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Technical Efficiency and CO_2 Reduction Potentials - An analysis of the German Electricity Generating Sector

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Abstract

In this paper, we analyze the technical efficiency of CO_2 reduction potentials of German power and heat plants, using a non-parametric sequential Data Envelopment Analysis. We apply a metafrontier framework to evaluate plant-level efficiencies in the transformation of inputs into desirable (energy) and undesirable (CO_2 emissions) outputs, taking into account different fossil fuel generation technologies. We dispose of a unique data set for coal-, lignite-, gas- and biomass-fired power plants from 2003 through 2010 that provides an unbalanced panel of 1459 observations. We find intra-group differences within energy generation technology, but natural gas fired power plants clearly have the highest efficiency. Furthermore, the analysis points to significant savings potentials for CO_2 and fuel-input.

Keywords: Electricity Generation, Non-parametric Efficiency Analysis, Germany, Panel 2003-1010
JEL: L94, Q50, C14

1. Introduction

1.1. Motivation

The electricity and heat generating sector is not only a major backbone of the economic system but also a major producer of greenhouse gases (GHG), thus con-

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tributing to global climate change. Electricity and heat production accounts for nearly 30 percent of all GHG emissions in Europe with carbon dioxide emissions (CO_2) as the main pollutant. The reduction of CO_2 emissions in the electricity and heat production sector is therefore crucial in many countries in order to reach the CO_2 reduction targets agreed to under the Kyoto Protocol. Legislation of the last decade forced existing and newly constructed power plants across Europe to significant operational and managerial changes. The EU Directive for Large Combustion Plants (2001/80/EG) and its successors, including the Industrial Emissions Directive (2010/75/EU), set strict thresholds for the emission of several pollutants, such as NOx, SOx and dust. As CO_2 emissions were not included in this legislation, incentives to reduce them were only introduced with the start of the European CO_2 emission trading scheme (ETS) in 2005. However, incentives for CO_2 reduction were low, as prices for emission rights dropped rapidly due to an overallocation of emissions rights. Therefore, despite ambitious climate policy goals in Europe, European CO_2 emissions from electricity and heat generation remained rather stable over the 2000s with only a seven percent reduction in absolute terms.

Understanding the drivers of CO_2 emissions at plant level in the electricity and heat generation sector helps to identify successful climate policies. The drivers are threefold:

- Firstly, a reduction of CO_2 emissions can be achieved by increasing use of renewable carbon-free energy sources. The promotion of renewable technologies has led to installations of capacities achieving a share of about 30 percent in Europe. However, as there is no large-scale storage capacity for renewables currently available, conventional energy sources are and will be used in the near future as backup, which demands new efficient technologies with short start up times and ramping to react quickly to possible shortages of intermittent energy sources;

- secondly, thermal efficiency improvements are crucial for a decrease of CO_2 emissions. This comprises of, in general, the production of energy in the most efficient possible way regarding the plant operation with the use of fewer input factors to generate the same output (e.g. by replacing old, inefficient power plants with new stations based on more efficient combined cycle technologies);

- thirdly, changes in the fuel mix in the generation of electricity and heat (e.g. the switch from coal and lignite to natural gas) can contribute to a reduction of CO_2 emissions in the long run.

This paper concentrates on the last two dimensions and intends to identify technical efficiency improvements and potential long term changes in the fuel mix to reduce CO_2 emissions. We focus on the technical efficiency of conventional fossil fueled (non-renewable and non-nuclear) power generating companies in Germany. We use a simple production model that distinguishes desirable (energy) and undesirable (CO_2 emissions) outputs, but we consider neither costs nor prices (for problems comparing generation costs of conventional energy sources see e.g. Borenstein, 2012). While the empirical literature mainly focuses on single technologies (see e.g. Zhou et al., 2008, or Song et al., 2013, for overviews), this analysis concentrates on efficiency comparisons of different fossil fuel generation technologies, including coal-, lignite-, natural gas- and biomass-fired power plants, that currently play an important role in the transition toward carbon-free energy sources in the long run. In this paper we account for production technology heterogeneity using a metafrontier framework based on the non-parametric Data Envelopment Analysis (DEA). This allows us to disentangle of existing gaps between different generation technologies and provides a better distinction of efficiency variations across generation technologies.

1.2. The German Context

This paper is the first considering the German power plant fleet, which is the largest electricity generating sector in Europe and the sixth largest in the world. Further, with the largest share of GHG emissions in Europe coming from the German electricity and heat generating sector, the German performance situation plays an important role in European efforts to meet Kyoto Protocol targets. As Germany is the EU-member with the highest absolute emission reduction targets, the evaluation of performance improvements and the detection of CO_2 emission reduction potentials in Germany's electricity generating sector are crucial for scientific and political discussion. We create the first representative data set for German coal-, lignite-, gas- and biomass-fired power plants collected by the Research Data Centres (FDZ) of the German Federal Statistical Office and the Statistical Offices of the German Länder. It comprises of unique and comprehensive firm level data on commercial and industrial plants to analyze the efficiency and CO_2 reduction potentials of plant operation.

In Germany electricity is generated using multiple technologies. In 2012, the most important sources in terms of total electricity generation were lignite (26 percent), coal (19 percent), nuclear (16 percent), natural gas (12 percent), wind (8 percent), biomass (6 percent), hydro (4 percent), and solar (4 percent) (BMWi, 2012). With the government's decision to phase out nuclear by 2022, the fuel mix will change considerably. At the same time, the Act on the Sale of Electricity to the Grid

(*Stromeinspeisungsgesetz*) of 1990 and its successors implemented incentives to promote the installation of renewables. Today renewable energy sources account for about 20 percent of gross electricity consumption: even though their marginal costs are negligible, fluctuating feed-in and missing storage capacities imply that conventional - non-renewable - electricity generation capacity will still be needed to ensure security of supply by backing-up existing capacities. Therefore, capacities of about 7 GW of different conventional sources, mainly gas and coal, have been installed and gone online between 2012-2014, which underlines the importance of efficiency improvements and CO_2 emission reduction potentials.
The remainder of this paper proceeds as follows. Section 2 discusses the literature. Section 3 shows the methodology. The data and the empirical model are outlined in section 4. Section 5 shows the results and the last section concludes.

2. Literature review

In the energy sector, non-parametric and parametric efficiency analysis, such as Data Envelopment Analysis following Farrell (1957) and Stochastic Frontier Analysis following Meeusen and Broeck (1977), have a long tradition. However, the major focus is on electricity and gas networks (see e.g. Jamasb and Pollitt, 2001, and Jamasb and Pollitt, 2003). Efficiency analysis methods are now widely accepted and used by regulators in a large number of countries to identify inefficiencies and to set benchmarks in regulatory models (compare Haney and Pollitt, 2009, for an overview). Furthermore, methodological research is finding new insights concerning efficiency measurement methods and models, for example, dealing with the inclusion of undesirable outputs, the formulation of disposability, and the inclusion of environmental factors (Song et al., 2013; Zhou et al., 2008). Less attention is devoted to electricity generating units, but efficiency analysis of the power and heat supplying sector is gaining interest. The empirical literature is especially concerned with environmental efficiency analysis and energy policy analysis. It can be mainly grouped into cross-country comparisons using aggregate data and analyses on regional, firm or plant level. An example for the former is the work by Jaraite and Maria (2012) that investigates the environmental efficiency and productivity enhancing performance of the European Union's CO_2 Emissions Trading Scheme (EU ETS) in public power generation.

But there are also numerous country studies on technical and cost efficiency of fossil fueled power plants as well as it determinants for the U.S.[2] Olatubi and Dismukes (2000) analyze coal-fired steam plants' allocative efficiency while Kleit and Terrell (2001) analyze potential efficiency gains of deregulation using a Bayesian cost function approach for gas-fired power plants, and Knittel (2002) compares the effect of different regulatory methods on coal and gas power plants. Using a parametric approach Hiebert (2002) analyzes the cost efficiency of different fuel types and finds evidence for a positive impact of regulatory restructuring on efficiency. Craig and Savage (2013) analyze the effects of market restructuring with an increased competition on the thermal efficiency of electricity generation plants from 1996 to 2006. Their empirical findings show that access to wholesale electricity markets, together with retail choice, led to efficiency gains of investor-owned plants and that benefits from competition spilled over to public electricity generation.

