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COST EFFICIENCY OF RENEWABLE DISTRICT HEATING SYSTEMS: THE CASE OF AUSTRIA

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Abstract

Heat generation based on conventional fossil fuels is considered to be the cause of a significant proportion of greenhouse gas emissions. Achieving the climate protection goals therefore requires a transition to renewable energy sources such as biomass. Establishing renewable district heating (DH) systems is considered as an important cornerstone of a decarbonized energy system. This study estimates the cost efficiency of biomass-based DH systems. It expands the benchmarking currently used in Austria which relies on simple key performance indicators by a new type of multi-variate approach based on efficiency estimates from Data Envelopment Analysis (DEA). The performance indicator calculated in this way considers all essential factors of production simultaneously and estimates the cost saving potentials of each individual system examined. By decomposing cost efficiency into a technical and allocative component, the causes of inefficiency are revealed. A subsequent regression analysis examines how system-specific technical, structural features and the regional environmental conditions of the respective systems influence their performance. Finally, the results of the regression analysis are used to calculate the managerial inefficiency purged of the influence of structural peculiarities and operating environment. This part of the overall inefficiency is caused by the operator's decisions and can therefore be reduced by changing the operator's behaviour. The applicability of the approach developed here is shown empirically using a sample of biomass-based DH systems from Austria.

JEL-Classification: D24, Q41, Q42

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1. Introduction and background

Heat generation relying on conventional fossil fuels is recognized as a major contributor to greenhouse gas emissions, constituting a central challenge in the battle against climate change. In Austria, for instance, the heating sector is responsible for more than half of the final energy consumption and almost 60% is still covered by fossil energy (IEA, 2020). The transition from traditional district heating (DH) systems to decarbonized systems will support international, national, and local ambitions for decarbonization by obtaining lower greenhouse gas emissions. In Austria's National Energy and Climate Plan (NECP) (FMST, 2019), district heating networks based on renewable energy sources (RES) are considered as an important cornerstone of the future energy system.

With a share of 55%, biomass is Austria's most relevant renewable energy source. Traditionally, biomass in Austria is mainly consumed for heat purposes (84% in 2021). Around three quarters of biomass heat are used for single combustion systems, the remaining quarter for DH, which showed the highest increase, its production having more than tripled since 2005 (Österreichischer Biomasse-Verband, 2023). Biomass can be obtained from several sources including woody biomass, edible crops, non-edible crops, crop residues, and waste. In comparison to fossil fuels, biomass is renewable and easy to grow and replace fast without depleting natural resources. Biomass can be stored and used on demand. In addition, biomass also has the potential to reduce the dependency on fossil fuels, which are the main source of carbon dioxide release in the atmosphere (Ransikarbum and Pitakaso, 2021).

One of the core strengths of DH systems is their ability to integrate a wide range of energy sources, including RES as well as the use of waste heat. Nevertheless, the majority of district heat is still produced from fossil fuels (globally: coal 45% and natural gas 40%) (IEA, 2020). Currently (in 2021), DH provides about 28% of the Austrian households with the energy requested for space heating and domestic hot water preparation. Around 40% of the heat is produced in heat boilers, while the other part is produced in combined heat and power (CHP) units. Most used heat sources are biomass (49%) and natural gas (35%), followed by municipal waste (7%), coal (6%), and oil (3%). (FGW, 2021). Therefore, the rapid expansion of DH alongside the adoption of climate-neutral heat sources is necessary to accelerate decarbonization efforts and replace reliance on fossil fuels.

However, DH systems require flexibility to address the spatial and temporal mismatches between heat demand and supply. These elements cater to dynamic biomass boiler operation based on techno-economic criteria, integration of fluctuating renewables or waste heat, and tackling challenges like reduced loads during summer months (Kelz et al. 2020). To counter resulting inefficient operation of installed biomass boilers at low capacities, flexibility is essential, achieved either through optimized biomass boiler operation or by supplementing low heat demand with other renewable sources. Thermal heat storage stands as a viable option for this, with technology selection based on energy storage requirements and operating temperatures (Kaisermayer et al, 2022).

In Austria, approximately 2,400 biomass heating plants and 150 biomass CHP plants are operational (Strimitzer, 2021). Some of these plants are equipped with oil and/or natural gas boilers for peak load coverage and backup purposes. Most of the installations are located in smaller rural areas and have been in operation for 20 to 30 years. As a result, extensive and system-wide retrofitting measures will become necessary within a few years (FGW, 2021).

Although improvements in the quality and efficiency of Austrian biomass-based DH systems were observed in the past (BMLFUW, 2015), there is still scope for optimization of existing plants and networks, not least due to the growing number of DH systems. Thus, this study estimates the cost efficiency of biomass-based DH systems using Data Envelopment Analysis (DEA). DEA is a linear-programming method which is widely used for efficiency measurement. DEA allows to measure the efficiency of a DH system (consisting of heat generation and DH network), relative to all other systems, with the simple restriction that all observations lay on or below the efficiency frontier. The distance between the evaluated observation and the frontier measures the relative efficiency. Thus, DEA informs about performances of a given system compared to the efficient units but not compared to a "theoretical optimum".

Building of DH systems is supported by public subsidies in many European countries. In Austria, for instance, the funding of new constructions and expansions of biomass-based DH projects has constantly been expanded and modernized[2]. In order to ensure the efficient and sustainable use of these subsidies, the application of an accompanying quality management system "QM Heizwerke" is mandatory to receive funding in Austria. This quality management system is managed within the program "klimaaktiv Heizwerke und Wärmenetze" (formerly "klimaaktiv QM Heizwerke") as part of the climate protection initiative of the federal climate protection ministry in Austria. QM Heizwerke has the aim to improve the technical quality and efficiency of biomass-based DH systems (see Metz and Schrammel, 2019) and provides quality control in the planning, construction and operation of such systems. A well-functioning and comprehensive benchmarking system is essential for effective quality control also provided by QM Heizwerke. To create the benchmarks, key figures are calculated from operating reports submitted annually by the system operators. The benchmarks are made available to the operators and support the assessment of the system operation and the identification of possible optimization potentials.

This study expands the benchmarking currently used in Austria (Metz and Schrammel, 2019), which relies on simple key performance indicators by a new type of multi-variate approach based on efficiency estimates from DEA. The performance indicator calculated in this way considers all essential factors of production in biomass-based DH systems simultaneously and estimates the cost saving potentials of each individual system examined. By decomposing cost efficiency into a technical and an allocative component, the causes of inefficiency are revealed. A subsequent regression analysis examines how system-specific technical structural features and local environmental conditions influence their performance. Finally, managerial efficiency is estimated and saving potentials are derived using the results of these analyses.

In this paper we focus on biomass-based DH systems, while previous studies investigate all types of DH systems (among others Agrell and Bogetoft 2016; Lygnerud and Peltola-Ojala 2010, Munksgaard et al. 2005, Ziemele et al. 2017). Biomass-based DH systems generate heat in decentralized locations and distribute it through a network of insulated pipes for residential and commercial heating requirements such as space heating and hot water preparation as well as process heat in some cases. These thermal energy systems consist of at least heat generation

[2] The standard funding rate is 25% of the environment-relevant investment costs, which can be raised to a maximum of 35% by additional fees (sustainability fee for the purchase of regional wood chips and eligibility for EU-funding due to high efficiency). The funding is restricted to projects with investment costs higher than 10,000 Euros and CO_2 emission savings of at least four tons per year (BMLFUW, 2015).

units (boilers or CHP), a distribution network and consumers, whose requirements are covered by non-fossil energy (use of predominantly biomass energy and/or waste heat) from regional resources. This definition does not include the usual delimitation criteria such as system size, flow temperature, connected load, size of the supply area, transport distances or the number of consumers (see, e.g., Graubner-Müller, 2018 or Deutsches Umweltbundesamt, 2007). Rather, with the regionality and the use of locally available renewable heat sources, criteria are selected that address important aspects of a sustainable heat supply.

Apart from the uniqueness of focusing solely on regionally limited operational biomass-based DH systems, this study assesses the performance of these systems in isolation, considering comparable system configurations. However, it does not engage in a comparison of heating systems utilizing (combinations of) different technologies involving both renewable and fossil fuel sources. Strictly speaking, it satisfies the assumption of technological homogeneity of the examined objects in the DEA. Against the background of the impending decarbonization and the increasing use of renewable energy sources, this approach is more appropriate than the methods used so far, mainly comparing different technologies with each other, which work according to the same principles but employ heterogeneous technologies due to the use of different fuels. Thus, it is not possible to draw any conclusions on improvement potentials from the efficiency indicators furnished by such analyses, as the systematically less productive technologies can never reach the state of the more productive ones. An additional innovation is the decomposing of cost efficiency into the components of technical and allocative efficiency for DH systems.

The applicability of the approach developed here is shown empirically using a sample of biomass-based DH systems from Austria. The efficiency of biomass-based DH is not only interesting from an academic point of view, but also involves a number of stakeholders for whom the results are relevant, such as DH system operators (or owners), heat consumers (with regard to heat prices), quality managers within the framework of the QM Heizwerke program (which not only exists in Austria but as part of the international working group "QM for Biomass District Heating Plants" also in Switzerland, Bavaria, Baden-Württemberg and Friuli-Venezia Giulia), subsidy providers or subsidy processors and political decision-makers with regard to whether subsidies are related to inefficiency. Furthermore, the results could be relevant for regulators/supervisors, energy agencies, planners, component and plant manufacturers as well as suppliers to the DH systems and lenders to the operators for creditworthiness.

The remainder of the paper is structured as follows. Section 2 provides an overview of the related literature. Section 3 introduces the estimation methods applied in our study. Section 4 describes the dataset and develops the empirical model. Section 5 presents the empirical results, and Section 6 concludes with some final remarks.

2. Literature review

Data Envelopment Analysis (DEA) has been widely used in the efficiency evaluation of multiple input–output problems, including energy and environmental studies (see, e.g., Zhou et al., 2008, Sueyoshi et al., 2017 or Xu et al., 2020 for comprehensive overviews). DEA applications in the area of renewable energy can be found among others in Eder and Mahlberg (2018) and Eder et al. (2021) for biogas, Lee et al. (2015) for photovoltaics, Liu et al. (2015) for wind power, and Longo et al. (2015) for heat pumps. Cucchiella and Gastaldi (2014), for instance, compared the efficiency of renewable energy technologies (photovoltaic, wind, biomass, hydro) with DEA at regional level in Italy considering investment and operating costs as inputs and installed power capacity, energy intensity and the CO_2 avoided as outputs.

