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ORIGINAL RESEARCH

An environmental Luenberger–Hicks–Moorsteen total factor productivity indicator: empirical analysis considering undesirable outputs either as inputs or outputs, and attention for infeasibilities

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Abstract
The measurement of economic growth is important for identifying the development patterns followed by different economies. In the light of sustainable development goals, one needs to be able to track the green growth, i.e., they must the adjusted in regard to generation of undesirable outputs that are usually non-marketed. This contribution puts forward an empirical case of the economically developed countries grouped in OECD and measures their total factor productivity (TFP) growth. This is done by exploiting a novel formulation of the Luenberger–Hicks–Moorsteen (LHM) TFP indicator based on the Kuosmanen (Am J Agric Econ 87(4):1077–1082, 2005) proposal. We argue that undesirable outputs must be regarded as special outputs but not inputs in both the production technology and TFP measure. We compare two models: one that considers undesirable outputs as special outputs in the directional distance functions of TFP indicator following Kuosmanen (Am J Agric Econ 87(4):1077–1082, 2005), and another that considers undesirable outputs as inputs following Abad (J Environ Manage 161:325–334, 2015). This proposed approach assumes that input- and output-orientations are taken, with the latter handling both desirable and undesirable outputs simultaneously. Still, we compare our results with those based on the other more conventional frameworks. The empirical case deals with OECD country-level data for 1991–2019. The results suggest that there exist substantial differences in the resulting measures of the TFP growth depending on the distance functions used in the calculation of the LHM indicator.

Keywords Green growth · Total factor productivity · Indicator · Data envelopment analysis · OECD

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1 Introduction

Total factor productivity (TFP) growth can be regarded as a key source of real welfare gains for both producers and consumers. This makes it an omnipresent measure in the scientific analysis dedicated to economic growth and development. Even though the importance of the TFP growth is undeniable, there exists no single-best methodological approach for the measurement thereof (Del Gatto et al., 2011).

There exist different indices and indicators that can be used to gauge the productivity growth. Indeed, O'Donnell (2012) argues that not each of these measures can be termed a TFP indicator or index since some of these cannot completely explain the evolution in the productivity growth due to the input and output changes, i.e., they do not satisfy the completeness property. It is worth noting that such a widely employed measure as the Malmquist productivity index (Caves et al., 1982) does not satisfy the completeness property and therefore it should be termed a productivity index accordingly. Among candidate indices and indicators satisfying the aforementioned completeness property, the Hicks–Moorsteen index (Bjurek, 1996) can be considered.

The Hicks–Moorsteen index features a certain drawback in that it relies on a multiplicative construction. Such a setting does not allow handling zero values that may potentially be present in empirical data. As a remedy to this issue, Briec and Kerstens (2004) suggest exploiting the additive structure of the Luenberger productivity indicator introduced by Chambers (2002) in the calculations based on the idea of the Hicks–Moorsteen TFP index transposed to the indicator context. Thus, Briec and Kerstens (2004) propose the Luenberger–Hicks–Moorsteen (LHM) TFP indicator as a new measure of TFP growth. In this context, one should note that -despite its popularity- the completeness property is not maintained by the original Luenberger productivity indicator (O'Donnell, 2012), but the LHM TFP indicator is additively complete.

A number of options are available for practical implementation of the (total factor) productivity measures. In general, one distinguishes between the parametric and nonparametric strands of the analysis. The parametric approach rests on particular functional forms used for approximation of the representation of the underlying technology. The nonparametric approach treats time in a discrete manner and representations of the production technology are established for each time period subject to certain economic axioms. This latter approach is based on the activity analysis framework (Koopmans, 1953) and its reformulation is known as nonparametric frontier modelling (Data envelopment Analysis (DEA): see Färe et al. (1994)). Atkinson et al. (2003) discuss the calculation and decomposition of the productivity growth based on parametric (stochastic) and nonparametric approaches.

The measurement of productivity growth and economic development has been discussed in the wider context of sustainability. To this end, both national and international actions are being taken to maintain sustainability. Major economies have turned to sustainability-oriented frameworks (e.g., the European Union has adopted the European Green Deal policy). International organizations such as the United Nations have also stressed the need for adopting relevant policies (United Nations, 2015) and measures (United Nations, 2009). In the efficiency and productivity analysis literature, there has been much effort in responding to such societal needs. Ancev et al. (2017) present a survey documenting the major concepts and models for the measurement of green efficiency and productivity growth. Dakpo et al. (2016) and Dakpo and Ang (2019) also provide surveys on production modelling when undesirable outputs need to be accounted for.

In the context of green growth, the use of resources plays a crucial role. For contemporaneous economies, the conversion and use of the energy resources is vital. Such recent trends as supply chain and energy transmission disruptions call for further actions towards sustainable energy systems and economies with lower reliance on fossil materials. Energy use (or conservation) and mix also impact the greenhouse gas emission that can be curbed by improving the energy systems. A decoupling of the economic growth and energy use (Moreau & Vuille, 2018) may be ensured by improving energy efficiency. These points can be addressed by using the nonparametric frontier models (Sueyoshi et al., 2017), among other approaches. The recent studies by Chen and Jin (2020), Moutinho and Madaleno (2021), and Zoriehhabib et al. (2021) apply various methods for representing the production technologies with environmental pressures at different levels of aggregation.

The LHM TFP indicator is also exploited to assess the economic performance in the presence of environmental pressures. This requires the inclusion of relevant variables in the (environmental) production technology and the imposition of additional economic axioms. However, there have been multiple frameworks developed with different methodological implications. The theoretical and empirical comparisons of the LHM TFP indicator and other measures of productivity growth have been offered by Kerstens et al. (2018) who discuss the relationships with the Luenberger indicator, and by Ang and Kerstens (2020) who shed light on the Bennett indicator as a superlative version of the LHM indicator. Abad (2015) utilizes the output and input directional distance functions to develop an environmentally adjusted TFP measures and presents an LHM TFP indicator whereby undesirable outputs are included in the production technology and the distance functions. However, the input distance function of the Abad (2015) approach suggests reducing the inputs and undesirable outputs simultaneously for a given level of desirable outputs. While such a setting may seem appealing in its interpretation, we think that it makes the difference between inputs and undesirable outputs less clear from a methodological viewpoint. This is why we propose an alternative framework based on Kuosmanen (2005) instead of Abad (2015).

The empirical applications of the LHM indicator adjusted for undesirable outputs are relatively scarce. The study by Managi and Kaneko (2006) is the earliest attempt to utilize the LHM TFP indicator for measurement of the environmental-economic performance. Still, the latter study relies on the strong disposability of the undesirable outputs without focusing on the different roles of the desirable and undesirable outputs. Focusing on recent examples, one can mention, e.g., Mocholi-Arce (2021) who apply the LHM indicator for environmentally adjusted measurement of water companies' TFP growth. Also, Hamid and Wang (2022) use the LHM indicator to measure the productivity gains in South Asian agriculture.

In this contribution, we offer an alternative formulation of the distance functions involved in the calculations of the LHM TFP indicator for green growth. The proposed LHM TFP indicator is constructed based on definitions by Briec and Kerstens (2004). In particular, we build our model on the premises of the weak disposability technology as described by Kuosmanen (2005). To the best of our knowledge, we are the first LHM TFP indicator that employs the Kuosmanen (2005) weak disposability technology to measure green growth. Contrary to much of the earlier literature, we suggest using the output distance function for measuring inefficiency associated with both desirable and undesirable outputs. In another context, this has been done by, e.g., Vardanyan et al. (2006). The green LHM TFP indicator is decomposed into the three terms each relating to (i) frontier shift, (ii) catch-up, and (iii) scale change. This decomposition is in line with Diewert and Fox (2014, 2017) and Ang and Kerstens (2017). The LHM TFP indicator with this decomposition of Diewert and Fox (2014, 2017) and Ang and Kerstens (2017) is also applied in the studies by Hamid and Wang (2022) and Tang and He (2021), among others.

To be precise, this study offers four major contributions. First, even though there have been articles applying LHM TFP indicators with undesirable outputs, this is -to the best of our knowledge- the first integration of Kuosmanen's (2005) formulation in the LHM indicator. Furthermore, it is certainly the first empirical application for the OECD economies. Second, the LHM TFP indicator is well-defined for weak conditions imposed upon a technology (Briec & Kerstens, 2011): notably strong disposability. Therefore, infeasibilities may occur for environmental production technologies that impose weak disposability following Kuosmanen (2005). Thus, we report the infeasibility patterns in our analysis. Third, we compare the estimates of the green TFP growth obtained by the LHM TFP indicator based on different environmental production technologies. In particular, we contrast the Abad (2015) proposal with our own based on the Kuosmanen (2005) formulation. Fourth, we are among the few to apply the notion of innovative countries proposed in Färe et al (1994) to see which OECD countries shift the production frontiers over time. This approach to identify the innovative observations based on the frontier movement over time has also been applied in studies by, e.g., Beltrán-Esteve and Picazo-Tadeo (2017), Fujii et al. (2016) and Miguéis et al. (2012), among others.

