

Article

Technical Efficiency in the European Dairy Industry: Can We Observe Systematic Failures in the Efficiency of Input Use?

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Abstract: The paper provides findings on the technical efficiency of the European dairy processing industry, which is one of the most important subsectors of the food processing industry in the European Union (EU). The ability to efficiently use inputs in the production of outputs is a prerequisite for the sustainability and competitiveness of the agri-food sector as well as for food security. Thus, the aim of this paper is to provide a robust estimate of technical efficiency by employing new advances in productivity and efficiency analysis, and to investigate the efficiency of input use in 10 selected European countries. The analysis is based on two-stage stochastic frontier modelling incorporating country-specific input distance function (IDF) estimates and a meta-frontier input distance function estimate, both in specification of the four-component model, which currently represents the most advanced approach to technical efficiency analysis. To provide a robust estimate of these models, the paper employs methods that control for the potential endogeneity of netputs in the multi-step estimation procedure. The results, based on the Amadeus dataset, reveal that companies manufacturing dairy products greatly exploited their production possibilities in 2006–2018. The dairy processing industry in the analysed countries cannot generally be characterized by a considerable waste of resources. The potential cost reduction is estimated at 4–8%, evaluated on the country samples mean. The overall technical inefficiency (OTE) is mainly a result of short-term shocks and unsystematic failures. However, the meta-frontier estimates also reveal a certain degree of systematic failure, e.g., permanent managerial failures and structural problems in European dairy processing industry.



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1. Introduction

A functional, sustainable, competitive, and structurally balanced agri-food sector has an irreplaceable position in the European economy. The importance of this sector in modern society is emphasized by global trends, among which population explosions, migration waves, and climate change can be highlighted. Additionally, the COVID-19 pandemic has strengthened the role of national food security.

The food processing industry is one of the most important sectors of the European economy. According to Eurostat [1], it is the largest manufacturing sector in the European Union (EU), representing 14% of total manufacturing employment, 12% of total manufacturing turnover, and 10% of value added in 2018. The manufacture of dairy products, with a 17% share of total food industry turnover, 12% share of value added, and 10% share of total food industry employment, is one of the most important subsectors of the European food processing industry.

The development of the European food processing industry in recent decades has been affected by several economic, social, and technological trends and challenges, especially the globalization and liberalization of food markets, the global financial crisis, the change

in consumer preferences towards healthy foods, socially responsible consumption and organic foods, and the implementation of EU regulations focusing on food safety and environmental issues [2,3]. Additionally, the COVID-19 pandemic crisis has created a new era in which the food processing industry is facing various challenges, including the change of consumer purchasing behaviour, transportation network disturbances, labour absenteeism, and the closure of various food manufacturing industries [4]. These trends, connected with a high level of market saturation and concentration of the food retailing sector [5], contribute to a highly competitive environment. To enhance the sustainability and competitiveness of companies/sectors, managers and policymakers have dealt with factors determining productivity, namely, the technology in use, the quality of inputs, the ability to efficiently use inputs in the production of outputs, and the exploitation of economies of scale [6].

These factors have also received special attention in the research of the food processing industry over the last decade. For example, Náglová and Šimpachová Pechrová [7]; Čechura and Hockmann [8]; Rudinskaya [9]; Rezitis and Kalandzi [10]; Špička [11], Popović and Panić [12], and Setiawan et al. [13] investigated the technical efficiency of the food processing industry. Soboh et al. [14] and Dimara et al. [15] dealt with technical and scale efficiency, that was investigated also by Baran [16]. Allendorf and Hirsch [5] analysed technical change and technical efficiency. Čechura et al. [6] assessed the exploitation of economies of scale and production possibilities, along with the impact of technical change. Kapelko et al. [3,17,18], Rudinskaya and Kuzmenko [19], and Čechura [20] investigated productivity dynamics based on technical change, technical inefficiency change, and scale inefficiency change. The majority of these studies are oriented only to one selected country. The exceptions are Kapelko [3], who investigated meat manufacturing firms, fruit and vegetable processing firms, dairy manufacturing firms, and bakery and farinaceous products manufacturing firms in 18 European member states; Allendorf and Hirsch [5], who analysed the dairy and meat processing sectors in eight European countries; Čechura et al. [6], who investigated the milling, fruit and vegetable, dairy, and meat processing sectors in 24 EU member countries; and Soboh et al. [14], who focused on dairy processing firms in six European countries.

With regard to the dairy processing industry, several studies that investigate technical efficiency of European dairy processing industry can be highlighted. Table 1 summarizes these studies. These studies revealed that evaluated on the sample means dairy processing companies in majority of analysed countries greatly exploited their production possibilities in the short-term. However, substantial differences were found between the best and worst producers as well as among countries representing the potential for costs reduction. The studies in Table 1 are in agreement on lower technical efficiency of the Eastern European dairy processing industries compare to the Western European ones. The technical efficiency development was predominantly positive in recent decades and contributed to productivity growth. The need of technical efficiency improvements was prompted by an increase in the price of the main input—milk. Significant short-term changes in technical efficiency were found in the period of the financial crisis. The shortcoming of these studies is that they take into account only transient (short-term) technical efficiency (TTE), which varies across companies because of the shocks associated with new production technologies, human capital, and learning-by-doing. Persistent (long-term) inefficiency (PTE), which could arise due to the presence of rigidity within a firm's organization and production process, is unrecognized in these studies despite the fact that it can lead to the underestimation of technical inefficiency. To the best of our knowledge, there are no empirical studies examining both parts of overall technical efficiency in the European dairy processing industry.

Table 1. Recent studies of technical efficiency of European dairy processing industry. Source: authors.

Study	Countries	Years	Method
Čechura and Hockmann [8]	CZ	2003–2012	Stochastic frontier analysis (SFA)
Čechura et al. [6]	AT, BE, BG, CZ, DE, DK, EE, ES, FI, FR, UK, GR, HU, IR, IT, LT, LV, NL, PL, PT, RO, SW, SL, SI, SR	2003–2012	SFA
Kapelko and Oude Lansink [21]	AT, BE, FI, FR, DE, LU, NL, NO, CH, BIH, BG, HR, CZ, EE, HU, PL, RO, SR, SL, SI, IT, PT, ES	2005–2012	Data envelopment analysis (DEA)
Kapelko and Oude Lankink [22]	ES	2001–2009	DEA
Rezitis and Kalandzi [10]	GR	1984–2007	DEA
Rudinskaya [9]	CZ	2005–2012	SFA
Soboh et al. [14]	BE, DK, FR, DE, IR, NL	1995–2005	SFA
Špička [11]	CZ, PL, SK	2008–2013	DEA

Note: AT denotes Austria, BE denotes Belgium, BG denotes Bulgaria, BIH denotes Bosnia and Herzegovina, CH denotes Switzerland, CZ denotes Czechia, DE denotes Germany, DE denotes Denmark, EE denotes Estonia, ES denotes Spain, FI denotes Finland, FR denotes France, GR denotes Greece, HR denotes Croatia, HU denotes Hungary, IT denotes Italy, LV denotes Latvia, LT denotes Lithuania, LU denotes Luxembourg, PL denotes Poland, PT denotes Portugal, RO denotes Romania, NL denotes the Netherlands, NO denotes Norway, SK denotes Slovakia, SI denotes Slovenia, SR denotes Serbia, SW denotes Sweden, UK denotes the United Kingdom.

The aim of this study is to fill the gap in the empirical literature on the efficiency of the European food processing industry by providing technical efficiency estimates in selected European countries, along with a meta-frontier analysis for cross-country efficiency comparison in the dairy processing industry. In particular, we aim to provide a robust estimate of technical efficiency by employing new advances in productivity and efficiency analysis, and to investigate the efficiency of input use in the analysed countries. The study provides an insight into the decomposition of overall technical efficiency into transient technical efficiency, representing short-term deviations from the frontier, and persistent technical efficiency, which captures systematic deviations from frontier technology.

