The Development of Environmental Productivity: the Case of Danish Energy Plants

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Abstract

The Danish "Klima 2020" plan sets an ambitious target for the complete phasing-out of fossil fuels by 2050. The Danish energy sector currently accounts for 40% of national CO_2 emissions. Based on an extended Farrell input distance function that accounts for CO_2 as an undesirable output, we estimate the environmental productivity of individual generator units based on a panel data set for the period 1998 to 2011 that includes virtually all fuel-fired generator units in Denmark. We further decompose total productivity into technical efficiency, best practice ratio, and scale efficiency and use a global Malmquist index to calculate the yearly changes. By applying time series clustering, we can identify high, middle, and low performance groups of generator units in a dynamic setting. Our results indicate that the sectoral productivity only slightly increased over the fourteen years. Furthermore, we find that there is no overall high achiever group, but that the ranking, although time consistent, varies between the different productivity measures. However, we identify steam turbines and combustion engines for combined heat and power production as potential high performers, while combustion engines that only produce electricity are clearly low performers.

JEL classification: C50, D22, D24, O30

Keywords: Environmental productivity, energy sector, productivity analysis, CO_2 mitigation, renewable energy, transition

1. Introduction

The formulation of the 20-20-20 targets by the leaders of the EU in 2007 was later followed by the adoption of the "Klima 2050" plan by the Danish government, which set an ambitious roadmap for Denmark towards a low carbon society.[1] It is commonly acknowledged that a shift from a high-carbon society to a low-carbon society is unachievable through product innovations alone, but also necessitates increases in efficiency and the realisation of saving potentials. These are equally important pillars in the transition process, a fact recognised in the targets of both plans.

This applies especially to the energy sector which causes about 40% of total CO_2 emissions in Denmark. A characteristic trait of the Danish energy system is that it has a large number of district heating networks, many of which are supplied by combined heat and power (CHP) stations.

Given the technological path dependency which is inherent to energy systems, a radical technological change is not only unrealistic, but would also be an overly expensive solution. Therefore, besides technical progress, incremental process innovations that lead to increases in technical efficiency (Agrell and Bogetoft, 2005), and rescaling generator unit capacities to increase scale efficiency (Agrell and Bogetoft, 2005; Tovar et al., 2011) are equally important elements in the transition of the energy system towards low-carbon targets.

Based on a comprehensive panel data set of production data from virtually all fuel-fired Danish electricity, heating, and CHP units, we analyse the performance of the industry over a period of 14 years by using a distance function as a benchmarking tool that accounts for CO_2 emissions (Agrell and Bogetoft, 2005; Zhou et al., 2010; Yang et al., 2011; Zhang and Choi, 2013). Similarly to Agrell and Bogetoft (2005) and Yang et al. (2011), we use an extended Farrell input distance function with two desirable outputs (heat and electricity), one undesirable output (CO_2), and one input (fuel). Thus, our benchmarking tool not only rewards fuel savings, but also reductions in CO_2 emissions that follow from changes in fuel composition. In contrast to many other studies of the performance of heat and power production, we take into account fuel as the only input, while we disregard other inputs such as labour, capital, and materials. Hence, our analysis focuses on the energy conversion so that, e.g., investments in fuel-saving technologies necessarily result in higher productivity measures, which is not the case for traditional total factor productivity measures, where the increase in capital costs can result in lower productivity measures.

We divide overall productivity into three subcomponents, best practice ratio, technical efficiency, and scale efficiency, and use the global Malmquist productivity index proposed by Pastor and Lovell (2005) to quantify yearly changes in the three subcomponents, i.e. technical change, efficiency change, and scale efficiency change. This enables us to derive a comprehensive picture of the productivity development over time. Table 1 demonstrates how our measures correspond with the transition pillars, innovation and efficiency.

As our benchmarking measure is based on individual generator units, we are able to investigate the relationship between the performance and various characteristics of the generator units. These characteristics are, for instance, age, capacity, technology, output, and the role within the energy system. Based on these criteria, we address the following

Abbreviations: $PROD$ environmental total productivity; TE technical efficiency; BPR best practice ratio; SE scale efficiency; MTR meta technology ratio.

[1] More information on the 20-20-20 targets can be found at http://ec.europa.eu/clima/policies/package/ (May 5, 2014). The "Klima 2050" plan describes the roadmap for the complete phasing-out of fossil fuels in Denmark by the year 2050.

Table 1: Correspondence between productivity measures and transition pillars

Pillars		Productivity Measures
Innovation	⇒	technical change
Efficiency gains	⇒	technical efficiency change, scale efficiency change

questions: (a) is there a high performing group and if so, who are the high performers given the transition pillars innovation and efficiency; (b) are high performers consistent (i) over time and (ii) over both transition pillars; (c) who are the followers; and (d) what characterises a potential low performance group. This information allows a more comprehensive analysis of the sectoral performance and may contribute to a more targeted energy policy. The ongoing reform of the emissions reference document for large combustion plants (European Commission, 2013) stresses the relevance of this topic. Our study helps to underpin the specificities of the CHP-intensive Danish energy system in this context.

In order to answer the above-mentioned questions, we perform a feature-based time series cluster analysis (Wang et al., 2006) over all three efficiency measures to identify and describe the three different performance groups. Finally, a multinomial logit regression analysis provides more detailed information on how the above mentioned characteristics affect the attribution of a generator unit to one of the three performance groups. A detailed analysis of the performance of different generator unit groups completes the analysis.

The article is organised as follows: section two provides a brief overview of the Danish energy sector and it's development over the last 40 years; section three describes the data; section four provides a comprehensive description of the methodologies used in the analysis; section five presents and discusses the results, and section six concludes.

2. The Danish power and heat generation sector

The Danish energy sector has some unique characteristics that are important for the interpretation of the results of this study. In contrast to other countries, Denmark decided already in the late seventies to become more independent from fossil fuel imports. The decision was not based on climate concerns, but rather on a desire for political independence and a secure national energy supply.

Except for the former Soviet Union countries, no other country pursued district heating as consistently as Denmark. Nearly 100% of municipal solid waste and a large share of industrial waste are burned for energy supply in smaller, local district heating plants and in medium-sized CHP plants. Furthermore, Denmark uses a large proportion of its domestic natural gas resources to produce heat and power. Many of the district heating plants are CHP plants whose construction and operation have been promoted by a number of governmental support actions throughout the years. Hence, the focus on small local district heating plants and CHP plants has led to a sector that today contains only a limited number of larger stations—of which many are CHP plants in urban areas.

The Danish energy sector is divided into four main classes of plants:

- *Centralised plants* are situated in 15 legally defined areas. The generator units of these plants are predominantly CHP units, although they also comprise the largest electricity-only stations. Usual fuels in this category are natural gas and coal. Despite a huge increase in wind energy generation, these units still produce about 50% of the electricity in Denmark (Danish Energy Agency, 2013).

- *Decentralised plants* comprise a larger group of plants with large and medium-sized mainly CHP units fuelled by natural gas, waste, and biomass.
- *Industrial plants* are mainly medium-sized CHP units that together with the decentralised plants represent about 20% of the electricity supply in Denmark (Danish Energy Agency, 2013).
- *District heating plants* are mostly small-scale generators producing chiefly heat and only to a very limited extent contribute to the electricity supply.
- *Other plants*, which mainly comprise smaller local units with a specific supply function (e.g. supply of hospitals) and emergency backup generator units.