So far, there have only been a few studies that estimate the efficiency of DH systems. Rączka, (2001), for example, applied a two-stage procedure to identify factors influencing the technical efficiency of DH systems from Wielkopolska Region (Poland), which are fuelled by coal (incl. lignite), oil and natural gas (used together with coal). In the first step, a radial, input-oriented DEA model was applied to obtain technical efficiency scores. In the second step a regression analysis using the Tobit model explains the variability of the efficiency index. Raczka showed that government intervention at the household segment of the market reduced the efficiency of heat generation. For the cross-section sample investigated, public heat systems perform on average better than municipal and industrial ones. Moreover, the study found out that the quality of the fuel and capital utilization improve the technical efficiency.

In the context of economic regulation[3] Agrell and Bogetoft (2005) estimated the impact of governmental, market and managerial imperfections of the Danish DH and cogeneration system by assessing environmental and economic efficiency. Beside the radial model the additive DEA model was applied (both input-oriented, with constant returns to scale - CRS - and variable returns to scale - VRS) to calculate technical, environmental, cost-, and structural efficiency along with cost estimates. Furthermore, the Malmquist index was used to evaluate the efficiency change over time. The analysis focused on energy input from oil, coal, gas, woodchips or pellets, straw, other biofuels; primary electrical energy input; secondary heat input from generating systems, industrial sources, waste incineration. The authors concluded that the impact of governmental action (system size, fuel choice, network configuration) is three times more important than managerial performance.

Based on the databases used by Agrell and Bogetoft (2005) Munksgaard et al. (2005) illustrated that the rank order and the efficiency of each system are strongly dependent on the model originally applied and the combination of inputs and outputs included in the model. The authors conclude that the selection of the proper scale of operation is important for the DEA for DH systems. When a regulation system is based on a long-term model, short-term objectives and consequently financial difficulties for DH systems may not be considered. However, a short-term model is not appropriate in achieving long-term efficiency goals, such as a lower level of CO_2.

Lønborg (2005) analysed the cost efficiency of DH (and water supply) in Denmark and explained the variation in efficiency in a two-step approach. In the first step of the analysis, the efficiency of all units within each sector is evaluated using a radial, input-oriented DEA model with CRS and VRS. The second step identified causes to the variance in efficiency by using the efficiency score from the DEA in step one as the dependent variable in a regression analysis with a range of political, technical and financial explanatory variables. The results showed that the variation in efficiency cannot be explained by ownership and only partly by asset specificity, but is somewhat congruent with the intensity of the interests of constituents.

Agrell and Bogetoft (2016) derived endogenous sector-wide prices for DEA evaluations. They developed a game theoretic approach, where the industry suggests prices to collectively maximize net revenue or compensation and a principal chooses a benchmarking unit to

[3] For an overview of applications of Data Envelopment Analysis in regulation see Agrell and Bogetoft (2017).

constrain the set of acceptable prices. The model was empirically applied by using panel data from Danish DH systems. The empirical study suggested to rely on the risk-reducing strategy of emphasizing input-output dimensions with low variability within the sample. Another result was the potential direct distortion of total allocation efficiency when responding strategically to collective incentives.

Lygnerud and Peltola-Ojala (2010) analysed DH companies' efficiency of providing DH to small houses in Finland and Sweden with DEA. The study found that Finnish companies are more efficient than Swedish companies in offering district heat to small house customers. However, the choice of inputs does not conform to production theory, which forms the basis for estimates of production efficiency, since production and demand are actually mixed.

Ziemele et al. (2017) applied DEA and a regression model to assess the sustainability of heat energy tariff in a DH system. They evaluated the performance of Latvian DH companies by using several efficiency indicators describing technical, scale, dynamic and financial parameters. The results illustrate how the price of a fossil-fuel impacts the share of heat energy production and the balance point between investment at the source and on the heat consumer side.

Concerning economies of scale, Sjödin and Henning (2004) calculated the marginal costs of a Swedish DH utility. The authors conclude that using prices based on marginal costs should enable an efficient resource-allocation. It is found that the fixed rate should be replaced by a time-of-use rate, which would give a more accurate signal for customers to change their heat consumptions. Park et al. (2016) investigated the cost efficiency of DH systems in South Korea by using a variable cost function and cost-share equation. They used a seemingly unrelated regression model, with quarterly time-series data – covering the period 1987 to 2011 with the explanatory variables price of labour, price of material, capital cost, and production level. The results indicate that economies of scale are present and statistically significant.

Based on an extended Farrell input distance function that accounts for CO_2 as an undesirable output, Henningsen et al. (2015) used a somewhat different approach to estimate the environmental productivity of individual generator units based on a panel data set for the period 1998 to 2011 that includes virtually all fuel-fired generator units in Denmark. The authors decomposed total environmental energy conversion productivity into conversion efficiency, best conversion practice ratio, and conversion scale efficiency and use a global Malmquist index to calculate the yearly changes. By applying time series clustering, high, middle, and low performance groups of generator units were identified in a dynamic setting. The research outcome only showed a slightly increasing sectoral productivity over the investigated time span of fourteen years. Moreover, the results indicate that there is no overall high achiever group, but that the ranking varies between the different productivity measures. Steam turbines and combustion engines for combined heat and power production seemed to perform well, while combustion engines that only produce electricity are low performers.

Daugavietis et al. (2022) investigated the sustainability of DH systems by using five frequently applied multi-criteria decision analysis (MCDA) methods, with DEA among them. The authors' analysis indicated that all methods are appropriate for sustainability analyses of DH systems, although there are differences in the calculation process and in the interpretation of results.

The cited examples mainly focus on heterogenous technologies using different fossil fuels and renewable energies (e.g., solar, wind, biomass and others). As already mentioned above, the current study evaluates just the performance of technological homogenous biomass-based DH systems.

3. Methodology

This study introduces a three-stage approach to estimate cost saving potentials of biomass-based DH systems. In the first step, cost efficiency scores as well as technical efficiency scores of all systems of the sample are estimated applying DEA. These results are referred to as overall cost efficiency and overall technical efficiency. In the second step, the influences of structural characteristics of the systems, which the operator cannot influence (at least in the short term), and the characteristics of the regional environment on overall efficiency are determined with a regression analysis. In the third step, the results of the regression analysis are used to derive managerial efficiency from the overall cost efficiency as well as from the overall technical efficiency estimated in the first step. Managerial efficiency can be influenced by the DH system operator by appropriate reorganization of the operation. Finally, the potential savings in input quantities and costs are deduced from the managerial inefficiency.

3.1. Estimation of overall cost efficiency and technical efficiency

Cost efficiency measures the relation between the observed costs and the optimal costs. The first approaches estimating cost efficiency using DEA were developed by Tone (2002), Tone and Tsutsui (2007), Camanho and Dyson (2008), Portela and Thanassoulis (2014) and others. Mendelová (2021) offers a comprehensive overview of the existing approaches with their strengths and weaknesses. One limit of several approaches is that they do not take slacks into account. Weaknesses motivated Mendelová (2021) to improve the existing approaches by considering slacks.

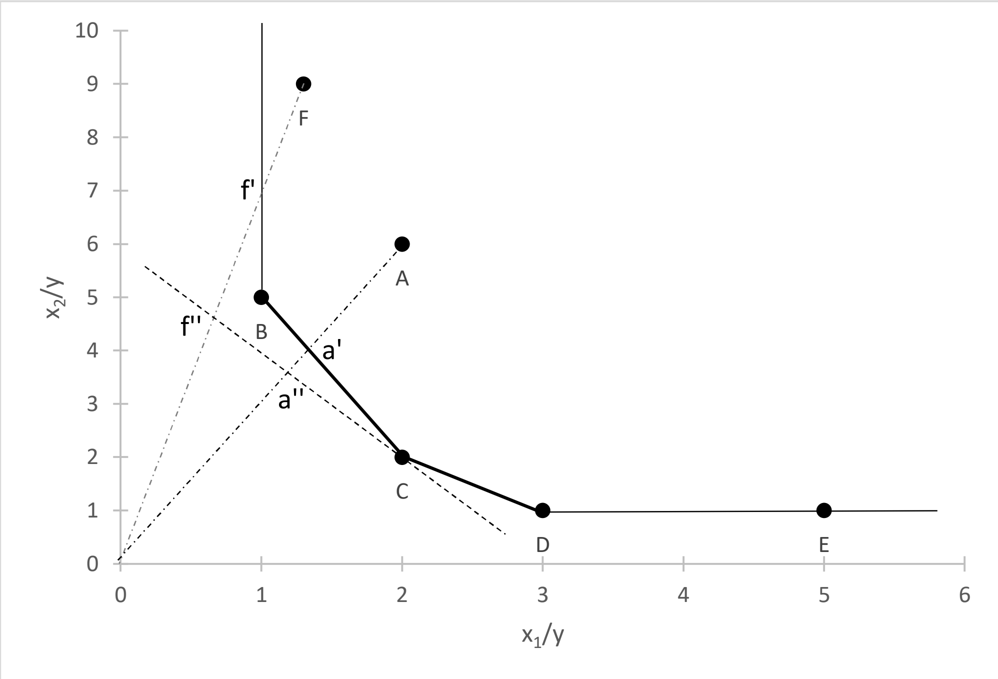
In a similar way to Mendelová (2021), our model allows us to decompose cost efficiency into the components of technical efficiency and allocative efficiency. *Technical efficiency* includes both the inefficiency due to "distance" between the best practice systems and the observed system (proportional reduction or radial inefficiency) as well as the inefficiency due to slack variables (non-radial inefficiency). These slacks indicate the potential need for non-proportional reduction of inputs. By including the slacks, the efficiency estimate is consistent with the definition of Pareto-Koopmans efficiency.[4] *Allocative efficiency* is obtained as a residual of cost efficiency and technical efficiency. Allocative inefficiency occurs if the input mix does not correspond to input price relations. Minimal cost at given prices are estimated solving a traditional DEA cost model. Prices are allowed to differ across the evaluated units (in our case biomass-based DH systems).

