4). This consistent increase of inefficiency until 2014 across all countries could be due to the global financial crisis, which, due to the slowdown in economic development, weakened the demand for food and, as a result, caused a decrease in household expenditure on food products (European Commission, 2016). This could be especially a case for costly dietetic foods as price constrains consumption and expensive foods decrease their selection by consumers (Skuland, 2015). Moreover, crisis could switch demand from costly food products such as dietetic food to cheaper food alternatives. Furthermore, this period is also characterized by the volatility of agricultural commodity prices, which impacted the cost base of food manufacturers. The dramatic increase in costs was only partially passed on consumers and consumer prices increased steadily (European Commission, 2016; Kowalski & Wigier, 2014). Therefore, the increase in prices was absorbed by the food industry itself, which could cause increases in firms' inefficiency. Another finding to note is a rather small fluctuation in within-country

Table 3. Results of Simar and Zelenyuk (2006) adapted Li test (test statistic and significance level) for inefficiency indicators (for pooled and within-country inefficiency, and country gap)

Pooled inefficiency					
	France	Italy	Norway	Poland	Spain
France	–	8.160***	5.437***	11.478***	10.095***
Italy		–	9.066***	8.574***	18.674***
Norway			–	20.440***	1.196
Poland				–	35.014***
Spain					–
Within-country inefficiency					
	France	Italy	Norway	Poland	Spain
France	–	69.516***	42.713***	49.344***	102.495***
Italy		–	39.250***	41.502***	34.346***
Norway			–	−1.835**	28.568***
Poland				–	25.817***
Spain					–
Country gap					
	France	Italy	Norway	Poland	Spain
France	–	83.037***	103.148***	36.022***	114.129***
Italy		–	63.375***	3.507***	49.437***
Norway			–	31.818***	22.812***
Poland				–	13.218***
Spain					–

Notes: *** Denotes statistically significant differences between models at the critical 1 per cent level; ** Denotes statistically significant differences between models at the critical 5 per cent level.

inefficiency during the analyzed period (Table 5). Therefore, the results might suggest that the challenges associated with global financial crisis mostly impacted the dietetic food firms competitiveness and performance on the European market, while their performance against country benchmarks remained fairly stable. This could be explained by the dramatic fall of the world trade during financial crisis, including food products (Levchenko et al., 2010; Headey, 2011). The only exception seems to be dietetic food firms in France, for which the ability to perform efficiently was constrained both for pooled and within-country inefficiency during the period related with global financial crisis. As a consequence of developments in pooled inefficiency and within-country inefficiency, the evolution of the country gap follows the trends of pooled inefficiency; that is, an increase in inefficiency until 2014 and then a decrease in 2015 with fluctuations thereafter (Table 6).

Finally, we are interested in assessing contributions of each input, output and investment to dynamic inefficiencies, that is which variables are most and which are least inefficient. This

Table 4. Evolution of firm pooled inefficiency, average values reported

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017
France	0.416	0.507	0.514	0.567	0.566	0.602	0.389	0.335	0.294
Italy	0.418	0.496	0.503	0.548	0.517	0.585	0.431	0.444	0.479
Norway	0.523	0.651	0.639	0.686	0.697	0.704	0.549	0.572	0.495
Poland	0.325	0.364	0.363	0.458	0.445	0.468	0.325	0.276	0.280
Spain	0.499	0.549	0.594	0.613	0.617	0.642	0.484	0.499	0.501
Overall	0.446	0.516	0.533	0.577	0.565	0.602	0.440	0.442	0.451

Table 5. Evolution of firm within-country inefficiency, average values reported

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017
France	0.366	0.449	0.485	0.513	0.500	0.496	0.141	0.119	0.131
Italy	0.172	0.229	0.201	0.257	0.226	0.235	0.285	0.288	0.332
Norway	0.100	0.092	0.114	0.086	0.060	0.064	0.098	0.040	0.045
Poland	0.067	0.051	0.067	0.032	0.112	0.163	0.112	0.127	0.150
Spain	0.254	0.231	0.130	0.121	0.151	0.164	0.225	0.242	0.223
Overall	0.235	0.259	0.231	0.239	0.239	0.239	0.215	0.223	0.244