3. Data

Our empirical analysis is based on a full sample of all fuel-fired electricity and heat producing generator units in Denmark from 1998 to 2011.[2] Tables 2 and 3 describe the composition of the data set and present descriptive statistics of relevant variables, respectively. The capacity of the generator units with regards to electricity production, heat production, and fuel input is measured in megawatts (MW), while the actual electricity production, heat production, and fuel use are measured in terajoules (TJ). CO_2 emissions are measured in metric tons (t) and are calculated using an engineer's approach based on the fuel input using conversion coefficients published by the Danish Energy Agency (2010).[3] As several generator units use a mix of different types of fuel, e.g. a mix of fossil fuels and renewable fuels, the ratios between CO_2 emissions and fuel use are not limited to the used conversion coefficients, but have a nearly continuous distribution (see figure 1). This shows that reductions in CO_2 emissions can not only be achieved by radical changes such as new technologies that use different fuels, but also by gradually changing the mix of fuels.

The discrepancies between the arithmetic means and the median values in table 3 reflect the focus of the Danish energy sector on small-scale local generator units. This is particularly the case for electricity producers. In 2011, the 1% largest electricity producers accounted for 51% of total electricity production. Likewise, the top 1% district heating producers accounted for 37% of total heat production. So, despite the political effort to decentralise energy production, the contribution of small local generator units is still limited and raises the question of how efficiently the sector operates on the whole.

[2] The data set also includes electricity and heat producing generator units that use other sources of energy. In order to focus on generator units with a similar technology, we decided to only analyse fuel-fired generator units. This covers a very large share of the generator units in the data set and implies that we do not include generator units in our sample that use solar cells, solar thermal collectors, hydro energy, geothermal energy, heat pumps, or excess heat from industrial production.

[3] The conversion coefficients are presented in appendix table 1.

Table 2: Composition of data set

Variable		♯
Number of observations		24411
Number of years		14
Number of generator units		2488
Number of power plants		1415
Frequency of generator technologies		
	Boiler	1840
	Combustion engine	518
	Steam turbine	80
	Gas turbine	31
	Other	19
Frequency of embeddedness types		
	Decentralised power plants	656
	District heating	647
	Industrial power plants	73
	Central power plants	39
Frequency of production types		
	electricity only	126
	heat only	1387
	CHP	1061
Number of generator units with zero CO_2		649

Table 3: Descriptive statistics

	Mean	Median	Stdv	Min	Max
Start of operation	1990	1994	11.61	1900	2011
Operating time in years	19	17	11.61	0	110
Electricity capacity in MW*	11.67	0.96	55.48	0.00	640.00
Heat capacity of in MW**	12.29	3.50	40.07	0.01	585.00
Input capacity in MW	22.46	5.00	98.07	0.03	1582.00
Yearly electricity production in TJ*	147.92	11.02	850.84	0.00	14795.92
Yearly heat production in TJ**	83.71	11.13	406.79	0.00	9798.09
Total fuels in TJ	210.35	16.00	1470.19	0.00	37545.39
CO_2 emissions in t	14.5	0.30	127.02	0.00	3560.33

Note: * = only generator units that produce electricity, ** = only generator units that produce heat.

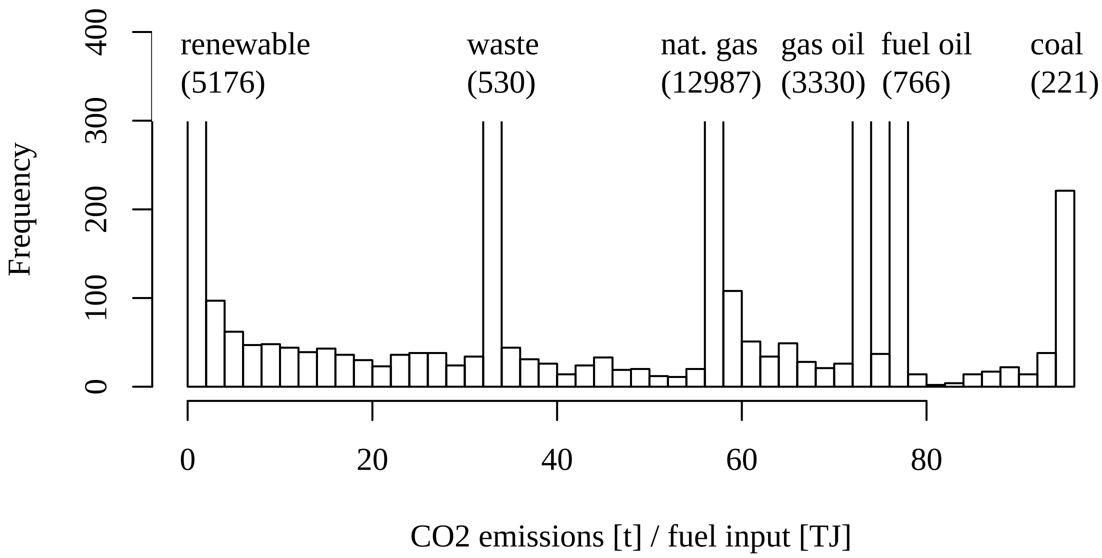


Figure 1: Histogram of ratios between CO_2 emissions and fuel input (frequencies of the truncated columns in parenthesis

4. Methodology

Our analysis of the environmental efficiency and productivity of the generator units takes into account one traditional input (fuel), two desirable outputs (heat and electricity), and one undesirable output (CO_2) as described in the previous section. Conducting efficiency analysis means that a choice has to be made regarding the "direction" in which the deviation from the best available "frontier" technology should be measured. Different approaches to account for undesirable outputs in productivity and efficiency analysis exist (e.g. Scheel, 2001). In general, inefficiency could be measured as the potential reduction of the traditional inputs, the potential increase of the desirable outputs, the potential reduction of the undesirable outputs, or any combination of these three "directions" where the directional vector could be either defined in absolute quantities (as often done with directional distance functions) or in relative terms (as done in Farrell distance functions). In our analysis, we use an extended Farrell input distance function, where we measure inefficiency in terms of the potential proportional reduction in both the traditional inputs and the undesirable outputs, while holding the desirable outputs unchanged:

$$D_{b,x}(y, b, x) = \min\{\gamma > 0, (y, \gamma\, b, \gamma\, x) \in T\}, \tag{1}$$

where y is a vector of desirable output quantities, b is a vector of undesirable output quantities, x is a vector of input quantities, and T denotes the technology set. This corresponds to a traditional Farrell input distance function, where the undesirable output is treated as an additional input (specification "INP" in Scheel, 2001). Hence, an alternative interpretation of the model is that energy production uses clean (non-CO_2 polluted) air or CO_2 quota as an additional input. There are three reasons for using this "direction".

First, for many generator units in our data set, the quantity of one of the desirable outputs, heat, is exogenously determined by the demand of the respectively supplied consumers. As the ratio between the (two) desirable outputs is technically predetermined for many generator units in our sample (at least when we only consider efficient points of production), for these generator units, the other desirable output (electricity) is also exogenously determined by the demand for heat. Hence, these generator units cannot increase their environmental technical efficiency or productivity by increasing the desirable output quantities (y), but they have to reduce the traditional input quantities (x) and/or the undesirable output quantities (b).

Second, some generator units in our data set can only use a specific type of fuel. As the ratio between fuel and CO_2 is given for a specific fuel type, the only possibility for these generator units to increase environmental efficiency and productivity is to proportionally reduce the fuel input and the undesirable output (CO_2), if the output quantities are given.

Third, we do not assume that the desirable outputs are null-joint with the undesirable outputs, because in our empirical application, desirable outputs can be produced even without producing undesirable outputs, i.e. (y, b, x) can be in the technology set for $b = 0$ and $y > 0$. In contrast to the directional distance function suggested by Chung et al. (1997), our approach, the extended Farrell input distance function, does not require null-jointness between the desirable outputs and the undesirable outputs.

