International Journal of Sustainable Energy Planning and Management Vol. 07 2015 79-98

International Journal of
Sustainable Energy Planning and Management

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

Geraldine Henningsen[a,*], Arne Henningsen[b], Sascha T. Schröder[a], Simon Bolwig[a]

[a] Department of Management Engineering, Technical University of Denmark, Productionstorvet 426, 2800 Kgs. Lyngby, Denmark.
[b] Department of Food and Resource Economics, University of Copenhagen, Rolighedsvej 25, 1958 Frederiksberg C, Denmark.

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 environmental energy conversion productivity into conversion efficiency, best conversion practice ratio, and conversion 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 emission mitigation;
Renewable energy;
Transition:

URL: dx.doi.org/10.5278/ijsepm.2015.7.7

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 improvements that lead to increases in environmental efficiency [1],

* Corresponding author e-mail: gehe@dtu.dk

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.

Abbreviations:

EECP	= environmental energy conversion productivity;
CE	= conversion efficiency;
BCPR	= best conversion practice ratio;
CSE	= conversion scale efficiency;
MTR	= meta technology ratio.

Table 1: Correspondence between productivity measures and transition pillars

Pillars		Productivity measures
Innovation	⇒	changes in the best practice conversion technology
Efficiency gains	⇒	changes in conversion efficiency, changes in conversion scale efficiency

and rescaling generator unit capacities to increase scale efficiency [1, 22] are equally important elements in the transition of the energy system towards low-carbon targets.

Based on a 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 [1, 26, 24, 25]. Similarly to [1] and [24], we use an extended Farrell input distance function with two desirable outputs (heat and electricity), one undesirable output (CO_2), and one input (fuel), while we disregard other inputs such as labour, capital, and materials. Traditional and environmental total factor productivity measures that are commonly applied in studies on the performance of heat and power production take into account all production inputs so that, e.g., investments in fuel-saving and/or CO_2-reducing technologies can lower productivity measures, because the increase of the productivity measure due to reduced fuel-use and/or CO_2 emissions can be smaller than its decrease due to increased capital costs. In contrast, investments in fuel-saving and/or CO_2-reducing technologies necessarily result in higher productivity measures in our analysis.

As our productivity measure can be improved both by a more efficient conversion of fuel into heat and/or electricity (energy conversion efficiency) and by changes of the fuel composition towards less CO_2 emitting fuels (environmental efficiency), we call our obtained productivity measure "environmental energy conversion productivity".

We divide the environmental energy conversion productivity into three subcomponents: conversion efficiency, best conversion practice ratio, and conversion scale efficiency, and use the global Malmquist productivity index proposed by [18] to quantify yearly changes in the three subcomponents, e.g., changes in conversion efficiency, changes in the best practice conversion technology, and changes in the conversion scale efficiency. 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 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; and (c) what characterises a potential low performance group. This information allows a comprehensive analysis of the sectoral performance and may contribute to understanding the environmental efficiency of a complex energy system. The ongoing reform of the emissions reference document for large combustion plants [13] 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 [23] over all three subcomponents of environmental energy conversion productivity to identify and describe 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 identified 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 its 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 heat and power 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 have CHP units whose construction and operation have been promoted by a number of governmental support actions throughout the years. CHP units have an inherently higher total efficiency than electricity-only or heat-only units. This effect is reinforced by dimensioning and sizing the generation units for the respective local heat demand, leading to economies of scope in comparison to generator units with only one output. 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 [12].
- *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 [12].
- *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 [11].[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 stepwise changes of the mix of fuels.

As all generator units in our sample—no matter whether they produce no CO_2 or strictly positive amounts of CO_2—produce heat and electricity by burning some kind of fuel and as the share of renewables can be incrementally increased to 100% so that the CO_2 emissions are gradually reduced to zero (see Figure 1), it is reasonable to assume that generator units that produce no CO_2 and generator units that produce strictly positive amounts of CO_2 use the same or a very similar technology so that we do not need to separate between

[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 A.1.

Table 2: Composition of data set

Variable		#
Number of observations		24411
Number of years		14
Number of generator units		2488
Number of plants		1415
Frequency of generator technologies		
	Boiler	1840
	Combustion engine	518
	Steam turbine	80
	Gas turbine	31
	Other	19
Frequency of embeddedness types		
	Decentralised plants	656
	District heating plants	647
	Industrial plants	73
	Centralised plants	39
Frequency of production types		
	Electricity only	126
	Heat only	1387
	CHP	1061
Number of generator units producing no 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	0.0010	640.00
Heat capacity of in MW**	12.29	3.50	40.07	0.0100	585.00
Input capacity in MW	22.46	5.00	98.07	0.0250	1582.00
Yearly electricity production in TJ*	147.92	11.02	850.84	0.0001	14795.92
Yearly heat production in TJ**	83.71	11.13	406.79	0.0001	9798.09
Total fuels in TJ	210.35	16.00	1470.19	0.0010	37545.39
CO_2 emissions in t	14.5	0.30	127.02	0	3560.33

Note: * = only generator units that produce electricity, ** = only generator units that produce heat. All figures are rounded to two decimals, except for the minimum values, which are rounded to four decimals.