The study addresses the following research questions: (i) The first relates to the impacts and dynamics of the overall technical efficiency. The aim is to assess whether there is indication that the countries follows a sustainable development path characterized by reduced waste of resource due to inefficient input use. (ii) The second question deals with the sources of overall technical efficiency. The study evaluates whether we can observe systematic failures in the efficiency of input use or whether the deviations from the frontier technologies are due to the transient reasons. Answering these research questions provides important information for policy makers. The structure of the paper is as follows: Section 2 presents the theoretical background of our approach; Section 3 then introduces the model, empirical strategy, and dataset; Section 4 presents the results; and Section 5 discusses our findings and compares them with other studies.

2. Theoretical Background

Technical efficiency was originally defined by Koopmans [23] as the situation where an increase in any output is impossible without a reduction in at least one other output or an increase in at least one input and where a reduction in any input requires an increase in at least one other input or a reduction in at least one output. Debreu [24] and Farrell [25] introduced radial measures of technical inefficiency. Fried et al. [26] suggested an input-conserving orientation. Their measure is defined as the maximum equi-proportionate reduction in all inputs that is feasible with a given technology and outputs. With an output-augmenting orientation, the measure is defined as the maximum equi-proportionate expansion in all outputs that is feasible with a given technology and inputs. A value of unity indicates technical efficiency because no radial adjustment is feasible, and a value different from unity indicates the severity of technical inefficiency.

According to Coelli et al. [27], different methods have been considered for the estimation of the technical inefficiency of the production plan. Two widely used approaches

are data envelopment analysis (DEA), which is non-parametric and deterministic, and stochastic frontier analysis (SFA), which is, on the contrary, parametric and stochastic. There are advantages and disadvantages to each approach (e.g., [28]). The DEA approach is computationally simple, but it is sensitive to outliers since the model ignores measurement error and other sources of statistical noise—all deviations from the frontier are interpreted as the results of technical inefficiency [27].

The stochastic modelling of technical efficiency introduced independently by Meeusen and van den Broeck [29] and Aigner et al. [30] is based on a decomposition of the error term into a symmetric random error and one-sided technical inefficiency. Since the introduction of this frontier modelling within the context of panel-data models, there has been considerable research done in order to extend it to generate consistent and unbiased estimates, see Figure 1. As mentioned by Alem [31], several models have been developed that are based on assumptions about the temporal behaviour of the inefficiency and account for heterogeneity, which can be divided into two categories: observed, which is reflected in the measured variables, and unobserved, which is typically interpreted as the effect of unobservable factors on the outcome of interest [26,32].

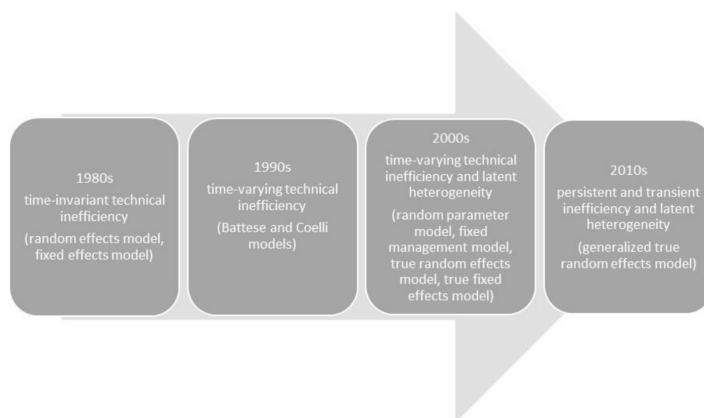


Figure 1. Development of stochastic frontier models. Source: authors.

Initial studies considering heterogeneity assumed that the time-invariant part of the model represents inefficiency, and the time-varying part represents firm-specific heterogeneity. Later, the firm-specific heterogeneity was assumed to be time-invariant, while the time-variant part was considered as inefficiency [28]. The latest approach emphasises the importance of considering latent heterogeneity in generating an unbiased estimate of time-invariant technical inefficiency, as well as the possibility of efficiency improvement [33,34]. In this approach, the overall technical inefficiency of a producer can be decomposed into transient and persistent parts. Transient technical inefficiency arises as a result of non-systematic managerial failures that can be resolved in the short term. According to Pisulewski and Marzec [35] as well as Njuki and Bravo-Ureta [36], the transient part of inefficiency relates to shocks associated with new production technologies and human capital. Kumbhakar and Lien [37] add that transient technical efficiency can represent the managerial ability to learn by doing. Persistent technical inefficiency represents structural problems in the organization of the production process or a systematic lack of managerial skills [38]. Moreover, it can be an indicator of a non-competitive market condition. Badunenko and Kumbhakar [34] state that persistent inefficiency could not exist in a competitive market, i.e., persistently inefficient firms would not survive in the business. The distinction between persistent and transient technical inefficiency has significant political implications because the persistent part of technical inefficiency is unchangeable without a new policy or fundamental change in the ownership and management of companies. Transient technical inefficiency can be adjusted over time without a major policy change [28].

The properties of the above-mentioned models are described by Kumbhakar et al. [28] and others. A comparison of the majority of SFA panel-data models, proving the sensitivity of technical efficiency estimates to the model specification, is presented by Alem [31] and Rashidghalam et al. [39]. Moreover, Badunenko and Kumbhakar [34] provide a judgement on the reliability of transient and persistent technical efficiency estimates.

3. Materials and Methods

3.1. Methodology Used in the Study

Two-step stochastic frontier modelling is applied to get a robust comparison of the efficiency of input use in the dairy processing industry among the analysed countries. The first step includes the estimation of the country-specific input distance functions, technical efficiency scores, and efficient output levels of dairy processing companies in 10 European member states (Austria (AT), Belgium (BE), Czechia (CZ), Germany (DE), Finland (FI), France (FR), Italy (IT), Spain (ES), Sweden (SW), and the United Kingdom (UK)) using the SFA approach. The second step includes the meta-frontier estimation and a comparison of the technical efficiency among the countries.

3.1.1. Input Distance Function

The analysis is based on an assumption that the transformation process is well approximated by an input distance function (IDF) that measures the largest factor of proportionality ρ by which the input vector x can be scaled down in order to produce a given output vector y with the technology existing at a particular time t [40]. The IDF is formally defined as

$$D^I(y, x, t) = \max \left\{ \rho : \frac{x}{\rho} \in L(y) \right\} \quad (1)$$

where x denotes the input vector, y denotes the output vector, t is a time variable, and $L(y)$ represents the input requirement set. For any input-output combination (x, y) belonging to the technology set, the input distance function takes a value no smaller than unity. According to Karagiannis et al. [41], a value of unity simply indicates that the input-output combination (x, y) belongs to the input isoquant, which represents the minimum input quantities that are necessary to produce a given output vector y .

In other words, if $D^I(y, x, t) = 1$, the given output vector y is produced with the minimum amount of inputs at a given time and with the given technology, and the firm is technically efficient [40]. That is, the IDF provides a measure of technical efficiency since it is reciprocal to the Farrell [25,41] input-based technical efficiency:

$$TE^I = 1 / (D^I(y, x, t)) \quad (2)$$

According to Greene [42], the IDF exhibits the following properties: symmetry, monotonicity, linear homogeneity, and concavity in inputs and quasi-concavity in outputs. For the interpretation of the empirical estimates, the duality between the cost and input distance functions is another important property:

$$C(w, y, t) = \min_x \left\{ wx : D^I(y, x, t) \geq 1 \right\} \quad (3)$$

where w denotes a vector of input prices. The minimisation problem provides the relation between the derivatives of the IDF and the cost function [43]. In particular, the derivative with respect to the j th input gives:

$$\frac{\delta D^I(x^*(w, y, t), y, t)}{\delta x_j} = \frac{w_j}{C(w, y, t)} = r_j^*(x, y, t) \quad (4)$$

That is, the derivative of the input distance function with respect to a particular input is equal to the cost-deflated shadow price of that input. More conveniently, in terms of the log derivative of the distance function, we can rewrite this expression to

$$\frac{\delta \ln D^I(x^*(w, y, t), y, t)}{\delta \ln x_j} = \frac{w_j x_j^*(w, y, t)}{C(w, y, t)} = S_{j,t} \quad (5)$$

where $S_{j,t}$ is a cost-share of the particular input.

