Size, Subsidies and Technical Efficiency in Renewable Energy Production: The Case of Austrian Biogas Plants

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ABSTRACT

This study estimates the efficiency of biogas plants and identifies determinants of inefficiencies. Data Envelopment Analysis is applied on a sample of 86 Austrian biogas plants for the year 2014, covering about one third of the installed electric capacity of Austrian biogas plants. We decompose technical efficiency into scale efficiency and pure technical efficiency (managerial efficiency). In a second-stage regression analysis the effects of subsidies and other variables on managerial efficiency are investigated. The main results are: i) 34% of biogas plants in our sample are technically efficient, 40% are scale efficient and 50% are managerial efficient; ii) small biogas plants (≤100 kW) are scale inefficient exhibiting increasing returns to scale; iii) production subsidies show a significant, negative relationship to managerial efficiency. The results are consistent with the hypothesis that production subsidies provide a disincentive to managerial effort of plant operators.

Keywords: Data Envelopment Analysis, pure technical efficiency, scale efficiency, returns to scale, feed-in tariffs

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1. INTRODUCTION

World electricity generation from biogases[1] grew from 3.7 TWh in 1990 to 13 TWh in 2000 and 80 TWh in 2014. With an average annual growth rate of 13.1% since 1990, biogases are the third fastest growing source of renewable electricity in OECD countries, only outpaced by electricity from solar photovoltaic (44.1%) and wind power (22.1%) (IEA, 2016a).

The rise of electricity generation from biogas is mainly driven by OECD Europe accounting for 74% of world production. Germany, Italy and the UK are the largest producers in Europe generating 39%, 10% and 10% of world production in 2014, respectively. The second largest producer is the United States accounting for 16% of world production.

1. Biogases produced by anaerobic digestion of biomass and thermal processes (gasification or pyrolisis) are included. However, the contribution of thermal conversion of organic matter to gas to global energy scenario is negligible (World Bioenergy Association, 2016). Biogases from anaerobic digestion cover landfill gas, sewage sludge gas and other biogases, such as biogas produced from the anaerobic fermentation of animal manure, agricultural residues and energy crops. Breweries and other agro-food industries are included.

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As many renewable electricity technologies, such as solar photovoltaic and wind power, electricity generation from biogas struggles to compete with less costly but environmental unfriendly fossil fuel electricity generation technologies. Therefore, many countries promote the development and deployment of renewable energy and electricity generation from biogas in particular. The IEA estimates that in 2015, $150 billion were spent to support renewable energy worldwide—with the United States, Germany, China, Italy, Japan, the United Kingdom and Spain leading the way (IEA, 2016b).

For instance, in the U.S. electricity generation from biogas is supported by the Renewable Energy Production Tax Credit or the Business Energy Investment Tax Credit. Further support is provided by farm bill programs, especially the Rural Energy for America Program. In the EU indicative targets on the share of renewable electricity for each EU Member State for 2010 were introduced by the Renewable Electricity Directive (directive no. 2001/77/EC). Collectively, 22.1% of total Community electricity consumption should have come from electricity generated from renewable energy resources[2] in 2010. Within this framework, all EU Member States have implemented policy support for electricity generation from renewable energy sources (RES-E). As documented by a 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. However, FITs for renewable electricity generation have become the preferred renewable energy support mechanism in EU member countries. For instance, Germany, the UK, Italy and France provide FITs for biogas plants.

In that regard, Austria is by no means an exception. The national target for Austria was to increase the share of electricity produced from renewables in gross electricity consumption from 70% in 1997 to 78.1% in 2010.[3] In order to achieve this target, the Austrian authorities enacted the green electricity law (BGBl. I Nr. 149/2002) and the green electricity act (BGBl. II Nr. 508/2002), which became effective in 2003. Those legislations guarantee FITs for green electricity fed in to the power grid for a period of 13 years. The amount of the FIT depends on the renewable energy technology and the capacity of the power plant. Additionally, investment grants are provided, where eligibility and extend varies by Austrian federal states.

Since 2003 the gross electricity generation from renewable energy resources increased from 35 TWh in 2003 to 45 TWh in 2010 and 50 TWh in 2014 (Statistics Austria). Biogas contributes to this increase: A rise of electricity generation from biogas plants from 42 GWh in 2003 to 543 GWh in 2014 (E-Control) demonstrates the effectiveness of FIT policies. In 2014 biogas provided about 1% of total renewable electricity production in Austria. The number of biogas plants increased from 87 with an installed capacity of 15 MW in 2003 to 289 plants with an installed capacity of 80.5 MW in 2014. All of these plants make use of the FIT provided by the green electricity act.[4]

In 2014 the average FIT for biogas plants was 17.53 cent/kWh_{el}, whereas the average exchange price for electricity was 3.54 cent/kWh_{el} (E-Control). The difference between FITs and the exchange price is financed through fees paid by electricity consumers. The expiration of FITs for many plants in the foreseeable future and the large gap between FITs and exchange prices illustrate the need for increasing the competitiveness of Austrian biogas plants. The efficient operation of biogas plants seems to be a necessary condition for making biogas plants ready for the market.

2. Including hydro power, biomass, wind, solar, geothermal, wave, tidal, landfill gas, sewage plant gas and biogas.

3. Assuming gross electricity consumption is 56.1 TWh in 2010.

4. 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.

The aim of this study is to i) assess the technical efficiency of Austrian biogas plants and identify efficient plants which can serve as a benchmark for other plants, ii) analyse returns to scale of biogas technology, and iii) investigate the impact of subsidies and other variables on pure technical efficiency (managerial efficiency). Data Envelopment Analysis (DEA) is applied to estimate technical efficiency and returns to scale of 86 biogas plants in Austria. The sample covers nearly one third of total electricity generation of Austrian biogas plants. A second-stage regression analysis investigates the effect of subsidies and other factors on managerial efficiency.

The previous literature roughly applies two approaches for assessing the efficiency of biogas plants. The first approach uses multi-criteria decision analysis methods dominated by DEA (see e.g. Braun et al., 2007; Madlener et al., 2009; Đatkov and Effenberger, 2010). The second approach is based on the derivation and selection of meaningful performance figures as in Đatkov et al. (2012, 2014).

One advantage of DEA is that it can be used to test for returns to scale and to determine the most productive scale size for biogas plants. It is also possible to decompose the technical efficiency measure to depict the source of inefficiency. That is whether inefficiency is caused by inefficient operation (managerial inefficiency) or by disadvantageous scale size (scale inefficiency). The choice for DEA is motivated by the aforementioned merits and the extensive data requirements needed for the efficiency assessment methods based on performance figures.

A novelty of this study is that a nearly complete set of inputs and outputs for a large sample of biogas plants is applied. Previous studies (e.g., Filler et al., 2007; Madlener et al., 2009) suffer from i) omitting essential inputs such as capital, heat or other costs and ii) small sample size. Contrary to standard radial efficiency measures a comprehensive efficiency measure (Asmild and Pastor, 2010) is utilized, providing a more accurate performance index. As far as we know, this analysis is the first exhaustive study on biogas plants using DEA. There exists a large literature examining the effect of subsidies on farm efficiency,[5] and some few studies analyse the impact of subsidies on the efficiency of renewable energy manufacturers (e.g. Zhang et al., 2014). Though, as far as we know, we are the first examining the relationship between subsidies and pure technical efficiency of renewable energy producers.

