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**Conference Paper**

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2015: Ökonomische Entwicklung -  
Theorie und Politik - Session: Industrial Organization III, No. C11-V2

**Provided in Cooperation with:**

Verein für Socialpolitik / German Economic Association

*Suggested Citation:* Seifert, Stefan (2015) : Productivity Growth and its Sources - A StoNED  
Metafrontier Analysis of the German Electricity Generating Sector, Beiträge zur Jahrestagung des  
Vereins für Socialpolitik 2015: Ökonomische Entwicklung - Theorie und Politik - Session: Industrial  
Organization III, No. C11-V2, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften,  
Leibniz-Informationszentrum Wirtschaft

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# Productivity Growth in Conventional Electricity and Heat Generation in Germany - A StoNED Metafrontier Analysis

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September 5, 2015

## Abstract

Productivity growth in electricity generation can have multiple positive effects, as e.g. setting free scarce resources, a generally lower use of natural resources and subsequently lower CO<sub>2</sub> emissions. Increasing (scale) efficiency, technical change or the introduction of new technologies are ways to raise productivity in a sector. This paper analyzes productivity growth for conventional combustion power plants in Germany. A unique panel data set ranging from 2003 to 2010 including in total 1555 observations allows to estimate production frontiers for coal, lignite, gas and biomass fired power plants. Production functions are estimated using stochastic non-smooth envelopment of data (StoNED) in a meta-frontier framework. Productivity growth is assessed at representative units using a metafrontier Malmquist decomposition. Results indicate (1) a stagnation of productivity for the whole sector, (2) technical progress for biomass plants with a catch-up to the other technologies (3) and the highest productivity for gas-fired power plants.

**JEL-Codes:** L94,D24,O13,C14

**Keywords:** Electricity and Heat Generation, Productivity Growth, Stochastic non-smooth envelopment of data (StoNED), Metafrontier Malmquist Decomposition, Germany, Panel 2003 - 2010

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<sup>0</sup>Acknowledgements:

I thank the participants of the North-American Productivity Workshop 2014 in Ottawa, the German Statistical Week 2014 in Hannover, the Annual Conference of the European Association for Research in Industrial Economics, and the DIW Brown Bag Seminar in Berlin for fruitful discussions and helpful comments.

<sup>0</sup>This paper is produced as part of the project KOMIED (Municipal infrastructure companies against the background of energy policy and demographic change), a project financed by Leibniz Association

# 1 Introduction

Productivity growth in electricity and heat generation can have multiple positive effects: First, productivity gains can be translated in lower prices for electricity, a major input of the whole economy. Further, productivity gains can set free resources for other uses, as e.g. labor and capital. Furthermore, productivity gains can lead to overall reduced consumption of scarce natural resources as fossil fuels. Thus, besides positive environmental effects, productivity growth can also reduce import dependencies. And finally, a more productive use of combustion materials can reduce CO<sub>2</sub> output and ultimately help reaching ambitious climate goals. To achieve such productivity gains, multiple channels are available. Increasing (scale) efficiency of existing plants helps using resources more productive and allows lowered resource use with preexisting industry structures. Further, technical progress and learning allows to achieve new productivity levels with existing technologies. Finally, introduction of new technologies with often steep learning curves may allow to reach new productivity levels.

In the literature, productivity and efficiency of power generating units has been studied by numerous papers (for overviews see Song et al., 2013; Zhou et al., 2008). However, most studies focus on the measurement of inefficiency and its determinants. Besides cross-country comparisons (e.g. Sueyoshi and Goto, 2013; Zhang and Choi, 2013), empirical evidence exists for several countries. More recently, the Chinese power generating sector has drawn major attention, and regulatory reforms and their impact on efficiency has been analyzed by a number of papers, including analysis on the plant level (e.g. Zhao and Ma, 2013; Du et al., 2013, 2009) and on regional level (e.g. Bi et al., 2014; Wang et al., 2013; Lin and Du, 2013). Likewise, a vast number of studies of the power generating sector exists for the US, however, most often in a cross-sectional setting and evidence from intertemporal analysis is limited (e.g. Craig and Savage, 2013; Fleishman et al., 2009). Other countries are analyzed as well in panel settings and for example the Chilean hydroelectric power generation has been studied by Atkinson and Halabi (2005) and Iran's power generation has been analyzed by Fallahi et al. (2011). Empirical evidence on efficiency in European electricity generation is limited and to the authors knowledge the study of Seifert et al. (2014) on efficiency in Germany is the only study on the plants level.

Productivity developments and technical change in the electricity generating sector has attracted less attention and little empirical evidence can be found. See and Coelli (2013) have analyzed productivity growth and its components in the Malaysian electricity generating sector. Using a parametric approach (Stochastic Frontier Analysis, SFA) they analyze a panel from 1998 to 2005. For this period, the authors find an annual total factor productivity (TFP) growth of 2.5%. Decomposition of the results show a

strong contribution of technical progress to this development, and the authors argue that these improvements can be mainly attributed to investments into new capacities. Opposing results are found in a study by Heshmati et al. (2014) on productivity developments in Korean power plants by means of a simple linear regression model and a semi-parametric smooth coefficient model (SPSC). Based on a sample covering a similar time period, 1995 - 2006, results indicate productivity decline and technical regress over the sample period and over the whole frontier, irrespective of the methodology chosen. The authors argue, that this finding can be explained by higher energy security, practices of demand side management in the electricity markets and thus lower rates of generation intensity per unit. For the US Atkinson and Primont (2002) analyze productivity of fossil-fuel fired steam electric utilities between 1961 and 1997 by means of stochastic cost and distance functions. The authors find overall small productivity gains of around 0.3 to 0.7% per year, with productivity losses for nearly half of the observation period. Results furthermore indicate overall small technical progress (0.7 to 1.2%) with technical regress during the beginning of the sample period. Similarly, Rungsuriyawiboon and Stefanou (2008) and Genius et al. (2012) analyze productivity of fossil-fuel fired steam electric power generation during the time period of 1986 - 1999 using identical data sets. The former study finds annual TFP growth of 2.3%, mainly driven by allocative efficiency gains and accompanied by periods of both, technical progress and regress. The latter study further analyzes partial productivity of labor and fuel inputs in this context. Results indicate small productivity growth of 0.4% for fuel, but much stronger gains for labor. However, technical progress is found to be very low in magnitude for fuel input (around 0.15%) and slightly negative for labor input. For both studies, Rungsuriyawiboon and Stefanou (2008) and Genius et al. (2012), differences in the point estimates in comparison to Atkinson and Primont (2002) can be attributed to the shorter observation period that leaves out years in which productivity decline and technical regress seem to dominate.

To summarize, the literature does not show a clear picture of trends in productivity development in electricity generation. Generally, productivity growth point estimates surely vary with the context of the analysis, but are generally found to be low in magnitude. Further, results of the studies mentioned above indicate technical progress and regress, but again, generally with estimates of low magnitude. The literature on productivity growth in electricity (and heat) generation indicates several gaps that should be addressed in this paper: First, most studies can not account for heterogeneity in the combustion technologies. Second, the studies from the field of efficiency and productivity analysis are typically based on Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis (SFA). Whilst the former is purely deterministic and

does not account for noise in the data, the latter needs the assumption of a functional form as Cobb-Douglas and Translog. Finally, there is only little empirical evidence on productivity in electricity generation in general and for Europe in particular.

This paper tries to contribute to the literature by analyzing technical change for the first time for the German electricity and heat generating sector. Based on an unique and uncommonly rich data set, productivity changes and its components are analyzed for coal, lignite, gas and biomass-fired power plants between 2003 and 2010. Productivity growth is decomposed using a Malmquist decomposition that is adjusted to a metafrontier framework following Battese et al. (2004), which allows to account for technological heterogeneity among the different fuel types. Further, using stochastic non-smooth envelopment of data (StoNED, Kuosmanen and Kortelainen, 2012) for frontier estimation allows to combine both, a frontier estimation without any assumptions on its functional form whilst allowing for disentangling noise and inefficiency.

The German electricity generating sector is an especially interesting case to study with considerable changes in the industry structure, and with a special role of conventional energy sources. With a total generation capacity of 190 GW Germany's power plant fleet is the largest in Europe and the sixth largest in the world. Around the half of this capacity are conventional combustion plants, including coal, lignite, gas and biomass-fired stations. For coal and lignite capacities have been stable since the 2000s, while a considerable number of new installations and capacity extensions have taken place for gas and biomass. However, supporting policies have also fostered sizeable investments in renewable energy sources. In 2013, wind and solar contribute around 70 GW in capacity, after only 15 GW ten years before. On the other side, with the nuclear phase-out - agreed on in 2002 and reconditioned in 2011 - substantial capacity of around 12 GW will go off-line until 2022. These changes in the capacity structure have also impacted the electricity generation. While coal and lignite are still the most important single fuel sources accounting for nearly 50% of total generation, wind and solar already contributed more than 10% of total generation in 2013. For the conventional combustion technologies, this change in the energy mix poses a new challenge: as long as no storage facilities are available for wind and solar, conventional combustion capacities will be needed as a back-up for these intermittent source. At the same time, the nuclear capacities that go off-line need replacement, partly by conventional sources. In this environment, combustion technologies are competing with virtually zero-variable cost competitors, wind and solar, creating considerable pressure on productivity developments in such plants.

The remainder of study is organized as follows: section 2 presents the theoretical background of the metafrontier approach and will outline the methodology to estimate the

production frontier and the frontier shift. The data set is outlined in section 3. Results are presented in section 4, and section 5 summarizes this paper.

## 2 Methodology

In this paper, productivity growth in the German electricity sector is studied in a production context using a metafrontier Malmquist decomposition. The analysis is based on a metafrontier framework, following Battese et al. (2004), that is outlined in section 2.1. Production functions are estimated using stochastic non-smooth envelopment of data (StoNED) outlined in section 2.2. To evaluate productivity changes in a setting with multiple technologies, a metafrontier Malmquist productivity index is constructed as outlined in 2.3.1. Finally, section 2.3.2 outlines at which points productivity is measured and how those points are derived.