With respect to the output vector y , application of the envelope theorem to the minimisation problem $C(w, y, t) = \min_x \{wx : D^I(y, x, t) \geq 1\}$ leads to

$$\frac{\delta \ln D^I(x^*(w, y, t), y, t)}{\delta \ln y_m} = -\frac{\delta \ln C(w, y, t)}{\delta \ln y_m} = e_{mi,t} \quad (6)$$

Hence, the elasticity of the IDF with respect to the m th output is therefore equal to the negative of the cost elasticity of that output, and as such it indicates the importance of output in terms of cost [44].

In this study, we assume that the transformation process can be well approximated by the IDF in a translog functional form. This second-order local approximation of any twice-differentiable function satisfies Diewert's minimum flexibility requirement for flexible form [35]. The translog input distance function for output (y), J-inputs (x), and time (t) is defined as

$$\ln D_{it}^I = \alpha_0 + \alpha_m \ln y_{it} + 1/2 \alpha_{mm} (\ln y_{it})^2 + \sum_{j=1}^J \gamma_{mj} \ln y_{it} \ln x_{j,it} + \sum_{j=1}^J \beta_j \ln x_{j,it} + 1/2 \sum_{j=1}^J \sum_{k=1}^K \beta_{jk} \ln x_{j,it} \ln x_{k,it} + \delta_t t + 1/2 \delta_{tt} t^2 + \delta_{mt} \ln y_{m,it} t + \sum_{j=1}^J \delta_{jt} \ln x_{j,it} t \quad (7)$$

where subscripts i , with $i = 1, 2, \dots, N$, and t , with $t = 1, \dots, T$, refer to a certain company and time (year), respectively. α , β , γ , and δ are vectors of the parameters to be estimated. The symmetry restrictions imply that $\beta_{jk} = \beta_{kj}$. The time trend included in the IDF allows for capturing the joint effects of embedded knowledge, technology improvements and learning-by-doing in input quality improvements [45]. Here, δ_t and δ_{tt} capture the global effect of technical change on the IDF, while δ_{mt} and δ_{jt} measure the bias of technical change.

The IDF is homogenous of degree 1 in inputs. According to Sipiläinen [46], it requires

$$\sum_{j=1}^J \beta_j = 1; \sum_{j=1}^J \beta_{jk} = 0; \sum_{j=1}^J \gamma_{mj} = 0; \sum_{j=1}^J \delta_{jt} = 0. \quad (8)$$

Implying the homogeneity property of the IDF [47], which is imposed by normalising all the inputs by one input, we can rewrite the IDF as

$$\ln D_{it}^I - \ln x_{1,it} = \alpha_0 + \alpha_m \ln y_{it} + 1/2 \alpha_{mm} (\ln y_{it})^2 + \sum_{j=2}^J \gamma_{mj} \ln y_{it} \ln \tilde{x}_{j,it} + \sum_{j=2}^J \beta_j \ln \tilde{x}_{j,it} + 1/2 \sum_{j=2}^J \sum_{k=2}^K \beta_{jk} \ln \tilde{x}_{j,it} \ln \tilde{x}_{k,it} + \delta_t t + 1/2 \delta_{tt} t^2 + \delta_{mt} \ln y_{m,it} t + \sum_{j=2}^J \delta_{jt} \ln \tilde{x}_{j,it} t \quad (9)$$

where $\ln \tilde{x}_{j,it} = \ln x_{j,it} - \ln x_{1,it}$

Moreover, all variables in logarithm are normalized by their sample mean. In this case, the first-order parameters can be interpreted as output elasticity and input cost shares, evaluated on the sample mean, respectively.

After introducing a statistical error term (v_{it}) and latent heterogeneity (μ_i), and replacing $\ln D_{it}^I$ with inefficiency terms, persistent technical inefficiency (η_i) and transient technical inefficiency (u_{it}), that is $\eta_i + u_{it} = \ln D_{it}^I$, the IDF takes the form of a generalized true random effects model (GTRE, [33]):

$$\begin{aligned} -\ln x_{1,it} &= \alpha_0 + \alpha_m \ln y_{it} + 1/2 \alpha_{mm} (\ln y_{it})^2 + \sum_{j=2}^J \gamma_{mj} \ln y_{it} \ln \tilde{x}_{j,it} + \\ &+ \sum_{j=2}^J \beta_j \ln \tilde{x}_{j,it} + 1/2 \sum_{j=2}^J \sum_{k=2}^K \beta_{jk} \ln \tilde{x}_{j,it} \ln \tilde{x}_{k,it} + \delta_t t + 1/2 \delta_{tt} t^2 + \\ &+ \delta_{mt} \ln y_{m,it} t + \sum_{j=2}^J \delta_{jt} \ln \tilde{x}_{j,it} t - \eta_i - u_{it} + \mu_i + v_{it} \end{aligned} \quad (10)$$

where $v_{it} \sim N(0, \sigma_v^2)$, $u_{it} \sim N^+(0, \sigma_u^2)$, $\eta_i \sim N^+(0, \sigma_\eta^2)$, $\mu_i \sim N(0, \sigma_\mu^2)$.

3.1.2. Heterogeneity in Technology

The literature provides broad evidence for significant heterogeneity in dairy processing technology. Since we are estimating a joint country input distance function for the entire food processing industry (due to a data limitation, the low number of observations in an industry does not allow us to estimate country IDF for the dairy processing sector in the majority of countries), we need to consider two types of heterogeneity for processing technology, i.e., the potential existence of inter- and intra-sector heterogeneity. The intra-sector heterogeneity is captured by μ_i in (10). To capture the inter-sector heterogeneity, first-order parameters in (10) are expanded based on dummy variables for four major sectors in the food processing industry (namely the manufacture of dairy products, processing of meat, milling, and manufacture of bakery and farinaceous products):

$$\begin{aligned}\alpha_{ms} &= \alpha_m + \sum_s \alpha_s d_s, \forall m \\ \beta_{js} &= \beta_j + \sum_s \beta_s d_s, \forall j \\ \delta_{ts} &= \delta_t + \sum_s \delta_s d_s\end{aligned}\quad (11)$$

where d represents dummy variables which account for inter-sectoral differences in technology.

3.1.3. Estimation Strategy

Since the endogeneity problem usually frustrates researchers in productivity and efficiency analysis and leads to inconsistent estimates, this study uses methods which control for the potential endogeneity of netputs and thereby allow us to obtain consistent estimates of technology as well as efficiency measures. The study addresses two potential sources of endogeneity (due to the heterogeneity and due to simultaneity of input with technical efficiency) by using the system generalized method of moments (GMM) estimator. In particular, the GMM estimator allows us to deal with the endogeneity bias that arises when one or more explanatory variables are correlated with the error term. This correlation can have different origins, e.g., measurement errors, omitted variables bias, and simultaneity [48].

Moreover, the study compares the GMM estimates with the generalized true random effects model estimates. Analogically to the random effect model, the GTRE assumes that μ_i are independent of explanatory variables. The violation of this assumption can originate from the heterogeneity bias as a kind of omitted variable bias, which is a typical problem of hierarchical data. To deal with this heterogeneity bias, the study applies Mundlak's [49] formulation and adds group-means for each time-varying explanatory variable in the first-order level.

Since the GMM model deals with both sources of endogeneity, it represents our model of first choice. If the GMM model does not provide consistent estimates, the GTRE model with Mundlak's adjustment is our second choice. The standard GTRE model allows for an overall model comparison.

