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Analysis of Environmental Total Factor Productivity Evolution in European Agricultural Sector

Tomas Baležentis
Lithuanian Institute of Agrarian Economics, 4A A. Vivulskio Str., 03220 Vilnius, Lithuania, e-mail: tomas@laei.lt

Stéphane Blancard
CESAER UMR1041, AgroSup Dijon, INRA, Université Bourgogne Franche-Comté, F-21000 Dijon, France, e-mail: stephane.blancard@agrosupdijon.fr

Zhiyang Shen†
Anhui University of Finance & Economics, 962 CaoShan RD, 233030 Bengbu, China and Export-Import Bank of China, 30 FuXingMenNei Str., 100030 Beijing, China, e-mail: zhiyang86@163.com

Dalia Štreimikienė
Lithuanian Institute of Agrarian Economics, 4A A. Vivulskio Str., 03220 Vilnius, Lithuania, e-mail: dalia@mail.lei.lt

ABSTRACT

Productivity analysis has been an important avenue for economic research. Therefore, medleys of quantitative techniques have been proposed to operationalize productivity analysis. In this article, an extended by-production model is discussed and applied to ensure a link between the production and the pollution-generating subtechnologies. The corresponding dual formulations are provided to interpret the economic role of pollution-generating inputs in the subtechnologies. Finally, we integrate the proposed model with the environmental Luenberger–Hicks–Moorsteen productivity indicator based upon input and output directional distance functions. The proposed model is applied to measure the green economic growth of agricultural sectors of the selected European countries.
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Subject Areas: By-Production Approach, Environmental Performance, European Agriculture, Luenberger–Hicks–Moorsteen Productivity Indicator, and Undesirable Outputs.

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†Corresponding author.

INTRODUCTION

Productivity analysis has been an important avenue for economic research as it provides insights into the factors and magnitude of changes in transformation of inputs (labor, capital, etc.) into outputs (value added, etc.). The emergence of the big data and streaming data in agriculture has allowed for a deeper analysis of the underlying agricultural processes (Kamilaris, Kartakoullis, & Prenafeta-Boldú, 2017; Coble, Mishra, Ferrell, & Griffin, 2018). Therefore, medleys of quantitative techniques have been proposed to operationalize productivity analysis. In the multiple-input and/or multiple-output context, the notion of the multiple factor productivity or total factor productivity (TFP) is often used. Indeed, TFP measures the productivity by means of aggregate inputs and aggregate outputs. Due to O'Donnell (2012), only certain indices and indicators satisfy the property of being completely decomposable with regard to the two aforementioned aggregates and thus can be termed as measures of TFP. Following Chambers (1988) and Machek and Špička (2013), one can distinguish between the two groups of TFP measures: the price-based measures and distance function-based ones. The price-based measures of TFP allow aggregating inputs and outputs by applying price data. Such an approach has both merits and deficiencies. On the one hand, the price-based aggregation allows just two observations to be compared and, thus, appears as less data intensive. On the other hand, reliable price data are often unavailable and, therefore, makes the analysis less certain. Examples of the price-based indices include the Fisher and Tornqvist indices. The distance function-based indices are based on the production frontiers and measures of the productive efficiency (distance functions). These measures require no price information, yet more data points are needed to approximate the production frontier and estimate the distance functions than it is the case for the price-based measures. The estimation of the production frontier can be carried out either parametrically (Cechura, Kroupova, & Rudinskaya, 2015; 2017) or nonparametrically (Coelli & Rao, 2005; O'Donnell, 2012). Note that the parametric approach often relies on the Stochastic frontier analysis. It allows for statistical inference, yet requires assumptions on the functional forms of representations of the production technology. Furthermore, certain desirable axioms might be violated if estimation is not restricted. As for nonparametric analysis, it is widely applied as no assumptions regarding the functional form of representations of the production technology are needed and such axioms as convexity are satisfied. In this article, we focus on the nonparametric analysis of TFP.

Among the distance function-based approaches, Malmquist, Luenberger, Färe-Primont, and Hicks–Moorsteen indices or indicators are the key ones. Even though the Malmquist productivity index proposed by Caves, Christensen, and Diewert (1982) and the Luenberger productivity indicator proposed by Chambers (2002) are the most widely applied measures, O'Donnell (2012) showed they cannot be completely decomposed with respect to inputs and outputs. The Hicks–Moorsteen productivity index was proposed by Bjurek (1996) and satisfies the conditions defined by O'Donnell (2012). As the additive measures of productivity allow for greater flexibility in the analysis, Briec and Kerstens (2004) offered the Luenberger–Hicks–Moorsteen (LHM) TFP indicator. The LHM indicator allows for zero values in the data as it decomposes additively and can be regarded as a TFP indicator as the decomposition can be carried out with respect to inputs and outputs.

The economic activities often induce undesirable externalities (e.g., pollution). The traditional economic growth theory did not account for this issue when defining the measures of TFP. However, the concerns of the global warming and climate change (Zhou & Wang, 2016; Liobikienė, Mandravickaitė, Krepštulienė, Bernatonienė, & Savickas, 2017; Zhao et al., 2017; Yeboah-Assiamah, Muller, & Domfeh, 2018) have altered the economic theory as the principles of ecological economics have been addressed in models underpinning the research related to the production economics. Distance functions and data envelopment analysis (DEA) played a rather important role in nonparametric analysis of so-called green TFP. The environmental directional distance function (DDF) proposed by Chung, Färe, and Grosskopf (1997) has been applied in developing environmentally sensitive measures of efficiency and productivity (Azad & Ancev, 2014; Wang & Wei, 2016; Li & Lin, 2017). Dakpo, Jeanneaux, and Latruffe (2016) and Tyteca (1996), Zhou, Poh, and Ang (2016), Feng, Wang, Liu, and Huang (2017) presented surveys on applications of DEA for measurement of the environmental performance and green TFP.

The main contribution of this article is that we propose a refined reduced form of modeling by-production technology in a nonparametric framework. We point out some potential improvements for the initial by-production model introduced by Murty, Russell, and Levkoff (2012) related to nonlinearity, weak connections between subtechnologies, and unclear economic interpretation of the shape of production possibility sets. The refined model can overcome the enumerated limitations and thereby impose a single shadow price of pollution-generating inputs for the two subfrontiers that describe the role of pollution-generating inputs in producing desirable and undesirable outputs, respectively.

The LHM indicator has also been extended to tackle the measurement of environmental performance via the green TFP. Abad (2015) used the generalized environmental DDFs to construct the environmental LHM TFP indicator. In the latter approach, inputs and undesirable outputs are treated in the same manner. Further on, Seufert, Arjomandi, and Dakpo (2017) presented yet another instance of the environmental LHM indicator relying on the by-production approach (Murty et al., 2012; Ray, Mukherjee, & Venkatesh, 2018).[i] The indicator proposed by Seufert et al. (2017), indeed, is output oriented (i.e., desirable and undesirable outputs are optimized). In this article, we contribute to the discussion on the environmental LHM TFP indicators by proposing a nonoriented measure, which also considers inputs throughout the optimization.

Productivity gains are also important for agriculture (Dheera–Aumpon, 2018). We focus attention on energy use in agricultural sectors of different EU countries. Many studies have compared the development of agricultural productivity and efficiency in the EU over the past few decades (e.g., Ball, Butault, San Juan, & Mora, 2010; Vlontzos, Niavis, & Manos, 2014; Cechura et al., 2015; Kijek, Nowak, & Domanska, 2016; Baráth & Fertő, 2017; Cechura, Grau, Hockmann, Levkovych, & Kroupova, 2017; Dakpo, Jeanneaux, & Latruffe, 2017; Vlontzos,

[i] Weak disposability approach (Färe, Grosskopf, Lovell, & Pasurka, 1989; Kuosmanen, 2005) can be used as an alternative for modeling the environmental production technology.

Niavis, & Pardalos, 2017). However, most of the findings reported in these studies do not deal with the environmental TFP at a macro level. Consequently, there is a clear lack in the literature, except for Vlontzos et al. (2014, 2017), who dealt with efficiency rather than TFP change. This article, therefore, attempts to analyze the dynamics in the green TFP in the selected EU member states by applying a new decomposition of the environmental LHM TFP indicator. The energy-related GHG emission is included in the analysis as the undesirable output contributing to the climate change. The research relies on country-level data from EUROSTAT (European Commission, 2019) and FAOSTAT (FAO, 2019). The period covered is years 1995–2016.

This article unfolds as follows. Section "Modeling undesirable outputs in nonparametric approaches" briefly overviews the main literature on modeling the environmental technologies in productivity and efficiency analysis. Further on, section "Methodology" presents the methods used (by-production technology and the associated measures of efficiency, environmental LHM indicator). Section "Data and results" brings forward the results of empirical analysis focused on the European agricultural sector. Finally, the section "Conclusions" concludes.

i MODELING UNDESIRABLE OUTPUTS IN NONPARAMETRIC APPROACHES

The ecological considerations have appeared due to the threat of the global climate change (Chen, Cheng, Nikic, & Song, 2018). Accordingly, there have been a number of attempts to devise frameworks (Song, Fisher, & Kwoh, 2019) and particular techniques (Song, Peng, Wang, & Dong, 2018; Song & Wang, 2018) for measurement of the productive efficiency in the presence of undesirable outputs. In this section, we briefly outline the major strands in this regard.