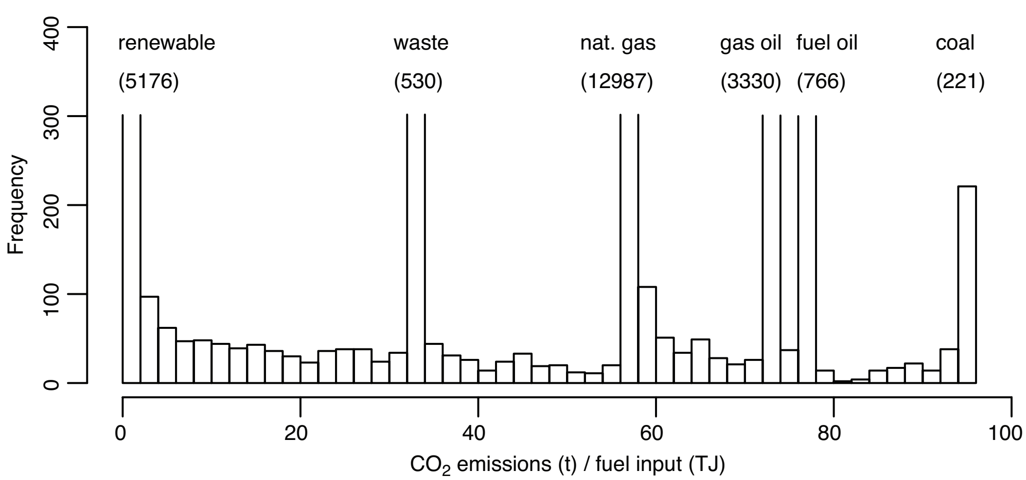

Figure 1: Histogram of ratios between CO_2 emissions and fuel input. The truncated columns mostly correspond to generator units that only use a single fuel type. The fuel type and the frequency are indicated above these columns.

two distinct technologies—technologies with no CO_2 emissions and technologies with strictly positive CO_2 emissions—in our analysis.

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.

4. Methodology

Our analysis of the environmental energy conversion 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., 20]. 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:

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

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.

As briefly outlined in the introduction, the generator units have two (not mutually exclusive) basic pathways to increase their environmental energy conversion productivity (for constant output quantities): (i) fuel-saving measures that proportionally reduce fuel use and CO_2 emissions and (ii) changes of the fuel composition towards less CO_2 emitting fuels, which reduce CO_2 emissions, whereas the total fuel use is expected to remain approximately constant. The direction of the distance function that we use in our analysis corresponds to the first pathway but it also takes into account the second pathway. For instance, if a given generator unit changes its fuel composition so that its CO_2 emissions decrease by 10%, while the total fuel input and the output quantities remain unchanged, our distance function approach indicates that the environmental energy conversion productivity has improved. However, the improvement of the environmental energy conversion productivity is less than it would have been if the same generator unit had reduced both its CO_2 emissions and its fuel input by 10%, while leaving the fuel composition and the output quantities unchanged. Hence, our distance function approach rewards reductions of CO_2 emissions that go along with fuel reductions (first pathway) more than reductions of CO_2 emissions that keep the total fuel input constant (second pathway).

The directional distance function defined in (1) corresponds to a traditional Farrell input distance function, where the undesirable output is treated as an additional input [specification "INP" in 20]. 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 energy conversion 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 energy conversion 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, some generator units produce strictly positive quantities of heat and/or electricity by exclusively using renewable fuels so that they—according to our way of calculating CO_2 emissions—do not emit CO_2, e.g., $(y,\ b,\ x)$ can be in the technology set for $b = 0$ and $y > 0$. In contrast to the directional distance function suggested by [9], our approach, the extended Farrell input distance function, does not require null-jointness between the desirable outputs and the undesirable outputs.

In contrast to [14], we do not explicitly assume weak disposability. Weak disposability means that desirable and undesirable outputs can be reduced proportionally, e.g., if $(y,\ b,\ x)$ is in the technology set and $0 \leq \theta \leq 1$, then $(\theta y,\ \theta b,\ x)$ is also in the technology set [14]. We cannot be sure that the (true) production technology of the analysed generator units fulfils this assumption. For instance, it could be the case that after changing the fuel mix so that CO_2 emissions are reduced from b to θb with $0 \leq \theta \leq 1$, while keeping total fuel input constant at x, the maximum possible output quantities are reduced from y to ψy with $0 \leq \psi \leq \theta$, which means that weak disposability is not fulfilled.

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 environmental energy conversion function rather than on a traditional production function. The best practice frontier that we obtain in our analysis does not describe the best practice technology for energy production, because it ignores non-fuel inputs. As non-fuel inputs are costly, energy producing companies should not use this frontier technology to assess their productive performance. However, our analysis indicates the best practice frontier for environmental energy conversion, e.g., the conversion of fuel to heat and electricity taking into account CO_2 emissions. Thus, we can use the obtained frontier to assess how the environmental energy conversion would improve if the generator units switch to the best available technology for environmental energy conversion (not taking into account the costs of changing the technology). This is what we want to investigate in 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 environmental energy conversion function, which ignores the capital input, the investment in CO_2-reducing technology illustrated in Figure 2 clearly increases the environmental energy conversion efficiency, because the point of production moves closer to the frontier of the set of possible energy conversions (densely dashed horizontal line).