The OECD countries have received attention in the economic literature due to their dominating role in the global economy. Initially, the focus is on such issues as the TFP growth, technological change, and input markets (Chen & Yu, 2014; Maudos et al., 1999). The developed economies require not only sustaining economic growth and development but also tackling the sustainability goals. This has been stressed in recent research on the OECD countries. For instance, Sinha et al. (2022) assess the waste generation in the OECD countries considering different contextual variables related to policies, governance, economic structure etc. Chen et al. (2018) factorize the carbon dioxide emission in the OECD countries taking the economic growth into consideration. Thus, the TFP analysis should also be revisited by incorporating the undesirable outputs related to sustainability goals in the analytical models. This contribution focuses on a nonparametric modelling of the underlying environmental production technology and its use for measurement of the adjusted TFP growth. The empirical data for 1991–2019 are employed for the analysis.

2 Methods

In this section, the major principles applied for the nonparametric analysis of the green TFP growth are discussed. The cornerstone of the model is the environmental production technology that is established in line with Kuosmanen (2005). The directional distance function is then defined in its general form. Finally, the computations allowing for a decomposition of the LHM TFP indicator are discussed along with the relevant linear programs.

2.1 Environmental production technology and directional distance function

On the premises of the activity analysis framework, we assume that multiple inputs are transformed into multiple outputs, including desirable and undesirable ones. The quantities of inputs are denoted by $\mathbf{x} \in \mathbb{R}_+^N$, the quantities of the desirable outputs are represented by $\mathbf{y} \in \mathbb{R}_+^M$, and the quantities of the undesirable outputs are given by $\mathbf{z} \in \mathbb{R}_+^J$. For a given time period index t, the environmental production technology can be described as a set:

$$T(t) = \left\{ (\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t) \in \mathbb{R}_+^{N+M+J} : \mathbf{x}^t \text{ can produce } \left(\mathbf{y}^t, \mathbf{z}^t\right) \right\}. \tag{1}$$

This environmental production technology satisfies usual assumptions, such as no free lunch, convexity, strong disposability of inputs and good outputs, the weak disposability of undesirable outputs as introduced by Shephard (1970) and Shephard and Färe (1974), and the null-jointness condition linking desirable and undesirable outputs (e.g., Färe & Grosskopf, 2004). These production axioms of no free lunch (A1), convexity (A2), strong disposability of inputs and desirable outputs (A3), weak disposability of undesirable and desirable outputs (A4), and null-jointness assumption (A5) are defined as follows:

$$\begin{aligned}
&\text{A1}: (0,\ 0, 0) \in T(t) \ \text{ and if } \ (0, \mathbf{y}^t, \mathbf{z}^t) \in T(t), \ \text{ then } \ \mathbf{y}^t = 0 \ \text{ and } \ \mathbf{z}^t = 0;\\
&\text{A2}: T(t) \ \text{ is convex};\\
&\text{A3}: \text{If } (\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t) \in T(t) \ \text{ and } (\mathbf{x}^t, -\mathbf{y}^t, -z^t) \le (\tilde{\mathbf{x}}^t, -\tilde{\mathbf{y}}^t, -\tilde{\mathbf{z}}^t), \ \text{then } (\tilde{\mathbf{x}}^t, \tilde{\mathbf{y}}^t, \tilde{\mathbf{z}}^t) \in T(t);\\
&\text{A4}: \text{If } (\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t) \in T(t) \ \text{ and } \ 0 \le \theta \le 1, \ \text{ then } \ (\mathbf{x}^t, \theta\mathbf{y}^t, \theta\mathbf{z}^t) \in T(t);\\
&\text{A5}: \text{If } (\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t) \in T(t) \ \text{ and } \ \mathbf{y}^t = 0, \ \text{ then } \ \mathbf{z}^t{=}0.
\end{aligned} \tag{2}$$

The no free lunch (A1) axiom permits for inaction and prevents positive outputs from being produced from zero inputs. Axiom (A2) allows for convexity of the technology. Axiom (A3) implies that production plans dominated by the efficient frontier production plans are feasible: thus, inputs can be wasted and desirable and undesirable outputs can be destroyed. To incorporate undesirable outputs into the production technology, the additional assumptions of weak disposability (A4) and null-jointness (A5) of good and bad outputs are usually introduced. Axiom (A4) reflects that a unique constraint θ is imposed on both desirable and undesirable outputs allowing for proportional decreases in both outputs. The null-jointness assumption (A5) requires that undesirable outputs can only be eliminated if and only if desirable outputs are also at null level.

Optimization of the economic activities must obey some economic logic. Taking into account the nature of the environmental production technology, one considers the possibilities to improve the key elements of a production plan. Specifically, conservation of resources (inputs), augmentation of production of the desirable (marketed) outputs, and limiting the generation of undesirable outputs are the key objectives. Obviously, the conservation of resources is beneficial from cost-saving and/or environment-oriented perspectives. Similarly, the reduction in generation of the undesirable outputs is required to curb the unintended environmental pressures and, possibly, mitigate the abatement costs. As for the desirable outputs, an increase in the production levels thereof (at the given or lower input levels) creates the economic surplus. These considerations can be embedded in the activity analysis framework via the directional distance functions (DDFs). The generalized DDF (Chung et al., 1997; Färe et al., 2005) defines a simultaneous adjustment as discussed above of the input and output variables observed for a certain time period $a \in \{t, t+1\}$ given a technology established for time period $b \in \{t, t+1\}$. In particular, the aforementioned generalized DDF can be formally given as:

$$D^b(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a;\ \mathbf{g}_x^a, \mathbf{g}_y^a, \mathbf{g}_z^a) = \max\left\{\delta \ \in \ \mathbb{R}_+ : \ (\mathbf{x}^a - \delta\mathbf{g}_x^a, \mathbf{y}^a + \delta\mathbf{g}_y^a, \mathbf{z}^a - \delta\mathbf{g}_z^a) \ \in \ T(b)\right\}, \tag{3}$$

where vector $\mathbf{g} = (\mathbf{g}_x^t,\ \mathbf{g}_y^t, \mathbf{g}_z^t) \in \mathbb{R}_+^{N+M+J}$ sets the directions for adjustment in the inputs, desirable outputs, and undesirable outputs. The inefficiency (i.e., the adjustment required in the inputs and outputs as indicated by the vector $\mathbf{g}$) is then measured by the scalar δ that exceeds zero value in the presence of technical inefficiency and is zero otherwise. Observe that the presence of time indexes, a and b, allows one to measure the mixed-period inefficiencies. In such mixed-period cases, δ may become negative.

2.2 Environmental LHM indicator and its decomposition

In this sub-section, we discuss the key definitions necessary to establish the green LHM TFP indicator and its components. The competing approaches for handling the undesirable outputs in the environmental production technology are also covered. These differences carry over to the distance functions that are used for constructing the LHM indicator.

2.2.1 An environmental LHM indicator

Briec and Kerstens (2004) put forward the LHM productivity indicator that decomposes in an additive fashion so as to satisfy the completeness condition described in O'Donnell (2012). This makes this LHM indicator a TFP measure. In this contribution, we seek to further enhance the LHM TFP indicator by considering the undesirable outputs in addition to the inputs and desirable outputs that are conventionally used in the efficiency and productivity analysis. The resulting measure can gauge the green TFP growth that is relevant in the light of the sustainability considerations.

It is well known that the undesirable outputs can enter the efficiency and productivity analysis models in several manners. Even putting the issue of the environmental production technology aside, the measures of the environmental-economic efficiency and productivity growth can be designed in the following strands: see the surveys by Ancev et al. (2017), Dakpo et al. (2016), and Dakpo and Ang (2019). As the inputs and undesirable outputs need to be minimized, it is natural to consider them in the same DDF and arrive at a straightforward interpretation of the resulting efficiency measure. Another option is to consider adjustments in the inputs and output (both desirable and undesirable ones) separately in the sense of the DDFs. We establish a weakly disposable technology and adapt the generalized DDF in (3) to the latter case that resembles Vardanyan and Noh (2006).

Productivity change can be gauged by relying on a change in the distance to a fixed frontier throughout two time periods. In the case of the LHM TFP indicator, the measurements of the distances to the frontiers (surfaces) are carried out in two ways: (i) by minimizing the input use or (ii) by simultaneously minimizing the generation of the undesirable outputs and augmenting the production of the desirable outputs. Note that the output levels, resp. input levels, are fixed in the case of (i), resp. (ii). The directional vector $\mathbf{g}$ is adjusted to take the required direction of the movement towards the production frontier surface into account.

Let us consider two time periods t and $t+1$. When period t is treated as the base, then the green LHM TFP indicator relies on the average of the changes in the input- and output-oriented distances to the production surface:

$$LHM^t = \begin{pmatrix} [D^t(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t) - D^t(\mathbf{x}_k^t, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})] \\ -[D^t(\mathbf{x}_k^{t+1}, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{0}) - D^t(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{g}_x^t, \mathbf{0}, \mathbf{0})] \end{pmatrix}, \quad (4)$$

where the first two terms on the right-hand-side indicate the alteration in the distance to the production surface when input quantities are fixed at time period t and output quantities change with time, and the last two terms reflect the dynamics in the distance to the production surface of time period t assuming outputs (both desirable and undesirable ones) are fixed at time period t and the input quantities change with time. Thus, the change in the output-oriented distance is reduced by the change in the input-oriented distance. The value of $LHM^t > 0$ indicates an increase in TFP, whereas $LHM^t < 0$ implies a decline in the TFP.

