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Greenhouse Gas Emission Reduction Potentials in Europe by Sector: A Bootstrap-Based Nonparametric Efficiency Analysis

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Abstract
The reduction of greenhouse gas emissions is the key action to limit global warming. An important source of greenhouse gas emissions and pollution is the inefficiency of production processes. We report results from a stochastic nonparametric efficiency analysis using directional distance functions to take account of undesirable outputs like greenhouse gases. With this approach, we are able to provide estimates of the potential emission reductions for 7 main sectors in 16 European countries. A specially adapted bootstrapping approach allows to implement a bias correction of the estimates and to compute confidence intervals. The results show that static efficiency improvements are a quantitatively important element of the emission reductions which are required to achieve the reduction targets of the European Union.

Keywords Climate policy · Environmental efficiency · Nonparametric measurement · bootstrapping · Europe

JEL classification Q54 · E23 · C14

1 Introduction

The reduction of greenhouse gas (GHG) emissions on a global level is the key measure to counteract the detrimental effects of climate change and global warming. Other approaches to limit global warming, like carbon removal or geoengineering approaches are either infeasible or extremely risky (see Nordhaus (2019, p. 1998) for a clear statement). This is largely undisputed in the economic literature (see the survey articles by Myhre et al. (2001), Aldy et al. (2010), Hsiang and Kopp (2018) and Tol (2018), among others) and is the basis for several international agreements. The most prominent agreements are the

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Kyoto Protocol of 1997 and the Paris Agreement on climate change of 2015 to reduce GHG emissions to reach the 2°C target, meaning the stabilization of the increase in temperature at “well below 2°C above pre-industrial levels”.[1]

The European Union (EU) as a key actor in this area has achieved an agreement among its member countries to reduce GHG emissions by 40% until 2030, 60% until 2040 and 80% until 2050, compared to the levels of 1990 (EU 2011, p. 3). Recently these targets have been tightened to reduce GHG emissions by 55% until 2030, 80% percent until 2040 and to reach climate neutrality by 2050, also accounting for the effects of carbon removal technologies, land use change and forestation (see EU (2020) and especially figure 1 therein).

Efforts to improve the productive efficiency of sectors could be a potentially important building block of an emission reduction strategy. Therefore, it is important to know to which extent GHG emissions could be reduced by achieving productive efficiency while holding the economic inputs and outputs constant. In our companion paper (Krüger and Tarach 2020) we applied nonparametric methods of efficiency analysis in the presence of undesirable outputs derived from a variant of data envelopment analysis (DEA) to give an account of the potential reductions of GHG by country and sector for the period 2008–2016. The main finding there is that efficiency improvements can contribute considerably to emission reduction, albeit the extent to which the measured potentials could be realized in practice remains open. However, the measurement approach used in the companion paper is purely deterministic and prone to biases. Furthermore, no account of the estimation uncertainty is provided there.

In this paper we pick up these issues by combining the nonparametric efficiency measurement approach with a specifically designed bootstrapping procedure to achieve a bias correction and to compute confidence intervals for assessing estimation uncertainty. To our knowledge this is the first time that a nonparametric approach combined with stochastic elements is applied in an environmental efficiency measurement context. We report estimates of aggregate emission reduction potentials for 16 major EU countries and 7 main sectors of the private economy. As emissions we consider a broad GHG aggregate as well as splits to single GHGs (CO_2, CH_4 and N_2O). The results show that the bias correction leads to larger emission reductions compared to the “raw” measures from our companion paper which are based on the purely deterministic approach. We can show that the potentials for emission reduction are concentrated in certain countries and sectors. In addition, we find that the estimation uncertainty is substantial in these cases.

In contrast to much of the literature on eco-efficiency which is also concerned with emission reduction on a macroeconomic level or the level of major sectors we assess the contribution of potential efficiency improvements to the EU reduction targets by expressing them as potential reductions measured in physical units, i.e. CO_2 equivalents (CO_2e). The usual practice in the literature (see Camarero et al. (2014), Färe et al. (2004), Korhonen and Luptacik (2004), Kortelainen (2008), Kuosmanen and Kortelainen (2005), Rashidi and Farzipoor Saen (2015), Zaim and Taskin (2000), Zhou and Ang (2008) and Zofío and Prieto (2001), among others) is to focus on relative measures instead. More closely related to our analysis are studies such as Domazlicky and Weber (2004) and Krautzberger and Wetzel (2012) which are also based on a methodological setting employing directional distance functions and are also confined to specific industries.

[1] This 2°C target is defined in Article 2 of the Paris Agreement jointly with the plea to pursue an even tighter target of 1.5°C, see https://newsroom.unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement.

The exposition in this paper starts with a description of the data and the country-sector coverage in Sect. 2. This is followed by the description of the nonparametric methodology we use to obtain our estimates of emission reduction potentials in Sect. 3. In this section, the implementation of the bootstrapping approach as well as the computation of the bias-corrected measures and the confidence intervals are also outlined. Section 4 contains the discussion of the results from several specifications of the undesirable outputs. The specifications comprise a single total GHG aggregate as well as splits to CO_2, CH_4 and N_2O. We also discuss the results of a variant where possible enhancements of the economic output are permitted in addition to the emission reductions. Policy recommendations are provided at the end of the section. The final Sect. 5 concludes with an evaluation of the contribution of the emission reduction by efficiency improvements to the EU emission reduction targets and discusses the feasibility of the potential reductions measured.

2 Data Description

The data required for the efficiency analysis comprise the inputs, the good (desirable) outputs and the bad (undesirable) outputs, i.e. the emissions of greenhouse gases. In the subsequent measurement of inefficiency and the potential emission reduction derived thereof we always include the two conventional inputs labor and capital as well as value added as the single economic output. The emissions as undesirable outputs are used in different forms. As the description of the methods will show, the inefficiency is measured as the potentially reachable *enhancement* of the good output and/or the potentially reachable *reduction* of the emissions. The economic data, meaning the inputs and the good (desirable) output are taken from the EU-KLEMS database. The November 2019 release we use is described by Stehrer et al. (2019) and can be obtained from https://euklems.eu. Labor input is measured in total hours worked by employees (comprising self-employed persons and expressed in full-time equivalents). Capital input is quantified by the real fixed capital stock (at constant 2010 prices). The output variable is gross value added (also at constant 2010 prices).[2] Using this variable is associated with a much more comprehensive data coverage compared to the alternative of using a gross output measure with materials and energy as additional input variables.[3]

The emissions data to quantify the bad (undesirable) outputs[4] are taken from two sources.[5] As greenhouse gas (GHG) emissions, we focus on the three main greenhouse gases (GHGs) which are emitted by anthropogenic sources, namely carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O). The global warming potentials usually differ for each GHG, but they can be converted to CO_2 equivalents (abbreviated CO_2e and measured in tons, kilotons or megatons). CO_2 emissions are retrieved from the World Input Output Database (WIOD) described in Timmer et al. (2015) and can be downloaded from http://

[2] We always mean the good (desirable) economic output when we simply refer to the output in the following.

[3] This alternative would also increase the dimensionality of the input-output space which is a crucial issue for nonparametric analyses in general.

[4] We subsequently refer to emissions when we mean the bad (undesirable) outputs.

[5] These data bases are used instead of the Emissions Database for Global Atmospheric Research (EDGAR) because of their conformability to an economic sector classification and their coverage of more recent periods.

www.wiod.org. The data for CH_4 and N_2O emissions are retrieved from the Eurostat Air Emission Accounts (AEA).[6] In the AEA database, CH_4 and N_2O emissions are already expressed in tons of CO_2e and so we obtain our measure of total GHG emissions by simply adding them to the CO_2 emissions from the WIOD. There are further GHGs which are of minor quantitative importance and therefore neglected.[7]

All three major GHGs have specific anthropogenic sources. CO_2 emissions stem primarily from burning fossil fuels (coal, oil and natural gas), but also from industrial processes such as the manufacturing of cement. In addition, CO_2 is emitted or absorbed by land use, land use change and forestry (LULUCF). Although its global warming potential per ton is less than that of CH_4 or N_2O, CO_2 is quantitatively the most important GHG. In 2010 CO_2 emissions (without LULUCF) accounted for 82% of total GHG emitted by the EU (Debelke and Vis 2015, p. 96).

CH_4 has an atmospheric lifetime of 12 years, meaning that on average it stays in the atmosphere for only 12 years before it is broken down into CO_2 and water (Hsiang and Kopp 2018, p. 12). It has a global warming potential of 25 CO_2e (meaning one ton of CH_4 has the global warming potential of 25 tons of CO_2, Eurostat 2015, p. 105). The two major anthropogenic sources of CH_4 emissions are industrial livestock farming and the exploitation of fossil fuels. Natural gas (largely consisting of CH_4) may be leaking when recovered from gas or oil fields or during transport and storage. CH_4 is also contained in coal beds (coal mine methane), especially in deeper coal beds and coals with higher carbon content (i.e. hard coal), and may similarly leak during coal mining (Kholod et al. 2020). In the EU, CH_4 emissions already declined between 1990 and 2010 by 32% (Debelke and Vis 2015, p. 96).

N_2O is a very potent GHG with the same global warming potential as 298 tons of CO_2 (Eurostat 2015, p. 105) during an atmospheric lifetime of 116 ± 9 years (Tian et al. 2020). In addition, N_2O has a depleting effect on the stratospheric ozone layer. The major anthropogenic source of N_2O is the agricultural sector, in particular the large-scale use of nitrogen fertilizers. According to Tian et al. (2020) agricultural emissions accounted for about 70% of anthropogenic N_2O emissions globally in 2007–2016. Other comparatively smaller anthropogenic sources include the fossil fuel and chemical industry. In contrast to rising or stagnant N_2O emissions in most other countries globally, European emissions from agriculture declined by 21% between 1990 and 2010 (Tian et al. 2020, p. 254), which the authors attribute to European agricultural policies favoring more efficient fertilizer use. Besides, non-agricultural N_2O emissions in the EU were reduced even more strongly during that period, mainly due to improved abatement technologies in the chemical industry (Tian et al. 2020, pp. 253–255).

Assessing the data coverage in the database we are able to achieve an almost complete coverage for 16 countries and 7 sectors during the period 2008–2016 on a classification of sectors (industries) according to NACE Rev. 2 (equivalent to ISIC Rev. 4). The countries covered comprise (with World Bank country codes in parentheses):

6 These data can be accessed at https://ec.europa.eu/eurostat/web/products-datasets/-/env_ac_ainah_r2.

7 Further anthropogenic GHGs are sulphur hexafloriode, hydrofluorcarbons and perfluorcarbons, which are not included in our measure of total GHG emissions. They made up only 2% of total GHG emissions in the EU-28 in 2010 (Debelke and Vis 2015, p. 96), slightly rising to about 2.5% in 2018 (EEA data).

Austria (AUT)	Germany (DEU)	Poland (POL)
Belgium (BEL)	Greece (GRC)	Slovakia (SVK)
Czech Republic (CZE)	Ireland (IRL)	Spain (ESP)
Denmark (DNK)	Italy (ITA)	Sweden (SWE)
Finland (FIN)	Netherlands (NLD)	United Kingdom (GBR)
France (FRA)		

The sectors covered are:

A	Agriculture, Forestry and Fishing
B	Mining and Quarrying
C	Manufacturing
D	Electricity, Gas, Steam and Air Conditioning Supply
E	Water Supply Sewerage, Waste Management and Remediation Activities
F	Construction
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
H	Transportation and Storage

The emissions data in the AEA database are only available for a sector combining the sectors D and E. So we had to aggregate the economic input-output data of the sectors D and E to a combined sector, henceforth named DE. Cross checking assures that the sums of the values of the sectors D and E are very close to the values of the combined sector DE which is also available in the EU-KLEMS data.[8] Since the sector D is considerably larger than E in most countries we refer to the combined sector DE frequently as “energy” or as “energy and water” in the subsequent discussion.

We exclude Estland, Lithuania, Luxembourg and Slovenia from our analysis despite full data coverage. The reason is that these are very small countries and Luxembourg is merely a large city rather than a country. Including those small countries can severely bias the entire efficiency analysis when they determine parts of the frontier function and overstate the potential emission reductions. Growiec (2012) provides further discussion of this issue. In some of these countries we also suspect recording errors in the data for some sectors (e.g. zero emissions in sector G in Slovenia).

