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Eco-efficiency considering NetZero and Data Envelopment Analysis: A critical literature review

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Abstract

We highlight the state-of-the-art in the eco-efficiency measurement using Data Envelopment Analysis, including Malmquist-Luenberger productivity index. We also consider productivity change over time, provide directions for future studies in the field, and gather the most recent policy suggestions for governments, organisations and sectors for reducing CO2 emissions. A structured literature search of the Web of Science academic database reveals 311 papers published between 1989 and 2022. We carry out network analysis of citations to show the evolution of the literature in this research topic. In doing so, we (a) examine the key-route main path of knowledge flows, (b) provide basic bibliometric information about the most active journals and authors, (c) conduct a qualitative in-depth analysis of the identified most important studies and (d) identify the research fronts and relate them to the emerging issues on the topic researched, focusing on the most recent period between 2000 and 2022. Based on the insights of the literature review, the second part of this paper critically analyses the papers on the key-route (main path) of this subject. This review can be used as guidance and a starting point for researchers and practitioners that want to further investigate optimal policies to reach NetZero.

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1. Introduction

In real production processes, there are often undesirable outputs, such as pollutants, waste and CO_2 emissions, which are produced inevitably with desirable outputs. Those undesirable outputs may cause a severe negative impact on the environment if they are emanated in an uncontrolled way. For example, the Intergovernmental Panel on Climate Change (IPCC) reported in 2014 that scientists are more than 95% certain that global warming is being caused mainly by the increased concentrations of greenhouse gases and other human (anthropogenic) activities. In other words, global warming is primarily a problem of very high CO_2 concentration in the atmosphere, which acts as a blanket, obstructing extra heat from being radiated into space and warming the earth's surface beyond the normal levels (Bolin et al., 1986). NRC (2010) reported that, although CO_2 emissions coming from a variety of natural sources are those that prevent the earth's temperature from falling to non-human-friendly levels, human-related CO_2 emissions that have risen since the industrial revolution are responsible for the increased concentration in the atmosphere. As fossil fuels like coal, oil and natural gas are burned for energy and, at the same time, forests are cut down and burned to create pastures and plantations, carbon accumulates and overloads our atmosphere. Therefore, it is crucial to increase awareness of the global warming issue and investigate the best practices that should be adopted in the production process to minimise the negative impact of human activity on the environment.

Eco-efficiency of production concerns the capability to produce goods and services while causing minimal environmental degradation. In recent years, eco-efficiency has received increasing public attention and plays an important role in both the business community and the public sector, which now pay more attention to the environmental impacts of their activities. Konar and Cohen (1997) argue that the increasing focus on eco-efficiency is partly due to more rigorous environmental legislation and what is more important is that the environmental actions influence the public image and financial performance of organisations, *e.g.,* firms, industries, and nations. At the 26th UN Climate Change conference (COP26) in November 2021, governments outlined steps they each need to take to limit global warming. Hundreds of cities and private companies have already pledged to get to "net zero" – removing as much CO2 as they produce – by 2050.

Data Envelopment Analysis (DEA) is one of the main optimization tools used to assess the eco-efficiency during the last three decades and so it is important to further develop this model and use it in practice to achieve NetZero. The DEA origins lie on the seminal work of Farrell (1957). About twenty years later, Charnes et al. (1978) generalised the Farrell's measure to account for multiple inputs and outputs and introduced the first DEA model in the form of a fractional program; efficiency is measured as the ratio of the aggregated inputs over the aggregated outputs. Banker et al. (1984) extended the work of Charnes et al. (1978) to allow for different assumptions about the production technology of operational units. Since then, a significant number of studies have contributed to the extension of the DEA models so now these can be used to provide efficiency measurement in a wide range of applications. An insight into the main concepts used in DEA is provided by Thanassoulis (2001) and Cooper, Seiford and Zhu (2011). Emrouznejad and Yang (2018) provide an extended list of publications on the DEA field since 1978.

Conventional DEA can measure eco-efficiency at a single point in time. Malmquist productivity index (MPI) was developed to measure productivity change over different time periods. Based on the work of Malmquist (1953) and Caves et al. (1982), Färe et al. (1992) introduced a non-parametric MPI measured with respect to the DEA frontier under the constant returns to scale (CRS) assumption. Färe et al. (1994) relaxed the CRS assumption to allow for variable returns to scale (VRS).

The DEA methodology can play a fundamental role in measuring eco-efficiency and defining optimal policies to achieve NetZero. Therefore, a critical review of the latest developments in the field is of great importance; it will provide researchers with a clear view of the state-of-the-art and emerging research directions, supporting stakeholders in targeting decarbonisation through research-led policy suggestions. Considering this, in this paper, we provide a structured and critical review of the literature on eco-efficiency and CO_2 emissions using a bibliometric method - the analysis of the historiograph. This paper aims to highlight the state of the art in the eco-efficiency measurement – also considering the measurement of productivity change over time using the MPI, provide directions for future studies on the field, and gather the most recent policy suggestions for governments, organisations and sectors emerging from the DEA studies in eco-efficiency. Based on the analysis and discussion in the main part of the study, the review concludes with some recommendations for NetZero policymakers and suggestions for future directions for prospective researchers in the field.

The remainder of the paper is organised as follows: Section 2 is a brief introduction to DEA, which is one of the main tools used to assess eco-efficiency. Section 3 describes the Malmquist–Luenberger productivity index, which can be used to assess the productivity evolution over multiple periods. Section 4 gives detailed information on the method for this structured literature review. This is followed by a bibliometric analysis of the results. A critical review of the papers on the historiograph is provided in Section 5. Section 6 discusses recommendations for policymakers, and Section 7 concludes this paper and provides direction for future research.

2. Data Envelopment Analysis

DEA, first proposed by Charnes, Cooper and Rhodes (1978, CCR model), is a mathematical tool for evaluating relative efficiencies of decision-making units (DMUs) with multiple inputs and multiple outputs. DEA can work on a group of homogenous DMUs which refer to (1) the DMUs have the same tasks or objectives, (2) they have the same external environment, and (3) they have the same inputs and outputs and achieve their goals through the process of transforming inputs into outputs. So far, DEA has been widely used as an evaluation tool in both public and private sectors (Cook and Seiford 2009). In the next subsections, we first propose the foundations and axioms of

DEA. Second, we provide the classification of existing DEA models especially in the field of eco-efficiency. Third, we introduce the DEA model with undesirable variables which is widely used in environment-related research.

2.1 Foundations and assumptions

Consider a set of N homogeneous DMUs, each one of which consumes P inputs $x_j = (x_{1j}, \ldots, x_{Pj}) \in \mathbb{R}_+^P$ and produces S outputs $y_j = (y_{1j}, \ldots, y_{Sj}) \in \mathbb{R}_+^S$, $j = 1, 2, \ldots, N$. It is assumed that all data are non-negative, but each DMU has at least one non-zero input and output. Let $(x, y) \in \mathbb{R}_+^{P+S}$ denote an activity vector. An activity is called feasible if the specific output level can be produced from the specific input level. We call production possibility set (PPS) the set of all the feasible activities. Let P denote the PPS. Then,

$$P = \{(x, y) \in \mathbb{R}_+^{P+S} \mid x \text{ can produce } y\}.$$

The efficient frontier is defined as the boundary of P. Therefore, its shape depends on the observed set of DMUs and the assumptions we are willing to make about the returns to scale (RTS) of the DMUs. The RTS of the production technology shows how a proportionate increase in the inputs of a DMU will affect the outputs that are produced. If increasing the inputs DMUs by a unit increases the outputs produced by the same proportion, the production technology exhibits constant returns to scale (CRS). If it results in a non-proportionate increase in the outputs, then the production exhibits variable returns to scale (VRS). Similarly, if the resulting increase in the outputs is of a higher proportion, DMUs operate under increasing returns to scale (IRS). In such economies of scale, if a DMU increases its scale, then its efficiency will be increased. A DMU operates under decreasing returns to scale (DRS) if the increase in the outputs is less than the increase in the inputs, i.e., we have diseconomies of scale and the efficiency of a DMU decreases as its scale increases.