Analogously, time period $t + 1$ can be treated as the base period. Then, the LHM TFP indicator is reformulated as:

$$LHM^{t+1} = \begin{pmatrix} [D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t) - D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})] \\ -[D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{0}) - D^{t+1}(\mathbf{x}_k^t, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^t, \mathbf{0}, \mathbf{0})] \end{pmatrix}. \tag{5}$$

with an interpretation very similar to (4).

The two LHM TFP indicators in (4)–(5) relying on different base periods are then unified by taking an arithmetic average to avoid an arbitrary choice between the t and $t + 1$ base periods:

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

2.2.2 Reducing bad outputs along with inputs: an alternative approach

In an alternative approach, when undesirable outputs are regarded as inputs and reduced along with the inputs simultaneously (see, e.g., Abad, 2015 for details), the average of LHM productivity change between periods t and $t + 1$ can be defined as:

$$LHM_{\text{bads as inputs}}^{t,t+1} = \frac{1}{2}\begin{pmatrix} \left[D^t(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_{\mathbf{y}}^{\mathbf{t}}, \mathbf{0}) - D^t(\mathbf{x}_k^t, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{0})\right] \\ -[D^t(\mathbf{x}_k^{t+1}, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{g}_z^{t+1}) - D^t(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{g}_x^t, \mathbf{0}, \mathbf{g}_z^t)] \\ +[D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{0}) - D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{0})] \\ -[D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{g}_z^{t+1}) - D^{t+1}(\mathbf{x}_k^t, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^t, \mathbf{0}, \mathbf{g}_z^t)] \end{pmatrix}, \tag{7}$$

In our empirical application, we compare two possible models for LHM TFP: model (7) where bad outputs are regarded as inputs, and model (6) where these are defined as weakly disposable outputs.

2.2.3 A decomposition for the LHM indicator

As suggested by Diewert and Fox (2014, 2017) and further implemented by Ang and Kerstens (2017), the green LHM TFP indicator can be directly decomposed so as to reveal the sources of the TFP gains by taking either an input or an output orientation. The following three terms of a decomposition can be considered:

$$LHM^{t,t+1} = TEC^{t,t+1} + TP^{t,t+1} + SEC^{t,t+1}, \tag{8}$$

where *TEC* stands for the technical inefficiency change or the catch-up effect, *TP* indicates the technological progress or a frontier shift, and *SEC* captures the productivity gains due to scale (efficiency) change.

In our research, we rely on the output-oriented decomposition of the TFP growth. It can be interpreted as a reduction in the undesirable outputs and an increase in the desirable outputs (at the given input level) due to the TFP growth. Hence, a corresponding subscript is appended to the notations in the equations below. Turning to the first term *TEC* on the right-hand-side of (8), the output-oriented DDFs measure change in the distance to the contemporaneous frontiers (surfaces):

$$TEC^{t,t+1}_{output} = D^t\left(\mathbf{x}^t_k, \mathbf{y}^t_k, \mathbf{z}^t_k; \mathbf{0}, \mathbf{g}^t_y, \mathbf{g}^t_z\right) - D^{t+1}\left(\mathbf{x}^{t+1}_k, \mathbf{y}^{t+1}_k, \mathbf{z}^{t+1}_k; \mathbf{0}, \mathbf{g}^{t+1}_y, \mathbf{g}^{t+1}_z\right), \quad (9)$$

where $TEC^{t,t+1}_{output} > 0$ indicates that a certain observation approached the contemporaneous production frontier over time, i.e., increased its TFP from this viewpoint (the movement and curvature of the frontier are ignored in this term); and $TEC^{t,t+1}_{output} < 0$ indicates a TFP loss due to shifting away from the production frontier over time.

The output-oriented second *TP* term looks at the frontier movement that may occur if novel production technologies are successfully implemented by the best-performing observations (countries) in between two time points. It essentially measures the distances between the production surfaces for periods t and $t+1$ at the input/output bundles for each of these time periods. Assuming the output-orientation, the *TP* term is formally defined as:

$$TP^{t,t+1}_{output} = \frac{1}{2}\left(\begin{array}{l} \left[D^{t+1}(\mathbf{x}^t_k, \mathbf{y}^t_k, \mathbf{z}^t_k; \mathbf{0}, \mathbf{g}^t_y, \mathbf{g}^t_z) - D^t(\mathbf{x}^t_k, \mathbf{y}^t_k, \mathbf{z}^t_k; \mathbf{0}, \mathbf{g}^t_y, \mathbf{g}^t_z)\right] \\ +\left[D^{t+1}(\mathbf{x}^{t+1}_k, \mathbf{y}^{t+1}_k, \mathbf{z}^{t+1}_k; \mathbf{0}, \mathbf{g}^{t+1}_y, \mathbf{g}^{t+1}_z) - D^t(\mathbf{x}^{t+1}_k, \mathbf{y}^{t+1}_k, \mathbf{z}^{t+1}_k; \mathbf{0}, \mathbf{g}^{t+1}_y, \mathbf{g}^{t+1}_z)\right] \end{array}\right), \quad (10)$$

where the gap between frontiers for periods t and $t+1$ is captured at the quantities of period t by the first two terms, and at the quantities of period $t+1$ by the last two terms. The TFP gains are identified by $TP^{t,t+1} > 0$, and TFP loss is represented by $TP^{t,t+1} < 0$.

The last term *SEC* of the decomposition in (8) represents the TFP growth due to changes in the curvature of the production frontiers. Those changes are essentially related to the changes in the distance to the region of a production surface corresponding to the most optimal scale size. The *SEC* term is obtained through a rather complex calculation whereby input- and output-oriented DDFs with inputs and outputs from mixed periods are involved. The changes in the distance to the production surfaces are measured by fixing the inputs (or outputs) and allowing the efficient levels of outputs (or inputs) to vary over time when looking at the surface of either period t or period $t+1$. Assuming an output-orientation, these calculations are given as:

$$\mathrm{SEC}^{t,t+1}_{output} = \frac{1}{2}\left(\begin{array}{l} \left[D^t(\mathbf{x}^{t+1}_k, \mathbf{y}^{t+1}_k, \mathbf{z}^{t+1}_k; \mathbf{0}, \mathbf{g}^{t+1}_y, \mathbf{g}^{t+1}_z) - D^t(\mathbf{x}^t_k, \mathbf{y}^{t+1}_k, \mathbf{z}^{t+1}_k; \mathbf{0}, \mathbf{g}^{t+1}_y, \mathbf{g}^{t+1}_z)\right] \\ -\left[D^t(\mathbf{x}^{t+1}_k, \mathbf{y}^t_k, \mathbf{z}^t_k; \mathbf{g}^{t+1}_x, \mathbf{0}, \mathbf{0}) - D^t(\mathbf{x}^t_k, \mathbf{y}^t_k, \mathbf{z}^t_k; \mathbf{g}^t_x, \mathbf{0}, \mathbf{0})\right] \\ +\left[D^{t+1}(\mathbf{x}^{t+1}_k, \mathbf{y}^t_k, \mathbf{z}^t_k; \mathbf{0}, \mathbf{g}^t_y, \mathbf{g}^t_z) - D^{t+1}(\mathbf{x}^t_k, \mathbf{y}^t_k, \mathbf{z}^t_k; \mathbf{0}, \mathbf{g}^t_y, \mathbf{g}^t_z)\right] \\ -\left[D^{t+1}(\mathbf{x}^{t+1}_k, \mathbf{y}^{t+1}_k, \mathbf{z}^{t+1}_k; \mathbf{g}^{t+1}_x, \mathbf{0}, \mathbf{0}) - D^{t+1}(\mathbf{x}^t_k, \mathbf{y}^{t+1}_k, \mathbf{z}^{t+1}_k; \mathbf{g}^t_x, \mathbf{0}, \mathbf{0})\right] \end{array}\right), \quad (11)$$

where the first four terms represent curvature of the production surface at t and the last four terms relate to the curvature at $t+1$.