The estimation of the GTRE model and the GTRE model with Mundlak's adjustment is undertaken as a multistep procedure. We follow Kumbhakar et al. [50] and rewrite the model in (10) as

$$\begin{aligned}-\ln x_{1,it} = & \alpha_0^* + \alpha_m \ln y_{it} + 1/2 \alpha_{mm} (\ln y_{it})^2 + \sum_{j=2}^J \gamma_{mj} \ln y_{it} \ln \tilde{x}_{j,it} + \\ & + \sum_{j=2}^J \beta_j \ln \tilde{x}_{j,it} + 1/2 \sum_{j=2}^J \sum_{k=2}^K \beta_{jk} \ln \tilde{x}_{j,it} \ln \tilde{x}_{k,it} + \delta_t t + 1/2 \delta_{tt} t^2 + \\ & + \delta_{mt} \ln y_{m,it} t + \sum_{j=2}^J \delta_{jt} \ln \tilde{x}_{j,it} t + \alpha_i + \varepsilon_{it}\end{aligned}\quad (12)$$

where $\alpha_0^* = \alpha_0 - E(\eta_i) - E(u_{it})$, $\alpha_i = \mu_i - (\eta_i) - E(\eta_i)$ and $\varepsilon_{it} = v_{it} - (u_{it} - E(u_{it}))$.

This specification ensures that α_i and ε_{it} have zero mean and constant variance. The multistep procedure consists of three steps. In step 1, standard random effect panel

regression is used to estimate β , γ , δ , α_m , and theoretical values of α_i and ε_{it} , denoted by $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}$. In step 2, the transient technical inefficiency, u_{it} , is estimated using $\hat{\varepsilon}_{it}$ and the standard stochastic frontier technique with assumptions: $v_{it} \sim N(0, \sigma_v^2)$, $u_{it} \sim N^+(0, \sigma_u^2)$. In step 3, the persistent technical inefficiency, η_i , is estimated using and the stochastic frontier model with the following assumptions: $\eta_i \sim N^+(0, \sigma_\eta^2)$, $\mu_i \sim N(0, \sigma_\mu^2)$. These steps are done in the SW STATA 14.0.

Furthermore, the total technical efficiency (OTE) is quantified based on Kumbhakar et al. [50]:

$$OTE_{it} = \exp(-\hat{\eta}_i) \times \exp(-\hat{u}_{it}). \quad (13)$$

The GMM model extends this estimation procedure. The study follows the four-step procedure of Bokusheva and Čechura [51]. In step 1, the two-step system generalized method of moments estimator [52,53] is used to obtain consistent estimates of the IDF parameters. The Arellano and Bover [52]/Blundell and Bond [53] approach builds a system of two equations, the original equation (in levels) and the transformed one (in differences), and employs two types of instruments: level instruments for the differenced equations and lagged differences for the equations in levels [54]. The validity of these instruments is tested by the Hansen J-test [55], which analyses the joint validity of the instruments, and the Arellano-Bond test [56], which analyses the autocorrelation in the idiosyncratic disturbance term (v_{it}) that could render some lags invalid as instruments. In step 2, residuals are used from the system GMM level equations to estimate a random effects panel model employing the generalized least squares (GLS) estimator. The transient and persistent technical inefficiency is estimated in steps 3 and 4 based on the same procedure as described above. These estimates are also done in the SW STATA 14.0.

3.2. Data Used in the Study

The study uses an unbalanced panel data set drawn from the Amadeus database collected by Bureau van Dijk—Moody's Analytics company. The database contains information on around 21 million European companies and provides detailed information about company financials in a standard format, financial strength indicators, sectoral activities, and corporate structures. Moreover, the database is unified between different countries to guarantee the comparability of data. The scope of the database and the comparability of data are the reasons why this database is widely used in economic research. These are examples of studies of technical efficiency of dairy processing industry based on Amadaus database: Kapelko and Oude Lansink [21], Čechura et al. [6], Soboh et al. [14], and Špička [11].

This study uses information from the final accounts of companies whose main activity was food processing (Division C10: Manufacture of food products according to the Statistical classification of economic activities in the European Community, abbreviated as NACE) in the period from 2006 till 2018. Moreover, the study is concentrated on an analysis of C10.5: Manufacture of dairy products (including subgroups: 10.51, 10.52). The study focuses on 10 countries which together represents 76% of European food processing turnover according to Eurostat [1]. Specifically, the analysis uses the following data: output (y), labour (xL), capital (xC), and material (xM). The output is represented by operating revenue (turnover) deflated by the sectoral index of food processing prices (EU level or country level if it was disposable; 2010 = 100) and changes in a company's stock. Labour is represented by the cost of employees deflated by the index of producer prices in the industry (country level; 2010 = 100). Capital is the book value of fixed assets deflated by the index of producer prices in the industry (country level; 2010 = 100). Finally, material is the total cost of materials and energy deflated by the index of producer prices in the industry (country level; 2010 = 100). The source of price indexes is the EUROSTAT database.

Since not all information can be found in the database, only those companies with non-zero and positive values are used for the variable of interest. Moreover, companies with less than three consecutive observations are rejected from the dataset. This procedure decreases the problem associated with the entry and exit of producers from the database

and allows the use of the GMM estimator with a sufficient number of lagged instruments. The study is constrained by that to the use of an unbalanced panel data set containing 11,605 food processing companies with 95,003 observations in the first step: country-specific IDF estimation. The second step: meta-frontier IDF estimation uses only data of dairy processing companies, and the structure of this data sub-set is presented in Table 2.

Table 2. Structure of the data set. Source: Amadeus database and Eurostat.

Country	AT	BE	CZ	DE	ES	FI	FR	IT	SW	UK	Total
I	15	40	58	80	114	36	211	97	22	62	735
N	131	336	498	658	1108	285	1940	915	150	496	6517
RS1	48	40	43	32	41	84	33	58	54	60	48
RS2	44	74	79	59	82	97	48	95	70	90	63

Note: I is the number of dairy processing firms (10.5), N is the total number of observations (10.5) RS1 is the revenue share (in %) of Amadeus sample food processing firms on the total revenue of food processing firms, RS2 is the revenue share (in %) of Amadeus dairy processing firms on the total revenue of dairy processing industry; AT denotes Austria, BE denotes Belgium, CZ denotes Czechia, DE denotes Germany, ES denotes Spain, FI denotes Finland, FR denotes France, IT denotes Italy, SW denotes Sweden, UK denotes the United Kingdom.

4. Results

The country-specific IDF estimates (country-specific IDF estimates are available on request from the authors or in [57]) reveal that the technology of the food processing industry exhibits common patterns in the analysed European countries. Common features are found in the case of cost elasticity, as well as in the cost structure. As expected, and in line with the information provided by the dataset, the highest cost shares have material inputs between 0.50 and 0.64. The labour cost share is approximately 30%, with the lowest cost share in Germany (25.8%) and the highest in France (38.3%). The rest is represented by the share of capital. Moreover, food processors in general cannot benefit greatly from the exploitation of economies of scale since the size seems to be optimal in the majority of cases. The elasticities of output, which reveal whether the technology exhibits increasing, constant, or decreasing returns to scale (i.e., whether a proportionate increase in all inputs results in a larger, equal, or less than proportionate increase in the aggregate output, respectively [58]), are close to one in the majority of countries, evaluated on the sample mean. The deflection towards a higher absolute value than one is a characteristic of the Nordic countries (Finland and Sweden).

