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Deutsches Institut für Wirtschaftsforschung 2015

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IMPRESSUM

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http://www.diw.de

ISSN electronic edition 1619-4535

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Measuring Productivity When Technologies Are Heterogeneous - A Semi-Parametric Approach for Electricity Generation

Stefan Seifert*

November 25, 2015

Abstract

While productivity growth in electricity generation is associated with multiple positive effects from an economic and environmental perspective, measuring it is challenging. This paper proposes a framework to estimate and decompose productivity growth for a sector characterized by multiple technologies. Using a metafrontier Malmquist decomposition and frontier estimation based on stochastic non-smooth envelopment of data (StoNED) allows for productivity estimation with few microeconomic assumptions. Additionally, evaluation of productivity at representative hypothetical units permits distribution-free analysis for the whole distribution of power plant sizes. The proposed framework is used to analyze a unique and rich dataset of coal, lignite, gas, and biomass-fired generators operating in Germany from 2003 to 2010. The results indicate stagnating productivity for the sector as a whole, technical progress for biomass plants, and very high productivity for gas-fired plants.

JEL-Codes: D24,C14,O13,L94

Keywords: Productivity estimation, Metafrontier Malmquist Decomposition, Stochastic Non-Smooth Envelopment of Data (StoNED), Electricity and Heat Generation in Germany, 2003 - 2010

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[0]This paper was part of the project KOMIED (Municipal infrastructure companies against the background of energy policy and demographic change) financed by Leibniz Association

1 Introduction

Productivity growth in electricity generation is associated with multiple positive effects: First, productivity growth can free resources for other uses, e.g., labor and capital. Furthermore, productivity growth can lead to overall reduced consumption of scarce natural resources, like fossil fuels. Therefore, productivity growth can also reduce import dependencies. More productive use of combustible materials can reduce also CO_2 emissions, either by reducing the fuel input or by replacing more CO_2 intensive technologies (Davis and Wolfram, 2012). Thus, productivity growth may ultimately help achieve ambitious climate goals. Finally, in addition to the positive environmental effects, productivity growth in electricity generation can be translated into lower electricity prices, a major input for the whole economy (Fabrizio et al., 2007). To achieve such productivity gains, multiple channels are available.

Increasing technical efficiency of existing plants helps use resources more productively and allows for reduced resource use within pre-existing industry structures. Further, technical progress and learning allows to achieve new productivity levels with existing technologies, but may demand a restructuring of the power plant fleet. Similarly, reducing scale inefficiencies may facilitate productivity gains, but either needs technical change to reduce potential scale inefficiencies (i.e. by increasing the range of optimal plant sizes) or plants modified toward the optimal size. Finally, introduction of new technologies, often with steep learning curves, may allow existing plants to achieve new productivity levels (Jamasb, 2007). However, measuring productivity growth and disentangling the different drivers (e.g. efficiency gains or technical change) is challenging as the sector is characterized by heterogeneous technologies, in terms of fuel sources, combustion technologies, and plant sizes.

Motivated by the need to develop a more accurate measure of productivity growth, this paper proposes a framework to estimate and decompose productivity in a sector with technological heterogeneity and applies it to analyze Germany's electricity sector. The use of a metafrontier Malmquist productivity index based on Chen and Yang (2011) incorporates productivity growth at the subtechnology level when estimating sectoral productivity developments. Analysis based on the semi-parametric stochastic non-smooth envelopment of data (StoNED), as proposed by Kuosmanen and Kortelainen (2012), estimates productivity growth with only a few microeconomic assumptions on the shape of the production function while allowing for a parametric treatment of operational inefficiency and random disturbance. The estimator also estimates overall productivity growth without any distributional assumptions or assumptions about the functional form while reducing sensitivity to outliers. Further, constructing hypothetical but representative evaluation units measures productivity developments for the whole distribution of power plant sizes without influencing the frontier estimate. Using this framework, I measure productivity growth and its components for the first time for the German electricity generating sector. The German electricity generating sector is an important and an especially interesting case to study with considerable changes in the industry structure, and with a special role of conventional energy sources. The study uses a unique and uncommonly rich dataset of 1555 coal, lignite, gas and biomass-fired power plants operating in Germany between 2003 and 2010.

Results show that the approach is stable for small and large samples and allows disentangling the different effects at the subtechnology and sector levels. Empirical results indicate that the German electricity generating sector has undergone a period of productivity stagnation and technological regress. However, results also indicate technical progress for biomass-fired power plants allowing them to catch-up to the productivity of other technologies. Nonetheless, gas-fired plants are found to have the highest productivity throughout the observation period.

The remainder of this paper is organized as follows. Section 2 gives an overview of Germany's electricity generating sector, and summarizes the related literature. Section 3 presents the model and the proposed productivity decomposition. Section 4 describes the estimation strategy and section 5 presents the dataset. Section 6 explains the results of the analysis, and section 7 concludes.

2 Background

2.1 Measuring productivity growth in electricity generation

The Malmquist productivity index is probably the most prominent approach to measure productivity growth and is also used to analyze electricity generation (e.g. Färe et al., 1990). Based on the seminal paper by Caves et al. (1982), which introduced this distance function based approach, a large number of productivity decompositions have since been developed and applied to a variety of sectors (see Färe et al., 2008, for an overview). To account for technological heterogeneity as in electricity generation, O'Donnell et al. (2008) extend this approach based on the metafrontier framework, in the spirit of Hayami and Ruttan (1970) and Battese et al. (2004), to measure productivity against the sector production function, also termed metatechnology, while accounting for the productivity developments of subtechnologies. Chen and Yang (2011) extend this approach to account for scale-related productivity growth as in Ray and Desli (1997) while allowing for efficiency gains and technical change on the level of the subtechnologies.

While this extended Malmquist approach is not applied to electricity generation, studies accounting for heterogeneity in electricity generation use similar ideas to allow for technological differences based on the power plants location (e.g. Zhang and Choi, 2013) or plant fuels (e.g. Seifert et al., 2014; Zhang et al., 2013). Accounting for such technological differences when measuring productivity developments allows for the identification of productivity trends as well as the major components on sectoral and subtechnological level, i.e. efficiency gains, technical change, and scale adjustments, which are generally deemed major drivers of productivity growth.

In the empirical literature on power plant productivity, results generally indicate relatively small magnitude productivity changes in developed economies. For example, Heshmati et al. (2014) find productivity decline between 1995 and 2006 for Korean electricity generation, and Atkinson and Primont (2002) find only small productivity gains between 1961 and 1997 for United States electricity generation. Rungsuriyawiboon and Stefanou (2008) and Genius et al. (2012) obtain similar results, i.e. partial productivity growth with respect to labor, but not with respect to fuel. On the contrary, higher productivity growth rates are reported by See and Coelli (2013) for Malaysia, and by Du et al. (2013) and Gao and Van Biesenbrock (2014) for China, thus suggesting that developing countries may not have exploited potential productivity gains.

Increasing efficiency and producing with best practice is one key element to increase productivity. While a large number of studies address the measurement of inefficiency,[1] the regulatory environment is critical for inducing efficiency gains. The introduction of alternative regulatory schemes and more market-oriented mechanisms in the US is shown to incentivize inefficiency reductions for both conventional combustion plants (Craig and Savage, 2013; Fabrizio et al., 2007; Knittel, 2002; Kleit and Terrell, 2001) and nuclear power plants (Davis and Wolfram, 2012). Further, evidence suggests that such efficiency gains are actually driven by changes in the incentive structure imposed by the regulatory framework, rather than by changes in ownership (Bushnell and Wolfram, 2005). To realize such efficiency gains, Cicala (2015) shows that deregulation can improve fuel procurement practices leading to lower input prices. Likewise, Chan et al. (2014) point out that fuel quality is a key determinant for efficiency of combustion plants, and that operating and maintenance practices can lead to considerable efficiency improvements. Labor quality is also identified as a major determinant of power plant operational efficiency (Bushnell and Wolfram, 2007).

Technical progress and the introduction of new technologies also drive productivity growth (Aghion and Howitt, 1992). Although learning by doing and learning by research are typically considered as the two drivers of technical progress, they have considerably different effects on the different subtechnologies of the electricity generat-

[1] For extensive overviews see Seifert et al. (2014); Song et al. (2013); Zhou et al. (2008).

ing sector. As Rubin et al. (2015) and Jamasb (2007) illustrate, evolving technologies, such as biomass and waste to electricity, show higher learning rates than mature technologies, such as coal and lignite combustion technologies. Other plant-level studies question whether such learning rates actually transform into productivity gains finding either low levels of technical progress (Atkinson and Primont, 2002; Genius et al., 2012) or even technical regress (Oh, 2015; Heshmati et al., 2014). In contrast, See and Coelli (2013) find considerable technical productivity growth for mature technologies as a result of capacity installations. Further, increased competitive pressure, induced by subsidized emerging technologies, such as wind and solar, or electricity deregulation, can affect innovation and technical progress. The widely supported belief in "creative destruction" argues that competition actually forces firms to innovate in order to remain competitive. Experimental evidence supports the hypothesis (e.g Aghion et al., 2014), although other theoretical (Vives, 2008) and empirical (Sanyal and Ghosh, 2013) studies indicate a decline in innovation as a result of deregulation and competition.
Scale change or scale efficiency change is also a driver of productivity growth. Further, not using economies of scale in the production of electricity may be directly translated into damages to scale in the production of undesirable outputs, such as CO_2 emissions (Sueyoshi and Goto, 2013). From a production perspective, adjusting the scale of a power plant fleet takes considerable time, even requiring a complete restructuring of the fleet's generation capacities. From a cost perspective, however, adjusting to optimal scale size is not necessarily based on restructuring generation capacities. Empirical analyses of scale effects typically indicate increasing returns to scale for electricity generation. Nerlove (1963), Christensen and Greene (1976), Betancourt and Edwards (1987) and Kleit and Terrell (2001), who study US electricity generation, all found considerable scale economies at low levels of output, which, however, diminish with firm size. For Korean electricity generation, Oh (2015) indicates scale economies across all firm sizes.