The value added and capital stock data are directly expressed in Euro for the majority of the countries (appropriately deflated with base year 2010). In the case of the non-Euro countries Czech Republic, Denmark, Poland, Sweden and the United Kingdom these variables are expressed in the respective national currencies. To convert the data to a common currency we use purchasing power parities (PPPs) from the OECD National Accounts Statistics (OECD 2020). While exchange rates only convert currencies, PPPs also take account of different price levels of the countries. This is important since price levels tend to be systematically higher in high-income countries than in low-income countries. Using exchange rates would therefore overstate the values of the variables in the case of high-income countries and understate them in low-income countries. Instead, PPPs convert expenditures to a

[8] An exception are two capital stock values of Belgium in 2008 and 2009 where the sums of the values of the sectors D and E deviate from those of the combined sector DE by 18 and 5 percent, respectively. Here we use the time series of the sum of the single sectors which looks more plausible than the time series of the combined sector. In the case of Spain only data for the combined sector are available and therefore these data are used directly.

common price level. This is also important for countries with a common currency (as the Euro) which also can have rather different national price levels.[9]

We split these data in two five-year subperiods $t_1 = 2008–2012$ and $t_2 = 2012–2016$ and take medians over these subperiods for the subsequent empirical analysis. This eliminates the effects of single or even two outlying observations and makes the efficiency analysis more robust. The way of taking medians to robustify the analysis is in our view preferable to the alternative of outlier detection by methods such as those proposed by Wilson (1993) and subsequent outlier elimination. This procedure also solves the problem with two missing values in sector C of Ireland.[10] Thus, when we refer to the first and second subperiod in the following we always mean the medians of the inputs and outputs (including emissions) over the indicated five-year intervals.

The aggregate GHG emissions over all countries and sectors are 3341 mt of CO_2e in the first subperiod, declining to 3070 mt in the second subperiod. Figure 1 shows stacked barplots of the three GHG emission variables for both subperiods (the corresponding data are reported in Table 1 in the appendix). The left-hand side of each plot depicts the bars for the sectors, followed by the bars of the countries on the right-hand side (separated by the thick vertical line). This kind of plot gives a succinct summary of the distribution of the aggregate emissions over sectors and countries jointly with an indication of the distribution of the different GHGs (CO_2, CH_4 and N_2O in mt of CO_2e). More descriptive information on the data is discussed in the companion paper of Krüger and Tarach (2020).

From Fig. 1 we immediately see that the sectors C and DE are most emission intensive, while A and H also contribute considerably, and the remaining sectors (B, F and G) are of minor importance. CO_2 is the quantitatively most important emission category in all sectors except A where CH_4 and N_2O emissions are dominating. CO_2 is the main emission category in all countries, including those with large aggregate emissions (Germany, Spain, France, the United Kingdom, Italy and Poland), although the contribution of CH_4 and N_2O is also visible here. While the overall quantity declines from the first to the second subperiod, the distribution of the emissions across sectors and countries is rather similar in both subperiods.

3 Nonparametric Efficiency Measurement and Bootstrapping

For the estimation of the potential emission reductions we apply nonparametric methods of efficiency analysis. These methods are an extension of data envelopment analysis (DEA), developed by Charnes et al. (1978) and Banker et al. (1984). The specific modification we rely on is based on the concept of the directional distance function (DDF), introduced by Chambers et al. (1996) and extended to an environmental context by Chung et al. (1997). This approach allows to measure inefficiency as the distance to a piece-wise linear frontier function along a mix of possible reduction of inputs and enhancement of some outputs

[9] PPPs are also central for the construction of comparable national accounts provided in the Penn World Table (see Feenstra et al. 2015).

[10] In the case of Ireland the capital stock values for the final years 2015 and 2016 are missing in sector C. Since the preceding values 2012–2014 show a rising trend and capital is an accumulating stock variable we can safely suppose that the missing values are larger than the value in 2014. Then taking the 5-year median over the subperiod 2012–2016 will result in just the value of 2014 irrespective of the exact magnitudes of the missing values.

(the good, desirable outputs), while other outputs (the bad, undesirable outputs) are supposed to be reduced (see Färe and Grosskopf (2004)). This property of reducing outputs allows to incorporate undesirable outputs like GHG emissions in a consistent way (Zhou et al. 2008b). Like in DEA, here also no price information is required and no functional form assumptions about the underlying technology (e.g. a production function) need to be imposed. These are major advantages of the nonparametric approach.

3.1 Technology Set

The nonparametric approach of efficiency analysis is based on the concept of an abstract technology set, comprising the feasible input-output combinations. It can be stated as

$$\mathcal{T} = \{(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) \in \mathbb{R}_{+}^{m+s+r} \, : \, \boldsymbol{x} \geq \boldsymbol{0} \text{ can produce } (\boldsymbol{y}, \boldsymbol{u}) \geq \boldsymbol{0}\}, \tag{1}$$

where $\boldsymbol{x}$ denotes the m-vector of the input quantities, $\boldsymbol{y}$ the s-vector of the quantities of the good (desirable) outputs and $\boldsymbol{u}$ the r-vector of the quantities of the bad (undesirable) outputs.[11] Since we are dealing with sectors within countries it is suitable to suppose that each sector operates with a different technology set.[12]

To impose some structure on the technology set it is supposed to be closed and convex (Färe and Primont 1995). Furthermore, it is supposed that standard axioms such as strong disposability of the inputs and the good outputs are satisfied. Two additional axioms are required in the context of an environmental efficiency analysis to incorporate the special role of undesirable outputs in a consistent way. The first is null-jointness, meaning that it is not possible to produce positive quantities of the good outputs without generating emissions (i.e. if $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) \in \mathcal{T}$ and $\boldsymbol{u} = \boldsymbol{0}$ then $\boldsymbol{y} = \boldsymbol{0}$). The second is weak disposability stating that proportional reductions of emissions are always feasible as long as the good outputs are reduced by the same proportion (i.e. if $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) \in \mathcal{T}$ then $(\boldsymbol{x}, \alpha\boldsymbol{y}, \alpha\boldsymbol{u}) \in \mathcal{T}$ for $\alpha \in [0, 1]$). For more detailed discussions of these axioms see (Färe and Grosskopf (2004), Färe et al. (2005) and Zhou et al. (2008a)).[13]

3.2 Directional Distance Functions

The directional distance function (DDF) is defined on the technology set $\mathcal{T}$ as proposed by Chambers et al. (1996) and extended to the incorporation of undesirable outputs by Chung et al. (1997). It is a generalization of the (Shephard 1970) distance function to the case of non-proportional changes of the inputs and outputs and can be formally stated as

[11] In the subsequent discussion of the results we will frequently simply refer to the outputs when we mean the good outputs and to the emissions when we mean the bad outputs.

[12] Here we also include conventional inputs as labor and capital. Related papers such as (Picazo-Tadeo et al. 2012) measure eco-efficiency scores by directional distance functions without using inputs.

[13] An alternative to this approach is the so-called by-production approach proposed by Murty et al. (2012) which relies on the availability of abatement options (and requires appropriate data). This approach models the technology set as the intersection of two parts to be estimated separately. One part is related to the production of the good outputs and the other part is related to the production of the bad outputs. This setting avoids the assumptions of weak disposability and null-jointness. Further discussion and critique is provided by Dakpo et al. (2016).

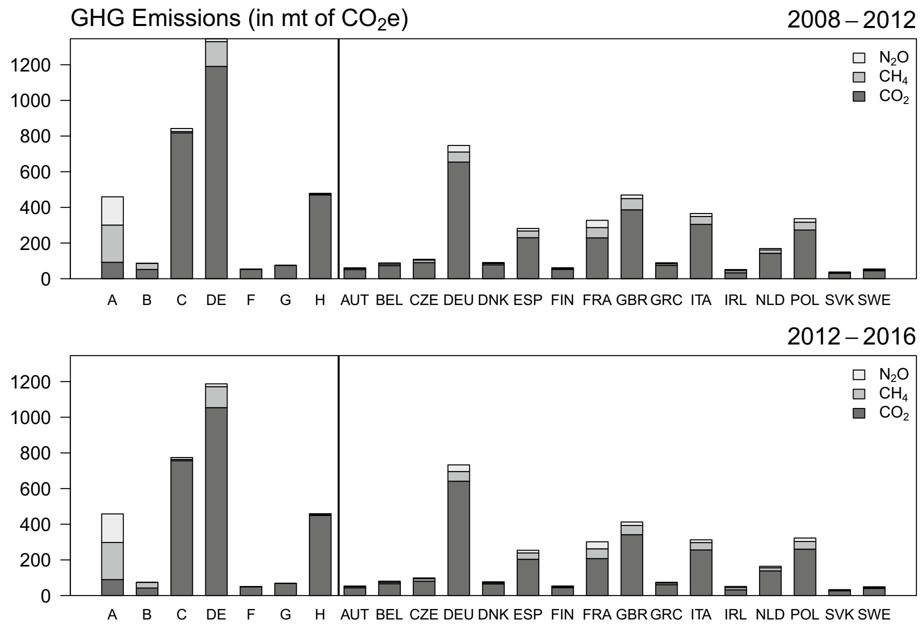

Fig. 1 GHG Emissions across Sectors and Countries

$$DDF(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u};\boldsymbol{g}_x,\boldsymbol{g}_y,\boldsymbol{g}_u) = \sup\{\delta \geq 0 : (\boldsymbol{x}-\delta\boldsymbol{g}_x,\boldsymbol{y}+\delta\boldsymbol{g}_y,\boldsymbol{u}-\delta\boldsymbol{g}_u) \in \mathcal{T}\}. \qquad (2)$$

Herein, the inefficiency measure δ expresses the distance of a particular input-output combination $(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u})$ towards the boundary of the technology set along a particular direction $\boldsymbol{g}_x \geq \boldsymbol{0}$, $\boldsymbol{g}_y \geq \boldsymbol{0}$, $\boldsymbol{g}_u \geq \boldsymbol{0}$. This measure is equal to zero if the input-output combination is a point on the boundary (is on the frontier function) and it is larger than zero if the input-output combination is below the boundary (is below the frontier function).

In the following we mostly impose the restriction $\boldsymbol{g}_x = \boldsymbol{0}$ and $\boldsymbol{g}_y = \boldsymbol{0}$, meaning that the inefficiency is measured exclusively as the extent of possible reduction of the bad outputs. In our application the entities under investigation are sectors in different countries. On such a high level of aggregation it is appropriate to assume that no reduction of input usage is intended. Since we are mainly interested in measuring the maximum potential emission reductions, we also exclude the possibility of output enhancement for most of the analysis. In one variant we only impose $\boldsymbol{g}_x = \boldsymbol{0}$ so that the output enhancement would also be possible.

The data required for the computation of the DDF pertain to n countries in a particular sector. The analysis is performed for each sector separately, so that an additional index to distinguish sectors is not necessary. The data for the m inputs are contained in the $m \times n$ matrix $\boldsymbol{X}$ with the ith column $\boldsymbol{x}_i$ comprising the input quantities of country i $(i = 1, \ldots, n)$. Likewise, the data for the s good outputs are contained in the $s \times n$ matrix $\boldsymbol{Y}$ and the data for the r bad outputs are contained in the $r \times n$ matrix $\boldsymbol{U}$, with the ith columns $\boldsymbol{y}_i$ and $\boldsymbol{u}_i$ comprising the observations pertaining to country i for the good and bad outputs, respectively.

In (2) the direction vectors $\boldsymbol{g}_y$ and $\boldsymbol{g}_u$ are not specified. A frequent choice in applications is to make the directions proportional to the variables $\boldsymbol{y}_i$ and $\boldsymbol{u}_i$ which serves to let the inefficiency measure be invariant to units of measurement (see e.g. Chung et al. (1997) and

Färe et al. (2007)). Since this is restrictive it would be beneficial to compute the directions endogenously. Hampf and Krüger (2015) propose one possibility to endogenize the direction in an environmental efficiency setting and Färe et al. (2013) provide a related proposal to compute endogenous directions in the case of a slacks-based inefficiency measure. As pointed out by Chen and Delmas (2012), these proposals have the additional advantage of avoiding the problem of dominated (weakly-efficient) reference points on the frontier function.

We follow Hampf and Krüger (2015) and propose the following optimization problem to endogenize the computation of the direction vector

$$\begin{array}{lrcl} \max\limits_{\delta,\boldsymbol{\alpha}_y,\boldsymbol{\alpha}_u,\boldsymbol{\lambda}} & \delta & & \\ \text{s.t.} & \boldsymbol{x}_i & \geq & \boldsymbol{X\lambda} \\ & \boldsymbol{y}_i + \delta\boldsymbol{\alpha}_y \odot \boldsymbol{y}_i & \leq & \boldsymbol{Y\lambda} \\ & \boldsymbol{u}_i - \delta\boldsymbol{\alpha}_u \odot \boldsymbol{u}_i & = & \boldsymbol{U\lambda} \\ & \boldsymbol{1}'\boldsymbol{\alpha}_y + \boldsymbol{1}'\boldsymbol{\alpha}_u & = & 1 \\ & \boldsymbol{\lambda}, \boldsymbol{\alpha}_y, \boldsymbol{\alpha}_u & \geq & \boldsymbol{0} \end{array} \tag{3}$$

where '$\odot$' denotes the direct (Hadamard) product. Herein, $\boldsymbol{\lambda}$ is a n-vector containing the weight factors to determine the reference point on the frontier function. The direction weights $\boldsymbol{\alpha}_y$ and $\boldsymbol{\alpha}_u$ are computed jointly with δ and $\boldsymbol{\lambda}$ with the objective of maximizing the distance towards the frontier function. The identification of δ is permitted by the additional constraint $\boldsymbol{1}'\boldsymbol{\alpha}_y + \boldsymbol{1}'\boldsymbol{\alpha}_u = 1$. In this specification the direction vectors are proportional to $\boldsymbol{y}_i$ and $\boldsymbol{u}_i$ which lets the inefficiency measure be invariant to the units of measurement.