As far as heterogeneity is concerned, the results do not reveal any significant heterogeneity effect on output elasticities for the majority of countries. In other words, inter-sectoral heterogeneity in cost elasticity is not a common feature of European food processing sectors. When the focus is primarily on the manufacture of dairy products, an exception can be found in Spain, where an absolute value of output elasticity slightly higher than one reveals that dairy processors exhibit moderate economies of scale, evaluated on the country sample mean. Inter-sectoral heterogeneity is not a statistically significant feature of food processing industries, even in the case of cost shares. This fact holds true especially for labour. The heterogeneity parameters of labour are statistically significant (at the 10% level) only in the Spanish and Swedish dairy industries (without a common pattern). More frequent occurrence of significant inter-sectoral heterogeneity is revealed in the case of material cost shares. The dairy processing sector is characterized by higher material cost shares in the majority of countries compared to the rest of the food processing sectors.

The common patterns of the food processing industry in the analysed European countries are also revealed in the term of technical change. The technology exhibits positive technical change in most of the analysed countries, and this is accelerating over time. With a focus on the dairy processing industry and an evaluation on the country sample means, a technological regression is revealed only in Belgium and Finland. This may indicate a low level of innovation (especially process one) in these countries and may imply significant structural weakness [59]. In general, the lack of innovation activities may result in lower competitiveness. On the contrary, a successful innovation process resulting in cost diminution is an important source of competitive advantage. These results have important

political implications. Strengthening the innovative activity of companies is unlikely to be possible without investment incentives and continued support for the building of an innovation-friendly business environment. Supporting the innovation activity of food processors is an important source not only of profitability and competitiveness but also of food security, safety, and sustainability.

Table 3 summarises parameter estimates of the stochastic meta-frontier input distance function models in the three alternative specifications for the dairy processing industry in 10 European countries. Considering theoretical consistency, the IDF estimates should satisfy the properties of monotonicity and concavity in inputs. The violation of these assumptions may result in misleading values of computed elasticities and technical efficiency scores. The monotonicity assumption is met if the IDF is non-increasing in output and non-decreasing in inputs. In order to verify this property, it is sufficient that the first-order parameters are negative for the output ($\beta_m \leq 0$) and positive for the inputs ($\beta_j \geq 0$ for $j = L, K$) and $\beta_L + \beta_M < 1$, where L stands for labour and M represents material [60]. Concavity in inputs requires that the Hessian matrix of second-order derivatives of the IDF of the function with respect to the inputs is negatively semidefinite, according to Diewert and Wales [61]. This is fulfilled on the sample mean, if $\beta_{jj} + \beta_j^2 - \beta_j \leq 0$ for $j = L, M$. Table 3 proves that these conditions hold for all model specifications, evaluated on the sample mean.

Table 3. Meta-frontier model estimates. Source: authors' own calculation.

10.5		GTRE		GTRE with Mundlak				GMM	
Variable	Coef.	St.Er.	P > z	Coef.	St.Er.	P > z	Coef.	St.Er.	P > t
ln_y	-0.9601	0.0064	0.0000	-0.8886	0.0207	0.0000	-0.9801	0.0039	0.0000
ln_xL	0.2976	0.0161	0.0000	0.3039	0.0230	0.0000	0.2620	0.0088	0.0000
ln_xM	0.6483	0.0146	0.0000	0.6375	0.0222	0.0000	0.6864	0.0084	0.0000
t	-0.0074	0.0008	0.0000	-0.0090	0.0009	0.0000	-0.0069	0.0010	0.0000
ln_y_2	-0.0032	0.0057	0.5740	-0.0007	0.0053	0.8890	0.0045	0.0052	0.3920
ln_xL_2	0.0538	0.0072	0.0000	0.0582	0.0077	0.0000	0.0656	0.0127	0.0000
ln_xM_2	0.1322	0.0098	0.0000	0.1326	0.0090	0.0000	0.1472	0.0080	0.0000
ln_xLxM	-0.0847	0.0079	0.0000	-0.0863	0.0077	0.0000	-0.0949	0.0103	0.0000
t_2	0.0005	0.0004	0.1400	0.0000	0.0003	0.9240	0.0009	0.0005	0.0780
ln_yt	0.0005	0.0005	0.2800	0.0008	0.0005	0.0950	0.0004	0.0010	0.6780
ln_xLt	-0.0001	0.0011	0.9380	0.0003	0.0011	0.7700	-0.0014	0.0030	0.6390
ln_xMt	-0.0001	0.0012	0.9650	-0.0004	0.0012	0.7760	0.0033	0.0026	0.1920
ln_yxL	-0.0055	0.0073	0.4570	-0.0016	0.0069	0.8200	0.0008	0.0079	0.9180
ln_yxM	-0.0080	0.0059	0.1760	-0.0101	0.0057	0.0750	-0.0246	0.0069	0.0000
_cons	-0.0714	0.0136	0.0000	-0.0772	0.0135	0.0000	-0.0915	0.0095	0.0000
ln_y_gmean				-0.0867	0.0200	0.0000			
ln_xL_gmean				-0.0049	0.0201	0.8080			
ln_xM_gmean				-0.0013	0.0232	0.9550			
t_gmean				0.0007	0.0066	0.9110			
Overall TE	Mean	Std.D.		Mean	Std.D.		Mean	Std.D.	
	0.9553	0.0139		0.9624	0.0099		0.9200	0.0179	
Transient TE	0.9561	0.0139		0.9629	0.0099		0.9500	0.0177	
Persistent TE	0.9992	0.0000		0.9994	0.0000		0.9684	0.0044	

Note: GMM model-AR (2) = -0.06 and Hansen test = 347.25 (No. of instruments=226).

The first-order parameters of the IDFs are highly significant even at the 1% significance level and have a similar pattern, indicating the high material intensity of the dairy industry. The share of material in the total input is about 60%, the share of labour is about 30%, and the output elasticity varies between (-0.98) and (-0.89). The time parameter (δ_t) has a low negative value representing the cost decrease with a decelerating rate ($\delta_{tt} > 0$) over the analysed period. However, the second-order time parameter (δ_{tt}) is statistically significant only at the 10% significance level in the GMM model. The parameters of biased technical change are not statistically significant even at the 10% significance level. The rest of the second-order parameters have a similar pattern as well.

The results reveal high overall technical efficiency. Evaluated at the sample averages, the overall technical efficiency is between 92% and 96%, that is, dairy processors can reduce

their costs from 4% up to 8%, subject to the model specification, to produce the same volumes of outputs. As far as the standard deviations are concerned, we may observe that the dairy producers operate very close to the estimated mean value of technical efficiency. Figure 2 shows that the models provide a similar overall technical efficiency distribution.

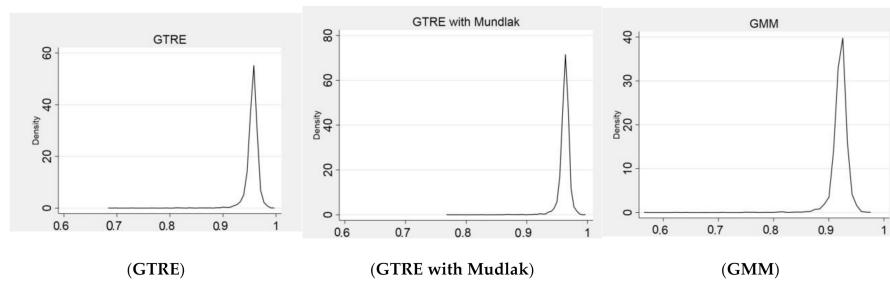


Figure 2. Kernel density comparison (overall technical efficiency). Source: authors' own calculation.

Persistent technical inefficiency is estimated only in the GMM model and is quite low. That is, with similar estimates of transient technical efficiency, we do not see significant differences in overall technical efficiency among the model specifications. These results suggest that the efficiency estimates seem to be robust.

Table 4 provides the statistical characteristics of the country-specific overall technical efficiency and its decomposition into transient and persistent parts. The overall technical efficiency estimates indicate that, evaluated at the country sample means, dairy processing companies can reduce their costs from 5% up to 24% while producing the same volumes of output.

Table 4. Country-specific overall technical efficiency and its decomposition (GMM). Source: authors' own calculation.