2.2 Germany's electricity generating sector

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. Figure 1 shows that conventional combustion plants, including coal, lignite, gas and biomass-fired power plants, account for almost 95 GW. While capacities have been stable for coal and lignite, considerable new installations and capacity extensions for gas and biomass have taken place. At the same time, policy is fostering sizable investments in renewable energy sources. In

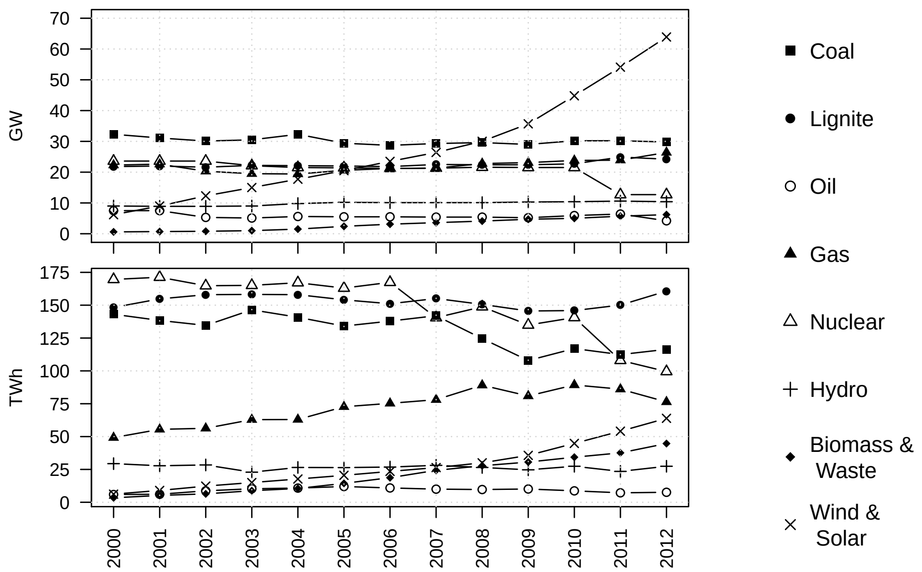

Figure 1: Germany's electricity generation capacities (top) and generation (bottom) from 2000 to 2012 (Source: BMWi, 2012)

2013, wind and solar contributed around 70 GW in capacity, up from 15 GW 2003.[2] Germany's nuclear phase-out - agreed upon in 2002 and renewed in 2011 - will result in 12 GW of capacity being eliminated by 2022. These changes in the capacity structure also impact 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. Similarly, for gas-fired plants we observe a strong increase in output between 2000 and 2012 of more than 50%.

Although Germany's energy mix is undergoing long-term changes to enhance the role of renewables, conventional combustion technologies are still required to not just back up these intermittent sources, but also to partially replace nuclear capacity. Thus, competition with the almost zero-variable cost competitors, wind and solar, will cause considerable pressure on productivity developments in Germany's conventional combustion technologies. There is already discussion about the necessity of capacity markets for Germany (BMWi, 2014). Further, technological plurality underscores the need to account for productivity development at the subtechnology level in order to derive reliable productivity growth estimates of the existing industry structure.

[2]The newly installed capacities are of very different size. Accounting for installations above 10 MW between 2003 and 2010, the average renewable installation has a capacity of about 22 MW, while gas-fired plants have an average size of more than 150 MW. Total installations above 10 MW for gas-fired plants and renewables are both above 7 GW; however, 320 installations of renewables and only 46 gas-fired plants above 10 MW were constructed from 2003 to 2010.

3 Model

3.1 Production processes with heterogenous technologies

I $(i = 1, ..., I)$ decision making units (DMUs, power plants in this case) are observed in T $(t = 1, ...T)$ periods. Each power plant uses a technology to transform an m dimensional input vector x_{it} $(x \,\epsilon\, \mathbb{R}^m_+)$ into scalar output y_{it} $(y \,\epsilon\, \mathbb{R})$. Further, denote by Ψ^*_t the entirety of feasible production plans, $(x_{it}, y_{it}) \in \Psi^*_t$. In t, the boundary of Ψ^*_t can be represented by the production function $f^*_t : \mathbb{R}^m_+ \rightarrow \mathbb{R}_+$. Following microeconomic theory, f^*_t 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 $u > 0$ such that $y_{it} = f^*_t(x_{it}) * exp(-u_{it})$. This production function, termed metafrontier (Hayami and Ruttan, 1970), represents the maximum production for each input level for the I observations in period t. To model heterogeneity in electricity generation, assume that each DMU has chosen one of C $(c = 1, ..., C)$ technologies and could thus realize all potential input-output combinations in Ψ^c_t. c represents the plants' combustion technology by fuel type, and choosing c prevents the plants from fuel-switching. Therefore, this divides the sample into C groups with each group representing one combustion technology. A production function f^c_t (group technology or subtechnology) defines the attainable maximum output for a given level of input with technology c. Again, observed output may deviate from this maximum due to inefficiency such that $y_{it} = f^c_t(x_{it}) * exp(-u^c_{it})$. By definition, the production possibility set for each group technology is a subset of the metatechnology, $\Psi^c_t \subseteq \Psi^*_t$. Therefore, the metatechnology production function envelops all group technologies, $f^*_t(x) \geq f^c_t(x)\ \forall x$.

To formalize the relationship between DMUs and frontiers, D^*_t denotes the output distance function of a an input-output combination (x^c_t, y^c_t) to f^*_t. Likewise, denote the distance of an observation that has chosen c to the corresponding f^c_t by D^c_t, and define

$$\begin{aligned} D^*_t(x, y) &= inf\{\phi^* > 0 : (x, y/\phi^*) \in \Psi^*_t\} \qquad (1) \\ D^c_t(x, y) &= inf\{\phi^c > 0 : (x, y/\phi^c) \in \Psi^c_t\} \end{aligned}$$

where ϕ^* and ϕ^c give the potential expansion of output for a given input level relative to f^*_t and f^c_t. Doing so relates the locations of the metafrontier and the group frontiers using the technology gap ratio (TGR). The TGR measures the distance between group and metatechnology for an input-output combination as $TGR_t(x, y) =$

$D_t^*(x,y)/D_t^c(x,y)$. If $TGR=1$, technology c can produce maximum output for a given input level. 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.

3.2 Estimating and decomposing productivity growth

Using the definition of a distance function introduced in equation 1, the output-oriented Malmquist productivity index (MPI) is calculated following Färe et al. (1994a), which is based on a constant returns to scale (CRS) technology as

$$MPI_t^{crs}(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D_t^{crs}(x_{t+1}, y_{t+1})}{D_t^{crs}(x_t, y_t)} \tag{2}$$

where the MPI measures productivity growth relative to some 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:

$$MPI_{t,t+1}^{crs}(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{D_t^{crs}(x_{t+1}, y_{t+1})}{D_t^{crs}(x_t, y_t)} \times \frac{D_{t+1}^{crs}(x_{t+1}, y_{t+1})}{D_{t+1}^{crs}(x_t, y_t)}\right]^{1/2} \tag{3}$$

To account for a variable returns to scale (VRS) technology, the use of a scale change factor following the decomposition by Färe et al. (1994b) differentiates three different factors technical efficiency change (EC), technical change (TC) and scale efficiency change (SEC), and superscript RTS refers to the returns to scale of the technology as

$$MPI_{t,t+1}^{crs}(x_t, y_t, x_{t+1}, y_{t+1}) = EC^{vrs} \times TC^{vrs} \times TC^{crs}/TC^{vrs} \times SC \tag{4}$$

$$EC^{vrs} = \frac{D_{t+1}^{vrs}(x_{t+1}, y_{t+1})}{D_t^{vrs}(x_t, y_t)} \tag{5}$$

$$TC^{RTS} = \left[\frac{D_t^{RTS}(x_{t+1}, y_{t+1})}{D_{t+1}^{RTS}(x_{t+1}, y_{t+1})} \times \frac{D_t^{RTS}(x_t, y_t)}{D_{t+1}^{RTS}(x_t, y_t)}\right]^{1/2} \tag{6}$$

$$SEC = \frac{D_{t+1}^{crs}(x_{t+1}, y_{t+1})/D_{t+1}^{vrs}(x_{t+1}, y_{t+1})}{D_t^{crs}(x_t, y_t)/D_t^{vrs}(x_t, y_t)} \tag{7}$$

Note that the VRS based Malmquist index measures productivity changes and its components relative to a technology in two consecutive periods. An MPI score greater than unity indicates productivity growth, $EC>1$ indicates an increase in technical efficiency over time, $TC>1$ indicates positive technical change (i.e. an upward shift

of the technology), and $SEC > 1$ indicates an increase in scale efficiency.[3]
Next, productivity growth in a sector with multiple group technologies is analyzed by using a metafrontier Malmquist productivity index (MMPI) that measures productivity growth relative to the metafrontier as the benchmark technology with $MMPI = EC^{*} \times TC^{*,vrs} \times TC^{*,crs}/TC^{*,vrs}$. Note that the Malmquist decomposition neglects the position of the frontier of the C subtechnologies relative to the metafrontier. The relationship is incorporated by two additional decomposition factors following Chen and Yang (2011). That is, a Pure Technological Catch-Up ($PTCU$) component is used to measure the change of the TGR by comparing the TGR for one DMU in two consecutive periods. A Frontier Catch-Up (FCU) component measures the change in the distance over a whole band of technology gaps. Define the two components

$$PTCU^{c}_{t,t+1} = \frac{TGR^{c}_{t+1}(x_{t+1}, y_{t+1})}{TGR^{c}_{t}(x_t, y_t)} = \frac{D^{*}_{t+1}(x_{t+1},y_{t+1})/D^{c}_{t+1}(x_{t+1},y_{t+1})}{D^{*}_{t}(x_t,y_t)/D^{c}_{t}(x_t,y_t)} = EC^{*} \times \frac{1}{EC^{c}} \tag{8}$$

$$FCU^{c}_{t,t+1} = \left[\frac{TGR^{c}_{t}(x_{t+1}, y_{t+1})}{TGR^{c}_{t+1}(x_{t+1}, y_{t+1})} \times \frac{TGR^{c}_{t}(x_t, y_t)}{TGR^{c}_{t+1}(x_t, y_t)}\right]^{1/2} = \frac{TC^{*}_{t,t+1}}{TC^{c}_{t,t+1}} \tag{9}$$