The PPS is defined on the following assumptions (Banker, 1984):

i. (Inclusion of observations) $(x_j, y_j) \in P \quad \forall$ DMU$_j$, $j = 1, \ldots, N$, ie., all observed DMUs are included in P.

ii. (Strong disposability/Monotonicity) If $(x, y) \in P$ and $x' \geq x$, $y' \leq y$, where $x, x' \in \mathbb{R}^m, y, y' \in \mathbb{R}^r$, then $(x', y') \in P$, i.e., inefficient production is possible.

iii. (Convexity) If $(x_j, y_j) \in P, j = 1, \ldots, N$, then, for any vector of non-negative scalars λ_j such that $\sum_{j=1}^{N} \lambda_j = 1 \Rightarrow (\sum_{j=1}^{N} \lambda_j x_j, \sum_{j=1}^{N} \lambda_j y_j) \in P$, i.e., linear interpolation between feasible input-output correspondences leads to new feasible input-output correspondences.

iv. (Minimum Extrapolation) If P_1 satisfies (i)-(iv) then $P \subseteq P_1$, i.e., P is the smallest set meeting assumptions (i)-(iii).

If DMUs operate under the CRS, the following assumption is also made for the PPS:

v. (Ray assumption) If $(x, y) \in P \Rightarrow (tx, ty) \in P$ for any positive scalar t, i.e., scaling a feasible input-output activity up or down, leads to a new feasible activity.

Based on the observed input and output quantities the PPS under all the different RTS assumptions is formulated as:

$$P = \left\{ (x, y) \in \mathbb{R}_{+}^{P+S} \mid \sum_{j=1}^{N} \lambda_j x_j \leq x, \sum_{j=1}^{N} \lambda_j y_j \geq y, \lambda \in \Lambda \right\},$$

where Λ is defined depending on the RTS under which DMUs operate; under the CRS assumption, $\Lambda = \mathbb{R}_{+}^{N}$, under the VRS, $\Lambda = \{\mathbb{R}_{+}^{N} \mid \sum_{j=1}^{N} \lambda_j = 1\}$, if IRS is assumed $\Lambda = \{\mathbb{R}_{+}^{N} \mid \sum_{j=1}^{N} \lambda_j \leq 1\}$, and under the DRS $\Lambda = \{\mathbb{R}_{+}^{N} \mid \sum_{j=1}^{N} \lambda_j \geq 1\}$.

Besides these, there may be other assumptions, such as the Free Disposal Hull assumption (FDH). If the Cobb-Douglas (C-D) type production function is assumed, other assumptions should be considered for shaping the PPS, including geometric convexity, free disposability, and minimality, etc. See Banker *et al.* (1986) for details.

In DEA, the most common assumptions that are made about the production technology are the CRS and the VRS. Figure 1 is an illustration of the PPS as this is defined by a set of eight DMUs that consume one input to produce one output (Table 1), under the CRS and the VRS assumption. The lined area represents the PPS under the CRS assumption is denoted by the lined area, whereas the PPS under the VRS assumption is represented by the grey shaded area.

Table 1: Input and output data

DMU	A	B	C	D	E	F	G	H
Input	2	7	6	5	3	8	6	4
Output	1	3	7	5	4	5	4	3

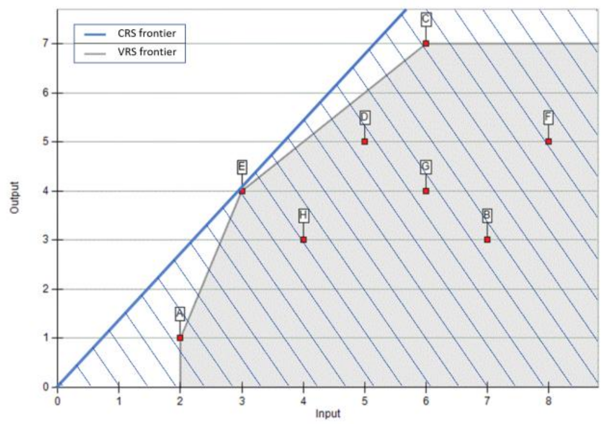

Figure 1: The PPS under the CRS and the VRS assumption

Efficiency measurement can be input or output oriented, depending on the preferences of the decision maker and/or the type of the problem. The Farrell's input efficiency measure is defined as the maximum possible contraction of all the inputs of a DMU given that output level is not decreased. Similarly, the Farrell's output efficiency measure is the maximum feasible radial expansion of all the outputs of a DMU without increasing the consumption of its inputs. The Farrell's input and output technical efficiencies, θ^* and φ^* respectively, are defined as

$$\theta^* = inf\{\theta \,|\, (\theta x, y) \in P\},$$

$$\varphi^* = sup\{\varphi \,|\, (x, \varphi y) \in P\}.$$

2.2 Models classification

In this subsection, first, the CCR and the BCC models are formulated, and then, the existing DEA models are summarised in a Table.

Under the CCR assumption, the Farrell's output efficiency can be obtained by solving the linear version of the output-oriented multiplier or envelopment CCR model, provided in Table 2 below.

Table 2: The output-oriented linear CCR model in the multiplier and the envelopment form.

Multiplier form	Envelopment form
$\min\ \phi_{j_0} = \dfrac{1}{\theta_{j_0}} = \sum_{s=1}^{S} v_p x_{pj_0}$	$\max\ \phi_{j_0}$
s.t. $\sum_{p=1}^{P} u_s y_{sj_0} = 1$	s.t. $x_{pj_0} - \sum_{j=1}^{N} \mu_j x_{pj} \geq 0 \quad \forall p,$
$\sum_{s=1}^{S} u_s y_{sj} - \sum_{p=1}^{P} v_p x_{pj} \leq 0, \quad \forall j,$	$\phi_{j_0} y_{sj_0} - \sum_{j=1}^{N} \mu_j y_{sj} \leq 0, \quad \forall s,$
$u_s, v_p \geq 0,\ p = 1,\ldots,P, s = 1,\ldots,S.$	$\mu_j \geq 0,\ j = 1,\ldots,N.$

Under the VRS assumption, the linearised, output-oriented BCC models are given in Table 3.

Table 3: The output-oriented, linear BCC model in the multiplier and the envelopment form.

Multiplier form	Envelopment form
$\min\ \phi_{j_0} = \sum_{s=1}^{S} v_p x_{pj_0} - u^{j0}$	$\max\ \phi_{j_0}$
s.t. $\sum_{p=1}^{P} u_s y_{sj_0} = 1$	s.t. $x_{pj_0} - \sum_{j=1}^{N} \mu_j x_{pj} \geq 0 \quad \forall p,$

$$\sum_{s=1}^{S} u_s y_{sj} - \sum_{p=1}^{P} v_p x_{pj} + u^{j_0} \le 0, \quad \forall j, \qquad \phi_{j_0} y_{sj_0} - \sum_{j=1}^{N} \mu_j y_{sj} \le 0, \quad \forall s,$$

$$u_s, v_p \ge 0, p = 1,\ldots,P, s = 1,\ldots,S. \qquad \sum_{j=1}^{N} \lambda_j = 1, \quad \forall j,$$

u^{j_0} free in sign.

$$\lambda_j \ge 0, \mu_j \ge 0, j = 1,\ldots,N.$$

The BCC model differs from the CCR model in the convexity constraint. In the envelopment form this corresponds to the extra constraint $\sum_{j=1}^{N} \lambda_j = 1, \lambda_j \ge 0$, whereas in the multiplier form, it corresponds to the free in sign variable u_{j_0}.

The following Table 4 gives a classification of the DEA models, based on several factors including the formulation of the PPS, preference, measure, type of variables, and problem structure, etc.

Table 4. Classification of existing DEA models.