### 2.1 Metafrontier Framework

The metafrontier framework is a methodological toolkit that allows to account for heterogeneity in the units of analysis. Introduced by Hayami and Ruttan (1970) and operationalized for efficiency analysis methods by Battese et al. (2004), it has since then found application for different sectors. Examples from the literature on efficiency analysis in the electricity generating sector include the study by Zhang and Choi (2013), in which the metafrontier is used to control for the location of a plant in different countries, and the studies by Zhang et al. (2013) and Seifert et al. (2014) that use this framework to differentiate technologies based on the fuel input types.

To describe the production process some notation needs to be introduced. Assume  $I$  ( $i = 1, \dots, I$ ) decision making units (DMUs, power plants in this case) are observed in  $T$  ( $t = 1, \dots, T$ ) periods. Each power plants uses a technology to transform an  $m$  dimensional input vector  $x_{it}$  ( $x \in \mathbb{R}_+^m$ ) into the scalar output  $y_{it}$  ( $y \in \mathbb{R}$ ). Further, denote by  $\Psi$  the entirety of feasible production plans,  $(x_{it}, y_{it}) \in \Psi$ . The transformation process can be represented by the production function  $f_t : \mathbb{R}_+^m \rightarrow \mathbb{R}_+$ . Following microeconomic theory  $f$  is a monotonically increasing, concave and continuous function that gives the maximum output attainable for a given input level. Now, output of firm  $i$ ,  $y_{it}$ , may deviate from this maximum for given inputs due to inefficiency  $u > 0$  and a random disturbance  $v$  such that  $y_{it} = f_t(x_{it}) * \exp(\varepsilon) = f_t(x_{it}) * \exp(v_{it} - u_{it})$ . This production function is called the metafrontier and represents the maximum production for each input level for the  $I$  observations in period  $t$ . Furthermore, assume that each DMU has chosen one of  $C$  ( $c = 1, \dots, C$ ) technologies and could thus realize all potential input-output combinations in  $\Psi^c$ . In this paper  $c$  represents the

combustion technology that prevents the plants from simply switching from one fuel to another. This allows us to divide the sample into  $C$  groups with each group representing one combustion technology. For each group a production function (group technology) defines the maximum attainable output for a given level of input. Again, observed output may deviate from this maximum due to inefficiency and noise such that  $y_{it}^c = f_t^c(x_{it}^c) * \exp(\varepsilon) = f_t^c(x_{it}^c) * \exp(v_{it}^c - u_{it}^c)$ .

By definition, the production possibility set for each group technology  $\Psi^c$  is a subset of the metatechnology  $\Psi$ . Therefore, the metatechnology production function envelopes all group technologies such that  $f(x) \geq f^c(x) \forall x$ . This furthermore allows to relate the locations of the meta- and the group frontiers using the technology gap ratio ( $TGR$ ) that measures the distance between the group and the metatechnology as  $TGR = f^c(x)/f(x)$ . This measure indicates whether technology  $c$  is able to produce maximum output for a given input level if  $TGR = 1$ . On the contrary, if  $TGR < 1$  firms using this group technology can potentially achieve a higher output level by switching to the technology defining the metafrontier for this input level.

## 2.2 Frontier Estimation

For the estimation of the group frontiers and the metafrontier a StoNED approach (Kuosmanen and Kortelainen, 2012) is used in this paper. This approach consists mainly of two steps: first, an piece-wise linear average production function  $g(x)$  is estimated using convex non-parametric least squares (CNLS). This estimation is free of any distributional assumptions or assumptions on a functional form. In a second stage, based on distributional assumptions, estimates for the parameters of inefficiency and noise ( $u$  and  $v$ ) are obtained. In the second step, the average production function  $g(x)$  is shifted upwards by the expected value of inefficiency to get a frontier estimate  $\hat{f}(x)$ . Thus, this method combines aspects of the two standard methods DEA and SFA: similarly to DEA, the production frontier is estimated without specification of a functional form and based only on few microeconomic assumptions on the shape of a production function (concavity, monotonicity and continuity). However, similar to SFA, disentangling noise and inefficiency is possible based on distributional assumptions on inefficiency and noise. Therefore, StoNED combines strengths of both methodologies, DEA and SFA.

For the first stage Kuosmanen (2008) derives a representation of the infinitely many monotonically increasing, concave and continuous (not necessarily differentiable) functions that would solve the corresponding least squares problem to derive the average production function. Kuosmanen and Kortelainen (2012) extend this approach to the case of a production function with multiplicative noise and inefficiency, i.e.

$y = f(x) * \exp(\varepsilon) = f(x) * \exp(v - u)$ . Kuosmanen and Kortelainen (2012) derive a quadratic programming problem (QP) to obtain slope and intercept estimates for the average production function based on the log-transformation of the multiplicative model. This procedure is used to estimate a production function for each group technology and for the metatechnology in each year separately by solving the following non-linear QP.

$$\begin{aligned}
 \min_{\alpha, \beta, \hat{y}} \quad & \sum_{i=1}^n (\ln y_{it} - \ln \hat{y}_{it})^2 \\
 \hat{y}_{it} = \quad & \alpha_{it} + \beta'_{it} x_{it} \\
 \alpha_{it} + \beta'_{it} x_{it} \leq \quad & \alpha_{ht} + \beta'_{ht} x_{it} \quad \forall i, h = 1, \dots, n \\
 \beta_{it} \geq \quad & 0 \quad \forall i = 1, \dots, n
 \end{aligned}$$

This QP tries to find the  $\alpha$  and  $\beta$  coefficients that minimize the sum of the squared residuals,  $\eta_{it} = \ln y_{it} - \ln \hat{y}_{it}$ .  $\alpha$  and  $\beta$  are the solution to this QP and represent firm-specific estimates for the intercept and the slope of a firm specific hyperplane tangent to the average production function  $g(x)$ . Microeconomic requirements on this hyperplanes are imposed as constraints: The first constraint establishes a linear form for the estimated hyperplanes leading to a piece-wise linear estimate of the function similar to DEA. The second constraint imposes concavity of the estimated function using Afriats theorem (Afriat, 1967). Finally, the third constraint imposes monotonicity. As no further restrictions are imposed on the sign of  $\alpha$ , the estimated frontier is allowed to have variable returns to scale (VRS). However, a constant return to scale (CRS) model can be imposed by setting  $\alpha = 0$ . Furthermore, the model delivers fitted values  $\hat{y}_{it}$  on the hyperplanes. The lower envelope of these fitted values is used as the estimated average production function  $\hat{g}(x)$  (see Kuosmanen and Kortelainen, 2012).

What should be noted is the size of the QP. To estimate the  $n * m + n$  parameters in the VRS case and the  $n * m$  parameters under CRS, the second and the third constraint sum up to  $n * n + n$  constraints. Especially the concavity constraints impose a large number of restrictions ( $n * n$ ) and can create a computational burden. To overcome this restriction, a sweet spot approach following Lee et al. (2013) is implemented. This algorithm is based on the assumption that the relevant hyperplane of an observation is most likely only influenced by observations close to the unit of interest. Therefore, in a first stage, for each unit, only constraints relative to observations within 30 percent of the maximum Euclidean distance of one arbitrarily chosen input are included. After solving this initial model, for each observation the most violated constraint is added. This procedure is used iteratively until no constraint is violated, which assures optimality of the solution.

After obtaining the  $\alpha$  and  $\beta$  coefficients in the first stage, the residuals  $\eta_{it} = \ln y_{it} - \ln \hat{y}_{it}$



are used to recover estimates for the parameters of the distributions of inefficiency and noise,  $\sigma_u$  and  $\sigma_v$  in each  $t$  for each of the  $C$  group technologies and the metafrontier. Based on these estimates,  $g(x)$  is shifted to obtain a frontier estimate. This needs more detailed distributional assumptions in advance. Following Kuosmanen and Kortelainen (2012), a normal distribution is imposed for the noise term,  $v \sim N(0, \sigma_v^2)$ . The inefficiency term is assumed to take only positive values, and to follow a half-normal distribution,  $u \sim |N(0, \sigma_u^2)|$ . Thus, the composed error term  $\varepsilon = v_i - u_i$  is assumed to follow a normal-half normal distribution. To recover these parameters, Kuosmanen and Kortelainen (2012) suggest decomposing the residuals from the first stage ( $\eta_{it}$ ) using a pseudolikelihood estimators (PSL) as proposed by Fan et al. (1996) (FLW). Following FLW, for each period  $t$  and for each technology  $c$  a log-likelihood function for the normal-half-normal model can be expressed as function of a single parameter  $\lambda \equiv \sigma_u/\sigma_v$  such that

$$\ln L(\lambda) = -n \ln \hat{\sigma} + \sum_{i=1}^n \ln \Phi\left[\frac{-\hat{\varepsilon}_i \lambda}{\hat{\sigma}}\right] - \frac{1}{2\hat{\sigma}^2} \sum_{i=1}^n \hat{\varepsilon}_i^2$$

with  $\Phi$  denoting the CDF of a standard normal and

$$\begin{aligned} \hat{\varepsilon}_i &= \eta_i - (\sqrt{2}\lambda\hat{\sigma})/[\pi(1+\lambda^2)]^{1/2} \\ \hat{\sigma} &= \left( \left[ \frac{1}{n} \sum_{i=1}^n \eta_i \right] / \left[ 1 - \frac{2\lambda^2}{\pi(1+\lambda^2)} \right] \right)^{1/2} \end{aligned}$$

Maximization of the likelihood function delivers estimates of  $\lambda$  and subsequently  $\hat{\sigma}$ . Further, estimates of  $\hat{\sigma}_u$  and  $\hat{\sigma}_v$  are available with  $\hat{\sigma}_u = \hat{\sigma}\hat{\lambda}/(1+\hat{\lambda})$  and  $\hat{\sigma}_v = \hat{\sigma}/(1+\hat{\lambda})$ . Given this estimate of the variance of the inefficiency the expected value of inefficiency  $\hat{\mu}$  can be calculated as  $E(u_i) = \hat{\mu} = \hat{\sigma}_u \times \sqrt{2/\pi}$ . This procedure is done for each technology and the metatechnology in each of the  $T$  periods leading to  $T(C+1)$  estimates of  $\sigma_u$ ,  $\sigma_v$  and  $\mu$ . The estimated production functions are then derived as the average production functions shifted upwards by the expected value of inefficiency, such that  $\hat{f}_t(x) = \hat{g}(x) * \exp(\hat{\mu})$  for each  $t$ .

