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Consolidating the Water Industry: An Analysis of the Potential Gains from Horizontal Integration in a Conditional Efficiency Framework*

Michael Zschille[†]

Abstract

The German potable water supply industry is regarded highly fragmented, thus preventing efficiency improvements that could happen through consolidation. Focusing on a hypothetical restructuring of the industry, we use a cross-section sample of 364 German water utilities in 2006, applying Data Envelopment Analysis (DEA), to analyze the potential efficiency gains from hypothetical mergers between water utilities at the county level. A conditional efficiency framework is applied to account for the water utilities' operating environments. A conditional order- m approach is applied for the detection of potential outlying observations. Merger gains are decomposed into a technical efficiency effect, a harmony effect and a scale effect. The greatest efficiency improvement potentials turn out to result from reducing individual inefficiencies while pure merger gains are found to be low. The results suggest improving incentives for efficient operations in water supply and a consolidation of the smallest water utilities.

JEL-Codes: C14, L22, L25, L95

Keywords: Water Supply, Horizontal Integration, Data Envelopment Analysis, Conditional Efficiency, Nonparametric Estimation

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1 Introduction

1.1 Motivation and industry background

Potable water supply in Germany is the subject of intense political debate. The debate focuses on prices charged for potable water to the final customers and on how to appropriately regulate the water industry (Hirschhausen et al, 2009). However, the industry structure itself still lacks appropriate attention. Like other countries, including Japan and Portugal, the German water industry is highly fragmented, consisting of 6,211 water utilities in 2007, of which 5,972 deliver water to final customers (Statistisches Bundesamt, 2009). In contrast, water industries in England, Wales and the Netherlands are highly consolidated. In England and Wales, 22 companies, of which 10 are integrated water and sewerage companies, supply water to final customers (Bottasso and Conti, 2009). There are only 13 water companies serving the Netherlands (De Witte and Marques, 2010a).

Water supply in West Germany was highly fragmented for political reasons. By West German constitution, potable water provision was a municipal government responsibility. Municipalities could either provide their own water services or contract with a third party. Municipalities had wide latitude, including cooperating with other municipalities. These possibilities led to a variety of organizational arrangements. Utilities in Germany will supply water as well as other services, like electricity, natural gas, and other services. These other services might include local public transport and telecommunications. These municipal multi-product companies are usually known as "*Stadtwerke*" that can either be publicly or privately owned, and in some cases, partially privatized.

In contrast to West German structures, prior to reunification East Germany had 15 water utilities supplying water to final customers, divided at the regional level. In addition, there was one bulk water supply company (Statistisches Amt der DDR, 1990). After reunification, the task of water supply was assigned to municipal governments. The 16 water utilities were split into more than 550 utilities, using the West German model (Bundesministerium für Wirtschaft und Arbeit, 2005). This was followed with some re-consolidation, such that water utilities in the former East Germany are often organized as jointly held companies serving several municipalities.

However, former West German water utilities usually provided water and other services only to customers within its municipal territories. In its 2010 biannual report, the German Monopolies Commission (Monopolkommission, 2010) recommends both incentive-based regulation and a substantial consolidation of the

German water industry, since efficiency gains might result. Following the Monopolies Commission report, the German Federal Government (Bundesregierung, 2010) decided against regulating the water industry.¹ Even though the federal government will not force consolidation, water utilities are encouraged to investigate the potential for mergers with other companies. The issue of industry restructuring and consolidation thus still is of great interest. It is arguable that larger companies might be able to operate more efficiently, better handle the consequences of climate change, as well as find it easier to meet the increasing regulations on water quality (Mosheim, 2006) and the sustainable use of raw water resources as opposed to smaller companies. Related to possible scale advantages, Zschille (2013) analyzes the returns to scale characteristics of German water utilities. Accounting for the water utilities' operating environments, the results of Zschille (2013) indicate increasing returns to scale especially for smallest water utilities. Thus, scale adjustments, e.g. through mergers, might improve the efficiency of water supply. Potential merger gains may result from reduced management overhead in the integrated companies as well as the possibility of further optimizations in raw water abstraction and production.

Due to the high importance of water industry restructuring considerations in Germany and other countries, this paper contributes to the literature by analyzing the potential efficiency gains from mergers between water utilities using the Data Envelopment Analysis (DEA) approach proposed by Bogetoft and Wang (2005). In the water industry it is especially important to appropriately take the operating environment into account for efficiency analysis. Thus we apply the conditional efficiency framework proposed by Daraio and Simar (2005, 2007) in order to allow for the consideration of structural variables in DEA. Based on the conditional DEA estimates, we then analyze hypothetical cases of horizontal integration between water utilities located within the same county. To validate the results, we further calculate conditional efficiency scores and merger gains including bias corrections according to Simar and Wilson (1998, 2008, 2011a). We contribute to the literature on conditional efficiency approaches and their applications by analyzing the potential efficiency gains from mergers in a conditional efficiency framework. To our knowledge, this article is the first analysis of the potential gains from horizontal integration in the water industry.

¹Water utilities in Germany are natural monopolies in their service areas. Public water utilities currently do not face an effective price control. Private water utilities face an *ex-post* price control based on German cartel law. This price control however only is executed in the federal state of Hesse. There is currently no effective regulation of German public and private water utilities.

1.2 State of the literature

The existence of economies of scale can be used as a first indicator for potential efficiency gains from mergers. Extensive reviews of the empirical literature on scale economies in water supply are provided by Saal et al (2013), Abbott and Cohen (2009) and Walter et al (2009). Most experience in water industry restructuring and on the estimation of scale economies originate from England and Wales, where significant structural and regulatory reforms started being implemented in 1989. Saal et al (2007) find negative scale effects in the productivity growth of water and sewerage companies (WaSCs) over the 1985-2000 period. Short- and long-run diseconomies of scale for WaSCs are found in Ballance et al (2004), while they find constant returns for water only companies (WoCs). The results of Ashton (2003) indicate the existence of slight diseconomies of scale for English and Welsh water companies using panel data for 1991-1996. This result is confirmed by Saal et al (2011) for WoCs using an unbalanced panel of 234 observations for the years 1993-2009. In contrast, Bottasso and Conti (2009) find small economies of scale for the English WoCs using panel data from 1995 to 2005. The results show that consolidation might be beneficial especially in densely populated service areas.

Focusing on French water supply, Garcia and Thomas (2001) analyze a sample of water utilities in Bordeaux for the years 1995-1997. For the majority of water utilities in the sample, Garcia and Thomas find economies of scale greater than one, suggesting that mergers between water utilities are beneficial. They further show that merging up to 5 water utilities would be most beneficial in the Bordeaux case.

Several studies focus on scale economies in Italian water supply, which, like Germany, is highly fragmented with around 6,000 water utilities (Antonioli and Filippini, 2001; Fabbri and Fraquelli, 2000). Fabbri and Fraquelli (2000) find economies of scale for the majority of water utilities in the sample observed in 1991. Arguing that the sample average firm supplies water to about 160,000 inhabitants and that the national average firm serves about 9,000 inhabitants, Fabbri and Fraquelli conclude that most Italian water utilities could benefit from an increase in firm size. In contrast, Antonioli and Filippini (2001) find weak diseconomies of scale for a panel of 32 water distribution companies over the 1991-1995 period.

De Witte and Marques (2011) and Marques and De Witte (2011) analyze scale economies of Portuguese water utilities observed in 2005. They find that the 2005 number of 300 water utilities should be reduced to 60 water utilities. Martins et al

(2012) estimate a short-run total cost function for a sample of Portuguese water utilities observed in 2002 and find economies of scale for all analyzed output levels.

Japan is another example of a highly fragmented water industry. According to Urakami and Parker (2011), in 2005 there were more than 17,000 water utilities operating. Mizutani and Urakami (2001) find low diseconomies of scale and significant economies of density for a sample of water utilities in 1994, whereas Urakami (2006) and Urakami and Parker (2011) confirm the existence of scale economies.

Kim and Clark (1988) analyze a sample of US water utilities in 1973. The results indicate weak economies of scale for the smallest utilities, whereas for the overall output level, Kim and Clark conclude that there are no significant economies of scale. Torres and Morrison Paul (2006) analyze a sample of US water utilities in 1996 and find economies of scale given that consolidation leads to a higher output density. They argue that a consolidation of smaller utilities is efficient given that economies from an increase in output volumes compensate for diseconomies in the expansion of the distribution network. Garcia et al (2007) focus on vertical integration in the Wisconsin water industry over the 1997-2000 period. They find evidence for scale economies in vertically integrated companies that both produce and distribute water, while they find no evidence for scale economies in pure water production or water distribution companies.

Nauges and Berg (2010) analyze the scale characteristics of water utilities in 14 developing and transition countries and find economies of scale for 62% of the water utilities. For a sample of Peruvian water utilities from 1996 through 2005, Corton (2011) finds economies of scale for all water utilities considered.