Factors for classification	**DEA models**
PPS	CCR model (Charnes *et al.* 1978), BCC model (Banker *et al.* 1984), C-D DEA model (Banker *et al.* 1996), NIRS model (Färe *et al.* 1985), NDRS model (Färe *et al.* 1994), FDH model (Deprins *et al.* 1984), etc.
Preference	The common method to incorporate the preference of decision makers (DMs) is to add weight constraints. Allen *et al.* (1997) classified the weights restrictions in DEA models into four categories: (1) Absolute weights restrictions, (2) Assurance regions of Type I, (3) Assurance regions of Type 2, and (4) weight restrictions on virtual inputs and outputs. In this thread, there are more research works, *e.g.,* Roll *et al.* (1991), Cook *et al.* (1990), Dyson and Thanassoulis (1988), Thompson *et al.* (1986,1990), Cooper *et al.* (2006), Cook *et al.* (2000), Cook and Zhu (2007,2008). Besides these, Charnes *et al.* (1989, 1990) proposed cone ratio DEA model which assumes the preference structure of DMs satisfies cone restrictions.
Measure	The common measurements in DEA models include radial measure (Farrell, 1957), Russell measure (Fare and Lovell 1978, Russell 1988, 1990, Pastor *et al.* 1999), slack-based measure (Tone 1997, 2001), Zieschang measure (Zieschang 1984), directional distance (Luenberger 1992, 1995), Range adjusted measure (Cooper *et al.* 1999), Bounded adjusted measure (Cooper *et al.* 2011).
Type of variables	DEA model with non-discretionary variables (Banker and Morey 1986a, Cooper 2006), DEA model with non-controllable variables (*e.g.* Cooper *et al.* 2007), DEA model with bounded variables (*e.g.* Cooper *et al.* 2007), **DEA model with undesirable variables** (e.g. Seiford and Zhu 2002, Färe and Grosskopf 2004, Hua and Bin 2007), DEA model with ordinal variables (Cook *et al.* 1993,1996, Cook and Zhu 2006), DEA model without explicit inputs (*e.g.* Thanassoulis *et al.* 1996, Despotis 2005a, 2005b, Yang *et al.* 2014), categorical DEA model (*e.g.* Banker and Morey 1986b, Syrjanen 2004, Lober and Staat

	2010), stochastic DEA model (*e.g.* Thore 1987, Land *et al.* 1992, 1994, Cooper *et al.* 1996, 2004, Olesen and Petersen 1995), DEA model with interval data (Despotis *et al.* 2002), and DEA model with fuzzy data (Emrouznejad and Tavana 2014).
Problem structure	Two-stage DEA model (*e.g.,* Seiford and Zhu 1999, Kao and Huang 2008, Chen *et al.* 2009, Wang and Chin 2010), Network DEA model (*e.g.,* Färe and Grosskopf 2000, Tone *et al.* 2009, Hsieh and Lin 2010).
Others	Super-efficiency DEA (*e.g.,* Anderson and Peterson 1993, Banker et al. 1996c), Cross-efficiency DEA (*e.g.,* Sexton and Silkman 1986, Doyle and Green 1994, Yang *et al.* 2013), Game DEA (*e.g.,* Rousseau and Semple 1995, Liang *et al.* 2008), etc.

2.3 DEA model with undesirable variables

In conventional DEA model, there is an assumption implied inherently, i.e., the outputs are "the more, the better" and the inputs are "the less, the better". However, in real practices of assessing eco-efficiency, there are often undesirable outputs, e.g., the pollutions, waste and CO2 emissions, which are produced inevitably with desirable outputs in the production. To address those undesirable outputs, DEA models with undesirable variables are proposed and have been widely used in environmental studies (*e.g.,* Seiford and Zhu 2002). The earliest research can be traced back to the method proposed by Koopmans (1951), which negates the undesirable inputs or outputs into desirable inputs or outputs. However, this approach may produce negative values for some indicators. In order to avoid the negative values, Ali and Seiford (1990), Pastor (1996), Scheel (2001), and Seiford and Zhu (2002) use another transformation of undesirable outputs using the function $f(U) = -U + \beta$, where β is a constant to ensure the non-negativity. It is easy to imagine that the evaluation results have strong relations to the value of β. Subsequently, Golany and Roll (1989) and Lovell *et al.* (1995) use the reciprocal form of undesirable outputs, i.e., $f(U) = 1/U$. Chung *et al.* (1997) apply the directional distance function (DDF), which is proposed by Chambers *et al.* (1996), in environmental studies. Fukuyama and Weber (2010), Cook *et al.* (2010) and Lozano *et al.* (2013 & 2023) extend the DEA model with undesirable variables to the cases of two-stage and network DEA.

The theoretical foundation of the DEA model with undesirable outputs can be described as follows. Let us consider a complex productive process that uses a vector of inputs X to obtain a set of desirable outputs denoted by the vector Y and a vector of undesirable outputs denoted by the vector B. We assume that there are n DMUs ($j = 1, \dots, n$ DMUj), thus we need to expand the definition on PPS in formula (1) as follows:

$$PPS_D = \{(X, Y, B) | X \ can \ produce \ (Y, B)\}. \quad (2)$$

This PPS presents a description of all technologically feasible relationships between inputs and outputs (including desirable and undesirable outputs). In order to model some particular properties of joint production on desirable and undesirable outputs, the technology in formula (2) could also be formulated as input sets $I(Y, B)$ or output sets $P(X)$ as $I(Y, B) = \{X: (X, Y, B) \in PPS_D\}$ and $P(X) = \{(Y, B): (X, Y, B) \in PPS_D\}$ respectively. Thus, it is easy to see the following formula holds:

$$X \in I(Y, B) \Leftrightarrow (Y, B) \in P(X) \Leftrightarrow (X, Y, B) \in PPS_D. \quad (3)$$

The null-joint production assumption is introduced by Shephard and Färe (1974), which denotes if DMUs want to produce a positive amount of desirable outputs some undesirable outputs will also be produced. Thus, we know the formula $(Y, B) \in P(X) \ and \ B = 0 \Rightarrow Y = 0$ holds.

Second, the weak disposability of outputs is also assumed to consider explicitly that disposal of undesirable outputs is not free-lunch since it is commonly assumed in traditional production theory. Färe *et al.* (1989) point out that the weak disposability of outputs constitutes an appropriate assumption about the technology because reducing undesirable outputs needs resources which could be allocated formerly on desirable outputs. This assumption indicates that it is impossible to reduce undesirable outputs without reducing desirable outputs.

The third assumption is known as the strong disposability of desirable outputs, which implies that it is possible to reduce desirable outputs without reducing undesirable outputs, as shown in the formula $(Y, B) \in P(X) \ and \ Y' \leq Y \Longrightarrow (Y', B) \in P(X)$.

Based on the above assumptions, the *PPS* (CCR-type) in DEA model with undesirable outputs can be formulated as follows:

$$PPS_D = \{(X, Y, B) | \sum_{j=1}^{n} \lambda_j X_j \le X, \sum_{j=1}^{n} \lambda_j Y_j \ge Y, \sum_{j=1}^{n} \lambda_j B_j = B\}. \quad (4)$$

3. Malmquist–Luenberger productivity index (MLPI)

3.1 Malmquist productivity index (MPI)

The Malmquist productivity index (MPI) is an important concept in research on eco-efficiency that is first introduced by Malmquist (1953) and has further been studied and developed in the non-parametric framework by several authors (*e.g.* Färe and Grosskopf 1992, Thrall 2000). Lall *et al.* (2002) point out productivity has been widely recognized as an indirect measure of economic prosperity, standard of living and the competitiveness of an economy. MPI is an index which represents Total Factor Productivity (TFP) growth of a DMU, in that it reflects (a) progress or regress in efficiency along with (b) progress or regress of the frontier technology between two periods of time under the multiple inputs and multiple outputs framework (Cooper *et al.* 2007). MPI index is based on the benchmark technology. Ray and Desli (1997) make the proper CRS and VRS decomposition of traditional MPI. In their research, the MPIs under the CRS and VRS assumptions are also defined in geometric mean forms. The MPI index can be decomposed into Catch-up effect and Frontier-shift effect, which denote the change of technical efficiency and the change of production technology respectively. Pastor and Lovell (2005) argue that the traditional MPI fails to satisfy circularity and may encounter infeasibility problem, *i.e.,* the geometric mean MPI is not circular, and its adjacent period components can provide different measures of productivity change. Thus, they introduced a global MPI that is circular and gives a single measure of productivity change.

3.2 Malmquist-Luenberger productivity index (MLPI)

As we discussed above, in real practices of assessing eco-efficiency, there are often undesirable outputs, *e.g.,* CO2 emissions, which are produced inevitably with desirable outputs in the production. In order to recognize the undesirable outputs, the MLPI index based on DDF function acts as an extension of traditional MPI. The MLPI is originally developed by Chambers *et al.* (1996) and applied by Chung *et al.* (1997) in environmental studies, which has been widely used to measure the productivity of DMUs with undesirable outputs. For example, Färe *et al.* (2001) employ MLPI to account for both marketed output and the output of pollution abatement activities of U.S. state manufacturing sectors for 1974–1986. Kumar (2006) examines conventional and environmentally sensitive total factor productivity in 41 developed and developing countries over the period of 1971 to 1992. Zhang *et al.* (2011) evaluate China's growth in total factor productivity with undesirable outputs during the period from1989 to 2008. Arabi *et al.* (2014) use slack-based MLPI to measure the efficiency, eco-efficiency, and technological changes of the power plants over the 8-year period in Iran, while Mahmudi et al. (2019) proposed multistage PCA, Clustering, Game theory DEA model for dealing with Bad output such as CO2 emission. The following Table 2 lists some of previous studies on eco-efficiency using MLPI index. He *et al.* (2013) measure the energy efficiency and productivity change of China's iron and steel industry over the period 2001–2008.

