Cost efficiency and economies of diversification of biogas-fuelled cogeneration plants in Austria: a nonparametric approach

Andreas Eder

Institute for Industrial Research, Vienna University of Economics and Business

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Abstract

This paper investigates the existence and the degree of economies of diversification for small-scaled, renewable-fuelled cogeneration systems using 2014 cross-sectional data from 67 Austrian biogas plants. In addition, cost efficiency of those biogas plants is estimated with a non-parametric linear programming technique, known as Data Envelopment Analysis. This is the first study applying the methodology proposed by Chavas and Kim (2010). Economies of diversification are decomposed into three additive parts: a part measuring complementarity among outputs; a part reflecting economies of scale; a part reflecting convexity. Furthermore, this paper extends the decomposition introduced by Chavas and Kim (2010) in such a way that the contribution of each input to economies of diversification and its components can be investigated. The results indicate substantial cost savings from diversification. For very-small scaled plants (<100 kW_{el}) most of the cost savings come from scale economies. For larger plants (>250 kW_{el}) positive complementarity and convexity effects are the main source of economies of diversification and outweigh the negative effect from scale diseconomies. In addition to substantial fuel/feedstock cost reductions, significant costs saving effects from the jointness in labour and other inputs positively contribute to the complementarity effect. While on average capital and labour costs positively contribute to economies of scale, feedstock costs work in the direction of diseconomies of scale.

Keywords: Data Envelopment Analysis, Economies Scale, Economies of Scope, Renewable Energy Sources, Energy Efficiency

JEL-Code: C61, D22, D24, Q16, Q42

1. Introduction

Cogeneration or combined heat and power (CHP) is the simultaneous generation of both electricity and useful heat from the same fuel. Cogeneration is well known as an energy-efficient technology. While the average global efficiency of fossil-fuelled power generation has remained stagnant for decades at 35% to 37%, cogeneration allows up to 90% of fuel inputs to be converted to useful energy due to the utilization of waste heat (IEA, 2011). Compared to separate generation of heat and power with conventional energy supply systems, cogeneration can generate substantial savings in primary energy costs. Dependent on the system replaced, the

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[2] Institute for Industrial Research, Mittersteig 10/4, 1050 Vienna, Austria and Vienna University of Economics and Business, Welthandelsplatz 1, 1020 Vienna, Austria. E-mail: andreas.eder@s.wu.ac.at

technology and fuel used, 10-40% of fuel requirements can be saved (Madlener and Wickert, 2007).

In particular, renewable-fuelled cogeneration seems to be an appropriate technology to contribute to the EU climate and energy targets for 2030. That is a 27% reduction of primary energy use compared with projected levels and 27% of final energy consumption from renewable resources. In 2015 about 25% of gross final energy consumption of the EU-28 is estimated to be consumed in form of electricity. However, final energy for heating and cooling is estimated to be responsible for about 45% of gross final energy consumption, followed by transport with 27% (Eurostat, 2017). Though, heating and cooling makes up the big bulk in gross final energy consumption energy carriers in the heating sector were brought into focus of the European energy policy only recently (directive no. 2009/28/EC).[3] Whereas in 2015 28.8% of electricity consumption was electricity from renewable energy sources (RES-E) the share of renewables in heating and cooling (RES-H) is only 18.6% (Eurostat, 2017).That illustrates the need to focus on the heating sector, increase RES-H to decarbonise the energy system and stimulate heat recycling and heat savings (Connolly et al., 2014).

The EU policy focus on renewable electricity is rooted in the Renewable Electricity Directive (directive no. 2001/77/EC), which firstly provided indicative targets on the share of renewable electricity for each Member State but ignored the heat and transport sector. Based on the Renewable Electricity Directive (directive no. 2001/77/EC) and its repeal through the Renewable Energy directive (directive no. 2009/28/EC) all EU Member States have implemented policy support for RES-E, see e.g. Klessmann et al. (2011) and Kitzing et al. (2012). Within this framework the Austrian authorities enacted the green electricity law (BGBl. I Nr. 149/2002; BGBl. I Nr. 75/2011), which promotes RES-E with fixed electricity prices (feed-in tariffs) for 13 years. Among others, electricity generated from biogas is one of the technologies promoted by the Austrian green electricity law (see e.g. Eder et al., 2017; Eder and Mahlberg, 2018).

Commonly, Austrian biogas plants convert local feedstock such as maize silage, grass silage, manure or organic waste into biogas, which is then used in small-scaled CHP units to produce jointly heat and power. Heat is predominantly distributed through local district heating grids to cover heat demand in rural areas. Electricity is fed into the power grid. Due to regulatory incentives most of the plants are dominated by electricity generation.[4] Absent or weak locational signals led to placement of generation at sites, where heat demand is low and expenditures for district heat connections are high. Though, utilization of waste heat and energy efficiency improved substantially between 2006 and 2014 (Eder et al., 2017).

[3] Connolly et al. (2014) document that in a number of reports regarding the decarbonisation of the EU energy supply the heating sector is not a main focus area. With respect to the heat sector almost all reports, including the "Energy Roadmap 2050" from the European Commission, focus on increased electrification along with ambitious energy efficiency measures (e.g. energy efficiency of buildings). CHP and district heating are not expected to play a major role. In February 2016, the Commission proposed an EU heating and cooling strategy: (https://ec.europa.eu/energy/sites/ener/files/documents/1_EN_ACT_part1_v14.pdf).

[4] The Austrian green electricity law implies a purchase guarantee for electricity generated in biogas plants and fixed electricity prices (feed-in tariffs) for 13 years. Production subsidies for heat are not available. In 2016 the average feed-in tariff for biogas plants was 17.31 cent/kWh_{el}, whereas the average exchange price for electricity was 2.70 cent/kWh_{el} (E-Control, 2017). Commonly, heat prices are negotiated bilaterally between the biogas plant operator and the buyer (e.g. district heating grid providers or consumers). Investment grants are provided for different plant areas (e.g. heat utilisation), where eligibility and extend varies by Austrian federal states.

This paper aims to evaluate the benefits of diversification for biogas-fuelled cogeneration plants. It examines economies of diversification, reflecting the cost reduction associated with producing electricity and heat in a single integrated firm compared to two firms each specialized in one of the outputs. Based on the cost function approach of Chavas and Kim (2010) a sample of 67 Austrian biogas plants is applied to estimate the existence, the degree and the sources of economies of diversification for biogas-fuelled cogeneration plants. The approach of Chavas and Kim (2010) provides several benefits over other methods developed for measuring diversification benefits. Section 2.1 i) shortly surveys the methodological literature on economies of scope, its generalizations and extensions[5], ii) points out the merits of the approach developed by Chavas and Kim (2010) and motivates its application. Following Tone (2002) the joint production of heat and power is modelled by a nonparametric cost-based production technology estimated with Data Envelopment Analysis (DEA). Estimates of the cost frontier are derived and used to evaluate economies of diversification at all observed output vectors. In addition to the analysis of diversification economies, cost efficiency of Austrian biogas plants is evaluated.

As outlined by Pope and Johnson (2013) economies of scope have been of interest and estimated for a variety of industries including agriculture (Paul and Nehring 2005), transportation (Rawley and Simcoe 2010; Growitsch and Wetzel, 2009), healthcare (Preyra and Pink, 2006), education (Sav, 2004), banking (Ferrier et al., 1993), R&D (Arora et al., 2009; Chavas et al., 2012), semiconductor manufacturing (Macher, 2006) and telecommunication (Evans and Heckman, 1984). Bruno (2011) provides a literature review on economies of scope estimated for public utilities in the energy, telecommunications and water sector. As far as the author knows, Kwon and Yun (2003) and Liu (2015) are the only studies estimating economies of scope for cogeneration systems. While Kwon and Yun (2003) examine scope economies of relatively large cogeneration units[6], this is the first study on economies of diversification for small-scaled, renewable-fuelled cogeneration plants and for biogas plants in particular.

The contribution of this work to the literature is fourfold: i) it is the first study applying the method proposed by Chavas and Kim (2010) and it generates interesting insights regarding the usefulness and the limitations of this approach; ii) the paper also provides a theoretical contribution by extending the decomposition of economies of diversification introduced by Chavas and Kim (2010). The method of Chavas and Kim (2010) allows identifying the sources of economies of diversification by decomposition into a scale, convexity, complementarity and a fixed cost effect. In this study, economies of diversification, as well as the scale, convexity, and complementarity effect are further decomposed into input cost saving components. This allows identifying the contribution of each input to total cost saving arising from diversification. In addition, the role of each input in generating synergies among outputs, scale economies and convexity effects is analyzed; iii) as far as the author knows this the second attempt after Filler et al. (2007) to evaluate cost efficiency of biogas plants; iv) finally, this study adds to the literature on estimating economies of scope for cogeneration systems.

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5. Section 2.1 clarifies that economies of scope is a special case of the more general measure of economies of diversification introduced by Chavas and Kim (2010).

6 The electricity (heat) output of the average plant in the study of Kwon and Yun (2003) is nearly ten-times (1000-times) as large as in the sample of this study.

The paper proceeds as follows: Section 2 motivates the choice of the methodology and gives a detailed description of the methods applied. Section 3 presents the data and motivates the sample selection. Section 4 reports the results on cost efficiency and economies of diversification for biogas-fuelled cogeneration plants and section 5 concludes with a short review of the results, its implications and avenues to future research.

2. Methodology

2.1 Motivation and Literature

The concept of economies of scope stems from Panzer and Willing (1981) and Baumol et al. (1982). Economies scope exist if the total costs of producing a bundle of $k \geq 2$ goods in two or more completely specialized firms is higher than the cost of producing this bundle of goods in a single firm. Thus, the concept of Panzer and Willing (1981) and Baumol et al. (1982) relies on the comparison of k completely specialized firms with orthogonal output vectors – that is each firm produces a single output - to a large firm producing the sum of all k outputs.

Measuring economies of scope requires data on the stand-alone costs of production for each output. Since data on completely specialized firms (or stand alone production) is not always available the classic definition of economies of scope has been generalized and extended. These measures are referred to e.g. as expansion path subadditivity (EPSUB) in Berger et al. (1987), economies of scope in Preyra and Pink (2006) or economies of diversification[7] in Ferrier et al. (1993) as well as Chavas and Kim (2010), and include the classic measure of economies of scope as a special case. While the aforementioned generalized measures of economies of scope use less specialized regions of the cost function and allow evaluating the cost of partial specialization, economies of scope focuses on measuring the cost of complete specialization.