A $PTCU$ score larger than unity indicates a shrinking technology gap, i.e. a catch-up relative to the metafrontier for a specific firm, where a value smaller than one for the FCU component 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), I derive an MMPI decomposition including the FGNZ scale efficiency change component. First, MMPI is multiplied and divided by PTCU and FCU relative to the VRS frontiers to derive

$$\begin{aligned} MMPI^{crs} =& MMPI^{crs} \times PTCU^{vrs} \times FCU^{vrs} \\ & \times \frac{1}{EC^{*,vrs}} \times EC^{c,vrs} \times \frac{1}{TC^{*,vrs}} \times TC^{c,vrs} \\ =& [EC^{*,vrs} \times TC^{*,vrs} \times TC^{*,crs}/TC^{*,vrs} \times SEC^{*}] \times PTCU^{vrs} \times FCU^{vrs} \\ & \times \frac{1}{EC^{*,vrs}} \times EC^{c,vrs} \times \frac{1}{TC^{*,vrs}} \times TC^{c,vrs} \end{aligned} \tag{10}$$

where $EC^{*,vrs}$ and $TC^{*,vrs}$ can cancel out. Further, with $EC^{c,vrs}$ and $TC^{c,vrs}$ we already have included a VRS-based group frontier Malmquist productivity index ($GMPI$), $GMPI^{vrs} = EC^{c,vrs} \times TC^{c,vrs}$. Finally, multiplication and division adds the scale

[3] There is considerable debate about the interpretation of the Färe et al. (1994b) decompostion. Ray and Desli (1997) propose a decomposition based on another scale change factor, but it is not applicable to this study because it does not indicate scale effects in the one-output case if there is no or little variation in the inputs.

efficiency change component against the group frontier, and simplification yields

$$
\begin{aligned}
MMPI^{crs} =&EC^{c,vrs} \times TC^{c,vrs} \times PTCU^{vrs} \times FCU^{vrs} \times SEC^{*} \times TC^{*,crs}/TC^{*,vrs} \\
=&EC^{c,vrs} \times TC^{c,vrs} \times SEC^{c} \times PTCU^{vrs} \times FCU^{vrs} \\
&\times SEC^{*}/SEC^{c} \times TC^{*,crs}/TC^{*,vrs} \\
=&GMPI^{c,vrs} \times SEC^{c} \times PTCU^{vrs} \times FCU^{vrs} \\
&\times SEC^{*}/SEC^{c} \times TC^{*,crs}/TC^{*,vrs}
\end{aligned} \tag{11}
$$

where MMPI measures productivity growth against the metafrontier. Again, $MMPI > 1$ indicates productivity growth, and $MMPI < 1$ indicates a decline. The decomposition relates this productivity growth to productivity growth on a group frontier level measured with a VRS group frontier Malmquist productivity index, GMPI, with $GMPI^{c,vrs} = EC^{c,vrs} \times TC^{c,vrs}$. Again, $GMPI > 1$, $EC > 1$, and $TC > 1$ indicate productivity growth, efficiency increase, and positive technical change, respectively. $PTCU$ and FCU work as outlined above.
Finally, two other components remain in the decomposition: The first, SEC^{*}/SEC^{c}, relates the scale efficiency change component against the metafrontier and the groupfrontier. If $SEC^{*}/SEC^{c} > 1$, the scale gains against the metafrontier are greater than the scale gains against the group frontier. The second, $TC^{*,crs}/TC^{*,vrs}$, indicates a greater technical change at the optimal plant size compared to the technical change measured against the VRS frontier if $TC^{*,crs}/TC^{*,vrs} > 1$, and vice versa.

4 Estimation strategy

4.1 Stochastic non-smooth envelopment of data

To measure productivity using the approach outlined in section 3.2 the boundaries of the technology sets Ψ_t^* and Ψ_t^c need to be estimated in order to measure the corresponding distance functions D_t^* and D_t^c. For the estimation of the group frontiers and the metafrontier, I use stochastic non-smooth envelopment of data (StoNED) (Kuosmanen and Kortelainen, 2012). This approach consists mainly of two steps: first, estimate a piece-wise linear average production function $g(x)$ using convex non-parametric least squares (CNLS). This estimation is free of any distributional assumptions or assumptions on a functional form but incorporates shape restrictions based on microeconomic theory. In a second stage, based on distributional assumptions, estimates for the parameters of inefficiency (u) are obtained to shift the estimated average production function $\hat{g}(x)$ upwards by the expected value of inefficiency to get a frontier estimate

$\hat{f}(x)$, while taking a random disturbance (v) into account. Thus, this method combines aspects of the two standard methods DEA and SFA.[4]

For the first stage, Kuosmanen (2008) derives a representation of the infinitely many monotonically increasing, concave, and continuous (not necessarily differentiable) functions that solve the corresponding least squares problem. Kuosmanen and Kortelainen (2012), who extend the approach to the case of a production function with a multiplicative error term $\varepsilon_i = v_i - u_i$ with noise v_i and inefficiency u_i such that $y_i = f(x_i) * exp(\varepsilon_i) = f(x_i) * exp(v_i - u_i)$, derive a quadratic programming problem (QP) to obtain intercept and slope estimates for the average production function based on the log-transformed multiplicative model.[5] This paper uses the extension to estimate the average production function $g_t(x)$ in each year separately for each group technology and for the metatechnology by solving the following non-linear QP

$$\begin{aligned} &\min_{\alpha,\beta,\hat{y}} \sum_{i=1}^{n} (\ln y_{it} - \ln \hat{y}_{it})^2 && (12)\\ &\hat{y}_{it} = \alpha_{it} + \beta'_{it} x_{it} \\ &\alpha_{it} + \beta'_{it} x_{it} \leq \alpha_{ht} + \beta'_{ht} x_{it} && \forall i, h = 1, ..., n \\ &\beta_{it} \geq 0 && \forall i = 1, ..., n \end{aligned}$$

where x_{it} and y_{it} represent all observed input-output combinations for plants using technology c if a group frontier in t is estimated. Otherwise, include all in t observed points if the metafrontier is estimated. The QP tries to find the α and β coefficients that minimize the sum of the squared residuals η_{it} with $\eta_{it} = \ln y_{it} - \ln \hat{y}_{it}$. α and β are firm-specific estimates for intercept and 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, the second constraint imposes concavity of the estimated function using Afriats theorem (Afriat, 1967), and the third constraint imposes monotonicity. As no further restrictions are imposed on the sign of α, the estimated frontier is allowed to have VRS. Note that a CRS model can be imposed by setting $\alpha = 0$. Furthermore, the QP delivers fitted values $\hat{y}_{it}$ on these hyperplanes. The $\hat{y}_{it}$ are typi-

[4]Similar to DEA, the production frontier is estimated without specification of a functional form and based on only a few microeconomic assumptions concerning the shape of a production function (concavity, monotonicity, and continuity). Similar to SFA, disentangling noise and inefficiency is possible based on distributional assumptions for v and u. Thus, StoNED combines the advantages of both methodologies and, as Kuosmanen and Kortelainen (2012) point out, DEA and SFA are special cases of the StoNED with additional assumptions either on the error term (no noise for DEA), or the functional form (specified $f(x)$ for SFA)

[5]Additional assumptions: u_i and v_i are assumed to be independent. v_i has a symmetric distribution with finite variance σ_v^2, u_i takes only positive values and has a finite variance σ_u^2.

cally unique, whereas the αs and βs are typically non-unique. Therefore, following the minimal extrapolation principle (Banker et al., 1984), using the lower envelope of these fitted values estimates the average production function $\hat{g}(x)$.[6]

To estimate the $n*m+n$ parameters in the VRS case ($n*m$ parameters under CRS), the second and the third constraint sum up to $n*n+n$ constraints ($n*n$ under CRS). Since the concavity constraints impose a large number of restrictions ($n*n$), which is computationally burdensome for large datasets, this paper uses a sweet spot approach following Lee et al. (2013). This algorithm is based on the assumption that the relevant hyperplane of an observation is most likely influenced only 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, the most violated constraint for each observation is added. This procedure is repeated iteratively until no constraint is violated, thus assuring optimality of the solution.

After obtaining the α and β coefficients in the first stage, the residuals, η_{it}, are used to recover estimates for the parameters of the distributions of inefficiency and noise in each t for each of the C group technologies and the metafrontier. Based on these estimates, $\hat{g(x)}$ is shifted to obtain a frontier estimate. To derive these parameters, more detailed distributional assumptions are needed 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 $\varepsilon_i = v_i - u_i$ is assumed to follow a normal-half-normal distribution. To recover the variance parameters, σ_u and σ_v, Kuosmanen and Kortelainen (2012) suggest decomposing the residuals from the first stage (η_{it}) using a pseudolikelihood estimator (PSL), as proposed by Fan et al. (1996) (FLW).[7] Therefore, for each t and for each c a log-likelihood function for the normal-half-normal model as a function of a single parameter $\lambda \equiv \sigma_u/\sigma_v$, with Φ denoting the cumulative distribution function of a standard normal, is expressed such that

[6]Thus, $g(x)$ has a piece-wise linear shape similar to DEA.

