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Trend Projections of Greenhouse Gas Emission Reduction Potentials: A Bootstrap-Based Nonparametric Efficiency Analysis

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ABSTRACT

We use nonparametric methods to compute the environmental inefficiency of 100 countries over the period 1990-2017 on the macro-level. The inefficiency is expressed as the potential reduction of GHG emissions, holding economic output constant. Based on that, we estimate different trend functions and project the trends further until 2050. Confidence intervals to indicate the uncertainty inherent in the long- run projections are obtained by bootstrapping. We compare the efficient emissions remaining after subtracting the potential reductions with the official EU climate targets. It becomes apparent that a sizable contribution could be made by reducing inefficiency. However, even after removing the entire inefficiency, the results also indicate that this alone is probably not sufficient to break the increasing trend of GHG (and especially CO_2) emissions. Thus, further policy measures are required for breaking the trend.

Keywords: Climate Policy, Environmental Efficiency, Nonparametric Measurement, Trend Projections, Bootstrapping
JEL Classifications: Q54, E23, C14, C53

1. INTRODUCTION

In the international scientific and political debate, it is widely agreed that a significant and rapid reduction of anthropogenic greenhouse gas (GHG) emissions, and particularly CO_2 emissions, is necessary to stabilize the global average temperature and prevent harmful consequences of climate change. Despite international climate protection efforts, such as the most recent adoption of the Paris Agreement in 2015, global emissions continue to increase. For example, global CO_2 emissions peaked at 36.3 gigatons (gt) in 2021, an increase of 6% compared to 2020 (International Energy Agency, 2021a). In addition, the latest World Energy Outlook from the International Energy Agency (2021b) suggests that current climate policies will not achieve the required reductions in CO_2 emissions to reach zero emissions by 2050.

While technological progress and the substitution of fossil fuels with renewable energy sources are widely discussed in the climate debate and are expected to make a major contribution to climate protection, less is known about potential emission reductions as a result of reducing inefficiency. However, identifying existing inefficiencies in current production technologies and unexploited reduction potentials could provide useful information for policy makers and international climate policy.

A commonly used approach for conducting efficiency analysis is the nonparametric data envelopment analysis (DEA). In the DEA approach, a piece-wise best practice function (frontier) is estimated using historical input and output data. While DEA was originally used only for economic performance studies, it has been developed in recent decades to incorporate the joint production of "good" or desirable outputs and "bad" outputs such as emissions. By using directional distance functions (DDFs), the distance to the frontier of given input-output combinations can be measured to determine the degree of inefficiency. Since then, DEA has also been frequently used in environmental research to examine environmental performance and efficiency, expressed as the extent of the potential reduction of the "bad" outputs.

Zhang and Choi (2014), for example, provide an overview on energy and environmental modeling in the period from 1997 to 2013. Generally, the DEA and DDF approaches are mainly used to study environmentally sensitive productivity growth and environmental efficiency at the country or regional level (e.g. Anser et al., 2020; Chen and Jia, 2017; Halkos and Tzeremes, 2012; Jeon and Sickles, 2004; Kumar, 2006; Yörük, 2007) and at the firm or sector level (e.g. Färe et al., 2005; Krautzberger and Wetzel, 2012; Kumar Mandal and Madheswaran, 2010; Stergiou and Kounetas, 2022; Weber and Domazlicky, 2001; Wu et al., 2019; Zhang, 2009). While most of these studies conclude that, on average, efficiency improvements are possible, or even find a decrease in (environmental) productivity, a quantification of the associated potential emission reductions in physical units is widely missing. Also most of the literature on eco-efficiency relies on relative measures instead of physical units (Färe et al., 2004; Kuosmanen and Kortelainen, 2005 and Zofío and Prieto, 2001; among others). A first quantification of emission reduction potentials as a result of inefficiency can be found in Hampf and Krüger (2015). For a sample of major pollution emitting countries, Hampf and Krüger (2015) find sizable reduction potentials if macroeconomic inefficiency is completely removed. Related studies for EU countries and several industrial sectors are conducted by Krüger and Tarach (2020; 2022), and Fait and Wetzel (2024) also find substantial emission reduction potentials at the country as well as at the sector level.

In addition to quantifying potential emission reductions due to inefficiencies, the impact of exploiting these reduction potentials on the future growth of GHG emissions is also rather unknown. For this purpose, trend functions can be used to project remaining emissions (i.e., after subtracting potential reductions) into the future and determine the contribution of eliminating inefficiencies to achieving climate targets.

The aim of this work is therefore to identify global emission reduction potentials and to determine the potential contribution of removing macroeconomic inefficiencies to future reduction targets. For this, we rely on the nonparametric DEA framework using DDFs. Unlike most previous studies, we endogenously determine optimal directions of emission reductions as suggested by Hampf and Krüger (2015). To avoid downward biased estimates, we implement a bootstrap bias correction based on a version of the algorithm of Simar and Wilson (1998). Furthermore, a key aspect of this work is the dynamic projection of the identified reduction potentials into the future to determine how the growth of global GHG emissions will change if possible reduction potentials are exploited and to what extent this will contribute to the achievement of international climate targets. Our empirical analysis is conducted for a comprehensive sample of 100 countries for the period from 1990 until 2017. Trend projections are run until 2050. In addition, we provide sub- group analyses for the Top 10 emitters (based on historical GHG emissions) and major EU countries. To provide insight into the role of different GHGs, efficiency analyses and trend projections are not only performed for a single emission variable (total GHGs), but also for a variant where total GHG emissions are split into CO_2 and non-CO_2 emissions.

Overall, our work contributes to the literature in several ways: Methodologically, our work combines several aspects, such as the endogenous determination of optimal directions, the use of trend functions to estimate projections of future emissions, and the application of a bootstrap procedure. In addition, we consider a comprehensive sample and different emission variables, which contributes to a better understanding of the impact of efficiency improvements on the trajectory of global GHG emissions. Therefore, our results provide useful guidance for policy makers regarding unexploited reduction potentials to achieve global climate targets.

The outline of the paper is as follows: Section 2 describes the data sources and adjustments to the data used to construct the input and output vectors, and provides insights into the current levels of GHG emissions for the subgroups. Section 3 briefly outlines the empirical framework for the inefficiency measure, the bootstrap procedure, and the trend projections. Section 4 discusses the results for the different trend functions and emission variables, while Section 5 finally concludes.

2. DATA DESCRIPTION

The data used for the empirical analysis rely on two main sources. The first is the Penn World Table (PWT) version 10 for the inputs and the economic output. The data can be found at https://www.rug.nl/ggdc/productivity/pwt. A detailed description is provided on this site and in Feenstra et al. (2015). The economic output is the output- side real GDP at chained PPPs (in million 2017 US$), variable rgdpo in the PWT. A substantial advantage of the more recent PWT versions compared to older versions is that GDP measures are also computed from the output side, which are more suitable for productivity analyses than expenditure-side measures (Feenstra et al., 2009; for a comparison and detailed discussion).

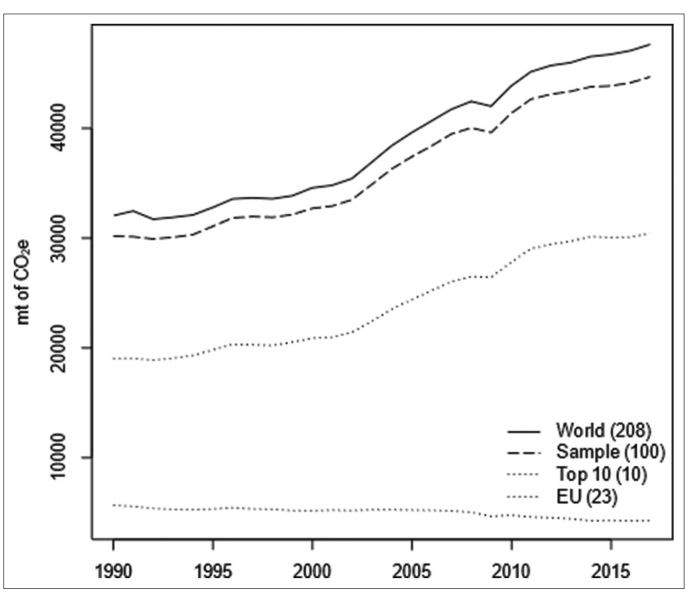
As economic inputs we use labor and capital. The labor input is measured as the raw labor input (variable emp = number of persons engaged in the PWT). As an alternative, we considered a human capital measure computed as raw labor multiplied by the index of human capital per person (variable hc in the PWT). This measure is, however, dominated by the differences in the raw labor input and is highly correlated with raw labor (correlation >0.98). Physical capital is measured as the capital stock at constant 2017 national prices (in million 2017 US$) (variable rnna in the PWT), converted to international prices at chained PPPs by multiplying with the factor rgdpo/rgdpna, where rgdpna is the real GDP at constant 2017 national prices (in million 2017 US$). Such a measure is also used in Krüger (2016). The data are available from 1950 to 2019 with gaps for a substantial number of countries.