The seminal works of Koopmans (1951), Debreu (1951), Shephard (1953), and Farrell (1957) have developed the basis of the Neo-Walrasian production theory. The key concept within this theory is the production possibility set, which is a representation of the feasible combinations of inputs and outputs. Initially, research tended to emphasize desirable outputs (e.g., economic growth), while negative externalities (e.g., pollution) remained ignored in the measurement of the productive performance. To ensure economic interpretation, some assumptions are usually imposed on the production possibility set, for instance, returns to scale and disposability of outputs and inputs.

Pollution issues and global warming have drawn attention by economists and policy makers to the green, or low-carbon, growth. Indeed, environmental deterioration may have a negative effect on the economic performance in the long run. Indeed, environmental deterioration is often caused by undesirable outputs of the production process (or bad outputs or bad by-products). Incorporating undesirable factors into performance evaluation, therefore, has become a topical issue in the literature. For modeling the bad outputs, there have been two main approaches.

The first approach is to model bad outputs as (i) traditional inputs or (ii) outputs with data transformation. In these instances, the classical assumption of free disposability is maintained. The bad outputs are treated as outputs by taking reciprocals of the initial quantities (Lovell et al., 1995), or adding big enough positive numbers to negated values of bad outputs (Seiford & Zhu, 2002; Wu et al., 2013). However, considering bad outputs as inputs may not reflect the real mechanism inside the production activity, and it is inconsistent with physical laws. Therefore, such data transformation-based approaches cannot be interpreted in a reasonable way (Färe, Grosskopf, Lovell, & Pasurka, 1989; Färe & Grosskopf, 2004; Dakpo et al., 2016; Ray et al., 2018).

The second approach seeks to introduce additional economic axioms on production possibility sets, such as weak disposability and cost disposability assumptions. Weak disposability is introduced by Shephard (1970) and Shephard and Färe (1974). Another important condition is that of null-jointness, which links desirable and undesirable outputs (Färe & Grosskopf, 2004). This approach allows proportional decrease in both types of outputs and emphasizes the linkages among good and bad outputs. Thus, pollution is impossible to be fully disposed of in the production activity. Note that this approach is not applicable when emission is easily controlled, as it is the case with SO_2 emission, which can be soluble in water totally. Chen, Wang, and Lai (2017) proposed the semidisposability approach to handle the latter case.

The by-production technology proposed by Murty and Russell (2002) and Murty et al. (2012) rests on costly disposability assumption. An advantage of the by-production technology is the introduction of pollution-generating inputs. This approach assumes two independent subtechnologies and allows for full disposability in pollution. One subtechnology models production of the desirable outputs, whereas another one models generation of the bad outputs. Yet, the computational difficulty associated with nonlinear programs is an obvious pitfall associated with the by-production model. Some empirical applications employ DDFs to deal with nonlinearity (Cui & Li, 2017; Arjomandi, Dakpo, & Seufert, 2018; Murty & Russell, 2018; Shen, Baležentis, Chen, & Valdmanis, 2018; Dakpo & Oude Lansink, 2019).

Cui and Li (2017) proposed a dynamic by-production model relying on the carry-over factors (Tone & Tsutsui, 2010). Dakpo and Oude Lansink (2019) presented the dynamic by-production model that links the subsequent time periods by considering adjustment costs (Silva, Oude Lansink, & Stefanou, 2015). In addition, Dakpo and Oude Lansink (2019) proposed some constraint links between subtechnologies in order to assume equal amount inputs use to one another. Murty and Russell (2018) discussed the linkages between axiomatic and by-production approaches. Lozano (2015) pointed out that the by-production model follows the network DEA models with parallel structure (Kao, 2017) and presented the slack-based by-production model. Shen et al. (2018) presented the by-production model for measurement of the aggregate efficiency.

We discuss the differences among variations of the by-production model in detail in the next section. In the rest of this article, we follow the by-production approach. We seek to overcome the limitations of the model by proposing its linearized version. Furthermore, we integrate the by-production model into the framework for measurement of the TFP change.

METHODOLOGY

This section presents the outline of methods applied. First, we focus on the by-production approach and present the corresponding programs for estimation of the distance functions. Second, the LHM indicator is presented for measurement of the TFP based on the by-production approach.

The By-Production Technology

Before proceeding with the refined by-production model, let us review the conventional one. Assume that production possibilities for decision-making units (DMUs) can be described by considering $M + J$ outputs and $N + P$ inputs. Among the outputs, there are M desirable (good) outputs and J undesirable (bad) by-products. Turning to inputs, there are N nonpolluting (clean) inputs, which only contribute to generation of the desirable outputs and P pollution-generating (dirty) inputs, which contribute to generation of the undesirable outputs. Ray et al. (2018) noted that inputs and undesirable outputs are different in that the latter ones are not available prior to the production process, they are not transformed during the production process, and their stocks increase after the production process completes.

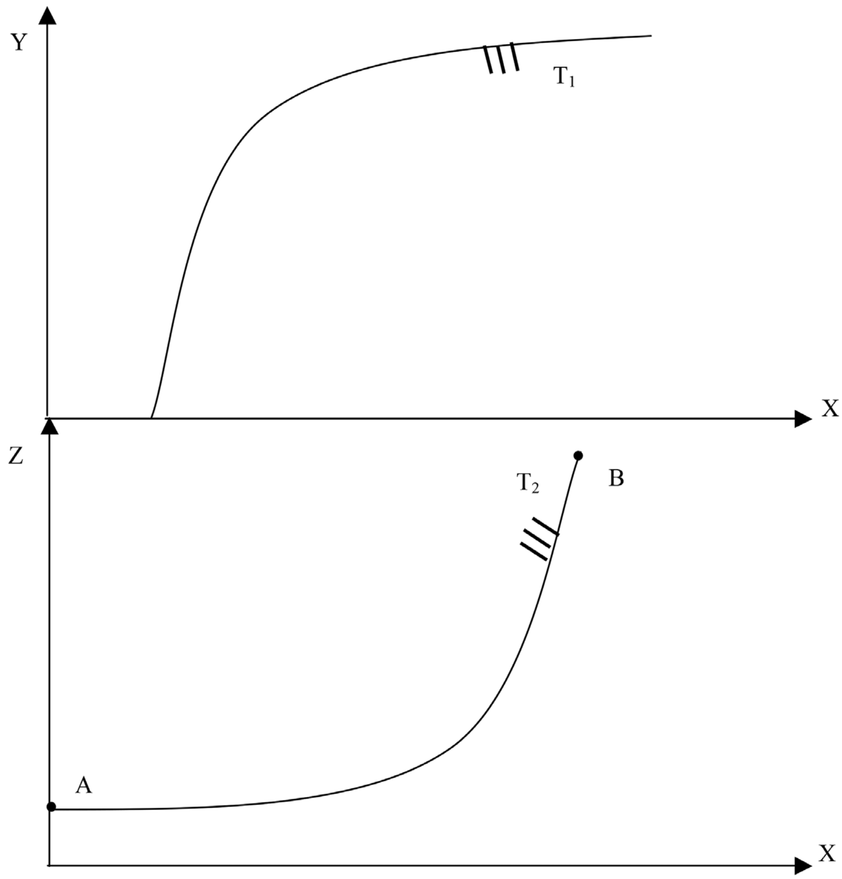
Murty and Russell (2002) and Murty et al. (2012) argue that the weak disposability assumption (WDA) may lead to unacceptable economic implications. Compared to the WDA, where desirable and undesirable outputs are produced in the same production technology, Murty et al. (2012) isolated pollution-generating inputs and proposed a by-production model including two subtechnologies: one subtechnology models the traditional production process where desirable outputs are produced by employing all the inputs (T_1); another one focuses on a pollution-generating process where undesirable outputs are generated by employing pollution-generating inputs (T_2). Let $\mathbf{x}^{n,t} \in R_+^J$ and $\mathbf{x}^{p,t} \in R_+^P$ be the vectors of nonpolluting and polluting inputs, respectively. Furthermore, let $\mathbf{y}^t \in R_+^M$ and $\mathbf{z}^t \in R_+^J$ be the vectors of desirable and undesirable vectors, respectively. The by-production technology is then defined as:

$$
\begin{aligned}
T_{BP}(t) &= T_1(t) \cap T_2(t) \\
&= \left\{(\mathbf{x}^{n,t}, \mathbf{x}^{p,t}, \mathbf{y}^t, \mathbf{z}^t) \in R_+^{N+P+M+J} : (\mathbf{x}^{n,t}, \mathbf{x}^{p,t}) \text{ can produce } \mathbf{y}^t; \right. \\
&\qquad \left. \mathbf{x}^{p,t} \text{ can generate } \mathbf{z}^t \right\}; \\
T_1(t) &= \left\{(\mathbf{x}^{n,t}, \mathbf{x}^{p,t}, \mathbf{y}^t) \in R_+^{N+P+M} | f(\mathbf{x}^{n,t}, \mathbf{x}^{p,t}, \mathbf{y}^t) \leq 0\right\}; \\
T_2(t) &= \left\{(\mathbf{x}^{p,t}, \mathbf{z}^t) \in R_+^{P+J} | g(\mathbf{x}^{p,t}) \leq \mathbf{z}^t\right\};
\end{aligned} \tag{1}
$$

where $f(.)$ and $g(.)$ are continuously differentiable functions. As the measures of TFP involve mixed-period measures of efficiency, we introduce time index t. When defining a technology, all the inputs and outputs belong to the same period and we omit time notation when no mixed-period measures are discussed in the sequel.