Country	Overall Technical Efficiency				Transient Technical Efficiency				Persistent Technical Efficiency			
	Mean	Std.Dev.	Min.	Max.	Mean	Std.Dev.	Min.	Max.	Mean	Std.Dev.	Min.	Max.
Austria	0.7548	0.0541	0.5414	0.8577	0.8319	0.0438	0.6454	0.9153	0.9066	0.0300	0.8234	0.9371
Belgium	0.9297	0.0158	0.794	0.9684	0.9309	0.0159	0.7949	0.9695	0.9988	0.0000	0.9988	0.9988
Czechia	0.9121	0.0185	0.723	0.9686	0.9123	0.0185	0.7232	0.9688	0.9997	0.0000	0.9997	0.9997
Finland	0.9028	0.0219	0.784	0.9635	0.903	0.0219	0.7842	0.9637	0.9997	0.0000	0.9997	0.9997
France	0.9320	0.0243	0.3968	0.9947	0.9328	0.0243	0.3971	0.9954	0.9992	0.0000	0.9992	0.9992
Germany	0.9303	0.0271	0.4859	0.9846	0.9307	0.0271	0.4862	0.9851	0.9995	0.0000	0.9995	0.9995
Italy	0.8393	0.0345	0.5913	0.9398	0.9227	0.0279	0.6312	0.9783	0.9095	0.0240	0.8168	0.9620
Spain	0.9267	0.0249	0.6573	0.9806	0.9269	0.0249	0.6574	0.9808	0.9998	0.0000	0.9998	0.9998
Sweden	0.9466	0.0192	0.8194	0.9892	0.9483	0.0192	0.8209	0.991	0.9982	0.0000	0.9981	0.9982
United Kingdom	0.9427	0.0266	0.7332	0.9847	0.9434	0.0266	0.7337	0.9854	0.9993	0.0000	0.9993	0.9993

As far as intra-sectoral differences are concerned, the overall technical efficiency is relatively dense around the mean and the distribution is skewed to higher values. In the majority of the analysed countries, the interquartile ranges are quite narrow, see Figure 3. The outliers in boxplots indicate high polarization between the most technically efficient producer and the least technically efficient one. The highest polarization is evident in Austria. On the other hand, the lowest polarization can be seen in Czechia and Finland. As the overall technical efficiency is associated with cost savings, it can be assumed that Austria, with the highest polarization, will face structural changes in the future. That is, we can expect changes in business activities or even the cessation of production for firms with the lowest technical efficiency and resource reallocation to more successful producers.

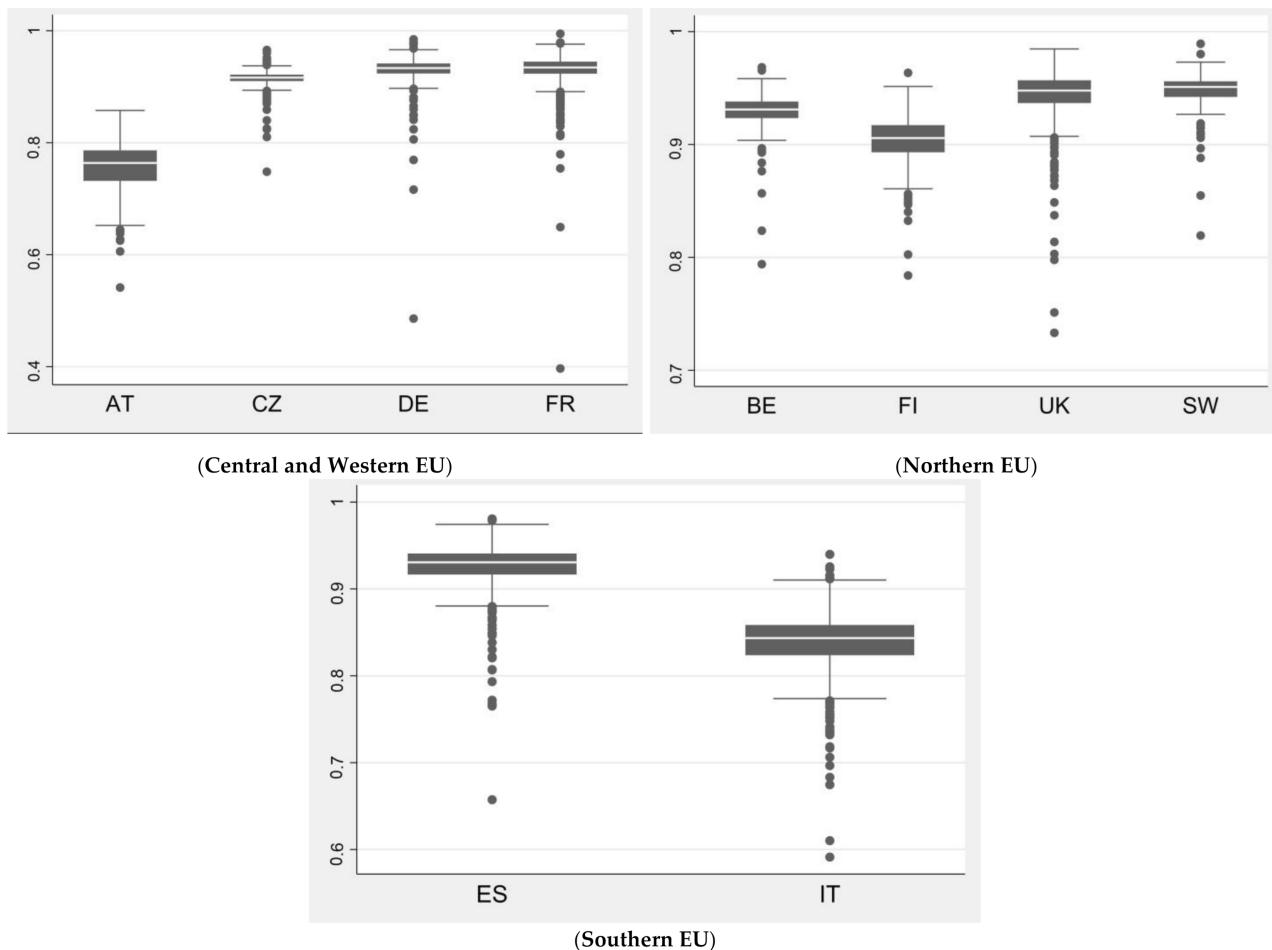


Figure 3. Country-specific overall technical efficiency (GMM). Source: authors' own calculation. Note: AT denotes Austria, BE denotes Belgium, CZ denotes Czechia, DE denotes Germany, ES denotes Spain, FI denotes Finland, FR denotes France, IT denotes Italy, SW denotes Sweden, UK denotes the United Kingdom.

The overall technical efficiency consists of the transient and persistent technical efficiency. The persistent part of overall technical efficiency indicates systematic failures or structural problems and unsuitable factor allocations, which are difficult to change over time, as well as non-competitive market conditions. However, the persistent technical efficiency is statistically significant only in the cases of Austria and Italy. Table 4 shows that the average persistent technical efficiency scores are about 91% in these two countries. A slightly higher variability for persistent technical efficiency is revealed in Austria. However, the Italian dairy sector is characterized by the highest polarization between the most efficient producer and the least efficient. This suggests that many firms systematically fail to catch up to best practices and thus show considerable resource inefficiency as compared to firms operating on the technological frontier.

Table 4 also provides country-specific transient technical efficiency scores. The intra-sectoral differences of transient technical efficiency are pronounced especially in Austria, Italy, and Germany. However, the highest polarization is revealed in France, followed by Germany, where the developments of transient technical efficiency over time have a similar pattern and the lowest values are connected with the 2009 crisis; see Figure 4. The fluctuations of technical efficiency in the short-term may also be the result of shocks associated with the introduction of new technologies or changes in human capital. Considering the development presented in Figure 4, we can conclude that the most important feature is an increasing trend in transient technical efficiency in the analysed period.