## 2.3 Estimation and Decomposition of Productivity Growth

### 2.3.1 Metafrontier Malmquist Decomposition

Based on the consistent estimate of the production function in each  $t$  we are now interested in measuring productivity growth and its components using a Malmquist productivity index (MPI) in a metafrontier setting. Therefore, we will briefly introduce the standard VRRS Malmquist decomposition in the spirit of Fare et al. (1994). In a second step, this productivity index will be extended to a metafrontier Malmquist

productivity index (MMPI) using the insights of Chen and Yang (2011). This MMPI measures productivity growth on the metafrontier level but includes also information about productivity growth on group level including productivity trends relative to the whole sector (the metafrontier). Further, this MMPI is based on the Fare et al. (1994) scale change factor, contrary to Chen and Yang (2011), which base their decomposition on the Ray and Desli (1997) scale change component.

Let denote  $D_t^o$  the distance of a an input-output combination  $(x^c, y_t^c)$  to the boundary of the technology set, i.e. the best practice frontier, such that  $\phi$  gives the potential expansion of output for a given input level.

$$D_t^o(x, y) = \inf\{\phi > 0 : (x, y/\phi) \in \Psi\}$$

Using such a distance function one may calculate the standard Malmquist productivity index following Färe et al. (1994), which is based on a CRS technology.

$$MPI_t^{o,crs}(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D_t^{o,crs}(x_{t+1}, y_{t+1})}{D_t^{o,crs}(x_t, y_t)}$$

In this formulation, the MPI measures productivity growth relative to the period- $t$  benchmark technology. However, as there is no argument to favor this over a period- $t+1$  benchmark technology, typically the geometric mean of both is taken:

$$MPI_{t,t+1}^{o,crs}(x_t, y_t, x_{t+1}, y_{t+1}) = \left[ \frac{D_t^{o,crs}(x_{t+1}, y_{t+1})}{D_t^{o,crs}(x_t, y_t)} \times \frac{D_{t+1}^{o,crs}(x_{t+1}, y_{t+1})}{D_{t+1}^{o,crs}(x_t, y_t)} \right]^{1/2}$$

As we assume VRS for the technologies to estimate, we introduce a scale change factor following the decomposition by Fare et al. (1994) and differentiate three different factors: technical efficiency change ( $EC$ ), technical change ( $TC$ ) and scale change ( $SC$ ).

$$MPI_{t,t+1}^{o,crs}(x_t, y_t, x_{t+1}, y_{t+1}) = EC^{vrs} \times TC^{vrs} \times TC^{crs}/TC^{vrs} \times SC$$

with

$$EC = \frac{D_{t+1}^o(x_{t+1}, y_{t+1})}{D_t^{o,crs}(x_t, y_t)}$$

$$TC = \left[ \frac{D_t^o(x_{t+1}, y_{t+1})}{D_{t+1}^o(x_{t+1}, y_{t+1})} \times \frac{D_t^o(x_t, y_t)}{D_{t+1}^o(x_t, y_t)} \right]^{1/2}$$

$$SC = \frac{D_{t+1}^{crs}(x_{t+1}, y_{t+1})/D_{t+1}^{vrs}(x_{t+1}, y_{t+1})}{D_t^{crs}(x_t, y_t)/D_t^{vrs}(x_t, y_t)}$$

This VRS based Malmquist index measures productivity changes and its components for one technology (i.e. the metatechnology). An MPI score greater than unity indicates productivity growth. Likewise,  $EC > 1$  indicates an increase in technical efficiency over time;  $TC > 1$  indicates positive technical change, i.e. an upward shift of a production function; and  $SC > 1$  indicates an increase in scale efficiency.

However, this Malmquist decomposition neglects the position of the frontier of the  $C$

subtechnologies relative to the metafrontier. This relationship can be incorporated by two additional decomposition factors as introduced by Chen and Yang (2011). They suggest that the position of the group technologies relative to the metafrontier is measured by two further elements in the Malmquist decomposition: First, the change of the distance between the group and the metafrontier can be measured using a Pure Technological Catch-Up (*PTCU*) component. This component measures the change of the TGR by comparing the TGR for one DMU in two consecutive periods. Second, the authors introduce a Frontier Catch-Up (*FCU*) component. This component measures the change in the distance over a whole band of technology gaps. Now let  $D^c$  denote the distance of an input output combination to the frontier of subtechnology  $c$  while  $D^*$  denotes the distance to the metatechnology and define *PTCU* and *FCU* for two consecutive periods as

$$PTCU_{t,t+1}^c = \frac{TGR_{i+1}^c(x_{t+1}, y_{t+1})}{TGR_i^c(x_t, y_t)} = \frac{D_{i+1}^*(x_{t+1}, y_{t+1})/D_{i+1}^c(x_{t+1}, y_{t+1})}{D_i^*(x_t, y_t)/D_i^c(x_t, y_t)}$$

$$FCU_{t,t+1}^c = \left[ \frac{TGR_i^c(x_{t+1}, y_{t+1})}{TGR_{i+1}^c(x_{t+1}, y_{t+1})} \times \frac{TGR_i^c(x_t, y_t)}{TGR_{i+1}^c(x_t, y_t)} \right]^{1/2} = \frac{TC_{t,t+1}^*}{TC_{t,t+1}^c}$$

A *PTCU* score larger than unity indicates a shrinking technology gap, i.e. a catch-up relative to the metafrontier for a specific firm. On the contrary, for the *FCU* component, a value smaller than one indicates a catch-up, but measured for the whole band of *TGRs* between the input-output combinations in  $t$  and  $t + 1$ .

Using the insights of Chen and Yang (2011) a VRS based Malmquist decomposition can be extended to the Metafrontier Malmquist Productivity Index (MMPI). Using the definitions above, it is easy to show that this MMPI can be decomposed into Technical Efficiency Change and Technical Change for the VRS group frontiers, a Scale Efficiency component for each of the  $C$  groups, and the Pure Technological Catch-Up component, and the Frontier Catch-Up component for all group frontiers relative to the metafrontier. Finally, two "residual" components terms that further relate the scale efficiency component of meta- and group frontier and the technical change component of the VRS and the CRS frontiers (see Appendix for details). Thus, we can write the MMPI as:

$$MMPI^{crs} = EC^{c,vrs} \times TC^{c,vrs} \times SC^c \times PTCU^{vrs} \times FCU^{vrs} \times SC^* / SC^c \times TC^{*,crs} / TC^{*,vrs}$$

This productivity index delivers the productivity growth of the metafrontier as MMPI score. Further, it contains information on the productivity growth of the subtechnology  $c$  by incorporating the VRS Malmquist decomposition on group level (groupfrontier Malmquist productivity index, GMPI), and information on this productivity growth relative to the metafrontier productivity developments. Rewriting this decomposition underlines the different aspects:

$$MMPI^{crs} = GMPI^{c,vrs} \times SC^c \times PTCU^{vrs} \times FCU^{vrs} \times SC^* / SC^c \times TC^{*,crs} / TC^{*,vrs}$$

### 2.3.2 Construction of Hypothetical Evaluation Units

Standard Malmquist decomposition is typically based on balanced panel data sets, which is not the case for our sample. However, different adjustments are possible to use such methods for non-balanced panels see (see Kerstens and Van de Woestyne, 2014, for an overview): one may either just drop the "incomplete" observations or backward merge observations that actually merged during the observation period. Other approaches to balance the panel include imputation of missing data, creation of artificial units or achieving balancedness at least on a two-year basis. However, in our model set-up such methods seem not to be applicable as inclusion of artificial units or exclusion of observations may impact the precision of the frontier estimation. To avoid the problem of unbalancedness we evaluate productivity changes in hypothetical units that are not included in the estimation of the frontier. Productivity growth is then decomposed for these hypothetical units using the Malmquist decomposition outlined above. This offers some advantages: first, frontier estimation is done using the maximum number of observations as no observations are excluded for balancedness. Second, as we look at hypothetical units we can describe technical change for the whole range of potential input values. Furthermore, hypothetical units allow to assume that the evaluated units contain on average no noise making a deterministic treatment of the distance to the frontier available. Therefore, inefficiency does not need to be calculated using the widely used and unbiased but statistically inconsistent efficiency estimate of Jondrow et al. (1982). And finally, such a construction of hypothetical evaluation units allows to actually analyze our data which was not possible on real existing units due to data privacy limitations (see section 3).