As we use fuel as the only input and disregard other inputs such as labour, capital, and materials, our production model is based on an energy conversion function rather than on a traditional production function. This has to be considered when interpreting the results of our analysis.

In the example illustrated in figure 2, a producer invests in a CO_2-reducing technology which increases the firm's capital stock from k_0 to k_1 and reduces CO_2 emissions from b_0 to b_1, while (for simplicity) the producer's fuel input and output quantities remain unchanged. In figure 2, the relative distance from the point of production to the frontier of the technology set is not affected by the investment. When considering both capital and fuel as inputs (as in a traditional production function framework), this means that the environmental technical efficiency of this producer remains unchanged. However, in the case of our energy conversion function, which ignores the capital input, the investment in CO_2-reducing technology illustrated in figure 2 clearly increases the environmental technical efficiency, because the point of production moves closer to the frontier of the set of possible energy conversions (densely dashed horizontal line).

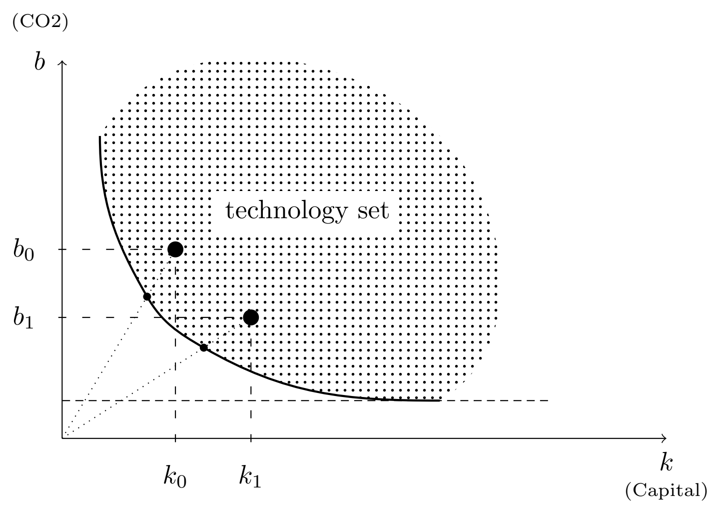


Figure 2: Investments in energy-saving technology

We follow Banker et al. (1984) and Scheel (2001)[4] and assume that the technology set in a specific time period s can be obtained from the observations in our data set by:

$$T^s = \{(y, b, x) | \lambda^\top Y^s \leq y, \lambda^\top B^s \geq b, \lambda^\top X^s \geq x, \lambda \geq 0, \lambda^\top e = 1\}, \tag{2}$$

where λ is a vector of weights, e is a vector of ones, and Y^s, B^s and X^s are the matrices of desirable output quantities, undesirable output quantities and input quantities, respectively, of all observations in our data set for time period s. A superscript G instead of s indicates that the observations from all time periods are taken to obtain the "global" technology, i.e. $Y^G \equiv \{Y^1, \ldots, Y^K\}$, $B^G \equiv \{B^1, \ldots, B^K\}$, $X^G \equiv \{X^1, \ldots, X^K\}$, where K indicates the number of time periods in the data set (Pastor and Lovell, 2005).

Given the definition of the technology set in equation (2), we can use Data Envelopment Analysis (DEA) (Charnes et al., 1978; Banker et al., 1984) to measure the environmental productivity and efficiency of Danish energy generator units as defined in equation (1):

$$\begin{aligned} D^s_{b,x}(y^t_i, b^t_i, x^t_i) = \; & \min_{\gamma, \lambda} \gamma, \\ \text{s.t.} \; & \lambda^\top Y^s \geq y^t_i, \\ & \lambda^\top B^s \leq \gamma \, b^t_i, \\ & \lambda^\top X^s \leq \gamma \, x^t_i, \\ & \lambda \geq 0, \\ & \lambda^\top e = 1, \end{aligned} \tag{3}$$

where the subscript i and the superscript t indicate the generator unit and the time period, respectively.

By removing restriction $\lambda^\top e = 1$ from equation (2), we obtain a technology set that exhibits constant returns to scale. Thus, by removing restriction $\lambda^\top e = 1$ from the linear programming problem in equation (3), we obtain distance measures that are benchmarked against the so-called cone technology (Balk, 2001). We indicate these distance measures by a checkmark (i.e. $\check{D}^s_{b,x}(y^t, b^t, x^t)$).

Based on the obtained distance measures, we assess the environmental productivity and efficiency of Danish energy generator units. We measure the overall environmental productivity of a generator unit i at time t by:

$$PROD^t_i \equiv \check{D}^G_{b,x}(y^t_i, b^t_i, x^t_i), \tag{4}$$

i.e. using the (hypothetical) global cone technology as a benchmark. This productivity measure can be decomposed into three components:

$$PROD^t_i = TE^t_i \cdot BPR^t_i \cdot SE^t_i, \tag{5}$$

where

$$TE^t_i \equiv D^t_{b,x}(y^t_i, b^t_i, x^t_i) \tag{6}$$

is the technical efficiency indicating the productivity of the observation relative to the best contemporaneous technology,

$$BPR^t_i \equiv D^G_{b,x}(y^t_i, b^t_i, x^t_i) / D^t_{b,x}(y^t_i, b^t_i, x^t_i) \tag{7}$$

[4] Our definition of the technology set corresponds to the technology set $T^{[INP]}$ in Scheel (2001).

is the best practice ratio[5] indicating the productivity of the best contemporaneous technology relative to the best global technology at the observation's scale of production, and

$$SE_i^t \equiv \check{D}_{b,x}^G(y_i^t, b_i^t, x_i^t)/D_{b,x}^G(y_i^t, b_i^t, x_i^t) \tag{8}$$

is the scale efficiency indicating the optimality of the observation's scale of production, i.e. the productivity of the best actual global technology relative to the best (hypothetical) global cone technology at the observation's scale of production.[6]

Although the levels of environmental productivity and their components are certainly relevant for our analysis, their changes over time may be even more relevant. Therefore, we additionally calculate and analyse changes in environmental productivity and their components using a global Malmquist productivity index (Pastor and Lovell, 2005):[7]

$$dPROD_i^{t-1,t} \equiv dTE_i^{t-1,t} \cdot dBPR_i^{t-1,t} \cdot dSE_i^{t-1,t}, \tag{9}$$

where

$$dPROD_i^{t-1,t} \equiv \frac{\check{D}_{b,x}^G(y_i^t, b_i^t, x_i^t)}{\check{D}_{b,x}^G(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})} \tag{10}$$

is the ratio between the environmental productivities in years t and $t-1$,

$$dTE_i^{t-1,t} \equiv \frac{D_{b,x}^t(y_i^t, b_i^t, x_i^t)}{D_{b,x}^{t-1}(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})} \tag{11}$$

is the ratio between the environmental technical efficiencies in years t and $t-1$,

$$dBPR_i^{t-1,t} \equiv \frac{D_{b,x}^G(y_i^t, b_i^t, x_i^t)}{D_{b,x}^G(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})} \cdot \frac{D_{b,x}^{t-1}(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})}{D_{b,x}^t(y_i^t, b_i^t, x_i^t)} \tag{12}$$

is the ratio between the best practice ratios in years t and $t-1$, and

$$dSE_i^{t-1,t} \equiv \frac{\check{D}_{b,x}^G(y_i^t, b_i^t, x_i^t)}{\check{D}_{b,x}^G(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})} \cdot \frac{D_{b,x}^G(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})}{D_{b,x}^G(y_i^t, b_i^t, x_i^t)} \tag{13}$$

is the ratio between the scale efficiencies in years t and $t-1$.