The optimization problem (3) is nonlinear and therefore difficult so solve. This is caused by δ and $\boldsymbol{\alpha}_y$ or $\boldsymbol{\alpha}_u$ arising multiplicatively. By defining $\boldsymbol{\gamma}_y = \delta\boldsymbol{\alpha}_y$ and $\boldsymbol{\gamma}_u = \delta\boldsymbol{\alpha}_u$ the problem can be transformed to a well-behaved linear programming problem

$$\begin{array}{lrcl} \max\limits_{\boldsymbol{\gamma}_y,\boldsymbol{\gamma}_u,\boldsymbol{\lambda}} & \boldsymbol{1}'\boldsymbol{\gamma}_y + \boldsymbol{1}'\boldsymbol{\gamma}_u & & \\ \text{s.t.} & \boldsymbol{x}_i & \geq & \boldsymbol{X\lambda} \\ & \boldsymbol{y}_i + \boldsymbol{\gamma}_y \odot \boldsymbol{y}_i & \leq & \boldsymbol{Y\lambda} \\ & \boldsymbol{u}_i - \boldsymbol{\gamma}_u \odot \boldsymbol{u}_i & = & \boldsymbol{U\lambda} \\ & \boldsymbol{\lambda}, \boldsymbol{\gamma}_y, \boldsymbol{\gamma}_u & \geq & \boldsymbol{0} \end{array} \tag{4}$$

Taking the constraint $\boldsymbol{1}'\boldsymbol{\alpha}_y + \boldsymbol{1}'\boldsymbol{\alpha}_u = 1$ from (3) into account we easily see that the value of the objective function $\boldsymbol{1}'\boldsymbol{\gamma}_y + \boldsymbol{1}'\boldsymbol{\gamma}_u = \delta \cdot (\boldsymbol{1}'\boldsymbol{\alpha}_y + \boldsymbol{1}'\boldsymbol{\alpha}_u)$ is equal to δ as before. Program (4) can be easily solved by the ordinary simplex algorithm.[14] The solution values for δ, $\boldsymbol{\alpha}_y$ and $\boldsymbol{\alpha}_u$ can be backed out from the solutions for $\boldsymbol{\gamma}_y$ and $\boldsymbol{\gamma}_u$ by $\delta = \boldsymbol{1}'\boldsymbol{\gamma}_y + \boldsymbol{1}'\boldsymbol{\gamma}_u$ as well as $\boldsymbol{\alpha}_y = \boldsymbol{\gamma}_y/\delta$ and $\boldsymbol{\alpha}_u = \boldsymbol{\gamma}_u/\delta$. For a particular country i the solution values are denoted δ_i, $\boldsymbol{\alpha}_{yi}$, $\boldsymbol{\alpha}_{ui}$, $\boldsymbol{\gamma}_{yi}$, $\boldsymbol{\gamma}_{ui}$ and $\boldsymbol{\lambda}_i$ $(i = 1, \dots, n)$.[15]

With these solution values we can compute the efficient input-output combination on the frontier function with the coordinates $\hat{\boldsymbol{x}}_i = \boldsymbol{X\lambda}_i$, $\hat{\boldsymbol{y}}_i = \boldsymbol{Y\lambda}_i$ and $\hat{\boldsymbol{u}}_i = \boldsymbol{U\lambda}_i$. The potential reductions of the r bad outputs for country i in the sector under consideration can be computed as $\boldsymbol{u}_i - \hat{\boldsymbol{u}}_i = \boldsymbol{\gamma}_{ui} \odot \boldsymbol{u}_i = \delta_i\boldsymbol{\alpha}_{ui} \odot \boldsymbol{u}_i$. We see that the potential emission reductions

[14] For the computation of the solutions in this paper the R-package "lpSolve" is used.

[15] In the case of the efficient countries (with $\delta = 0$) the solution for $\boldsymbol{\alpha}_y$ and $\boldsymbol{\alpha}_u$ is indeterminate. Clearly, there exists no direction towards the frontier function if an observation already stays on the frontier function.

depend on the magnitude of the inefficiency measure δ_i as well as on the optimized direction vector $\boldsymbol{\alpha}_{ui}$ of country i. The total emission reduction potential of country i is the sum over all emission categories $RP_i = \mathbf{1}'(\boldsymbol{u}_i - \hat{\boldsymbol{u}}_i)$ with $\mathbf{1}$ denoting a conformable vector of ones and the prime denoting transposition. The sum can, of course, only be validly computed if the emission variables are denominated in a common unit of measurement. This is indeed the case in our application where greenhouse gas emissions are expressed in CO_2 equivalents. To report the results later on we further aggregate the potential emission reductions across countries and sectors. Potential output enhancement can likewise be computed as $\hat{\boldsymbol{y}}_i - \boldsymbol{y}_i = \boldsymbol{\gamma}_{yi} \odot \boldsymbol{y}_i = \delta_i \boldsymbol{\alpha}_{yi} \odot \boldsymbol{y}_i$ for the case where we do not impose $\boldsymbol{\gamma}_{yi} = \mathbf{0}$ or $\boldsymbol{\alpha}_{yi} = \mathbf{0}$ a priori.

3.3 Variable Returns to Scale

The above stated optimization problems compute the inefficiency measures under the assumption of constant returns to scale (CRS). In a cross-country sectoral setting with countries of rather different size and with a rather different sectoral structure CRS seems to be an overly restrictive assumption. So it would be beneficial to get rid of this rather unrealistic assumption and to measure inefficiency under variable returns to scale (VRS). In nonparametric approaches of efficiency measurement VRS is usually induced by adding the constraint $\mathbf{1}'\boldsymbol{\lambda} = 1$ to the optimization problems. In the case of environmental efficiency analysis this would violate the weak disposability property. Zhou et al. (2008a) show how to induce VRS in a way which is consistent with weak disposability. This implementation again leads to a linear programming problem

$$\begin{array}{lrcl}
\max\limits_{\beta,\boldsymbol{\gamma}_y,\boldsymbol{\gamma}_u,\boldsymbol{\zeta}} & \mathbf{1}'\boldsymbol{\gamma}_u + \mathbf{1}'\boldsymbol{\gamma}_u & & \\
\text{s.t.} & \beta\boldsymbol{x}_i & \geq & \boldsymbol{X}\boldsymbol{\zeta} \\
& \boldsymbol{y}_i + \boldsymbol{\gamma}_y \odot \boldsymbol{y}_i & \leq & \boldsymbol{Y}\boldsymbol{\zeta} \\
& \boldsymbol{u}_i - \boldsymbol{\gamma}_u \odot \boldsymbol{u}_i & = & \boldsymbol{U}\boldsymbol{\zeta} \\
& \mathbf{1}'\boldsymbol{\zeta} & = & \beta \\
1 \geq \beta \geq 0 \;, & \boldsymbol{\zeta}, \boldsymbol{\gamma}_y, \boldsymbol{\gamma}_u & \geq & \mathbf{0}
\end{array} \tag{5}$$

with an additional parameter β which is bounded in [0, 1]. Details can be found in Zhou et al. (2008a). As before, we obtain the solution values for $\boldsymbol{\gamma}_y, \boldsymbol{\gamma}_u$ which allow to back out $\delta = \mathbf{1}'\boldsymbol{\gamma}_y + \mathbf{1}'\boldsymbol{\gamma}_u$, $\boldsymbol{\alpha}_y = \boldsymbol{\gamma}_y/\delta$ and $\boldsymbol{\alpha}_u = \boldsymbol{\gamma}_u/\delta$ and to compute the emission reduction potentials. This problem can again be easily solved by the simplex algorithm. Here also, the solution values are denoted δ_i, $\boldsymbol{\alpha}_{yi}$, $\boldsymbol{\alpha}_{ui}$, $\boldsymbol{\gamma}_{yi}$, $\boldsymbol{\gamma}_{ui}$ and $\boldsymbol{\lambda}_i$ for a particular country i ($i = 1, \ldots, n$). We stick to the VRS assumption throughout this paper.

3.4 Bootstrapping

The inefficiency measures and the derived reduction potentials are estimates from a data sample which are subject to measurement error and therefore stochastic in nature. Frontier function estimation is associated with a further peculiarity. Specifically, the empirical implementation of the linear programming problems (4) or (5) is based on the observed input-output combinations in the data. This lets the empirically estimated frontier function provide a closer envelopment of the data than the true (unobserved) frontier function. As a consequence, the empirically determined technology set $\hat{\mathcal{T}}_{\text{DDF}}$ underlying the subsequent analysis is a subset of the true technology set $\mathcal{T}$, i.e. $\hat{\mathcal{T}}_{\text{DDF}} \subseteq \mathcal{T}$. This leads to downward-biased estimates of the inefficiency measures and the emission reduction potentials. This bias can be substantial and bootstrapping provides a practical way to achieve a correction (see Simar and Wilson 2008, 2011).

We resort to a bootstrapping approach to compute bias-corrected estimates of the reduction potentials and to establish confidence intervals for these measures. The specific approach pursued here is analogous to the procedure proposed by Simar and Wilson (1998) adapted to the setting of directional distance functions. Compared to the double-bootstrap algorithm of Simar et al. (2012) the chosen approach is more transparent and easier to communicate. The approach of Simar et al. (2012) uses a complicated orthogonal transformation of the data and two smoothing loops which requires the selection of two critical bandwidth parameters instead of one. This bandwidth choice is particularly problematic in small-sample situations. Moreover, the algorithm seems not to be adapted to the inclusion of bad outputs since the direction vector pertaining to the outputs is restricted to be non-negative.

The smoothed bootstrap algorithm adapted from Simar and Wilson (1998) to the DDF setting starts with some preparatory steps. First, the DDF and the optimal directions are computed from the original data by solving (5) to obtain $\hat{\delta}_i$ as well as the optimal directions $\boldsymbol{\alpha}_{yi}$ and $\boldsymbol{\alpha}_{ui}$ for all $i = 1, \dots, n$. The directions are computed once and kept fixed during the whole procedure. Furthermore, the bandwidth parameter h for the smoothing is chosen as described in Simar and Wilson (2011) where also some R code is provided.

The main part of the bootstrapping algorithm cycles B times through the following steps:

- A bootstrap resample is obtained by first drawing with replacement from $D = \{\hat{\delta}_1, \dots, \hat{\delta}_n, -\hat{\delta}_1, \dots, -\hat{\delta}_n\}$ which implements a boundary reflection about zero. The result of this step is denoted $\tilde{\delta}_i\,(i = 1, \dots, n)$.
- The smoothing step is performed by adding $h \cdot \varepsilon_i$ to each draw, where the ε_i are independent standard normal draws, thus obtaining $\tilde{\delta}_i + h \cdot \varepsilon_i$ and finally returning $\delta_i^* = \left| \bar{\delta} + (\tilde{\delta}_i + h \cdot \varepsilon_i - \bar{\delta}) / \sqrt{1 + h^2/\tilde{\sigma}_{\delta}^2} \right|$ for all $i = 1, \dots, n$ where $\bar{\delta}$ and $\tilde{\sigma}_{\delta}^2$ denote the sample mean and variance of $\tilde{\delta}_i\,(i = 1, \dots, n)$, respectively.
- These resampled inefficiencies are used to construct the bootstrap resample of the reference points by setting $\boldsymbol{x}_i^* = \boldsymbol{x}_i$, $\boldsymbol{y}_i^* = \boldsymbol{y}_i + (\hat{\delta}_i - \delta_i^*)\boldsymbol{\alpha}_{yi} \odot \boldsymbol{y}_i$, $\boldsymbol{u}_i^* = \boldsymbol{u}_i - (\hat{\delta}_i - \delta_i^*)\boldsymbol{\alpha}_{ui} \odot \boldsymbol{u}_i$ for all $i = 1, \dots, n$. By that operation the observation $(\boldsymbol{y}_i, \boldsymbol{u}_i)$ is first projected on the frontier (by $+\hat{\delta}_i$) and then randomly away from the frontier (by $-\delta_i^*$) along the fixed direction $(\boldsymbol{\alpha}_{yi} \odot \boldsymbol{y}_i$ and $-\boldsymbol{\alpha}_{ui} \odot \boldsymbol{u}_i)$. The resulting bootstrap resample consists of $\boldsymbol{X}^* = (\boldsymbol{x}_1^*, \dots, \boldsymbol{x}_n^*)$, $\boldsymbol{Y}^* = (\boldsymbol{y}_1^*, \dots, \boldsymbol{y}_n^*)$ and $\boldsymbol{U}^* = (\boldsymbol{u}_1^*, \dots, \boldsymbol{u}_n^*)$.
- The efficiency measures are computed by solving (keeping the directions fixed)