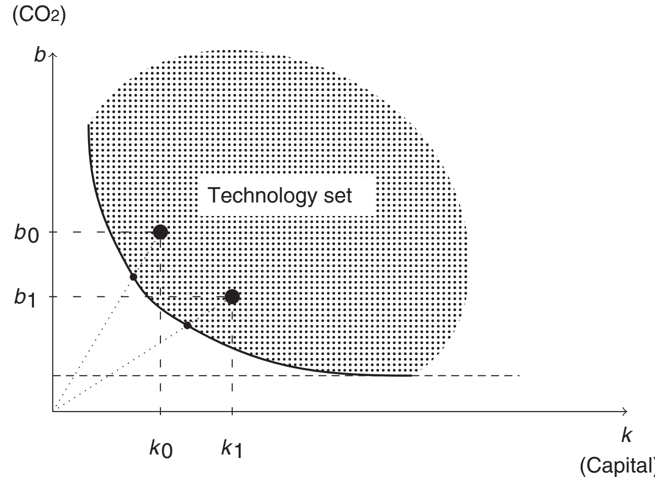

Figure 2: Investments in CO_2-reducing technology

The argumentation based on the example in Figure 2 also holds for investments in fuel-saving technologies that as a consequence reduce CO_2 emissions. We only present the simpler example that assumes an unchanged fuel input, because simultaneously looking at the capital stock, CO_2 emissions, and fuel input requires a 3-dimensional graph, which would make the illustration more complex than necessary.

We follow [3] and [20][4] and assume that the technology set in a specific time period s can be obtained from the observations in our data set by:

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

[4] Our definition of the technology set corresponds to the technology set $T^{[INP]}$ in [20].

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, e.g., $Y^G \equiv \{Y^1,...,Y^K\}$, $B^G \equiv \{B^1,...,B^K\}$, $X^G \equiv \{X^1,...,X^K\}$, where K indicates the number of time periods in the data set [18].

Given the definition of the technology set in equation (2), we can use Data Envelopment Analysis (DEA) [6, 3] to measure the environmental energy conversion productivity of an energy generator unit i at time t relative to the best practice conversion technology at time s as defined in equation (1):

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

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 [2]. We indicate these distance measures by a checkmark (e.g., $\check{D}^S_{b,x}(y^t, b^f, x^t)$).

Given the specification of the DEA model in (3), the best practice frontier for generator units that produce no CO_2 is only constructed by the 649 generator units that produce no CO_2. However, due to the convexity assumption in our DEA model, the best practice frontier for generator units that produce (small) strictly positive amounts of CO_2 can be constructed by a combination of generator units that produce no CO_2 and generator units that produce strictly positive amounts of CO_2. As the generator units can gradually change the share of renewables in the fuel composition until it reaches 100% (see section 3, particularly Figure 1), the convexity assumption is also reasonable between generator units that produce no CO_2 and generator units that produce strictly positive amounts of CO_2.

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

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

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

$$EECP^t_i = CE^t_i \cdot BCPR^t_i \cdot CSE^t_i, \tag{5}$$

where

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

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

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

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

$$CSE^t_i \equiv \check{D}^G_{b,x}(y^t_i, b^t_i, x^t_i) \,/\, D^G_{b,x}(y^t_i, b^t_i, x^t_i) \tag{8}$$

is the conversion scale efficiency indicating the optimality of the observation's scale of production, e.g., 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 energy conversion productivity and their components are certainly relevant for our analysis, their changes over time

[5] In the productivity and efficiency literature, this term is usually called "best practice gap" [e.g. 18]. 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 17, footnote 4]. To avoid confusion, we call this ratio "best conversion practice ratio" rather than "best conversion practice gap," which is analogous to [17] who propose renaming the "technology gap ratio" as "metatechnology ratio" in the "metafrontier" literature.

may be even more relevant. Therefore, we additionally calculate and analyse changes in environmental energy conversion productivity and their components using a global Malmquist productivity index [18]:[7]

$$dEECP_i^{t-1,t} \equiv dCE_i^{t-1,t} \cdot dBCPR_i^{t-1,t} \cdot dCSE_i^{t-1,t}, \tag{9}$$

where

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

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

$$dCE_i^{t-1,t} \equiv \frac{D^t_{b,x}(y_i^t, b_i^t, x_i^t)}{D^{t-1}_{b,x}(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})} \tag{11}$$

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

$$dBCPR_i^{t-1,t} \equiv \frac{D^G_{b,x}(y_i^t, b_i^t, x_i^t)}{D^G_{b,x}(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})} \cdot \frac{D^{t-1}_{b,x}(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})}{D^t_{b,x}(y_i^t, b_i^t, x_i^t)} \tag{12}$$

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

$$dCSE_i^{t-1,t} \equiv \frac{\check{D}^G_{b,x}(y_i^t, b_i^t, x_i^t)}{\check{D}^G_{b,x}(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})} \cdot \frac{D^G_{b,x}(y_i^{t-1}, b_i^{t-1}, x_i^{t-1})}{D^G_{b,x}(y_i^t, b_i^t, x_i^t)} \tag{13}$$

is the ratio between the conversion 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 that have similar characteristics of the three time series CE, $BCPR$, and CSE. 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 [15]. 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 [23] and apply a feature-based time series clustering approach. As suggested by [23], 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" [19] using the add-on packages "Benchmarking" [4, 5] for Data Envelopment Analysis, "cluster" [16] for cluster analysis, "NbClust" [7] for obtaining the optimal number of clusters, and "mlogit" [10] for estimating the multinomial logit model.