The second data source are historical emissions data provided by the Potsdam Institute for Climate Impact Research (PIK). Their PRIMAP-hist national historical emissions (version 2.1) time series provides emissions data for a comprehensive country sample as annual time series over the period 1850-2017. The data sources and methods are described in detail in Gütschow et al. (2016) and Gütschow et al. (2019). The data are retrieved from https://www.climatewatchdata.org. When considering a single emission variable, we use an aggregate of GHG emissions consisting of all Kyoto gases (excluding land use, land use change and forestry, LULUCF) according to the fourth assessment report, measured in megatons (mt) of CO_2 equivalents (CO_2e). In the case of two emission variables, we single out carbon dioxide and work with the two emission variables CO_2 and other (non-CO_2) GHG emissions, computed by subtracting CO_2 from the aggregate GHG emissions.

The analysis is based on a balanced panel of n = 100 countries for the period 1990-2017. We deliberately exclude countries which are merely large cities rather than countries (e.g. Hong Kong, Luxembourg, Macao, and Singapore) and countries which are small major oil producing countries (e.g. Bahrain, Brunei, Kuwait, Qatar, and Saudi Arabia). These countries are likely to bias frontier function estimates, as discussed in Growiec (2012). We also exclude a couple of very small countries because they caused a breakdown of the bootstrapping procedure. The remaining 100 countries are representative for the world, since they account for about 94% of the world GHG emissions (computed from the average of the last 10 years of the sample (period 2008-2017) for each country to avoid the influence of a particular year). The sample countries are listed in Table A1 in Appendix A, jointly with their GHG emission shares in the average of the last ten sample years.

Figure 1 shows the development of the total GHG emissions over time for the world (i.e. all 208 countries in the PIK database), our total sample of 100 countries, and the two subgroups of the top 10 emitting countries and the 23 EU countries in the sample. We see that the sample countries cover the majority of GHG emissions and track the world's emissions quite well over time. The part accounted for by the Top 10 group is substantial and grows in a similar way as the total. In this group China is by far the largest contributor (followed by the US, India and Russia, Table A1). China's emission trajectory and also projections are investigated in detail in Grubb et al. (2015) and Sanwal and Zheng (2018). By contrast, the aggregate GHG emissions of the EU countries are rather small and appear to be declining, especially after 2010.

Figure 1: Time series of total greenhouse gas emissions aggregated over Countries



3. MEASUREMENT AND TREND PROJECTION

This section outlines the basic ideas of the nonparametric measurement approach for the inefficiencies employed in this paper. The outline gives the intuition of the approach whereas the formal details and further discussion is relegated to an appendix (Appendix B). The inefficiencies are expressed in CO_2 equivalents and subtracted from the actual emissions to obtain the so-called efficient emissions which are subsequently projected into the future. The way to estimate the trend functions to conduct the projections is also explained in this section.

3.1. Nonparametric Inefficiency Measurement

We use nonparametric methods of efficiency analysis to determine the potential emission reductions of the countries. The approach is based on data envelopment analysis (DEA), developed by Charnes et al. (1978) and Banker et al. (1984), and in particular the ex- tension to the case of the directional distance functions (DDF), introduced by Chambers et al. (1996), which easily allows to introduce emissions as undesirable outputs of a pro- duction process, see Chung et al. (1997). By this approach, inefficiency is measured as the distance to a piece-wise linear frontier function along a specific direction (Färe and Grosskopf, 2004 and Zhou et al., 2008b). The great advantage of this approach is that functional form assumptions about the underlying technology (e.g. a production function) are not needed and that it relies only on quantities of the inputs and outputs without requiring price information.

In our application, we use these methods to measure the extent of the inefficiency by the maximum possible reduction of the GHG emissions to reach a point on the frontier function which is determined by the most efficient country observations. We investigate two cases, one with total GHG emissions as the single emission variable and another with CO_2 and other GHG (calculated as GHG-CO_2) as two separate emission variables. In the latter case, a weighting of the extent of reduction of the two emission variables is necessary which is endogenously determined by an extension of the nonparametric method due to Hampf and Krüger (2015). All calculations are performed under variable returns to scale which is less restrictive than the more common assumption of constant returns to scale (Zhou et al., 2008a) for the adaption to the DDF setting with undesirable outputs).

To perform a bias correction and to establish confidence intervals for the in-sample period a bootstrap approach specifically adapted to the frontier function estimation with DDF is used. This bootstrap orginiates in the ideas of Simar and Wilson (1998) (see also Simar and Wilson (2008, 2011); Simar et al., 2012). Krüger and Tarach (2022) is a recent application of this approach. Appendix B provides the formal details also on the implementation of the bootstrapping.

3.2. Estimation of Trend Functions

For projecting the remaining emissions into the future, we rely on two forms of trend functions.[1] More precisely, let y_t denote the sum of emissions remaining after subtracting the potential reductions measured by efficiency improvements. These are then called the efficient emissions. The first trend function is a simple log-linear trend

$$\ln y_t = \beta_1 + \beta_2 \cdot t + u_t \tag{1}$$

with the sample period running over $t = 1990,\ldots, 2017$. As usual, β_2 represents the (constant) growth rate of y_t. The trend regression is estimated by a robust regression estimator proposed by Koller and Stahel (2011; 2017) with the data from the period 1990-2017 and then projected into the future with $t = 2018,\ldots, 2050$. This estimator is highly robust with respect to outlying observations combined with improved efficiency properties in small samples. We use the implementation in the R-package "robustbase."

The simple log-linear trend function is restricted to a monotonically increasing or decreasing form of the trend. It fits quite well in sample, however. Adding further polynomial terms in t is not sensible since polynomials generally have the strong tendency to diverge out of their sample range, rendering the projections meaningless.

A functional form based on a logistic function with a certain (sample-determined) saturation level may be another reasonable choice here. Therefore, we apply the four-parameter logistic model

$$y_t = \beta_1 + \frac{\beta_2 - \beta_1}{1 + \exp(\beta_4(\ln t - \ln \beta_3))} + u_t \tag{2}$$

used in bioassay studies to estimate so-called dose-response curves (Ritz and Streibig, 2005; and Ritz et al., 2015). This is a flexible functional form to fit a logistic model for y_t without having to pre-assign values for the lower and upper limits.[2] By construction, this function is bounded by the lower limit β_1 and the upper limit β_2. The parameter β_3 represents the half-way between the limits and β_4 represents the slope around β_3.[3] The parameters of this logistic trend function are also estimated by a robust estimator based on Tukeys biweight loss combined with quasi-Newton (BFGS) optimization, which is implemented in the R-package "dr4pl," and the trend is projected until 2050 as for the log-linear trend.

The confidence intervals for the out-of-sample projections are computed point-wise for each point in time. Specifically, we apply the BC_a (bias-corrected and accelerated) confidence interval of Efron (1987) to the logged values and then exponentiate the confidence bounds. This procedure is valid because of the transformation-respecting property of BC_a confidence intervals. In addition, we reach second-order accuracy of the confidence intervals (Efron and Tibshirani (1994, p. 187) for more on these properties). The computation is based on the package "boot" for R (Davison and Hinkley, 1997).

4. RESULTS AND DISCUSSION

In this section, the empirical results of the two trend functions (log-linear and logistic) from section 3.3 are discussed. For both functions, the efficient emissions, i.e. the emissions remaining after subtracting potential reductions, are considered for the total sample and the two subgroups of Top 10 emitters and EU countries. Trend projections are provided for total GHG, CO_2 and non-CO_2 emissions.

