Measuring and explaining productivity growth of renewable energy producers: An empirical study of Austrian biogas plants[1]

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Abstract
This study explores productivity growth for a group of 65 Austrian biogas plants from 2006 to 2014 using Data Envelopment Analysis. The sample covers about 25 % of the installed electric capacity of Austrian biogas plants. Productivity growth is measured by calculating the Malmquist productivity index, and the contributions of technical change, efficiency change and scale change to productivity growth are isolated. Average annual productivity growth between 2006 and 2014 is 1.1 %. The decomposition of the Malmquist index shows that the annual scale change, technical change, and efficiency change for the average plant is 0.6 %, 0.3 % and 0.3 %, respectively. Those results indicate that the exploitation of returns to scale is a major driver of productivity growth in the Austrian biogas sector. However, there is a large variation in productivity growth across biogas plants. A second-stage regression analysis identifies important determinants of productivity growth. The results show that i) the exploitation of returns to scale as well as changes in ii) output diversification iii) capital intensity, iv) capacity utilization and v) feedstock prices are positively associated with productivity growth.

Keywords: Data Envelopment Analysis, Malmquist Productivity Index, Renewable Energy Sources, Biogas Energy, Cogeneration

JEL codes: C61, D24, Q16, Q42

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1. Introduction

Reducing greenhouse gas emissions, improving energy efficiency and promoting renewable energy sources are the main pillars of the EU climate policy. Indicative targets on the share of renewable electricity for each Member State to be achieved in the year 2010 were introduced by the Renewable Electricity Directive (directive no. 2001/77/EC). According to the Renewable Energy Directive (directive no. 2009/28/EC) the share of renewable energy sources in total EU energy consumption should be increased to 20 % in 2020. In October 2014 the European Council agreed on the new target of 27 % for 2030. Within this framework, all EU Member States have implemented policy support for electricity generation from renewable energy sources (RES-E). As documented by Klessmann et al. (2011) and Kitzing et al. (2012) RES-E support schemes vary across EU Member states, including feed-in-tariffs (FITs), feed-in-premiums, tender schemes, quota obligations, investment grants, tax incentives and loans. All of these schemes subsidize RES-E generation in one way or another.

Among others[2], electricity generated from biogas is one of the technologies promoted by the Austrian green electricity law (BGBl. I Nr. 149/2002; BGBl. I Nr. 75/2011).[3] Biogas plants convert feedstock, e.g. maize silage, grass silage, manure or organic waste, by anaerobic digestion into biogas. Whereby, maize is the primarily feedstock component for biogas generation in Austria (Stürmer, 2017). Most commonly, biogas is used in a cogeneration unit (CHP) to produce combined heat and power. The green electricity law (GEL) implies a purchase guarantee for RES-E and technological specific fixed electricity prices (feed-in-tariffs or FITs) for at least 13 years. Production subsidies for heat are not available.[4] Commonly, heat prices are negotiated bilaterally between the biogas plant operator and the buyer (e.g. district heating grid providers, consumers). Investment grants are provided for different plant areas (e.g. heat utilization), where eligibility and extend varies by Austrian federal states.

The GEL became effective in 2003 and the rise of RES-E eligible to FIT remuneration began, which excludes middle and large sized hydropower plants in Austria. The amount of green electricity - mostly generated from wind power, solar power and biomass - fed into the power grid increased from 597 GWh in 2003 to 7,998 GWh in 2016 (E-Control, 2017). In 2003 green electricity roughly covered 1 % of total electricity demand[5], whereas in 2016 nearly 12 % of Austria´s demand is covered by RES-E eligible to FIT remuneration.[6]

The stable and predictable investment environment created by the FIT support scheme combined with low agricultural commodity prices up to the year 2006 led to a biogas boom be-

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[2] Small hydro power plants, photovoltaic and wind power plants, landfill and sewage gas, geothermal energy, as well as solid and liquid biomass are promoted by the Austrian green electricity law.

[3] The green electricity law was frequently amended. FITs are announced in the green electricity acts (e.g. BGBl. II Nr. 508/2002). For a detailed documentation of relevant laws and enactments see: at http://www.oem-ag.at/de/gesetze-regelwerk/

[4] Though, the green electricity law 2012 (BGBl. I Nr. 75/2011) provides incentives for the utilization of heat generated in biogas plants. A premium on top of the FIT of 1 to 2 cent/kWh_{el} for certain plants with high fuel conversion efficiency is provided.

[5] Electricity demand is gross electricity generation plus net imports (imports-exports). According to E-Control (2017) gross electricity generation was 59,986 GWh and net imports amounted to 7,273.

[6] Small hydropower plants eligible to FIT remuneration are not included in these calculations (green electricity). They generated 3,386 GWh electricity in 2003 and 1,772 GWh in 2016 (E-Control, 2017). The average FIT for small hydropower plants was 4.86 cent/ kWh_{el} in 2016.

tween 2003 and 2007. The number of plants increased from about 70 in 2002 to about 295 at the beginning of 2008 with a rise of the installed electric capacity from 15 to 76 MW.[7] After that boom the number of biogas plants roughly stagnated. Some of the existing plants expanded their capacity, so the total capacity reached 83 MW at the end of 2016, which generated 565 GWh electricity (OeMAG, 2017). The period of stagnation, 2007 to 2016, was accompanied by high and volatile feedstock prices relative to the preceding years.

The GEL is quite successful in increasing RES-E. Though, increasing RES-E is not the only objective of the GEL. In general, renewable energy policies (should) aim at making renewable energy technologies ready for the market such that they are able to compete with fossil fuel electricity generation technologies. In particular, the biogas technology suffers from a lack of competitiveness. The FIT, according to the GEL, should be oriented towards the average production costs of cost efficient biogas plants. In 2016 the average FIT for biogas plants was 17.31cent/kWh_{el}, whereas the average exchange price for base load electricity was 2.70 cent/kWh_{el} (E-Control, 2017).[8] The difference between FITs and the exchange electricity price is financed through fees paid by electricity consumers and amounted to 83 Million Euros in 2016 for biogas. The expiration of FITs for many plants in the foreseeable future further illustrates the need for increasing the competitiveness of Austrian biogas plants.

Productivity is an essential determinant of a firm's competitiveness. Productivity influences a firm´s i) output given a fixed amount of inputs, ii) unit cost and iii) profit. On the macro-level productivity growth is an important driver of economic growth. Therefore, it is crucial to measure and understand productivity growth of RES-E. While there is an extensive literature analyzing productivity growth of fossil-fuelled power plants (see e.g. Zhou et al., 2008) only few studies measure the productivity growth of renewable energy plants, except for hydroelectric power facilities. Even less try to explore the determinants of productivity growth in RES-E. Our study aims to fill this gap in the literature. As far as we know, the work of Rácz and Vestergaard (2016) is the only existing study on productivity growth of biogas plants.

This study explores productivity growth for a sample of 65 biogas plants from 2006 to 2014 using a non-parametric approach that is Data Envelopment Analysis (DEA). The sample covers about 25 % of the installed electric capacity of Austrian biogas plants. We measure productivity growth using the Malmquist productivity index, employing a decomposition under variable returns to scale proposed by Ray and Desli (1997). This decomposition isolates the contributions of technical change, efficiency change and scale change to productivity growth. Moreover, we complement the non-parametric analysis with pooled ordinary least squares (OLS) regressions to explain differences in productivity change of biogas plants in terms of a number of variables, including capacity/size, output diversification, capital subsidies, capacity utilization, capital intensity, feedstock prices and regional location.

We find that average annual productivity growth between 2006 and 2014 is 1.1 % but the productivity of the average plant declined by 3.8 % in 2013. The decomposition of the Malmquist index shows that the annual scale change, technical change, and efficiency change for the average plant is 0.6 %, 0.3 % and 0.3 %, respectively. Those results indicate that the exploitation of re-

[7] All of these plants make use of the FIT provided by the green electricity act. Plants not receiving FITs are of minor importance. They only produce 36 GWh electricity, which is 6 % of the electricity produced from biogas in 2014 (Statistics Austria, 2016).

[8] Note that exchange prices are marginal costs whereas FITs are based on full costs.

turns to scale is an important driver of productivity growth in the Austrian biogas sector. However, the meaning of this average values is weakened by the huge heterogeneity of productivity growth found in this study. A majority of 41 plants experienced productivity gains between 2006 and 2014; 24 biogas plants show a productivity decline. The second-stage pooled OLS regressions reveal that biogas plants expanding their capacity, diversifying their outputs, increasing their capacity utilization and capital intensity as well as experiencing a stronger rise in feedstock prices have higher productivity growth.

The study proceeds as follows. Section 2 shortly reviews the relevant literature. Section 3 outlines the methodology leading to our decomposition. Section 4 describes the data and develops the empirical model. Section 5 presents the results of the analysis and section 6 concludes with some final remarks.

2. Literature Review

Many studies analyze the productive efficiency and productivity growth of power generation plants and power distribution companies. The Malmquist-productivity index requires estimating distance functions or efficiency scores. Measuring distance functions can employ either parametric or non-parametric methods. Among the most important methods are the parametric method of Stochastic Frontier Analysis (SFA) and the nonparametric method of Data Envelopment Analysis (DEA); see e.g. Fried et al. (2008). Zhou et al. (2008) survey the literature on the application of DEA to energy and environmental studies. More recent literature on applying the Malmquist index and DEA to the electricity industry is reviewed in Gharneh et al. (2014). With respect to the parametric approach, Ramos-Real (2005) reviews some studies applying econometric methods to analyse the productive efficiency and productivity growth of generating plants. Barros (2008) gives a short review of selected applications to the energy sector, which either rely on SFA or DEA.

While there is an extensive literature analyzing productivity growth of fossil fuel power plants, only few studies measure the productivity growth of renewable energy plants, except for hydroelectric facilities. Examples for analysing productivity growth of hydroelectric power plants are Barros (2008) and Briec et al. (2011). There are some studies analyzing the static efficiency of wind farms; see e.g. Iglesias et al. (2010), Barros and Antunes (2011), Ederer (2015). However, none of them provide an intertemporal analysis of efficiency and productivity change. As far as we know, Vaz and Ferreira (2015) is the only study analysing productivity growth of wind farms. Though, the period under investigation is limited to 2010-2011. Braun et al. (2007) and Madlener et al. (2009) examine the static efficiency of 41 Austrian biogas plants using DEA. Đatkov and Effenberger (2010) and Filler et al. (2007) apply DEA on a sample of German biogas plants. The eco-efficiency of 15 biogas plants in Northern-Italy is analyzed in Lijo et al. (2017) by combining life cycle assessment methods and DEA.

The study most closely related to ours is that of Rácz and Vestergaard (2016). As far as we know, this is the only existing study analyzing productivity growth of biogas plants. Rácz and Vestergaard (2016) calculate Malmquist indices using DEA for 19 Danish centralized biogas power plants for the period 1992-2005. The authors use animal manure and other organic waste as input variables but neglect labour and capital. The biogas generated in the power plant is used as single output. Our study can draw from a much richer set of inputs and outputs, avoiding the omission of significant variables. The consequences of such model misspecifications are described e.g. in Smith (1997). Furthermore, the sample in this study is larger and includes 65 biogas plants. Though, we only have data for 2006 and 2012-2014. The sample of Rácz and Vestergaard (2016) changes over time. It starts with 7 plants in 1992 and end-ups with 19 plants in the period 1998 to 2005. Our sample of 65 plants remains invariant over time. Finally, we provide second-stage regressions in order to explain the variation in productivity growth across biogas plants; they do not.