5.1. Overall environmental productivity

The four Subfigures ((a)–(d))[8] in Figure 3 display the development of the median environmental energy

[6] It would be possible to use a metafrontier approach with a separate frontier for each production technology so that the term CE_i^t would be decomposed into $TCE_i^t \times MTR_i^t$, where TCE_i^t is the conversion efficiency with respect to the frontier of the corresponding conversion 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 energy conversion efficiency of the generator units so that a decomposition of CE_i^t into TCE_i^t and MTR_i^t does not provide information that we could use to answer our research questions. 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 [18] assume that the actual technology exhibits global constant returns to scale, the term $dCSE_i^{t-1,t}$ is not included in their decomposition.

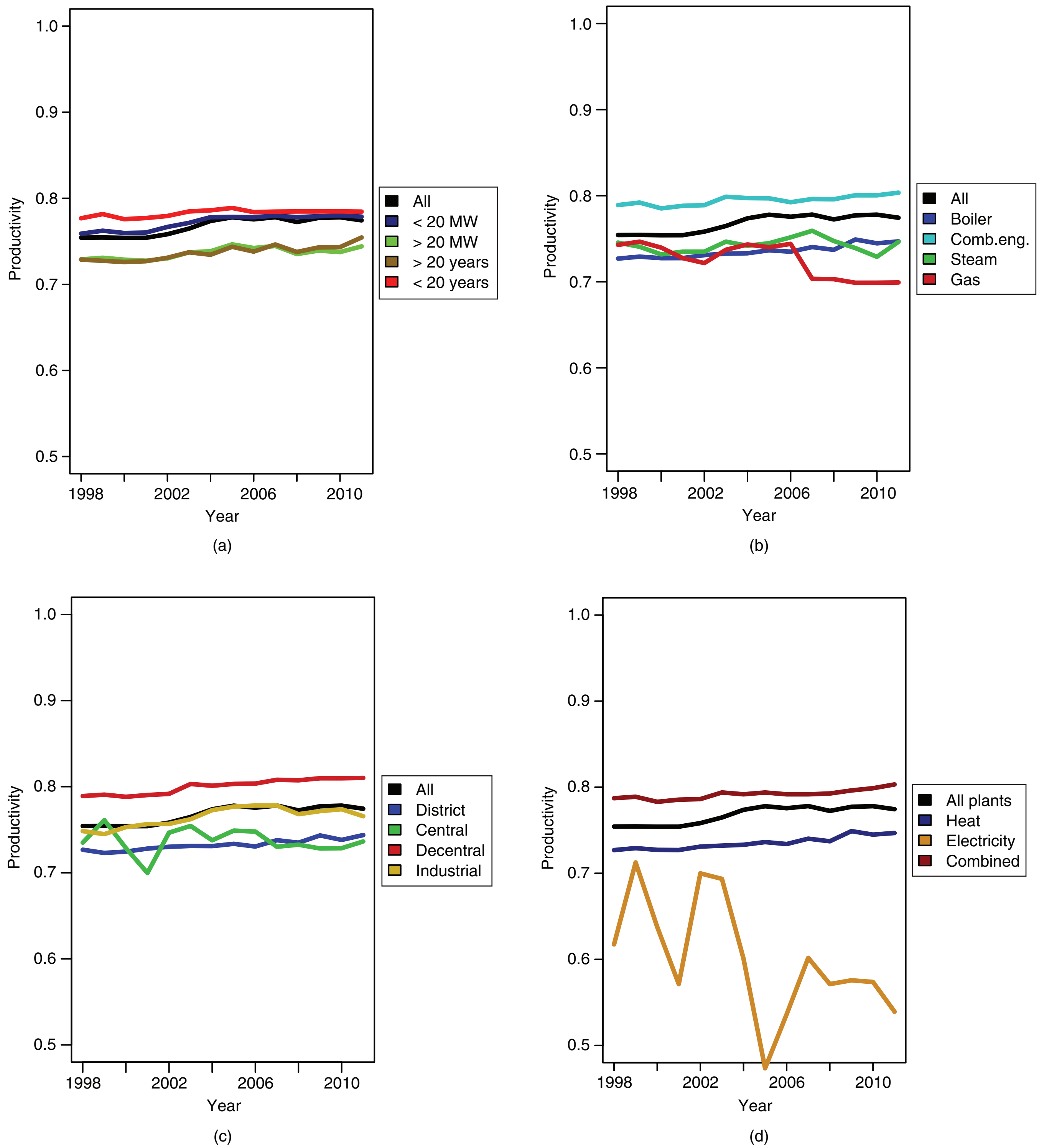

Figure 3: Yearly median values of environmental energy conversion productivity

conversion productivity ($EECP$) 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 energy conversion productivity. As the smaller generator units (< 20 MW) dominate the sector in terms of numbers, it is not surprising that the median environmental energy conversion 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 energy conversion productivity of older generator units, but rather by the stagnating or even slightly decreasing environmental energy conversion 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 electricity system which can be induced by wind power. This is confirmed by Sub-figure (d), where we find an opposing trend in the environmental energy conversion productivity of pure electricity producers whose environmental energy conversion productivity plummeted by 13% over the period of our analysis.