Due to the varying evidence on economies of scale, no general conclusions on optimal firm size can be drawn. Results heavily depend on the analyzed country, on the characteristics of the operating environment and on firm characteristics like the joint provision of water and sewerage services. As a general consensus, the existence of scale economies usually is confirmed for small-scale water utilities up to some threshold level for firm size where economies of scale turn into diseconomies, as shown for example in Fabbri and Fraquelli (2000), Fraquelli and Moiso (2005) or Garcia and Thomas (2001). For the case of Germany, Sauer (2005) shows that the firm size optimum of rural water utilities lies around an output level of 3.592 million cubic meters of water and a network length of 808.8 km with 18,453 connections (Sauer, 2005). On average, optimal firm size is found to be three times larger than under the current market structure. The optimal firm size level derived by Sauer (2005) however is significantly smaller than in em-

pirical analyses for other countries like, e.g., for Italy or Portugal. This might be explained by the underlying data sample, which only contains information on rural water utilities. Zschille (2013) analyzes the returns to scale characteristics of a sample of German water utilities in a nonparametric framework. Increasing returns to scale are confirmed especially for smallest water utilities and are found to decrease with increasing firm size levels. Optimal firm size is found to be larger than the sample median firm size.

In addition to the issue of economies of scale, scientific literature provides little empirical evidence on the efficiency impact of horizontal integration in the water industry. De Witte and Dijkgraaf (2010) provide a post-merger analysis of the Dutch water sector and fail to confirm significant merger economies. They find no significant economies of scale or increased incentives to reduce inefficiencies within the water companies. Ballance et al (2004) provide an analysis of mergers in the English and Welsh water industry by comparing the cost functions of merged firms and non-merger firms and fail to confirm significant differences between both types. They find no evidence for a significant decline in costs after a merger. Urakami and Parker (2011) analyze mergers in the Japanese water supply industry and find some positive but small impact of consolidation on efficiency by slowing down cost increases to a small extent.

However, the current literature provides no empirical evidence on the *ex-ante* analysis of potential merger gains in the water industry. Bruno (2012) provides an analysis of the potential efficiency gains from mergers between water regulatory authorities in Italy. Further empirical evidence on the potential efficiency gains from hypothetical mergers so far is only known for other industries like e.g. for electricity supply, hospital services and urban transit, see Bagdadioglu et al (2007), Kristensen et al (2010) and Viton (1992), respectively.

The remainder of this paper is structured as follows: in Section 2 we describe the methodological framework of our analysis, Section 3 presents the data sample and results are shown in Section 4. Section 5 concludes.

2 Methodology

2.1 Data Envelopment Analysis and bias corrections

The analysis of the potential gains from mergers requires a frontier estimate of the water utilities' underlying production technology set. This can be accomplished, e.g., with Stochastic Frontier Analysis (SFA) or Data Envelopment Anal-

ysis (DEA). We choose a DEA approach for our analysis. In contrast to parametric approaches, strong *a priori* assumptions about the functional form of the technology set can be avoided. We assume an input orientation to analyze the possible proportional reduction of all inputs while outputs are assumed to remain constant. This is a valid assumption because demand for water is, essentially, exogenous and not directly influenced by the water utilities.

Different returns to scale technologies can be assumed for the construction of a technology set. Following standard microeconomic theory, with a constant returns to scale (CRS) assumption, it is always possible to scale firm sizes either up or down. Scaling firm sizes up or down is not always possible with a variable returns to scale (VRS) assumption. Thus, the VRS assumption restricts the possibilities for analyzing merger gains by strictly bounding the DEA technology set. The assumption of non-decreasing returns to scale (NDRS) implies that an up-scaling of firm sizes is always possible, but down-scaling is not. Smaller water utilities thus obtain higher efficiency scores than under the assumption of CRS. In the first step of the merger analysis, we evaluate potential merger gains relative to the VRS technology representing the observed industry structure of German water supply. In a second step, we then expand the technology set to the NDRS case. Given the small-scale structure of the water utilities in Germany and the existence of larger water utilities in other countries like the UK (England and Wales) and the Netherlands, an expansion of the technology set from VRS to NDRS appears reasonable.

The DEA linear program for the determination of the Farrell (1957) efficiency score for each observation i under the assumption of VRS is given by

$$\begin{aligned}\hat{\theta}_{VRS}^i(x, y) = \inf \{ \theta \mid & y^i \leq \sum_{k=1}^K \lambda^k y^k; \\ & \theta x^i \geq \sum_{k=1}^K \lambda^k x^k; \\ & \sum_{k=1}^K \lambda^k = 1, \lambda \in \mathbb{R}_+^K \},\end{aligned}\tag{1}$$

with x denoting a p -dimensional vector of inputs, y a q -dimensional vector of outputs, λ a set of weights and $k = \{1, \dots, K\}$ the full set of observations. For the assumption of NDRS, the returns to scale restriction $\sum_{k=1}^K \lambda^k = 1$ in Eq. 1 is replaced by $\sum_{k=1}^K \lambda^k \geq 1$.

DEA efficiency scores obtained from the linear program in Eq. 1 are upward

biased by construction. Since the estimated technology can only represent a subset of the true, unknown technology, estimated efficiency scores are thus higher than the true efficiency scores (Simar and Wilson, 1998). Accordingly, merger gain estimates might also be biased in the DEA framework. Following Simar and Wilson (1998, 2008), the bias of the DEA efficiency scores is defined as

$$BIAS(\hat{\theta}_{vrs}(x, y)) \equiv E(\hat{\theta}_{vrs}(x, y)) - \theta(x, y), \quad (2)$$

where $\hat{\theta}_{vrs}(x, y)$ represents the standard DEA efficiency score estimate and $\theta(x, y)$ the true, unknown efficiency score of a decision making unit (DMU). Since $\theta(x, y)$ is unknown, the bias estimate is unknown. However, a bias estimate can be obtained from the bootstrap analogue of the bias definition. In order to obtain the bootstrap DEA efficiency scores, Simar and Wilson (2008, 2011a) suggest using subsampling or the m -bootstrap approach for the replication of the data generating process (DGP) that yields the observed data.² The basic idea of both approaches is to generate pseudo samples $\chi_{n_{m,B}}^*$ through drawing subsamples of size $m = n^\kappa$ from the original data with $\kappa \in (0, 1)$ and e.g. $B = 2000$ bootstrap replications (Simar and Wilson, 2008, 2011a). Bootstrap efficiency scores $\hat{\theta}_{vrs,b}^*(x, y)$ are then obtained relative to the reference sample $\chi_{n_{m,B}}^*$. Based on the set of bootstrap efficiency scores, a bias estimate is obtained as

$$\widehat{BIAS}_B(\hat{\theta}_{vrs}(x, y)) = \left(\frac{m}{n}\right)^{\frac{2}{p+q+1}} * (B^{-1} \sum_{b=1}^B \hat{\theta}_{vrs,b}^*(x, y) - \hat{\theta}_{vrs}(x, y)) \quad (3)$$

with the correction factor $\left(\frac{m}{n}\right)^{\frac{2}{p+q+1}}$ accounting for the size m of the subsample $\chi_{n_{m,B}}^*$ compared to the full sample size n . Bias corrected DEA efficiency scores are finally calculated as

$$\hat{\hat{\theta}}_{vrs}(x, y) = \hat{\theta}_{vrs}(x, y) - \widehat{BIAS}_B(\hat{\theta}_{vrs}(x, y)). \quad (4)$$

2.2 Detection of influential observations

Since DEA is sensitive to outliers or extreme observations in the data, a profound validation of the data is necessary. Cazals et al (2002) propose the order- m estimator as an alternative to DEA estimation. Unlike DEA, the order- m estimator

²Subsampling describes the generation of pseudo samples from the original data sample using resampling without replacement whereas the m -bootstrap represents resampling with replacement (Simar and Wilson, 2011a).

can be characterized as a partial frontier measure not enveloping all observations and not relying on a convexity assumption. Furthermore, it reduces the influence of outlying observations and of noise in the data.³

Following Daraio and Simar (2005), a technology set can be represented by a probabilistic formulation and an input oriented full-frontier Farrell (1957) efficiency score assuming free disposability is defined as

$$\theta(x, y) = \inf\{\theta | F_X(\theta x | y) > 0\}, \quad (5)$$

with $F_X(x, y) = \text{Prob}(X \leq x | Y \geq y)$ describing the input levels of all observations producing at least output level y (Simar and Wilson, 2008). An efficiency estimator $\hat{\theta}(x, y)$ can be obtained using an estimator of $F_{X,n}(x|y)$ defined as

$$\hat{F}_{X,n}(x, y) = \frac{\sum_{i=1}^n \mathbb{1}(X_i \leq x, Y_i \geq y)}{\sum_{i=1}^n \mathbb{1}(Y_i \geq y)}, \quad (6)$$

with $\mathbb{1}(\cdot)$ denoting an indicator function (Daraio and Simar, 2005).