Rácz and Vestergaard (2016) find that average annual total factor productivity increased by 2.5 % annually in the examined period. That is more than twice as much than our estimates (1.1 % annually). Following Färe et al. (1994), the authors decompose productivity growth into technical change, pure efficiency change and scale change. As outlined in the following sections, we argue that the decomposition of Färe et al. (1994) is not appropriate in the case of biogas plants because many of them exhibit increasing returns to scale. In such a case, the Färe et al. (1994) decomposition overestimates technical change because it is measured relative to a constant returns to scale technology. That is why we use the decomposition proposed by Ray and Desli (1997), which measures technical change relative to a variable returns to scale technology.

3. Methodology

We assume that for each time period $t = 1, \dots, T$ the production technology S^t models the transformation of N inputs, $x^t \in \mathbb{R}_+^N$, into M outputs, $y^t \in \mathbb{R}_+^M$, $S^t = \{(x^t, y^t) \in \mathbb{R}_+^{N+M}: x^t \text{ can produce } y^t\}$. This means the technology consists of the set of all feasible input/output vectors. Following Shephard (1970), the input distance function is defined at t as $D^t(x^t, y^t) = sup\{\theta: (x^t/\theta\,, y^t) \in S^t\} = (inf\{\theta: (\theta x^t, y^t) \in S^t\})^{-1}$. This function is defined as the reciprocal of the "minimum" proportional contraction of the input vector, x^t, given outputs, y^t. The distance function completely represents the production technology. Note that $D^t(x^t, y^t) \geq 1$ if and only if $(x^t, y^t) \in S^t$. In addition, $D^t(x^t, y^t) = 1$ if and only if (x^t, y^t) is on the frontier of the technology. In the terminology of Farrell (1957), that occurs when the production process is technically efficient. If $D^t(x^t, y^t) > 1$ production is technically inefficient. The Farrell input oriented measure of technical efficiency is given as the value of the function $TE^t(x^t, y^t) = min\{\theta: (\theta \cdot x^t, y^t) \in S^t\}$. It follows that $TE^t(x^t, y^t) = [D^t(x^t, y^t)]^{-1}$.

Let $D_{CRS}^t(x^t, y^t)$ denote the distance function satisfying constant returns to scale (CRS) and $D_{VRS}^t(x^t, y^t)$ be the distance function satisfying variable returns to scale (VRS). Scale efficiency refers to the deviation between CRS and VRS technologies. It is defined by the ratio of the distance functions $SE^t(x^t, y^t) = D_{VRS}^t(x^t, y^t)/D_{CRS}^t(x^t, y^t)$ and measures how far the scale size of a plant is away from optimal. For firms operating at the optimal scale size CRS holds. Because the CRS-frontier envelops the VRS-frontier and all observations, $D_{CRS}^t(x^t, y^t) \geq D_{VRS}^t(x^t, y^t)$ holds and the measure for scale efficiency has an upper bound of one. At $SE^t(x^t, y^t) = 1$ the plant is scale efficient. A value smaller than one indicates a potential to increase efficiency by extending the plant's production activity.

We estimate productivity change by computing the Malmquist productivity index which combines input oriented distance functions at different points in time. To define this index, we need not only distance functions within the same period t (so called own-period distance functions) but also distance functions with respect to two different time periods (so called cross-period or mixed period distance functions) such as $D^t(x^{t+1}, y^{t+1}) = max\{\theta: (x^{t+1}/\theta, y^{t+1}) \in S^t\}$. This distance function measures the minimal proportional change in inputs required to make (x^{t+1},y^{t+1}) feasible in relation to the technology at t. Similarly, one may define a distance function that measures the minimal proportional change in inputs required to make (x^t, y^t) feasible in relation to the technology at $t+1$ which we call $D^{t+1}(x^t, y^t)$. In order to compute the productivity change of individual plants between t and $t+1$, we need to estimate four different distance functions, namely $D^t(x^t, y^t)$, $D^{t+1}(x^t, y^t)$, $D^t(x^{t+1}, y^{t+1})$, and $D^{t+1}(x^{t+1}, y^{t+1})$. The Malmquist productivity index $PRODCH(x^t, y^t, x^{t+1}, y^{t+1})$ measures the change in productivity for an individual plant and is defined as

$$PRODCH(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{D^t_{CRS}(x^t, y^t)}{D^t_{CRS}(x^{t+1}, y^{t+1})} \frac{D^{t+1}_{CRS}(x^t, y^t)}{D^{t+1}_{CRS}(x^{t+1}, y^{t+1})}\right]^{1/2}.$$

This index is based on distance functions satisfying CRS and measures productivity change at optimal scale. This is the potential productivity change that a plant could enjoy if it were producing efficiently from a technical and scale perspective in both periods (Zofío, 2007). One advantage of the Malmquist productivity index is that the component distance functions allow breaking down productivity change into components and in this way identifying its main drivers. The index can be decomposed in different ways. Of the many different possibilities[9] we choose the form proposed by Ray and Desli (1997) and decompose the index in the following manner:

$$\begin{aligned} &PRODCH(x^t, y^t, x^{t+1}, y^{t+1}) \\ &\qquad = PEFFCH(x^t, y^t, x^{t+1}, y^{t+1}) \cdot TECHCH(x^t, y^t, x^{t+1}, y^{t+1}) \\ &\qquad \cdot SCH(x^t, y^t, x^{t+1}, y^{t+1}) \end{aligned}$$

where $PEFFCH(x^t, y^t, x^{t+1}, y^{t+1})$ represents pure efficiency change, $TECHCH(x^t, y^t, x^{t+1}, y^{t+1})$ represents technical change, and $SCH(x^t, y^t, x^{t+1}, y^{t+1})$ represents scale change factor. We define technical change as:

$$TECHCH(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{D^{t+1}_{VRS}(x^{t+1}, y^{t+1})}{D^t_{VRS}(x^{t+1}, y^{t+1})} \frac{D^{t+1}_{VRS}(x^t, y^t)}{D^t_{VRS}(x^t, y^t)}\right]^{1/2}$$

which captures the shift in technology between two periods measured at input and output levels from periods t and $t+1$, respectively. Thus technical change is measured as the geometric mean of those two shifts, i.e. as the geometric mean of the ratios of VRS distance functions. This component indicates the general development of productivity of the benchmark plants and correctly measures technical change in the presence of VRS. Pure efficiency change is defined as

$$PEFFCH(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D^t_{VRS}(x^t, y^t)}{D^{t+1}_{VRS}(x^{t+1}, y^{t+1})}$$

[9] For an overview of the many decompositions of the Malmquist productivity index see e.g. Balk (2001), Lovell (2003), Zofío (2007) as well as Diewert and Fox (2017).

and measures the change in relative technical efficiency calculated relative to VRS technology. This is the change in the distance of observed from potential production between years t and $t+1$. Thus, $PEFFCH(x^t, y^t, x^{t+1}, y^{t+1})$ captures the "catch-up" process to the industry frontier. The $SCH(x^t, y^t, x^{t+1}, y^{t+1})$ is defined as

$$SCH(x^t, y^t, x^{t+1}, y^{t+1}) = \left[\frac{SE^t(x^{t+1}, y^{t+1})}{SE^t(x^t, y^t)} \frac{SE^{t+1}(x^{t+1}, y^{t+1})}{SE^{t+1}(x^t, y^t)}\right]^{1/2}$$

and measures changes in the deviation between the productivity change assuming VRS and CRS. It is computed as the geometric mean of the ratios of scale efficiencies and takes into account the contribution of returns to scale (Zofío, 2007).

Improvements in productivity over time result in a Malmquist productivity index above unity, whereas deterioration in performance is associated with a Malmquist productivity index below unity. The same holds true for all components of the Malmquist productivity index.

The distance functions can be calculated in several ways. In our empirical work we follow Färe et al. (1994) and compute them by applying the linear programming approach outlined by Charnes et al. (1978), Banker et al. (1984), and Färe et al. (1985), which is known as Data Envelopment Analysis (DEA). One could also calculate the distance functions using frontier econometric approaches. The main strength of DEA method may be its lack of parameterization; it requires no assumptions about the form of the production technology.[10]

In the following linear programs, we assume that there are $k = 1, \dots, K$ biogas plants using $n = 1, \dots, N$ inputs x_{nk}^t producing $m = 1, \dots, M$ outputs y_{mk}^t at each time period $t = 1, \dots, T$. For each observation inputs and outputs are non-negative. The own-period distance function $D^t(x^t, y^t)$ for period t for each individual plant is computed by solving the following optimization problem:

$$\begin{aligned} & TE^t(x^t, y^t) = [D^t(x^t, y^t)]^{-1} = \min \theta_0 \\ \text{s.t.}\quad & \theta_0 x_{n0}^t - \textstyle\sum_k \lambda_k^t x_{nk}^t \geq 0, \textstyle\sum_k \lambda_k^t y_{mk}^t \geq y_{m0}^t, \theta_0 \text{ free}, \lambda_k^t \geq 0, \\ & \textstyle\sum_k \lambda_k^t = \text{free (in case of CRS)}, \textstyle\sum_k \lambda_k^t = 1 \text{ (in case of VRS)} \end{aligned}$$

where θ_0 is the efficiency score of the plant under investigation and λ_k^t are the peer weights. This procedure minimizes the efficiency score θ_0 of a biogas plant and must be repeated for every plant in the sample. The computation of the own-period distance function $D^{t+1}(x^{t+1}, y^{t+1})$ for period $t+1$ is done by solving a very similar linear program where t is substituted by $t+1$. For statistical tests on returns to scale as described in Simar and Wilson (2002), we also compute the own-period distance functions satisfying non-increasing returns to scale (NIRS). The linear program used for this estimation is distinguished from the problem shown above by restricting the sum of peer weights below 1 ($\sum_k \lambda_k^t \leq 1$).

[10] Recent comprehensive overviews of concepts and models in DEA are provided e.g. in Bogetoft and Otto (2011) and Zhu (2015).

The linear optimization problem for the cross-period distance functions is somewhat different from the own-period distance functions. The first of these for $D^t(x^{t+1}, y^{t+1})$ is computed as

$$TE^t(x^{t+1}, y^{t+1}) = [D^t(x^{t+1}, y^{t+1})]^{-1} = \min \theta_0$$
$$\text{s.t.} \quad \theta_0 x_{n0}^{t+1} - \sum_k \lambda_k^t x_{nk}^t \geq 0, \sum_k \lambda_k^t y_{mk}^t \geq y_{m0}^{t+1}, \theta_0 \text{ free}, \lambda_k^t \geq 0,$$
$$\sum_k \lambda_k^t = \text{free (in case of CRS)}, \sum_k \lambda_k^t = 1 \text{ (in case of VRS)}.$$

The remaining linear program for $D^{t+1}(x^t, y^t)$ is specified like that for $D^t(x^{t+1}, y^{t+1})$, but superscripts t and $t+1$ are transposed.

4. Data and Empirical Model

The data in our analysis comes from the Austrian Compost and Biogas Association (ACBA). The ACBA collects data via online questionnaires filled in by biogas plant operators. Data is cross-checked by special trained persons. The collected data include detailed information on technical characteristics of the biogas plants, economic data as well as material and energy flows. The data received by the ACBA is an unbalanced panel of 74 to 86 biogas plants covering the years 2006, 2012, 2013 and 2014. Since we are interested in measuring the long-run productivity development of the Austrian biogas sector between 2006 and 2014 we drop all observations with missing data for 2006 from our analysis. After excluding all plants starting their operation after 2006 we obtain a balanced sample of 65 biogas plants for the years 2006, 2012, 2013 and 2014. Those 65 plants cover about 25 % of the installed electric capacity and net electricity generation of Austrian biogas plants in 2014.

This representative sample of Austrian biogas plants includes a wide range of plant types and operating conditions. All plants have in common, that they use the biogas produced in the digesters to generate electricity and heat in a combined heat and power plant (CHP). Electricity is fed into the power grid. Heat is required as process heat. The surplus heat is used for supplying district heating and drying services. Unutilized heat is wasted into the atmosphere. The electricity demand of the biogas plants is covered by electricity from the power grid as well as from own production. Digestate can be used as valuable organic fertilizer.