$$
\begin{array}{lrcl}
\max\limits_{\beta,\delta,\zeta} & & \delta & \\
\text{s.t.} & \beta \boldsymbol{x}_i & & \geq \boldsymbol{X}^* \boldsymbol{\zeta} \\
& \boldsymbol{y}_i & + \; \delta \boldsymbol{\alpha}_{yi} \odot \boldsymbol{y}_i & \leq \boldsymbol{Y}^* \boldsymbol{\zeta} \\
& \boldsymbol{u}_i & - \; \delta \boldsymbol{\alpha}_{ui} \odot \boldsymbol{u}_i & = \boldsymbol{U}^* \boldsymbol{\zeta} \\
& & \boldsymbol{1}' \boldsymbol{\zeta} & = \beta \\
& 1 \geq \beta \geq 0 \;\; , & \boldsymbol{\zeta} \geq \boldsymbol{0} &
\end{array}
\tag{6}
$$

  for each $i = 1, \dots, n$, where $\boldsymbol{x}_i$, $\boldsymbol{y}_i$ and $\boldsymbol{u}_i$ constitute the original observation for country i and $\boldsymbol{X}^*$, $\boldsymbol{Y}^*$ and $\boldsymbol{U}^*$ are taken from the preceding step. The results are the bootstrap inefficiency measures $\hat{\delta}_i^*$ for all $i = 1, \dots, n$. From the bootstrap inefficiency measures the emission reduction potentials $\Delta\hat{\boldsymbol{u}}_i^* = \hat{\delta}_i^* \boldsymbol{\alpha}_{ui} \odot \boldsymbol{u}_i$ or potential output enhancement $\Delta\hat{\boldsymbol{y}}_i^* = \hat{\delta}_i^* \boldsymbol{\alpha}_{yi} \odot \boldsymbol{y}_i$ are obtained for all $i = 1, \dots, n$.[16]

Cycling through the preceding steps B times we obtain the bootstrap resamples $(\hat{\delta}_{i,b}^*, \Delta\hat{\boldsymbol{y}}_{i,b}^*, \Delta\hat{\boldsymbol{u}}_{i,b}^*)$ with $b = 1, \dots, B$ for each country $i = 1, \dots, n$ in a given sector.

Based on the bootstrap resamples the bias correction and percentile confidence intervals can be obtained. Letting z_j be the generic notation of either interesting variable (e.g. aggregates of reduction potentials over sectors or countries), we denote the estimate from the original data by $\hat{z}_j$ and the bootstrap resamples by $\hat{z}_{j,b}^*$ for each $b = 1, \dots, B$.

The bias correction is performed by computing $\hat{z}_{\mathrm{bc},j} = \hat{z}_j - \widehat{\mathrm{bias}}_j$ with $\widehat{\mathrm{bias}}_j = B^{-1}\sum_{b=1}^{B} \hat{z}_{j,b}^* - \hat{z}_j$. This measure is only computed for those cases j (countries or sectors) where $|\widehat{\mathrm{bias}}_j|/\hat{\sigma}_j > 1/\sqrt{3}$ with $\hat{\sigma}_j^2 = (B-1)^{-1}\sum_{b=1}^{B}(\hat{z}_{j,b}^* - \bar{z}_{j,b}^*)^2$ and $\bar{z}_{j,b}^* = B^{-1}\sum_{b=1}^{B}\hat{z}_{j,b}^*$. The rationale for this rule is that the absolute bias has to be sufficiently large compared to the standard deviation in order to achieve a reduction in the mean squared error from the bias correction (see Simar and Wilson 2008, p. 449f.).

Percentile confidence intervals $[\hat{z}_{\mathrm{cl},j}, \hat{z}_{\mathrm{cu},j}]$ are established using the $\alpha/2$ and $1-\alpha/2$ percentiles of $\{\hat{z}_{j,1}^*, \dots, \hat{z}_{j,B}^*\}$, denoted $\hat{z}_{\mathrm{cl},j}$ and $\hat{z}_{\mathrm{cu},j}$, respectively, for some confidence level $1-\alpha$. For the usual value of $\alpha = 0.05$ we thus have $\Pr(\hat{z}_{\mathrm{cl},j} \le z_j \le \hat{z}_{\mathrm{cu},j}) = 0.95$.

One problem that occasionally arises during the bootstrap resamples is that we obtain reduction potentials which are larger than the actual emission quantities. To deal with this problem we prune out those cases in the spirit of an accept-reject procedure. The bias correction and the confidence intervals are established from this truncated distribution. Since we base the confidence intervals on a large number of bootstrap replications (actually $B = 20{,}000$)[17] there always remains a sufficient number of replications for obtaining reliable estimates of the confidence bounds. The bias correction, which is more concerned with the center of the distribution instead of the tails, is even less affected by the pruning operation anyway.

4 Results and Discussion

The exposition of the results in this section is structured along four specification variants: (a) with a single emission variable (total GHG emissions in CO_2e), (b) with two emission variables (CO_2 and other (non-CO_2) GHG emissions) and (c) with three emission variables (CO_2, CH_4, N_2O measured in CO_2e). Whereas we fix $\boldsymbol{\alpha}_y = \boldsymbol{0}$ in these variants, we pursue an additional variant (d) where we also allow for enhancement of the (good) output. We consider the two subperiods t_1 = 2008-2012 and t_2 = 2012–2016 where all inputs and outputs are computed as medians over the indicated years to achieve greater robustness of the results.[18] Most of the discussion focuses on the second subperiod, since there is not much change in the pattern of results across sectors and countries between both subperiods and the results for the more recent subperiod are of greater relevance for the current discussion about climate change. All variants include the conventional inputs capital K and labor L as

[16] As a computational detail an offset is added to δ in (6) and subtracted after the solution is obtained. This allows for negative values for δ arising during the bootstrap replications.

[17] We also explored an even higher number of 50,000 bootstrap replications for selected variants and reached essentially the same findings.

[18] Recall that the median is a more robust measure of location compared to the mean.

well as the single economic output Y as defined in Sect. 2. Finally, in Sect. 4.4 we conclude this section with an extensive discussion of policy implications.

4.1 Total Greenhouse Gas Emissions

We start with total GHG emissions as the single emission variable. Figure 2 depicts the results for the first subperiod in the upper panel and for the second subperiod in the lower panel. In each panel we depict the actual emissions (open circles, connected by a dashed line) and the bias-corrected emission reduction potentials (bullet points, connected by a solid line) aggregated for the 7 sectors on the left side and the 16 countries on the right side. The vertical lines extending above and below the bullet points indicate the 95% bootstrap confidence intervals as explained above. The scale on the ordinate reveals that all values are expressed in million tons (mt) of CO_2e.

The corresponding numerical results are reported in Table 2 in the appendix for reference. There we see that the sum of actual emissions over all sectors and countries amounts to 3341 mt of GHG (in CO_2e) in the first subperiod which decrease to 3070 mt in the second subperiod. Total bias-corrected reduction potentials are 1522 mt (with 95% confidence interval [1236, 1886]) in the first subperiod and 1448 mt (with 95% confidence interval [1177, 1801]) in the second subperiod. These amount to 46% and 47% of the actual emissions in the two subperiods, respectively.

Figure 2 shows that the bias-corrected reduction potentials are quite sizable in some sectors and in a number of countries. Notice that the countries are of rather different size economically and this is also reflected in the differences of the actual GHG emissions. The bias correction lets the estimates of the reduction potentials appear much larger compared to their “raw” counterparts discussed at length in the companion paper of Krüger and Tarach (2020).[19] Most of the confidence intervals are quite narrow pointing to rather precise estimates of the potential emission reductions. There are some exceptions, however, where the confidence intervals are wider. These exceptions pertain to sectors or countries with larger actual emissions and larger reduction potentials (e.g. sectors C and DE or Germany).

We first turn to the lower panel with the results for the second subperiod. Regarding the sectors the estimated reduction potentials are particularly large in sector DE (mostly energy) and C (manufacturing) where they amount to 49% and 52% of the actual emissions, respectively.[20] This is followed by sectors A (agriculture) and H (transport) where the reduction potentials are smaller in absolute terms, amounting to 57% and 29% of the actual emissions, respectively. For the remaining sectors the reduction potentials are small to negligible.

Germany (DEU) is the country with the largest actual emissions, but its reduction potential is of the same size as that of the United Kingdom (which is considered as an EU

[19] The gray line depicts the “raw” reduction potentials (without bias correction) which are throughout smaller than their bias-corrected counterparts and track them quite closely, except in some cases where the actual emissions are particularly large.

[20] In sector DE emissions are to a large extent determined by the share of fossil power generation. France and Sweden are very efficient and have shares of nuclear and water power of about 80% (see NEA-OECD (2018, p. 19) and Byman (2016, p. 8), respectively). Thus, the reduction potentials of the other countries implicitly require similar shares of non-fossil power generation which may be realized by either nuclear power, water power or other renewable forms (biomass, solar, wind).

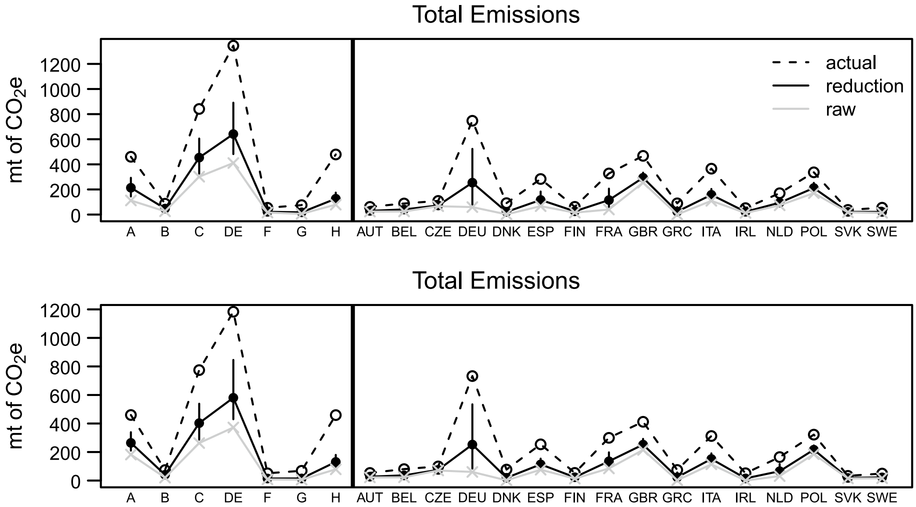

Fig. 2 Potential Emission Reduction of Total GHG for the Period 2008–2012 (upper panel) and the Period 2012–2016 (lower panel), Variant (a)

member country during the sample period until 2016) which has the second largest actual emissions. Other countries with sizable reduction potentials are Poland, Italy, France and Spain (with decreasing reduction potentials in this order). The reduction potentials amount to 34% of the actual emissions in the case of Germany, 61% for the United Kingdom, 67% for Poland, 48% for Italy, 45% for France and Spain. Reduction potentials of the other 10 countries in our sample are absolutely smaller and thus are not as easily visible. Nonetheless, for both groups of countries reduction potentials are very much in proportion to their actual GHG emissions. During 2012–2016, these 10 smaller countries account for almost one quarter of total GHG emissions in our sample. As can be verified from Table 2, summing the reduction potentials of these countries results in almost one quarter of the total reduction potential as well. Hence, although we primarily focus our discussion here on the results for the largest countries, we want to stress that the joint contribution of the smaller countries to emission reduction is as important as that of the largest countries.

Comparing these results with those for the first subperiod in the upper panel of the figure we find the distributions across sectors and countries to be rather similar in both subperiods. The major difference is the overall magnitude of the actual emissions and the estimated reduction potentials which are both larger in the first compared to the second subperiod. There are exceptions from this rule in the some sectors and countries as can be seen from a closer inspection of Table 2 in the appendix but these are of minor quantitative importance. Combined with the greater relevance of the more recent subperiod for the current debate about climate change, this similarity justifies the focus on the subperiod 2012–2016 in the subsequent discussion of the other variants

4.2 CO_2 and other GHG (CH_4 and N_2O) Emissions

In this subsection, we proceed by splitting total GHG emissions into CO_2 and other GHG emissions (which is the sum of CH_4 and N_2O, or equivalently total GHG minus CO_2, expressed in CO_2e). Bias-corrected estimates of reduction potentials and confidence intervals are calculated for each of the two emission variables as well as for their sum (total GHG emissions). Figure 3 shows actual emissions and reduction potentials for the sectors and countries in the sample, and Table 3 in the appendix permits a closer look at the exact quantities. Aggregated over all sectors and countries we find total GHG reduction potentials of 1642 mt (with 95% confidence interval [1321, 2049]), amounting to 53% of the actual emissions.