The free disposability is imposed on T_1 for all inputs and desirable outputs (A1), while the costly disposability is assumed in T_2 for pollution-generating inputs and undesirable outputs (A2). This implies joint disposability of the pollution-generating inputs and undesirable outputs (Ray et al., 2018). Formally, these axioms are given by (note that time indexes are dropped for brevity):

Figure 1: Graphical representation of the VRS by-production technology.



$$A1: \text{ if } (\mathbf{x}^n, \mathbf{x}^p, \mathbf{y}, \mathbf{z}) \in T_1, \text{ then } (\tilde{\mathbf{x}}^n, \tilde{\mathbf{x}}^p, \tilde{\mathbf{y}}, \tilde{\mathbf{z}}) \in T_1 \text{ for all } (-\tilde{\mathbf{x}}^n, -\tilde{\mathbf{x}}^p, \tilde{\mathbf{y}}) \leq (-\mathbf{x}^n, -\mathbf{x}^p, \mathbf{y}).$$

$$A2: \text{ if } (\mathbf{x}^p, \mathbf{z}) \in T_2, \text{ then } (\tilde{\mathbf{x}}^p, \tilde{\mathbf{z}}) \in T_2 \text{ for all } (\tilde{\mathbf{x}}^p, -\tilde{\mathbf{z}}) \leq (\mathbf{x}^p, \mathbf{z}). \tag{2}$$

We also assume variable returns to scale (VRS). By denoting $\mathbf{x}^t = (\mathbf{x}^{n,t}, \mathbf{x}^{p,t})$, one can derive the output correspondence set as in Equation (3):

$$P_t(\mathbf{x}^t) = \left\{(\mathbf{y}^t, \mathbf{z}^t) \in R_+^{M+J} : (\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t) \in T_{BP}(t)\right\}. \tag{3}$$

A simple case with single input (*X*), single desirable output (*Y*), and single undesirable output (*Z*) under a VRS technology can be shown in Figure 1.

Limitations Associated with the Conventional By-Production Technology

The by-production technology can then be used to estimate the environmentally adjusted efficiency scores by an improved output-oriented Färe–Grosskopf–Lovell indicator, which can be defined as:

$$E_{FGL}(\mathbf{x}^t,\mathbf{y}^t,\mathbf{z}^t) = \frac{1}{2}\min\left\{\frac{\sum\delta^m}{M} + \frac{\sum\theta^j}{J}|(\mathbf{y}^t\otimes^{-1}\boldsymbol{\delta},\boldsymbol{\theta}\otimes\mathbf{z}^t)\in P_t(\mathbf{x})\right\} \tag{4}$$

where $\mathbf{y}^t\otimes^{-1}\boldsymbol{\delta} = (y^{1,t}/\delta^1,\ldots,y^{P,t}/\delta^P)$ and $\boldsymbol{\gamma}\otimes\mathbf{z}^t = (\gamma^1 z^{1,t},\ldots,\gamma^J z^{J,t})$. Therefore, Equation (4) maximizes the desirable outputs and minimizes the undesirable ones by nonradial efficiency scores δ_g and γ_b, respectively. The reduced form of by-production technology renders the following nonlinear program in the envelopment form for observation $(\mathbf{x}_{k'},\mathbf{y}_{k'},\mathbf{z}_{k'})$, $k' = 1, 2, \ldots, K$, under a VRS technology:

$$\begin{aligned}
&\min_{\delta,\theta,\lambda,\sigma}\frac{1}{2}\left(\sum_{m=1}^{M}\delta^m/M + \sum_{j=1}^{J}\theta^j/J\right)\\
s.t.\ &\sum_{k=1}^{K}\lambda_k y_k^{m,t} \ge y_{k'}^{m,t}/\delta^m,\quad \forall m = 1,\ldots,M,\\
&\sum_{k=1}^{K}\lambda_k x_k^{n,t} \le x_{k'}^{n,t},\quad \forall n = 1,\ldots,N,\\
&\sum_{k=1}^{K}\lambda_k x_k^{p,t} \le x_{k'}^{p,t},\quad \forall p = 1,\ldots,P,\\
&\sum_{k=1}^{K}\sigma_k z_k^{j} \le \theta^j z_{k'}^{j},\quad \forall j = 1,\ldots,J,\\
&\sum_{k=1}^{K}\sigma_k x_k^{p,t} \ge x_{k'}^{p,t},\quad \forall p = 1,\ldots,P,\\
&\sum_{k=1}^{K}\lambda_k = 1,\\
&\sum_{k=1}^{K}\sigma_k = 1,\\
&\lambda_k \ge 0,\quad \forall k = 1,\ldots,K,\\
&\sigma_k \ge 0,\quad \forall k = 1,\ldots,K.
\end{aligned} \tag{NLP1}$$

In Equation NLP1, dual weighting is used to account for the inner (dual) structure of the by-production model. Specifically, intensity variables λ_k define the frontier for T_1, whereas σ_k define that for T_2. Indeed, the first subtechnology, T_1, corresponds to a conventional production technology where all the inputs are used to produce desirable outputs. The second subtechnology, T_2, models transformation of the pollution-generating inputs (e.g., fossil energy consumption) into the undesirable outputs. Therefore, the desirable outputs are maximized for a given level of all the inputs in T_1, whereas the quantity of undesirable outputs is minimized for a given level of pollution-generating inputs in T_2.

As per the setting in NLP1, certain difficulties arise in linking two subtechnologies in terms of benchmark selection. For instance, let us assume that two countries are considered in the analysis (e.g., the United States and Iceland). Say the United States shows a high level of GDP and is fully efficient in regard to the frontier of T_1 (i.e., it is fully efficient in turning the factor inputs into the GDP), whereas Iceland shows low levels of pollutant emissions and is fully efficient in regards to the frontier relative to T_2 (i.e., it produces the lowest pollution for a given level of pollution-generating inputs). At this point, a question may arise: are the benchmark points the same across the two frontiers for a certain country and can they be used as reasonable yardsticks? Indeed, the independent modeling of the two subtechnologies may not allow it to represent the true production process. Thus, an explicit link between the two technologies is essential.

Moreover, the production possibility sets, as defined in the conventional by-production model, may not provide a clear economic interpretation under the VRS technology. More specifically, point A in Figure 1—where frontier T_2 originates from—indicates that a certain amount of undesirable output can be generated by input being held at the null level. Alternatively, assuming that there is point B at the extremum of boundary-defining frontier T_2, it is implied that a given (finite) level of input can cause infinite pollution. This setting contradicts the material balance condition.

Considering the properties of the by-production model offered by Murty et al. (2012), we identify the following issues, which need to be tackled in order to ensure consistency of the analysis:

Remark 1: *The model offered by Murty et al. (2012) is a nonlinear one and might be less operational than linear models due to the existence of local optima.*

Remark 2: *The two subtechnologies in the by-production model are not linked explicitly and might render different benchmarks.*

Remark 3: *The production possibility sets applied in the conventional setting may not provide a clear economic interpretation.*

Accordingly, we first modify the model by Murty et al. (2012) and propose a by-production model along with its dual formulation based on the output DDF in section “Directional by-production model and its dual formulation.” The resulting model is a linear one. We further explicitly link the two subtechnologies by introducing an additional constraint in section “A refined model with single shadow prices of pollution-generating inputs.”