For the analysis we construct hypothetical observations  $(x_p^c, y_{t,p}^c)$  that resemble an average plant at the  $p$ -percentile of the plant size in terms of input with the expected output including the expected inefficiency of such an observation. To do so, we fix an input vector constructed at the  $p = \{10\%, 25\%, 50\%, 75\%, 90\%\}$  percentiles from the distributions of the inputs over the pooled observations of all years for each of the  $C$  technologies. For each of these input values, corresponding output values  $y_{t,p}^c$  are constructed using the CNLS average production function estimate  $\hat{g}^c(x)$  in each year. For each of these observations the corresponding output  $y_{t,p}^c$  is calculated as the value on  $\hat{g}^c(x)$  using the lower envelope of the fitted values of the StoNED QP  $\hat{y}_{it}^c$  (see Kuosmanen, 2008, Theorem 4.1). This lower envelope is constructed as a simple linear programming problem (LP) that envelopes the fitted values from the StoNED estimation similar to a VRS-DEA and allows to extrapolate points on  $\hat{g}^c(x)$  for unobserved inputs. Slope and intercept parameters  $a$  and  $b$  are obtained by solving the following LP:

$$y_{t,p}^c(x_p^c) = \min_{a,b} \{a + b'x_p^c \mid a + b'x_p^c \geq \hat{y}_{it}^c\}$$

The corresponding frontier reference point  $\tilde{y}_{t,p}^c$  is derived by multiplication with the expected value of inefficiency,  $\mu_t^c$ :

$$\tilde{y}_{t,p}^c = y_{t,p}^c(x_p^c) * \exp(\mu_t^c)$$

Thus, we construct for each of the  $C$  groups five evaluation units with fix inputs over time and output corresponding to the estimated average production function. Each of this units has an inefficiency identical to the expected inefficiency. Thus, these hypothetical units resemble an average plant at their  $p$ -percentile of their group  $c$ . This procedure has several implications in the Malmquist decomposition. First, we can assume that the average unit does not incorporate noise. Thus,  $D_t^o$  collapses to a simple ratio in the one-output case, and, for example, the distance function of input-output combinations in  $t$  relative to the benchmark technology in  $t + 1$  can be calculated as  $D_{t+1}^o(x_{t,p}^c, y_{t,p}^c) = y_{t,p}^c / \tilde{y}_{t+1,p}^c$ . Further, as there is no variations in the inputs -  $x_p^c$  is constant over time -  $PTCU = 1/FCU$  in each period as the scale of the operations does not change. This also influences the interpretation of the scale change component that now measures change of the optimal scale size over time, not whether a firm moved closer to optimal scale size. Finally, and most importantly, the deterministic treatment of the inefficiency allows to measure the MMPI independent from distributional assumptions. For illustration, replace the distance function in the MPI definition and let  $\xi_t$  be the expected inefficiency in period  $t$  from some distributional assumption in the StoNED estimation to obtain:

$$\begin{aligned} MPI_{t,t+1}^{crs}(x_t, y_t, x_{t+1}, y_{t+1}) &= \left[ \frac{D_t^{crs}(x_{t+1}, y_{t+1})}{D_t^{crs}(x_t, y_t)} \times \frac{D_{t+1}^{crs}(x_{t+1}, y_{t+1})}{D_{t+1}^{crs}(x_t, y_t)} \right]^{1/2} \\ &= \left[ \frac{y_{t+1}/y_t * \exp(\xi_t)}{y_t/y_{t+1} * \exp(\xi_t)} \times \frac{y_{t+1}/y_{t+1} * \exp(\xi_{t+1})}{y_t/y_{t+1} * \exp(\xi_{t+1})} \right]^{1/2} = \frac{y_{t+1}}{y_t} \end{aligned}$$

Thus, the productivity measure depends only on few assumptions, namely concavity, monotonicity and continuity of the production technology. However, the components of the decomposition may vary with the assumptions on the distributions of inefficiency and noise.

### 3 Empirical Model and Data

This section provides the background for the empirical analysis. First, the selection criteria for the construction of the different subtechnologies will be explained. Afterwards, section 3.1 outlines the modeling approach for the input-output transformation process. Finally, section 3.2 shows the data sources and descriptive statistics for the

data set and the units under analysis.

As outlined in section 2.1, a production process is modeled using a metafrontier approach. In this framework, firms choose a technology among a set of available subtechnologies, whilst the entirety of these technologies is collected in the metatechnology. To adapt this framework in our context of electricity and heat generating power plants, we model all power plants in the sample together as metatechnology, while subtechnologies are based on the primary fuel of the production process. Four different conventional combustion power plants are considered as subtechnologies: coal, lignite, gas and biomass-fired power plants. In 2010, these four groups accounted for a over 60% of German electricity generation and build - together with nuclear power - the backbone of German electricity generation. However, nuclear sources are neglected in this analysis due to Germany’s nuclear phase out until 2022. Table 1 lists the included fuels in the different groups.

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, municipal waste

**Table 1:** Subsets by Fuels

### 3.1 Input and Output Specification

To model the production process of power plants, a standard set-up for inputs and outputs is used (e.g. Zhao and Ma, 2013; Lam and Shiu, 2001). For the model formulation it is assumed that capital, labour and energy are used as inputs to produce energy in form of heat and electricity as output. The analysis focus on operational rather than environmental performance and undesirable outputs are therefore not included in the model specification.

Capital input is approximated with the plants average available capacity in MW, which is the average of the monthly available capacity throughout the year. Using the average rather than the maximum capacity we control for potential capacity extensions or

reduction during the year. The measure therefore includes the decision of the owner to maintain full capacity or not. Contrary to most other studies, we are able to measure labor input using the sum of hours worked, rather than a head count. This measure is more accurate to approximate labor input as it accounts for part-time workers. As a third input, energy use is measured using the fuel input of the primary fuel in GJ. As typically a secondary fuel is only used for the start-up of the plants, neglecting the secondary fuel input is expected to have little influence on the results. On the output side, we consider heat and electricity supplied as sole outputs measured as the sum of both in MWh. Net values are used as own consumption reduces the actual provided energy and should not influence a productivity measure.

### **3.2 Data Sources and Descriptive Statistics**

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. The data is based on the survey EVAS 43311 for power plants and connected with EVAS 43111 for labor input data. For data privacy reasons remote data processing is used and one can neither obtain nor report detailed information - such as minima and maxima - about the data set.

Based on monthly questionnaires, the surveys delivers annual data for electricity generating facilities from 2003 till 2010. The included power plants have a bottleneck capacity of at least 1 MW and can be both, large scale electricity and heat suppliers or small scale power plants for industrial use (also autoproducers). Private as well as public and mixed ownership facilities are covered. In total, 1555 observations in eight years are included (compare table 2). The number of firms in the panel increases over the observation period from 156 in 2003 to over 200 plants for the last four years. The largest sample is available for gas-fired plants, whereas this subsample includes a considerable share of small industrial plants. For coal and lignite fired power plants sample size remains stable over the observation period. For the group of biomass-fired stations the sample size steadily increases over the eight years. For coal and gas-fired stations the sample covers between 30% and 40% of the total capacity of plants using these fuels. For lignite-fired plants, these numbers vary more strongly and between 33% (2004) and 80% (2008) are covered. Among the biomass-fired stations about 10 to 18% of total available capacity is covered.

	2003	2004	2005	2006	2007	2008	2009	2010
Coal	22	27	27	27	29	28	27	27
Lignite	8	10	11	11	15	15	14	11
Gas	114	137	120	142	139	147	146	145
Biomass	12	15	15	19	20	23	25	27
Meta	156	189	173	199	203	213	212	210

**Table 2:** Sample sizes for different subsets and total sample

Detailed descriptive statistics for the input and output variables are provided in the appendix (tables 12 to 15). However, mean and quantile values show up to be rather stable over time. The descriptives underline that on average, lignite fired power plants are the largest plants in the sample, while especially biomass and gas-fired plants are considerably smaller. For gas-fired stations, the descriptives furthermore reveal a very skewed distribution in terms of plant size with a few large plants and a larger number of very small plants.

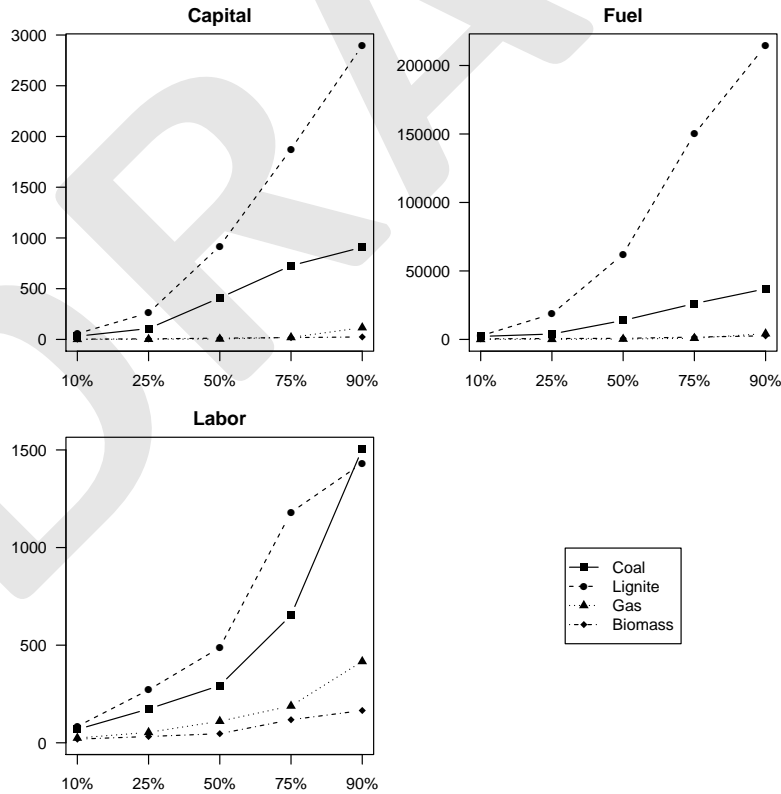
For the construction of the hypothetical evaluation units, for each fuel type the whole sample pooled over the observation period is used. The resulting evaluations units are presented in table 3 and figure 1, and underline again the large dispersion in terms of plant size between the different combustion technologies. However, we furthermore see that all the intervals for the different technologies overlap, such that e.g. the 90% quantile of the coal fired power plants is larger than the 10% quantile of the lignite fired plants. This means that parts of the metafrontier estimate will be influenced by only one combustion technology, while others will be influenced by plants of different combustion technologies. At this overlapping points, plants can be benchmarked against plants using a different fuel when looking at the metafrontier. This is especially pronounced for the biomass-fired stations as their evaluation units are framed by gas-fired stations, i.e. the smallest biomass evaluation unit is larger than the smallest gas-fired stations, but the largest biomass station is still smaller than the largest gas-fired stations.