In order to systematically approach the dynamic aspects of questions (a)–(c) in section 1, we run a time series cluster analysis to distinguish groups of the generator units

[5] This term is usually called "best practice gap" (e.g. Pastor and Lovell, 2005). However, in the case of a Farrell distance function (rather than a directional distance function), *increases* in the (best practice) ratio imply *decreases* in the gap between the contemporaneous frontier and the global frontier (see also O'Donnell et al., 2008, footnote 4). To avoid confusion, we call this ratio "best practice ratio" rather than "best practice gap," which is analogous to O'Donnell et al. (2008) who propose renaming the "technology gap ratio" as "metatechnology ratio" in the "metafrontier" literature.

[6] It would be possible to use a metafrontier approach with a separate frontier for each production technology so that the term TE_i^t would be decomposed into $TTE_i^t \cdot MTR_i^t$, where TTE_i^t is the technical efficiency with respect to the frontier of the corresponding technology and MTR_i^t is the metatechnology ratio. However, we decided not to use the metatechnology approach in our analysis for two reasons. First, we want to use a common benchmark to assess the environmental technical efficiency of the generator units so that a decomposition of TE_i^t into TTE_i^t and MTR_i^t would make the comparison more difficult. Second, some technologies (e.g. gas turbines) are only used by a few generator units in Denmark so that the frontier of these technologies cannot be reliably determined by Data Envelopment Analysis (DEA) due to the curse of dimensionality.

[7] As Pastor and Lovell (2005) assume that the actual technology exhibits global constant returns to scale, the term $dSE_i^{t-1,t}$ is not included in their decomposition.

that have similar characteristics of the three time series TE, BPR, and SE. Three main approaches to times series clustering exist: (i) raw data time series clustering, (ii) model-based time series clustering, and (iii) feature-based time series clustering (Liao, 2005). As technology sets obtained by DEA generally shift non-smoothly between time periods, the observed time series of productivity measures also shift non-smoothly over time, which makes the application of raw data time series clustering problematic. Furthermore, as our panel is rather unbalanced, the model-based time series clustering approach is infeasible. Therefore, we follow Wang et al. (2006) and apply a feature-based time series clustering approach. As suggested by Wang et al. (2006), we reduce the time dimensionality by describing each individual time series through a number of distributional parameters: (i) the arithmetic mean of the time series for all time series, and for time series with more than two observations also (ii) the standard deviation of the time series, (iii) the slope of a linear time trend (fitted by OLS), and the (iv) standard deviation, (v) skewness and (vi) kurtosis of the de-trended time series.

As these distributional parameters contain missing values, we apply a k-medoid clustering algorithm. This is a modified version of the well-known k-means clustering algorithm, but unlike k-means clustering, the k-medoid algorithm forms the clusters around one "medoid" observation in each cluster, which makes this algorithm robust to missing values.

5. Results and discussion

All calculations and estimations were conducted within the statistical software environment "R" (R Core Team, 2014) using the add-on packages "Benchmarking" (Bogetoft and Otto, 2011, 2013) for Data Envelopment Analysis, "cluster" (Maechler et al., 2013) for cluster analysis, "NbClust" (Charrad et al., 2013) for obtaining the optimal number of clusters, and "mlogit" (Croissant, 2013) for estimating the multinomial logit model.

5.1. Overall environmental productivity

The four subfigures ((a)–(b)) in figure 3 display the development of the median environmental productivity ($PROD$) over the period of our analysis (1998–2011), subdivided by (a) age and input capacity, (b) generator technology, (c) embeddedness type, and (d) production type. All in all we can observe a slight increase (2.7 %) in the median environmental productivity. As the smaller generator units ($<$ 20 MW) dominate the sector in terms of numbers, it is not surprising that the median overall productivity is mainly driven by this group.

Over time, the productivity gap between older generator units ($>$ 20 years) and younger generator units ($<$ 20 years) decreases by 37%. However, this effect is unfortunately not primarily driven by strong increases in the environmental productivity of older generator units, but rather by the stagnating or even slightly decreasing environmental productivity of younger generator units after 2005. Hence, despite an overall small but positive trend over time, the younger generator units stand out due to their less positive development, particularly after 2005. These generator units are mainly smaller combustion engines, whose main purpose is to level out fluctuations in the power system which can be induced by wind power. This is confirmed by sub-figures (d), where we find an opposing trend in the environmental productivity of pure electricity producers whose environmental productivity plummeted by 13% over the period of our analysis.