While complete specialization is only relevant in a number of special cases (e.g. Kwon and Yun, 2003), partial specialization is the dominant pattern shown by the data analysed in this study. This study investigates the potential diversification benefits for biogas-fuelled cogeneration systems having two outputs, electricity and heat. Only six out of 86 plants are completely specialized in electricity production and plants completely specialized in heat production are non-existent. Most of the plants in this sample are generating some amount of electricity and heat. As pointed out by Evans and Heckman (1984), when data on completely specialized firms is unavailable these areas of the cost function may not be well characterized. Therefore, as specialization is a matter of degree, evaluating the cost of partial specialization seems to be appropriate.

As pointed out by Pope and Johnson (2013) the generalized measures of economies of scope (e.g. Berger et al. 1987, Ferrier et al. 1993, Preyra and Pink 2006) share the common criticism that they reflect an aggregation of several distinct effects. In addition, the approach of Ferrier et al. (1993) rules out the possibility of diseconomies of diversification. Chavas and Kim (2010) introduce an approach for measuring economies of diversification, which i) allows for partial specialization, ii) allows for diseconomies of diversification and ii) provides a

[7] Note that the definition of economies of diversification introduced by Ferrier et al. (1993) is a special case of EPSUB and is different to the definition of economies of diversification introduced by Chavas and Kim (2010). Throughout this paper the term economies of diversification is used in the sense of Chavas and Kim (2010).

decomposition of economies of diversification into complementarity among outputs, economies of scale, convexity effects, and fixed cost effects.[8] For that reasons, the generalization and decomposition of economies of scope proposed by Chavas and Kim (2010) is the appropriate method for this study, aiming to analyse the benefits of jointly producing electricity and heat in cogeneration plants.

2.2 Conceptual model

The conceptual model presented in this study is based on the generalization and decomposition of economies of scope presented in Chavas and Kim (2010). This approach requires an empirical estimation and assessment of the cost function or cost frontier. First, this section presents i) measures of economies of diversification and ii) the decomposition of economies of diversification introduced by Chavas and Kim (2010), as well as an extension developed by the author. Second, this section outlines the empirical estimation of iii) the cost frontier and iv) cost efficiency.

2.2.1 Measuring economies of diversification

Consider a firm with a vector $x = (x_1,..., x_M)$ reflecting *M* inputs consumed for producing a vector of *S* outputs $y = (y_1,..., y_S)$, where prices of inputs are given by a vector $w = (w_1,..., w_M)$. Assume, that the outputs $y = (y_1,..., y_S)$ of the original firm are strictly positive: $y_S > 0$, $\forall\ s = 1,..., S$. For now, it is assumed that the cost function is known. It describes the minimal cost for producing a given amount of feasible outputs, *y*. The minimal cost for producing the outputs of the original firm is given by $C(y)$. The approach introduced by Chavas and Kim (2010) investigates under what conditions the multiproduct firm would gain (or lose) from reorganizing its production activities in a more specialized way. The reorganization involves breaking up the firm into *K* specialized firms, $2 \le K \le S$. Let $y^k = (y_1^k,..., y_S^k)$ denote the outputs produced by the *k*-th specialized firm, $k = 1,..., K$.[9] To keep the analysis meaningful the aggregate outputs of the *K* specialized firms amount to the outputs of the original firm, that is $\sum_{k=1}^{K} y^k = y$. The minimal cost for producing the output of the *k*-th specialized firm is given by $C(y^k)$. Chavas and Kim (2010) compare the cost of the original firm versus the costs of *K* "more specialized" firms. In this context, consider the following measures, evaluating the benefits of output diversification:

$$S^1(y) \equiv \sum_{k=1}^{K} C(y^k) - C(y) \tag{1a}$$

$$S^2(y) \equiv \frac{S^1}{C(y)} = \frac{\sum_{k=1}^{K} C(y^k) - C(y)}{C(y)} \tag{1b}$$

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[8] While the measure for economies of diversification and its decomposition introduced by Chavas and Kim (2010) relies on estimating a cost function or cost frontier, a related measure for economies of scope developed in Chavas and Kim (2007) relies on production function/frontier estimates and only requires physical input data.

[9] Each of the *K* specialized firms is "more specialized" than the original firm, that is $y^k \neq y/K$ and produces some positive output, $y^k \neq 0$.

Economies of diversification exist if $S^i > 0$, $i = 1,2$. That is the cost of producing the output vector y in K specialized firms is higher than in an integrated firm. This identifies the presence of synergies or positive externalities in the production process among outputs. Diseconomies of diversification exit if $S^i < 0$, $i = 1,2$, which means that the cost of producing the output vector y in K specialized firms is lower than in the original, integrated firm. While S^1 is measured in monetary units, S^2 is a unit-free measure, which reflects the proportional reduction in cost obtained by producing outputs y in a single integrated firm as compared to K specialized firms.

Note that S^i, $i = 1,2$, depends on the pattern of specialization supposed for the K specialized firms. As pointed out by Chavas and Kim (2010) economies of diversification can involve any pattern of specialization, which fulfil the restriction $\sum_{k=1}^{K} y^k = y$. Following Chavas and Kim (2010), this study examines the benefits of diversification focusing on a particular pattern of specialization, as described in Appendix A.1. This pattern of specialization relies on parameters $(\beta_1,...,\beta_K)$, where $\beta_k \in (1/K,1]$ measures the degree to which the k-th firm is specialized in the production of one or more of the outputs $s = 1,...,S$. The approach of Chavas and Kim (2010) also allows for a set of outputs $i \in I_B$ that no particular firm specializes in.[10] Where in such a case I_B is non-empty and $K < S$, this study focuses on situations where I_B is empty. In addition we consider a system with two outputs, where $S = K = 2$. That means that the original output vector is produced by two specialized firms, each specialized in the production of one of the outputs. As discussed in Appendix A.1, the degree of specialization of the k-th firm increases with β_K. The pattern of specialization described in Appendix A.1 includes as a special case the situation where $\beta_K = 1$, $\forall\ k = 1,...,K$, and I_B is empty. This is the case of complete specialization investigated by Panzar and Willing (1981) and Baumol et al. (1982). For a given pattern of specialization $\beta = (\beta_1,...,\beta_K)$ equation (1a) and (1b) become

$$S^1(y,\beta) \equiv \sum_{k=1}^{K} C(y^k(\beta)) - C(y) \tag{2a}$$

$$S^2(y,\beta) \equiv \frac{S^1(y,\beta)}{C(y)} = \frac{\sum_{k=1}^{K} C(y^k(\beta)) - C(y)}{C(y)} \tag{2b}$$

Equation (2a) and (2b) provide a measure for the benefits of diversification associated with the specialization scheme β.

2.2.2 Decomposing economies of diversification

As pointed out by Pope and Johnson (2013) the extended and generalized measures of economies of scope relying on partial specialization schemes (e.g. Berger et al. 1987, Ferrier et al.

[10] If I_B is non-empty the production of the outputs $i \in I_B$ is equally divided among the K specialized firms, where each specialized firm $k = 1,...,K$ produces $y_i^k = y_i / K$.

1993, Preyra and Pink 2006) usually reflect an aggregation of several distinct effects. Chavas and Kim (2010) are aware of that and provide a decomposition of S^1, which is easily carried over S^2. The benefits (losses) of diversification are decomposed into four additive components as follows:

$$S^1(y,\beta) \equiv S_c + S_R + S_V + S_f \tag{3a}$$

Using the fact that $S^2 = S^1/C(y)$ the decomposition for S^2 can be derived from (3a):

$$S^2(y,\beta) = \frac{S^1}{C(y)} \equiv \frac{S_c}{C(y)} + \frac{S_R}{C(y)} + \frac{S_V}{C(y)} + \frac{S_f}{C(y)} \tag{3b}$$

The derivation of the decomposition in (3a) is available in Appendix A.2. S_c is the complementarity effect. $S_C > 0$ if complementarity among outputs $y = (y_1,..., y_S)$ exist, that is the increase of some output tend to reduce the marginal cost of producing other outputs. Intuitively, S_C assesses the role of synergies between production processes.

The term S_R reflects scale effects. Specialized plants are a subset of integrated plants and hence specialized firms are always smaller in terms of aggregate output than integrated plants. Comparing the costs of plants with different size involves that increasing returns to scale (decreasing returns to scale) could generate benefits (losses) of diversification. Indeed, S_R depends on returns to scale of the production technology (Chavas and Kim, 2010): the term S_R i) vanishes under constant returns to scale, ii) is positive under increasing returns to scale and iii) negative under decreasing returns to scale. This illustrates the role of returns to scale in the determination of diversification economies (cf. Pope and Johnson, 2013).

S_V captures convexity effects and depends on the convexity/concavity property of the cost function $C(y)$ in y (Chavas and Kim, 2010): the term S_V is i) non-negative when $C(y)$ is convex in y, ii) zero when $C(y)$ is linear in y and iii) negative when the $C(y)$ is concave in y. Intuitively, a convex cost function implies that marginal costs tend to increase with increasing outputs along the same hyperplane.