5.2. Time series cluster analysis

According to [21], cluster validation can be based on three approaches: (1) using external validation criteria; (2) using internal validation criteria based on information obtained during the clustering process to evaluate how well the result fits the data; and (3) using relative validation criteria, that compare the outcomes of different cluster structures. Our initial aim is to identify three performance groups, high performers, middle performers, and low performers. But in order to check the validity of our initial assumption of three clusters, we also use internal and relative validity criteria provided in the “NbClust” package [7] [see 8, for a more detailed description of the validation criteria]. We evaluated the optimal number of clusters based on 28 different criteria. Given the distribution of the 28 validation criteria over the number of optimal cluster, the centre of the distribution and the highest frequency (9 out of 28) occurs at an optimal number of three clusters.[9] As three clusters fit well with our initial external validation criterion, we follow the suggestion despite the fact that, given the size of our dataset, the classification into only three clusters is rather coarse.

In order to identify the three performance groups, e.g., clustering generator units whose productivity development shows comparable profiles over time, we base the cluster analysis entirely on the productivity development profiles of the three performance measures and do not include time-invariant characteristics of generator units. By following this approach, we ensure that the group formation is only based on the productivity development profiles, while we in the second stage of our analysis (see section 5.3) look at the performance patterns across generator unit groups that are formed on the base of time-invariant characteristics.

Figure 4 illustrates, using boxplot diagrams, the development over time of all three components of the environmental energy conversion productivity measure, e.g., $BCPR$, CE, and CSE, 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 CSE of clusters 2 and 3) are surprisingly distinct. This is especially the case for CE.

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, e.g., 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.

[8] A more detailed version of Figure 3(d) can be found in the appendix (Figure A.1).

[9] These criteria are not solid statistical tests and should only be used as indicators. Given the ambiguous results of the different validation criteria, the final decision regarding the number of clusters remains with the analysts.