In a series of papers Sueyoshi and Goto (and Ueno) use a sample of thermal power plants in the U.S. to answer different research questions: a positive effect of the U.S. Clean Air Act (CAA) on environmental efficiency and a positive effect of regulation on operational and overall efficiency is shown by means of non-parametric efficiency measures (Sueyoshi et al., 2010). Sueyoshi and Goto (2012) compare different radial and non-radial DEA formulations for environmental assessment and find different results depending on the DEA formulation, indicating the need for multiple analysis when DEA is used for policy purposes. Finally, Sueyoshi and Goto (2013) analyze returns to scale and damages to scale (DTS) of North American power plants and the impact of the CAA on power plant efficiency. Their findings indicate increasing DTS for three different bad outputs, indicating the need for managerial improvements and/or engineering innovation.

Although most research focuses on U.S. generation capacity, other countries are investigated as well, with China and Korea being of special interest. Technical efficiency of Chinese thermal power plants on a regional level is analyzed by Lam and Shiu (2001) using DEA showing considerable inefficiencies in electricity generation. Similarly, Lin and Du (2013) find considerable intra-group inefficiencies on a regional

[2]For the U.S. there is also a stream of literature analyzing nuclear power plants. Regarding the former, Zhang (2007) examines a sample of 73 investor-owned nuclear power plants between 1992 and 1998 and considers efficiency changes due to electricity restructuring. Fabrizio et al. (2012) study the impacts of deregulation and consolidation on operating performance They find a 10 percent performance increase due to a reduction of reactor outage duration. Fabrizio et al. (2007) examine the performance during the transition of cost-of-service regulation to market oriented environments with respect to ownership. They show that publicly owned plants had the lowest efficiency gains while investor-owned plants had the highest efficiency gains.

level, but by means of a parametric metafrontier analysis. Yang and Pollitt (2009) and Yang and Pollitt (2010) compared different DEA formulations to analyze technical and environmental efficiency of Chinese thermal power plants. Zhao and Ma (2013) study the impact of deregulation reform in 2003 on the operational efficiency of China's large coal-fired power plants between 1997 and 2010. They find that the plants have converged to the technological frontier and that the unbundling reform increased productivity. Finally, the Korean energy generation sector is analyzed in several studies.Heshmati et al. (2014) use a semiparametric model to assess the effect of a power plants' characteristics on its productivity based on a panel approach. Beside technical regress in the sector, results indicate a considerable heterogeneity in the plants' output response to changes in the production factors. Furthermore, the Korean electricity generating sector has been analyzed by means of parametric methods by Heshmati et al. (2012) and non-parametrically by Zhang et al. (2013). Both papers use a metafrontier approach to compare different combustion technologies, as e.g. by fuel type (coal vs. oil) or by combustion process (combined cycle vs. steam generation), with both papers finding considerable technology gaps. Finally, the Korean electricity generation is compared to Chinese generating utilities by Zhang and Choi (2013), which is, to the authors' knowledge, the only cross-country comparison of electricity generating utilities.
Other single country studies exist for Indian coal and oil-fired plants (Thakur et al., 2006) as well as Spanish coal-fired plants (Arocena and Waddams Price, 2002), while Barros (2008) analyzes hydroelectric power plants in Portugal. However, never have the German power plants, the largest industrial sector in Europe, been empirically analyzed with respect to their efficiency. By comparing four different combustion technologies in a metafrontier framework, which has not, to our knowledge, been conducted in the previous literature, the drivers of CO_2 emission reduction with respect to efficiency improvements as well as technology switches in the long run can be determined.

3. Methodology

3.1. The Metafrontier Framework

To measure power plant efficiency, non-parametric efficiency analysis, in the spirit of Farrell (1957) and Debreu (1951), is used in this paper. Contrary to parametric approaches, such as Stochastic Frontier Analysis (SFA, e.g. Meeusen and Broeck, 1977), this allows for the flexible estimation of a production function without any *a priori* specification of a functional relationship of inputs and outputs. Furthermore, the non-parametric approach can incorporate multiple dimensions on both the input and the output side, including undesirable outputs. To account for differences in production processes, we follow the approach by Hayami and Ruttan (1970) and O'Donnell et al. (2008) and model a set of group technologies that are enveloped by a common metatechnology.

Assume we observe $K_t, k_t = 1, ..., K_t$ firms - in our case power plants - with subscript t indicating our observation period, $t \in [1, T]$. In period t each firm is transforming M $(m = 1, ..., M)$ inputs x_{tm} into N $(n = 1, ..., N)$ desirable outputs y^d_{tn}. As a byproduct of the transformation process, J undesirable outputs $(j = 1, ..., J)$ y^u_{tj} are produced. In the following, x_{tk}, y^d_{tk} and y^u_{tk} denote the vectors of input, desirable output and undesirable output of firm k in period t. With respect to intertemporal aspects, we assume that input-output combinations observed in one period are available in all the subsequent periods ("firms do not forget"). In the model, bad outputs are treated as inputs under the assumption that the firm is willing to reduce both, inputs and undesirable outputs. Thereby, undesirable output can be reduced without a reduction in desirable outputs, which induces strong disposability. Thus, a technology set T_t including all feasible input-output combinations in t and satisfying free disposability of inputs and outputs can be written as

$$T_t = \left\{ (x, y^d, y^u) | x \geq \sum_{t=1}^{t} \sum_{k=1}^{K_t} \lambda_{tk} x_{tk}, y^u \geq \sum_{t=1}^{t} \sum_{k=1}^{K_t} \lambda_{tk} y^u_{tk}, y^u \leq \sum_{t=1}^{t} \sum_{k=1}^{K_t} \lambda_{tk} y^d_{tk}, \lambda^c \in \Lambda \right\} \tag{1}$$

This technology set includes all feasible input output combinations available in t based on the assumptions above. This also implies that the set of feasible production plans in $t+1$ is at least as large as the set in t. The parameter Λ can be used to impose further restrictions on the technology as e.g. convexity or certain scaling assumptions (Bogetoft and Otto, 2011). Given this technology set, observation k_t can only be treated as efficient if there is no vector $(\tilde{x}, \tilde{y}^u, \tilde{y}^d) \in T_t$ with $\tilde{x} \leq x_{tk}, \tilde{y}^u \leq y^u_{tk}, \tilde{y}^d \geq y^d_{tk}$ and at least one inequality being fulfilled strictly.

In the production of electricity and heat, power plants can be further grouped e.g. by the combustion technology or the fuel they use. As similar inputs are used to produce similar outputs, the different combustion technologies can be seen as subtechnologies of the underlying metatechnology set T. For such a subtechnology c $(c = 1, ..., C)$ a group technology set T^c can be defined using the K^c_t observations in this group in this period and can be written as

$$T^c_t = \left\{ (x, y^d, y^u) | x \geq \sum_{t=1}^{t} \sum_{k=1}^{K^c_t} \lambda_{tk} x_{tk}, y^u \geq \sum_{t=1}^{t} \sum_{k=1}^{K^c_t} \lambda_{tk} y^u_{tk}, y^u \leq \sum_{t=1}^{t} \sum_{k=1}^{K^c_t} \lambda_{tk} y^d_{tk}, \lambda \in \Lambda \right\} \tag{2}$$

with the same properties as the metatechnology set. However, in this case the set includes only input output combinations available for the group c. Similar to T, T_t^c increases with t, however, $T_t^c \subseteq T_t$ for each t and for each c.

3.2. Group Frontier and Metafrontier Estimation

To estimate efficiency Data Envelopment Analysis (DEA), as proposed by Charnes et al. (1978) and Banker et al. (1984), is used. DEA is a linear programming technique that envelopes all input - output combinations with a piecewise linear frontier that sets the benchmark against which firms are evaluated. It aims at finding an efficiency score θ_{tk} that radially contracts inputs x_{tk} and undesirable outputs y_{tk}^d while remaining within the technology set specified by the data and the assumptions about the technology. Throughout this paper, input orientation is assumed, because this includes the key variable of interest, CO_2 emissions. We impose variable returns to scale (VRS, $\Lambda^{VRS} = \left\{\lambda_k \geq 0, \sum_{k=1}^{K_t} \lambda_k = 1\right\}$) to account for firm heterogeneity in terms of size. Furthermore, constants returns to scale (CRS, $\Lambda^{CRS} = \{\lambda_k \geq 0\}$) are imposed to measure efficiency potentials due to scale change. To use information from the panel structure of the data, a sequential DEA approach is implemented (Tulkens and Vanden Eeckaut, 1995). In this set-up an observation in period t is not only benchmarked against observations from the same period but against all observed input output combinations in the panel until t.