In the spirit of Diewert and Fox (2017) and Ang and Kerstens (2017), one can further revise (11) by virtue of the translation property of the DDF (i.e., $D(\mathbf{x} - \delta\mathbf{g}_x, \mathbf{y} + \delta\mathbf{g}_y, \mathbf{z} - \delta\mathbf{g}_z; \mathbf{g}) = D(\mathbf{x}, \mathbf{y}, \mathbf{z}; \mathbf{g}) - \delta$) as follows:

$$SEC_{output}^{t,t+1} = \frac{1}{2}\begin{pmatrix} \left[D^t(\mathbf{x}_k^t, \mathbf{y}_k^{t,*}, \mathbf{z}_k^{t,*}; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t) - D^t(\mathbf{x}_k^t, \mathbf{y}_k^{t+1,**}, \mathbf{z}_k^{t+1,**}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})\right] \\ -\left[D^t(\mathbf{x}_k^{t+1}, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{0}) - D^t(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{g}_x^t, \mathbf{0}, \mathbf{0})\right] \end{pmatrix} + \frac{1}{2}\begin{pmatrix} \left[D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t,**}, \mathbf{z}_k^{t,**}; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t) - D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1,*}, \mathbf{z}_k^{t+1,*}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})\right] \\ -\left[D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^{t+1}, \mathbf{0}, \mathbf{0}) - D^{t+1}(\mathbf{x}_k^t, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{g}_x^t, \mathbf{0}, \mathbf{0})\right] \end{pmatrix}, \tag{12}$$

where projections on the production surface of period t are defined as

$$\begin{aligned} \left(\mathbf{y}_k^{t,*}, \mathbf{z}_k^{t,*}\right) &= \left(\mathbf{y}_k^t, \mathbf{z}_k^t\right) + D^t\left(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t\right)\left(\mathbf{g}_y^t, \mathbf{g}_z^t\right), \\ \left(\mathbf{y}_k^{t+1,**}, \mathbf{z}_k^{t+1,**}\right) &= \left(\mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}\right) + D^t\left(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})(\mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}\right), \end{aligned} \tag{13}$$

and the projections on the production surface of period $t+1$ are

$$\begin{aligned} \left(\mathbf{y}_k^{t,**}, \mathbf{z}_k^{t,**}\right) &= \left(\mathbf{y}_k^t, \mathbf{z}_k^t\right) + D^{t+1}\left(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t\right)\left(\mathbf{g}_y^t, \mathbf{g}_z^t\right), \\ \left(\mathbf{y}_k^{t+1,*}, \mathbf{z}_k^{t+1,*}\right) &= \left(\mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}\right) + D^{t+1}\left(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}\right)\left(\mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}\right). \end{aligned} \tag{14}$$

A single asterisk marks a projection onto a contemporaneous surface whereas a double asterisk indicates a projection onto a surface from another time period. The differences in the distances are rendered by alterations in the efficient levels of inputs and outputs as a result of the movement along the production surface. Thus, the aforementioned differences essentially measure the curvature of the production surface.

2.3 Estimation strategy

As mentioned before, either parametric or nonparametric strands can be followed when calculating or estimating the DDFs. In this research, we resort to the nonparametric approach that (i) allows one avoiding a specification for the functional form for the DDF and (ii) effectively involves desirable economic axioms (e.g., convexity and monotonicity). As a result, the nonparametric frontier method is used to construct a piece-wise linear production frontier surface.

Kuosmanen (2005) and Kuosmanen and Podinovski (2009) propose an improved weak disposability model in the undesirable outputs which also maintains convexity of the production possibility set, as well as variable returns to scale. Following Kuosmanen and Podinovski (2009) we can define the variable returns to scale nonparametric environmental production technology as follows:

$$\hat{T}(t) = \Big\{(\mathbf{x}^t, \mathbf{y}^t, \mathbf{z}^t) \in \mathbb{R}_+^{N+M+J} : \begin{array}{l} \sum_{k=1}^{K} \theta_k \lambda_k y_k^{m,t} \geq y^{m,t}, \quad \forall m = 1, \cdots, M; \\ \sum_{k=1}^{K} \theta_k \lambda_k z_k^{j,t} = z^{j,t}, \quad \forall j = 1, \cdots, J; \\ \sum_{k=1}^{K} \lambda_k x_k^{n,t} \leq x^{n,t}, \quad \forall n = 1, \cdots, N; \\ \sum_{k=1}^{K} \lambda_k = 1; \\ \lambda_k \geq 0, \quad \forall k = 1, ..., K; \\ 0 \leq \theta_k \leq 1, \quad \forall k = 1, ..., K\}, \end{array} \quad . \tag{15}$$

where θ_k are the observation-specific abatement factors.

The empirical calculation of the LHM TFP indicator given by (4) requires solving a series of these linear programming problems. In this sub-section, we present but two instances of such programs, whereas the rest can be easily recovered by analogy. We further consider two programs where input/output bundles observed during time period $a \in \{t, t+1\}$ are benchmarked using observations from period $b \in \{t, t+1\}$ for the construction of the production surface. These correspond to activities of the OECD economies in this contribution. Let there be K countries (index $k = 1, 2, \ldots, K$ keeps track of the countries). Then, the output-oriented DDF $D^b(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{0}, \mathbf{g}_y^a, \mathbf{g}_z^a)$ is calculated by means of the following linear program (LP1):

$$\begin{aligned} D^b(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{0}, \mathbf{g}_y^a, \mathbf{g}_z^a) &= \max_{\delta, \lambda_k, \sigma_k} \delta \\ s.t. \sum_{k=1}^{K} \lambda_k y_k^{m,b} &\geq y^{m,a} + \delta g_y^{m,a}, \quad \forall m = 1, \ldots, M; \\ \sum_{k=1}^{K} \lambda_k z_k^{j,b} &\leq z^{j,a} - \delta g_z^{j,a}, \quad \forall j = 1, \ldots, J; \\ \sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^{n,b} &\leq x^{n,a}, \quad \forall n = 1, \ldots, N; \\ \sum_{k=1}^{K} (\lambda_k + \sigma_k) &= 1; \\ \lambda_k &\geq 0, \quad \forall k = 1, ..., K; \\ \sigma_k &\geq 0, \quad \forall k = 1, ..., K. \end{aligned} \tag{LP1}$$

where $\boldsymbol{\lambda}$ and $\boldsymbol{\sigma}$ are the vectors of intensity variables, δ is the value of the output DDF representing simultaneously the degree by which the desirable outputs can be augmented and by which the undesirable outputs can be contracted in proportion to the directional vector $(\mathbf{0}, \mathbf{g}_y^a, \mathbf{g}_z^a)$. The input directional distance function $D^b(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{g}_x^a, \mathbf{0}, \mathbf{0})$ is obtained via solving the following linear program (LP2):

$$\begin{aligned} D^b(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{g}_x^a, \mathbf{0}, \mathbf{0}) &= \max_{\phi, \lambda_k, \sigma_k} \phi \\ s.t. \sum_{k=1}^{K} \lambda_k y_k^{m,b} &\geq y^{m,a}, \quad \forall m = 1, \ldots, M; \end{aligned}$$

$$\sum_{k=1}^{K} \lambda_k z_k^{j,b} \leq z^{j,a}, \quad \forall j = 1, \ldots, J;$$
$$\sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^{n,b} \leq x^{n,a} - \phi g_x^{n,a}, \quad \forall n = 1, \ldots, N;$$
$$\sum_{k=1}^{K} (\lambda_k + \sigma_k) = 1;$$
$$\lambda_k \geq 0, \quad \forall k = 1, ..., K;$$
$$\sigma_k \geq 0, \quad \forall k = 1, ..., K; \tag{LP2}$$

where $\boldsymbol{\lambda}$ and $\boldsymbol{\sigma}$ are the vectors of intensity variables and ϕ represents the value of the input-oriented DDF that solves the linear program. It basically refers to the maximum reduction in the input quantities for a given directional vector and technology. Note that the reference set is constructed by considering observations from period b, whereas the evaluated countries come from period a in both (LP1) and (LP2).

An economy is operating fully efficiently when δ in (LP1) (or ϕ in (LP2)) equals zero. We also select the directional vector such that its elements are the actual quantities of the relevant indicators (inputs or outputs): i.e., the proportional DDF is maintained throughout the analysis. Thus, efficiency scores can be interpreted in percentage terms. Remark that the inequality in the constraint on the bad outputs departs from the conventional weak disposability model (Kuosmanen, 2005) and indicates that the shadow prices of bad outputs must be positive and, hence, that bad outputs are regarded as having social costs (see Leleu, 2013, for details). Note that the estimation of the LHM indicator also requires mixing the periods of input and output vectors in certain instances, yet these calculations are straightforward generalizations of the linear programming models (LP1) and (LP2) given above.