Table 5. Previous studies on eco-efficiency using MLPI index.

Authors (year)	**Research field and data**	**Major issues addressed**	**Methodological approaches**			
			Efficiency measure			**Time-series measure**
			Type	**Orientation**	**Models**	
Zhang et al. (2015)	Province-level	Total-factor carbon emission performance of the Chinese transportation industry	Non-radial	Output	DDF+CCR	MLPI index
Fan *et al.* (2015)	Industrial sub-sectors of Shanghai	Industrial total factor CO_2 emission performance	Non-radial	Output	DDF+CCR	MLPI index
Du *et al.* (2014)	Province-level	Measurement of the sources of economic growth	Non-radial	Output	CCR+DDF	MLPI index
He *et al.* (2013)	Iron and steel firm	Traditional energy efficiency, productivity, and environmentally sensitive productivity growth	Non-radial	Output	CCR+DDF	MLPI index
Zhang and Choi (2013a)	Plant-level	Total-factor carbon emission change	Non-radial	Non-orientation	CCR+DDF	MLPI index

Zhang and Choi (2013b)	Plant-level	Pure CO_2 emission change	Non-radial	Non-orientation	CCR + DDF	MLPI index
Wu *et al.* (2012)	Regional industrial sector	Total-factor energy efficiency change	Radial	Input	DDF +CCR	MLPI index
Zhang *et al.* (2011)	Province-level	Environmentally sensitive productivity growth and environmental regulatory cost	Radial	Output	DDF +CCR	MLPI index
Chang and Hu (2010)	Chinese provinces	Energy productivity growth	Non-radial	Non-orientation	DDF +CCR	MLPI index
Kaneko and Managi (2004)	Province-level	Environmentally sensitive productivity growth	Non-radial	Output	CCR +DDF	MLPI index

Several weaknesses of the MLPI in its original form have been found in the application process of the MLPI index. Aparicio *et al.* (2013) summarize these main weaknesses, including (a) infeasibility problem may occur when the estimation of the shift in technology between two periods of time is based on the distance from the period t observation to the period s technology, (b) slacks may be neglected when using DEA model based on DDF, and (c) inconsistency is implied in the set of postulates traditionally assumed in the joint production of desirable and undesirable outputs. Based on these considerations, Aparicio *et al.* (2013) propose a redefinition of the assumption set to solve the inconsistency problem. Arabi et al (2015) dealt with issue of infeasibility in the MLPI and Oh (2010b) proposes the global MLPI which is circular and free of the infeasibility problem. The key point of the global MLPI is to use all DMUs from all periods to form a global frontier as the production technology. Tohidi *et al.* (2012) propose a new global cost MPI, which is circular and that gives a single measure of productivity change.

4. Structured literature review method

4.1. Quantitative approach based on citation network

The present structured literature review combines insights from Lage and Godinho

(2010), Jabbour (2013) and Mariano *et al.* (2015) with a quantitative approach based on citation network methods recently disseminated by Liu and Lu (2013), Lu and Liu (2013), and Liu *et al.* (2016).

First, we identify the papers of interest using a set of keywords (table 3), which we entered into the Web of Science (WoS) database. We retrieved 311 papers published between 1989 and 2021. We reviewed each of the abstracts to ensure their relevance to the topic of interest. We employed bibliometrics to identify basic statistics for the most cited authors (Table 4) and the most active journals (Table 5).

Because of the large number of papers in our sample we used a citations-based method known as historiograph, in order to identify the most relevant papers. These papers are considered the most important along the development of the researched topic.

The analysis of the historiography was first introduced by Eugene Garfield and Irving Sher in the 1960s (c.f. Garfield and Sher, 1963). They described the historiography as a chronological map allowing the historical reconstruction of scientific development of a field and its chronological representation. Typically, it shows only a portion of the most cited works within the field. Thus, it is a genealogical approach to the study of a discipline, showing when it starts and what its descendants are. We choose to provide the historiograph of the DEA field as output as this paper is the first review of the scientific development of this discipline. Finally, each of the papers in the historiograph was reviewed and subjected to in depth qualitative analysis (Table 6). To conduct this analysis, we used the citations-based software HistCite.

Using a citations-based approach to study paper citations networks has become popular in recent years, and provides an understanding of various dynamics such as collaboration among researchers (Lee *et al.* 2014), knowledge patterns (Calero-Medina and Noyons 2008), and emerging knowledge trends within disciplines (Ding *et al.* 2013; Emrouznejad and Marra 2014, Lampe and Hilgers 2015). The underlying idea is that the study of citation relationships among science publications provides an understanding of the knowledge flows among researchers over time, that is, allowing for the fact that more recent works rely on previous, older, scientific publications.

Table 6. Keywords used in this research.

		And	And
Or	Data Envelopment Analysis, DEA Malmquist-Luenberger productivity index, MLPI	CO2	Undesirable outputs

5. Findings from the literature review: Evolution of the field and analysis of the historiograph

In this section we present the bibliometric analysis of our sample (section 5.1), and the qualitative and critical analysis of the papers on the historiography, following the evolutionary pattern of the topic under investigation (section 5.2). Papers are classified according to the following critical aspects of application of DEA and summarised in Table 6:

a) Evaluated DMUs, including type, location and quantity.
b) Number of inputs / output variables.
c) Variables: Good inputs, bad/undesirable outputs.
d) Analysis scope.
e) Model.

5.1 Bibliometric analysis and research trends

We present the bibliometric analysis of our sample according to the 20 most active authors based on the number of published papers (Quantity) in Table 4. We provide two scores: Total Local Citation Score (TLCS) and Total Global Citation Score (TGCS) which respectively count the number of citations received by the sample studied, and the total number of citations received within the entire ISI database.

Table 7. Top 20 most cited authors.

	Research	Quantity	Total Local Citation Score (TLCS)	Total Global Citation Score (TGCS)
1	Färe R.	10	429	1410
2	Grosskopf S.	9	429	1396
3	Lovell, C.A.K.	3	159	675
4	Pasurka C.	5	310	600
5	Zhou P.	9	124	283
6	Chung Y.H.	1	123	339
7	Ang B.W..	3	71	212
8	Zhang N.	10	70	201
9	Sueyoshi T.	11	68	212
10	Choi Y.	5	62	98
11	Noh D.W.	3	58	209
12	Goto M.	7	54	115
13	Oh M.H.	3	49	67
14	Weber W.	5	84	272
15	Kumar S.	5	43	113
16	Emrouznejad A.	10	39	341
15	Wang H.	2	36	84
16	Han J.Y.	1	35	94
17	Wang K.	7	34	182
18	Liang L.	9	30	198
19	Allen K.	1	29	97
20	Dyckhoff H.	1	29	97

The most cited and productive authors are Fare R. and Grosskopf S. with respectively 10 and 9 published papers, a TLCS of 249, and TGCS of 1410 and 1396. This shows their importance within the topic researched and within the DEA in general. This is in line with other studies which rank DEA authors (Liu *et al.* 2016). They are followed by Lovell C.A.K., Zhou P. and Chung Y.H. They all have high TLCS and TGCS.

Table 8 ranks the most active journals based on the number of papers published, and considers also their TLCS and TGCS. As expected, the highest number of publications are concentrated in field journals such as *Energy Economics* (40 papers), *Energy Policy* (34), *European Journal of Operational Research* (26) and Annals of Operations Research (18).

Table 8. Top 20 most active journals.