Table 1: Characteristics of biogas plants in our sample in 2014

	Mean value	**Standard deviation**	**Median**	**Minimum**	**Maximum**
First start-up (year)	2004.38	1.27	2005	1999	2006
Number of digesters	2.17	0.38	2	2	3
Size					
Total digester volume (m^3)	3,024	1,840	2,664	410	11,200
CHP nominal capacity el. (kW_{el})	312	215	250	25	1,000
Feedstock processed (t FM)	7,241	4,979	5,450	790	22,111
Feedstock shares in total FM input					
Maize (%)	40	27	47	0	91
Manure (%)	21	23	9	0	90
Other renewable raw materials (%)	18	17	14	0	75
Grass (%)	14	23	2	0	88
Waste (%)	8	24	0	0	100

Note: The sample size is 65.

Table 1 shows some characteristics of the biogas plants in our sample for the year 2014. The sample includes plants with an installed nominal electrical capacity of the combined heat and power unit (CHP) from 25 kW_{el} to 1000 kW_{el}. It is worth to note, that 17 plants or a quarter of the sample increased their capacity by 20 to 150 % between 2006 and 2014. This resulted in an increase of the average electric capacity by 10 %. The increase of the average feedstock input from 6104 t fresh matter (FM) to 7241 t FM between 2006 and 2014 confirms the upscaling trend and is only to a negligibly extend attributable to eight plants starting operation after January 2006.

The average share of other renewable raw materials, such as sugar beets and crop residuals, in total feedstock input is monotonically increasing from 10 % in 2006 to 18 % in 2014. This trend is accompanied by a slightly falling share of maize and liquid manure in the substrate mix. However, changes in average feedstock composition between 2006 and 2014 are only of minor importance and maize silage makes up the bulk of feedstock input in 2006 and 2014.

There are fifty-seven agricultural biogas plants in our sample using maize, animal manure, grass and other renewable raw materials. Six plants are mixed plants also processing organic waste from gastronomy or food processing industry and in some cases from households. The share of waste in the input mass (in t of FM) for those plants ranges from 3 to 96 %. Two plants are pure waste plants solely processing organic waste in all years. The business concepts of waste and agricultural biogas plants are somewhat different. While for waste plants the processing of waste (part of the feedstock used) generates operating revenues (so-called “income from disposal”), for agricultural plants feedstock causes operating costs. Therefore, waste plants have an incentive to increase the amount of waste disposed to maximize revenues. By contrast, agricultural plants usually try to minimize the amount of feedstock used.

With regard to the choice of inputs and outputs, Cook et al. (2014) points out that “if the DEA problem is a general benchmarking problem, then the inputs are usually the 'less-the-better' type of performance measures and the outputs are usually the 'more-the-better' type of performance measures.” Based on this definition of inputs and outputs, we selected five inputs and four outputs summarized in Table 2.

Table 2: Selection and description of input and output variables

Variables	Description
Desirable Inputs	
Feedstock (Nm^3 CH_4)	Aggregated methane content of the substrates, excluding waste. Reflects the energy content of the feedstock.
Capital (Euros)	Capital stock at the end of the year including e.g. CHP, digesters,...
Labour (h)	Working hours for operating and managing the plant
Electricity consumption (kWh_{el})	Electricity consumption for operating the plant
Other costs (Euros)	Include insurance, maintenance and other costs
Outputs	
Electricity sold (kWh_{el})	Amount of Electricity sold generated by the CHP
Heat sold (kWh_{th})	Amount of Heat sold generated by the CHP
Waste disposed (t FM)	Amount of organic waste processed

All other types of *feedstock* (except of waste) are considered as desirable input. In order to reduce the number of inputs we derive a single measure for feedstock input. Thereby it is important to take account of the different energy contents of the various kinds of feedstock. The aggregation of the different substrates is based on guide values for the methane content of each substrate (cf. Appendix A).

Other inputs included in the analysis are i) *labour*, ii) *capital stock*, iii) *electricity demand* and iv) *other costs* (including insurance, maintenance and other costs). Electricity consumption is known for those plants covering their demand from the power grid. For the other plants, covering their demand from own production, an electricity consumption of 12.5 % of sold electricity is assumed.[11] Imputations of electricity demand values concern 36 % and 46 % of the sample in 2012 and 2014, respectively. The input variable "capital" reflects the sum of all investments from starting plant operation until the end of the year under consideration. "Capital" includes investments in digesters, digester heating, CHPs, stirrers and pumps, other machinery, power grid connection, local and district heating grid as well as others. Unluckily, data about the capital stock at the end of 2012 and 2013 is unavailable. Since investments during 2012 and 2013 are extremely rare, the capital stock of 2014 serves as a proxy for the capital stock in 2012 and 2013.

The biogas produced in the digesters is used in a CHP to produce combined heat and power. *Electricity* as well as *heat sold* are identified as outputs. As mentioned above, twelve biogas plants dispose *waste* and generate operating revenue out of this function. Taking this fact into account, following the studies about economic performance of the waste sector reviewed by Simões and Marques (2012) and in contrast to previous studies about biogas plants, such as Filler et al. (2007) and Madlener et al. (2009), we model *waste* as an output in our DEA-models.[12]

CO_2 emissions emerging from the combustion process and methane emissions, emerging e.g. from leakages, are (undesirable) outputs. Another output is digestate emerging from the anaerobic digestion. It can be used to fertilize agricultural land and permanent grassland. Due to data unavailability, those outputs have to be excluded from the productivity analysis. The input and output variables selected for this study are summarized in Table 2. Note that cultivation, harvesting and transportation of feedstock are not considered, as they are processes outside of the system boundaries chosen in this study.

Table 3 provides summary statistics of the applied input and output variables for all years considered in the productivity analysis. Table 3 indicates a general increase in input and output volumes between 2006 and 2014 confirming the expansionary tendencies of the sector. However, the major increase in input and output volumes occurred between 2006 and 2012. In fact, some input volumes and total electricity output show a contraction in 2013 and 2014.

[11] According to experts (e.g. engineers planning biogas plants) 12.5% is a typical value if an appropriate heat use is considered and therefore a good approximation.

[12] Allen (1999) and Dyckhoff and Allen (2001) argue that waste burned in a power plant is an undesirable object. Its destruction is desired and, therefore, waste should be maximized.

Table 3: Descriptive statistics of input and output variables used for DEA and Malmquist-productivity-analysis

	Feedstock (Nm^3 CH_4)	% change	Capital (Euros)	% change	Labour (h)	% change	Electricity used (kWh_{el})	% change	Other costs (Euros)	% change	Electricity sold (kWh_{el})	% change	Heat sold (kWh_{th})	% change	Waste disposed (t FM)	% change
2006																
Avg	508,530		1,259,744		1,382		209,304		94,229		1,906,822		370,375		374	
Min	0		187,430		150		13,069		400		104,550		0		0	
Max	2,433,890		5,380,000		7,200		1,060,074		392,801		8,480,591		6,000,000		10,278	
St. Dev	470,048		859,151		1,112		176,249		74,187		1,567,501		873,757		1,553	
2012																
Avg	611,601	20.3%	1,413,318	12.2%	1,703	23.2%	248,750	18.8%	141,342	50.0%	2,435,176	27.7%	1,165,764	214.8%	657	75.7%
Min	0		204,741		420		12,037		4,531		96,297		0		0	
Max	1,634,680		5,734,800		14,000		862,558		624,469		8,577,008		6,178,000		15,337	
St. Dev	426,273		921,226		1,805		165,243		112,722		1,750,075		1,185,016		2,687	
2013																
Avg	615,778	0.7%	1,413,318	0.0%	1,834	7.7%	242,095	-2.7%	142,594	0.9%	2,363,455	-2.9%	1,264,885	8.5%	540	-17.8%
Min	0		204,741		410		12,570		6,500		100,560		0		0	
Max	2,030,360		5,734,800		14,000		865,172		619,799		6,921,377		9,154,251		13,577	
St. Dev	443,945		921,226		1,822		159,744		120,270		1,655,983		1,519,365		2160	
2014																
Avg	589,903	-4.2%	1,413,318	0.0%	1,869	1.9%	241,816	-0.1%	135,019	-5.3%	2,324,796	-1.6%	1,307,123	3.3%	628	16.3%
Min	0		204,741		320		12,652		6,900		101,214		0		0	
Max	1,708,525		5,734,800		14,000		915,856		531,800		7,326,850		6,584,899		14,681	
St. Dev	431,144		921,226		1,829		166,497		104,425		1,613,574		1,309,297		2,583	

Note: Sample size is 65.

5. Empirical Results

5.1 Scale effects

Choosing the proper technology for efficiency and productivity estimates is important for economic and statistical reasons. If a technology does not exhibit CRS everywhere (globally), then some production units may improve their efficiency by adjusting their size and exploiting returns to scale. Assuming a CRS-technology in such cases distort measures of efficiency and leads to statistically inconsistent estimates of efficiency (Simar and Wilson, 2002).

Knowledge about returns to scale of the production technology also plays a prominent role in choosing the proper decomposition of the Malmquist productivity index presented in section 2. If a technology exhibits non-constant returns to scale, the use of the decomposition introduced by Färe et al. (1994) is criticized by various authors: Lovell (2003) criticizes that i) technical change is measured relative to a CRS-technology and has no economically meaningful interpretation and ii) the scale efficiency change component is not measuring the contribution of returns to scale to productivity change. Lovell (2003) concludes that there exist three economically meaningful decompositions of the Malmquist productivity index. The decomposition proposed by Ray and Desli (1997) is one of them and their scale change factor can be accepted as an adequate reflection of the contribution of returns to scale to productivity change. Additionally, Ray and Desli (1997) criticize the internal inconsistency of the decomposition introduced by Färe et al. (1994). They argue that if the technology exhibits CRS technical change is measured correctly but no scale effects exist, and any measure of it is misleading.

Column two and three of Table 4 show the input-oriented, average technical efficiency under CRS-, VRS-, and NIRS-technology for the years 2006 and 2014. Technical efficiency under VRS, CRS and NIRS varies around a mean of 0.896, 0.819 and 0.826 in 2014, respectively. This result indicates an average potential for input savings of up to 18.1 %. The average efficiency under VRS, CRS and NIRS show a slight increase between 2006 and 2014. Efficiency scores are in a range between 0.38 and 1 under CRS and NIRS, and between 0.53 and 1 under VRS.

The deviations between average technical efficiency under CRS-/NIRS- and VRS-technology suggest that the biogas technology does not exhibit CRS and NIRS. However, to determine if those differences are due to non-constant returns to scale or due to sampling variation we apply formal statistical tests for global returns to scale proposed by Simar and Wilson (2002).

Table 4: Global returns to scale test (Simar and Wilson, 2002)

Test 1: H_0: CRS vs. H_1: VRS	Average $TE_t(x_t, y_t)$ under CRS	Average $TE_t(x_t, y_t)$ under VRS	Test Statistic (TS)	Critical Value (c_α) for $\alpha = 0.05$	p-value for rejecting H_0
2014	0.819	0.896	0.914	0.926	0.014
2006	0.813	0.879	0.925	0.930	0.023
Test 2: H_0: NIRS vs. H_1: VRS	Average $TE_t(x_t, y_t)$ under NIRS	Average $TE_t(x_t, y_t)$ under VRS	Test Statistic (TS)	Critical value for $\alpha = 0.05$	p-value for rejecting H_0
2014	0.826	0.896	0.921	0.963	0.000
2006	0.816	0.879	0.928	0.955	0.000

Note: The critical value and the p-value are based on 2000 bootstrap replicates of the test statistic.