The lowest panel of the figure reveals that sector A is by far the largest emitter of other GHG, and these emissions also account for the majority of emissions in this sector (about 80%). In addition to sector A, emissions of other GHG are sizable in absolute terms in sector DE, although they amount only to about 10% of the sector's total GHG emissions. In contrast, emissions of other GHG in sector B are small in absolute size, but nonetheless make up 42% of total GHG emissions here. Figure 3 shows that the sectors C and H emit mostly CO_2. Together with sector DE they account for the majority of CO_2 emissions in our sample. One result of this subsection, which is evident from the middle panel of Fig. 3, is that sector C has almost the same CO_2 reduction potential as sector DE, although it emits clearly less CO_2, which points to the relevance of the manufacturing sector for saving CO_2 emissions. Another finding is that there is overall higher inefficiency regarding other GHG rather than CO_2 in relative terms. In particular, the share of reduction potentials to actual emissions for other GHG is with 64% (largely concentrated in sector A) considerably above the corresponding value for CO_2 (51%).

Looking at the countries we observe that reduction potentials for other GHG are particularly sizable for the two largest emitters of other GHG, namely France and Germany, where they make up 42% and 26% of the countries' total GHG reduction potentials, respectively. This indicates that it is important also to include the agricultural sector with its CH_4 and N_2O emissions in the respective emission reduction plans in France and Germany. For some other large countries, the potentially feasible reductions for other GHG are comparably smaller than for CO_2 (at or below 17% of total GHG reduction potentials in the cases of the United Kingdom, Poland, Italy and Spain). Confidence intervals are generally quite narrow for reductions of other GHG for most sectors and countries.

Next, we further split the other GHG emissions into CH_4 and N_2O emissions. Figure 4 shows the results of this split (see also Table 4). The differences to the results above can be explained by the direction choice where now one further possibility is available. During the second subperiod 2012–2016, our sample countries and sectors emitted a total of 3070 mt CO_2e, out of which 6% were N_2O emissions, 12% CH_4 emissions, and 82% CO_2 emissions. As above, the shares of reduction potentials in actual emissions are higher for N_2O (81%) and CH_4 (57%) than for CO_2 (45%). For total GHG this translates into a share of reduction potentials in actual emissions of 48%, or 1487 mt (with 95% confidence interval [1214, 1840]).

Since the use of nitrogen fertilizers is the major source of N_2O emissions, their reduction potentials are clearly largest in sector A. Here, we find that the lower bound of the confidence interval indicates that reduction potentials below 65% of actual emissions are unlikely at the 95% confidence level. Our results imply that there is the potential for the sample countries to continue the N_2O reduction path that has already started in Europe during 1990–2010 (see Tian et al. (2020) for regional trends of anthropogenic N_2O emissions for the period 1980–2016). Sector A also is the major source of CH_4 emissions (mainly from animal livestock) and our results reveal that it has a sizable potential for reducing CH_4. Our bias-corrected estimate is 69% of actual emissions (144 mt of CO_2e) and a reduction potential of less than 50% of actual emissions is unlikely based on the 95% confidence interval. In addition to sector A, Fig. 4 reveals that sector DE contributes substantially to

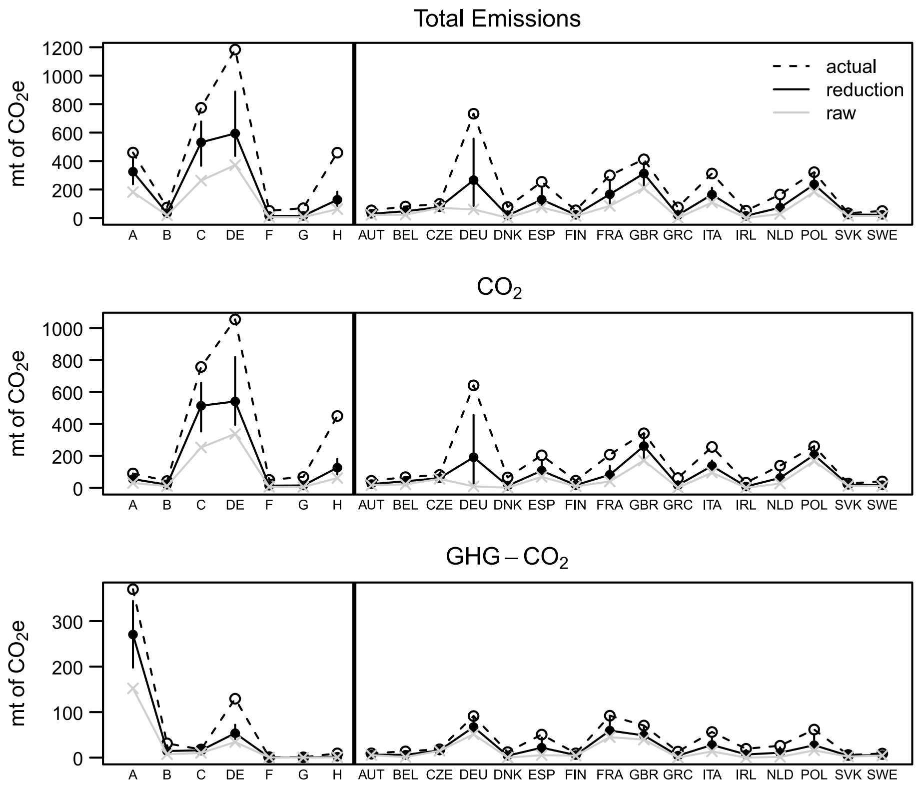

Fig. 3 Potential Emission Reduction of CO_2 and Other GHG for the Period 2012–2016, Variant (b)

CH_4 emissions with a rather small reduction potential. Finally, for sector B the CH_4 reduction potentials are an order of magnitude smaller than those of sector A, and for the other sectors they are negligible.

4.3 Combined Direction with Output Enhancement

In the preceding subsections we have measured inefficiency exclusively in the direction of reducing emissions, holding the good output and the inputs constant. As noted in Sect. 3.2, it is not sensible to measure inefficiency in the direction of reducing the inputs at this high level of aggregation. However, instead of pure emission reductions a combination of emission reductions and output enhancement (i.e. economic growth) is a realistic objective of policy makers. We account for this possibility by permitting more flexible directions $\boldsymbol{\alpha}_y \geq \mathbf{0}$ in the linear program of equation (3).[21] By this, we allow emission reductions to be traded off against output enhancement, so that inefficiency measures reflect a combination of emission reduction and output enhancement.

These estimates are reported (again for the second subperiod) in Fig. 5 and Table 5. For the emission variable we use total GHG, so that reduction potentials can be directly

[21] The boundary solution of pure emission reductions is still possible but needs no longer be optimal.

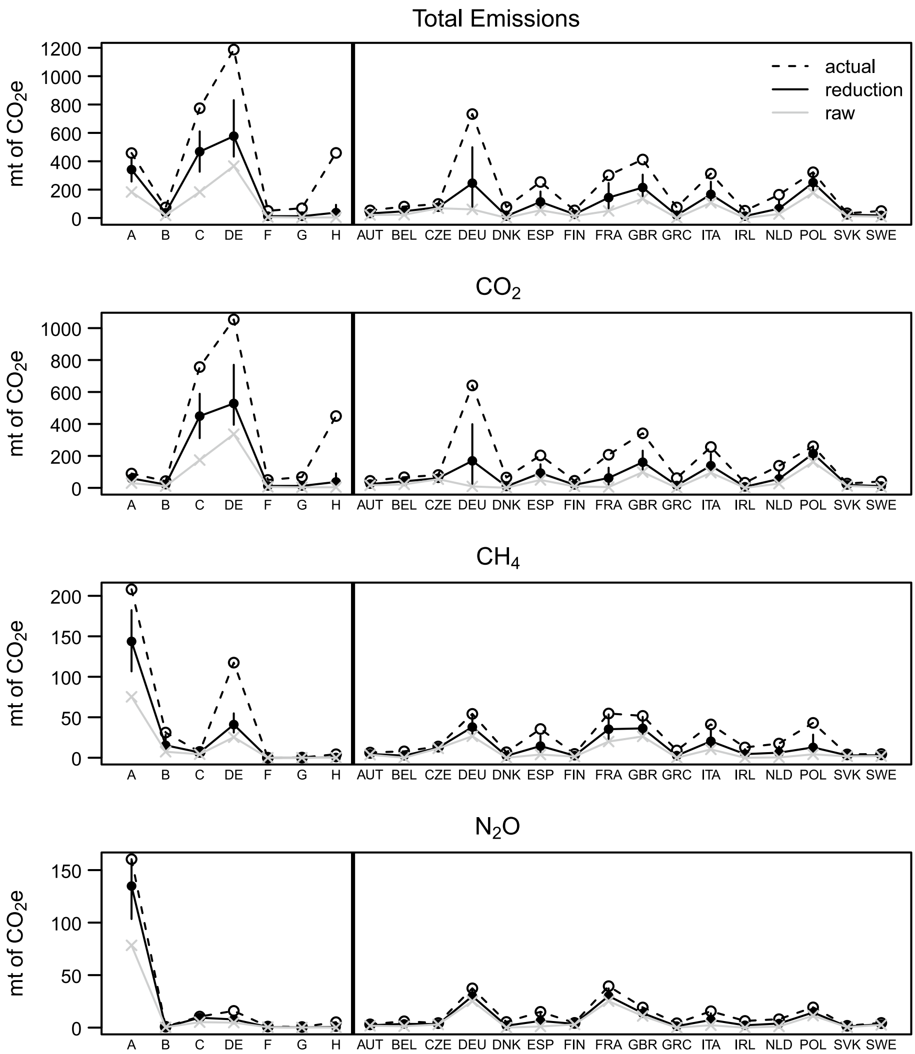

Fig. 4 Potential Emission Reduction of CO_2, CH_4 and N_2O for the Period 2012–2016, Variant (c)

compared with those from Sect. 4.1 for the period 2012–2016. In total, allowing for output enhancement causes reduction potentials to decline from 1448 mt to 1272 mt (with 95% confidence intervals changing from [1177, 1801] to [1028, 1595]), or equivalently from 47% to 41% of the actual emissions. This decline is rather small, indicating that most inefficiency is due to generating too much emissions instead of producing too less of the economic output. When comparing the upper panel of Fig. 5 with the lower panel of Fig. 2, we notice only slight differences regarding the distribution across sectors. It is visible that reduction potentials for sector C (manufacturing) decline the most (by about 100 mt) from 52% to 40% of actual emissions. For the other sectors the differences are much smaller.

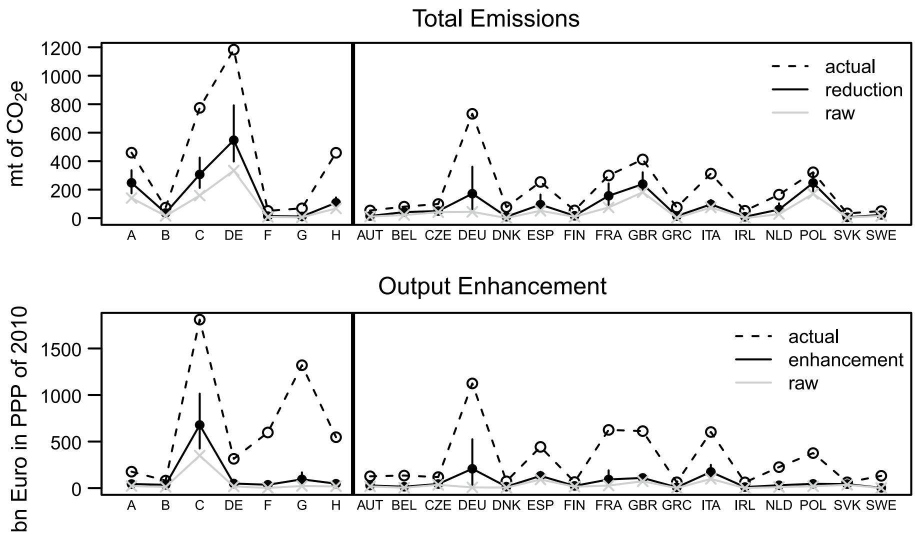

Fig. 5 Potential Emission Reduction of Total GHG and Output Enhancement for the Period 2012–2016, Variant (d)

This is in line with our estimates for output enhancement potentials, which are low in all sectors except C (see Fig. 5, lower panel).[22] Hence, we find that a great deal of inefficiency in the direction of output enhancement, being large enough to substantially lower the scope for emission reductions, is present only in sector C.

For most countries we find reduction potentials of somewhat smaller size than in Sect. 4.1. Figure 5 (upper panel) reveals a distribution across countries which is very similar to that of Fig. 2 (lower panel). There are three exceptions (Belgium, France and Poland) where we obtain even higher reduction potentials than in Sect. 4.1. This can be attributed to the bias correction applied to the "raw" estimates.