In Sect. 2.2, we have discussed the two formulations of the LHM TFP indicator with undesirable outputs. Both instances of the LHM indicator [see (6) and (7)] are obtained by using the same environmental production technology [see (15)]. The computation differs only due to a different specification of the DDFs. To empirically calculate the LHM TFP indicator proposed by Abad (2015), the following linear program is invoked to obtain the output-oriented DDF (LP3):

$$D^b(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{0}, \mathbf{g}_y^a, \mathbf{g}_z^a) = \max_{\delta, \lambda_k, \sigma_k} \delta$$
$$s.t. \sum_{k=1}^{K} \lambda_k y_k^{m,b} \geq y^{m,a} + \delta g_y^{m,a}, \quad \forall m = 1, \ldots, M;$$
$$\sum_{k=1}^{K} \lambda_k z_k^{j,b} \leq z^{j,a}, \quad \forall j = 1, \ldots, J;$$
$$\sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^{n,b} \leq x^{n,a}, \quad \forall n = 1, \ldots, N;$$
$$\sum_{k=1}^{K} (\lambda_k + \sigma_k) = 1;$$
$$\lambda_k \geq 0, \quad \forall k = 1, ..., K;$$

$$\sigma_k \geq 0, \quad \forall k = 1, ..., K. \tag{LP3}$$

Similarly, the input-oriented DDF suggested by Abad (2015) is obtained as a solution of the linear programming problem given as (LP4):

$$\begin{aligned}
& D^b(\mathbf{x}^a, \mathbf{y}^a, \mathbf{z}^a; \mathbf{g}_x^a, \mathbf{0}, \mathbf{0}) = \max_{\phi, \lambda_k, \sigma_k} \phi \\
s.t. & \sum_{k=1}^{K} \lambda_k y_k^{m,b} \geq y^{m,a}, \quad \forall m = 1, \ldots, M; \\
& \sum_{k=1}^{K} \lambda_k z_k^{j,b} \leq z^{j,a} - \phi g_z^{j,a}, \quad \forall j = 1, \ldots, J; \\
& \sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^{n,b} \leq x^{n,a} - \phi g_x^{n,a}, \quad \forall n = 1, \ldots, N; \\
& \sum_{k=1}^{K} (\lambda_k + \sigma_k) = 1; \\
& \lambda_k \geq 0, \quad \forall k = 1, ..., K; \\
& \sigma_k \geq 0, \quad \forall k = 1, ..., K.
\end{aligned} \tag{LP4}$$

2.4 Environmental LHM indicator and infeasibility

It has been proven that the strong disposability axiom leads to determinacy of the Hicks–Moorsteen (HM) TFP index (Briec & Kerstens, 2011): it has also been suggested that the same finding holds for the LHM TFP indicator. However, this study seeks to evaluate the environmental-economic performance whereby such an assessment requires a weak disposability technology in the sense of Kuosmanen (2005). This calls for further attention as to the eventual determinacy of the green LHM TFP indicator.

Indeed, the earlier literature has already provided certain evidence on the presence of infeasibilities in the environmental HM index (see, e.g., Zaim, 2004, 2006). Briec and Kerstens (2009) suggest providing the details of such infeasibilities in case they emerge. Against this background, one may be interested in ascertaining whether the green LHM TFP indicator is susceptible to the issue of infeasibilities. As far as we know, there has been no empirical research to test this issue on in the context of a weak disposability technology.

3 Data and empirical results

The proposed methodology is applied on the data set comprising of production and environmental variables for the OECD countries. Therefore, this Sect. 3 presents the data and the empirical results. The proposed approach is also contrasted to the earlier proposal by Abad (2015) (as described in Sect. 2.2.2).

Table 1 Descriptive statistics for input and outputs variables

Variable	Unit	Mean	Std. dev	Min	Max	Trend (%)
Labor force	Million	15.9	26.2	0.1	158.3	0.91
Capital stock	Million $	5,537,810.3	10,316,479.0	46,356.6	69,059,096.0	3.04
GDP	Million $	1,289,620.8	2,729,589.5	8078.4	20,566,034.0	2.51
CO_2	Million tons	353.4	889.7	1.9	5729.9	0.05

3.1 Data set

This data covers a selection of 34 OECD countries including Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Republic of Korea, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States. The period covered are the years from 1991 to 2019. This yields a total of 986 observations (34 countries $\times$ 29 years).

We use two inputs, namely labor force and capital stock. There is one desirable output, GDP, representing the level of economic activity. In addition, there is one undesirable output, carbon dioxide emissions, quantifying the global country-level environmental pressure. The labor force is measured as the number of persons (in millions) employed in each of the 34 OECD countries. For the capital stock, the perpetual inventory method is applied. The latter variable is measured in millions of 2017 US dollars thanks to the application of purchasing power parities. The real GDP is measured in millions of 2017 US dollars by also employing purchasing power parities. The two inputs and GDP come from the Penn World Table 10.0 (Feenstra et al., 2015) provided by the University of Groningen. The carbon dioxide emissions are measured in millions of tons. The carbon dioxide emissions considered is that from fuel combustion and is based on a sectoral approach (International Energy Agency, 2021).

Table 1 presents the descriptive statistics and average growth rates for inputs and outputs. As one can observe, the capital input shows the highest average growth rate of over 3.04% per annum on average. GDP comes next with a growth rate of some 2.51% p.a. Labor force grows only at 0.91% p.a. Finally, the carbon dioxide emissions show the lowest rate of growth of 0.05% p.a. These figures imply an increasing accumulation of capital within the OECD countries which exceeds the rate of GDP growth. This possibly implies a negative change in TFP prevailing in certain countries and regions.

3.2 Empirical results

We first report the occurrence of the infeasibilities in the case that mixed-period DDFs are considered. Table 2 brings together the infeasibility results. There are no infeasibilities for contemporaneous DDFs obtained. While the total number of observations is 986 (34 countries $\times$ 29 years), each distance function is compared to two time periods yielding 952 results (34 countries $\times$ 28 years). Table 2 shows that a total of 28 infeasibilities appear in the production

Table 2 Number of Infeasibilities in LHM TFPiIndicators (6) and (7)

Model (6)$LHM^{t,t+1}$		Model (7)$LHM^{t,t+1}_{\text{bads as inputs}}$	
Distance Function	Frequency	Distance Function	Frequency
$D^{t+1}(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{g}_z^t)$	28/952	$D^{t+1}(\mathbf{x}_k^t, \mathbf{y}_k^t, \mathbf{z}_k^t; \mathbf{0}, \mathbf{g}_y^t, \mathbf{0})$	28/952
$D^t(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1})$	12/952	$D^t(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{0})$	12/952

plan for period t with respect to the technology of period $t+1$, and 12 infeasibilities show up in the production plan for period $t+1$ with respect to the technology of period t, respectively. The empirical results reported in the remainder are based on the feasible solutions only. The number of infeasibilities turns out to be independent of whether we apply model (6) or model (7).

To demonstrate the main feature of the proposed model for the measurement of the environmental LHM TFP, we contrast it to two alternative options: (i) we treat carbon dioxide emission as an input in the LHM TFP indicator, and (ii) we apply the model without carbon dioxide emission in the LHM TFP indicator. Figure 1 summarizes the empirical results for the cumulative growth for these three LHM models involving different assumptions on the treatment of the undesirable output.

It is easy to note that the proposed model relying on the assumption of weak disposability diverges from the other two models, whereby carbon dioxide emissions are either treated as

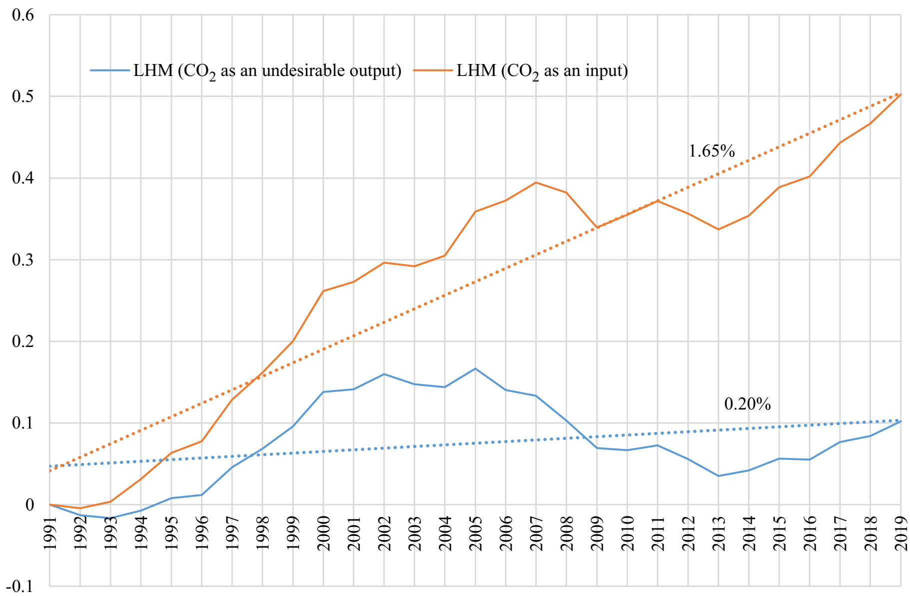

Fig. 1 Dynamics in the cumulative average LHM productivity indicator for the whole group of the OECD countries based on models (6) and (7), 1991–2019. *Note* CO_2 is treated either as an undesirable output or as an input following Eqs. (6) or (7) respectively; the regression-based annual rates of growth in TFP are given near the trend lines

an input or simply ignored. While the period of 1991–2002 enjoys a similar upward trend in cumulative TFP change for all three approaches, later on the proposed approach tends to yield much lower cumulative growth rates opposed to the two options without weakly disposable outputs.