We test the null-hypothesis that the production frontier exhibits CRS (NIRS) versus the alternative hypothesis of VRS (VRS) - labelled as test 1 (test 2) in Table 4. Colum four of Table 4 shows the test statistic which is $\sum_{k=1}^{65}[D_{VRS}^{t}(x^{t},y^{t})]/\sum_{k=1}^{65}[D_{CRS}^{t}(x^{t},y^{t})]$ for test 1 and $\sum_{k=1}^{65}[D_{VRS}^{t}(x^{t},y^{t})]/\sum_{k=1}^{65}[D_{NIRS}^{t}(x^{t},y^{t})]$ for test 2. Those test statistics are the input-oriented equivalent to formula 4.6 in Simar and Wilson (2002) and they are by construction smaller than one. The smaller the test statistic, the larger is the deviation between CRS- (NIRS-) and the VRS-technology. The test is applied for t=2006 and t=2014. The critical value shown in column 5 of Table 4 is such that $\Pr(TS < c_{\alpha}|H_0) = \alpha$. c_α is derived from the empirical distribution of the test statistic, which is unknown but is estimated based on 2000 bootstrap pseudo-samples. For the size of the test α, a significance level 0.05 is chosen. We reject the null hypothesis if the test statistic is smaller than c_α.

The results presented in Table 4 show that the null-hypothesis of CRS- and the NIRS-technology are rejected at the 5 % significance level for the year 2006 and 2014. All in all, the results of the global returns to scale tests suggest the use of non-decreasing returns to scale (NDRS-) or VRS-technology for estimating efficiency scores. The results of the local returns to scale analysis (see Eder & Mahlberg, 2018) proposed by Färe et al. (1985) show that a minority of larger plants in the sample exhibit decreasing returns to scale. However, the majority of 52 % or 49 % of the plants exhibit local increasing returns to scale in 2006 and 2014, respectively.[13] Combining these latter results with the fact that no decomposition of the Malmquist productivity index based on NDRS exists leads us to the application of a VRS technology.

Clearly, the results show that the biogas production technology exhibits non-constant returns to scale and for most of the plants in our sample increasing returns to scale prevail. Therefore, we are interested in the contribution of returns to scale to productivity change and prefer the decomposition proposed by Ray and Desli (1997) above all others.

The results presented in this section are in line with anecdotal evidence suggesting increasing returns to scale in biogas production; see e.g. Walla and Schneeberger (2008). Remember that cultivation, harvesting and transportation of feedstock as well as digestate handling are not considered in this analysis. Therefore, a more than proportional increase of physical inputs needed for those processes as plant size increases could mitigate or, for certain feedstock types, even outweigh positive scale effects (Skovsgaard and Klinge Jacobsen, 2017).

5.2 Malmquist productivity index and decomposition

The upper part of Table 5 shows some information about the distribution of the Malmquist productivity index. Between 2006 and 2014, average annual productivity increased by 1.1 % for the average plant. This corresponds to a cumulative average productivity growth of 9.4 % between 2006 and 2014. Column two of Table 5 shows that cumulative productivity growth for the average plant between 2006 and 2012 was 10.5 % with an average annual growth rate of 1.68 %. Due to missing data for the years 2007-2011 we do not know if productivity increased monotonically, or the development between 2006 and 2012 was accompanied by fluctuations in that period. However, average productivity between 2012 and 2013 declined by 3.8 % and was mainly driven by technical regress. Between 2013 and 2014 average productivity increased by 0.9 % due to a positive scale change factor and nearly reached the average productivity level of 2012.

[13] Biogas plants with local increasing returns to scale are found in the range of 25 to 500 kW_{el} installed electric capacity.

Table 5: Summary statistics for productivity change and its components

	2006 to 2012	2012 to 2013	2013 to 2014	2006 to 2014
PRODCH				
geometric mean	1.105	0.962	1.009	1.094
coefficient of variation	0.292	0.172	0.181	0.308
minimum	0.439	0.520	0.636	0.274
25^{th} percentile	0.926	0.884	0.899	0.917
75^{th} percentile	1.309	1.050	1.088	1.343
maximum	2.133	1.487	1.596	2.389
number of plants with PRODCH > 1	43	26	32	41
number of plants with PRODCH < 1	22	39	33	24
number of plants with PRODCH = 1	0	0	0	0
PEFFCH				
geometric mean	1.015	1.007	1.000	1.023
coefficient of variation	0.155	0.100	0.121	0.152
minimum	0.673	0.615	0.659	0.630
25^{th} percentile	0.976	1.000	0.945	0.983
75^{th} percentile	1.040	1.063	1.032	1.130
maximum	1.618	1.228	1.402	1.538
number of plants with PEFFCH > 1	23	24	17	26
number of plants with PEFFCH < 1	22	14	22	20
number of plants with PEFFCH = 1	20	27	26	19
TECHCH				
geometric mean	1.052	0.949	1.001	1.022
coefficient of variation	0.208	0.085	0.137	0.209
minimum	0.371	0.734	0.463	0.303
25^{th} percentile	0.989	0.915	0.970	0.943
75^{th} percentile	1.182	0.989	1.064	1.136
maximum	1.900	1.316	1.528	1.673
number of plants with TECHCH > 1	43	14	36	38
number of plants with TECHCH < 1	18	47	26	22
number of plants with TECHCH = 1	0	0	0	0
SCH				
geometric mean	1.042	1.004	1.009	1.047
coefficient of variation	0.151	0.067	0.054	0.121
minimum	0.856	0.835	0.884	0.867
25^{th} percentile	0.971	0.984	0.972	0.984
75^{th} percentile	1.088	1.028	1.026	1.089
maximum	1.669	1.318	1.761	1.615
number of plants with SCH > 1	37	32	26	33
number of plants with SCH < 1	24	29	36	27
number of plants with SCH = 1	0	0	0	0

Note: Sample size is 65. Due to infeasible solutions the summary statistics for TECHCH and SCH are based on a sample of 61, 61, 62 and 60 plants for the period 2006-2012, 2012-2013, 2013-2014 and 2006-2014, respectively.

Table 5 also reveals the wide variation in productivity change across biogas plants.[14] For instance, productivity growth rates between 2006 and 2014 are found in a range between -73 % and 139 %. One quarter of the plants show a productivity decline of more than 8.3 % and the upper quarter exhibit productivity increases of more than 34.3 %. Figure 2 in Appendix B shows that between 2006 and 2014 seven plants exhibit a decline in productivity of more than 20 % and eight plants show a productivity growth of more than 50 %. All in all, a majority of 63 % of the plants experienced a rise in productivity and 37 % a decline between 2006 and 2014. Whereby, the largest component contributing to productivity progress is in 47 %, 37 % and 16 % of the cases technical change, efficiency change and scale change, respectively. Productivity regress is dominated in 59 %, 36 % and 5 % of the cases by efficiency decline, technical regress and a negative scale change factor, respectively.

The second part of Table 5 shows summary statistics for the pure efficiency change index or “catch-up” term. Between 2006 and 2014 average annual efficiency increased by 0.3 % for the average plant, corresponding to a cumulative average efficiency growth of 2.3 % in that period. Whereas the average plant shows an average annual efficiency increase of 0.2 % between 2006 and 2012, efficiency increased by 0.7 % in 2013 and remained constant during 2014. The dispersion of the pure efficiency change index is smaller than the productivity change index. Between 2006 and 2014 40 % and 31 % of the biogas plants show an efficiency increase and efficiency decline, respectively. 29 % of the plants are efficient or on the production possibility frontier in 2006 and 2014 showing no efficiency change.

Part three of Table 5 shows summary statistics for the technical change index. Average annual technical change is 0.3 % between 2006 and 2014 and 0.8 % between 2006 and 2012 for the average plant. The difference between those two numbers can be explained by an average technical regress of 5.1 % between 2012 and 2013. There is hardly any average technical change between 2013 and 2014 (+0.1 %). Technical change varies widely across biogas plants showing a technical regress of 70% for the worst and a technical progress of 67 % for the best plant between 2006 and 2014. Thirty-eight plants exhibit a positive technical change and 22 a negative technical change between 2006 and 2014.

The lower part of Table 5 provides summary statistics for the scale change index. Average annual scale change is 0.6 % between 2006 and 2014 and 0.7 % between 2006 and 2012 for the average plant. Between 2012 and 2013 the average scale change factor increased by 0.4 %. The corresponding value for the period 2013 to 2014 is 0.9 %. 61 %, 52 % and 42 % of the biogas plants have a positive scale change for the period 2006 to 2012, 2012 to 2013, 2013 to 2014, respectively. The scale change index shows the lowest dispersion among the components of productivity change and lies in the range of between 0.87 and 1.62 for the period 2006-2014. 55 % of the biogas plants have a positive scale change factor and 25 % of the biogas plants have a scale change factor larger than 1.089 between 2006 and 2014.

Table 6 sums up the results discussed above by providing the annual growth rates for productivity, efficiency, the scale change index and the technical change index for the average plant. Average annual productivity change between 2006 and 2012 (1.7 % for the average plant) is driven by technical progress (0.8 %) and a positive scale change factor (0.7 %). Whereby, both components almost equally contribute to productivity growth. Increases in pure technical effi-

[14] Appendix B provides detailed information (histograms) about the frequency distribution of the Malmquist productivity index and its components.

ciency are only of minor importance. Table 3 shows that productivity growth between 2006 and 2012 can also be explained by average output growth rates (28% to 215%) exceeding average input growth rates (12% to 23%), except for growth of other costs (50%). Since there is no data for the years 2007 to 2011 we have no knowledge about the productivity development in those years. The average annual growth rates for the period 2006 to 2012 presented in Table 6 may hide substantial yearly fluctuations.

Table 6: Annual growth rates (productivity-, efficiency-, technical- and scale-change) for the average plant

	Average annual growth rate of average plant between 2006 to 2012 (%)	Growth rate of average plant between 2012 to 2013 (%)	Growth rate of average plant between 2013 to 2014 (%)
PRODCH	1.7	-3.8	0.9
PEFFCH	0.2	0.7	0.0
TECHCH	0.8	-5.1	0.1
SCH	0.7	0.4	0.9

The productivity downturn of 3.8 % between 2012 and 2013 is largely explained by a technical regress of 5.1 %. Average efficiency gains of 0.7 % and a positive scale change factor of 0.4 % somewhat outweigh the technical regress. Table 3 indicates that the productivity decline in 2013 is driven by negative average output growth rates (-3% and -18%), except for heat sold (+8%), and mostly positive average input growth rates (0%-8%) with a remarkable increase in average labour requirements (+8%).

Between 2013 and 2014 average productivity increased by 0.9 % and is attributable to the exploitation of returns of scale or a positive scale change factor of 0.9 %. Efficiency change and technical change is roughly zero. Table 3 shows that average feedstock input (-4%) and other costs (-5%) decline sharper than electricity output (-2%). The other output growth rates are positive (3% and 16%) contributing to productivity progress. Labour requirements increase by 2 % and may negatively affect productivity growth.

5.3 Explaining productivity growth and its components

In order to identify determinants of productivity change and its components a second stage regression analysis is carried out. Environmental factors such as capital subsidies, age of the plant, feedstock prices and regional differences across Austrian federal states are considered as potential candidates, having an impact on productivity growth and its components. We also test for the effect of factors which are to a certain extent under the control of the biogas plant operator, such as capacity utilization, size of the plant, output diversification or heat utilization and the capital labour ratio, on productivity growth.