Instead of estimating efficiency scores relative to a full frontier, the idea of the order- m approach is to determine efficiency relative to subsamples of size m , leading to an estimate of expected input efficiency $\theta_m(x, y)$. An estimator of the order- m input efficiency score is defined as

$$\hat{\theta}_{m,n}(x, y) = \hat{E}(\tilde{\theta}_m(x, y) | Y \geq y) = \int_0^\infty (1 - \hat{F}_{X,n}(ux | y))^m du. \quad (7)$$

The integral in Eq. 7 can be solved by numerical methods (Simar and Wilson, 2008). The order- m efficiency score is obtained by comparing the observed input usage of an observation with the expected minimum input usage of m observations producing at least an output level of y . In contrast to DEA efficiency scores, order- m efficiency scores thus are not bounded by 1. An input oriented order- m efficiency score greater than one indicates that an observation is relatively more efficient than the average of a random sample of size m .

Simar (2003) suggests using the order- m approach to detect potentially outlying observations in a data sample.⁴ An observation might be an outlier if the order- m efficiency score remains greater than one even when m increases. Simar (2003) suggests estimating leave-one-out order- m efficiency scores $\hat{\theta}_{m,n}^{(i)}(x_i, y_i)$ for each observation $i = 1, \dots, n$ where observation i is left out from the reference set.

³See Cazals et al (2002) for details on the order- m approach.

⁴See Coelli et al (2005), Thanassoulis et al (2008) or De Witte and Marques (2010b) for overviews of alternative outlier detection procedures.

Leave-one-out efficiency scores are calculated for several values of m . Under an input orientation, values greater than one even when m increases indicate potentially outlying observations. Determining a threshold level $(1 + \alpha)$, an observation might be an outlier if $\hat{\theta}_{m,n}^{(i)} \geq 1 + \alpha$. Simar (2003) further suggests considering the number $N_{\text{input}}(x_i, y_i)$ of observations with outputs being greater or equal to y_i .

For a further analysis of potential outliers, Simar (2003) suggests a procedure to flag potential outlying observations. For different values of α , the share of observations lying above the threshold values depending on m is considered in a graphical analysis. By construction, these shares are decreasing in m . A strong negative slope of the curve indicates a potential outlier. A similar analysis can be performed under an output orientation. Observations that are found to be extreme both under an input and output orientation require further analysis and might be deleted from the sample.

2.3 Accounting for the operating environment

Water operations depend on the operating environment and on service area characteristics. Examples include the differences between rural and urban areas as well as the availability and characteristics of the raw water resources. Thus it is a fundamental to consider the operating environment when analyzing water utilities to ensure that water utilities are only compared with those facing similar operating environments. The literature provides different approaches to the consideration of environmental variables in DEA. In most applications multi-stage approaches are used, including the calculation of standard DEA efficiency scores in a first step, a regression analysis of the efficiency scores on structural variables in a second step and different approaches to account for the relevant structural variables in the following steps.⁵ Daraio and Simar (2005, 2007) and Simar and Wilson (2007, 2011b) argue that typical multi-stage approaches rely on a separability condition between the input and output space used in DEA and the space of environmental variables z , i.e. that the DEA frontier is not influenced by the environmental variables. To overcome this separability condition, Daraio and Simar suggest estimating the DEA technology set by conditioning on the characteristics of the operating environment of each individual observation. This approach requires the smoothing of the z -variables through the estimation of appropriate bandwidths for each z -variable to construct a Kernel function. Daraio and Simar (2005) recommend

⁵A short overview of possible approaches to incorporate the operating environment into DEA is given in Coelli et al (2005).

using a Kernel function with compact support, i.e. a Kernel function $K(\cdot)$ with $K(u) = 0$ if $|u| > 1$ with $u = \frac{|z_i - z_k|}{h}$. Here, z_i denotes the vector of environmental variables of the decision making unit (DMU) under consideration, z_k the environmental variables of all other observations and h the selected bandwidth. We apply an *Epanechnikov* Kernel for this purpose. This procedure guarantees that only those observations are selected into the set of possible peer units of a DMU that lie within the neighborhood around z_i . Following Bădin et al (2010), we estimate optimal conditional bandwidths based on a least squares cross validation approach.

Daraio and Simar (2005) introduce the concept of conditional efficiency measures for the order- m and Free Disposal Hull (FDH) estimators. The conditional order- m efficiency estimator is defined as

$$\hat{\theta}_{m,n}(x, y|z) = \hat{E}(\tilde{\theta}_m^z(x, y) | Y \geq y, Z = z) = \int_0^\infty (1 - \hat{F}_{X,n}(ux|y, z))^m du. \quad (8)$$

The conditional efficiency framework is extended to the DEA case by Daraio and Simar (2007). The conditional DEA technology set under the assumption of variable returns to scale is defined as

$$\begin{aligned} \hat{\Psi}_{VRS}^z = \{ (x, y) \in \mathbb{R}_+^{p+q} \mid & y \leq \sum_{\{k|z_i-h \leq z_k \leq z_i+h\}} \lambda^k y^k; \\ & x \geq \sum_{\{k|z_i-h \leq z_k \leq z_i+h\}} \lambda^k x^k; \\ & \sum_{\{k|z_i-h \leq z_k \leq z_i+h\}} \lambda^k = 1, \lambda \in \mathbb{R}_+^K \}. \end{aligned} \quad (9)$$

As shown in Eq. 9, only those observations that lie within the chosen bandwidth h around z_i are used for the construction of the DEA frontier for DMU i . Efficiency scores $\hat{\theta}_{VRS}^i(x, y|z)$ for each observation i can then be derived from the technology set in Eq. 9.

We further estimate bias corrected conditional DEA efficiency scores using the m -bootstrap. For this purpose, for each observation i we restrict the reference set to those observations k facing a similar operating environment like observation i and resample from this subset of observations. Bias corrected conditional DEA efficiency scores are then obtained as described in Section 2.1 for the standard DEA case.

2.4 Potential merger gains

Based on the estimated conditional DEA frontier, it is possible to analyze hypothetical cases of horizontal integration between water utilities in more detail. Considering a merger of J firms out of the full set of observations $k = \{1, \dots, K\}$ into the integrated firm denoted by DMU^J , Bogetoft and Wang (2005) propose a simple direct pooling of the inputs x and outputs y of the individual firms to be merged. We thus obtain an integrated firm DMU^J that uses $\sum_{j \in J} x^j$ units of input to produce $\sum_{j \in J} y^j$ units of output.

Following the notation of Bogetoft and Wang (2005), the input oriented Farrell efficiency measure of the integrated company is then defined as

$$E^J = \min\{E \in \mathbb{R}_+^{p+q} | (E \sum_{j \in J} x^j, \sum_{j \in J} y^j) \in \hat{\Psi}_{DEA}^{*,z}\}. \quad (10)$$

The underlying DEA technology set is denoted by $\hat{\Psi}_{DEA}^{*,z}$. For the analysis of hypothetical cases of horizontal integration, we use the technology set estimated before any merger as the reference set. As indicated by the superscript z , the conditional pre-merger technology set from Eq. 9 is used for this purpose.⁶ The efficiency of the merged entity, E^J , represents the *potential overall gains from merging*. It is the efficiency evaluation of a hypothetical DMU using the sum of inputs of the pre-merger firms to produce the sum of the pre-merger outputs. A merger is assumed to be beneficial for $E^J < 1$. A value of $E^J = 0.9$ e.g. indicates a potential for input savings of 10% by merging the companies in J . For $E^J > 1$, a merger is assumed to have a negative impact on efficiency.⁷ Fig. 1 illustrates the Bogetoft and Wang (2005) merger analysis approach for the two input and one output case. We illustrate a hypothetical merger between the two companies A and B , both producing output $y = 1$, that are individually compared to the input set $L(y = 1)$. Aggregating inputs and outputs of A and B yields the hypothetically merged company $(A + B)$ with output level $y = 2$ and the merged observation is

⁶In our analysis we focus on hypothetical mergers between water utilities located in the same *Landkreis*, the German equivalent of a county. For the application of the conditional efficiency approach, structural variables are re-calculated for the integrated companies.

⁷Under the assumption of NDRS and thus of additivity for the underlying technology set, the overall merger gains E^J will always be less than or equal to one in a standard DEA framework. Due to the application of the conditional efficiency framework in our analysis, the set of peer units for a merged water utility is likely to be different as compared to the individual pre-merger companies due to the re-calculation of environmental variables. It is thus possible that hypothetically integrated companies lie outside the NDRS technology, i.e. it is possible to achieve overall merger gains greater than one.

thus compared to $L(y = 2)$. Projecting $(A + B)$ onto $L(y = 2)$ yields the reference point $(A + B)'$ and the overall potential gain from merging is defined as $E^{(AB)} = [(A + B)'] / [(A + B)]$, i.e. it represents the efficiency score of $(A + B)$ relative to $L(y = 2)$.