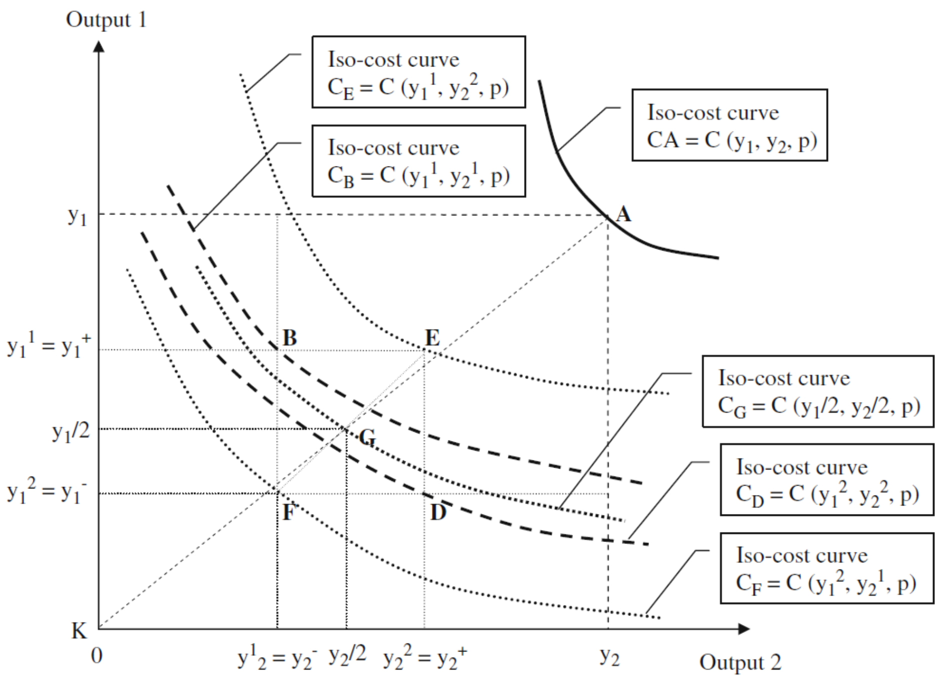
S_f reflects the effects of fixed costs on diversification economies. Since we consider long-run cost functions where all costs are adjustable, fix costs do no play a role in this analysis. In addition, Chavas and Kim (2010) show that partial specialization and $y_i > 0$, $\forall \; i = 1,..., S$ imply that $S_f = 0$.

In the absence of fixed costs economies of diversification can arise from complementarity among outputs, from increasing returns to scale, and/or from convex cost functions. Chavas and Kim (2010) show that under complete specialization and in the absence of fixed costs the scale effects and the convexity effects always cancel each other. In such a situation, considered e.g. by Baumol et al. (1982) or Kwon and Yun (2003), positive complementarity effects are necessary and sufficient to imply economies of scope. However, under partial specialization, as considered in this study, the presence of complementarity among outputs is not sufficient to generate benefits of diversification. For instance, strong decreasing returns to scale $(S_R < 0)$ and concave cost functions $(S_V < 0)$ could generate losses of diversification $(S^i < 0)$, even in the presence of positive complementarity effects $(S_C > 0)$.

2.2.3 A graphical illustration

To clarify the underlying concept of this study, Figure 1 provides and graphical illustration of the measure and decomposition of economies of diversification. An integrated firm with two outputs $(S = K = 2)$ is considered, which is broken into two specialized firms $k = 1,2$. Each of the specialized firm is specialized in the production of one of the outputs. Fixed costs are assumed to be zero. C_X is the cost function evaluated in point *X=A,…,G* in Figure 1. The integrated firm produces the output vector $y = (y^1, y^2)$ given by point *A*. The production vector of the specialized i) plant $k = 1$ is represented by $y^1 = (y_1^1, y_2^1)$ or point *B* and ii) plant $k = 2$ is given by $y^2 = (y_1^2, y_2^2)$ or point *D*. Where plant $k = 1$ is specialized in the production of output 1, producing two thirds of output 1 of the original firm $(\beta_1 = 2/3)$. Plant $k = 2$ is specialized in the production of output two, producing slightly less than two thirds of output 2 of the original firm $(\beta_2 < 2/3)$. Note that for any pattern of specialization $y^1 + y^2 = y$ has to hold. Therefore, the specialization pattern $\beta = (\beta_1 = 2/3, \beta_2 < 2/3)$ determines that plant i) $k = 1$ produces slightly more than one third of output two of the original firm and ii) $k = 2$ produces exactly one third of output one of the original firm.

Figure 1: Measuring and decomposing economies of diversification (with $y_i = y_i^1 + y_i^2$, $i = 1,2$).



Source: Chavas and Kim (2010)

Measuring the benefits of diversification involves comparing the costs of point *A* (production costs of the integrated firm) to the sum of the costs of point *B* and point *D* (production costs of the two specialized firms). According to equation (2a) economies of diversification is measured as $S^1=C_B+C_D-C_A$.[11] Alternatively, this can be written as $S^1=[(C_B-C_F)-(C_E-C_D)]+(2C_G-C_A)+(C_E+C_F-2C_G)$. With $S_C=[(C_B-C_F)-(C_E-C_D)]$, $S_R=(2C_G-C_A)$, $S_V=(C_E+C_F-2C_G)$ and $S_f=0$ by assumption, this is the decomposition given in equation (3a).

The complementarity effect is given by $S_C=[(C_B-C_F)-(C_E-C_D)]$. S_C measures how the marginal cost of y_1 varies with y_2. (C_B-C_F) evaluates the marginal cost of y_1 at y_2^- and (C_E-C_D) the marginal cost of y_1 at y_2^+.[12] If the marginal cost of y_1 decreases as y_2 increases $(C_B-C_F)>(C_E-C_D)$ and it follows that $S_C>0$.[13]

$S_R=(2C_G-C_A)$ is derived by comparing the costs of two small plants (C_G), each producing half of the outputs of the original firm, with the cost of the original plant (C_A). It evaluates whether the cost of producing the original output in a large integrated firm is lower (higher) than in two half-sized plants with the same pattern of specialization as the original plant. If the cost of the large firm is smaller (larger) than the sum of the costs of the small plants the scale effect is positive (negative) and increasing (decreasing) returns to scale prevail. Since the scale effect is calculated without considering (C_B) and (C_D) it is independent of the pattern of specialization β.

Finally, $S_V=(C_E+C_F-2C_G)$ is the convexity effect. It evaluates the convexity (concavity) of the cost function C_X along the hyperplane *FGE*.[14]

2.2.4 Decomposing the decomposition into input cost saving components

The measure of Chavas and Kim (2010) can be easily extended to evaluate the contribution of each input to the benefits (losses) of diversification. The minimal cost for producing an output vector y can be written as $C(y)=C_1^*(y)+...+C_M^*(y)$. The vector elements in $C^*(y)=(C_1^*(y),...,C_M^*(y))\in\Re_+^M$ represent the cost of each input $m=1,...,M$ required for producing y at minimal total cost. Similar, the minimal cost evaluated at outputs y^k of specialized

[11] According to equation (2b) economies of diversification is measured as $S^2=(C_B+C_D-C_A)/C_A$.

[12] To be more precise, (C_B-C_F) evaluates the cost of increasing y_1 from y_1^- to y_1^+ at y_2^-. Similar, (C_E-C_D) describes the cost of increasing y_1 from y_1^- to y_1^+ holding y_2 constant at y_2^+. If the cost function is twice continuously differentiable, Chavas and Kim (2010) show that $S_c=[(C_B-C_F)-(C_E-C_D)]$ indeed depends on how the marginal cost of output one changes as output two increases. This corresponds to the definition of complementarity among outputs as introduced by Baumol et al. (1982, pp. 74-79).

[13] Note that S_C can be rewritten as $S_c=[(C_B-C_E)-(C_F-C_D)]$, which evaluates how the marginal cost of y_2 varies with y_1.

[14] Note that by definition:

$$\theta C_E+(1-\theta)C_F=\theta C(y_1^1,y_2^2)+(1-\theta)C(y_1^2,y_2^1)\begin{Bmatrix}\geq\\=\\\leq\end{Bmatrix}C(\theta(y_1^1,y_2^2)+(1-\theta)(y_1^2,y_2^1)) \text{ when the cost function is } C_X \text{ is } \begin{Bmatrix}convex\\linear\\concave\end{Bmatrix} \text{ in } y=(y_1,y_2), \text{ for } \theta\in[0,1].$$

Choosing $\theta=1/2$ the right hand side of the (in)equation above becomes C_G and it follows:

$$\frac{1}{2}C_E+\frac{1}{2}C_F\begin{Bmatrix}\geq\\=\\\leq\end{Bmatrix}C_G\Leftrightarrow C_E+C_F\begin{Bmatrix}\geq\\=\\\leq\end{Bmatrix}2C_G\Leftrightarrow S_V\begin{Bmatrix}\geq\\=\\\leq\end{Bmatrix}0, \text{ when the cost function } C_X \text{ is } \begin{Bmatrix}convex\\linear\\concave\end{Bmatrix} \text{ in } y=(y_1,y_2).$$

plants $k = 1,...,K$ is given by $C(y^k) = C_1^*(y^k) + ... + C_M^*(y^k)$ and the individual input cost components are summarized in the vector $C^*(y^k) = (C_1^*(y^k),...,C_M^*(y^k)) \in \Re_+^M$. The solution of the optimization problem (5) in section 2.3.1 gives the individual input cost components $C_1^*(y),...,C_M^*(y)$. The contribution of each input $m = 1,...,M$ to cost reductions (cost increases) associated with diversification is measured by:

$$S_m^1(y) = \sum_{k=1}^{K} C_m^*(y^k) - C_m^*(y), m = 1,...,M \tag{4a}$$

$$S_m^2(y) = \frac{S_m^1(y)}{C_m^*(y)} = \frac{\sum_{k=1}^{K} C_m^*(y^k) - C_m^*(y)}{C_m^*(y)}, m = 1,...,M \tag{4b}$$

$S_m^i(y) > 0$ ($S_m^i(y) < 0$), $i = 1,2$, indicates that input *m* positively (negatively) contributes to economies of diversification. Similar to (1a) and (1b), (4a) represents a monetary measure and (4b) describes the proportional reduction in input cost $m = 1,...,M$, obtained by producing outputs *y* in a single integrated firm as compared to *K* specialized firms. Clearly, the sum of each individual input cost savings has to coincide with the benefits of diversification in equation (3a), that is $\sum_{m=1}^{M} S_m^1(y) = S^1(y)$.

Equivalently to the overall measure above, the components of economies of diversification in equation (3a) can be further decomposed. This allows evaluating the contribution of each input to i) complementarity among outputs, ii) (dis)economies of scale, and iii) convexity effects. The contribution of each input $m = 1,...,M$ to S_i, *i=C,R,V* is denoted as $S_{i,m}(y)$. All individual input cost saving components have to sum up to the overall complementarity, scale and convexity effect. That is $\sum_{m=1}^{M} S_{i,m} = S_i$, for all *i=C,R,V*. The formulas for calculating $S_{i,m}(y)$ for *i=C,R,V* and $m = 1,...,M$ are available in Appendix B.