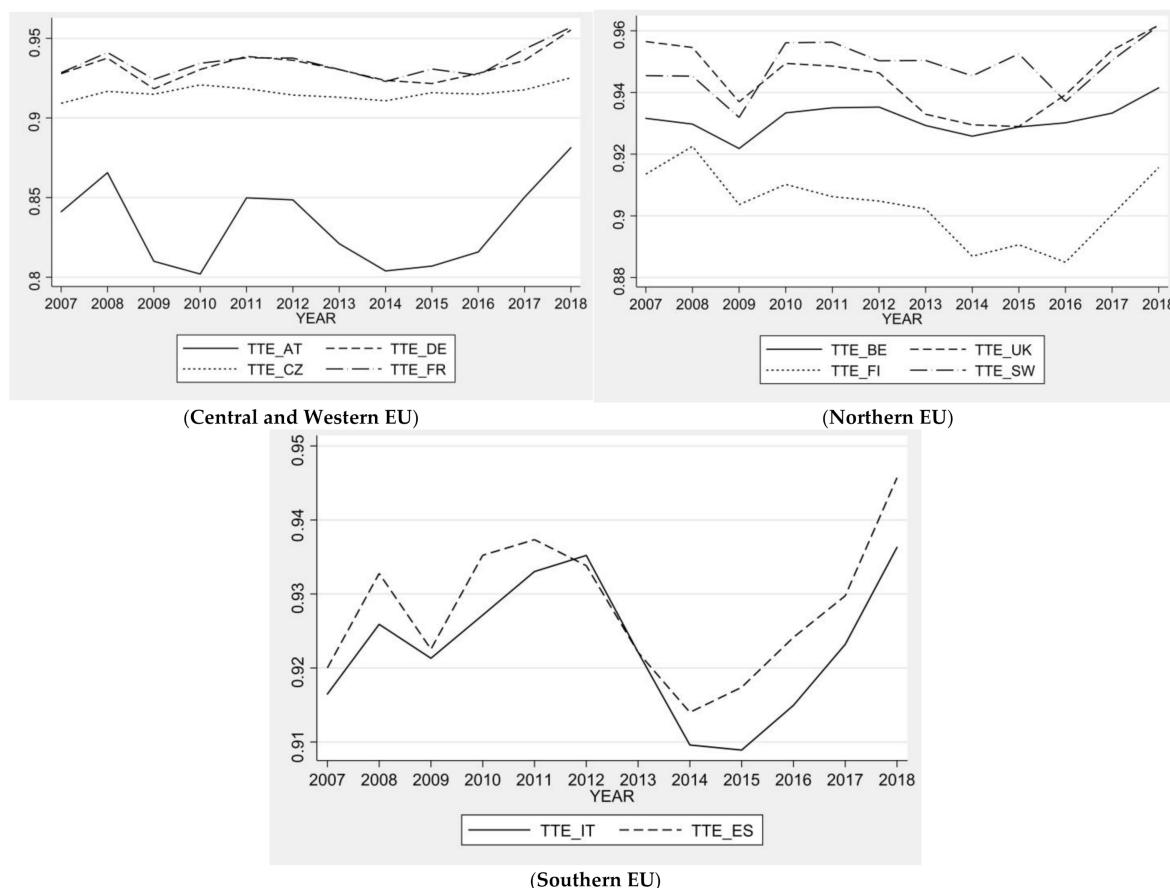


Figure 4. Country-specific transient technical efficiency development (GMM). Source: authors' own calculation. Note: AT denotes Austria, BE denotes Belgium, CZ denotes Czechia, DE denotes Germany, ES denotes Spain, FI denotes Finland, FR denotes France, IT denotes Italy, SW denotes Sweden, UK denotes the United Kingdom.

Table 5 presents meta-frontier technical efficiency estimates and indicates that the overall technical efficiency is high in all countries and there are no considerable differences among them. The lowest value of overall technical efficiency can be observed in Sweden, evaluated on mean values. Moreover, the Swedish dairy industry can be characterized by the highest variability measured by standard deviation. On the contrary, the highest average value of overall technical efficiency is found in France and Finland.

Table 5. Meta-frontier overall technical efficiency and its decomposition (GMM). Source: authors' own calculation.

Country	Overall Technical Efficiency				Transient Technical Efficiency				Persistent Technical Efficiency			
	Mean	Std.Dev.	Min.	Max.	Mean	Std.Dev.	Min.	Max.	Mean	Std.Dev.	Min.	Max.
Austria	0.9202	0.0092	0.8608	0.9392	0.9511	0.0093	0.8888	0.9682	0.9675	0.0017	0.9631	0.9701
Belgium	0.9181	0.0200	0.7490	0.9537	0.9495	0.0155	0.8379	0.9873	0.9669	0.0101	0.8696	0.9750
Czechia	0.9191	0.0217	0.6862	0.9639	0.9492	0.0220	0.7069	0.9894	0.9682	0.0033	0.9586	0.9832
Finland	0.9212	0.0183	0.8179	0.9741	0.9498	0.0181	0.8326	0.9871	0.9699	0.0051	0.9562	0.9868
France	0.9212	0.0152	0.5673	0.9715	0.9506	0.0153	0.5903	0.9963	0.9690	0.0034	0.9611	0.9844
Germany	0.9185	0.0254	0.6251	0.9673	0.9494	0.0249	0.6484	0.9893	0.9674	0.0059	0.9318	0.9831
Italy	0.9206	0.0139	0.7570	0.9576	0.9505	0.0141	0.7785	0.9832	0.9686	0.0027	0.9627	0.9757
Spain	0.9197	0.0145	0.7566	0.9578	0.9503	0.0147	0.7784	0.9820	0.9678	0.0030	0.9591	0.9754
Sweden	0.9171	0.0314	0.7384	0.9732	0.9454	0.0317	0.7705	0.9945	0.9700	0.0062	0.9520	0.9785
United Kingdom	0.9190	0.0195	0.7105	0.9613	0.9495	0.0191	0.7491	0.9825	0.9679	0.0044	0.9484	0.9806

Figure 5 illustrates the competitive position of selected countries in terms of a country-average technical efficiency comparison with the average value of the whole set. As can be seen, the Swedish, Belgian, and German dairy processing industries are failing to catch up with the best-practice technology. While in Belgium and Germany the dairy processing industry lags behind in both transient (TTE) and persistent (PTE) technical efficiency, in Sweden the transient technical inefficiency poses a greater problem for the dairy processing industry than the persistent component.

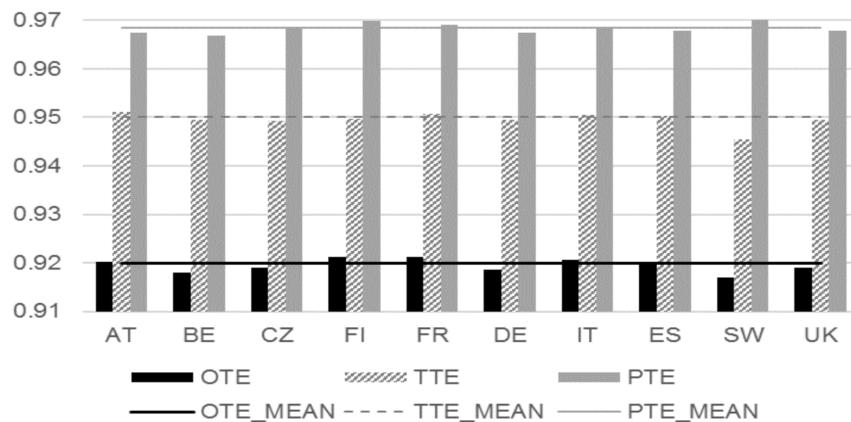


Figure 5. Meta-frontier technical efficiency comparison (GMM). Source: authors' own calculation. Note: AT denotes Austria, BE denotes Belgium, CZ denotes Czechia, DE denotes Germany, ES denotes Spain, FI denotes Finland, FR denotes France, IT denotes Italy, SW denotes Sweden, UK denotes the United Kingdom.