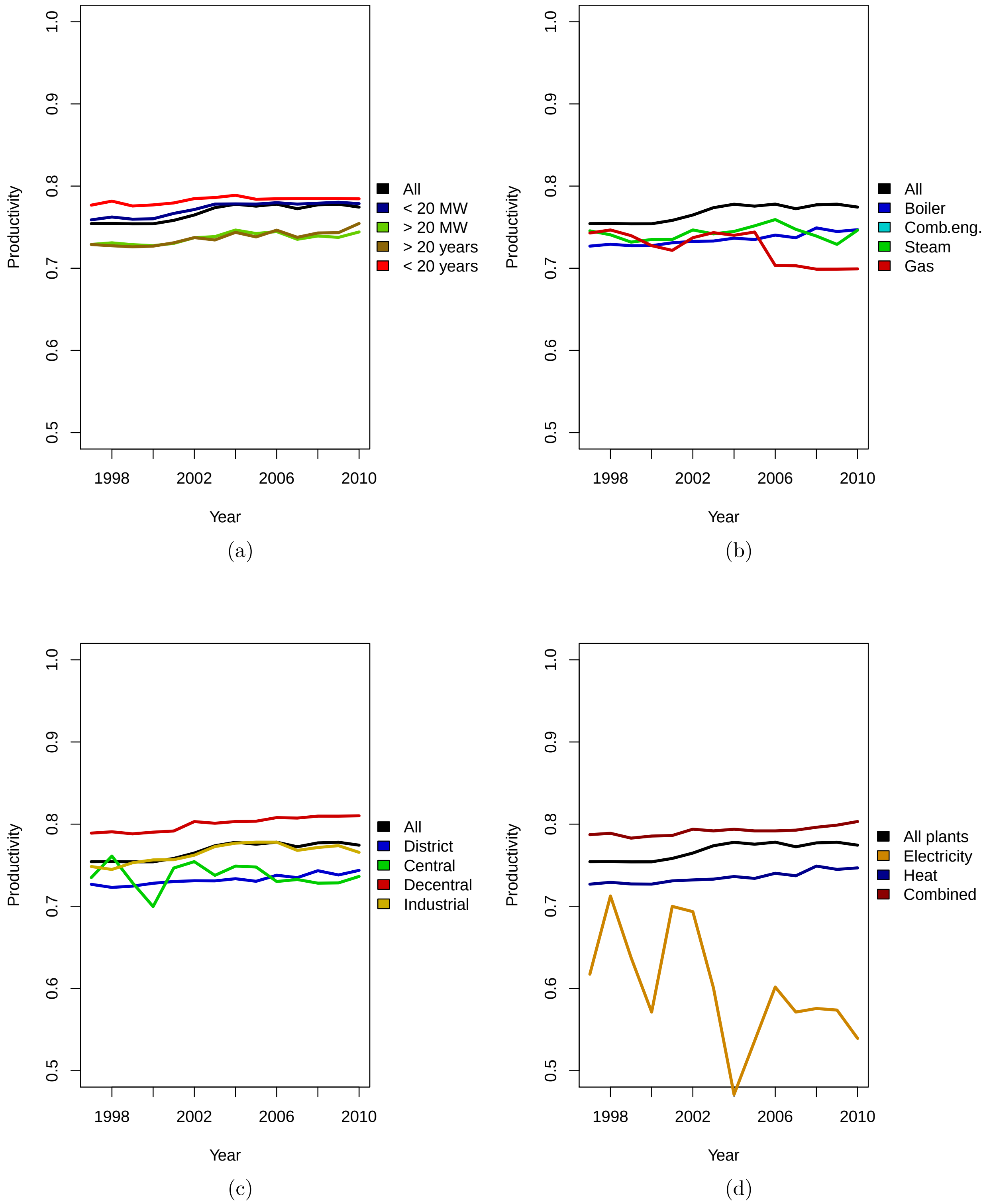


Figure 3: Yearly median values of overall environmental productivity

5.2. Time series cluster analysis

We evaluated the optimal number of clusters based on 28 different criteria (see Charrad et al., 2013, for an overview of these criteria). The criteria suggest to extract three clusters.[8] As three clusters fit well with our initial aim of characterising the high performance, middle performance, and low performance groups, we follow the suggestion despite the fact that, given the size of our dataset, the classification into only three clusters is rather coarse.

Figure 4 illustrates, using boxplot diagrams, the development over time of all three components of the overall productivity measure, i.e. BPR, TE, and SE, for each of the three clusters, where the red line marks the smoothed development of the median over time. Although there is a considerable overlap between the full ranges of the three different clusters, the median development over time and the median levels of the productivity measures (with the exception of the SE of clusters 2 and 3) is surprisingly distinct. This is especially the case for TE.

Hence, we can conclude that for each productivity measure there is a moderate to strong consistency in the ranking of the clusters over time. Furthermore, our findings suggest that there is no consistently high performing group over all three productivity measures, i.e. the ranking of the levels of the clusters changes between the three productivity measures. In section 5.3, we take a more detailed look at different producer groups to confirm this finding.

Figure 5 gives an overview of the composition of the three clusters. Although, as mentioned before, the classification into three clusters is rather rough, we see a pattern emerge in that, on the one hand, the larger and newer CHPs and the large electricity producers group together (cluster 1, blue), while on the other hand, the smaller district heating and small electricity producers form a cluster (cluster 3, green). The middle group (cluster 2, orange) is a conglomerate of medium-sized district heating and decentralised CHP and heat producers.

In order to identify the generator unit specific variables that drive the classification into the different clusters, we run a multinomial logit regression on the five characteristics, input capacity ($size$), age (age), sectoral embeddedness (emb), generator technology ($tech$), and production type ($pType$), as well as on the median of the utilised input capacity ($util$) and the median of the share of renewables in the fuel composition ($renewRatio$). The results are displayed in table 4.

We test several model specifications by means of a likelihood ratio test and find no significant effect for $size$ and $renewRatio$, so we drop these variables from the regression analysis. Furthermore, we find that $pType$ and $tech$ correlate to a degree that including both variables leads to extremely large standard errors. Therefore, we also remove $pType$ from the regression analysis. Given the descriptive results in figure 5, it is surprising that $size$ has no explanatory value. A very likely reason is that $size$ is correlated with other explanatory variables and at the same time, the separation between the clusters is not sufficiently distinct (see the wide and overlapping ranges the $size$ of the three clusters in figure 5(d)). The same applies to age which, although relevant in the model context, is itself not statistically significant.

Not surprisingly, utilised capacity, $util$, is a large driver of group membership. An increase in $util$ by ten percentage points increases the probability of being included in

[8] These criteria are not solid statistical tests and should only be used as indicators. The decision regarding the number of clusters remains with the analysts.

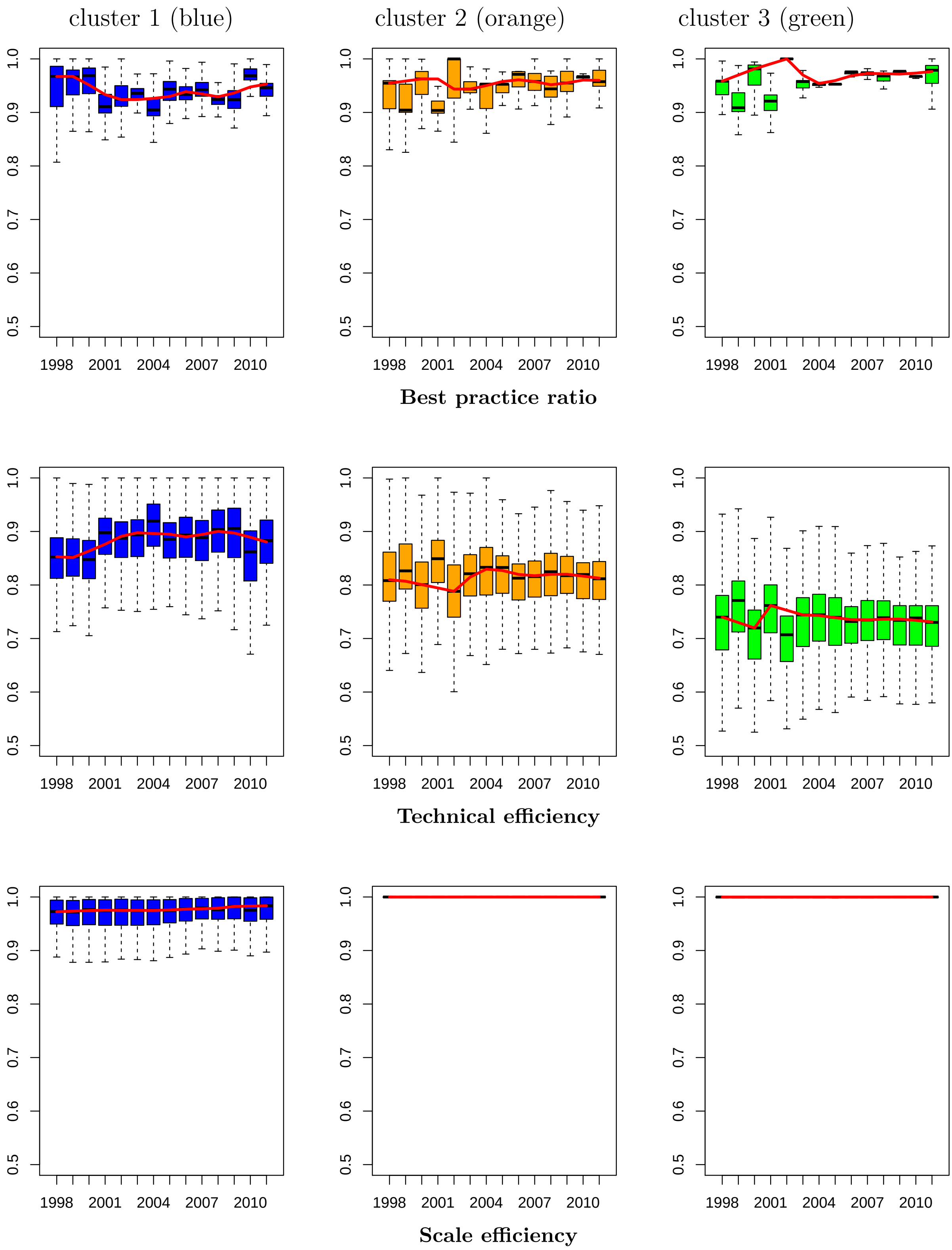
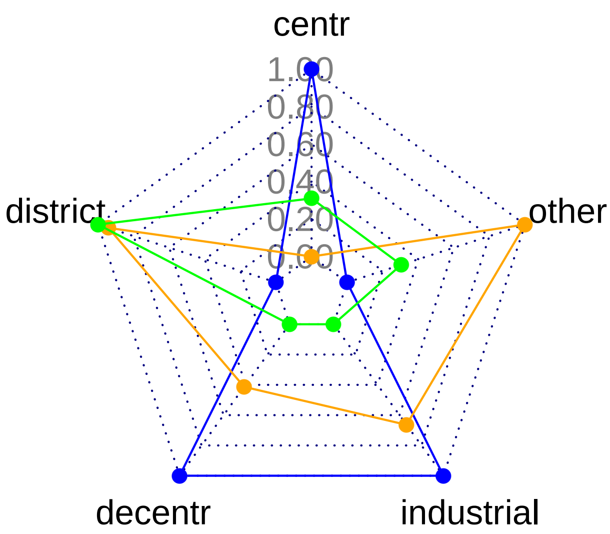
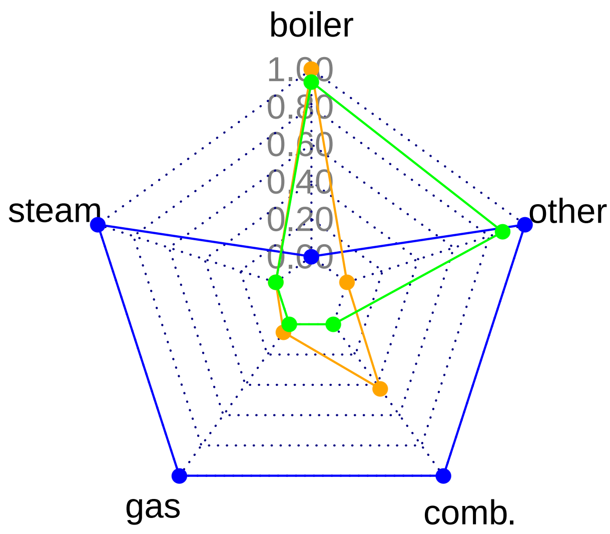