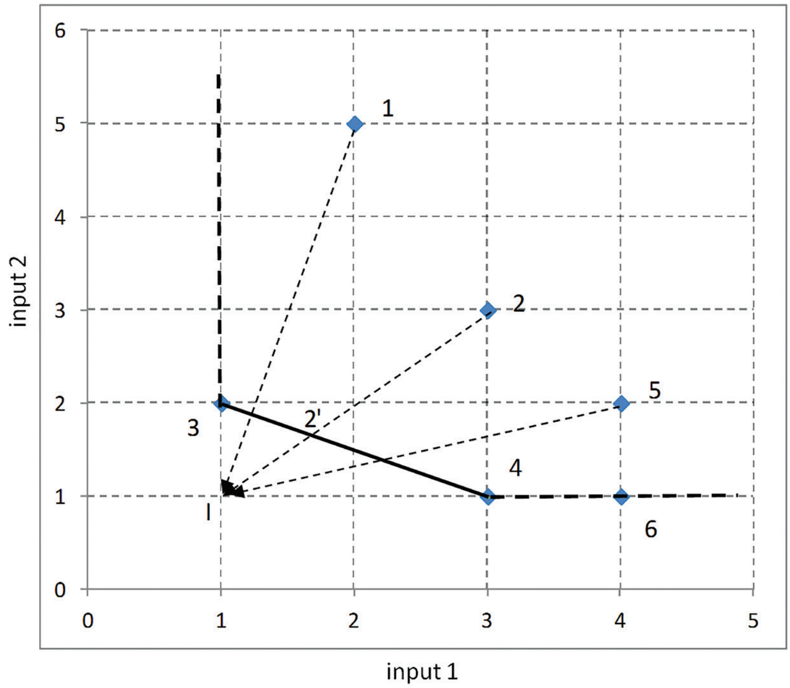
The article proceeds as follows: Section 2 outlines the methods used in this analysis. Section 3 describes the data and develops the empirical model. Section 4 presents the results of the analysis and section 5 concludes with some final remarks.

2. METHOD

In this section we outline how technical efficiency is measured by DEA. DEA is a non-parametric frontier technique introduced by Charnes at al. (1978) and Banker et al. (1984) that measures the inefficiency of a particular plant by its distance from the best practice frontier constructed by the best-performing plants (or firms) within a sample. This method is well established for evaluating the relative inefficiency of a set of comparable observations that transform multiple inputs into multiple outputs. Based on linear programming techniques and without introducing any subjective weights or assuming any functional form of a production function, DEA provides an estimate of inefficiency of each plant compared to the best practice frontier.

5. Latruffe and Minviel (2013) provide an excellent literature review on the impact of public subsidies on farm technical efficiency.

Figure 1: Efficiency Estimation using Range Direction Model (RDM)



The basic principle of our approach is shown in Figure 1. A set of plants 1, 2,... 6 with each plant consuming different amounts of two inputs, input 1 and input 2, and producing the same amount of a single output. For a given amount of produced output, plants using smaller amounts of the inputs will be the efficient ones. Therefore, DEA applied to this set of plants will identify plants 3 and 4 as efficient. The piecewise linear frontier is represented by the line between plant 3 and 4. Those plants provide an envelope around the entire data set plants. The plants 1, 2, and 5 are within this envelope and classified as inefficient. The data envelope has been notionally extended by the vertical line beginning at 3 and the horizontal line beginning at 4 to enclose the data set. The inefficiency measure of e.g. plant 2 equals the ratio $\overline{22'}/\overline{2I}$ reflecting the relative distance between 2 and 2' where I symbolizes an ideal point. Plant 6 is on the horizontal line extending the efficiency frontier and not fully efficient since it could reduce input 1 to the level of plant 4 while keeping input 2 and the output constant. The difference between the levels consumed by input 1 of plants 6 and 4 is called non-radial slack. It is usually not included in efficiency measures.

It is assumed that the production technology T models the transformation of inputs, $x \in \mathbb{R}_+^N$, into outputs, $y \in \mathbb{R}_+^M$, $T = \{(x, y): x \text{ can produce } y\}$. This means the technology consists of the set of all feasible input/output vectors. Following Chambers et al. (1998), the directional technology distance function is defined as $\vec{D}(x, y; g_x, g_y) = sup\{\beta : (x - \beta g_x, y + \beta g_y) \in T\}$, where $g_x \in \mathbb{R}_+^N$ and $g_y \in \mathbb{R}_+^M$ are the direction vectors. This function rescales the inputs and outputs simultaneously. If we choose $g_x = x$ and $g_y = 0$, then we define the special case of a proportional input distance function $\vec{D}(x, y; x, 0) = sup\{\beta : (x - \beta x, y) \in T\}$ which measures the proportional contraction of the input vector, x, given outputs, y. The distance function completely represents the production technology. Note that $1 > \vec{D}(x, y; x, 0) \geq 0$ if and only if $(x, y) \in T$. In addition, $\vec{D}(x, y; x, 0) = 0$ if and only if (x, y) is on the boundary or frontier. In the terminology of Chambers et al. (1998), that occurs when the production process is technically efficient. If $\vec{D}(x, y; x, 0) > 0$, then the production process is technically inefficient. Thus, $\vec{D}(x,y;x,0)$ is an input oriented measure of technical inefficiency. The input oriented measure of technical efficiency is given by the value of the function $TE(x,y) = 1 - \vec{D}(x,y;x,0)$.

The distance functions may be estimated in several ways. In our empirical work we compute them by applying the linear programming approach outlined by Portela et al. (2004) called Range Directional Model (RDM), which is an extension of the Data Envelopment Analysis (DEA). The RDM is superior over usual DEA (cf. Charnes at al., 1978; Banker et al., 1984) since from its results an efficiency measure can be derived which captures radial inefficiency as well as non-radial slacks. Another advantage is its translation invariance and unit invariance. One could also calculate the distance functions using frontier econometric approaches. The main strength of DEA and derived approaches may be its lack of parameterization; it requires no assumptions about the form of the production technology.

We assume that there are $k = 1,\ldots,K$ plants using $n = 1,\ldots,N$ inputs x_{nk}. These inputs are used to produce $m = 1,\ldots,M$ outputs y_{mk}. For each observation inputs and outputs are non-negative. The computation of the efficiency scores can be reduced to a linear program for each individual plant in which the following optimization problem is solved:

$$\begin{aligned}
&\max_{\lambda,\beta} \beta^{RDM} \qquad (1)\\
&\text{s.t. } \sum_{k=1}^{K} \lambda_k y_{mk} \geq y_{m0}, \ \sum_{k=1}^{K} \lambda_k x_{nk} \leq x_{n0} - \beta^{RDM} R_{n0}^{-}, \ \lambda_k \geq 0, \ \beta^{RDM} \ free,\\
&\sum_{k=1}^{K} \lambda_k = 1 \text{ (in case of VRS)}, \ \sum_{k=1}^{K} \lambda_k \leq 1 \text{ (in case of NIRS)},\\
&\sum_{k=1}^{K} \lambda_k \text{free (in case of CRS)},
\end{aligned}$$

where $R_{n0}^{-} = x_{n0} - min_k \{x_{nk}\}$ referred to as the range of possible improvement of the *n*th input, β^{RDM} is the inefficiency score of the plant under investigation. This procedure maximizes the inefficiency score β^{RDM} of a single plant and must be repeated for every plant in the sample. The efficiency of the plant under investigation would be $TE^{RDM}(x,y) = 1 - \beta^{RDM}$. This measure is closely related to the technical efficiency derived from the proportional input distance function in the sense that $g_x = R_{n0}^{-}$ instead of $g_x = x$. Contrary to a traditional radial DEA-model projecting to the origin, Model (1) projects inefficient plants to an ideal point (see Figure 1). Apart from this there is close similarity between the Model (1) efficiency measure and radial measures of efficiency traditionally used in DEA.

Let TE_C^{RDM} denote the efficiency measure satisfying constant returns to scale (CRS) and TE_V^{RDM} be the efficiency measure satisfying variable returns to scale (VRS). The model assuming CRS estimates technical efficiency developed by Farrell (1957) whereas the model assuming VRS estimates pure technical efficiency (managerial efficiency). Technical efficiency captures pure technical efficiency and scale efficiency. Pure technical efficiency ignores the impact of scale-size by comparing a plant only to other ones of similar scale. Scale efficiency refers to the deviation between CRS and VRS technologies. It is defined by the ratio of the efficiency measures $SE^{RDM}(x,y) = TE_C^{RDM}(x,y) / TE_V^{RDM}(x,y)$ and measures how far the scale size of a plant is away from optimal. For plants operating at the optimal scale size CRS holds. Because the CRS-frontier envelops the VRS-frontier $TE_C^{RDM}(x,y) \leq TE_V^{RDM}(x,y)$ holds for all observations, and the measure for scale efficiency has an upper bound of one. At $SE^{RDM}(x,y) = 1$ the plant is fully scale efficient.