$S_{C,m|} > 0$ shows that input *m* is a joint input in the production of outputs *y* and positively contributes to the complementarity among outputs. $S_{C,m}$ quantifies the cost saving effects from the jointness of input *m* in the production of outputs *y*. $S_{R,m|} > 0$ ($S_{R,m|} < 0$) indicates that the costs for input *m* increase less (more) than proportionally as output/plant size increases. Therefore, (dis)economies of scale for input *m* exist and input *m* positively (negatively) contributes to the scale effect S_C. $S_{V,m|} > 0$ ($S_{V,m|} < 0$) if input *m* positively (negatively) contributes to the convexity effect.

2.3 Empirical Implementation

2.3.1 Estimating the cost frontier

The cost function can be estimated using either econometric (parametric) or mathematical programming (non-parametric) approaches. In this study empirical estimates of the cost frontier are obtained by applying a non-parametric, linear-programming approach, commonly known as data envelopment analysis (DEA), for several reasons: In contrast to parametric techniques, DEA allows estimating the cost frontier without input price data and it does not require assuming a functional form of the cost function, which is an unnecessarily strong assumption (Pope and Johnson, 2013). DEA constructs a cost frontier based on the assumptions of i)free disposability (monotonicity), ii) no free lunch as well as iii) closed, non-empty and convex production technology sets (see Briec et al., 2004).

A property of the analysed data is that only cost values are available. It is not possible to split the value data into quantities and prices. Furthermore, prices are different across plants, e.g. heterogenous feedstocks with various prices are used. In such a situation Portela (2014) and Sahoo et al. (2014) suggest to estimate the cost frontier/cost efficiency with value data using a cost-based production technology introduced by Tone (2002). In line with Tone (2002) it is assumed that the cost-based production technology (production possibility set) T models the transformation of costs, $C \in \Re_{+}^{M}$, into outputs, $y \in \Re_{+}^{S}$, $T=\{(C,y)$: C can produce $y\}$. This means the production possibility set consists of the set of all feasible cost/output vectors. The cost frontier is defined as $C(y) = \min_C \{eC : (C, y) \in T)\}$, where $e \in \Re_{+}^{M}$ is a row vector with all elements being equal to one. This means, for a given $y \in \Re_{+}^{S}$ the cogeneration plant chooses a feasible cost vector $C^{*}(y),$ so as to minimize total cost given by $C(y) = eC^{*}(y).$ This approach implies that minimal costs might only be achieved if both, physical inputs and prices can be adjusted.[15]

Assume we observe $j = 1,..., n$ plants, where each plant uses $m = 1,..., M$ inputs given by the vector $x_j = (x_{1j},..., x_{Mj})$ to produce $s = 1,..., S$ outputs reflected by $y_j = (y_{1j},..., y_{Sj})$. The prices of the inputs are given by the vector $w_j = (w_{1j},..., w_{Mj})$ and the cost of each input m $(C_{mj} = w_{mj} x_{mj})$ is represented by the vector $C_j = (x_{1j} w_{1j},..., x_{Mj} w_{Mj}) = (C_{1j},..., C_{Mj})$. For each observation inputs, outputs and prices are non-negative. The evaluation of the cost frontier to derive the minimal expenditures required for the production of a given output vector $\tilde{y} = (\tilde{y}_1,..., \tilde{y}_S)$ can be reduced to a linear program in which the following optimization problem is solved:

$$\min_{\lambda, C} eC = \sum_{m=1}^{M} C_m$$

s.t. $C_m \geq \sum_{j=1}^{n} \lambda_j C_{mj}, \forall m = 1,...M$

[15] As pointed out by Portela (2014) a plant can only achieve the minimum costs if the plant can to some extent influence the prices it pays for the inputs. Biogas plants can influence input prices by switching to different feedstock types. While such price changes reflect qualitative differences in feedstock, input markets also allow biogas plant operators to impact prices via negotiations.

$$\tilde{y}_s \le \sum_{j=1}^{n} \lambda_j y_{sj}, \forall s = 1,...,S$$

$$\sum_{j=1}^{n} \lambda_j = 1;\ \lambda_j \ge 0, \qquad (5)$$

Among the weights λ_j, the decision variables of this problem are the individual input cost components. Summing up the optimal input cost components $C_1^*,...,C_M^*$ gives the minimal total cost for producing $\tilde{y}$. Evaluating the cost frontier (minimal cost) at appropriate output bundles, is all what is needed for calculating economies of diversification and its decomposition. The constraint $\sum_{j=1}^{n} \lambda_j = 1$ allows for increasing, decreasing and constant returns to scale.[16] It provides the basis for investigating the scale effect S_C and convexity effects S_V in (3a). Assuming CRS would imply zero scale and convexity effects. Note that the cost-based production possibility set T[17] is convex and hence the cost frontier is convex in y. This means that $S_V > 0$ by assumption and its contribution to economies of diversification can only be positive. Assuming a non-convex production possibility set would allow for negative convexity effects.

2.3.2 Estimating cost efficiency

According to Tone (2002), the cost efficiency score for each plant is obtained by the following steps: First, solve the linear program (5) for the observed output vector y_j of the plant under investigation. This gives the minimal cost (target cost), $eC^*(y_j)$, for producing the observed output y_j. Second, the cost efficiency score is obtained by dividing the minimal cost, $eC^*(\mathrm{y_j})$, through the observed cost of plant j producing y_j, eC_j, and is defined as $\gamma_j^* = \frac{eC^*(y_j)}{eC_j} = \frac{C(y_j)}{eC_j}$, where $0 < \gamma_j^* \le 1$. Cost efficient plants with $\gamma_j^* = 1$ are producing at minimal cost and are located on the boundary of T. Cost inefficient plants with $\gamma_j^* < 1$ are in the interior of T. $1 - \gamma_j^*$ measures the distance of the observed cost of plant j to the cost frontier (minimal cost). For instance, a score $\gamma_j^* = 0.9$ indicates that producing y_j can be achieved with 10% lower costs.

3. Data and Empirical Model

The data in this analysis comes from the Austrian Compost and Biogas Association (ACBA). The ACBA collects data via online questionnaires filled in by biogas plant operators. The collected data include detailed information on technical characteristics of the biogas plants, economic data as well as material and energy flows. The sample consists of 86 biogas plants for the year 2014.

16 "However, in our case the term "returns to cost" seems to be more appropriate, since we are dealing with a production possibility set that is defined based on a relationship between input costs and outputs" (Tone, 2002).

17 $T = \left\{ (C, y) : C_m \ge \sum_{j=1}^{n} \lambda_j C_{mj}, \forall m = 1,..., M; y \le \sum_{j=1}^{n} \lambda_j y_{sj}, \forall s = 1,..., S; \lambda_j \ge 0, \forall j = 1,...n; \sum_{j=1}^{n} \lambda_j = 1 \right\}$

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

This study restricts the sample to agriculture biogas plants (using e.g. maize, animal manure and other energy crops as feedstock) solely using the biogas for generating electricity and heat in a CHP. Biogas plants which i) upgrade the biogas to biomethane, ii) use waste as feedstock and iii) do not use surplus heat are excluded. Thereby the sample reduces to 67 agricultural biogas plants, covering about 25% of the installed electric capacity of Austrian biogas plants in 2014.

The main reason for restricting the sample is to avoid zero values in our analysis. That is, 19 plants are excluded to avoid zero output values for, heat, waste or biomethane. The method introduced by Chavas and Kim (2010) assumes that all outputs are strictly positive. An unwelcome effect of zero output values is, at least in the two output case, that the complementarity effects are zero by definition (see section 2.2) and do not have an economically meaningful interpretation. Furthermore, reducing sample heterogeneity with respect to plant type and operating conditions increases the comparability of plants within the sample.

Table 1: Selection and description of input and output variables

Variables	Description
Inputs	
Capital costs (EUR)	Depreciation of the capital stock over 13 years. Capital stock includes e.g. CHP, digesters, power grid connection, district heating grid (connection), ...
Labour costs (EUR)	Working hours for operating and managing the plant multiplied by a wage of 21.5 EUR per hour
Feedstock costs (EUR)	Include harvesting and transport of the feedstock as well as digestate handling
Other costs (EUR)	Include insurance, maintenance and other costs
Outputs	
Electricity sold (kWh_{el})	Amount of Electricity sold generated by the CHP
Heat sold (kWh_{th})	Amount of Heat sold generated by the CHP

This study selects four inputs and two outputs for estimating the cost frontier and cost efficiency. Those inputs and outputs are summarized in Table 1. Descriptive statistics on the variables used in this analysis are available in Table 2.

The capital stock reflects the sum of all investments from starting plant operation until the end of the year 2014. Capital includes digesters, digester heating, CHPs, stirrers and pumps, other machinery, power grid connection, local and district heating grid (connection) as well as others.

Assuming that the biogas plant depreciates over 13 years, the capital costs are calculated by dividing the capital stock through 13.[18]

Labour costs are estimated by multiplying the working hours for operating and managing the plant by an hourly wage of 21.5 EUR. The hourly wage is based on information released by the Austrian Federal Ministry of Agriculture, Forestry, Environment and Water Management (BMLFUW, 2015). Unluckily, the data from the ACBA only includes labour hours but no information on hourly wages or total labour costs.

Feedstock costs constitute a major part of total costs. On average the share of feedstock costs in total costs amounts to 44%, followed by other costs (25%), capital costs (23%) and labour costs (8%). However, the share of feedstock costs in total costs ranges from 13% to 62%. This large variation partly reflects the heterogeneity in applied feedstock or feedstock prices. While the use of energy-rich energy crops such as maize is very cost-intensive, the application of low-energy animal manure and crop residuals is far less costly. Maize is the dominant feedstock in our sample accounting for 55% of feedstock input (energy related) on average. Note, that feedstock costs include costs for harvesting and transporting the feedstock as well as costs for digestate handling.

Other costs include maintenance costs, insurance costs and other costs. Costs for electricity and heat consumption are excluded from the analysis due to missing or poor price data. As documented in BMLFUW (2015) the share of electricity costs in total costs is negligible (less than 1%).