A pooled OLS regression model is used to regress the Malmquist productivity index, the pure efficiency change index, the technical change index, and the scale change index on a bunch of explanatory variables. The standard errors are clustered on the plant identifier to correct for the correlation in individual errors and heteroscedasticity. We prefer the pooled OLS model over the fixed effects estimator due to i) small within plant variation, ii) a short panel with three time periods and iii) the fact that we are interested in the effect of time-invariant variables such as plant type or regional dummies on productivity growth and its components.[15] We estimate the following equations:

$$Y_{i,t} = \alpha + \beta X_{i,t} + \gamma time + \varepsilon_{i,t}$$

$$i = 1, \ldots, 65 \qquad t = 2006\text{-}12, 2012\text{-}13, 2013\text{-}14$$

whereby the dependent variable $Y_{i,t}$ is either PRODCH, PEFFCH, TECHCH or SCH. The term 'time' captures time specific effects, which are not explained by the variation in $X_{i,t}$. It is represented by a dummy variable for the period 2012 to 2013 (Dummy 2012-2013) and 2013 to 2014 (Dummy 2013-2014) with the period 2006 to 2012 as reference point.

$X_{i,t}$ covers the following time invariant variables: i) Dummy variables for Austrian federal states to control for geographical and state-specific particularities (Wirth et al., 2013). Dummies for Upper Austria, Styria, Tyrol and Vorarlberg are included with Lower Austria as the reference state; ii) a dummy for plants processing organic waste (Waste plant dummy) to test whether waste disposing plants experience different productivity developments than agricultural biogas plants. Distinct regulations applying for waste and agricultural plants could translate into different productivity changes; and iii) a dummy variable equal to one if a capital subsidy is received in the early days of the plant for financing the initial investments (Capital subsidy dummy). Furthermore, we control for the age (Age) of the plant and allow for a non-linear relationship between plant age and productivity growth by including age-squared (Age sq.) as explanatory variable in our models.

What follows is a description of time-varying variables included in $X_{i,t}$:

i) To test whether larger plants have different productivity developments than smaller plants we include the installed electric capacity (in kW) of the biogas plant in the base year (2006, 2012 and 2013) as a measure of plant size (Size) in the regression analysis. As noted earlier, about a quarter of the plants increased its capacity between 2006 and 2012. To test for scale effects we include the change in size (Δ Size), measured as the first difference of the installed capacity, in our regression model. As shown in a previous subsection about half of the plants exhibit local increasing returns to scale and the biogas production technology can be characterized by a global NDRS-technology. Therefore, we expect that the scale change factor and productivity growth show a high correlation with the change in plant size. To test the hypothesis that the contribution of returns to scale to productivity growth (scale change) is greater for smaller plants we include an interaction term between the size of the plant and the change of plant size in our model. Note that the size variable (Size) in our specifications is centred at the median plant size (250 kW).

ii) Variation in capacity utilization is recognized as one important factor explaining the procyclicality of productivity (Basu, 1996). Various measures and estimates of capacity utilization are proposed in the literature (Morrisson, 2012). We use a very simple technical approach to derive a proxy for capacity utilization: capacity utilization is measured as the ratio of yearly actual electricity generation divided by the maximum potential electricity output. The maximum potential electricity output of a biogas plant is ultimately constrained by the electric capacity of the CHP, and is reached if the CHP is running with

[15] Cross sectional estimates for the period 2006 to 2014, 2006 to 2013 and 2006 to 2012 are available on request. The results obtained are similar to the pooled OLS estimates.

full load throughout the year (8,760 hours). Multiplying the installed capacity of the CHP (measured in kW) by 8,760 gives the maximum potential electricity output.

iii) To investigate the impact of output diversification on productivity change we construct a Herfindahl-Index by using heat and electricity sold, both measured in kWh. The Herfindahl-Index is a measure of concentration and lies between 0.5 and 1. The index is one if there is only a single output (no diversification) and 0.5 if the amount of electricity sold is equal to the amount of heat sold (full diversification). Note that the data shows that electricity output is always positive and the amount of electricity sold is usually higher than the amount of heat sold. Therefore, the constructed index can also be considered as a measure of heat utilization. A negative change in the Herfindahl-Index between years is equivalent to an increased output diversification or higher heat utilization. A positive change indicates higher output concentration and lower heat utilization. Anecdotal evidence suggests the existence of economies of scope for cogeneration systems and is confirmed by empirical studies such as Kwon and Yun (2003). Therefore, we expect that output diversification is positively correlated with productivity growth. A negative relationship between the change in the Herfindahl-Index (Δ Output concentration) and productivity change can be expected.

iv) It follows from a simple neoclassical growth model with a Cobb-Douglas production function, having labour and capital as the only input factors, that capital intensity (capital per worker) is a critical determinant of labour productivity (output per worker). A higher capital stock per unit of labour increases labour productivity. Micro-level studies on the determinants of labour productivity usually control for capital intensity in the regression models (see e.g. Heshmati and Rashidghalam, 2016; Giannangeli abd Gomez-Salvador, 2008; Mcguckin et al., 1998). By including the change of the capital-labour ratio (Δ Capital intensity) as a left-hand-side variable in our regressions, we test the hypothesis that capital deepening raises productivity. Capital intensity is measured as the total capital stock (EUR) divided by yearly labour requirements (h). As the biogas sector is characterized by low investment activities since 2008, we expect that capital deepening increases multifactor productivity by raising the productivity of all other factors of production, e.g. labour productivity.

v) A sharp increase of feedstock prices starting in 2007 led to a shift in relative input prices faced by many biogas plant operators. The type of feedstock used varies widely across biogas plants and a considerable variation in feedstock price changes can be observed. Hicks (1932) argues that "... a change in relative prices of factors of production is itself a spur to invention, and to invention of a particular kind – directed to economizing the use of a factor which has become relatively expensive (pp. 124–125)." We follow the argumentation of Kumar and Managi (2009) considering technical change as an appropriate measure for testing the induced innovation hypothesis. Including the change in feedstock price (Δ Feedstock price) in our regression models allows us to test the hypothesis of factor price-induced technical change. We expect that changes in feedstock prices, measured as total feedstock costs (EUR) divided by feedstock input (Nm^3CH_4), are positively correlated with productivity growth and technical change.

vi) To test the hypothesis of converging efficiency and productivity levels of biogas plants we include the initial efficiency level (efficiency score at the start of each time period) as explanatory variable in our regression models. To be more precise, we test if plants with low initial efficiency level experience higher efficiency and productivity growth than plants with high initial efficiency (beta-convergence). A statistically significant negative coefficient estimate for the initial efficiency variable would favour the beta-convergence hypothesis.

Table 7 reports the results from our regressions. Column 5 shows that productivity growth is not correlated with plant size. The productivity development of smaller plants is by no means different from larger plants. However, the change in plant size (capacity) associates positively with productivity growth; biogas plants increasing their capacity have on average higher productivity growth. The insignificant interaction term between plant size and change in plant size indicates that the effect of a change in capacity on productivity growth does not depend on plant size.

Interestingly, the estimated coefficient of the interaction term is statistically significant in models using the components of productivity growth as independent variable (see columns 2 to 4, Table 7). We find that the larger the size of a plant i) the greater the effect of a capacity increase on technical change and ii) the smaller the effect of a capacity increase on efficiency change and scale change. The latter indicates that increasing returns to scale are stronger for smaller plants and are a less important source of productivity growth for larger plants.

Remember that the plant size variable is centred at the median plant size (250 kW). Therefore, the estimated coefficients of the change in plant size and their significance shown in Table 7 reflect the effect of a capacity change on SCH, TECHCH, PEFFCH and PRODCH for a plant of median size. Centring the size variable at different levels allows us to explore the range of plant size for which an increase in capacity translates into a higher scale change factor. On average, increasing the scale of operation (capacity) positively contributes to the scale change index for plants in the range of 0 to 190 kW (0 to 160 kW) at the 10 % (5 %) significance level; those plants are able to exploit returns to scale by increasing their size.

We also estimate models with a dummy variable capturing investment activities and excluding the capacity change variable, as well as the interaction term between capacity change and size of the plant. The results are available in Appendix E. The investment dummy is equal to one if investments were undertaken and zero otherwise. While 66 % of the biogas plants in the sample increased their capital stock between 2006 and 2012, 34 % do not show any investment activity in that period. We find that there is a statistically significant positive relationship between i) productivity growth and investment activity, as well as ii) scale change and investments. Unfortunately, we are not able to distinguish between types of investments (e.g. installed electric capacity, heat grid…). However, the results suggest that investments triggered productivity growth mainly via scale change.

Unsurprisingly, changes in capacity utilization positively correlate with productivity growth. In line with Borger and Kerstens (2000), the results suggest that changes in technical efficiency are partially due to changes in capacity utilization. However, disentangling the effects of capacity utilization change and technical efficiency change is difficult. Though, the decomposition of the Malmquist-index provided by Borger and Kerstens (2000) is able to differentiate between changes in capacity utilization and changes in technical efficiency, their approach is only applicable to output oriented distance functions.

Table 7: Regression results of pooled OLS-Model

Independent	**Dependent Variable**			
Variables	PEFFCH	TECHCH	SCH	PRODCH
(Intercept)	1.310000***	1.008700***	0.970990***	1.286900***
	(0.092540)	(0.081093)	(0.076099)	(0.150338)
Initial efficiency level	-0.404543***	0.052148	0.038796	-0.375547***
	(0.077009)	(0.072430)	(0.052249)	(0.123720)
Waste plant dummy	-0.007319	0.013916	0.079780	-0.022269
	(0.016837)	(0.068028)	(0.095214)	(0.051223)
Capital subsidy dummy	-0.015279	-0.019863	-0.021538	-0.026465
	(0.025588)	(0.026429)	(0.020580)	(0.044112)
Age	-0.007668	0.006335	-0.003909	0.019791
	(0.016328)	(0.028031)	(0.024277)	(0.040994)
Age sq.	0.000755	-0.000126	-0.000816	-0.000494
	(0.000855)	(0.001445)	(0.001328)	(0.002121)
Size	0.000024	-0.000113	-0.000013	-0.000054
	(0.000032)	(0.000069)	(0.000051)	(0.000059)
Δ Size	0.000588**	0.001073**	0.000423	0.001730**
	(0.000284)	(0.000518)	(0.000442)	(0.000784)
Size * Δ Size	-0.000003*	0.000009**	-0.000006***	-0.000002
	(0.000002)	(0.000003)	(0.000002)	(0.000004)
Δ Capacity utilization	0.200711**	0.013513	0.129297	0.354004**
	(0.078034)	(0.085653)	(0.116731)	(0.164641)
Δ Output concentration	-0.241025***	-0.122538	-0.158427*	-0.437017***
	(0.062633)	(0.102070)	(0.087203)	(0.154463)
Δ Capital intensity/100	0.005877**	0.008429***	-0.001036	0.016111***
	(0.002562)	(0.001630)	(0.002549)	(0.002847)
Δ Feedstock price	0.000315**	0.000181	0.000169	0.001104**
	(0.000148)	(0.000377)	(0.000280)	(0.000453)
Upper Austria	-0.043301	0.036072	-0.019898	0.007322
	(0.035111)	(0.028674)	(0.025368)	(0.056886)
Styria	0.017007	-0.024094	-0.007296	0.004041
	(0.018121)	(0.022938)	(0.016607)	(0.034301)
Tyrol	0.006287	-0.155590***	0.009226	-0.101944
	(0.021036)	(0.058814)	(0.045042)	(0.070197)
Vorarlberg	0.008300	-0.190578***	-0.031246	-0.087945
	(0.024412)	(0.068615)	(0.097933)	(0.059857)
Dummy 2012-2013	0.090847*	-0.102604	0.097584	-0.055361
	(0.047971)	(0.089990)	(0.087939)	(0.133151)
Dummy 2013-2014	0.079146	-0.051798	0.123942	-0.024627
	(0.053079)	(0.106168)	(0.107593)	(0.138724)
R-squared	0.41	0.42	0.25	0.41
Adj. R-squared	0.34	0.36	0.16	0.35
Number of obs.	195	184	184	195

Note: Estimated coefficients of the pooled-OLS model are reported. Standard errors clustered on the plant identifier are shown in parenthesis. Four infeasible solutions for the period 2006-2012 and 2012-2013 as well as three infeasible solution for the period 2013-2014 for TECHCH and SCH reduce the number of observations in model 2 and 3 to 184. The variable "Size" is centred at the median plant size of 250 kW. $p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Changes in output concentration are negatively associated with productivity growth. We find that output diversification is a statistically significant positive determinant of productivity growth and efficiency change. That is, on average, biogas plants which increase their heat output are moving closer to the production-possibility frontier.