The results in Fig. 1 suggest that the alternative model (7) yields more optimistic results for the whole period of 1991–2019 compared to the proposed environmental LHM TFP approach (6). Indeed, the decline in the TFP obtained for the period 2005–2013 based on the proposed framework yields a net increase in the cumulative TFP when looking over the whole period from 1991 to 2019, whereas the alternative approach (see (7)) shows an increase in the cumulative TFP. Specifically, cumulative average TFP change based on the proposed approach corresponds to the average increase in the TFP of 0.20% p.a. Similarly, the model treating carbon dioxide emission as an input gets an average rate of growth of 1.65% p.a. These findings clearly confirm the differences of the proposed methodology compared to the Abad (2015) proposal.

Up to now, we have looked into the differences across the different approaches towards measurement of the dynamics in the environmental LHM TFP indicator at the aggregate level. We now pick by way of example some specific countries with different trends in the environmental TFP when measured by these same approaches. The countries we select are the US and France and the results are depicted in Fig. 2. More specifically, we now focus on our proposed approach where carbon dioxide emission is treated as an undesirable output and the approach following Abad (2015) where the same emission is treated as an input.

It turns out that the trends in the change of the environmental TFP are reversed depending on the approach employed. By applying our proposed approach, France shows a negative cumulative change in the environmental TFP corresponding to an

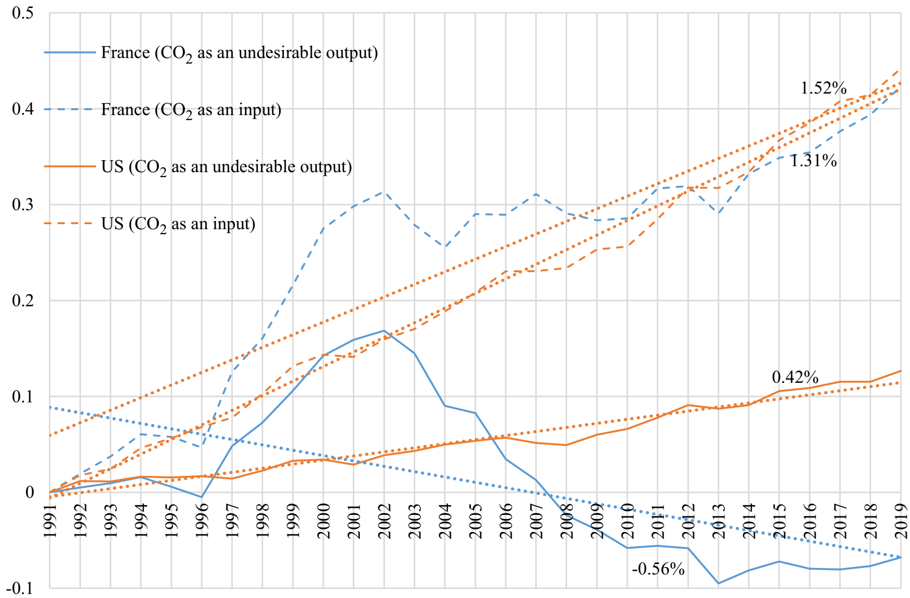

Fig. 2 Dynamics in the cumulative average LHM productivity indicators for France and the US under the two models (6) and (7), 1991–2019. *Note* CO_2 is treated either as an undesirable output or as an input following (6) or (7) respectively; the regression-based annual rates of growth in TFP are given near the trend lines

average rate of growth of − 0.56% p.a. Similarly, the US shows an upward trend in the cumulative environmental TFP corresponding to the average rate of growth of 0.42% p.a. These trends are significantly different if the measurement is based upon the approach where carbon dioxide emission is treated as an input. Both France and the US now switch to a positive cumulative change in the environmental TFP with the associated average rates of growth being 1.31% p.a. and 1.52% p.a., respectively. Therefore, the results considering the change in the environmental LHM TFP indicators are highly impacted by the choice of modelling approach. This holds at both the aggregate levels and the level of individual countries.

Furthermore, we have applied the additive decomposition of the environmental LHM TFP indicator [see (8)]. Therefore, we decompose the cumulative growth in the environmental TFP into the three terms, i.e., technological change, technical inefficiency change, and scale inefficiency change. By doing so, we can identify the underlying sources of growth in the green TFP for the OECD countries. Figure 3 presents these decomposition results at the aggregate level.

We start with discussing technical efficiency change (*TEC)*, then we move to technological change (*TP)*, and then we end with scale efficiency change (*SEC).* The technical inefficiency change component (*TEC*) follows a negative trend after the period of 1998–1999 and becomes negative soon afterwards. This decline in TEC is represented by a negative rate of growth of − 0.27% p.a.

The technical change component (*TP*) reveals a positive trend implying that countries tend to increase their environmental TFP by moving towards the efficiency frontier. Indeed, the average rate of growth is 1.10% p.a. Looking at the trend in the dynamics of this particular component reveals that TFP gains are mainly achieved during the period 1991–2005, while the subsequent years see little serious TFP gains due to technical change.

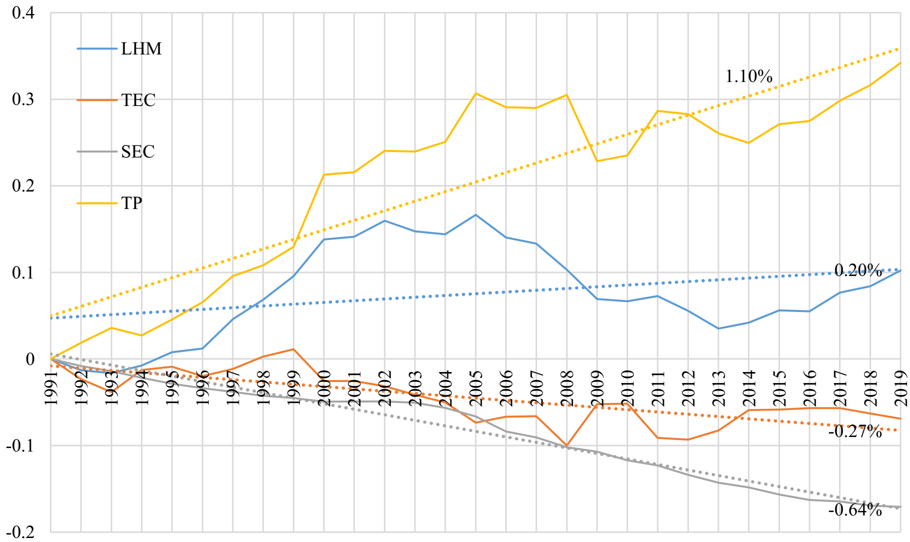

Fig. 3 Decomposition of the cumulative average LHM productivity indicator based on the proposed approach, 1991–2019. *Note* (6) is applied; the regression-based annual rates of growth in TFP are given near the trend lines

The scale inefficiency change (*SEC*) component has been following a clearly negative trend throughout the whole period 1991–2019. Specifically, the average rate of growth is − 0.64% p.a. Such a trend clearly indicates a deviation away from the most productive scale size represented by a constant returns to scale region within a technology. Thus, both the smallest and largest economies should ideally seek to increase their environmental LHM TFP by optimizing their scale of operations.

To reveal the components of change in the environmental LHM TFP indicator across different countries, Table 3 presents the country-specific results. Countries are listed in simple alphabetic order. As a general observation, the average rate of growth in the environmental LHM TFP indicator, as measured on the weakly disposable technology, varies considerably across the OECD countries. The highest value is observed for Poland (2.01% p.a.), whereas Turkey is attributed with the lowest value of − 3.47% p.a. Also observe that the overall average growth rate of LHM TFP is weakly positive and that the only positive contribution is due to technological change.

Poland, Luxembourg, Belgium, Slovakia, Finland, Denmark, Czech Republic, Australia, Sweden, Spain, Italy, and Ireland comprise the best-performing group, where the average rate of growth in the environmental TFP is 0.71% p.a. at least. Most of these countries rely on gains from technical progress (*TP*). The relatively more recently developed countries like Slovakia appear as an exception in this pattern. Indeed, Slovakia's growth in the environmental TFP is mainly determined by technical efficiency gains and scale efficiency changes respectively.

Another group of countries, viz. Israel, Greece, United States, Estonia, Norway, and Austria, show higher-than-average rates of growth in the environmental LHM TFP. Within this group, the rates of growth vary in between 0.61% p.a. for Israel and 0.29% p.a. for Austria. Note that most of these countries struggle with a negative change in technical efficiency as well as in scale efficiency. Technological change remains the sole positively contributing component, except for Estonia.

Switzerland, Netherlands, Iceland, Canada, Netherlands, Japan, New Zealand, Portugal, Hungary, and Germany fall within a category of worse-performing countries in terms of growth in the environmental TFP. Specifically, the average growth in TFP ranges in between 0.15% p.a. for Switzerland and − 0.41% p.a. for Germany. Indeed, most of the countries falling within this particular group are highly industrialized. Technological change is positive, except for New Zealand. With the exception for Hungary, there is also a negative contribution of the scale inefficiency component.

The worst-performing group of countries encompasses France, Slovenia, Republic of Korea, United Kingdom, Chile, Mexico, and Turkey. Indeed, the average rate of growth in the environmental TFP falls below the value of − 0.56% p.a. Within this group, Chile and Turkey are the only countries exhibiting a decline in the LHM TFP indicator due to losses in all components, namely technical and scale efficiency changes, and technological progress.