Fig. 1 illustrates the principles of decomposing cost efficiency into its components within our framework. In this example, six observations, labelled A through F, use the two inputs x_1 and x_2 at prices p_1 and p_2 to produce an output y. In this figure the solid piecewise linear line symbolizes the isoquant of the efficiency frontier. The thicker line represents the Pareto-Koopman efficiency frontier connecting observations B, C, and D. All observations at this efficiency frontier are technically strongly efficient. The thin vertical and horizontal lines represent the Farrell efficiency frontier. All observations on this frontier, such as E, are only

[4] This efficiency must be clearly distinguished from the efficiency in the sense of the Planning Handbook (CARMEN, 2022) or energy efficiency, which are more like productivity measures. For a distinction between efficiency and productivity in the DEA context, see e.g., Luptacik (2010).

technically weakly efficient. They can produce the same amount of output with less use of either input. The broken tangent to the isoquant at point C symbolizes the isocost line. The slope of this line is determined by the ratio of the two input prices. Observation C is the only cost efficient observation. Although observations B and D are technically efficient, they are not cost efficient. Observations A and F are neither technically efficient nor cost efficient.

Fig. 1. Measuring cost efficiency, technical efficiency, and allocative efficiency



The estimation of the cost efficiency and its components is shown as an example using the observations A (case without slack) and F (case with slack). In observation A, the technical efficiency as well as the cost efficiency are determined along the dotted line from A and the origin. Technical efficiency is given by the distance from 0 to a' relative to the distance from 0 to A. A simple radial projection from A to a' is sufficient to measure technical efficiency relative to the Pareto-Koopman efficiency frontier. This is equivalent to a relation between the costs in a' and in A. Cost efficiency is defined as the distance from 0 to a'' relative to the distance from 0 to A. Again, this is equivalent to the relation between the costs in a'' and in A. This results in allocative efficiency as the residue between cost efficiency and technical efficiency or as the distance from 0 to a'' relative to the distance from 0 to a'. Again, this is equivalent to the relation between the costs in a'' and in a'. Estimating technical efficiency of observation F is more complicated compared to A. A simple proportional reduction of the input amounts to f' is not sufficient to arrive at the Pareto-Koopmans efficiency frontier and to fully measure technical efficiency. A further reduction of the input x2 from f' to B needs to be included. The technical efficiency can only be represented as a relation between the costs of observation B and of observation F. The cost efficiency of observation F is defined analogously to that of observation A as the distance from 0 to f'' relative to the distance from 0 to F. Allocative efficiency is also defined as the residual between cost efficiency and technical efficiency, but cannot be regarded as a simple mathematical formula of relative distances. An observation is considered efficient if it obtains a score of one, whereas scores that are lesser than one mean relative inefficiency. Inefficiency is calculated by one minus efficiency.

In the following mathematical representation of the models, we consider n DH systems that use m inputs to produce s outputs. For each DH system HS$_o$, $o \in \{1, \dots, n\}$ input quantity, input price, and output quantity vectors are denoted by $x_o = (x_{1o}, x_{2o}, \dots, x_{mo}) \in R_+^m$, $p_o = (p_{1o}, p_{2o}, \dots, p_{mo}) \in R_+^m$ and $y_o = (y_{1o}, y_{2o}, \dots, y_{so}) \in R_+^s$, respectively. For reasons discussed in Section 4, we consider one input (the m-th for simplicity) to be exogenously fixed, in the sense of Banker and Morey (1986). The observed costs of each DH system HS$_o$ can be computed as $TC_o = \sum_{i=1}^{m} p_{io}\, x_{io}$.

Technical efficiency in the sense of Farrell (1957) is estimated using the following radial, input-oriented DEA model assuming variable returns to scale according to Banker et al. (1984):

$$
\begin{aligned}
\min_{\theta, s_i^-, s_r^+, \lambda_j} \theta_o \text{ subject to } & \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} = \theta_o x_{io} - s_i^-, \qquad i = 1, \dots, m-1 \\
& \textstyle\sum_{j=1}^{n} \lambda_j x_{mj} = x_{mo} - s_m^-, \\
& \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} = y_{ro} + s_r^+, \qquad r = 1, \dots, s \\
& \textstyle\sum_{j=1}^{n} \lambda_j = 1 \\
& \lambda_j, s_i^-, s_r^+ \geq 0, \qquad j = 1, \dots, n
\end{aligned}
$$

where θ_o denotes technical efficiency score of HS$_o$ according to Farrell (1957), λ_j the intensity of observation j, s_i^- the slack of input i and s_r^+ the slack of output r. This model is solved in two phases. First, θ_o^* is obtained. Second, a linear problem with the objective function $\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$ subject to the same constraints of the optimization problem shown above and θ_o fixed at θ_o^* is maximized to attain optimal slacks s_i^{-*} and s_r^{+*}. Each evaluated heating system must undergo this optimization problem once. The optimal solution of the technical efficiency score $\theta_o^* \in (0,1]$. All DH systems where $\theta_o^* = 1$ are Farrell efficient but not necessarily Pareto-Koopmans efficient. A DH system is Pareto-Koopmans efficient only if it is Farrell efficient, and all slacks are zero. To estimate Pareto-Koopmans efficiency the slacks have to be included. Pareto-Koopmans efficiency is defined as the ratio of Pareto-Koopmans efficient costs TC_o^{Tech} to observed costs TC_o as follows: $TE_o = \frac{TC_o^{Tech}}{TC_o} = \frac{\sum_{i=1}^{m} p_{io}(\theta_o^* x_{io} - s_i^{-*})}{\sum_{i=1}^{m} p_{io} x_{io}}$.

Minimal costs are obtained by solving the following linear optimization problem assuming variable returns to scale according to Ray (2004, p. 220):

$$
\begin{aligned}
\min_{\lambda_j, x_{io}} TC_o = \textstyle\sum_{i=1}^{m-1} p_{io}\, x_{io} \text{ subject to } & \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}, \qquad i = 1, \dots, m-1 \\
& \textstyle\sum_{j=1}^{n} \lambda_j x_{mj} \leq x_{mo} \\
& \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \qquad r = 1, \dots, s \\
& \textstyle\sum_{j=1}^{n} \lambda_j = 1 \\
& \lambda_j \geq 0, \qquad j = 1, \dots, n
\end{aligned}
$$

This optimization problem has to be solved once for each evaluated DH system. The optimal solutions of this problem are the minimum costs of each evaluated system $TC_o^{min} = \sum_{i=1}^{m} p_{io}\, x_{io}^*$. Cost efficiency is calculated as the ratio of the minimum costs to the observed costs in the following way: $CE_o = \frac{TC_o^{min}}{TC_o} = \frac{\sum_{i=1}^{m} p_{io} x_{io}^*}{\sum_{i=1}^{m} p_{io} x_{io}}$. As with technical efficiency, cost efficiency is $CE_o \in (0,1]$. DH systems with this efficiency score equal to one are declared as cost efficient. For these installations, the observed costs are equal to the minimum. All others are cost inefficient.

Based on the results from the two optimization problems shown above the allocative efficiency can be derived as the gap between Pareto Koopman efficient cost and the minimum cost. These are the costs that can only be reduced by changing the ratio of the use of the individual inputs. Allocative efficiency can be computed as $AE_o = \frac{TC_o^{min}}{TC_o^{Tec}} = \frac{\sum_{i=1}^{m} p_{io} x_{io}^*}{\sum_{i=1}^{m} p_{io}(\theta_o^* x_{io} - s_i^{-*})}$. It can also be interpreted as the residual between cost efficiency and technical efficiency as follows: $AE_o = \frac{CE_o}{TE_0}$.

Putting everything said above together, cost efficiency can be decomposed into the components of technical efficiency and allocative efficiency as follows: $CE_o = TE_0 \cdot AE_o$. This decomposition captures all possible causes of the observed costs being higher than the minimum costs. Firstly, this can be due to technical inefficiency, if more input resources are used than technologically required. Secondly, it can be due to allocative inefficiency as a result of cost suboptimal use ratios of the individual input resources.

Mendelová (2021) provides an extended concept to estimate *price efficiency*. Price efficiency measures the ability of a system operator to negotiate favourable prices in the purchasing of inputs. However, a discussion with experts of the Austrian biomass-based DH branch revealed that the system operators are not able to influence the purchase prices of the inputs. Almost all system operators are small companies that do not have sufficient market power to negotiate purchase prices with suppliers. They are regarded as price takers on the input markets. Therefore, our estimation approach does not consider price efficiency. This simplifies the procedure considerably compared to Mendelová (2021).

3.2. Decomposition of overall efficiency

Certain conditions (structural characteristics, environmental conditions, etc.) are different for the individual DH systems of our sample and expected to affect the usage of inputs and the achievement of outputs. These influencing factors cannot be changed by the operator, and cannot be included in the DEA when estimating efficiency. For these reasons the efficiency scores calculated by the DEA do not correspond with true managerial efficiency. In order to obtain the managerial efficiency scores, the efficiency scores from the DEA must be adjusted. Different approaches have been developed for this. Harrison and Rouse (2016) and Ruggiero (2019) offer recent overviews of the related literature.

In our study we apply an approach similar to Ray (1991). This procedure consists of the following three steps: (1) Specifying the inputs and the outputs and estimating overall technical and overall cost efficiency for each DH system in the sample by solving the two DEA models shown in the previous subsection. (2) Specifying the external factors influencing input use and output achievements but not under the operator's control and estimating an appropriate statistical relationship between estimated efficiency and the external factors in a regression analysis; Contextual variables are used in the second-stage regression model with the DEA efficiency scores as the dependent variable. And finally (3) using the results of the regression analysis from step (2) to calculate managerial efficiency from the overall cost efficiency as well as from the overall technical efficiency obtained in (1) and to derive the potential resource savings and cost savings.

To produce meaningful results, the efficiency score predicted by the regression analysis ($\widehat{TE}_o, \widehat{CE}_o$) must never fall below the observed efficiency score (TE_o, CE_o). The residuals should be nonpositive. However, because the regression analysis is based on least squares principles, the predicted values may be both above and below those observed. The residuals can be either positive or negative. Greene (1980) has shown that one can obtain consistent estimators of the parameters by adding the largest positive residual (e) to the intercept and recomputing the residuals by subtracting this value from each residual obtained by least squares. Applying this procedure, the adjusted residuals all become nonpositive. That ensures that the predicted values never fall below the observed values.