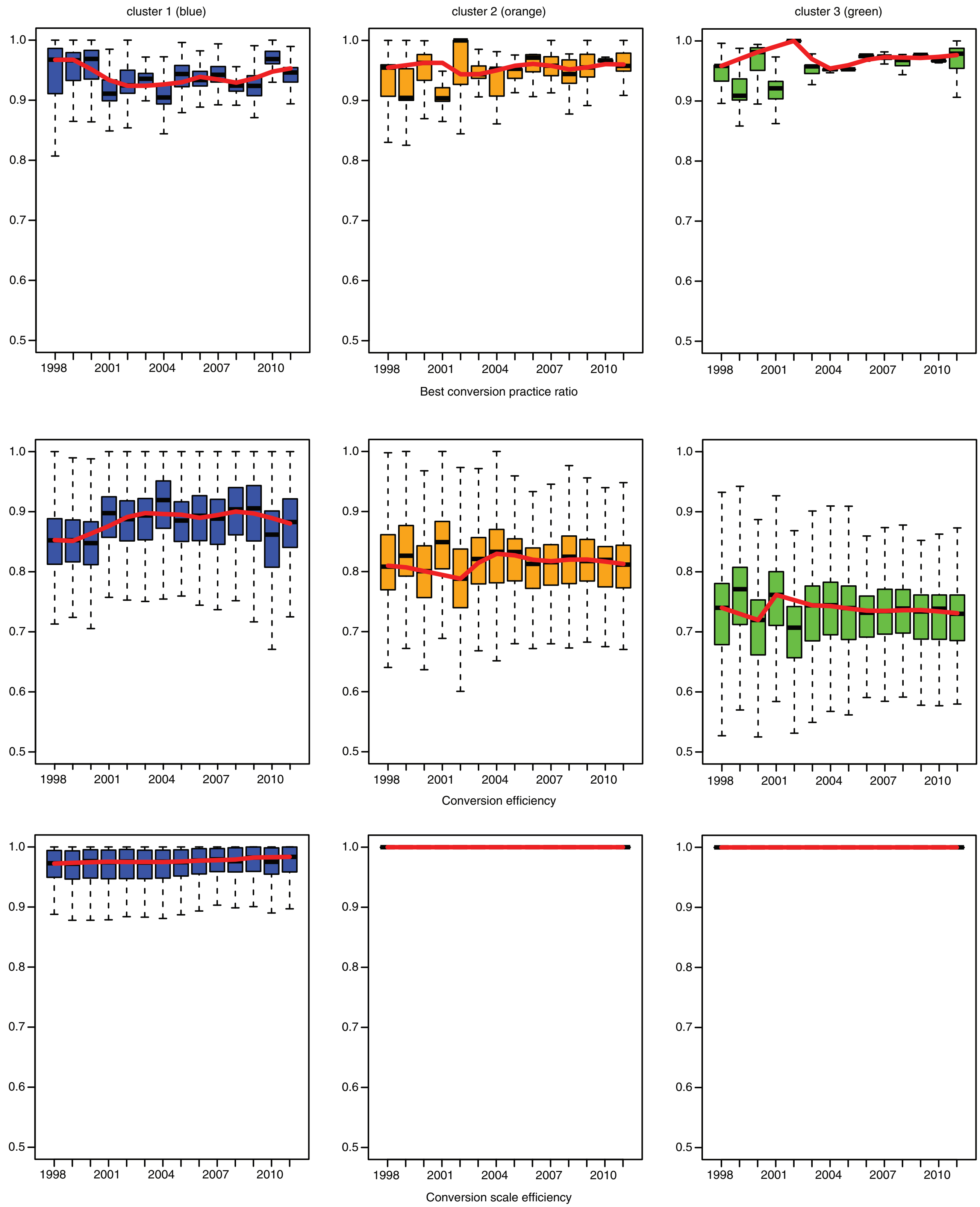

Figure 4: Development over time for the three different clusters

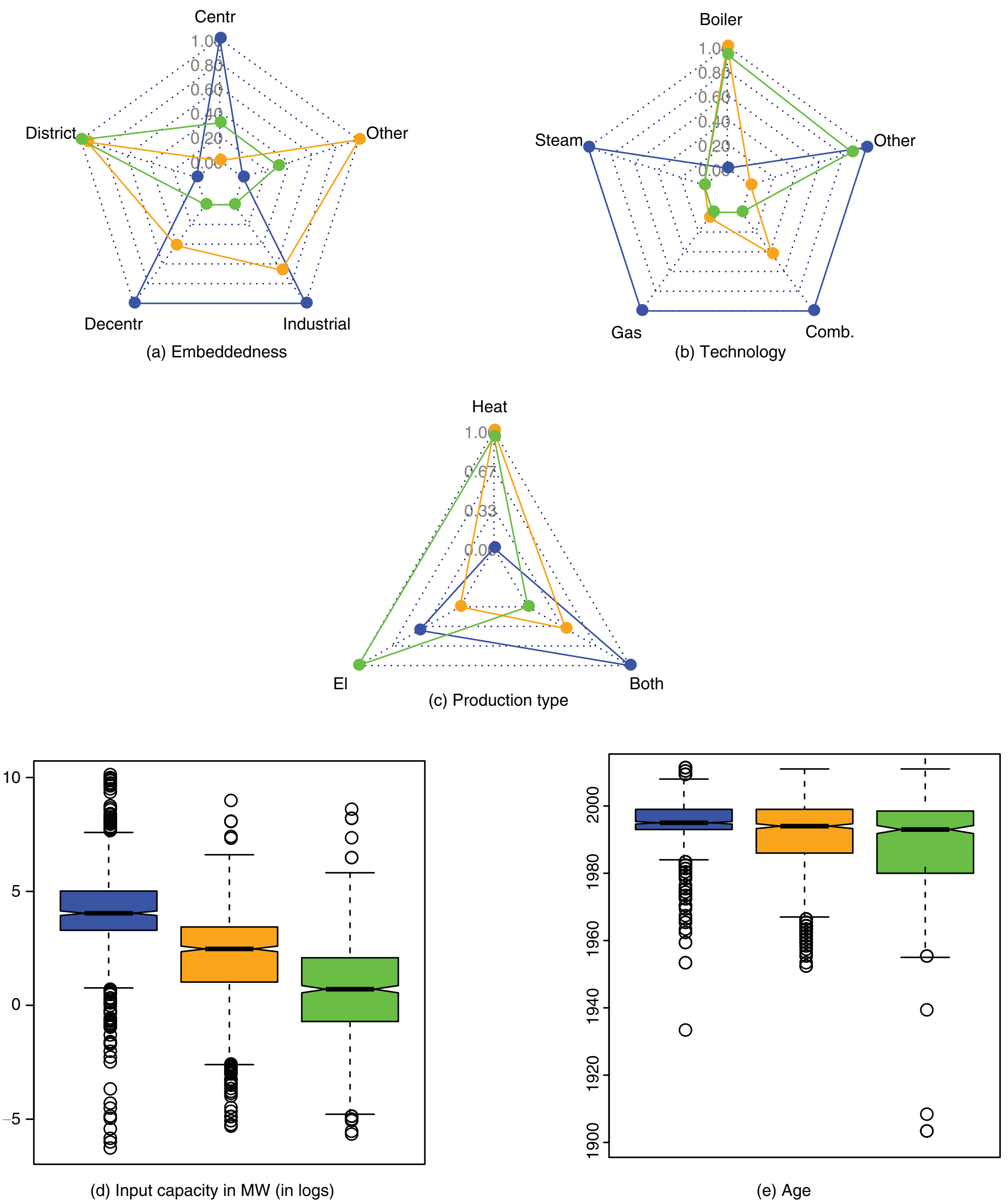

Figure 5: Cluster characteristics

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.

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. This counter-intuitive finding might follow from the fact that our data set only contains information on the age of the unit but not on the age of the technology actually in use. Therefore, the estimate of the effect of our variable age may not be an accurate measure of the real effect of the age of the technology.

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 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, $EECP$, CE, $BCPR$, and CSE,

Table 5: Results for different groups of generator units

emb	age	tech	pType	size	nObs	nGU	el1	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 = centralised 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
EECP, CE, BCPR, CSE	median values of the environmental energy conversion productivity, the conversion efficiency, the best conversion practice ratio, and the conversion 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 conversion scale efficiencies is virtually one, we used the threshold 0.98 instead of the median for colouring the column with the conversion scale efficiencies
dEECP, dCE, dBCPR, dCSE	median value of the change of the environmental energy conversion productivity, the change in conversion efficiency, the change in the best conversion practice ratio, and the change in the conversion 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

as well as their changes, $dEECP$, dCE, $dBCPR$, and $dCSE$, 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).

$EECP$ & $dEECP$. All CHPs with combustion engines show high and consistent levels of environmental energy conversion productivity, while not surprisingly we find the lowest environmental energy conversion 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 energy conversion productivity over time. However, this seems not to be the case for several groups of industrial plants that considerably improve their environmental energy conversion productivity over time.