Table 2: Descriptive statistics of variables used for DEA

Variables	Mean value	Standard deviation	Minimum	Maximum
Inputs				
Capital costs (EUR)	103,025	70,649	15,749	441,139
Labour costs (EUR)	32,859	20,079	6,784	122,937
Feedstock costs (EUR)	230,387	173,327	18,200	794,468
Other costs (EUR)	121,553	83,053	6,900	367,510
Outputs				
Electricity sold (kWh_{el})	2,249,752	1,659,471	114,568	8,760,670
Heat sold (kWh_{th})	1,457,774	1,262,616	70,000	6,584,899
Other Variables				
Herfindahl index	0.56	0.08	0.50	0.81
Size (Capacity, kW_{el})	299	215	55	1,000

Note: The sample size is 67.

Since this analysis focuses on cogeneration units and potential diversification benefits associated with the joint production of electricity and heat, the output measures include electricity sold and heat sold. From the original sample of 86 biogas plants, six plants are completely specialized in electricity production without any heat output. Those plants are excluded to avoid zero output values and to simplify the analysis. There are no plants completely specialized in heat

[18] All biogas plants under investigation receive a feed-in tariff for electricity generation, which is guaranteed for 13 years under the Austrian green electricity law and green electricity act. Since operation under market conditions is not viable in most cases, a depreciation period of 13 years seems to be appropriate (see BMLFUW, 2015).

production. Partial specialization is the dominant pattern in the sample. That is most of the plants in the original sample are selling some amount of electricity and heat. In the selected sample the average electricity output accounts for 62% of total output, indicating that the cogeneration plants in this sample are primarily designed to produce electricity. Only 11 plants show a mild and partial specialization in heat production with heat output exceeding electricity output. As a direct measure of specialization degree, a Herfindahl index is calculated. The sample mean of the Herfindahl index for the selected sample is about 0.56, which indicates a high degree of diversification. The large variation of inputs and outputs in Table 2 partly reflects the differences in size across biogas plants. The installed electric capacity reaches from 55 kW_{el} for the smallest to 1000 kW_{el} for the largest cogeneration system.

A shortcoming of the data is that only value cost data for estimating the cost frontier and cost efficiency is available. It is not possible to split the value cost into quantities and prices. Furthermore, prices are different across plants, e.g. feedstocks with various prices are used. In such a situation where prices are unknown and different across plants Portela (2014) suggests to estimate cost efficiency using value cost data, but technical efficiency should not be computed from cost data. In line with Portela (2014) we choose the cost efficiency model introduced by Tone (2002) for estimating cost efficiency (see section 2). Unluckily, the data do not allow decomposing cost efficiency into technical and allocative efficiency. Note that the approach of Tone (2002) takes price inefficiencies into account. That is cost inefficiencies are partly attributable to excessive prices paid for inputs. This implies that the minimum cost target for a plant is only achievable if the plant can to some extent influence the prices it pays for the inputs (Portela, 2014).

4. Empirical Results

4.1 Cost efficiency

The upper part of Table 3 shows the distribution of cost efficiency scores and the lower part of Table 3 some summery statistics of cost efficiency scores. Plants are grouped by size into ranges of less or equal 100 kW_{el} (very small), between 100 and less or equal 250 kW_{el} (small), between 250 and less or equal 500 kW_{el} (medium) and above 500 kW_{el} (large).

Table 3: Distribution of cost efficiency scores under different plant sizes

		Size (installed electric capacity, kW_{el})			
		≤ 100	100 to ≤ 250	250 to ≤ 500	> 500
Share of efficient plants		0.05	0.05	0.10	0.29
Share of plants with efficiency:	0.9 to 1.0	0.00	0.05	0.05	0.29
	0.8 to 0.9	0.05	0.11	0.20	0.29
	0.7 to 0.8	0.14	0.21	0.45	0.00
	0.6 to 0.7	0.33	0.32	0.20	0.14
	0.5 to 0.6	0.33	0.26	0.00	0.00
	below 0.5	0.10	0.00	0.00	0.00
Geometric Mean		0.63	0.69	0.79	0.88
Standard Deviation		0.13	0.13	0.11	0.12
Minimum		0.42	0.54	0.64	0.69
Maximum		1	1	1	1
Number of obs.		21	19	20	7

Note: The sample size is 67.

The results indicate that average cost efficiency increases with plant size. Through abolishing inefficiencies and operating on the cost frontier very small-, small-, medium- and large-sized plants can save on average 37%, 31%, 21% and 12% of their total costs, respectively. In money values this amounts to 78,601 EUR, 119,011 EUR, 141,605 EUR, and 120,866 EUR, respectively. It is worth to mention that cost efficiency is estimated under the assumption of variable returns to scale. This means that plants of similar size are compared to each other and scale inefficiencies are not included in the estimates presented above. Therefore, increasing cost efficiencies with respect to plant size cannot be traced back to (increasing) returns to scale properties of the production technology but reflect pure technical and allocative inefficiencies.[19]

The analysis shows that in total six out of 65 biogas plants are cost efficient. Those plants operate at the cost frontier with minimal total costs and without improvement potentials. Row four in Table 3 shows that the share (number) of cost efficient plants increases from 5% (1) for very small- as well as small-sized plants to 10% (2) for medium-sized and 29% (2) for large-sized plants. 76% of very small- and 58% of small-sized plants exhibit inefficiencies larger than 30%. For medium- and large-sized plants the share of plants with inefficiencies larger than 30% decreases to 20% and 14%, respectively.

Most of the cost saving potentials outlined in the second paragraph of this section stem from excess feedstock costs and other costs. For very small-sized plants out of 78,601 EUR total average cost saving potential 40,527 EUR come from other costs and 29,676 EUR from feedstock. Or on average cost efficient plants of similar size can produce the same amount of outputs with 69% and 28% lower other costs and feedstock costs, respectively. Similar patterns can be observed for plants in the range of 100 to 250 kW_{el} and 250 to 500 kW_{el}: For small-sized plants out of 119,011 EUR total average costs saving potential, 58,730 EUR (36,052 EUR) come from other costs (feedstock costs). For medium-sized plants out of 141,605 EUR total average costs saving potential, 63,728 EUR (51,302 EUR) come from other costs (feedstock costs). That is small-sized plants can save 53% of other costs and 19% of feedstock costs by abolishing all inefficiencies. For medium-sized plants the corresponding numbers are 35% and 14%. For large-sized plants on average inefficiencies in capital employment (53,553 EUR) make up the largest bulk, followed by other costs (40,647 EUR), feedstock (15,402 EUR) and labour (11,265 EUR). In cost saving rates this means that large-sized plants can save on average 16% of other costs, 12% of capital costs and 7% of labour costs.

4.2 Economies of Diversification

4.2.1 Sources of economies of diversification

Economies of diversification are a property of the underlying production technology. For a given pattern of specialization β, two plants operating under the same technology and producing the same amount of outputs would exhibit i) the same benefits of diversification as measured by equation (2a) or (2b) and ii) the sources of the diversification benefits given by equation (3a) or (3b) would be identical.

However, there is a large heterogeneity among co-generation plants with respect to size and diversification (see Table 2). Those plants are located at different points of the underlying

[19] The concepts of scale, pure technical and allocative efficiency are explained e.g. in Cooper et al. (2006).

production technology and estimates for economies of diversification can vary depending on the point of evaluation. In this study, economies of diversification and its components are evaluated for each plant in the sample at its observed output vector. Summary statistics of these estimates (sample average, standard deviation, minimum and maximum values) are reported in Table 4 and in Appendix C, Table C.1. Table 4 and Table C.1 summarize the level and sources of diversification benefits for different plant sizes and various levels of β.

Table 4 reports the relative measure of diversification benefits as shown by equation (2b) as well as its components given by equation (3b) along with equation (A.3a) to (A.3c). The relative measure of diversification benefits, $S^2=S^1/C(y)$, describes the proportion of costs that could be saved by producing an output vector y (electricity and heat) in an integrated plant compared to two smaller plants, which are more specialized (where the degree of specialization is determined by β). Similar, the components of S^2 which are complementarity ($S_C/C(y)$), scale ($S_R/C(y)$) and convexity ($S_V/C(y)$) effects reflect proportional cost reductions.

Table C.1 presents the absolute gains of diversification given by equation (2a) as well as its sources described by equation (3a) along with equation (A.3a)-(A.3c). S^1 measures the absolute cost savings from producing outputs y in an integrated plant compared to two smaller plants, which are more specialized. $S^1=S_C+ S_R+ S_V$ is decomposed into a complementarity (S_C), scale (S_R) and convexity (S_V) component.

Note that in this analysis the output vector y of the integrated, larger and more diversified plant is the observed output vector of each plant in the sample. The cost of producing this output vector is compared to the cost of producing the same amount of outputs in two smaller but more specialized plants. All costs reflect minimum costs and are evaluated at the cost frontier, which means that cost inefficiencies do not play a role and have no impact on economies of diversification.

To obtain the output vectors of two smaller but more specialized plants y is split into two output vectors, where one output vector is dominated by electricity generation and the other by heat generation. The degree of specialization of the two small plants is determined by β. This study focuses on the cases where $\beta_k = \beta$ is equal to 0.7, 0.8 and 0.9. For instance, $\beta = 0.8$ reflects a situation where one specialized plant produces 80% of electricity output and 20% of heat output of the original firm. The other specialized plant generates 20% of electricity output and 80% of heat output of the integrated firm.

In Table 4 and Table C.1 the level and sources of diversification benefits (losses) under different plant sizes and different specialization patterns, β, are investigated. Columns 2 to 5, 6 to 9, and 12 to 13 in Table 4 show the results for specialization patterns $\beta = 0.7$, $\beta = 0.8$ and $\beta = 0.9$, respectively. For each of these three scenarios, estimates for economies of diversification and its components are presented for different plant sizes. Plants are grouped into four classes according to their installed electric capacity. Estimates for plants in the range of less or equal 100 kW_{el} (very small), between 100 and less or equal 250 kW_{el} (small), between 250 and less or equal 500 kW_{el} (medium) and above 500 kW_{el} (large) are presented in the first, second, third and fourth column of the particular scenario, respectively.