[7]Kuosmanen and Kortelainen (2012) also consider a Method of Moments estimator similar to modified ordinary least squares (MOLS). This estimator is less efficient and therefore not used in this paper.

$$\ln L(\lambda) = -n \ln \hat{\sigma} + \sum_{i=1}^{n} \ln \Phi \left[\frac{-\hat{\epsilon}_i \lambda}{\hat{\sigma}} \right] - \frac{1}{2\hat{\sigma}^2} \sum_{i=1}^{n} \hat{\epsilon}_i{}^2 \tag{13}$$

$$\text{with} \qquad \hat{\epsilon}_i = \hat{\eta}_i - (\sqrt{2}\lambda\hat{\sigma})/[\pi(1+\lambda^2)]^{1/2} \tag{14}$$

$$\text{and} \qquad \hat{\sigma} = \left(\left[\frac{1}{n} \sum_{i=1}^{n} \hat{\eta}_i \right] \Big/ \left[1 - \frac{2\lambda^2}{\pi(1+\lambda^2)} \right] \right)^{1/2} \tag{15}$$

Maximization of the likelihood function delivers estimates of λ and subsequently $\hat{\sigma}$. Further, $\hat{\sigma}_u = \hat{\sigma}\hat{\lambda}/(1+\hat{\lambda})$ and $\sigma_v = \hat{\sigma}/(1+\hat{\lambda})$ provide the estimates of $\hat{\sigma}_u$ and $\hat{\sigma}_v$. Given this estimate of the variance of the inefficiency, the expected value of inefficiency, $\hat{\mu}$, is calculated as $E(u_i) = \hat{\mu} = \hat{\sigma}_u \times \sqrt{2/\pi}$. This estimation is carried out separately for each technology and the metatechnology, in each of the T periods, and under CRS and VRS, leading to $2 * T(C+1)$ estimates of σ_u, σ_v and μ. Next, to derive the estimated production functions, the average production functions is shifted upwards by the corresponding expected value of inefficiency such that $\hat{f}_t(x) = \hat{g}_t(x) * exp(\hat{\mu}_t)$.

4.2 Construction of evaluation points

Typically standard Malmquist decomposition is based on balanced panel datasets, but this is not the case for our sample.[8] Therefore, to avoid the problem of unbalancedness, I evaluate productivity changes for representative hypothetical evaluation units that are not included in the estimation of the frontier. Estimating and decomposing productivity growth with hypothetical units offers several advantages. First, frontier estimation is done using the maximum number of observations without excluding observations for balancedness or distortions by imputed units. Second, constructing a continuum of evaluation points obtains productivity growth estimates for the whole range of relevant firm sizes. Third, creating hypothetical units allow the assumption that the evaluated units contain on average no noise, i.e. it permits a deterministic treatment of the distances to the frontiers, D_t^c and D_t^*. Fourth, constructing hypothetical evaluation units allows analysis of the dataset in this paper that is not possible on real-world units due to data privacy limitations (see section 5).

[8] However, different adjustments are possible to use such methods for non-balanced panels (see Kerstens and Van de Woestyne, 2014, for an overview): either 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, and achieving balancedness at least on a two-year basis. However, in this paper's model set-up, such methods are not to applicable, because inclusion of artificial units or exclusion of observations can alter the precision of the StoNED estimator if included in the frontier estimation, or impact the productivity growth estimate.

For the analysis we construct for each c hypothetical observations $(x_p^c, y_{t,p}^c)$ that represent average plants using c at the p-percentile of the plant size in terms of inputs, with fixed inputs over time. The corresponding output is constructed as the expected output including the expected inefficiency. To do so, for each c, we pool the observations over the whole observation period and draw for each of the m inputs the p-th percentiles with $p = \{10\%, 25\%, 50\%, 75\%, 90\%\}$. The corresponding output in t, $y_{t,p}^c$, is calculated as the value on $\hat{g}_t^{c,VRS}(x)$ using the lower envelope of the fitted values $\hat{y}_{it}^{c,VRS}$ of the StoNED QP under VRS (see Kuosmanen, 2008, Theorem 4.1). Note that this lower envelope is constructed as a simple linear programming problem (LP) that envelops the fitted values from the StoNED estimation similar to a VRS-DEA and allows extrapolating points on $\hat{g}_t^{c,VRS}(x)$ for unobserved inputs. Slope and intercept parameters a and b of this lower envelope are obtained by solving the following LP that delivers the corresponding expected output for the evaluation unit

$$y_{t,p}^c(x_p^c) = \min_{a,b}\{a + b'x_p^c \mid a + b'x_p^c \geq \hat{y}_{it}^c\} \tag{16}$$

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

$$\widetilde{y}_{t,p}^{c,VRS} = y_{t,p}^c(x_p^c) * exp(\mu_t^{c,VRS}) \tag{17}$$

Deriving the frontier reference points on the CRS frontier and on the metafrontiers uses a similar procedure. i.e. project the input on the relevant average production function, and shift the projection by the corresponding expected value of inefficiency to obtain the frontier estimate. Thus, I construct for each of the C groups five evaluation units with fixed inputs over time and output corresponding to the estimated average VRS production function in t, $\hat{g}_t^{c,VRS}(x)$. Note that each of these units inherits the expected inefficiency relative to the VRS frontier. Thus, these hypothetical units resemble an average plant at the p-percentile of its group c.

This procedure has three important implications for the Malmquist decomposition. First, by assuming that the average unit does not incorporate noise, D_t^c and D_t^* do not need to be calculated using the widely used, and although unbiased, statistically inconsistent estimator for $E[u_i|\epsilon_i]$ suggested by Jondrow et al. (1982), but instead can be based on the consistently estimated frontier. Thus, D_t^c and D_t^* collapse to simple ratios 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 $D_{t+1}^c(x_{t,p}^c, y_{t,p}^c) = y_{t,p}^c / \widetilde{y}_{t+1,p}^{c,RTS}$. Second, as there is no variation in the inputs - x_p^c is constant over time - $PTCU = 1/FCU$ in each period, because the scale of the operations does not change. Latter implication also influences the interpretation of the scale efficiency change component that now measures the change of the optimal scale size over time, and not whether a firm moves closer to optimal scale size. Third, and most importantly, the deterministic treatment of the inefficiency allows to measure the MMPI independent of distributional assumptions. To illustrate this third implication, replace the distance function in the MPI definition (equation 3) and let ξ_t be the expected inefficiency in period t from some distributional assumption in the StoNED estimation to see that inefficiency cancels out:

$$\begin{aligned} MPI^{crs}_{t,t+1}(x_t, y_t, x_{t+1}, y_{t+1}) &= \left[\frac{D^{crs}_t(x_{t+1}, y_{t+1})}{D^{crs}_t(x_t, y_t)} \times \frac{D^{crs}_{t+1}(x_{t+1}, y_{t+1})}{D^{crs}_{t+1}(x_t, y_t)} \right]^{1/2} \\ &= \left[\frac{y_{t+1}/y_t * exp(\xi_t)}{y_t/y_t * exp(\xi_t)} \times \frac{y_{t+1}/y_{t+1} * exp(\xi_{t+1})}{y_t/y_{t+1} * exp(\xi_{t+1})} \right]^{1/2} = \frac{y_{t+1}}{y_t} \end{aligned} \quad (18)$$

Thus, the overall productivity measures, MMPI and GMPI, are independent of distributional assumptions on the inefficiency component, but depend only on a few assumptions, namely concavity, monotonicity and continuity of the production function. However, the components of the decomposition may vary with the assumptions on the distributions of inefficiency and noise.

5 Data

To estimate and decompose the productivity growth of Germany's electricity generation, this paper uses the most comprehensive dataset ever compiled on conventional generation capacities in Germany.[9] For data privacy, the dataset only uses remote data processing, and detailed information such as minima and maxima are not reported. The dataset includes electricity generating facilities with a bottleneck capacity of at least 1 MW in operation between 2003 and 2010. The sample includes large scale electricity and heat suppliers, small scale power plants for industrial use including partial autoproducers, as well as private, public, and mixed ownership facilities. Nuclear plants are neglected due to Germany's nucelar phase-out by 2022.

To adopt the framework presented in section 3 to the 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. The conventional combustion power plants considered as subtechnologies are coal, lig-

[9]The data supplied by the Research Data Centres of the Federal Statistical Office and the statistical offices of the Länder are based on the monthly survey EVAS 43311 for power plants, and matched with EVAS 43111 for labor input data.

	2003	2004	2005	2006	2007	2008	2009	2010	$\sum$
Coal	22	27	27	27	29	28	27	27	214
Lignite	8	10	11	11	15	15	14	11	95
Gas	114	137	120	142	139	147	146	145	1090
Biomass	12	15	15	19	20	23	25	27	156
Meta	156	189	173	199	203	213	212	210	1555

Table 1: Sample sizes for four fuel subsets and total sample

nite, gas and biomass.[10] In 2010, these four fuels produced over over 60% of German electricity generation.

5.1 Key variables

Capital (CAPITAL), labor (LABOR), and combustion materials (FUEL) are used as inputs to produce energy (ENERGY) in the form of heat and electricity as sole output. The analysis focuses on operational rather than environmental performance and therefore undesirable outputs are not included in the model specification.[11]
CAPITAL is approximated with the plants average available capacity in MW, the average of the monthly available capacity throughout the year. Using the average rather than the maximum capacity controls for potential capacity extensions or reduction throughout the year. CAPITAL also includes the plant owner's decision to maintain, or not, full capacity. LABOR is the sum of hours worked. This measure is more accurate to approximate labor input than a head count as it accounts for part-time labor. FUEL is measured using the fuel input of the primary fuel in GJ. Since a secondary fuel typically is used only for start-up, neglecting the secondary fuel input is expected to have little influence on the results. ENERGY is the heat and electricity supplied as sole outputs measured as the sum of both in MWh. Net values are used because own consumption reduces the actual provided energy and it must not influence a productivity measure.

[10] Specifically, the different groups contain plants with the following fuels:
Coal: Coal, coal coke, briquette and derivatives, and other coals
Lignite: Lignite, black lignite, lignite dust, briquette and coke, fluidized bed lignite, and other lignites
Gas: Natural gas, marsh gas, coke oven gas, furnace gas, and other synthetic gases
Biomass: Wood, straw, liquid biomass, biogas, landfill gas, biosolids, sewage sludge and gas, and municipal wastes

[11] See Seifert et al. (2014) for an application of this dataset analyzing environmental performance by including undesirable outputs in the form of CO_2 emissions.

5.2 Descriptive statistics

The panel comprises 1555 observations over the study period (see Table 1; also see Table 7 to 10 in the Appendix). The number of firms increases over the observation period from 156 in 2003 to over 200 plants from 2006 onward. Gas-fired plants represent the largest part of the sample. The number of coal and lignite-fired power plants remains stable across the study period, while the number of biomass-fired plants steadily increases. For coal and gas-fired plants 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 plants about 10 to 18% of total available capacity is covered.