Directional By-Production Model and Its Dual Formulation

Given observations outlined in section “Limitations associated with the conventional by-production technology,” we first construct a by-production model based on a directional output distance function. A generalized directional output distance function defines a simultaneous increase in desirable outputs and a contraction in undesirable outputs observed at period $a \in \{t, t+1\}$ given a technology defined in terms of quantities in period $b \in \{t, t+1\}$. Similarly, a directional input distance function defines contraction of inputs at a given level of outputs. The corresponding directional functions are given as follows:

$$D^b\left(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{0}, \mathbf{g}_y^a, \mathbf{g}_z^a\right) = \text{Max}\left\{\delta \in R_+ : \left(\mathbf{x}^a, \mathbf{y}^a + \delta\mathbf{g}_y^a, \mathbf{z}^a - \delta\mathbf{g}_z^a\right) \in T_{BP}(b)\right\},$$
$$D^b\left(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{g}_x^a, \mathbf{0}, \mathbf{0}\right) = \text{Max}\left\{\delta \in R_+ : \left(\mathbf{x}^a - \delta\mathbf{g}_x^a, \mathbf{y}^a, \mathbf{z}^a\right) \in T_{BP}(b)\right\}, \tag{5}$$

where $(g_y^a, g_z^a) \geq 0$ are directional vectors of desirable and undesirable outputs; δ measures the maximum possible increase in desirable outputs and decrease in undesirable outputs; and $(a, b) \in \{t, t+1\} \times \{t, t+1\}$ allows for the mixed-period DDFs.

For an arbitrary observation $(\mathbf{x}_{k'}^t, \mathbf{y}_{k'}^t, \mathbf{z}_{k'}^t)$, $k' = 1, 2, \ldots, K$, the directional by-production model under VRS takes the following form:

$$\begin{aligned}
& D^b\left(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{0}, \mathbf{g}_y^a, \mathbf{g}_z^a\right) = \max_{\delta, \lambda_k, \sigma_k} \delta \\
s.t.\ & \sum_{k=1}^{K} \lambda_k y_k^{m,b} \geq y_{k'}^{m,a} + \delta g_y^{m,a}, \quad \forall m = 1, \ldots, M, \\
& \sum_{k=1}^{K} \lambda_k x_k^{n,b} \leq x_{k'}^{n,a} \quad \forall n = 1, \ldots, N, \\
& \sum_{k=1}^{K} \lambda_k x_k^{p,b} \leq x_{k'}^{p,a}, \quad \forall p = 1, \ldots, P, \\
& \sum_{k=1}^{K} \sigma_k z_k^{j,b} \leq z_{k'}^{j,a} - \delta g_z^{j,a}, \quad \forall j = 1, \ldots, J, \\
& \sum_{k=1}^{K} \sigma_k x_k^{p,b} \geq x_{k'}^{p,a}, \quad \forall p = 1, \ldots, P, \\
& \sum_{k=1}^{K} \lambda_k = 1, \\
& \sum_{k=1}^{K} \sigma_k = 1, \\
& \lambda_k \geq 0, \quad \forall k = 1, \ldots, K, \\
& \sigma_k \geq 0, \quad \forall k = 1, \ldots, K,
\end{aligned} \tag{LP1}$$

where $(\mathbf{g}_y^a, \mathbf{g}_z^a)$ is the directional vector (in the current setting, we focus on simultaneous expansion of the desirable outputs and contraction of the undesirable ones). The resulting model is a linear one.

Each linear program has the corresponding dual model. Therefore, we present the dual model for Equation LP1 in order to gain insights into the underlying economic logics. The dual model is formulated as follows:

$$D^b(\mathbf{x}^a,\ \mathbf{y}^a,\mathbf{z}^a;\mathbf{0},\ \mathbf{g}_y^a,\mathbf{g}_z^a) = \min_{\pi_y^m,\pi_x^n,\pi_x^p,\omega_x^p,\omega_z^j,v_1,v_2} \left(\sum_{n=1}^{N}\pi_x^n x_{k'}^{n,a} + \sum_{p=1}^{P}\pi_x^p x_{k'}^{p,a} - \sum_{m=1}^{M}\pi_y^m y_{k'}^{m,a} - v_1\right) + \left(\sum_{j=1}^{J}\omega_z^j z_{k'}^{j,a} - \sum_{p=1}^{P}\omega_x^p x_{k'}^{p,a} + v_2\right)$$

$$\begin{aligned}
s.t.\ & \sum_{m=1}^{M}\pi_y^m y_k^{m,b} - \sum_{n=1}^{N}\pi_x^n x_k^{n,b} - \sum_{p=1}^{P}\pi_x^p x_k^{p,b} + v_1 \le 0, \quad \forall k = 1,\ldots,K,\\
& \sum_{p=1}^{P}\omega_x^p x_k^{p,b} - \sum_{j=1}^{J}\omega_z^j z_k^{j,b} - v_2 \le 0, \quad \forall k = 1,\ldots,K,\\
& \sum_{m=1}^{M}\pi_y^m g_y^{m,a} + \sum_{j=1}^{J}\omega_z^j g_z^{j,a} = 1,\\
& \pi_y^m \ge 0 \quad \forall m = 1,\ldots,M,\\
& \pi_x^n \ge 0 \quad \forall n = 1,\ldots,N,\\
& \pi_x^p \ge 0 \quad \forall p = 1,\ldots,P,\\
& \omega_x^p \ge 0 \quad \forall p = 1,\ldots,P,\\
& \omega_z^j \ge 0 \quad \forall j = 1,\ldots,J,\\
& v_1 = 0 \text{ if } T_1 \text{ is under CRS},\ v_2 = 0 \text{ if } T_2 \text{ is under CRS},
\end{aligned} \tag{LP2}$$

where π_y^m, π_x^n, and π_x^p are the shadow values associated with the desirable outputs, nonpolluting inputs, and polluting inputs rendered by subtechnology T_1, and ω_x^p and ω_z^j are the shadow values associated with the polluting inputs and undesirable outputs resulting in subtechnology T_2, and v_1, v_2 allow for VRS. As one can note, the two shadow values for the pollution-generating inputs vary across the two subtechnologies (π_x^p and ω_x^p). Indeed, this is due to the lack of link between these subtechnologies. Therefore, the shadow prices of the pollution-generating inputs differ depending on the shadow values used (shadow price equals the ratio of shadow value of a pollution-generating input to that of a desirable output multiplied by the market price of a desirable output). Although the directional by-production model above can solve the limitation discussed in Remark 1, we also detect an issue for this setting of the by-production approach:

Remark 4: *These two sets of different shadow prices of pollution-generating inputs across subtechnologies represent their dual role as inputs and outputs.*

Moreover, the calculation of the input-oriented measures of efficiency is complicated as the optimal values for pollution-generating inputs may be different across the two subtechnologies. The fifth constraint of LP1 does not guarantee a reduction of pollution-generating inputs as the benchmark input quantities can be higher than the observed ones (this is implied by inequality sign "≥"). Thus, it may undermine the TFP calculation that considers both input- and output-oriented measures.

To remedy this inconsistency, we further propose a refined directional by-production model in the next subsection.

A Refined Model with Single Shadow Prices of Pollution-Generating Inputs

As it was noted in section "Directional by-production model and its dual formulation," the two vectors of prices of pollution-generating inputs appear due to the lack of the link between the two subtechnologies. Therefore, Lozano (2015) followed the principles of the network DEA (Kao, 2017) and devised the free-link network slack-based model. Here, we resort to the case of DDF and present the envelopment form of the modified primal model, which clearly depicts the link between the two subtechnologies:[ii]

$$
\begin{aligned}
& D^b\big(\mathbf{x}^a,\ \mathbf{y}^a, \mathbf{z}^a;\ \mathbf{0}, \mathbf{g}_y^a, \mathbf{g}_z^a\big) \ = \ \max_{\delta,\theta,\lambda,\sigma} \delta \\
s.t.\ & \sum_{k=1}^{K} \lambda_k y_k^{m,b} \geq y_{k'}^{m,a} + \delta g_y^{m,a}, \quad \forall m = 1, \ldots, M, \\
& \sum_{k=1}^{K} \lambda_k x_k^{n,b} \leq x_{k'}^{n,a}, \quad \forall n = 1, \ldots, N, \\
& \sum_{k=1}^{K} \lambda_k x_k^{p,b} \leq x_{k'}^{p,a}, \quad \forall p = 1, \ldots, P, \\
& \sum_{k=1}^{K} \sigma_k x_k^{p,b} \boxed{= \sum_{k=1}^{K} \lambda_k x_k^{p,b}}, \forall p = 1, \ldots, P, \\
& \sum_{k=1}^{K} \sigma_k z_k^{j,b} \leq z_{k'}^{j,a} - \delta g_z^{j,a}, \forall j = 1, \ldots, J, \\
& \sum_{k=1}^{K} \lambda_k = 1, \\
& \sum_{k=1}^{K} \sigma_k = 1, \\
& \lambda_k \geq 0, \quad \forall k = 1, \ldots, K, \\
& \sigma_k \geq 0, \quad \forall k = 1, \ldots, K,
\end{aligned} \tag{LP3}
$$

where the fourth constraint ensures that the benchmarks (i.e., the resulting linear combinations rather than both sets of weights) for the two subtechnologies

[ii] Note that we omit constraint $\sum_{k=1}^{K} \sigma_k x_k^{p,b} \leq x_{k'}^{p,a}, \forall p = 1, \ldots, P,$ which is redundant due to the third and fourth constraints in LP3.

coincide. This new constraint requires that polluting inputs used in two subtechnologies are essentially equivalent. As the activity variables λ and σ allow for the presence of two subtechnologies, the corresponding shadow prices of polluting inputs in the dual model then appear to be the same (hence "single" prices) across the two frontiers. The shadow prices of polluting inputs implied by the third constraint in LP3 are related to production of desirable outputs only. Conversely, the shadow prices of pollution-generating inputs implied by the fourth constraint in LP3 play a dual role in both subtechnologies and, thus, should be decomposed into two parts for desirable and undesirable outputs, respectively (this issue will be further discussed in LP4). In addition, subtechnology T_2 assumes joint disposability of pollution-generating inputs and undesirable outputs. We highlight the difference between LP1 and LP3 in the rectangular-shaped area.