A value smaller than one indicates a potential to increase efficiency by rescaling the plant's production. Finally, in order to identify the type of returns to scale under which a plant operates, we also consider an efficiency measure satisfying non-increasing returns to scale (NIRS).

The Efficiency score from the RDM is not a comprehensive efficiency measure since it does not encapsulate all sources of inefficiency. For a discussion of the importance of non-radial slacks as a source of inefficiency see e.g. Sahoo et al. (2011) and the literature cited therein. Guided by the argument that slacks are important in identifying properly the efficiency of plants and in the spirit of Asmild and Pastor (2010) we define an input-oriented comprehensive efficiency measure as

$$CTE^{RDM}(x,y)=1-\frac{n}{n+m}\beta^{*RDM}-\frac{1}{n+m}\left(\sum_{n=1}^{N}\frac{\tau_{n0}^{-*}}{R_{n0}^{-}}+\sum_{m=1}^{M}\frac{\tau_{m0}^{+*}}{R_{m0}^{+}}\right) \tag{2}$$

where β^{*RDM} is the optimal solution to (1), $R_{m0}^{+}=\max_k\{y_{mk}\}-y_{m0}$ is the range of possible improvement of the mth output, and τ_{n0}^{-*} and τ_{m0}^{+*} represent the optimal input and output slacks, respectively. These slacks have to be computed by the following second phase additive model derived from model (2) in Asmild and Pastor (2010):

$$\max_{\mu,\tau}\left(\sum_{n=1}^{N}\frac{\tau_{n0}^{-}}{R_{n0}^{-}}+\sum_{m=1}^{M}\frac{\tau_{m0}^{+}}{R_{m0}^{+}}\right) \tag{3}$$

$$\text{s.t. } \sum_{k=1}^{K}\lambda_k y_{mk}-\tau_{m0}^{+}=y_{m0},\ \sum_{k=1}^{K}\lambda_k x_{nk}+\tau_{n0}^{-}=x_{n0}-\beta^{*RDM}R_{n0}^{-},\ \sum_{k=1}^{K}\lambda_k=1,\ \lambda_k\geq 0\,.$$

Such a procedure is only applicable for estimating efficiency assuming VRS. For a detailed discussion on this issue see Asmild and Pastor (2010). Since in our analysis a comprehensive efficiency measure under CRS is not applicable due to zero input and output values, we report the non-comprehensive efficiency measures $TE_C^{RDM}(x,y)$ and $TE_V^{RDM}(x,y)$ derived from (1) in section 4.1 and use them for the scale efficiency and returns to scale analysis. However, since slacks represent a non-negligible source of inefficiency in our analysis, the more accurate comprehensive efficiency measure under VRS is used as dependent variable in the censored regression model (Tobit-model, see, e.g., Cameron and Trivedi, 2005) in section 4.2.

3. 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. The collected data include detailed information on technical characteristics of the biogas plants, investments as well as material and energy flows. The sample consists of 86 biogas plants for the year 2014 and covers about 30% of biogas plants in Austria or one third of the installed electric capacity and gross electricity generation of Austrian biogas plants.

This sample of Austrian biogas plants includes a wide range of plant types and operating conditions. All plants have in common that they convert feedstock by anaerobic digestion into biogas. Most plants are agricultural plants using e.g. maize, animal manure and other energy crops as feedstock. Some plants use waste from e.g. gastronomy or food processing industry, which highlights their role as waste recycler and waste disposer. The vast majority of biogas plants uses the biogas produced in the digesters to generate electricity and heat in a combined heat and power plant (CHP). Only few plants upgrade biogas to biomethane for injection into the natural gas grid. Electricity is fed into the power grid. Heat is always used on the plant for heating the digesters. The surplus heat can be used for supplying district heating and drying services. Unutilized heat is wasted

Table 1: Characteristics of Biogas Plants in the Sample

	Mean	Std. Dev.	Median	Min.	Max.
First start-up (year)	2004.67	1.42	2005	1999	2008
Number of digesters	2.2	0.46	2	2	4
Size					
Total digester volume (m^3)	3,140	2,208	2,657	410	16,000
CHP nominal capacity el. (kW_{el})	311	266	250	25	1,672
Feedstock processed (t FM)	7,330	5,779	5,450	790	36,463
Feedstock shares in total FM input					
Maize (%)	39	27	40	0	100
Manure (%)	21	23	12	0	91
Other renewable raw materials (%)	17	18	11	0	75
Grass (%)	14	23	2	0	93
Waste (%)	9	27	0	0	100

Notes: The sample size 86. FM stands for fresh matter.

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. Extracting gas from digestate stored in sealed tanks is frequently applied.

Table 1 shows some characteristics of the biogas plants in our sample. The sample includes plants with an installed nominal capacity of the combined heat and power unit (CHP) from 25 kW_{el} to 1,672 kW_{el}. There are seventy-four agricultural biogas plants in the sample using maize, animal manure, grass and other renewable raw materials. Eight 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 6 to 96%. Four plants are pure waste plants solely processing organic waste. The business concepts of waste and agricultural biogas plants are different. While for waste plants the processing of feedstock (waste) also generates operating revenues (so-called "income from disposal"), for agricultural plants feedstock only 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 given the amount of outputs.

With regard to the choice of inputs and outputs Cook et al. (2014) point 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, we selected six inputs and four outputs summarized in Table 2.

All types of *feedstock* (except of waste) are considered as 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 (see Appendix A).

Other inputs included in the analysis are i) *labour*, ii) *capital stock*, iii) *electricity demand*, and iv) *heat demand* as well as v) *other costs* (including insurance and maintenance costs). Electricity consumption is known for those plants covering their demand from the power grid. For the other plants an electricity consumption of 12.5% of electricity production is assumed.[6] The capital input variable is total investments until the end of 2014 including digesters, digester heating, CHPs,

6. According to experts (e.g. engineers planning biogas plants) 12.5% is a typical value and therefore a good approximation.

Table 2: Selection and Description of Input and Output Variables

Variables	Description
Inputs	
Feedstock (Nm³ CH_4)	Aggregated methane content of the substrates, excluding waste. Reflects the energy content of the feedstock.
Capital (Euro)	Total investments until 2014 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
Heat consumption (kWh_{th})	Heat demand primarily for digester heating
Other costs (Euro)	Include e.g. insurance and maintenance 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
Biomethane sold (kWh_{ho})	Amount of biomethane injected into the natural gas grid
Waste disposed (t FM)	Amount of organic waste processed

stirrers and pumps, other machinery, power grid connection, local and district heating grid, gas processing, gas grid connection and others.

The biogas produced in the digesters is used in a CHP to generate electricity and heat. *Electricity* and *heat* sold are therefore identified as outputs. Furthermore, three plants in our sample do not only produce heat and electricity, they also upgrade biogas to *biomethane* for injection into the natural gas grid. Biomethane, having a methane content of more than 98% compared to 55–60% of biogas, is considered as output as well. 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), *waste* is modelled as an output in our DEA-models.[7]

Table 3 provides some descriptive statistics for the selected input and output variables. CO_2 and methane emissions are undesirable outputs. Digestate can be used to fertilize agricultural land and permanent grassland. Due to data unavailability those outputs have to be excluded from the efficiency analysis. Note that cultivation, harvesting and transportation of feedstock are not considered as they are processes outside of the system boundaries chosen in this study.

4. RESULTS

4.1 Estimated Efficiency Scores

Table 4 describes the distribution of the estimated efficiency scores under different plant size. Technical efficiency scores obtained from the Range Directional Model (RDM) assuming constant returns to scale and pure technical efficiency scores derived from the RDM assuming vari-

7. 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

Variables	Mean	Std. dev.	Min.	Max.
Inputs				
Feedstock (Nm³ CH_4)	560,503	448,915	0	2,137,830
Capital (Euro)	1,479,738	1,357,643	180,173	1,0340,234
Labour (h)	2,185	3,270	190	20,700
Electricity consumption (kWh_{el})	240,606	189,517	7,800	1,095,084
Heat consumption (kWh_{th})	369,671	264,185	53,100	1,876,600
Other costs (Euro)	147,395	162,854	6,900	1,174,366
Outputs				
Electricity sold (kWh_{el})	2,223,593	1,733,947	95,281	8,760,670
Heat sold (kWh_{th})	1,109,677	1,273,382	0	6,584,899
Biomethane sold (kWh_{ho})	207,815	1,313,461	0	1,1253,906
Waste disposed (t FM)	1,083	4,611	0	36,463

Note: The sample size is 86.