Lignite-fired plants are the largest plants in the sample, while especially biomass and gas-fired plants are considerably smaller. For gas-fired plants, the data shows a right-skewed distribution with a larger number of small plants. The stable mean and quantile values support the choice of fixed inputs over time for the hypothetical evaluation units. The hypothetical units emphasize the large dispersion in terms of plant size for the combustion technologies (see Figure 2 for the evaluation units; also see Table 6 in the Appendix). Note, however, the overlapping intervals for the different technologies, such that e.g. the 90% quantile of the coal-fired power plants is larger than the 10% quantile of the lignite-fired plants, meaning that only one combustion technology influences parts of the metafrontier estimate, whereas the plants of different combustion technologies influence other parts. Thus, plants can be benchmarked against plants using a different fuel when evaluated against the metafrontier. This is especially noticeable for the biomass-fired plants, since the smallest biomass evaluation unit is larger than the smallest gas-fired unit, but the largest biomass unit is still smaller than the largest gas-fired unit.

6 Results

6.1 Frontier estimation results

Figure 3 and 4 report the results of the frontier estimates for the different technologies as well as the metafrontier in terms of annual expected efficiency (also see Table 11 in the Appendix).[12] A value of 1 indicates full efficiency and no potential output expansion with the same technology. In general, results reveal rather low expected inefficiency in Germany's electricity generating sector, i.e. on average the power plants

[12] All calculations use R 3.2 (R Core Team, 2015) with the packages quadprog, alabama, bbmle and lpSolve. Detailed results for the frontier estimates are available from the author upon request.

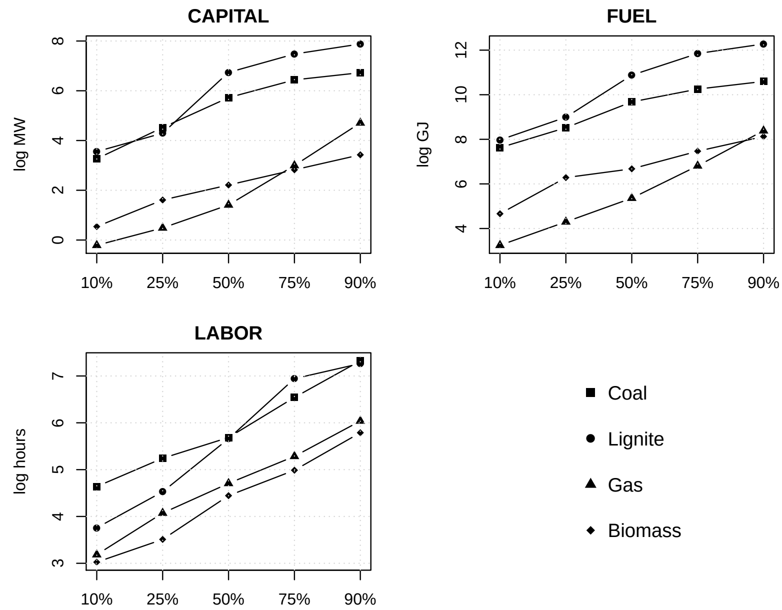

Figure 2: Descriptive statistics: Hypothetical evaluation units

operate close to the best practice frontiers spanned by plants with the same fuel. 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 few technological differences among the plants, and constantly high load. The on average smaller gas- and biomass-fired also operate on average on a high efficiency level, which indicates potential output expansion of only 2%. Figure 3 and 4 also indicate a stable upward trend of efficiency of gas-fired plants carrying over to the metafrontier results, as the gas-fired plants are the largest subsample. Under the CRS assumption, the results are similar with highest efficiency scores for baseload plants and higher intertemporal variations for the gas- and biomass-fired plants.

Tables 2 and 3 report the technology gap ratios (TGR) between the meta- and group frontier estimates (also see Tables 12 to 15 in the Appendix). Gas-fired plants show the smallest technology gap, meaning that they generally operate closest to the metafrontier. Coal-fired plants show a technology gap at the beginning of the observation period that eventually closes over time. On the contrary, the largest gap can be found for biomass-fired plants with considerable variation over time. This means that switching the combustion technology from biomass to gas would have resulted in a considerable increase in potential output for the plants. Finally, the lignite-fired plants show that

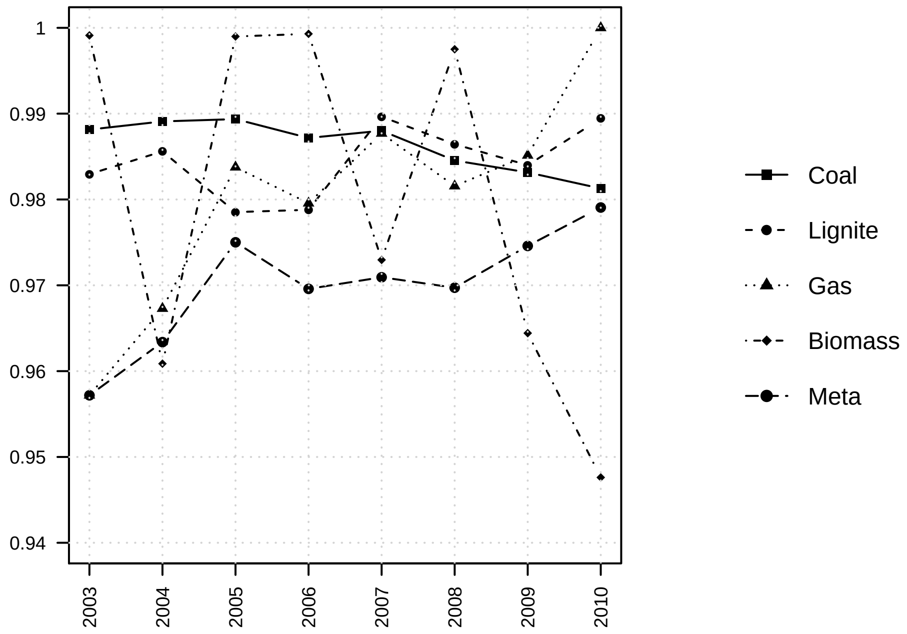

Figure 3: Annual expected efficiency for cross-sectional frontiers in percent under VRS

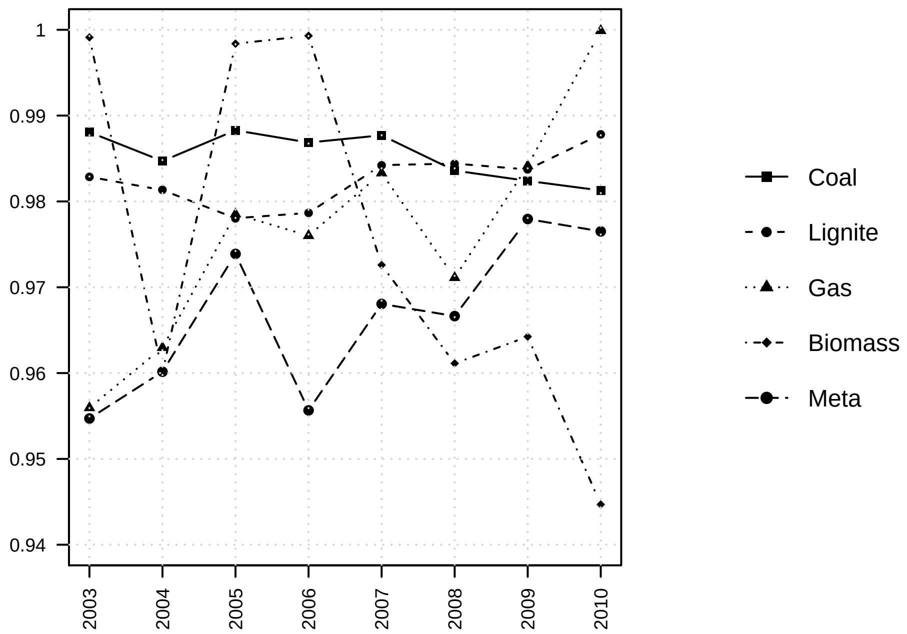

Figure 4: Annual expected efficiency for cross-sectional frontiers in percent under CRS

	Coal	Lignite	Gas	Biomass
2003	0.9636	0.9621	0.9804	0.8118
2004	0.9646	0.9558	0.9778	0.9784
2005	0.9764	0.9771	0.9786	0.9212
2006	0.9736	0.9738	0.9838	0.9160
2007	0.9748	0.9648	0.9812	0.9403
2008	0.9764	0.9669	0.9877	0.9302
2009	0.9820	0.9736	0.9829	0.9855
2010	0.9948	0.9759	0.9647	0.9857

Table 2: Average TGR over time

their technology gap decreases with plant size.[13]

In summary, the frontier estimation results indicate fairly low inefficiency in the Germany's electricity generating sector. The results also emphasize a high productivity of gas- and coal-fired plants, whereas biomass and small lignite-fired plants continue to exhibit noteworthy technology gaps. The indicated savings potentials are much lower than in Seifert et al. (2014), which uses nearly identical data and a similar model specification. While both the inefficiency estimates and the technology gaps remain the same order, the magnitude is lower.[14]

Two further methodological points should be noted here. First, while the results show that the metafrontier envelops all group frontiers, this is not automatically the case. To ensure this envelopment, one may consider using a further constraint in the frontier estimation similar to the SFA metafrontier approach suggested by Battese et al. (2004). Second, the potential inconsistency of CRS and VRS frontier estimates, i.e. the CRS does not envelop the VRS in every point or intersects it, infers that the frontier reference points of all observations should be compared for the different scale assumptions. In this paper, if such an inconsistency occurs, the CRS frontier estimate is shifted up by increasing the corresponding σ_u such that CRS equals VRS in the most productive scale size similar to DEA (cp. Bogetoft and Otto, 2011, for details).While ad-hoc, this solution at least provides consistency of the scale change components.

[13]As large lignite-fired plants are the largest plants in the sample, there are no comparable technologies. Thus, lignite-fired plants necessarily span the metafrontier at the upper end, leading to almost no technology gap. Conversely, the smallest lignite-fired plants operating at the scale of gas- and coal-fired plants indicate indicate a considerable technology gap.