Table 4 shows that on average diversification effects are positive throughout plant sizes and specialization patterns. For $\beta = 0.8$ the estimates indicate that producing outputs in a single integrated firm is associated with average cost reductions of 80%, 37%, 18% and 21% for very small-, small-, medium- and large-sized plants, respectively. Table C.1 shows the corresponding average absolute cost savings amount to 97,701 EUR for very small-, 90,724 EUR for small-, 84,461 EUR for medium- and 207,057 EUR for large-sized plants. A regression analysis[20] indicates that on average relative diversification measures decrease but monetary diversification measures increase with plant size. Both monetary and relative diversification measures increase with the degree of specialization β. The high standard deviations of diversification effects for small- and medium-sized plants indicate that plants in this range are quite heterogeneous. For instance, at $\beta = 0.8$ the minimal cost saving rate for medium-sized plants is negative (-0.02%) and the plant with the highest diversification benefits in that size class saves 43% of total costs by an integrated production of outputs.

Not only the magnitude but also the sources of diversification benefits vary substantially across plant size. For very small plants the main source of diversification benefits comes from the scale component. In the case of β being equal to 0.8, 69% out of 80% of cost reductions are attributable to the scale effect for very small-sized plants. For small-sized plants the scale effect is still positive but less important; for $\beta = 0.8$ 9% out of 37% of cost reductions come from the scale effect. This result indicates that on average plants in the range of 0 to 250 kW_{el} operate under increasing returns to scale. However, the extraordinary high standard deviation of scale effects for small-sized plants indicates the onset of decreasing returns to scale for plants in the range of 100 to 250 kW_{el}. Negative average scale effects for medium- and large-sized plants are found, which suggests that on average these plants operate under decreasing returns to scale. To sum up, the contribution of the scale effect to diversification benefits declines with plant size and becomes, on average, even negative for plants above 250 kW_{el} capacity.

Complementarities in the production of electricity and heat are, on average, the major source of economies of diversification for small-, medium- and large-sized plants. In general, complementarity effects are always positive, and on average the size of the complementarity effect increases with plant scale. Table C.1 shows that the average benefits of jointly producing heat and electricity in an integrated firm, which stems from the complementarity among outputs, amounts to 14,160, 45,201, 79,941, and 265,680 EUR for very small-, small-, medium- and large-sized plants, respectively. These absolute values make up 11%, 17%, 16%, 27% of total costs of the integrated average very small-, small-, medium and large-sized plant.

While the scale effect is not affected by the specialization pattern β, the magnitude of the complementarity effect increases with the level of specialization. This general result is intuitive: when the disintegrated plants become more specialized they give up more benefits of integration implying greater complementarity effects. While the complementarity effect increases with plant size the scale effect works in the opposite direction. At $\beta = 0.7$ ($\beta = 0.8$) for 11 (4) medium- or large-sized plants, which operate under decreasing returns to scale, the negative scale effect

[20] Results are available on request. The independent variables used for the regression analysis are size (see Table 2), the Herfindahl index (see Table 2) and the degree of specialization, β, assumed for the disintegrated plants. Those variables are used to explain the variation in the overall diversification effect as well as the variation in its three components.

Table 4: Relative scope measure (S^2) and its decomposition under different plant sizes

	$\beta = 0.7$				$\beta = 0.8$				$\beta = 0.9$			
	Size (installed electric capacity, kW_{el})				Size (installed electric capacity, kW_{el})				Size (installed electric capacity, kW_{el})			
	≤ 100	100 to ≤ 250	250 to ≤ 500	> 500	≤ 100	100 to ≤ 250	250 to ≤500	> 500	≤ 100	100 to ≤ 250	250 to ≤500	> 500
Diversification effect, $S^2=S^1/C(y)$												
Mean	0.75	0.24	0.05	0.06	0.80	0.37	0.18	0.21	0.85	0.52	0.32	0.38
Standard Dev.	0.08	0.17	0.11	0.07	0.08	0.15	0.15	0.09	0.08	0.14	0.18	0.10
Minimum	0.64	0.05	-0.05	-0.02	0.65	0.18	-0.02	0.11	0.66	0.30	0.08	0.26
Maximum	1.00	0.76	0.24	0.16	1.00	0.84	0.43	0.33	1.00	0.92	0.62	0.52
Complementarity effect, $S_C/C(y)$												
Mean	0.06	0.09	0.09	0.14	0.11	0.17	0.16	0.27	0.15	0.25	0.23	0.37
Standard Dev.	0.05	0.07	0.10	0.09	0.07	0.09	0.14	0.10	0.09	0.12	0.17	0.11
Minimum	0.00	0.00	0.00	0.03	0.00	0.01	0.00	0.14	0.00	0.06	0.03	0.24
Maximum	0.13	0.21	0.25	0.26	0.21	0.32	0.39	0.40	0.28	0.45	0.51	0.54
Scale effect, $S_R/C(y)$												
Mean	0.69	0.09	-0.07	-0.10	0.69	0.09	-0.07	-0.10	0.69	0.09	-0.07	-0.10
Standard Dev.	0.09	0.21	0.04	0.04	0.09	0.21	0.04	0.04	0.09	0.21	0.04	0.04
Minimum	0.58	-0.14	-0.15	-0.15	0.58	-0.14	-0.15	-0.15	0.58	-0.14	-0.15	-0.15
Maximum	1.00	0.60	0.02	-0.04	1.00	0.60	0.02	-0.04	1.00	0.60	0.02	-0.04
Convexity effect, $S_V/C(y)$												
Mean	0.00	0.07	0.03	0.01	0.00	0.12	0.09	0.04	0.02	0.19	0.16	0.10
Standard Dev.	0.00	0.06	0.04	0.02	0.01	0.08	0.05	0.03	0.01	0.10	0.06	0.04
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.09	0.03
Maximum	0.00	0.14	0.14	0.05	0.02	0.22	0.21	0.09	0.04	0.31	0.29	0.14
Number of obs.	21	19	20	7	21	19	20	7	21	19	20	7

Note: The sample size is 67. Economies of diversification are evaluated for each plant at its observed output vector y_j.

dominates the positive complementarity effect and losses of diversification prevail. Most of these plants exhibit low complementarity effects due to the fact that their observed output vector is more specialized (Herfindahl index above 0.6).[21] At high levels of β (e.g. $\beta = 0.9$) estimates of economies of diversification (overall effect) are positive throughout all plants due to strong complementarity components.

Table 4 shows that on average convexity effects are of minor importance for very small- and large-sized plants. Though, for small- and medium-sized plants the convexity component is a non-negligible contributor to economies of diversification. On average, at $\beta = 0.8$ about one half (one third) of the average diversification effect is attributable to the convexity component for medium-sized (small-sized) plants. The convexity effect is positive by assumption and Table 4 shows that the magnitude of the convexity effect increases with β. The regression analysis mentioned before shows that on average convexity effects increase with plant size and level of specialization β. This result might indicate that marginal costs tend to increase faster for larger plants with higher output level.

The analysis shows that overall diversification benefits are positive. Though, the decomposition brings important insights: for plants operating under decreasing returns to scale the diversification benefits from complementarity among outputs are much higher than the overall diversification effect. This is because decreasing returns negatively contribute to the overall diversification effect and in few cases even outweigh the positive complementarity effect. The results illustrate the importance of disentangling generalized measures of economies of scope (e.g. Berger et al. 1987, Ferrier et al. 1993, Preyra and Pink 2006), which deal with partial specialization schemes. While under full specialization the convexity and the scale component always cancel each other and a positive complementarity effect is a necessary and sufficient condition for economies of scope (see Chavas and Kim, 2010), under partial specialization generalized measures of economies of scope are an aggregation of several distinct effects. Not disentangling the effects in the presence of decreasing (increasing) returns to scale and non-convex (convex) cost functions leads to an underestimation (overestimation) of positive synergies between outputs.

4.2.2 Contribution of inputs to economies of diversification

While the previous section analyzes the sources of economies of diversification, this section investigates cost savings from diversification by input. This enables to identify the inputs, which exhibit the largest cost saving potentials when a plant diversifies. Not only the overall diversification effect is decomposed into specific input cost reductions but also the complementartiy, scale and convexity effect. This allows evaluating the jointness of specific inputs in the production of heat and electricity as well as the contribution of individual inputs to scale economies.

Column 5 in Table 5 (Table 6) reports the absolute (relative) average cost savings from diversification for each input as described by equation 4a (4b). Columns 2 to 4 in Table 5 and Table 6 provide the decomposition of the complementarity, scale and convexity effect into input

[21] The (regression) analysis shows a strong negative correlation between the complementarity effect and the Herfindahl index. Ceteris paribus, the estimates of the complementarity effect are decreasing with increasing specialization of the integrated plant.

cost saving components as described by equations (B.1) to (B.3) in Appendix B. The large variation in magnitude and sources of economies of diversification as documented in the previous section is neglected and sample averages are reported in Table 5 and Table 6. Therefore, the last row in Table 5 (Table 6) provides information on the sample average of the monetary (relative) diversification measure presented in equation 2a (2b) and its components given by equation 3a (3b) along with equations A.3a to A.3c in Appendix A. All estimates in this section are based on specialization level $\beta = 0.8$.

The lower row of the last column in Table 5 shows that the average benefits of diversification over 65 plants amount to 103,195 EUR for $\beta = 0.8$.[22] The bulk of this comes from capital (41,148 EUR) and feedstock/fuel (37,047 EUR) cost savings followed by labour (18,793 EUR) and other costs (6,207 EUR).

However, the overall effect hides the role played by the components. As illustrated in the previous section and as shown in the last row of Table 5 complementarities among the joint generation of power and heat constitute the major source of cost savings from diversification (68,877 EUR). The average convexity effect is 26,678 EUR and the contribution of the average scale effect to diversification economies is only of minor importance (7,640 EUR).

Table 5: Contribution of inputs to diversification benefits and components for cogeneration units in Austria (EUR)

Absolute annual cost saving (EUR)	Complementarity Effect, $S_{C,m}$	Scale Effect, $S_{R,m}$	Convexity Effect, $S_{V,m}$	Diversification effect, S_m^1
Capital Cost (*m*=1)	4,621	28,662	7,865	41,148
Labour Cost (*m*=2)	5,709	14,434	-1,351	18,793
Feedstock Cost (*m*=3)	45,151	-20,631	12,527	37,047
Other Cost (*m*=4)	13,396	-14,824	7,636	6,207
Total Cost	68,877	7,640	26,678	103,195

Note: Sample averages of 65 biogas-fuelled cogeneration plants are reported. Economies of diversification are evaluated for each plant at its observed output vector y_j. $\beta = 0.8$. Values are in EUR.