4.4 Policy Recommendations

Altogether, the preceding discussion shows that there is a sizable extent of inefficiency in the sectors which could be transformed into emission reductions. Therefore, the question arises how can policy support the realization of the potentials in practice. Policy should aim at inducing firms to improve their productive efficiency (which then improves the efficiency of the sectors we measure here) to move towards the frontier function combined with specific measures to channel this movement in the right direction, i.e. mainly in the direction of emission reduction and less in the direction of output enhancement. In the long-run, effort to generate technological progress to shift the frontier function towards less emission intensive modes of production would also work in the right direction, although this aspect is beyond the scope of the measurement exercise we conduct here.

[22] Even for sector G (mainly wholesale and retail trade), which produces substantial value added, output enhancement potential is quite low, indicating that this sector is overall quite efficient in transforming inputs to output.

As a theoretical guidepost for structuring the discussion of policy measures we use the macroeconomic model of Stern and Kander (2012). From the first-order condition in equation (15) of that paper one can derive an equation for energy demand as

$$E = \gamma_E^{1/\sigma(1-\phi)} \cdot Y \cdot \left(\frac{p_E}{p}\right)^{-1/(1-\phi)} \cdot A_E^{\phi/(1-\phi)} \tag{7}$$

with E denoting the energy input in the underlying CES production function, Y gross output, and p_E/p the price of energy relative to the price of output. A_E is an augmentation factor of the energy input in the production function. This factor increases if a sector in a country improves its energy efficiency. It can be viewed as also comprising the aspect of energy quality as discussed in Stern and Kander (2012) and Stern (2010). Increasing energy quality acts like a further factor (named Q in Stern and Kander (2012)). If we consider E as the input of mostly fossil fuels, changing the energy mix towards renewable energy sources operates analogous to an improvement of energy quality associated with less GHG emissions. The parameter ϕ is related to the elasticity of substitution σ between energy and a capital-labor aggregate by $\phi = (\sigma - 1)/\sigma$ and γ_E is a further production function parameter related to the energy input.

Various estimates of the parameters are reported in table 1 of Stern and Kander (2012). They can be roughly summarized as $\gamma_E \approx 0.2$, $\sigma \approx 2/3$ and $\phi \approx -1/2$. Taken at face value we get a calibrated version of the energy demand equation as

$$E = 0.2 \cdot Y \cdot \left(\frac{p_E}{p}\right)^{-2/3} \cdot A_E^{-1/3}. \tag{8}$$

This shows that the energy demand and therefore GHG emissions (assuming that a substantial part of energy is generated from fossil sources) are linearly related to the level of gross output. Emissions are decreasing with a higher relative price of energy p_E/p as well as with an improvement of productive efficiency leading to a larger A_E. These variables are linked to various policy measures which are discussed in the following. In addition to the direct effect of p_E/p there is a further, indirect, effect working through A_E, i.e. adopting more energy efficient and therefore less emission intensive technologies in the medium to long run when p_E/p is higher.

To increase the productive efficiency of sectors, a large variety of policy measures can be beneficial. Examples of these measures directed generally towards inefficiency reduction are fostering competition, reducing some regulations, incentivizing research and development and protecting intellectual property. Yet, the effect of these policy measures has to be channeled towards improvements in energy efficiency (A_E) or energy quality which are associated with emission reductions. There are many diverse policy measures available which could be appropriately combined and coordinated.

This policy mix, of course, has to comprise traditional instruments of environmental policy such as phasing out the most emission-intensive modes of power generation (i.e. coal), abandoning certain modes of travel (e.g. short-distance flights) or setting energy consumption standards for new products (e.g. cars, heating). Incentives or subsidies for behavior modification (i.e. switching to electric cars, more attractive public transport, thermal insulation of buildings) could also direct efficiency improvement in the desired direction.

A well-designed carbon price is a key measure to influence the relative price of fossil-fuel based energy (p_E/p) and thus, by the energy demand relation, also combustion thereof (Sen and Vollebergh 2018; Best et al. 2020). Important for the design here is a broad sector and country coverage (Aldy et al. 2010, p. 928). One finding of our efficiency analysis, in particular from Sect. 4.2, is that emission reduction potentials for the manufacturing sector are substantial, i.e. of similar magnitude as for the energy sector. We also find substantial reduction potentials in the transport sector, although these are smaller in relative terms. Currently, European emission trading still covers only power generation, heavy industry and intra-European aviation (Delreux and Ohler 2019, p. 7). Thus, comprehensive EU-wide carbon tax policies could push manufacturing and transport sectors closer to their frontier in the desired direction of reducing CO_2 emissions. An extension of emission trading to these sectors, if designed effectively (i.e. with a steadily decreasing cap of overall emissions), would also work in the desired direction. However, for the manufacturing sector, we also find in Sect. 4.3 that there is considerable inefficiency in the output direction. Therefore, a uniform carbon price could easily be set too low in order to channel the direction of inefficiency reduction towards CO_2 reduction in those sectors where much efficiency can also be gained by output enhancement instead.

Furthermore, innovations are important for decarbonization. Sufficient carbon pricing works in the direction of inducing innovations for technologies with high potential for GHG emission reductions and therefore increases A_E (Aghion et al. 2016; van den Bergh and Savin 2021). These include in particular renewable energy technologies (i.e. wind and solar), large-scale and cost-efficient energy storage, and electric cars. Equally important may be all types of innovations which are able to substantially improve the energy efficiency of products or production processes, in particular if the energy used there is still fossil-fuel based.[23] To induce innovative activity, public funding of research and development could be specifically targeted at these areas. As knowledge creation is a public good, there is considerable under-investment in these areas to be expected (Knopf et al. 2013, p. 233). However, it seems generally difficult to anticipate which technologies will be most crucial for the energy system of the future. Thus, with respect to the direction of research and development funding, "policy-makers have to strike a delicate balance between supporting promising developments whilst avoiding the temptation to prematurely pick winners" (Knopf et al. 2013, p. 234).

These policy measures appear to be well adapted to the sectors C, DE and H with a large amount of CO_2 emissions, while sector A (agriculture) is special in its emission mix caused by the use of fertilizers, animal livestock, as well as its essentiality for human nutrition. When comparing our results for N_2O to other studies, these seem to be quite optimistic. For example, Winiwarter et al. (2018) estimate that if only the lowest-cost N_2O abatement measures were implemented, global emissions thereof could be reduced by 6.2% compared to a baseline scenario, while if also high-cost abatement measures were implemented, global N_2O reduction potentials would amount to 26%. Independent of the exact quantity of N_2O reduction potentials, there are several N_2O abatement measures available which in the agricultural sector generally comprise any measures that improve the efficiency of nitrogen application to crops (Winiwarter et al. 2018, table 1). There is also evidence that organic farming, in particular biodynamic farming, reduces N_2O emissions per yield and is associated with a modest uptake of CH_4 (Skinner et al. 2019, p. 4).

The extent of measured inefficiency is, of course, not confined to Europe. In other countries, emerging economies in particular, there are also huge quantities of potential emission

[23] An example are activities such as steel or cement production, where substitution of fossil fuel may be more difficult and where there are sizable regional differences in energy efficiency (Oda et al. 2012).

reductions to be expected which could be realized by means of efficiency improvements. Thus, strengthening international cooperation and technology transfer from advanced countries towards emerging countries at favorable conditions could tremendously enhance the overall benefit.

5 Discussion and Conclusion

The bottom line of the results of the above analysis with the stochastic nonparametric approach to environmental efficiency analysis is that the bootstrap bias-corrected estimates of potential reductions of GHG emissions by reducing the inefficiency relative to the most efficient countries in each of seven sectors are quantitatively substantial. Along with the bias-correction also confidence bounds are established which show that the reduction potentials are estimated with great precision in some sectors while being wider in other sectors. The comparison with the results of the companion paper (Krüger and Tarach 2020) shows that the bias correction leads to substantially increased estimates of the potential emission reductions.

To put the magnitudes of the estimated potential emission reductions into perspective we compare them to the emission reduction targets recently tightened by the European Commission (see EU 2020). Therein, an emission target of 45% (meaning a reduction by 55%) compared to the GHG emission levels in 1990 until 2030 is postulated. Since the 16 sample countries of our study overall emitted roughly 5000 mt of GHG in 1990 (retrieved from the EEA greenhouse gas data viewer) this implies a necessary emission reduction of about 2750 mt until 2030. As stated by the European Environmental Agency (EEA 2019), it is highly likely that the target level of a reduction of 20% compared to 1990 is to be achieved or is even slightly outperformed by 2020. Thus, an emission reduction of about 1000 mt is already achieved to date. The remaining 1750 mt until 2030 are not far away from the bias-corrected estimates of the total potential emission reductions aggregated over both countries and sectors (ranging from 1271 mt in variant (d) to 1642 mt in variant (b)) and are well within the confidence intervals. The distribution of the EU reduction targets across sectors also corresponds to the pattern of our estimated reduction potentials. Therefore, becoming more efficient can provide a substantial part of the reductions until 2030, especially in the sectors with large emission volumes.

The distribution of the reduction potentials across countries reflects their (economic) size. Naturally, larger countries tend to have larger manufacturing and transportation sectors which goes along with a need for a larger energy generating sector. These are the sectors with the largest actual emission quantities and also with the largest reduction potentials. Poland seems to be an exception operating with a much higher emission intensity.[24] Agriculture is another sector with large GHG emissions which are here more caused by CH_4 and N_2O rather than CO_2. Thus, in addition to conventional environmental policy measures and new technologies which come to mind first, structural change in a direction towards the less emission intensive sectors could contribute to the realization

[24] This is in broad agreement with the literature on eco-efficiency, where also some countries as Austria, Germany and Sweden are found to be rather efficient while eastern European countries such as Poland appear very inefficient (see Camarero et al. (2014) and Kortelainen (2008)).

of reduction potentials. Exactly this form of structural change is taking place since several decades in the form of tertiarization (where tertiarization means an increasing share of the less emission intensive service sector at the expense of the primary and secondary sectors; Fourastié 1949).

Of course, it is not realistic to expect that these emission reductions can be fully achieved within the next decade. The reasons for this assessment are manifold. Policy measures become effective with a time lag. Despite structural change going in the right direction it is a rather sluggish process taking place over longer spans of time. Here, the demand side and the slowly changing consumer preferences play a major role. Economic actors also adapt to changing conditions such as prices and also adverse reactions are to be expected (such as "rebound effects"; Greening et al. 2000). Structural change is also impeded by the specific roles of the countries in the context of international specialization which prevents that all countries will reach the same sectoral structure (de Araújo et al. 2020).

On the other hand, the present analysis is purely static (mostly confined to the medians to 2012–2016) and does not take account of the emission reducing effects of technological change. New technologies and in particular less emission intensive forms of energy generation and mobility are crucial for reaching the targets. Since the European countries are only responsible for a small share of global GHG emissions, spillover effects and the transfer of these emission reducing technologies to countries outside Europe is the key factor for new technologies to become effective for large scale emission reduction. This leads to the natural extension of this work towards a dynamic analysis (by projecting the potential emission reductions into the future) or an extension with a global country sample.