For both trend functions, the figures for presenting the results are constructed in a similar way. In each panel, the solid gray line depicts the actual emissions of the respective country group and the GHG under consideration. The solid black line shows the efficient emission levels of the sample period up to the vertical line. After the vertical line the solid line represents the projections from the respective trend functions. The trend curve is extended backwards by the dotted line to show the in-sample fit. The dashed lines represent the 95% BC_a bootstrap confidence intervals for the in-sample values and for the projections. Furthermore, the squares depict the targets of the remaining emissions set by the EU, i.e. the reduction of total GHG emissions to 80% of the 1990 levels by 2020, to 45% by 2030, and to near zero (supposed 5%) by 2050 (European Council, 2009; European Union, 2021). The quantitative target for 2040 is not yet determined. We suppose 20% as an intermediate target to be reached by 2040. Note that these percentages are also applied to the total sample and to the Top 10 group.

4.1. Log-Linear Trend Projections

We first turn to the projections using the log-linear trend function in equation (1). Figure 2 shows that efficient total GHG emissions during the sample period range from 15 to 20 gigatons (gt) CO_2e for the total sample, 10-15 gt CO_2e for the Top 10 emitters, and 2.5-3.5 gt CO_2e for the EU countries. Thus, the Top 10 emitters and the EU account for the majority of all remaining emissions, with the Top 10 emitters clearly dominating. This is also reflected in the trend of efficient emissions over the sample period for the total sample, which is almost the same as for the Top 10 emitters, but on a slightly higher level. For both, the total sample and the Top 10 emitters, efficient GHG emissions increase steadily until the 2007-08 global financial crisis and then decline slightly until the mid-2010s. In the last years of the sample period, efficient emissions return to an increasing trend. In line with this, the log-linear trend functions predict further exponential growth in efficient total GHG emissions until 2050.

In contrast, the development and projection of efficient emissions of total GHGs is different in the EU countries. During the sample

1 Because of the general vagueness of those assertions about the future the climate literature prefers the term "projection" instead of "forecast" or "prediction" (see Hsiang and Kopp (2018, p. 10))

2 An even more flexible form is the five-parameter logistic model $y_t = \beta_1 + (\beta_2 - \beta_1)/(1 + \exp(\beta_4(\ln t - \ln \beta_3)))^{\beta_5} + u_t$ with the additional parameter β_5, which controls the degree of asymmetry. In the bootstrapping exercise this function proved not to be usable due to severe convergence problems in the numerical optimization.

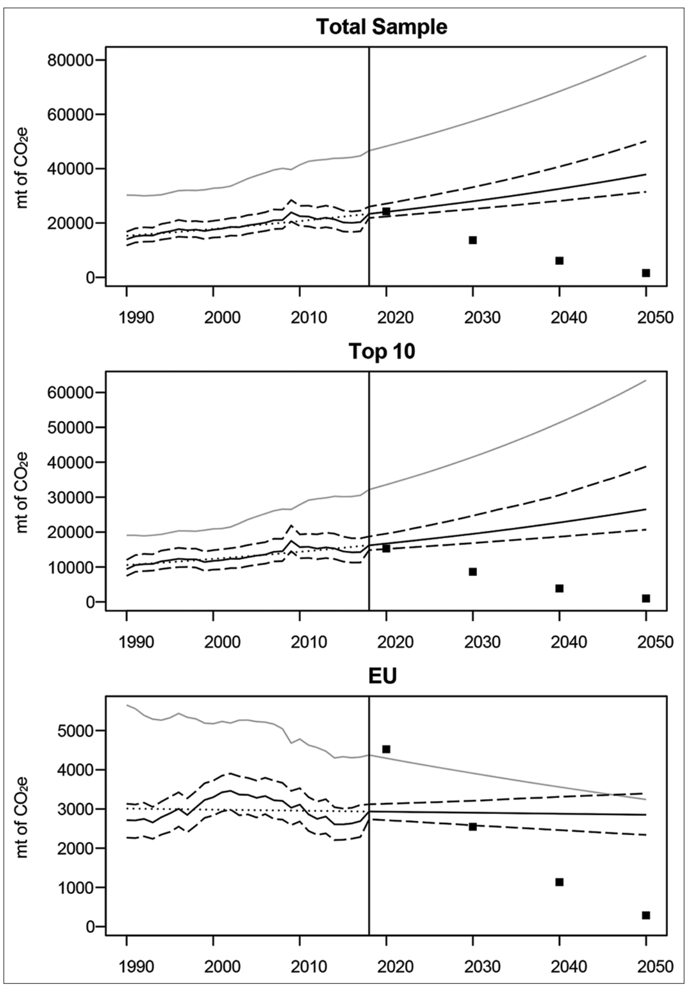
3 Note that we are not interested here in the particular parameter values themselves, but only in the trend function determined by them

period, efficient emissions fluctuate considerably, but are only slightly higher in 2018 compared to 1990. Consistent with the trend in efficient emissions during the sample period, the log-linear trend projection yields a fairly constant level of efficient emissions for total GHGs until 2050. However, for all samples, the bootstrap confidence intervals are rather wide, especially at the end of the projection period and for the total sample as well as for the Top 10 emitters, indicating substantial uncertainty in the estimates of emission reduction potentials.

Considering now the emission targets formulated by the EU (indicated by ■), one can see that for the total sample and the Top 10 emitters the 2020 target lies within the 95% confidence intervals, while the efficient emissions of total GHGs of the EU countries are already well below the 2020 target. Furthermore, the 2030 target is also within the 95% confidence interval of the log-linear trend projections for the EU countries. In contrast, for the total sample and the Top 10 emitters, efficient total GHG emissions are above the 2030 target, and the 2040 and 2050 targets cannot be met by any of the three samples by reducing inefficiencies and associated emissions. At first glance, the performance of the sample looks rather poor, but directing technological change and sectoral structural change directly to modes of production which are less emission intensive would be appropriate to shift the trend downwards. Furthermore, the efficient emission levels at the end of the projection period are quite moderate compared to the trend projections of actual emissions (gray solid line). This is especially true for the total sample and the Top 10 emitters, while for the EU countries actual emissions show a decreasing trend in the projection period. The efficient emissions, however, are achievable only if it is assumed that the reduction potentials due to the macroeconomic inefficiencies are fully realized. Of course, it is arguable whether this assumption is realistic, but it is apparent that eliminating inefficiencies in current production technologies and associated emissions could make a significant contribution to achieving the climate targets.

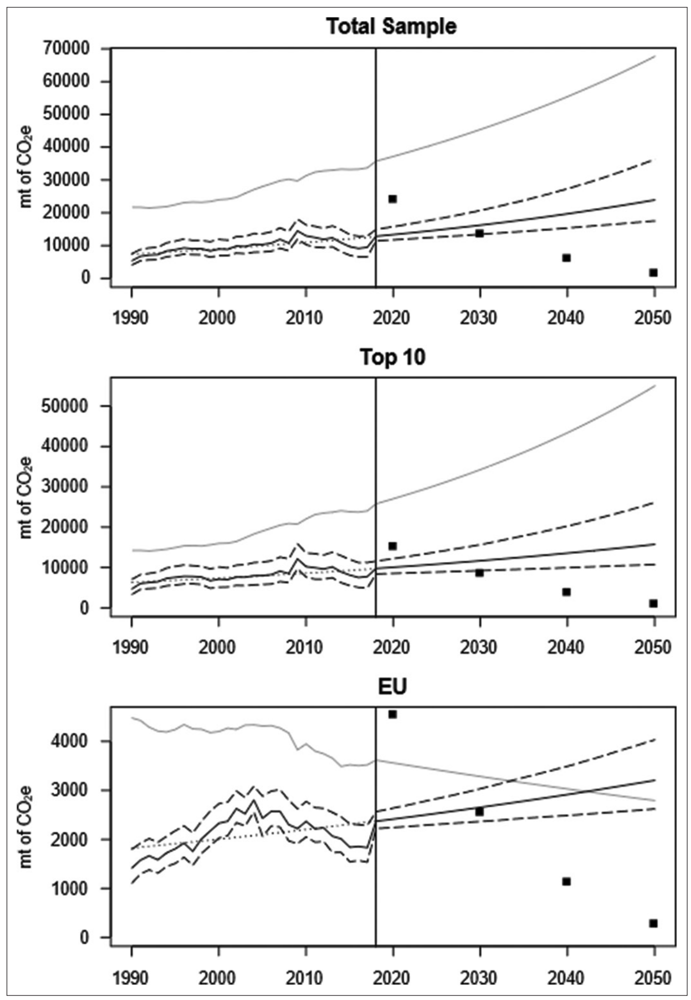
Turning to Figures 3 and 4, depicting the log-linear projections of efficient CO_2 and non-CO_2 emissions, it is noticeable that the efficient emissions of total GHG are mainly driven by CO_2