The adjusted predicted efficiency ($\widehat{TE}'_o = \widehat{TE}_o + e, \widehat{CE}'_o = \widehat{CE}_o + e$) scores estimate the maximum efficiency in use of DH system inputs attainable given a specific level of contextual variables. The managerial inefficiency (i.e., the inefficiency not caused by external factors) results from the difference between the adjusted predicted efficiency and the observed one ($\widehat{TE}'_o - TE_o, \widehat{CE}'_o - CE_o$). The managerial inefficiency is measured as the difference of observed from adjusted predicted efficiency and not from 1. One problem in this regression model is that the predicted value ($\widehat{TE}_o, \widehat{CE}_o$) may not lie below 1. The problem is further aggravated for the upwardly adjusted predicted value ($\widehat{TE}'_o, \widehat{CE}'_o$). As usually done with respect to the linear probability model, we replace the adjusted predicted value ($\widehat{TE}'_o, \widehat{CE}'_o$) by 1 if that happens and measure managerial inefficiency as 1 minus the observed efficiency ($1 - TE_o, 1 - CE_o$) (Ray, 1991, p. 1627).

In addition to its simplicity, the second stage regression has the advantage that regression coefficients measure the marginal effects of changes in different contextual variables on the DEA efficiency score. However, the statistical properties of the estimators have been questioned in the literature. It has to be considered that the second stage regression is invalid unless the contextual variables are all uncorrelated with the inputs (Ray, 2020). In order to meet this criterion and to ensure the validity of the results of the regression analysis the contextual variables are selected in such a way that they are strictly exogenous, i.e., completely uncorrelated with the inputs.

As already indicated above, Ordinary Least Squares (OLS) is chosen as the regression analysis method. There is a broad discussion in the literature according the superiority of the Tobit method over the OLS. The Tobit method has actually been used very frequently. However, Banker et al (2019) showed ordinary least squares regression to be more robust than Tobit.

4. Data

Biomass-based DH systems have the capability to include a fossil fuel boiler alongside biomass boilers, enabling them to address peak load demands. Because of the fossil fuel boilers, the DH systems are able to provide heat even during maintenance work and other downtimes of the biomass plant. To qualify as a renewable energy heating system, the proportion of heat generated with fossil fuels must not exceed 20% of the total fuel heat input. Furthermore, some systems also distribute heat purchased from third parties (so-called "secondary heat") via the heating network. Secondary heat usually is residual heat or waste heat of processes of nearby industrial companies or of nearby biogas plants. While some systems solely distribute self-generated heat, others exclusively distribute secondary heat, and yet others provide a combination of both self-produced and secondary heat distribution.

Biomass fuels (wood chips, wood shavings, pellets, and bark used), fossil fuels (heating oil and natural gas) and secondary heat are three inputs used in the production process of the systems. Apart from that, the systems consume electricity in various sub-processes. Furthermore, the systems require the components themselves (i.e., physical capital), human labour as well as repair and maintenance. Repair and maintenance include both spare parts and specialized labour, which are usually purchased externally from third parties. The entire systems use these inputs to deliver heat and provide services[5] to heat consumers. Accordingly, the entire system uses a total of seven inputs to produce two outputs. For the individual inputs, indicators are determined for both quantities and prices. For the individual outputs, indicators of quantities are created. A detailed description of these indicators can be found in Appendix A of this paper.

This study uses data from the database of "QM Heizwerke", the quality management system for biomass-based DH systems in Austria. The implementation of this quality management is mandatory for all operators who receive investment funding from Austria´s environmental support scheme. Operators are obliged to provide data on the performance of their systems in the form of annual operating reports. These data are entered into the QM Heizwerke database (referred to as QM database).[6]

For our analyses, we use data from a total of 114 biomass-based DH systems of the reporting years 2015, 2016 and 2017. However, we cannot observe the performance of every system every year. The data for all three years are only known for about 32% of the observations; for also about 32 % only two years are observed and for about 36 % only data for one year are available. The sample sizes are 81 in 2015, 75 in 2016 and 68 in 2017. Tables 1, 2, and 3 present descriptive statistics for the data of 2016. They show the typical conditions in the biomass-based DH sector in Austria. The corresponding descriptive statistics for 2015 and 2017 can be found in Appendix B of this paper.

Table 1 shows clear differences between individual biomass-based DH systems in all indicators, which can be seen from the high standard deviation and the range between minimum and maximum. This applies to both the input and the output quantities. The number of employees in full time equivalents (FTE) is very low for all systems. Some systems use almost no labour

[5] The usual services are answering various inquiries from customers, advising customers on various heating topics, issuing and concluding written contracts, issuing and sending invoices, etc.

[6] The database is managed by AEE - Institute for Sustainable Technologies (AEE INTEC) on behalf of the responsible federal ministry. For details of this initiative and the data source of this study see BMLFUW (2015) as well as BMNT (2019).

because the operational processes are largely automated. The production and distribution of heat in a DH system is generally characterized by high capital intensity. As already mentioned, there are systems that use neither biomass fuels nor fossil fuels, since they do not generate heat, but only distribute secondary heat.

Table 1: Input and output quantities in 2016

Name of variable	Unit	Mean	Standard dev.	Minimum	Maximum
Input quantities:					
Capital	EUR	244,383	196,375	32,830	1,001,397
Labour	FTE	0.73	0.73	0.04	3.58
Biomass fuel	MWh	5,458	5,759	0	37,433
Fossil fuel	MWh	234	472	0	2,919
Secondary heat	MWh	4,146	14,198	0	103,483
Electricity used	MWh	146	203	13	1,329
Maintenance	EUR	13,387	15,464	500	86,317
Output quantities:					
Heat delivered	MWh	7,629	12,143	699	95,898
Services to heat customers	Unitless	58	75	1	542

Notes: Sample size is 75. FTE stands for full time equivalents. The energy contents are given for the fuels. EUR refers to euros in constant 2016 prices.

Table 2: Input prices in 2016

Name of variable	Unit	Mean	Standard dev.	Minimum	Maximum
Capital	EUR per EUR	0.75	0	0.75	0.75
Labour	TEUR per FTE	46.98	0	46.98	46.98
Biomass fuel	EUR per MWh	28.72	11.96	16.39	70.00
Fossil fuel	EUR per MWh	55.17	11.80	30.00	90.38
Secondary heat					
Lower bound	EUR per MWh	15.00	0	15.00	15.00
Upper bound	EUR per MWh	25.00	0	25.00	25.00
Electricity used	EUR per MWh	96.00	0	96.00	96.00
Maintenance	EUR per EUR	1	0	1	1

Note: Sample size is 75. TEUR stands for 1,000 EUR and FTE for full time equivalents. The fuel prices are given per MWh of energy content.

Table 2 presents the input prices. The price of physical capital is equal to 0.75 because the federal governments' funding rate is at least 25% for all systems. The operators use 100% of the systems but only pay for 75%. The price of labour is not available from the QM database, thus it is assumed to be equal to the average personnel expenses per FTE and year in the DH sector according to Statistics Austria. The price of the biomass fuels is equal to the weighted average of the prices of the individual biomass fuel types, which are available from the QM database for each DH system. The prices of the fossil fuels of each DH system are known from the QM database. The secondary heat price is not available in the QM database, but assumed to be within a range of 15 to 25 EUR according to the knowledge of sector experts. The price of electricity is assumed to be equal to the electricity market price for commercial customers according to Statistics Austria. The price of maintenance is set equal to 1, as a price is available neither from the QM database nor from any other data source. Because the composition of the spare parts and the work done varies greatly from system to system and is not known in detail from the QM database, it is also not possible to estimate a composite price from known market prices.

Table 2 shows that secondary heat prices are consistently lower than biomass fuel and fossil fuel prices. This creates an incentive for the DH system operator to buy as much secondary heat as possible. Because secondary heat mostly turns residual heat or waste heat from processes of nearby industrial companies or of the nearby biogas plants, the available quantity is subject to an upper limit. From both follows that the quantity for the DH systems is actually externally given. Due to these considerations, secondary heat is modelled as a fixed input in the efficiency estimates (cf. section 3.1).

Table 3: Costs per MWh heat delivered for 2016

Name of variable	Unit	Mean	Standard dev.	Minimum	Maximum
Capital	EUR	33.09	11.78	3.89	55.64
Labour	EUR	6.45	5.49	0.05	27.76
Biomass fuel	EUR	25.82	12.83	0	50.33
Fossil fuel	EUR	2.57	4.99	0	28.48
Secondary heat					
lower bound	EUR	3.02	6.67	0	19.87
upper bound	EUR	5.04	11.11	0	33.11
Electricity	EUR	2.03	1.01	0.31	6.53
Maintenance	EUR	3.01	3.33	0.03	15.02
Total costs					
lower bound	**EUR**	**76.00**	**19.63**	**21.86**	**111.28**
upper bound	**EUR**	**78.02**	**16.96**	**32.65**	**111.28**

Note: Sample size is 75.

Table 3 shows the different types of costs per unit of heat delivered. Obviously, the cost of physical capital and the cost of biomass fuel are by far the largest cost components. The bandwidth for all cost components is very wide, which is manifested in high standard deviation values and in clear differences between maximum and minimum. For secondary heat, we indicate a lower limit and an upper limit corresponding to the price range. The overall mean total costs per MWh heat delivered are between 76.00 EUR and 78.02 EUR per MWh, although the range here is also remarkably high.

5. Empirical Results

5.1. Overall efficiency

Table 4 presents descriptive statistics of overall cost efficiency and its components of technical and allocative efficiency.[7] The results of the individual years are not comparable because both the samples and the environmental conditions, including the relative input prices, differ significantly from each other. For this reason, the estimates of the production possibilities and, as a result, the efficiency scores vary systematically. The influence of year-specific effects becomes evident in the next subsection about the results of regression analyses.

The average overall cost efficiency is 0.73, 0.78 and 0.81 in 2015, 2016 and 2017. Without taking into account the environmental conditions and the structural characteristics of the individual systems, average cost savings would be around 27%, 22% and 19%, respectively. However, the results of the next subsection show that not all of these potential cost savings can be effectuated without discrimination. Table 4 illustrates a considerable dispersion of cost

[7] The choice of the variable returns to scale assumption is confirmed by the results of two tests on global returns to scale for the respective years of 2015, 2016 and 2017. The detailed test results can be found in Table C.1 in Appendix C.

efficiency. The number of fully cost efficient systems with an efficiency score of 1 is in all years small and their proportion low. This indicates that many systems show potential for cost reduction.