In each subtechnology c efficiency measures θ_{tk}^{VRS} and θ_{tk}^{CRS} for each observation k using combustion technology c in period t can be derived by solving the following linear programming problem with the relevant constraints on Λ:

$$
\begin{aligned}
\min_{\theta,\lambda_{t1},\ldots,\lambda_{tK_t^c}} \quad & \theta_{tk} \\
s.t.\ \theta_{tk} x_{tk} \geq & \sum_{t=1}^{t}\sum_{k=1}^{K_t^c}\lambda_{tk} x_{tk} \\
\theta_{tk} y_{tk}^u \geq & \sum_{t=1}^{t}\sum_{k=1}^{K_t^c}\lambda_{tk} y_{tk}^u \\
y_k^d \leq & \sum_{t=1}^{t}\sum_{k=1}^{K_t^c}\lambda_{tk} y_{tk}^d \\
& \lambda \epsilon \Lambda
\end{aligned}
\tag{3}
$$

The solution to this problem refers only to the subset of observations that use technology c and delivers an efficiency score θ_{tk} as a scalar with $0 < \theta_{tk} \leq 1$; $\theta = 1$ indicates full efficiency and $(1 - \theta_k)$ is the input savings potential. Furthermore, the LP delivers weights λ_{tk} that determine the point on the frontier against which efficiency for firm k is evaluated. The weights, therefore, construct a group technology in which efficiency is only measured relative to other firms using technology c. The shape of the frontier depends on the scale assumption, with VRS and CRS imposed by the restrictions on λ outlined above. The size of the reference set - the right hand side of the constraints - increases with t as we sequentially add observations period by period. As the efficiency estimate for an observation can only decrease when adding additional observations to the reference set, efficiency estimates obtained in this LP will be smaller or equal to estimates resulting from separate annual frontier estimates.
Similar to (3), we can construct the efficiency measure for each observation relative to the metatechnology set T. It can be constructed by solving the following linear programming problem for all K_t observations:

$$\begin{aligned} &\min_{\theta^{meta},\lambda_{t1},\ldots,\lambda_{tK_t}} \theta_{tk}^{meta} \\ s.t.\ \theta_{tk}^{meta} x_{tk} &\geq \sum_{t=1}^{t}\sum_{k=1}^{K_t} \lambda_{tk} x_{tk} \\ \theta_{tk}^{meta} y_{tk}^{u} &\geq \sum_{t=1}^{t}\sum_{k=1}^{K_t} \lambda_{tk} y_{tk}^{u} \\ y_{k}^{d} &\leq \sum_{t=1}^{t}\sum_{k=1}^{K_t} \lambda_{tk} y_{tk}^{d} \\ &\lambda \epsilon \Lambda \end{aligned} \tag{4}$$

Similar to the first LP, we obtain efficiency scores θ_{tk}^{meta} $(0 < \theta_{tk}^{meta} \leq 1)$ indicating input savings potentials and weights λ_{tk} that determine the reference points on the frontier. However, in this program unit k is compared to all units in the data set thus including all C subtechnologies. Again, the shape of the frontier depends on the definition of Λ and we impose again CRS and VRS.
One important aspect of the metafrontier is that it envelopes all group frontiers,as we assume the same returns to scale. Thus, under the same scale assumption the efficiency score obtained in the metafrontier framework, the metafrontier technical

efficiency (MTE) will always be smaller than or equal to the efficiency score measured against the group technology. This difference can be used to decompose inefficiency into two components: first, group technical efficiency (GTE) estimated relative to the group frontier (obtained from (3)) and a component that measures the distance between the group frontier and the metafrontier, the metatechnology ratio (MTR). For technology-c firm k in t this MTR is defined as $MTR_{tk} = \frac{\theta_{tk}^{meta}}{\theta_{tk}}$ and indicates for a given amount of output the share of inputs necessary when using the metatechnology relative to the inputs necessary using the group technology (O'Donnell et al., 2008). As by definition $\theta^{meta} \leq \theta$ it follows that $0 < MTR_{tk} \leq 1$ with $MTR_{tk} = 1$ if an observation reaches full efficiency against both the group technological frontier and the metatechnology. On the contrary, $MTR_{tk} < 1$ indicates the need for a technology switch to reach the metafrontier, as the frontier for this observations is spanned by observations from another group.

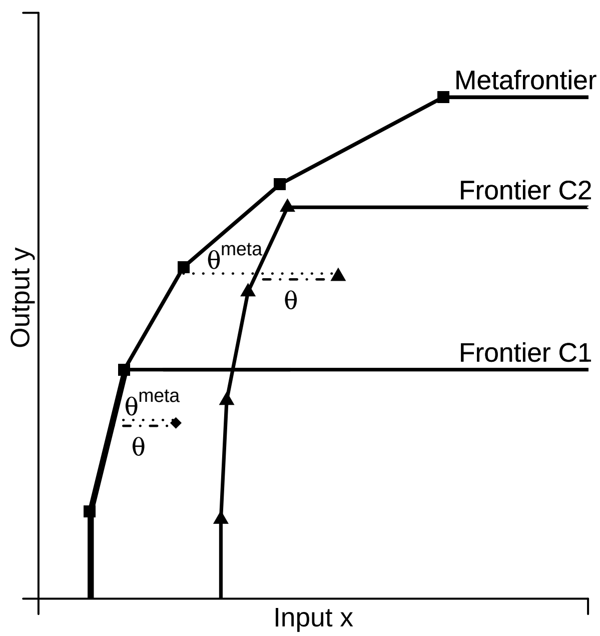

Figure 1: Exemplary Illustration of the Metafrontier Framework (Own Illustration)

Figure 1 depicts the metafrontier framework exemplary for the case of one input and one undesirable output under VRS. A number of observations from different technologies span the metafrontier in the piece-wise linear DEA-style and envelopes the two group frontiers for the subtechnologies, $C1$ and $C2$, that are spanned only by observations using this technology. Now, an observation in each group depicted as rhombus ($C1$) and triangle ($C2$) is benchmarked against both - the group frontier (θ) and the metafrontier (θ^{meta}) - using the maximal reduction of inputs while staying in the technology set. Obviously, the potential input reduction against the metafrontier is at least as large as the reduction against the group frontier leading to $\theta^{meta} \leq \theta$. Now the MTR can be calculated as the ratio of both, θ^{meta}/θ and is one only if the group technology is identical to the metafrontier, which is the case for $C1$. On the contrary, we see that $C2$ generally shows inefficiency against the metafrontier and $MTR < 1$ will hold although an observation is efficient against the group frontier. Thus, the benchmarking against the metatechnology not only helps us identify the efficiency of observations in the group, but also to locate the group frontier relative to the metafrontier.

3.3. Scale Efficiency and Returns to Scale

Using the weights obtained in the LP, one can identify whether an observation is above or below the optimal firm size, which is determined by the efficient firm under CRS in every dimension. For firm k, firm size is below the optimal scale size (operation under increasing returns to scale) if $\sum_{k=1}^{K_t} \lambda_{tk} < 1$ and above the optimal scale size (operating under decreasing returns to scale) if $\sum_{k=1}^{K_t} \lambda_{tk} > 1$. The losses of not having optimal scale size can be measured as scale efficiency SE, which is calculated as the ratio of the efficiency score under VRS and CRS and bounded above by one:

$$SE = \frac{\theta_{tk}^{CRS}}{\theta_{tk}^{VRS}} \leq 1 \tag{5}$$

3.4. EPRI and CPRI

Overall measures of environmental and energy efficiency are of special interest to directly determine savings potentials in terms of energy input and emission output. Although a single efficiency score is obtained for each observation, not all improvement potentials are uncovered. While the LP solution delivers a reference point with maximum radial contraction of x_{tk} and y_{tk}^{u}, there might be still further improvement potential if the constraints of the LP are not binding (Bogetoft and Otto, 2011). We incorporate those slacks in an overall measure of efficiency using an energy potential reduction index (EPRI) and a CO_2 emission potential reduction index (CPRI) relative to the group frontiers. The EPRI is defined as

$$EPRI_t = \frac{\sum_{k=1}^{K_t} (1-\theta_{tk}) * x_{tkm} + S_{tkm}}{\sum_{k=1}^{K_t} x_{tkm}} \tag{6}$$

with S_{tkm} being the slack for the energy input of observation k in period t. Likewise, the CO_2 emission potential reduction index is defined as

$$CPRI_t = \frac{\sum_{k=1}^{K_t} (1-\theta_{tk}) * y^u_{tkj} + S_{tkm}}{\sum_{k=1}^{K_t} y^u_{tkj}} \tag{7}$$

with S_{tkj} as slack of the emission (bad) output of observation k in period t. EPRI and CPRI measure the total energy and emission savings potential of the industry by summing up potential radial contraction and slacks. Contrary to a mean efficiency score, the measures weight observations relative to their share of total emission/energy use and thus measure actual energy input and CO_2 emission savings potentials. Furthermore, if the EPRI exceeds the CPRI, additional emission savings potentials are possible due to the relationship of energy input and emission output.