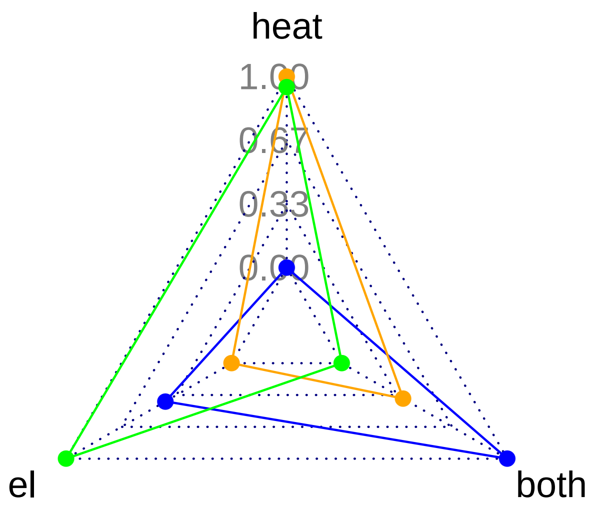
Figure 4: Development over time for the three different clusters



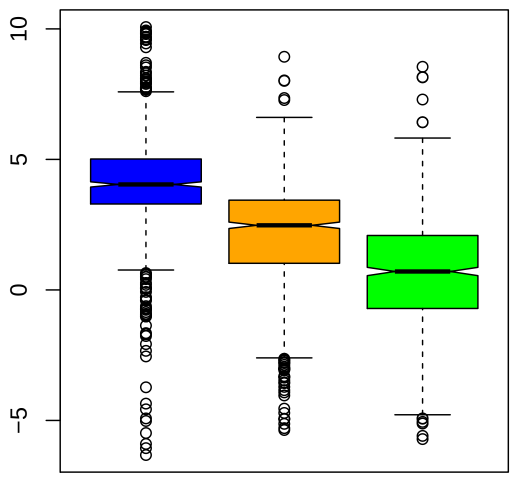
(a) Embeddedness



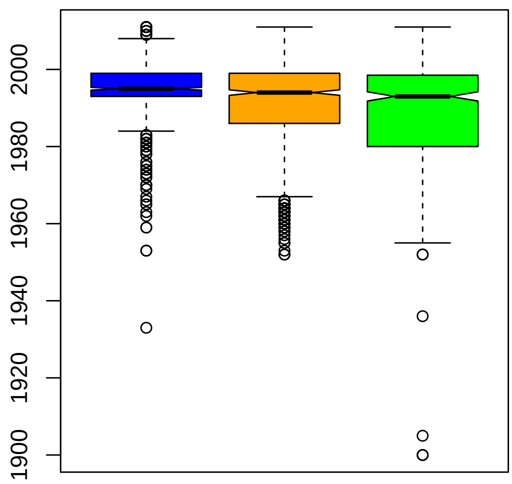
(b) Technology



(c) Production type



(d) Input capacity in MW (in logs)



(e) Age

Figure 5: Cluster characteristics

Table 4: Results of the multinomial logit estimation

	me_1	β_2	$se(\beta_2)$	me_2	β_3	$se(\beta_3)$	me_3
(intercept)		9.70	16.48		2.10	17.05	
util	0.31	-2.51***	0.34	0.21	-5.18***	0.44	-0.64
age	0.00	-0.00	0.01	-0.00	0.00	0.01	0.00
tech: steam turbine	0.26	-2.77***	0.54	-0.24	-2.28***	0.57	-0.01
tech: gas turbine	0.26	-2.66***	0.53	-0.17	-2.59***	0.61	-0.06
tech: combustion engine	0.27	-2.60***	0.25	-0.07	-3.34***	0.31	-0.21
tech: other technology	0.24	-2.82***	0.62	-0.34	-1.70***	0.55	0.11
emb: district heating	-0.15	2.09***	0.75	0.39	0.53	0.60	-0.21
emb: decentralised	-0.05	1.20*	0.71	0.40	-0.71	0.54	-0.32
emb: industrial	-0.13	1.89***	0.71	0.36	0.46	0.55	-0.20
emb: other plant	-0.34	3.74***	0.73	0.37	2.73***	0.59	-0.05

Note: β_j are the estimated coefficients that correspond to cluster j, where the coefficients of cluster 1 are normalised to zero; $se(\beta_j)$ are the standard errors of β_j; me_j are the median marginal effects on the probability of belonging to cluster j.

cluster 1 (blue) by 3.1 percentage points and decreases the probability of being included in cluster 3 (green) by 6.4 percentage points. As the variables *tech* and *emb* are categorical variables, their marginal effects must be seen in relation to the basic level, which is 'boiler technology' in the case of *tech* and 'centralised plant' in the case of *emb*. Hence, the probability of being included in cluster 1 is 26 percentage points higher for a gas turbine than it is for a generator unit with boiler technology. By and large, the marginal effects of *emb* and *tech* reflect the results displayed in the radar plots 5(a) and 5(b), respectively.

5.3. Grouping of generator units by type

Table 5 summarises our findings on a more detailed level. We form groups for all combinations of the embeddedness type, technology, production type, age and size. The characteristics "age" and "size" are divided into three age classes and three size classes, respectively (see Table 6). Groups which include less than five generator units are not included in Table 5. We calculate the respective group median values for all productivity measures, $PROD$, TE, BPR, and SE, as well as their changes, $dPROD$, dTE, $dBPR$, and dSE, where an orange background indicates poor performance, a white background indicates moderate performance, and a green background indicates a good performance (for details see Table 6).