Figure 2: Projections of Efficient Emissions (total greenhouse gas, log-linear trend)



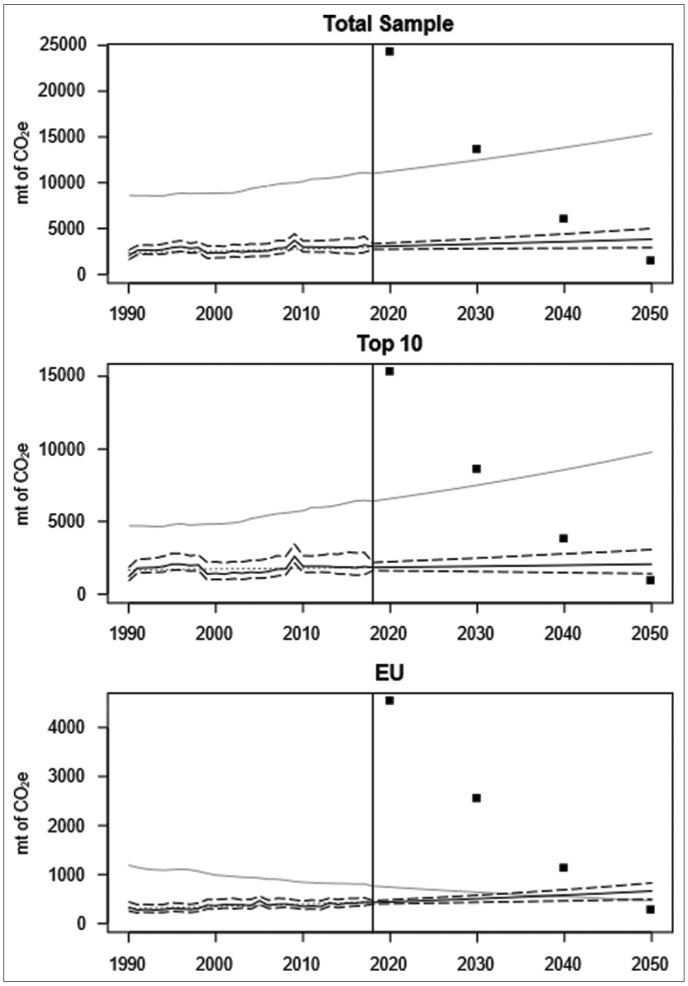
Actual emissions and trend projection (gray solid line), efficient emissions after subtracting potential reductions and trend projection (black solid line), 95% confidence intervals (dashed lines), backward trend projections (dotted line)

Figure 3: Projections of Efficient Emissions (CO_2, log-linear trend)



Actual emissions and trend projection (gray solid line), efficient emissions after subtracting potential reductions and trend projection (black solid line), 95% confidence intervals (dashed lines), backward trend projections dotted line)

Figure 4: Projections of Efficient Emissions (non-CO_2, log-linear trend)



Actual emissions and trend projection (gray solid line), efficient emissions after subtracting potential reductions and trend projection (black solid line), 95% confidence intervals (dashed lines), backward trend projections dotted line)

emissions. For both, efficient emissions during the sample period and trend projections, the patterns are very similar for total GHG and CO_2 emissions for all three panels. Again, the confidence intervals for efficient CO_2 emissions during the projection period are quite large, as in the case of total GHG emissions. However, in contrast to total GHG emissions, the trend function for the EU countries shows an increasing trend, implying that the level of efficient CO_2 emissions is increasing over the projection period, whereas actual CO_2 emissions are characterized by a decreasing trend.[4] Considering only CO_2 emissions, the 2020 target is overachieved, and the 2030 target is (almost) within the 95% confidence interval of all groups. The CO_2 targets for 2040 and 2050 still seem beyond reach when considering only the elimination of macroeconomic inefficiencies.

Regarding the non-CO_2 emissions, a different result can be observed. Overall, efficient non-CO_2 emissions are quite low during the sample and projection periods for all country groups, and the confidence intervals are narrower than for CO_2 and total GHGs, implying that the estimates are more precise. Moreover, the trend functions show nearly constant or only slightly increasing values for efficient emissions, so that even the 2050 emissions target is only slightly below the confidence interval in all panels. Overall, this suggests that substantial reductions in non-CO_2 emissions may already be possible if past rates of reduction (based on the technological trends during the sample period) continue on average over the next few decades.

Overall, one can see that a significant contribution could be made to achieve the climate targets if the existing inefficiencies of current production technologies could be completely eliminated or at least to a considerable extent. A particularly large potential therefore exists in the reduction of CO_2 emissions, while other non-CO_2 GHGs are already at a comparatively low level.

4.2. Logistic Trend Projections

Analogous to the log-linear trend projections, the logistic trend projections are estimated with the trend function (2) for total GHG, CO_2, and non-CO_2 emissions for the total sample, the Top 10 emitters, and the EU countries. Figures 5-7 again show the actual and efficient emissions, i.e. the remaining emissions after subtracting the potential reductions estimated jointly with the trend functions.

During the estimation period up to the vertical line, the efficient emission levels are un- changed compared to the previous section, as they are obtained from the same efficiency analysis and the bootstrap procedure and likewise provide the basis for both trend functions. For the projection period, on the other hand, there are significant differences from the log-linear function for almost all subgroups and emission categories.

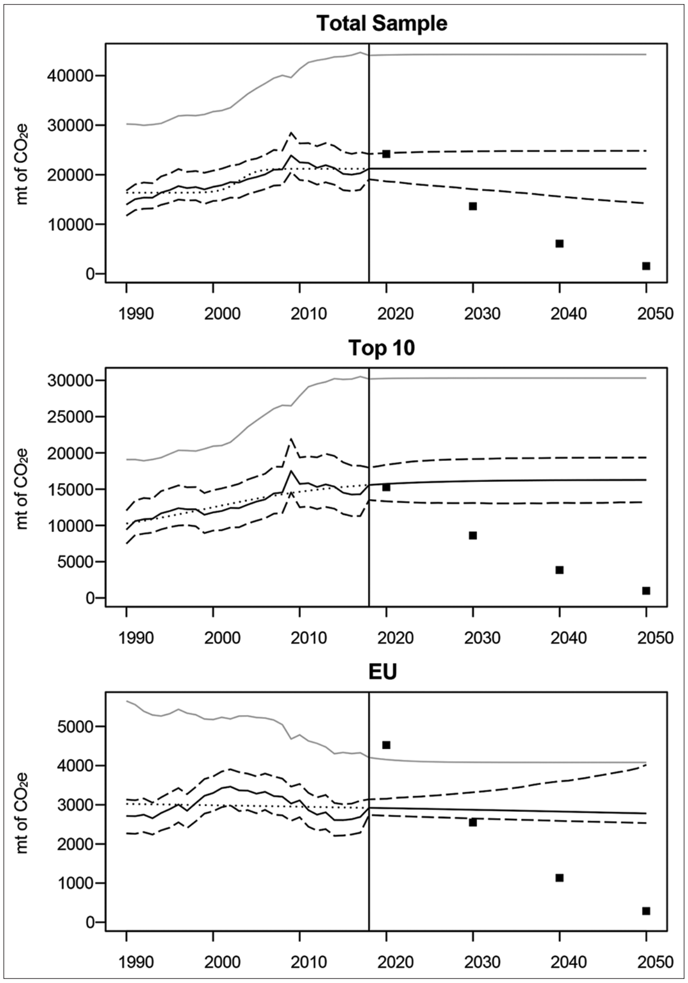
Considering total GHGs (Figure 5), under the logistic trend function, efficient emissions for both the total sample and the Top 10 emitters remain fairly constant over the projection period. Therefore, the efficient GHG emission levels are also significantly lower at the end of the projection period compared to the log-linear trend projections. The trend lines for the actual emissions (gray solid lines) also quickly turn to a constant shape. However, with the exception of the 2020 target, the efficient emissions are still higher than the percentage emission levels targeted by the EU.