[Figure 1 about here.]

The potential overall gains from merging still include the inefficiencies of individual firms from before merging that cannot be attributed to a merger. Thus we need to project the individual companies onto the efficient pre-merger DEA frontier $(\hat{\theta}_{DEA}^j(x, y|z)x^j, y^j)$ using the conditional efficiency scores of the individual companies. The performance of the merged entity is then determined by the sum of the efficient individual input quantities and the sum of the initial output quantities:

$$E^{*J} = \min\{E \in \mathbb{R}_+^{p+q} | (E \sum_{j \in J} \hat{\theta}_{DEA}^j(x, y|z)x^j, \sum_{j \in J} y^j) \in \hat{\Psi}_{DEA}^{*,z}\}. \quad (11)$$

The performance measure E^{*J} represents the *corrected overall potential gains from merging*. As before, a merger is evaluated as being beneficial for $E^{*J} < 1$ and costly otherwise. With reference to Fig. 1, the correction for individual pre-merger inefficiencies is illustrated for the case of point B . While A is located on the frontier and is thus efficient, point B is not. Therefore, for the analysis of pure merger gains, we focus on the aggregation of A and B^* , the projection of B onto the efficient frontier. The aggregation yields the new point $(A + B^*)$, which is again compared to $L(y = 2)$. The corrected overall gain from merging can thus be represented by $E^{*(AB)} = [(A + B^*)'] / [(A + B^*)]$.

The framework of Bogetoft and Wang (2005) allows for the decomposition of the potential merger gains according to

$$E^J = LE^J * HA^J * SI^J \quad (12)$$

with LE^J denoting a learning effect, HA^J a harmony effect and SI^J a size effect. The learning or technical efficiency effect in this decomposition represents efficiency improvement potentials resulting from individual inefficiencies and is calculated as

$$LE^J = \frac{E^J}{E^{*J}} \quad (13)$$

with $0 < LE^J \leq 1$ since $E^J \leq E^{*J}$. Such efficiency improvements usually cannot be attributed to a merger. Thus, it is more meaningful to represent the potential

gains from horizontal integration by the corrected merger gains E^{*J} and the corresponding decomposition into the harmony and the scale effect. With reference to Fig. 1, the learning effect thus represents the movement from $(A + B)$ to $(A + B^*)$, since $(A + B^*)$ will usually lie on a different ray than $(A + B)$ when at least one pre-merger company is inefficient and when the pre-merger companies are not located on the same ray.

The harmony effect, sometimes referred to as the scope or synergy effect, aims to represent the potential efficiency gains from a reallocation in the mixture of inputs and outputs within a merged firm as compared to the pre-merger firms. Individual firms use different combinations of inputs and outputs, with reallocation becoming possible in a merged company. Combining such different production plans might enable to reach a higher output level with the given inputs or, vice versa, to reduce the input quantities while holding the output level constant.

The harmony effect HA^J is defined as

$$HA^J = \min\{HA \in \mathbb{R}_+^{p+q} | (HA \sum_{j \in J} \alpha \hat{\theta}_{DEA}^j(x, y|z)x^j, \sum_{j \in J} \alpha y^j) \in \hat{\Psi}_{DEA}^{*,z}\}, \quad (14)$$

where α denotes a vector of weights; in most applications, $\alpha = \frac{1}{J}$. In this case, the harmony effect is determined by the arithmetic average of the efficient input quantities within the merged unit and the arithmetic average of the output quantities. Firm size after a merger is thus assumed to remain unchanged here while only the change in the mixture of inputs and outputs is considered. This assumption holds for the case of similar pre-merger firm sizes. In the case of differing pre-merger firm sizes however, scale effects might to some extent be captured by the harmony effect. Different weights α , e.g. based on a measure of firm size, can be used to avoid the inclusion of scale effects in the harmony measure. Efficiency gains resulting from the harmony effect might also be realized without any merger through the cooperation of individual companies. In Fig. 1, we assume $\alpha = 2$ and rescale $(A + B^*)$ to $(A + B^*)/2$. Due to the rescaling, the new point is compared to $L(y = 1)$ and the harmony effect is obtained as $HA^{(AB)} = [((A + B^*)/2)'] / [(A + B^*)/2]$.

The third effect is the size or scale effect. Based on the idea of returns to scale it is arguable that firms can produce outputs more efficiently at larger scale. It is aimed to represent savings potentials from operating at the full scale of a merged firm rather than at the average scale. The size effect SI^J is defined as

$$SI^J = \min\{SI \in \mathbb{R}_+^{p+q} | (SI * HA^J \sum_{j \in J} \hat{\theta}_{DEA}^j(x, y|z)x^j, \sum_{j \in J} y^j) \in \hat{\Psi}_{DEA}^{*,z}\}. \quad (15)$$

Even with a harmony effect equal to one, there might be potential for efficiency improvements through operating at a larger scale. Considering again the merger case illustrated in Fig. 1, we first correct $(A + B^*)$ for the harmony effect and obtain $HA(A + B^*)$, which is again assumed to produce merged output $y = 2$. Thus, the size effect is represented by the radial efficiency of $HA(A + B^*)$ relative to $L(y = 2)$ obtained as $SI^{(AB)} = [(A + B^*)'] / [HA(A + B^*)]$.

As described in Section 2.1, standard DEA efficiency scores tend to overestimate true, unknown efficiency scores by construction (Simar and Wilson, 1998). Thus, the potential efficiency gains from mergers similarly tend to be biased. Furthermore, as described in subsequent sections, the underlying data sample of the presented analysis contains only a few large observations, thus restricting the possibilities for analyzing mergers. Bias corrected DEA efficiency scores can be used to account for the sparsity of large observations in the merger analysis. With the aim of obtaining bias corrected merger gain estimates, we first estimate bias corrected conditional DEA efficiency scores for the full set of observations obtained after outlier detection using the m -bootstrap. We then use the bias corrected conditional DEA efficiency scores to project all observations onto the frontier, i.e. we assume efficient input quantities for all observations after correcting for the potential bias. The set of input-efficient observations then serves as the reference set for the merger analysis.

3 Data description

The analysis is based on data from the Statistics of German Waterworks published by Bundesverband der Energie- und Wasserwirtschaft (2008) and is a cross-section sample for the year 2006.⁸ The original data sample includes 1,096 water utilities. Due to missing or erroneous data, the sample reduces to a set of 651 observations, including pure water production companies, pure water distribution companies and integrated utilities that both produce and distribute water.⁹ In our analysis we focus only on vertically integrated water utilities that both produce and distribute water; excluding all other types. The final sample includes 364

⁸As of 2014, Germany had made no major structural or regulatory changes to their water supply since 2006.

⁹On average, the excluded observations are smaller than the remaining observations. We note that the excluded observations might be relevant for the merger analysis since merger gains are more likely to accrue for small water utilities. However, due to missing or erroneous data, it is necessary to exclude these observations.

companies. We allow for a low share of water input purchased from other water utilities, e.g. to meet peak demands, of up to 20% of total water input to ensure the comparability of the water utilities in our sample.¹⁰ The 364 water utilities in our data sample deliver water to around 20.45 million inhabitants, as compared to the total number of inhabitants in Germany of about 80 million. Final water deliveries of the sampled companies is about 1.14 billion cubic meters; with final water deliveries for all of Germany equaling about 4.54 billion cubic meters in 2007 (Statistisches Bundesamt, 2009). The sample contains both small and large companies; including the largest German water utilities. The data sample can thus be characterized as being representative. In addition to water supply, utilities sometimes also provide other services like electricity or natural gas supply. In our analysis, we only focus on the potable water services provided by the utilities.¹¹

Table 1 shows the summary statistics of the sample of 364 observations. Similar to other applications in the literature, e.g. De Witte and Marques (2010a), we assume a simple production model where the *length of the entire network* in a service area and the *number of employees* represent capital and labor inputs. As the number of employees is not available in full-time equivalents, the impact of part-time employment is thus captured in our model. Since the share of part-time employment in Germany usually is low, we assume the number of employees in the water utilities to be comparable. For the representation of the main activities of water utilities, the output measures in our model are *final water deliveries*, defined as the sum of water supplied to residential and non-residential customers, and *bulk water supplies*, which is the water supplied to other water utilities.¹²

¹⁰The consideration of firms with different degrees of vertical integration would furthermore complicate the analysis of horizontal integration gains through simultaneous changes in horizontal and vertical firm characteristics.

¹¹All variables used in our analysis only represent the potable water activities of the companies. We are however aware of possible scope effects between the services provided by multi-utilities. Given our model specification, this might only be the case for labor input, e.g. due to a shared management overhead. We assume this effect to be small. The sample of 364 observations contains 121 observations of water-only companies and 63 observations of water and sewerage companies. The remaining companies provide one or more services in addition to water supply. Such integrated firm structures can impact potential merger benefits, which cannot be captured by our model. Mühlenkamp (2012) and Rottmann (2010) provide some general overview over German multi-utilities. Other studies, e.g. by Farsi et al (2008), Fraquelli et al (2004), and Piacenza and Vannoni (2004), focus on the analysis of multi-utilities in other countries.