[14]The differences can be explained by the frontier estimation approach. Seifert et al. (2014) use a deterministic sequential DEA approach that strongly reacts on highly efficient units, whereas the StoNED approach assumes noise in the data. Thus, a sequential DEA approach may underestimate efficiency in the presence of noise, while StoNED might overestimate efficiency when there is little noise present.

	Coal	Lignite	Gas	Biomass
10%	0.9769	0.9484	0.9798	0.8949
25%	0.9742	0.9591	0.9772	0.9326
50%	0.9718	0.9705	0.9773	0.9465
75%	0.9757	0.9817	0.9814	0.9479
90%	0.9802	0.9840	0.9824	0.9463

Table 3: Average TGR per plant size

6.2 Malmquist decomposition results

MMPI

The $MMPI$ measures productivity growth against the sector production function, and an MMPI of 1 indicates no productivity change over the observation period. Further, productivity is evaluated at 20 hypothetical evaluation units that resemble average plants of the different subtechnologies. Figure 5 summarizes the estimates of annual productivity growth on the metafrontier level plotted against the plant size in log MW (see Table 16 for details).

Overall, MMPI shows very small productivity changes at nearly all evaluated points. As Figure 5 highlights, medium sized plants show productivity losses over the study period, but the smallest and largest evaluated points show productivity gains. With the exception of small biomass-fired plants, no evaluation point has annual productivity changes larger than 1%. Coal- and lignite-fired plants show a small reduction or stagnation in productivity over all analyzed input quantiles. Similarly, overall productivity changes for gas-fired plants are fairly small, irrespective of the analyzed input quantile. Gas-fired plants show annual productivity gains of about 0.2% for the smaller quantiles, but also stagnation or small losses for larger plants. Biomass plants show large productivity gains especially at the lower quantiles. These large gains can be explained by strong gains in the first period, 2003 to 2004, which can be attributed to poor data availability for this plant size in the first years. Excluding the first years of these observations, however, leads to annual productivity gains over the whole range of inputs, thus indicating a robust productivity increase for these plants.

MMPI decomposition

Decomposing the overall productivity measure helps to understand the underlying mechanics of productivity growth. Table 4 reports the results of the suggested decomposition as productivity growth on the group level (GMPI) and Table 5 indicates the

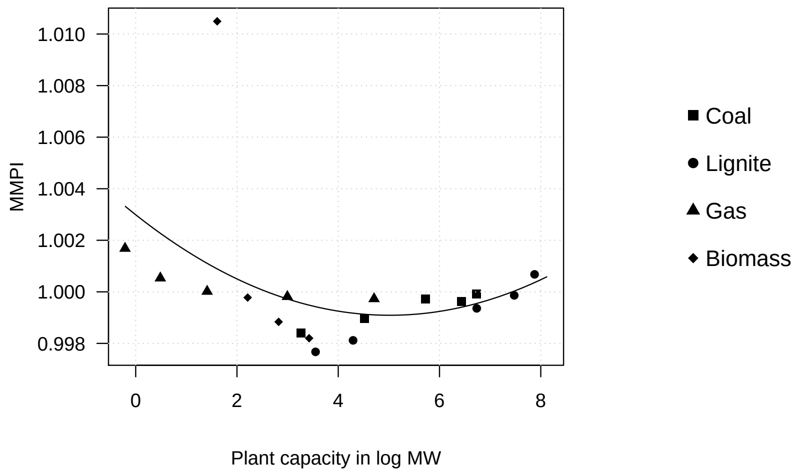

Figure 5: Geometric mean of MMPI for different plant sizes: average annual productivity growth

	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 4: Geometric mean of GMPI: average annual productivity growth

		Coal	Lignite	Gas	Biomass
$EC^{c,vrs}$		0.9990	1.0009	1.0063	0.9925
$TC^{c,vrs}$	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^{c}	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
SEC^{*}	10%	1.0000	1.0000	0.9993	1.0000
	25%	1.0003	1.0003	0.9992	1.0000
	50%	1.0007	1.0013	0.9997	1.0000
	75%	1.0011	1.0018	1.0000	1.0000
	90%	1.0014	1.0018	1.0001	1.0001
$TC^{*,crs}$	10%	0.9949	0.9948	0.9973	0.9967
	25%	0.9953	0.9952	0.9974	0.9950
	50%	0.9958	0.9963	0.9966	0.9950
	75%	0.9962	0.9968	0.9954	0.9949
	90%	0.9967	0.9977	0.9954	0.9954
$TC^{*,vrs}$	10%	0.9949	0.9949	0.9980	0.9967
	25%	0.9951	0.9949	0.9982	0.9950
	50%	0.9951	0.9950	0.9970	0.9950
	75%	0.9951	0.9950	0.9954	0.9949
	90%	0.9953	0.9959	0.9953	0.9952

Table 5: Geometric means GMPI decomposition components

components of the decomposition, namely an efficiency change, technical changes, scale efficiency changes and pure technological catch up (see Figure 6 to 9 in the Appendix for time series plots of the decomposition results on the subtechnology level).

The *GMPI* estimates also indicate little productivity changes on the group level similar to the MMPI results. While the GMPI results are nearly identical to MMPI results for lignite-fired plants, there is a greater variation in productivity estimates for the coal-fired plants. For the gas-fired plants, the GMPI indicates stronger productivity decline compared to the MMPI. One noteworthy difference is that the GMPI indicates productivity gains for all evaluated units in the group of biomass-fired plants with annual productivity growth between 0.4 and 2.8%, excluding the smallest evaluation point. Thus, productivity growth for the biomass-fired plants measured in the group is higher than measured against the metafrontier for the same evaluation units. Note that this productivity growth for a subset of the power plant fleet cannot be detected when looking only at the sector as a whole. Further, the differentiation by technology avoids the problem of smaller subsamples becoming smoothed out by larger subsamples.

The *Efficiency Change (EC)* component reflects the change in the distance of the average plant to the best practice for the different group frontiers. Since EC depends only on the shift factor from the average production function to the frontier in two consecutive periods, i.e. the expected inefficiency μ_t and μ_{t+1}, the calculated EC is identical for the different evaluation units. In general, the efficiency change component indicates trends similar to the GMPI, with smaller changes for baseload plants and higher volatility for small scale plants. Again, results are of small magnitude and range between 0.75% average annual efficiency loss for biomass and 0.6% efficiency increase for gas. As the expected efficiency estimates in Figure 3 and 4 show, average intra-group efficiency is already fairly high for each technology. Annual estimates indicate a positive trend only for the gas-fired plants, while the larger estimated efficiency change component of biomass-fired plants is due to a higher variance.

The *Technical Change (TC)* component reflects the annual shift of the frontier irrespective of the potential efficiency or scale effects. Thus, the TC component does not evaluate changes for the average firm, but rather the changes at the best practice frontier. The results of each technology show the same direction for all plant sizes, i.e. common frontier shifts over the whole range. While the results indicate technical regress for lignite and gas-fired plants, the TC component indicates almost no frontier shift for coal-fired plants. 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 early years, but a positive trend is also found when omitting these periods. Overall, the results are in line with the expectations given the overall few installations of capacity for coal and lignite. On the other hand, biomass combustion technology, which is not as mature as the other technologies, allows for larger initial productivity gains.

The *Pure Technological Catch Up (PTCU)* components measures the group frontier shifts relative to the metafrontier shifts. The PTCU component does not evaluate changes for the average firm, but instead evaluates changes at the best practice of a group relative to the best practice for the whole sector. The results indicate catch-up for coal, lignite, and biomass, while values below one are found for gas. Again, the magnitude of this effect is low for coal, lignite and gas, and more pronounced for biomass. Comparing the PTCU component and TC components with the TGR, reveals an interesting pattern. The generally higher values for PTCU compared to the TC component indicate that group frontiers partly catch-up to the metafrontier due to the latter's downward shift. In other words, overall production potentials in the sector decreased across the study period. The comparison also indicates that the decrease in TGR for coal and biomass (see Table 12 and Table 15) is partly driven by technology developments in the whole sector. Finally, the negative PTCU and TC scores for gas-fired plants indicate that gas is losing production potentials more rapidly than the sector as a whole. Total productivity, however, remains rather stable, because the effects are partly offset by the positive efficiency development of gas-fired plants.

The *Scale Efficiency Change (SEC^{c}, SEC^{*})* components against both metafrontier and group frontiers indicate the changes in optimal firm sizes. Given that initial scale efficiency estimates are already high, with a minimum of 96% for biomass-fired plants and around 98% for the other technologies, only small gains are available in terms of scale efficiency. The result is now reflected in the very small SEC component for all technologies. Further, results indicate stable scale efficiencies and almost no scale efficiency change effects against both, metafrontier and group frontiers.[15]

The nearly identical *Metafrontier Technical Change* components ($TC^{*,crs}$, $TC^{*,vrs}$) emphasize the flat shape of the VRS frontier. Generally, the results indicate losses of production possibilities of about 0.5% annually. Thus, the German electricity generating sector faced technical regress in the 2003 to 2010 period over the whole set relevant plant sizes. This is in line with Seifert et al. (2014) that find only few frontier-shifting DMUs over the observation periods.

[15] Seifert et al. (2014) find higher inefficiencies stemming from having non-optimal plant size, thus emphasizing 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, whereas the DEA estimate by Seifert et al. (2014) indicates considerable gaps between these frontiers.

7 Conclusion

This paper proposes a framework to estimate productivity growth in electricity generation, a sector characterized by multiple production technologies. A Malmquist productivity index accounts for productivity developments on sectoral and subtechnology level, including standard productivity decomposition factors (efficiency change, technical change, scale efficiency change). Frontier estimation with the stochastic non-smooth envelopment of data (Kuosmanen and Kortelainen, 2012, StoNED,) allows a flexible, non-parametric estimation of overall productivity changes with few microeconomic assumptions. The use of representative hypothetical evaluation points estimates productivity changes for the whole range of relevant plant sizes without any distributional assumptions, and allows the use of a non-balanced panel without imputation of additional data points. The framework is applied to measure and decompose productivity growth in the German electricity generation sector based on a unique and rich dataset of coal-, lignite-, gas-, and biomass-fired generation operating from 2003 to 2010.