Table 4: Frequency Distribution of Technical and Pure Technical Efficiency of Biogas Plants under Different Plant Sizes

		Technical efficiency—TE_C^{RDM}			
		Small Less or equal 100 kW_{el}	Medium 101 to 500 kW_{el}	Large Above 500 kW_{el}	All
Share of efficient plants		0.07	0.40	0.89	0.34
Share of plants with efficiency:	0.9 to 1.0	0.03	0.21	0.00	0.13
	0.8 to 0.9	0.07	0.29	0.00	0.19
	0.7 to 0.8	0.03	0.08	0.00	0.06
	0.6 to 0.7	0.17	0.02	0.11	0.08
	0.5 to 0.6	0.28	0.00	0.00	0.09
	below 0.5	0.34	0.00	0.00	0.12
Number of observations		29	48	9	86
Median efficiency score		0.57	0.95	1.00	0.87
		Pure technical efficiency—TE_V^{RDM}			
		Small Less or equal 100 kW_{el}	Medium 101 to 500 kW_{el}	Large Above 500 kW_{el}	All
Share of efficient plants		0.34	0.52	0.89	0.50
Share of plants with efficiency:	0.9 to 1.0	0.10	0.23	0.00	0.16
	0.8 to 0.9	0.07	0.21	0.00	0.14
	0.7 to 0.8	0.17	0.02	0.00	0.07
	0.6 to 0.7	0.17	0.02	0.11	0.08
	0.5 to 0.6	0.14	0.00	0.00	0.05
Number of observations		29	48	9	86
Median efficiency score		0.84	1.00	1.00	0.98
Ø nominal capacity CHP (kW_{el})		89	340	866	311

Note: Relative frequencies are reported based on efficiency scores derived from model (1) in section 2.

able returns to scale are reported, all based on model (1).[8] Biogas plants are grouped into small- (≤ 100 kW), medium- (100- ≤ 500 kW) and large-sized (> 500 kW) plants according to the installed electric capacity of the CHP.[9]

As indicated in the first row of Table 4, 29 biogas plants or 34% of the total sample are technically efficient. Those plants have pure technical efficiency and scale efficiency scores of one, meaning that they are operated efficiently and have optimal scale size (equiv. exhibiting constant returns to scale or operating at most productive scale size). The share of technically efficient plants is monotonically increasing with plant size. While only 7% of small-sized plants are technically efficient, 40% of medium-sized and 89% of large-sized plants are technically efficient. The vast majority, 79%, of small-sized plants have technical efficiency scores below 0.7. Only one (2%) medium-sized and one (11%) large-sized plant have technical efficiency scores less than 0.7.

Table 5 reports some descriptive statistics on efficiency scores by plant size and the number of plants being in the range of constant, increasing and decreasing returns to scale. As shown in the first row the average technical efficiency score is monotonically increasing with plant size: from 0.59 for small-sized, to 0.92 for medium-sized, and up to 0.96 for large-sized plants. The Kruskal-Wallis test indicates significant differences not only among technical efficiency but also among pure technical and scale efficiency of biogas plants across different size categories.

The average pure technical efficiency of the sample is 0.91 (cf. table 5). The corresponding values for small-, medium- and large-sized plants are 0.82, 0.95 and 0.97, respectively. The lower part of Table 4 shows the distribution of pure technical efficiency scores across plant size categories. 43 biogas plants or 50% of evaluated biogas plants are operated efficiently. The share of efficiently operated plants increases from 34% (10 plants) for small-sized to 52% (25 plants) for medium-sized and 89% (8 plants) for large-sized plants. The other 50% of purely technically inefficient plants are not only inefficiently managed but most of them also exhibit scale inefficiencies.[10] Purely technical inefficient plants can increase their efficiency by using fewer inputs and producing the same amount of outputs since other comparable efficient peer plants do so as well.

Due to inappropriate plant size (scale inefficiency) technical efficiency is low at some biogas plants. Table 5 indicates that 60% (52 plants) of biogas plants in the sample are scale inefficient. While the vast majority of small-sized plants are scale inefficient (93%), the share of scale inefficient plants decreases to 50% for medium-sized plants, and only 11% (1 plant) of large-sized plants are scale inefficient. The average scale efficiency is 0.73 for small, 0.97 for medium and nearly 1 for large-sized plants.

While scale efficient plants operate under constant returns to scale, scale inefficient plants exhibit either increasing or decreasing returns to scale. For instance, plants with increasing returns to scale can increase their efficiency by increasing their inputs and thereby over proportionately increasing their outputs. To identify the type of returns to scale under which a biogas plant operates the method developed by Färe et al. (1985) is used.

8. In addition to RDM we have estimated efficiency by applying traditional radial DEA models assuming CRS (Charnes at al., 1978) and VRS (Banker et al., 1984). The efficiency scores turned out to be highly correlated with the RDM efficiency scores.

9. The chosen thresholds correspond to the FIT scheme enacted by the Austrian green electricity act in 2002 (see section 4.2). Choosing other thresholds for plant size does not alter the main conclusions derived from Table 4. The sensitivity of the results is checked by using e.g. the following thresholds: ≤ 100 kW, 100-≤ 250 kW, 250-≤ 500 kW, > 500 kW or ≤ 100 kW, 100–500 kW, ≥ 500 kW.

10. 44% (38 plants) of plants in our sample have both inefficiencies. For five plants (6%) the efficiency scores under VRS and CRS are equal to but smaller than one. Those five plants are classified as purely technically inefficient but scale efficient.

Table 5: Descriptive Statistics of Efficiency Scores by Plant Size

	Small Less or equal 100 kW_{el}	Medium 101 to 500 kW_{el}	Large Above 500 kW_{el}	All
Technical efficiency				
Mean	0.59	0.92	0.96	0.81
Standard deviation	0.19	0.09	0.11	0.21
Max.	1.00	1.00	1.00	1.00
Min.	0.21	0.62	0.68	0.21
Number of efficient plants	2	19	8	29
% of efficient plants	0.07	0.40	0.89	0.34
Pure technical efficiency				
Mean	0.82	0.95	0.97	0.91
Standard deviation	0.17	0.08	0.10	0.13
Max.	1	1	1	1
Min.	0.56	0.62	0.70	0.56
Number of efficient plants	10	25	8	43
% of efficient plants	0.34	0.52	0.89	0.50
Scale efficiency				
Mean	0.73	0.97	1	0.89
Standard deviation	0.17	0.04	0.01	0.16
Max.	1	1	1	1
Min.	0.21	0.84	0.98	0.21
Number of efficient plants	2	24	8	34
% of efficient plants	0.07	0.50	0.89	0.40
Number of plants in the range of				
Increasing returns to scale	27	23	0	50
Constant returns to scale	2	24	8	34
Decreasing returns to scale	0	1	1	2
Share of plants in the range of				
Increasing returns to scale	0.93	0.48	0.00	0.58
Constant returns to scale	0.07	0.50	0.89	0.40
Decreasing returns to scale	0.00	0.02	0.11	0.02
Number of obs.	29	48	9	86

Note: Reported values are based on efficiency scores derived from model (1) in section 2.

The results are summarized in the lower part of Table 5: 58% of the plants in our sample operate under increasing returns to scale indicating that they are too small for being technically efficient. The vast majority of small-sized biogas plants operates under increasing returns to scale: 93% or 27 out of 29 plants. The share of medium-sized plants operating under increasing returns to scale declines to 48% (23 out of 48), and there is no large plant exhibiting increasing returns to scale. Half of the medium-sized plants are scale efficient and operate under constant returns to scale. 89% of the large plants operate under constant returns to scale and have most productive scale size. Only two plants exhibit decreasing returns to scale.