Table 4: Overall technical efficiency and overall cost efficiency

Type of efficiency	Mean	Standard dev.	Minimum	Maximum	No. of efficient systems
2015:					
Cost efficiency	0.73	0.17	0.32	1	12
Technical Efficiency	0.88	0.17	0.38	1	43
Allocative Efficiency	0.83	0.11	0.59	1	12
2016:					
Cost efficiency	0.78	0.16	0.46	1	14
Technical Efficiency	0.91	0.14	0.53	1	50
Allocative Efficiency	0.86	0.13	0.46	1	14
2017:					
Cost efficiency	0.81	0.16	0.46	1	18
Technical Efficiency	0.93	0.13	0.52	1	45
Allocative Efficiency	0.88	0.12	0.46	1	18

Note: Sample sizes are 81, 75, and 68 in 2015, 2016 and 2017, respectively.

The decomposition of cost efficiency into technical efficiency and allocative efficiency shows that technical efficiency is on average higher than allocative efficiency. The average technical efficiency in individual years is 0.88, 0.91 and 0.93 and the allocative efficiency 0.83, 0.86 and 0.88. This implies a lower contribution of technical inefficiency to cost inefficiency compared to allocative inefficiency. In other words, on average, cost inefficiency is caused less by technical than by allocative inefficiency. Apparently, the systems operators succeed less in operating in accordance with the ratios of input prices than in using resources in accordance with their technical possibilities. As with cost efficiency, the systems perform quite differently. The potential for saving resources can be substantial for individual systems. On average, however, the potential is low. In terms of technical efficiency, the number of fully efficient units with efficiency scores of 1 is considerable.

5.2. Determinants of overall efficiency

In this subsection we investigate factors potentially explaining the variation in cost efficiency and technical efficiency. A second-stage regression using a random effects model is applied.[8] In particular, we are interested in the influences of the regional environments and the technical structures of the systems on both types of efficiency. Note that overall cost efficiency scores and overall technical efficiency scores as defined in section 3 are used as dependent variables. They are converted to percent to make the estimated coefficients easier to interpret. A complete list of the determinants, their definitions, descriptions of the hypotheses tested, and the sources of the data is provided in Table 5. Descriptive statistics of all variables of the regression analyses are available in Appendix C in Table C.2.

[8] The results of Breusch and Pagan Lagrangian multiplier tests for random effects clearly show that a random effects model is preferable to a pooled OLS model for both regression analyses. The null hypothesis that variances across entities is equal to zero (i.e., no panel effect) could be rejected. Details see Table C.3 in Appendix C.

Table 5: Description of determinants of overall efficiency			
Variable name	**Definition**	**Hypothesis**	**Source of data**
Properties of regional environment:			
Living space	Dwelling type and socio-economic conditions of the dwelling in NUTS-3 (in %)	Different heating technologies suit different types of housing because, for instance, single and multi-family dwellings differ in size and total heat demand, resulting in different heating densities. Different dwelling archetypes: (cf. Elementenergy, 2022)	Abart-Heriszt et al. (2019)
Heating degree days	Heating degree days in NUTS-3 (in 1,000 days)	Positive correlation: The higher the heating degree days the higher the technical efficiency since the utilisation is higher. We could explain a significant negative correlation as follows: The fuel is stored outside, when the outside temperature is low, it takes longer to reach the right temperature, therefore more inefficient. Note: Heating degree days represent the connection between the room temperature and the outside temperature for the heating days of a measurement period (e.g., heating year) and are therefore an aid for determining the heating costs or the energy requirement. The higher the number of heating degree days in a heating period, the higher the energy consumption.	Eurostat
Area used for forestry	Share of area used for forestry in NUTS-3 (in %)	Positive correlation: the higher the share of forest area, the higher cost efficiency (short transportation needs)	Abart-Heriszt et al. (2019) and Statistics Austria
Population density	Population density in NUTS-3 (in persons per square kilometre)	Positive correlation: the higher the population density, the higher cost efficiency (short transportation needs)	Eurostat
Rural dummy	Value of 1 for predominantly rural regions (NUTS-3), O else	Generally, heating networks with low heat density are characterized by relatively high investment costs and high heat losses. Also, the heat distribution costs are higher in suburban and rural areas with less concentrated heat demands, but lower in dense areas with concentrated heat demands (Werner, 2017).	Location information (NUTS 3 region) in the QM database and the region typology of Statistics Austria
Urban dummy	Value of 1 for predominantly urban regions (NUTS-3), 0 else	See rural dummy	Location information (NUTS 3 region) in the QM database and the region typology of Statistics Austria

Intermediate dummy	Value of 1 for intermediate regions (NUTS-3), 0 else	See rural dummy	Location information (NUTS 3 region) in the QM database and the region typology of Statistics Austria
Income	Regional gross domestic product in NUTS-3 (in Euro per inhabitant) (in 1,000 EUR)	A positive relationship between income and cost efficiency is expected because wealthy regions may demand more biomass district heat.	Eurostat
Employment	Share of employment in industry and business on total employment (in %)	A positive relationship is expected because regions with higher employment in secondary sector may demand more biomass district heat.	Abart-Heriszt et al. (2019) and Statistics Austria
Properties of systems:			
Size customer	Heat delivered divided by number of customers (in MWh)	Positive correlation expected: Few but large customers need less customer service (e.g., issued and sent invoices, collection, answering queries, etc.) than many small ones with the same amount of heat supplied.	deduced from QM database
Biomass share	Share of biomass fuel on total fuel (in %)	Positive correlation: High share of biomass implies fuel cost savings (lower fuel costs than fossil fuels)	deduced from QM database
Fossil share	Share of fossil fuel on total fuel (in %)	Negative correlation: reverse situation to share biomass	deduced from QM database
Secondary heat share	Share of secondary heat (heat bought from third) on total fuel	Positive correlation: the higher the share of secondary the higher efficiency (due to low market price of secondary heat)	deduced from QM database
Size system	Sum of nominal capacity of all boilers and secondary heat bought from the market (in MW)	Expected insignificant coefficient because size effects are already sufficiently taken into account in the estimation of the efficiency scores.	QM database
Age	Number of years since commissioning of the first system parts (in years)	Negative correlation: the older, the less efficient (e.g., due to higher maintenance cost or due to general technological improvements over time)	deduced from QM database
Age squared	Number of years since commissioning of the first system parts squared (in years squared)	Negative correlation: the older, the less efficient (e.g., due to higher maintenance cost or due to general technological improvements over time)	deduced from QM database

Customer density	Number of consumers per network route length (in no. of customers per kilometre)	The economic viability of DH depends on the distances between heat generators and customers. Positive correlation: The higher the density, the more heat can be delivered and sold over a unit of the grid, reducing losses and investment costs and thus increases efficiency (cf. Dochev et al., 2018)	deduced from QM database
Linear heat density	Heat delivered per network route length (in MWh per meter and year)	The economic potential of heating systems depends, among other things, on the distances between heat generation and consumption and heat demand density. The share of DH is determined above all by the connection rate that can be realized in the DH regions, which in turn is closely related to the spatial energy planning framework conditions (cf. Büchele et al., 2021) Heat distribution pipes should be short to limit heat losses and distribution costs. Pipes that are too long are not competitive with local heat generation units, such as heat pumps, biomass boilers, or electric boilers. Short pipes appear in areas with high heat demand within a certain land area (also known as high heat demand density areas), while longer pipes are required in areas with low heat demand densities (Borsche et al. 2023). The linear heat density of a DH network is defined as sold heat per year and per meter of network route length. Heat losses of the heat distribution are closely related to the linear heat density and should, according to quality standards, not exceed 10 % of the heat fed into the DH network (Good and Nussbaumer, 2004; CARMEN, 2022). An assessment of the connection load reveals that at constant linear heat density, the heat distribution costs increase with increasing network size. Consequently, strong economy of scale in the heat production is necessary to justify large DH systems (Nussbaumer and Thalmann, 2014).	deduced from QM database
Pressureless share	Share of heat delivered via pressureless distributor on total heat delivered (in %)	The more heat is delivered via a non-pressurized distributor, the more cost-effective and simpler the heat distribution. A positive sign is therefore to be expected.	deduced from QM database
Network share	Share of cost of capital for heat distribution (network) on total cost of capital (in %)	The high capital costs of heat network infrastructure must be offset by sufficient heat sales through the network over a reasonable period of time. As such, a higher linear heat density generally indicates improved financial viability. To improve the efficiency of any network and minimise capital costs, the overall length of network should be minimised where possible. (https://www.heatnetworksupport.scot/wp-content/uploads/2017/10/Module-5-Infrastructure.pdf)	deduced from QM database
heat price	Heat price reported by system operators (in EUR per MWh)	Changing price relations between different energy sources may impair the economic feasibility of a DH systems	QM database
Condensation dummy	value of 1 for systems using flue gas condensation, 0 else	Positive sign: Flue gas condensation improves efficiency	deduced from QM database
Dummy variables for years			
2015 dummy	value of 1 for efficiency scores of year 2015, 0 else	Systematic differences between years (year specific effects)	deduced from QM database
2016 dummy	value of 1 for efficiency scores of year 2016, 0 else	Systematic differences between years (year specific effects)	deduced from QM database
2017 dummy	value of 1 for efficiency scores of year 2017, 0 else	Systematic differences between years (year specific effects)	deduced from QM database

Table 6 presents the results of the random effects regression model, listing only those variables that are significant in at least one of the two analyses. Estimated coefficients and robust standard errors as well as significance levels are reported.

The cost efficiency results indicate that the regional environment (rural dummy) does not have a significant impact. Apparently, the systems act very well adapted to their surroundings. However, several structural features seem to be positively correlated with cost efficiency. Our results indicate that the higher the customer density and the higher the linear heat density, and the higher the share of cost of capital for heat distribution on total cost of capital (network share), the higher the cost efficiency. An increase in customer density by one consumer per network kilometre (route length) is accompanied by an increase in efficiency of 1.15%. Furthermore, if the annual heat consumed is 1 MWh per meter network route length higher (increase of 1 MWh/m in linear heat density), then the efficiency is 1.80% higher. Finally, if the share of cost of capital for heat distribution (network) on total cost of capital is 1% higher, then the system will show 0.28% higher efficiency.