In many cases, losses in the LHM TFP indicator due to scale inefficiency change exceed the gains from improvements in technical efficiency. Therefore, there seems to be some increasing misallocation of production factors among these OECD countries. However, these results are based on the dynamic change in TFP. It is needed to look at the levels of efficiency to determine changes in the ranking of these countries in terms of the transformation of inputs into outputs.

The use of this TFP framework is also useful for the identification of the notion of innovative countries. Indeed, we seek to identify the innovative OECD countries which push the production frontier upwards towards the region associated with higher TFP. Following Färe et al., (1994: pp. 78–79) and transposing their multiplicative framework in

Table 3 Annual growth rates of cumulative LHM indicator and its components, 1991–2019

Country	LHM (%)	TEC (%)	SEC (%)	TP (%)
Australia	0.91	– 0.18	– 0.41	1.50
Austria	0.29	– 0.89	– 1.12	2.29
Belgium	1.89	– 0.89	– 0.11	2.89
Canada	– 0.05	– 0.53	– 0.46	0.93
Chile	– 1.15	– 0.48	– 0.33	– 0.34
Czech Republic	1.00	0.12	– 0.46	1.35
Denmark	1.13	– 0.25	– 0.87	2.25
Estonia	0.38	– 0.98	3.18	– 1.82
Finland	1.44	– 0.41	– 0.57	2.43
France	– 0.56	0.00	– 1.61	1.05
Germany	– 0.41	0.29	– 1.53	0.83
Greece	0.46	– 0.72	– 0.63	1.81
Hungary	– 0.26	– 0.57	0.17	0.14
Iceland	0.09	0.00	– 0.76	0.86
Ireland	0.71	– 0.32	– 0.20	1.24
Israel	0.61	– 0.23	0.05	0.79
Italy	0.79	– 0.41	– 0.17	1.38
Japan	– 0.12	– 0.33	– 0.43	0.64
Luxembourg	1.89	– 1.44	1.38	1.96
Mexico	– 2.21	– 0.21	– 2.50	0.49
Netherlands	– 0.07	– 0.40	– 1.02	1.35
New Zealand	– 0.15	0.01	– 0.07	– 0.09
Norway	0.31	– 0.20	– 1.44	1.96
Poland	2.01	1.45	– 0.20	0.76
Portugal	– 0.19	– 0.85	– 1.48	2.13
Rep. of Korea	– 0.73	– 0.59	– 0.97	0.82
Slovakia	1.63	0.57	1.67	– 0.61
Slovenia	– 0.65	– 0.89	– 1.15	1.39
Spain	0.81	– 0.07	– 0.22	1.10
Sweden	0.90	0.39	– 1.66	2.17
Switzerland	0.15	0.00	– 1.86	2.01
Turkey	– 3.47	– 0.06	– 3.14	– 0.27
United Kingdom	– 0.96	0.04	– 1.73	0.72
United States	0.42	0.00	– 1.03	1.45
Average	0.20	– 0.27	– 0.64	1.10

(6) is applied; the regression-based annual rates of growth are given

Table 4 Number of time periods countries appear as innovators, 1991–2019

Country	Number of periods	Initial period	Last period
United States	20	1991–1992	2018–2019
France	7	1993–1994	2015–2016
Poland	5	1999–2000	2018–2019
Luxembourg	4	1992–1993	1997–1998
Japan	3	1995–1996	2002–2003
Turkey	3	2001–2002	2004–2005
Iceland	2	2011–2012	2014–2015
Estonia	1	2000–2001	–
Italy	1	1995–1996	–
Norway	1	2003–2004	–
Switzerland	1	2017–2018	–

Model (6) is applied

an additive context, the innovative countries can be identified by considering three criteria simultaneously: (i) a positive technical change must be observed (i.e., $TP^{t,t+1} > 0$); (ii) the production plan for period $t + 1$ must be negative with respect to the technology of period t (i.e., $D^t(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}) < 0$); and (iii) the production plan for period $t + 1$ must be efficient with respect to the technology of period $t + 1$ (i.e., $D^{t+1}(\mathbf{x}_k^{t+1}, \mathbf{y}_k^{t+1}, \mathbf{z}_k^{t+1}; \mathbf{0}, \mathbf{g}_y^{t+1}, \mathbf{g}_z^{t+1}) = 0$). Beltrán-Esteve and Picazo-Tadeo (2017), Fujii et al. (2016) and Miguéis et al. (2012) are other empirical applications of this notion of innovative countries.

Table 4 presents an exhaustive summary of all instances of these innovative countries for the period 1991–2019. In particular, we report the number of time periods a certain country has been identified as being innovative along with the first and the last periods in which this occurs. Note that these results are based on the environmental LHM TFP indicator as proposed in this contribution in model (6).

The United States appear as an innovative country for the highest number of times (20 times during the period 1991–2019). Then, France follows with seven instances. Poland appears as innovative countries for five times. Note that all of these listed countries virtually cover the whole period and can be regarded as persistent innovators. Iceland shows a lower number of occurrence (10 times), yet these are also scattered over the whole period of 1991–2019. Countries such as Poland and Germany appear as innovators around the period of 2006–2007 and have remained in that position until 2014. Finally, countries such as Ireland, Japan, Estonia, Luxembourg, Mexico, Chile, and the United Kingdom appear as innovative for a certain time period but cease to be so afterwards. Therefore, in principle one could identify successful cases of persistent innovations and less successful instances, where such a status has been lost.

4 Conclusions

This paper presented a new formulation of the environmental-economic LHM TFP indicator. It relies on the weak disposability technology as formulated by Kuosmanen (2005) adjusted for the positive shadow prices of the undesirable outputs that ensure theoretical consistency. The proposed model involves the desirable and undesirable outputs in the output directional distance function in different ways, as opposed to the handling of the undesirable outputs as inputs in the earlier LHM formulations of Abad (2015). The empirical results of the Kuosmanen (2005) formulation are contrasted with those based on the earlier Abad (2015) model where the same directional distance function is used to handle the inputs and undesirable outputs. The decomposition of the proposed total factor productivity indicator allows to reflect the total factor productivity gains from (i) technical efficiency change, (ii) frontier shift, and (iii) changes in the frontier gradient (i.e., the scale effect). Furthermore, we focus on the issue of infeasibilities.

In this contribution, we have proposed an environmental LHM indicator and its decomposition. The directional distance functions are defined so that the input distance function seeks to minimize the use of inputs, whereas the output distance function seeks to expand (resp. contract) the production of desirable (resp. undesirable) outputs. The change in the environmental TFP is then factorized with respect to technical progress, technical inefficiency change, and scale inefficiency change.

The application of the proposed LHM indicator for a sample of OECD countries over the period 1991–2019 shows that this new framework yields different results compared to models where the undesirable outputs are treated as inputs following Abad (2015). Therefore, the proposed approach merits further applications in different domains to obtain more robust and conclusive results regarding the environmental performance, and particularly, the dynamics in the environmental TFP. Indeed, the differences in the results between the different approaches are obtained at both the aggregate level and at the country level (as exemplified by France and the US).

Focusing on the empirical example, the cumulative average TFP change for the whole sample based on the proposed approach corresponds to an average growth in the LHM TFP of 0.20% p.a. The components of technical inefficiency change and scale inefficiency change are those negatively affecting the growth in the environmental TFP. Indeed, the scale inefficiency component follows a persistently negative trend throughout 1991–2019 thus indicating an increasing misallocation of the production factors among the OECD countries. The United States appeared as an innovative country for the highest number of times, followed by France, and then Poland, Luxembourg, and Japan follow suit. These results can be applied to identify the best practice as well as the sources of changes in environmental TFP.

In the case of regulatory settings, the potential infeasibility of the current environmental LHM TFP indicator can be a major issue. We are very likely the first to report the non-negligible incidence of these infeasibilities. In this case, it may be advisable to opt for an alternative way of modeling undesirable outputs. Perhaps, the by-production approach that maintains strong disposability could be envisioned (see the surveys by Ancev et al. (2017); Dakpo et al., 2016; and Dakpo & Ang, 2019). This is an open issue for future work.

References

Abad, A. (2015). An environmental generalised Luenberger–Hicks–Moorsteen productivity indicator and an environmental generalised Hicks–Moorsteen productivity index. *Journal of Environmental Management, 161*, 325–334.

Ancev, T., Azad, M. A. S., & Akter, M. (2017). Environmentally adjusted productivity and efficiency: A review of concepts, methods and empirical work. In T. Ancev, M. A. S. Azad, & F. Hernández-Sancho (Eds.), *New directions in productivity measurement and efficiency analysis: Counting the environment and natural resources* (pp. 9–58). Elgar.