The growth of the capital-labour ratio shows a statistically significant, positive relationship with efficiency change, technical change and productivity growth. Capital deepening[16] seems to be an important determinant of productivity growth. Anecdotal evidence suggests that changes in the capital-labour ratio are a proxy for improved monitoring techniques/components. Such improvements are accompanied by an increase in the capital stock. Perhaps more important, the time spent on monitoring and adjustment activities can be reduced substantially while biological disturbances in the digester are shortened, which in turn raises biogas yield.

The results in Table 7 show that variations in feedstock prices are positively associated with productivity growth. Interestingly, this productivity enhancing effect comes not from technical change as suggested by the price-induced innovation hypothesis, but from a boost of relative efficiency change. The results suggest that biogas plants, which are confronted with rising feedstock prices, tend to economise on feedstock. This effect increases with the magnitude of the price rise. Jaraite and Di Maria (2012) study the environmental efficiency and productivity of the public power generating sector in the EU and find similar results: rising prices of crude oil and gas have a positive effect on productivity change via efficiency improvements. These effects are stronger for countries which rely heavily on oil or gas and have limited possibilities to switch between fuels in the short-run.

The initial efficiency level shows a statistically significant, negative relationship with efficiency change and productivity growth. These results provide some evidence for the hypothesis of converging efficiency and productivity levels. Plants with low efficiency levels tend to have, on average, higher efficiency and productivity growth rates (β-convergence). However, the dispersion of efficiency scores across biogas plants is highly persistent over time (no σ-convergence).[17]

Furthermore, we find that technical change is significantly lower in Tyrol and Vorarlberg relative to Lower Austria. The differences between technical changes across Austrian federal states are remarkable: while Upper Austria, Lower Austria and Styria show a technical progress of 16 %, 10 % and 2 %, respectively, Tyrol has a technical regress of 23 % and Vorarlberg exhibits a negative technical change of 16 %. These results might reflect geographic learning or knowledge spillover effects between producers. At the end of 2014 the installed electric capacity of Lower Austria, Upper Austria, Styria, Tyrol and Vorarlberg represented about 40 %, 17.5 %, 17.5 %, 4 % and 4 % of the total installed capacity of Austrian biogas plants, respectively. Furthermore, work groups, which aim at further training of biogas plant operators through knowledge transfer and guidance, are organised from ACBA on the level of federal states. In addition, federal states interpret the legislation for the operating license differently. The authorities focus on different priorities. For instance, requirements of safety equipment vary across federal states.

It is also interesting to mention that biogas plants receiving a capital subsidy do not show, on average, different productivity developments than plants without receiving a capital subsidy. Productivity growth of waste plants is not statistically different to that of agricultural plants.

5.4 Sensitivity of Results

Several experts, engaged in the field of efficiency and productivity analysis, pointed out that waste and agricultural plants may not be directly comparable. For example, they have different business

[16] A situation where the capital stock grows faster than labour requirements.

[17] The standard deviation for efficiency scores estimated under VRS-technology is 0.15, 0.13, 0. 13, 0.13 for the year 2006, 2012, 2013, 2014, respectively.

models and do not share the same technology. In order to check the sensitivity of our results we exclude waste processing plants from the sample. The remaining 57 agricultural plants ('N=57 sample') are used to estimate the input distance functions and the Malmquist productivity index as outlined in section 2. Furthermore, similar regression analyses, as described in section 3.2, are performed.

The estimates for the average annual growth rates of productivity, efficiency, technical, and scale change based on the 'N=57 sample' are available in Appendix C. The long-term average annual productivity growth rates for the average plant between 2006 and 2012/2014 are similar to the estimates based on the 'N=65 sample'. Though, productivity growth of the average plant for the period 2012 to 2013 and 2013 to 2014 is somewhat different to the estimates presented previously. For instance, while the productivity growth estimate for 2013 to 2014 is 0.9 % based on the large sample, it is 1.6 % based on the 'N=57 sample'.

Table 9 in Appendix D shows the regression results for the 'N=57 sample'. The estimated models are exactly the same as described in the previous section. The model with efficiency change as independent variable displays the largest sensitivity. The estimated coefficients for changes in substrate prices and changes in the installed capacity are still positive but become statistically insignificant. The coefficient of the change in capacity utilization is significantly different from zero at the 10 % significance level.

Similar to the results presented in Table 7 we find that capacity change (size change) is an important determinant of the scale change factor. However, the range of plants for which an increase in plant size raises the scale change factor differs. Remember, the results in Table 7 show that plants in the range of 0 to 160 kW can improve their scale change factor by increasing the installed capacity. Table 9 indicates that this range is much broader, reaching from 0 to 275 kW.

The model explaining technical change is highly robust to sample variations. The sign of the estimated coefficients and their significance level are hardly changing.

With respect to productivity growth, the estimated coefficients of capacity utilization and feedstock prices show a lower significance level (10 %). Nevertheless, estimates of the investment dummy model[18] indicate that feedstock prices are a highly significant (1 % level) determinant of productivity change, irrespective of the sample used. Table E.1 and Table E.2 in Appendix E report the results of the investment dummy models for the 'N=65 sample' and N=57 sample'.

All in all, it turns out that the regression results are rather insensitive to the applied sample and to various model specifications. Changes in i) plant size, ii) capacity utilization, iii) output diversification, iv) capital intensity and v) feedstock prices are important determinants of productivity growth.

6. Conclusion

In this study, we apply the linear-programming approach of Data Envelopment Analysis (DEA) to measure productivity change of 65 Austrian biogas plants between 2006 and 2014. Productivity change is decomposed into technical change (i.e., shift of the technology frontier), technical efficiency change (i.e., movements towards the technology frontier) and scale change (i.e., exploitation of returns to scale) as proposed by Ray and Desli (1997).

[18] That is replacing the capacity change variable and the interaction term with an investment dummy.

Productivity is an essential determinant of a plant's i) output given a fixed amount of inputs, ii) units costs and iii) profit. Reducing costs and increasing profits of renewable electricity generation i) fosters the deployment of renewable energy sources (RES-E) technologies, ii) enables to reduce the financial burden faced by electricity consumers, and hence iii) could further raise the public acceptance of renewable energy technologies. Therefore, it is crucial to measure and understand productivity growth of RES-E. Only few studies analyze the productivity growth of renewable energy plants, except for hydroelectric power facilities. Our study aims to fill this gap in the literature. As far as we know, we are the first evaluating productivity change of biogas plants based on a broad sample and an extensive set of inputs and outputs.

Our results indicate that on average productivity increased by 9.4 % over the whole sample period meaning an average annual increase of 1.1 %. The exploitation of returns to scale is an important driver of productivity growth, which is indicated by an average scale change of 4.7 % over the whole sample period (or 0.6 % per year). The technical efficiency increase turned out to be much lower. It amounts to merely 2.3 % over the whole period (or 0.3 % per year). The regression analysis shows that plants with low initial efficiency exhibit larger efficiency gains. Technical change component of 2.2 % over the whole period (or 0.3 % per year) turns out to be even smaller.

While average annual productivity growth was 1.7 % between 2006 and 2012, productivity change slowed down in 2013 and 2014. If the rather low productivity growth of the last years continues, and input price changes are absent, only minor unit cost reductions in biogas production can be expected. Technical change is low, which might reflects that technical innovations where hardly implemented in Austrian biogas plants. The exploitation of returns to scale seems to be the most important driver of productivity growth in the period 2006-2014. However, if technical progress is missing (outward shift of the production possibility curve) productivity growth will be exhausted over time.

A second-stage pooled-OLS regression confirms that biogas plants, which expand their electric capacity, have on average higher productivity growth. Especially small plants increasing their capacity reap productivity gains via increasing returns to scale. Increasing returns to scale are a less important source of productivity growth for larger plants. Feedstock prices show a positive relationship with productivity and efficiency change. This may indicates that biogas plant operators react to feedstock price increases with efficiency improvements.

Further, the regression analysis shows that output-mix diversification is an important determinant of productivity growth. Though, complete specialization in electricity generation declined substantially between 2006 and 2014[19], most of the plants are still partially specialized in electricity production. That means electricity output exceeds heat output. The focus of biogas plant operators on electricity generation is largely driven by regulatory measures.[20] Absent or weak locational signals led to placement of generation at sites, where heat demand is low and expenditures for district heat connections are high. Policy makers should be aware that co-generation units are characterized by positive synergies among power and heat generation, which

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[19] The percentage of plants without any heat utilization in the sample declined from 49 % in 2006 to 8 % in 2014.

[20] The green electricity law implies a purchase guarantee for electricity generated in biogas plants and fixed electricity prices (feed-in tariffs) for 13 years. Production subsidies for heat are not available. In 2015 the average feed-in tariff for biogas plants was 17.60 cent/kWh$_{el}$, whereas the average exchange price for electricity was 3.23 cent/kWh$_{el}$. Commonly, heat prices are negotiated bilaterally between the biogas plant operator and the buyer (e.g. district heating grid providers).

are primarily based on cost reductions through fuel savings (cf. Kwon and Yun, 2003).[21] Policies that incentivize biogas plant operators to diversify outputs can generate substantial productivity gains. For plant operators the regression results indicate that increasing the size, more full-load hours or shorter operational interruptions (e.g. through regular maintenance) and diversification (e.g. increased heat utilization) may contribute to an improvement of productivity.

The results of this study are in line with anecdotal evidence and previous analysis suggesting increasing returns to scale in biogas production; see e.g. Walla and Schneeberger (2008) and Skovsgaard and Klinge Jacobsen (2017). Policy makers and regulators should consider that larger plants might generate biogas at lower unit costs due to increasing returns to scale. Incentivising the cooperation of farmers in one region to run a collaborative biogas plant is one possibility to exploit returns to scale. Another option is to set a uniform feed-in tariff for all biogas plants, which does not cover the costs of small-scaled plants.

The fact that harvesting and transportation of feedstock as well as the handling of digestate are not considered in our study might be seen as a limitation. Skovsgaard and Klinge Jacobsen (2017) show in a Danish case study that per unit transport costs for biogas plants increase with scale, which partly offsets the economies of scale found for capital and operational expenditures. This finding is in line with the studies of Walla and Schneeberger (2008) and Stürmer et al. (2011). Hence, one possible avenue for future research could reconsider scale effects based on an investigation of cost efficiency including costs for i) feedstock transportation and ii) digestate handling. Last but not least similar analyses of technical and cost efficiency as well as productivity and profitability change should be carried out for other renewable energy technologies such as wind power plants, solar power plants, biomass power plants, etc. Those technologies play a major role in the energy transition to a sustainable and eco-friendly energy system with low carbon emissions.

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Appendix A

Table A.1: Guide values for methane, dry matter and organic dry matter content per t of FM

	Ø Nm3 CH4/t FM	**DM (in % FM)**	**Organic DM (in % of DM)**
Waste	145	24%	85%
Grass	110	33%	93%
Cascading use	85	65%	90%
Maize	115	35%	98%
Other renewables	105	33%	95%
Manure	20	10%	85%

Note: FM is fresh matter; DM is dry matter; Source: ACAB.