Appendix

Table 1 GHG emissions across sectors and countries

	Period 2008–2012				Period 2012–2016			
	CO_2	CH_4	N_2O	GHG	CO_2	CH_4	N_2O	GHG
Sectors								
A	92.193	208.540	158.558	460.256	89.712	208.016	160.372	459.659
B	52.031	33.637	0.941	86.494	42.449	31.123	0.898	73.785
C	817.971	7.452	17.099	841.163	756.424	7.236	10.555	774.389
DE	1190.735	138.968	16.030	1345.091	1053.977	117.502	15.930	1183.434
F	52.972	0.079	1.073	54.123	49.755	0.067	1.045	50.885
G	74.259	0.316	0.563	75.132	67.838	0.250	0.596	68.618
H	469.594	4.549	4.685	478.748	449.482	4.335	5.210	458.907
Countries								
AUT	51.107	6.920	3.191	61.114	43.931	6.470	3.172	53.483
BEL	73.401	8.399	6.847	88.198	66.619	7.929	6.059	80.396
CZE	90.279	14.302	4.285	108.843	80.649	13.945	4.396	99.051
DEU	654.103	56.302	36.961	747.224	641.271	54.210	37.423	732.635
DNK	78.315	7.153	5.405	90.926	64.979	6.857	5.402	77.228
ESP	230.152	37.313	14.355	283.416	203.419	35.532	15.064	254.097
FIN	52.091	5.091	4.471	61.539	44.399	4.740	4.543	53.900
FRA	229.250	57.504	40.761	327.310	207.434	54.678	39.493	299.578
GBR	386.425	62.979	20.077	467.680	341.522	51.729	19.234	412.077
GRC	74.828	9.422	5.151	89.561	61.145	9.045	4.219	74.408
ITA	304.934	43.995	16.758	365.478	255.947	41.205	15.619	312.340
IRL	33.364	12.069	6.111	51.442	32.168	12.760	6.373	51.625
NLD	142.834	18.525	8.112	170.053	138.514	17.553	8.051	164.691
POL	273.152	43.978	19.542	336.437	260.262	43.084	19.303	321.933
SVK	30.617	4.469	2.317	37.254	27.183	4.162	1.758	33.054
SWE	44.903	5.119	4.607	54.534	40.197	4.632	4.497	49.180
Total								
Σ	2749.754	393.539	198.949	3341.008	2509.637	368.528	194.605	3069.678

GHG (CO_2, CH_4, N_2O) and their totals (column GHG) are expressed in mt of CO_2e. Minor discrepancies may arise when the sum of the individual GHGs is compared to their totals. This is due to taking the sum and the median operations in different orders for the totals

Table 2 Potential emission reduction of total GHG for the Period 2008-2012 (upper panel) and Period 2012–2016 (lower panel), Variant (a)

	Total GHG Period 2008-2012			Total GHG Period 2012–2016		
	Actual	Estimate	Conf. interval	Actual	Estimate	Conf. interval
Sectors						
A	460.256	213.643	[144.405, 292.685]	459.659	264.259	[210.028, 338.978]
B	86.494	47.723	[31.040, 71.862]	73.785	40.674	[25.127, 59.511]
C	841.163	453.659	[326.684, 605.299]	774.389	402.751	[287.109, 538.407]
DE	1345.091	641.263	[481.872, 890.818]	1183.434	580.397	[430.116, 845.409]
F	54.123	21.969	[17.803, 29.988]	50.885	14.559	[10.164, 22.237]
G	75.132	17.891	[9.874, 29.784]	68.618	14.956	[8.742, 25.026]
H	478.748	126.126	[93.834, 174.577]	458.907	130.819	[96.634, 179.703]
Countries						
AUT	61.114	29.662	[25.144, 35.780]	53.483	27.579	[23.597, 33.000]
BEL	88.198	40.568	[27.973, 61.432]	80.396	36.432	[25.800, 50.537]
CZE	108.843	72.512	[68.170, 78.469]	99.051	75.065	[71.876, 79.836]
DEU	747.224	254.258	[77.702, 523.120]	732.635	252.501	[84.405, 534.271]
DNK	90.926	21.414	[4.333, 50.740]	77.228	19.342	[4.014, 45.480]
ESP	283.416	116.465	[73.985, 183.253]	254.097	113.490	[82.492, 153.683]
FIN	61.539	26.210	[16.878, 43.054]	53.900	23.291	[15.014, 39.776]
FRA	327.310	115.542	[52.775, 206.256]	299.578	135.333	[94.202, 197.693]
GBR	467.680	293.249	[263.718, 333.514]	412.077	252.008	[224.468, 292.130]
GRC	89.561	23.852	[3.886, 59.044]	74.408	23.218	[4.581, 56.536]
ITA	365.478	157.301	[119.860, 203.656]	312.340	151.437	[122.248, 190.379]
IRL	51.442	22.263	[14.082, 34.416]	51.625	15.396	[2.101, 34.861]
NLD	170.053	94.760	[79.141, 114.023]	164.691	65.654	[36.604, 115.461]
POL	336.437	211.488	[181.380, 252.492]	321.933	216.391	[194.421, 246.129]
SVK	37.254	21.470	[18.714, 25.195]	33.054	18.647	[15.938, 22.180]
SWE	54.534	21.231	[15.523, 29.114]	49.180	22.442	[17.679, 29.551]
Total						
Σ	3341.008	1522.274	[1236.410, 1885.573]	3069.678	1448.417	[1176.830, 1801.477]

Total GHG are expressed in million tons (mt) of CO_2 equivalents and reported with three digits following the decimal point. 95% percent bootstrap confidence intervals are in square brackets

Table 3 Potential emission reduction of CO_2 and other GHG for the Period 2012–2016, variant (b)

	Total GHG		CO_2			Other GHG		
	Estimate	Conf. interval	Actual	Estimate	Conf. interval	Actual	Estimate	Conf. interval
Sectors								
A	325.387	[237.312, 418.086]	89.712	54.631	[38.818, 75.084]	369.947	270.482	[197.798, 344.269]
B	34.018	[22.052, 54.283]	42.449	19.460	[12.755, 32.516]	31.335	14.527	[8.577, 27.235]
C	531.433	[366.803, 678.055]	756.424	513.651	[352.589, 656.921]	17.966	16.116	[12.732, 17.898]
DE	594.143	[436.285, 888.159]	1053.977	540.416	[394.722, 819.663]	129.456	53.675	[41.127, 72.248]
F	14.128	[8.990, 21.900]	49.755	13.337	[8.381, 20.830]	1.131	0.762	[0.587, 1.086]
G	14.854	[7.496, 27.264]	67.838	14.625	[7.364, 26.891]	0.780	0.229	[0.131, 0.422]
H	127.955	[85.080, 184.512]	449.482	125.931	[83.823, 181.453]	9.425	2.023	[1.130, 3.633]
Countries								
AUT	29.638	[23.148, 39.612]	43.931	23.227	[17.342, 31.954]	9.552	6.411	[5.621, 7.914]
BEL	47.080	[25.862, 71.281]	66.619	40.947	[24.050, 60.221]	13.777	6.122	[1.651, 12.214]
CZE	76.153	[71.936, 82.703]	80.649	60.313	[56.710, 66.069]	18.402	15.840	[15.079, 17.177]
DEU	265.944	[85.221, 557.340]	641.271	191.177	[27.081, 455.785]	91.364	67.273	[53.497, 88.284]
DNK	17.115	[2.825, 47.659]	64.979	12.769	[2.580, 37.879]	12.249	4.337	[0.247, 10.173]
ESP	128.989	[82.070, 211.433]	203.419	107.048	[75.074, 168.102]	50.678	21.811	[6.443, 44.074]
FIN	22.655	[14.696, 40.503]	44.399	16.973	[10.183, 32.577]	9.502	5.632	[4.434, 8.367]
FRA	166.415	[95.332, 268.695]	207.434	81.502	[46.430, 137.705]	92.144	59.382	[46.109, 88.175]
GBR	312.612	[230.036, 388.475]	341.522	261.110	[186.959, 327.932]	70.555	48.821	[40.614, 66.674]
GRC	20.325	[1.994, 51.685]	61.145	15.959	[1.086, 41.210]	13.263	4.361	[0.397, 10.663]
ITA	164.720	[119.502, 212.120]	255.947	136.883	[102.482, 171.134]	56.393	27.840	[15.104, 44.591]
IRL	15.246	[2.540, 36.284]	32.168	8.243	[1.253, 20.714]	19.457	6.982	[0.210, 16.791]
NLD	72.755	[34.253, 132.484]	138.514	61.949	[31.583, 110.987]	26.178	10.794	[2.332, 22.501]
POL	236.028	[193.817, 303.716]	260.262	206.024	[174.238, 250.767]	61.671	27.304	[16.968, 51.591]
SVK	23.882	[15.266, 31.372]	27.183	19.455	[12.423, 25.303]	5.871	4.176	[2.578, 5.694]
SWE	22.244	[16.225, 30.308]	40.197	16.608	[11.477, 23.412]	8.983	5.626	[4.669, 7.620]

Table 3 (continued)

	Total GHG		CO_2			Other GHG		
	Estimate	Conf. interval	Actual	Estimate	Conf. interval	Actual	Estimate	Conf. interval
Total								
Σ	1642.282	[1321.325, 2049.171]	2509.637	1282.153	[998.849, 1646.980]	560.041	360.167	[280.535, 443.626]

GHG (CO_2, other GHG) and their totals are expressed in million tons (mt) of CO_2 equivalents and reported with three digits following the decimal point. 95% percent bootstrap confidence intervals are in square brackets

Table 4 Potential emission reduction of CO_2, CH_4 and N_2O for the Period 2012–2016, variant (c)

	Total GHG		CO_2			CH_4			N_2O		
	Estimate	Conf. interval	Actual	Estimate	Conf. interval	Actual	Estimate	Conf. interval	Actual	Estimate	Conf. interval
Sectors											
A	341.330	[257.191, 425.650]	89.712	59.234	[42.863, 76.725]	208.016	143.696	[106.738, 182.262]	160.372	134.820	[103.471, 158.586]
B	36.853	[23.132, 58.477]	42.449	20.796	[13.217, 34.021]	31.123	15.370	[8.694, 28.111]	0.898	0.599	[0.407, 0.869]
C	467.694	[326.398, 610.573]	756.424	449.334	[311.293, 588.609]	7.236	6.496	[5.303, 7.211]	10.555	9.449	[7.631, 10.503]
DE	577.091	[432.825, 830.843]	1053.977	528.289	[394.903, 770.177]	117.502	40.962	[31.199, 54.817]	15.930	7.811	[5.838, 10.624]
F	12.988	[8.426, 19.625]	49.755	12.315	[7.893, 18.757]	0.067	0.024	[0.018, 0.036]	1.045	0.645	[0.494, 0.960]
G	12.608	[6.094, 23.242]	67.838	12.324	[5.910, 22.841]	0.250	0.078	[0.046, 0.126]	0.596	0.206	[0.127, 0.339]
H	37.940	[3.892, 92.966]	449.482	37.040	[3.723, 90.690]	4.335	0.354	[0.024, 1.741]	5.210	0.544	[0.145, 1.210]
Countries											
AUT	32.156	[22.853, 45.152]	43.931	23.951	[17.068, 34.342]	6.470	4.681	[3.803, 6.290]	3.172	2.243	[1.767, 3.137]
BEL	47.297	[25.222, 71.832]	66.619	40.992	[23.300, 61.279]	7.929	2.619	[0.141, 6.063]	6.059	3.538	[1.468, 5.807]
CZE	76.383	[70.334, 84.408]	80.649	60.562	[55.347, 67.520]	13.945	12.442	[11.744, 13.399]	4.396	3.334	[3.023, 3.941]
DEU	245.496	[76.096, 498.813]	641.271	169.158	[18.291, 398.438]	54.210	37.954	[27.648, 52.652]	37.423	29.974	[25.817, 36.728]
DNK	13.531	[2.267, 45.434]	64.979	9.314	[1.990, 36.235]	6.857	2.346	[0.105, 5.386]	5.402	1.869	[0.110, 4.350]
ESP	113.582	[59.533, 186.568]	203.419	92.713	[53.212, 147.129]	35.532	14.451	[4.788, 27.122]	15.064	6.372	[1.457, 13.158]
FIN	26.336	[14.704, 44.648]	44.399	19.105	[10.089, 34.013]	4.740	2.603	[1.469, 4.304]	4.543	3.610	[3.037, 4.394]
FRA	143.806	[57.583, 246.310]	207.434	61.895	[9.513, 125.914]	54.678	35.281	[20.628, 53.518]	39.493	30.094	[25.871, 37.332]
GBR	214.855	[148.945, 305.637]	341.522	160.572	[108.855, 232.902]	51.729	36.289	[27.030, 50.561]	19.234	13.751	[11.451, 18.696]
GRC	18.977	[1.744, 46.205]	61.145	14.885	[0.840, 37.384]	9.045	2.662	[0.156, 6.454]	4.219	1.429	[0.107, 3.272]
ITA	166.767	[113.828, 255.337]	255.947	139.122	[99.935, 213.384]	41.205	20.349	[11.267, 33.504]	15.619	7.289	[2.703, 13.552]
IRL	13.628	[1.097, 33.587]	32.168	6.870	[0.647, 18.920]	12.760	4.496	[0.127, 10.618]	6.373	2.257	[0.067, 5.358]
NLD	66.267	[31.673, 120.175]	138.514	56.109	[29.483, 100.711]	17.553	6.242	[0.817, 13.765]	8.051	3.886	[1.287, 7.243]
POL	249.855	[190.148, 310.531]	260.262	214.603	[169.505, 254.559]	43.084	12.780	[4.562, 28.561]	19.303	14.423	[11.715, 18.580]
SVK	22.744	[14.832, 31.106]	27.183	18.341	[12.173, 24.952]	4.162	2.912	[1.980, 4.037]	1.758	1.076	[0.530, 1.670]
SWE	18.192	[10.291, 32.972]	40.197	11.423	[5.485, 23.201]	4.632	2.880	[2.060, 4.461]	4.497	3.266	[2.665, 4.307]

Table 4 (continued)

	Total GHG		CO_2			CH_4			N_2O		
	Estimate	Conf. interval	Actual	Estimate	Conf. interval	Actual	Estimate	Conf. interval	Actual	Estimate	Conf. interval
Total											
Σ	1486.927	[1213.634, 1839.676]	2509.637	1119.317	[872.839, 1435.472]	368.528	208.709	[166.668, 253.340]	194.605	157.971	[123.828, 189.328]