For the EU countries, the efficient emissions of total GHGs show a slightly decreasing trend in the projection period under the logistic trend function. However, since the lower confidence bound is higher, the 2030 target is no longer within the confidence interval, unlike for the log-linear trend projection. In addition, the upper confidence bound is also higher and shows an increasing trend, which means that the projection of efficient GHG emissions for EU countries is subject to increasing uncertainty over time.

Turning to Figures 6 and 7, depicting the projections of efficient CO_2 and non-CO_2 emissions in the logistic trend function, there are some similarities and differences compared to the log-linear

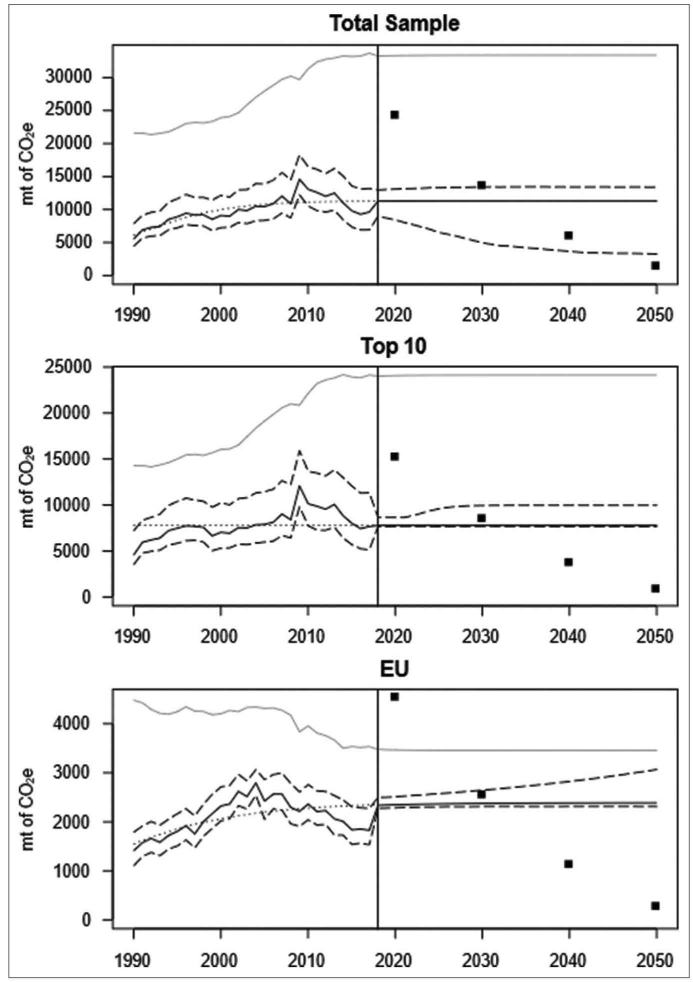
4 The crossing of the trend lines is merely a manifestation of the great deal of estimation uncertainty associated with the long-run trend projections.

Figure 5: Projections of Efficient Emissions (total greenhouse gas, logistic trend)



Actual emissions and trend projection (gray solid line), efficient emissions after subtracting potential reductions and trend projection (black solid line), 95% confidence intervals (dashed lines), backward trend projections dotted line)

Figure 6: Projections of efficient emissions (CO_2, logistic trend)



Actual emissions and trend projection (gray solid line), efficient emissions after subtracting potential reductions and trend projection (black solid line), 95% confidence intervals (dashed lines), backward trend projections dotted line)

function.[5] During the projection period, efficient CO_2 emissions are significantly lower for the logistic trend function than for the log-linear function. For the total sample and the Top 10 emitters, the efficient CO_2 emissions projected by the logistic trend becomes nearly half of the log-linear trend projection towards the end of the projection period. Besides, for the total sample, the 2020 target is over-achieved, while the 2030 and 2040 targets are within the confidence intervals. However, the lower confidence bound is quite low, again implying some uncertainty in the estimates in this direction. For the Top 10 emitters and EU countries, the 2020 target is also over-achieved, and the 2030 target is within the confidence bounds, as in the case of the log-linear function. For the EU countries, efficient CO_2 emissions also increase slightly during the projection period in the case of the logistic trend function, but this increase is less pronounced than for the log-linear function.

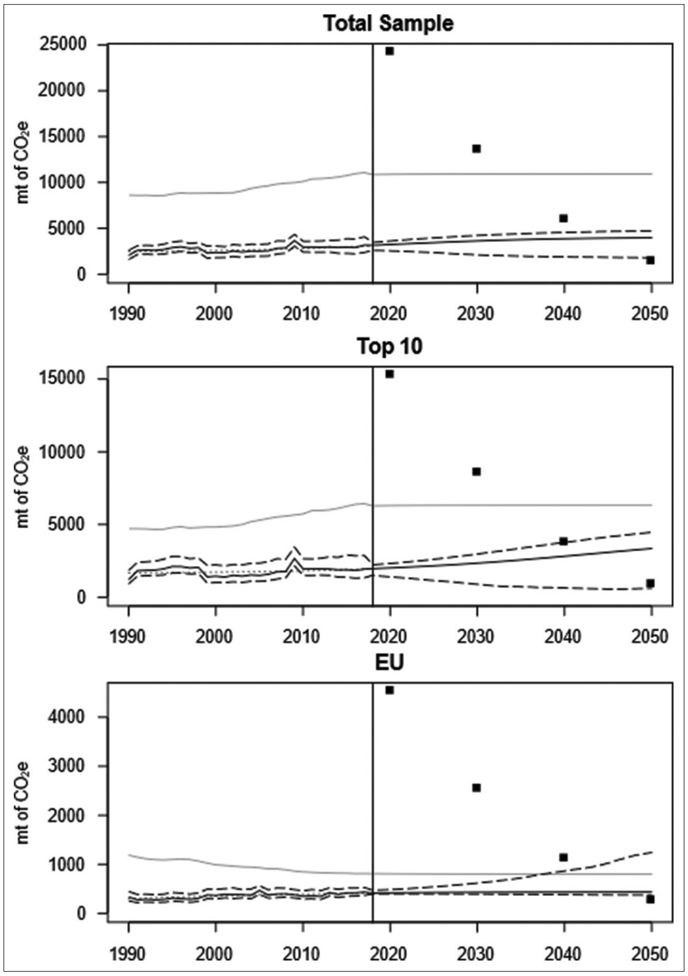
With respect to non-CO_2 emissions, the trend projections for the Top 10 emitters and the EU countries differ significantly for the logistic and log-linear functions. For the logistic trend function, there is a more significant increase in efficient non-CO_2 emissions, especially for the Top 10 emitters. In addition, in the case of the Top 10 emitters, the non- CO_2 emissions are almost of the same magnitude as the CO_2 emissions, i.e. the difference between the efficient emissions at the end of the projection period is considerably lower under the logistic trend function compared to the log-linear trend function.

However, the confidence intervals are wider for all groups, indicating greater uncertainty in the estimates compared to the log-linear trend function. For this reason, even the 2040 target would be over-achieved (achieved) by the total sample and the EU countries (Top 10 emitters), and the 2050 target could also be almost achieved by all groups if existing inefficiencies could be removed.

Comparing the fit of both trend functions (measured by an R^2 measure computed as the variance of the fitted values divided by the variance of the actual efficient emissions) we find a generally better (or at least very close) in-sample fit of the logistic trend function compared to the log-linear trend function. The exception is the case of CO_2 and the Top 10 group, where the logistic trend

5 Note that the results for CO_2 in Figure 6 are not computed with a robust estimator due to severe convergence problems during the bootstrapping.