Appendix B: Frequency distributions of Malmquist productivity indices and components

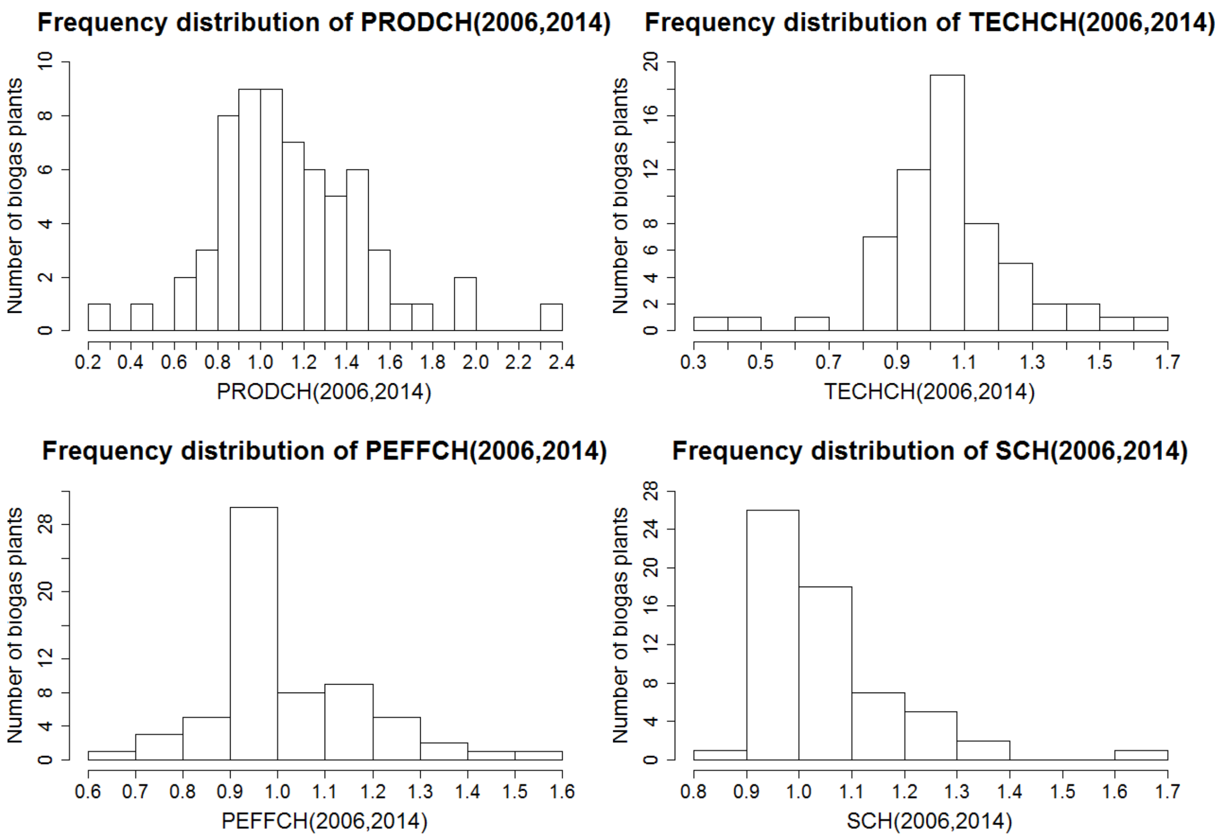

Figure 2: Frequency distribution of productivity change and its components, 2006-2014.

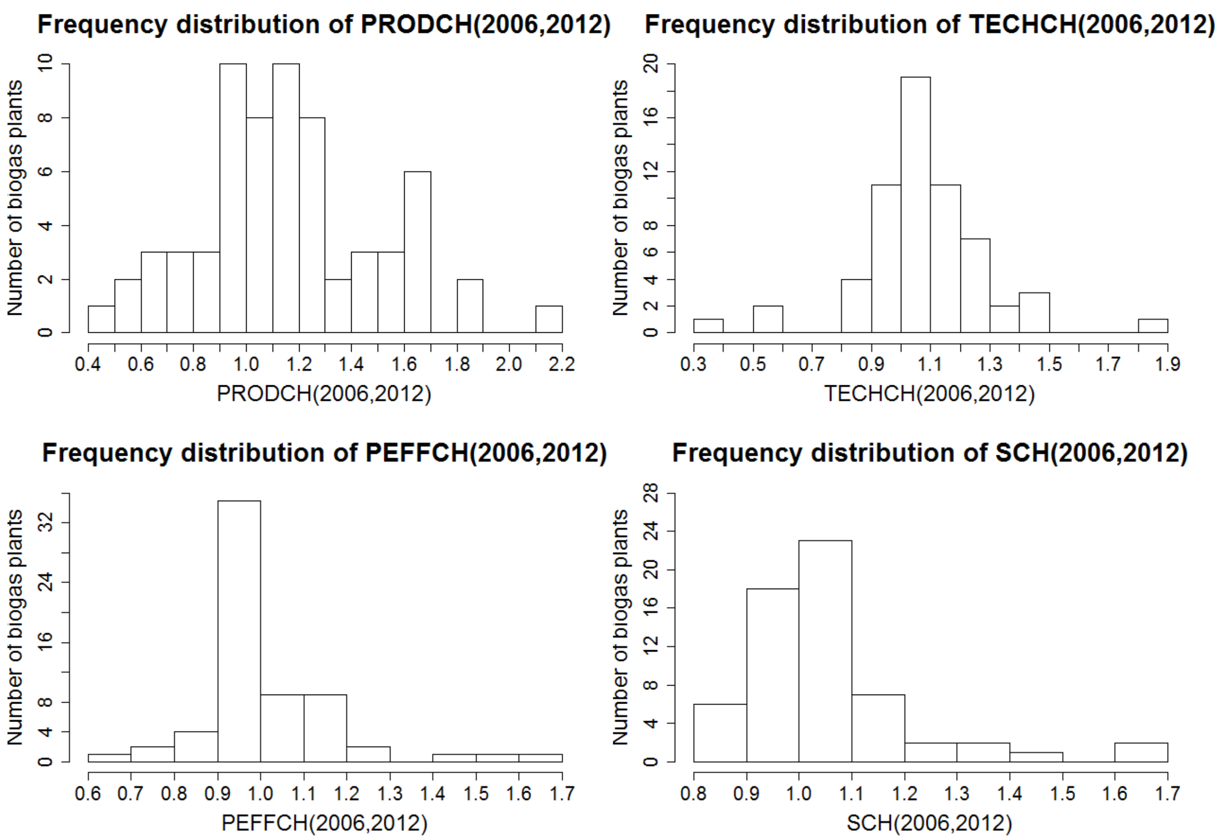

Figure 3: Frequency distribution of productivity change and its components, 2006-2012.

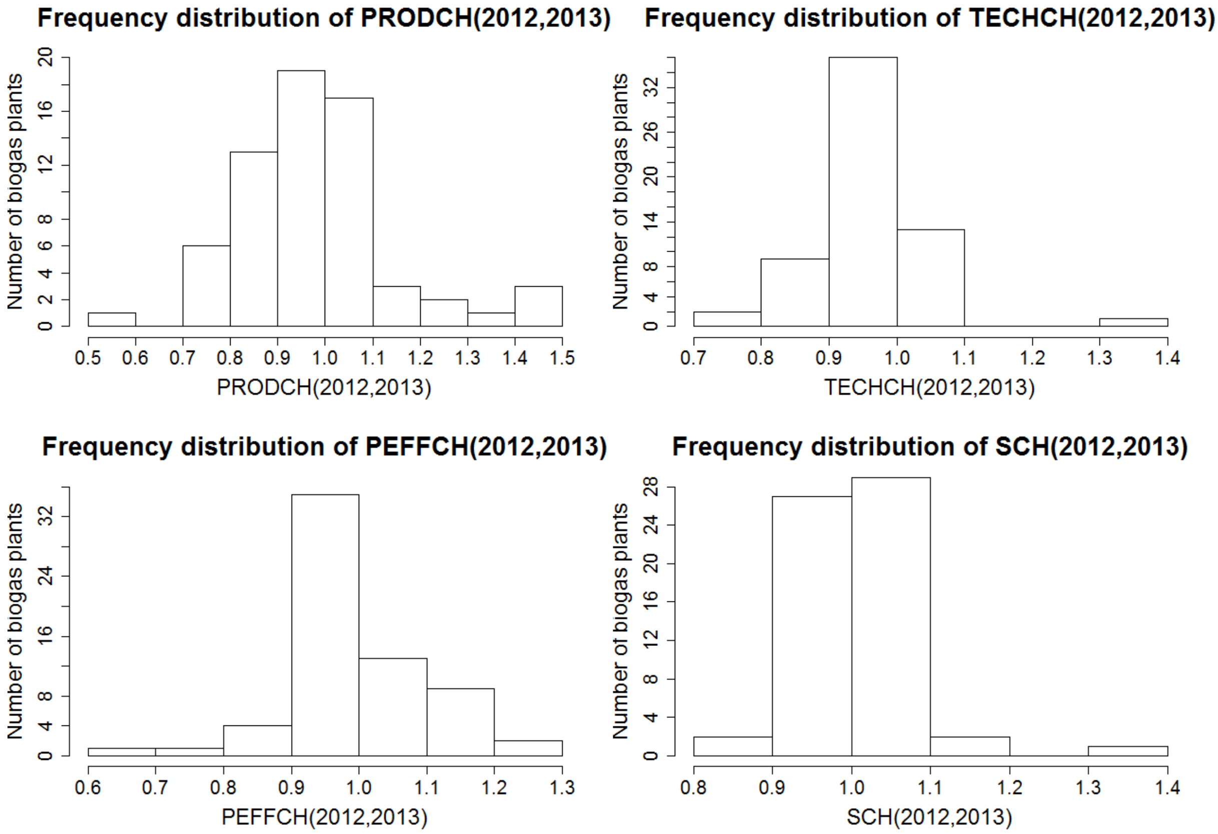

Figure 4: Frequency distribution of productivity change and its components, 2012-2013.

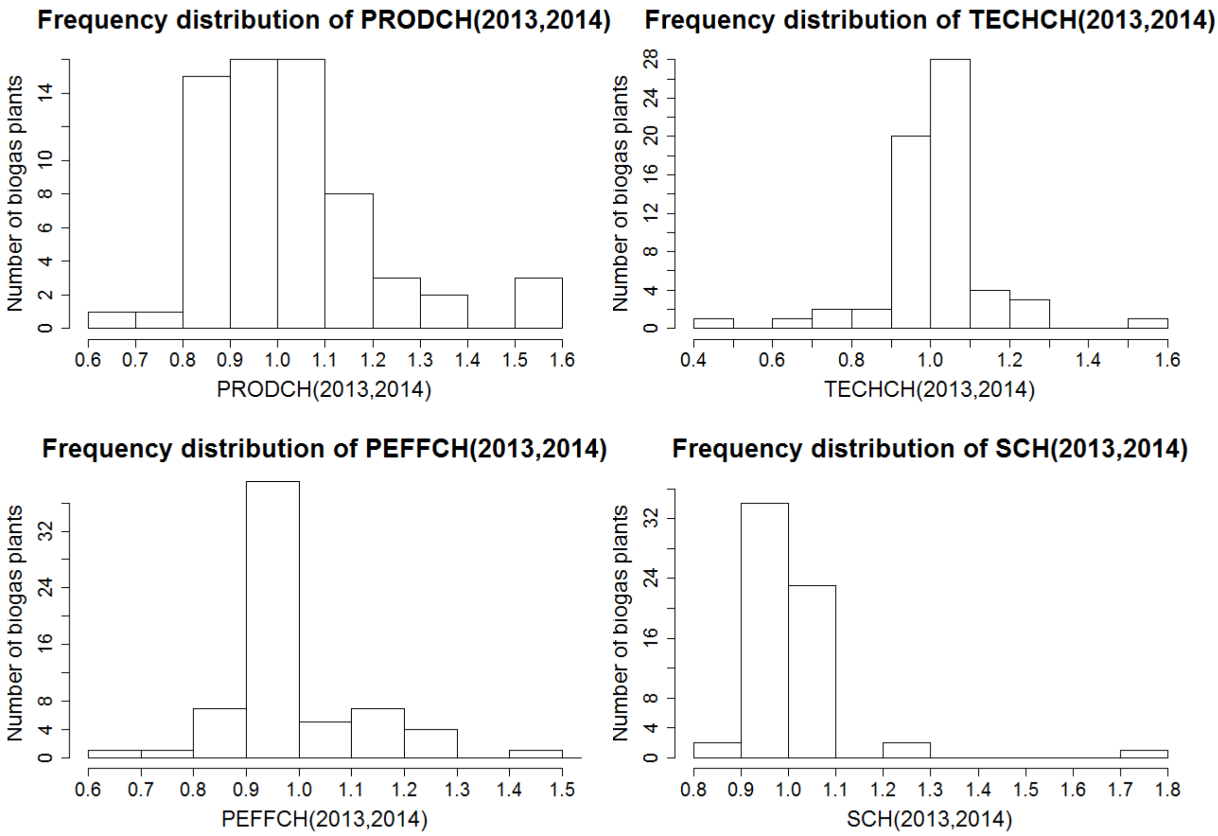

Figure 5: Frequency distribution of productivity change and its components, 2013-2014.