		10%	25%	50%	75%	90%
Coal	Capital	31.40	107.20	410.00	727.10	908.00
	Fuel	2190.7	3946.4	13867.0	26144.7	26968.7
	Labor	68.5	173.4	293.3	653.3	1504.7
Lignite	Capital	57.33	261.33	920.00	1875.45	2895.25
	Fuel	2598.8	18571.7	62275.4	149977.9	214503.3
	Labor	83.9	270.8	487.7	1180.5	1432.3
Gas	Capital	0.99	1.87	4.40	19.50	116.34
	Fuel	35.7	85.7	247.0	876.3	4213.0
	Labor	24.5	53.4	110.6	188.5	416.7
Biomass	Capital	2.53	5.51	12.47	18.00	24.31
	Fuel	440.8	644.3	772.9	1699.1	2618.4
	Labor	18.6	32.2	46.6	118.1	165.4

*Note:* Fuel input is measured in thousand GJ, Labor in 100 hours

**Table 3:** Descriptive Statistics: Hypothetical Evaluation Units



**Figure 1:** Descriptive Statistics: Quantile Units

## 4 Results

The following two subsections will outline the results of our analysis of productivity changes and its components. The first section discusses the frontier estimation results as well as challenges in the estimation procedure. The second section outlines, the estimates of productivity change for the sector as a whole (MMPI) as well as the different components of Malmquist decomposition. All calculations are done using R 3.2 (R Core Team, 2015) with the packages quadprog, alabama, bbmle and lpSolve.

### 4.1 Frontier Estimation Results

The results of the frontier estimates for the different technologies as well as the metafrontier are provided in Table 4 in terms of expected inefficiency.<sup>1</sup> In this table, a value of 1 indicates full efficiency and no more potential output expansion. Generally, results indicate fairly low expected inefficiency in the German electricity generating sector meaning that the power plants operate close to the best-practice frontier. As expected, under the VRS assumption the large scale baseload plants fired with coal and lignite perform best with on average 98.6 and 98.3% expected efficiency. This can be explained by the usage of a mature technology with little differences among the different plants and a constantly high number of load hours for all those plants. However, the on average smaller gas- and biomass fired plants perform on average also very well indicating potential output extensions of only 2%. Results furthermore indicate a fairly stable upward trend for both, gas and biomass-fired stations. For the metafrontier, expected inefficiency develops parallel to the gas-fired stations. This is not surprising, as the gas-fired stations are the largest subsample in the estimation of the metafrontier. Under CRS results are fairly similar with highest efficiency scores for the baseload plants and more intertemporal variation among gas- and biomass fired stations.

The technology gap ratios (TGR) that measure the gap between meta- and groupfrontier estimates are shown in the tables 5 to 8. Results indicate the smallest technology gap for gas-fired plants, meaning that they generally operate closest to the frontier. The results for the coal-fired stations are similar and indicate only a small technology gap. On the contrary, the largest gap can be found for biomass-fired stations, although this gap closes over time. This means, that switching the combustion technology from biomass to gas would have increased potential output in the beginning of the observation period; however, these potential gains diminish over time as biomass can close this technology gap. Finally, an interesting pattern is visible for the lignite fired-stations

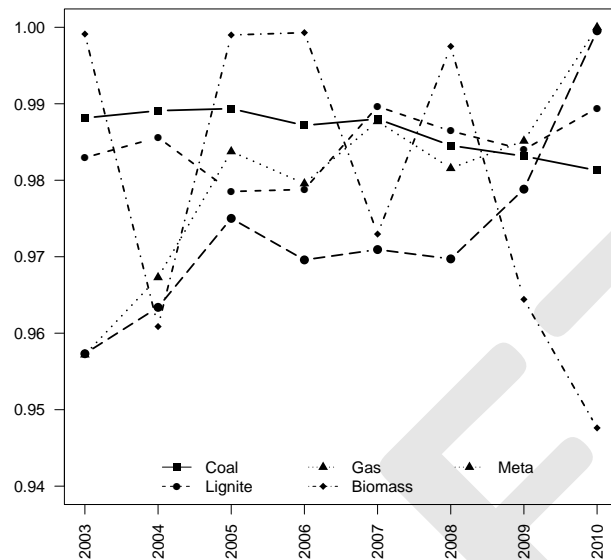
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<sup>1</sup>As the amount of actual estimation results is fairly large, detailed results for the frontier estimates are available from the author upon request.

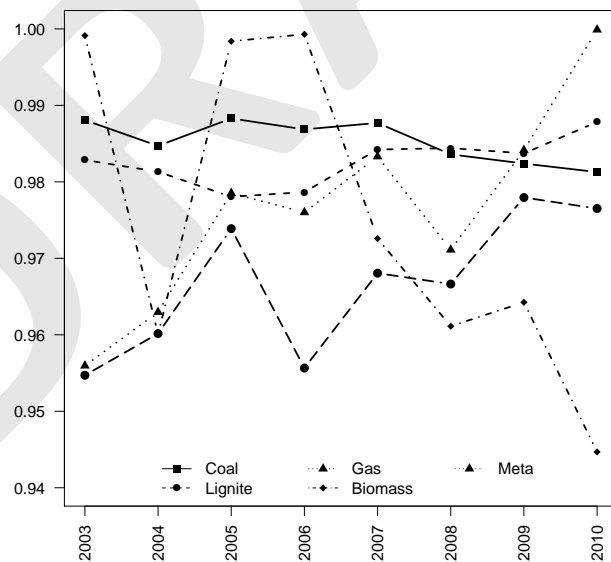
as their technology gap decreases with plant size. Since lignite-fired stations are the largest in the sample, there are just no technologies to compare the largest plants with, meaning that the lignite-fired stations necessarily span the metafrontier at the upper end leading to nearly no technology gap. Conversely, the smallest lignite-fired stations operate at the scale of gas- and coal-fired stations and results indicate a considerable technology gap for those plants.

To summarize, our frontier estimation results indicate fairly low inefficiency in the German electricity generating sector. Further, results indicate leading positions for gas- and coal-fired stations, while biomass faces a certain technology gap that can be closed over time. The indicated savings potentials are much lower than in Seifert et al. (2014) with nearly identical data and a similar model specification; however, inefficiency estimates and technology gaps remain the same order but lower in magnitude. The differences can be explained by the frontier estimation approach: while Seifert et al. (2014) use a deterministic sequential DEA approach, that strongly reacts on highly efficient units and carries them through the panel structure of the data, the StoNED approach used in this paper assumes noise in the data. Thus, whilst the sequential DEA approach might underestimate efficiency in the presence of noise, StoNED might overestimate efficiency if only little noise is present.

Two further methodological points should be noted here: first, the results show that the metafrontier envelopes all group frontiers. However, as this is not automatically case, one may consider using a further constraint in the frontier estimation similar to the SFA metafrontier approach suggested by Battese et al. (2004). Second, a problem that did occur in the estimations is the inconsistency of CRS and VRS frontier estimates if the CRS does not envelope the VRS in every point or intersects it. In this study, the frontier reference points of all observations have been compared for the different scale assumption. If this inconsistency occurred, the CRS frontier estimate has been further shifted upwards by increasing the corresponding  $\sigma_u$  such that CRS equals VRS in the most productive scale size similar to DEA (cp. Bogetoft and Otto, 2011, for details). This solution is rather ad-hoc but assures the consistency of the scale change components.



**Figure 2:** Annual Expected Efficiency for Cross-Sectional Frontiers in Percent under VRS



**Figure 3:** Annual Expected Efficiency for Cross-Sectional Frontiers in Percent under CRS

<b>VRS</b>	Coal	Lignite	Gas	Biomass	Meta
2003	0.9881	0.9830	0.9572	0.9991	0.9573
2004	0.9891	0.9856	0.9673	0.9609	0.9634
2005	0.9894	0.9785	0.9838	0.9990	0.9750
2006	0.9872	0.9788	0.9796	0.9993	0.9696
2007	0.9880	0.9896	0.9877	0.9730	0.9709
2008	0.9845	0.9864	0.9816	0.9975	0.9697
2009	0.9832	0.9840	0.9851	0.9644	0.9788
2010	0.9813	0.9894	1.0000	0.9476	0.9995
Mean	0.9863	0.9844	0.9803	0.9801	0.9730

<b>CRS</b>	Coal	Lignite	Gas	Biomass	Meta
2003	0.9881	0.9829	0.9560	0.9991	0.9547
2004	0.9847	0.9813	0.9630	0.9601	0.9602
2005	0.9883	0.9780	0.9785	0.9984	0.9739
2006	0.9869	0.9787	0.9760	0.9993	0.9557
2007	0.9877	0.9842	0.9833	0.9726	0.9681
2008	0.9836	0.9844	0.9711	0.9611	0.9666
2009	0.9824	0.9837	0.9841	0.9642	0.9780
2010	0.9813	0.9878	0.9999	0.9447	0.9765
Mean	0.9854	0.9826	0.9765	0.9749	0.9667

**Table 4:** Annual Expected Efficiency for Cross-Sectional Frontiers in Percent under VRS

<b>Lignite</b>	10%	25%	50%	75%	90%	Mean
2003	0.9425	0.9547	0.9674	0.9720	0.9738	0.9621
2004	0.9411	0.9458	0.9490	0.9696	0.9735	0.9558
2005	0.9563	0.9685	0.9751	0.9907	0.9948	0.9771
2006	0.9533	0.9644	0.9740	0.9872	0.9900	0.9738
2007	0.9449	0.9511	0.9677	0.9800	0.9802	0.9648
2008	0.9445	0.9564	0.9714	0.9798	0.9825	0.9669
2009	0.9497	0.9639	0.9778	0.9875	0.9893	0.9736
2010	0.9553	0.9681	0.9816	0.9865	0.9881	0.9759
Mean	0.9484	0.9591	0.9705	0.9817	0.9840	

**Table 6:** Technology Gap Ratio: Lignite

<b>Coal</b>	10%	25%	50%	75%	90%	Mean
2003	0.9658	0.9630	0.9596	0.9635	0.9659	0.9636
2004	0.9644	0.9610	0.9582	0.9664	0.9729	0.9646
2005	0.9767	0.9743	0.9700	0.9770	0.9840	0.9764
2006	0.9789	0.9744	0.9681	0.9702	0.9762	0.9736
2007	0.9740	0.9726	0.9727	0.9754	0.9791	0.9748
2008	0.9758	0.9742	0.9736	0.9768	0.9816	0.9764
2009	0.9828	0.9793	0.9788	0.9818	0.9871	0.9820
2010	0.9968	0.9949	0.9935	0.9939	0.9949	0.9948
Mean	0.9769	0.9742	0.9718	0.9757	0.9802	