3.5. Outliers and Innovators

As DEA is purely deterministic, results are prone to measurement and data errors. In sequential DEA, an outlier not only influences the results in the period it is observed, it also impacts results in all subsequent periods. Therefore, a careful analysis of potential outliers is necessary. In this paper, the iterative superefficiency analysis, as proposed by Banker and Gifford (1988), is used. The underlying idea is the efficiency measurement for every observation relative to a frontier spanned by all observations but the firm of interest. Superefficient units achieve efficiency scores greater than one and are eliminated if their efficiency score exceeds a pre-determined threshold. In this analysis superefficiency is measured in the sequential DEA formulation, thus including all observation until t that have not been excluded so far, and are excluded if they obtain a superefficiency score greater than two. That ensures that observations with likely data errors are identified, but also allows for a sufficiently large data set to remain including observations with considerable technical progress.

Furthermore, we use the idea of the superefficiency analysis method to identify innovators. We define an innovator in period t as a unit observed in t that could have shifted the frontier from $t-1$ - in that sense it is superefficient against the frontier from the past period. This can be realized by solving equations 3 and 4 with changes in the reference set. Instead of measuring efficiency against all observation including t the reference set includes only observations until $t-1$ and the summation of the right hand side variables has an upper bound of $t-1$. It should be noted that the number of innovators can be larger than the number of efficient units as an innovator may be "masked" by another efficient observation from the same period. However, it can also be smaller if no efficiency score can be determined, e.g. if a new observation has a higher output than the largest unit in the period before and no frontier to benchmark against can be found.

4. Data and Empirical Model

4.1. Data Sources

In this paper a unique data set from the Research Data Centres (FDZ) of the German Federal Statistical Office and the Statistical Offices of the Länder is used. Annual data from 2003 through 2010 is obtained from the monthly surveys (EVAS 43311) on electricity generating facilities with more than 1 MW capacity. These power plants can be both, large scale electricity and heat suppliers or small scale power plants for industrial use. Private, public and mixed ownership facilities are included. The final data set includes a total 1459 observations over eight years covered and is a representative sample of the approximate 1000 electricity generating units in Germany that exceed 1 MW in capacity.[3]

4.2. Input and Output Specification

To model the production technology of power plants, it is assumed that labor (L), capital (C) and energy (F) are used to produce output in form of delivered energy (E). As a byproduct of this transformation process CO_2 emissions (EM) emerge. This extends the standard approach, as found for example in Lam and Shiu (2001) or Olatubi and Dismukes (2000), by including an undesirable output in the technical efficiency formulation. It thereby accounts for the managerial capabilities to reduce emissions. In the measurement of inputs and outputs we also follow the literature (e.g. Zhang et al., 2013). Labor input is measured as average monthly hours worked. Capital input is approximated by the mean available gross capacity in MW including

[3]For data privacy reasons, we are obliged to use remote data processing and can neither see nor report detailed information - such as minima and maxima - about the data set.

Coal	Lignite	Gas	Biomass
Coal, coal coke, Coal briquette, coal derivatives and other coals	Lignite, black lignite, lignite briquette, lignite coke, fluidized bed lignite, lignite dust, other lignites	Natural gas, marsh gas, coke oven gas, furnace gas, other synthetic gases	Wood, straw, liquid biomass, biogas, landfill gas, sewage gas, biosolid and sewage sludge

Table 1: Subsets by Fuels

capacity for cogeneration. The mean value is chosen over the nameplate capacity to account for the owner's choice not to maintain a certain part of the capacity and to control for potential capacity extensions. Energy input is measured as the total annual fuel input in GJ. On the output side, we assume that plants are delivering energy (E) in form of heat and electricity, measured as the sum of both in GWh. As consumption by the plants reduces the actual supply of electricity and heat, net values are taken. Furthermore, CO_2 emissions are included as a byproduct of the production of energy as undesirable output. They are calculated using emission factors for the net calorific value obtained from the German Federal Environmental Agency and measured in tons of CO_2. That allows not only fuel- but also location (or fuel-source) specific estimation of CO_2 emissions. However, although power plants may use a secondary fuel, due to data limitations we are only able to assess emissions stemming from primary fuel inputs.

Technical efficiency is measured as metafrontier technical efficiency (MTE) and as group technical efficiency (GTE). For the metafrontier the sample size by year varies between 145 observations in 2003 and 199 observations in 2008 and 2009. To construct group technological frontiers, we define four technology subsets based on the major fuel input as listed in Table 1. Coal-fired power plants (214 observations), lignite-fired power plants (81), conventional gas-fired power plants (1091), and biomass plants (73) are considered. Although further refinements would be possible, this rough classification ensures sufficiently large subsets necessary for DEA. The variation of the sample sizes of the different subsets depends on the fuel and sample sizes are fairly stable for coal and lignite, but vary considerably for natural gas (114 in 2003, 147 in 2008) and biomass (3 in 2003, 17 in 2010). From this sample, in total 18 observations are eliminated in the superefficiency analysis, most are gas-fired (12). This leads to a final sample size of 1441 observations over 8 years. Descriptive

	Coal	Lignite	Gas	Biomass
Capital	382.45	919.79	51.97	9.20
Fuel	19,358	71,422	1,595	868
Labor	736,286	524,701	225,679	51,799
CO_2	1,800	8,021	126	82
Output	2,582	7,230	291	95

Notes: Energy input F in thousand GJ, CO_2 in thousand tons, and Output in GWh

Table 2: Input and Output Means by Fuel for Aggregate Sample 2003 - 2010

statistics for the inputs and outputs of the different subsamples averaged over the whole observation period are presented in Table 2; mean input and output values by year can be found in Figure 2. Extensive descriptive statistics of annual input and ouput values can be found in the appendix. In total, the sample covers between 21.4 and 38.1 GW of installed capacity, representing between 29 and 48 percent of total installed capacity using these fuels. The descriptives show that coal- and lignite-fired power plants are, on average, much larger than the natural gas and biomass plants in the sample and cover more than two-thirds of the installed capacity under analysis. However, the largest spread between small and large plants can be observed among the gas-fired power plants, which reflects the fact that this subset contains plants for electricity supply but also small-scale industrial plants. The large number of small gas-fired plants is underlined by the descriptives as the 75 percent quartile is below the mean for most of the input/output variables.

5. Results

Four different conventional combustion technologies are compared in a metafrontier framework. This section presents the results, first with respect to the metafrontier, then with respect to group-specific frontier estimates. All calculations are done using remote data processing based on R. For data privacy reasons no detailed (observation-specific) results can be presented.

5.1. Metafrontier Results

In the metafrontier framework, efficiency is estimated against a frontier enveloping all observations irrespective of their subtechnology. Table 3 shows the sequential DEA technical efficiency scores per year for all observations against this frontier. It indicates that the mean as well as the median slightly decreases over the sample