GHG (CO_2,CH_4, N_2O) and their totals are expressed in million tons (mt) of CO_2 equivalents and reported with three digits following the decimal point. 95% percent bootstrap confidence intervals are in square brackets. Minor discrepancies may arise when the sum of the individual GHGs is compared to their totals. This is due to taking the sum and the median operations in different orders for the totals

Table 5 Potential emission reduction of total GHG and output enhancement for the Period 2012–2016, variant (d)

	Output			Total GHG		
	Actual	Estimate	Conf. interval	Actual	Estimate	Conf. interval
Sectors						
A	176.698	44.130	[30.172, 62.709]	459.659	248.062	[174.338, 336.317]
B	80.654	35.034	[19.751, 55.689]	73.785	36.179	[22.278, 56.240]
C	1809.919	678.039	[425.829, 1014.403]	774.389	306.796	[212.143, 424.805]
DE	314.613	49.079	[28.352, 85.066]	1183.434	547.370	[397.768, 792.031]
F	597.705	35.946	[12.313, 75.856]	50.885	14.100	[10.217, 21.628]
G	1320.321	94.173	[45.442, 168.895]	68.618	11.536	[7.331, 18.844]
H	546.876	47.462	[27.166, 78.382]	458.907	107.550	[82.477, 145.105]
Countries						
AUT	126.909	28.021	[20.330, 37.812]	53.483	14.858	[11.615, 19.785]
BEL	134.940	15.215	[6.451, 31.835]	80.396	42.007	[24.473, 69.574]
CZE	118.664	44.038	[37.385, 54.093]	99.051	49.621	[42.766, 60.568]
DEU	1124.347	207.739	[26.270, 524.734]	732.635	171.658	[62.563, 360.565]
DNK	72.893	15.874	[6.789, 27.895]	77.228	10.218	[1.709, 22.885]
ESP	442.674	131.032	[99.570, 175.213]	254.097	94.736	[58.357, 165.020]
FIN	65.276	24.055	[16.677, 35.392]	53.900	16.570	[10.382, 28.677]
FRA	625.329	92.779	[36.879, 190.854]	299.578	156.579	[84.457, 243.573]
GBR	612.464	109.440	[80.558, 146.340]	412.077	238.760	[194.299, 321.503]
GRC	62.585	8.165	[1.552, 18.656]	74.408	14.299	[3.408, 34.666]
ITA	602.858	174.096	[111.289, 249.810]	312.340	96.580	[77.844, 127.095]
IRL	61.638	11.475	[1.313, 30.100]	51.625	9.361	[1.278, 21.550]
NLD	225.522	30.538	[15.204, 57.622]	164.691	60.244	[34.418, 103.644]
POL	376.336	45.867	[24.653, 80.858]	321.933	247.319	[184.337, 315.200]
SVK	62.312	43.017	[36.939, 50.859]	33.054	5.665	[4.376, 7.861]
SWE	132.039	2.511	[0.847, 5.233]	49.180	22.626	[17.129, 30.944]
Total						
Σ	4846.786	983.863	[676.145, 1380.091]	3069.678	1271.601	[1028.342, 1594.755]

Total GHG and economic output are expressed in million tons (mt) of CO_2 equivalents and in bn (in PPP of 2010), respectively. Both are reported with three digits following the decimal point. 95% percent bootstrap confidence intervals are in square brackets

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References

Aghion P, Dechezleprêtre A, Hemous D, Martin R, Van Reenen J (2016) Carbon taxes, path dependency, and directed technical change: evidence from the auto industry. J Polit Econ 124:1–51
Aldy JE, Krupnick AJ, Newell RG, Parry IW, Pizer WA (2010) Designing climate mitigation policy. J Econ Literature 48:903–934
Banker RD, Charnes A, Cooper WW (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manag Sci 30:1078–1092
Best R, Burke PJ, Jotzo F (2020) Carbon pricing efficacy: cross-country evidence. Environ Resour Econ 77:69–94
Byman K (2016) Electricity Production in Sweden—IVA's Electricity Crossroads Project. Royal Swedish Academy of Engineering Sciences, Report
Camarero M, Castillo-Giménez J, Picazo-Tadeo AJ, Tamarit C (2014) Is eco-efficiency in greenhouse gas emissions converging among European Union countries? Empir Econ 47:143–168
Chambers RG, Chung Y, Färe R (1996) Benefit and distance functions. J Econ Theory 70:407–419
Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2:429–444
Chen C-M, Delmas MA (2012) Measuring eco-inefficiency: a new frontier approach. Oper Res 60:1064–1079
Chung YH, Färe R, Grosskopf S (1997) Productivity and undesirable outputs: a directional distance function approach. J Environ Manag 51:229–240
Dakpo KH, Jeanneaux P, Latruffe L (2016) Modelling pollution-generating technologies in performance benchmarking: recent developments, limits and future prospects in the nonparametric framework. Eur J Oper Res 250:347–359
de Araújo IF, Jackson RW, Neto ABF, Perobelli FS (2020) European Union membership and CO_2 emissions: a structural decomposition analysis. Struct Chang Econ Dyn 55:190–203
Debelke J, Vis P (2015) EU climate policy explained. Rouledge, London
Delreux T, Ohler F (2019) Climate policy in European Union politics. In: Laursen F (ed) Oxford Research Encyclopedia of Politics. Oxford University Press, Oxford
Domazlicky BR, Weber WL (2004) Does environmental protection lead to slower productivity growth in the chemical industry? Environ Resour Econ 28:301–324
EEA (2019) Trends and Projections in Europe 2019. European Environmental Agency, EEA Report, No 15/2019
EU (2011) A roadmap for moving to a low-carbon economy in 2050. European Commission, COM(2011) 112 final, Brussels
EU (2020) Stepping up Europe's 2030 climate ambition. European Commission, COM(2020) 562 final, Brussels
Eurostat (2015) Manual for Air Emission Accounts, 2015 Edition. Publications Office of the European Union, Luxembourg
Färe R, Grosskopf S (2004) New directions: efficiency and productivity, vol 3. Springer, New York
Färe R, Primont D (1995) Multi-output production and duality: theory and applications. Springer, New York
Färe R, Grosskopf S, Hernandez-Sancho F (2004) Environmental performance: an index number approach. Resour Energy Econ 26:343–352
Färe R, Grosskopf S, Noh D-W, Weber W (2005) Characteristics of a polluting technology: theory and practice. J Econ 126:469–492
Färe R, Grosskopf S, Pasurka CA Jr (2007) Environmental production functions and environmental directional distance functions. Energy 32:1055–1066
Färe R, Grosskopf S, Whittaker G (2013) Directional output distance functions: endogenous directions based on exogenous normalization constraints. J Prod Anal 40:267–269
Feenstra RC, Inklaar R, Timmer MP (2015) The next generation of the Penn World Table. Am Econ Rev 105:3150–82
Fourastié J (1949) Le grand espoir du XXème siècle. Presses Universitaires de France, Paris

Greening LA, Greene DL, Difiglio C (2000) Energy efficiency and consumption—the rebound effect—a survey. Energy Policy 28:389–401

Growiec J (2012) The world technology frontier: what can we learn from the US States? Oxford Bull Econ Stat 74:777–807

Hampf B, Krüger JJ (2015) Optimal directions for directional distance functions: an exploration of potential reductions of greenhouse gases. Am J Agric Econ 97:920–938

Hsiang S, Kopp RE (2018) An economist's guide to climate change science. J Econ Perspect 32:3–32

Kholod N, Evans M, Pilcher RC, Roshchanka V, Ruiz F, Coté M, Collings R (2020) Global methane emissions from coal mining to continue growing even with declining coal production. J Clean Prod 256:120489

Knopf B, Chen Y-HH, De Cian E, Förster H, Kanudia A, Karkatsouli I, Keppo I, Koljonen T, Schumacher K, Van Vuuren DP (2013) Beyond 2020: strategies and costs for transforming the European energy system. Climate Change Econ 4:1340001

Korhonen PJ, Luptacik M (2004) Eco-efficiency analysis of power plants: an extension of data envelopment analysis. Eur J Oper Res 154:437–446

Kortelainen M (2008) Dynamic environmental performance analysis: a Malmquist index approach. Ecol Econ 64:701–715

Krautzberger L, Wetzel H (2012) Transport and CO_2: productivity growth and carbon dioxide emissions in the European commercial transport industry. Environ Resour Econ 53:435–454

Krüger JJ, Tarach M (2020) Greenhouse gas emission reduction potentials in Europe: a nonparametric efficiency analysis approach using sectoral data. SSRN Working Paper 3716203

Kuosmanen T, Kortelainen M (2005) Measuring eco-efficiency of production with data envelopment analysis. J Ind Ecol 9:59–72

Murty S, Russell RR, Levkoff SB (2012) On modeling pollution-generating technologies. J Environ Econ Manag 64:117–135

Myhre G, Myhre A, Stordal F (2001) Historical evolution of radiative forcing of climate. Atmos Environ 35:2361–2373

NEA-OECD (2018) Nuclear Technology Development and Economics. Nuclear Energy Data. NEA No. 7416

Nordhaus W (2019) Climate change: the ultimate challenge for Economics. Am Econ Rev 109:1991–2014

Oda J, Akimoto K, Tomoda T, Nagashima M, Wada K, Sano F (2012) International comparisons of energy efficiency in power, steel, and cement industries. Energy Policy 44:118–129

OECD (2020) Purchasing power parities (PPP). https://doi.org/10.1787/1290ee5a-en

Picazo-Tadeo AJ, Beltrán-Esteve M, Gómez-Limón JA (2012) Assessing eco-efficiency with directional distance functions. Eur J Oper Res 220:798–809

Rashidi K, Farzipoor Saen R (2015) Measuring eco-efficiency based on green indicators and potentials in energy saving and undesirable output abatement. Energy Econ 50:18–26

Sen S, Vollebergh H (2018) The effectiveness of taxing the carbon content of energy consumption. J Environ Econ Manag 92:74–99

Shephard RW (1970) Theory of cost and production functions. Princeton University Press, Princeton

Simar L, Wilson PW (1998) Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Manag Sci 44:49–61

Simar L, Wilson PW (2008) The measurement of productive efficiency and productivity growth. Oxford University Press, Oxford, chap. Statistical inference in nonparametric frontier models: recent developments and perspectives 421–521

Simar L, Wilson PW (2011) Estimation and inference in nonparametric frontier models: recent developments and perspectives. Found Trends Econ 5:183–337

Simar L, Vanhems A, Wilson PW (2012) Statistical inference for DEA estimators of directional distances. Eur J Oper Res 220:853–864

Skinner C, Gattinger A, Krauss M, Krause H-M, Mayer J, Van Der Heijden MG, Mäder P (2019) The impact of long-term organic farming on soil-derived greenhouse gas emissions. Sci Rep 9:1–10

Stehrer R, Bykova A, Jaeger K, Reiter O, Schwarzhappel M (2019) Industry Level Growth and Productivity Data with Special Focus on Intangible Assets: Report on methodologies and data construction for the EU KLEMS Release 2019. Vienna Institute for International Economic Studies

Stern DI (2010) Energy quality. Ecol Econ 69:1471–1478

Stern DI, Kander A (2012) The role of energy in the industrial revolution and modern economic growth. Energy J 33:125–152

Tian H, Xu R, Canadell JG, Thompson RL, Winiwarter W, Suntharalingam P, Davidson EA, Ciais P, Jackson RB, Janssens-Maenhout G et al (2020) A comprehensive quantification of global nitrous oxide sources and sinks. Nature 586:248–256
Timmer MP, Dietzenbacher E, Los B, Stehrer R, De Vries GJ (2015) An illustrated user guide to the world input-output database: the case of global automotive production. Rev Int Econ 23:575–605
Tol RS (2018) The economic impacts of climate change. Rev Environ Econ Policy 12:4–25
van den Bergh J, Savin I (2021) Impact of carbon pricing on low-carbon innovation and deep decarbonisation: controversies and path forward. Environ Resour Econ 80:705–715
Wilson PW (1993) Detecting outliers in deterministic nonparametric frontier models with multiple outputs. J Bus Econ Stat 11:319–323
Winiwarter W, Höglund-Isaksson L, Klimont Z, Schöpp W, Amann M (2018) Technical opportunities to reduce global anthropogenic emissions of nitrous oxide. Environ Res Lett 13:014011
Zaim O, Taskin F (2000) Environmental efficiency in carbon dioxide emissions in the OECD: a non-parametric approach. J Environ Manag 58:95–107
Zhou P, Ang B (2008) Linear programming models for measuring economy-wide energy efficiency performance. Energy Policy 36:2911–2916
Zhou P, Ang BW, Poh KL (2008a) Measuring environmental performance under different environmental DEA technologies. Energy Econ 30:1–14
Zhou P, Ang BW, Poh K-L (2008b) A survey of data envelopment analysis in energy and environmental studies. Eur J Oper Res 189:1–18
Zofío JL, Prieto AM (2001) Environmental efficiency and regulatory standards: the case of CO_2 emissions from OECD industries. Resour Energy Econ 23:63–83