CE & dCE. Concerning environmental energy conversion 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 energy conversion efficiency. A positive result is that a number of groups experienced increases in environmental energy conversion 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 energy conversion efficiency.

$BCPR$ & $dBCPR$. While the change of the best conversion practice ratio over time indicates change of the best practice conversion technology, the median (or average) value of the $BCPR$ over the entire sampling period is of minor relevance. A low median value of $BCPR$ 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 conversion practice ratio ($dBCPR$). All groups of electricity-only producers and most groups of combustion engines (CHP and electricity-only) experience a declining best conversion 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.

CSE & $dCSE$. Most groups of large CHP generator units and some groups of medium-sized generator units are conversion 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 conversion scale efficiency of large-scale production with boiler technologies. On the other hand, all groups of small generator units are virtually fully energy conversion 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 (this finding coincides with the results of the cluster analysis, see the bottom row of graphs in Figure 4).

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 energy conversion 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 energy conversion productivity by an extended Farrell input distance function that takes CO_2 emissions into account. We have decomposed the environmental energy conversion productivity measure into its three subcomponents: conversion efficiency, best conversion practice ratio, and conversion 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, as is demonstrated by the cluster with predominantly new CHP units performing best. Opposing this aspect, 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 conversion efficiency indicates that their economic benefits come from an island operation mode to cover e.g., predominantly industrial demand.

Our results support the argument about the high environmental energy conversion efficiencies of CHP units by another dimension: their conversion scale efficiency is suboptimal for almost all groups above 2 MW. 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 energy conversion 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 conversion efficiency gains. On the one hand, for the time period analysed, this may have been a rather costly path to follow. On the other hand, the study shows that a complex, CHP-dominated conventional electricity generation system can adapt to a changing environment in times of increasing fluctuation of electricity generation. 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.

Acknowledgements

The authors are grateful to Uwe Jensen, Mette Asmild, Sebastian Petersen, and Giovanni Millo for their valuable suggestions that were very helpful for improving this paper. Furthermore, we want to thank Kaj Stærkind from the Danish Energy Agency for providing access to the data. Geraldine Henningsen and Simon Bolwig are indebted to The Danish Council for Strategic Research for financial support. Of course, all remaining errors are the sole responsibility of the authors.

References

[1] AGRELL, P. J., AND BOGETOFT, P. Economic and environmental efficiency of district heating plants. *Energy Policy 33* (2005), 1351–1362.

[2] BALK, B. M. Scale efficiency and productivity change. *Journal of Productivity Analysis 15* (2001), 159–183.

[3] BANKER, R. D., CHARNES, A., AND COOPER, W. W. Some models for estimating technical and scale inefficiencies in data envelopment analaysis. *Management Science 30*, 9 (September 1984), 1078–1092.

[4] BOGETOFT, P., AND OTTO, L. *Benchmarking with DEA, SFA, and R,* vol. 157 of *International Series in Operations Research & Management Science*. Springer, 2011.

[5] BOGETOFT, P., AND OTTO, L. *Benchmarking with DEA and SFA*, 2013. R package version 0.23.

[6] CHARNES, A., COOPER, W. W., AND RHODES, E. Measuring the efficiency of desicion making units. *European Journal of Operational Research Policy 2* (1978), 429–444.

[7] CHARRAD, M., GHAZZALI, N., BOITEAU, V., AND NIKNAFS, A. NbClust: *An Examination of Indices for Determining the Number of Clusters*, 2013. R package version 1.4.

[8] CHARRAD, M., GHAZZALI, N., AND NIKNAFS, V. B. A. Nbclust: An R package for determining the relevant number of clusters in a data set. *Journal of Statistical Software 61*, 6 (2014), 1–36.

[9] CHUNG, Y. H., FÄRE, R., AND GROSSKOPF, S. Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management 51*, 3 (1997), 229–240.

[10] CROISSANT, Y. *mlogit: Multinomial Logit Model*, 2013. R package version 0.2–4.

[11] DANISH ENERGY AGENCY. Energistatistik, 2010.

[12] DANISH ENERGY AGENCY. Energy statistics 2012. data tables, statistics and maps. Tech. rep., Copenhagen, 2013.

[13] EUROPEAN COMMISSION. Best Available Techniques (BAT) Reference Document for the Large Combustion Plants. Draft 1 (June 2013), European IPPC Bureau, Sustainable Production and Consumption Unit, Institute for Prospective Technological Studies, Joint Research Centre, Seville, 2013.

[14] FÄRE, R., GROSSKOPF, S., NOH, D.-W., AND WEBER, W. Characteristics of a polluting technology: Theory and practice. *Journal of Econometrics 126*, 2 (2005), 469–492.

[15] LIAO, T. W. Clustering of time series data—a survey. *Pattern Recognition 38* (2005), 1857–1874.

[16] MAECHLER, M., ROUSSEEUW, P., STRUYF, A., HUBERT, M., AND HORNIK, K. *cluster: Cluster Analysis Basics and Extensions*, 2013. R package version 1.14.4.

[17] O'DONNELL, C. J., RAO, D. S. P., AND BATTESE, G. E. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics 34* (2008), 231–255.

[18] PASTOR, J. T., AND LOVELL, C. A. K. A global Malmquist productivity index. *Economics Letters 88*, 2 (2005), 266–271.