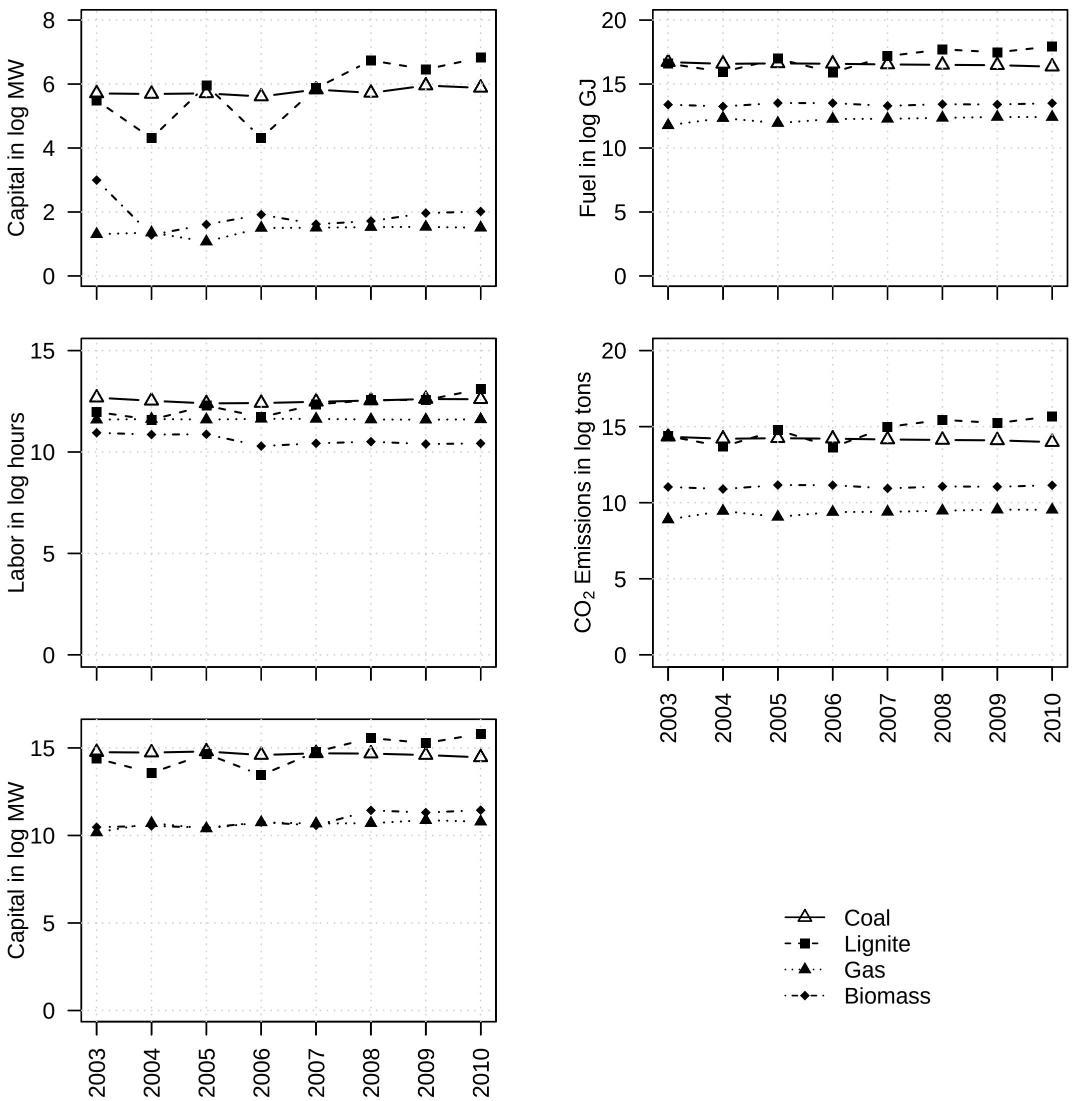

Figure 2: Annual Average of Inputs, Desirable and Undesirable Output by Fuel Type in logs

Year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	$\theta = 1$	N
2003	0.168	0.444	0.638	0.643	0.840	1	23	145
2004	0.158	0.468	0.624	0.651	0.839	1	24	176
2005	0.149	0.475	0.625	0.651	0.841	1	17	153
2006	0.160	0.390	0.547	0.571	0.758	1	6	183
2007	0.138	0.390	0.531	0.560	0.718	1	10	188
2008	0.180	0.395	0.531	0.561	0.730	1	11	199
2009	0.184	0.369	0.511	0.544	0.697	1	1	199
2010	0.107	0.374	0.517	0.553	0.717	1	9	198
Mean	0.155	0.413	0.565	0.592	0.767	1		1441

Table 3: Sequential DEA Results for Aggregate Sample

period from 64 to 55 percent (from 64 to 51 percent, respectively). The maximum of 100 percent is attained in each year, but the number of fully efficient units decreases over time.

Table 4 shows the metafrontier technical efficiency (MTE) for the power plants by fuel type. Efficiency estimates are determined against the frontier spanned by all technologies covered in the sample - the metatechnology - under the VRS assumption. Fully efficient units are identified within each technology for different years, indicating that production at an efficient point on the metafrontier is possible using each technology. Natural gas-fired power plants are the only ones obtaining full efficiency in each year of the observation period.

Mean MTE over the whole observation period is highest for lignite-fired power plants (68 percent), followed by gas- (57 percent) and lignite-fired plants (55 percent). Biomass-fired plants show considerable inefficiency, achieving a mean MTE of only 33 percent. For coal, lignite- and gas-fired plants, mean efficiency over the sample period decreases through 2009, but increases in 2010. This can be partly attributed to the increase in sample size due to the sequential structure of the DEA. As new observations are added year by year, efficient observations from the past period as well as observations from the period of analysis must be outperformed to be efficient. This structure makes it more and more difficult to reach full relative efficiency.

Although the analysis of the MTE shows inefficiencies in every technological group and comparably high mean efficiencies for the large-scale coal- and lignite-fired plants, the MTR scores listed in Table 5 - indicating the difference between the group technology frontiers and the metafrontier (see Figure 1) - draw a different picture. While mean MTR under VRS is 82 percent for coal-, 76 percent for lignite-,

Year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	$\theta = 1$	N
				Coal				
2003	0.370	0.474	0.546	0.655	0.943	1.000	5	22
2004	0.372	0.445	0.535	0.644	0.841	1.000	5	26
2005	0.391	0.482	0.590	0.644	0.761	1.000	2	27
2006	0.341	0.473	0.618	0.635	0.762	0.974	0	27
2007	0.325	0.481	0.557	0.623	0.742	1.000	2	28
2008	0.304	0.481	0.532	0.612	0.752	0.994	0	27
2009	0.290	0.472	0.519	0.589	0.749	0.993	0	26
2010	0.329	0.475	0.560	0.626	0.770	1.000	2	26
				Lignite				
2003	0.378	0.552	0.847	0.763	1.000	1.000	3	6
2004	0.348	0.419	0.583	0.627	0.783	1.000	1	8
2005	0.421	0.688	0.906	0.803	1.000	1.000	2	5
2006	0.334	0.414	0.624	0.629	0.894	1.000	1	9
2007	0.341	0.449	0.614	0.681	0.881	1.000	2	13
2008	0.334	0.482	0.599	0.675	0.888	1.000	1	15
2009	0.337	0.428	0.615	0.651	0.870	0.988	0	14
2010	0.386	0.541	0.658	0.723	0.918	1.000	1	11
				Gas				
2003	0.194	0.440	0.646	0.641	0.834	1.000	15	114
2004	0.223	0.507	0.651	0.663	0.841	1.000	17	136
2005	0.199	0.475	0.622	0.648	0.839	1.000	12	118
2006	0.160	0.373	0.547	0.562	0.753	1.000	4	141
2007	0.170	0.368	0.530	0.547	0.694	1.000	5	137
2008	0.180	0.392	0.531	0.552	0.710	1.000	9	145
2009	0.184	0.366	0.516	0.539	0.689	1.000	1	144
2010	0.170	0.366	0.503	0.546	0.701	1.000	6	144
				Biomass				
2003	0.168	0.204	0.240	0.410	0.531	0.821	0	3
2004	0.158	0.239	0.338	0.420	0.444	1.000	1	6
2005	0.149	0.324	0.499	0.549	0.750	1.000	1	3
2006	0.171	0.257	0.306	0.392	0.324	1.000	1	6
2007	0.138	0.302	0.315	0.415	0.496	1.000	1	10
2008	0.193	0.305	0.351	0.410	0.445	1.000	1	12
2009	0.224	0.290	0.319	0.413	0.468	0.965	0	15
2010	0.107	0.250	0.306	0.389	0.488	0.953	0	17

Table 4: Metafrontier Analysis Results: Metafrontier Technical Efficiency

Year	Coal	Lignite	Gas	Biomass
2003	0.844	0.834	0.999	0.4095
2004	0.843	0.690	0.999	0.4254
2005	0.823	0.834	0.999	0.584
2006	0.830	0.716	0.999	0.4207
2007	0.828	0.759	1.000	0.4449
2008	0.823	0.765	1.000	0.4825
2009	0.815	0.731	1.000	0.4988
2010	0.822	0.787	1.000	0.5166
Mean	0.828	0.764	0.999	0.472

Table 5: Metafrontier Analysis Results: Metafrontier Technology Ratio

and only 47 percent for biomass-fired plants, all natural gas-fired plants obtain an MTR score between 99 and 100 percent. This underlines that gas-fired plants shape the metafrontier and are benchmarked against their own group technological frontier.

A closer inspection of the peer units in the DEA program shows that efficiency scores of all technologies are affected by the universe of combustion technologies and all four technologies serve as peers for each other. However, gas-fired plants show an outstanding role serving as benchmark for the majority of observations. This means that those plants span a considerable part of the frontier making them the comparison unit for coal, lignite- and biomass-fired plants. However, this also indicates that in the long run considerable input savings potentials indicated by the metafrontier efficiency scores are only achievable by technology switches to natural gas. The analysis of the peers furthermore indicates that a considerable number of units from the starting point of the panel serve as peers seven years later. This indicates that there was no shift in certain regions of the best practice frontier, meaning no or only little technological progress over time. However, an analysis of the dynamics of the frontier is out of scope of this paper. In total, the metafrontier results indicate substantial savings potentials from efficiency gains and savings potentials from switching to the best available technology in the long run. Although reaching the metafrontier is possible using coal-, lignite-, gas- or biomass-based combustion, our results indicate that natural gas-fired plants dominate. They determine the best practice and serve as benchmark for the other technologies.