Figure 7: Projections of efficient emissions (non-CO_2, logistic trend)



Actual emissions and trend projection (gray solid line), efficient emissions after subtracting potential reductions and trend projection (black solid line), 95% confidence intervals (dashed lines), backward trend projections dotted line)

curve is completely flat and the fit is accordingly almost zero. During the projection period, however, it is readily visible that the logistic trend functions show a strong tendency to turn quickly to constant saturation levels, which appears to be rather unrealistic compared to the log-linear trend estimates. For that outcome, it is crucial that we only observe the "early" part of the S-shape of the logistic function in the data.

Overall, regardless of the form of the trend function, we find that macroeconomic inefficiencies in current production processes contribute significantly to the emission of harmful GHGs into the atmosphere. Exploiting the associated reduction potentials and eliminating inefficiencies could therefore contribute significantly to flatten GHG emissions growth in the future and achieving the emission targets.

5. CONCLUSION AND POLICY IMPLICATIONS

In light of the increasing prevalence of natural disasters as a result of rising anthropogenic GHG emissions, international climate protection is becoming an increasingly important issue. It is expected that technological progress and the shift to renewable resources in energy generation will make a significant contribution to reducing global emissions. In contrast, less is known about the emission savings which can be achieved through efficiency improvements and to what extent an elimination of existing inefficiencies could influence future GHG emissions trends. Benchmarking approaches, such as the nonparametric DEA, offer a possibility to identify existing inefficiencies in current production technologies and are frequently used in the economic and also environmental research. While previous benchmarking studies considering the simultaneous production of good and bad outputs, such as emissions, have focused primarily on determining environmental efficiency and environmentally sensitive productivity growth, the quantification of potential emissions reductions from eliminating inefficiencies is missing to date.

In this paper, nonparametric methods are used to (a) measure the degree of inefficiency in current production technologies for a comprehensive sample of 100 countries and (b) estimate dynamic trend projections of GHG reduction potentials. Our analysis relies on a bootstrap procedure for measuring inefficiency to avoid downward biased results and two specifications of trend functions for the projection of emission reduction potentials. In addition, a detailed analysis of different country and GHG subsets is provided. The sample period covers 1990 until 2017, and trend projections are run until 2050.

During the sample period, we find sizable reduction potentials for GHG, CO_2 and non-CO_2 emissions under both trend functions. Comparing actual and efficient total GHG emissions, i.e. remaining emissions after subtracting reduction potentials from 1990 to 2017, emissions could be reduced by 50% on average if macroeconomic inefficiencies were fully eliminated. Thereby, total emissions are mainly driven by CO_2 emissions and the group of Top 10 emitters, while EU countries and non-CO_2 emissions are comparatively minor contributors.

Regarding the projection of efficient emissions, the two trend functions provide different results. Under the log-linear trend function, we find that efficient emission of total GHG, i.e. remaining GHG emissions after subtracting reduction potentials, increase exponentially after the sample period until 2050 for the total sample and the group of the Top 10 emitters. In contrast, under the logistic trend function, efficient GHG emissions for both samples remain rather constant or only slightly increase during the projection period. Therefore, efficient emission levels are significantly lower at the end of the projection period under the logistic trend function than under the log-linear trend function. Distinct differences are also observed regarding the role of CO_2 emissions. While under the log- linear trend function, CO_2 emissions are mainly driving efficient GHG emissions, efficient non-CO_2 emissions are of a similar size as efficient CO_2 emissions under the logistic trend function.

Despite the different results of the trend functions and higher efficient emission levels in the log-linear trend projection, we observe that efficiency improvements can have a sizable effect on future emission levels. Therefore, projected efficient emissions levels are substantially lower in both specifications compared to trend projections of actual emissions. In addition, our comparison of efficient emission levels and future emission targets show that some of these targets are achievable or even overachieved if macroeconomic inefficiency is removed. In this context, the great importance of increasing efficiency for the reduction of greenhouse gases is evident. Looking at the log-linear trend projections, for example, one can see that at the end of the projection period, actual emissions are significantly more distant from the 2050 target than efficient emissions. Following this example for the total sample, increasing efficiency could contribute a reduction of up to 47% to reach the target compared to the "business as usual" scenario (actual emission trend projection). This is further underpinned by estimates for the EU that are significantly lower for both actual and efficient emissions than for the Top 10 emitters. In the EU, increasing efficiency has played an important role in climate policy for many years and has also become a central component of the latest climate package, "Fit for 55" (EU, 2021). Although it is rather unclear whether the full elimination of inefficiency will be actually feasible, the results point to potentially large unexploited reduction potentials.

There is still a need for future research in this area. As already stated by Hampf and Krüger (2015), industry structure is a major factor influencing the emission levels of countries and should therefore be considered in the efficiency analysis. However, since sector-level data is still largely lacking for many countries, sectoral analyses are mostly feasible for EU countries as, for example, performed by Fait and Wetzel (2024), Krüger and Tarach (2020; 2022). Unfortunately, the rather short time spans of sectoral data availability prevent analogous long-run projection exercises as performed in this paper on the sectoral level for the years to come.

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APPENDIX

Table A1: Country list and GHG Emissions shares (in percentages)

China	26.25	Tanzania	0.18
United States of America	14.98	Austria	0.18
India	5.63	New Zealand	0.18
Russian Federation	4.67	Bolivia	0.18
Japan	2.94	Serbia	0.16
Brazil	2.35	Syrian Arab Republic	0.15
Germany	2.06	Portugal	0.15
Iran	1.82	Kenya	0.15
Indonesia	1.73	Ecuador	0.14
Canada	1.58	Finland	0.14
Mexico	1.55	Hungary	0.14
Republic of Korea	1.53	Bulgaria	0.13
United Kingdom	1.25	Ireland	0.13
Australia	1.19	Sweden	0.13
South Africa	1.19	Mali	0.13
France	1.09	Denmark	0.13
Italy	1.04	Norway	0.12
Turkey	1.00	Democratic Republic of Congo	0.12
Thailand	0.95	Switzerland	0.11
Poland	0.90	Paraguay	0.11
Pakistan	0.87	Slovakia	0.10
Ukraine	0.87	Cameroon	0.09
Spain	0.78	Uganda	0.09
Malaysia	0.76	Yemen	0.09
Argentina	0.74	Zambia	0.08
Kazakhstan	0.69	Tunisia	0.08
Nigeria	0.69	Uruguay	0.08
Viet Nam	0.67	Nepal	0.08
Taiwan	0.66	Mozambique	0.08
Egypt	0.65	Mongolia	0.08
Venezuela	0.61	Cambodia	0.07
Algeria	0.47	Madagascar	0.07
Iraq	0.47	Burkina Faso	0.07
Netherlands	0.44	Guatemala	0.07
Philippines	0.42	Sri Lanka	0.07
Colombia	0.34	Jordan	0.06
Czech Republic	0.30	Dominican Republic	0.06
Bangladesh	0.29	Croatia	0.06
Romania	0.28	Ghana	0.06
Belgium	0.27	Cote d'Ivoire	0.06
Ethiopia	0.26	Niger	0.05
Myanmar	0.25	Zimbabwe	0.05
Greece	0.24	Senegal	0.05
Morocco	0.23	Lithuania	0.05
Sudan	0.23	Estonia	0.05
Chile	0.23	Slovenia	0.04
Peru	0.22	Botswana	0.04
Angola	0.21	Honduras	0.04
Israel	0.19	Kyrgyzstan	0.04
Trinidad and Tobago	0.19	Nicaragua	0.04
		Total	94.02

Countries sorted according to their mean shares in total world GHG emissions over the last 10 years in the sample (2008-2017), summing to a total share of 94% of world GHG emissions

Appendix B: Nonparametric efficiency measurement and bootstrapping

In this appendix we outline the formal details of the nonparametric approach from the literature on efficiency analysis which is used to measure the macroeconomic inefficiency as well as the bootstrap approach employed to establish bias correction and confidence intervals.