Indeed, there have been several attempts to establish a single benchmark for the two subtechnologies. For instance, Dakpo et al. (2017) kept the constraints presented in Equations NLP1 and LP1 and supplemented the model with equality of the optimal values (linear combinations) of polluting inputs in the two subtechnologies (cf. equation (1) in Dakpo et al., 2017). Ray et al. (2018) further set the linear combination of polluting input in T_2 equal to the observed quantity and assumed that intensity variables would sum up to less than unity in T_2 (cf. equation (30) in Ray et al., 2018). Both of the latter two settings, indeed, imply that the benchmarks for the pollution-generating inputs must equal the observed quantities thereof. In this regard, the model given in LP3 allows for more flexibility as the optimal quantity of the pollution-generating inputs is allowed to be equal to or lower than the observed quantity. Furthermore, the fourth constraint in LP3 ensures that the potential productivity level is properly estimated when solving LP3. Indeed, the distance to the frontier can be underestimated in case the optimal levels of inputs do not correspond across the two subtechnologies. A simple example to illustrate this issue is provided in online Annex A. As it was already told, Lozano (2015) offered an exit for this shortcoming and proposed the more relaxed linkage between the two subtechnologies.

The corresponding dual program of LP3 is presented in Equation LP4. We modify the dual program given by EquationLP2 by augmenting the shadow value of the pollution-generating inputs in T_1 so that it would include the shadow value of pollution-generating inputs resulting from subtechnology T_2. Therefore, the virtual profit of T_1 is adjusted to account for the shadow price of pollution-generating inputs rendered by subtechnology T_2. The modified linear program for by-production model with single prices for pollution-generating inputs is given as follows:[iii]

$$D^b(\mathbf{x}^a,\ \mathbf{y}^a,\mathbf{z}^a;\ \mathbf{0},\mathbf{g}_y^a,\mathbf{g}_z^a) \ = \min_{\pi_y,\pi_x^n,\psi_x^p,\omega_x^p,\omega_z,v_1,v_2} \left[\sum_{n=1}^{N} \pi_x^n x_{k'}^{n,a} + \sum_{p=1}^{P} \psi_x^p x_{k'}^{p,a} - \sum_{m=1}^{M} \pi_y^m y_{k'}^{m,a} - v_1 + \sum_{j=1}^{J} \omega_z^j z_{k'}^{j,a} + v_2 \right]$$

[iii] Note that the objective function contains term $\sum_{p=1}^{P} \omega_x^p x_k^{p,a}$ twice (with plus and minus sign) after the transformation. We omit this term from LP4 for the sake of brevity.

$$
\begin{aligned}
s.t.\ & \sum_{m=1}^{M} \pi_y^m y_k^{m,b} - \sum_{n=1}^{N} \pi_x^n x_k^{n,b} - \left(\sum_{p=1}^{P} \psi_x^p x_k^{p,b} + \sum_{p=1}^{P} \omega_x^p x_k^{p,b} \right) + v_1 \leq 0, \\
& \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \forall k = 1, \ldots, K, \\
& \sum_{p=1}^{P} \omega_x^p x_k^{p,b} - \sum_{j=1}^{J} \omega_z^j z_k^{j,b} - v_2 \leq 0, \quad \forall k = 1, \ldots, K, \\
& \sum_{m=1}^{M} \pi_y^m g_y^{m,a} + \sum_{j=1}^{J} \omega_z^j g_z^{j,a} = 1, \\
& \pi_y^m \geq 0, \quad \forall m = 1, \ldots, M, \\
& \pi_x^n \geq 0, \quad \forall n = 1, \ldots, N, \\
& \psi_x^p \geq 0, \quad \forall p = 1, \ldots, P, \\
& \omega_z^j \geq 0, \quad \forall j = 1, \ldots, J, \\
& v_1 = 0 \text{ if } T_1 \text{ is under CRS}, \ v_2 = 0 \text{ if } T_2 \text{ is under CRS}.
\end{aligned} \tag{LP4}
$$

Here, we also highlight the difference between LP2 and LP4 in rectangular-shaped areas. The shadow prices of pollution-generating inputs (π_x^p) are explicitly decomposed into two parts: one (ψ_x^p) represents the role of producing desirable outputs; another (ω_x^p) is related to the generation of undesirable outputs. The latter variables are the common factor that provides the link between the two subtechnologies. Now, LP4 can provide a clear economic explanation of the underlying mathematical model: (i) the objective function is to maximize the operating shadow profit (revenue less cost) based on T_1 and T_2; (ii) compared to LP2, the first and second constraints in LP4 share a common factor $\sum_{p=1}^{P} \omega_x^p x_k^{p,b}$ with opposite signs that implies an optimal cost of polluting inputs used to generate bad outputs. In LP2, this element had not been explicitly separated from the cost of producing good outputs, which might have caused ambiguous economic interpretation. Therefore, the proposed model establishes the link between two subtechnologies with clear economic interpretation.

Note that the modification of the shadow values and, consequently, virtual profits in a subtechnology implies a change in the overall shadow profit. Specifically, the virtual profit for the whole production system is now based on a single vector of prices of the pollution-generating inputs (as opposed to two vectors in Equation LP2).

iii Measures of the TFP Change

The final stage we propose is to convert the efficiency problem in the productivity problem. Briec and Kerstens (2004) proposed the LHM indicator, which is regarded as a TFP measure. Compared to technological productivity indicators, the LHM has some merits. As an additively complete TFP measure, it can be expressed in terms of changes in the aggregate input and output. The additive nature also allows for zero values in inputs and outputs.

We follow Ang and Kerstens (2017) and Balezentis et al. (2017) to decompose the change in the TFP by means of the LHM indicator. Distance functions rendered by Equations LP3 or LP4 are employed for computation of the measures of TFP change. Note that, in some cases, the inputs and outputs come from different periods—which allows measuring the gradient of the production frontier. In the latter instances, the variables (input/output quantities and corresponding directional vectors) are mixed on the right-hand side of Equations LP4, whereas the changes in LP3 occur constraint-wise. In addition, input DDFs are involved into the calculations.

The change in the TFP is calculated as follows:

$$LHM^{t,t+1} = \frac{1}{2}\begin{pmatrix} [D^t(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t) - D^t(\mathbf{x}_k^t, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})] \\ -[D^t(\mathbf{x}_k^{t+1}, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{0}) - D^t(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{g}_x^t, \mathbf{0}, \mathbf{0})] \\ +[D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t) - D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})] \\ -[D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{0}) - D^{t+1}(\mathbf{x}_k^t, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^t, \mathbf{0}, \mathbf{0})] \end{pmatrix}, \tag{6}$$

where positive values indicate the gains in the TFP. Specifically, the TFP is measured in regard to changes in the input use, production of the desirable outputs, and generation of the undesirable ones.

The TFP decomposes into the three terms with each of them representing the effects of the technical efficiency change, technical change, and scale efficiency change:

$$LHM^{t,t+1} = TEC^{t,t+1} + TP^{t,t+1} + SEC^{t,t+1}. \tag{7}$$

These terms can be calculated by employing DDFs. The values of the three terms are interpreted in the same manner as it is the case for the LHM indicator.