5.2. Group Frontier Results

5.2.1. Group Technical Efficiency

In the metafrontier framework, efficiency is not only measured against a metafrontier technology common for all observations, but also against specific group frontiers. In this case, for an observation using technology c efficiency is measured against a frontier spanned only by observations using the same technology. As we measure efficiency for four different subtechnologies over eight years, 32 separate frontiers are used to estimate efficiency, 32 further CRS frontiers are estimated to analyze scale properties of the technologies. The descriptive statistics of the input-oriented analysis of technical efficiency relative to the VRS frontiers are shown in Table 6. The evolution of 25, 50 and 75 percent quantiles of the efficiency are also shown in Figure 3.

For coal-fired power plants mean efficiencies between 75 and 77 percent are found indicating average input savings potentials of 23 to 25 percent, respectively. Minima between 31 and 45 percent indicate also considerable differences among the plants and substantial savings potentials for the most inefficient observations. Generally, efficiency scores for coal fired plants are found to be stable, and a noticeable number of observations achieve efficiency scores of one in every year.

For lignite-fired plants, which beside coal-fired stations, is the second baseload technology in our sample, mean efficiency is also rather stable between 85 and 94 percent. For these plants minimum efficiency is also fairly high, ranging between 55 and 73 percent. Similar to the coal-fired plants, at least one unit is found to be efficient in each year, but with a decreasing number over time. As one may explain the high minima and mean efficiencies with the fairly low sample sizes, one has to consider that the sample nearly covers the population in most years. Furthermore, e.g. for the 2009 sample, the reference set includes already 70 observation points. In general, coal and lignite show up to be fairly stable in terms of efficiency, which is rather not surprising given their constantly high degrees of utilization as base- or mid-load plants.

Contrary to the baseload plants, gas-fired power plants are typically used to serve demand peaks and show, therefore, a lower degree of utilization. For those plants, results indicate considerable variation in terms of efficiency and we find minima indicating more than 80 percent input savings potentials. Furthermore, results indicate a rather downward trend in mean efficiency ranging from 64 percent in 2004 to 54 percent in 2010. Additionally, the number of efficient units decreases over time, indicating that only few observations are able to push the frontier outwards. In total, in combination with the metafrontier results, this finding shows that the technology with a dominant position in the metafrontier is only used efficiently by a small num-

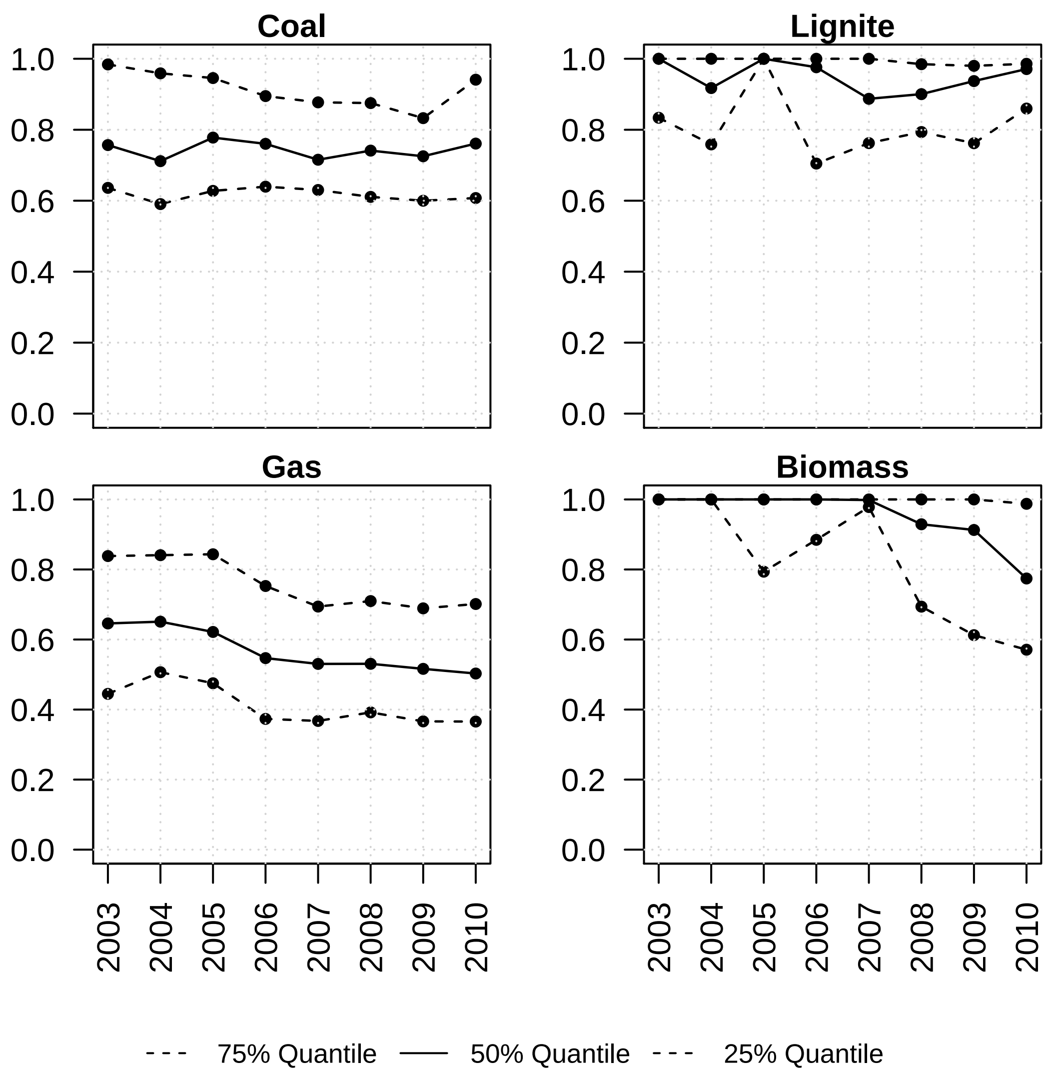

Figure 3: Group Frontier Analysis Results: Group Technical Efficiency

ber of observations, while a large share of the plants fail to exploit their potential.

For the biomass-fired plants, we find mean efficiency ranging between 100 percent in 2003 and 79 percent in 2010. For this small sample, reaching relatively high efficiency scores is fairly easy in the beginning of the sample period, as the set of reference units is small. As the size of the comparison group increases mean and minimum efficiency decrease. This also explains why a considerable share of units in each year reaches full efficiency. Nevertheless, the results also indicate considerable variation in terms of efficiency in this small sample underlining input and emission output savings potentials also for these small scale plants.

In general, for the different technologies, inefficiencies are found with considerable variation in magnitude. Furthermore, efficiency decreases for all technologies over the time span underlining the importance of the size of the reference set in such an analysis. However, for coal-, lignite- and gas- fired plant, an increase in efficiency is found in the last year of the sample period. When comparing mean efficiency over the years, biomass is found to be the most efficient technology in the intra-group comparison, however, clearly facing also problems in sample size. The two base-load fuels coal and lignite are ranked behind, while gas-fired stations are found to be - on average - the group with the highest intra-group inefficiency. Moreover, results indicate that for each technology group frontiers are pushed outwards indicating technical change in the observation period. However, a deeper analysis of this point is out of the scope of this paper and demands future research.