Table 6. Evolution of firm country gap, average values reported

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017
France	0.050	0.059	0.029	0.054	0.066	0.106	0.248	0.216	0.163
Italy	0.246	0.267	0.301	0.291	0.291	0.350	0.146	0.156	0.146
Norway	0.423	0.559	0.526	0.601	0.638	0.639	0.451	0.532	0.451
Poland	0.258	0.313	0.297	0.426	0.333	0.305	0.213	0.149	0.130
Spain	0.245	0.317	0.463	0.492	0.466	0.478	0.258	0.257	0.278
Overall	0.211	0.256	0.302	0.338	0.326	0.363	0.225	0.219	0.207

is possible through nonradial model, as shown by Eq. (5). Because nonradial model might be biased for the metafrontier framework (Yu et al., 2022), as country gap might be lower than 0, we apply this model assuming all firms in the sample that is to compute pooled dynamic inefficiency. Table 7 summarizes the results for output-, input- and investment-specific dynamic inefficiencies for the entire period 2009–2017.

Table 7. Input-, output- and investment-specific pooled inefficiency, average values reported, 2009–2017

Country	Output	Materials	Employees	Investments
France	0.449	0.091	0.079	96.858
Italy	0.998	0.094	0.105	86.891
Norway	2.158	0.114	0.112	111.629
Poland	0.288	0.173	0.030	77.831
Spain	3.889	0.114	0.111	73.103
Overall	1.556	0.117	0.087	89.262

The results show that over the entire period 2009–2017 investments are the most inefficient factor for dietetic food firms in all countries, followed by output, materials and employees. On average across all countries, the average employee-specific, materials-specific, output-specific and investment-specific dynamic inefficiency was 0.087, 0.117, 1.556 and 89.262, respectively. These findings indicate a substantial scope for reducing the use of employees (8.7%) and materials (11.7%) and for increasing output and investment more than 1.5 times and 89 times, respectively. The result on such a large values of investments inefficiency is common in dynamic efficiency studies (e.g., Kapelko & Oude Lansink, 2017). Moreover, the results show that Norwegian firms are least efficient in using labor and investments compared to other countries, while firms in Spain and Poland are using their output and materials least efficiently, respectively. Conversely, firms in Poland are least inefficient regarding output and employees, whereas Spanish firms perform best with respect to investments, and French companies with respect to materials. Therefore, the good efficient performance of Polish firms shown in Table 2 is due to dimension of output and employees, and worst efficiency of firms in Norway exhibited in Table 2 is related mainly with investments and labor. Overall, the results indicate that in order to improve efficiency the firms main efforts should focus on investment dimension of the production set. Firms could improve efficiency in the use of investments by, for example, a better training of personal in the use of new technologies that could reduce investments' adjustment costs.

Conclusions

The demand for healthy food has been growing worldwide, which has caused the growth of the industries supplying this kind of product, including the dietetic food manufacturing sector. The aspect of food healthiness forms part of the characteristics of sustainable food consumption, and is also related to CSR. The present paper is the first to assess and compare the inefficiency of dietetic food manufacturing firms in Europe between five countries representing Western, Southern, Eastern and Northern European regions. Given the potential importance of adjustment costs in this industry, the present study applied the dynamic measures of firm inefficiency using DEA. For this purpose, we used the concept of a metafrontier and analyzed the inefficiency differences between countries by estimating dynamic inefficiencies with regard to a metafrontier and a country-specific frontier, and computed the difference and gap between these frontiers. Furthermore, we applied recent results for testing the main assumptions of the DEA model. Given the increasing importance of European dietetic food industry as a result of consumer awareness for healthy foods, the study of the efficiency of this industry is essential. It is important for various business stakeholders, such as business managers and policy makers, to know how well production inputs are being converted into outputs and investments given the production technology, how firms are performing in changing economic conditions, and which policies to use in order to improve the performance.