Statistical tests on returns to scale,[11] as described in Bogetoft and Otto (2011), support the hypothesis that the biogas technology exhibits increasing returns to scale. This can be explained by i) declining investment costs per m^3 digester volume, ii) increasing electric efficiency of the CHP, and iii) a less than proportional increase in labour requirements, as the size of the plant increases (Walla and Schneeberger, 2008). Remember that cultivation, harvesting and transportation of feedstock are not considered in this analysis. Therefore, a more than proportional increase of physical inputs needed for feedstock transportation and digestate handling as plant size increases could mitigate or even outweigh the positive scale effects found in this study (Skovsgaard and Klinge Jacobsen, 2017).

To sum up, on average small-sized plants are less efficient compared to medium- and large-sized biogas plants. They are not only less efficient due to their disadvantageous scale size (scale inefficiency) but also because of their inefficient operation (pure technical or managerial inefficiency).

4.2 Explaining Pure Technical Efficiency

In this section we investigate factors potentially explaining the variation in pure technical efficiency (managerial efficiency). A second-stage regression using a Tobit model is applied. In particular, we are interested in the effect of investment subsides (IS) and production subsidies (PS) on pure technical efficiency. Note that the comprehensive measure of pure technical efficiency $CTE^{RDM}(x,y)$ as defined in section 2 is used as dependent variable. We consider the comprehensive measure as more precise since it captures not only the radial part of inefficiency but also the non-radial slacks. Descriptive statistics of the variable CTE^{RDM} are available in Appendix B.

To investigate the relationship between PS and pure technical efficiency, we make use of the variation in FITs for renewable electricity as fixed in the green electricity act (BGBl. II Nr. 508/2002). The FIT scheme for green electricity produced in Austrian biogas plants determines four tariff levels depending on plant size and taking into account economies of scale: i) less or equal 100 kW_{el} (16.5 Cent/kWh_{el}), ii) 101 to 500 kW_{el} (14.5 Cent/kWh_{el}), iii) 501 to 1000 kWel (12.5 Cent/kWh_{el}) and iv) above 1000 kW_{el} (10.3 Cent/kWh_{el}). For waste processing plants those tariffs are reduced by 25%. Additionally, since 2012 each plant receives a premium of 4 Cent/kWh_{el} compensating for increased operating costs (§ 22 BGBl. I Nr. 75/2011; ACBA). The FIT is guaranteed for 13 years.

PS are calculated by subtracting the average exchange price for electricity in 2014 (3.53 Cent/kWh_{el}, E-Control) from the individual FIT (including the 4 Cent/kWh_{el} premium). Biogas plants are then divided into four groups according to the level of the PS they receive. For each category a dummy variable is constructed, coded with one if the respective PS applies and being zero otherwise. Descriptive statistics for the dummy variables labelled i) PS 1 (16.97 cent/kWh_{el}), ii) PS 2 (14.97 cent/kWh_{el}), iii) PS 3 (12.85 to 12.97 cent/kWh_{el}), and iv) PS 4 (below 12.85 cent/kWh_{el}) are shown in Appendix B.[12] Plants with coding one in variable PS 1 are used as the reference group in our regression analysis.

Contrary to the nation-wide applicable FIT regulation, the regulations on investment grants vary across Austrian federal states (Walla and Schneeberger, 2008; Wirth et al., 2013). While 82% of

11. We are testing the hypotheses that the technology set from which our observations are sampled exhibit i) constant returns to scale and ii) non increasing returns to scale. Both hypotheses can be rejected indicating that the technology set exhibits increasing returns to scale.

12. PS 1 = 16.5 + 4 – 3.53 = 16.97; PS 2 = 14.5 + 4 – 3.53 = 14.97; PS 3 = 12.5 + 4 – 3.53 = 12.97 (agricultural plants), and PS 3 = (16.5 * 0.75) + 4 – 3.53 = 12.85 (waste plants). PS 1 applies to all agricultural plants ≤ 100 kW_{el}; PS 2 applies to all agricultural plants with 101 to 500 kW_{el}; PS 3 applies to all agricultural plants with 501 to 1000 kW_{el} and all waste plants ≤ 100 kW_{el}; PS4 includes all agricultural plants > 1000 kW_{el} and all waste plants > 100 kW_{el}.

biogas plants received investment subsidies in Lower Austria, the share of biogas plants receiving investment subsidies is only 38% in Styria and 21% in Upper Austria.[13] Investment subsidies are granted for the construction (mainly for heat usage) and mobile machinery of biogas plants. Access to funding also depends on plant size, whereas small biogas plants had easier access to investment subsidies. The relative and absolute amount of the investment grant is usually limited by an upper threshold (e.g. 30% of total investment and 150,000 EUR in Lower Austria).

We apply two measures of investment subsidies in our analysis: i) a dummy variable taking the value one if any investment subsidy is received (IS DUMMY) and ii) the absolute amount of the investment subsidy measured in EUR (IS VALUE). 55% of biogas plants in our sample receive investment subsidies. On average investment subsidies amount to 12% of the total capital stock in 2014. Investment subsidies reach values up to 37% of the capital stock, playing a substantial role in financing biogas plants. Investment subsidies are to a large extent received prior to 2007 and are supposed to be obtained at a time close to the start-up date.

The main objective of the Austrian FIT policy and the investment subsidy programs is to increase the generation of green electricity. Investment subsidy programs also intended to create capacities for green electricity, heat and fuel production to guarantee an adequate number of farmers a reliable base of life (BMLFUW, 2004).

From a theoretical perspective the effect of investment and production subsidies on technical efficiency can be either negative or positive. If subsidies provide incentives to implement efficiency-improving innovations or keep technologies up to date, the effect of subsidies on technical efficiency could be positive. On the other hand, we could expect a negative impact of subsidies on pure technical efficiency, if subsidies provide a disincentive to managerial effort of plant operators and are used to increase leisure consumption (Martin and Page, 1983). With respect to the rent seeking theory of Tullock (1980) economic agents spend resources to obtain subsidies and political favours thereby restricting the amount of resources needed for efficient plant operation. Thus, the effect of subsidies on pure technical efficiency is an empirical question.

Remember, that the dependent variable in our regression analysis is pure technical efficiency, reflecting operational or managerial inefficiencies net of scale effects (see section 2). Nevertheless, we control for size in our regression models. Plant size is measured by the installed electric capacity of the CHP (in kW_{el}), and is reflected by the variable SIZE. We introduce the plant size in addition to the variables for the FITs in order to disentangle the effects of FITs and of size.

Other factors included in the regression analysis are inter alia based on the studies of Filler et al. (2007) and Pöschl et al. (2010). As far as we know, Filler et al. (2007) are the only ones investigating the determinants of technical inefficiencies of biogas plants through a second-stage regression analysis. They conclude that the number of full-load hours of the CHP and the number of digesters are positively related to technical efficiency. They do not find any effects of feedstock composition, organic loading rate, frequency of digester loading and size, measured as the installed electric capacity of the CHP, on technical efficiency. Pöschl et al. (2010) assess the energy efficiency of different biogas systems by primary energy input to output ratios. They find that significant variation in energy efficiency arises from feedstock resource, plant size, biogas utilization pathways and digestate management technique. In particular, energy efficiency could be enhanced by upgrading biogas for gas grid injection and recovery of residual biogas from enclosed digestate storage units.

13. Information on the distribution of biogas plants across Austrian federal states in our sample is available in Appendix B.

The independent variables in our regression analysis include dummies for Austrian federal states to control for geographical and state-specific particularities (Wirth et al., 2013). We include several dummies to test whether certain plant types are more efficient than others:

i) A dummy for plants processing organic waste (WASTE) is included to test whether waste disposing plants are operated more efficiently than agricultural biogas plants. Distinct regulations applying for waste and agricultural plants could translate into different efficiency levels;
ii) A dummy for plants which upgrade biogas to biomethane (BIOMETHANE) for injection into the gas grid;
iii) We test the hypothesis that plants extracting gas from enclosed digestate storage units are more efficient by including a dummy for plants having a gas tight final depot (GAS TIGHT);
iv) The number of digesters may reflect different technological varieties of biogas plants. Therefore, we include two dummies capturing the effect of three-digester- (THREE) and four-digester-systems (FOUR) relative to two-digester systems (TWO).