Nonparametric Efficiency Measurement

The starting point of the nonparametric approach is the concept of a technology set, comprising the feasible input-output combinations

$$\mathcal{T} = \{(\mathrm{x},\mathrm{y},\mathrm{u}) \in \mathbb{R}_{+}^{m+s+r} : \mathrm{x} \geq 0 \ can\ \ produce\ (\mathrm{y},\mathrm{u}) \geq 0\} \tag{B1}$$

where x denotes the m-vector of the input quantities, y the s-vector of the quantities of the good (desirable) outputs and u the r-vector of the quantities of the bad (undesirable) outputs.[6] This technology set it is supposed to be closed, bounded and convex (Färe and Primont, 1995). In addition, standard axioms such as strong disposability of the inputs and the good outputs are supposed. In an environmental context with undesirable outputs two additional axioms are required. Null-jointness requires that it is not possible to produce positive quantities of the good outputs without generating emissions (i.e. if $[x, y, u] \in T$ and $u = 0$ then $y = 0$). Weak disposability requires that emissions are to be reduced in equal proportion with the quantities of the good outputs (i.e. if $[x, y, u] \in T$ then $[x, \alpha y, \alpha u] \in T$ for $\alpha \in [0, 1]$). Detailed discussions of these axioms can be found in Färe and Grosskopf (2004), Färe et al. (2005) and Zhou et al. (2008a).

Defined on the technology set is the DDF proposed by Chambers et al. (1996) and ex- tended to the incorporation of undesirable outputs by Chung et al. (1997). It can be formally stated as

$$DDF(\mathrm{x},\mathrm{y},\mathrm{u};\mathrm{g}_x,\mathrm{g}_y,\mathrm{g}_u) = \sup\{\delta \geq 0 : (\mathrm{x}-\delta \mathrm{g}_x, \mathrm{y}+\delta \mathrm{g}_y, \mathrm{u}-\delta \mathrm{g}_u) \in \mathcal{T}\} \tag{B2}$$

where the inefficiency measure δ expresses the distance of a particular input-output combination (x, y, u) towards the boundary of the technology set along a particular direction $g_x \geq 0$, $g_y \geq 0$, $g_u \geq 0$. This measure is larger than zero if the input-output combination is below the boundary (is below the frontier function) and is equal to zero if the input-output combination is a point on the boundary (is on the frontier function).

With data for the m inputs contained in the $m \times n$ matrix X, for the s good outputs contained in the $s \times n$ matrix Y, and the data for the r bad outputs contained in the $r \times n$ matrix U, the DDF for a country i can be computed as the solution of the linear programming problem

$$\begin{array}{llcclcl} \max\limits_{\delta,\boldsymbol{\lambda}} & & & \delta & & \\ \text{s.t.} & \boldsymbol{x}_i & - & \delta \boldsymbol{g}_x & \geq & \boldsymbol{X\lambda} \\ & \boldsymbol{y}_i & + & \delta \boldsymbol{g}_y & \leq & \boldsymbol{Y\lambda} \\ & \boldsymbol{u}_i & - & \delta \boldsymbol{g}_u & = & \boldsymbol{U\lambda} \\ & & & \boldsymbol{\lambda} & \geq & \mathbf{0}, \end{array} \tag{B3}$$

where x_i, y_i, and u_i denote the ith column of the matrices X, Y, and U, respectively, comprising the quantities of country i ($i = 1,..., n$). The constraints jointly determine the technology set and lead to a piece-wise linear frontier function as its boundary. The inequality constraints pertain to the inputs and the (good) outputs, while the equality constraints for the bad outputs take account of weak disposability. As an ordinary linear programming problem the solution of (B3) can be easily computed by the simplex algorithm.

The solution of (B3) consists of the value for the inefficiency measure of country i, δ_i, and the n-vector $\lambda_i \geq 0$ of the weight factors. These weight factors combine the input and output quantities of the countries for computing the efficient input-output combination on the frontier function along the specified direction with coordinates $\hat{\mathrm{x}}_i = \mathrm{X}\lambda_i$, $\hat{\mathrm{y}}_i = \mathrm{Y}\lambda_i$, and $\hat{\mathrm{u}}_i = \mathrm{U}\lambda_i$. The potential reductions of the r bad outputs for country i can be computed as $\mathrm{u}_i - \hat{\mathrm{u}}_i = \delta_i \mathrm{g}_u$ and the sum over all emissions by $RP_i = 1'(\mathrm{u}_i - \hat{\mathrm{u}}_i)$, with 1 denoting a conformable vector of ones and the prime denoting transposition. For this summation to be valid the emissions have to be expressed in a common unit of measurement, i.e. CO_2 equivalents.

Since our objective in this paper is to determine the maximum emission reduction feasible within the data-determined technology set, we impose the restriction $g_x = 0$ and $g_y = 0$ in the following. The direction vector g_u is computed endogenously as the solution of the linear programming problem, following the proposal of Hampf and Krüger (2015).[7] Chen and Delmas (2012) point out that this has the additional advantage of avoiding the problem of dominated (weakly-efficient) reference points on the frontier function. In addition, it is beneficial to specify the directions as being proportional to the variables u_i, which lets the inefficiency measure be invariant to units of measurement (e.g. Chung et al., 1997 and Färe et al., 2007).

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

7 See Färe et al. (2013) for a related proposal to compute endogenous directions in the case of a slacks-based inefficiency measure.

Following Hampf and Krüger (2015), the following modified optimization problem to endogenize the computation of the direction vector

$$\begin{array}{llcrcr} \max\limits_{\delta,\boldsymbol{\alpha}_u,\boldsymbol{\lambda}} & & & \delta & & \\ \text{s.t.} & \boldsymbol{x}_i & & & \geq & \boldsymbol{X\lambda} \\ & \boldsymbol{y}_i & & & \leq & \boldsymbol{Y\lambda} \\ & \boldsymbol{u}_i & - & \delta\boldsymbol{\alpha}_u \odot \boldsymbol{u}_i & = & \boldsymbol{U\lambda} \\ & & & \boldsymbol{1}'\boldsymbol{\alpha}_u & = & 1 \\ & & & \boldsymbol{\lambda},\boldsymbol{\alpha}_u & \geq & \boldsymbol{0} \end{array} \tag{B4}$$

is solved, where "$\odot$" denotes the direct (Hadamard) product. The direction weights α_u are computed jointly with δ and λ to determine the largest distance towards the frontier function. The identification of δ is permitted by the additional constraint $1'\alpha_u = 1$.

Because of δ and α_u arising multiplicatively in (B4) the optimization problem becomes nonlinear and is therefore difficult to solve. Defining $\gamma_u = \delta\alpha_u$ the problem can be transformed to a well-behaved linear programming problem

$$\begin{array}{llcrcr} \max\limits_{\boldsymbol{\gamma}_u,\boldsymbol{\lambda}} & & & \boldsymbol{1}'\boldsymbol{\gamma}_u & & \\ \text{s.t.} & \boldsymbol{x}_i & & & \geq & \boldsymbol{X\lambda} \\ & \boldsymbol{y}_i & & & \leq & \boldsymbol{Y\lambda} \\ & \boldsymbol{u}_i & - & \boldsymbol{\gamma}_u \odot \boldsymbol{u}_i & = & \boldsymbol{U\lambda} \\ & & & \boldsymbol{\lambda},\boldsymbol{\gamma}_u & \geq & \boldsymbol{0}. \end{array} \tag{B5}$$

The value of the objective function $1'\gamma_u = \delta\, 1'\alpha_u$ is equal to δ as before, which is easily seen by taking the constraint $1'\alpha_u = 1$ from (B4) into account. Program (B5) can be solved by the ordinary simplex algorithm.[8] The solution values for δ and α_u can be backed out from the solutions for γ_u by $\delta = 1'\gamma_u$ as well as $\alpha_u = \gamma_u/\delta$.[9]

The optimization problems compute the inefficiency measures under the assumption of constant returns to scale (CRS). This is very restrictive in a cross-country setting with countries of rather different size. Measuring inefficiency under variable returns to scale (VRS) is usually induced by adding the constraint $1'\lambda = 1$ to the optimization problems (Banker et al., 1984). In the case of environmental efficiency analysis, however, this would violate the weak disposability property. Zhou et al. (2008a) show how to induce VRS in a way that is consistent with weak disposability, leading to the modified linear programming problem

$$\begin{array}{llcrcr} \max\limits_{\beta,\boldsymbol{\gamma}_u,\boldsymbol{\zeta}} & & & \boldsymbol{1}'\boldsymbol{\gamma}_u & & \\ \text{s.t.} & \beta\boldsymbol{x}_i & & & \geq & \boldsymbol{X\zeta} \\ & \boldsymbol{y}_i & & & \leq & \boldsymbol{Y\zeta} \\ & \boldsymbol{u}_i & - & \boldsymbol{\gamma}_u \odot \boldsymbol{u}_i & = & \boldsymbol{U\zeta} \\ & & & \boldsymbol{1}'\boldsymbol{\zeta} & = & \beta \\ & 1 \geq \beta \geq 0 & , & \boldsymbol{\zeta},\boldsymbol{\gamma}_u & \geq & \boldsymbol{0} \end{array} \tag{B6}$$

with an additional parameter β, which is bounded in $[0, 1]$. This problem can again be easily solved by the simplex algorithm. As before, we obtain the solution values for γ_u, which allow to back out $\delta = 1'\gamma_u$ and $\alpha_u = \gamma_u/\delta$ and to compute the emission reduction potentials. We stick to the VRS assumption throughout this paper. For a particular country $i \in \{1,..., n\}$ the solution values are denoted δ_i, α_{ui}, γ_{ui} and λ_i.