The main findings of this study indicate that Polish dietetic food firms are the least dynamically inefficient among the countries analyzed. Polish firms are also among the least inefficient when assessed with regard to own-country benchmarks; hence, their managerial inefficiency is low. Another interesting result is that firms in Norway are the most inefficient when assessed with reference to all other countries, but are the least inefficient when evaluated against own-country benchmarks; as a consequence, their country gap (that is, program inefficiency) is the largest. Furthermore, managerial inefficiency dominates for firms in France and Italy, while program inefficiency is the main reason for pooled inefficiency for firms in Norway, Poland and Spain. We also find that dynamic inefficiency increased in the period related to global financial crisis, but started to recover afterwards. The analysis of the reasons for time variation in inefficiencies is worthy of further investigation. Finally, the results show that the main source of overall inefficiency were investments.

The results of this study could be of interest to dietetic food firm managers and policy makers. Assessing the differences in efficiency between European countries can provide benchmarking information for managers to improve the performance and competitiveness of firms. Cross-country benchmarking can also guide the implementation of reforms and policies. In particular, since firms in France and Italy suffer mostly from managerial inefficiency, the policies should be targeted at firms and improvement of performance within firms; for example, through education and training programs for managers. Our results also imply that policies for firms in Norway, Poland and Spain should focus on the improvements in the production environment, because their inefficiency is dominated by program inefficiency. This could be done, for example, by improvements in transport infrastructure, deregulation of financial markets or relaxing labor laws.

This study has not sought to cover all activities of firms devoted to offer dietetic food products. For example, dairy firms often offer many products under the label "dietetic food". The present study is limited in the sense that we have focused on firms whose main activity is concerned with the production of dietetic food, omitting firms that offer such foods in addition to their regular range of products. Therefore, future studies could analyze a broader range of food firms, including those for which dietetic food is not a main activity. As consumer needs are a powerful cause of innovations, the food industry is increasingly responding to changing consumer preferences by introducing innovations (European Commission, 2016). Hence, it would be interesting for future research to analyze the innovativeness of the European dietetic food industry and its relation to firm performance and efficiency. From the methodological point of view, future study could be extended towards economic inefficiency measures, considering optimal amounts of outputs and inputs consistent with profit maximization, along the proposal by Ang and Oude Lansink (2018). Also, dynamic productivity change over time could be assessed, exploiting the usage of dynamic Luenberger indicator of Oude Lansink et al. (2015) and extending it towards profit productivity change measures (Juo et al., 2015). As a future research, alternative methodologies could be used for comparing efficiency between groups of firms including proposals of Camanho and Dyson (2006) or Aparicio and Santin (2018). Since inputs and outputs often present some variability and imprecision in their measurement, future research could extend the conventional dynamic DEA model used in this study towards, for example, dynamic fuzzy DEA (for a static case, see Sengupta, 1992a, 1992b). Similarly, the DEA model we use treat firms as black boxes, without consideration of internal or linking activities, therefore the next step in the future analysis would be the extension towards dynamic network DEA model (see, Färe & Grosskopf, 1996). Both the application of fuzzy and network dynamic models would require a different dataset than the one used in this study. Finally, the current study opens up a future research area for comparing the efficiency of dietetic food industry with other branches of food manufacturing.

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Author contributions

Conceptualization: M.K.; J.H.; data curation: M.K.; formal analysis: M.K.; funding acquisition: M.K.; J.H.; A.O.; A.P.; investigation: M.K.; methodology: M.K.; software: M.K.; validation: M.K.; visualization: M.K.; project administration: J.H.; writing – original draft: M.K.; writing - review & editing: M.K.; J.H.; A.O.; A.P.

Disclosure statement

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