¹²With a median level of 1.15 million cubic meters of final water deliveries, the sampled water utilities deliver more than the national average of 0.76 million cubic meters per water utility (Statistisches Bundesamt, 2009). This might be explained by the poor data availability for smaller companies, since they are often part of the municipal administration.

Furthermore, we take the number of *connections to final customers* into account to ensure that water companies supplying water in areas of low per-capita water demand are not discriminated against.

Since we allow for a low share of purchased water input, the amount of own water production could be included as an additional output to differentiate between utilities with complete own water production from those water utilities with a share of purchased water input of up to 20%, as discussed earlier. The amount of own water production is highly correlated with the amount of water delivered to final customers (Pearson correlation coefficient of 0.9984), the variable would thus not have any additional explanatory power in our model. With the aim of reducing the dimensionality problem of DEA, we thus omit the amount of own water production variable from our model.

[Table 1 about here.]

In addition to the input and output measures, several structural variables that are assumed to have an influence on firm performance are included. We only consider exogenous structural variables that are not influenceable by the firms' management.¹³ The network length usually is an important variable to proxy the capital input of a water utility. It can, however, also be regarded as an output variable (Thanassoulis, 2000) in addition to water output and the number of connections in order to control for the size of a service area and different densities of supply. Since we include the network length on the input side rather than on the output side, we define the variable *output density* to control for different service area densities. It is calculated as the sum of water deliveries to final customers and to other water utilities over the length of the entire distribution network. Following the empirical evidence in the literature, we presume a positive impact on efficiency. Examples include, among others, Picazo-Tadeo et al (2009), García-Sánchez (2006) or Tupper and Resende (2004).

To control for network quality, we define the *share of water losses* as the difference between total water input and total water output over total water input. It is arguable that the share of water losses is endogenous since water losses can be influenced by investments into network infrastructure or better maintenance. However, pipe bursts and water losses also depend on other factors like, for example, the type of soil in a service area (Coelli and Walding, 2006). We thus assume

¹³We are aware of other potential factors and characteristics of the water utilities' operating environments with a possible influence on efficiency. However, given data availability, we can only include three *z*-variables in our analysis.

water losses to be exogenously given.¹⁴ At the mean, the share of water losses for the water utilities in our sample is around 12%, whereas it is about 10% for entire Germany based on aggregated statistical information for all German water utilities (Statistisches Bundesamt, 2009).¹⁵

In addition to network quality, water quality could be important. However, the sample data does not include measures for the quality of the delivered water. Given Germany's strong regulations on potable water quality, the need for a water quality measure appears to be negligible. In order to control for differences in the source of water, we take the *share of groundwater input* in total water input into account. Groundwater usually is of good quality and requires less treatment to meet the potable water quality standards than surface water does. However, groundwater abstraction increases pumping needs versus the use of surface water (Filippini et al, 2008), while capital costs for groundwater usage are lower than for the use of storage water (Coelli and Walding, 2006). We presume a positive impact of the share of groundwater usage on efficiency. With a mean level of around 83%, the share of groundwater input of the utilities in our sample is significantly higher than the national average of 62% (Statistisches Bundesamt, 2009).¹⁶

4 Results

We begin by illustrating the impact of the operating environment on order- m efficiency scores.¹⁷ Unlike DEA, the efficiency impact of the operating environment can be better illustrated in the order- m framework since, in contrast to full frontier approaches like DEA, the z -variables not only influence the shape of the estimated technology sets, but also alter the distribution of inefficiency scores (Bădin et al,

¹⁴A similar assumption on the exogeneity of water losses in the short run is made in Zschille and Walter (2012).

¹⁵As indicated by the minimum value of the share of water losses, the sample includes observations with very low shares of water losses of below 1%, which is unrealistic from an engineering perspective. Since we however can observe a continuum of water utilities with similarly low losses, we do not remove such observations from the data sample.

¹⁶One explanation might be our focus on vertically integrated companies with own water production and distribution. Such vertically integrated utilities usually use groundwater resources, while surface water resources like e.g. reservoir or river water are usually used by larger bulk water supply companies, which are not part of our final sample.

¹⁷All calculations are conducted using the statistical software *R* with the additional packages "Benchmarking" version 0.18 by Bogetoft and Otto (2011), "FEAR" version 1.13 by Wilson (2008) and "np" version 0.40-3 by Hayfield and Racine (2008).

2012). We apply a nonparametric Kernel regression analysis to regress the ratio of the conditional to the unconditional order- m efficiency scores against the set of z -variables characterizing the water utilities' operating environments: *output density*, *water losses* and *share of groundwater input*. Efficiency impacts of each variable are illustrated in the nonparametric Kernel regression plots in Fig. 2. Table 2 summarizes the standard and the conditional order- m efficiency scores with $m = 75$ and Table 3 summarizes the nonparametric regression results and reports the corresponding significance levels from a Kernel regression significance test (Racine, 1997; Daraio and Simar, 2014).

[Figure 2 about here.]

As indicated in Fig. 2, the regression line of the ratio between conditional and standard order- m efficiency scores on the variable *output density* is decreasing. For low output densities, the ratio of conditional to unconditional efficiencies is higher than one and efficiency is thus higher when accounting for output density, underlining that additional inputs are required in low-density areas, thus leading to efficiency disadvantages. This result indicates significant returns to density for water utilities supplying water in rural areas, which are decreasing with increasing output density. As reported in Table 3, the efficiency impact of *output density* is statistically significant at the 1% level. The nonparametric regression lines for the *share of water losses* and the *share of groundwater input* are weakly decreasing, though almost constant. Both variables only show a weak and, as shown in Table 3, insignificant impact on order- m efficiency scores. However, since such irrelevant variables are oversmoothed in the bandwidth selection approach (Bădin et al, 2010), all three z -variables are used in the conditioning of the order- m efficiency scores and in the subsequent merger analysis. As shown in Table 2, accounting for the operating environment in the order- m efficiency scores only leads to weak changes in mean efficiency. However, we observe a strong increase in minimum efficiency scores and a strong decrease in maximum efficiency. Thus, the standard deviation of the order- m efficiency scores strongly decreases.

[Table 2 about here.]

For the detection of potential outliers in the sample data, we combine the conditional efficiency approach proposed by Daraio and Simar (2005) with the order- m approach to outlier detection proposed by Simar (2003). Following the suggestions of Simar (2003), we analyze the variation of the order- m efficiency

scores and the share of observations outside the leave-one-out order- m frontier for different values of m with $m = 25, 50, \dots, 175, 200$. The results of the order- m approach depend on the appropriate choice of m . Following the suggestions of Simar (2003) for the optimal choice of m , we select $m = 75$. We find that 19 companies in the sample are extreme and outlying observations.¹⁸ These observations are characterized by extreme order- m efficiency scores both in the input and output directions even under increasing values of m . The mean output levels of the removed observations are found to be higher than the full sample averages. However, smaller or smallest water utilities are similarly removed from the sample. The largest observations in the sample are endpoints either in the input or output directions, but obtain non-extreme efficiency scores in the other direction and are thus not deleted from the sample. Furthermore, it is beneficial to keep these large observations in the sample to improve the firm size coverage of the technology set for the subsequent merger analysis.¹⁹

[Table 3 about here.]

Table 2 reports the conditional efficiency scores obtained after the conditional outlier detection procedure. Due to the deletion of outlying observations from the sample, the number of observations is reduced to a total of 345. As compared to the conditional order- m efficiency scores before outlier detection, on average we find a weak decrease in the conditional order- m efficiency scores from 1.0017 to 0.9933. Similarly, we only observe weak changes in the minimum and maximum order- m efficiency scores. The only weak changes in the order- m efficiency scores underline the robustness of the order- m estimator against extreme or outlying observations.

In addition, Table 2 summarizes conditional DEA and bias corrected conditional DEA efficiency scores for the sample of 345 observations after outlier detection, each under the assumption of VRS and NDRS. Bias corrected DEA

¹⁸As a rule of thumb, Simar (2003) suggest $\sqrt{(n)}/n$ as a reasonable upper bound for the share of outliers in a data sample. In the case of the $n = 364$ observations, this rule of thumb suggests an upper bound of 5.24% of outliers in the sample. The 19 deleted observations correspond to a share of outlying observations of 5.22%.