Journal	Quantity	Total Local Citation Score (TLCS)	Total Global Citation Score (TGCS)
Energy Economics	40	163	1079
Energy Policy	34	141	882
European Journal of Operational Research	26	111	678
Annals of Operations Research	18	30	191
Journal of Cleaner Production	12	33	40
Ecological Economics	10	76	198
Energy	9	66	251
Omega – International Journal of Management Science	9	24	210
Journal of Environmental Management	8	161	473
Journal of Operational Research Society	7	4	70
Renewable & Sustainable Energy Reviews	7	28	23
Applied Energy	6	58	88
Environmental & Resource Economics	6	21	95
Socio-Economic Planning Sciences	6	3	59
Economic Modelling	5	9	66
Transportation Research Part D – Transportation and Environment	5	14	25
Ecological Indicators	4	26	6
International Journal of Production Economics	4	21	155
Sustainability	4	13	7
Technological Forecasting and Social Change	4	1	103

Following Kumar et al. (2022) we conducted a bibliographic coupling. The map of articles based on the bibliographic coupling is presented in Figure 2. This analysis allows us to identify research trends. In the map, the size of nodes shows the total number of times each node is cited in Web of Science. The link between a pair of two nodes shows the number of common references they have in common, for this reason, we can assume that nodes within the same cluster share a common knowledge base and represent a consistent thematic cluster. We can observe five clusters and we describe their characteristics as follows:

Cluster 1 is the biggest in red and includes 52 articles. It is characterised by the foundational paper by Fare et al. (1989). Within this cluster we also found among the most relevant papers Boussemart et al., (2017) which seeks to estimate carbon shadow prices at a worldwide level.

The second biggest cluster consists of 50 articles and is depicted in green. Here we found most recent published articles including Alizadeh et al., (2020) and Feng et al., (2015). The former presents a new dynamic network-based DEA (DNDEA) model and find evidence that the privatization of the electricity distribution sector led to a huge increase in the efficiency. The last appears also in the historiograh analysis (summarised in Table 9).

Table 9. Analysis of papers on the historiograph.

Research	**Type**	**Location**	**Quantity**	**No of**	**Good outputs**	**Bad / Undesirable outputs**	**Analysis scope**	**Model**
Färe *et al.*(1989)	Plants	USA	30	4	Paper	(i) biochemical oxygen demand, (ii) total suspend solids, (iii) Sulphur oxides, (iv) particulates	Eco-efficiency and shadow prices of undesirable outputs	Enhanced hyperbolic productive efficiency measure
Färe *et al.* (1993)	Plants	USA	30	4	Paper	(i) biochemical oxygen demand, (ii) total suspend solids, (iii) Sulphur oxides, (iv) particulates	Eco-efficiency and shadow prices of undesirable outputs	Output distance function

Chung et al. (1997)	Paper and pulp mills	Sweden	39	4	Pulp	(i) biological oxygen demand, (ii) chemical oxygen demand (iii) suspended solids	Productivity index for modelling the joint production of good and bad outputs	Output based DDF in ML productivity index
Dyckhoff and Allen (2001)	Plants	N/A	N/A	N/A	Product (such as electric power and heat)	Pollutants (e.g., waste gas, waste water, gas, cinder) (bad inputs: reducts, such waste to be burned)	Generalisation of DEA models for eco-efficiency measurement	Generalised parametric additive model with a multi-dimensional value function
Färe *et al.* (2001)	Provinces /States	USA	48	2	Gross State Product (GSP)	(i) Sulphur oxides (SO_x), (ii) nitrogen oxides (NO_x), CO	Total factor productivity	ML productivity index
Lee et al (2002)	Plants	Korea	43	4	Electricity generation	(i) Sulfur oxides (SO_x), (ii) nitrogen oxides (NO_x), (iii) total suspended particulates (TSP)	Shadow prices of pollutants	Output-based DDF
Kuosmanen and	Towns	Finland	3 with another 30 being	3	Economic value added	(i) CO_2 equivalents, (ii) acid equivalents (iii) smog (iv) dispersion of particles	Environmental damage index	Eco-efficiency measure

Kumar	Countries	Global	41	3	GDP	CO_2 emissions	Total factor productivity	ML productivity index
Fare et al. (2007)	Plants	USA	92	5	Net electrical generation (kWh)	(i) Sulfur dioxide (SO_2), (ii) nitrogen oxides (NO_x)	Relationship between environmental production function and environmental DDF	Environmental production function with an activity analysis approach; output-based DDF
Watanabe	Industries	China	219	3	Industrial value added	(i) Sulfur, (ii) dioxide	Environmental efficiency	BCC model and output-based DDF
Zhou et al. (2010)	Countries (top CO_2 emitters)	Global	18	3	GDP	(i) CO_2 emissions	Relative CO_2 emission performance measurement	Malmquist CO_2 emission performance index (MCPI); Bootstrapping MCPI; Multiple linear regression
Fare and	N/A	N/A	N/A	N/A	N/A	N/A	Development of SBM model based on DDF	SBM model and DDF
Zhou et al.	Countries	Global	126	1	(i) Electricity generated;	C(i) O_2 emissions	Environmental efficiency	Non-radial DDF
Arabi et al. (2014)	Plants	Iran	18	2	Power generated	(i) deviation from generation plan, (ii) SO_2, NO_x, CO_2 emissions	Eco-efficiency and technological changes	Slacks-based model for ML index
Feng et al.	Countries	OECD	21	3	GDP	(i) CO_2 emissions	Carbon emissions abatement (CEA) allocation	Centralized CRS and VRS model

Rashidi and	Countries	OECD	34	3	GDP per unit of energy use	(i) CO_2 emissions	Eco-efficiency	Bounded adjusted measure (BAM) DEA model
Hampf and Rodseth (2015)	Plants	US	160	2	electricity	(i) CO_2 emissions	Feasible emission rates from electricity generating units	Joint production model and materials balance model with subsampling bootstrap
Apergis et al. (2015)	Countries	OECD	20	4	GDP	(i)	Energy efficiency	SBM with undesirable outputs and Generalized linear mixed models (GLMM) using Markov Chain Monte Carlo (MCMC)
Lee and	State-level plants	US	48	1	electricity	(i) CO_2, (ii) SO_2, (iii) NO_x	Directional shadow prices of CO_2, SO_2 and NO_x	Directional marginal productivity with DDF
Du and Mao	Plants	China	1158	3	Electricity	(i) CO_2 emissions	Environmental efficiency and shadow price of CO_2 emissions	Quadratic, output-based DDF
Mahdiloo et al. (2015)	Suppliers	Korea-China	20	2	(i)Sales, (ii) return on assets, (iii) environmental R&D investment	(i) CO_2 emissions	Selection of green suppliers	MOLP for technical, environmental and eco-efficiency; cross-efficiency MOLP

Wang and Wei (2016)	Provinces	China	30	3	GDP	(i) CO_2 emissions	Energy productivity indicator	Russell measure and input-based DDF in Luenberger aggregated specific energy productivity indicator
Emrouznejad	Industries	China	17	3	Gross Industrial Output	(i) CO_2 emissions	Energy efficiency and productivity evolution	Range-adjusted measure (RAM)-based global MLP index
Emrouzneja	Industries	China	30	3	Gross Industrial Output	(i) CO_2 emissions	Eco-efficiency and productivity change	Global MLP index
Wang et al.	Cities	China	285	3	GDP	(i) CO_2 emissions	Energy efficiency and shadow price of CO_2 emissions	Modified SBM linking good and bad outputs
Yang et al. (2017)	Industrial sub-sectors	China	36	3	Gross Industrial Output	(i) CO_2 emissions	Impact of carbon intensity constraint policy on green productivity growth	Non-radial, non-oriented DDF in Luenberger indicator and quasi-difference-in-differences (quasi-DID) method
Wang et al. (2018)	Industries	China	Not mentioned	3	Electricity generation	(i) CO_2 (ii) SO_2, (iii) NO_x, (iv) soot	Environmental and emission abatement efficiency	DEA-based model combined with materials balance principle (MBP); global MI

Song et al. (2018)	Areas	China	30	3	Gross regional production	(i) total discharge of industrial wastewater, (ii) discharge of industrial waste gas (SO_2), (iii) amount of industrial solid waste	Environmental efficiency and productivity	Ray SBM; Ray SBM-ML index; spatial econometrics

Further we can observe the blue cluster, which includes 25 articles, among which we have Monastyrenko (2017) on EU electricity producers and the CO2 emissions produced (undesirable outputs). This study finds evidence of a decreasing trend in average eco-efficiency which contradicts the expected moderate efficiency gains of liberalization. Within this cluster we also find Wang et al. (2019) work on drivers of CO2 emissions in China electricity sector that finds emission efficiency improvement to be the primary contributor to the emission abatement in all power plants analysed.

The yellow cluster, including 10 articles, shows among its most prominent papers: An et al. (2019) Emrouznejad (2019) and Miao (2019). The first focuses on water pollution and proposes a new slacks-based measure (SBM) model with undesirable inputs. Emrouznejad et al., (2019) seeks to address the problem of allocating CO2 emissions quota set by the Chinese government in the manufacturing industry. To do so, they present a novel inverse DEA model which allows to achieve the proposed goal of allocating CO2 quota under several assumptions.