**Table 5:** Technology Gap Ratio: Coal

<b>Gas</b>	10%	25%	50%	75%	90%	Mean
2003	0.9778	0.9775	0.9784	0.9829	0.9854	0.9804
2004	0.9750	0.9727	0.9739	0.9815	0.9856	0.9778
2005	0.9830	0.9764	0.9720	0.9787	0.9828	0.9786
2006	0.9820	0.9832	0.9847	0.9870	0.9821	0.9838
2007	0.9830	0.9823	0.9809	0.9803	0.9795	0.9812
2008	0.9879	0.9879	0.9879	0.9878	0.9870	0.9877
2009	0.9847	0.9812	0.9813	0.9827	0.9844	0.9829
2010	0.9651	0.9565	0.9589	0.9704	0.9723	0.9647
Mean	0.9798	0.9772	0.9773	0.9814	0.9824	

**Table 7:** Technology Gap Ratio: Gas

<b>Biomass</b>	10%	25%	50%	75%	90%	Mean
2003	0.4881	0.8357	0.9057	0.9118	0.9178	0.8118
2004	0.9730	0.9775	0.9790	0.9816	0.9806	0.9784
2005	0.9271	0.9071	0.9229	0.9245	0.9244	0.9212
2006	0.9211	0.9117	0.9164	0.9157	0.9149	0.9160
2007	0.9474	0.9396	0.9398	0.9389	0.9356	0.9403
2008	0.9351	0.9262	0.9308	0.9300	0.9287	0.9302
2009	0.9836	0.9810	0.9897	0.9922	0.9807	0.9855
2010	0.9840	0.9816	0.9874	0.9885	0.9872	0.9857
Mean	0.8949	0.9326	0.9465	0.9479	0.9463	

**Table 8:** Technology Gap Ratio: Biomass

## 4.2 Productivity Growth and its Components

In this paper productivity changes are measured using a metafrontier Malmquist productivity index (MMPI) decomposition. The first subsection will show the results for the overall productivity measure on metafrontier (MMPI). Subsequently, productivity growth estimates on group frontier level (GMPI) and the detailed decomposition results will be outlined.

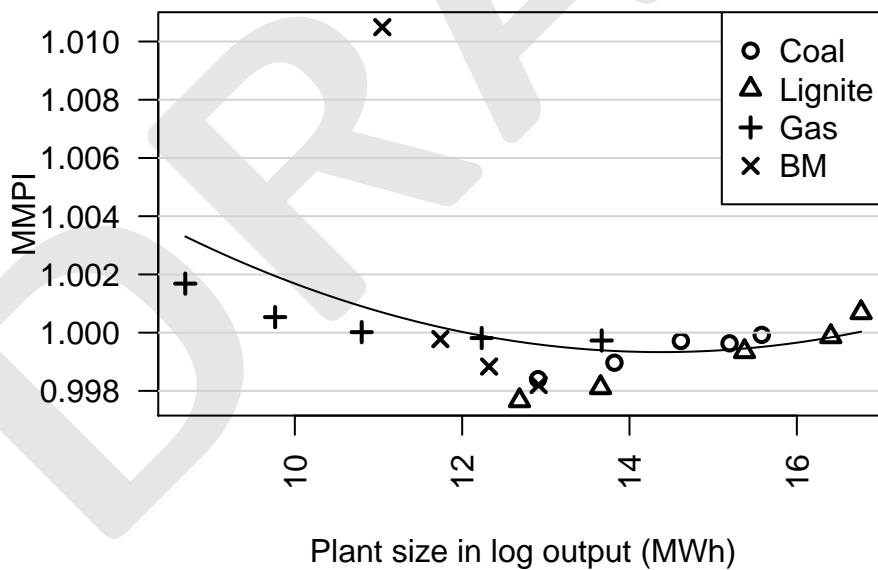
### MMPI

The *MMPI* measures productivity growth on for the whole sector. Productivity is evaluated at 20 points determined by the evaluation units as outlined in section 2.3.2, and an MMPI of 1 indicates no productivity change over the observation period. Table 9 and figure 4 summarize the estimates of annual productivity growth on the metafrontier level. The MMPI shows overall very small productivity changes at nearly all evaluated points. Generally, as figure 4 suggests, productivity losses are observed for the medium sized plants, while productivity gains are observed for the smallest and largest evaluated points. Except for smallest biomass-fired stations no evaluation point is found to have productivity changes larger than 1% annually. For coal- and lignite-fired plants results indicate a reduction or stagnation in productivity over all analyzed input quantiles, although low in magnitude. Similarly, overall productivity changes for gas-fired plants are fairly small, irrespective of the input quantile under analysis. For gas-fired stations results indicate annual productivity gains of about 0.2% for the smaller quantiles, but also small losses for the larger plants. Finally, for the

biomass plants results indicate productivity gains especially at the lower quantiles (10 and 25%). These large leaps can be explained by strong gains in the first period, 2003 to 2004, which can be attributed to the instability of the frontier estimate for small samples. However, excluding the first years of the observations leads to annual productivity gains over the whole range of inputs indicating a robust productivity increase for these plants.

	Coal	Lignite	Gas	Biomass
10%	0.9984	0.9977	1.0017	1.0934
25%	0.9990	0.9981	1.0005	1.0105
50%	0.9997	0.9994	1.0000	0.9998
75%	0.9996	0.9999	0.9998	0.9988
90%	0.9999	1.0007	0.9997	0.9982

**Table 9:** Geometric Mean of MMPI - Annual Productivity Growth



**Figure 4:** Geometric mean of MMPI for different plant sizes



## MMPI decomposition

As outlined in section 2.3.1 overall productivity growth on the metafrontier level can be decomposed into several components. Table 10 shows overall productivity growth on the group level (GMPI); table 11 indicates the components of the decomposition, namely an efficiency change, a technical change, a scale efficiency change and a pure technological catch up component.

	Coal	Lignite	Gas	Biomass
10%	0.9944	0.9978	0.9971	1.2047
25%	0.9953	0.9989	0.9948	1.0288
50%	0.9978	1.0004	0.9938	1.0071
75%	0.9988	1.0003	0.9934	1.0052
90%	1.0004	1.0008	0.9932	1.0040

**Table 10:** Group Frontier Malmquist Productivity Index - Geometric Mean of Productivity Changes

The *GMPI* estimates indicate overall very little productivity changes on the group level, similar to the MMPI results. Noteworthy differences are that the GMPI indicates productivity gains for all evaluated units in the group of biomass-fired stations with annual productivity growth between 0.4 and 2.8%. Thereby, productivity for the biomass-fired stations measured in the group increased stronger than the MMPI for the same evaluation units. This means that there is productivity growth for a subset of the power plant fleet that would not have been measured when looking at the sector as a whole. Further, the differentiation by technology using hypothetical units avoids that these effects are averaged out.

The *efficiency change (EC)* component reflects the change in the distance of the average plant to the best practice for the different group frontiers. As EC depends only on the shift factor from the average production function to the frontier in two consecutive periods, i.e. the expected inefficiency  $\mu_t$  and  $\mu_{t+1}$ , the calculated EC is constant for the different evaluation units. In general, the efficiency change component indicates similar trends as the GMPI with smaller changes for the baseload plants and higher volatility for the small scale plants. Again, results show up to be of small magnitude, ranging between 0.4% average annual efficiency loss for biomass and 0.6% efficiency increase for gas. As the expected inefficiency estimates presented in 4.1 show, average

		Coal	Lignite	Gas	Biomass
EC		0.9990	1.0009	1.0063	0.9925
TC	10%	0.9994	0.9967	0.9954	1.1017
	25%	1.0000	0.9972	0.9943	1.0182
	50%	1.0007	0.9984	0.9938	1.0074
	75%	1.0006	0.9989	0.9936	1.0064
	90%	1.0009	0.9997	0.9935	1.0058
PTCU	10%	1.0045	1.0019	0.9981	1.1054
	25%	1.0047	1.0020	0.9969	1.0232
	50%	1.0050	1.0021	0.9971	1.0124
	75%	1.0044	1.0021	0.9982	1.0116
	90%	1.0042	1.0021	0.9981	1.0105
SEC	10%	1.0001	0.9997	0.9990	0.9994
	25%	1.0006	0.9997	0.9982	0.9996
	50%	1.0012	0.9997	0.9983	0.9995
	75%	1.0012	0.9996	0.9994	0.9995
	90%	1.0012	0.9996	0.9999	0.9995

**Table 11:** GMPI Decomposition -  
Geometric Means of Components of Productivity  
Changes

intra-group efficiency is already fairly high for each technology leading to only little potential efficiency changes in the observation period. Furthermore, a look at the annual estimates shows no clear time trend for any of the technologies, but underlines the higher volatility of the estimates for the gas and biomass-fired plants.

The *technical change (TC)* component reflects the annual shift of the frontier irrespective of potential efficiency or scale effects. Thus, the TC component does not evaluate changes for the average firm, but changes at the best practice frontier. Results show in each technology for all plant sizes the same direction, i.e. common frontier shifts over the whole range. For gas-fired plants results indicate technical regress, but again low in magnitude with 0.5 to 0.65%. Similarly, results indicate technical regress for the lignite-fired stations ranging from 0 to 0.3% technical regress. For coal, the TC component indicates basically no frontier shift at all. On the contrary, strong positive values between 0.6 and 10% technical change are found for the biomass plants. Again, the strongly positive values for the small biomass plants is driven by a large change in the first periods, but a positive trend is found also when neglecting these periods. Thus, our results indicate a considerably positive technical change only for biomass fired stations, while no considerable frontier shifts can be detected for the other technologies. This is not surprising given the overall little installations of capacity for coal and lignite. On the other hand, biomass combustion technology is not as mature as

the other technologies, which allows for larger initial productivity gains.