¹⁹We note that the removed observations might represent extreme best practices even when controlling for the operating environment. However, to ensure the validity of the results, we decide to remove the detected potential outliers, thus leading to more conservative estimates of potential merger gains. The application of robust methods, like the order- m approach, would be beneficial in the subsequent merger analysis. However, by construction, the merger analysis approach relies on full frontier measures like DEA.

efficiency scores are estimated using the m -bootstrap with 2000 bootstrap replications. In line with the order- m analysis, we choose a subsample size of $m = 75$ for the bootstrap procedure. Under the assumption of VRS, we find mean efficiency to lie around a level of 88.5% in the standard DEA case and of 87.4% when including bias corrections. However, we observe low minimum efficiency levels of 30.4% in the standard DEA case and of 27.6% when including bias corrections. As expected, mean efficiency is weakly lower when assuming NDRS with 85.8% in the standard DEA case and 84.7% when including bias corrections. The results, both under VRS and NDRS, thus indicate strong inefficiencies of the observed water utilities.

Turning to the analysis of hypothetical mergers between neighboring water utilities, we focus on mergers between water utilities that are located within the same *Landkreis*.²⁰ Since the observed water utilities are usually organized municipally, the county level represents the next higher step of potential aggregation.²¹ We analyze cases of horizontal integration between all water utilities within one county for which data is available. However, it is not possible to cover all water utilities within one county. In total we consider mergers of 224 water utilities into 83 hypothetical new companies. While the input and output measures for the merged companies are obtained by direct pooling of the individual pre-merger input and output quantities, we recalculate the structural variables for each of the merged entities.²²

The counties under consideration are spread across Germany. Most are, however, located in the federal states of Bavaria, Hesse, Lower Saxony and Rhineland-Palatinate. We can only analyze few merger cases in the former East Germany since the water utilities located in this area are already larger than water utilities in the former West German territories, and already deliver water at a county level in some cases. Table 4 provides the summary statistics for the potential merger gains for the set of 83 cases of horizontal integration. Under the VRS assumption, we only obtain merger gain estimates for 55 out of 83 hypothetical merger com-

²⁰A *Landkreis* is the German equivalent of a county as defined by the *NUTS 3* code of the *NUTS*-classification (*Nomenclature des unités territoriales statistiques*).

²¹The idea of aggregating water utilities originates from observations of consolidated water utilities on the county level especially in East Germany. We cannot guarantee that the simulated mergers represent merger cases between really neighboring water utilities. However, due to the usually low number of water utilities within a county, the merger simulation approach appears reasonable.

²²Environmental variables of hypothetically merged entities are re-calculated by aggregating the underlying raw data used to calculate the environmental variables of the individual pre-merger companies.

panies. Thus, in 28 cases the merged company is larger than the maximum firm size level observed in the data. In 40 out of the 55 cases, a merger between the water utilities would be beneficial when looking at the potential overall gains E^J . Since those results still include the individual inefficiencies within water utilities before merging, we consider the projections of the individual water utilities and calculate the corrected potential merger gains E^{*J} . The merger gains on average decrease significantly after correcting for individual inefficiencies. In 36 merger cases we find potential losses from a merger as indicated by values of E^{*J} being greater than one. At the mean we find potential losses from the corrected merger gain estimates of about 10%.

After calculating overall gains from merging, we provide the decomposition into the learning effect, the harmony effect and the scale effect. At the mean, about 14% of the overall merger gains E^J could be realized by improving efficiency within the individual pre-merger water utilities. The learning effect thus inhibits the greatest potential for efficiency increases versus harmonization and scale effects. Such efficiency improvement potentials are usually not attributable to a merger since efficiency could be improved by, for example, sharing best practices between individual water utilities.

Considering both harmony and scale effects, on average we find potential efficiency losses resulting from both effects. On average, the mergers would result in an efficiency loss of 0.7% resulting from harmonization effects and efficiency losses of almost 12% resulting from scale effects. Under the assumption of a VRS technology, in most cases mergers would result in efficiency losses and are thus not recommendable. Strong potentials for efficiency increases arising from a harmonization in the individual production plans of the different water utilities, as indicated by the harmony effect, are only found in a few cases. Due to the different sizes of the firms prior to merging, scale effects might, to some extent, be captured by the harmony effect, thus resulting in lower estimates for the scale effects shown in Table 4. We therefore use the number of connections to customers as firm-size related weights α when pooling the inputs and outputs for the considered merger cases (cf. Eq. 14). Table 4 reports the weighted results for the harmony and scale effects. Using weights, the harmony effect estimates on average increase, while the scale effect estimates decrease. However, on average both the harmony and scale effect indicate potential efficiency losses resulting from the mergers.

[Table 4 about here.]

As mentioned in Section 2, DEA efficiency scores are usually biased upwards (Simar and Wilson, 1998), thus leading to biased merger gain estimates. Fur-

ther, since the estimates of the merger gains are likely to be influenced by the low number of observations of large companies, we account for this sparsity of observations of large companies by running a conditional DEA with bias corrections based on a m -bootstrap approach with $B = 2000$. We maintain the assumption of an underlying VRS technology. Results are reported in Table 4. Using bias corrections, the overall merger gains E^J indicate high efficiency improvement potentials of about 13% on average. Those effects diminish when accounting for individual pre-merger inefficiencies. Considering the mean of the corrected merger gain measure, we find potential merger losses of almost 3%. In 22 cases, a merger would result in potential efficiency losses. However, considering the median value $E^{*J} = 0.96$, more than 50% of the merger cases would result in efficiency gains even after correcting for individual pre-merger inefficiencies. The decomposition again indicates that efficiency improvement potentials are merely based on learning effects rather than on pure merger gains. However, in contrast to the results of the DEA approach without bias corrections, on average we find efficiency improvement potentials resulting from harmonization effects of about 8%. Scale effects, however, are found to result in efficiency losses on average. The efficiency losses resulting from the scale effects can be explained by the underlying VRS technology.

Given the general small-scale structure of German water supply as compared to other countries, hypothetical merger gains might be underestimated such that real merger gains are likely to be greater. Furthermore, in places like England, Wales, and the Netherlands, water utilities are found to be generally larger than the German water utilities. Thus, it is arguable to not only consider merger gains relative to the VRS frontier, but to extend the estimated technology set from a VRS to a NDRS technology, thus favoring larger observations. We note that the additivity property of the NDRS technology allows for the analysis of all 83 merger cases. We further note that the assumption of NDRS implies non-negative estimates of the scale effect in the non-weighted merger gain decomposition. Assuming NDRS, we find potential overall gains from merging in 80 merger cases. As indicated by the potential overall gains $E^J = 0.84$, the mergers would, on average, result in efficiency improvement potentials of 16%. Correcting for individual inefficiencies of pre-merger companies however, these efficiency improvement potentials diminish to less than 1% on average. However, in contrast to the VRS results without bias corrections, on average the decomposition of the potential merger gains indicates weak potential efficiency losses from harmonization effects but weak efficiency gains based on scale effects. The results of the decomposition remain similar when using size-related weights in the decomposition of the harmony

and scale effects.

As for the analysis in the VRS framework, we further analyze merger gains relative to a bias corrected NDRS frontier. Compared to the NDRS results without bias corrections, efficiency improvement potentials resulting from the mergers on average increase to almost 27% as indicated by $E^J = 0.73$. With an average corrected merger gain estimate of $E^{*J} = 0.88$, pure merger gains amount to about 12%. As indicated by an average learning effect of $LE = 0.83$, most efficiency improvement potentials again result from the reduction of individual pre-merger inefficiencies. However, the decomposition of real merger gains into harmony and scale effects shows that, on average, both effects would result in efficiency improvement potentials. We find efficiency improvement potentials resulting from harmonization effects of about 10% on average and of about 2% resulting from scale effects. Using alternative size-related weights, the efficiency improvement potentials resulting from the harmony effects weakly decrease to less than 9%, while efficiency improvement potentials resulting from the scale effects increase to about 3%, on average.

Fig. 3 provides boxplot illustrations of the overall merger gains in the bias corrected NDRS framework and the corresponding decomposition for different groups of firm sizes. We divide the sample of 83 integrated companies into four groups based upon the quartiles of the amount of water delivered.²³ The two plots in the left part of Fig. 3 indicate that there are strong overall gains from merging based on strong learning effects. Considering group-specific median values, we find potential efficiency gains resulting from harmonization effects for all groups of utilities. We only find scale effects for the group of smallest utilities. Using weights, at the median we find weak merger gains from the harmony effect and from the scale effect for all groups.

[Figure 3 about here.]

In Fig. 4, we illustrate the relationship between the merger gain estimates obtained from conditional bias corrected DEA assuming NDRS to those without conditioning on the z -variables. Overall merger gain estimates are generally higher in the conditional efficiency DEA framework and efficiency improvement potentials resulting from the mergers are thus lower. We obtain a Spearman rank correlation coefficient of 0.42 between the conditional and standard merger gain estimates. The decomposition of the overall merger gains into learning, harmony

²³Calculated as the sum of water delivered to final customers and the amount of bulk water supplies.

and scale effects however shows that this effect is primarily driven by individual inefficiencies before the merger. The learning effect estimates are higher in the conditional efficiency DEA framework, illustrating the high influence of the conditioning z -variables on individual pre-merger efficiency scores. We find a correlation between conditional and standard learning effect estimates of 0.45. The decomposition of the pure merger gains into harmony and scale effects indicates that conditioning on the z -factors in some cases leads to higher estimates of harmony and scale effects and in some cases to lower estimates. We find a correlation between the harmony effect estimates of 0.39 and of 0.31 between the scale effect estimates. Thus, the results underline the relevance of accounting for the operating environment in merger assessments.