Table 6: Determinants of overall efficiency - Outcomes of regression analysis

	Cost Efficiency		Technical Efficiency	
Rural dummy	7.212		10.391	*
	(6.133)		(6.013)	
Customer density	1.151	***	0.577	**
	(0.336)		(0.284)	
Linear heat density	1.797	***	1.518	*
	(0.670)		(0.847)	
Network share	0.276	**	0.136	
	(0.119)		(0.107)	
Condensation dummy	3.609		6.141	*
	(4.310)		(3.434)	
2016 dummy	8.330	***	4.676	***
	(1.542)		(1.745)	
2017 dummy	10.719	***	6.399	***
	(2.119)		(2.104)	
R-Squared: within	0.394		0.089	
between	0.379		0.319	
overall	0.393		0.296	
Wald chi2(22):	137.25	***	66.07	***

Notes: Sample size: number of observations is 224 and number of groups is 114
The values of the dependent variables are multiplied by 100 to express it as a percentage.
Sandwich robust standard errors are reported in parenthesis (Huber, 1981) correcting for heteroscedasticity. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1;
The variables not shown are insignificant in all variants. All models include an intercept and the controls listed in Table 5. Full results are available in Appendix C, Table C.4.

In contrast to cost efficiency, the regional environment bears some relevance to technical efficiency. This is indicated by the significant coefficient of the dummy variable for systems in rural regions. Accordingly, systems in rural regions are about 10.4% more technically efficient than in intermediate regions. The structure of the network plays an important role for technical efficiency as well as for cost efficiency, although the coefficients and the significance levels are somewhat lower. Systems with higher consumer density (one more customer per kilometre) are technically about 0.58% more efficient. In addition, systems with a higher linear heat density (one more MWh per meter) are technically 1.52% more efficient. The share of cost of capital for heat distribution (network share) on total cost of capital does not seem to correlate with technical efficiency as opposed to cost efficiency. In contrast to cost efficiency, the technical efficiency of systems with flue gas condensation (condensation dummy) is significantly higher by 6.14% than for systems without (examined plants only have passive flue gas condensation systems without heat pumps, if at all).

The significant coefficients of the year-specific dummy variables (2016 dummy, 2017 dummy) indicate systematic differences between the individual years. They confirm the considerations made previously, according to which the efficiency scores of the three years cannot be compared directly, but only have to be interpreted separately. Differences may indicate inter alia technological changes.

5.3. Managerial inefficiency and saving potentials

This subsection combines the results of the two previous subsections and, according to the approach presented in section 3.2, determines the managerial inefficiency from the overall inefficiency scores estimated with DEA and from the residuals estimated in the regression analysis. In this way, we deduce managerial inefficiency from overall inefficiency (i.e., one minus overall efficiency). As already explained, the difference between overall inefficiency and managerial inefficiency is that part of the overall inefficiency which cannot be influenced by the operators. The managerial inefficiency is interpreted as an indicator of the saving potentials.

Table 7 presents the results of this estimation. While the first column shows the average overall efficiency, the second column offers the average overall inefficiency. The efficiency scores and the inefficiency scores complement each other to sum up to one. The next column presents the average managerial inefficiency.

Table 7: From overall efficiency to managerial inefficiency (arithmetic means)

	Overall efficiency	**Overall inefficiency**	**Managerial inefficiency**
2015:			
Cost efficiency	0.73	0.27	0.23
Technical efficiency	0.88	0.12	0.12
2016:			
Cost efficiency	0.78	0.22	0.21
Technical efficiency	0.91	0.09	0.09
2017:			
Cost efficiency	0.81	0.19	0.18
Technical efficiency	0.93	0.07	0.07

Note: Sample sizes are 81, 75, and 68 in 2015, 2016 and 2017, respectively.

In terms of cost inefficiency, the average overall inefficiency and the average managerial inefficiency are 0.27 and 0.23 in 2015, 0.22 and 0.21 in 2016 and 0.19 and 0.18 in 2017. This results in an estimated average cost saving potential of around 23% in 2015, around 21% in the in 2016 and 18% in 2017. The difference between the overall cost inefficiency and the managerial inefficiency seems to be small if only the mean values are considered. However, according to our results, this difference can be considerable for individual systems. Sometimes it accounts for the larger part of the overall inefficiency and, accordingly, reduces the estimated cost reduction potential. An interpretation of the overall cost inefficiency as a potential for cost savings would therefore be misguiding.

Regarding technical inefficiency, there is no difference between overall inefficiency and managerial inefficiency. Managerial inefficiency equals overall inefficiency. It averages 0.12 in 2015, 0.09 in 2016 and 0.07 in 2017. According to this, the resource saving potential amounts to 12% in 2015, 9% in 2016 and 7% in 2017. The distinction between the managerial inefficiency in cost and in technology can be attributed to the influence of prices.

5.4. Sensitivity of Results

In order to check the sensitivity of the results we exclude systems distributing secondary heat, either solely or in addition to self-produced heat, from the sample. The remaining systems distribute only self-produced heat to heat consumers (‘heat producer-sample’). The sample size decreases to 62 in 2015, 60 in 2016 and 59 in 2017. This sensitivity check is motivated by the fact that DH systems that buy at least part of the distributed heat from third parties at a reasonable price have a different cost structure and are also technologically structured somewhat differently because, among other things, they are equipped with smaller systems for heat generation (heating house, boiler, etc.). For this sample, overall cost scores, overall technical efficiency scores and overall allocative efficiency scores are estimated using DEA outlined in Section 3.1. Furthermore, the regression analysis and the estimation of saving potentials as described in Sections 5.2 and 5.3., respectively, are repeated. This robustness checks show that the main results presented in section 5.1 and 5.2 are quite insensitive to the sample applied.

The overall cost efficiency is on average 0.73, 0.78 and 0.81 in 2015, 2016 and 2017 using the entire sample and 0.72, 0.78 and 0.82 using the ‘heat producer sample’. The technical efficiency in individual years is on average 0.88, 0.91 and 0.93 and using the entire sample and 0.87, 0.89 and 0.91. Consequently, on average the differences between the diverse sample estimates are very small. Interestingly, the overall cost and technical efficiency scores of individual systems in both samples are equal. A closer look at the results of DEA for the entire sample shows that all systems which buy and distribute secondary heat only compare to each other, i.e., they only benchmark each other, but never with producers. Consequently, the efficiency scores of the producers do not change if the systems buying and distributing secondary heart disappear from the sample.

Additionally, the regression results presented in section 5.2 are rather insensitive to the sample used for our analysis. In the regression analysis of the overall cost efficiency for the 'heat producers sample', the same coefficients are significant or insignificant as in the analysis for the 'entire sample'. The levels of significance and magnitudes of the coefficients are slightly different. The signs of the coefficients are the same. Therefore, very similar conclusions can be drawn as for the entire sample.

In the regression analysis of the overall technical efficiency, the significances change a bit more. The coefficients of the dummy variable for systems in rural regions, for the consumer density of the network, for the dummy for systems using flue gas condensation and for the dummy for the year 2017 remain significant and retain their positive sign with roughly the same amounts. The coefficients of the linear heat density of the network and the dummy variables for the year 2016 lose their significance. Interestingly, the coefficients of the share of investments in network in total investment and the intercept, which are insignificant in the regression analysis with the entire sample, now become slightly significant. Thus, the conclusions drawn from the regression analysis of the overall technical efficiency for the two samples are very similar. The regression results of the random effects-model for the ‘heat producer sample’ are available in Appendix C in Table C.5.

Managerial inefficiency scores for the 'heat producer sample' closely resemble those of the entire sample. Likewise, the estimated cost saving potentials are comparable. Regarding cost efficiency, managerial inefficiency is, on average, again almost as large as the overall inefficiency. In individual systems, the management inefficiency can be much smaller, resulting in correspondingly lower estimated potential cost savings compared to the potential savings from overall cost inefficiency. In any case, deriving the cost-saving potential from overall cost inefficiency could result in an overestimation. In the case of technical inefficiency, on the other hand, the difference between overall inefficiency and managerial inefficiency in the 'heat producing sample' as well as in the entire sample is zero both on average and for each individual system. The potential for resource saving can thus be directly deduced from the overall technical inefficiency.

As a further sensitivity analysis, the cost efficiency for both samples were estimated in all years with a capital price of 0.70, which corresponds to a funding ratio of 30%. These results are very highly correlated with those with a capital price of 0.75 (correlation coefficient > 0.999). The deviations of the individual results only occasionally exceeded 0.01. The maximum deviation was 0.012. The results are insensitive to a change in the funding rate assumption as long as it is within a realistic range.

6. Conclusions

In this study we introduce a novel model designed explicitly for estimating the cost efficiency of biomass-based district heating (DH) systems. These systems play a crucial role in the decarbonization of the heat and hot water supply of industry, public buildings and households, thus contributing significantly to climate change mitigation. Achieving cost efficiency is important for the competitiveness of biomass-based DH systems. If operating cost efficiently, these systems can offer competitive pricing to their heat customers.

The estimation of the cost saving potentials is based on a three-stage approach. In the first step cost efficiency and technical efficiency are estimated using Data Envelopment Analysis (DEA). In the second stage, a regression analysis determines the most important external factors influencing the efficiencies estimated in the first stage. The third stage uses the results from the previous steps to derive managerial inefficiency, that part of inefficiency which can be influenced by the system operators. From the management inefficiency suitable saving potentials are derived.

Our model represents a notable advancement of existing benchmarking procedures that rely on various ratios. By combining several dimensions into a single key figure, the DEA provides a comprehensive approach to determine saving potentials. It evaluates the systems according to the best practice principle and takes into account size effects as well as the regional environment and technical and structural conditions of the systems that cannot be changed in the short run.

To demonstrate its usability, our approach is applied to a sample of biomass-based DH systems in Austria for the years 2015, 2016 and 2017. On the one hand, the empirical results show considerable saving potentials for individual systems, which can be realized less by purely technical optimizations than by adjustment of the input mix to the relative input prices. The proportion of managerial inefficiency in overall inefficiency varies from system to system. On average, however, the systems are characterized by high efficiency. On the other hand, the network architecture has a substantial impact on the overall performance. Given that the regional environment does not seem to significantly affect the performance, the analysis indicates that the systems are well adapted to their surroundings.