The *Pure Technological Catch Up (PTCU)* component measures the group frontier shifts relative to shifts of the metafrontier. Thus, the PTCU component does not evaluate changes for the average firm, but changes at the best practice of a group relative to the best practice for the whole sector. The results indicate a catch-up for coal, lignite and biomass, while values below one are found for gas-fired station. Again, the magnitude of this effect is found to be low for coal, lignite and gas, but much more pronounced for biomass. When comparing the PTCU component with the TC component and the TGR, one can see very high correlations revealing some interesting pattern. The generally higher values for PTCU compared to the TC component indicate that group frontiers partly caught-up to the metafrontier due to a downward shift of the latter. This means, that overall production potentials in the sector decreased. Furthermore, this also indicates that the decrease in the TGR for coal and biomass (compare 5 and 8) is partly driven by developments of the technology of the whole sector. Finally, the negative PTCU and TC scores for gas-fired stations indicate that gas is losing production potentials faster than the sector as a whole. However, this effect is partly offset by the positive EC component for gas.

Finally, the *Scale Efficiency Change (SEC)* component indicates changes in the optimal scale size of the firm. Given that initial scale efficiency estimates are already high with a minimum of 96% for biomass-fired stations and around 98% for the other technologies, only little gains are available in terms of scale efficiency. This is now reflected in the very small SEC component for all technologies that indicate basically no scale efficiency effects. Comparing this results to Seifert et al. (2014), which find much higher inefficiencies stemming from having non-optimal plant size, underlines again the effect of the estimation method on the results. The StoNED results indicate a very flat shape of the VRS production function, close to the CRS function, whilst the DEA estimate indicates considerable gaps between these frontiers for most technologies.

## 5 Conclusion

This paper analyzes productivity growth of the German electricity generating sector, which is the largest European electricity generating sector 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. Using a panel data set from 2003 to 2010 productivity growth for four different conventional combustion technologies, namely coal, lignite, gas and biomass is analyzed. A metafrontier framework allows to assess changes within these groups and evaluation of technological catch-up between technologies. For this purpose, a new metafrontier Malmquist decomposition in the style of Ray and Desli (1997) has been developed based on the work by Chen and Yang (2011). Finally, the use of the newly developed StoNED approach (Kuosmanen and Kortelainen, 2012) allows to base the estimation on a small number of assumptions with superior properties compared to standard DEA or SFA methods. The results indicate relatively small productivity changes irrespective of the fuel source. Further, our results indicate an overall reduction in production potential, i.e. a downwards shift of the sector production function. In the absence of efficient carbon capture technologies this is closely related to constant or even increasing CO<sub>2</sub> emissions per output unit. This casts doubt on the supporting effect of conventional energy sources in reaching Germany's ambitious climate goals. However, our results also indicate that biomass-fired stations experienced a considerable positive technical change during the sample period helping them to catch up to the conventional sources. This catch-up is accompanied by an efficiency decrease. This indicates that new potentials are not fully used, but that the frontier shift is driven by newly installed capacities rather than by technical progress of existing installations. As biomass is considered as less CO<sub>2</sub> intensive, this technology can support emission reduction. However, overall potential of use of biomass-fired power plants is naturally limited. For gas-fired power plants results indicate technical regress that is however offset with an increase in efficiency. On the contrary, the technology gap of the coal-fired power plants decreases over time due to the general downward shift of the metafrontier.

In comparison to the existing literature on productivity in the electricity generating sector our result show productivity growth estimates of a magnitude similar to other studies. Further, our results support the existing explanations of productivity changes. Similar to See and Coelli (2013) we find a technology with considerable capacity installations to possess higher rates of technical change. However, contrary to their finding, we do not observe a translation into overall productivity gains. Further, similar to Heshmati et al. (2014), results indicate no productivity gains for mature technologies.

However, contrary to their results, this analysis does not detect a stable downward trend in productivity.

Finally, the paper shows StoNED to be useful when estimating productivity changes. Although the frontier is absolutely flexible in its shape, results underline stability of the estimation procedure also for small data sets. Further, overall productivity evaluation is independent from distributional assumption and relies only on microeconomic assumptions on the shape of a production function. Generally, the method might underestimate intertemporal changes as the frontier is less sensitive against a small number of observations as for example newly installed capacities; however, the risk of overestimating productivity changes due to erroneous data is reduced.

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## A Appendix

### A.1 Derivation of Metafrontier Malmquist Decomposition

The aim of the MMPI decomposition is an index that explains productivity growth in the metafrontier with the elements of the group frontiers and connecting decomposition elements that link GMPI and MMPI. Output oriented MMPI and GMPI under VRS in the spirit of Fare et al. (1994) are defined as

$$\begin{aligned} MMPI^{crs} &= EC^{*,vrs} \times TC^{*,vrs} \times TC^{*,crs} / TC^{*,vrs} \times SC^{*} = \\ &MMPI^{vrs} \times TC^{*,crs} / TC^{*,vrs} \times SC^{*} \\ GMPI^{crs} &= EC^{c,vrs} \times TC^{c,vrs} \times TC^{c,crs} / TC^{c,vrs} \times SC^c = \\ &GMPI^{vrs} \times TC^{c,crs} / TC^{c,vrs} \times SC^c \end{aligned}$$

with the decomposition elements Efficiency Change ( $EC$ ), Technical Change under VRS ( $TC^{VRS}$ ) and CRS ( $TC^{CRS}$ ) and Scale Change ( $SC$ ). Ignoring the superscript of the relevant returns-to-scale assumption they are defined as

$$\begin{aligned} EC &= \frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)} \\ TC &= \left[ \frac{D_t(x_{t+1}, y_{t+1})}{D_{t+1}(x_{t+1}, y_{t+1})} \times \frac{D_t(x_t, y_t)}{D_{t+1}(x_t, y_t)} \right]^{1/2} \\ SC &= \frac{D_{t+1}^{crs}(x_{t+1}, y_{t+1}) / D_{t+1}^{vrs}(x_{t+1}, y_{t+1})}{D_t^{crs}(x_t, y_t) / D_t^{vrs}(x_t, y_t)} \end{aligned}$$

To connect the MMPI and the GMPI Chen and Yang (2011) introduce two more elements in their decomposition, the pure technological catch-up (PTCU) and the Frontier Catch-Up (FCU). They are defined as:

$$\begin{aligned} PTCU_{t,t+1}^c &= \frac{TGR_{t+1}^c(x_{t+1}, y_{t+1})}{TGR_t^c(x_t, y_t)} = \frac{D_{t+1}^*(x_{t+1}, y_{t+1}) / D_{t+1}^c(x_{t+1}, y_{t+1})}{D_t^*(x_t, y_t) / D_t^c(x_t, y_t)} \\ FCU_{t,t+1}^c &= \left[ \frac{TGR_t^c(x_{t+1}, y_{t+1})}{TGR_{t+1}^c(x_{t+1}, y_{t+1})} \times \frac{TGR_t^c(x_t, y_t)}{TGR_{t+1}^c(x_t, y_t)} \right]^{1/2} = \frac{TC_{t,t+1}^*}{TC_{t,t+1}^c} \end{aligned}$$

To derive a Metafrontier Malmquist decomposition, first rewrite PTCU to see that the catch-up is influenced by the efficiency change components. This decomposition of the PTCU indicates that if a firm is able to catch up faster to the metafrontier than to the group frontier, the shift of the group frontier needs to be larger. This leads to a PTCU value larger than one.

$$PTCU_{t,t+1}^c = \frac{D_{t+1}^*(x_{t+1}, y_{t+1}) / D_t^*(x_t, y_t)}{D_t^c(x_t, y_t) / D_{t+1}^c(x_{t+1}, y_{t+1})} = EC^{*} \times \frac{1}{EC^c}$$

Now, MMPI is multiplied and divided by PTCU and FCU relative to the VRS frontiers to derive

$$\begin{aligned} MMPI^{crs} &= MMPI^{crs} \times PTCU^{vrs} \times FCU^{vrs} \times \frac{1}{EC^{*,vrs}} \times EC^{c,vrs} \times \frac{1}{TC^{*,vrs}} \times TC^{c,vrs} \\ MMPI^{crs} &= [EC^{*,vrs} \times TC^{*,vrs} \times TC^{*,crs} / TC^{*,vrs} \times SC^{*}] \times PTCU^{vrs} \times FCU^{vrs} \times \\ &\frac{1}{EC^{*,vrs}} \times EC^{c,vrs} \times \frac{1}{TC^{*,vrs}} \times TC^{c,vrs} \end{aligned}$$

$EC^{*,vrs}$  and  $TC^{*,vrs}$  can cancel out. Further, with  $EC^{c,vrs}$  and  $TC^{c,vrs}$  we already have included the  $GMPI^{vrs}$ . Finally, multiplication and division adds the scale change component against the group frontier. Simplification yields the decomposition outlined in section 2.3.1:

$$\begin{aligned}
 MMPI^{crs} &= EC^{c,vrs} \times TC^{c,vrs} \times PTCU^{vrs} \times FCU^{vrs} \times SC^* \times TC^{*,crs} / TC^{*,vrs} \\
 MMPI^{crs} &= EC^{c,vrs} \times TC^{c,vrs} \times SC^c \times PTCU^{vrs} \times FCU^{vrs} \times SC^* / SC^c \times TC^{*,crs} / TC^{*,vrs} \\
 MMPI^{crs} &= GMPI^{c,vrs} \times SC^c \times PTCU^{vrs} \times FCU^{vrs} \times SC^* / SC^c \times TC^{*,crs} / TC^{*,vrs}
 \end{aligned}$$

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## A.2 Descriptive Statistics