$PROD$ and $dPROD$ All CHPs with combustion engines show high and consistent levels of overall environmental productivity, while not surprisingly we find the lowest environmental productivity levels amongst electricity-only generator units. A more concerning finding is that nearly all electricity-only generator units show high rates of productivity decline over the observation period. Another concerning result is that the majority of the groups do not experience any progress in their environmental productivity over time. However, this seems not to be the case for several groups of industrial plants that considerably improve their overall environmental productivity over time.

TE and dTE Concerning environmental technical efficiency, The CHP units are again superior to units which only produce electricity or heat. Regarding technologies, most groups of combustion engines and steam turbines exhibit high levels of environmental

Table 5: Results for different groups of generator units

emb	age	tech	pType	size	nObs	nGU	cl1	cl2	cl3	util	Prod	dProd	TE	dTE	BPR	dBPR	SE	dSE
decentral	med	combi	CHP	large	108	8	91	0	9	51.4	0.855	-0.0024	0.955	0.0000	0.964	-0.0008	0.917	-0.0002
decentral	new	combust	CHP	large	29	6	48	52	0	0.8	0.808	-0.0001	0.872	0.0047	0.971	-0.0059	1.000	0.0000
decentral	med	combust	CHP	large	98	7	100	0	0	45.5	0.818	-0.0001	0.920	-0.0014	0.959	-0.0025	0.915	0.0005
industry	med	gas	CHP	large	60	5	77	0	23	60.8	0.738	0.0004	0.841	0.0009	0.941	-0.0032	0.925	0.0014
industry	new	steam	CHP	large	83	8	100	0	0	87.8	0.732	0.0136	0.838	0.0000	0.915	0.0010	0.942	-0.0005
central	med	steam	CHP	large	98	7	100	0	0	57.4	0.764	-0.0023	0.914	0.0000	0.955	0.0017	0.888	0.0015
decentral	med	steam	CHP	large	87	7	100	0	0	60.4	0.741	-0.0027	0.907	0.0000	0.900	0.0055	0.926	-0.0001
industry	med	steam	CHP	large	64	6	83	17	0	75.2	0.730	0.0018	0.859	0.0000	0.923	0.0043	0.944	-0.0008
central	old	steam	CHP	large	158	16	58	9	33	34.9	0.742	-0.0038	0.840	-0.0111	0.954	0.0028	0.931	0.0021
industry	old	steam	CHP	large	52	5	65	17	17	38.8	0.739	0.0123	0.883	0.0000	0.923	-0.0034	0.935	-0.0016
decentral	new	combust	elec	large	24	7	0	25	75	0.1	0.743	-0.0228	0.751	-0.0119	0.982	-0.0067	1.000	0.0000
central	old	steam	elec	large	39	5	8	8	85	1.2	0.588	0.0094	0.606	0.0129	0.971	-0.0042	0.995	-0.0000
distr heat	new	boiler	heat	large	118	16	1	18	81	0.8	0.730	0.0000	0.758	0.0067	0.969	-0.0018	1.000	0.0000
distr heat	med	boiler	heat	large	168	12	0	67	33	0.9	0.731	0.0000	0.773	0.0006	0.959	-0.0006	1.000	-0.0000
distr heat	old	boiler	heat	large	914	72	0	62	38	0.9	0.732	0.0000	0.780	0.0007	0.954	-0.0016	1.000	-0.0000
industry	old	boiler	heat	large	121	9	55	23	22	5.3	0.672	0.0001	0.754	-0.0009	0.953	0.0013	1.000	0.0000
decentral	new	combust	CHP	med	623	76	93	5	2	39.1	0.834	-0.0001	0.915	0.0006	0.941	-0.0048	0.972	0.0000
industry	new	combust	CHP	med	237	28	76	24	0	36.1	0.792	-0.0000	0.870	-0.0005	0.934	-0.0061	0.982	0.0000
local	new	combust	CHP	med	68	7	63	37	0	32.6	0.780	-0.0000	0.850	0.0053	0.930	-0.0098	0.995	0.0000
decentral	med	combust	CHP	med	2482	205	89	10	0	43.1	0.816	0.0009	0.893	0.0033	0.944	-0.0045	0.972	0.0002
industry	med	combust	CHP	med	403	32	76	24	0	40.4	0.789	0.0001	0.859	-0.0020	0.943	-0.0014	0.980	0.0008
local	med	combust	CHP	med	349	26	83	17	0	40.9	0.778	-0.0006	0.845	0.0034	0.935	-0.0059	0.991	0.0002
decentral	med	gas	CHP	med	64	5	78	22	0	33.1	0.740	-0.0063	0.805	-0.0085	0.947	0.0012	0.976	0.0008
industry	med	gas	CHP	med	64	5	22	66	12	83.4	0.708	0.0003	0.804	0.0032	0.953	-0.0007	0.931	0.0003
decentral	new	boiler	heat	med	157	26	6	85	8	14.6	0.794	0.0000	0.822	0.0010	0.958	-0.0005	1.000	0.0000
distr heat	new	boiler	heat	med	802	129	6	58	36	15.6	0.744	0.0000	0.786	-0.0022	0.955	-0.0012	1.000	0.0000
industry	new	boiler	heat	med	31	6	52	45	3	61.0	0.729	0.0001	0.797	-0.0003	0.940	0.0057	0.978	-0.0000
decentral	med	boiler	heat	med	1409	116	2	56	42	2.5	0.748	0.0000	0.788	0.0011	0.959	-0.0012	1.000	0.0000
distr heat	med	boiler	heat	med	1857	163	5	52	42	2.2	0.732	0.0000	0.776	0.0012	0.955	-0.0014	1.000	0.0000
industry	med	boiler	heat	med	224	22	35	24	42	27.2	0.678	0.0000	0.748	0.0005	0.948	-0.0005	1.000	0.0000
decentral	old	boiler	heat	med	305	30	0	67	33	3.2	0.785	-0.0001	0.817	0.0011	0.959	-0.0018	1.000	0.0000
distr heat	old	boiler	heat	med	1188	128	3	39	58	0.7	0.716	0.0000	0.752	0.0020	0.958	-0.0013	1.000	0.0000
industry	old	boiler	heat	med	68	7	54	34	12	50.3	0.653	0.0000	0.735	-0.0108	0.933	0.0036	1.000	-0.0000
decentral	new	combust	CHP	small	45	6	84	16	0	56.0	0.806	-0.0000	0.877	-0.0008	0.935	-0.0078	0.999	0.0000
industry	new	combust	CHP	small	232	27	54	40	6	43.2	0.785	-0.0000	0.853	-0.0095	0.912	0.0135	1.000	0.0000
local	new	combust	CHP	small	414	50	28	51	21	38.9	0.770	0.0000	0.820	0.0001	0.928	0.0036	1.000	-0.0000
decentral	med	combust	CHP	small	647	51	82	15	2	43.5	0.822	-0.0000	0.883	0.0039	0.926	-0.0062	1.000	-0.0000
industry	med	combust	CHP	small	331	25	31	69	0	46.6	0.775	-0.0000	0.834	-0.0002	0.930	-0.0020	1.000	-0.0000
local	med	combust	CHP	small	1189	102	7	74	19	48.6	0.770	-0.0001	0.815	0.0026	0.935	-0.0062	1.000	-0.0000
decentral	new	combust	elec	small	15	5	20	80	0	20.4	0.768	-0.0118	0.791	-0.0098	0.982	-0.0060	1.000	0.0000
industry	new	combust	elec	small	15	5	0	0	100	0.7	0.679	0.0041	0.721	-0.0061	0.965	-0.0050	1.000	0.0000
local	new	combust	elec	small	58	16	40	10	50	38.2	0.597	-0.0183	0.655	-0.0484	0.896	-0.0145	0.999	0.0000
local	med	combust	elec	small	52	20	8	35	58	43.5	0.470	-0.1708	0.532	-0.0918	0.918	-0.0031	1.000	0.0000
decentral	new	boiler	heat	small	73	11	1	4	95	9.7	0.704	0.0000	0.725	0.0004	0.964	-0.0015	1.000	0.0000
distr heat	new	boiler	heat	small	309	38	0	47	53	20.4	0.720	0.0000	0.756	-0.0008	0.959	-0.0016	1.000	0.0000
decentral	med	boiler	heat	small	467	39	2	47	51	3.0	0.738	-0.0000	0.766	0.0012	0.960	-0.0006	1.000	0.0000
distr heat	med	boiler	heat	small	229	20	0	62	38	47.7	0.723	-0.0000	0.763	-0.0011	0.953	-0.0032	1.000	0.0000
distr heat	old	boiler	heat	small	93	12	0	30	70	1.0	0.744	0.0000	0.763	0.0001	0.966	-0.0013	1.000	0.0000

Note: the abbreviations and colours used in this table are described in Table 6.