Ang, F., & Kerstens, P. J. (2017). Decomposing the Luenberger–Hicks–Moorsteen total factor productivity indicator: An application to US agriculture. *European Journal of Operational Research, 260*(1), 359–375.
Ang, F., & Kerstens, P. J. (2020). A superlative indicator for the Luenberger–Hicks–Moorsteen productivity indicator: Theory and application. *European Journal of Operational Research, 285*(3), 1161–1173.
Atkinson, S., Cornwell, C., & Honerkamp, O. (2003). Measuring and decomposing productivity change: Stochastic distance function estimation versus data envelopment analysis. *Journal of Business and Economic Statistics, 21*(2), 284–294.
Beltrán-Esteve, M., & Picazo-Tadeo, A. J. (2017). Assessing environmental performance in the European Union: Eco-innovation versus catching-up. *Energy Policy, 104*, 240–252.
Bjurek, H. (1996). The Malmquist total factor productivity index. *Scandinavian Journal of Economics, 98*(2), 303–313.
Briec, W., & Kerstens, K. (2004). A Luenberger–Hicks–Moorsteen productivity indicator: Its relation to the Hicks-Moorsteen productivity index and the Luenberger productivity indicator. *Economic Theory, 23*(4), 925–939.
Briec, W., & Kerstens, K. (2009). Infeasibilities and directional distance functions: With application to the determinateness of the Luenberger productivity indicator. *Journal of Optimization Theory and Applications, 141*(1), 55–73.
Briec, W., & Kerstens, K. (2011). The Hicks–Moorsteen productivity index satisfies the determinateness axiom. *Manchester School, 79*(4), 765–775.
Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica, 50*(6), 1393–1414.
Chambers, R. G. (2002). Exact nonradial input, output, and productivity measurement. *Economic Theory, 20*(4), 751–765.
Chen, B., & Jin, Y. (2020). Adjusting productivity measures for CO_2 emissions control: Evidence from the provincial thermal power sector in China. *Energy Economics, 87*, 104707.
Chen, J., Wang, P., Cui, L., Huang, S., & Song, M. (2018). Decomposition and decoupling analysis of CO_2 emissions in OECD. *Applied Energy, 231*, 937–950.
Chen, P. C., & Yu, M. M. (2014). Total factor productivity growth and directions of technical change bias: Evidence from 99 OECD and non-OECD countries. *Annals of Operations Research, 214*(1), 143–165.
Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management, 51*(3), 229–240.
Dakpo, K. H., & Ang, F. (2019). Modelling environmental adjustments of production technologies: A literature review - Externalities and environmental studies. In T. ten Raa & W. H. Greene (Eds.), *The Palgrave handbook of economic performance analysis* (pp. 601–657). Palgrave Macmillan.
Dakpo, K. H., Jeanneaux, P., & Latruffe, L. (2016). Modelling pollution-generating technologies in performance benchmarking: Recent developments, limits and future prospects in the nonparametric framework. *European Journal of Operational Research, 250*(2), 347–359.
Del Gatto, M., Di Liberto, A., & Petraglia, C. (2011). Measuring productivity. *Journal of Economic Surveys, 25*(5), 952–1008.
Diewert, W. E., & Fox, K. J. (2014). Reference technology sets, free disposal hulls and productivity decompositions. *Economics Letters, 122*(2), 238–242.
Diewert, W. E., & Fox, K. J. (2017). Decomposing productivity indexes into explanatory factors. *European Journal of Operational Research, 256*(1), 275–291.
Färe, R., & Grosskopf, S. (2004). Modeling undesirable factors in efficiency evaluation: Comment. *European Journal of Operational Research, 157*(1), 242–245.
Färe, R., Grosskopf, S., & Lovell, C. A. K. (1994). *Production frontiers*. Cambridge University Press.
Färe, R., Grosskopf, S., Noh, D., & Weber, W. (2005). Characteristics of a polluting technology: Theory and practice. *Journal of Econometrics, 126*(2), 469–492.
Fare, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review, 84*(1), 66–83.
Feenstra, R. C., Inklaar, R., & Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review, 105*(10), 3150–3182.
Fujii, H., Cao, J., & Managi, S. (2016). Firm-level environmentally sensitive productivity and innovation in China. *Applied Energy, 184*, 915–925.
Hamid, S., & Wang, K. (2022). Environmental total factor productivity of agriculture in South Asia: A generalized decomposition of Luenberger–Hicks–Moorsteen productivity indicator. *Journal of Cleaner Production, 351*, 131483.
International Energy Agency. (2016). CO_2 Emissions from Fuel Combustion, Paris.

Iram, R., Zhang, J., Erdogan, S., Abbas, Q., & Mohsin, M. (2020). Economics of energy and environmental efficiency: Evidence from OECD countries. *Environmental Science and Pollution Research, 27*(4), 3858–3870.

Kara, S. E., Ibrahim, M. D., & Daneshvar, S. (2021). Dual efficiency and productivity analysis of renewable energy alternatives of OECD countries. *Sustainability, 13*(13), 7401.

Kerstens, K., Shen, Z., & Van de Woestyne, I. (2018). Comparing Luenberger and Luenberger–Hicks –Moorsteen productivity indicators: How well is total factor productivity approximated? *International Journal of Production Economics, 195*, 311–318.

Koopmans, T. C. (1953). Activity analysis and its applications. *American Economic Review, 43*(2), 406–414.

Kuosmanen, T. (2005). Weak disposability in nonparametric production analysis with undesirable outputs. *American Journal of Agricultural Economics, 87*(4), 1077–1082.

Kuosmanen, T., & Podinovski, V. (2009). Weak disposability in nonparametric production analysis: Reply to Färe and Grosskopf. *American Journal of Agricultural Economics, 91*(2), 539–545.

Leleu, H. (2013). Shadow pricing of undesirable outputs in nonparametric analysis. *European Journal of Operational Research, 231*(2), 474–480.

Managi, S., & Kaneko, S. (2006). Economic growth and the environment in China: An empirical analysis of productivity. *International Journal of Global Environmental Issues, 6*(1), 89–133.

Maudos, J., Pastor, J. M., & Serrano, L. (1999). Total factor productivity measurement and human capital in OECD countries. *Economics Letters, 63*(1), 39–44.

Miguéis, V. L., Camanho, A. S., Bjørndal, E., & Bjørndal, M. (2012). Productivity change and innovation in Norwegian electricity distribution companies. *Journal of the Operational Research Society, 63*(7), 982–990.

Mocholi-Arce, M., Sala-Garrido, R., Molinos-Senante, M., & Maziotis, A. (2021). Water company productivity change: A disaggregated approach accounting for changes in inputs and outputs. *Utilities Policy, 70*, 101190.

Moreau, V., & Vuille, F. (2018). Decoupling energy use and economic growth: Counter evidence from structural effects and embodied energy in trade. *Applied Energy, 215*, 54–62.

Moutinho, V., & Madaleno, M. (2021). Assessing eco-efficiency in Asian and African countries using stochastic frontier analysis. *Energies, 14*(4), 1168.

O'Donnell, C. J. (2012). An aggregate quantity framework for measuring and de- composing productivity change. *Journal of Productivity Analysis, 38*(3), 255–272.

Shephard, R. W. (1970). *Theory of cost and production functions*. Princeton University Press.

Shephard, R. W., & Färe, R. (1974). The law of diminishing returns. *Zeitschrift Für Nationalökonomie, 34*, 60–90.

Sinha, A., Schneider, N., Song, M., & Shahzad, U. (2022). The determinants of solid waste generation in the OECD: Evidence from cross-elasticity changes in a common correlated effects framework. *Resources, Conservation and Recycling, 182*, 106322.

Sueyoshi, T., Yuan, Y., & Goto, M. (2017). A literature study for DEA applied to energy and environment. *Energy Economics, 62*, 104–124.

Tang, L., & He, G. (2021). How to improve total factor energy efficiency? An empirical analysis of the Yangtze River economic belt of China. *Energy, 235*, 121375.

United Nations. (2009). Eco-efficiency indicators: measuring resource-use efficiency and the impact of economic activities on the environment. Greening of Economic Growth Series, ST/ESCAP/2561.

United Nations. (2015). Paris Agreement. United Nations Framework Convention on Climate Change. http://unfcc.int/paris_agreement/items/9485.php.

Vardanyan, M., & Noh, D. W. (2006). Approximating pollution abatement costs via alternative specifications of a multi-output production technology: A case of the US electric utility industry. *Journal of Environmental Management, 80*(2), 177–190.

Xu, X. L., Qiao, S., & Chen, H. H. (2020). Exploring the efficiency of new energy generation: Evidence from OECD and non-OECD countries. *Energy and Environment, 31*(3), 389–404.

Zaim, O. (2004). Measuring environmental performance of state manufacturing through changes in pollution intensities: A DEA framework. *Ecological Economics, 48*(1), 37–47.

Zaim, O. (2006). A framework for incorporating environmental indicators to the measurement of human well-being. In M. McGillivray (Ed.), *Inequality, poverty and well-being* (pp. 94–207). Palgrave-Macmillan.

Zoriehhabib, M., Rostamy-Malkhalifeh, M., & Lotfi, F. H. (2021). Efficiency measurement of the environmental systems: A two-stage structure considering undesirable outputs. *Management of Environmental Quality, 32*(2), 227–242.