Table 6: Contribution of inputs to diversification benefits and components for cogeneration units in Austria (%)

Relative annual cost saving (%)	Complementarity Effect, $S_{C,m} / C_m^*$	Scale Effect, $S_{R,m} / C_m^*$	Convexity Effect, $S_{V,m} / C_m^*$	Diversification effect, $S_m^2 = S_m^1 / C_m^*$
Capital Cost (*m*=1)	2.22	53.83	8.98	65.02
Labour Cost (*m*=2)	21.54	57.75	-4.99	74.30
Feedstock Cost (*m*=3)	22.29	1.40	6.38	30.07
Other Cost (*m*=4)	19.48	-0.48	8.97	27.96
Total Cost	15.72	20.83	6.61	43.16

Note: Sample averages of 65 biogas-fuelled cogeneration plants are reported. Economies of diversification are evaluated for each plant at its observed output vector y_j. β =0.8. Values are in %.

The last row in column two of Table 6 indicates that if a plant diversifies on average 15.8% of total costs of the integrated plant can be saved due to the presence of complementarities among the production of heat and power. Regarding the cost reduction rates for each input, the

[22] For β=0.9 average diversification benefits increase to 157,060 EUR due to rising complementarity and convexity effects.

largest are found for feedstock (22.3%), labour (21.5%) and other costs (19.5%). Somewhat surprisingly, on average only 2.2% of the capital costs can be saved. In terms of money value column two in Table 5 indicates that by far the most of the average cost savings (68,877 EUR in total) comes from the jointness in fuel (45,151 EUR). Next most results from the jointness in other costs (13,396 EUR), labour (5,709 EUR), and capital (4,621 EUR). Since on average feedstock makes up about 50% of total costs the large monetary savings from the jointness i fuel are not surprising. Though, in addition the cost savings coming from the jointness of other inputs are not negligible.

Unexpectedly, the estimates for the jointness in capital are rather low. This would indicate that the jointenss of capital in the production of power and heat is only of minor importance. However, the low estimates for the jointness in capital – Kwon and Yun (2003) find much larger effects - might be explained by the fact that the capital stock variable includes investments in district heating grids. Therefore, the capital stock not only covers costs for heat generation but also for heat transmission. Whereas strong complementarities among the generation of power and heat stemming from the jointness of capital can be expected (see Kwon and Yun, 2003), capital complementarites among the transmission of electricity and heat do not exit. That might explains the low estimates for the jointness in capital.[23]

The last row of column three in Table 6 indicates that on average 20.8% of total costs of the integrated plant can be saved if two identical small plants merge to one large plant, where the latter produces twice as much output as one small plant but exhibits the same degree of diversification. Whereas this relative average scale effect is quite substantial the average monetary scale effect is negligible (7,640 EUR). As indicated in Table 4, this is because very-small sized plants exhibit strong positive scale effects (increasing returns to scale). For medium- and large-sized plants scale effects are moderately negative (mild decreasing returns to scale). Since the total costs of very-small and small plants carry not much weight relative to larger plants, the overall average scale effect in monetary terms is low but still positive.

Column three in Table 5 and Table 6 show that the big bulk of overall average scale effect comes from savings in capital and labour costs. In terms of money value, average capital cost savings from integrated production compared to production in half-sized plants amount to 28,662 EUR followed by average labour cost savings with 13,323 EUR. On average, the contribution of feedstock (-20,631 EUR) and other costs (-14,824 EUR) to average scale effect is negative. This indicates that on average producing outputs in two small plants generates savings (losses) in feedstock (capital) costs and other (labour) costs compared to a situation where the same amount of outputs is produced in a single integrated plant being twice as large. It shows that on average capital and labour costs (feedstock and other costs) increase less (more) than proportionally as output increases. While on average capital and labour costs positively contribute to economies of scale, feedstock and other costs work in the direction of diseconomies of scale.[24]

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[23] Unluckily, the data does not allow disaggregating the capital stock. Therefore, it is not possible to disentangle investments in power and heat generation from investments in heat transmission (e.g. district heating grid).

[24] For very-small sized plants the contribution of feedstock saving rates to relative scale effects are throughout positive and relatively large (economies of scale in fuel expenditures). Though, the effect becomes moderately negative for small, medium and large-sized plants (diseconomies of scale in fuel expenditures). This explains why the average feedstock saving rate is slightly positive but average feedstock saving measured in money value is strongly negative.

This result is in line with the findings of Skovsgaard and Klinge Jacobsen (2017). In the case of Danish biogas plants they find that economies of scale in capital and operational expenditures dominate the diseconomies of scale from transportation of feedstock and digestate.

Though, on average only 6.61% of total costs can be saved due to convexity effects the average monetary savings amount to 26,678 EUR. While the saving rate is the lowest compared to other sources of economies of diversification, measured in money value the average convexity effect is the second largest source of diversification benefits. This is because on average relative convexity effects are stronger for larger plants with higher total costs and are a less important source of diversification benefits for smaller plants with low total costs.

Colum four in Table 5 and Table 6 indicate that capital, feedstock and other cost savings attributable to the convexity effect are positive but labour expenditures negatively contribute to the convexity effect. This might show that on average plants operate under increasing marginal costs for capital, fuel and other costs but under diminishing marginal labour costs/increasing marginal products of labour. Perhaps on average the employment of labour input is beyond its optimal level.

5. Conclusion

This paper examines economies of diversification[25] for small-scaled, renewable-fuelled cogeneration systems using data from Austrian biogas plants. It is the first study applying the methodology proposed by Chavas and Kim (2010) for analyzing economies of diversification, which allows i) for partial specialization and ii) decomposing economies of diversification into a scale, complementarity and convexity effect. Using 2014 cross-sectional data of 67 Austrian biogas plants a cost frontier is estimated with non-parametric linear programming techniques (Tone, 2002), known as Data Envelopment Analysis (DEA). Based on DEA-estimates of the cost frontier the presence, magnitude and sources of cost benefits arising from diversification are assessed.

First, it is found that economies of diversification among the generation of heat and power exist for biogas-fuelled cogeneration plants. Dependent on the degree of specialization of the replaced system total average cost reductions of more than 43% are estimated.

Second, this relatively large average cost saving potential is driven by huge positive scale effects found for very-small scaled biogas plants (< 100 kW_{el}). Mild average negative scale effects are found for medium and large-sized plants (> 250 kW_{el}). Those results indicate that very-small scaled plants operate under increasing returns to scale and that diseconomies of scale prevail for larger plants. In addition, the analysis shows that on average capital and labour costs positively contribute to economies of scale but feedstock and other costs work in the direction of diseconomies of scale. This is in line with the findings of Skovsgaard and Klinge Jacobsen (2017).

Third, complementarities among generation of heat and power exist and tend to increase with the capacity of the cogeneration plant. Total average cost reductions of more than 15.72% are estimated arising from positive synergies between heat and power generation. Using biogas in cogeneration units for the joint provision of heat and power does not only induce average fuel

[25] Economies of diversification is a generalized measure of economies of scope (see section 2.1).

cost reductions of more than 22% but also provides substantial cost saving effects from the jointness in labour and other costs.

Fourth, convexity effects positively contribute to economies of diversification and become a more important source of economies of diversification as plant size increases. To sum up, for very-small scaled plants economies of diversification tend to be important because of large positive scale effects but complementarity and convexity effects are negligible. For larger plants scale effects become less important and complementarity and convexity effects are the main source of economies of diversification.

The results illustrate the importance of disentangling generalized measures of economies of scope (see e.g. Berger et al. 1987, Ferrier et al. 1993, Preyra and Pink 2006), which deal with partial specialization schemes. As pointed out by Pope and Johnson (2013) those measures constitute an aggregation of several distinct effects. Not disentangling the effects in the presence of increasing (decreasing) returns to scale and convex (non-convex) cost functions leads to an overestimation (underestimation) of positive synergies between outputs.

Further, the results show that biogas plants can reap substantial cost benefits through complementarity among the production of heat and power. In practice, for most of the plants in the sample this means to increase the utilization of useful heat. Contrary to electricity, heat cannot be transported at longer distances and it has to be generated at sites close to heat demand. Regulations in Austria with absent or weak locational signals led to placement of biogas plants at sites, where heat demand is low and expenditures for district heat connections are high.[26] Policies aiming to promote renewable electricity could incorporate incentives for the joint generation of renewable heat and electricity in order to reap the benefits of cogeneration and to improve energy efficiency. In addition, very-small (< 100 kW_{el}) scaled plants operate under increasing returns to scale and can benefit from up-scaling their production activity. In general, sensible designed subsidies for renewable energy production, which incorporate knowledge about the characteristics of production technologies, such as economies of scale and economies of scope, can lower the costs of the energy transition.

The analysis in this study could be extended by not only considering heat and power but also other potential outputs. First, biogas can be upgraded to biomethane through separating carbondioxid and other gases from methane. As a result biomethane has a methane content of more than 98% compared to 55-60% of biogas. Biomethane can be injected into the natural gas grid or used as vehicle fuel. Further, biogas plants can dispose/recycle waste. Evaluating how heat, power, biomethane and waste are traded off against each other is an interesting topic for future research. Second, the analysis of economies of diversification for cogeneration systems can be extended by incorporating greenhouse gas emission as bad/undesirable/unintended outputs into the production technology (see e.g. Dakpo et al., 2016). This might allows evaluating the environmental benefits of cogeneration arising from greenhouse gas reductions.

[26] Though, utilization of waste heat and energy efficiency improved substantially between 2006 and 2014 (see Eder et al., 2017).