Furthermore, the age of the plant (AGE) is included to test for the presence of learning effects. Including the square of the age of the plant allows for decreasing returns to experience.

According to Filler (2007) the organic loading rate (LOADING RATE) can have an impact on biogas yield: Higher loading rates (equivalent with long hydraulic retention times) increase the methane yield in m^3 per day. However, higher loading rates decrease the methane yield per kg organic dry matter utilized. So there might be an optimal loading rate with respect to efficiency balancing substrate and capital utilization. To test this hypothesis, we do not only include the organic loading rate but also its quadratic term. Descriptive statistics of the independent variables included in our regression analysis are available in Appendix B.

Table 6 presents the results of the censored regression model (Tobit model). Estimated coefficients and robust standard errors are reported. Model 1 and Model 3 include a dummy (WASTE) for capturing the effect of waste processing plants. In Model 2 and Model 4 substrate shares of total feedstock use are applied (cf. Table 1), with maize share as the reference category. Regardless of the applied measure for waste plants, we do not find systematic differences in pure technical efficiency between waste plants and agricultural plants. As expected the effect of substrate composition or substrate shares is insignificant indicating that we took the different energy contents of the various feedstocks properly into account when estimating efficiency scores.

The regression results show that the estimated coefficients of both investment subsidy measures have a negative sign throughout model 1 to 4. However, the null-hypotheses that the coefficients of the IS DUMMY and IS VALUE are equal to zero cannot be rejected in model 2 and model 4 at the 10% significance level. The statistically significant effect of investment subsidy measures in model 1 and model 3 on pure technical efficiency is not robust to various model specifications. We conclude that the relationship between investment subsidies and pure technical efficiency scores is negative but statistically insignificant.

Biogas plants receiving 14.97 cent/kWh_{el} production subsidies (PS 2) are more purely technically efficient than plants receiving 16.97 cent/kWh_{el} (PS 1). This effect is statistically significant, at least at the 5% significance level, throughout all model specifications presented in Table 6. Similarly, plants receiving 12.85 to 12.97 cent/kWh_{el} (PS 3) and less than 12.85 cent/kWh_{el} (PS 4) are more purely technically efficient compared to plants receiving 16.97 cent/kWh_{el} (PS 1) controlling for other factors such as plant size. The estimated coefficients for each dummy (PS 2, PS 3, PS 4)

Table 6: Determinants of Pure Technical Efficiency (*CTE^{RDM}*) – Tobit Regression

	Model 1	Model 2	Model 3	Model 4
IS DUMMY	–0.08**	–0.06		
	(0.04)	(0.04)		
IS VALUE / 1,000,000			–0.27**	–0.14
			(0.11)	(0.11)
PS 2	0.17***	0.13**	0.18***	0.13**
	(0.05)	(0.05)	(0.05)	(0.05)
PS 3	0.32**	0.18*	0.41***	0.21*
	(0.13)	(0.11)	(0.13)	(0.11)
PS 4	1.17***	0.83***	1.27***	0.86***
	(0.21)	(0.18)	(0.22)	(0.18)
SIZE / 1000	–0.03	0.08	–0.06	0.08
	(0.16)	(0.16)	(0.16)	(0.16)
BIOMETHANE	0.96***	0.98***	0.93***	0.96***
	(0.09)	(0.09)	(0.09)	(0.09)
GAS TIGHT	0.13***	0.12**	0.13***	0.12***
	(0.05)	(0.05)	(0.05)	(0.04)
WASTE	–0.23		–0.33*	
	(0.17)		(0.17)	
Waste share		0.09		0.07
		(0.15)		(0.15)
Manure share		0.24		0.26
		(0.22)		(0.22)
Grass share		–0.09		–0.09
		(0.07)		(0.07)
Other renewables share		0.02		0.01
		(0.09)		(0.09)
Log Likelihood	11.84	12.83	12.21	12.47
Total number of obs.	86	86	86	86
Uncensored obs.	43	43	43	43
Right-censored obs.	43	43	43	43
Wald Test	195.07	200.69	194.63	202.05

Note: Sandwich robust standard errors are reported in parenthesis (Huber, 1981) correcting for heteroscedasticity. All models include an intercept, controls for Austrian regions, age, age squared, organic loading rate, organic loading rate squared, and different digester systems. Full results are available in Appendix C, Table C.1. ***p < 0.01, **p < 0.05, *p < 0.1.

are monotonically increasing with decreasing production subsidies. That is, the lower the production subsidy, the higher is the operational efficiency compared to plants receiving the highest output price for electricity. Those results are robust to various model specifications and statistically significant at least at the 10% significance level.

Furthermore, we find that plants having an enclosed digestate storage unit (GAS TIGHT) and plants upgrading biogas to biomethane for injection into the natural gas grid are more efficient. Plants having two main digesters and two post-digesters are more efficient compared to plants having one main digester and one post-digester.

The estimates of model 1-4 applying ordinary least squares (OLS) are available in Appendix C (Table C.2) showing an R-squared of 0.42. For the most part, these results are similar and confirm the conclusions from the regressions based on the Tobit-model.

4.3 Sensitivity of Results

In order to check the sensitivity of the results we exclude waste processing plants and biomethane producers from the sample.[14] The remaining 73 agricultural plants ('N=73 sample') are used to estimate the efficiency scores using DEA outlined in section 2. Furthermore, the regression analysis as described in section 4.2 is repeated. This robustness checks show that the main results presented in section 4.1 and 4.2 are quite insensitive to the sample applied.

The average pure technical efficiency score is 0.91 using the entire sample ('N=86 sample') and 0.92 using the 'N=73 sample'. While on average the differences between the diverse sample estimates are negligible, for some individual biogas plants the estimated efficiency scores vary substantially. The maximum difference in estimated efficiency scores for a single plant is 0.31. Using the 'N=73 sample' eight additional biogas plants are indicated as efficient being classified as inefficient when applying the 'N=86 sample'.

However, the regression results presented in section 4.2 are rather insensitive to the sample used for our analysis. Production subsidies, gas tight final depots and four-digester systems remain statistically significant determinants of pure technical efficiency, at least at the 10% significance level. Using the 'N=73 sample' the effects of both investment subsidy measures become statistically insignificant in all model specifications, though remaining a negative sign. The regression results of the Tobit-model and OLS-estimates for the 'N=73 sample' are available in Appendix D.

5. CONCLUSIONS AND POLICY IMPLICATIONS

This study applies Data Envelopment Analysis (DEA) to estimate technical efficiency of Austrian biogas plants. After decomposing technical efficiency into pure technical (managerial) and scale efficiency we i) use the scale efficiency scores to test for scale effects and ii) investigate the effect of production subsidies, investment subsidies and other variables on managerial efficiency employing a second-stage regression analysis.

As far as we know we are the first i) using DEA for examining returns to scale of biogas plants and ii) investigating the effect of subsidies on biogas plants' managerial efficiency. Our results indicate that the biogas production technology exhibits increasing returns to scale. Biogas plants with less or equal than 100 kW_{el} installed capacity are found to be scale inefficient due to positive scale effects. The regression analysis suggests that biogas plants receiving higher production subsidies in the form of feed-in-tariffs (FITs) have lower managerial efficiency relative to less subsidized plants. This result is robust after controlling for the size of the plant and a variety of plant type measures as well as to different samples applied. Moreover, we find that plants with an enclosed digestate storage unit linked to the biogas collection system are more efficient.

FITs are usually differentiated by technology to reflect the differences in generation costs between the various renewable energy technologies. However, policy makers also introduced different FITs for the same technology (e.g. biogas technology in Germany). A typical example are FITs which differ according to the size of the renewable energy project, reflecting the higher generation

14. The application of the outlier-detection method introduced by Wilson (1993) and described in Bogetoft and Otto (2011) indicates that the only outlier observations in our sample are the three plants producing biomethane.

costs of small scale renewable energy projects due to economies of scale. This shows that policy makers are willing to accept scale inefficiencies in renewable energy generation to reach ambitious renewable energy targets. This study indicates that biogas plants with less or equal than 100 kW_{el} installed capacity are scale inefficient. Currently 40% of the Austrian biogas plants are in this size class representing 10% of the installed electric capacity of the Austrian biogas sector (E-Control, personal communication on 22 January 2016). Those plants receive the highest FIT questioning the efficiency of such support-schemes.