Appendix C

Table C.1: Annual growth rates (productivity-, efficiency-, technical- and scale-change) for the average plant

	Average annual growth rate of average plant between 2006-2012 (%)	Growth rate of average plant between 2012-2013 (%)	Growth rate of average plant between 2013-2014 (%)	Average annual growth rate of average plant between 2006-2014 (%)
PRODCH	1.9	-4.5	1.6	1.2
PEFFCH	0.2	0.5	-0.5	0.2
TECHCH	0.6	-5.1	3.4	0.3
SCH	0.9	-0.6	-0.5	0.6

Note: Sample size is 57 – only agriculture plants. Biogas plants processing waste are excluded.

Appendix D

Table D.1: Regression results of pooled OLS-Model, Agricultural plants only

Independent Variable	**Dependent Variable**			
	PEFFCH	**TECHCH**	**SCH**	**PRODCH**
(Intercept)	0.355178***	-0.066232	-0.100734	0.270786
	(0.114193)	(0.092571)	(0.115561)	(0.185893)
Initial efficiency level	-0.448972***	0.084923	0.048871	-0.342168**
	(0.088865)	(0.081591)	(0.072579)	(0.140284)
Capital subsidy dummy	-0.009595	-0.034059	0.007222	-0.032893
	(0.028275)	(0.021788)	(0.011035)	(0.045549)
Age	0.000803	0.020283	0.013729	0.021822
	(0.021319)	(0.033400)	(0.029343)	(0.058648)
Age sq.	0.000487	-0.001168	-0.000599	-0.000749
	(0.001416)	(0.001943)	(0.001876)	(0.003329)
Size	0.000011	-0.000062	-0.000051	-0.000049
	(0.000039)	(0.000058)	(0.000032)	(0.000079)
Δ Size	0.000284	0.001486***	0.000941**	0.002015**
	(0.000333)	(0.000556)	(0.000367)	(0.000893)
Size * Δ Size	-0.000001	0.000011***	-0.000008***	-0.000002
	(0.000002)	(0.000003)	(0.000002)	(0.000004)
Δ Output concentration	-0.186301***	-0.162452	-0.146551	-0.425157***
	(0.069344)	(0.107835)	(0.094970)	(0.159542)
Δ Capacity utilization	0.178995*	-0.006866	0.227676	0.358397*
	(0.096957)	(0.089741)	(0.185953)	(0.200428)
Δ Capital intensity/100	0.005528**	0.008338***	-0.000217	0.016194***
	(0.002721)	(0.001346)	(0.002930)	(0.003449)
Δ Feedstock price	0.000278	0.000420	0.000167	0.000927*
	(0.000182)	(0.000387)	(0.000217)	(0.000513)
Upper Austria	-0.033699	0.031479	0.006943	0.009599
	(0.039471)	(0.024940)	(0.014182)	(0.060318)
Styria	0.017809	-0.031279	-0.005767	-0.004966
	(0.018129)	(0.019523)	(0.012312)	(0.035143)
Tyrol	0.023347	-0.180350***	0.080627	-0.101680
	(0.031109)	(0.067405)	(0.051192)	(0.091408)
Dummy 2012-2013	0.036559	-0.095667	-0.018979	-0.064491
	(0.057849)	(0.102385)	(0.061900)	(0.169731)
Dummy 2013-2014	0.012761	-0.016539	-0.025931	-0.028684
	(0.064452)	(0.113170)	(0.061561)	(0.183060)
R-squared	0.37	0.53	0.38	0.44
Adj. R-squared	0.30	0.47	0.32	0.38
Number of obs.	171	165	165	171

Note: Estimated coefficients of the pooled-OLS model are reported. Standard errors clustered on the plant identifier are shown in parenthesis. Six infeasible solutions for TECHCH and SCH reduce the number of observations in model 2 and 3 to 165. The variable "Size" is centred at the median plant size of 250 kW. $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix E

Table E.1: Regression results of pooled OLS-Model, Investment Dummy

Independent Variable	**Dependent Variable**			
	PEFFCH	**TECHCH**	**SCH**	**PRODCH**
(Intercept)	1.363945***	0.995389***	1.005806***	1.341705***
	(0.109758)	(0.084219)	(0.083609)	(0.193461)
Initial efficiency level	-0.418664***	0.103802	0.011885	-0.370784***
	(0.082361)	(0.079662)	(0.059570)	(0.138362)
Waste plant dummy	-0.005154	0.023353	0.063242	-0.031013
	(0.018378)	(0.074284)	(0.093647)	(0.053529)
Capital subsidy dummy	-0.019733	-0.014563	-0.030910	-0.032762
	(0.025762)	(0.024920)	(0.021764)	(0.042269)
Age	-0.019978	-0.021895	-0.026967	-0.035013
	(0.015798)	(0.032205)	(0.024816)	(0.038991)
Age sq.	0.001326	0.001561	0.000324	0.002420
	(0.000813)	(0.001827)	(0.001361)	(0.002011)
Size	0.000001	-0.000032	-0.000081	-0.000091
	(0.000032)	(0.000068)	(0.000056)	(0.000062)
Investment dummy	0.016221	0.073275	0.099197**	0.177541**
	(0.041399)	(0.055245)	(0.038622)	(0.085340)
Δ Output concentration	-0.214034***	-0.135430	-0.090826	-0.365035***
	(0.061337)	(0.113638)	(0.076098)	(0.138698)
Δ Capacity utilization	0.184099**	-0.053882	0.126057	0.302637*
	(0.081665)	(0.090165)	(0.110259)	(0.157350)
Δ Capital intensity/100	0.005858**	0.009084***	-0.001069	0.016507***
	(0.002493)	(0.002024)	(0.003055)	(0.002740)
Δ Feedstock price	0.000305**	0.000336	0.000262	0.001229***
	(0.000125)	(0.000377)	(0.000275)	(0.000370)
Upper Austria	-0.051943	0.036203	-0.031519	-0.010702
	(0.035970)	(0.029444)	(0.025654)	(0.058942)
Styria	0.017641	-0.047994**	0.002218	-0.005607
	(0.018170)	(0.022784)	(0.017427)	(0.033223)
Tyrol	0.003324	-0.166017***	0.004158	-0.119208*
	(0.022352)	(0.059777)	(0.043758)	(0.067074)
Vorarlberg	0.026275	-0.193669**	0.000529	-0.044811
	(0.033107)	(0.074380)	(0.088465)	(0.066909)
Dummy 2012-2013	0.115139*	-0.021648	0.205783**	0.145104
	(0.062020)	(0.115305)	(0.097533)	(0.155377)
Dummy 2013-2014	0.106143	0.027276	0.236845**	0.181092
	(0.065312)	(0.127946)	(0.116113)	(0.159549)
R-squared	0.37	0.33	0.19	0.41
Adj. R-squared	0.31	0.26	0.11	0.35
Number of obs.	195	184	184	195

Note: Estimated coefficients of the pooled-OLS model are reported. Standard errors clustered on the plant identifier are shown in parenthesis. Four infeasible solutions for the period 2006-2012 and 2012-2013 as well as three infeasible solution for the period 2013-2014 for TECHCH and SCH reduce the number of observations in model 2 and 3 to 184. The variable "Size" is centred at the median plant size of 250 kW. $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table E.2: Regression results of pooled OLS-Model, Investment Dummy, Agricultural plants only

Independent Variable	Dependent Variable			
	PEFFCH	**TECHCH**	**SCH**	**PRODCH**
(Intercept)	0.382366***	-0.003697	-0.048246	0.345884*
	(0.122466)	(0.093012)	(0.121945)	(0.207880)
Initial efficiency level	-0.455946***	0.120727	0.034312	-0.333220**
	(0.090826)	(0.080248)	(0.079548)	(0.146686)
Capital subsidy dummy	-0.011618	-0.031463	-0.005814	-0.043324
	(0.028080)	(0.021117)	(0.013503)	(0.042020)
Age	-0.004359	-0.035395	-0.022882	-0.050626
	(0.020535)	(0.044661)	(0.029042)	(0.057403)
Age sq.	0.000830	0.002042	0.001578	0.003655
	(0.001336)	(0.002725)	(0.001939)	(0.003247)
Size	-0.000001	0.000040	-0.000142***	-0.000098
	(0.000037)	(0.000049)	(0.000038)	(0.000078)
Investment dummy	0.000470	0.074829	0.127672***	0.204191**
	(0.039275)	(0.057661)	(0.044115)	(0.081708)
Δ Output concentration	-0.177663**	-0.130656	-0.078723	-0.349357**
	(0.068487)	(0.123707)	(0.080874)	(0.134522)
Δ Capacity utilization	0.162511*	-0.124450	0.191455	0.250265
	(0.097533)	(0.094352)	(0.170841)	(0.177171)
Δ Capital intensity/100	0.005389**	0.008860***	-0.000528	0.015937***
	(0.002690)	(0.001832)	(0.003530)	(0.003015)
Δ Feedstock price	0.000304*	0.000549	0.000317	0.001186**
	(0.000179)	(0.000391)	(0.000204)	(0.000462)
Upper Austria	-0.037302	0.030331	-0.011887	-0.011869
	(0.039152)	(0.025926)	(0.017060)	(0.060184)
Styria	0.015965	-0.049540**	-0.007817	-0.027232
	(0.017661)	(0.022391)	(0.016320)	(0.033382)
Tyrol	0.022311	-0.186032***	0.064211	-0.127137
	(0.031817)	(0.067508)	(0.048506)	(0.083374)
Dummy 2012-2013	0.037172	0.040632	0.109550	0.161966
	(0.070033)	(0.147636)	(0.074536)	(0.187612)
Dummy 2013-2014	0.013334	0.123268	0.104471	0.199507
	(0.075917)	(0.151891)	(0.073635)	(0.198768)
R-squared	0.36	0.38	0.29	0.44
Adj. R-squared	0.30	0.32	0.22	0.38
Number of obs.	171	165	165	171

Note: Estimated coefficients of the pooled-OLS model are reported. Standard errors clustered on the plant identifier are shown in parenthesis. Six infeasible solutions for TECHCH and SCH reduce the number of observations in model 2 and 3 to 165. The variable "Size" is centred at the median plant size of 250 kW. p<0.01, ** p<0.05, * p<0.1.