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Appendix A

A.1 Pattern of Specialization

Chavas and Kim (2010) consider a nontrivial partition of the output index $I=\{1,...,S\}$, given by $\{I_{A1}, ...I_{AK}, I_B\}$, where $IA=\{IA1,..., IAK\}$. I_{Ak} is the set of outputs the k-th firm is specialized in, $k=1,...K$, with $2\leq K\leq S$ and I_B is the set of outputs no particular firm specializes in. $\beta_k \in (1/K, 1]$ characterises the degree to which the k-th firm, $k=1,...,K$, is specialized in the production of outputs $i\in I_{Ak}$. The output vector of the original firm is given by $y=(y_1,...,y_S)$ and the output vector of the k-th specialized firm by $y^k=(y_1^k,...,y_S^k)$, $k=1,...K$. Let y_s be the s-th output of the original firm and y_s^k the s-th output of the k-th specialized firm, $k=1,...K$. Following Chavas and Kim (2010), the following pattern of specialization is considered:

$$y_s^k = y_s^+ \equiv \beta_k y_s \qquad \text{if } s\in I_{Ak} \qquad \text{(A.1a)}$$

$$y_s^k = y_s^- \equiv y_s(1-\beta_{k'})/(K-1) \qquad \text{if } s\in I_{Ak'}\neq I_{Ak} \qquad \text{(A.1b)}$$

$$y_s^k = y_i / K \qquad \text{if } s\in I_B \qquad \text{(A.1c)}$$

for some $\beta_k \in (1/K, 1]$, $k=1,...,K$. The reorganization of the original firm into K more specialized firms is fully characterized by I_A, I_B and $\beta=(\beta_{1,...,}\ \beta_K)$. The k-th firm becomes more specialized in the production of outputs in the set I_{Ak}. β_k measures the proportion of the original outputs $s\in I_{Ak}$ produced by the k-th specialized firm. For example, this study considers a situation where $I_A=\{\{1\},\{2\}\}=\{1,2\}$, I_B is empty and $S=K=2$. Equation (A.1a) and (A.1b) give $y^1=(y_1^1,y_2^1)=(\beta_1 y_1,(1-\beta_2)y_2)$, and $y^2=(y_1^2,y_2^2)=((1-\beta_1)y_1,\beta_2 y_2)$. If $\beta_k=\beta=0.7$ for all $k=1,2$, firm 1 produces 70% of output 1 and 30% of output 2 and firm 2 produces 30% of output 1 and 70% of output 2. $\beta_k=\beta=1$ for all $k=1,2$ implies complete specialization, where firm one (two) only produces output one (two). $\beta_k=\beta=1/2$ for all $k=1,2$, would imply that the subdivided firms are as diversified as the original firm. In general, the degree of specialization of the k-th firm increases with β_k.

A.2 Derivation of the Decomposition

Remember the index for S outputs is given by $I=\{1,...,S\}=\{I_{A1}, ...I_{AK}, I_B\}$. The output vector of the original firm is denoted as $y=(y_{A1}, ..., y_{AK}, y_B)$. Also, let $y_{A,i:j}=(y_{Ai}, y_{A,i+1}, ...,y_{A,j-1}, y_{Aj})$ for $i<j$. And from equation (A.1a)-(A.1c) the output vector of the specialized firm $k=1,...,K$ is written as $y^k=(y_{Ak}^+, y_{A/Ak}^-, y_B/K)$. Where $y_{Ak}^+=\{y_s^+ : s\in I_{Ak}\}$ is the set of outputs the k-th firm is specialized in and $y_{A/Ak}^-=\{y_s^- : s\in I_A/I_{Ak}\}$ the set of outputs the

k-th firm is not specialized. The vector $y_A^+ = (y_{A1,\ldots,}^+ y_{AK}^+)$ only contains the outputs, in which firms are specialized in and $y_A^- = (y_{A/A1,\ldots,}^- y_{A/AK}^-)$ is the vector of outputs, in which firms are not specialized in.

Following Chavas and Kim (2010) economies of diversification in the production of outputs $y=(y_{A1}, \ldots, y_{AK}, y_B) \in \Re_{++}^S$ exit if and only if $S^1(y, \beta)$ in equation (2a) is strictly positive. In this analysis we are interested in long-run cost functions without fixed-costs, which means that S_f in (3a) is zero. Then the benefit (loss) of diversification $S^1(y, \beta)$ evaluated at $y=(y_{A1}, \ldots, y_{AK}, y_B) \in \Re_{++}^S$ can be decomposed as follows:

$$S^1(y,\beta) \equiv S_c + S_R + S_V \qquad \text{(A.2)}$$

where

$$S_C \equiv \left\{ \sum_{k=1}^{K-1} C(y_{A,1:k-1}^-, y_{Ak}^+, y_{A,k+1:K}^-, y_B / K) - \sum_{k=1}^{K-1} C(y_{A,1:k-1}^-, y_{Ak}^-, y_{A,k+1:K}^-, y_B / K) \right\} - \left\{ \sum_{k=1}^{K-1} C(y_{A,1:k-1}^-, y_{Ak}^+, y_{A,k+1:K}^+, y_B / K) - \sum_{k=1}^{K-1} C(y_{A,1:k-1}^-, y_{Ak}^-, y_{A,k+1:K}^+, y_B / K) \right\} \qquad \text{(A.3a)}$$

$$S_R \equiv KC(y/K) - C(y) \qquad \text{(A.3b)}$$

$$S_V \equiv C(y_A^+, y_B / K) + (K-1)C(y_A^-, y_B / K) - KC(y/K) \qquad \text{(A.3c)}$$

If we assume that the cost function $C(y)$ is continuous everywhere on $\Re_+^S$ and continuously differentiable almost everywhere on $\Re_+^S$ then (A.3a) can be rewritten as

$$S_C = \sum_{k=1}^{K-1} \left\{ \int_{y_{Ak}^-}^{y_{Ak}^+} \frac{\partial C(y_{A,1:k-1}^-, \gamma, y_{A,1:k+1}^-, y_B / K)}{\partial \gamma} d\gamma - \int_{y_{Ak}^-}^{y_{Ak}^+} \frac{\partial C(y_{A,1:k-1}^-, \gamma, y_{A,1:k+1}^+, y_B / K)}{\partial \gamma} d\gamma \right\} \qquad \text{(A.3a')}$$

Equation (A.3a)-(A.3c) identifies three components of diversification benefits in (3a). The fixed-cost component S_f is zero by assumption. S_C is the complementarity component; S_R the scale component; and S_V the convexity component (see Chavas and Kim, 2010).

Appendix B: Decomposing the Decomposition by Input

$$S_{C,m} \equiv \left\{ \sum_{k=1}^{K-1} C_m^*(y_{A,1:k-1}^-, y_{Ak}^+, y_{A,k+1:K}^-, y_B / K) - \sum_{k=1}^{K-1} C_m^*(y_{A,1:k-1}^-, y_{Ak}^-, y_{A,k+1:K}^-, y_B / K) \right\}$$
$$- \left\{ \sum_{k=1}^{K-1} C_m^*(y_{A,1:k-1}^-, y_{Ak}^+, y_{A,k+1:K}^+, y_B / K) - \sum_{k=1}^{K-1} C_m^*(y_{A,1:k-1}^-, y_{Ak}^-, y_{A,k+1:K}^+, y_B / K) \right\}$$, for input *m=1,...,M* (B.1)

$S_{R,m} \equiv KC_m^*(y / K) - C_m^*(y)$, for input *m=1,...,M* (B.2)

$S_{V,m} \equiv C_m^*(y_A^+, y_B / K) + (K-1)C_m^*(y_A^-, y_B / K) - KC_m^*(y / K)$, for input *m=1,...,M* (B.3)

Appendix C

Table C.1: Monetary scope measure (S^1) and its decomposition (S_C, S_R, S_V) under different plant sizes

	$\beta = 0.7$				$\beta = 0.8$				$\beta = 0.9$			
	Size (installed electric capacity, kW_{el})				Size (installed electric capacity, kW_{el})				Size (installed electric capacity, kW_{el})			
	≤ 100	100 to ≤ 250	250 to ≤ 500	> 500	≤ 100	100 to ≤ 250	250 to ≤ 500	> 500	≤ 100	100 to ≤ 250	250 to ≤ 500	> 500
Diversification effect, S^I												
Mean	91,476	52,929	20,700	58,903	97,701	90,724	84,461	207,057	104,197	131,121	160,274	376,874
Standard Dev.	6,088	23,118	49,083	76,083	8,719	26,408	69,286	102,245	11,173	38,476	80,959	138,737
Minimum	83,041	16,472	-33,220	-18,104	83,041	55,384	-10,866	97,864	84,723	80,728	54,682	215,362
Maximum	101,296	105,683	123,068	194,183	111,733	139,395	216,357	397,086	122,169	205,574	310,922	626,854
Complementarity effect, S_C												
Mean	8,151	23,553	44,993	139,431	14,160	45,201	79,941	265,680	18,964	67,489	116,777	373,156
Standard Dev.	6,302	20,646	46,153	101,737	9,326	31,459	68,428	119,721	12,035	42,078	81,800	153,801
Minimum	0	0	0	34,949	0	1,857	0	134,919	0	10,006	17,475	192,369
Maximum	18,036	67,430	128,147	310,504	28,472	102,113	195,892	476,326	38,410	145,411	259,059	642,531
Scale effect, S_R												
Mean	83,323	9,417	-38,160	-93,369	83,323	9,417	-38,160	-93,369	83,323	9,417	-38,160	-93,369
Standard Dev.	1,374	40,560	22,565	46,661	1,374	40,560	22,565	46,661	1,374	40,560	22,565	46,661
Minimum	82,102	-46,129	-64,641	-181,624	82,102	-46,129	-64,641	-181,624	82,102	-46,129	-64,641	-181,624
Maximum	89,238	83,260	5,459	-58,217	89,238	83,260	5,459	-58,217	89,238	83,260	5,459	-58,217
Convexity effect, S_V												
Mean	2	19,959	13,867	12,841	218	36,106	42,681	34,746	1,911	54,215	81,657	97,087
Standard Dev.	8	18,225	13,607	23,745	590	26,733	17,297	34,122	1,057	34,120	17,713	40,417
Minimum	0	0	0	0	0	0	17,402	6,674	0	356	56,941	36,805
Maximum	35	45,650	43,278	65,303	2,089	72,976	76,985	102,384	4,143	101,073	112,443	165,948
Number of obs.	21	19	20	7	21	19	20	7	21	19	20	7

Note: The sample size is 67. Economies of diversification are evaluated for each plant at its observed output vector y_j.