However, there is one issue left that could make our results vulnerable. 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. 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.

Our study highlights that in addition to the presence of scale inefficiencies, production subsidies in the form of FITs can stimulate substantial managerial inefficiencies. This article indicates that the managerial inefficiency of biogas plants increases with the level of the production subsidy (FIT – electricity exchange price) they receive. The result is consistent with the hypothesis that production subsidies provide a disincentive to managerial effort (Martin and Page, 1983). FITs for agricultural biogas plants can be seen as an income enhancing tool for farmers rather than an opportunity to advance the biogas technology and might have contributed to reduce managerial motivation and effort of plant operators.

Green and Yatchew (2012) find that FIT programs are very effective in producing rapid deployment of renewable energy capacities, but they have also proved to be costly to ratepayers. However, setting FITs that avoid inefficiencies and achieve expansion targets for renewable energy is not easy. Since policy makers can never know the true cost structure of individual renewable energy plants, defining renewable expansion targets for each technology and determining corresponding FITs through a tendering mechanism could be a solution.[15] In addition, a tendering mechanism might avoid high returns on capital employed for renewable energy projects as found in Haar and Haar (2016).[16]

Biogas plant operators could benefit from making their digestate storage units gas tight and linking them to the biogas collection system. This measure would not only increase efficiency but also reduces methane emissions to the atmosphere making the biogas plant more environmentally friendly.

Future research should evaluate the profit-, revenue-, and cost-efficiency of biogas plants. Estimating eco-efficiency, which incorporates the environmental performance of biogas plants, is also an interesting and relevant issue for future research. Last but not least the presented study of technical efficiency could be extended to an intertemporal analysis investigating efficiency change, technical change and productivity change over time.

15. We thankfully integrate this idea from an anonymous referee in our conclusions.

16. Haar and Haar (2016) find returns on capital employed in the range of 20% to 50% for solar photovoltaic projects and 11% to 68% for wind farm projects under the renewable energy support prices in a group of European countries. Haar and Haar (2016) conclude that, when measured by the returns provided to renewable energy investors, many schemes across Europe were wasteful and inefficient.

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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 Nm^3 CH_4/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 stands for fresh matter, DM is dry matter; Source: ACBA.

APPENDIX B

Table B.1: Descriptive Statistics of Variables used in Regression Analysis

Variables	Mean	Std. Dev.	Min.	Max.
Dependent variable				
CTE^{RDM}	0.92	0.09	0.70	1.00
Independent variables				
State dummies				
Lower Austria	0.51	0.50	0.00	1.00
Styria	0.19	0.39	0.00	1.00
West Austria	0.12	0.32	0.00	1.00
Mid-West Austria	0.19	0.39	0.00	1.00
Plant type dummies				
Waste plant	0.14	0.35	0.00	1.00
Biomethane plant	0.03	0.18	0.00	1.00
Gas tight final depot	0.85	0.36	0.00	1.00
Digester system dummies				
Two digesters	0.83	0.38	0.00	1.00
Three digesters	0.15	0.36	0.00	1.00
Four digesters	0.02	0.15	0.00	1.00
Production subsidy dummies				
PS 4: < 12.85 cent / kWh_{el}	0.08	0.28	0.00	1.00
PS 3: 12.85 - ≤12.97 cent / kWh_{el}	0.14	0.35	0.00	1.00
PS 2: 14.97 cent / kWh_{el}	0.50	0.50	0.00	1.00
PS 1: 16.97 cent / kWh_{el}	0.28	0.45	0.00	1.00

(continued)

Table B.1: Descriptive Statistics of Independent Variables used in Regression Analysis *(continued)*

Variables	Mean	Std. Dev.	Min.	Max.
Investment subsidy				
IS Dummy	0.55	0.50	0.00	1.00
IS Value (Euro)	135,184	147,974	0.00	650,000
Other plant characteristics				
Size (CHP capacity el., kW_{el})	310.57	265.53	25.00	1672.00
Age (years)	9.33	1.42	6.00	15.00
Loading Rate (kg oDS/d/m³)	1.79	0.90	0.23	4.82

Note: The sample size is 86. West-Austria is Tyrol and three plants in Vorarlberg; Mid-West Austria includes Upper Austria and two plants in Salzburg.

APPENDIX C

Table C.1: Determinants of Pure Technical Efficiency – Tobit Regression Results; N=86 sample

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.55	0.12	0.46	0.04
	(0.35)	(0.39)	(0.36)	(0.40)
Styria	0.01	–0.01	0.03	0.01
	(0.05)	(0.05)	(0.04)	(0.05)
West Austria	0.04	–0.02	0.06	–0.00
	(0.07)	(0.07)	(0.07)	(0.07)
Mid-West Austria	–0.02	–0.00	0.00	0.02
	(0.04)	(0.04)	(0.04)	(0.04)
WASTE	–0.23		–0.33*	
	(0.17)		(0.17)	
BIOMETHANE	0.96***	0.98***	0.93***	0.96***
	(0.09)	(0.09)	(0.09)	(0.09)
SIZE / 1000	–0.03	0.08	–0.06	0.08
	(0.16)	(0.16)	(0.16)	(0.16)
PS 2	0.17***	0.13**	0.18***	0.13**
	(0.05)	(0.05)	(0.05)	(0.05)
PS 3	0.32**	0.18*	0.41***	0.21*
	(0.13)	(0.11)	(0.13)	(0.11)
PS 4	1.17***	0.83***	1.27***	0.86***
	(0.21)	(0.18)	(0.22)	(0.18)
AGE	0.48	1.46*	0.60	1.56*
	(0.78)	(0.86)	(0.78)	(0.88)

(continued)

Table C.1: Determinants of Pure Technical Efficiency – Tobit Regression Results; N=86 sample *(continued)*

	Model 1	Model 2	Model 3	Model 4
AGE_SQ	–0.15	–0.70	–0.19	–0.76*
	(0.39)	(0.44)	(0.39)	(0.45)
LOADING_RATE	–0.57	–0.60	–0.59	–0.60
	(0.59)	(0.62)	(0.64)	(0.65)
LOADING_RATE_SQ	0.73	0.77	0.80	0.83
	(1.08)	(1.13)	(1.19)	(1.21)
GAS TIGHT	0.13***	0.12**	0.13***	0.12***
	(0.05)	(0.05)	(0.05)	(0.04)
THREE DIGESTERS	–0.12**	–0.11**	–0.12**	–0.10*
	(0.05)	(0.05)	(0.05)	(0.05)
FOUR DIGESTERS	0.41***	0.52***	0.32***	0.51***
	(0.12)	(0.10)	(0.12)	(0.11)
IS DUMMY	–0.08**	–0.06		
	(0.04)	(0.04)		
IS VALUE / 1000000			–0.27**	–0.14
			(0.11)	(0.11)
Waste share		0.09		0.07
		(0.15)		(0.15)
Manure share		0.24		0.26
		(0.22)		(0.22)
Grass share		–0.09		–0.09
		(0.07)		(0.07)
Other renewables share		0.02		0.01
		(0.09)		(0.09)
Log Likelihood	11.84	12.21	12.83	12.47
Total number of obs.	86	86	86	86
Uncensored obs.	43	43	43	43
Right-censored obs.	43	43	43	43
Wald Test	195.07	194.63	200.69	202.05

Note: Sandwich robust standard errors are reported in parenthesis (Huber, 1981) correcting for heteroscedasticity. ***p < 0.01, **p < 0.05, *p < 0.1.