Coal	2003	2004	2005	2006	2007	2008	2009	2010
q25	85.80	73.80	103.80	108.80	92.00	101.20	127.60	107.20
med	301.10	292.00	301.30	273.40	373.00	343.00	410.00	410.00
q75	616.00	519.90	624.40	554.90	652.00	636.30	704.30	727.10
q25	8303.00	4990.50	7939.60	7592.70	7003.20	5695.80	5026.00	3946.40
med	18150.70	15588.70	16450.90	15955.90	15346.00	15432.10	15256.60	13867.00
q75	30560.70	26158.90	29756.50	27563.40	30623.40	28676.10	26494.00	26144.70
q25	219.80	206.10	191.50	197.20	196.50	184.80	181.10	173.40
med	321.30	282.10	242.30	246.20	259.70	259.20	298.30	293.30
q75	709.60	677.60	627.60	610.00	575.90	603.50	644.90	653.30
q25	1023.30	688.70	1079.20	1105.90	963.20	871.50	962.50	835.60
med	2569.40	2480.10	2673.40	2180.40	2473.40	2424.10	2214.50	1970.40
q75	3677.30	3217.90	3563.50	3249.40	3442.70	3562.60	2996.00	3283.40

*Notes:* Capital is measured in MW, Fuel in thousand GJ, Labor in 100 hours, Output in GWh

**Table 12:** Descriptive statistics: Coal



<b>Lignite</b>	2003	2004	2005	2006	2007	2008	2009	2010
q25					76.17	74.00	73.33	
Capital med	650.17	224.04	387.00	323.50	838.33	843.33	638.75	920.00
q75					1875.46	1795.46	1606.88	
q25					8507.91	8232.74	7819.58	
Fuel med	45486.90	17054.39	23644.58	20071.29	51660.31	49248.29	39191.50	62275.41
q75					158507.91	148580.79	133057.01	
q25					106.00	106.75	96.84	
Labor med	348.40	170.69	217.26	207.59	284.01	284.02	287.06	487.67
q75					1066.79	1034.82	906.60	
q25					746.88	717.27	663.44	
Output med	5226.30	1688.11	2338.15	1975.76	6014.39	5742.40	4313.03	7338.54
q75					15111.15	14161.93	12410.95	

*Notes:* Capital is measured in MW, Fuel in thousand GJ, Labor in 100 hours, Output in GWh

**Table 13:** Descriptive statistics: Lignite

<b>Gas</b>	2003	2004	2005	2006	2007	2008	2009	2010
q25	1.68	1.42	1.20	1.44	1.49	1.83	2.00	1.87
med	3.69	3.96	2.93	4.50	4.52	4.61	4.63	4.40
q75	31.07	20.00	20.10	19.02	13.18	16.75	16.87	19.50
q25	46.40	68.17	61.80	81.20	75.72	85.65	85.15	85.73
med	130.51	234.01	155.00	214.97	215.88	232.82	249.22	246.96
q75	828.08	878.63	947.31	904.91	712.01	1106.88	959.98	876.26
q25	54.49	67.03	54.12	66.64	66.25	60.46	55.35	53.42
med	108.46	113.31	109.01	114.30	113.45	109.26	108.47	110.58
q75	207.81	204.46	213.46	202.58	201.60	198.07	182.89	188.54
q25	9.64	12.57	12.15	16.21	16.64	18.95	18.16	19.93
med	26.16	45.74	32.83	46.72	43.45	44.49	52.67	45.56
q75	184.53	201.00	218.20	215.01	141.68	224.62	207.12	194.12

*Notes:* Capital is measured in MW, Fuel in thousand GJ, Labor in 100 hours, Output in GWh

**Table 14:** Descriptive statistics: Gas

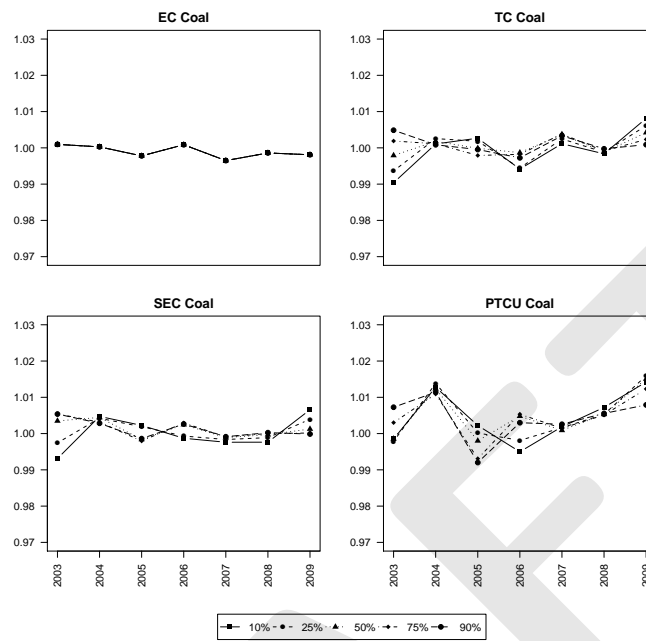
<b>Biomass</b>	2003	2004	2005	2006	2007	2008	2009	2010
q25	7.82	1.73	4.37	3.70	3.08	4.87	4.94	5.51
med	14.98	6.00	9.91	10.50	8.99	10.88	11.22	12.47
q75	27.26	10.57	12.56	14.30	16.04	17.52	17.50	18.00
q25	629.60	468.65	487.68	616.28	391.44	549.83	552.61	644.27
med	1332.16	708.52	1363.10	986.29	1227.98	1225.32	710.38	772.94
q75	2148.86	1701.91	2576.62	1579.75	1709.17	1512.06	1703.58	1699.10
q25	89.57	63.86	87.77	41.67	34.81	36.67	30.14	32.23
med	116.19	106.11	121.62	110.84	92.87	84.87	47.15	46.63
q75	213.13	158.60	219.80	146.03	131.26	144.39	127.74	118.08
q25	34.90	35.22	47.81	38.11	36.31	43.44	47.31	59.47
med	111.56	85.39	90.42	82.55	102.91	109.42	106.38	96.68
q75	225.52	170.10	165.90	129.17	132.34	153.93	165.36	167.30

*Notes:* Capital is measured in MW, Fuel in thousand GJ, Labor in 100 hours, Output in GWh

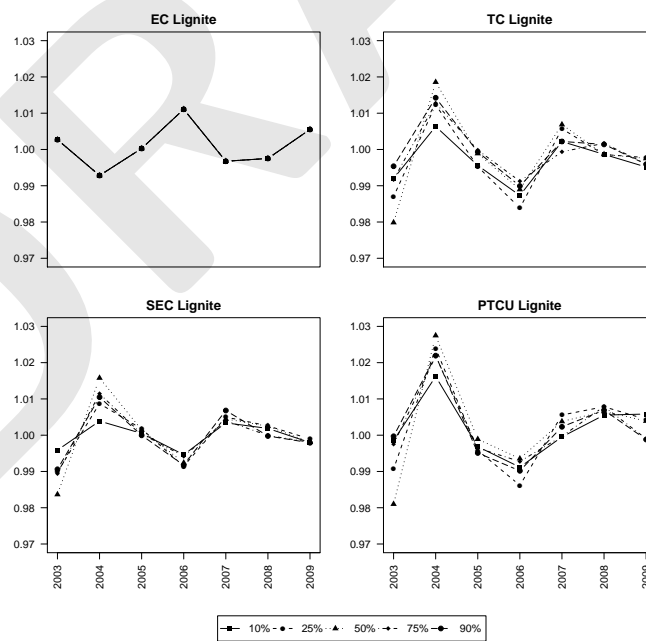
**Table 15:** Descriptive statistics: Biomass

### A.3 Graphical illustration of MMPI decomposition

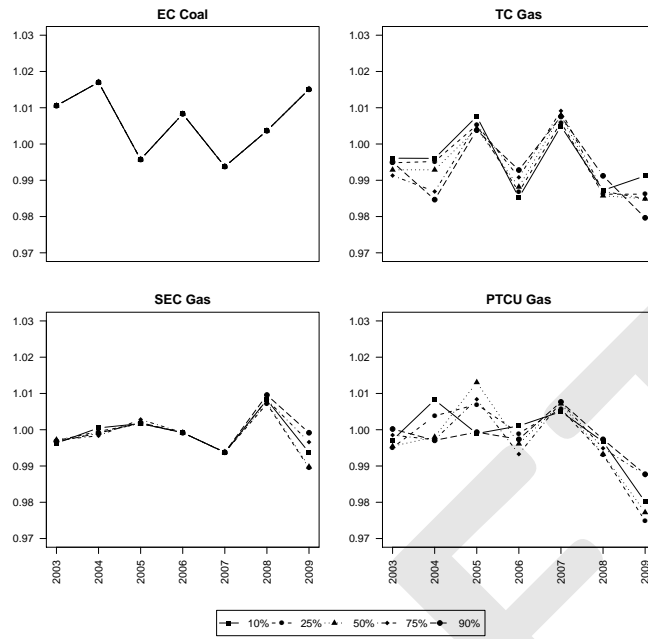
#### MMPI decomposition for coal-fired stations



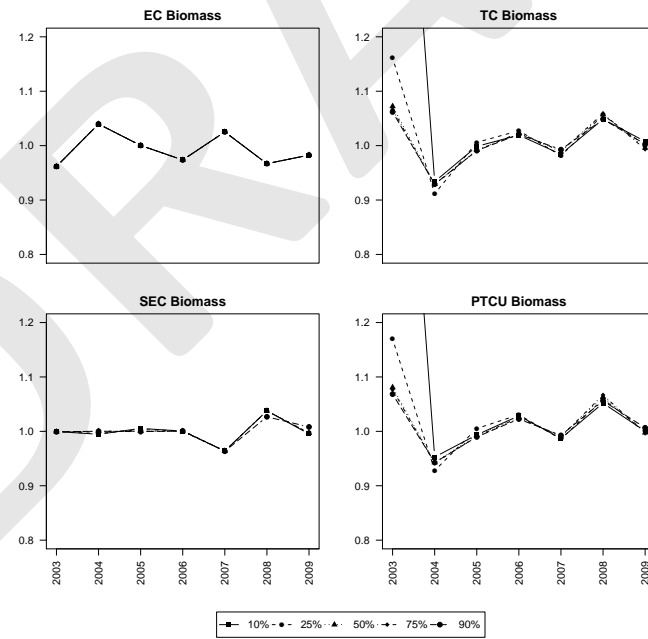
#### MMPI decomposition for lignite-fired stations



## MMPI decomposition for gas-fired stations



## MMPI decomposition for biomass-fired stations



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