[19] R CORE TEAM. R: *A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2014.

[20] SCHEEL, H. Undesirable outputs in efficiency valuations. *European Journal of Operational Research 132*, 2 (2001), 400–410.

[21] THEODORIDIS, S., AND KOUTROUBAS, K. *Pattern Recognition*. Academic Press, 2008.

[22] TOVAR, B., RAMOS-REAL, F. J., AND DE ALMEIDA, E. F. Firm size and productivity. evidence from the electricity

distribution industry in brazil. *Energy Policy 39* (2011), 826–833.

[23] WANG, X., SMITH, K., AND HYNDMAN, R. Characteristic-based clustering for time series data. *Data Mining and Knowledge Discovery 13* (2006), 335–364.

[24] YANG, M., YANG, F.-X., AND CHEN, X.-P. Effects of substituting energy with capiatal on china's aggregated energy and environmental efficiency. *Energy Policy 39* (2011), 6065–6072.

[25] ZHANG, N., AND CHOI, Y. Total-factor carbon emission performance of fossil fuel power plants in china: A metafrontier non-radial Malmquist index analysis. *Energy Economics 40*, 0 (2013), 549–559.

[26] ZHOU, P., ANG, B. W., AND HAN, J. Y. Total factor carbon emission performance: A Malmquist index analysis. *Energy Economics 32* (2010), 194–201.

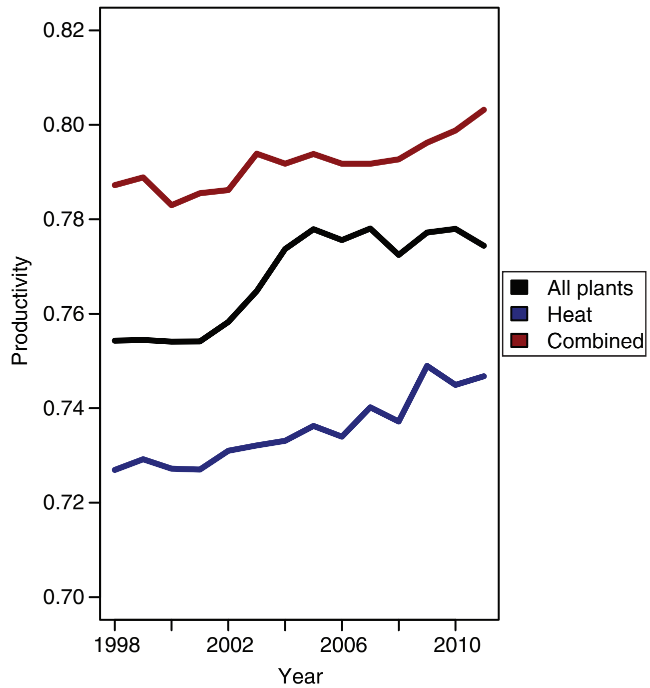

Figure A.1: Detailed view of Figure 3(d) (yearly mean values of environmental energy conversion productivity)

Appendix A. Additional tables and figures

Table A.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: [11, p. 59]

Table A.2: Cluster characteristics

cluster	**centralised**	**district**	**decentralised**	**industrial**	**other plant**	**boiler**	**steam turb**	**gas turb**	**combustion**	**other tech**	**heat**	**electricity**	**combined**
1	36	54	391	181	83	102	67	25	531	22	103	17	627
2	7	411	252	140	152	650	13	7	292	6	650	11	307
3	16	433	159	57	104	615	13	6	117	18	619	26	124

Table A.3: Summary statistics over cluster performance

measure	cluster	mean(BPCR)	se(BPCR)	slope(BPCR)	mean(CE)	se(CE)	slope(CE)	mean(CSE)	se(CSE)	slope(CSE)	size	age
mean	1	0.9324	0.0296	0.0003	0.8569	0.0480	−0.0001	0.9680	0.0099	0.0009	501	1995
mean	2	0.9469	0.0299	0.0024	0.8133	0.0595	−0.0018	0.9959	0.0050	-0.0001	45	1991
mean	3	0.9545	0.0254	0.0020	0.7076	0.0843	−0.0009	0.9942	0.0039	-0.0009	31	1988
sd	1	0.0279	0.0161	0.0119	0.1172	0.0361	0.0195	0.0386	0.0127	0.0080	2246	8
sd	2	0.0170	0.0165	0.0147	0.0376	0.0379	0.0253	0.0107	0.0147	0.0069	291	13
sd	3	0.0249	0.0133	0.0123	0.0718	0.0657	0.0621	0.0471	0.0201	0.0264	265	16
median	1	0.9394	0.0274	−0.0012	0.8827	0.0375	0.0011	0.9775	0.0071	0.0003	57	1995
median	2	0.9485	0.0289	0.0027	0.8094	0.0495	−0.0012	0.9999	0.0002	0.0000	12	1994
median	3	0.9599	0.0250	0.0025	0.7261	0.0677	−0.0014	0.9997	0.0003	0.0000	2	1993
mad	1	0.0108	0.0058	0.0020	0.0352	0.0108	0.0045	0.0197	0.0050	0.0009	43	3
mad	2	0.0088	0.0053	0.0023	0.0257	0.0183	0.0056	0.0001	0.0002	0.0000	11	6
mad	3	0.0060	0.0051	0.0012	0.0270	0.0322	0.0080	0.0003	0.0003	0.0000	2	9