The results of the study indicate that the assessment of the cost efficiency of biomass-based DH systems should be based on a holistic consideration including all types of costs (comprising also the cost of physical capital input) instead of a partial consideration based on individual key figures. Furthermore, in order to find out all causes of inefficiencies, a complete decomposition of the cost efficiency must consider the influences of structural system properties as well as the local environment. The latter enables a distinction to be made between managerial inefficiency and overall inefficiency. Realistic and achievable saving potentials can be derived only from diagnosing management inefficiency.

Limitations of the study relate to the empirical part, in particular to data availability and data quality. In terms of data availability, there is a lack of data on the immediate vicinity of systems (i.e., municipality or political district). Information is only available for the larger NUTS 3 region, making it imprecise to estimate the impact of the environment. In the case of system data, the lack of data from the same systems over several years currently makes it difficult to compile time series and compare annual results. With regard to data quality, some challenges with inaccurate information and missing entries on individual system characteristics should be mentioned.

In addition to economic efficiency, future research should consider ecological efficiency and account for greenhouse gas emissions to get a complete picture of the performance of the analysed systems including their environmental impact. Furthermore, subsequent studies should expand its investigation over more extended timeframes to observe changes in efficiency and productivity over time, as well as to identify the factors driving these changes.

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Appendix A

Detailed definitions of input and output indicators:

The following indicators computed based on data stored in the QM database the serve as a proxy for each input quantity, input price and output quantity.

- Input quantities:
  - Capital = capital services for heat production + capital services for heat distribution (cf. user cost of capital approach; lifespans of heat production devices was assumed as 25 years and of heat distribution 40 years)
  - Labour = Total personnel expenditure (sum from maintenance und administration) / average annual labour costs of one full time worker (cf. Statistics Austria)
  - Biomass fuel = total energy content of biomass fuels (energy content of wood chips + energy content of wood shavings + energy content of pellets + energy content of bark)
  - Fossil fuel = total energy content of fossil fuels (include natural gas and heating oil)
  - Secondary heat = heat bought from third parties
  - Electricity used = total electricity used in all parts of the system (heat production and heat distribution)
  - Maintenance = total maintenance costs
- Input prices:
  - Capital = 0.75 EUR per unit (uniform for all DH systems because the subsidy rates are at least 25%, the operators only bear 75% of the capital costs themselves)
  - Labour = approx. 47 TEUR (average annual labour costs of one full time worker derived from Structural Business Statistics of Statistics Austria)
  - Biomass fuel = average price of all types of biomass fuels
  - Fossil fuel = average of price oil and natural gas
  - Secondary heat = price of secondary heat could not be observed. Based on statements of experts, the price is assumed to be between15 EUR and 25 EUR per MWh
  - Electricity used = 98 EUR per MWh in 2015, 96 EUR per MWh in 2016 and 91 EUR per MWh in 2017 (market price for commercial customers from Energy Statistics of Statistics Austria, price assumed to be uniform for all DH systems)
  - Maintenance = 1 (uniform for all DH systems since prices and quantities are not separable)
- Output quantities:
  - Heat delivered = total heat delivered to heat customers via heat network and pressureless heat distributer
  - Customer services = number of customers (note: According to information from experts in the biomass DH sector, the required customer services increase in direct proportion to the number of heat consumers.)

Capital input:

This section provides a short description of our definition and treatment of capital input within our model. Theory emphasizes that capital goods, usually owned by the firm and summarized as its capital stock, provide a flow of capital services, which constitute the actual input in the production process. Under the concept of "user cost of capital" the price of that service flows is defined as the rental price the firm would have to pay in a complete market if it did not own the capital goods itself and a rental market for that capital service existed. Thus, the user cost of capital takes into account the expected rate of return over the expected lifetime of the asset (Schreyer and Pilat, 2001). Because there is no natural unit of measurement for the physical input of capital, both the capital stock and capital services must be measured in monetary units, i.e., in constant prices of a base year. Capital services are, by definition, proportional to the capital stock, and the user cost of capital is applied for the determination of the ratio of proportionality between a (homogenous) capital stock and the service it delivers and for the aggregation of heterogenous assets. Thus, in our empirical approach the capital service input is measured in euros in prices of the base year of the empirical model (e.g., 2016), and the weighting between the two capital assets of DH systems, heat production and distribution network, takes into account their different lifetimes.

The literature on the measurement of capital stocks, capital services, capital income, deterioration and depreciation is vast and goes back at least to Jorgenson (1973), while early comprehensive reviews can be found in Hulten (1990) and Hulten and Wykoff (1996). The literature is also diverse, mainly due to the varying perspective of concepts and methods, which can be microeconomic or macroeconomic, managerial or policy-oriented. Most importantly, from a macroeconomic perspective the framework is not the individual capital asset but the collection of assets. However, in the context of performance analysis of plants, the perspective is microeconomic, as the plant is a small collection of assets. When information is available on individual investment streams of a small number of assets in a firm or plant, this information should be considered in the evaluation methods.

Capital input is an often-neglected input in the measurement of the technical efficiency of plants (i.e., production facilities). Previous work in the DEA tradition often equated capital input with investment, either accumulated or current (e.g., Eder and Mahlberg, 2018), considered capital input in the form of a proxy variable (e.g., length of distribution network in the case of Agrell and Bogetoft, 2005) or altogether neglected the capital input (e.g., Henningsen et al, 2015). Among the named reasons for incomplete consideration of capital input we find: data availability and problems, unclear translation of investment or accounting data into actual capital input and non-controllability of the variable. However, when the production process at hand is capital intensive, neglect or biased treatment of capital input might lead to biased results.

In the case of the present analysis, we base the data preparation of the variable for capital input on the stream of investment that is available for every plant separately for heat production facilities and heat distribution network. The stream of investments encompasses the years 2006 – 2017, which in most cases includes the whole period of existence of the plants. All plants, including all its part-investments, are still operative at the year considered for analysis (2015, 2016, and 2017), thus no retirement of productive capital has to be taken into account. Furthermore, from a technical perspective there is almost no deterioration of the capacity of the assets to provide the required service over its lifetime (this is to be expected due to ongoing maintenance work, which is also included as a separate input in the production efficiency model). We assumed a lifetime of 25 years for heat production facilities and of 40 years for heat distribution network.

In such a situation and with stable asset prices, simple accumulation of investment streams until the year of analysis would be a good approximation of capital input. However, we employ a more refined method of calculating the capital input that considers i) the development of asset prices, ii) some possible deterioration of the technical capacity of the assets to provide the required service and iii) the correct weighting for aggregating the services of two types of assets with different lifetimes and different deterioration schemes. During the time span covered by the investment streams the annual price increase of assets of constant quality is estimated to be approximately 1 percent. This means that earlier investment amounts must be compounded accordingly. For the deterioration scheme we experimented with different values of linear deterioration (0%, 5%, 10%) until the end of the assumed lifetime of the production capital. Since the results do not change significantly, we present only those based on the assumption of no deterioration. To be able to aggregate the services provided by different types of production capital we rely on the user cost of capital. In this concept the cost of capital is assumed to be proportional to the real capital stock, given that the real capital stock is defined as the capacity to provide capital services. The factor of proportionality was chosen so that at a discount rate of 5% the capital would completely be amortized after the lifetime of the asset. As a consequence, the capital service of the asset with the shorter assumed lifetime (heat production assets) is weighted higher in the aggregation. At the end of the data preparation the capital input is measured in prices of the year of the analysis and describes a situation of a hypothetical rent of the production capital.

Appendix B

Descriptive statistics of input and output indicators for 2015 and 2017:

Table B1: Input and output quantities in 2015

Name of variable	Unit	Mean	Standard dev.	Minimum	Maximum
Input quantities:					
Capital	EUR	228,670	174,073	14,475	991,090
Labour	FTE	0.67	0.67	0.01	3.86
Biomass fuel	MWh	6,512	8,305	0	40,352
Fossil fuel	MWh	242	501	0	2 430
Secondary heat	MWh	3,804	13,364	101,397	0
Electricity used	MWh	145	201	9	1,301
Maintenance	EUR	12,956	14,797	206	78,604
Output quantities:					
Heat delivered	MWh	8,231	13,338	561	89,640
Services to heat customers	Unitless	51	51	1	237

Note: Sample size is 81. FTE stands for full time equivalents. The energy contents are given for the fuels. EUR refers to euros in constant 2016 prices.

Table B2: Input and output quantities in 2017

Name of variable	Unit	Mean	Standard dev.	Minimum	Maximum
Input quantities:					
Capital	EUR	236,188	202,475	33,158	1,011,411
Labour	FTE	0.63	0.65	0.00	3.12
Biomass fuel	MWh	5,347	5,440	0	27,137
Fossil fuel	MWh	272	435	0	1,889
Secondary heat	MWh	2,353	7,756	45,332	0

Electricity used	MWh	115	146	7	1,005
Maintenance	EUR	17,277	22,944	291	117,944
Output quantities:					
Heat delivered	MWh	5,754	5,976	671	34,050
Services to heat customers	Unitless	54	76	1	571

Note: Sample size is 68. FTE stands for full time equivalents. The energy contents are given for the fuels. EUR refers to euros in constant 2016 prices.

Table B3: Input prices for 2015

Name of variable	Unit	Mean	Standard dev.	Minimum	Maximum
Capital	EUR per EUR	0.75	0	0.75	0.75
Labour	TEUR per FTE	46.98	0	46.98	46.98
Biomass fuel	EUR per MWh	30.04	12.64	16.09	70.00
Fossil fuel	EUR per MWh	57.42	11.37	30.00	84.62
Secondary heat					
Lower bound	EUR per MWh	15.00	0	15.00	15.00
Upper bound	EUR per MWh	25.00	0	25.00	25.00
Electricity used	EUR per MWh	98.00	0	98.00	98.00
Maintenance	EUR per EUR	1	0	1	1

Note: Sample size is 81. The fuel prices are given per MWh of energy content.