Table C.2: Determinants of Pure Technical Efficiency – OLS Regression Results; N=86 sample

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.57**	0.47*	0.53**	0.45
	(0.25)	(0.26)	(0.25)	(0.27)
Styria	0.01	0.01	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
West Austria	0.03	–0.00	0.04	0.01
	(0.04)	(0.05)	(0.04)	(0.05)
Mid-West Austria	0.00	0.01	0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
WASTE	–0.15**		–0.16**	
	(0.07)		(0.08)	
BIOMETHANE	0.11*	0.12*	0.11*	0.11*
	(0.06)	(0.07)	(0.06)	(0.07)
SIZE / 1000	–0.04	–0.03	–0.04	–0.03
	(0.06)	(0.06)	(0.06)	(0.06)
PS 2	0.12***	0.10***	0.12***	0.10***
	(0.03)	(0.03)	(0.03)	(0.03)
PS 3	0.18***	0.13***	0.20***	0.14***
	(0.05)	(0.05)	(0.05)	(0.05)
PS 4	0.31***	0.20*	0.34***	0.21*
	(0.10)	(0.10)	(0.10)	(0.10)
AGE	0.46	0.72	0.52	0.74
	(0.52)	(0.55)	(0.52)	(0.56)
AGE_SQ	–0.17	–0.33	–0.19	–0.34
	(0.26)	(0.28)	(0.27)	(0.28)
LOADING_RATE	–0.34	–0.21	–0.37	–0.22
	(0.37)	(0.40)	(0.37)	(0.40)
LOADING_RATE_SQ	0.50	0.28	0.57	0.31
	(0.76)	(0.79)	(0.75)	(0.80)
GAS TIGHT	0.06**	0.06**	0.06**	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)
THREE DIGESTERS	–0.05	–0.03	–0.05	–0.03
	(0.03)	(0.04)	(0.03)	(0.04)
FOUR DIGESTERS	–0.09	–0.06	–0.09	–0.06
	(0.08)	(0.08)	(0.08)	(0.08)
IS DUMMY	–0.04	–0.03		
	(0.02)	(0.03)		
IS VALUE / 1000000			–0.11	–0.05
			(0.08)	(0.08)

(continued)

Table C.2: Determinants of Pure Technical Efficiency – OLS Regression Results; N=86 sample *(continued)*

	Model 1	Model 2	Model 3	Model 4
Waste share		–0.06		–0.06
		(0.09)		(0.09)
Manure share		0.06		0.07
		(0.13)		(0.13)
Grass share		–0.06		–0.06
		(0.05)		(0.05)
Other renewables share		0.02		0.02
		(0.07)		(0.07)
R^2	0.42	0.42	0.42	0.41
Adj. R^2	0.28	0.24	0.28	0.23
Number of obs.	86	86	86	86

Note: Standard errors are reported in parenthesis. ***p < 0.01, **p < 0.05, *p < 0.1.

APPENDIX D

Table D.1: Determinants of Pure Technical Efficiency – Tobit Regression Results; N=73 sample

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.81	0.74	0.37	0.29
	(0.91)	(0.89)	(0.87)	(0.86)
Styria	0.05	0.05	0.04	0.05
	(0.06)	(0.06)	(0.07)	(0.07)
West Austria	0.19*	0.18*	0.14	0.14
	(0.11)	(0.10)	(0.10)	(0.10)
Mid-West Austria	0.06	0.07	0.09	0.09
	(0.07)	(0.07)	(0.07)	(0.06)
SIZE / 1000	–0.13	–0.15	–0.14	–0.16
	(0.22)	(0.21)	(0.22)	(0.22)
PS 2	0.16**	0.16**	0.13*	0.14*
	(0.07)	(0.07)	(0.08)	(0.08)
PS 3	0.35**	0.42**	0.31*	0.37**
	(0.17)	(0.16)	(0.17)	(0.17)
AGE	0.15	0.29	1.10	1.25
	(1.94)	(1.89)	(1.85)	(1.82)
AGE_SQ	–0.05	–0.10	–0.54	–0.60
	(1.03)	(1.00)	(0.98)	(0.96)

(continued)

Table D.1: Determinants of Pure Technical Efficiency – Tobit Regression Results; N=73 sample *(continued)*

	Model 1	Model 2	Model 3	Model 4
LOADING_RATE	–1.35	–1.40	–1.43	–1.49
	(0.91)	(0.93)	(0.88)	(0.91)
LOADING_RATE_SQ	2.89	3.02*	2.99*	3.14*
	(1.79)	(1.81)	(1.79)	(1.83)
GAS TIGHT	0.15**	0.16***	0.15**	0.15**
	(0.06)	(0.06)	(0.06)	(0.06)
THREE DIGESTERS	–0.08	–0.08	–0.09	–0.10
	(0.08)	(0.08)	(0.08)	(0.08)
FOUR DIGESTERS	0.64***	0.57***	0.68***	0.61***
	(0.16)	(0.16)	(0.16)	(0.16)
IS DUMMY	–0.04		–0.03	
	(0.05)		(0.06)	
IS VALUE / 1000000		–0.21		–0.17
		(0.16)		(0.16)
Manure share			0.37	0.38
			(0.34)	(0.35)
Grass share			–0.12	–0.11
			(0.10)	(0.10)
Other renewables share			0.11	0.12
			(0.14)	(0.14)
Log Likelihood	–6.77	–6.41	–4.91	–4.62
Total number of obs.	73	73	73	73
Uncensored obs.	34	34	34	34
Right-censored obs.	39	39	39	39
Wald Test	145.82	144.63	153.44	152.77

Note: Sandwich robust standard errors are reported in parenthesis (Huber, 1981) correcting for heteroscedasticity. ***p < 0.01, **p < 0.05, *p < 0.1.

Table D.2: Determinants of Pure Technical Efficiency – OLS Regression Results; N=73 sample

	Model 1	Model 2	Model 3	Model 4
(Intercept)	1.01**	0.99**	0.85*	0.83
	(0.49)	(0.49)	(0.50)	(0.50)
Styria	0.03	0.03	0.03	0.03
	(0.04)	(0.04)	(0.04)	(0.04)
West Austria	0.10	0.10*	0.08	0.09
	(0.06)	(0.06)	(0.07)	(0.07)

(continued)

Table D.2: Determinants of Pure Technical Efficiency – OLS Regression Results; N=73 sample *(continued)*

	Model 1	**Model 2**	**Model 3**	**Model 4**
Mid-West Austria	0.04	0.04	0.05	0.05
	(0.04)	(0.03)	(0.04)	(0.03)
SIZE / 1000	–0.05	–0.06	–0.06	–0.07
	(0.12)	(0.12)	(0.12)	(0.12)
PS 2	0.09**	0.09**	0.07*	0.07*
	(0.04)	(0.04)	(0.04)	(0.04)
PS 3	0.16*	0.17*	0.14	0.15*
	(0.08)	(0.09)	(0.08)	(0.09)
AGE	–0.35	–0.33	0.03	0.05
	(1.07)	(1.07)	(1.09)	(1.09)
AGE_SQ	0.23	0.22	0.03	0.02
	(0.58)	(0.58)	(0.60)	(0.60)
LOADING_RATE	–0.62	–0.62	–0.71	–0.71
	(0.52)	(0.52)	(0.52)	(0.52)
LOADING_RATE_SQ	1.23	1.24	1.32	1.32
	(1.02)	(1.01)	(1.02)	(1.02)
GAS TIGHT	0.06	0.06	0.06	0.06
	(0.04)	(0.04)	(0.04)	(0.04)
THREE DIGESTERS	–0.04	–0.05	–0.06	–0.06
	(0.05)	(0.05)	(0.05)	(0.05)
FOUR DIGESTERS	–0.05	–0.06	–0.04	–0.05
	(0.12)	(0.13)	(0.12)	(0.13)
IS DUMMY	–0.02		–0.01	
	(0.03)		(0.03)	
IS VALUE / 1000000		–0.06		–0.04
		(0.10)		(0.10)
Manure share			0.06	0.06
			(0.18)	(0.17)
Grass share			–0.09	–0.08
			(0.06)	(0.06)
Other renewables share			0.07	0.07
			(0.09)	(0.09)
R^2	0.22	0.23	0.27	0.27
Adj. R^2	0.04	0.04	0.05	0.05
Number of obs.	73	73	73	73

Note: Standard errors are reported in parenthesis. ***p < 0.01, **p < 0.05, *p < 0.1.