The term of technical efficiency change captures the change in the TFP due to gains or losses in technical efficiency of a particular DMU (country in our case). In the case of technical efficiency change, the following calculation is applied:

$$TEC^{t,t+1} = D^t(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t) - D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}). \tag{8}$$

The gains in TFP due to the movement of the frontier are measured by the technical change component. The technical change component is obtained by considering distances to frontiers of the two consecutive time periods:

$$TP^{t,t+1} = \frac{1}{2}\begin{pmatrix} [D^{t+1}(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t) - D^t(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t)] \\ +[D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}) \\ -D^t(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})] \end{pmatrix}. \tag{9}$$

Finally, the scale efficiency change component measures the change in the TFP due to movement toward the most productive scale size. The latter component is obtained by measuring the changes in the gradient of the frontier in the region delineated by the input-output vectors for the two subsequent time periods:

$$SEC^{t,t+1} = \frac{1}{2}\begin{pmatrix} \left[D^t\left(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}\right) - D^t\left(\mathbf{x}_k^{t}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}\right)\right] \\ -\left[D^t\left(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t}, \mathbf{z}_k^{t}; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{0}\right) - D^t\left(\mathbf{x}_k^{t}, \mathbf{y}_k^{t}, \mathbf{z}_k^{t}; \mathbf{g}_x^{t}, \mathbf{0}, \mathbf{0}\right)\right] \\ +\left[D^{t+1}\left(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t}, \mathbf{z}_k^{t}; \mathbf{0}, \mathbf{g}_y^{t}, \mathbf{g}_z^{t}\right) - D^{t+1}\left(\mathbf{x}_k^{t}, \mathbf{y}_k^{t}, \mathbf{z}_k^{t}; \mathbf{0}, \mathbf{g}_y^{t}, \mathbf{g}_z^{t}\right)\right] \\ -\left[D^{t+1}\left(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{0}\right) - D^{t+1}\left(\mathbf{x}_k^{t}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^{t}, \mathbf{0}, \mathbf{0}\right)\right] \end{pmatrix}. \tag{10}$$

DATA AND RESULTS

In this section, we apply the proposed measures for a sample of the European countries. More specifically, we focus on the agricultural sector. As the proposed approach needs to be tested in comparison with the conventional approach, this section is divided into two parts. First, we present the results based on the modified by-production approach. Second, we compare the modified by-production model to the conventional one.

Data for European Agriculture

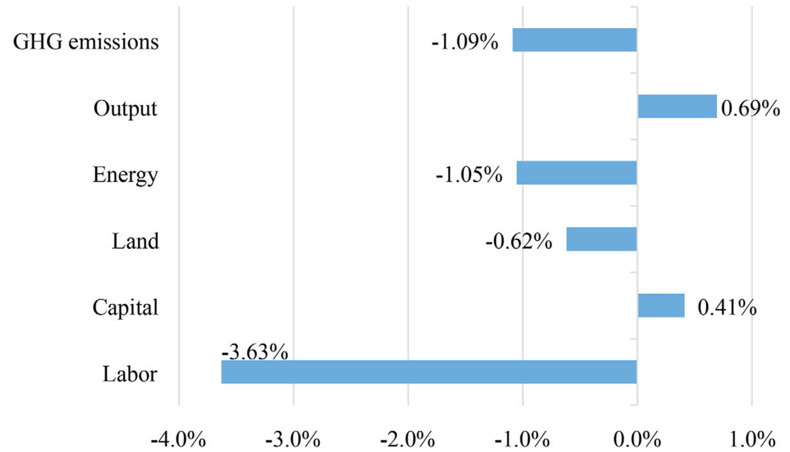
In this article, we seek to estimate the growth in TFP for agricultural sectors of a sample of the European counties. Besides conventional production process, we also focus on environmental pressures caused by energy-related emissions. Therefore, the data from Eurostat (European Commission, 2019) and FAOSTAT (FAO, 2019) databases are applied to describe the environmental technology involving both agricultural production and environmental impacts. The technology includes one desirable output (i.e., agricultural output), one undesirable output (energy-related GHG emission), and four inputs (labor, energy, land, and capital consumption).

The data on agricultural output come from the economic accounts for agriculture provided by Eurostat. Agricultural output is measured in purchasing power standards at the constant prices of 2010. The GHG emission in tones of CO_2 equivalent is obtained from the Eurostat database. Energy-related GHG emission from agriculture (excluding fisheries) is considered.

The data on final energy consumption (measured in tones of oil equivalent) in agriculture and forestry come from the Eurostat energy statistics database. Capital input can be measured by considering the capital stocks (which can be obtained by employing the perpetual inventory method) or capital consumption. In our article, we follow Baráth and Fertő (2017) and consider fixed capital consumption from the economic accounts for agriculture (European Commission, 2019) as a capital input. Fixed capital consumption is measured in terms of purchasing power standards with constant prices of 2010. Data on agricultural land area come from FAOSTAT. Labor input is measured in annual work units and the data are taken from the agricultural labor input statistics database by Eurostat.

Due to data availability, we chose 17 European countries featuring rather similar production structure. These countries are Austria, Belgium, Bulgaria, Czech

Figure 2: Stochastic rates of growth in inputs and outputs for the whole sample, 1995–2016.



Republic, Denmark, Estonia, Finland, France, Hungary, Latvia, Lithuania, the Netherlands, Poland, Romania, Slovakia, Slovenia, and Sweden. The data cover years 1995–2016. The missing values have been extrapolated by using the most recent data. Germany has been dropped from the analysis due to lack of the data.

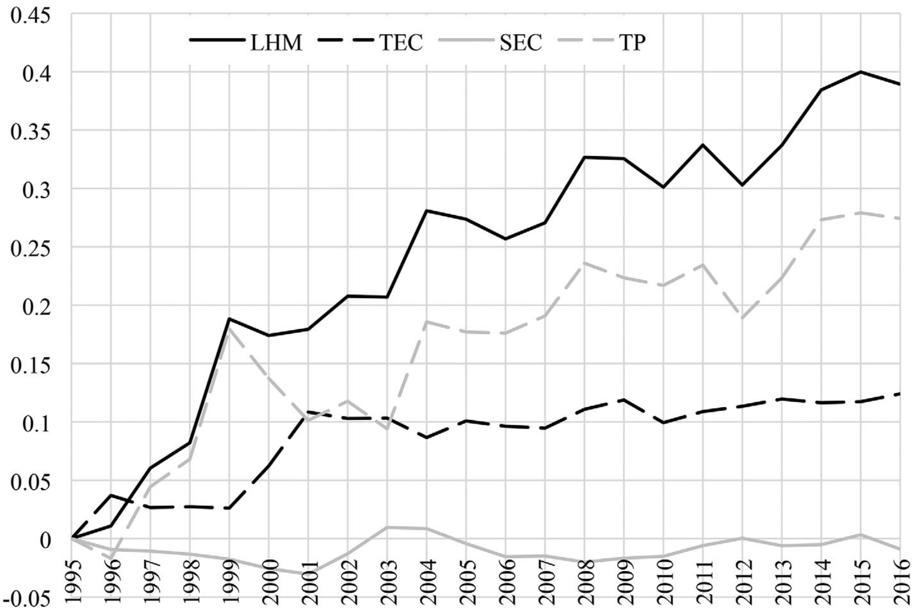
Application of the Modified By-Production Model

The period of 1995–2016 marked an increasing output level and decrease in both input use and undesirable output at the sample level. The dynamics in inputs and outputs for the whole sample is given in Figure 2. The input use decreased by 0.62–3.63% per annum on average with exception for capital consumption, which went up by 0.41% per annum on average. These trends indicate the increasing capital intensity, which is linked to mechanization and automatization of agriculture in Europe (as well as in other parts of the world). However, the average annual growth rate of the agricultural output was 0.69% for 1995–2016. Therefore, all the inputs showed lower rates of growth if compared to agricultural output.

The aggregate energy-related GHG emission declined by some 1.09% per annum on average. Again, this value is lower than the growth in the desirable output. These findings imply that both conventional TFP based on the changes in the (aggregate) input and desirable output and environmental TFP based on the changes in the (aggregate) input and output increased at the sample level during 1995–2016. However, this finding does not preclude the presence of the opposite trends in certain countries.

As it was shown in Equation (7), the change in TFP decomposes into the three terms associated with different sources of productivity gains or losses. Figure 3 presents the cumulative results for 1995–2016. The environmental TFP went up at an average annual rate of 1.73% during the period covered. The growth in TFP was especially robust during the initial period of 1995–1998. The subsequent

Figure 3: Decomposition of the LHM indicator based on the modified by-production approach (average values for the sample), 1995–2016.

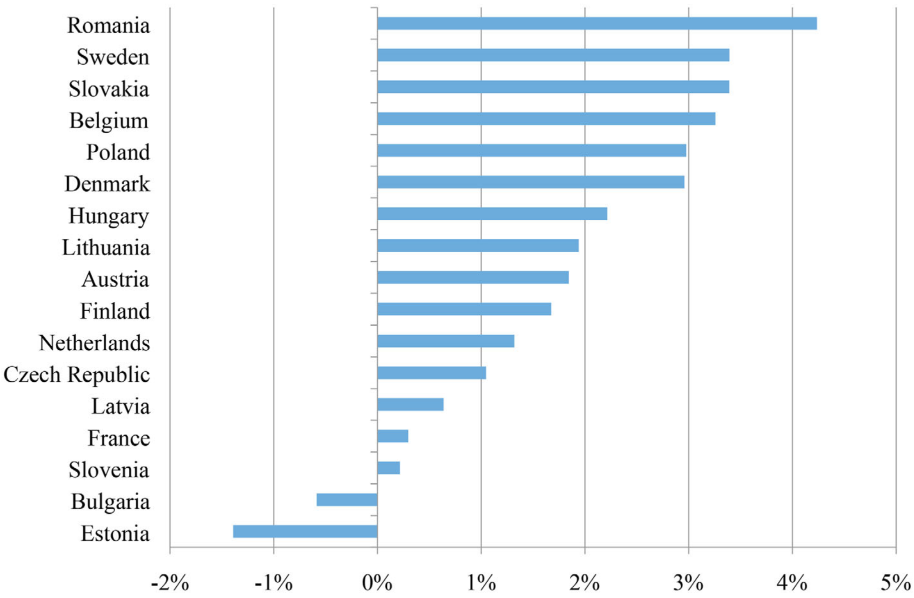


stagnation during 1998–2000 can be attributed to the Asian crisis and the resulting turmoil in the European food and agricultural commodity markets. More specifically, declining prices did not stimulate agricultural production and investments into modern farming practices. However, the growth in the TFP continued during the period of 2001–2008 with certain declines due to unfavorable climatic conditions in most cases. The economic crisis of 2008 rendered subdued growth in the agricultural TFP during 2008–2010 with a recovery afterward.