The results indicate relatively small productivity changes irrespective of the fuel source, and an overall reduction in production potential, i.e. technical regress and a downward shift of the sector production function. Coal- and lignite-fired plants, the mature baseload technologies, generally indicate stable productivity over the observation period and little variability in the decomposition factors, where gas-fired plants indicate technical regress offset by efficiency gains that lead to an overall stagnation of productivity. Although biomass-combustion technology is undergoing considerable positive technical change, catching up to other sources, its production potentials are not fully captured. The resulting biomass-fired productivity gains are accompanied by an efficiency decrease, thus suggesting that newly installed capacities drove the frontier shift and not technical enhancement of existing installations. Compared to the literature on electricity generating sector productivity, the productivity growth estimates in this paper are of a magnitude similar to other studies, with an overall stagnation of productivity in electricity generation in an developed economy. The results support existing explanations of productivity changes similar to See and Coelli (2013), i.e. a technology with considerable capacity installations to possess higher rates of technical change, although no translation into overall productivity gains is detected. Similar to Heshmati et al. (2014), the results indicate no productivity gains for mature technologies, but unlike Heshmati et al. (2014), no stable downward trend in productivity is detected.

We conclude that the StoNED approach combined with the proposed framework produces good estimates of productivity changes. Although the estimated frontier is flexible in its shape, this paper confirms the application of the estimation procedure to small datasets. Further, overall productivity evaluation is independent from distributional assumptions and relies only on few microeconomic assumptions on the shape of a production function. We note that while the proposed method could underestimate intertemporal changes as the frontier is less sensitive against a small number of observations, it reduces the risk of overestimating productivity changes due to erroneous data. Measuring productivity growth against both the frontier of the sector and the frontiers of the subtechnologies allows a more complete understanding of the underlying mechanisms of productivity growth. That is, the framework can measure productivity growth for a subset of a power plant fleet that would not otherwise be captured when looking only at the sector as a whole. Further, the differentiation by technology allows analysis of productivity growth in small subsamples with results that would have otherwise been smoothed out by larger subsamples.

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 2015 in Munich, the Jahrestagung of the Verein für Socialpolitik 2015 in Münster, and the DIW Brown Bag Seminar in Berlin for fruitful discussions. Especially, I thank Pio Baake, Astrid Cullmann, Tomaso Duso, Christian von Hirschhausen, Andy Johnson, Subal Kumbhakar, Timo Kuosmanen, Anne Neumann, and Antti Saastamoinen for helpful comments, and Adam Lederer and Ann Stuart for editing.

A Appendix

A.1 Descriptive Statistics

		10%	25%	50%	75%	90%
Coal	CAPITAL	26.23	92.00	306.00	625.00	834.23
	LABOR	103.45	189.17	294.77	693.86	1515.17
	FUEL	2047.64	5019.72	15955.95	28342.76	40014.60
Lignite	CAPITAL	35.00	71.33	843.33	1767.00	2645.83
	LABOR	42.86	92.55	287.24	1036.20	1429.8
	FUEL	2898.96	8031.95	52948.50	139666.15	214484.43
Gas	CAPITAL	0.81	1.63	4.10	20.00	110.80
	LABOR	24.16	58.72	110.64	197.22	419.39
	FUEL	25.73	73.52	212.83	906.29	4380.39
Biomass	CAPITAL	1.72	5.00	9.13	16.83	30.73
	LABOR	20.59	33.45	85.16	146.58	326.47
	FUEL	105.89	535.60	793.09	1748.89	3379.45

Note: Fuel input is measured in 1000 GJ, Labor in 1000 hours

Table 6: Descriptive statistics: Hypothetical evaluation units

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
CAPITAL	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
FUEL	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
LABOR	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
ENERGY	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: Missing values are not reported due to data privacy restrictions, CAPITAL is measured in MW, FUEL in thousand GJ, LABOR in 100 hours, ENERGY in GWh

Table 7: Descriptive statistics: Coal

Lignite		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	
ENERGY	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: Missing values are not reported due to data privacy restrictions, CAPITAL is measured in MW, FUEL in thousand GJ, LABOR in 100 hours, ENERGY in GWh

Table 8: Descriptive statistics: Lignite

Gas		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
CAPITAL	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
FUEL	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
LABOR	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
ENERGY	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: Missing values are not reported due to data privacy restrictions, CAPITAL is measured in MW, FUEL in thousand GJ, LABOR in 100 hours, ENERGY in GWh

Table 9: Descriptive statistics: Gas

Biomass		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
CAPITAL	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
FUEL	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
LABOR	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
ENERGY	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: Missing values are not reported due to data privacy restrictions, CAPITAL is measured in MW, FUEL in thousand GJ, LABOR in 100 hours, ENERGY in GWh

Table 10: Descriptive statistics: Biomass

A.2 Annual expected inefficiency

VRS	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

CRS	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 11: Annual expected efficiency for cross-sectional frontiers in percentages under VRS and CRS

A.3 Technology Gap Ratios

Coal	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 12: TGR: Coal

Lignite	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 13: TGR: Lignite

Gas	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 14: TGR: Gas

Biomass	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 15: TGR: Biomass

A.4 MMPI estimates

	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 16: Geometric mean of MMPI: average annual productivity growth