Table 6: Abbreviations and colours used in Table 5

Column	explanation
the first five columns define groups of generator units	
emb	embeddedness type of the plant: central = central plant, decentral = decentralised plant, distr heat = district heating plant, industry = industrial plant, local = local plant
age	age of the generator unit: new = built 1998 or later, med = built between 1983 and 1997, old = built 1982 or earlier
tech	technology of the generator unit: boiler = boiler, combi = combined generator unit, combust = combustion engine, gas = gas turbine, steam = steam turbine
pType	type of production: CHP = combined heat and power generation, elec = electricity production only, heat = heat production only
size	the size of the generator unit: large = 20 MW or more input capacity, med = 2 MW or more but less than 20 MW input capacity, small = less than 2 MW input capacity
the remaining columns provide information on the groups of generator units	
nObs	number of observations in our data set that belong to the group of generator units
nGU	number of generator units in our data set that belong to the group of generator units; only groups with at least five generator units are shown in Table 5
cl1	percentage of observations in the group of generator that are in cluster 1
cl2	percentage of observations in the group of generator that are in cluster 2
cl3	percentage of observations in the group of generator that are in cluster 3
util	median value of the capacity utilisation of the observation in the group of generator units in percent
Prod, TE, BPR, SE	median values of the overall environmental productivity, the technical efficiency, the best practice ratio, and the scale efficiency as defined in equations (4), (6), (7), and (8), respectively, of all observations in the group of generator units; values above the median value in this column are highlighted by a green background colour, while values below the median value in this column are highlighted by an orange background colour, where the intensity of the colour increases with the difference to the median; as the median value of the column of the median scale elasticities is virtually one, we used the threshold 0.98 instead of the median for colouring the column with the scale elasticities
dProd, dTE, dBPR, dSE	median value of the change of the overall environmental productivity, the change in technical efficiency, the change in the best practice ration, and the change in the scale efficiency as defined in equations (10), (11), (12), and (13), respectively, of all observations in the group of generator units; a one has been subtracted from these values in order to improve readability; values above zero indicate increasing productivities and are highlighted by a green background colour, while values below zero indicate decreasing productivities and are highlighted by an orange background colour, where the intensity of the colour increases with the difference from zero

technical efficiency. A positive result is that a number of groups experienced increases in environmental technical efficiency over the observation period, which means that poorly performing generator units in particular improved their performance during the sampling period. This is especially the case for groups of combustion engines and boiler technologies. However, new electricity-only units stand out as they not only have a low median level, but also some of the highest regression rates in environmental technical efficiency.

BPR and $dBPR$ While the change of the best practice ratio over time indicates technical change, the median (or average) value of the BPR over the entire sampling period is of minor relevance. A low median value of BPR indicates that there were large changes to the technology over time, e.g. strong technical progress or strong technical regress. Therefore, we only look at the median values of the changes in the best practice ratio ($dBPR$). All groups of electricity-only producers and most groups of combustion engines (CHP and electricity-only) experience a declining best practice ratio. This does not necessarily mean that there is in fact technical regress, but it means that the most productive generator units that define the technology frontier become less productive over time. Two groups of new small combustion engines (CHP) and most groups of steam turbines (CHP) experience significant technical progress. Boiler technologies in general experience technical stagnation.

SE and dSE Most groups of large CHP generator units and some groups of medium-sized generator units are scale inefficient due to decreasing returns to scale at these size classes. This finding implies that they are oversized. At first glance, this does not seem to apply to boiler technologies, but a closer look reveals that all groups of large boilers have very low levels of capacity utilisation. Hence, we cannot assess the scale efficiency of large-scale production with boiler technologies. On the other hand, all groups of small generator units are virtually fully scale efficient. This result indicates that there are no significantly increasing returns to scale even for the smallest generator units, meaning that small generator units do not reduce the sectoral environmental productivity while large generator units may do so.

Table 5 confirms that there is no overall best performance group of generator units, but that the performance of each group differs between productivity measures. On the one hand, most groups of steam turbines and combustion engines for CHP perform quite well in most productivity measures. On the other hand, combustion engines that only produce electricity are clearly low performers because they have extremely low environmental technical efficiencies and virtually all their productivity measures decline over time. The industrial units among them are operated as peaking units as illustrated by the low utilisation. Therefore, they do not constitute a major environmental concern. In contrast, the decentralised and local units exhibit utilisation rates of up to 43.5%. This point illustrates that they have their own operational patterns and are not used as peaking units as may be expected for electricity-only generators in a system with high shares of fluctuating renewable generation. With the increasing amount of small generators, this issue should be addressed by improved system integration and economic signals that prevent island operation.

6. Conclusion

Based on a data set of virtually all fuel-fired electricity and heat producing generator units in Denmark, we have analysed the development of their environmental productivity by an extended Farrell input distance function that takes CO_2 emissions into account. We have decomposed the overall productivity measure into its three subcomponents: technical efficiency, best practice ratio, and scale efficiency.

Our results show that the ranking of the performance groups is constant over time, but clearly differs between the different productivity measures. Steam turbines and combustion engines for CHP tend to have a high performance according to most productivity measures. On the other hand, combustion engines that only produce electricity clearly belong to the poorest performance group. It is striking that they are predominantly newer units with many hours of operation. Their lack of efficiency indicates that their economic benefits come from an island operation mode to cover predominantly local demand.

Our results support the argument about the high technical efficiencies of CHP units by another dimension: their scale efficiency is suboptimal for almost all groups above 2MW. However, we do not expect that this effect outweighs the environmental gains due to co-generation.

All in all, our findings reveal that despite a comprehensive climate policy portfolio in Denmark, the sectoral improvement of CO_2-based environmental productivity is depressingly low and it seems that the transition of the energy system is being mainly driven by the inclusion of new technologies like wind power or solar panels and only to a lesser extent by the realisation of efficiency gains. This may be a very costly path to follow. As the energy sector is one of the main contributors to Denmark's CO_2 emissions, a more thorough and comprehensive understanding of the effects of climate policies on the development of environmental productivity at the sectoral level as well at the firm level is absolutely essential.

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A. Additional tables

Table 1: CO_2 emissions of different fuel types

Fuel type	CO_2 [kg/TJ]
coal	95
petro coke	92
orimulsion	80
fuel oil	78
waste oil	78
gas oil	74
refinery gas	56.9
LPG	65
natural gas	56.74
waste	32.5
electricity	140.27
biogas	0
straw	0
wood chips	0
wood and biomass waste	0
wood pellets	0
bio oil	0
fuel free	0

Source: Danish Energy Agency (2010, p. 59)