Component-wise, much of the growth in the environmental TFP can be attributed to technical progress. This implies that the production frontier moved outward with respect of the point of the origin for the countries surveyed during the period of 1995–2016. The annual growth rate of technical progress was 1.2 p.p. Technical efficiency change contributed to the average cumulative TFP change by 12.4% during 1995–2016 with the average annual stochastic growth rate of 0.5 p.p. This indicates the magnitude of the gains in the TFP from country-specific movement toward the production frontier due to country-specific technological innovations. The remaining component—scale efficiency change—had a negligible effect on growth in the TFP. Specifically, the average cumulative effect of the scale efficiency change was close to zero. This estimate indicates the gains in TFP due to movement toward the most productive scale size. Of course, such movements are rather limited in the case of certain agricultural inputs (e.g., labor and land).

We further seek to explore the differences among the countries surveyed in terms of the annual TFP growth rate. Figure 4 presents the stochastic rates of growth

Figure 4: Annual stochastic growth rates in TFP for selected countries, 1995–2016.

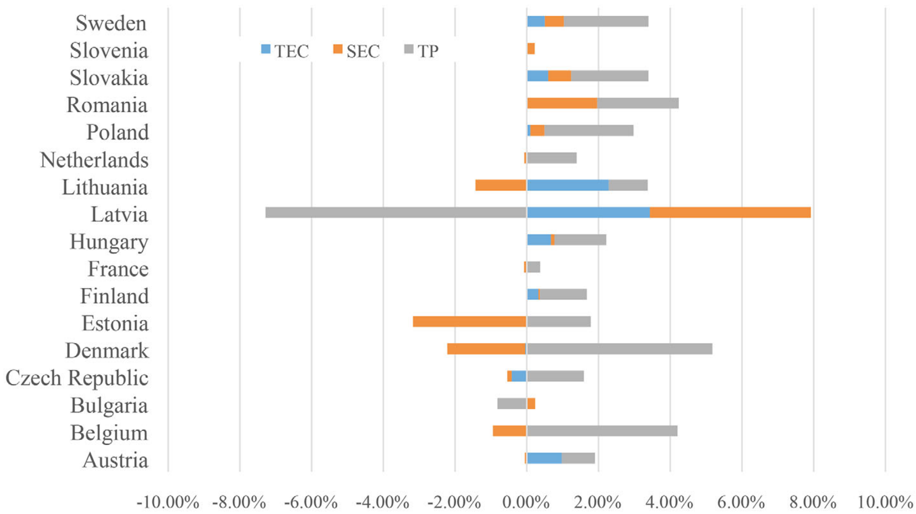


of the environmental TFP based on the modified LHM indicator. The negative growth rates were observed for two countries, namely Estonia and Bulgaria. As regards Estonia, the country exhibited the steepest decrease in the TFP of 1.39% per annum. The rate of growth for Bulgaria was –0.59% per annum. These results are related to an increased carbon emission factor there.

France, Latvia, and Slovenia showed the average growth rates ranging in between 0.2% and 0.6%. These countries did not manage to decouple energy-related GHG emission from economic growth in agriculture. For Czech Republic, Austria, Lithuania, the Netherlands, and Finland, the growth rates of 1.1–2% were observed during 1995–2016. The latter group of countries managed to improve their environmental and economic performance, yet still remained below the average intensity of resource use of environmental pressures. Lithuania, Denmark, Poland, Belgium, Slovakia, and Sweden exhibited the rates of growth scattered around 3%. Finally, Romania was attributed with the highest rate of growth of 4.2%. This country managed to increase its agricultural output along with remarkable savings in input use and energy-related GHG emission.

As it is shown by Equation (7), the LHM indicator decomposes into three parts. Accordingly, Figure 5 presents the decomposition of the rates of growth given in Figure 4. As it is suggested by decomposition of the sample average (Figure 3), much of the change in the environmental TFP can be explained by technical progress. However, certain countries showed divergence from the latter pattern.

Figure 5: Decomposition of the average growth rates of TFP for selected countries, 1995–2016.



Slovakia and Poland showed positive contributions of the technical efficiency change component. This indicates the two countries reduced their inefficiencies and moved closer to the production frontier. The contributions of the scale efficiency change component appeared for more countries than it was the case with the technical efficiency change component. However, the directions of this contribution varied. For instance, Bulgaria, Finland, Lithuania, and Sweden all benefited from gains in scale efficiency. On the contrary, Denmark, Belgium, and Slovakia saw a decrease in their environmental TFP due to movement further from the point of the most productive scale size. This indicates the need for improvements in factor utilization in some countries.

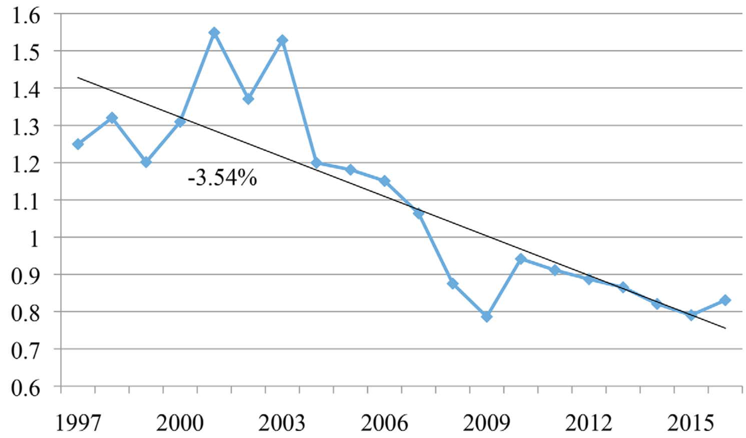
The convergence among the European countries in terms of their levels of the cumulative environmental TFP poses yet another important facet of the analysis. To test the convergence, we fitted the linear regression where the coefficient of variation (calculated for the cumulative TFP within a certain year) was conditioned on the time index. The results are given in Figure 6.

As the trend line coefficient in Figure 6 suggests, there has been a general tendency of decrease in the coefficient of variation over the time. Therefore, the results imply that the countries covered in the study tended to converge in terms of the environmental TFP. However, the empirical trend followed the S-shape, thus implying cyclical behavior of the sample countries.

Comparison with the Conventional Model

For the sake of brevity, we refer to the modified approach presented in this article as the "new" model, whereas the initial by-production model proposed by Murty et al.

Figure 6: Dynamics in the coefficient of variation for the cumulative TFP, 1995–2016.



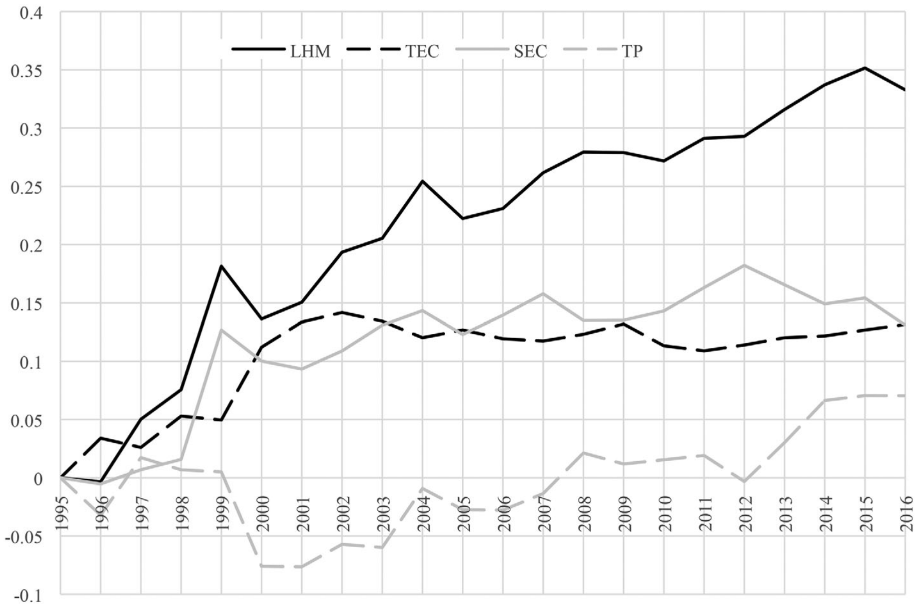
Note: The period of 1995–1996 has been removed due to excessively high value of the coefficient of variation.