A.5 MMPI decomposition by fuel type

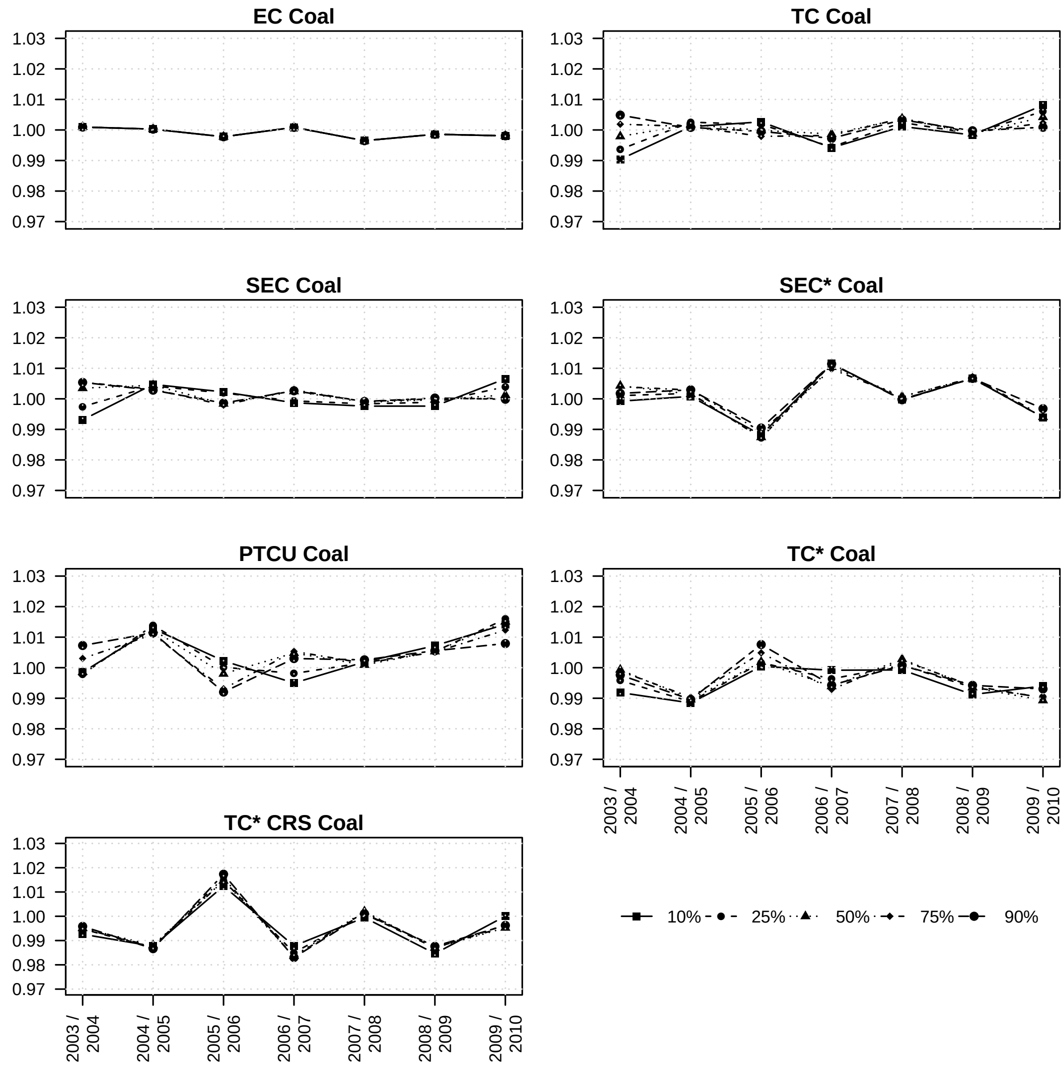

Figure 6: MMPI decomposition for coal-fired stations

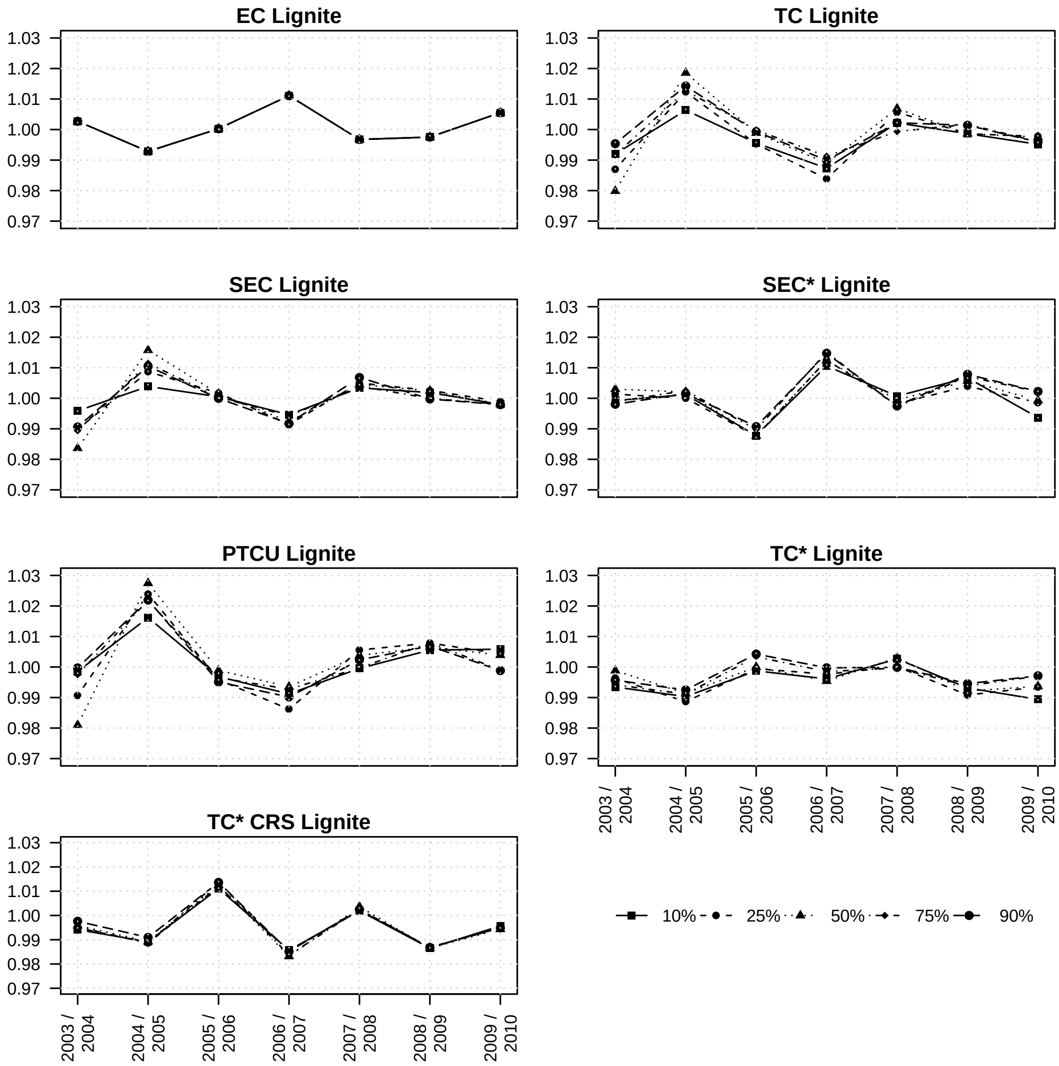

Figure 7: MMPI decomposition for lignite-fired stations

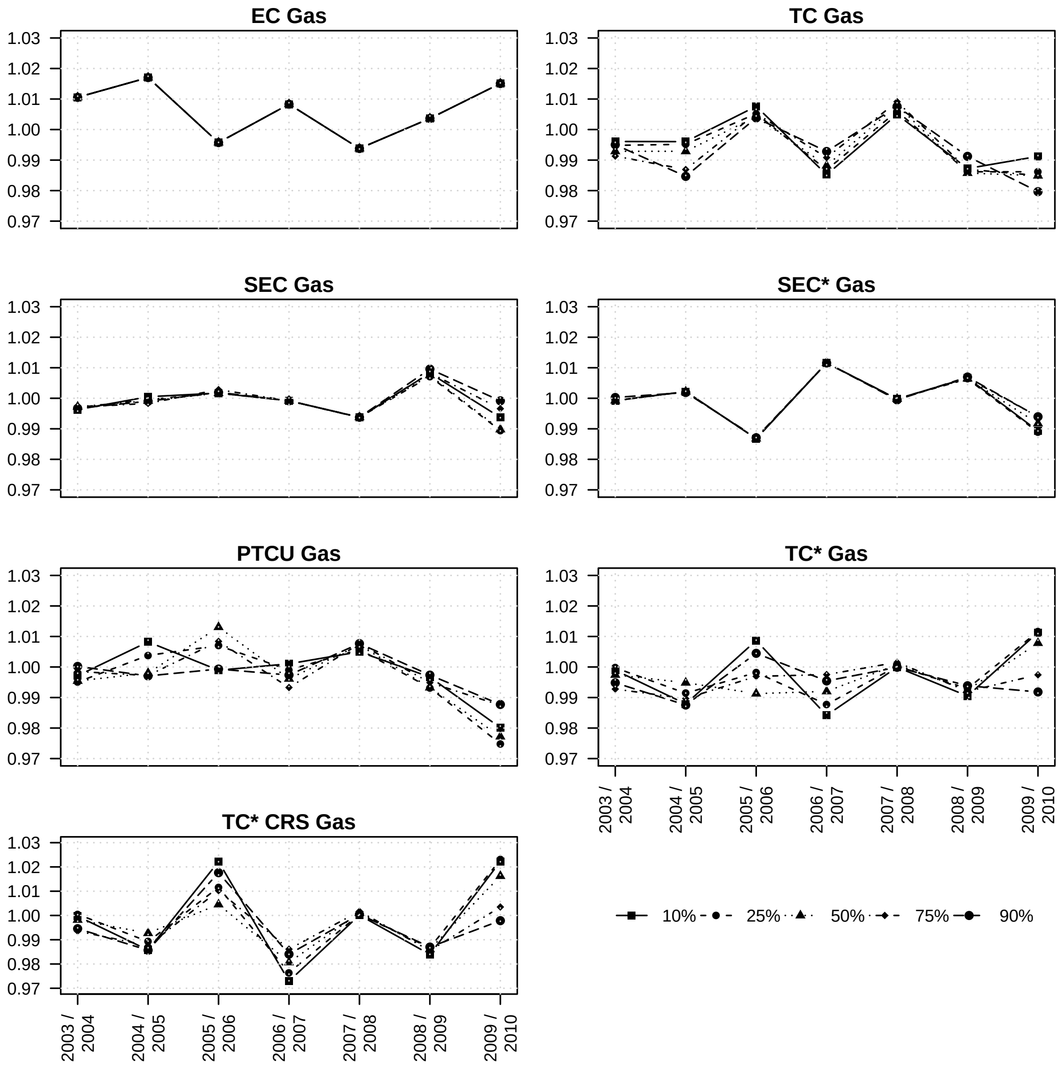

Figure 8: MMPI decomposition for gas-fired stations

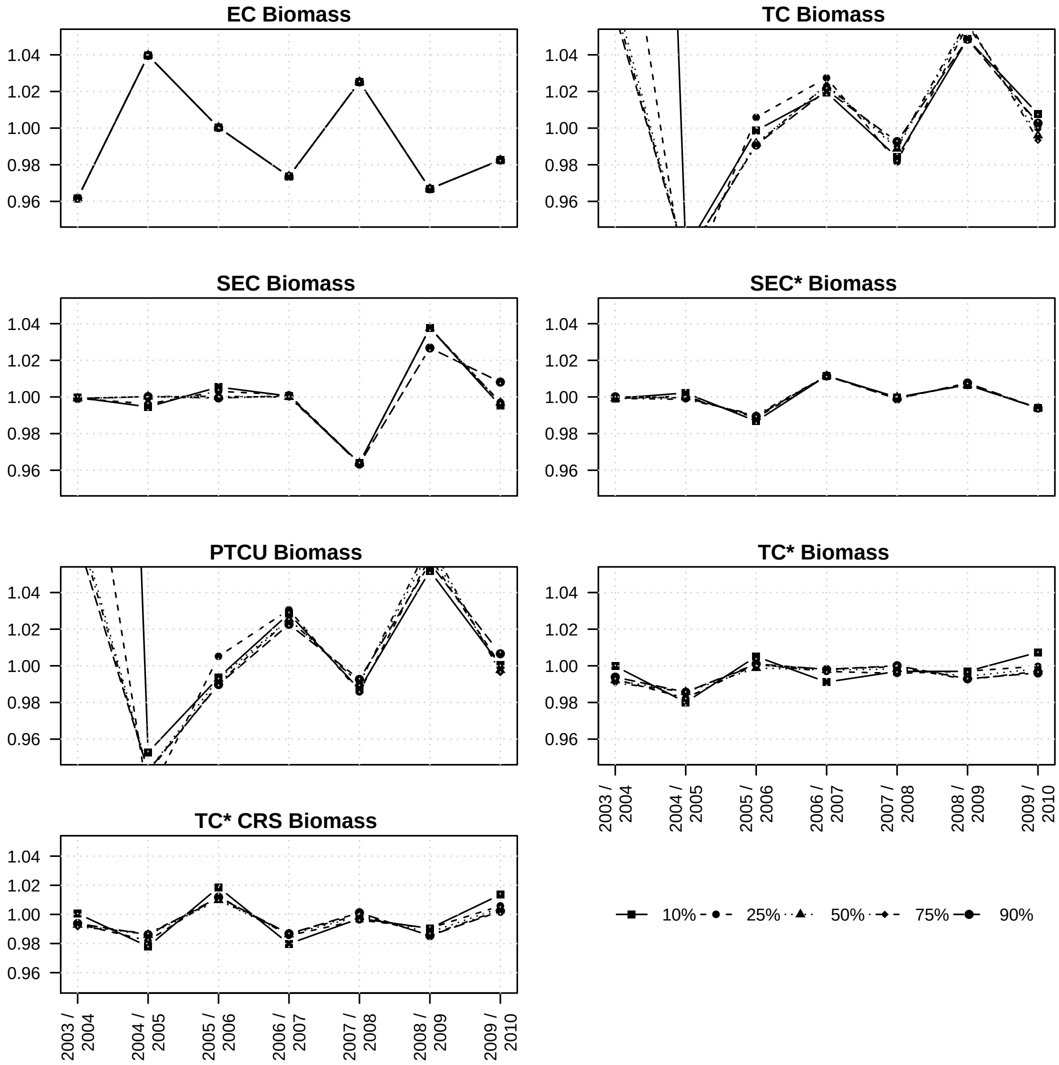

Figure 9: MMPI decomposition for biomass-fired stations

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