Based on the solution, the potential emission reductions for country i can be computed as $u_i - \hat{u}_i = \gamma_{ui} \odot u_i = \delta_i\alpha_{ui} \odot u_i$. The potential emission reductions depend on the magnitude of the inefficiency measure δ_i as well as on the optimized direction vector α_{ui} of country i. The total emission reduction potential of country i is then again the sum over all emission variables $RP_i = 1'(u_i - \hat{u}_i)$. This aggregation is only valid if the r bad outputs are denominated on a common unit of measurement such as CO_2 equivalents.

Bootstrapping

By construction, the estimated frontier functions computed according to (B3), (B5) or (B6) lead to the closest possible envelopment of the observed input-output combinations. Since no account is taken for measurement error, this leads to downward-biased estimates of

8 For the actual computation of the solutions in this paper the R-package "lpSolve" is used.

9 In the case of the efficient countries (with $\delta = 0$) the solution for α_u is indeterminate. Clearly, there exists no direction towards the frontier function if an observation already stays on the frontier function.

the inefficiency measures and the derived emission reductions potentials. Therefore, we implement a bootstrap bias correction based on a version of Simar and Wilson (1998) (see also Simar and Wilson, 2008; 2011), adapted to the DDF setting.[10] Bootstrapping also allows to establish confidence intervals around the trend estimates, which we discuss subsequently.[11]

The smoothed bootstrap algorithm from Simar and Wilson (1998), which we adapt to the DDF setting, starts with computing the DDF and the optimal directions from the original data by solving (B6) to obtain $\hat{\delta}_i$ as well as the optimal directions α_{ui} for all $i = 1..., n$. These directions are kept fixed during the bootstrap replications. Also, the bandwidth parameter h for the smoothing is chosen as described in Simar and Wilson (2011), where some R code is provided.

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

- A bootstrap resample is obtained by first drawing with replacement from $D = \{\hat{\delta}_1,...,\hat{\delta}_n,-\hat{\delta}_1,...,-\hat{\delta}_n\}$, which implements a boundary reflection about zero. The result of this step is denoted $\tilde{\delta}_i\left(i=1,...,n\right)$.
- 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 $\delta_i^* = \left|\bar{\delta}+\left(\tilde{\delta}_i + h\cdot\varepsilon_i - \bar{\delta}\right)/\sqrt{1+h^2/\tilde{\sigma}_\delta^2}\right|$ for all $i = 1,...,n$, where $\bar{\delta}$ and $\tilde{\sigma}_\delta^2$ denote the sample mean and variance of $\tilde{\delta}_i\left(i=1,...,n\right)$, respectively.
- These resampled inefficiencies are used to construct the bootstrap resample of the reference points by setting $\mathrm{x}_i^* = \mathrm{x}_i$, $\mathrm{y}_i^* = \mathrm{y}_i$, $\mathrm{u}_i^* = \mathrm{u}_i - \left(\hat{\delta}_i - \delta_i^*\right)\alpha_{ui} \odot \mathrm{u}_i$ for all $i = 1,..,n$. By that operation, the observation (y_i, 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 $(-\alpha_{ui} \odot u_i)$. The resulting bootstrap resample is $\mathrm{X}^* = \left(\mathrm{x}_1^*,...,\mathrm{x}_n^*\right)$, $\mathrm{Y}^* = \left(\mathrm{y}_1^*,...,\mathrm{y}_n^*\right)$ and $\mathrm{U}^* = \left(\mathrm{u}_1^*,...,\mathrm{u}_n^*\right)$.
- The efficiency measures are computed by solving (keeping the directions fixed)

$$\begin{array}{llcl}
\max\limits_{\beta,\delta,\boldsymbol{\zeta}} & \delta & & \\
\text{s.t.} & \beta\boldsymbol{x}_i & \geq & \boldsymbol{X}^*\boldsymbol{\zeta} \\
 & \boldsymbol{y}_i & \leq & \boldsymbol{Y}^*\boldsymbol{\zeta} \\
 & \boldsymbol{u}_i - \delta\boldsymbol{\alpha}_{ui}\odot\boldsymbol{u}_i & = & \boldsymbol{U}^*\boldsymbol{\zeta} \\
 & \mathbf{1}'\boldsymbol{\zeta} & = & \beta \\
 & 1\geq\beta\geq 0 \quad , \quad \boldsymbol{\zeta}\geq\mathbf{0} & &
\end{array} \tag{B7}$$

for each $i = 1.,n$, where x_i, y_i, and u_i constitute the original observation for country i, and X^*, Y^*, and U^* are taken from the preceding step. The results are the bootstrap inefficiency measures $\hat{\delta}_i^*$ for all $i = 1,...,n$. From the bootstrap inefficiency measures the emission reduction potentials $\Delta\hat{\mathrm{u}}_i^* = \hat{\delta}_i^*\alpha_{ui} \odot \mathrm{u}_i$ are obtained for all $i = 1,...,n$.[12]

Cycling through the preceding steps $B = 2000$ times we obtain the bootstrap resamples $\left(\hat{\delta}_{i,b}^*, \Delta\hat{u}_{i,b}^*\right)$ with $b = 1,...,B$ for each country $i = 1,...,n$. We run this procedure for each sample year separately but suppress the time index to avoid notational clutter.

Based on the bootstrap resamples, the bias correction can be obtained. Letting z_t be the generic notation of a variable of interest (i.e. the quantity of emissions remaining after deducting the reduction potentials, aggregated over countries for a particular year t), we denote the estimate from the original data by $\hat{z}_t$ and the bootstrap resamples by $\hat{z}_{t,b}^*$ for each $b = 1,...,B$. The bias correction is performed by computing $\hat{z}_{\mathrm{bc},t} = \hat{z}_t - \widehat{\mathrm{bias}}_t$ with $\widehat{\mathrm{bias}}_t = B^{-1}\sum_{b=1}^{B}\hat{z}_{t,b}^* - \hat{z}_t$. This measure is only computed when $\left|\widehat{\mathrm{bias}}_t\right|/\hat{\sigma}_t > 1/\sqrt{3}$ with $\hat{\sigma}_t^2 = \left(B-1\right)^{-1}\sum_{b=1}^{B}\left(\hat{z}_{t,b}^* - \bar{z}_{t,b}^*\right)^2$ and $\bar{z}_{t,b}^* = B^{-1}\sum_{b=1}^{B}\hat{z}_{t,b}^*$. This rule ensures that the bias is only corrected if a reduction in the mean squared error of the estimate can be achieved (Simar and Wilson, 2008, pp. 449f.).

During the bootstrap resamples, we can obtain reduction potentials which are larger than the actual emission quantities. This problem is dealt with by pruning out those cases in the spirit of an accept-reject procedure. The bias correction and the confidence intervals are established from this truncated distribution. The number of bootstrap replications is sufficiently large to obtain reliable magnitudes after the pruning operation.

10 This bootstrap algorithm is simpler than that of the more complicated double bootstrap proposal of Simar et al. (2012), which we discuss in Krüger and Tarach (2022). See Alshehhi and Zervopoulos (2023) for an alternative approach with a Bayesian foundation.

11 The assessment of uncertainty is a controversially discussed issue in the area of climate change (see Dessai and Hulme (2004) for a review).

12 As a computational detail an offset is added to δ in (B7) and subtracted after the solution is obtained. This allows for negative values for δ arising during the bootstrap replications.