(2012) is referred to as the conventional approach (Equations (1) and (2)). Note that we use DDF in both cases. We begin the exposition by presenting the dynamics in the average cumulative environmental TFP (Figure 7). The conclusions obtained by applying the conventional model are virtually the same as those based on the modified approach with some quantitative (rather than qualitative) differences.

The conventional approach identified the same shocks in the TFP change. Decomposition of the overall TFP change yielded the same results as it was the case in the new by-production model, namely the technical progress appeared as the dominating factor of change in the TFP in both settings. The major difference is that the new by-production model yielded higher estimates of the cumulative TFP growth if opposed to the conventional one. Therefore, the restrictions on input quantities imposed in the new model decreased the estimates of growth in the TFP.

As the LHM indicator satisfies the properties of the TFP indicators outlined by O'Donnell (2012), one can decompose the LHM indicator into the input and output change indicators (Ang & Kerstens, 2017). Thus, the conventional and new by-production approach-based indicators can be compared in terms of contributions of the input and output indicators. Figure 8 presents the decomposition of the LHM indicators in terms of input and output contributions. As one can note, the differences mainly occurred on the input side. For Sweden, Slovakia, Poland, the Netherlands, Hungary, France, Finland, and Bulgaria, the contribution to the TFP growth by input indicator increased when switching to the new by-production model. In the case of Hungary, France, and Finland, the direction of the contribution was even reversed. For Romania, Lithuania, Estonia, Czech Republic, and Austria, switching to the new by-production model rendered a decrease in the input indicator.

Figure 7: Decomposition of the LHM indicator based on the conventional by-production approach (average values for the sample), 1995–2016.



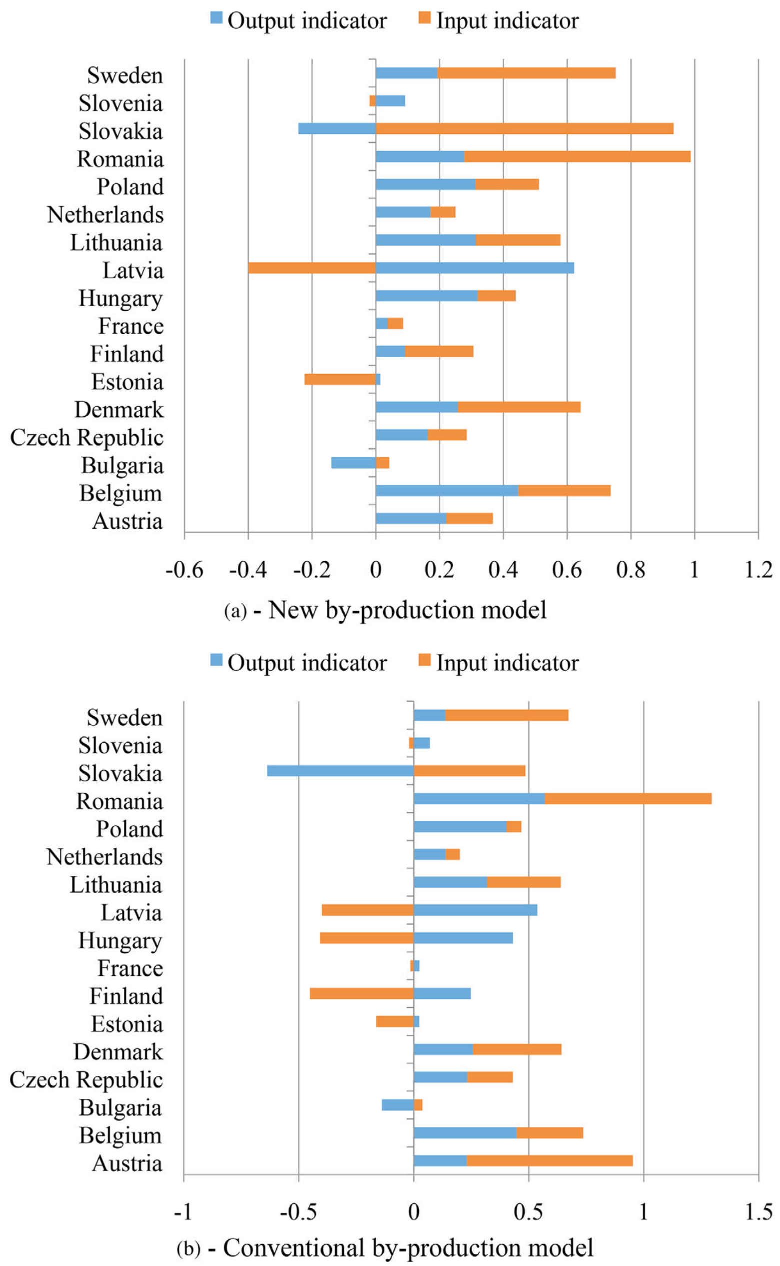
Turning to the output side, Romania, Poland, Lithuania, Hungary, Finland, Estonia, Czech Republic, Bulgaria, and Austria showed a decrease in the output indicator due to switching to the new by-production model. However, the magnitude of such a change varied across the countries. Specifically, Romania, Poland, Hungary, and Czech Republic experienced the steepest decreases. Sweden, Slovenia, the Netherlands, and Latvia saw an increase in the output indicators due to switching to the new by-production model. For Slovakia, the value of the output indicator also went up, yet remained negative.

In general, the input indicator showed more variability than the output indicator across the two settings of the conventional and new by-production models. Specifically, the coefficient of correlation between input (respectively, output) indicators for the new and the conventional models was 0.72 (respectively, 0.91). As it was expected, the restriction on the inputs in the new by-production model has had a stronger effect on the input indicators if opposed to the output ones.

CONCLUSIONS

In this article, the by-production model ensuring the link between the two subtechnologies is compared to the conventional approach. More specifically, we show the economic interpretation of the restriction on the quantities of the pollution-generating inputs by presenting the dual model. Indeed, the extension of the conventional by-production model ensures the presence of a single vector of the shadow values of the pollution-generating inputs.

Figure 8: Contributions of input and output indicators to the LHM indicator.



Notes: Cumulative values for 1995–2016 are presented. The input indicator has been negated in order to depict its contribution to TFP.

The modified by-production model utilizes the generalized DDF. Therefore, the simultaneous expansion of desirable outputs and contraction of the undesirable ones is facilitated when constructing the measures of the environmental TFP. The LHM indicator was adapted for the modified by-production model and decomposed into the components of technical efficiency change, scale efficiency change, and technical progress.

The modified by-production approach was applied to measure the environmental TFP change in agricultural sectors of the selected European countries. The results indicated that a positive change in the environmental TFP was observed during 1995–2016. The major driving force was technical progress. Also, the results suggested that there had been convergence among the countries analyzed in terms of TFP change. Methodologically, we showed that the proposed by-production model rendered lower estimates of TFP if opposed to the conventional by-production model. Furthermore, the input indicator was affected to a higher extent (if compared to the output indicator).

The modification of the by-production model can be applied either in a self-standing manner (for measurement of efficiency and shadow prices) or integrated into the measurement of the TFP. Indeed, other indices and indicators of the TFP can be applied along with the proposed models.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Supporting Information

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Tomas Baležentis is Professorial Research Fellow at Lithuanian Institute of Agrarian Economics and Professor at Vilnius University. He holds PhD degrees from Vilnius University and University of Copenhagen. His research focuses on efficiency and productivity analysis, agricultural economics, and energy economics. He has published in outlets, such as *Energy Economics*, *Energy Policy*, *China Economic Review*, and *European Journal of Operational Research*, among others.

Stéphane Blancard is Full Professor in agricultural economics at AgroSup Dijon (France). A member of CESAER unit, his research deals mainly with the measurement and analysis of the agricultural performance at the farm or country scale. In recent years, a part of his research has also been concerned with the construction of composite indicators to evaluate the economic and energy vulnerability of countries.

Zhiyang Shen is third-level Manager in the Economic Research Division of Strategic Planning Department at the Export-Import Bank of China and Research Fellow at Anhui University of Finance & Economics. He holds a PhD in economics from University of Lille 1, France. He focuses on the efficiency and productivity analysis. He has published in outlets, such as *European Journal of Operational Research*, *OMEGA*, *International Journal of Production Economics*, *China Economic Review*, *Energy Policy*, among others.

Dalia Štreimikienė is Leading Research Associate at Lithuanian Institute of Agrarian Economics and Full Professor at Vilnius University. She holds a PhD degree from Vilnius Gediminas Technical University. Her main areas of research are sustainability assessment in energy and agriculture, climate change mitigation policies, and multicriteria decision aiding support.