The purple cluster includes works by Goto et al., (2014) and Sueyoshi and Goto (2019) whose work focus on Japanese context and evaluate its energy plan for 2030.

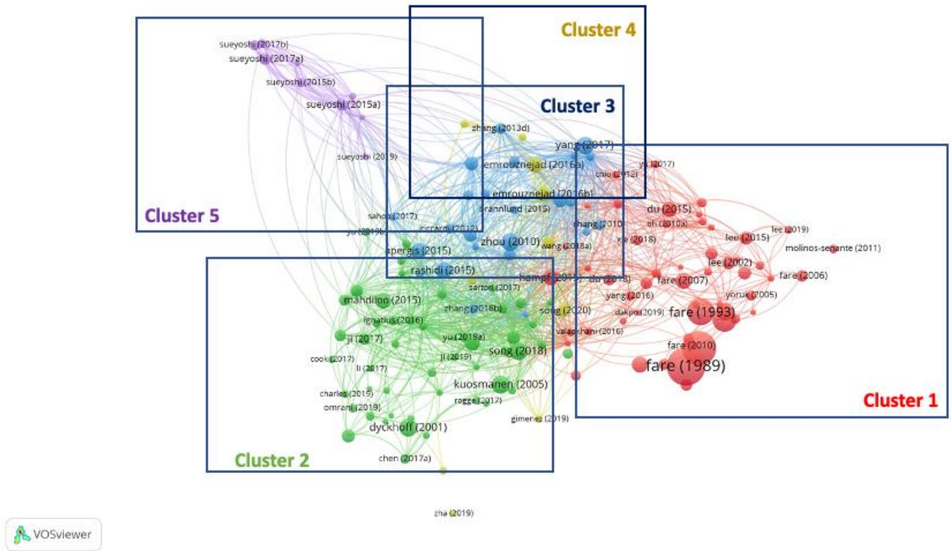

Figure 2. Clusters based on bibliographic coupling

Finally, Figure 3 displays the co-occurrence network of words used in the papers analysed in the bibliographic coupling. Words related to DEA, undesirable outputs, environmental efficiency clearly stand out as expected given the nature of this literature review. More interestingly, we observe greenhouse gas emission (Oukil; 2023), fuel power plants and electricity generations as recurring keywords. Indeed, the analysis of papers reveals that these are among the most studied contexts analysed in our sample papers (c.f. Monastyrenko (2017); Hampf and Rodseth (2015)). The economic perspective emerges also from the map with work related to the Kuznets curve and countries' economic growth (c.f. Wang and Wei, 2014; Xia et al. 2022). Corporate sustainability, financial performance, and managerial disposability are all grouped within the same blue map reflecting work by Sueyoshi and Yuan (2016, 2017) Sueyoshi and Goto (2015).

Figure 3. Word co-occurrence map of articles

5.2 Critical review of papers on the historiography and key theoretical perspectives

This section presents a qualitative analysis of the papers identified by the historiograph. The emphasis is on the evolution over time of the methods proposed to overcome some of the limitations relevant to topics such as energy consumption and energy efficiency performance.

Färe *et al.* (1989) developed and implemented a performance index, entitled the hyperbolic efficiency measure, which treats desirable outputs and undesirable outputs differently. Furthermore, this index can treat them differently in a variety of ways. We view this measure as an alternative to the "enhanced" multilateral productivity index introduced by Pittman (1983), which shows how to adjust productivity calculations. In Färe *et al.* (1989)'s study, the restriction that production technology satisfies strong disposability of outputs is relaxed to allow for the fact that undesirable outputs may be freely disposable, and the efficiency measures are modified to allow for an asymmetric treatment of desirable and undesirable outputs. Based on the above research, Färe *et al.* (1993) show how to estimate output distance functions as frontiers in order to generate shadow values of the undesirable outputs that are required to make both types of adjustment. A distinguishing feature of their framework is that it provides three pieces of information at the same time: it describes the structure of production technology, it provides a measure of productive efficiency for each producer, and it provides shadow prices for each producer.

However, Chung *et al.* (1997) point out that undesirable outputs are often produced together with desirable outputs. Because "prices" are typically unavailable for bad outputs, this joint production of good and bad outputs is typically ignored in traditional measures of productivity. Therefore, they introduce a DDF, which is used as a component in a new productivity index that readily models joint production of desirable outputs and undesirable outputs, credits firms for reductions in undesirable outputs and increases in desirable outputs, and does not require shadow prices of undesirable outputs. This index is called MLPI index, which can solve the problem caused by the joint production of desirable and undesirable outputs. Subsequently, Färe *et al.* (2001) employ the MLPI to account for both marketed output and the output of pollution abatement activities of U.S. state manufacturing sectors. Furthermore, they decompose this MLPI into the change in productivity into measures of change in efficiency and technical change. Weber and Domazlicky (2001) use the directional output distance function (Chambers *et al.* 1996) to construct a MLPI of total factor productivity growth for manufacturing when both good and bad outputs are jointly produced. Boyd *et al.* (2002) present a methodology and empirical results based on the MLPI index which treats pollution as an undesirable output. They provide the measurement of pollution-related inefficiencies and two measures of regulatory impact, the loss ratio and the shadow price of pollution. Subsequently, Lee *et al.* (2002) estimate the shadow prices of pollutants with a nonparametric directional distance function approach, where the inefficiency involved in the production process is taken into account, unlike the previous studies. They argue there are four main contributions of their work: (1) their study takes production/environment inefficiency into account in deriving the shadow prices of pollutants; (2) They propose a criterion for an appropriate efficiency rule to make the estimation of shadow prices reasonable in the real world; (3) They incorporate the weak efficiency assumption over the whole range of the frontier in the output domain, which can overcome the major problem of positive shadow prices for pollutants, and (4) they handle the directional efficiency in a new way, i.e., the directional vector is calculated by using the annual plans of power plants in terms of production and environment. Soon after that, Färe *et al.* (2005) use a quadratic directional output distance function to measure the technical efficiency of 209 electric utilities that produce electricity and a polluting by product. Kuosmanen and Kortaleinen (2005) study the eco-efficiency of road transportation in three towns in Finland. They define an eco-efficiency measure, by considering the economic value added and the environmental pressures that are involved in the production process, rather than using specific inputs and outputs. Kumar (2006) examines conventional and environmentally sensitive total factor productivity. Their study uses MLPI based on DDF function and find that TFP index value is not different when accounting for the CO_2 emissions relative to the situation when they are freely disposable. However, for the TFP's components (*e.g.,* technical and efficiency changes), the null hypothesis of whether the indexes are the same under two different scenarios cannot be accepted. They also examine the issues of catch-up and convergence, or in some cases possible divergence, in productivity within a global framework, as well as the impact of openness on conventional and environmentally sensitive measures of productivity.

Soon after the MLPI index is proposed, its original form has been found to have some significant problems. Oh (2010b) points out that the commonly used geometric mean form of the MLPI index in previous studies has significant weaknesses, including circularity and potential infeasibility problem in measuring cross-period DDFs. To overcome such problems, he employs concepts of the global Malmquist productivity growth index of Pastor and Lovell (2005) to propose a global MLPI, which can be decomposed into different components as different sources of productivity growth. In the same year, Oh (2010a) also presents an alternative environmentally sensitive productivity growth index - a meta frontier approach, which can incorporate group heterogeneities into a conventional MLPI index. This new alternative index allows the calculation of both efficiency and technical changes for DMUs operating under different technologies, as well as the computation of changes in the technological gap between regional and global frontier technologies. Based on the meta frontier approach, Chiu *et al.* (2012) evaluate the effects of technology heterogeneities and undesirable output on environmental efficiency measurement and decompose the index into different components as the sources of productivity growth. Moreover, there are also other variants of the MLPI, *e.g.,* Oh and Heshmati (2010) propose a new concept of the successive sequential production possibility set and an innovative index for measuring environmentally sensitive productivity growth. They show the rationale of this methodology that is to exclude a spurious technical regress from the macroeconomic perspective. Zhou *et al.* (2010) introduce a Malmquist CO_2 emission performance index for measuring changes in total factor carbon emission performance over time. This index is the reciprocal of the Shephard input distance function for undesirable outputs theoretically.