Table B4: Input prices for 2017

Name of variable	Unit	Mean	Standard dev.	Minimum	Maximum
Capital	EUR per EUR	0.75	0	0.75	0.75
Labour	TEUR per FTE	46.98	0	46.98	46.98
Biomass fuel	EUR per MWh	28.89	12.28	16.39	70.00
Fossil fuel	EUR per MWh	56.30	11.98	23.00	90.00
Secondary heat					
Lower bound	EUR per MWh	15.00	0	15.00	15.00
Upper bound	EUR per MWh	25.00	0	25.00	25.00
Electricity used	EUR per MWh	91.00	0	91.00	91.00
Maintenance	EUR per EUR	1	0	1	1

Note: Sample size is 68. The fuel prices are given per MWh of energy content.

Table B5: Costs per MWh heat delivered for 2015

Name of variable	Unit	Mean	Standard dev.	Minimum	Maximum
Capital costs	EUR	32.41	14.69	3.69	68.17
Labour costs	EUR	6.36	5.11	0.02	31.79
Biomass fuel	EUR	26.49	13.77	0	50.01
Fossil fuel	EUR	2.63	5.19	0	23.05
Secondary heat					
lower bound	EUR	3.07	6.49	0	20.80
upper bound	EUR	5.12	10.81	0	34.67
Electricity costs	EUR	2.09	1.09	0.28	6.57
Maintenance costs	EUR	2.94	3.12	0.05	14.21
Total costs					
lower bound	**EUR**	**75.99**	**23.97**	**23.25**	**133.53**
upper bound	**EUR**	**78.08**	**21.37**	**34.56**	**133.53**

Note: Sample size is 81. TEUR stands for 1,000 EUR and FTE for full time equivalents.

Table B6: Costs per MWh heat delivered for 2017

Name of variable	Unit	Mean	Standard dev.	Minimum	Maximum
Capital costs	EUR	35.66	11.96	8.12	77.00

Labour costs	EUR	5.93	4.00	0.01	19.32
Biomass fuel	EUR	27.88	12.96	0	64.89
Fossil fuel	EUR	3.27	5.57	0	25.96
Secondary heat					
lower bound	EUR	2.50	6.51	0	22.35
upper bound	EUR	4.17	10.85	0	37.26
Electricity costs	EUR	1.82	0.95	0.28	5.32
Maintenance costs	EUR	3.76	4.03	0.24	19.41
Total costs					
lower bound	**EUR**	**80.82**	**20.01**	**34.11**	**135.13**
upper bound	**EUR**	**82.48**	**18.07**	**45.03**	**135.13**

Note: Sample size is 68. TEUR stands for 1,000 EUR and FTE for full time equivalents.

Appendix C

Table C.1: Global returns to scale test

Test 1: H_0: CRS vs. H_1: VRS	Average technical efficiency under CRS	Average technical efficiency under VRS	Test Statistic	Critical Value for $\alpha = 0.05$	p-value for rejecting H_0
2015	0.892	0.926	0.9470	1.0008	0.0000
2016	0.913	0.953	0.9586	1.0227	0.0000
2017	0.915	0.966	0.9469	1.0193	0.0000
Test 2: H_0: NIRS vs. H_1: VRS	**Average technical efficiency under NIRS**	**Average technical efficiency under VRS**	**Test Statistic**	**Critical Value for $\alpha = 0.05$**	**p-value for rejecting H_0**
2015	0.912	0.926	0.9814	0.9925	0.0058
2016	0.947	0.953	0.9942	0.9992	0.0009
2017	0.937	0.966	0.9701	1.0135	0.0000

Notes: CRS stands for constant returns to scale, VRS for variable returns to scale and NIRS for non-increasing returns to scale. Tests for global returns to scale proposed by Simar and Wilson (2002) and described in Bogetoft and Otto (2011). The sample sizes are 81, 75, and 68 in 2015, 2016, and 2017, respectively. The critical value and the p-value are based on 2000 bootstrap replicates of the test statistic. The tests are performed using efficiencies estimated by radial DEA models without considering non-radial slacks.

Table C.2: Descriptive statistics of variables used in regression analysis of overall efficiency

Variable name	Unit	Mean	Standard dev.	minimum	maximum
Dependent Variables					
Overall cost efficiency	Percent	77.07	16.97	32.48	100
Overall technical efficiency	Percent	90.32	14.77	38.23	100
Independent variables					
Properties of regional environment					
Living space	Percent	77.65	10.21	40.83	95.84
Heating degree days	1,000 days	3.26	0.47	2.45	4.81
Area used for forestry	Percent	44.43	13.84	11.58	74.81
Population density	Percent	124.22	112.34	24.70	435.40
Rural Dummy	Unitless	0.57	0.50	0	1
Urban Dummy	Unitless	0.16	0.36	0	1
Intermediate Dummy	Unitless	0.27	0.45	0	1
Income	1,000 EUR	36.88	8.63	21.30	54.20
Employment	Percent	23.46	4.99	15.03	32.39
Properties of systems					

Size customers	MWh	352.79	1,974.90	21.67	29,328.55
Biomass share	Percent	80.67	35.09	0	100
Fossil share	Percent	4.19	7.86	0	47.66
Secondary heat Share	Percent	15.15	34.41	0	100
Size system	MW	5.85	7.63	0.45	68
Age	Years	5.14	2.33	0	11
Age squared	Years squared	31.80	25.53	0	121
Customer density	customer per network kilometer	10.68	4.73	1.52	24.76
Linear heat density	MWh per network meter	1.55	1.58	0.29	17.18
Pressureless share	Percent	0.41	2.76	0	24.42
Network network	Percent	41.03	19.62	0	95.63
Heat price	EUR per MWh	78.76	12.30	31	110.60
Condensation dummy	Unitless	0.09	0.29	0	1
Dummy variables for years					
2015 dummy	Unitless	0.36	0.48	0	1
2016 dummy	Unitless	0.33	0.47	0	1
2017 dummy	Unitless	0.30	0.46	0	1

Note: Sample size is 224

Table C.3: Breusch and Pagan Lagrangian multiplier test for random effects

	Cost efficiency	Technical efficiency
chi2	36.05	18.74
Prob > chi2	0.00	0.00

Note: Number of observations is 224.

Table C.4: Determinants of overall efficiency – Random effects regression results, entire sample

	Cost Efficiency	Technical Efficiency	
Living space	0.022	-0.033	
	(0.208)	(0.182)	
Heating degree days	-0.666	-7.640	
	(6.061)	(5.681)	
Area used for forestry	0.116	0.302	
	(0.202)	(0.246)	
Population density	0.000	0.005	
	(0.027)	(0.030)	
Rural dummy	7.212	10.391	*
	(6.133)	(6.013)	
Urban dummy	0.484	3.488	
	(6.958)	(9.327)	
Income	-0.267	-0.004	
	(0.385)	(0.392)	
Employment	-0.622	-0.326	
	(0.429)	(0.379)	
Size customers	0.001	0.001	
	(0.007)	(0.005)	
Biomass share	0.346	0.270	
	(0.221)	(0.308)	
Secondary heat share	0.289	0.334	

	(0.231)		(0.312)	
Size system	0.223		-0.086	
	(0.217)		(0.157)	
Age	2.398		-0.025	
	(1.535)		(1.600)	
Age squared	-0.199		0.006	
	(0.131)		(0.134)	
Customer density	1.151	***	0.577	**
	(0.336)		(0.284)	
Linear heat density	1.797	***	1.518	*
	(0.670)		(0.847)	
Pressureless share	0.507		0.153	
	(0.509)		(0.526)	
Network share	0.276	**	0.136	
	(0.119)		(0.107)	
Heat price	-0.015		-0.068	
	(0.123)		(0.108)	
Condensation dummy	3.609		6.141	*
	(4.310)		(3.434)	
2016 dummy	8.330	***	4.676	***
	(1.542)		(1.745)	
2017 dummy	10.719	***	6.399	***
	(2.119)		(2.104)	
Intercept	21.195		65.558	
	(36.873)		(46.758)	
R-Squared: within	0.394		0.089	
Between	0.379		0.319	
Overall	0.393		0.296	
Wald chi2(22):	137.25	***	66.07	***

Notes: Sample size: number of observations is 224 and number of groups is 114
The value of the dependent variable was multiplied by 100 to express it as a percentage.
Sandwich robust standard errors are reported in parenthesis (Huber, 1981) correcting for heteroscedasticity. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1;

Table C.5: Determinants of overall efficiency – Random effects regression results, heat producer sample

	Cost Efficiency		Technical Efficiency	
Living space	0.147		-0.033	
	(0.212)		(0.207)	
Heating degree days	0.586		-3.624	
	(6.100)		(5.433)	
Area used for forestry	0.044		0.161	
	(0.212)		(0.214)	
Population density	0.009		0.021	
	(0.029)		(0.030)	
Rural dummy	9.449		12.173	*
	(6.321)		(7.171)	
Urban dummy	1.522		1.280	
	(7.198)		(8.502)	
Income	-0.083		-0.093	
	(0.378)		(0.413)	
Employment	-0.696		-0.355	
	(0.476)		(0.496)	
Size customers	-0.006		0.012	

	(0.011)		(0.008)	
Biomass share	0.217		0.099	
	(0.198)		(0.273)	
Size system	-0.224		-0.494	
	(0.493)		(0.477)	
Age	1.810		0.602	
	(1.680)		(1.861)	
Age squared	-0.148		-0.058	
	(0.137)		(0.151)	
Customer density	0.834	**	0.711	*
	(0.414)		(0.386)	
Linear heat density	2.040	**	0.704	
	(0.867)		(0.814)	
Pressureless share	0.259		-0.009	
	(0.519)		(0.438)	
Network share	0.341	**	0.243	*
	(0.140)		(0.136)	
Heat price	-0.115		-0.081	
	(0.136)		(0.136)	
Condensation dummy	4.722		7.172	**
	(3.993)		(3.451)	
2016 dummy	7.636	***	2.836	
	(1.587)		(1.809)	
2017 dummy	9.560	***	4.710	**
	(2.228)		(2.317)	
Intercept	29.596		73.309	*
	(38.758)		(42.654)	
R-Squared: within	0.422		0.056	
between	0.343		0.286	
overall	0.355		0.306	
Wald chi2(22):	111.83	***	48.05	***

Notes: Sample size: number of observations is 181 and number of groups is 91
The value of the dependent variable was multiplied by 100 to express it as a percentage.
Sandwich robust standard errors are reported in parenthesis (Huber, 1981) correcting for heteroscedasticity. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1;