[Figure 4 about here.]

5 Interpretation of results and concluding remarks

In this article we provide the first analysis of the potential gains from horizontal integration in the German potable water sector. While merger gains in the water industry have only been analyzed on an *ex-post* basis so far, we provide new insights into a hypothetical restructuring of the industry. Similar to other network industries, water supply heavily depends on the characteristics of the operating environment. Applying a conditional efficiency approach, we take different variables characterizing the water utilities' operating environments into account in our analysis and contribute to the scientific literature by analyzing the potential gains from mergers within a conditional efficiency framework. We detect outliers using a conditional order- m approach.

Investigating the hypothetical consolidation of the German water industry at the county level, we find substantial gains from horizontal integration in only some of the analyzed cases. Results vary depending on the underlying RTS assumption of the estimated technology set. The decomposition of the potential overall gains from mergers shows that the technical efficiency effect turns out to be the main source for efficiency gains. Thus, greatest efficiency improvement potentials for the water utilities result from technically more efficient operations rather than from mergers and corresponding changes in market structures. Having corrected for individual inefficiencies, pure merger gains exist in the majority of cases but are found to be low. The results indicate efficiency improvement potentials resulting from harmonization effects. Scale effects are found to be weak

or even negative. However, we observe scale effects to be the highest for the group of smallest water utilities. This result is in line with the results of Zschille (2013), indicating strong increasing returns to scale for smallest water utilities that decrease with increasing firm size levels. Despite the application of a bootstrap procedure for the calculation of bias corrected efficiency scores, the mostly low merger gains and the correspondingly low harmony and scale effects might be explained by the low number of sufficiently large observations in the data sample. Thus, the best practices of large firms in the sample are likely to cause the underestimation of the true best practices across the entire industry. Regarding the small-scale industry structure of German water supply, the sample might not cover the full range of possible firm sizes when estimating the DEA technology set. The empirical evidence in the literature on the existence of returns to scale in water supply across different countries suggests that optimal firm size for water utilities is usually reached at higher output levels. Our results however are in line with the empirical evidence in the literature indicating low merger gains in water supply across different countries based on post-merger analyses, see e.g. Urakami and Parker (2011), De Witte and Dijkgraaf (2010) or Ballance et al (2004).

Since scale effects are found to be low or even negative in some cases, the necessity of mergers is questionable. Major efficiency gains result from the technical efficiency effect and there might be possibilities to realize those efficiency improvement potentials through arrangements other than a merger, e.g. through sharing best practices between companies. However, if technical inefficiencies in a water utility are a result of mismanagement, a merger could lead to better management abilities and improved performance.²⁴ In addition to reducing inefficiencies in the individual water utilities, potential scope effects could result e.g. from a simple cooperation between different companies.

We note that the estimated potential merger gains might not fully represent the efficiency gains of real mergers. First, we assume a consolidation of water supply at the county level. As water supply is usually municipally organized, the county level represents the next higher level of potential aggregation. However, we cannot model full-county mergers due to a lack of data. Given the existence of county-based water utilities in some parts of Germany, the merger simulation on a county level appears reasonable. However, we are aware that the simulated merger cases might not represent merger that are likely to be realized. Second, water supply is often organized within a multi-output utility providing other services like electricity or natural gas supply in addition to water services. Since our

²⁴The opposite case is also possible if an inefficient water utility takes over an efficient one.

analysis only considers the water divisions of such multi-output utilities, potential merger gains are likely to be overestimated in cases where a multi-output utility is involved in the merger simulation. In such situations, mergers between entire multi-output utilities might be of interest. However, given weak data availability and the focus on water supply, such merger cases are beyond the scope of this paper.

Further extensions of the model and a more detailed data set could improve the quality of our results. First, more observations of large-scale water utilities would be beneficial to ensure the appropriate definition of the DEA technology set for larger units. Since there are few larger water utilities in Germany, with the majority already in the data, considering water utilities from other countries might be beneficial. The results presented here can only give an indication of the potential efficiency gains from consolidation in the water industry. Second, the consideration of additional variables to control e.g. for water treatment and water or service quality could improve the results. Results might also change when relying on a cost model rather than on a production model. Since consolidation at the county level is found to increase efficiency in most cases, an analysis of consolidation at a regional level, as the water supply was structured in East Germany, would be of interest. Such an approach, however, is restricted by data availability and missing peer units since, even currently, the largest modern German water utility is smaller than East German utilities were prior to 1990. Beyond horizontal integration, an analysis of efficiency gains from vertical integration e.g. between water production, distribution and retail services might be of interest.

Regarding the international evidence on scale economies in water supply and the high fragmentation in Germany, as compared to water industries in other countries, consolidation in Germany is likely to result in increased efficiency. However, mergers decisions are made by the firms involved, since merger effects also depend on other characteristics of the water utilities that are not covered by our model, like, for example, firm culture. One important factor is that political circumstances are a factor in water utility consolidation. Municipal governments usually prefer to control local utilities and are likely to resist consolidation efforts.

We have, so far, neglected the impact of mergers on market power. In competitive industries, mergers lead to greater market power for the integrated company and can thus result in negative welfare effects. In water supply, however, utilities are de facto local monopolies with strong market power by definition. De Witte and Dijkgraaf (2010) further point out that mergers lead to a reduced number of companies that can be analyzed in benchmarking studies for regulatory purposes,

thus meaning that the impact of best practices might be underestimated. Since we analyze a hypothetical consolidation of the water industry at the level of the more than 400 German counties, a sufficiently large number of companies for benchmarking purposes would be maintained.

We show that there are substantial inefficiencies in the German water sector. While mergers can contribute to a reduction of those inefficiencies, the greatest improvement potentials rely on technical efficiency effects that do not necessarily require a merger of different companies. Regarding policy recommendations, more incentives are necessary to reduce the high inefficiencies in German water supply in combination with a consolidation of the smallest utilities.

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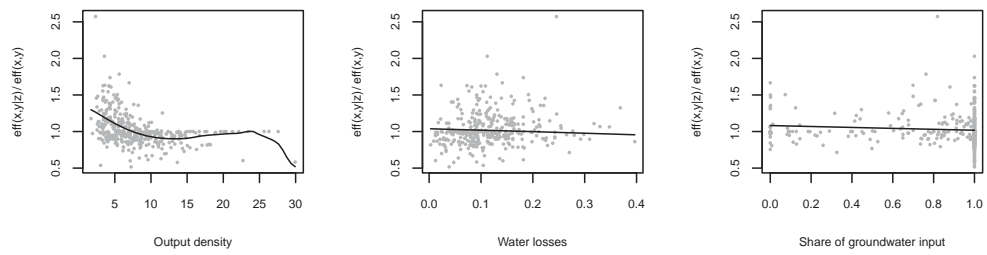


Figure 2: Impact of z -variables on order- m efficiency scores

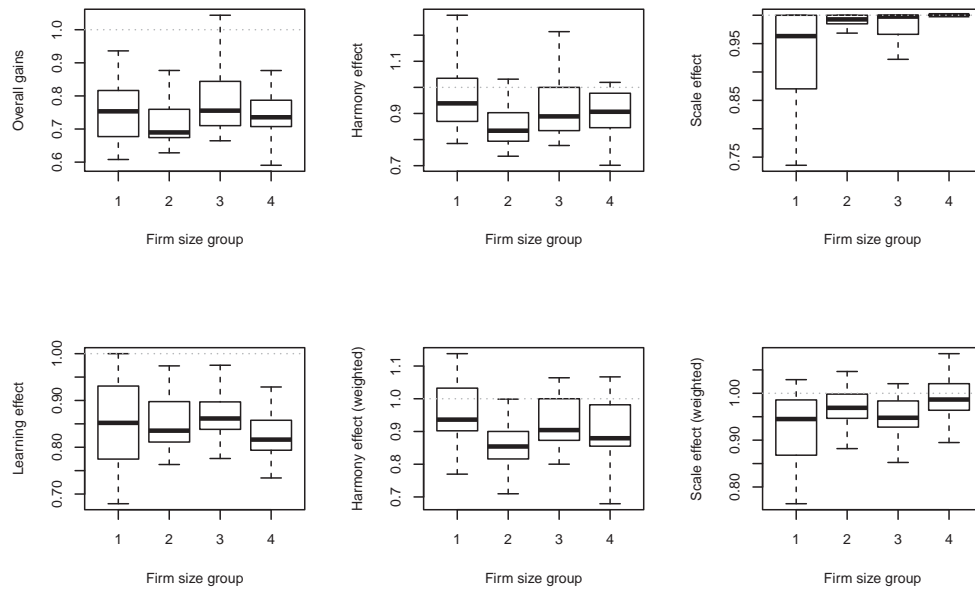


Figure 3: Merger gains and decomposition with bias corrections for different firm sizes by quartiles