The loss of resources due to structural problems and permanent managerial failures in the production process is pronounced in all countries and reaches a similar level. However, it holds in all cases that the persistent inefficiencies are not large, evaluated on the sample means. On the other hand, the outliers in boxplots (Figure 6) indicate high polarization between the most long-term technically efficient producer and the least technically efficient one in Belgium, Germany, and the United Kingdom. In other words, it reveals the existence of firms that are systematically failing to catch up to best practices and thus show considerable resource inefficiency. Different paths can be followed to eliminate this waste of resources and promote the sustainability of the dairy processing industry. According to Pisulewski and Marzec [35], management should focus on changes in the organization of the production process and managerial competency. According to Dimara et al. [15], policy makers should provide access to biotech innovations and food supply networks.

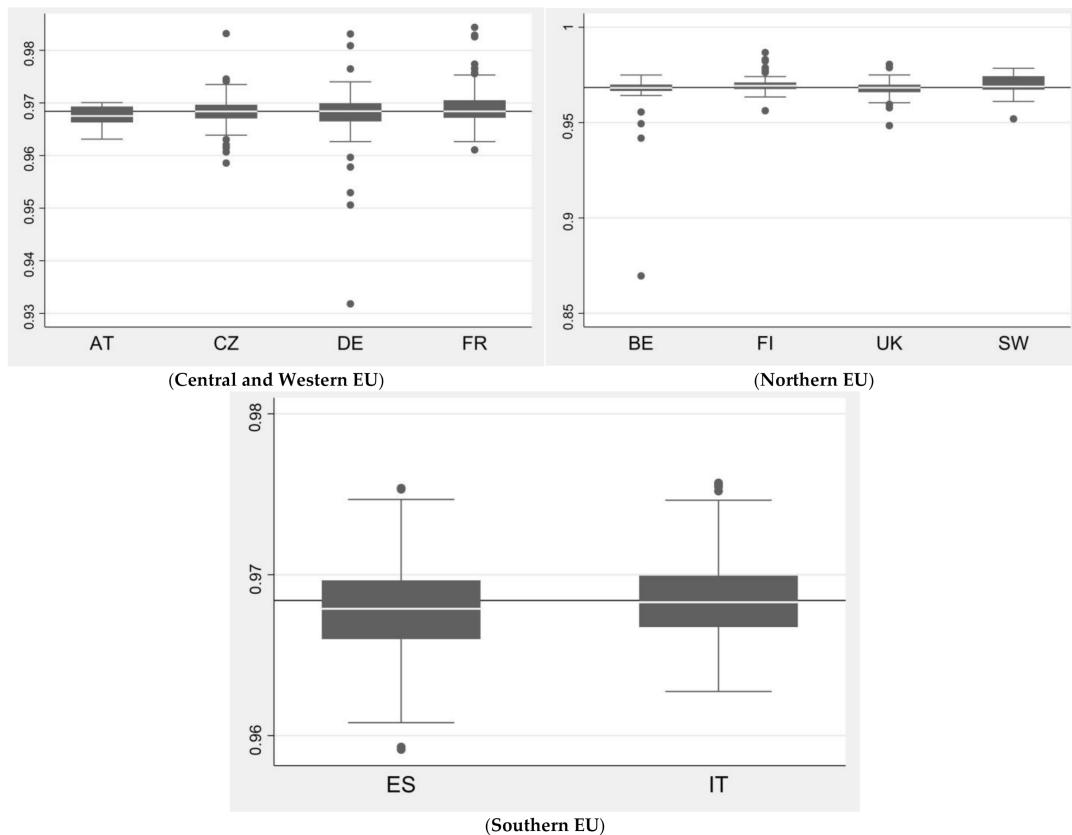


Figure 6. Meta-frontier persistent technical efficiency comparison (GMM). Source: authors' own calculation. Note: Reference line represents the sample average transient technical efficiency score; AT denotes Austria, BE denotes Belgium, CZ denotes Czechia, DE denotes Germany, ES denotes Spain, FI denotes Finland, FR denotes France, IT denotes Italy, SW denotes Sweden, UK denotes the United Kingdom.

5. Discussion

The country as well as meta-frontier technical efficiency estimates revealed high overall technical efficiency for all countries. The only exception is the country estimate for Austria. These results are consistent with the literature devoted to technical efficiency analysis in the food processing industry. For example, Čechura et al. [6] found high technical efficiency in the food processing industry in the analysis of entire EU food processing sectors. In addition, their meta-frontier analysis provides similar results as well. The authors show that the differences in average technical efficiency are not large for all EU member countries, including Serbia, even when there are huge differences between the best and worst food processors. High technical efficiency of the top 10% of food processors is a common feature for all countries in all analysed sectors. Similar findings were provided for Czechia by Čechura and Hockmann [8] and Špička [11]. On the other hand, lower technical efficiency scores were estimated for the Czech food processing industry by Náglová and Šimpachová Petrová [7]. The differences are due to the use of both a different data set and a different model specification. The authors analysed the manufacturing of food products and beverages. Moreover, they did not consider heterogeneity among sectors, which may result in higher inefficiency scores. The treatment of the unobserved heterogeneity component in the model specification is a potential source of the slightly lower technical efficiency scores obtained by Soboh et al. [14] as well.

Our technical efficiency complements the research of technical efficiency in the food processing industry by the decomposition of overall technical efficiency into transient and persistent components. Transient technical efficiency dominates in the technical efficiency country estimates. That is, the overall technical efficiency estimated for each country is largely due to the transient technical efficiency. Persistent technical efficiency is pronounced

only in Austria and Italy. These findings suggest that in the majority of countries, the inefficiencies in input use do not have a systematic character. This holds true for the food processing sector as a whole, since the country estimates are based on a joint IDF function for the four processing sectors. That is, the estimated inefficiencies have non-systematic sources such as non-systematic managerial failures, market shocks, shocks associated with new production technologies, and human capital. However, the meta-frontier estimates that compare the dairy frontier technologies among the countries show a certain degree of systematic failure. In particular, the average persistent technical efficiency is high and similar for all countries. The same holds true for transient technical efficiency. Thus, the meta-frontier analysis shows high overall technical efficiency in the dairy processing sectors in all analysed countries. These findings are fully in line with the meta-frontier analysis provided by Čechura et al. [6].

6. Conclusions

The study aimed to (i) assess whether there is indication that the countries follows a sustainable development path characterized by reduced waste of resources due to inefficient input use and (ii) whether we can observe systematic failures in the efficiency of input use or whether the deviations from the frontier technologies are due to the transient reasons. The results revealed that both components of overall technical efficiency are high. That is, we cannot observe considerable systematic failures in efficiency of input used as well as inefficiencies due to the transient reason, evaluated on sample means. This suggests that the European dairy processing industry as a whole seems to be highly competitive and the companies highly efficient. On the other hand, the figures show that there are companies that are falling behind and may leave the market.

The findings of this study seem to be of high relevance for policy makers since there is still limited knowledge about the inefficiency of input use in the processing industry and their sources and thus the potential contribution the sustainability improvements in the whole food value chain.

There are some limitations of the conducted research. This is especially related to the fact that the Amadeus data allows to work only with aggregate output and thus the diversification or economies of scope cannot be considered. On the other hand, the advantages are the employment of new advances in productivity and efficiency analysis and thus the robust estimate of technical efficiency in European dairy industry.

Future research should focus on investigation of the socioeconomic and environmental factors that can explain differences in persistent as well as transient inefficiency between dairy processing companies. Understanding these factors has important political implications especially in food processing industry that face the challenge of ensuring a sufficient food supply from limited resources for a growing population. Industrial policy agents can use the knowledge of these factors to make a business environment that improves sustainability and competitiveness of food processing industry.

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