5.2.2. Scale Efficiency and Returns to Scale

In the production of electricity, inputs are not just transformed into desirable outputs, but also undesirable outputs, in form of emissions, that are produced as byproducts. As Sueyoshi and Goto (2013) note, scale inefficiency does not just lead to an overuse of inputs but also results in an overproduction of the undesirable outputs (damages to scale). As our subsamples spread strongly with size, we calculate scale efficiency and the underlying returns to scale. Table 7 summarizes the results.
For coal- and lignite-fired plants - the plants with the highest capacity in the sample - results show that the majority of the plants are above optimal scale size and operate under decreasing returns to scale. However, for both technologies scale inefficiency is generally very high indicating that only small shares of the inefficiency shown in Table 6 can be attributed to not being optimally sized. As coal-fired plants - contrary to lignite-fired plants - are not restricted by local fuel supply, adjustment to optimal scale size is possible. Contrary to the baseload plants, the results for gas- and biomass-fired stations indicate that most plants are operating below optimal scale size and an increase in output would be beneficial. For the biomass-fired plants,

Year	Min.	Mean	Max.	$\theta = 1$	N	Min.	Mean	Max.	$\theta = 1$	N
			Coal					Lignite		
2003	0.413	0.768	1	6	22	0.5721	0.8917	1	4	6
2004	0.398	0.758	1	6	26	0.695	0.881	1	4	8
2005	0.446	0.777	1	4	27	0.732	0.946	1	4	5
2006	0.396	0.759	1	1	27	0.593	0.849	1	3	9
2007	0.359	0.747	1	3	28	0.617	0.878	1	4	13
2008	0.311	0.745	1	2	27	0.559	0.867	1	3	15
2009	0.341	0.722	1	1	26	0.592	0.870	1	1	14
2010	0.433	0.758	1	4	26	0.669	0.909	1	2	11
			Gas					Biomass		
2003	0.194	0.642	1	17	114	1.000	1.000	1	3	3
2004	0.223	0.664	1	18	136	0.827	0.971	1	5	6
2005	0.199	0.650	1	12	118	0.587	0.863	1	2	3
2006	0.160	0.563	1	4	141	0.572	0.903	1	4	6
2007	0.170	0.547	1	5	137	0.471	0.909	1	5	10
2008	0.180	0.552	1	9	145	0.622	0.848	1	4	12
2009	0.184	0.539	1	1	144	0.520	0.820	1	5	15
2010	0.170	0.546	1	6	144	0.288	0.739	1	3	17

Table 6: Group Frontier Analysis Results: Group Technical Efficiency (GTE)

scale efficiency indicates that a large share of the inefficiency found under CRS is attributable to not having optimal scale size. On the contrary, for the natural gas-fired plants, results indicate that, on average, only small gains by adjusting scale size are possible, but much improvement potential exists by using best practice and being technically efficient. However, for gas-fired and biomass plants, efficiency gains by scale change are not feasible in every case as biomass and industrial gas-fired plants face restricted fuel supply.
In total, scale efficiency estimates indicate that a share of the intra-group inefficiency can be explained by not having an optimal size. However, these savings potentials are more pronounced among the technologies of smaller scale, biomass and natural gas. Furthermore, results indicate that among the groups with high average capacity (lignite and coal) a considerable share of plants tends to be larger than the optimal scale size, as derived from the DEA, indicating damages to scale with respect to CO_2 emissions. On the contrary, for the smaller biomass- and natural gas-fired plants we find damages to scale for plants operating at increasing returns to scale.

	RTS	Coal	Lignite	Gas	Biomass
RTS	Increasing	0.139	0.160	0.802	0.750
	Constant	0.024	0.173	0.030	0.181
	Decreasing	0.837	0.667	0.169	0.069
SE	2003	0.914	0.936	0.863	0.705
	2004	0.915	0.927	0.894	0.632
	2005	0.914	0.937	0.902	0.698
	2006	0.926	0.947	0.862	0.774
	2007	0.931	0.912	0.868	0.728
	2008	0.941	0.893	0.875	0.739
	2009	0.942	0.882	0.877	0.694
	2010	0.922	0.849	0.875	0.706

Table 7: Group Frontier Analysis Results: Shares of Underlying Returns to Scale (RTS) & Mean Scale Efficiency (SE)

5.3. EPRI and CPRI

As mean efficiency evaluations deliver no clear picture about the underlying total input savings potentials, two additional indicators are constructed - the emission potential reduction index (EPRI) and the CO_2 emission potential reduction index (CPRI). They deliver the total share of fuel input and emission output that could have been saved given relative efficiency of all observations including adoption of best practice without switching the input fuel. The EPRI and CPRI for the different technologies are shown in Table 8.

	CPRI				EPRI			
Year	Coal	Lignite	Gas	Biomass	Coal	Lignite	Gas	Biomass
2003	0.022	0.000	0.566	0.287	0.023	0.000	0.278	0.287
2004	0.048	0.025	0.524	0.212	0.048	0.025	0.231	0.212
2005	0.018	0.191	0.496	0.210	0.017	0.191	0.236	0.210
2006	0.047	0.082	0.485	0.223	0.056	0.082	0.266	0.223
2007	0.097	0.086	0.516	0.251	0.100	0.086	0.287	0.251
2008	0.097	0.199	0.472	0.232	0.102	0.199	0.291	0.232
2009	0.102	0.187	0.438	0.259	0.108	0.187	0.311	0.259
2010	0.077	0.311	0.487	0.240	0.084	0.311	0.286	0.240
Mean	0.063	0.135	0.498	0.239	0.067	0.135	0.273	0.239

Table 8: Group Frontier Analysis Results: EPRI and CPRI

Both indicators suggest substantial savings potentials for all technologies. CPRI for biomass and gas-fired plants exceeds mean inefficiency considerably, indicating extensive CO_2 savings potentials. This result is driven by two factors: on the one hand, especially the largest plants show inefficiencies; on the other hand, a noticeable share of these savings potentials can be attributed to slacks in the LP. This is not the case for coal- and lignite-fired plants, for which results show savings potentials less than average inefficiency indicating savings especially for the smaller plants. However, the CPRI for the gas-fired plants shows an interesting pattern: while mean efficiency decreased over the sample period, CO_2 savings potentials decreased as well. This underlines the effect of decreased slacks with a larger number of plants in the reference set due to sequentially added observations in the DEA.

The results for the EPRI that explains fuel input reduction potentials show a similar pattern as the CPRI for biomass and coal, and only slightly higher EPRI values for lignite. For natural gas, potential CO_2 savings exceed potential fuel input savings strongly and can be partly explained by the considerable lower share of slacks in the EPRI measure. Furthermore, the results underline the difference between different types of gas and their CO_2 content. Thus, these savings potentials were not found if this variable was excluded from the analysis. Whilst for the coal and lignite-fired plants EPRI and CPRI tend to increase over the sample period, these measures are fairly constant for the biomass plants. Furthermore, for biomass-fired plants the measures stresses the importance of slacks: while we find no technical inefficiency in the first year of the sample for this technology, nevertheless the EPRI and CPRI measures indicate savings potentials for these plants.

To summarize, significant savings potentials with respect to CO_2 emissions and fuel input are found, most often exceeding the radial contraction of all inputs. The differences to the mean efficiency scores underline two important aspects: on the one hand, a simple efficiency measure does not indicate all savings potentials as slacks are not included in here. On the other hand, the results underline the considerable efficiency differences among the plants. Furthermore, as EPRI and CPRI are weighted with the plant size (contrary to simple average efficiency scores), these measures again highlight the losses due to suboptimal scale size.

6. Conclusion

This paper assesses the technical efficiency of fossil fueled power plants to estimate energy savings and CO_2 reduction potentials in the German electricity and heat generation sector. We contribute to the existing literature looking at the largest EU country in terms of CO_2 emissions and the largest European energy generating sector. We use a unique panel data set, with 1459 observations over the 2003-2010 period, during which Germany experienced considerable changes in electricity generation. Using a metafrontier framework, efficiency estimation accounts for technology heterogeneity and can, therefore, handle and compare generating companies with different technologies. This paper is the first empirical analysis comparing plants with four different combustion technologies.

The metafrontier results indicate substantial savings potentials in terms of both inputs and undesirable CO_2 emission outputs. Average metafrontier technical efficiency is found to be highest for the large-scale baseload plants using coal and lignite. However, results also show considerable inefficiencies of gas-fired stations, even as they obtain an MTR score of unity. This means that they shape the technology and serve as benchmark also for plants using other fuels. Thus, considerable efficiency increases are achievable only in the long run with technology switches to gas.

The group technical efficiency results suggest substantial savings potentials with respect to inputs and the undesirable output for every technology. Empirical findings show that intra-group differences are more pronounced among the gas-fired plants for which significantly lower minimum efficiencies are found. This implies that considerable emission reductions are feasible without switching technology but by using

best-practice, which makes those potential gains available already in the short run. Results furthermore indicate scale inefficiencies for each technology, but are especially pronounced for biomass-fired plants. An analysis of the underlying returns to scale of the plants suggest that baseload plants (coal and lignite) are, on average, larger than optimal, while the opposite is found for gas and biomass plants. This means that, especially among the groups with high average capacity, notable CO_2 emission and fuel input savings are possible by downward adjusting size of generating facilities.
Finally, our results stress two further aspects: on the one hand, using a panel data set allows more accurate efficiency estimations. The use of a sequential DEA program allows for efficiency to be measured against a much larger number of reference units, thus reducing the amount of slacks in the LP and better approaching the true underlying technology. However, persistence of peer units from early sample periods also suggests the need for an analysis of technical change in this sector which was out of scope of this study and needs further research.