There are also some comparative studies on DDF measure and MLPI index. Watanabe and Tanaka (2007) compare two efficiency measures, which consider only desirable output and both desirable and undesirable outputs respectively, of Chinese industry at the provincial level from 1994 to 2002 based on an output-based DDF. The comparison results reveal that efficiency levels are biased only if desirable output is considered. Färe *et al.* (2007) investigate the relationship between environmental production functions and environmental directional distance functions, which make different assumptions when modelling the joint production of good and bad outputs. This work provides the empirical basis for comparing the environmental production function to the environmental directional distance function. Mandal and Madheswaran (2010) measure environmental efficiency within a joint production framework of both desirable and undesirable output using DEA with DDF. It is interesting that CO_2 emission is treated as an input in one context and as an undesirable output in the other, with the environmental efficiency being defined accordingly. However, their work is unable to explain the interstate variations in environmental efficiency using a second stage regression analysis.

Krautzberger and Wetzel (2012) calculate a MLPI to investigate the effects of country-specific regulations on productivity and to identify innovative countries. They find a high variation in the CO_2-sensitive productivity development and a slight productivity decrease on average. Riccardi *et al.* (2012) compare different DEA models based on DDF in order to detect the efficiency of the cement sector both in the presence and in absence of carbon emissions. Their results show that the inclusion or the exclusion of undesirable factors (CO_2 emission) has a significant influence on policy implications. Yuan *et al.* (2013) measure two technical efficiencies with respect to the two technologies characterized by strong and weak disposability of pollutants. They define the environmental efficiency index as the ratio of the two technical efficiencies to reflect the opportunity cost to transform the strong disposability of pollutants into a weak one.

Currently, there are more and more variants of the MLPI index which incorporate different types of traditional DEA models. Based on the directional Russell measure of inefficiency, Mahlberg and Sahoo (2011) develop the non-radial Luenberger indicator, which is then shown as the sum of the individual input-specific Luenberger indicators. Zhou *et al.* (2012) further extend the MLPI index to the case of using a DEA model based on a non-radial DDF approach (weighted Russell direction distance model) to modelling energy and CO_2 emission performance. Halkos *et al.* (2013) use conditional DDFs which incorporate the effect of regional economic growth on regions' environmental efficiency levels. Zhang and Choi (2013a, b) combine the concept of the meta frontier Malmquist productivity index and the non-radial DDF to develop a new index called the non-radial meta frontier Malmquist CO_2 emission performance index. Their approach allows for the incorporation of technological heterogeneities and slack variables into the previously introduced Malmquist CO_2 emission performance index.

Wang *et al.* (2013) and Azadi et al (2022) propose a new total factor CO_2 emissions performance index based on DDF followed by stochastic frontier analysis techniques. Based on the consideration of the group heterogeneity of electricity generation, non-radial slacks, and undesirable outputs simultaneously, Zhang *et al.* (2013) propose a meta-frontier non-radial directional distance function to model energy and CO_2 emission performance in electricity generation. Soon after that, Zhang *et al.* (2014) further present certain composite sustainability efficiency indicators for China based on a sequential generalized DDF. Arabi *et al.* (2014) suggest the use of an SBM model that incorporates bad outputs, and endogenously determines the direction of a DMU's projection to the efficient frontier, and use this model in the calculation of MLPI. Ramli and Munisamy (2015) employ the Range Adjusted Measure (RAM) model, which accounts for both desirable and undesirable outputs in the production process, as the non-radial DDF to measure the eco-efficiency of the manufacturing sector in Malaysia. Rashidi and Sean (2015) apply the Bounded Adjusted Measure model that separates energy and non-energy inputs, and desirable and undesirable outputs, to assess the eco-efficiency of some OECD countries. Chen *et al.* (2015) propose an enhanced Russell-based directional distance measure model for dealing with desirable and undesirable outputs in DEA, which is analogous to the output-oriented slacks-based measure and output DDF approach. Du *et al.* (2015) estimate the Marginal Abatement Cost Curve of CO_2 emissions in China based on a parameterized output DDF. Lin and Du (2015) employ the non-radial DDF developed by Zhou *et al.* (2012) to evaluate China's regional energy and CO_2 emission performance. Liou *et al.* (2015) extend the conventional two-stage DEA model to construct an analytical model with undesirable outputs for energy-related efficiency. Long *et al.* (2015) compare total factor productivity and eco-efficiency in China's cement manufactures based on distance function and directional slack-based measure respectively. Li and Lin (2015) estimate the total-factor energy efficiency using an improved DEA model, which combines the super efficiency and sequential DEA models to avoid the discriminating power problem and technical regress. Emrouznejad and Yang (2016a) propose a RAM measure to formulate a non-oriented, global MLPI to assess the CO_2 emissions reduction in twodigit light manufacturing industries in China. Emrouznejad and Yang (2016b) use a global MLPI for evaluating the eco-efficiency of Chinese manufacturing industries and investigating their heterogeneities. Wang and Wei (2016) suggest a Russell measure with input-based DDF, that aggregates different energy inputs' and undesirable outputs' inefficiencies, and use this in the evaluation of the MLPI. Yang *et al.* (2017) combine the NNDDF of Zhou *et al.* (2012) and the global MLPI of Oh (2010b) to assess the green production performance of Chinese industrial sub-sectors.

Some studies combine DEA models, based on different assumptions, with the Materials Balance Principle. (MBP) Hampf and Rodseth (2015) suggest combining the joint production model that assumes strong disposability of inputs and desirable outputs and weak disposability of undesirable outputs, with the MBP. Wang *et al.* (2018) combine DEA-based efficiency measurement with the MBP based on the weak G-disposability to identify possible adjustments both on the polluting mass of input and output variables and on the abatement of pollutants. They decompose the overall efficiency into technical efficiency and the allocative efficiencies of polluting inputs and of polluting and non-polluting inputs.

Apergis *et al.* (2015) use a non-oriented SBM model with undesirable outputs. In a second stage, they combine it with Generalized Linear Mixed Models, simulated with Markov Chain Monte Carlo methodologies, to predict energy efficiency in OECD countries. Wang *et al.* (2017) propose a modification of the slacks-base measure that allows for weak disposability of bad outputs and the linkage of good and bad outputs to evaluate the abatement costs of CO_2 emissions in China (see also Taleb et al., 2022).

Feng *et al.* (2015) study the carbon emissions allocation abatement in China using centralised DEA models combined with second stage compensation schemes to manage interest agreement among DMUs. Lee and Zhou (2015) implement a directional marginal productivity (DMP) approach for the estimation of the directional shadow prices of the three main pollutants produced by coal power plants in the US. In contrast to the typical shadow price estimation, DMP allows for the joint estimation of the shadow prices of all the pollutants. Du and Mao (2015) employ an output-based DDF with a quadratic functional form, which is differentiable at any point of the frontier and can include the environmental production technology constraints, to estimate the shadow prices for coal-fired power plants in China. In order to decrease the computational burden of solving different models, Mahdiloo *et al.* (2015) suggest the use of multi-objective goal programming for the evaluation of technical, environmental and eco-efficiency; their model classifies a DMU as eco-efficient if and only if it is environmentally and technically efficient.

6. Recommendation for energy policy makers

In this section we analyse (i) the papers appearing on the historiograph which provides an evolutionary perspective of the topic studied, and (ii) papers emerging from the clusters identified through the bibliographic coupling analysis. A qualitative in-depth analysis of these allows us to elaborate the following main recommendations for policy makers. Among those papers, there are some providing policy suggestions. Other papers are focused on the development of methodologies. Those policy suggestions can be divided into three groups: suggestions for sectors, countries, and organizations or unions. The suggestions are summarised as follows:

(a) Policy suggestions at sector level: Zhang and Choi (2013) investigated the dynamic changes in CO2 emission performance of fossil fuel power plants in China and Korea and proposed three policy suggestions for China and Korea based on their empirical research as follows: (1) the “green growth” policy in Korea did not have a significant positive impact on its CO2 emission performance change, which leads to the conclusion that strict regulation is more effective than market-oriented in direct promotion policies, at least concerning green growth; (2) China and Korea should learn from each other's comparative advantages; (3) China needs to restructure more market-oriented competition, while the Korean government should promote the role of meta-frontier innovators via more transparent and predictable policies. Xu and Li (2015) provided five policy suggestions on China's transport sector as (1) China should implement targeted measures to reduce CO2 emissions in the transport sector at the different stages of economic growth; (2) energy-saving technology research and development should be further strengthened; (3) policies targeting decarbonization in urban transport should be strengthened; (4) policies aimed at reducing CO_2 emissions of private cars should not be the same at different stages of economic development; (5) both hybrid trucks and non-polluting rail transport and low-energy water transport should be further highlighted in cargo transport. Du and Mao (2015) investigated power plants' CO_2 abatement costs and made the following recommendations: (1) policy-makers should provide power plants with incentives to improve their efficiency, as there are potentials for further electricity production expansion and CO_2 emissions reduction; (2) The government should consider the existing differences in marginal CO_2 abatement costs among power plants, and should then fairly and cost-effectively allocate the emissions' abatement tasks; (3) the government can use the estimated shadow prices as initial market settings for the national carbon trading market; (4) replacement of the old equipment should be considered, however, environmental subsidies should be combined with competition policies so that the long-term productive efficiency of plants is not reduced. Wang *et al*. (2018) investigated the energy and emission abatement efficiency of the Chinese thermal power industry and suggested that China should prioritise the wider adoption of the existing end-of-pipe abatement technologies that currently show high performance, although the process of further absorbing SO_2 and NO_x will increase CO_2 emissions and reduce the global abatement performance. Munisamy and Ramli (2015) investigated the eco-efficiency in greenhouse emissions among Malaysia manufacturing industries and proposed several policy suggestions: (1) Environmental performance in the manufacturing sector can be improved via several approaches such as the implementation of clean coal technologies; (2) The installation of scrubbers is an alternative mechanism to control pollution during production activities, which are intended to reduce the emission of pollutants that are released into the atmosphere.; (3) The government can also formulate a policy for using alternative energy, which is much cleaner, or use the most cost-effective combination of energy and technology or make the emission-intensive sectors; (4) The government can also introduce is a carbon tax policy for manufacturers. Hampf and Rodseth (2015) assessed the efficiency of coal-fired power plants in the US. They note that the EPA standard of 40% is unlikely to be met even by best practice power plants, as efficiency results are affected by the age of plants. Therefore, efficiency improvement will only be realistic in the long run, involving significant costs for restructuring plants, and they suggested the application of the alternative emissions' standard of 1943 lb of CO2 per megawatt-hour of electricity to be used instead. Demiral and Sağlam (2021) suggested that the United States should (1) improve the states eco-productivity and eco-efficiency levels by tax incentives to the major cooperation; (2) urge the manufacturing heavy states to improve carbon capture and storage and use, electrification using affordable low carbon source, decarbonization of grid, energy management systems, and circular economy for the industries; (3) expand and extend the economic incentives promoting the development and use of renewable energy sources; (4) increase the incentives for electric vehicles and plug-in hybrid cars state-wide and nationwide; (5) state Renewable Portfolio Standards programs across the US. Gai *et al*. (2022) focused on China's textile industry and proposed that (1) the support of small and medium-size enterprises cannot be separated to realize the high-quality development and the better eco-efficiency; (2) local governments should introduce measures to enhance the harmonious relationship between economy and ecological environment; (3) governments should guide the foreign direct investment to invest in textile industries with high-quality and high added value; (4) firms improve their awareness of gradually strengthening environmental standards will guide enterprise managers to adopt environmentally friendly technologies in production, to meet emission standards. Xia *et al*. (2022) evaluated the eco-efficiency of tourism sectors and suggested that (1) the tourism sector should pay attention to coordinated development in the supply chain with respect to indirect carbon emission sources in order to promote carbon emission efficiency; (2) the government should adhere to promoting the decoupling of tourism carbon emissions from economic growth and scientifically evaluate the development status of tourism sectors; (3) the government can promote the green development of tourism sectors by encouraging tourism enterprises to provide low-carbon tourism products from the supply side to guide green tourism consumption, and avoiding blindly expanding the market scale.

(b) Policy suggestions at country level: Zhang *et al.* (2014) proposed that (1) Chinese policymakers should increase the emphasis on environmental regulations and on enhancing social equity; (2) the Chinese government needs to pursue different types of policies to improve the country's sustainability performance, especially for the central and western areas; (3) each province needs to be managed differently based on its level of economic development, social capital, and environmental protection. Du *et al*. (2015) presented that the Chinese government favours the introduction of a carbon emissions trading scheme in preference to the imposition of a carbon tax, and China should build a nationwide carbon emission trading market to improve efficiency and fairness of carbon reductions. Du and Lin (2015) proposed policy suggestions after investigating China's regional economies: (1) Chinese government should further promote the marketization in China's regions, especially for the provinces in the central and west areas; (2) Chinese government should further implement market reforms in the factor market; (3) the government is also suggested to optimize energy consumption structure through increasing the share of high quality and clean energy, as well as providing more financial support for the development of renewable energy; (4) Chinese government should also adjust industrial structure and support the development of industries with low energy consumption and less environmental pollutions; (5) The disparity in China's regional efficiency performances implies variations in the abatement costs of CO2 emissions. Wang and Wei (2016) suggested that (1) energy consumption structure in China should not be omitted; (2) oil and electricity inputs are the main contributors to the energy productivity growth, whereas coal and natural gas appear to be negative contributors; (3) China should focus on the shift in technology rather than on the catch-up effect, and (4) environmental regulations will contribute towards productivity growth. Emrouznejad and Young (2016a, 2016b) suggested that the Chinese government should encourage domestic manufacturers (1) to invest more in the research and development of advanced manufacturing technology to increase the gross industrial output production while lowering the CO_2 emissions' level; (2) to adopt the use of advanced experiences and equipment from other industrialised countries; (3) to decrease CO_2 emissions by providing incentives. Emrouznejad and Young (2016b) further recommended that the Chinese government should insist on the application of environmental protection laws and eliminate backward production capacities. Wang et al. (2017) recommended that the Chinese government should (1) consider local conditions when planning actions for the energy use performance improvement, rather than applying homogeneous strategies; (2) introduce emission trade system at the urban level; (3) each city should focus both on improving its energy efficiency and reducing its CO_2 emissions. Yang *et al.* (2017) suggested that regarding green production performance improvement, investment in research and development can have a positive effect, the increase in the share of industrial export values does not have a significant effect, while the technology spillover of foreign investment does not have any positive effect. Xiao *et al*. (2021) claimed the importance of recourse-based cities in China to the NetZero aim, and concluded that the government should (1) promote the process of industrial upgrading to the industrial sector which directly generates CO_2 emissions; and (2) actively hold bilateral cooperation between the government and industrial sectors by strengthening communication.

(c) Policy suggestions for organizations or unions: Rashidi and Sean (2015) evaluated the eco-efficiency of OECD countries and suggested that international organisations - such as the International Union for Conservation Nature (IUCN) and the United Nations Environment Programme (UNEP) - should superintend inefficient countries' operations, oblige them to comply with environmental rules, and penalize eco-inefficiencies. Bampatsou *et al*. (2021) presented that the EU countries should (1) enhance the diffusion of the various technological elements that enable the decoupling of resource use from economic growth across industries; and (2) develop technological advancement to bed and integrated into the economic models to create sustainable value for the circular economy. Moutinho and Madaleno (2021) presented that EU countries should (1) emphasis more on the reduction of gases to achieve environmental efficiency goals; (2) weigh the costs of environmental degradation and the benefits of increasing economic growth, heterogeneously and not by simply imposing general rules to be followed at the EU level. Henriques *et al*. (2022) presented that EU countries should (1) focus on creating opportunities for exploring high value-added clean technologies; (2) support the innovative technologies that allow decarbonizing hard-to-abate sectors (namely, transport and energy intensive industries); (3) implement the reinforcement of carbon prices in regard to the emission trading system and the promotion of more stringent rules in the field of renewable energy targets for the EU; (4) encourage the cooperation between EU countries.

7. Conclusions and direction for future research

In this study, we identified important research dealing with the analysis of CO_2 emissions studied using DEA. We first examine the historiography that identifies key milestones in knowledge flows characterizing the topic researched. Second, we provide basic bibliometric information about the most active journals and authors. Third, we conduct a qualitative in-depth analysis of the identified most important studies. Finally, we focus on the evolution of the field between 2000 and 2022 and identify the research fronts and relate them to the emerging issues on the topic researched. In particular, we conduct an in-depth analysis of the papers in the field by analysing the bibliometric of our sample according to the 20 most active authors based on the number of published papers. We point that the focus has been mostly on measuring the relationship between emissions of by-products and economic growth. A critical review of published papers on this topic indicates that while there is much research on CO_2 emissions, what is not done is to provide a proper practical framework that can easily be used by policy makers. This could be one of the main topics for future works. As another way to forward, especially for practitioners, it would be useful to develop software that can easily be used by policy makers with minimum technical information.

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