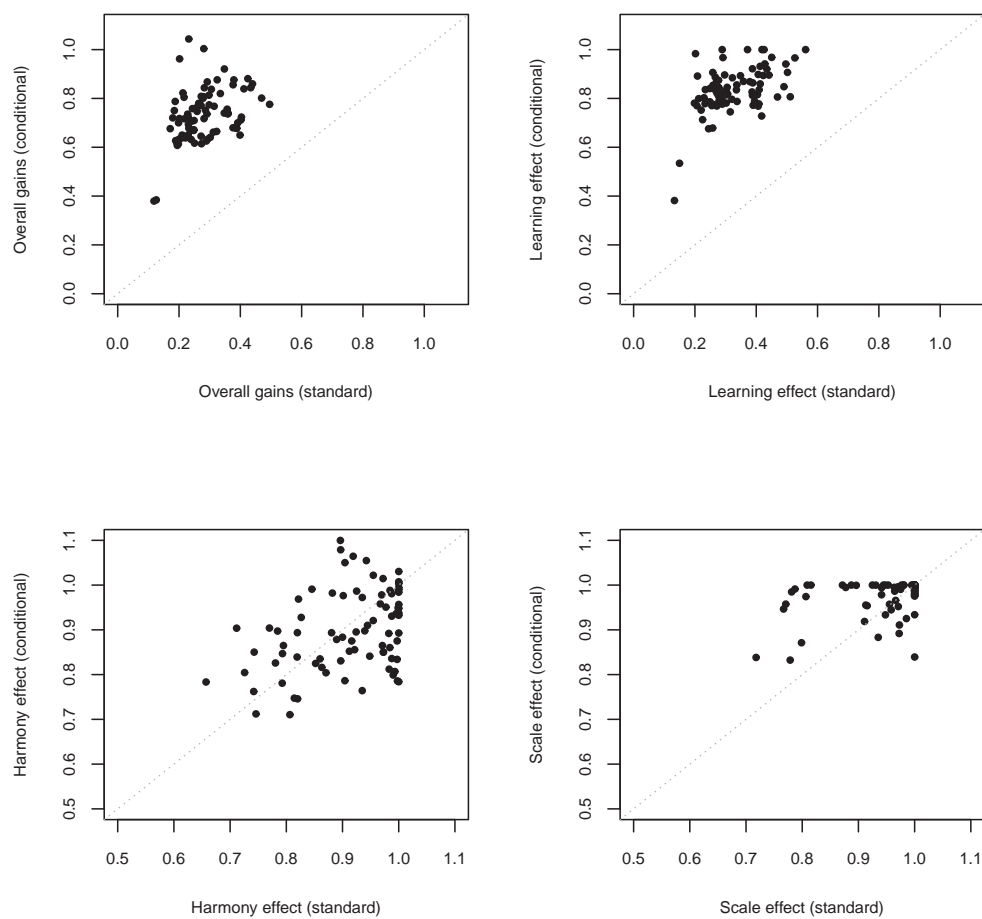


Figure 4: Correlation between standard and conditional bias corrected merger gain estimates under NDRS

Table 1: Descriptive statistics

	Min.	Median	Mean	Max.	Std. dev.
<i>Input variables</i>					
Network length <i>net</i> [km]	21.00	164.50	329.68	7,858.00	600.80
Employees <i>labor</i> [number]	2.00	10.00	29.85	2,326.00	139.97
<i>Output variables</i>					
Connections <i>con</i> [number]	911.00	5,437.50	10,837.61	262,000.00	22,751.33
Final water deliveries <i>wdel</i> [1000 m^3]	89.00	1,154.50	3,144.41	197,900.00	12,720.40
Bulk water supplies <i>bws</i> [1000 m^3]	0.00	1.00	264.21	14,670.00	1,130.43
Water produced <i>wprod</i> [1000 m^3]	99.00	1,344.00	3,697.09	217,890.00	14,337.20
<i>Environmental variables</i>					
Output density <i>dens</i> [ratio]	1.70	6.98	8.14	29.93	4.63
Water losses <i>losses</i> [ratio]	0.00*	0.11	0.12	0.40	0.06
Groundwater usage <i>ground</i> [ratio]	0.00	1.00	0.83	1.00	0.31

* Zero due to rounding.

Table 2: Summary of efficiency scores

	Obs.	Min.	Median	Mean	Max.	Std. dev.
<i>full sample</i>						
standard order- m	364	0.3394	1.0071	1.0193	2.1474	0.2345
conditional order- m	364	0.4725	1.0001	1.0017	1.2401	0.0571
<i>reduced sample after outlier detection</i>						
conditional order- m	345	0.4693	1.0000	0.9933	1.2408	0.0514
conditional DEA - vrs	345	0.3037	0.8727	0.8853	1.0000	0.1043
conditional DEA - ndrs	345	0.3037	0.8333	0.8575	1.0000	0.1048
<i>bias corrected efficiency scores after outlier detection</i>						
conditional DEA - vrs	345	0.2764	0.8571	0.8737	1.0000	0.1108
conditional DEA - ndrs	345	0.2905	0.8208	0.8465	1.0000	0.1087

Table 3: Kernel regression significance test

Variable	efficiency impact	p -value
<i>dens</i>	positive	0.000***
<i>losses</i>	weakly positive	0.675
<i>ground</i>	weakly positive	0.276

*** denotes significance at 1% level.

Table 4: Summary of potential merger gains and decomposition

	Symbol	Obs.	Min.	Median	Mean	Max.	Std. dev.	# > 1
<i>DEA-VRS</i>								
Overall gains	E^J	55	0.5065	0.8747	0.9409	2.2009	0.2501	15
Corrected gains	E^{*J}	55	0.5880	1.0589	1.1004	2.4127	0.2536	36
Learning effect	LE^J	55	0.3930	0.8613	0.8554	1.0000	0.0914	0
Harmony effect	HA^J	83	0.5586	1.0009	1.0065	1.6838	0.1328	42
<i>weighted</i>	HA_w^J	83	0.5051	1.0040	1.0300	1.7395	0.1414	45
Scale effect	SI^J	55	0.8347	1.0526	1.1193	2.5366	0.2615	38
<i>weighted</i>	SI_w^J	55	0.8413	1.0175	1.0940	2.4775	0.2506	34
<i>DEA-VRS with bias corrections</i>								
Overall gains	E_b^J	55	0.4524	0.8084	0.8696	2.2009	0.2686	10
Corrected gains	E_b^{*J}	55	0.5740	0.9553	1.0292	2.4478	0.2746	22
Learning effect	LE_b^J	55	0.3798	0.8512	0.8436	1.0000	0.0943	0
Harmony effect	HA_b^J	83	0.4534	0.9149	0.9187	1.5258	0.1261	15
<i>weighted</i>	$HA_{b,w}^J$	83	0.4589	0.9369	0.9411	1.5717	0.1332	15
Scale effect	SI_b^J	55	0.8279	1.0827	1.1505	2.5515	0.2838	43
<i>weighted</i>	$SI_{b,w}^J$	55	0.8435	1.0532	1.1244	2.5027	0.2697	39
<i>DEA-NDRS</i>								
Overall gains	E^J	83	0.3847	0.8376	0.8355	1.0901	0.1017	3
Corrected gains	E^{*J}	83	0.7985	0.9923	0.9907	1.1888	0.0884	39
Learning effect	LE^J	83	0.3832	0.8418	0.8456	1.0000	0.0947	0
Harmony effect	HA^J	83	0.8062	1.0065	1.0068	1.2190	0.0903	45
<i>weighted</i>	HA_w^J	83	0.7398	1.0135	1.0212	1.2754	0.0941	53
Scale effect	SI^J	83	0.8343	0.9999	0.9846	1.0000	0.0328	0
<i>weighted</i>	SI_w^J	83	0.8369	0.9840	0.9719	1.1256	0.0539	22
<i>DEA-NDRS with bias corrections</i>								
Overall gains	E_b^J	83	0.3797	0.7236	0.7309	1.0435	0.1083	2
Corrected gains	E_b^{*J}	83	0.7105	0.8818	0.8765	1.0789	0.0844	5
Learning effect	LE_b^J	83	0.3817	0.8293	0.8345	1.0000	0.0958	0
Harmony effect	HA_b^J	83	0.7105	0.8937	0.8982	1.0998	0.0894	15
<i>weighted</i>	$HA_{b,w}^J$	83	0.7087	0.8913	0.9107	1.1458	0.0924	12
Scale effect	SI_b^J	83	0.8324	0.9949	0.9770	1.0000	0.0397	0
<i>weighted</i>	$SI_{b,w}^J$	83	0.8274	0.9749	0.9646	1.1531	0.0576	19