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Appendix .1. Descriptive Statistics

This section presents the descriptive statistics of the sample used for the analysis. Obs gives the number of observations in this the year. Capital is annual mean available capacity measured in MW. Fuel is fuel input of the plant measured in 1000 GJ. Labor input is sum of working hours. CO_2 are CO_2 emissions in tons. Output is the sum of heat and electricity output in GWh. Empty entries are not reported due to data privacy regulations of the German statistical offices.

		2003	2004	2005	2006	2007	2008	2009	2010
Obs		22	26	27	27	28	27	26	26
Capital	Q25	85.80	87.57	103.76	108.83	91.18	99.33	123.44	100.81
	Med	301.08	295.75	301.33	273.42	339.50	306.00	385.13	358.00
	Mean	373.51	360.29	363.40	358.23	381.00	395.11	417.22	410.73
	Q75	615.98	526.42	624.37	554.92	577.75	577.60	674.85	687.94
Fuel	Q25	8,302,972	6,572,368	7,939,636	7,592,732	6,909,764	5,473,505	4,597,282	3,635,072
	Med	18,150,738	15,850,913	16,450,917	15,955,949	15,127,849	14,650,731	14,286,531	12,716,727
	Mean	22,687,637	18,822,660	20,525,256	19,790,614	19,828,787	18,865,968	17,841,286	16,939,149
	Q75	30,560,683	26,166,114	29,756,529	27,563,373	28,781,382	28,069,147	25,264,032	25,251,323
Labour	Q25	219,763	200,547	191,500	197,172	202,534	195,220	189,590	182,004
	Med	321,298	275,365	242,265	246,231	262,104	278,909	299,986	297,285
	Mean	614,582	662,093	683,032	779,873	796,615	818,125	761,259	748,566
	Q75	709,613	693,783	627,591	610,048	602,503	633,611	675,447	685,101
CO_2	Q25	772,176	611,230	738,386	706,124	642,608	509,036	427,547	338,062
	Med	1,688,019	1,474,135	1,529,935	1,483,903	1,406,890	1,362,518	1,328,647	1,182,656
	Mean	2,109,950	1,750,507	1,908,849	1,840,527	1,844,077	1,754,535	1,659,240	1,575,341
	Q75	2,842,143	2,433,449	2,767,357	2,563,394	2,676,669	2,610,431	2,349,555	2,348,373
Output	Q25	1,023,292	785,209	1,079,197	1,105,928	899,790	787,376	910,117	749,706
	Med	2,569,384	2,508,765	2,673,425	2,180,437	2,406,535	2,367,010	2,177,444	1,908,481
	Mean	2,848,504	2,575,559	2,746,387	2,640,324	2,612,668	2,539,724	2,372,948	2,350,606
	Q75	3,677,321	3,273,208	3,563,529	3,249,413	3,407,506	3,439,597	2,961,028	3,225,119

Table .9: Descriptive Statistics Coal

		2003	2004	2005	2006	2007	2008	2009	2010
Obs		6	8	5	9	13	15	14	11
Capital	Q25					75.00	74.00	73.33	
	Med	241.50	74.17	387.00	75.00	355.22	843.33	638.75	920.00
	Mean	837.18	540.51	914.38	622.94	996.50	1031.42	933.90	1225.19
	Q75					1902.25	1795.46	1606.88	
Fuel	Q25					8,496,479.00	8,232,743.00	7,819,584.50	
	Med	16,222,824.00	8,483,013.50	23,644,575.00	8,105,210.00	28,963,825.58	49,248,295.00	39,191,497.00	62,275,405.74
	Mean	60,440,524.67	40,737,250.88	72,696,696.20	47,034,143.35	82,861,512.74	79,371,963.67	73,459,216.14	92,152,325.52
	Q75					171,967,717.00	148,580,785.50	133,057,013.25	
Labor	Q25					91,604.00	106,750.50	96,842.75	
	Med	159,119.00	107,846.50	217,257.00	122,592.00	231,157.00	284,020.00	287,062.00	487,666.00
	Mean	463,134.67	321,747.38	488,670.00	317,579.78	562,537.85	592,535.53	562,041.36	706,981.55
	Q75					997,806.00	1,034,816.00	906,604.00	
CO_2	Q25					883,633.82	875,926.43	813,236.79	
	Med	1,761,170.09	882,233.40	2,624,547.83	842,941.84	3,214,984.64	5,121,822.68	4,151,410.01	6,476,642.20
	Mean	6,792,669.93	4,504,110.67	8,188,450.53	5,226,549.36	9,352,925.73	8,925,842.90	8,245,595.36	10,366,907.93
	Q75					19,604,319.74	16,870,220.17	15,144,927.79	
Output	Q25					727,923.00	717,265.50	663,440.25	
	Med	1,786,324.50	789,784.50	2,338,149.00	689,357.00	2,618,058.81	5,742,401.00	4,313,027.00	7,338,541.78
	Mean	6,300,040.00	4,091,255.13	7,658,764.00	4,993,616.94	8,087,684.37	7,994,358.13	7,381,801.21	9,409,286.22
	Q75					14,956,727.00	14,161,927.50	12,410,947.00	

Table .10: Descriptive Statistics Lignite

		2003	2004	2005	2006	2007	2008	2009	2010
Obs		114	136	118	141	137	145	144	144
	Q25	1.68	1.42	1.19	1.43	1.49	1.86	2.00	1.92
Capital	Med	3.69	3.88	2.93	4.48	4.52	4.61	4.64	4.52
	Mean	68.03	45.93	48.99	47.72	53.56	52.76	47.60	53.60
	Q75	31.08	16.84	19.23	19.90	13.40	20.00	18.17	19.63
	Q25	46,398	67,917	63,074	80,421	76,717	86,035	91,796	88,571
Fuel	Med	130,509	228,202	155,003	213,058	215,881	232,821	249,218	247,612
	Mean	1,605,909	1,411,957	1,620,838	1,594,739	1,612,984	1,786,560	1,556,512	1,564,499
	Q75	828,081	862,063	922,532	911,521	664,448	1,081,774	938,355	891,102
	Q25	54,489	65,009	54,739	66,074	66,155	61,265	55,781	53,065
Labor	Med	108,462	112,214	109,011	113,229	112,688	109,258	108,472	110,324
	Mean	192,560	204,466	275,481	244,013	234,089	224,012	217,451	215,076
	Q75	207,813	203,365	216,035	201,263	200,843	201,218	183,861	188,800
	Q25	2,598	3,803	3,532	4,504	4,296	4,818	5,141	4,960
CO_2	Med	7,309	12,779	8,680	11,931	12,089	13,038	13,956	13,866
	Mean	146,599	125,388	132,583	123,480	129,793	133,310	105,467	120,000
	Q75	46,373	48,276	51,662	51,045	37,209	60,579	52,548	49,902
	Q25	9,637	12,089	12,223	16,423	17,175	19,274	18,550	20,084
Output	Med	26,164	44,399	32,832	46,587	43,448	44,489	52,669	48,506
	Mean	282,162	264,353	304,193	295,534	288,211	318,026	280,628	291,865
	Q75	184,530	193,641	209,134	202,267	127,612	224,241	206,343	194,931

Table .11: Descriptive Statistics Natural Gas

		2003	2004	2005	2006	2007	2008	2009	2010
Obs		3	6	3	6	10	12	15	17
	Q25						4.38	4.72	5.40
Capital	Med	20.00	3.60	5.00	6.81	5.05	5.57	7.15	7.50
	Mean	17.67	4.01	4.83	7.63	7.87	9.50	10.24	10.51
	Q75						15.18	17.08	15.29
	Q25						464,489	505,825	640,721
Fuel	Med	653,153	569,579	741,618	734,533	594,993	676,049	661,495	729,525
	Mean	657,421	550,420	605,401	746,371	957,595	945,695	856,684	1,010,073
	Q75						910,828	971,945	1,375,426
	Q25						26,595	19,316	21,656
Labor	Med	56,728	52,109	52,795	29,482	33,780	36,666	32,626	33,690
	Mean	57,409	52,482	55,726	39,947	55,645	63,803	46,930	47,618
	Q75						92,164	44,448	46,631
	Q25						44,126	48,053	60,868
CO_2	Med	62,050	54,110	70,454	69,781	56,524	64,225	62,842	69,305
	Mean	62,455	52,290	57,513	70,905	90,972	89,841	81,385	95,957
	Q75						86,529	92,335	130,665
	Q25						42,442	44,264	59,113
Output	Med	35,340	38,041	34,372	46,844	39,092	92,272	81,691	93,262
	Mean	75,941	59,766	82,468	69,730	96,207	105,303	101,854	109,070
	Q75						110,151	119,173	131,339

Table .12: Descriptive Statistics Biomass

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